ORIENTING AND PREFERENCE: AN ENQUIRY INTO THE MECHANISMS UNDERLYING EMOTIONAL DECISION MAKING

Thesis by

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ABSTRACT

The present work is an extensive investigation of the contribution of orienting behavior to preference decision making in humans. The central claim of this thesis is that gaze assists cognition in choosing preference, integrating phenomena previously demonstrated in the literature, the mere exposure effect and preferential looking, in a positive feedback loop leading to the conscious decision. In other words, the more we look at something, the more we like it, but also the more we like it, the more we look at it. This leads to the effect we observed when tracking subjects' eye-movements while they were choosing the preferred stimulus in two-alternative forced-choice tasks: the likelihood of gazing towards choice continually increased as the decision moment was approaching. We called this pattern the "gaze cascade effect" to illustrate its reinforcing nature, and we showed that it is an indispensable part of any preference decision, no matter the circumstances, as long as subjects' gaze is natural and unrestricted. We obtained the cascade effect even when the stimuli were no longer present on the screen, and the decision was based entirely on internal reconstruction. Moreover, we influenced observers' preference by manipulating their gaze, an effect that could not be accounted for by mere exposure. These results demonstrate that preference formation starts early in the visual processing stream, sharing fast reciprocal connections with simpler, somatic-based behaviors, such as orienting. As general implications, our work contradicts views of the brain as a collection of sequential modules, starting with sensation, through perceptual integration and cognitive association to emotional valence, decision making, motor preparation and motor response. Instead, it supports more recent views, which assume a multitude of parallel modules heavily interconnected and exercising influences on each other from very early on in information processing.

SUMMARY

The Introduction of this thesis addresses the concepts our work from a cognitive science, psychology and biology standpoint. Thus, we dedicate one section each to the problem of decision making, to the problem of preference formation, and to a description of the origin and role of orienting behavior in mammals. We underline past and current research progress regarding each concept and relate it to the scope of this thesis. The Introduction also presents the motivation for our work and its sources of inspiration.

The Chapters present the work towards our goal, with each chapter being a logical continuation of the previous, while keeping a significant amount of novelty. They are all organized as individual research articles, with their own abstract and introduction, so some overlap of ideas, methods or concepts may occur. However, we feel that enough originality resides in the results of each chapter and their interpretation, to allow us to consider them separate sections of this thesis. Chapter 1 describes the central finding of our work, the "gaze cascade effect," as an illustration of the contribution that orienting has to preference decision making. Also here we introduce our model for this contribution. Chapter 2 uses a new method of investigating visual perception, with subjects inspecting stimuli through a small gaze-contingent window ("peephole"). The task, choosing the preferred stimulus, is accompanied by an extended, early-onset cascade effect, which shows that orienting starts its influence very early in the visual processing, and moreover that this influence is not dependent on holistic stimulus perception. Chapter 3 generalizes the effect to more real world situations, while observers choose the preferred jewelry or watches, objects with high preference valence but little

utility value. Also, we show here that the cascade effect is present beyond the realm of two-alternative forced-choice tasks. By calculating the “gaze entropy,” we are able to speculate on general decision making strategies in a comparison task with more than 2 alternatives. Chapter 4 shows that the cascade exists and continues even if stimuli are no longer present in the visual field, a clear sign that orienting can and does act independent of stimulation, under the direct influence of the decision making structures. Chapter 5 presents a simple mathematical model of decision making, which nicely captures why preference is unique in its intrinsic link to orienting. The last chapter describes a joint eye-movement and encephalography (EEG) study that points to neural correlates of the cascade effect, and thus of the contribution of orienting to preference decisions. Event-related potential, event-related synchronization/de-synchronization analyses were performed to investigate the electrophysiological differences between preference and control tasks, and their relationship with orienting.

The last section of the thesis describes the importance of our results for the field of cognitive sciences and related disciplines, from visual science to social psychology or even marketing and advertising.

1. INTRODUCTION

1.1 The problem of decision making

The Merriam-Webster Online Dictionary defines “to decide” as (1) “to select as a course of action” and (2) “to arrive to a solution that ends uncertainty or dispute about.” One should notice that, while (1) has a larger meaning base, (2) is what we usually call decision making – the process of selecting one of at least two possible alternatives. It is semantically correct to say that some species of bacteria decide to go into spore state when the environmental conditions prevent survival otherwise, but the behavior is programmed in the organism’s genome, and there are no alternatives that can be chosen. Similarly, Aplysia withdraws its siphon when touched and there is little the snail can do otherwise. The difference is that, with repeated touches, through habituation, Aplysia “learns” and stops responding. As we progress up the evolutionary tree, we notice that complex organisms are involved in “real” decision making more than primitive ones.

However, complex organisms still display simple behaviors that only involve automated responses, albeit with more adaptability. For example, when our hand touches a stove the hand withdraws in a reflex reaction that originates in the spinal cord. There is little to be done about it, and intense cerebral control is needed to overcome the response. However, the sensation of pain is entirely epiphenomenal and most likely has a learning role. We do not need it to withdraw the hand from the noxious stimulus, but it will help us remember not to touch a stove when we see one again. This is where decision making comes into play – based on past experience, we decide not to touch the stove, unless of course the reward of touching it is larger than the damage it could inflict (for example if a precious item would be destroyed unless we remove it from the stovetop).

The responses of a complex organism are therefore not one-dimensional anymore, but they still stem from a collection of simple, automated reactions on top of which some adaptability has been added, supposedly to generate the best behavior for the organism's benefit. Of course, it is likely that only humans have the ability to reason and analyze what is beneficial for them or a third party. When a cat makes a decision, we can analyze the situation and explain why it made it, but the animal, as far as we know, does not think about it the way we do. Our account is based on what we see the cat doing and in what environment. Many times however, the information we gather by perception is incomplete and has to be complemented with knowledge about cats, the particular type of decision, and our own understanding of why that decision might be beneficial.

The same observation applies to the complex decision making in which humans are always involved. We call "objective" the decisions based on verifiable information present in the environment, with little distortion by personal interpretation and "subjective" the ones that can only be made after using personal views, experience or background. Although it is impossible to dub a decision as entirely objective or subjective, which aspect dominates is usually commonsense. For example, we can objectively decide which of two circles is larger (visual illusions excepted) or which of two sounds is louder, but which ice-cream flavor tastes better is largely a subjective judgment.

Traditionally, it was easier to study objective decisions, since the criteria on which they are made are rooted in perception and are measurable by psychophysical or electrophysiological methods. When investigating subjective decisions however, everything from motivation to criteria was debatable and many times generated counter-intuitive accounts. The most striking demonstrations included explanations for which no objective reason could be found, as in the case of the mere exposure effect. Zajonc (Zajonc 1968; Kunstwilson and Zajonc 1980) noticed that subliminal exposure to meaningless, irregular polygons rendered them more preferred in a subsequent two-alternative forced-choice comparison. Not only was there no objective reason to prefer one polygon to the other, but also there was no objective explanation for why the stimuli presented subliminally would be preferred. It was clear that subjects' preference was related to the preceding mere exposure, which later authors claimed it enhanced the polygons' "perceptual fluency" (Nakamura and Mandler, 1987). A reinterpretation of this account would say that, in the absence of any cognitive reason to choose the preferred polygon, the brain attributed the subconscious exposure as liking.

The idea of attribution of internal states to external perception is not new. As far back as 1890 James and Lange developed their "theory of emotion," which stated that emotions are cognitive interpretations of a physical state (one cries, therefore one feels sad). In the 1960's, Schacter (Schachter 1964) modified the James-Lange theory by showing that, in addition to the internal physical state, the environmental conditions will have a say in what emotion a subject is feeling. His experiments showed how the same physical state (general arousal, i.e., by adrenalin administration) could induce opposite emotional states depending on the surrounding conditions (i.e., become sad when seeing a sad movie, feel happy when surrounded by people cheering). He called this the two-stage theory of emotion: the first stage was the initiation and development of the arousal state, while the second was the subconscious attribution of the general mood in the experimental environment to the emotion. The claim that emotional experience does not make sense in the absence of bodily changes has since been expanded in several directions, the best known being the “somatic marker hypothesis” by Damasio (Damasio 1996). The key assumption of this hypothesis is that marker signals arising from bioregulatory processes influence decision making. These signals can originate in the actual somatic state (which here is not limited to the musculo-skeletal system but extends to visceral organs as well), or in the mental representation of such state, including those expressed in emotions and feelings. When conscious, these markers constitute an alarm or an incentive for a particular decision. When unconscious, they provide a bias towards a choice. In Damasio’s view, the orbitofrontal cortex is essential for the linkage between somatic states (and their representation in the somatosensory brain) and affect and cognition. We emphasize the somatic marker hypothesis here since some of the ideas of this thesis relate to it, without totally embracing it. Further experiments showed that mood changes can follow simple imitation of emotional facial expressions, leading to the claim that affect is the mere illustration of somatic changes (Zajonc 1985). These claims however remained controversial because they could not explain for example why paralyzed individuals still display normal decision making and emotion. Also, there is an extensive body of research that contradicts more the experiments used to validate the somatic marker theory, rather than the concepts of the theory (North and O'Carroll 2001; Maia and McClelland 2004). Whether correct or not, Damasio’s idea has the undeniable merit to advance the existence of a backwards connection, from body to brain, which could prove very important in understanding how the human brain works.

Regarding the brain areas involved in decision making, objective decisions were again easier to investigate. Recent studies have shown neurons in various areas encoding the necessary information for present and future decisions, such as the expected value, expected utility, reward size and reward prediction error, and even whether the reward is expected or not. Electrophysiology in monkeys usually correlated well with fMRI experiments in humans. A few results to note here – the monkey caudate nucleus neurons respond to a reliably predicted reward, but not to unexpected ones (Kawagoe, Takikawa et al. 1998); activity correlated with reward size associated with eye-movements has been found in dorso-lateral prefrontal cortex (Leon and Shadlen 1999), supplementary eye fields (Amador, Schlag-Rey et al. 2004) and superior colliculus (Ikeda and Hikosaka 2003); dopamine neurons in substantia nigra and the ventral tegmental area encode the reward prediction error (Schultz 1998); the posterior cingulate cortex seems to be involved in updating expectations (McCoy, Crowley et al. 2003); other areas involved in the above-mentioned phenomena are the orbitofrontal cortex (Berns, McClure et al. 2001), the insula (Seymour, O'Doherty et al. 2004), the amygdala (Breiter, Aharon et al. 2001) and the ventral striatum (Pagnoni, Zink et al. 2002).

As it can be seen, decision making recruits multiple brain areas, between which reciprocal extensive connections have been demonstrated. While the exact pathways subtending this complex and ubiquitous process are far from clear, we note that all the above-mentioned papers involve experiments where the reward is external (i.e., juice, money), and the objectivity of the decisions came from the assertion that subjects will act to maximize the amount of reward. While this is a reasonable assumption, much less is known about decisions whose rewards are internal (thus subjective). On the other hand, most of the studies involved a specific motor action, which was rewarded or not according to a schedule set by the experimenters – namely eye-movements. It is not fortuitous that McCoy and Platt (McCoy and Platt 2005) talk, in their excellent review, about the "mechanisms of oculomotor decision-making." We can therefore assert that *orienting behavior*, illustrated in primates by gaze direction and control, is regarded as the natural action to signify reward desirability. There are multiple reasons for this, and we will discuss them in a subsequent section.

First however, we introduce the scope of the work herein, which is to delve into the mechanism of a highly subjective but natural process, namely preference decision making. However, we are not concerned much with why we prefer a particular stimulus, an interesting question in itself but quite difficult to answer at this time without speculating. Instead, we will assume that the preferred stimulus constitutes an internal reward, and we will try to unify previous demonstrations, using ideas such as somatic markers, internal attribution and exposure to help us understand *how* we come to like something. We will build a theory in which *orienting*, this evolutionarily simple yet very efficient behavior, is a key player. Before explaining the reason for choosing it as a contributor to preference decision making, we briefly introduce another "problem."

1.2 The Problem of Preference Formation

Preference judgments are undoubtedly an integral part of our lives. The conclusion "I like that" is drawn in our heads many times in the course of a day, and it clearly influences our behavior. Moreover, deciding *who* we like impacts our social interaction, with implications in everything from mutual benefit relationships, collaboration towards a goal, to mate choice and reproductive success. However, studying preference formation is difficult, because both self-introspection and verbal report are unreliable in finding reasons for why we like something or someone. The decision is usually made without awareness of the process involved and most explanations for our choices are post-hoc, not following clear, definable criteria – hence the subjective label that liking very often receives.

Much of the recent research on preference focused on the human face, seen as the main criterion for categorizing a person as physically attractive. While popular sayings state that beauty is only skin deep, it is clear that the attractiveness of a face increases its possessor's likelihood to be liked or chosen as a mate. Many studies therefore looked for certain facial features that render a face as attractive while attempting to explain the evolutionary reason for why those features are generally preferred. Thus, it has been claimed that preference evolved to offer the individual a better chance of survival – we prefer the types of stimuli, people, circumstances, for which we have been evolutionarily selected (Little and Perrett 2002). For example, we like those physical and traits that signal immunological, genetic and mental competence, or those that correlate with likelihood of prosperity and community status. Such traits are face symmetry, uniformity of facial texture, signs of high testosterone (in men; big jaw, thick eyebrows) or estrogens (in women: small chin and nose, thin eyebrows, prominent cheekbones), height, low waist-to-hip ratio in women, all of which have been regarded as clues of past or current health status.

On the other hand, the average stimulus theory (Langlois and Roggman 1990) claims that exposure to and experience with a certain class of stimuli accumulates over lifetime, and a morphological weighted average forms in our brain as a template to which the components of the class are compared. The closer a stimulus is to this template, the more attractive it is judged as. Verified first for faces (Langlois and Roggman 1990; Rhodes, Yoshikawa et al. 2001), it has been recently extended to other classes of objects, such as cars, fish and birds (Halberstadt and Rhodes 2000; Halberstadt and Rhodes 2003). This is presumably why, over decades of face attractiveness research, both in psychophysics and classical psychology, preference has often been linked to self, kinship or with individuals of the same race: the weight of such faces in composing the template is proportional to the extensive experience we have with the persons possessing them (including ourselves). Alas, there is no direct demonstration that such a template really exists or that it is really necessary for an integrated view of preference. This is why the theory has as many opponents as proponents, with studies showing significant abatements from its predictions. For example, a study found (Cellerino 2003) that feminized versions of the average female face are considered more attractive than the prototype. However, the fact that average stimuli remain high (even if not *the* highest) on preference lists, in spite of such manipulations, underlines the undeniable merits of the theory. For the scope of this thesis, the theory is also important in its implication that attractiveness may be based on memory. To further underline the controversy in the field, we mention that there are currently two distinct explanations for why we prefer average stimuli. The “good genes account” links averageness in faces with health status, and supposes that our preference serves an adaptive purpose, but this mechanism extended to non-face objects in general. The “perceptual bias account” supposes that the preference for averageness is an emergent property of our object recognition systems, and serves no adaptive function.

Yet another line of research claims that preference is a by-product of other mechanisms that ensure our adaptability and good functioning, such as the feeling of familiarity, habituation, sensitization or the desire for novelty (Kunstwilson and Zajonc 1980; Althoff and Cohen 1999). In fact, the problem of studying preference becomes apparent when one tries to assess the relative contributions of familiarity and novelty to its formation. It is clear that sometimes we prefer familiar stimuli and other times we prefer novel ones, so it seems logical that there should be a difference between the two situations at neural, mental and behavioral levels. Nevertheless, few studies barely touch the latter, and none to date (that we know of) investigates the former situation.

Lastly, a different view asserts that we prefer stimuli that activate the reward pathways in the brain and result in higher opioid release. The stimuli are classified in terms of reward and punishment, and their valence correlates with the subjective feeling of liking. Vessel and Biederman (2002) citing previous data, even advanced the idea that opioid receptors are scattered throughout the visual system, with their concentration increasing in a downstream gradient. The underlying assumption is that higher neuronal activity results in higher opioid release and therefore a more pleasurable experience. Using natural scenes, the authors assert that novel and highly interpretable scenes are the most pleasant to watch because they generate more neural activity at higher, association levels, such as the inferotemporal cortex and beyond, where the concentration of opiate receptors is greater. Their claim is still controversial, and a possible problem is the relative neglect with which they regard the classic reward-related areas, such as the ventral tegmentum, the striatum or the cingulate cortex. In this view, the visual system acts as an independent structure relative to appetitive behaviors, a claim that does not necessarily correlate with fMRI and electrophysiology data in reward studies. The merit of this claim resides however in linking preference to hedonic value, a plausible hypothesis that is gaining ground nowadays, and supposes extensive reciprocal connections between object and face processing areas to reward structures. Several studies (Kampe, Frith et al. 2001; O'Doherty, Winston et al. 2003) could not find brain areas correlated with face attractiveness per se. Instead, they found reward-related structures (ventral striatum, orbitofrontal cortex) that become active when observers look at attractive faces displaying particular potentially rewarding characteristics, such as a direct gaze towards the observer or a smile.

While all these claims are credible and not mutually exclusive, none yet offers an integral explanation for the problem of preference formation and all have questions that remain unanswered, the biggest of which is why preference developed in the first place. We will not try to unify these accounts of *why* we prefer. Instead, we will investigate *how* we arrive to such decisions, regardless of the exact criteria used. This is an equally interesting question, since it can not only shed light on mechanisms of consciousness, but also reveal how preference formation can be manipulated, raising questions about free will, a philosophical concept of longtime concern. In principle, our endeavor could show what a subjective decision is and whether the pertaining “personal interpretation” is a high level, cognitive, associative and affective introspection, a low level, bodily-based effect, or a combination of both. In particular, we study the link between preference decision making and orienting behavior, inspired by intriguing demonstrations pointing to a possible link between them – mere exposure effect (Zajonc 1968), preferential looking (Fantz 1964), the somatic marker hypothesis (Damasio 1996) or the two-stage theory of emotion (Schachter 1964).

1.3. Orienting behavior: origin, role and involvement in preference

The most primitive form of orienting behavior is the orienting reflex (Pavlov, 1927), which is basically an innate, automated, protective reaction to novelty. It consists of refocusing of sense organs towards the new, potentially dangerous stimulus, the freeze reaction, and generates cognitive, emotional and hormonal changes in the body (Sokolov 1963). The primary role of the reflex is to quickly prepare the organism for fight-or-flight, in case of a threatening situation. It is an evolutionarily early reaction, encountered in all vertebrates in its basic form. In addition to freezing and attention focusing, mammals exhibit voluntary attentive shifts, and an arousal of emotion, expressed facially or vocally. There are explanations (Porges 1995) of how these supplementary components were incorporated in the reflex, some of them more credible than others (e.g., the observed bradycardia is derived from a primitive gustative response in vertebrates).

The orienting reflex is subtended mainly by the retino-tectal pathway, which separates early from the primary visual pathway and has fast fibers going to the superior colliculi. However, on top of this reflex, the entire orienting behavior develops in higher mammals, primates and humans. Extensive connections from the superior colliculus to premotor and motor areas, as well as the gaze-controlling frontal cortex and the brainstem nuclei are proofs that the behavior encompasses much more than the automated reaction to novelty. Since vision is the dominant modality of primates and humans, orienting is somatically represented by gaze direction and control in these species, and is the main means of gathering information about stimuli in the environment. Be it voluntary or externally induced (startle), it is clear that orienting must play a role in visual and cognitive processing. Much of the previous research, as we mentioned in section 1.1, assumes that primates gaze towards the potentially more rewarding stimuli (when no immediate threat is present), thus indirectly linking it with the reward-punishment systems in the brain. Moreover, in humans gaze has been shown to signal interest, preference or desire to collaborate (Kleinke 1986; Emery 2000). This is presumably why we evolved to be so sensitive to other's gaze direction, which can easily function as a priming cue in reaction time experiments (Friesen and Kingstone 2003). Also, in infants, Fantz (Fantz 1964) showed that longer inspection times are correlated with preference, and this observation has been used ever since in the infant psychophysics literature. We notice therefore how a relatively simple behavior provides the developmental basis for higher-level, in this case social, functions. In the same line of thought, a few authors included what they called the "orienting complex" as the first stage of the emotional experience (Gazzanigga "Cognitive Neurosciences", Chapter 78). The following stages completing the emotion were information integration, response selection and affective context attribution.

We shall note here that gaze, besides being the principal component of the orienting complex, is also the means by which information is collected for later integration. However, the main claim of our research is that gaze is an integral part of the subjective decision making process, and ultimately, of the subsequent emotional experience, by *directly* influencing not only information integration, but also response selection *and* affective attribution. Moreover, we will go as far as to propose that gaze effectively assists the brain in making preference decisions. Our endeavor was motivated, on one hand, by the evidence that orienting could have been incorporated into the preference formation mechanism similar to its inclusion in other social and emotional experiences. On the other hand, extensive research showed not only that simple exposure to stimuli may render them more attractive, but also that visual training with a subset of a class of stimuli can skew the “attractiveness template” towards the average of that subset, as it has been recently demonstrated with human faces (Rhodes, Jeffery et al. 2003). We took this question further and investigated the time course of such visual processing influence in preference decisions. And since orienting (active in this case, as opposed to automatic) is the means of exposing oneself to a certain stimulus, the scope of our research has developed into studying the behavioral and neural aspects of orienting behavior’s contribution to preference decision making.

CHAPTER 1

Gaze bias both reflects and influences preference.

Since emotions operate along the dimension of approach and aversion, it is reasonable to assume that orienting behavior is intrinsically linked to emotionally involved processes such as preference decisions. Here we reveal a gaze "cascade effect," present when observers were shown pairs of human faces with the task of deciding which face was more attractive. Their gaze was initially distributed evenly between the two stimuli, but then gradually shifted towards the face eventually chosen. There was a significantly weaker gaze bias in a geometric discrimination task. In a second series of experiments, manipulation of gaze duration, but not exposure duration alone, biased observers' decisions of preference significantly. We thus account for the effect by conferring gaze an active role in preference formation. The gaze "cascade effect" was present when participants compared unfamiliar shapes for attractiveness, suggesting that orienting and preference formation are intrinsically linked in a positive feedback loop leading to the conscious decision.

Introduction

The subject of preference formation has been extensively studied, especially in relation to human faces. On one hand, most models seem to rely on the existence of an attractiveness "template" to which the current stimulus is compared. The vague nature of this template invited numerous speculations, and studies linked it to averageness/ typicality (Leopold, O'Toole et al. 2001), resemblance to self or relatives (for faces), symmetry (Rhodes, Proffitt et al. 1998), complexity, evolutionary beneficial cues, etc. On the other hand, there are observations that link preference to processes such as perceptual facilitation (Zajonc 1968; Mandler, Nakamura et al. 1987), or gaze contact as a social interaction cue communicating interest, attractiveness or desire to collaborate (Kleinke 1986; Emery 2000).

The role of orienting behavior, best illustrated by gaze direction, in establishing exposure to a stimulus and gathering important information about its characteristics is obvious. Gazing at an object, not just a face, inevitably leads to its foveation for deeper sensory processing. In this study we investigate the role of orienting in preference formation, an endeavor partly motivated by the aforementioned demonstrations suggesting a link between them. In the main experiment, we presented observers with pairs of human faces, and asked them to choose, at their own pace, the more attractive face (“face attractiveness” tasks, see **Results**), while we monitored their eye movements.

Our results point to an active role for gazing in preference formation, both for human faces and for unfamiliar abstract shapes. We postulate the direct contribution of orienting behavior, along with the cognitive systems assessing stimulus attractiveness, to the process leading to the decision in a two-alternative forced-choice (2AFC) task. Consistent with both preferential looking in infants (Fantz 1964; Birch, Shimojo et al. 1985) and the human observer’s sensitivity to the gaze direction of the stimulus face (vonGrunau and Anston 1995), our model suggests that the adult process of preference formation is not independent of more implicit, reflexive orienting mechanisms, but rather developed from them. Another set of experiments demonstrates that biasing observers’ gaze duration, but not just exposure duration, influenced their preference (see **Results**), consistent with the interdependence claim. Our model, described in the **Discussion** section, introduces a new view on how systematically subjective decisions are formed in relation to implicit somatic processes.

Method

All images were presented on a 19-inch ViewSonic CRT screen at 1152x864-pixel resolution. The viewing distance was always 57 cm, and each stimulus (two faces side by side) had an overall size of 30 (H) x 15(V) degrees of visual angle. Two face databases were used; Ekman face database© (Ekman, P., www.paulekman.com) and the AR face database[19]. The approval of California Institute of Technology IRB Committee and informed written consent from participants were obtained for all experiments.

Gaze data analysis. Observers' eye movements were tracked with a video-based eye tracker (MediaAnalyzer©, Egner & Scheier, www.mediaanalyzer.com) at a rate of 30 samples/ second. Post experiment, to every sampling point, we assigned a true value (1) if the observer's gaze was directed towards the chosen stimulus, and a false value (0) if the gaze was on the other stimulus. Gaze data outside either face was treated as "Not-a-Number" (NaN). We aligned all trials at the moment of decision, as we were interested in whether the likelihood curve is in any way correlated with the choice made. By averaging across trials and subjects, we obtained the likelihood that the choice was inspected, at each sampling point. There was a large variance in decision latency across trials, both within and in-between observers. We chose 1.67 seconds (50 samples) prior to the decision as the starting point of analysis, since this represents approximately the mean decision latency minus one standard deviation, and thus all sampling points had average values calculated across at least 67% of all trials. Note that, in this type of data analysis, the choice, not the task, matters, so comparisons between patterns in various tasks can be made. Once the likelihood was obtained, we plotted it against time to the decision, (i.e., the key press response) and fitted it with a sigmoid function (with 4 parameters; starting level, elevation, inflection point and slope), and the degree of fit was expressed by the R^2 value. All observers were naïve to the purpose of the experiments.

Face-attractiveness-difficult task. To control for the base attractiveness of the faces in the databases, we asked observers (*n* = 12 observers for the Ekman, and *n* = 12 for the AR database) to rate all the faces from 1 (very unattractive) to 7 (very attractive). We then calculated the average rating for each face, and paired them so that the difference in the average rating was lower than or equal to 0.25 points. The faces in a pair were matched for gender and race and displayed a neutral facial expression. Nineteen face pairs were presented. Five observers were instructed to inspect the face pairs freely for as long as they wanted, then to press one of two keys (corresponding to each possible outcome) when they decided which face was more attractive (two-alternative forced-choice task). Eye movements were recorded with a Sony 8 digital camera, and converted to 30 frames/second mpeg files with a Windows™-based video editing computer software. Eye position was automatically tracked by the MediaAnalyzer© software (Media Analyzer; Egner, S. & Scheier, C., www.mediaanalyzer.com). The results were manually corrected when necessary (never more than 7% of the entire number of frames). A likelihood curve was obtained by the method described above.

Face-attractiveness-easy task. 30 pairs of faces were employed from the AR face database; otherwise the procedure was identical to that in the previous task. The only difference was that, as established by the pre-rating we performed, one face was obviously more attractive than its counterpart (rating difference >3.25, on a 1 to 7 scale). A new group of observers (*n* = 5) were asked to choose the more attractive face. A likelihood curve was obtained by the method described above.

Face-disliking task. The stimuli, the procedure, and the analysis were identical to those in the attractiveness experiments, except that the observers were asked to choose the less attractive face. A new group of observers (*n* = 5) participated. The face pairs were the same as in the face attractiveness, difficult task.

Face-roundness task. The stimuli, the procedure, and the analysis were identical to those in the previous experiments, except that the observers were asked to choose the rounder face. A new group of observers (*n* = 5) participated. The face pairs were the same as in the face attractiveness, difficult task.

Fourier-descriptor-attractiveness task. Seventeen pairs of abstract shapes were generated using a Fourier-descriptor algorithm (Sakai and Miyashita 1991). The task and the instructions were identical to those in the previous tasks. A new group of observers (*n* = 5) were asked to choose the more attractive shape. No attractiveness match was performed pre-experiment.

Two-session face attractiveness task. Nine naïve observers participated in this experiment. 40 computer generated faces (Facegen Modeller, www.facegen.com) were grouped into 20 pairs according to gender and each observer's attractiveness ratings. Eye movements were tracked with the EyeLink 2 system (SR Research, www.eyelinkinfo.com), at a sampling rate of 500 Hz. Two identical sessions with the same sequence of face pairs were performed by the same observers, with an inter-session delay of one day. The same likelihood analysis, described above, was applied to the gaze data in both sessions, and likelihood curves were generated. The last 2.5 s were included in this analysis. There were 42 trials (23.3% of 180) in which the choice was changed in the second session. Likelihood analysis was performed on those trials as well, treating them as a separate group.

Gaze manipulation. Computer generated faces were used in all conditions. Observers were first asked to rate attractiveness of 40 male faces, then 40 female faces, on a scale from 1 to 7. Pairing was performed by the computer according to each observer's rating, so that only faces with the closest ratings were paired. The faces in each pair were subsequently shown alternatively on the screen, for 900 and 300 ms, respectively, for 2, 6 or 12 repetitions. Three independent sessions with different observer groups were run for the three repetition conditions (*n* = 15 for 2 and 6 repetitions, and 13 for 12 repetitions). The observers had to effectively follow the display, shifting their gaze towards the visible face on the screen. At the end of the presentation, they had to decide which face was more attractive. The order and duration of face presentation were randomized across trials. The same experimental paradigm was repeated in a separate manipulation condition, but the faces alternated between the top and the bottom halves of the screen, instead of left/right (*n* = 14). In one control experiment (*n* = 10), the stimuli, the procedure, and the task were identical (left/right face alternation), except that the observer was asked to maintain gaze at the center of the screen throughout each trial. In another control (*n* = 10) the faces alternated in the middle of the screen, in the same location, with the same temporal sequence as the original condition. In yet another control (*n* = 10), we employed the manipulation paradigm and asked participants to choose the rounder face. All controls were performed with 6 repetitions. In all conditions, we calculated a correlation coefficient by measuring how likely observers were to prefer the face shown longer. A percentage significantly higher than 50% meant that faces presented longer were preferred.

