An ensemble learning method for scene classification based on Hidden Markov Model image representation

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Abstract—Low level images representation in feature space performs poorly for classification with high accuracy since this level of representation is not able to project images into the discriminative feature space. In this work, we propose an efficient image representation model for classification. First we apply Hidden Markov Model (HMM) on ordered grids represented by different type of image descriptors in order to include causality of local properties existing in image for feature extraction and then we train up a separate classifier for each of these features sets. Finally we ensemble these classifiers efficiently in a way that they can cancel out each other errors for obtaining higher accuracy. This method is evaluated on 15 natural scene dataset. Experimental results show the superiority of the proposed method in comparison to some current existing methods.

Keywords—Markov Random Field; Ensemble learning method; Image classification; SVM; Optimization

I. INTRODUCTION

Scene classification has been an interesting problem in computer vision and machine learning. It has many applications in robot navigation, content base image retrieval, organizing photographs [1] and video content analysis [2]. Many methods have been proposed in recent years to classify scene category [3-8]. Choosing efficient features plays a substantial role in level of accuracy in image classification methods. Image feature extraction methods are categorized in three groups, low level features extraction such as color, texture and shape, local feature extraction such as bag of visual words [9] method and local-global feature extraction such as SPM [10] and PHOG [11]; PHOG performs based on the global spatial layout and it is not flexible when significant appearance of the image changes or heavy occlusions take place in it. Gist descriptor also encodes a set of spatial structure of a scene by using a set of perceptual dimensions including naturalness, openness, roughness, expansion and ruggedness [12]. SIFT as a local feature creates the gradient orientation histograms to represent local image patches [13]. On the other hand local binary pattern (LBP) uses local gray-level differences to describe local texture patterns [14]. LBP based magnitude coding plays a substantial role in extracting local structural information. Many versions of LBP have been developed such as Gabor LBP [15] and Gradient LBP [16]. The Gabor LBP and Gradient LBP construct LBP histograms based on Gabor magnitude and gradient responses, respectively. WaveLBP utilizes local patterns and the wavelet sub band characteristics with dense spatial sampling to create a descriptor that possesses robustness and discrimination. Combining WaveLBP with the GMM increases robustness and descriptive power of the WaveLBP as well [17]. Centrist provides a holistic and generalizable descriptor. It describes structural properties in the image while suppressing textural details, and represents rough geometrical information in the scene as well [18]. Classification methods cannot perform well unless the selected features present images in many views. Each type of feature has advantages in describing images in feature space, so in order to present images in a discriminative feature space, the classifier should use features with complimentary characteristic in different views. Many approaches have been proposed to use multi view features in classification. The critical idea is based on dimensional reduction approaches. These methods are categorized as linear such as PCA [19] and LDA [20] and nonlinear such as LLE [21], ISOMAP [22], LE [23], and LTSA [24]. Both, linear and nonlinear approaches have some disadvantages. PCA and LDA are linear methods, PCA is an unsupervised learning method and is inappropriate approach for classification; PCA ignores labels of classes in reducing the dimensional of features for classification. However, LDA is a supervised learning method, it constructs a goal function and tries to optimize it by maximizing trace of the between-class scatter matrix and coincidently minimizing trace of the within-class scatter matrix. Although both of LDA and PCA are linear, they just consider the global Euclidean structure and ignore the nonlinear structure hidden in the high-dimensional data. Nonlinear methods need many training data to perform perfectly. In order to address the mentioned problems, several dimensional reduction methods [25-29] have been proposed. They have been proposed to include multi complementary features into the feature vectors. These methods fuse multi features into a single feature vector. The proposed method does not fuse multi view of features into a single feature vector; it makes a classifier for each feature and then combines them using a cost function that they can cancel out their errors simultaneously. Rest of the paper is organized as follows. In Section II, we explain the proposed algorithm. In Section III,
the experimental results are discussed. The conclusion is presented in Section IV.

