International Journal of Latest Engineering Research and Applications (IJLERA) ISSN: 2455-7137

Volume – 02, Issue – 04, April – 2017, PP – 171-179

Very Large Object Classification Using PNN and DM Classifiers Along With PCA and FLD Feature Extraction

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Abstract: Image data is becoming more and more popular due to the prevalence of image capture devices.Nowadays the main challenging issue is how to retrieve the images efficiently and effectively from a huge number of images. Image classification is a technique of assigning each input vector pertaining to an image to one of a finite number of discrete class or category in large image dataset. In this paper it is examined and explored the thought of mixture models for image categorization. In this paper we first segment all images at segmentation stage in order to find out the color difference or color homogeneity between one pixel to neighboring pixels. Since Gaussian Mixture Models (GMM) is one of the most significant method for clustering in unsupervised context we use the concept for image categorization. Here in this paper we use K-means technique is applied for partitioning image pixels into coordinated clusters. Further transformation matrix for each of the clusters is obtained by applying subspace methods such as Principal Component analysis (PCA) and Fisher's Linear Discriminant (FLD) to all segment classes. The Expectation and maximization (EM) algorithm is applied to Gaussian mixtures. In this paper for better classification we use Distance Measures (DM) and Probability Neural Network (PNN).The results obtained in this paper gives the improved classification rates when compared to previous methods or traditional methods. The datasets can be used such as Wang, Caltech-101 and Caltech-256.

Keywords: Image Retrieval; Mixture Models; Principle Component Analysis; Fisher's Linear Discriminant; Distance measures; Probability Neural Network.

I. INTRODUCTION

The processing of an image and the analysis part plays an important or major role in image processing. To analyze an image in image processing the image segmentation part is mainly focused. The processing of converting a heterogeneous data into homogeneous data is called image segmentation. Image classification is a technique of assigning each input vector pertaining to an image to one of a finite number of discrete class or category in large image dataset. The data sets such as Wang, Caltech 101 & Caltech 256 is used searching for patterns and categorizing the object classes has drawn the good interest in computer vision community. Retrieving the images effectively and efficiently from a huge number of images have become the tough and challenging part in recent years. Moreover image data is becoming more and more popular due to prevalence of image captured devices.

The retrieval of image is one of the types of system that is normally defined as computer system for searching images and retrieving images from a large database of digital images. The most traditional one and the common methods of retrieving the images utilize some method of metadata such as captioning, keywords, or descriptions to the images so that retrieval part can be performed over the annotation words. There are two types of image annotation they are manual image annotation and automatic image annotation. The manual image annotation is expensive laborious and time consuming, to speak on this there has been a great extent of research done on automatic image annotation. Additionally, the increase in social web applications and the semantic web have animated the development of several web-based image annotation tools.

A study of subspace mixture models with different classifiers for very large object classification. The very large number of images is retrieved by using Gaussian Mixture Models and PNN and DM classifiers introduced by K. Mahantesh, V.N. Manjunath Aradhya, et al.,[1].The crisis of searching for patterns and categorizing object classes in an ever increasing challenging datasets is been introduced by Holub A, et al.,[2] for example, Wang, Caltech 101 & Caltech 256 has attracted generous interest PC vision community. Dhiraj Joshi, et al.,[3] introduced lately, there has been a steady push to create visual element descriptors which gives helpful low-level data from images. Feature extraction has turning out to be more mind boggling because of high intra-class variability delivered by the occurrences having a place with the same class. He proposed thoughts, impacts, and patterns of the new age and witnessed great interest and an abundance of guarantee in content based image retrieval as a rising innovation. While the most recent decade established framework to such guarantee, it additionally prepared for countless methods and systems, got numerous new individuals included, and triggered stronger association of weakly related fields. Shechtman E, et al., [4] introduced in image order, he come across two well-known methodologies, for example, learning-based and parametric classifiers. A vast arrangement of images are prepared to tune the parameter of a versatile model in first approach and the last comprising of set of images and making clusters of comparable illustrations inside of the information with no relating target values.

Bishop C.M, et al.,[9] introduced the principle destinations of PCA & FLD are, PCA lessens the dimension of highlight space and FLD amplifies betlatenten-class varieties alongside minimizing inside of class diffuse. The previously stated aforesaid algorithms are broadly utilized as state of the art subspace strategies in tackling face recognition issues.