Results

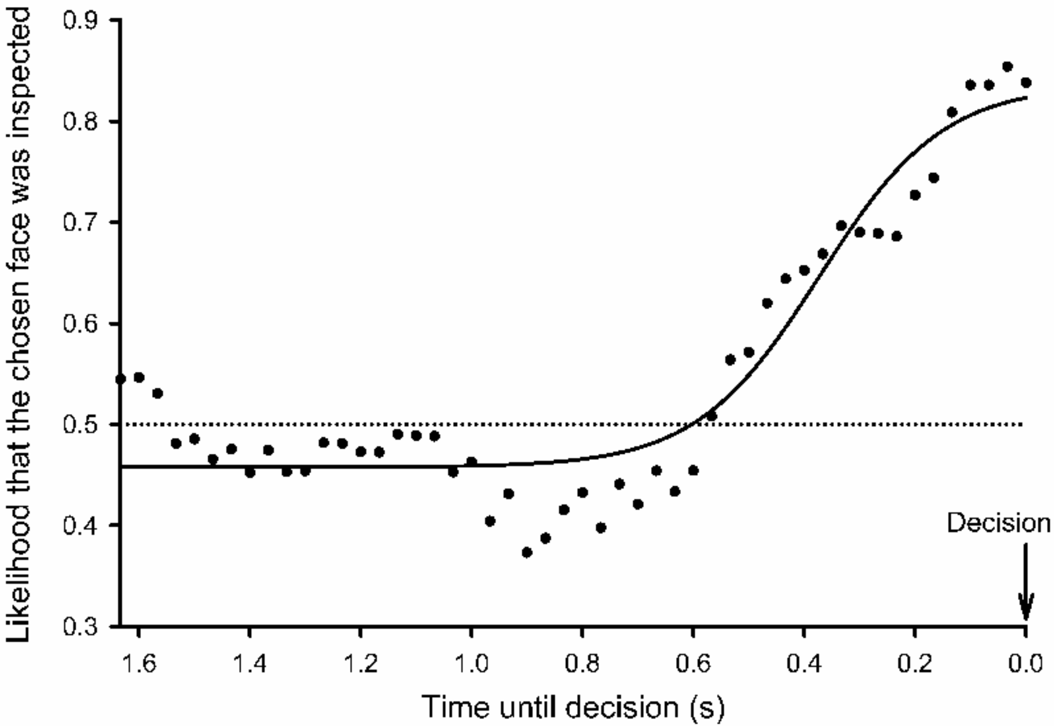
Experiment 1. Correlation and the likelihood curve

We monitored observers' gaze while they compared two stimuli on a computer monitor and made a 2AFC decision about them. The results were expressed in terms of the likelihood of gazing at the (eventually) chosen stimulus as a function of time until decision (see **Fig. 1** and **Method**).

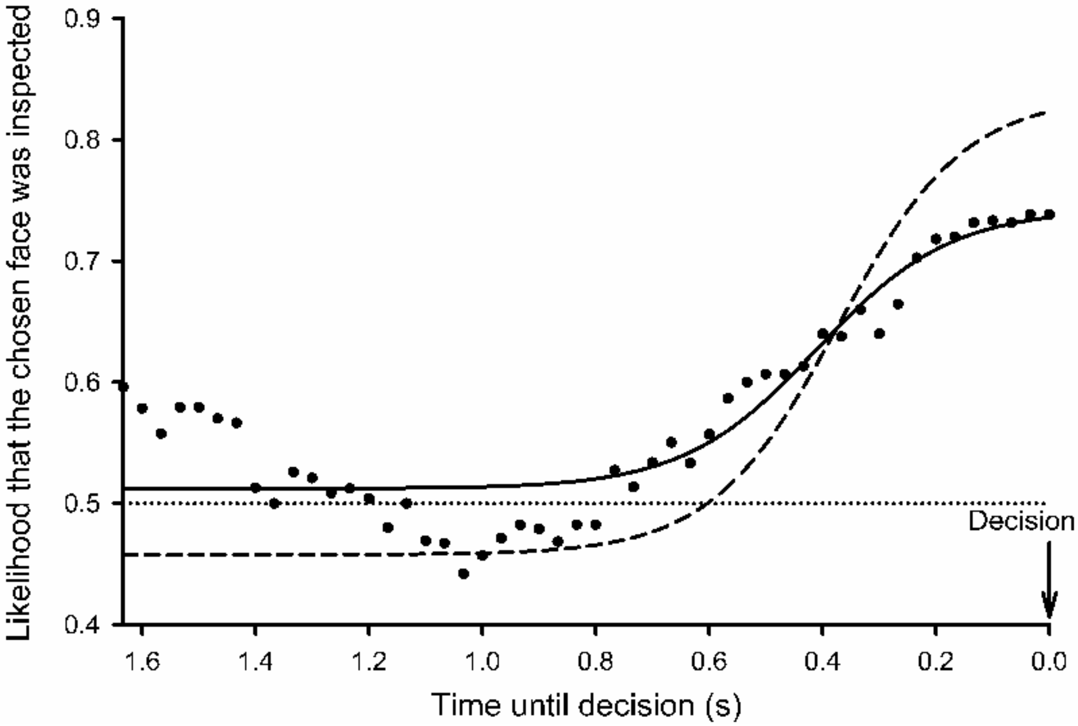
The main tasks in Experiment 1 involved attractiveness comparisons within pairs of faces. The baseline difference in the attractiveness ratings of the faces in a pair was either minimized ("Face-attractiveness-difficult task") or maximized ("Face-attractiveness-easy task"), based upon evaluation data previously collected (see **Method**).

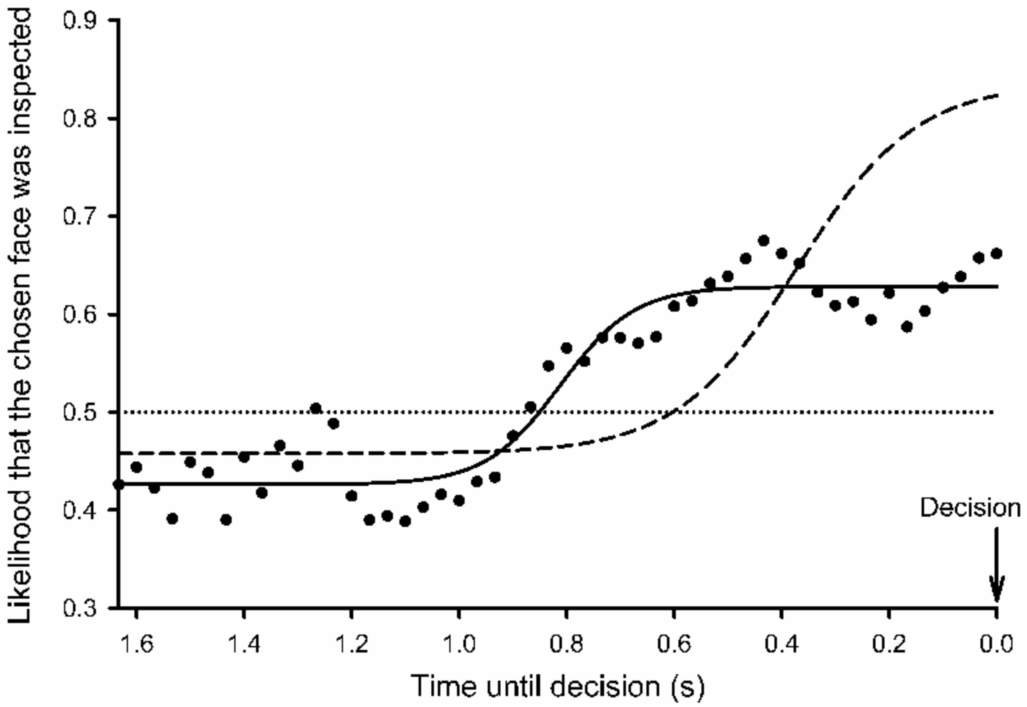
To ensure that the gazing behavior in the attractiveness tasks was not due to general factors such as selection bias (observers tend to look at their choice) or memorization of response (gazing is used to "capture" the chosen stimulus until the actual response is made), two control tasks were designed. In one task, we asked observers which face was rounder ("Face-roundness task"), and in the other, which face was *less* attractive ("Face-dislike task"). While semantically opposite, assessing stimuli as "attractive" and "not attractive" is known to involve different brain areas (Nakamura, Kawashima et al. 1998). For each of the four tasks described above we performed the gaze likelihood analysis described in **Method**. The resulting curves are presented in **Fig. 1**. Only the last 50 sampling points (1.67 s) were analyzed and are shown.

Shimojo - Figure 1a

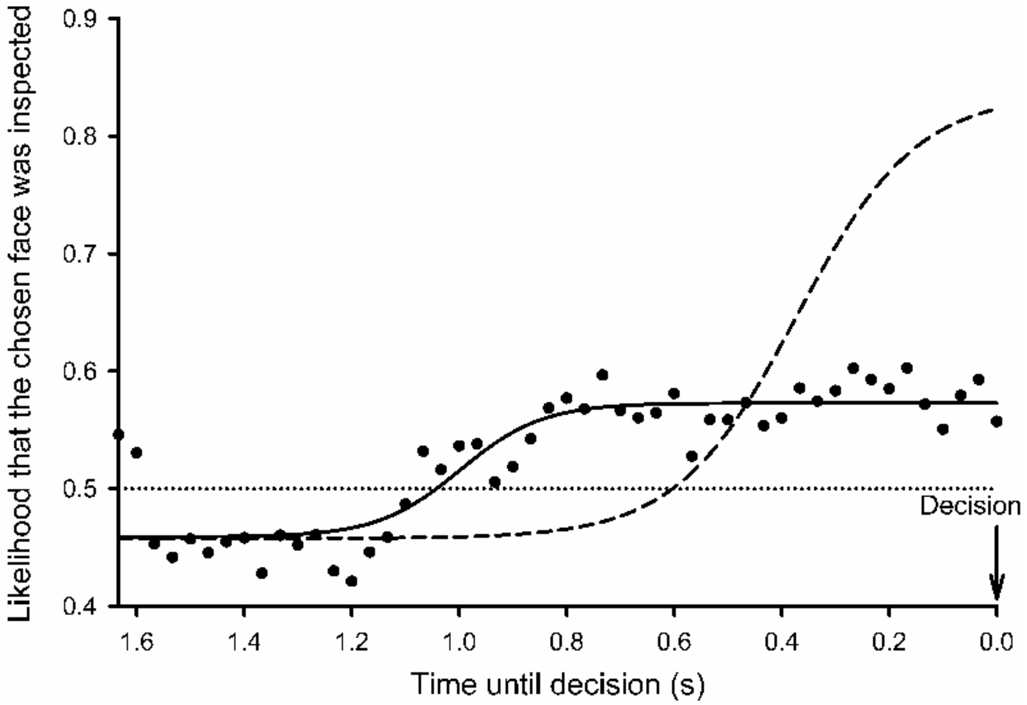


Shimojo - Figure 1b





Shimojo - Figure 1c



Shimojo - Figure 1d

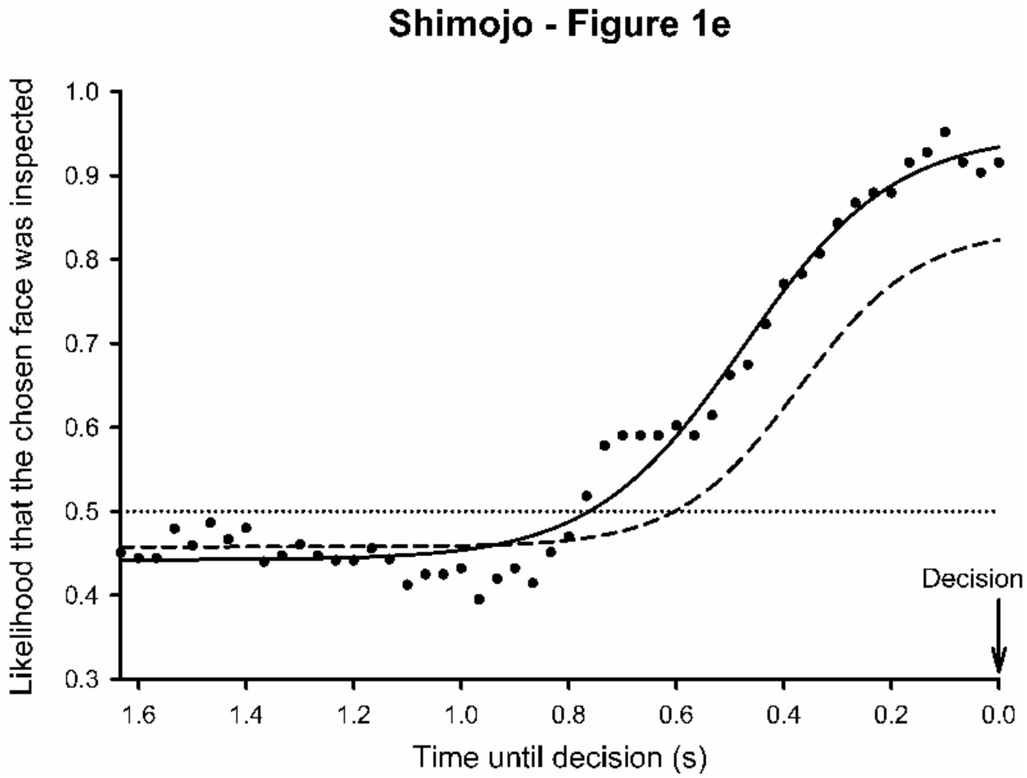


Figure 1. Results of Experiment 1. The likelihood that observer's gaze was directed towards the chosen stimulus is plotted against the time to decision in all five conditions. The data points represent the average across observers (*n* = 5 in all conditions) and trials (see **Method**). The solid lines represent the 4-parameter sigmoid regression curves; (**a**) Face-attractiveness-difficult – $R^2 = 0.91$. In panels **b**-**e**, the curve from **(a)** was replotted for effect size comparison (dotted line); (**b**) Face-attractiveness-easy – $R^2 = 0.85$; (**c**) Face-roundness – $R^2 = 0.91$; (**d**) Face-disliking – $R^2 = 0.80$; (**e**) Fourier-descriptor-attractiveness – $R^2 = 0.98$.

The first point about the curves is that, while they all start at chance level (no inspection bias early in the trial), they start rising up towards levels significantly above chance, with the largest effect in the difficult attractiveness task (up to 83%, **Fig. 1a**). The curves show a progressive bias in observers' gaze towards the chosen stimulus, irrespective of the task, with eventual saturation either before or at the point of decision. We fitted the raw data points from all tasks to 4-parameter (starting level, elevation, inflection point and slope) sigmoid curves. The R^2 values, given in the figure legends, are all above 0.8, indicating good fit. Analysis of the curve parameters led to several conclusions and hypotheses to be further tested.

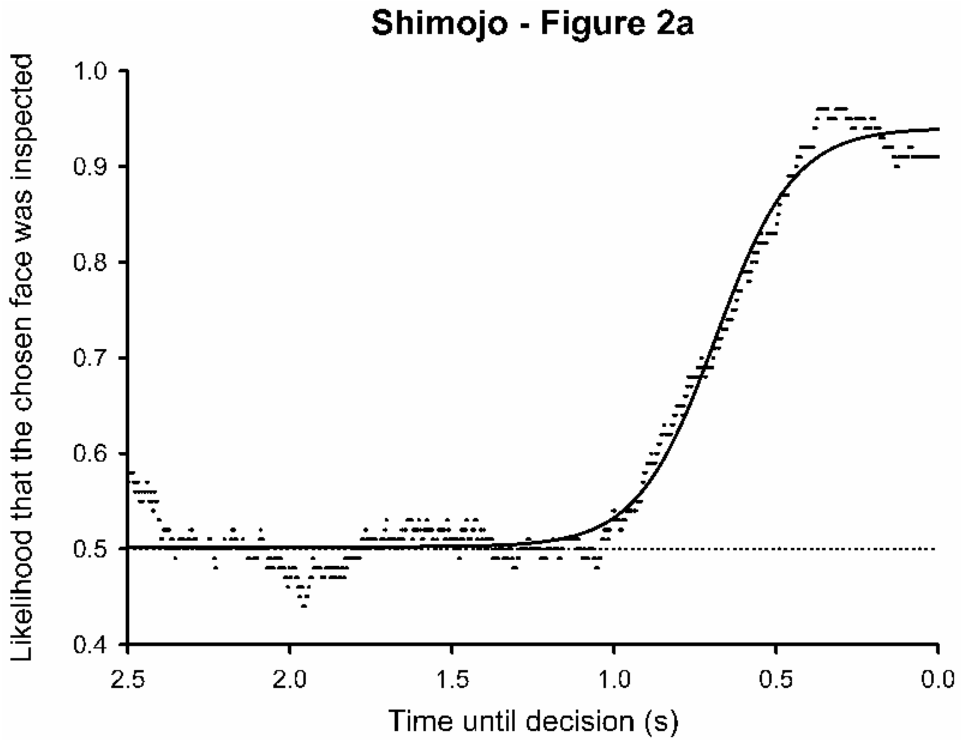
First, there was a significant difference between the heights of likelihood curves in the main tasks (involving attractiveness) and the control tasks (dislike and roundness). Pair wise Kolmogorov-Smirnov tests showed distances d = 0.52 between face-attractiveness-difficult and face-roundness ($P < 0.005$); d = 0.71 between face-attractiveness-difficult and face-disliking ($P < 0.0001$); d = 0.32 between face-attractiveness-easy and face-roundness ($P < 0.01$); d = 0.36 between face-attractiveness-easy and face-disliking ($P < 0.05$). Secondly, the curves did not reach a saturation level before decision in the main tasks (**Fig. 1 a, b**), unlike in the control tasks (**Fig 1 c, d**), suggesting that the gaze bias is continually reinforced when attractiveness comparisons are to be made. Because such a pattern can only be achieved by gradually increasing the duration of gazing at one of the stimuli, and decreasing inspection time for the other, we called this the "gaze cascade effect." Based on our findings, we propose a two-compartment model of preferential decision-making with two broad inputs of parallel information processing, one from the cognitive assessment systems and the other from the orienting behavior structures, feeding into a decision module (see details in **Discussion** and **Supplementary Material**).

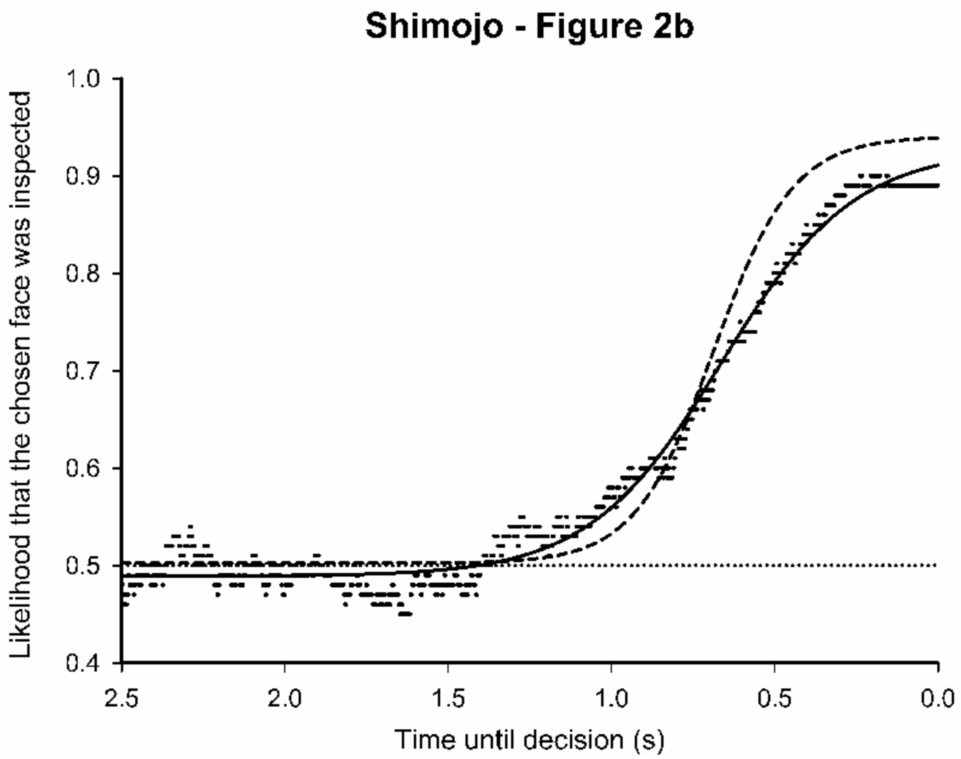
This model is also consistent with the significant difference found between the effect size in the two main tasks (attractiveness, easy vs. difficult). Comparing them (K-S d = 0.36, *P* = 0.02) shows that the gaze bias is actually larger when the faces in a pair were close in average attractiveness rating (therefore when the task was more difficult). This finding may seem especially counter-intuitive for the following reason: if the choice is more difficult, should not the observers distribute their gaze more evenly between the two stimuli, gathering as much relevant information as possible about both? This in turn would translate to a smaller gaze bias in the difficult task. However, we found the opposite result, i.e., a larger "cascade effect" in the difficult task, which is consistent with our model's prediction that when the cognitive biases are weak, gaze would contribute more to the decision making.

The "cascade effect" seen in the face attractiveness tasks might have evolved from social interaction, and thus could be absent when the stimuli were not overly familiar or natural (human faces). On the other hand, the effect could have deeper roots in basic orienting behavior, which may indeed have a longer evolutionary history. To test the generality of the effect over a class of stimuli different from human faces, we performed the same analysis while observers compared abstract shapes (Fourier-descriptor generated shapes[12]) for attractiveness.

The result is shown in **Fig. 1e**. The cascade effect exists, and is significantly stronger than the ones in any other task (K-S test for Fourier-descriptors vs. face-attractiveness-difficult d = 0.43, *P* = 0.03). This is consistent with our model, since a prior cognitive bias towards an unfamiliar object was expected to be weak in this task, and thus it had to be helped by the gaze bias to form the decision. We therefore maintain that orienting is essential particularly when the cognitive systems cannot be discriminative in making preference decisions over a range of stimuli.

Two critical questions remain before our model can be deemed feasible. The first is whether the effect we revealed accompanies preference decisions in any situation, not only when the stimuli are novel. It may be possible that the gaze cascade is necessary only for the first encounter of a particular stimulus pair, and the observer may entirely rely on memory of own past decision for later encounters. Alternatively, a sensory-motor commitment such as the gaze cascade may be always necessary when engaged in preference decisions. To test this possibility, we designed an experiment in which two identical sessions with the same sequence of face pairs (matched for attractiveness, see **Method**) were performed by the same group of observers (*n* = 9), with an inter-session delay of one day. We expected that the majority of trials would have the same two-alternative choice in both sessions. This is due not only to cognitive biases, but also to the degree of implicit and/or explicit memory of the initial choice. Interestingly, there were still 23.3% of trials (42 trials out of 180) in which the choice was reversed. We performed the likelihood analysis on the data from the two sessions as well as on only those trials that had shown reversal in decision between the sessions. The results are shown in **Fig. 2 a-c**. The "cascade effect" is present in all three cases, with the shape and magnitude expected for a difficult attractiveness task. We consider this direct evidence that the effect indeed reflects the process of decision making itself, and is not the consequence of the observers merely relying on memory, switching their preference, or making a particular decision. The second question still standing at this point is whether, in return, manipulating gaze can influence preference. Experiment 2 addresses it.





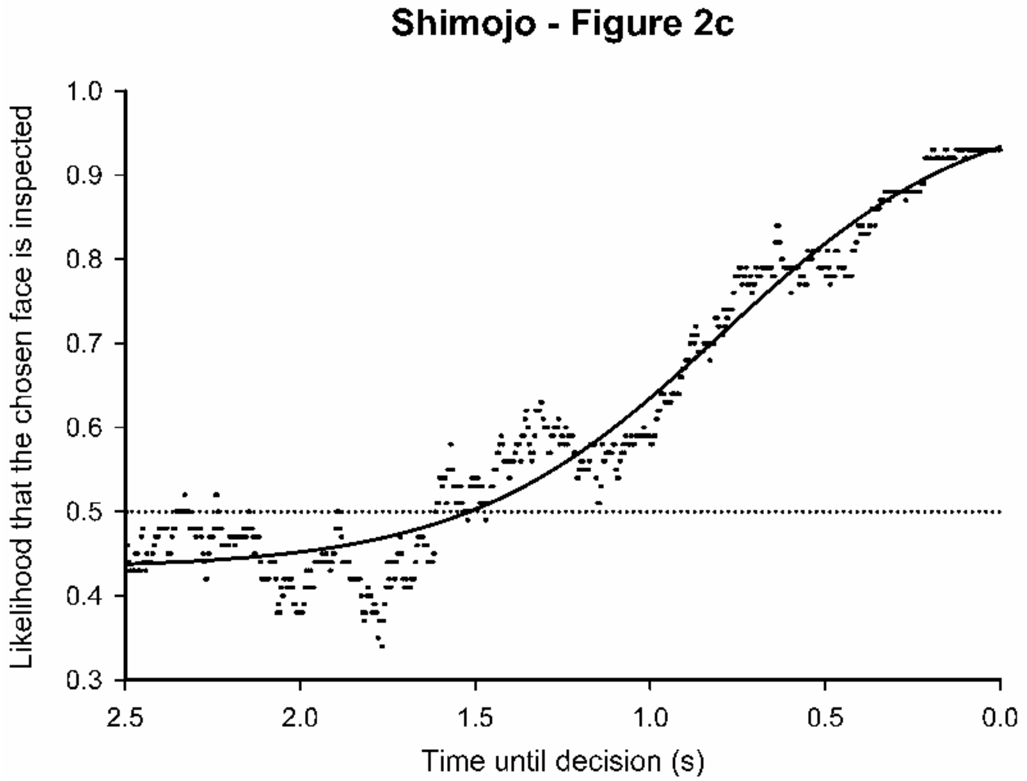


Figure 2. Results of Experiment 1, two-session condition. The likelihood that observer's gaze was directed towards choice is plotted against the time to decision. The data points represent the average across observers (*n* = 10) and trials (*N* = 20). The task was to indicate which face was more attractive and was performed twice on the same group of observers; (**a**) First session data; (**b**) Second session data, inter-session delay of one day; the curve from **a** replotted for comparison, dashed line; (**c**) Likelihood analysis across those trials in which the decision was changed from one session to the next.

Experiment 2. Gaze manipulation

For our model to be true, it must be possible to influence observers' choice in preference decisions by biasing their active gaze towards one of the stimuli. In the second experiment reported here we manipulated observers' gaze so that one face in a pair is inspected longer than the other. To ensure that observers indeed shifted their gaze and foveated one face at a time, and to avoid any effect of peripheral vision, only one face was present on the computer screen at any time, and the two stimuli alternated between the left and the right side of the screen, with different presentation durations (900 ms vs. 300 ms) for a number of repetitions (2, 6 and 12 respectively). Separate groups of naïve observers *(n* = 15, 15 and 13, respectively) participated. Because active gaze biases and exposure biases are difficult to distinguish in this experiment, we also performed two control experiments in which exposure, without orienting, was manipulated. In the first one, the same presentation sequence was used, but participants had to fixate in the middle of the screen throughout the trial. Such a condition however employed peripheral rather than foveal vision (as in the original manipulation), so a second control was run in which faces were presented alternatively in the middle of the screen. While visual stimuli were retinotopically and temporally identical to those in the original experiment, there was no gaze shift in this task.

To ascertain that a certain size or direction of the saccade is not important for a preference bias effect, we ran the same task (i.e., attractiveness) while faces alternated between the top and bottom sides of the screen. Finally, to find out whether such manipulation was specific to preference tasks, we employed the original gaze-manipulation paradigm asking participants to choose the rounder face.

The results are presented in **Table 1**. The percentage values indicate in how many cases the longer presented face was chosen in each condition. Any value significantly higher than 50% (t-test vs. chance level) was considered a preference bias effect. As it can be seen, the values are significantly above chance in the original manipulation in the case of 6 (59.0%, $P < 0.001$) and 12 repetitions (59.2%, $P < 0.005$), and in the vertical alternation experiment (60.2%, $P < 0.0001$) but not in the case of 2 repetitions or any of the control experiments. We conclude that gaze directly influences preference formation, and discuss the results in detail in the next section.

Table 1. Results of Experiment 2 (gaze manipulation). For a description of each condition, see **Method**. $P < 0.05$ denotes a preference bias significantly above 50% (chance level). The effect reaches significance only in three of the gaze manipulation conditions (indicated by *), but not in any of the control conditions. Six repetitions were run in all three control conditions and in the vertical alternation condition.

	Gaze manipulation 2 repetitions (N=15)	**Gaze manipulation 6 repetitions (N=15)**	**Gaze manipulation 12 repetitions (N=13)**	**Gaze manipulation vertical (N=15)**	**No gaze shift, central (N=10)**	**Gaze manipulation roundness (N=10)**	**No gaze shift, peripheral (N=10)**
Percent preference for longer shown face	51.2	59.0	59.2	60.2	45.8	51.8	49.8
p value t-test vs.50%	0.31	<0.001*	0.005*	<0.0001*	0.99	0.30	0.56

Discussion

In the present study, we introduce a novel method of eye movement analysis, meant to reveal trial-average gaze patterns in 2AFC tasks. Based on the likelihood that what will be chosen is inspected, the method uncovers a strong correlation between choice and inspection times, especially in the last second before decision. Moreover, in tasks involving attractiveness, the gaze bias is continually reinforced, a pattern that we call the "gaze cascade effect." Because of the earlier saturation and lower elevation in control tasks (**Fig. 1c, d**), we are ruling out as its cause memory and/or selection bias, i.e., that the final moments of gaze are allocated to the chosen stimulus merely as a means to "memorize" or "lock" the choice. While it is likely that this contributes to the effect, the large, progressive bias seen prior to attractiveness decisions cannot be solely attributed to general factors like selection, memorization or motor response. The "gaze cascade effect" illustrates the direct contribution that orienting behavior has in the preference decision making process.

