Automatic Image Classification using Machine Learning Techniques

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Abstract:- Due to the persistent development in internet and multimedia technologies, new methods are needed for efficiently representing images and classifying them. In this work, a hierarchical-based image classification system have been build, which can classify images of real world scenes into predefined classes. In this paper, image's global feature GIST is used to represent the natural scenic images and the performance of the hierarchical-based classification system is evaluated using both GMM and 1D HMM techniques. Experimental results show that the proposed global feature with hierarchical-based classification system is effective and accurate even for large datasets.

***Keywords:** Pattern classification, image feature extraction, global descriptors, hierarchical approach, GIST, spatial envelope, gaussian mixture model, 1d hidden markov model.*

1. INTRODUCTİON

Nowadays Scenic image categorization is widely used everywhere and its usage is growing rapidly. It has a great impact on scene image management and also scene image categorization is used as an effective preprocessing step in most of the image retrieval, database organization systems and search engines. It reduce the time required for search functions which operate on a large group of images. Furthermore, grouping digital photography images into meaningful classes based on their scenic environment assist trip agencies in vacation planning systems.

1.1 Related Work

Most of the studies in scene categorization concentrates on low-level image features [1], which can be processed again for increasing efficiency [2] or combined with other features [3] during classification or retrieval. Szummer and Picard [4] used color and texture based feature and k-NN classifier for classifying the indoor and outdoor scenes. Vailaya et al. [5] implemented a hierarchical version of scenic image classification using Bayesian binary classifiers. Oliva and Torralba [6] using spatial envelope properties and SVM classifier to develop a image classification system based on shape of a scene.

Scene classification is implemented as an aid for place recognition [7], scene matching, scene completion process [8] and geo-location inference task [9], [10]. Thus scene classification studies is the root of several researchs in the computer vision and graphics area.

2. HİERARCHİCAL-BASED IMAGE CLASSİFİCATİON

In a linear classification system, it takes long time consuming computation for finding the output class among 8 categories. But in hierarchical based method, problem is divided into 3 smaller computations (3 levels) to attain the final category label. This results in reduction of computation overhead when accessing large storage of data with many categories.

2.1 Hierarchical-based Modelling

As illustrated in Fig.1, a total of 7 models were hierarchically trained. Model 1 separates the database into 2 groups basically as man-made and natural. Here man-made group comprises of tall building, street, inside city and highway categories.

Whereas natural group consists of open country, mountain, coast and forest categories. Model 2 further divides the man-made group into two groups based on occurrence of structures in the image i.e. fine level or coarse level structures present in the image. Later those fine or coarse roup is finally divided into respective class labels. The same thing is done for natural group as well. Thus it needs overall 3 levels to find the class label.

During training the Hierarchical-based classification system, first collect the images from each category which are to be trained. Second, train model 1 using samples from two groups named man-made and natural categories at level 1. Third, train model 2 and 5 using samples from two groups fine structured or structured classes at level 2. Finally at last, model each category's feature to model which form Level-3 in Fig.1.

Now during testing, the model 1 at level 1 is tested against the unknown test sample for evaluating the likeliness. Next choose the left or right node which is most similar and continue the above step until the leaf node is achieved. And finally display the leaf node category.

The block diagram for GMM/HMM model creation in heirarchical based system in each individual level is shown in Fig.2. Image model creation consists of pre-processing, image feature extraction and classification modules. The classification step further consists of model training and its evaluation (testing).