The execution of PCA & LDA strategies can be better increased by outlining the adaptable structure of displaying occasional variables that can deal with numerous arrangement of components being produced by Gaussian Mixture Models, Ashok Rao, et al.,[10]. Being motivated by these facts and inherent benefits of combining sub space methods with mixture models in localized space, we study and explore PCA & FLD Mixture Models on fragmented image for categorizing images in large multi-class image datasets. The rest of the paper is organized as: Section 2 briefs proposed PCA & FLD Mixture Models in hybrid colour space. In Section 3, classification results on two widely used datasets and performance analysis on several benchmarks are reported. Conclusion and some future research issues are discussed at the end.

II. PROBLEM DEFINITION

In recent years, to create visual element descriptors which give valuable low level data from images there has been put a consistent effort. Because of high intra-class variability delivered by the occurrences fitting in with the same class highlight extraction part is turning out to be more unpredictable. In image classification there are two well-known methodologies one is learning-based classifiers and the other one is parametric classifiers. In the first approach a huge number or extensive arrangement of images are prepared to tune the parameter of a versatile model first and the last comprising of set of images and making clusters of comparable samples inside of the information with no comparing target values. The pack of features enhanced the order rate yet was not compelling to fabricate the neighborhood data.

To overcome this they had figured histograms of parts acquired after portioning image into pyramid like sub-areas reporting most successful results and they used combined arrangement of differing visual components, for example, color, shape and composition data to acquire between class discrimination. The other individual embraced MKL (Multiple Kernel Learning) setting to discover mixture of base bits which is suitable to the class kernels. The other individual processed separation between districts of two images utilizing IRM (Integrated Region Matching) in high dimensional feature space to order images in Simplicity image library.

Few interesting deals with the significance of assessing back likelihood and connecting neural systems to grouping can be found. After this they initially explored the Principal Component Analysis (PCA) and utilized the PCA anticipated segments as elements for face recognition and because of its unsupervised behavior label data of the information or data was absent. To overcome this Class label data of the information was better used by applying Fisher's Linear Discriminant (FLD) .The primary destinations of PCA & FLD are, PCA reduces the measurement of feature space and FLD boosts between-class varieties alongside minimizing inside of class scatter.

III. PROPOSED METHODOLOGY

The proposed system contains outlining element vectors after division and figuring separation in the middle of question and marked arrangement of images utilizing differing separation measure techniques and neural systems to get a normal characterization rate. This is affected by the thought that the recognition rate can be ad modeling my demonstrating every class into a mixture of a few parts of precise gathered nearby components and characterizing them in compacted and de-connected component space.

In such manner, it is first recognized profoundly rational locale by dividing the image into a few disjoint areas in complex hybrid color space. Later, every item class is divided into a few groups and every group thickness is evaluated by a Gaussian distribution work in PCA & FLD transformed space. An iterative EM algorithm is utilized to perform parametric estimation on the got Gaussian conveyances. At long last, it is considered Probabilistic Neural Network (PNN) and four separation measures for characterization to get a normal for each class recognition rate.

One point of preference of utilizing latent variables is that it diminishes the dimensionality of information. An extensive number of recognizable variables can be totaled in a model to speak to a hidden idea, making it less demanding to comprehend the information. In this sense, they serve a capacity like that of investigative hypotheses.

In the meantime, idle variables join detectable (sub-symbolic) information in this present reality to typical information in the demonstrated world. Inactive variables, as made by element expository techniques, for the most part speak to "shared" fluctuation, or the extent to which variables "move" together. Variables that have no relationship can't bring about a latent build in light of the basic element model.

A. Segmentation in Complex Hybrid Color Space

In this dissertation the earlier work is set up together of partitioning image into noteworthy disjoint districts in light of distinguishing color homogeneity of neighborhood pixels in complex hybrid color space. K-means clustering is requested viable separation of forefront pixels from foundation by holding low frequency components. The crucial steps included in segmentation procedure are as given below:

- Input(query image) RGB image is transformed into YCbCr and HIS color spaces.
- From the HSI color space consider H component and CbCr component in YCbCr.
- Enlarging three higher dimensional matrices to generate hybrid color space HCbCr.
- Further HCbCr color space is changed into LUV color space.
- At long last k-implies (k=3) clustering is requisitioned U & V parts.

