List of Figures

2.1	Architect	ture	of	the	model	of	sa	lier	ncy-	-bas	sed	vi	sual	atte	entic	on,	ada	apte	ed	fro	om	Itt	i et	a	l.	
	(1998).		•				•																•			

6

9

- 2.2 Illustration of the processing steps for obtaining the attended region. The input image is processed for low-level features at multiple scales, and center-surround differences are computed (eq. 2.3). The resulting feature maps are combined into conspicuity maps (eq. 2.6) and, finally, into a saliency map (eq. 2.7). A winner-take-all neural network determines the most salient location, which is then traced back through the various maps to identify the feature map that contributes most to the saliency of that location (eqs. 2.8 and 2.9). After segmentation around the most salient location (eqs. 2.10 and 2.11), this winning feature map is used for obtaining a smooth object mask at image resolution and for object-based inhibition of return.
- 2.3A network of linear threshold units (LTUs) for computing the argmax function in eq. 2.8 for one image location. Feed-forward (blue) units f_{Col} , f_{Int} , and f_{Ori} compute conspicuity maps for color, intensity, and orientation by pooling activity from the respective sets of feature maps as described in eqs. 2.5 and 2.6, omitting the normalization step \mathcal{N} here for clarity. The saliency map is computed in a similar fashion in f_{SM} (eq. 2.7), and f_{SM} participates in the spatial WTA competition for the most salient location. The feed-back (red) unit b_{SM} receives a signal from the WTA only when this location is attended to, and it relays the signal to the b units in the conspicuity maps. Competition units (c) together with a pool of inhibitory interneurons (black) form an across-feature WTA network with input from the f units of the respective conspicuity maps. Only the most active c unit will remain active due to WTA dynamics, allowing it to unblock the respective b unit. As a result, the activity pattern of the b units represents the result of the argmax function in eq. 2.8. This signal is relayed further to the constituent feature maps, where a similar network selects the feature map with the largest contribution to the saliency of this location (eq. 2.9). \ldots

- 2.4 An LTU network implementation of the segmentation operation in eqs. 2.10 and 2.11. Each pixel consists of two excitatory neurons and an inhibitory interneuron. The thresholding operation in eq. 2.10 is performed by the inhibitory interneuron, which only unblocks the segmentation unit S if input from the winning feature map $\mathcal{F}_{l_w,c_w,s_w}$ (blue) exceeds its firing threshold. S can be excited by a select signal (red) or by input from the pooling unit P. Originating from the feedback units b in figure 2.3, the select signal is only active at the winning location (x_w, y_w) . Pooling the signals from the S unit in its 4-connected neighborhood, P excites its own S unit when it receives at least one input. Correspondingly, the S unit projects to the P units of the pixels in the 4-connected neighborhood. In their combination, the reciprocal connections between the S and P units form a localized implementation of the labeling algorithm (Rosenfeld and Pfaltz 1966). Spreading of activation to adjacent pixels stops where the inbound map activity is not large enough to unblock the S unit. The activity pattern of the S units (green) represents the segmented feature map $\hat{\mathcal{F}}_w$
- 3.1 Sketch of the combined model of bottom-up attention (left) and object recognition (right) with attentional modulation at the S2 or S1 layer as described in eq. 3.2. . . . 18
- 3.2 Mean ROC area for the detection of two paper clip stimuli. Without attentional modulation ($\mu = 0$), detection performance is around 0.77 for all stimulus separation values. With increasing modulation of S2 activity, individual paper clips can be better distinguished if they are spatially well separated. Performance saturates around $\mu = 0.2$, and a further increase of attentional modulation does not yield any performance gain. Error bars are standard error of the mean. On the right, example displays are shown for each of the separation distances.

13

3.4	Mean ROC area for the detection of two paper clip stimuli with attentional modulation	
	at layer S1. The results are almost identical to those shown in figure 3.2 for modulation	
	at the S2 layer.	23

- 3.5 Performance for detecting two faces with modulation at layer S1. Comparison with attentional modulation at the S2 layer (figure 3.3) shows that results are very similar. 24