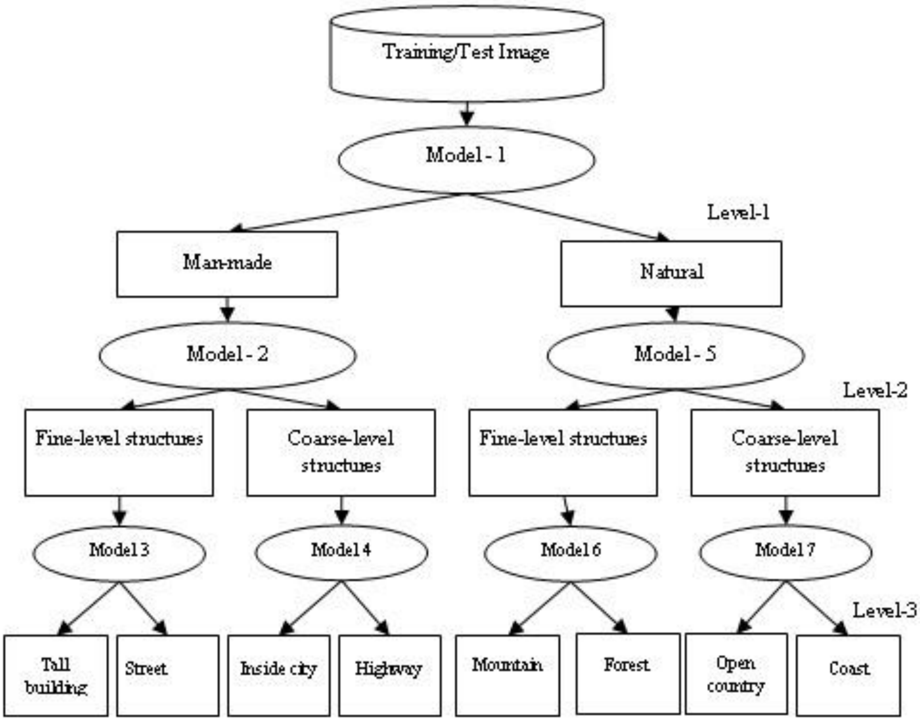


Fig.1 Hierarchical-based Image Classification approach

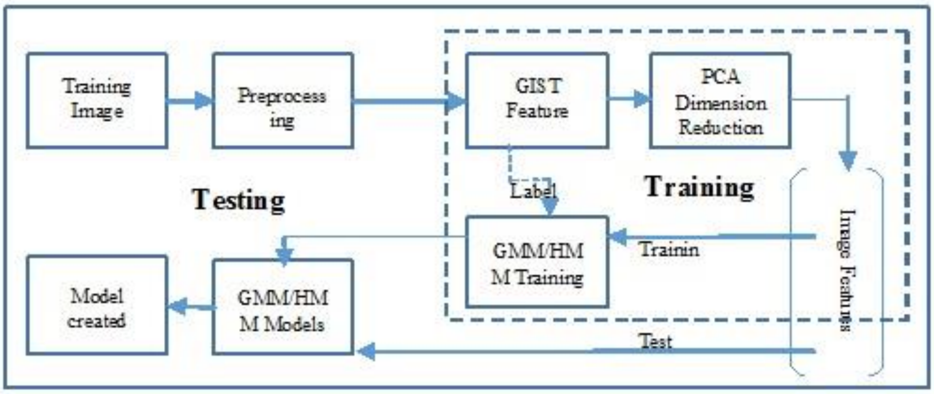
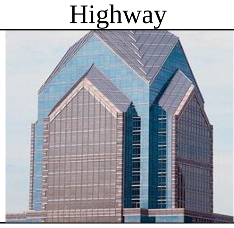


Fig 2: Block diagram for model creation in hierarchical based system

2.2 MIT spatial envelope dataset

Table: 1 Predominant structure of image categories in MIT dataset

			
Coast	Forest	Highway	Street
			
Mountain	Open Country	Tall Building	Inside City

From the MIT spatial envelope (SE) dataset, we selected eight outdoor scene categories: coast, forest, highway, inside city, mountain, open country, street and tall building. There are 2600 color images in total with around 300 in each category. All images in the dataset have the same resolution of 256×256. Table 1 shows few sample image of each scene category from this dataset.

2.3 GIST Descriptors

In this work, GIST feature are analyzed which represent the overall global characteristics of the scene images. GIST [1] or Spatial Envelope (SE) feature represents the spatial layout and scene properties, whose feature model several fundamental properties of a scene, extracting dominant spatial structures. Thus scene is transposed into global features which includes: naturalness, complexity, expansion, depth, openness, roughness, ruggedness and symmetry. Further Principal Component Analysis (PCA), which is an unsupervised feature selection approach to find patterns in a data and present it with reduced number of dimensions without much loss of informatio.

3. EXPERIMENTAL RESULTS

The GMM and HMM are powerful statistical methods employed in pattern recognition. GMM can also be viewed as one component of HMM under certain circumstances.

Table: 2 Performance for various Grid sizes in GIST feature for 6 components GMM and similarly for 9 states HMM with 4 mixtures

GIST Grid Size	GIST Gabor Filter for HMM	
3 * 3	75.7 %	84 %
4 * 4	87.3 %	89 %
5 * 5	85 %	82 %

In Table 2, the Grid size of the GIST feature is varied by 3-by-3, 4-by-4, 5-by-5 and their corresponding results are studied using GMM and 1D HMM. During training with GMM, every Gaussian component in the GMM represents a distinct kind of GIST feature.

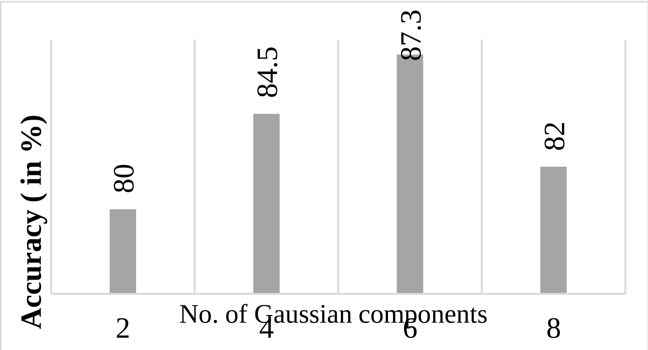


Fig 3: Performance chart for 4-b-4 GIST using various component GMMs

The number of Gaussians per GMM is varied and their corresponding results are analyzed at each level as shown in Fig.3.

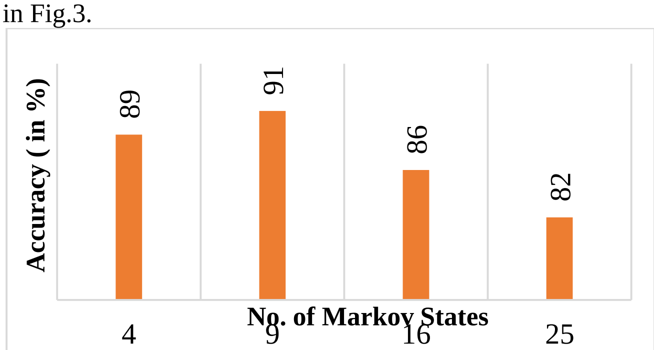


Fig.4 Performance chart for various Markov states in 1D-HMM

Similarly during training with 1D HMM, the optimum 1D HMM model is found by varying the number of states in the HMM as shown in Fig.4.

4. CONCLUSİON

Thus a Hierarchical-based image classification system is proposed and implemented in Matlab. The hierarchical structure and global GIST feature of the proposed system significantly reduces the computation time for processing and similarly the use of PCA feature selection for finding the best discriminating features, results in increased performance. To evaluate the performance of the system, a 3-level hierarchy for 8 categories is used. A test result shows an increase in performance from 88% using GMM to 91% using 1D-HMM. Thus the 1D-HMM+GIST categorization systems outperform the GMM+GIST in the classification accuracy.

5. REFERENCES

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