Above steps are successively processed in supervised context to acquire segmented image of profoundly intelligible areas safeguarding low frequency components which will be further abused for better image representation

B. Subspace Mixture Models

Because of the natural component that unimodel estimate of Gaussian conveyance is not possible to give better estimation to multi-class appropriations, along these lines acquainting inactive variables with speak to confounded conveyances to be shaped from less difficult segments. To catch the predominant correlations in the dataset, every object classification is divided into a few groups and thickness of these groups is assessed by Gaussian distribution work in two distinctive transformed spaces, for example, PCA & FLD. The parameter estimation is performed by an iterative EM algorithm on these arrangements of Gaussians. The accompanying segments quickly introduce the aforementioned Mixture Models.

1) The PCA Mixture Model

Mixture model gives a system to group information, let $A = a1, a2, \ldots\ldots an$be n-dimensional observed information of distinctive item class which can be separated into diverse clusters and can be indicated by a linear combination of complex densities which can be denoted by,

$$P(a) = \sum_{j=1}^{j} P\left({}^{a}/_{b_j}, \theta_j\right) P\left(b_j\right) \tag{1}$$

Where $P(a \,/\, bj\,, \theta j\,)$ and θj are the restrictive thickness, earlier likelihood and obscure model parameter of the jthcluster individually The obscure model parameter will be figured by utilizing EM algorithm spurred by the multivariate Gaussian conveyance allowing multi-modular contingent circulation which can be communicated as,

$$P\left({}^{a}/_{bj}, \theta j\right) = \frac{1}{(2\pi^{n/2})|\sigma_j{}^{1/2}|} e^{\frac{1}{2}(a-\mu_j)^{l} \sigma_j{}^{-1}(a-\mu_j)} \tag{2}$$

Whereμ_j &σ_j are the specimen mean and covariance of the jth group separately. A distribution can be composed as a direct superposition of Gaussian in the structure $P(a) = \sum_{j=1}^{j} \pi_j P(a \,/\, bj\,, \theta j)$ where π_j is known as the mixing coefficient which can be set to divisions of information focuses allocated to the jthcluster. We utilize Principal Component Analysis (PCA) to diminish the dimensionality of highlight space of the information. In PCA, set of watched n-dimensional information vector $A = aq, q = 1 \ldots N$ is lessened to a situated of m-dimensional element vector $U = uq, q = 1 \ldots M$by a transformation matrix W as,

$$U_p = W^T\left(a_p - \delta|a|\right) \tag{3}$$

Where, $W = w_c, c = 1 \ldots m$, is eigenvector comparing to the dth biggest eigen estimation of the example covariance matrix. PCA mixture model is determined by joining the over two models (Eq1 & 3) i.e. mapping mixture model onto the PCA transformed space and is given as,

$$P(s) = \sum_{j=1}^{j} P(U/b_j, \theta_j)P(b_j) \tag{4}$$

Where, $P(U/b_j, \theta_j)$ is the contingent thickness capacity of jth group in PCA feature vector and can be further improved as,

$$P(U/b_j, \theta_j) = \frac{1}{(2\pi^{m/2})|\sigma_j{}^s|^{1/2}} e^{\frac{1}{2}(a-\mu_j)^l \sigma_j{}^{-1}(a-\mu_j)} \tag{5}$$

$$= \prod_{k=1}^{m} \frac{1}{(2\pi^{1/2})\lambda_{jk}{}^{1/4}} e^{-\frac{U^2{}_k}{2\lambda_{kj}}} \tag{6}$$

Where $\lambda_{j1,}\lambda_{j2...}\lambda_{jm}$ are the m dominant eigen values of the feature covariance matrix $\sum_j^U$ in the jthcluster. Now the log likelihood function is given by,

$$lnP(A/\pi, \mu, \Sigma) = \sum_{n=1}^{N} ln \sum_{j=1}^{J} \pi_j \, P(a_n/\mu_j, \Sigma_j) \tag{7}$$

EM iterative algorithm is used to discover greatest probability answer for GMM. To locate a suitable introduction for a GMM, we make utilization of k-means clustering with a specific end goal to start implies meansμ_j, covariances Σ_j and mixing coefficientsπ_j.