In the light of our results, we propose a dual contribution model of preference formation in which two information processing inputs feed into a decision module. Naturally, the cognitive assessment systems (comparing stimulus characteristics with an attractiveness template, for example) would be one such input (see the **Supplementary Material**). The other input is based on the orienting behavior, and is directly related to the "cascade effect." The decision module would then be responsible for integrating information from these two inputs across time, and for making a choice when a certain threshold is reached. Assuming this signal-threshold comparison process dynamic and continuous, we introduce feedback to ensure the enhancement of the signal through time integration, so that a conscious decision is eventually made.

Although our model includes feedback on both pathways, it is the general belief that cognitive representations are flexible yet stable and therefore the short-term influence of feedback on the cognitive assessment input cannot be substantial. However, the contribution of gaze becomes important in preference decisions, because a gaze bias leads to increased exposure to one of the stimuli, which translates into increased preference. Preference in turn drives the gaze, thus continually reinforcing the attractiveness percept and leading to the conscious decision. Note that the unique shape of the gaze cascade curves (**Fig.1 a, b, e** and **2**) indicates that this positive feedback occurs very quickly and repeatedly within a single decision making process. Preferential looking and mere exposure meet in our model, being responsible for this loop that enhances the orienting input.

Since the reinforcement is specific to preference tasks, one would expect that the gaze bias part of the likelihood curve spans for longer in the control tasks, (which is what we found, **Fig. 1c, d**) since more time would be needed for the signal to pass the threshold. Quite surprising however is the result in the “dislike” task which, at least semantically, is related to preference. We speculate that the “dislike” decision might be based on more objective criteria, like in the roundness task, rather than obey the perceptual reinforcement by increased exposure, as in the attractiveness task. Such a difference in comparison strategies could be responsible for the lack of “cascade effect.”

As an interesting aspect of our results, when the method of gaze analysis was applied to trials aligned at the onset of the stimuli, no predictor or correlation was found in the likelihood data (not shown), indicating that the cascade effect is a late, robust, event that is directly time-locked and contributes to decision making, and not the result of an initial bias in viewing patterns. There was also no correlation between decision latency in various tasks and the size and length of the gaze "cascade" (**Table 2**), ruling out the possibility that smaller gaze biases are solely the result of shorter reaction times.

Table 2. Mean Reaction Times (RT) and their standard errors, for all free-viewing, one—session comparison tasks. For details of the experimental paradigms, see Methods. There were differences across conditions, but not in correlation with the size of the gaze cascade effect.

	Face attractiveness difficult	**Face attractiveness easy**	**Face roundness**	**Face disliking**	**Fourier descriptors attractiveness**
Mean RT ± s.e.m (seconds)	3.55 ± 0.18	3.09 ± 0.12	3.17 ± 0.13	4.63 ± 0.24	3.90 ± 0.19

Also, in the likelihood plots (**Fig. 1, a-e**), the raw data points from 200-300 ms before the start of each gaze bias appear to drop consistently below 50%. Considering the average gaze fixation duration (a few hundred ms), one can naturally expect this dip, i.e., a slight tendency to gaze more at the not-to-be-chosen stimulus before the maximum bias towards choice. The low magnitude of the dip compared with the later gaze bias renders it of little importance to the present study.

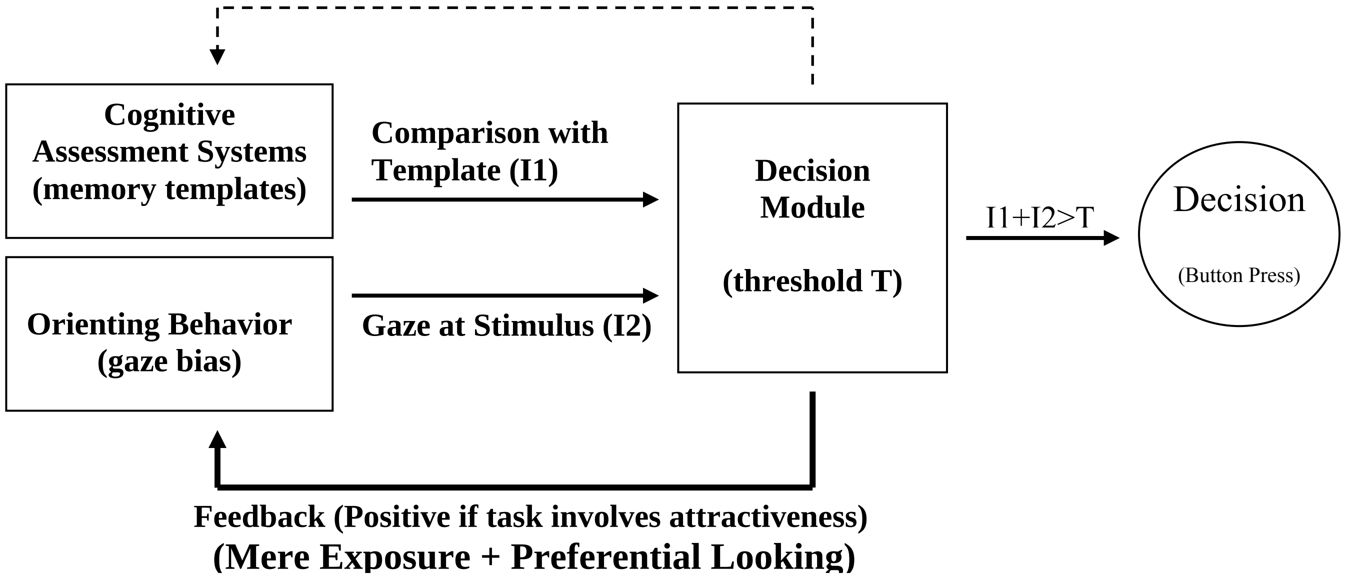
To further support our model, we show that manipulating observers' gaze durations leads to significant preference biases, an effect not explained by mere exposure or general perceptual facilitation, as seen from the results of the control experiments (**Table 1**). In fact, in the central alternation condition the effect was reversed, the shorter shown face being preferred in slightly more than 50 percent of cases. This weak tendency may be based on the habituation for stimuli that are repeatedly shown, an effect that has been known in infant psychophysics for a long time, and has been recently emphasized in adults as well (E. A. Vessel & I. Biederman, *OPAM Abstr., 2001).* Although seemingly inconsistent with the mere exposure prediction, the reversal does not alter our conclusion that orienting is necessary to bias preference. The absence of an effect in the 2-repetition task is consistent with the mere exposure literature as well as our model, suggesting that a sufficient amount of gaze bias needs to be achieved for the decision to be biased. We conclude that manipulation of gaze can directly influence preference comparisons, and that a particular size and direction of the saccades does not alter this result (as shown in the vertical presentation task, **Table 1**), supporting the existence of strong positive feedback in preference formation.

We believe that we bring converging evidence for a significant role of sensory-motor orienting in preference decisions. Our model incorporates and can explain previous demonstrations, such as preferential looking, mere exposure and perceptual facilitation. Furthermore it adds the substantial specification that the preference decision is an active, short-term process, in which the brain uses a circuit that includes the orienting behavior. Many classical psychologists believe that body states need to be interpreted cognitively for the emotional experience to happen (Schachter 1964; Laird 1974). Likewise, one's own gaze bias may be interpreted as preference at subconscious levels. The model can also account for the increased sensitivity that humans have for other’s gaze direction (Patterson 1995). If gaze participates directly in the process of preference formation, orienting towards someone may indicate interest of some kind, or even “preference in the making” for that person.

Although our model remains speculative, the gaze cascade effect itself is an entirely new finding, whose significance is further reinforced by the gaze manipulation results. Such a contribution of gaze to preference judgments opens the path for further investigation of the role of orienting in human emotional experience and judgment. While revealing the intricate relationship between preference and orienting across the consciousness threshold, the current paradigm may provide a powerful tool for exploring unknown aspects of communication in situations outside the laboratory.

Supplementary Material

Block diagram of our dual contribution model. The two inputs, I1 and I2, are integrated in the decision module and compared with a "consciousness threshold" T; when T is reached the decision is made. Feedback from the decision module into the structures from which the inputs originate enhances their respective signals. When the task involves attractiveness, the feedback becomes positive, through the interaction between exposure and preferential looking. It is this positive feedback loop that makes the critical difference in gaze between preference and other tasks. The dashed feedback line into the cognitive assessment systems illustrates the general belief that cognitive representations are flexible yet stable, thus cannot be changed significantly by short term exposure.



CHAPTER 2

Early interactions between orienting, visual sampling and decision making in facial preference

Decision making has been regarded as the last stage before action, certainly subsequent to sensory sampling and perceptual integration, in the human information processing. Our latest study showed that orienting contributes to preference decision making, by integrating preferential looking and mere exposure in a positive feedback loop leading to the conscious choice. Here we use a method of stimulus presentation that completely blocks holistic stimulus processing while preserving piecemeal perception by sampling through a gaze-contingent "peephole." This effectively zooms the visual processing in time domain, allowing us to show that orienting and preference decision making interact long before the actual overt choice. The finding also suggests that this interaction is independent of holistic properties of the stimuli and can be totally memory-driven.

Introduction

The orienting reflex is an automated redirection of attention towards an unexpected stimulus (Sokolov 1963). Developed as a novelty detection automatic mechanism (Posner, Pothbart et al. 1999), it provides the basis for the entire orienting behavior, whose component reactions are no longer automatic and whose scope goes far beyond a fight-or-flight reaction. The magnocellular pathway, along with the superior colliculi, has been implicated in the reflex. Most computational models of orienting behavior (Rucci, Edelman et al. 1999) involve the existence of a stimulus, usually in the peripheral vision, which "attracts" attention and leads to its foveation. Thus, orienting is treated as a stimulus-driven reaction, whose purpose is attention focusing on a relevant environmental stimulus, be it a threat, food or a mate. This action is viewed as necessary for information gathering, so that the best survival response is generated.

In addition, the behavior itself has recently been attributed active roles in high-level social as well as cognitive functions, such as mate selection (Hauser, Agnetta et al. 1998), recognition of emotions (Adolphs, Gosselin et al. 2005), and preference decision making (Shimojo, Simion et al. 2003). In many species, the mate selection ritual starts with orienting towards the potential partner, and in humans it is well known that gaze contact expresses interest or desire to collaborate (Kleinke 1986; Emery 2000). The long-known inability of amygdala patients to recognize fear facial expressions has been linked with defects in orienting towards the relevant eye areas of the face, suggesting that the cognitive defect is secondary to a gaze control one(Adolphs, Gosselin et al. 2005). These examples depart from the classic view that orienting strictly equals attention focusing, but there is little experimental data indicating *how* orienting can participate in higher-level mental functions.

In a past study (Shimojo, Simion et al. 2003), we showed that gaze assists the brain in making a decision, especially in preference tasks. Specifically, we noticed that, while comparing two stimuli for attractiveness, observers' increasingly biased their gaze towards the eventual choice, the closer to the conscious decision they were. Moreover, we showed that manipulating gaze can influence observers' preference. A simple model linked orienting to decision making, using phenomena well-described in the literature:

that the more we look at a stimulus, the more we like it (Zajonc 1968; Kunstwilson and Zajonc 1980), and that we tend to look more at what we like (Fantz 1964). The illustration of this positive feedback loop was the continually increasing gaze bias towards choice, that we called the “gaze cascade effect.”

Thus, orienting becomes an active part in the decision process, and is not merely a means for gathering relevant information. Such assertion would suppose fast connections between gaze control areas (Schall and Hanes 1993) and decision structures (Fellows and Farah 2003; Fellows and Farah 2005) or even face/object perception (Sigala, Gabbiani et al. 2002) and memory (Corkin 2001) areas, as well as feedback fibers updating gaze position and gathering fixation duration information. However, our past study employed only tasks in which the stimulus remained in the observers’ visual field, still tightly conditioning any orienting response to the presence of an attention grabber. It did not directly show gaze acting under the influence of higher-level areas, to complete the decision process. Moreover, since we allowed subjects to naturally choose the more attractive stimulus, the average reaction time analyzed was around 3 seconds, of which only the last second represented the gaze bias effect. Thus, assessing how early in the visual processing the orienting behavior intervenes was difficult because of possible confounds, such as selection bias and stimulus-locking by gaze.

The present study uses a new method of stimulus presentation, which prevents holistic stimulus perception, while allowing mental reconstruction by feature integration. To be more specific, we provide the subject only with a limited window ("peephole") that moves contingent with the gaze shift. The difficulty of this task enables us to zoom the decision process in time domain, reassessing, with better temporal resolution, whether gaze can contribute to preference formation while the whole stimulus is never shown, but sampling and integration of local visual information is still on-going. A positive result could be considered *direct* evidence of orienting as being embedded in the mechanism of preference decision making. Moreover, it would counter the old, information psychology textbook view of the brain as a series of modules starting with sensory processing, which unidirectionally feeds into perceptual integration, followed by cognitive interpretation, emotional valence attribution, then action preparation and execution.

Method

Pairs of images of human faces were placed on a CRT computer screen. The images were 480x480 pixel JPEG files, subtending 16x16 degrees of visual field, and were located on the horizontal midline of the computer screen and of the observers' field of view, and at equal distance left and right from the vertical midline. A blank screen was initially covering the images, with white squares clearly indicating the location of the face images underneath.

Using the on-line eye-tracking capability of EyeLink2 © (SR Research, www.eyelinkinfo.com), we created a gaze-contingent setup in which observers were revealed the portion of the underlying display that they chose to foveate. A small, circular 75 pixel diameter (2.5 degrees of visual angle) gaze-contingent window was visible at any given time. The very short delay of the Eyelink2© system (<3 ms) in transmitting data from the eye-tracking software back into the experimental setup ensured the contingency of whatever could be viewed to the observers' foveal vision.

Eleven naïve, healthy observers (Caltech undergraduate and graduate students) were run in this experiment after their written consent was obtained. They were paid $5 for the experiment. The task was to inspect both faces hidden under the blank screen and decide which one was more attractive (N=7, attractiveness task) or rounder (N=4, roundness task). The response was recorded with a corresponding button press for either the left or the right face. As mentioned, the observers could never see more than a circular 2.5 degree portion of the face image at any time, ensuring that only piecemeal perception of the stimuli could occur.

Eye-movements were tracked with the EyeLink2© system at 500 MHz, pupil reflection mode. Head movements were compensated for and we performed calibration before the experiment, as well as drift correction prior to each trial. Each experimental condition consisted of N = 30 trials. Eye movement data analysis was performed and the likelihood curve was computed as described in Shimojo, Simion et al. 2003. Since the data points contained in the likelihood curves were averages over binary values (0 and 1), we determined, for each sampling point *t*, the maximum probability value at which a coin would be considered fair with 95 percent confidence, given a number of tosses equal to the number of trials averaged at that sampling point. We called this the "significance threshold." The cascade effect was defined as that increasing part of the likelihood curve that irreversibly rose above this threshold. The time at which the bias started and the maximum likelihood just prior to the button press were considered significant parameters for comparing the effect in the two present conditions, as well as in our past experiments.

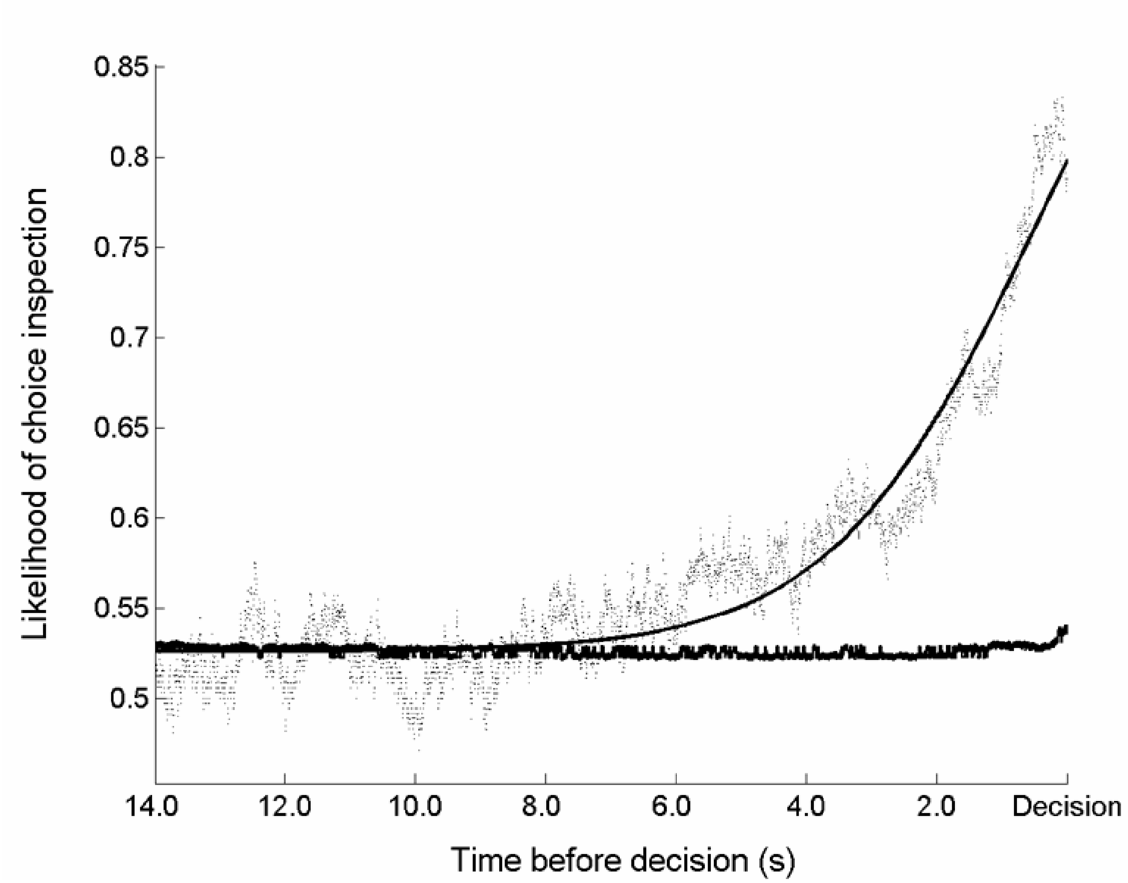
Results

The stimuli used in this study consisted of pairs of computer-generated human faces (www.facegen.com), hidden behind a blank screen. Using Eyelink2© (www.eyelinkinfo.com) we defined a small, circular gaze-contingent window through which observers could inspect the display underneath, as if looking through a "peephole." The size of the window was set so that only one feature (e.g., eye, nose, mouth, ear) of a face was visible at any point in time. Observers had to choose the more attractive face (main task) or the rounder face (control task). To complete the tasks, they had to actively move their eyes about the approximate location of the two faces, revealing a different facial feature with each fixation. This ensured that only a memory reconstruction of the faces could be achieved for comparison purposes. It is also important to note that, in this experiment, gaze is not determined by the stimulus, but rather controlled by the subject's task-dependent intention and memory. Finding no gaze bias in this task would suggest that the initial holistic matching between the face stimulus and the internal "attractiveness template" is the necessary condition for the gaze cascade to occur. An effect however would establish orienting as a necessary component of preference decisions even in the absence of stimulus-bound cues, thus entirely controlled by internal factors such as intention and memory. Additionally, the cascade's magnitude, profile and timing would reveal how early in the visual processing stream orienting and decision making interact.

Observers' gaze position was sampled at 500 Hz, and for each sampling point *t* we calculated the likelihood that gaze was directed to the face eventually chosen, as described in Shimojo, Simion et al., 2003. All trials were aligned at the moment of decision. Average decision times were 35.1±20.4s for the attractiveness task and 29.3±15.4s for the roundness task. The last 14s (approx. mean RT minus 1 standard deviation) were included in the gaze likelihood analysis. For comparison, we mention that in our previous study decision times were one order of magnitude shorter in the full-stimulus experiments (3-4s) and only the last 2.5s were included in the analysis. We view this difference between decision times as a "time lens" through which we can examine with better resolution the influence of gaze on preference formation.

To estimate the start point of a gaze bias we used a significance threshold method (see Methods). The "cascade" start point was defined as the time when the curve passed this threshold and never returned at or below it. Figure 1 shows the likelihood curves for the current study, plotted against time until decision, in the preference (A) and roundness (B) tasks. A level close to 50% means that the two faces were equally probable to be inspected. Any consistent and significant abatement above this level illustrates a gaze bias towards choice. The curves are the average of N = 7 (A) or N = 4 (B) subjects over n = 30 trials each.

(A)



(B)

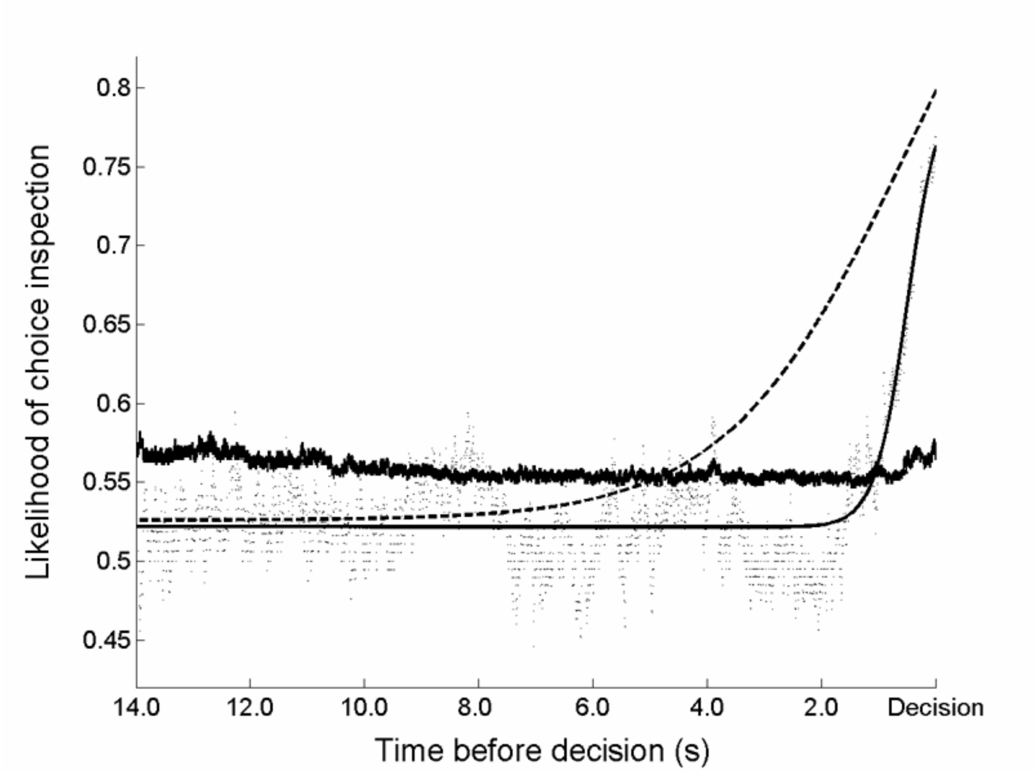


Figure 1. The likelihood that observers' gaze was directed towards the eventual choice is plotted against time before decision, in the attractiveness (A) and roundness (B) tasks. The last 14 seconds of each trial were analyzed. The solid lines represent the 4-parameter sigmoid fits of the raw-data (dots). The sigmoid fit from (A) is replotted in B (dashed line) for comparison. The corresponding significance thresholds for each task are also plotted, and are variable across time bins because of changes in sample size due to blinks, saccades or trials shorter than 14 seconds.

As predicted by our claim that orienting contributes to preference decision making, a “gaze cascade effect” occurs in the preference task. While the magnitude (maximum height 84%) is comparable with the ones in the full-stimulus tasks, the duration of the effect stands out when a gaze-contingent window is used. The curve starts to significantly depart from the 50% zone with around 7.5 s before decision, much earlier than the 800-1200 ms we computed in our original demonstration. In contrast, in the roundness task the gaze bias starts less than 1s before decision and its amplitude is significantly smaller (75%). The Kolmogorov-Smirnov test confirmed that the two curves are significantly different ($d_{KS} = 2.89$, $p<0.0001$).

Discussion

We found a gaze cascade effect in the gaze-contingent "peephole" experiment. The mere existence of the effect in the preference task demonstrates that the gaze bias accompanies such judgment, even when there is no initial holistic perception of the stimuli, thus the preference decision had to be made relying on constructed internal representation. Notable in the result, reflecting this special condition, is that the entire effect was elongated in time domain, with its onset more than 7 seconds before decision. The result is not consistent with alternative possibilities, which would predict either a much shorter (<1s) onset of the gaze cascade if gaze was merely a “memory-locking device” for the choice, or no cascade at all, if the holistic stimulus perception was a necessary condition for the gaze bias.

The result of the “round task” (Figure 1B) is also interesting from a few standpoints. As expected, we did not find an effect of the same length and magnitude as in the preference task. The curve does not depart from the 50% level until 800ms before decision, after which it raises sharply and continually to 75%. While these features make the curve similar to the gaze bias curves obtained in similar control tasks with full presentation of face stimuli in our previous study (Shimojo, Simion et al. 2003), they make a stark contrast with the 7.5 s development of the gaze cascade in the current main task, i.e., preference through the "peephole", particularly considering that the stimuli (face pairs), the response (button press), and the analysis were identical. This result most likely indicates that the observers gather local information and construct a more-or-less holistic internal representations of both stimuli first, inspecting equally both faces until one second before the decision. After reconstructing the outline of the two faces, the conscious, *objective* decision still has to be helped by a short duration gaze bias to complete the cognitive assessment. Note again that this scenario applies only to the control (roundness) task. The important distinction is that the gaze bias seems to not drive, but merely follow a comparison based on stimulus-bound properties in the case of the roundness control. This adds to our earlier evidence that choosing what we like is unique relative to other tasks in its intrinsic dependency to orienting.

Our present study introduces in our paradigm a new method of investigating human perception, in the total absence of peripheral vision. The lack of global information makes inspection through a small gaze-contingent window very difficult, especially with faces, traditionally known as holistic stimuli. However, this effectively acts as a temporal zoom lens allowing us to reveal through psychophysics the time course of the interactions between orienting, visual processing and decision making. A crucial observation about the reported setup is that the orienting behavior had to be guided internally rather than by stimulus properties. Nevertheless, the gaze bias, continually reinforced through positive feedback, drives the preference decision to completion in an even more dramatic manner than it did in the previous, full-stimulus tasks. It is in particular noteworthy that our subjects could have done the preference task the same way as the roundness task, but they did not. Instead, while the brain was still recruiting local information across fixations, the gaze cascade had already started and was developing. Based on the qualitative similarity of the gaze bias dynamics, except for the onset timing, we speculate that essentially the same interaction happens in the ordinary observation conditions, but the short decision times make its illustration more difficult. The results presented herein form in our view stronger evidence that the gaze is *intrinsically involved* in preference decision making. Lastly, the long duration of the effect (7.5 s) excludes the possibility that subjects made their decision prior to the gaze bias, which merely followed it because then the gaze cascade should be better time-locked to the response. Although already unlikely due to extensive evidence, this was still a potential confound in our original demonstration[5] due to the relatively short (~1 s) duration of the cascade in preference tasks with fully visible stimuli. The current finding effectively excludes this possibility.

As for more general implications, the present work puts orienting in the category of active, self-sustaining behaviors, which can be incorporated in more complex and dynamic processes, and weakens classical views, which condition orienting to the presence of attention grabbers in the environment. Our results are also highly inconsistent with the traditional sequential box model of cognition, but supports recent, parallel and dynamic models of the brain, in which sensory experience and higher-level brain functions such as emotional valence or decision making share fast reciprocal connections, continually influencing each other from very early on in the perceptual processing.

CHAPTER 3

Extending the gaze cascade effect: contributions of orienting to preference decision making in real-world situations.

We revealed (Shimojo, Simion et al. 2003) a continually increasing gaze bias towards the eventual choice in two-alternative forced-choice tasks, which we called the "gaze cascade effect," and we showed that it specifically accompanied attractiveness comparison decisions. We interpreted the bias as illustrating the contribution that orienting has to preference formation. A possible criticism of our claim could be that our study has limited applicability in the real world, since it used very specific classes of stimuli – human faces and abstract, non-natural shapes – and a strictly two-alternative forced-choice approach. Here we extend the validity of our previous results in two directions. First, we replicate entirely the "gaze cascade effect" as a prerequisite of a preference decision using commercially available objects such as rings and wristwatches. We also show that an objective (contrast discrimination) task is not accompanied by a similar gaze behavior. Second, we use a four-alternative forced-choice setup to show that a multiple comparison task is reducible, in principle, to a two-alternative task and also has a cascade effect as a prerequisite. Together, these results show that orienting participates in preference decision making in real-world situations.

Introduction

Fantz (Fantz 1964) described the phenomenon of preferential looking as the innate tendency of humans to look longer at stimuli they find pleasing. Since then, the assumption that infants like what they inspect longer has been central to the field of developmental psychology, and it became common knowledge that we look at what we like. On the other hand, work by other authors (Zajonc 1968; Kunstwilson and Zajonc 1980; Murphy and Zajonc 1993) showed that humans are more likely to prefer what they were exposed to, a "mere exposure effect" that works even in the absence of conscious perception. Its most common explanation is based on "perceptual fluency" – exposure facilitates internal access to the stimulus, which in turn becomes the choice in a subsequent two-alternative forced-choice preference task (Mandler, Nakamura et al. 1987). In summary, we also like what we look at. How can we reconcile these two apparently opposing observations about preference?

