Local Descriptor Groupings in Reinforcement Learning of Sensory-Motor Attention

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INFORMATIVE GROUPINGS

Informative features are selected using an information theoretic saliency measure on SIFT descriptors (for the informative approach see Fritz et al., ICPR 2004). These features support focusing attention on most salient image regions for further investigation (Fritz et al., AAAI 2004).

ATTENTION CONTROL

Attention on informative local image patterns is shifted between largest local maxima derived by the information theoretic saliency measure. Saccadic actions originate from a randomly selected maximum and target towards one of the n-best ranked maxima (here: n=10). Saccadic actions are categorized into 8 principal directions. At each local maximum, the extracted local feature is associated to a codebook vector of nearest distance in feature space.

Foci of Interest (FOIs) and codebook vectors
- Compute posterior entropy of local descriptors.
- Apply thresholding on descriptor entropy and generate entropy-sorted list.
- Start attention sequence with lowest entropy keypoint.
- Assign codebook vector to keypoint in the FOI.
- Codebook vectors (k=20) extracted from unsupervised learning on the keypoint distribution.
- Actions are categorized in 8 principle directions.
- The next action is derived from Q-Learning classifier.

RESULTS

We formalize the sequence of action selections in sequential attention as a Markovian Decision Process (MDP) with state space S, action space A, transition function P, reward function R and are searching for optimal solutions with respect to the object recognition task. Since the probabilistic transition function P cannot be known beforehand, the probabilistic model of the task is estimated via reinforcement learning, e.g., by Q-learning (Watkins & Dayan, Machine Learning 1992), which guarantees convergence to an optimal policy applying iterative updates of the Q-function

Q(s,a) = Q(s,a) + a[R + γ max a' Q(s',a') - Q(s,a)]

where s is the learning rate, γ controls the impact of a current action on future policy return values.

We call this approach Q-learning of Working Memory (Q-Learning WM).

Definitions:
- Markovian recognition state: s = [f1,a1,f2,a2,...] represents ST working memory.
- Reward function: entropy decreases R = −dH(E), H = conditional entropy.
- Entropy at each s: frequency of object specific traces visiting s.
- Actions: saccadic shifts in 2D, angle discretized, a1,...,a8, a = (N, NE, E, SE, ...).

ATTENTION SACCADIC SHIFTS

Human Previous research on behavioral modeling of saccadic image interpretation (Henderson, 2002 Psychological Science: 51 - 55) has emphasized the sampling of informative parts under visual attention to guide visual perception. We propose a system of sequential attention for object recognition that (i) groups images into local gradient based image regions, (ii) learns a predictive mapping from a current state to future saccades, (iii) proposes a model of object recognition being capable of integrating sequential information by recombination of entropy in the Bayesian modeling of object hypotheses. The innovative abstraction level of informative groupings provides perceptual meta-states in sensory-motor attention, enabling the learning of a purposeful grammar integrating atomic feature-saccade mappings into a meaningful recognition behavior. We determine highly accurate recognition of outdoor scenes in a mobile vision application, using the sensory-motor content of frame-saccadic object recognition.