There are two steps in EM iterative algorithm to be considered: **Expectation step (E-step)**

In E-step, current estimations of the parameter are utilized to assess the posteriori probabilities "ζ" with the assistance of the accompanying comparison,

$$\zeta(\mathcal{Z}_{nj}) = \frac{\pi_j P(a/\mu_j, \Sigma_j)}{\sum_{k=1}^{J} \pi_j P(s/\mu_j, \Sigma_j)} \tag{8}$$

Maximization step (M-step)

In M-step, we utilize these probabilities to re-appraise the methods means μ_j, covariances Σ_j and mixing coefficients π_j respectively using the below equations,

$$\mu_j{}^{new} = \frac{1}{N_j} \sum_{n=1}^{N} \zeta(\mathcal{Z}_{nj}) a_n \tag{9}$$

$$\sum_j^{new} = \frac{1}{N_j} \sum_{n=1}^{N} \zeta(\mathcal{Z}_{nj}) (a_n - \mu_j{}^{new}) (a_n - \mu_j{}^{new})^T \tag{10}$$

$$\pi_j{}^{new} = \frac{N_j}{N} \tag{11}$$

Each re-examined parameters coming about because of the E-step took after by the M-step is guaranteed to improve the log probability capacity and joins till the adjustment in the log probability falls beneath some edge and the proposed technique embodies planning element vectors after division and figuring separation in the middle of question and named arrangement of images utilizing assorted separation measure procedures and neural systems to get a normal order rate. This is induced by the thought that the recognition rate can be improvised my displaying every class into a mixture of a few segments of organized gathered nearby elements and arranging them in compacted and de-corresponded element space. In such manner, it is distinguished exceptionally lucid area by parceling the image into a few disjoint locales in complex crossover color space. Later, every object class is apportioned into a few groups and every group thickness is assessed by a Gaussian distribution work in PCA transformed space.

2) The FLD Mixture Model

FLD ventures high dimensional information onto a line and perform arrangement in one-dimensional space among general classes. The transformed space neglected to fasten satisfactory measure of elements keeping in mind the end goal to characterize profoundly complex information with numerous classes and extensive varieties. To defeat this disadvantage, FLD mixture model is utilized which considers a few change networks as mixtures among over all classes/classifications.

By apply PCA mixture model to the arrangement of mean μ_i of every classification with K-distinctive mixtures and acquired cluster meanB_j, changed lattice T_j & corner to corner network S_j alongside eigenvalues 'λ'_{jd} as slanting components which is the dth biggest Eigen estimation of co-fluctuation grid. With these outcomes we have a tendency to acquire between-class diffuse lattice and inside of class dissipate framework for the jthmixture part which can be formulated as,

$$U_{B_j} = T_j S_j T^T{}_j \tag{12}$$

$$U_{W_j} = \sum_{l\epsilon L_j} \frac{1}{n_l} \sum_{a\epsilon B_i} (a - m_l)(a - m_l)^T \tag{13}$$

With the assistance of over two classes dissipate mathematical statements, we compute change matrixW_j for jthmixture segment with a target to augment the accompanying model capacity to get summed up eigenvectors comparing to biggest eigenvalues.

$$Uk_s(S) = \frac{S^T U_c S}{S^T U_{W_j} S} \tag{14}$$

C. Classification

Keeping in mind the end goal to compute visual similarities between an inquiry and database image, numerous arrangement strategies have been produced for image recovery in view of observational appraisals of the distribution of components lately. Two different grouping investigations are completed, firstly by considering similarity/separation measure systems and besides PNN are connected to acquire a normal rightness rate. Detailed explanation can be found in the following sections.

1) Similarity Distance Measures

Distinctive similarity separation measures will influence the recognition rate, in such manner we consider five diverse separation measure methods such as Minkowski separation, Eucledian separation, Modified Squared Eucledian separation, and Correlation coefficient based separation and Angle Based separation to secure a normal characterization rate.