II. PROPOSED METHOD

The proposed method includes two steps; first a HMM grid-based model is applied on ordered grids represented by complementary image descriptors to represent image in the feature space; and in the second step, for each of these feature sets, a classifier is trained up and then an ensemble approach is used to fuse these classifiers efficiently in order to cancel out their errors for obtaining higher accuracy.

A. Step 1. HMM grid based image representation

We use a HMM based feature representation which can capture topological and spatial information existing in an image. First an image is divided into non-overlapping grids and then a HMM based feature representation is obtained by concatenating a set of probability values. Each value in this representation indicates the probability of a grid in the sequence belonging to one of the classes; we apply this model on all complementary features.

1.1 Encoding images

In this step, images are divided and then represented as a sequence of ordered grids. The proposed method extracts four complementary features for each grid in the sequence. The complementary features used in proposed method are SIFT [30], Gist [31], Centrist [32] and Gabor function [33-35]. Basically, we utilize both global and local image descriptors which possess their own advantages in representing image from different views in the feature space.

For example, for a given image X, it is encoded as a sequence of ordered grids such as $X = \{f(x_i)\}_{i=1,2,3,...,n}$, where $f(x_i) \in \mathbb{R}^m$. In this representation, $x_i$ is i-th grid in X and n is the number of the grids in X and $f(x_i)$ is feature vector extracted using one of complementary features from grid $x_i$.

1.2 Feature extraction based on HMM model

For each type of complementary features, the proposed method applies HMM in order to encode causality of local properties in the image. We use HMM with linear chain topology in order to determine the probability of grids belonging to each class. In this model, grids are the observations of the HMM and classes are the hidden states of the HMM. The proposed method scans sequence of grids in zigzag mode as input observations in HMM [36]. Zigzag scanning mode is able to keep correlation of the grids in both vertical and horizontal directions simultaneously and observations don’t lose their dependencies in the sequence (i.e. for the last grid in each row and column, the next grid observed has correlation with previous observed grid).

In this scanning mode the probability of belonging each observation to each class $p(c_i|x_j)$ is determined by HMM and all of probabilities are concatenated to each other respectively. For example, assume $[x_1, x_2, x_3,..., x_n]$ are sequence of grids and $p(c_j|x_j)$ indicates the probability of grid $x_j$ belonging to class $C_j$. The feature vector using proposed model is created such as (1)

$$V = [p(C_1 | x_1), ... , p(C_i | x_i), ... , p(C_j | x_j), ... , p(C_m | x_m)]$$

(1)

1.3 Parameter $p(C_j | x_i)$

In order to calculate the parameter $p(C_j | x_i)$ defined in (1), we use forward algorithm to determine it. We calculate this term using (2)

$$a_j(\alpha) \leftarrow p(x_i | s_i = c_j) \sum_{k=1}^{N} p(s_j = c_j | s_{(i-1)} = c_i) \alpha_j(k)$$

(2)

Where $m$ and $S_j$ indicate number of classes and hidden states (i.e. classes) respectively.

The term $p(x_i | s_i = c_j)$ indicates probability of observation when the hidden state is $C_j$. We use (3) to estimate this term.

$$p(x_i | s_i = c_j) = \frac{\exp \left( - \| x_i - N(t,j) \|_2^2 \right)}{\sum_{j=1}^{m} \exp \left( - \| x_i - N(t,i) \|_2^2 \right)}$$

(3)

Where $N(t,j)$ indicates the observation (i.e. grid) among all t-th grids in training images existing in class j that has nearest Euclidian distance with $x_i$. Intuitively, Euclidian distance between grid $x_i$ and nearest t-th grid in class j expresses similarity of $x_i$ with nearest i-th grid in class j. Equation (3) shows an estimation of $p(x_i | s_i = c_j)$ because $p(x_i | s_i = c_j)$ increases as Euclidian distance between $x_i$ and nearest i-th grid in class j decreases and vice versa. We sum up all possible transition in denominator in order to normalize the probability term to one.

The term $p(s_j = c_j | s_{(i-1)} = c_i)$ in (2) indicates the probability of transition between two classes (i.e. hidden states). Transition states and structure of Markov chain used in proposed algorithm is shown in Fig.1.

