On-line Adaption of Class-specific Codebooks for Instance Tracking

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In this work, we demonstrate that an off-line trained class-specific detector can be transformed into an instance-specific detector on-the-fly. To this end, we make use of a codebook-based detector [1] that is trained on an object class. Codebooks model the spatial distribution and appearance of object parts. When matching an image against a codebook, a certain set of codebook entries is activated to cast probabilistic votes for the object. For a given object hypothesis, one can collect the entries that voted for the object. In our case, these entries can be regarded as a signature for the target of interest. Since a change of pose and appearance can lead to an activation of very different codebook entries, we learn the statistics for the target and the background over time, *i.e.* we learn on-line the probability of each part in the codebook belonging to the target. By taking the target-specific statistics into account for voting, the target can be distinguished from other instances in the background yielding a higher detection confidence for the target, see Fig. 1.

A class-specific codebook as in [1, 2, 3, 4, 5] is trained off-line to identify any instance of the class in any image. It models the probability of the patches belonging to the object class $p\big(c{=}1|L\big)$ and the local spatial distribution of the patches with respect to the object center $p\big(\mathbf{x}|c{=}1,L\big)$. For detection, patches are sampled from an image and matched against the codebook, *i.e.* each patch $P(\mathbf{y})$ sampled from image location $\mathbf{y}$ ends at a leaf $L(\mathbf{y})$. The probability for an instance of the class centered at the location $\mathbf{x}$ is then given by

$$p\big(E(\mathbf{x})|L(\mathbf{y})\big) = p\big(\mathbf{y}-\mathbf{x}|c{=}1,L(\mathbf{y})\big)\cdot p\big(c{=}1|L(\mathbf{y})\big). \quad (1)$$

Since each patch P_i has been observed at a relative position $\mathbf{d}_i$ with respect to object center, the spatial distribution $p\big(\mathbf{y}-\mathbf{x}|c{=}1,L(\mathbf{y})\big)$ can be approximated by a sum of Dirac measures $\delta_{\mathbf{d}_i}$:

$$p\big(E(\mathbf{x})|L(\mathbf{y})\big) = \frac{1}{|\mathscr{P}_{L(y)}|}\left(\sum_{P_i\in\mathscr{P}_{L(y)}} p\big(c{=}1|L(\mathbf{y})\big)\cdot\delta_{\mathbf{d}_i}(\mathbf{y}-\mathbf{x})\right). \quad (2)$$

For tracking, however, one is not interested in the probability (2), but in the probability $p\big(E_I(\mathbf{x})|L(\mathbf{y})\big)$ where $E_I(\mathbf{x})$ is the evidence for a given instance I, namely the tracking target. In this case, $p\big(c{=}1|L(\mathbf{y})\big)$ needs to be replaced by the probability of a patch P_i belonging to the instance I, *i.e.* $p\big(P_i\in I|L(\mathbf{y})\big)$. Hence, we have

$$p\big(E_I(\mathbf{x})|L(\mathbf{y})\big) = \frac{1}{|\mathscr{P}_{L(y)}|}\left(\sum_{P_i\in\mathscr{P}_{L(y)}} p\big(P_i\in I|L(\mathbf{y})\big)\cdot\delta_{\mathbf{d}_i}(\mathbf{y}-\mathbf{x})\right) \quad (3)$$

$$= \frac{1}{|\mathscr{P}_{L(y)}|}\left(\sum_{P_i\in\mathscr{P}_{L(y)}} p\big(P_i\in I|c{=}1,L(\mathbf{y})\big)\cdot p\big(c{=}1|L(\mathbf{y})\big)\cdot\delta_{\mathbf{d}_i}(\mathbf{y}-\mathbf{x})\right).$$

While $p\big(P_i\in I|c{=}1,L(\mathbf{y})\big)$ needs to be estimated on-line, the other terms are already computed for the off-line creation of the codebook (2).

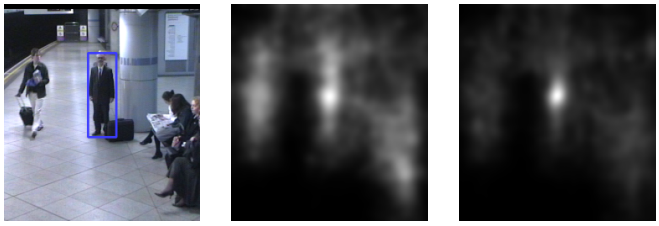

Figure 1: (a) Blue box indicates the instance of interest. (b) Voting image obtained by an off-line trained codebook for pedestrians. (c) Voting image obtained by the proposed instance-specific codebook.

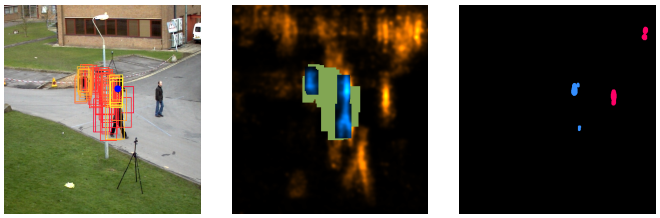

Figure 2: (a) After updating the particles, the multi-modal posterior distribution is approximated. The weights of the particles are indicated by color (*yellow: high, red: low*). The target is marked by a *blue dot*. (b) Based on the posterior, the voting space is clustered (*blue: foreground, red: background, green: uncertain*). (c) Votes that contributed to the detected local maxima are used to update the instance-specific statistics.

The probability $p\big(P_i\in I|c{=}1,L(\mathbf{y})\big)$ is estimated by counting the number of times a patch P_i votes for the target instance $\{y|P_i\in I\cap\mathscr{P}_{L(y)}\}$ and the number of times it votes for other objects $\{y|P_i\notin I\cap\mathscr{P}_{L(y)}\}$:

$$p\big(P_i\in I|c{=}1,L(\mathbf{y})\big) = \frac{|\{y|P_i\in I\cap\mathscr{P}_{L(y)}\}|}{|\{y|P_i\in I\cap\mathscr{P}_{L(y)}\}|+|\{y|P_i\notin I\cap\mathscr{P}_{L(y)}\}|}. \quad (4)$$

When the patch has not been previously activated for voting, we assume a fifty-fifty chance that the patch belongs to the instance I.

In order to compute (4), we have to estimate $\{y|P_i\in I\cap\mathscr{P}_{L(y)}\}$ and $\{y|P_i\notin I\cap\mathscr{P}_{L(y)}\}$. To this end, we assign a label to each vote based on the posterior distribution estimated by a particle filter (Fig. 2). Namely 1 (*blue*) or -1 (*red*) if we are confident that it either belongs to the instance or it does not. When the posterior is greater than zero but relatively low, we assign the label 0 (*green*) to it.

After labeling the elements in the Hough space, we search for strong local maxima in the positive and the negative cluster. The elements of the cluster labeled with 0 are discarded. Finally, we collect the votes that contributed to the local maxima and add them to the corresponding sets $\{y|P_i\in I\cap\mathscr{P}_{L(y)}\}$ and $\{y|P_i\notin I\cap\mathscr{P}_{L(y)}\}$. The details of the clustering and the algorithm are described in the paper.

We conclude that standard codebooks can be efficiently transformed into more instance-specific codebooks. Coupled with a particle filter, one obtains a powerful instance tracking method without the use of additional classifiers to distinguish several instances during tracking. Compared to a class-specific codebook, the accuracy is not only increased but the computation time is also reduced. Compared to on-line learning approaches, tracking is much more reliable subject to an off-line trained codebook. Although this prevents tracking arbitrary objects, it is not a practical limitation since the objects of interest usually belong to a well defined class.

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