4.2	S2-level features are patches of the four orientation sensitive C1 maps cut out of a	
	set of training images. S2 units have Gaussian tuning in the high-dimensional space	
	that is spanned by the possible feature values of the four maps in the cut-out patch.	
	During learning, S2 prototypes are initialized randomly from a training set of natural	
	images that contain examples of the eventual target category among other objects	
	and clutter. The stability of an S2 feature is determined by the number of randomly	
	selected locations in the training images, for which this unit shows the highest response	
	compared to the other S2 feature units. S2 prototypes with low stability are discarded	
	and re-initialized.	30
4.3	Examples for training stimuli for feature set A (top row), feature set B (second row),	
	test stimuli with two or more faces (third and fourth row), and for non-face distracters	
	(bottom row)	32
4.4	Fractions of faces in test images requiring one, two, three, or more than three fixations	
	to be attended when using top-down feature sets A or B, bottom-up attention, or	
	biasing for skin hue	33
4.5	Using ground truth about the position of faces in the test images, activation maps	
	can be segmented into face regions of interest (ROIs) and non-face regions. (a) input	
	image; (b) one of the S2 maps from set A; (c) one of the set B S2 maps; (d) bottom-up	
	saliency map; (e) skin hue distance map. Histograms of the map activations are used	
	for an ROI ROC analysis (see fig. 4.6)	34
4.6	By sliding a threshold through the histograms of map activations for face and non-face	
	regions for one of the maps shown in fig. 4.5, an ROC curves is established (inset). The	
	mean of the areas under the curves for all test images is used to measure how well this	
	feature is suited for biasing visual attention toward face regions.	35
4.7	The fraction of faces in test images attended to on the first fixation (the dark blue	
	areas in figure 4.4) and the mean areas under the ROC curves of the region of interest	
	analysis (see figures 4.5 and 4.6) for the features from sets A (green) and B (red) and	
	for bottom-up attention (blue triangle) and skin hue (yellow cross). The best features	
	from sets A and B (marked by a circle) show performance in the same range as biasing	
	for skin hue, although no color information is used to compute those feature responses.	36
5.1	Example for SIFT keypoints used for object recognition by Lowe's algorithm. (a) key-	
	points of the entire image; (b-d) keypoints extracted for the three most salient regions,	

- 5.4 Learning and recognition of object patches in a stream of video images from a camera mounted on a robot. Object patches are labeled (x axis), and every recognized instance is counted (y axis). The threshold for "good" object patches is set to 10 instances. Region selection with attention finds 87 good object patches with a total of 1910 instances. With random region selection, 14 good object patches with 201 instances are found. Note the different linear scales on either side of the axis break in the x axis. 50

5.8	The SIFT keypoints for the images shown in figure 5.7. The subsets of keypoints identified by salient region selection for each of the three objects are color coded with the same colors as in the previous figure. All other keypoints are shown in black. In figure 5.7 we show all regions that were found for each of the objects – here we show the keypoints from one example region for each object. This figure illustrates the enormous reduction in complexity faced by the recognition algorithm when attempting to match constellations of keypoints between the images.	55
5.9	(a) Ten of the 21 objects used in the experiment. Each object is scaled such that it consists of approximately 2500 pixels. Artificial pixel and scaling noise is added to every instance of an object before merging it with a background image; (b,c) examples of synthetically generated test images. Objects are merged with the background at a random position by alpha-blending. The ratio of object area vs. image area (relative object size) varies between (b) 5 % and (c) 0.05 %.	56
5.10	True positive rate (t) for a set of artificial images without attention (red) and with attention (green) over the relative object size (ROS). The ROS is varied by keeping the absolute object size constant at 2500 pixels ± 10 % and varying the size of the background images. Error bars indicate the standard error for averaging over the performance of the 21 classifiers. The human subject validation curve (blue) separates the difference between the performance with attention (green) and 100 % into problems of the recognition system (difference between the blue and the green curves) and problems of the attention system (difference between the blue curve and 100 %). The false positive rate is less than 0.07 % for all conditions.	57
6.1	(a) ROV Ventana with camera (C) and lights (L). (b) Manual annotation of video tapes in the video lab on shore.	62
6.2	Interactions between the various modules of our system for detecting and tracking marine animals in underwater video	64
6.3	Example frames with (a) equipment in the field of view; (b) lens glare and parts of the camera housing obstructing the view.	65
6.4	Processing steps for detecting objects in video frames. (a) original frame $(720 \times 480 \text{ pixels}, 24 \text{ bits color depth})$; (b) after background subtraction according to eq. 6.1 (contrast enhanced for displaying purpose); (c) saliency map for the preprocessed frame (b); (d) detected objects with bounding box and major and minor axes marked; (e) the detected objects marked in the original frame and assigned to tracks; (f) direction of motion of the object obtained from eq. 6.11.	66

- 6.6 A schematic for a neural implementation of across-orientation normalization using an inhibitory interneuron. This circuit would have to be implemented at each image location for this normalization to function over the entire visual field.
 68

