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Abstract

Sensory object recognition is the most fundamental of operations performed by the brain. A key computational difficulty of object recognition is that it requires both selectivity to particular objects (e.g., exact odor mixture identification) and generalization across objects (identifying particular features or components common to different odors). Although previous results (*1*) suggest that odor identity and intensity are represented in the activity of both PNs and KCs, it is not clear how these representations generalize across complex odor mixtures. In particular, it is not clear what types of information are available in KC population (or if its even possible to decode across KC populations?) and how is this information represented? Using the locust olfactory system as a model system, we found that Kenyon cells (KCs), the principal neurons of the mushroom body, an area required for associative learning can identify the presence of components in mixtures and thus enable odor segmentation. As a population, small groups of KCs can both identify and categorize odors with high accuracy. We identified and tested simple circuit requirements for this computation, and propose that odor representations in mushroom bodies are optimized for odor memorization, identification and generalization. These rules may be relevant for pattern classifying circuits in general.

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