We proposed (Shimojo, Simion et al. 2003) a model in which the above phenomena are an integral part of the mechanism of preference decision making. In fact, since we like what we look at and in turn we look at what we like, we envisioned them interacting in a positive feedback loop that leads to the conscious decision. The important distinction in our description of voluntary, natural preference choosing was the involvement of active orienting behavior (gaze). If we postulate that humans use their gaze to "generate exposure" to a stimulus, then add the positive feedback assumption, it follows that a small initial bias in inspection times will rapidly evolve in a large bias towards the eventual choice before the decision is made. This is exactly what we found in two-alternative forced-choice preference tasks. The likelihood that the observers' gaze was directed at the eventual choice started at a “neutral level” of 50% and increased to as much as 94% in the last 800-1200 ms of the decision. We called this phenomenon the “gaze cascade effect” and we claimed it is the somatic illustration of the internal mechanism of preference decision making.

Our conclusions, although backed by strong evidence (Chapter 1) and replicated even in the absence of peripheral vision (Chapter 2), followed experiments that involved special stimuli (faces or abstract, mathematically generated 2-D shapes) and a strict setup (two-alternative forced-choice tasks). The present work extends our investigation to the more complex preference decisions we may make outside the laboratory. First, we chose to test whether the “cascade effect” is present when the stimuli to be compared for attractiveness were not faces, but familiar objects with enough complexity so that a preference decision can be made. We opted for pictures of rings and watches, commercial objects with limited utility but large preference valence. For simplicity, we maintained the 2AFC set-up for this experiment (see Results). Second, since every moment we are bombarded with visual stimuli, often preference is based on multiple object comparisons. It can be argued that a two-alternative forced-choice setup does not reflect the natural process of decision making. However, it is difficult to replicate the natural environment in a psychophysics experiment without introducing uncontrollable variables. Thus, in a second experiment, we used a four-alternative forced-choice (4AFC) setup to investigate the contribution of orienting behavior to preference decisions based on multiple stimulus comparisons. Additionally, the results obtained were used to assess whether a 4AFC task is reducible, behaviorally, to the previously used 2AFC task.

While still different from natural settings, both experiments bring us closer to finding out whether the same cascade effect applies in "real world" situations. The principal measure was the likelihood that gaze was directed towards the eventual choice, with several distinctions applying to the second experiment: there are now three "non-choice" stimuli, which can be treated either together or separately, and the starting "unbiased level" is 25% instead of 50%. If our claims still stand, the gaze cascade effect should occur in these experiments as well, illustrating the definite contribution of orienting to everyday preference decisions. Moreover, analysis of the effect parameters could further shed light on the mechanism involved in preference formation in humans.

Method

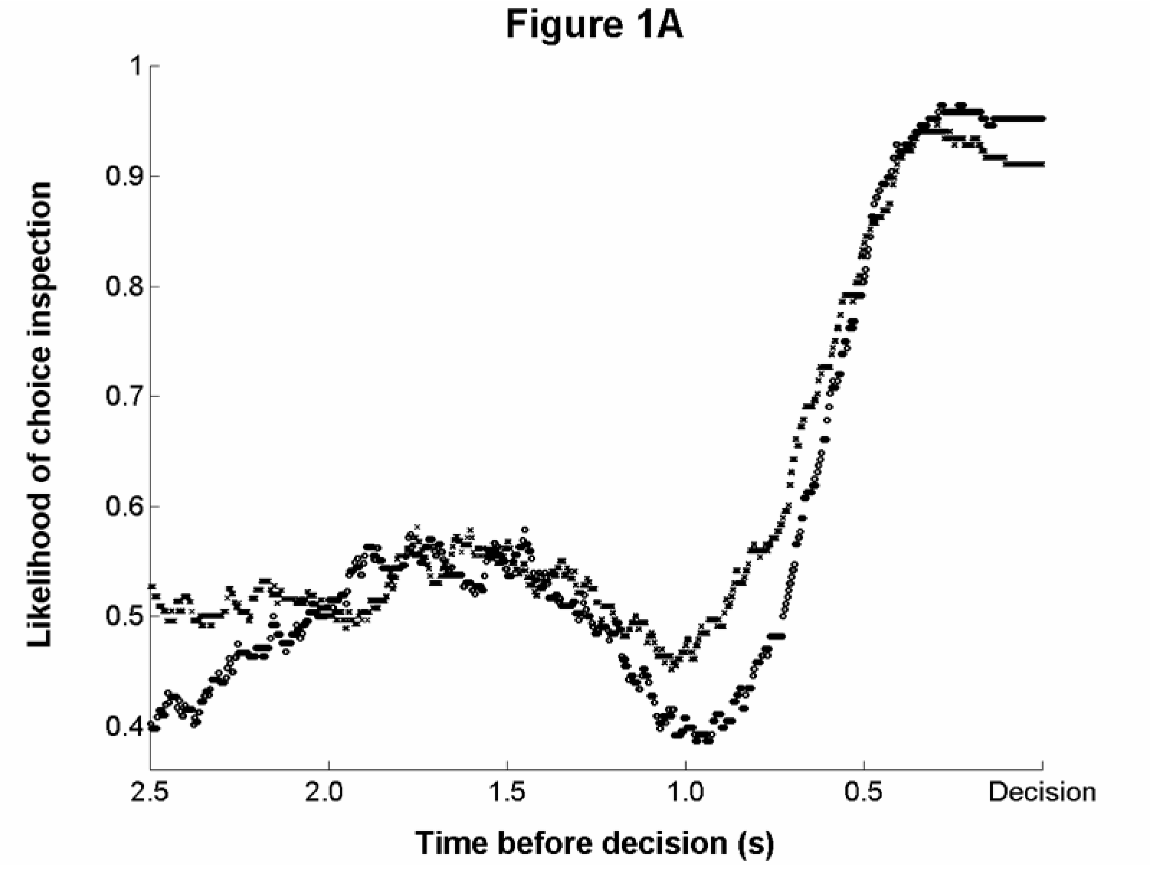
Observers (N = 8) were presented with n = 20 sets of four computer generated human faces (FaceGen software, www.facegen.com) on a CRT computer screen, after their informed written consent was obtained. Faces were displayed in the four quadrants of the screen, symmetrical with respect to the center of the screen. Each picture was a 400 x 400 pixel jpeg file, subtending approx. 13.3 x 13.3 degrees of visual angle. Pre-experiment rating ensured that faces with identical or similar attractiveness rating were included in the same set of four. Observers were instructed to fixate a central dot for 500 ms, after which the face set was displayed. The task was to freely inspect the four faces for as long as it was necessary to indicate the most attractive in a set. Eye movements were recorded at 500 Hz using the EyeLink 2 (SR Research, www.eyelinkinfo.com) eye-tracker and software. Gaze likelihood analysis was performed as described in Shimojo, Simion et al., 2003. The last 3.5 seconds before decision were analyzed because the figure represents the mean RT minus one standard deviation, ensuring an average across at least 67 percent of all trials at any point in time (on the abscissa). As a distinction from Shimojo, Simion et al., for the calculation of entropy, the correlation of gaze was performed not with the chosen face, but with each of four categories: (a) the least inspected face in every trial; (b) the second least inspected face; (c) the second most inspected face; (d) the most inspected face in every trial. Four likelihood vectors resulted and we performed the operation $\Sigma - p_i \log_2 p_i$ ($i = 1$ to 4) to compute the gaze entropy vector H. To calculate the alternative likelihood curves, instead of assigning a value of 1 when gaze was directed at the eventually chosen face (Figure 1, see Shimojo, Simion et al., 2003), we assigned 1 when gaze was directed *either* at choice *or* the most inspected face (Figure 4) and *either* at choice *or* the least inspected face (Figure 5) in every trial.

Results

Experiment 1 – Commercial objects

Subjects were presented with pairs of objects from the same category and were asked to make either a preference (which ring/watch is more attractive) or an objective (which object has higher luminance contrast) choice. We tracked their eye movements with EyeLink 2 © (SR Research, www.eyelinkinfo.com), and performed our usual gaze likelihood analysis(Shimojo, Simion et al. 2003). Namely, at each point in time, sampled at 500 Hz, we computed the likelihood that the subject's gaze was directed towards the eventual choice, by averaging across all trials (n = 56) and subjects (N = 6 for the attractiveness task, N = 4 for the objective task). We aligned all trials to the moment of decision to reveal any indicator of the decision process in the gaze pattern. Any portion of the likelihood curve significantly higher than 50% represented a bias towards the eventual choice. A cascade effect was defined as a continuous, non-saturating increase in the gaze bias, from the even inspection level (50%) to at least 75%. While the threshold is chosen arbitrarily, it is significantly smaller than what we found in previous preference tasks.

The likelihood curves are shown in Figure 1. There was no significant difference (Kolmogorov-Smirnov test) between the curves seen with rings and watches (Figure 1A) in either task, so we grouped them together and compared the results in the two conditions (Figure 1B). The cascade effect accompanied the preference decision but not the objective decision, which was accompanied by a saturating gaze bias, as in other control tasks (Shimojo, Simion et al. 2003). The Kolmogorov-Smirnov test confirmed that the curves are significantly different ($d = 0.36$, $P < 0.0001$). This result extends the generality and robustness of our model of preference formation in the realm of non-face, commercially-available objects. All the goodness-of-fit parameters, i.e., R^2, are above 0.9.



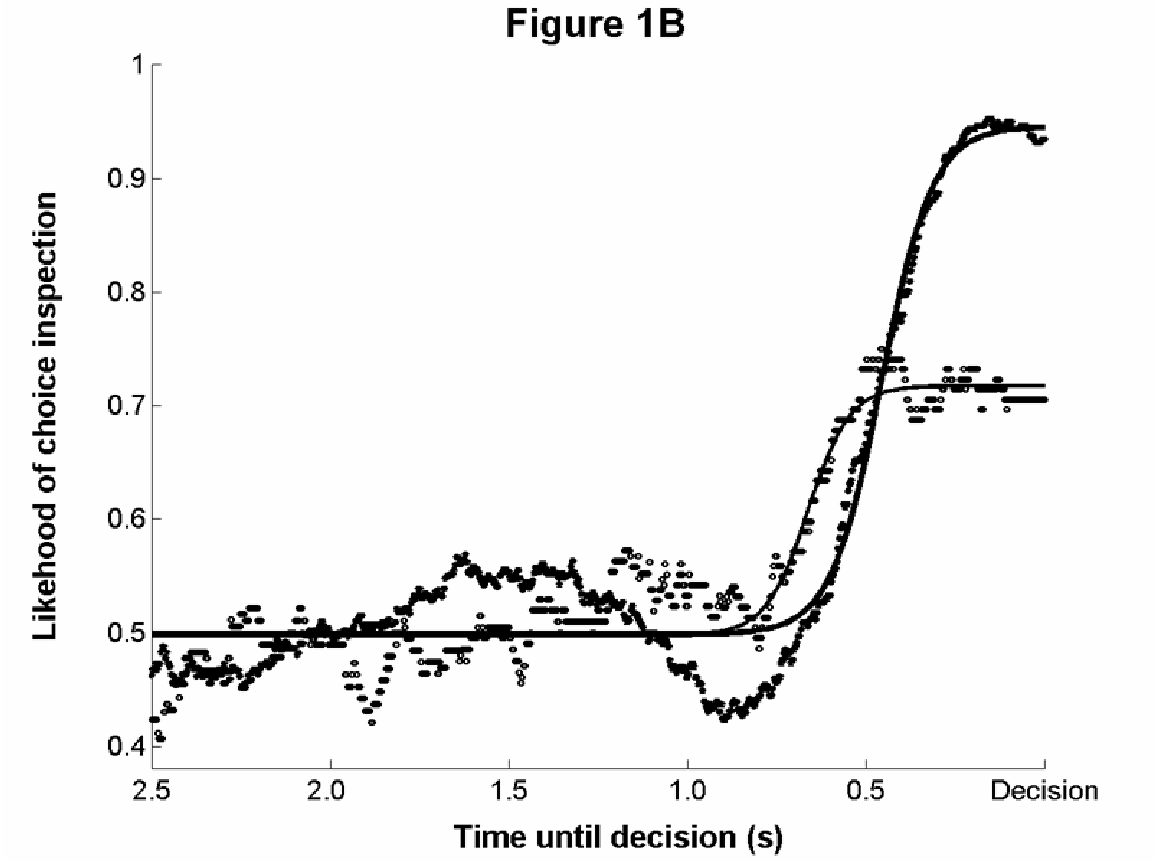


Figure 1. The gaze likelihood curves for the commercial objects 2 AFC task. A) the gaze likelihood curves for rings (x) and watches (o). Curves are not significantly different so they were pooled together. B) Gaze likelihood curves in the preference (x) and objective (o) tasks. Data was pooled across both categories of objects (rings and watches).

Experiment 2 – 4 AFC tasks

As in most of our past work, we used human faces as stimuli for their large valence in preference domain. Expectedly, the 4AFC task proved more difficult, with mean decision time 9.1s ± 5.6s (compared to the 3.5 – 4.5s range obtained in our 2AFC studies). We performed the gaze likelihood analysis described in Shimojo, Simion et al., 2003, with a few variations suitable for the new experimental setup. First, we assigned the value 1 to any time point when gaze was directed at choice, and 0 when directed at any the 3 not chosen faces. The resulting likelihood curve was obtained by aligning all trials at the decision point and averaging across trials (n = 20) and subjects (N = 8, Figure 2). Notably, an increasing gaze bias starts near the "neutral level" of 25% with 1 second before decision and progresses to a maximum value of 37.6%, in the shape and duration (1200 ms) of the cascade effect demonstrated in 2AFC tasks. As before, only the last 3500 ms (mean RT minus one standard deviation) were included in the analysis. The sigmoid fit ($R^2 = 0.7$) reveals a somewhat noisier curve, but overall the gaze cascade is present. A detailed discussion about the parameters of the effect and their implications follows in the next section.

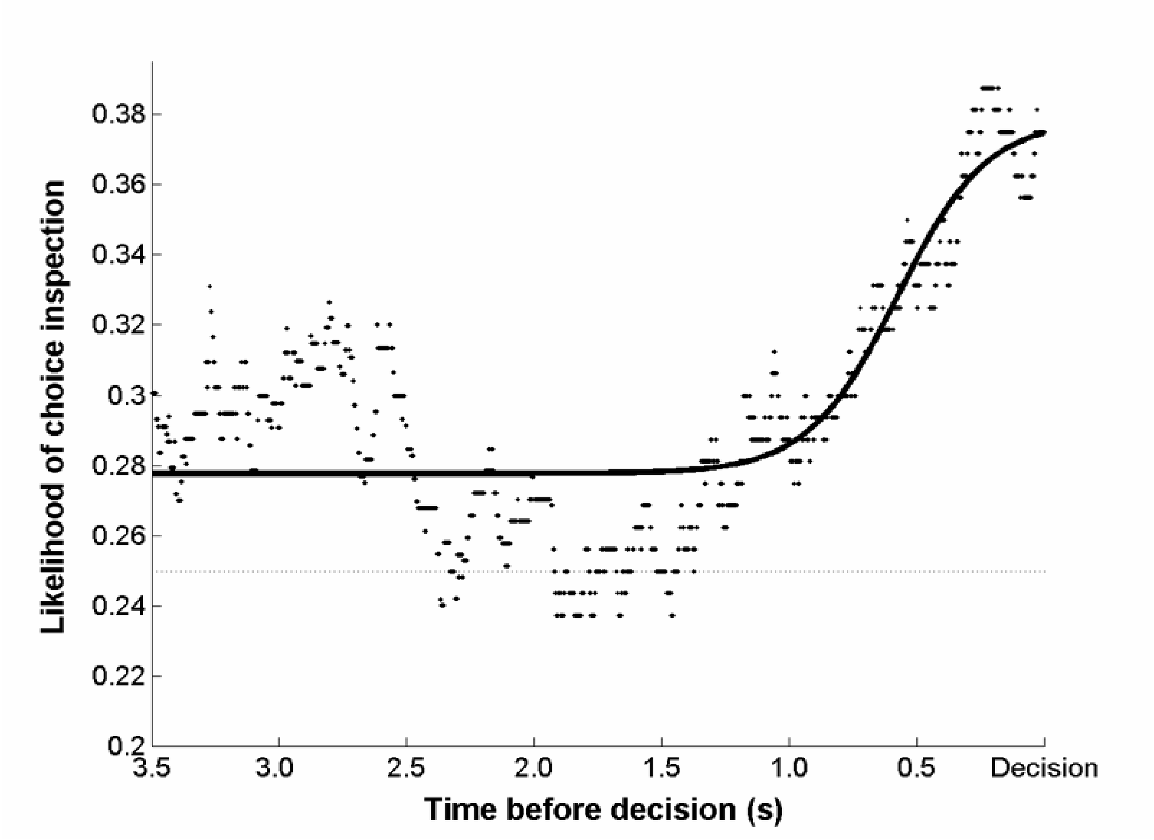


Figure 2. Gaze likelihood curve in the four-alternative forced-choice task. Notice the chance level at 25 percent. The flat portion of the curve, before the cascade effect, is not significantly different from chance.

The results go further than confirming the validity of our model in 4AFC tasks. A deeper look into the data could answer intriguing questions about the selection process in such tasks. On one hand, the decision could come by "eliminating" stimuli one by one until the choice is made. Conversely, any 4AFC decision could ultimately be reduced to two alternatives by an initial inspection and rapid elimination of all but 2 stimuli to choose from. Such a strategy would justify the use of simple 2AFC tasks to investigate mechanisms of decision making. Since we established an intrinsic link between orienting and preference, we designed a new method of analyzing the gaze patterns to investigate the issue mentioned above. The four faces in each trial can be rank-ordered according to the proportion of decision time allocated to them. We can then perform four separate gaze likelihood analyses to calculate, at each point in time, the probability that gaze was directed at (a) the least inspected face, (b) the second least gazed at face, (c) the second most looked at face and (d) the longest inspected face. Naturally, adding these four vectors should result in the unity vector. However, computing the "entropy" of gaze across time can reveal observers' decision strategies. We define entropy as:

$$H = \Sigma - p_i \log_2 p_{i,} \tag{1}$$

where p_i (i from 1 to 4) are the likelihood measures described above. H is thus bound by 2, when the gaze is distributed evenly (all p's equal 0.25), and by 0 when the gaze is highly biased towards one stimulus (one p approaches 1 and the other three are close to zero). If gaze is equally distributed between three stimuli, H = 1.58, and if only two are inspected, H = 1. We computed the entropy vector and plotted it against time until decision in Figure 3. As a first observation, the early portion of the curve is close to the maximum value of 2, suggesting that observers adopt an even inspection strategy in the beginning of the decision process. This suddenly changes in the last 1200 ms, which coincides with the cascade effect revealed in this task. The entropy H has a sharp drop to a value closer to 1, suggesting that the final choice is probably made after eliminating two stimuli. The curve in Figure 3 shows a very short plateau around 1.6 with 800 – 1000 ms before decision, indicative of a possible three alternative phase. However, the long lasting period of near-maximum entropy indicate that the elimination of two least preferred stimuli occurs simultaneously, late in the process.

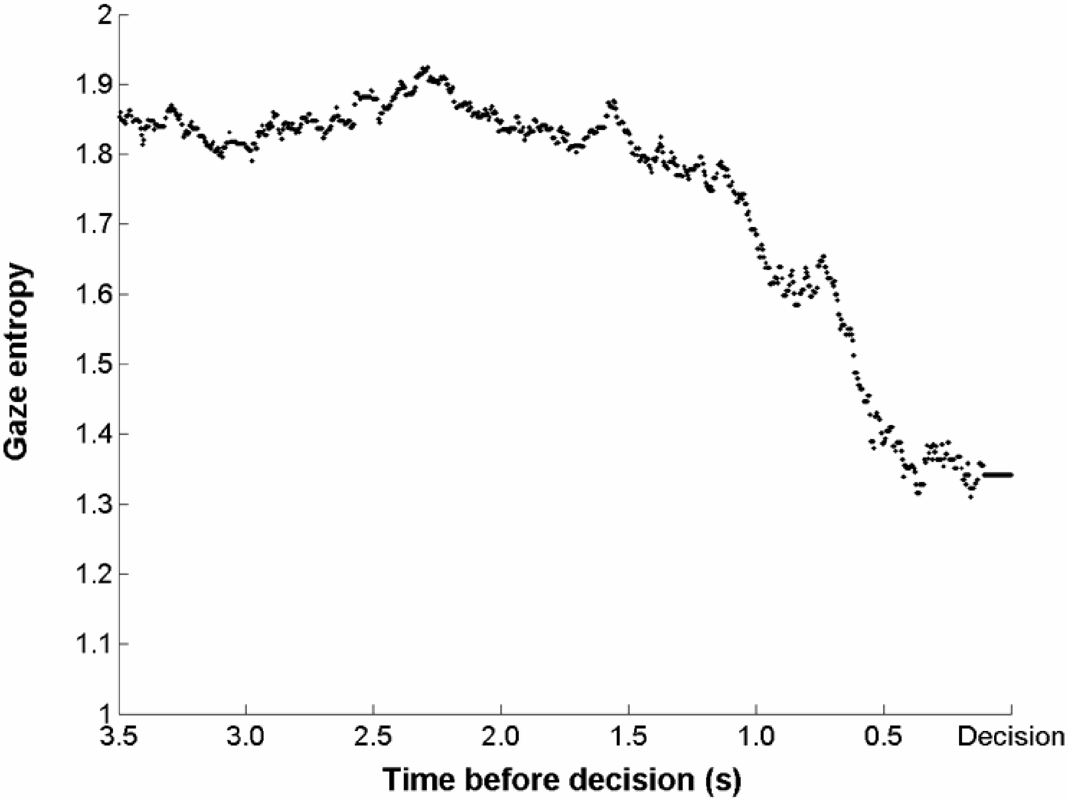


Figure 3. Gaze entropy in the four-alternative forced choice task. A value close to 2 indicates equal inspection of all 4 stimuli. In the last second before decision the entropy drops towards a value around 1.3, which demonstrates strong bias towards 2 of the 4 alternatives. The drop coincides with the cascade effect, starting 1.2 seconds before decision.

Although in the last 1200 ms before decision observers' gaze is significantly biased towards choice, as the likelihood curve shows, the eventually chosen face was inspected the longest only in 61 of 160 trials, with no significant variations among subjects. Assuming that most of the time the faces inspected longer are considered for decision, we could analyze the data by grouping the most inspected non-choice face and the chosen face together to confirm that the likelihood curve (Figure 4) mimics the one found in 2AFC tasks. As expected the baseline of the cascade effect was elevated in this illustration, since we a priori analyzed the gaze pattern with respect with the faces inspected longer. Such an effect was not general to the grouping of the chosen face with any of the others, because when we grouped the chosen face with the least inspected non-choice face a cascade effect was not found (Figure 5).

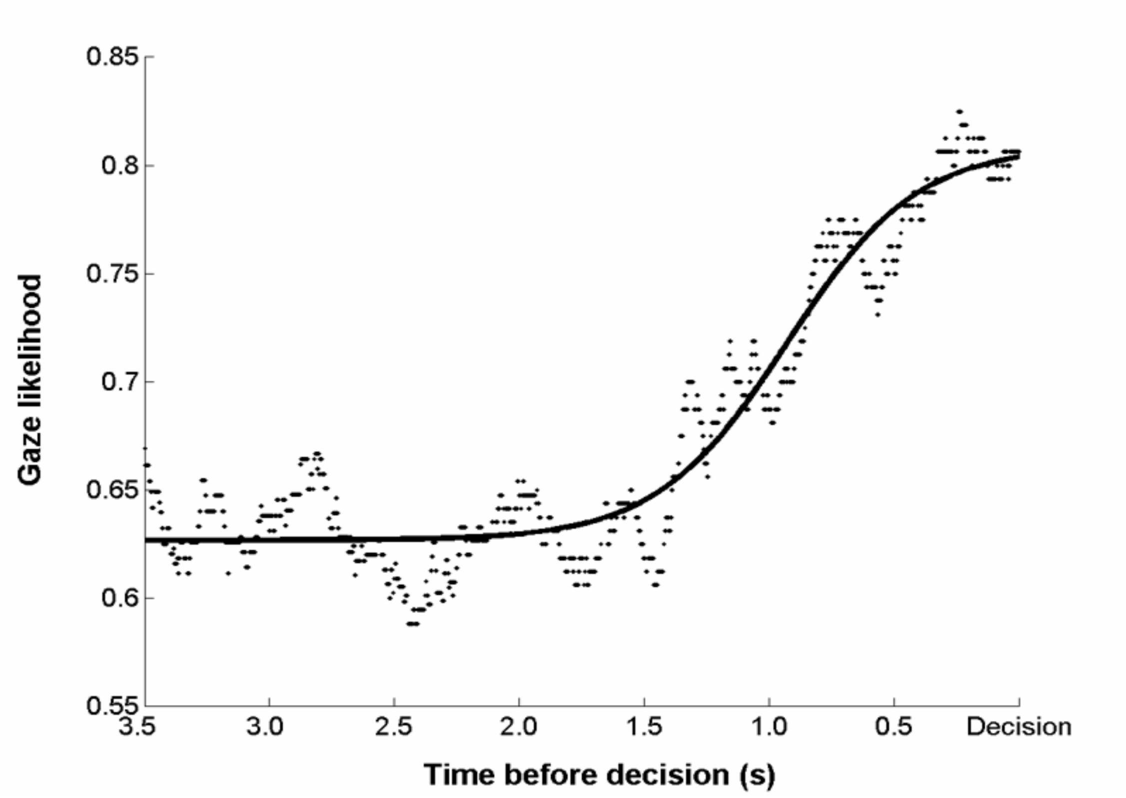


Figure 4. Likelihood of gazing at choice OR the longest-inspected non-choice stimulus. The gaze likelihood curve is biased towards the categories analyzed from very early on in the trial, but a cascade effect does emerge with 1.5 seconds before decision.

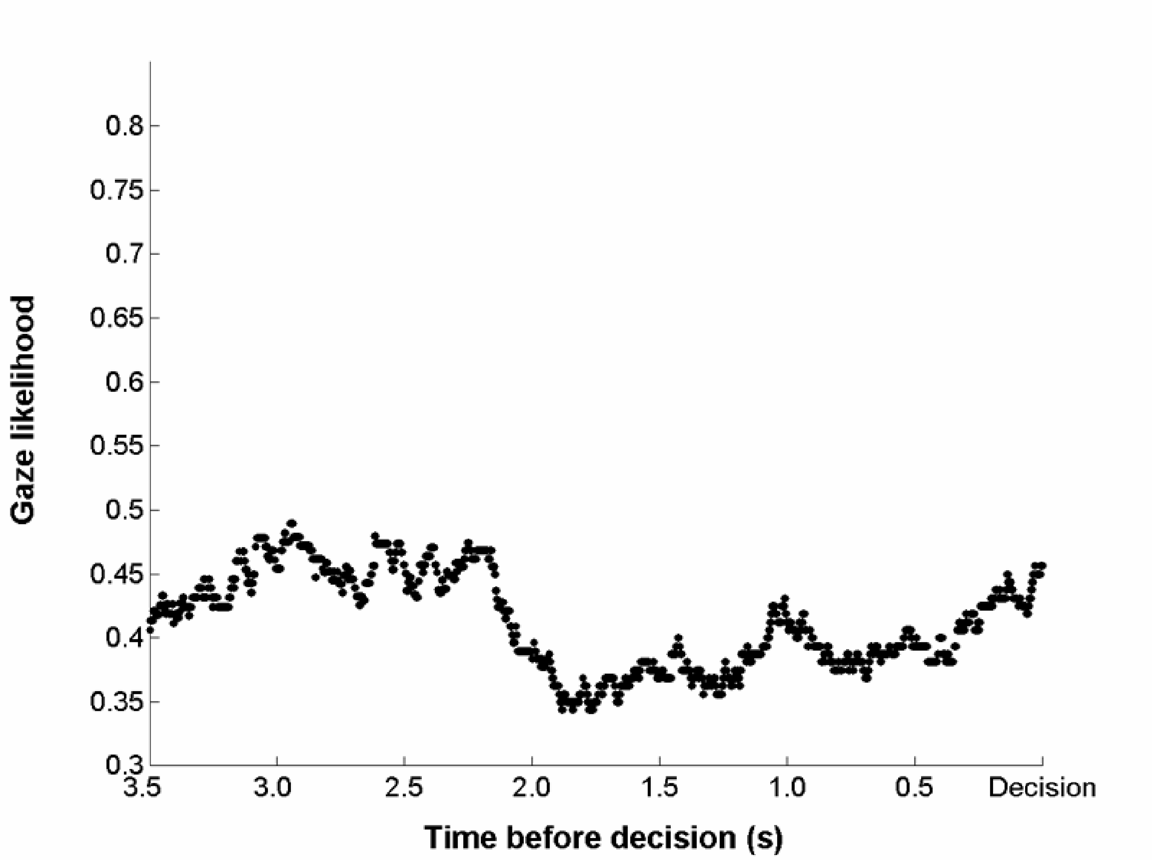


Figure 5. Likelihood of gazing at choice OR at the least inspected non-choice face. The curve stays under the chance level of 50%, as expected considering the analysis bias towards less inspected stimuli.