7.2	Experimental set-up. Each trial starts 1300 ms before target onset with a blank gray	
	screen. At 650 ± 25 ms before target onset, a white fixation dot $(4.1' \times 4.1')$ is presented	
	at the center of the display. At a variable cue target interval (CTI) before target onset,	
	a word cue (0.5° high, between 1.1° and 2.5° wide) appears at the center of the screen	
	for 17 ms (two frames), temporarily replacing the fixation dot for CTIs less than 650 ms.	
	At 0 ms, the target stimulus, consisting of a gray-level photograph and a color frame	
	around it, is presented at a random position on a circle around the fixation dot such	
	that the image is centered around 6.4° eccentricity. After a stimulus onset asynchrony	
	(SOA) of 200–242 ms, the target stimulus is replaced by a perceptual mask. The mask	
	is presented for 500 ms, followed by 1000 ms of blank gray screen to allow the subjects	
	to respond. In the case of an error, acoustic feedback is given (pure tone at 800 Hz for	
	100 ms), followed by 100 ms of silence. After this, the next trial commences	81
7.3	Histogram of the reaction times of all trials. Trials with reaction times below 200 ms	
	and more than four standard deviations above the mean (above 995 ms) were discarded	
	as outliers (1 % of the data). \ldots	83
7.4	Reaction times (top, blue) and error rates (bottom, red) for single task blocks, task	
	repeat trials, and task switch trials in mixed blocks for $n = 5$ subjects. Error bars are	
	s.e.m. For RT, both mixing and switch cost are significant at a CTI of 50 ms, but not	
	at CTIs of 200 ms and 800 ms ($p > 0.05$, t-test). The drop of the single task RT at	
	200 ms compared to 50 ms and 800 ms is not significant ($p > 0.05$, t-test). For error	
	rate, only switch cost at a CTI of 800 ms is statistically significant. There are no other	
	significant effects for error rate	84
7.5	Mixing cost in RT (blue) and error rate (red) for all subjects for $CTI = 50$ ms, plotted	
	by task group. While mixing cost in RT is significantly higher for IMG than for COL	
	tasks, mixing cost in error rate is significantly higher for COL than for IMG tasks	86
7.6	Switch cost in RT at a CTI of 50 ms for different switch conditions (blue) and pooled	
	over all conditions (white). The white bar corresponds to the difference labeled as	
	$C_{\text{switch}}^{\text{RT}}$ in figure 7.4. Error bars are standard errors as defined in eqs. 7.3 and 7.4.	
	Switch cost is only significant when switching between the IMG and COL task groups,	
	but not when switching within the groups.	87
A.1	Illustration of one-dimensional filtering and subsampling. (A) convolution with a filter	
	of length 3 (first to second row), followed by decimation by a factor of 2 (third and	
	fourth row) – the pixels marked with a red cross are removed; (B) integral operation	
	of convolution with a filter of length 4 and decimation by a factor of 2	96

A.2	Example of repeated filtering and subsampling of an image of size 31×31 pixels with	
	only one pixel activated with: (A) a 5×5 filter with subsequent subsampling; and (B)	
	a 6×6 filter with integrated subsampling. Bright pixels indicate high and dark pixels	
	low activity	97
A.3	Schematic of the correlation-based motion detector by Hassenstein and Reichardt (1956).	
	The activation of each receptor is correlated with the time delayed signal from its	
	neighbor. The leftwards versus rightwards opponency operation prevents full field illu-	
	mination or full field flicker from triggering the motion output signal. \ldots \ldots \ldots	100
A.4	Illustration of center-surround receptive fields for motion perception. The five dots at	
	the center of the display are salient even though they are stationary because they are	
	surrounded by a field of moving dots. \ldots	102
A.5	Feature maps for motion directions right (a), down (b), up (c), left (d), and the motion	
	conspicuity map (e) in response to a rightward moving white bar (f). \ldots	103
A.6	The Gaussian model for skin hue. The individual training points are derived from 3974	
	faces in 1153 color photographs. Each dot represents the average hue for one face and	
	is plotted in the color of the face. The green cross represents the mean (μ_r, μ_g) , and	
	the green ellipses the 1σ and 2σ intervals of the hue distribution	105
A.7	Example of a color image with faces (left) processed with the skin hue model from	
	eq. A.14, using the parameters from table A.2 (right). The color scale on the right	
	reflects how closely hue matches the mean skin hue, marked with a green cross in	
	figure A.6. Note that face regions show high values, but other skin colored regions do	
	as well, e.g. arms and hands or the orange T-shirt of the boy on the right. \ldots .	105
B.1	Screen shot of a typical display while running the SaliencyToolbox	108