![Fig. 1. Structure and transition states](image-url)
We use (4) to estimate the probability of the transition between hidden states in proposed model.

\[
p(s_t = c_j | s_{t-1} = c_i) = \frac{\exp\left(-\left| I(c_i, t) - I(c_j, t) \right|_1 \right)}{\sum_{c_i} \exp\left(-\left| I(c_i, t) - I(c_j, t) \right|_1 \right)} \tag{4}
\]

Where \( I(c_j,t) \) is a sample in the feature space that expresses minimum average distance between this sample and other samples that indicate \( t \)-th grids of all images in class \( j \). To find this sample in the feature space, we use K-means clustering [37] with one cluster.

Equation (4) demonstrates that probability of transition from class \( k \) in \( t \)-th observation to class \( j \) class increases as Euclidian distance between \( I(c_i, t) \) and \( I(c_j, t) \) decreases. Same as (3), we sum up all possible transition from class \( k \) in \( t \)-th observation to other classes in denominator in order to normalize the probability term to one.

Now we can create proposed feature vector in (1) which \( \alpha_j(x) = p(c_j|x) \) using forward algorithm

**B. Step 2. Ensemble classifier**

The purpose of the ensemble classifier is that another base classifier compensates the errors made by one base classifier. In this step we fuse base classifiers using a weighted combination of their contribution in classification to make final decision.

Base classifiers in this step are obtained by training of a separate RBF kernel based SVM classifier for each of four HMM based feature sets that we have applied HMM on complementary features. For all SVMs, we set up parameters in a way that we can determine the probability of belonging every image in training set to all classes. We consider each of these probabilities as a score of corresponded SVM classifier.

In order to fuse base classifiers and make final decision for labeling, the proposed method uses a convex function including some constrains defined in (5) to find the optimum contribution of all SVMs in their weighted combination. The optimum contribution (i.e. weight) of each classifier in making final decision is obtained by minimizing this function. These coefficients indicate the importance of each classifier in making final decision for labeling.

\[
J(W) = \min \sum_{j=1}^{N} \sum_{i=1}^{C} w_i \| p(x_j) - \tilde{D}(x_j) \|_2
\]

\[
ST \quad w_i > 0, \sum_{i=1}^{C} w_i = 1
\tag{5}

In (5) \( w_i \) is the weight of classifier number \( i \), \( C \) is the number of classifiers and \( \tilde{D}(x_j) \) is the label of the \( j \)-th image which is selected from the training set (i.e. \( D(x_j) \) is a binary vector that all of its members are zero except one of them which is the label of the class) and \( N \) is the number of all images in the training set. To solve (5), we use CVX [38]. To score each classifier for every image in training set, we use SVM package [39] trained by one-versus-all with RBF kernels. The probabilities obtained by SVMs to each class are used as score in (5).

**III. EXPERIMENTAL RESULTS AND DISCUSSIONS**

To evaluate the proposed algorithm, we executed this method on 15 natural scenes[6] which contains 4486 images with 15 classes. This dataset contains 200 to 400 images in each scene category. The experiment is performed with 100 randomly selected images per category for training and the rest are used for testing. We evaluated the proposed method by comparing our method with WaveLBP and its different versions [41], SIFT, PHOG [11], GIST, Gabor LBP and Gradient LBP based image descriptors.

**A. Number of grids in dividing image**

In this model, each image is encoded to sequence of some ordered grids. Depending on how images are distributed in the feature space, the optimal number of the grids for getting the best performance should be determined experimentally. We divided images to 3×3, 5×5 and 7×7 number of grids and then we performed experiment on these number of grids to find the best match of the algorithm for all defined complementary features.

To get the best performance, images should be divided to 3×3, 7×7, 5×5, 3×3 number of grids for the Gist, SIFT, Centrist, and Gabor descriptors respectively.