2) Probabilistic Neural Network (PNN)

Because of its astounding speculation execution SVM is most encouraging classifiers in machine learning. Then again, SVM's are ease back and still stays to be a bottleneck for huge datasets and multi-class arrangement. Donald Specht presented PNN; network is in view of ideas utilized for ordinary example recognition issues. Specifically PNN models the Bayesian classifier in order to minimize the danger of misclassification. Bayes' classifier is generally censured because of absence of information about the class likelihood conveyances and makes utilization of nonparametric systems to ascertain apriority probabilities pi, however likelihood thickness capacities $F(a)$are by and large more hard to gauge. Parzen builds a group of evaluations from kernels; general type of the estimator is given as,

$$F(a) = \frac{1}{m\lambda} \sum_{i=1}^{m} l\left(\frac{x - x_i}{\sigma}\right) \tag{15}$$

Where ai are indistinguishably disseminated and autonomous random variables with weighting capacity $l$to be bounded.Parzenextended to the multivariate appropriation and weighting capacity l as the multivariate exponential (Gaussian) capacity and comparison communicated in the structure

$$F(a) = \frac{1}{(2\pi)^{\frac{q}{2}}\sigma^p}\frac{1}{m}\sum_{i=1}^{m} e^{-\frac{(a-a_i)^T(a-a_i)}{2\sigma^2}} \quad (16)$$

The characteristic favorable position of PNN is the better speculation and merging properties when contrasted with that of Bayesian classifier in order issues. Proposed strategy is isolated into two stages i)Training & ii) Testing, brief portrayal of proposed algorithm is as given below:

Algorithm 1: Training stage begins
Output: A Knowledge Database (KDB)
Method:
Input: An arrangement of preparing specimen images
1. Accumulate training samples (Segmented images).
2. Apply proposed mixture model for distinctive "K" mixtures (k=4) on set of training tests to acquire feature vector.
3. Save the features in Knowledge Database.
Algorithm: Training stage closes
Ends

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IV. RESULTS & PERFORMANCE ANALYSIS

In this section, we present existing and proposed system results and analysis based on two popular and extensively used datasets in existing system: Caltech-101 & Caltech-256 consisting of various object categories. Caltech-101 dataset consists of 101 different object categories ranging from 31 to 800 images per category, and are subjected to high intensity variations, occlusions and affected by corner artifacts [23]. Caltech-256 was generated by Griffin et al., comprising 256 different object categories which has been manually screened out of Google images exhibiting high variations in intensity, clutter, object size, location, pose, and also increase in number of category with at least 80 images per category.

We initiate our proposed system by applying k-means for the image in complex hybrid color space into a collection of fuzzy clusters based on the color homogeneity of the pixels (as discussed in section 2.1). Segmented RGB image is converted to a gray scale image and further scaled down the image size to give a sensible number of features per image. It is also observed during preliminary experiments that, the mixture of four Gaussians (k=4) are optimal to achieve competitive classification rates. Further, training samples collected from segmented image are vectorized from 2D to 1D clusters. Each cluster density is estimated by a Gaussian distribution function in PCA & FLD transformed space. The parameter estimation is performed by an iterative EM algorithm and constructed feature vector for k=4 mixtures. Further, classification is per-formed in two ways: 1) Probabilistic Neural Network (PNN) technique and 2) Different distance measure techniques and recorded an individual average classification rates respectively. The datasets used in our proposed system is Wang dataset.

TABLE 1 shows the recognition rate for subspace and sub-space mixture models considering both distance measures and neural networks classifiers for Caltech-101 & Caltech-256 datasets. From the table it is noticed that PCA mixture model

TABLE 1 Recognition Accuracy Of Subspace Mixture Models For Caltech-101 &Caltech-256(Existing System)

Method	15 Train	30 Train
Recognition rate(%) : Caltech-101		
Serrre et al.[29]	35	42
Holub et al.[33]	37	43
Berg et al.[30]	45	-
Sancho et al.[28]	57.8	65.2
Recognition rate(%) : Caltech-256		
Van et al.[31]	-	27.17
Griffin et al.[1]	28.3	34.1
Sancho et al.[28]	33.5	40.1
Jianchao et al.[32]	28.30	34.10