Discussion

Numerous studies link gaze (thus indirectly orienting) to higher order brain functions (Althoff and Cohen 1999; Friesen and Kingstone 2003) and especially to social cognition(Blakemore, Winston et al. 2004). Our model of decision making in comparison tasks comes to unify previous concepts such as preferential looking and mere exposure and proposes a positive feedback mechanism for choosing preference. The reported results confirm the intrinsic involvement of orienting in this natural, ubiquitous and apparently effortless process by revealing a "gaze cascade effect" in two separate directions: with commercial objects and in a multiple comparison setup. As shown in Figures 1B and 2, an increasing gaze bias is present in the last 1000 – 1200 ms, and we see it as the means through which the decision becomes conscious, as proposed in the past. We notice that the maximum likelihood in the 4AFC is only 38%, which, although significantly higher than the unbiased level (25%), is much lower than the values found in the 2AFC tasks (80 – 90%). This result supports our claim that gaze behavior creates a "decision bias" that only has to pass a certain threshold for the choice to be made and contradicts the possibility that observers use their gaze as a memory device to "lock the choice" in the final moments of the decision. Such an account would predict a terminal bias as large as the ones in 2AFC tasks. The flat likelihood curve observed in the objective control task (Figure 1B) confirms the specificity of the positive feedback mechanism to preference decisions.

Entropy is used as a measure of order in complex systems. We adapted it to cognitive science and defined "gaze entropy" to gain insight on the decision making strategies in 4AFC tasks. As explained in the previous section, the entropy graph shows that the orienting behavior becomes increasingly ordered, illustrating the elimination of choices and the apparent comparison reduction to two stimuli with at least 600 ms before decision. Its temporal coincidence with the cascade effect would in turn support the validity of our model of preference formation outside the restrictive 2AFC protocols. Although a more thorough investigation is necessary for a conclusion on observers' decision strategy, this method might prove diagnostic in future studies of eye-movement behavior.

The present study suggests that gaze not only assists the decision making process in ways already described, but also illustrates the elimination of non-choice stimuli when multiple comparisons are involved. Notably, the most inspected face was chosen only in 38% of all trials (61 of 160). If we grouped the chosen face with the most inspected face (Figure 4) we obtained the classical gaze cascade effect, albeit with a starting level higher than chance (62.7%). Conversely, when the chosen face was grouped with the least inspected face, no effect was revealed (Figure 5. These results show that gaze is used in stimulus elimination, with the more preferred stimuli being inspected longer primarily in the later stages of the decision process.

These results are consistent with the main claim of our work, that orienting is intrinsically involved in the mechanism leading to conscious preference decisions. This influence may raise intriguing questions about free choice – are humans solely guided by the way they gaze? – but we must not forget that previous studies hinted to our conclusions. Moreover, orienting is quite old in animal evolution, serving important roles of novelty detection for threat avoidance and mate or prey approach. It is thus reasonable to believe that the subjective feeling of "liking" developed from, or was intimately linked to orienting, once social interaction became important. Together with our previous results, the present paper sheds light on this connection, proposing a new way of thinking about preference formation.

CHAPTER 4

Interrupting the cascade – orienting contributes to decision making even in the absence of visual stimulation.

Most systematic studies of human decision making only began to be conducted in the past decade. Many of them approach the subject from a cost analysis point of view, and assume that observers will make the highest utility choice. Hence, most researchers employ objectively measurable choices in their experiments. Very few articles investigate subjective decision making, such as that involving preference, although it is very often made and important for our daily life functioning. We have argued (Chapters 1, 2) that an orienting bias effectively leads to preference decision making by being the motor of a positive feedback loop involving mere exposure and preferential looking. The illustration of this process is a continually increasing gaze bias towards the eventual choice, which we called the gaze cascade effect. Here we interrupt the natural process of preference selection, but we show that the gaze behavior does not change, even after the stimuli have been removed from observers' visual field. This demonstrates that the once started, the orienting-involving process of decision cannot be stopped, and acts independent of the presence of the visual stimuli. We also show that the cascade effect is intrinsically linked to the decision itself, and not simply triggered by the state of preferring a particular stimulus.

Introduction

Our previous work linked orienting and preference decision making by revealing a particular gaze behavior when observers choose the stimulus they like in a two or four-alternative forced-choice task (Chapters 1, 3 of present thesis). Namely, whenever a decision is involved and the natural process of inspecting the stimuli is not disrupted, a continually increasing bias towards the eventual choice is observed in the last second before the actual conscious decision. Since this effect was not present in the case of control, non-preference tasks, we accounted for the behavior by postulating a positive feedback loop between the structures responsible for decision making, on one hand, and the areas controlling orienting, on the other hand. If we imagine that, once we gaze at a stimulus, it becomes more attractive to us by the well-known process of mere exposure (Zajonc 1968), and that we tend to gaze longer at stimuli that appear more attractive (Fantz 1964), the reinforcing nature of the gaze bias, which we called the "gaze cascade effect," is obvious. In fact, fixations on the eventual choice become longer, while fixations on the other stimulus become shorter as observers approach their decision (see Appendix).

Since the magnitude of the cascade effect is inversely proportional to the difficulty of the preference task (Shimojo, Simion et al. 2003), it seems that the brain actually integrates the gaze signal, and makes a decision when a certain "consciousness threshold" is met. Our past studies eliminated alternative causes for this behavior, and brought strong evidence in favor of the model described above. However, orienting is regarded as a "novelty detector" and is usually linked to the presence of salient features in the relevant stimuli. Using a gaze-contingent window ("peephole") paradigm, we already showed that holistic stimulus processing is not necessary for the cascade effect to happen (Chapter 2). In that study, observers had to use their gaze actively, since it was the very way by which they could reveal enough information about the stimuli, visible only through the "peephole." Obtaining a long (7 seconds) cascade effect in those conditions confirmed that the brain indeed integrates gaze information over time and decides only after a certain threshold has been passed. Additionally, it showed that orienting can be entirely memory (and intention) driven, independently of stimulus perception.

Our model supposes that orienting has been incorporated in the mechanism of preference decisions. An interesting question therefore is whether, once started, the process of decision making can be disrupted by interfering with the gaze behavior with which it is intrinsically connected. Additionally, none of our previous experiments distinguished preference formation from the actual state of liking a particular stimulus, which could have been developing unconsciously before the actual choice was made. The present study was designed to address both of these issues.

Specifically, observers were asked to choose the more attractive face from a pair while the stimulus presentation time was set by a computer random number generator. As such, in the longer trials the subjects were able to make a decision before the stimuli were taken off their visual field, while in the shorter ones the choice had to be made after the stimulus offset, while they gazed at a blank screen. The former situation investigates the gaze behavior after the decision has been made, but the stimuli were still on the presentation screen, therefore separating the pre- and post-decision states. If the general state of liking a particular stimulus (human face) was triggering or maintaining the cascade effect, we should observe an increasing gaze bias even after the decision has been made, especially since now subjects are conscious of their preference. In contrast, if the cascade effect was locked to the decision point, after which the gaze bias decreased, it would exclusively link it to the mechanism of decision making.

The latter situation, in which the faces disappear before the observers can choose, effectively allows us to investigate the interruption of the natural course of the gaze bias. Obviously, a decision still has to be made after the stimuli are no longer present, so the orienting behavior in those trials will tell us to what extent can the cascade be disrupted. This is especially important since after stimulus offset there is no visual target to orient to anymore. On one hand, the decision could be based on the gaze bias developed before the end of visual stimulation, and we should see a cascade locked to the "display-off" moment, albeit of smaller magnitude. On the other hand, the mechanism, once started, has to be completed, so we will observe a cascade effect even after the "display-off" moment. This latter prediction would be direct evidence for our earlier claim that orienting has been detached from its initial purpose, of attending to salient features of relevant stimuli, and has been incorporated into the mechanism of decision making to the point that the process has to complete before a decision can be made.

Method

Six naïve observers participated in this experiment after their written consent was obtained. They were paid $5 for their participation. Mean age was 26.8 years and they were all students (undergraduate or graduate) at the California Institute of Technology. They were presented with n = 40 pairs of computer generated human faces. The face generation software was provided by Facegen (www.facegen.com). Twenty pairs were of female faces. Only faces of the same gender were paired. Prior to the eye-tracking experiment, observers rated each face in the presentation set on a scale from 1 (very unattractive) to 7 (very attractive). A MATLAB © script performed the pairing of the faces by adjoining only faces with similar, if not identical, rating. To limit the effect of familiarity, faces were presented very briefly (500 ms) in this experiment. In the eye-tracking phase, observers' eye-movements were tracked with Eyelink 2 © (www.eyelinkinfo.com), at 500 Hz sampling rate, pupil tracking mode. Face pairs were presented on a CRT computer screen for a random amount of time, according to a MATLAB © script that drew the values from a normal distribution with mean 2.7 seconds and standard deviation 1.0 seconds. The presentation times, where necessary, were truncated at 800 ms and 5000 ms, respectively. The actual mean presentation time for the 240 face pairs (across all subjects) was 3105 ms. Observers were asked to compare the faces in a pair for attractiveness. They were informed that the presentation time will be random, but were instructed to make a natural, unrushed decision if possible. If the faces were still on the screen at decision time (128 out of 240 trials, called Early Decision trials), they pressed one of two buttons to indicate their choice (left v. right). After stimulus offset, they reconfirmed their decision by pressing a button again. They were instructed that they are allowed to change their mind, but in only 1 out of 240 trials this actually happened. If the faces were taken off the screen before the observers could make a decision (112 out of 240 trials, dubbed Late Decision trials), they needed to make a decision while the screen stayed blank, by pressing one of the two choice buttons. The trials were terminated by the final button press (decision reconfirmation or decision, respectively).

Faces on the screen were presented side by side, one on the left and one on the right. They were jpeg images spanning 400 x 400 pixels, or approximately 17 x 17 degrees of visual angle each.

The gaze likelihood analysis developed elsewhere (Shimojo, Simion et al., 2003) was used. We assigned to each time sample point a value of 1 if the gaze was on the choice face, a 0 if the gaze was on the non-choice face and a NaN (not-a-number) otherwise. The likelihood was obtained by averaging across all trials and subjects (N=240). The analysis was locked at various relevant events during each trial, such as decision, final button press, or the moment of stimulus offset. Because of the temporal variability across trials, the data points around the reference event were averaged across a greater number of trials compared to data points further away from them. This is why each analysis (see Figures 1, 2, 3) include a limited number of time sample points. We included as many data points as we could while still maintaining a meaningful number of trials across which an average could be made. The significance threshold method described in Simion & Shimojo, 2005 in press was used to identify the start point of a cascade effect. In essence the significance threshold at each time sample point is the minimum percentage that would render a coin unfair, given a number of tosses equal to the number of trials used to make a likelihood average at that sample point. A gaze cascade effect was defined as the portion of the curve that passes the significance threshold and never returns below it, while keeping a monotonically increasing profile.

To analyze the gaze behavior after stimulus offset, only gaze data occurring during the blank screen period was included in the likelihood calculation. The interest areas were defined as the areas previously occupied by the faces, and the same algorithm as above was used. To ensure that any effects were not due to the behavior trailing off from the period when the stimuli were still on the screen, we analyzed only those trials that had at least 300 ms of blank time.

All likelihood curves were fitted with 4-parameter sigmoid functions, with baseline, slope, elevation and sigmoid mid-point as relevant parameters.

Results

Naïve observers were presented with pairs of computer-generated human faces (www.facegen.com). The presentation times for each pair were drawn randomly from a normal distribution. To avoid too long or too short presentation times, we limited them to 0.8 and 5 seconds, respectively. The observers had to choose the more attractive face by pressing one of two possible buttons, and they were told that the decision has to be as natural as possible. Meanwhile, their eyes were tracked with Eyelink 2© (SR Research, www.eyelinkinfo.com). They were also informed that the presentation time will be random, so that in some trials they will be able to make a decision before the faces disappear, and in some they will not. However, we asked them not to rush their decisions. Overall, in 128 (53.33%) of 240 trials subjects chose their preferred face before the “display-off” moment, so our experiment was reasonably unbiased towards either slower or faster decisions.

The actual mean presentation time was 3101 ms (s.d. 1205 ms), which is reasonably close to our intended 2.7 second target. Obviously the trials in which subjects had enough time to decide (let us call them "Early Decision" trials) were clustered towards the longer presentation times, with mean 3545 ms (s.d. 1028 ms). The mean decision time in these trials was 2395 ms (s.d. 846 ms). In the Early Decision trials, subjects had to reconfirm their decision after the display was off, by repressing their choice button. The mean "Blank" time (i.e., between the offset of the stimuli and the button press) was 1125 ms (s.d. 584 ms).

The "Late Decision" trials are those trials that were too short for a decision to be made while the faces were on the screen. Mean presentation time in these trials was of course shorter, with mean 2621 ms (s.d. 1177 ms). The difference in presentation times between Early Decision and Late Decision trials is significant ($p < 0.001$), as expected. The mean decision time was 3455 ms (s.d. 1230 ms), again significantly higher than the one in Early Decision trials ($p < 0.0001$). Due to the nature of our selection into the two categories, we consider these numbers to have little relevance on the overall conclusions of this study. The mean "Blank" time in this case was 830 ms (s.d. 609 ms), significantly shorter than the one in the Early Decision trials ($p = 0.0002$). This comparison is important, because the blank screen period underlies functionally distinct phenomena, namely decision reconfirmation in the Early Decision trials and decision itself in the Late Decision trials. The only common feature between the two is the motor action (button press) that ended the trial. It might be surprising that a decision reconfirmation takes longer than a decision itself after stimulus offset, but we have to point out that in the Late

Decision trials the observers are still under the pressure to make their choice, as opposed to the Early Decision trials.

To investigate the gaze behavior in this task we used the gaze analysis method described elsewhere (Shimojo, Simion et al. 2003). We thus obtained the likelihood that observers would gaze at the eventually chosen face at each time sample. To estimate the start point of a cascade effect, we used a significance threshold method (see **Methods**, also Chapter 2). We consider the likelihood curve as illustrating a cascade effect if a) it passes the significance threshold and never returns below it and b) it is continual and non-saturating before the actual decision.

The gaze likelihood curve in Early Decision trials, locked at the moment of decision, is plotted against time in Figure 1. The time axis extends from 2.5 seconds before to 1.0 second after decision, because gaze behavior after the actual choice but while the faces were still on the screen was of particular interest for the purpose of the present study. This period had mean 1184 ms across all trials (s.d. 784 ms). The presence of a normal cascade effect starting 1 second before the decision is consistent with our previous claims that the gaze bias is a prerequisite for decision making. Moreover, the post-decision behavior eliminates the possibility that the bias is due to the general state of liking a particular stimulus. As we can see, the bias decreases significantly after decision, even though subjects are now aware of their preference. We conclude therefore that just the gaze cascade is not a consequence but rather a part of the process leading to preference decisions.

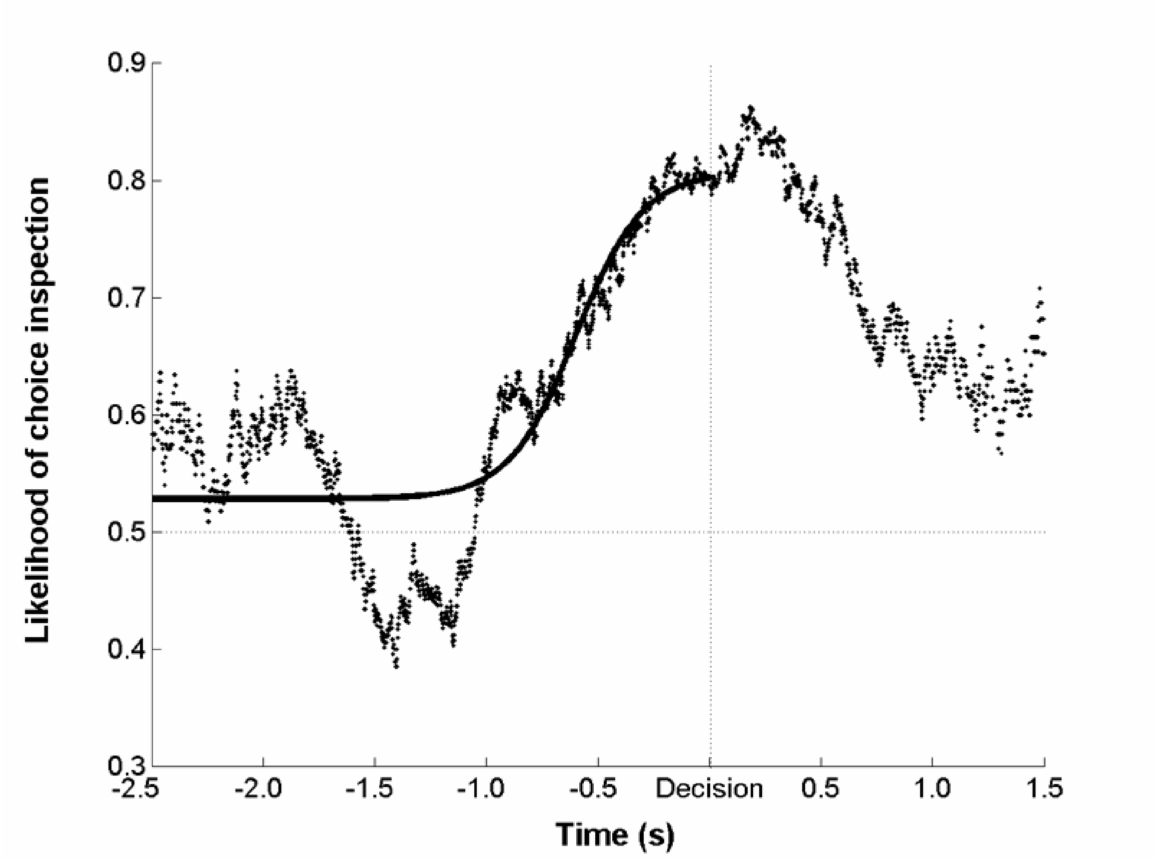


Figure 1. Gaze likelihood curve locked at the decision moment in Early Decision trials. The solid line represents, as always, a 4-parameter sigmoid fit. The horizontal line corresponds to the unbiased inspection level (50%). The vertical line corresponds to the decision moment, at which all trials were aligned. $R^2 = 0.75$. Note that the likelihood goes down after the decision.

Since orienting is classically linked to the presence of visual stimulation, we examined the gaze behavior locked to the moment of stimulus offset (the “display-off” moment). Figure 2 shows the likelihood curve as a function of time before and after the stimulus offset, for both Early and Late Decision trials. In the case of the former, we notice a bias towards choice before the reference point, expected since the actual decision is taking place prior to it. The likelihood curves after the stimulus offset are much noisier, due to the reduced number of data points to average across. Therefore, we will not speculate on the specifics of the curves in the 500 ms after the display-off moment.

The case of the Late Decision trials is more interesting. There is no clear gaze cascade before the moment of the stimulus offset, but we notice a significant (62%) gaze bias towards the eventual choice, so we have reasons to believe we interrupted the normal process of preference formation in these trials by interfering with the cascade effect. We also reveal a continuation of the bias after the reference point suggesting that the process needs to be completed for the decision to be made. While speculative, as mentioned above, this latter conclusion prompts the necessity of analyzing the “Blank” period in the Late Decision trials for any gaze behavior indicative of a cascade effect.

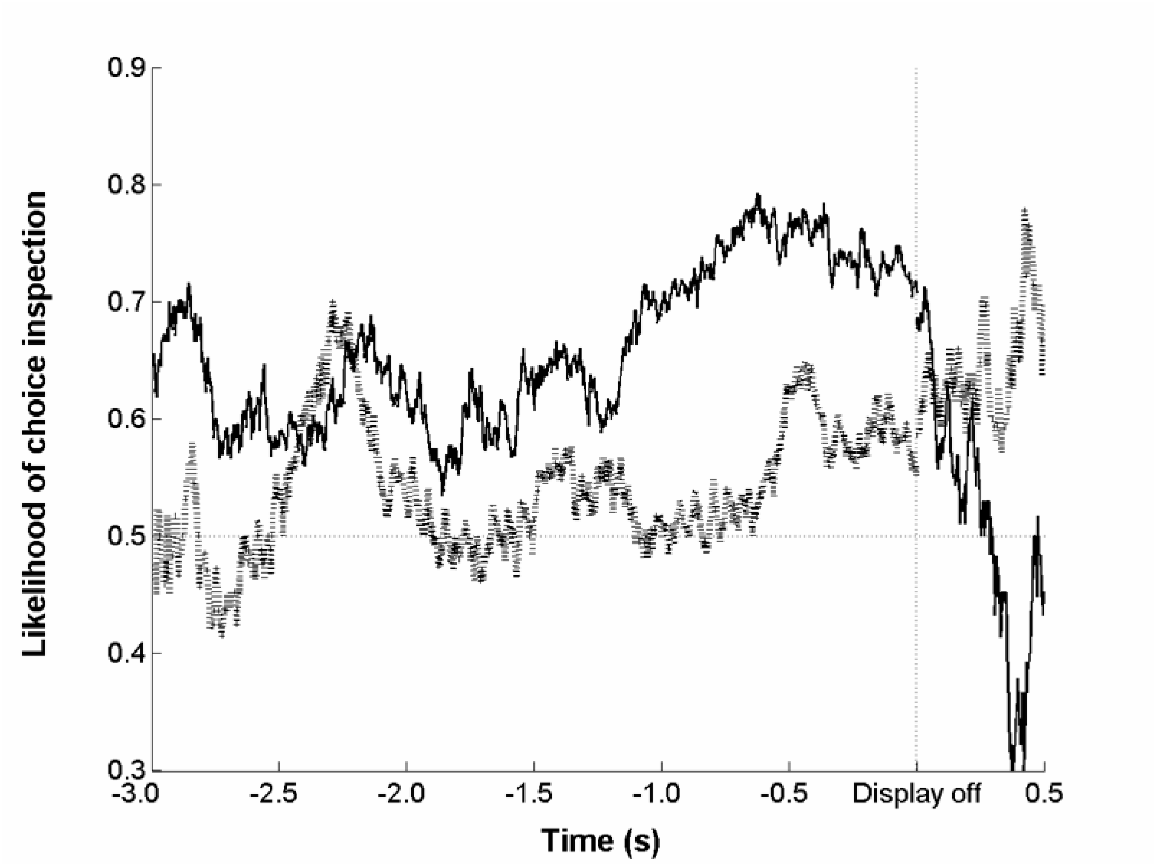


Figure 2. Gaze behavior around stimulus offset. Solid line – Early Decision trials. Dashed line – Late Decision trials. The vertical line represents the reference point (display-off). The horizontal line corresponds to the level of unbiased inspection (50%).

The likelihood curves during the "Blank" period are presented in Figure 3, plotted against time to the final button press, for both Early and Late Decision trials. As we mentioned before, the button press represents the decision, and the reconfirmation of decision, respectively. Included in the analysis are only the trials in which the Blank time was at least 300 ms, to avoid any trailing off of the gaze behavior from the epoch with the stimuli on the screen.

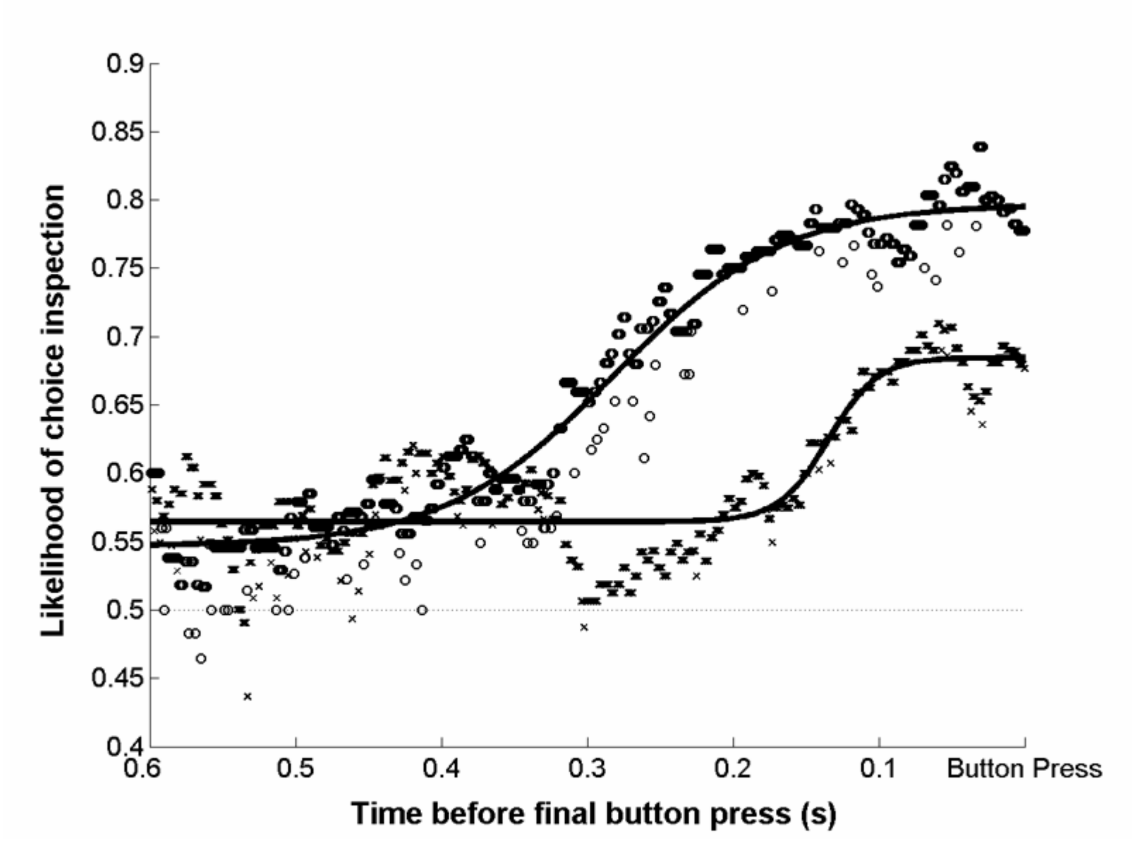


Figure 3. Gaze behavior after stimulus offset, locked at the moment of final button press. Late Decision (o) and Early Decision (x) trials are shown. Solid lines represent 4-parameter sigmoid fits. R2 = 0.95 for Late Decision trials (o) and R2 = 0.73 for Early Decision trials (x). The curves represent behavior occurring exclusively after the stimulus offset.

We notice a shorter (approx. 400 ms), but clear cascade effect in the Late Decision trials, as expected in the light of our model. In contrast, the Early Decision trials display a shorter and smaller gaze bias with a plateau-like shape, suggesting internal consistency between the motor action and orienting, a reappearing result from our past studies. The important point is that the curves are significantly different, both in terms of profile and magnitude. The Kolmogorov-Smirnov test confirmed the difference ($d = 0.43$, $p < 0.001$). The result forms again strong evidence that orienting is embedded in the mechanism of preference decision making and shows that once started, this contribution process has to be completed before a choice is made.

Discussion

We investigate, with a single experimental setup, a few aspects of the contribution that orienting has to preference decision making that remained unaccounted for in our previous studies. The gaze behavior in the Early Decision trials first confirms our earlier findings, showing that, whenever a decision of preference is involved, a cascade effect precedes the choice by approximately 1 second. Second, the fact that the likelihood of inspecting the chosen face decreases after the decision moment argues against a simple, one-directional view on the gaze bias – namely that it is generated by preferential looking alone (i.e., we tend to look more at what we like), or by the state of liking a particular stimulus itself. We note here that, in the light of this result, our positive feedback loop account needs a slight modification that does not alter our general conclusions. A model in which the more we look at a stimulus, the more we like it, and the more we like a stimulus, the more we look at it, is consistent with a cascade effect continuing indefinitely, even after the decision, a result which we did not obtain. However, the only adjustment that the model needs is that, by the very nature of orienting being incorporated in the mechanism of preference decision making, the positive feedback loop acts only on the yet-unconscious decision signal, bringing it closer to the moment of overt choice.

The likelihood curve locked at the stimulus offset point ("display-off" moment) in the Late Decision trials confirms that our experimental setup was successful in interrupting what we think is the natural process of preference formation, which involves a gaze cascade effect. The dashed curve in Figure 2 shows a significant bias towards the eventually chosen stimulus, oscillating around the 58% level. However, the decision signal is probably not strong enough yet for the choice to be made and this is why the observers have to complete it after that point.

The most important result of the present paper however comes from the analysis of the orienting behavior after the stimulus offset (the "Blank" period). As surprising as it sounds, observers complete the gaze cascade by fixating in the locations previously occupied by the faces for at least 830 ms, on average. We emphasize here the irrelevance of stimulus presence to the cascade effect itself, as long as a preference decision needs to be made. In a previous study (Chapter 2) we showed that mental feature integration, without holistic perception, is enough for the gaze cascade to happen, as long as, again, a preference choice was involved. Orienting and the presence of salient stimulus features were only weakly coupled in that experiment, since gaze had to be guided by the observers' memory and by the task's purpose. Among other results, that experiment seemed to indicate that orienting became so embedded in the process of decision, that stimulus presence was no longer necessary for triggering it, as Sokolov described it in the 1960's (Sokolov 1963). In our view, the Blank period result is clear evidence that the decoupling between orienting and the stimuli it is supposed to detect can be complete. In a flowery description, we say that orienting has been "high-jacked" by the preference decision mechanism, being used to assist the brain in reaching the conscious choice.

The difference between the gaze likelihood curves in the Early and Late Decision trials is also informative. First, it shows that a decision is the necessary endpoint of a "gaze cascade effect." Second, it argues against the possibility that the cascade effect is just a reconfirmation of a decision made before its start. If this were the case, the two curves should be similar, since the situation in the Early Decision trials (crosses in Figure 3) is precisely a decision reconfirmation. The smaller bias towards choice 200 ms before button press in these trials is also consistent with our earlier findings, which indicate that any selection is generally preceded by a gaze bias, probably for internal, cognitive-motor consistency. The distinction between a selection bias and a "gaze cascade effect" is a reappearing theme in our studies, but all the evidence indicates that the gaze behavior in subjective, emotionally charged decisions goes beyond simple selection bias, due to the positive feedback loop.

Taken together, the results of this study nicely complete our story, bringing definitive evidence that orienting has been high-jacked by the process of preference formation. Our research also suggests that by manipulating active orienting, even after visual stimulation has been interrupted, we can influence observers' preference, an idea with endless potential in advertising, social psychology or human communication sciences.