![Fig.2 tuning number of grids for complementary features](image)

**B. Feature configuration**

For features configuration defined in step 1, the proposed
method manipulates some variation on the aforementioned features. For SIFT and Centrist, the proposed algorithm applies PCA on the same position of grids in all images for each class to reduce dimension. Experimental result shows that Euclidian distance performs better in measuring the similarity of the samples when SIFT and Centrist descriptors dimensions are reduced by PCA transform.

We choose 20, 10 dimensions in PCA transformed feature space for SIFT and Centrist feature sets respectively due to their reconstruction error rate. For GIST, we compute the 32-dimensional GIST global descriptor using 8 orientations, 4 scales for each patch. For Gabor features, we use Gabor filter banks with 5 scales and 8 orientations and then we calculate mean and variance of coefficients magnitude for every filter bank response frequency.

![Fig.3. PCA on Centrist feature](image)

![Fig.4. PCA on SIFT feature](image)

TABLE I. shows classification accuracy of the aforementioned methods. TABLE I. shows performance of the proposed method and other methods in term of accuracy on 15 natural scenes dataset. In TABLE II., the result shows per class accuracy of applying HMM model on different types of features. The results in TABLE II. show that combining classifiers performs better than any single classifier separately. In the other word, classifiers can compensate their incorrect decisions due to their abilities in image representation in different views in the feature space.

| Methods          | Accuracy |
|------------------|----------|
| WaveLBPS + BoF   | 68.1     |
| WaveLBPM + BoF   | 66.7     |
| WaveLBPS + GMM   | 80.6     |
| WaveLBPM + GMM   | 81.3     |
| SIFT + GMM       | 80.8     |
| PHOG             | 63.5     |
| GIST             | 70.6     |
| Gabor LBP        | 70.8     |
| Gradient LBP     | 65.4     |
| Proposed algorithm | 85.97    |

| Class       | SIFT | Gist | Centrist | Gabor | Combine |
|-------------|------|------|----------|-------|---------|
| Bedroom     | 77.06| 73.89| 75.16    | 42.45 | 79.79   |
| CALsuburb   | 70.13| 83.46| 82.31    | 81.41 | 86.72   |
| Industrial  | 46.90| 82.28| 84.69    | 46.02 | 87.58   |
| Kitchen     | 73.60| 84.80| 80.01    | 40.08 | 88.62   |
| Livingroom  | 54.90| 80.02| 78.92    | 60.4  | 84.12   |
| MITcoast    | 76.73| 84.91| 60.04    | 46.18 | 83.4    |
| MITforest   | 69.96| 80.00| 81.07    | 80.59 | 85.38   |
| MIThighway  | 72.57| 82.57| 57.71    | 73.14 | 87.86   |
| MITinsidecity  | 61.68 | 81.93 | 64.48 | 63.45 | 84.1 |
| MITmountain   | 71.56 | 84.44 | 83.93 | 63.91 | 86.91 |
| MITopencountry| 65.23 | 86.15 | 72.01 | 60.01 | 86.15 |
| Sift/MITstreet| 52.17 | 82.92 | 61.35 | 85.52 | 87.83 |
| MITallbuilding| 74.58 | 88.56 | 87.82 | 50.92 | 89.44 |
| PARoffice      | 57.69 | 85.62 | 86.15 | 40.15 | 87.39 |
| Store          | 84.35 | 76.96 | 81.65 | 80.57 | 84.35 |
| Average accuracy| 67.27 | 82.56 | 75.82 | 60.98 | 85.97 |

IV. CONCLUSION

We proposed an ensemble learning approach for scene classification based on Hidden Markov Model feature representation. In this model, we use HMM to consider correlation and spatial causality between adjacent grids in image. HMM is applied on complementary image descriptors in order to model spatial relationship of local properties between adjacent grids into the feature vectors; and then a classifier is trained up on each set of feature vectors. Finally we define a convex function including some constrains to fuse classifiers in their optimum weighted combination for labeling. Experimental result shows that classification accuracy obtained by combining classifiers has superiority comparing to each classifier separately. The evaluation results on 15 natural scene dataset show the superiority of the proposed method in comparison to some recent works.

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