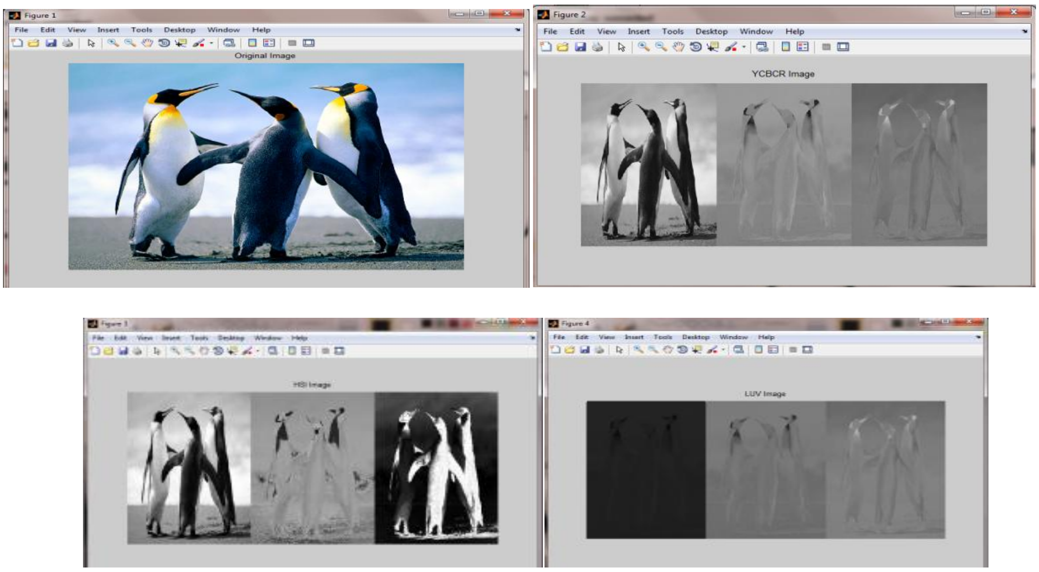

Fig.1. Original Image to YCBCR to HIS to LUV Color Conversions (Proposed system results)

along with distance measure (DM) as a classifier outperforms the other subspace and its mixture models. In general performance of mixture models is improved for segmented images in hybrid color space, especially for subspace mixture with PNN proved to be very efficient and progressive when compared to the mixture models with DM as classifier.

Table 2. Recognition Rate Of Subspace Mixture Models For Wang Dataset (time: 1min,24 sec)(Proposed system results)

Round Map	Recognition Rate(%)
Recognition rate(%) : Wang Dataset	
Round 1	79
Round 2	66
Round 3	81
Round 4	61
Round 5	69
Round 6	63
Round 7	69
Round 8	65
Round 9	71
Round 10	74
Average map result	**70**
Time elapsed	1 min 24 sec

Analysis has revealed the following observations:

- Performance of PCA is better contrasted with other standard subspace routines.
- Application of subspace mixture models has indicated increment in recognition exactness for sectioned images considering both DM and PNN classifiers.
- Although FLD+GMM has turned out to be extremely effective in face recognition, demonstrated nominal execution in item arrangement.
- PCA+GMM with division beat few of the main existing systems regarding recognition exactness.

IV. DISCUSSIONS & CONCLUSIONS

In pattern recognition the mixture of distributions and feature space transformation has picked up part of importance to generalize complex distribution models where it is the fact that classification methods and variety of feature extraction methods addressed in literature. In such manner, a study and investigation of subspace mixture models in PCA &FLD transformed space is introduced to generate governing features to increase the performance of image retrieval system. The advantage of considering probabilistic neural network and distance measures as classifiers has enlarged the recognition rate conversely with kernel codebook and KNN-SVM classifiers. Authors of [28] have consolidated features with various spatial localities with highest classification rates, whereas proposed strategy works on single level locality and mixture of Gaussians to deliver competitive classification rates.

The work of presenting discrete latent variables with concentrate multi-modular discriminative components from segmented areas simplifies prevalent Spatial Pyramid Matching methodology of sorting images in extensive image datasets. The capacity to solve the most complex circulation structure between the object classes by recognizing the inactive(latent) variables alongside the assistance of four Gaussian mixtures and in this manner assembling every conceivable position and introductions of an object in decreased feature space is proposed. It is likewise critical noticing that the mixtures of such examples can be utilized to pack compress the data, and few of them can even now enhance the recognition rate. In future, it merits exploring different discriminative probabilistic models alongside assorted neural system architectures for classification.

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