CHAPTER 5

A mathematical model of human decision making – why is preference so special? A feedback story.

Introduction

Decision making is one the most important aspects of our lives, being responsible for everything from our survival to everyday functioning, future planning, mate choice and social interaction. A comprehensive investigation of the decision process must account for a large array of possibilities, since “decision” can refer to anything: what to eat for breakfast, what to do next Saturday night, what career to choose in life or what to do when a threat is imminent. Moreover, one can study decision making from a few distinct perspectives, which future research will need to ultimately unify. In their excellent review, Montague and Berns (Montague and Berns 2002) lay the grounds for the modern investigation on human decision making, linking economics, mathematics and neuroscience and defining principles that an unifying theory will have to consider. As such, the authors underline that decision making has to involve a reward function, a value function, and a policy (mapping neural or behavioral states to actions).

Previous studies have accounted for one or more of these principles, thus creating the different perspectives we mentioned above. One can investigate the neural substrate of reward, valuation, or action selection. Such articles link decision making with reward size, reward prediction error, probability or expected value of the reward, each of which are assigned certain brain areas or circuits (Schultz 1998; Leon and Shadlen 1999; Berns, McClure et al. 2001; Breiter, Aharon et al. 2001). On the other hand, one can view decision making as a time-integral process, in which “neural integrators” play a key part. These models tend to be mainly computational, with limited reference to brain structures (Koulakov, Raghavachari et al. 2002; Mazurek, Roitman et al. 2003). A third approach is studying decisions from a somatic or behavioral point of view, such as Damasio’s somatic marker papers (Damasio 1996). However, no approach is all-inclusive yet, and it is becoming increasingly clear that all of them are useful in understanding one of the most complex activities that the brain engages in.

The limitation of most studies of decision making is that they always involve an external reward assumed to be a reinforcer. While we do not doubt the reward value of juice in thirsty animals or of money in humans, we note that the reward for most of our out-of-laboratory actions is internal, thus difficult to measure through psychophysics or physiology. Our own work (Chapters 1-4) focused on the preference decision making, where the reward value of choosing the stimulus we like has no obvious correlate. It is reasonable to believe that the subjective feeling of liking has developed to help us make the best choices from an ecological-evolutionary point of view, and this argument is extensively used as the basis for preference, as we outlined in the Introduction of this thesis. Namely, looking at preferred faces might activate reward pathways in the brain, as it has been shown in a recent study (Nakamura, Kawashima et al. 1998). Moreover, Kampe and colleagues (Kampe, Frith et al. 2001) showed that the gaze direction in a stimulus face has reward value in itself: activity in the ventral striatum was the highest when observers saw a face gazing directly at them, and lower if the presented faces were gazing away. Additionally, they replicated an older result, which said that faces gazing directly at the observers are generally considered more attractive than the ones gazing away. It is therefore unclear what the causality is between observing the gaze direction of another face, its perceived attractiveness, and the neural activity in the striatum. This is where our model, presented in Chapter 1, could offer an explanation: since a gaze bias represents the basis for preference formation, someone gazing at you might start finding you attractive. This mechanism could have developed through a co-evolution scenario, the preference for faces gazing at us being selected for because of the intrinsic link between orienting and liking. Of course, the previous statement is somewhat grandiose and speculative, and does not explain why preference for non-face objects follows the same dependence on orienting, other than that it is a fortuitous spin-off from face preference mechanisms.

This chapter presents a simple mathematical model of decision making that was developed starting from the very equation of the 4-parameter sigmoid function, which we used to fit our experimental data. Again, consistent with the scope of this thesis, we are not trying to find criteria for decisions. In the light of the findings detailed in the previous chapters, we show that, to simplify and quantify the differential dependence of subjective and objective decisions on gaze, we need just two independent variables. We already talked extensively about the necessity of a positive feedback loop to explain the continually increasing gaze bias that we called the “gaze cascade effect.” Our model will take that into account, and the relative weight of the positive feedback will play a key part in it. The new, and somewhat surprising parameter, but indispensable to explain our results, is the “negative feedback weight,” whose significance will be detailed in the next section. However, a deeper look at what decision making in a two-alternative forced-choice (2AFC, which our model strictly addresses) task involves will render the negative feedback not at all surprising. From an information processing point of view, if we assume that every time we make a choice we want to be as well informed as possible, the longer we inspect one of the stimuli, the more motivated we should be to inspect the other one. This is in order to gather as much information as we can about both, for our decision to be fair. Hence the negative feedback, whose weight will influence the way our orienting behavior helps cognition in making decisions. We predict that, in what we call "objective" decisions, the negative feedback will dominate, while in the "subjective" ones (i.e., preference) the positive feedback will be stronger, based on the connection between gaze, exposure, and liking (see Chapter 1). This should be reflected in the gaze likelihood function, which will be the output of our system of equations. The next section describes the assumptions of the model, and lays down the equations according to our understanding of the contribution that orienting behavior (represented, again, by gaze) has to the decision making mechanism.

Model's Description

The purpose of a mathematical model of 2AFC decision making is to find a simple system of equations that will be consistent with our dual-contribution behavioral account, fit the experimental data and be able to capture situations tackled in our previous work. The equations will be based on several assumptions following the theoretical framework of our past studies. The central player in such a model will be the likelihood that the stimulus eventually chosen is gazed at, which we will denote p. We shall remind the reader that the function we used to fit our gaze likelihood data was, in all cases, the 4-parameter sigmoid, which reads the following:

$$p(t) = p_0 + \frac{a}{1 + e^{-\frac{x - x_0}{b}}} \tag{1}$$

with p$_0$, a, b and t$_0$ as independent variables. We remind the reader that in all cases, the starting point of the likelihood curve (here p$_0$) is 0.5, so we will not treat it as an independent parameter. Let us rewrite

$$p(t) = \frac{a}{1 + e^{-\frac{x - x_0}{b}}} . \tag{2}$$

Deriving the function p we obtain

$$p'(t) = \frac{a}{b} \cdot \frac{e^{-\frac{x - x_0}{b}}}{(1 + e^{-\frac{x - x_0}{b}})^2} . \tag{3}$$

Rewriting p’ in terms of p we get

$$p'(t) = \frac{p(t)}{b} - \frac{p^2(t)}{ab} . \tag{4}$$

If we denote k = 1/b and w = 1/a, we have $p'(t) = k\,[p(t) - w\,p^2(t)]$. (5)

Let us look closer to this differential equation. The quantity p'(t) represents the rate at which the likelihood to inspect the choice progresses. As we can see, it is proportional with p itself, with a weighting constant u. Therefore, the larger the likelihood, the stronger its growth will be in the future. This is, in fact, a mathematical implementation of one branch of a positive feedback, a phenomenon we have been discussing all along. According to our behavioral model, we are more likely to look at one stimulus the more we looked at it in the past. This is especially apparent in attractiveness tasks, due to the interaction between mere exposure and preferential looking, but we will assume that it exists, in some form, in all 2AFC tasks, for example due to perceptual fluency (Mandler, Nakamura et al. 1987). To complete the description of the positive feedback, we need a decision variable, d, whose derivative should be proportional to the likelihood p with a weighting constant u

$$d(t) = u\ k\ p(t). \tag{6}$$

Note that k is a proportionality constant that appears in both (5) and (6), and is related to the speed at which information is gathered in a particular task once the gaze bias has started.

When we talk about probabilities however, it is clear that a phenomenon like positive feedback has to be balanced by something else. Mathematically, $p' = p$ illustrates an exponential function that will continually increase towards infinity, while our p needs to be between 0.5 and 1 (or, more exactly, between 0 and 0.5, since we are adding $p_0=0.5$ at the end anyway). The balance is offered by the second term of the equation, $-\,w\,p^2$. In essence this term tells us that, the more we have of p, the smaller its growth will be in the future, acting effectively as a *negative* feedback. Since p’ now decreases with p^2 “the more we looked at one stimulus, the more likely we are to switch and look at the other.” The introduction of negative feedback is not only a necessary and efficient way to keep p bound between 0 and 1, but also an illustration of a reasonable strategy to gather sufficient fair information about both stimuli before making a decision.

We notice thus that the maximum elevation of the gaze bias, denoted a in the original fitting equation, is equal to 1/w. It follows then that the larger the negative feedback strength w, the smaller the effect. As we expect, in objective tasks, the negative feedback is stronger, since there are more explicit criteria to make an informed decision, which is consistent with the gaze behavior results in control tasks throughout this thesis.

Several aspects of the positive feedback need further consideration however. Our behavioral model postulates (Chapter 1) the existence of a “decision module” with a contingent threshold. For ease of modeling, let us view the threshold T as constant, and the decision slider d starting midway between the two stimuli, and moving towards choice with time. The system converges only if p(0) is larger than 0, i.e., if there is an initial bias towards one stimulus, whose provenience will be left uncommented as always. This bias makes the gaze slightly more likely to be directed at that stimulus. When the gaze does happen, exposure should in turn “move” the slider more towards the same stimulus, reading (6). The value of the threshold T will be fixed and it will determine the cascade effect duration, by requiring that $c\ (t_{decision}) = T$. This identity represents one of several boundary conditions that our system needs to be solvable.

To recapitulate:

$$p' = k(p - w * p^2) \tag{7}$$

$$c' = u * k * p \, ,$$

with the boundary conditions:

$$c(t_{decision}) = T$$

$$p(0) = p_{init}$$

$$c(0) = 0 \; .$$

The constant p_{init} is the initial bias, however small but still larger than 0. For simplicity, let us set it to 0.0001 and underline that increasing its value 10 or even 100 times does not change the model results. As a last observation before solving the system, p is just a proxy for the real likelihood value seen in our experiments, which was bound by 0.5 and 1. A simple linear transformation will turn one into the other. We pointed out before that if *L* is the likelihood plotted in our work, we could write:

$$L = 0.5 + p \, . \tag{8}$$

We will now have to establish mathematical relations between our variables, u, w, k and the relevant cascade parameters as revealed by fitting with a 4-parameter sigmoid function: the cascade midpoint (x_0), the effect elevation (a), and the maximum slope (b). We remind the reader that the sigmoid function we used looks like this:

$$y = y_0 + \frac{a}{1 + e^{-\frac{x - x_0}{b}}} \, . \tag{9}$$

As pointed out before, the elevation a is linked to the strength of the negative feedback (w) only and if we invert a = 1/w we have

$$w = \frac{1}{a}. \tag{10}$$

Similarly (see the very definition of the variables above):

$$k = \frac{1}{b}. \tag{11}$$

We now need to remind the reader an important procedural aspect of the gaze cascade analysis. Usually the timelines plotted on the abscissas throughout this thesis were chosen depending on the timing of each task, so that we can average the likelihood over a reasonable (usually 66%) number of trials. However, the sigmoid fits were made with this timing determining the cascade midpoint, x_0. We emphasize here that, since our analysis was always locked at the decision moment, the duration of the cascade and the length of the plateau following it are more significant parameters of the orienting behavior. We will consider as "effect" (cascade in preference tasks, or bias in control tasks) that part of the likelihood curve contained between α*a and (1-α)*a, where α is a sufficiently small (α << 1) constant. For the moment, let us set α = 0.05. Thus, the length of the "effect" will be, in terms of the sigmoid as well as model parameters:

$$t_{effect} = 2 \cdot \ln 20 \cdot b = (1/k) \cdot 5.991. \tag{12}$$

The plateau duration, using the same criterion, reads:

$$t_{plateau} = t_{analysis} - t_0 - \ln 20 * b. \tag{13}$$

This quantity will have to be matched with the corresponding one in the model, and this is where the positive feedback strength, u, comes into play. Numerically solving (5) in Mathematica 5.1.1 © (www.wolfram.com), with $k = 1/b$ and $w = 1/a$, we can find the solution of the equation $p(t_{end}) = (1- \alpha) * (1/w)$, which will give us the endpoint of the bias effect in the model. The plateau duration will therefore be $t_{plateau\text{-}model} = t_{decision} - t_{end}$. The quantity $t_{decision}$ will be computed in Mathematica © too, by asking $d(t_{decision}) = T$ (the decision threshold, a constant whose value is irrelevant).

We thus have a way to match the parameters of the sigmoid fits for our experimental data with certain values for the two model weights, u and w. What follows are a few examples from our previous studies, in which we derive the feedback strengths and show that their relative magnitude is consistent with their labeling as control (objective), or preference (subjective, emotional).

Fitting the experimental data to the mathematical model

Let us consider a few examples of likelihood curves from our past experiments, and calculate u and w, to confirm the degree of "subjectivity" of the decision involved in the respective tasks. We will not reproduce the five graphs presented in Figure 1 in our original study (Shimojo, Simion et al. 2003), but we will list their sigmoid fit parameters. Figure 1A in Chapter 1 plots the gaze behavior curve from the like-difficult task. The parameters are: $a = 0.37$; $b = 164.1$; $x_0 = 1929$; $y_0 = 0.46$. In this task, $t_{analysis}$ is 2.5 seconds, so $t_{plateau} = 2500 - 1929 - \ln 20 * 164 = 79$ ms (values rounded to the nearest integer) and $t_{cascade} = 2*\ln 20*164 = 984$ ms. From the model, we get:

$w = 1/a = 2.70$

$k = 1/b = 0.0061$.

To obtain $t_{plateau}$ of 79 ms, $u = 78$. Of course, the numbers do not have much significance unless we compare them with their corresponding values in other tasks. The like-easy task (Figure 1B) has the following parameters: $a = 0.226$; $b = 180.2$; $x_0 = 1861$ ms and $y_0 = 0.512$. Solving as above, we obtain:

$w = 4.43$

$k = 0.0055$

$u = 126$.

Intriguing results in this task by comparison. The easier task has a stronger associated negative feedback, since there are perhaps more objective reasons to choose one face over the other, so information gathering makes sense. However, consistent with preferential looking, this task has a stronger positive feedback too. The effect is smaller only in this task because once started, the gaze cascade reaches the threshold T faster.

What happens in the control tasks though? The parameters of the sigmoid fit for the round task (Figure 1C, Chapter 1) are: $a = 0.2$; $b = 121.6$; $x_0 = 1278$ ms and $y_0 = 0.43$. Solving the model system, we have:

$w = 4.95$

$k = 0.0082$

$u = 49.7$.

As expected, the negative feedback takes over, while the positive feedback is much weaker in this task. Consistent with our initial assumptions, we can say "objectivity wins."

The result of the dislike task (Figure 1D, Chapter 1) offers further seeds of speculation on this theme. The parameters $a = 0.11$, $b = 114.1$, $x_0 = 993$ ms and $y_0 = 0.46$ give us:

$w = 9.09$

$k = 0.0088$

$u = 69$

As we can see, the positive feedback is stronger than in the round task, but so is the negative feedback. In fact, the latter is so strong, it keeps the gaze bias towards choice to a very low value. The source of the negative feedback in this task could also be due to preferential looking itself, since looking at the uglier face will probably make subjects avoid it in the future.

Finally, the Fourier-like task (Figure 1E, Chapter 1) displays an interesting array too. We list the parameters, $a = 0.5$, $b = 220.7$, $x_0 = 1766$, $y_0 = 0.44$ and compute:

$w = 1.98$

$k = 0.0045$

$u = 60$.

Surprisingly, the positive feedback in this task, as defined in the beginning of the model description, is rather low. However, the unusually small value of the negative feedback strength makes the cascade effect very powerful in this task. We see thus that, in the light of this mathematical construct, it is the balance between positive and negative feedbacks determining the behavior in various tasks. In the particular case of the Fourier shapes, the numbers can easily be explained. Such unfamiliar objects, when compared for attractiveness, might not exercise that strong a preferential looking effect. However, since there are no objective criteria on which subjects can rely when judging stimulus attractiveness in this task, the negative feedback weight is unusually low, leading to a gaze cascade effect.

Finally, we will consider the case of the peephole experiment, since the orienting behavior in the preference task is so peculiar that we think deserves consideration here. The parameters of the preference task (Figure 1A, Chapter 2) are $a = 0.47$, $b = 1561$, $x_0 = 13499$ ms, $y_0 = 0.52$. In consequence,

$w = 2.132$

$k = 0.00064$

$u = 250$.

Here we notice a very low strength for the negative feedback, expected for a preference task. However, the positive feedback value is much higher than the one computed in the full-stimulus tasks. This result is not surprising if we consider how scarce the criteria that observers use are in a gaze-contingent, “peephole” condition. Additionally, for the roundness task (Figure 1B, Chapter 2), from $a = 0.28$, $b = 282.5$, $x_0 = 13503$, $y_0 = 0.52$ we get

$w = 3.56$

$k = 0.0035$

$u = 190$.

Expectedly, we reveal a lower positive feedback weight and a stronger negative feedback in the roundness task compared to the attractiveness task. A comparison of the two weights with corresponding values in the full-stimulus experiments (Chapter 1) could lead to the wrong conclusion that we are presenting a roundness decision that is less objective than a preference task. Let us not forget that the paradigms are entirely different, and the way that information accumulates in the two experiments is significantly dissimilar. In fact, we offer an account for the variable k by speculating that it is probably linked to the speed of information gathering once the gaze bias starts. As the reader might have noticed, the value of k in the peephole tasks is much smaller than in the full stimulus tasks. Moreover, the preference task has an unusually low value, since it is probably more difficult to gather information through a peephole with the purpose of comparing facial attractiveness than it is to inspect for figuring out the rounder face. k could thus be linked to task difficulty, being inversely correlated with it. However, as we pointed out before (Chapter 1, 2), difficulty in the way we define it here does not correlate with decision times, which are highly variable and include pre-gaze bias times of even information gathering that we do not consider important for the phenomena studied in this work.

Discussion

To recapitulate:

(a) Attractiveness tasks have high positive feedback strength (large u) and low negative feedback weight (small w), resulting in large cascade effects that end close to the start of the sigmoid curve's upper plateau.

(b) Objective tasks generally have smaller values of u and larger values of w, resulting in low magnitude effects that end significantly after the start of the upper plateau.

(c) When comparing stimuli with a large difference in basic attractiveness rating, we can expect stronger positive feedback (preferential looking) but since the observers have more cognitive input and more criteria to analyze, the negative feedback should also be strong. The result of both large u and w closely mimics the curve we obtained in the attractiveness-easy task reported in our original paper: a relatively small cascade effect that still ends before the sigmoid saturates.

(d) The third variable, k, is most likely inversely correlated with the speed at which information accumulates after the gaze bias starts. The decision signal gets closer to the threshold T at a velocity inversely proportional to k. For example, “peephole” tasks have smaller values for k compared to the full-stimulus tasks.

We realize that the mathematical model is speculative and is based entirely on the very function that we used to fit our experimental data. The goal of this chapter was not to come up with a system of equations from a totally theoretical perspective, than match it with the actual data. Instead, we manipulate the four-parameter sigmoid, and show that, by rewriting it, we can reveal deeper aspects of the contribution that orienting has to decision making. This mathematical construct allows us to see that the positive feedback loop, while of utmost importance, does not tell the whole story. We are able now to say that objective information gathering does play a role in decision making but, depending on what the task is, it can dominate or be swamped by the strength of the positive feedback. Criticisms pointing out that we never considered this aspect in our work are now addressed globally, if indirectly. The same argument applies for task difficulty, for which we found a correlating parameter. However, in the light of our model, this parameter does not influence the feedback loops, and therefore has little impact on our earlier conclusions about the causes of the “gaze cascade effect.” More mathematical research is necessary to find out whether a better system of equations, arrived at independently but still based on theoretical assumptions consistent with phenomena in the literature, can fit the experimental data without considering the four-parameter sigmoid an a-priori appropriate function.

CHAPTER 6

Neural and behavioral correlates of preference decisions – an eye-movement / EEG study

Introduction

Electroencephalography (EEG) is a powerful technique of recording brain signals in humans. In the past, it was primarily used as a diagnostic tool for patients with epilepsy, brain tumors or infections. An array of electrodes placed on the subject's scalp will record emergent electrical activity of many neural dipoles in the vicinity of the electrode. While noisy due to interference from nearby sources as well as generic electrical power lines, the EEG signals can be very informative of the sources of activity in a particular task. Moreover, powerful analysis techniques were developed to extract as much meaningful information as possible off these signals. In this study, we used a 26-channel setup, recording from all regions of the observers' scalp while they were performing two-alternative forced-choice tasks. Meanwhile their eye-movements were also recorded for post-experiment analysis. We had two goals to achieve with the present work: first, to replicate the gaze bias patterns found in our past experiments (see Chapter 1); second, to correlate these patterns with neural activity as revealed by EEG. We used multiple approaches, such as computing event-related potentials (ERP), event-related synchronization / de-synchronization (ERS / ERD), analyzing the spectral power of the brain signals in different frequency bands and performing time-frequency Morlet-wavelet analysis. As our previous studies suggest, we should be able to find significant differences between preference and non-preference tasks in certain brain regions (prefrontal and frontal, associated with both gaze control and decision making). Moreover, we looked for correlates of decision making per se throughout the scalp locations investigated.

Due to the limited number of trials per condition (n = 36) and the relatively low number of subjects (N = 10), this study is not yet conclusive, but rather informative. The statistical power of the EEG part of the present work is not optimal yet since the recorded signals generally display low signal-to-noise ratio, and it will have to be expanded, designed and analyzed more rigorously. However, the results should give us a clear idea of where to look in the future for a comprehensive investigation of the neural correlates of preference, decision making, and their interaction with orienting.

Materials & Methods

Eye-tracking and eye-movement analysis

Ten naïve subjects participated in this experiment. They were paid $10 for their participation. Eye-tracking was performed with Eyelink 2 © (www.eyelinkinfo.com) at 500 Hz sampling rate. Stimuli were 400 x 400 pixel jpeg photographs of human faces (face like, face dislike, face roundness and face passive tasks) or 400 x 400 pixel photographs of Fourier descriptor-generated abstract shapes (Fourier task). Subjects were asked to make a choice with respect to the task of hand. There were n = 36 trials in the face conditions and n = 17 trials in the Fourier condition. The conditions were blocked, and the blocks were intermixed between subjects to counterbalance possible order biases. Gaze was analyzed using EyeLink DataViewer ©, offered by the Eyelink manufacturer, SR Research. Processing was done according to the likelihood analysis described in Chapter 1.

EEG recording & pre-processing

EEGs were recorded from 26 Ag/AgCl electrodes (ActiveTwo System, BioSemi Instrumentation, Netherlands) with a sampling rate of 256 Hz and a digitization rate of 24 bit by an AD-Converter. The electrodes were placed according to the extended International 10-20 electrode placement system (Fig. 1). Instead of a single standard ground electrode, we used two additional electrodes: they formed a feedback loop driving the average potential of the subject (the Common Mode voltage) as close as possible to the ADC reference voltage (the ADC reference can be considered as amplifier 'zero'). This way we could significantly decrease the power line contamination, protect the subjects from any excessive flow of currents. Any epoch containing brain potential exceeding 70 μV was considered as artefact and excluded from further analysis. The EEG signals were further band-pass filtered at 0.01-100 Hz and were algebraically re-referenced via a common or average reference scheme which was based on taking the average value of all the available EEG signals as the reference signal (Offner 1950).

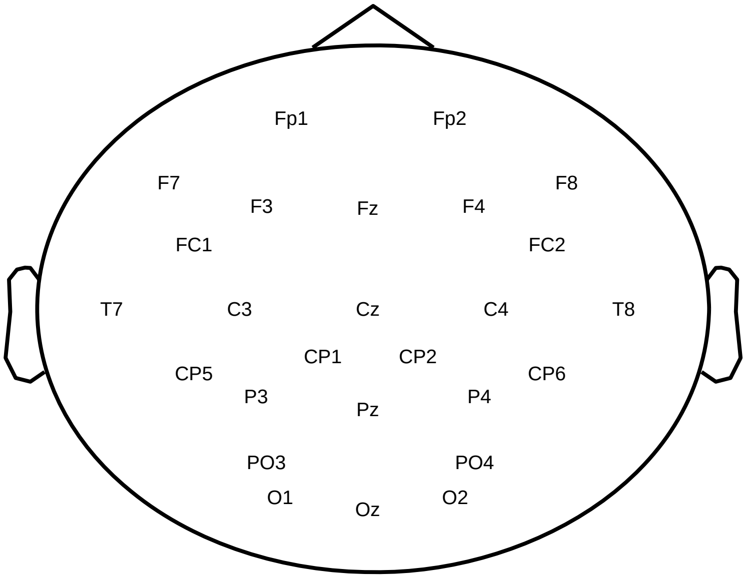


Figure 1 Positions of the 26 electrodes and their designations according to the extended international 10-20 electrode placement system (Jasper 1958).

Event-related-potential (ERP) analysis

ERP is a general class of brain potential displaying stable time relationship to a definable reference event (Naatanen 1992). In our experimental paradigm, events with fixed specific cognitive processing are: (a) onset of a trial, and (b) the decision moment as indicated by the response of subjects. Since the gaze-cascade effect was primarily found 1 s before the response, the latter event was strategically more meaningful for our study. Traditional ERP was calculated by aligning the spontaneous EEGs with the response moment. The duration of ERP epoch was 2 s. A 30 Hz low-pass filter was applied to the raw EEG signals before all ERP analyses.

Spectral analysis

The power spectral density (PSD) was calculated for each electrode for the last two seconds before the response. PSDs of the linearly detrended signals were computed for the individual trials separately by using fast-Fourier transforms (256 points) applying a 50% overlapping Hanning window, and consequently averaged over all trials. The detrending operation eliminated any DC offsets and slow drifts often caused by electrode movements.

Time-Frequency analysis

Traditional PSD offers a global estimate of frequencies present in the raw signals, but no information on time-varying nature of spectral power could be obtained. It has been well known that neural signals exhibit nonstationary and extremely complex behavior (Kawabata 1973; Tass, Rosenblum et al. 1998; Vandenhouten, Lambertz et al. 2000). Here we adopted wavelet transform based time-frequency analysis, which is well known for their optimal concentration in time and frequency spaces (Sinkkonen, Tiitinen et al. 1995; Tallon-Baudry, Bertrand et al. 1998). Wavelet transform is a method of signal decomposition onto a set of basis functions, obtained by contractions/dilations and translations of a unique function called the mother wavelet. Three important properties make the wavelet transform suitable for EEG analysis (Bhattacharya and Petsche 2001): (i) it removes the local polynomial trend, (ii) it is suitable for nonstationary signals, and (iii) it preserves the Fourier phase information.

The signal $\{x(t)\}$ was initially convolved with a complex Morlet wavelet $\omega(t, f_c)$ (also the mother wavelet) which was Gaussian in both frequency (s.d. σ_f) and in time (s.d. σ_t) domain around a chosen center frequency f_c. Morlet wavelets can be expressed as follows:

$$\varpi(t, f_c) = \frac{1}{\sqrt{\sigma_t \sqrt{\pi}}} \exp(-\frac{t^2}{2\sigma_t^2}) \exp(i2\pi f_c t),$$

where $\sigma_t=1/2\pi\sigma_f$. The center frequency f_c of the wavelet was varied in 1 Hz steps to cover the frequency range of 4 and 50 Hz. The squared-modulus of the complex convolved signal, $E(t, f_c)=|\omega(t, f_c) \otimes x(t)|^2$, represents the energy of the signal at narrow frequency bands as a function of time ($\otimes$ represent the convolution operator). This way, an optimal representation of the signal in the time-frequency plane could be obtained. Here, we set the ratio f_c/σ_f to 7 as used by others (Tallon-Baudry, Bertrand et al. 1998; Jensen and Tesche 2002). The mean of the energy of the pre-stimulus signal for each trial spanning from -500 ms to the onset of each trial was subtracted from the energy of the post-stimulus signal for each frequency.

This measure of time-varying frequency specific energy changes of the ongoing EEG activity provides an electrphysiological correlate of activated cortical areas involved in the task-related processing. Decrease (ERD – event-related-desynchronization) or an increase (ERS – event-related-synchronization) of spectral power in a given frequency band is considered to be due to an increase or decrease in synchrony of the underlying neuronal populations oscillating in the same frequency band (Pfurtscheller and Lopes da Silva 1999). Neuronal networks display different states of synchrony with oscillation at different frequencies (Lopes da Silva, van Rotterdam et al. 1970; Llinas 1988; Steriade, Gloor et al. 1990; Pfurtscheller, Neuper et al. 2000), and there are wide-spread evidences that oscillations in different frequency bands in the EEG signal play different functions ranging from elementary sensory information processing to complex long-term memory encoding (Petsche, Kaplan et al. 1997; Harmony, Fernandez et al. 1999; Klimesch 1999; Krause 1999; Basar, Basar-Eroglu et al. 2000; Weiss and Rappelsberger 2000; Basar, Basar-Eroglu et al. 2001; Gonzalez-Hernandez, Pita-Alcorta et al. 2002; Gruber, Muller et al. 2002; Molle, Marshall et al. 2002).

Spatial analysis

Since we have multiple observations recorded at the same time but from different spatial locations from the scalp, we can reconstruct the (hypothetical) state space trajectory of the underlying spatially distributed system. Taking simultaneous measurements from M EEG electrodes and considering the M-dimensional voltage vectors as points in the M-dimensional state space, we could study the dynamics of potential changes in time as a evolving trajectory in the M-dimensional state space. Three important descriptors of the trajectory dynamics are as follows (Hjorth 1973; Wackermann, Lehmann et al. 1993;

Wackermann 1996): (i) the global effective strength (Π) of the field that is represented by the extension of the point cloud in the state space, (ii) the change in speed or velocity of the field (Φ) that is represented by the density of distribution of the momentary states along the trajectory, and (iii) the (topological) complexity of the geometry of the attractor (Ω) that is represented by the different extensions along the principal axes of the point cloud. The computational steps for the calculation of these descriptors are briefly mentioned as follows.

