Higher-order Co-occurrence Features based on Discriminative Co-clusters for Image Classification

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Motivation

Co-occurrence based image features have attracted keen attentions due to the promising performances for image classification tasks [1, 2, 3, 6, 7]. For extracting the co-occurrences, it is common to transform the *quantitative* data into *qualitative* data (symbols) by means of quantization (clustering) at first; *e.g.*, continuous gradient orientation is coded into orientation bins [3], RGB colors are indexed [2] and local features are categorized into visual words [7]. Such point-wise clustering, however, is not necessarily suitable to characterize the pair-wise co-occurrences. And the higher-order co-occurrences beyond pair-wise has been rarely considered due to the exponential increase of the dimensionality by using those point-wise symbols. In this paper, we propose a method to extract image features based on effective higher-order co-occurrences. The proposed method constructs the co-clusters to discriminatively quantize joint primitive quantitative data, such as pair-wise pixel intensities, unlike the standard co-occurrence methods that utilize simple clusters trained in an unsupervised manner for quantizing point-wise data. The discriminative co-clusters effectively exploit the co-occurrence characteristics even by a fewer number of cluster components, resulting in low-dimensional co-occurrence features, which enables us to develop the higher-order co-occurrence features of feasible dimensionality.

Proposed method

Let $\mathcal{R}$ be the quantitative data space, $x_{\boldsymbol{p}} \in \mathcal{R}$ be the quantitative data at pixel position $\boldsymbol{p}$ in an image plane. We consider the general form for extracting co-occurrences:

$$\boldsymbol{M} = \left\{ \sum_{\{\boldsymbol{p},\boldsymbol{q}\}\in\mathbb{N}} \omega(\boldsymbol{p},\boldsymbol{q}) g_k(x_{\boldsymbol{p}}, x_{\boldsymbol{q}}) \right\}_{k=1,\cdots,D} \in \Re^D,$$

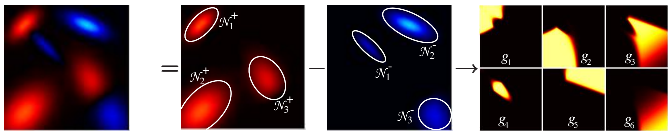
where $\mathbb{N}$ indicates the set of local neighbor pairs and ω is the weighting function on those pairs. We introduce the function $g_k(x_{\boldsymbol{p}}, x_{\boldsymbol{q}}) : \mathcal{R}\times\mathcal{R} \to \Re_+$ to assign the pair $(x_{\boldsymbol{p}}, x_{\boldsymbol{q}})$ with the k-th cluster ($k = 1,\cdots,D$) in the joint space $\mathcal{R}\times\mathcal{R}$, called *co-cluster*. The co-clusters g_k directly measure the co-occurrences and we construct them in a discriminative manner.

Discriminative co-cluster (Fig. 1). Suppose a two-class problem of images I_n with the class label $y_n \in \{+1,-1\}$. From the image I_n, we first extract primitive co-occurrence features $\tilde{\boldsymbol{M}}_n$ on $\mathcal{R}\times\mathcal{R}$ as in GLCM [1]; in practice, the space $\mathcal{R}$ which is usually continuous is finely partitioned into (large number of) L bins, resulting in $\tilde{\boldsymbol{M}}_n \in \Re^{L\times L}$. Then, the *linear* SVM is applied to those $(\tilde{\boldsymbol{M}}_n, y_n)$ in order to produce the classifier weight $\boldsymbol{W}$ on $\mathcal{R}\times\mathcal{R}$, actually $\boldsymbol{W} \in \Re^{L\times L}$. The classifier weight exploits the discriminative information: the positive weights in $\boldsymbol{W}$ contribute to '+1' class, while the negative ones to '-1' class. Finally, we perform clustering on the weight matrix $\boldsymbol{W}$ to produce the co-cluster assignment function g_k which is determined as the membership function to the k-th co-cluster on $\mathcal{R}\times\mathcal{R}$. We separately treat the weight $\boldsymbol{W}$ in terms of its sign (positive/negative) as the positive weight $\boldsymbol{W}^+ = \max(\boldsymbol{W},0)$ and the negative $\boldsymbol{W}^- = \max(-\boldsymbol{W},0)$, $\boldsymbol{W} = \boldsymbol{W}^+ - \boldsymbol{W}^-$, and apply the EM clustering method [5] to those respective weights; the cluster component is represented by Gaussian function $\mathcal{N}_k$ with the prior weights α_k. The function g_k is finally determined by

$$g_k(x_1,x_2) = \frac{\alpha_k \mathcal{N}_k(x_1,x_2)}{\sum_k \alpha_k \mathcal{N}_k(x_1,x_2)}, \ \forall x_1,x_2 \in \mathcal{R},$$

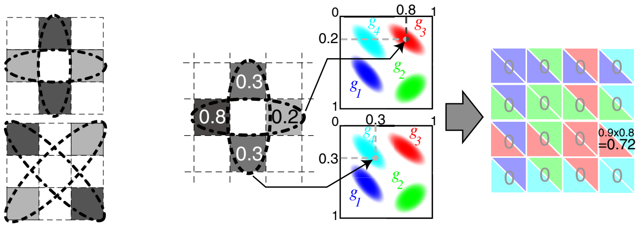
which is the posterior probability at (x_1,x_2), resulting in the normalized g_k: $\sum_k g_k(x_1,x_2) = 1$.

Higher-order co-occurrence (Fig. 2). By using the co-clusters g_k, the proposed higher-order co-occurrence features are defined by



classifier weight $\boldsymbol{W}$ positive $\boldsymbol{W}^+$ negative $\boldsymbol{W}^-$ co-clusters g_k

Figure 1: Construction of discriminative co-clusters g_k.



(b) *cross* quadruplet (c) higher-order co-occurrence

Figure 2: Higher-order co-occurrence.

$$\boldsymbol{H} = \left\{ \sum_{\{\boldsymbol{p},\boldsymbol{q},\boldsymbol{r},\boldsymbol{s}\}\in\mathbb{Q}} \omega(\boldsymbol{p},\boldsymbol{q},\boldsymbol{r},\boldsymbol{s}) g_k(x_{\boldsymbol{p}},x_{\boldsymbol{q}}) g_l(x_{\boldsymbol{r}},x_{\boldsymbol{s}}) \right\}_{k,l=1,\cdots,D} \in \Re^{D\times D},$$

where $\mathbb{Q}$ indicates the quadruplets. In this higher-order co-occurrence, it is important how to determine the quadruplets $\mathbb{Q}$, forms of which could be combinatorially increased. Co-occurrences are based on pairs which are oriented in various directions, and we configure the quadruplets, the pairs of pairs, in the form of *cross* as shown in Fig. 2a in order to extract diverse characteristics in image textures; the pairs in the cross are maximally (orthogonally) separated.

Results

We applied the proposed method to cancer detection using biopsy images [6] and pedestrian detection using the Daimler Chrysler dataset [4], both of which result in two class classifications. The primitive quantitative data $x_{\boldsymbol{p}}$ are pixel intensities for biopsy images and gradient orientations for pedestrian images. Even for smaller number of the co-clusters, D, the proposed method produces superior performances to the other methods, including the standard co-occurrence method; in equal error rate, 94.29% for cancer detection and 94.32% for pedestrian detection.

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