Twenty six (M=26) channel data ($\{x_1(k)\}$, $\{x_2(k)\}$, …., $\{x_{26}(k)\}$) are stacked column wise to form a multichannel EEG matrix of dimension Lx26, where L is the length of signal. Each row (u_n) corresponds to the state vector representing the spatial distribution of EEG amplitudes over the entire scalp at that instant. Further, the signal is centered to zero mean value in all channels ($\Sigma_n u_n=0$) and is also transformed to the average reference ($\Sigma_n u^i_n=0$ for each one). The first two descriptors are computed as follows

$$\Pi = \sqrt{\frac{\sum_n \|\mathbf{u}_n\|^2}{26L}}$$

$$\Phi = \frac{1}{2\pi}\sqrt{\frac{\sum_n \|u_n\|^2}{\sum_n \|(u_n - u_{n-1})/\Delta t\|^2}},$$

where Δt is the sampling period, u_n is the row vector of the multichannel EEG matrix, and $\| . \|$ is the 2-norm. Π^2 is equal to the mean squared global field power integrated over the considered time epoch (Lehmann and Skrandies 1984; Lehmann, Ozaki et al. 1987). Φ corresponds to the circular frequency of the periodical field changes, a rough measure for the generalized frequency of the underlying attractor.

The covariant matrix (dimension 26x26) of the above multichannel EEG matrix is formed as

$$\mathbf{C} = \frac{1}{L}\sum_n \mathbf{u}_n \mathbf{u}_n^T .$$

Next the eigenvalues $\{\lambda_1, \lambda_2, \ldots, \lambda_{26}\}$ (Golub and Van Loan 1996) of the matrix C are obtained and subsequently normalized (normalized eigenvalue, $\xi_i = \lambda_i/\Sigma_i\lambda_i$). The quantity, Ω is computed as follows

$$\log\Omega = -\sum_{i=1}^{26} \xi_i \log \xi_i \,.$$

Ω roughly quantifies the global amount of spatial synchronization. Large values of *Ω* indicate no linear spatial correlation between different electrode regions whereas the low values correspond to high correlation or global synchronization.

Results

Eye-movement analysis

We tracked subjects' eye-movements with Eyelink 2 © and recorded their scalp EEG signals with ActiveTwo © system (see **Method**) while they performed five different two-alternative forced-choice tasks. In the "like-face" task they were presented with pairs of human faces and had to indicate, as naturally as possible, which face they liked more. In the "round-face" task, they had to choose which face was rounder, while in the "dislike-face" task which face they liked less. A "passive" task asked them to view a pair of faces freely and press a button to terminate the trial. Finally, in the "Fourier" task, subjects saw two Fourier descriptor generated shapes and had to decide which one they liked more.

We performed the same likelihood analysis as described in Shimojo, Simion et al 2003. The curves for the five tasks employed, i.e. "like-face," "dislike-face," "round-face," "passive" and "Fourier" are presented in Figure 2. We notice a strong cascade effect in the "like-face" and "Fourier" tasks, but a smaller gaze bias in the "round-face" and "dislike-face" tasks, which replicates our earlier findings. Of note here are the higher than usual effects in "round-face" and "dislike-face" tasks. We find this result not surprising however, since in this particular experiment all the tasks were performed in one sitting, causing possible difficulties in strategy shifting for observers. We expected some contamination to occur from one task to the other, thus reducing the differences in the gaze bias, while keeping them significant. Additionally, we did not see a bias at all in the passive viewing task ("passive"), which is reassuring for our claims. But the focus of this chapter is not the gaze analysis. We will instead present the electrophysiological differences between tasks, as measured by EEG, and try to correlate them with the emergence and development of the cascade effect.

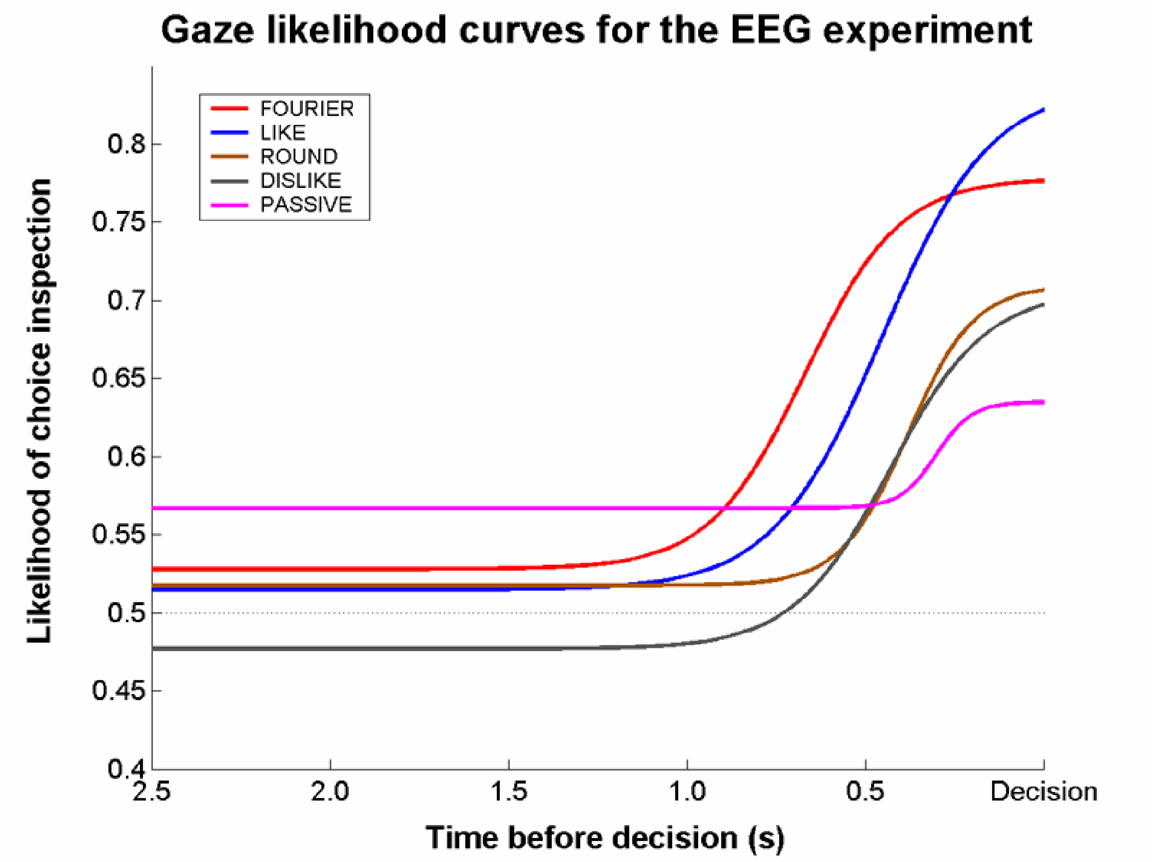


Figure 2. Gaze likelihood curves for the five tasks tested. Sigmoid fits were not performed in this analysis. Notice the clear separation between preference (like-face and Fourier) and non-

preference (round-face, dislike-face). The passive task curve shows that the motor action of button pressing does not generate a gaze bias.

Event-related-potential analysis

Fig. 3(a)-(d) shows the ERP profiles during the four tasks for four different brain regions. Due to high variabilities within and across trials and over subjects, the averaged ERP profiles have lesser structures (i.e., peaks) than classical ERP components (i.e., P300). Nevertheless several of noteworthy features emerge. First, brain potential with increasingly negative polarity was found for all the tasks before the response. This effect was more gradual (latency of 500 ms) in frontal and in occipital electrode regions but more abrupt (latency of 125 ms) in the central region.

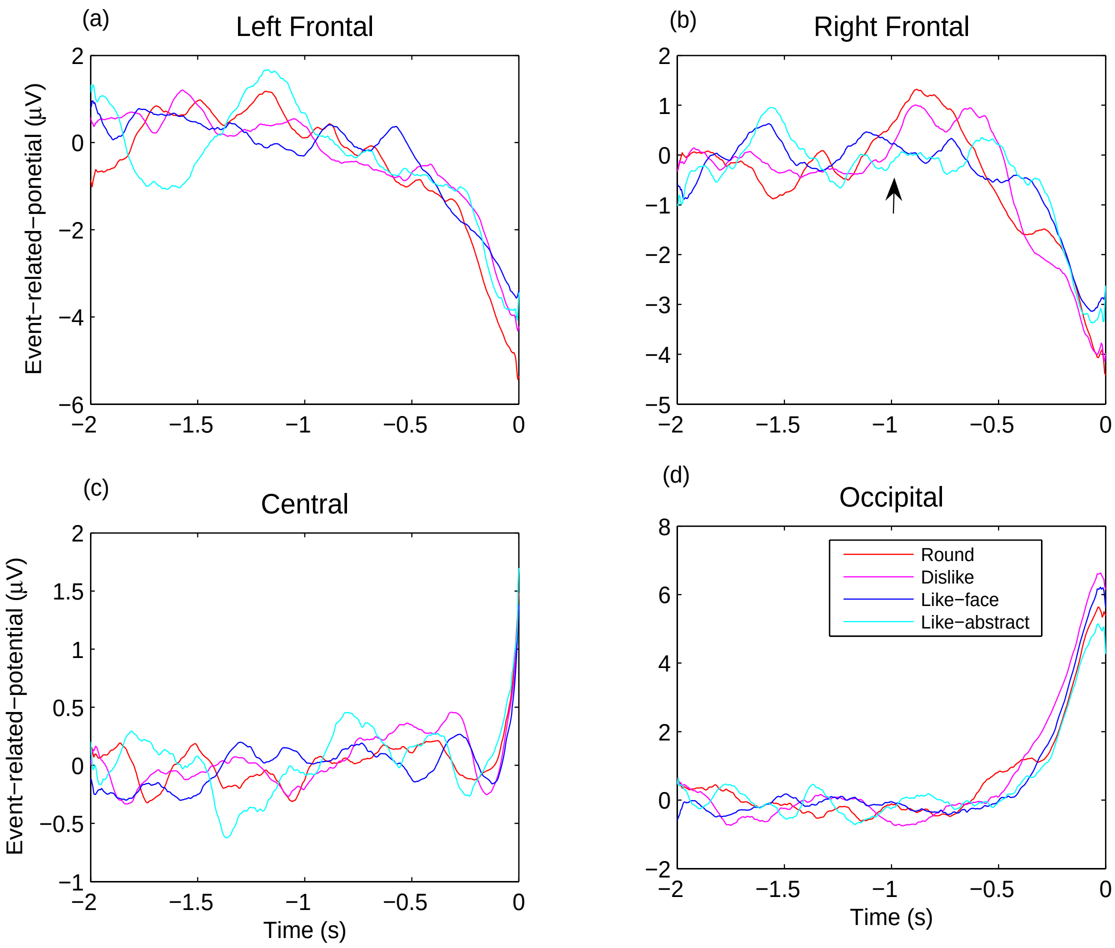


Figure 3. Event-related-potentials for the chosen four tasks (red line – face-roundness, magenta – face-dislike, blue – face-like, and cyan – abstract-like) at four brain regions, left frontal (a), right frontal (b), central (c), and occipital (d), respectively. ERPs were averaged across trials, subjects, and electrodes within brain regions. Time was indicated with respect to the moment of response (i.e., -1 s indicates 1 second before the response). The arrow in (b) indicates the onset of separation of ERPs of preference tasks from that of non-preference tasks.

Second, during two brief temporal segments (1750 – 1400 ms, 900-600 ms) ERPs of the two preference tasks (like-face and Fourier) are nicely separated from the ERPs of the two non-preference tasks (round-face and dislike-face). Preference ERPs showed larger positive amplitudes at the earlier segment whereas non-preference ERPs showed larger amplitudes at the latter segment. These differences are only evident in the right frontal brain region. Thirdly, ERP of Fourier task showed a large negative polarity with latency of 1.5 s in anterior brain regions.

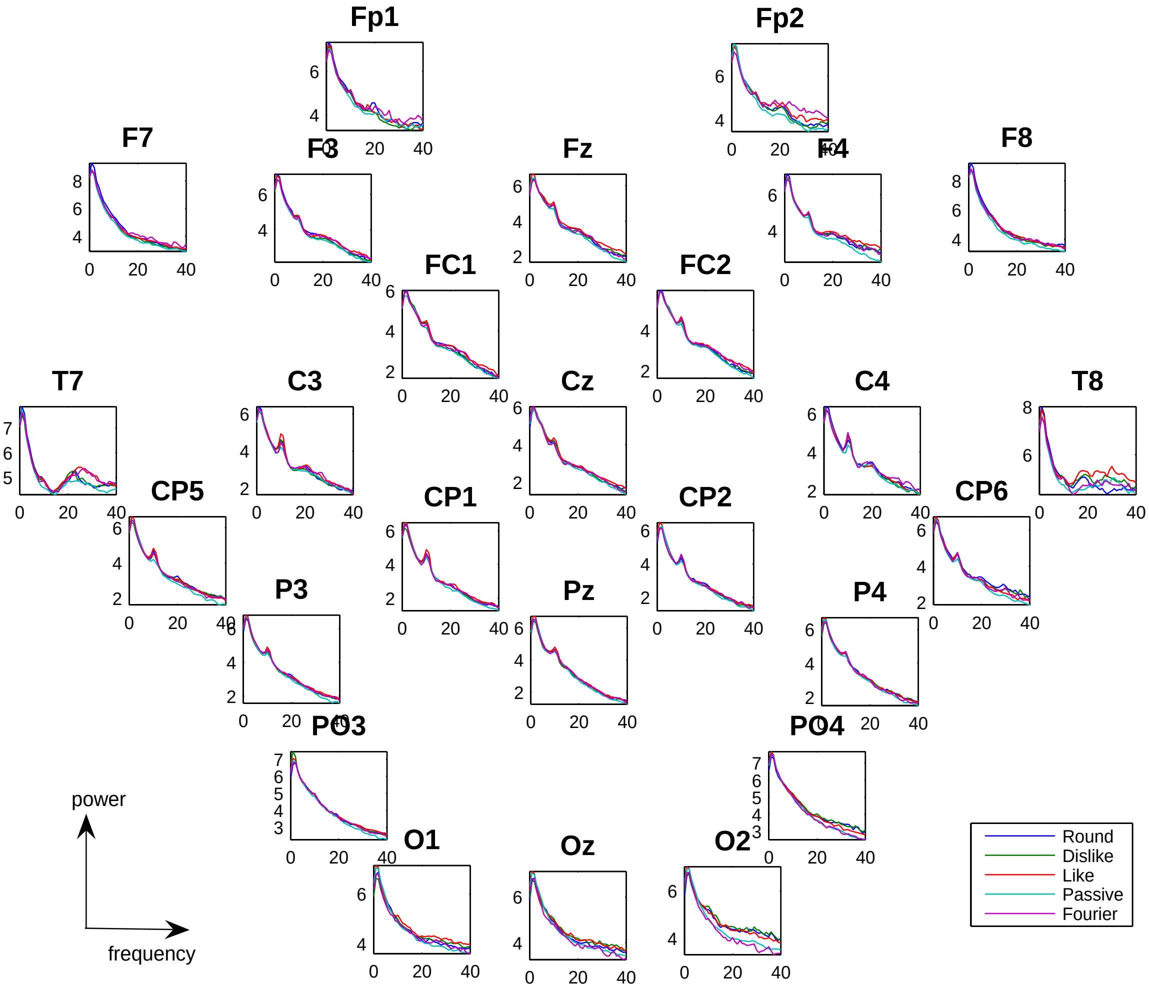


Figure 4. The power spectral density during the five tasks. The results were averaged across trials, and subjects. The graphs are organized topographically according to the approximate location of the 26 electrodes on the scalp (with nose pointing upwards).

Spectral Analysis

The power spectra were calculated for the individual trials from the EEG signals during the last 2 s before the response and then averaged. Figure 4 shows the power spectra averaged over all subjects topographically arranged according to the approximate electrode positions on the scalp. A clear spectral peak in the 8-12 Hz alpha band is observed in the electrodes centrally located over the scalp; somewhat weaker peaks were seen in the mid-frontal electrodes but occipital electrodes did not show any alpha peak.

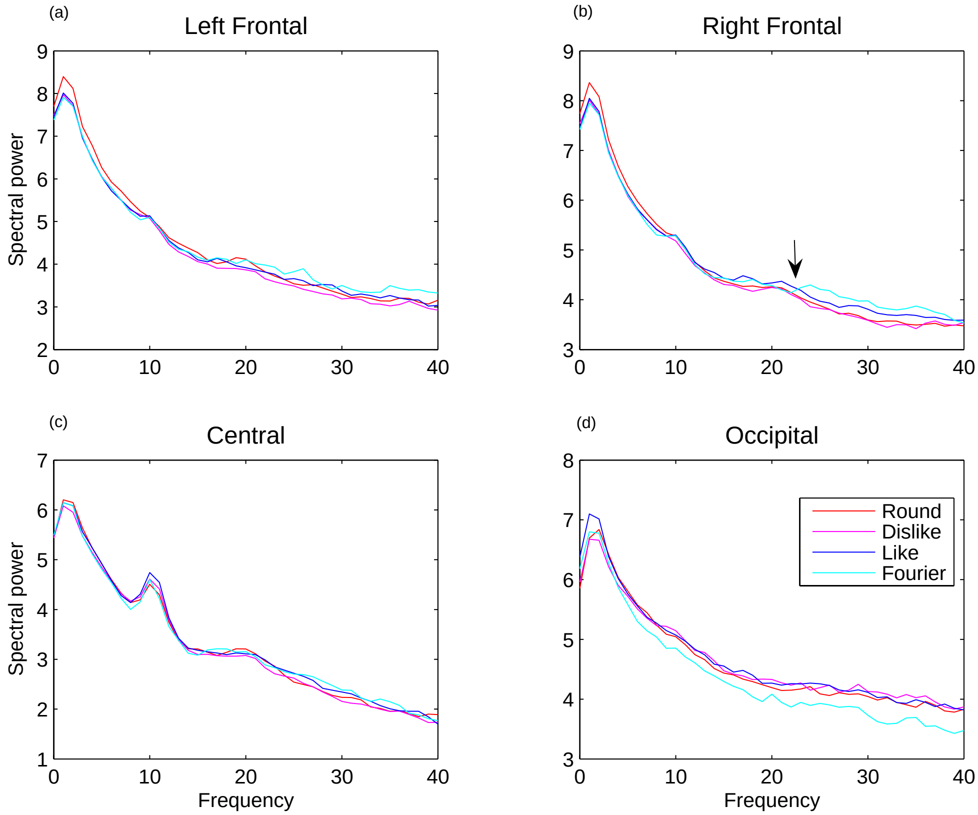


Figure 5. The power spectral density estimates for four brain regions during the four tasks. The results were averaged across electrodes within chosen brain regions, trials, and subjects.

Power spectra for selected brain regions are shown in Fig. 5. The right frontal spectral power in the high frequency (> 25 Hz) band was stronger for the preference tasks than the non-preference tasks. Interestingly in the occipital region, Fourier (or Fourier-task as mentioned in the legend of Fig. 4(d)) task, as compared to the other tasks, showed a higher spectral power in very low frequency band (> 3 Hz) but a lower power over a broad frequency range (8-40 Hz).

Time-Frequency Analysis

The temporal characteristics of the spectral power were further investigated by the wavelet-based time-frequency representations (TFR). The representations were base-line corrected, subsequently averaged over all trials, subjects, and topographically arranged. Fig. 6 shows the TFR profiles for the like-face task.

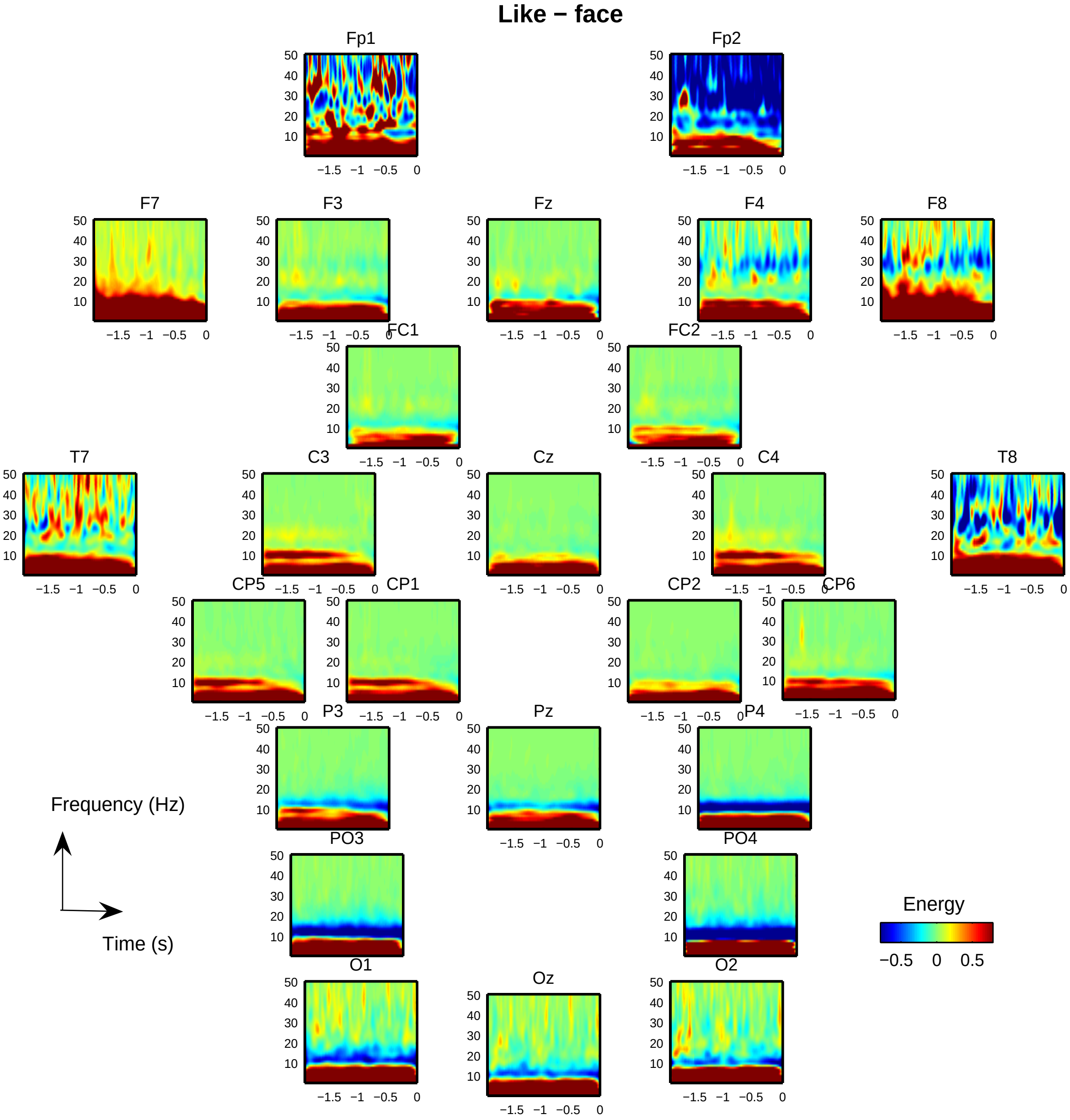


Figure 6. The time-frequency analysis of the signals recorded from 26 EEG electrodes for the like-face task. The results were averaged across trials, and subjects. The graphs are organized topographically according to the approximate locations of the 26 electrodes on the scalp (with nose pointing upwards). Note the stronger high frequency activities in the frontal and prefrontal regions.

Compared to the pre-stimulus or baseline period, task-related period shows robust and global increases in low frequency band (>5 Hz) over all electrodes. Sustained alpha band ERD was found in the posterior brain regions, but central brain regions showed predominantly alpha band ERS effect. ERS in the form of high frequency bursts were stronger in the prefrontal regions. Similar TFR profiles but for the dislike-face task were shown in Fig. 7. Unlike the like-face task, strong ERD in high frequency band (>20 Hz) was seen in the prefrontal region.

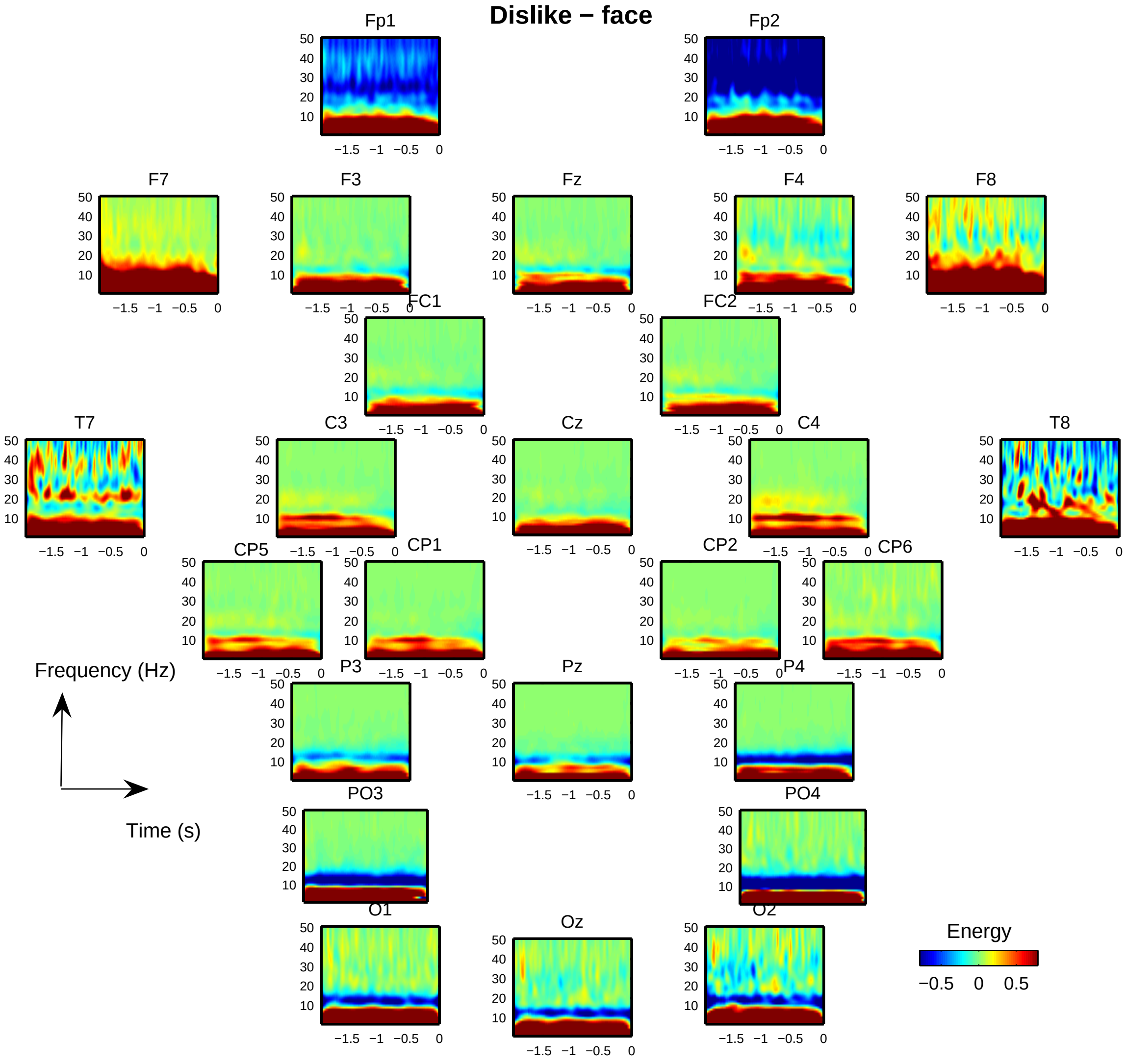


Figure 7. Same as in Fig. 6 but for the dislike-face task. Note the strong ERD effect in high frequency band (>20 Hz) in the prefrontal region. Also, notice the difference in FP1 between the dislike and like tasks.

Next we directly compare the TFR for preference tasks (both faces and abstract objects) to TFR for non-preference tasks (round-face and dislike-face) and the differential TFR images are shown in Fig. 8. We would like to mention the following key points. Firstly, right prefrontal electrode showed significantly higher power for the preference tasks till 1 s before the response; this effect was mostly pronounced in the low gamma (25-35 Hz) band.

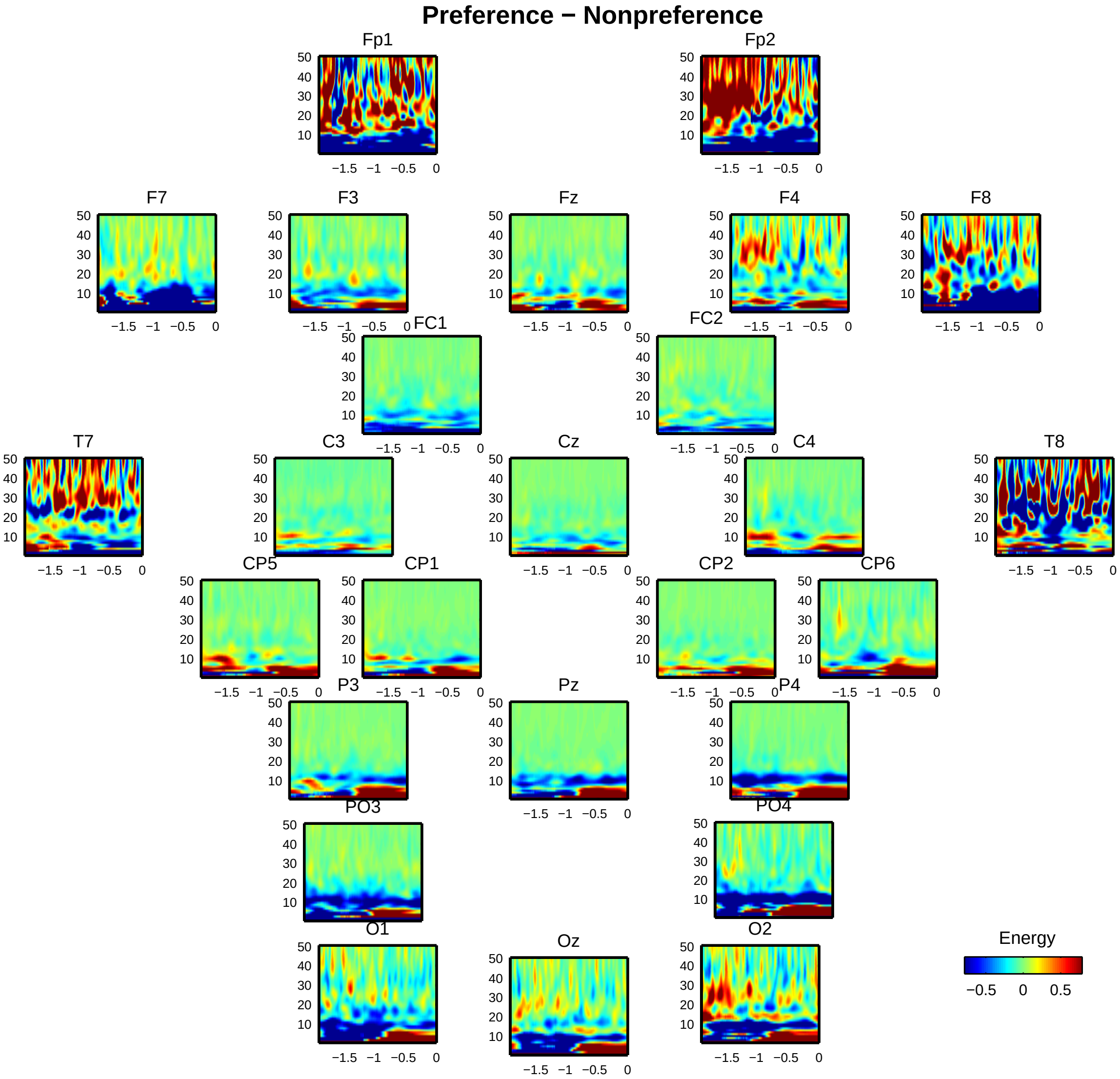


Figure 8. Differential TFR (preferential tasks – non-preferntial tasks). Results were averaged across trials, subjects, tasks. Same as in Fig. 5 but for the dislike-face task. Red color indicates higher power for preferential task and blue for non-preferential tasks. TFR for individual trials was corrected by the associated pre-stimulus baseline. Note the strong ERS effect in high frequency band (>20 Hz) in the prefrontal region and also in the right occipital region.

Second, larger spectral power in the low gamma band was found in the right occipital electrode for preference task till 1 s before the response. Intermittent high frequency bursts for preferential tasks were also produced by the temporal electrodes bilaterally. Finally, posterior electrodes spanning from occipital region to centro-parietal regions showed a striking transition in the low frequency (< 5 Hz) spectral power at around 900 ms before the response. Typically, the earlier (1900 – 900 ms) segment of higher power for non-preference tasks was followed by the latter segment (900 – 0 ms) of higher power for preference tasks.

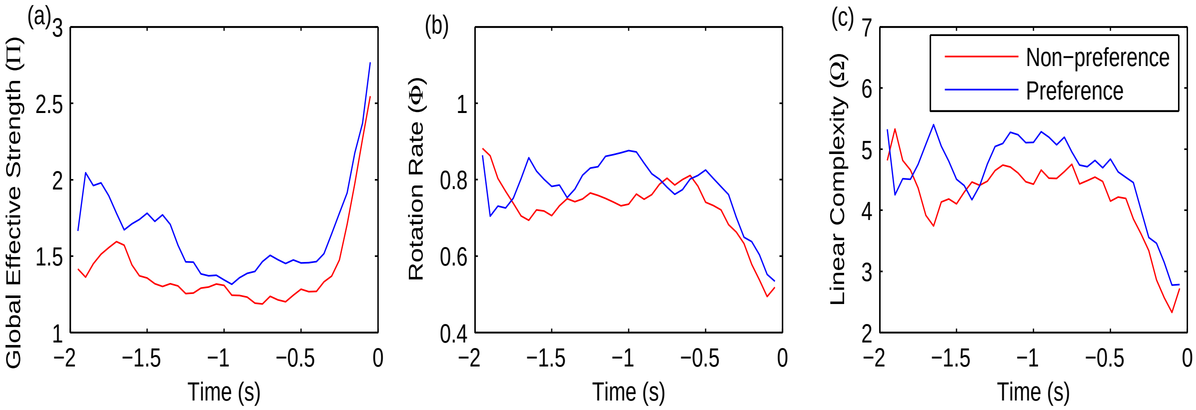


Figure 9. Time variations of three spatial descriptors of the underlying global trajectory dynamics. Note the clear and sustained differences between preference and non-preference tasks. See text for an explanation of each descriptor.

Spatial Analysis

Based on the multivariate embedding technique for spatially extended system, we computed three descriptors (See Methods) for the spontaneous EEG signals, and the results are shown in Fig. 9. At first glance, two things are very apparent: (i) the time-varying profiles have general similarity in shape across tasks, and (ii) all three descriptors, Π, Φ, Ω, were consistently higher for preference tasks than non-preference tasks. As the moment of response was approaching, Σ was gradually increasing whereas Φ and Ω were gradually decreasing; these tendencies were common for both types of tasks. Although motor response and a common decision mechanism were always involved for each trial irrespective of the task, which might partially explain the gradual change towards the response, the differences between the two profiles for each descriptor were possibly due to differences in the cognitive and emotional characteristics of the tasks (preference vs. non-preference).

Discussion

We have utilized whole scalp EEG recordings to investigate the brain responses during several types of decision making in a two-alternative forced choice paradigm. We analyzed the EEG signals using several approaches ranging from single channel ERP analysis, FFT based power spectral density estimates, wavelet based time-frequency representations, to multi-channel global analysis. Through extensive psychophysical studies involving eye-movement data analysis, we have found a strong correlation between choice and the likelihood of its inspection, especially in the last 1 s before decision. The primary aim of this study was to investigate the neuronal correlates of the preference decision making mechanism and also to identify the differences between making a preference decision and a non-preference one. EEG also offers an excellent time resolution of large scale brain electrical activity which could enable us to study the temporal dynamics of the neuronal information-processing mechanism, underlying complex cognitive tasks such as decision making.

Right frontal ERPs of preference tasks become different from ERPs of non-preference task as early as 1700 ms before the response. However, the differences become more apparent at 1 s before the response, a result in accordance with our gaze studies. Right frontal regions also showed higher spectral power in high frequency bands, mainly from higher beta band to lower gamma band, for preferential tasks during the early stage (1700 ms before response) of processing. Generally, an increase in spectral power at a electrode location is most likely due to an underlying increase of local synchronization, i.e., higher in-phase activity of neuronal assemblies or additional recruitment of neighboring neuronal populations (Srinivasan, Russell et al. 1999) or due to an increase in coupling strength between various neuronal elements of cortical networks (Muller, Lutzenberger et al. 2001). The phenomenon of neural oscillations and synchronizations has received a considerable amount of attention in cognitive neuroscience (Engel and Singer 2001; Schnitzler and Gross 2005) since there is evidence that oscillations belonging to specific frequency bands are associated with particular cognitive processes (Ward 2003). Higher beta (and also low gamma) oscillations, like reported here, are recently found to be crucial for the formation of long-range connected networks (von Stein and Sarnthein 2000; Gail, Brinksmeyer et al. 2004), which is also suggested by computational models (Kopell, Ermentrout et al. 2000).

Additionally, we found a clear transition of neuronal dynamics in terms of posterior delta (and low theta) oscillations at 1 s before the response. Low frequency oscillations in the theta band are prominent in the hippocampus but are also recorded in other cortical and limbic structures (Kahana, Seelig et al. 2001); they also play a crucial role in functional coupling of widely separated structures responsible for different components of the memory system (Sarnthein, Petsche et al. 1998; Tesche and Karhu 2000; Klimesch, Doppelmayr et al. 2001). As to low frequency oscillations in the delta band, research findings hint at functional correlates which are approximately similar to those for theta band when the brain is involved in cognitive processing (Basar, Basar-Eroglu et al. 2000; Basar, Basar-Eroglu et al. 2001). Increase of spectral power in the EEG frequencies from 1.56 to 5.46 Hz was reported during the performance of mental arithmetic which require attention to internal processing (Harmony, Fernandez et al. 1993). Delta power was also found to be increased during other mental tasks demanding higher internal concentration (Giannitrapani 1971; Dolce and Waldeier 1974; Sviderskaia 1977; Dostalek, Faber et al. 1979). Recently, it was shown that delta power was increased globally when the subjects mentally recalled emotional scenes from their personal experiences (Dan'ko, Bekhtereva et al. 2003). When the emotions were induced on the basis of a presented situation or scenic material, delta power was also increased like the internal induction of emotion (Dan'ko, Bekhtereva et al. 2003). This might explain why the low frequency power was enhanced for the preference decision which is intrinsically related to emotion.

The adopted global descriptors of brain electrical activity offer a tool for quantitative characterization of different brain functional states; we found a clear separation between preference and non-preference tasks by each descriptor. The linear complexity measure provides an approximation of the number of simultaneously activated neural processes (Lutzenberger, Birbaumer et al. 1992). From system perspective, higher values of complexity reflect the higher degrees of co-presence of functional specialization as well as functional integration within the system (Sporns, Tononi et al. 2000). From network perspective, higher values of complexity indicate stronger coupling between smaller network components, although the coupling between components cannot be too strong because it causes network instability (Strogatz 2001). In order to maximize the efficiency of information transmission between network components while maintaining the stability, coupling strengths needs to be within some specified limit.

All these results indicate a distributed and a long-range but optimally connected network of brain regions formed during the preference decision making mechanism. The application of synchronization analysis would be directly helpful to verify this hypothesis; however, we could not undertake such approach for this data set due to the absence of extra-cortical reference signal and limited number of artefact-free trials. It is a matter of ongoing research to precisely localize the spatially distributed local networks in the brain and to assess the degree of connectivity between these constituent network components.

General Discussion and Implications

The work presented herein has as its central subject the intrinsic link between orienting and preference decision making. Several directions of previous research pointed to existence of such a connection. Firstly, the mere exposure effect literature showed us that we tend to like stimuli we are exposed to even when the presentation is entirely subliminal. The principle at the basis of this phenomenon is applied everyday in modern advertising, where repeated exposure to the brand and its products is thought to increase viewer's preference towards them. Secondly, the preferential looking research interprets longer gaze times in infants as preference, a thesis that found many supporters as well as critics over the years. It became common understanding however that the property seems to be preserved in adults, who tend to look longer at stimuli they like, maybe under the influence of the brain reward mechanisms.

If we combine these two phenomena a positive feedback loop will naturally ensue, since the more we look at one stimulus, the more we like it, and the more we like it, the more we tend to look at it. Of note here is the importance of orienting behavior to this loop, since gaze direction and control is the crucial means for both exposure and preferential looking. We demonstrate in this thesis that the same mechanism is active over the time required for human observers to make a choice in multiple alternative choice tasks. We must therefore emphasize the first surprising aspect that our research reveals – namely, that phenomena like mere exposure and preferential looking can act just as effectively in the short-term as they do in the long-term.

We introduced a novel method of eye-movement analysis, which allowed us to illustrate with classical psychophysical methods the positive feedback loop that we described. The central measure of the entire work presented herein was the likelihood that the eventually chosen stimulus was gazed at, calculated at each time sample point. In most studies, the computation was performed with all trials aligned at the moment of decision, while the experimental setup was a two-alternative forced-choice task. We did generalize our results by showing that essentially the same behavior happens in four-alternative forced-choice tasks. We have to note however that this method of analyzing gaze data can be extended easily by applying it to trials aligned to any relevant point, revealing specific event-related aspects of the orienting behavior.

With the help of our method, we were able to show that, in two-alternative forced-choice tasks, observers' gaze starts being biased towards the eventual choice with approximately one second before decision. This bias is unusually strong in tasks in which observers had to choose the more attractive stimulus in a pair, with a particular profile that continually increases up until the decision point. We accounted for this behavior, which we called the "gaze cascade effect," by claiming that the positive feedback loop described above acts in preference tasks, thus reinforcing the percept until the observer comes to the conscious decision. On the contrary, the much smaller gaze bias seen in non-preference, control tasks, was explained by invoking a selection bias, probably necessary for the observer's internal cognitive-motor consistency. The important distinction is that in preference tasks orienting seems to be incorporated in the mechanism of decision, being the very basis of the positive feedback loop.

We validated our main claim, as well as excluding alternative explanations, in multiple occasions, most of them included in the present thesis. The gaze cascade effect was replicated over a large array of conditions and stimuli, such as using abstract shapes, jewelry and watches, preserving mental reconstruction while blocking holistic stimulus perception under the peephole paradigm, or employing a more complex, four-alternative forced-choice design. We showed that the effect is specific to preference, since it does not occur in control tasks, whether they refer to face roundness, abstract shape complexity or jewelry luminance contrast discrimination. We also demonstrated that manipulating gaze can indeed influence preference, an effect that is not explained by mere exposure and requires active orienting. Our random stimulus presentation setup showed that the cascade effect is a requirement for a preference decision and not a consequence of the state of liking a particular stimulus. It also added that the process of preference decision making, to which orienting is a major contributor, has to be completed once started, even after stimulus offset. This result decoupled orienting from its original purpose, which was strictly dependent on visual stimulation.

The mathematical model we developed, while largely speculative, is based on the reasonable assumption that an informed, objective comparison decision requires equal information sampling of all the stimuli involved. Therefore, it assumes that the default behavior is that the more we look at one stimulus, the less likely we are to look at it again. On top of this, in the subjective tasks, such as preference, the positive feedback loop acts in the opposite direction: the more we look at one stimulus, the more likely we are to gaze at it again. By combining the two behaviors, our model explains the gaze likelihood data in all the tasks we employed in the current thesis, preference or control while it also speculates on the timing of the gaze bias associated with each decision.

Our joint eye-movement / EEG study, besides replicating the gaze behavior revealed in our previous studies, shows a clear neural signal separation between the preference and control decision tasks, especially in the prefrontal electrodes (associated with activity in the frontal eye fields, responsible for gaze control) and left frontal ones (reflecting activity in decision making areas such as dorso-lateral prefrontal cortex).

Our enquiry will not stop here however. Future research will focus on employing powerful imaging techniques such as functional magnetic resonance imaging (fMRI) and mutual interaction electro-encephalography (EEG) to investigate the brain areas associated with the positive feedback loop between orienting and cognition that is responsible for preference formation. We already have an fMRI protocol in works for the near future, in which we will use an event-related design at the Brain Imaging Center at California Institute of Technology. The immediate purpose of this study is to find out the differential BOLD signals specific to preference vs. control (face roundness) decision making. The hope is to find structures associated with gaze control and direction (FEF, area LIP) active in correlation with decision making areas (orbito-frontal cortex, dorso-lateral prefrontal cortex) in preference, but not (or less so) in control tasks. Further experiments will distinguish between the components of this interaction, maybe by revealing specific brain areas involved in the perception of preference, its relationship with human face perception, whether and how the reward associated areas are involved in this mechanism, and so on. As we mentioned before, attractive stimuli could be perceived so because they activate appetitive behavior areas, acting as internal rewards, which would explain the preferential looking phenomenon itself.

It is well known that humans are very sensitive to changes in other's gaze direction (vonGrunau and Anston 1995). Gaze can induce attention shifts and can prime the location it is directed to (Friesen and Kingstone 2003). Whether the orienting involvement in preference is responsible for these phenomena is another intriguing question that we intend to answer. We can reasonably assume that, during the evolution of social cognition, gaze evolved as an important cue signaling interest and desire to communicate exactly because of its intrinsic link to preference formation. A gaze directed towards you could signal a developing cascade effect towards your person, rendering you more attractive in their eyes. This should in turn catch your interest, since it is probably advantageous for you to interact with them. Our dual 128-channel EEG setup, with which we can collect brain signals from two subjects while they interact socially, will help us gain insight into this issue. Additionally, psychophysical methods will be used to find correlations between the cascade effect and gaze direction detection, or gaze induced attention shifts.

The possibilities of extending this work are endless and they branch out into many subfields of neuroscience, from social cognition to brain-damaged patient assessment. For example, patients with damage in the frontal lobe, extending to the frontal eye-fields, show defects in gaze control. Whether they show a different orienting behavior with respect to preference decisions is an intriguing question that we are currently investigating, in collaboration with Dr. Ralph Adolphs's group at University of Iowa. Recently, Adolphs and colleagues also showed that the long-known inability of amygdala patients to recognize fearful faces comes from a defect in orienting towards the eye region of the face, rather than an inability to process emotional information per se. It would be thus interesting to analyze the gaze pattern of such subjects in the simple, two-alternative forced-choice preference task central to our work. The same argument applies to autistic patients, whose symptoms were lately associated with an adversity to make gaze contact with other individuals. We predict, in all these cases, that the gaze behavior will have a different profile than it does in normal observers – be it the total absence of cascade, a longer cascade and decision time, or lower elevation of the effect. However, how this would affect preference decision making is still an open issue that we hope to tackle soon.

Another important future direction to our research is the search for trial-by-trial predictors of choice. This endeavor is difficult because of the variable nature of the gaze behavior our tasks and also because the very nature of our analysis so far was based on averaging across trials, but we hope to extract such predictors from the eye-movements together with the EEG and fMRI signals. If successful, such results can have profound influence on various areas of psychology and cognitive science.

Besides adding new dimensions to the studies presented herein, there are still aspects of the data that, while not directly related to our focus of research, can provide insight into human face perception or reflex emotional response. By measuring pupil size changes in the various conditions tested we can potentially find somatic precursors of either preference, decision or both, even before any gaze behavior is obvious. Such a result would allow predictions on a trial-by-trial basis, as opposed to the gaze cascade, which emerges only by averaging across trials. The pupil size data from all experiments run in the past is available, and preliminary results are encouraging. Surprisingly enough, they point to pupil diameter as a predictor of choice, rather than of attractiveness, as extensive experimental psychology evidence shows. Statistical significance analysis needs to be refined on this data, but we already speculate that the cause of this discrepancy is the decision signal, which is particularly strong in our tasks, more so than the liking signal itself.

Moreover, so far we analyzed the eye-movement data only with respect to the direction of observers' gaze, and our interest areas extended to whole stimuli, such as human faces. Of main interest has always been the side that subjects gaze at, be it left or right, without emphasis on the particular region of the stimulus that was inspected at each point in time. However, particularly with faces, we know that the general pattern of free inspection concentrates on the eyes and mouth. It would therefore be interesting to find out whether the same result ensues when subjects compare pairs of faces on a certain dimension. Preliminary analysis seems to suggest that, especially towards the end of each trial, observers tend to look at what we called "the perceptual center of mass" of a half face. If proven true, this result would be surprising, since it would show that the brain subconsciously assumes that a face is symmetrical and adopts a cost-efficient solution for extracting maximum information in minimum time. This argument is seemingly weakened though by the fact that each observer appears to choose a particular half of both faces in a pair (some the left one, some the right one) and do not always inspect the most cost-advantageous half, the one towards the middle of the screen. We should not forget however that saccade control is not perfect, and overshoots always happen. This type of analysis can of course be extended to non-face and/or non-symmetrical stimuli, as well as to different types of decisions (i.e., preference vs. control), to gain more insight into the mechanisms and strategies of human decision making.

Overall, our research sees the brain as a dynamic, parallel structure, in which even so called “high-level” functions have roots in and developed from simpler, adaptive behaviors, with which they still share strong reciprocal connections. We advocate that decision making is an on-going process, starting very early in the visual processing stream, and it is only its conscious realization that we measure when observers respond to our task requirements, for example by pressing a button. We do not support a strictly modular view of the brain, and while we recognize the increased importance of certain brain regions or circuits in a particular function, we realize that such an association almost never provides the entire story. As we show that such a simple behavior as orienting plays a crucial role in preference formation, questions arise about the true nature of thinking, reasoning and consciousness, as well as their role in evolution. Do we really have criteria on which we make decisions, or are we only machines with the illusion of reasoning and self-awareness? Are we in fact that easy to manipulate in the real world? Many times, the affirmative answer seems obvious.

Dedicated to the memory of Joseph E. Bogen – teacher, mentor and best friend (1926-2005).

APPENDIX

Is the “gaze cascade” really a cascade?

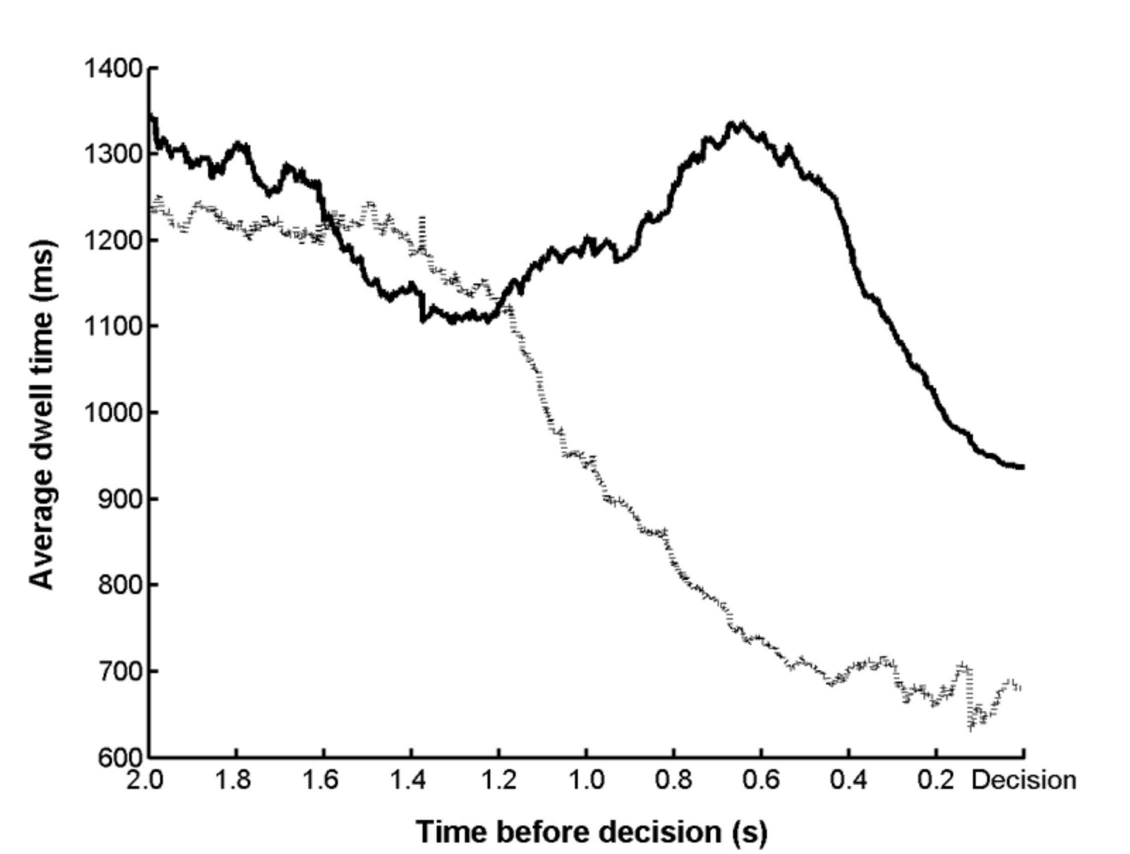
Throughout this thesis, we repeatedly talked about a “gaze cascade effect” as the requirement for a preference decision making. It referred to a continual increase in the likelihood that the eventually chosen stimulus is inspected, a bias that usually started around 1 seconds before the actual decision. A common concern among supporters as well as critics of our work was whether what we call the cascade effect is, in fact, conceptually a cascade. We called it so to emphasize its reinforcing nature, since we claimed it was the very illustration of the positive feedback loop underlying the mechanism of preference decisions. Once started, the process would continue in a cascade until the final choice is made.

However, due to the nature of the method we used to calculate the gaze likelihood curves in different conditions, it would have been possible that the effect was a consequence of a different, far less interesting phenomenon. Imagine that our story would simply reduce to the assertion that the last few fixations in most trials of a preference task are made on the choice face, for internal cognitive-motor consistency. Since the length of such fixations was highly variable, the continually increasing bias that we observed could have arisen from the simple operation of averaging across trials, without the phenomenology of a cascade. This possibility was already remote due to the clear differences between preference and control tasks, but no direct evidence was brought to invalidate such alternative claim. We present that evidence here.

When we computed the gaze likelihood curves, we assigned to each time sample point a value of 0, 1 or NaN (not-a-number) depending on where the gaze was directed to at that moment. In this separate analysis we will assign to each time point a value representing the length, in milliseconds, of the dwell that the time point belonged to, in each trial. We will come up therefore with two trial vectors, one for each stimulus (chosen v. non-chosen). Naturally, a positive value in one of the vectors will imply a NaN value in the other, since gaze can only be directed at one stimulus at any moment. If we align these vectors at the point of decision, and average across trials, what we obtain is the mean dwell time on the chosen and non-chosen stimulus, respectively, as a function of time until decision. The vectors for a typical preference and a control tasks (taken from the commercial object experiments presented in Chapter 3) are plotted in Figure 1. The curves are qualitatively similar for experiments in all other studies.

As it can be seen, the mean dwell time on choice and non-choice stimuli in preference tasks are not significantly different until approximately 1.5 seconds before decision, when inspection times on choice become longer, and those on non-choice shorter. This confirms our account that a real “cascade” occurs. The allocation of longer gaze times to the eventually preferred stimulus starts even before the likelihood curve display the gaze cascade effect (1.2 seconds before decision, compared to a gaze cascade of 0.7 seconds, see Chapter 3). In the last second of the decision fixations on both stimuli become smaller, which is an intriguing fact in itself, but explainable if we assume that the observers’ goal at this point is to gather relevant global information and compare it efficiently. However, we note that the difference, in milliseconds, between dwell times on choice and non-choice remains more or less constant, while the absolute value decreases for both. This in fact increases the proportion of time that is allocated to the eventual choice, effectively continuing the “cascade.” Figure 1B shows that the same thing is not true in the roundness task, where the dwell times separate earlier but remain much more similar throughout the trial. This analysis alone eliminates alternative explanations: the "gaze cascade" is, in fact, a cascade.

(A)



(B)

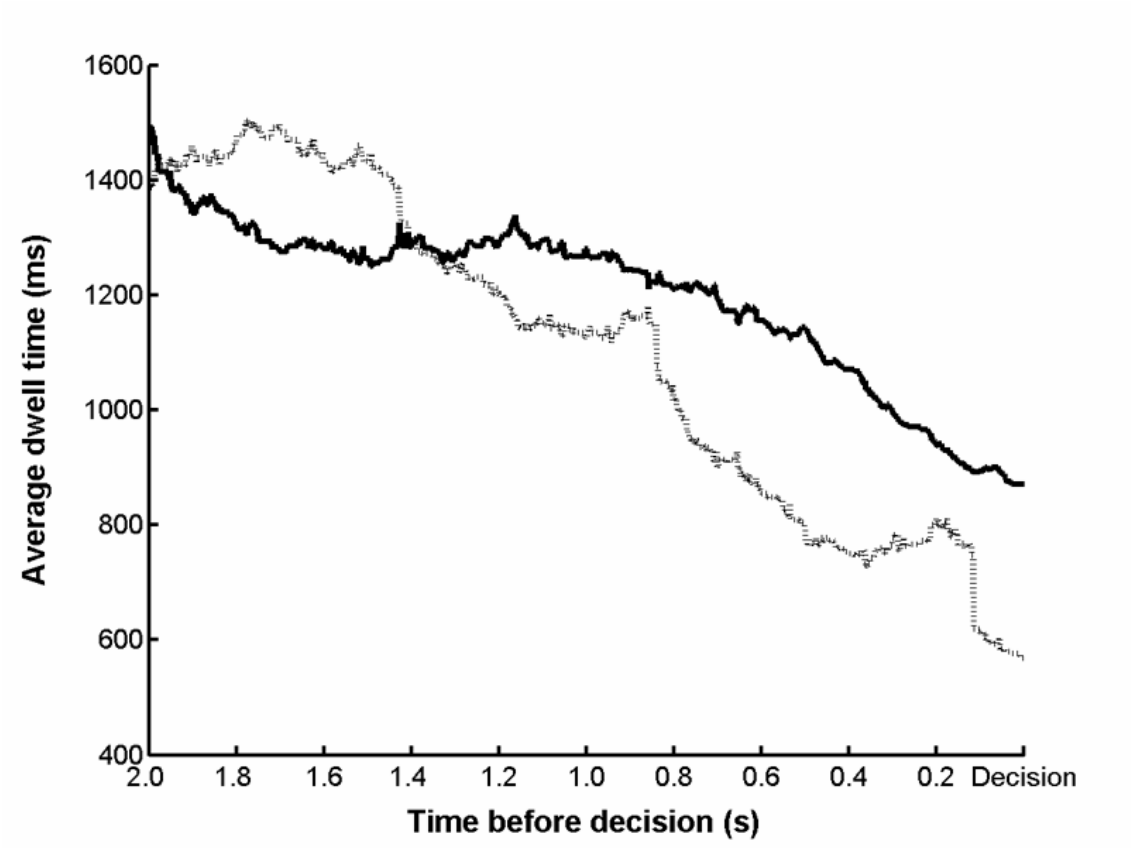


Figure 1. Average dwell time on choice (solid line) and non-choice (dotted line) in an A) preference and B) roundness task. The tasks used in the commercial object study (Chapter 3) are presented as an example. The analysis is locked at the moment of decision and represents an average across 336 or 168 trials. The effective number of data points on which the averaging was performed was actually lower, since at any point on the abscissa a NaN (not-a-number) value was assigned to one of the vectors.

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