ISSN: 2349-7300
ISO 9001:2008 Certified
International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJIRMPS)
Volume 1, Issue 2, December 2013

Image Classification using SVM-RBF in the field of Image Processing

Jitendra Kumar

Abstract*: Multi- class classification plays an important role in image classification. In this paper a feature sampling technique of image classification is to be proposed. For the process of optimization we used radial basis function algorithm for the proper selection of feature sub set selection. A function is radial basis (RBF) if its output depends on the distance of the input from a given stored vector. In a RBF network one hidden layer uses neurons with RBF activation functions describing local receptors. Then one output node is used to combine linearly the outputs of the hidden neurons. Different possibilities include: Modify the design of the SVM, as in order to incorporate the multi-class learning directly in the quadratic solving algorithm. Combine several binary classifiers: "One-against- One" (OAO) applies pair wise comparisons between classes, while "One-against-All" (OAA) compares a given class with all the others put together. OAO and OAA classification based on SVM technique is efficient process, but this SVM based feature selection generate result on the unclassified of data. When the scale of data set increases the complexity of pre-processing is also increases, it is difficult to reduce noise and outlier of data set.

***Keywords*: Image Classification, feature generation, cluster, SVM, RBF.**

I. INTRODUCTION

Image Processing is one of the important fields for the various advancements in context of various aspects of images. Although all the advances in image capturing, storage, and internet technologies have made vast amounts of image data available[1].Image information systems are becoming increasingly important with the advancements in broadband networks, high-powered workstations etc. However digital images can be formed by a variety of devices like digital scanners, cameras, co-ordinate measuring machines, digital video recorders, digital synthesizers and airborne radars [2]. A huge variety of images are becoming available to the public, from photo collection to web pages, or even video databases. Since visual media needs large amounts of memory and computing power for processing and storage, there is a requirement for efficiently index and retrieve visual information from image database. In recent years, image classification has become an interesting research field in application [3]. Efficient indexing and retrieval of large number of color images, classification plays an important and challenging role. The main motive of this research work is to find suitable representation for images and Classification generally requires comparison of images classification capability depending on the certain useful methods [4].Image classification is defined as the task of classifying the number of images into (semantic) categories based on the available training data. The main objective of digital image classification procedure is to categorize the pixels in an image into land over cover classes [5]. The output is thematic image with a limited number of feature classes as opposed to a continuous image with varying shades of gray or varying colors representing a continuous range of spectral reflectance [6, 7]. The wide range of digital numbers in different bands for particular features is known as a spectral pattern or spectral signature. A spectral pattern can be composed of adjacent pixels or widely separated pixels. Traditionally the digital image classification technique can be classified into two types: Unsupervised classification Techniques and Supervised classification Techniques [8]. On the other hand an image classification can also be classified in to two types: Linear Classification and Non-Linear Classification [10]. The rest of this paper is organized as follows. In section II related technique for image classification. Section III gives a proposed method. Section IV experimental result analysis V concludes this paper

II. RELATED WORK IMAGE CLASSIFICATION

Wei-jiu Zhang, Li Mao and Wen-boXuetld [2] Automatic Image Classification Using the Classification Ant-Colony Algorithm to enhance the versatility, robustness, and convergence rate of automatic classification of images, an ant-colony-based classification model is proposed in this paper. According to the characteristics of the image classification, this model adopts and improves the traditional Ant-Colony algorithm. It defines two types of ants that have different search strategies and refreshing mechanisms. The stochastic ants identify new categories, construct the category tables and determine the clustering centre of each category. SooBeom Park, Jae Won Lee, Sang Kyoon Kim etld[1] Content-based image classification using a neural network A method of content-based image classification using a neural network. The images for classification are object images that can be divided into foreground and background. To deal with the object images efficiently, in the pre-processing step we extract the object region using a region segmentation technique. Features for the classification are

ISSN: 2349-7300
ISO 9001:2008 Certified
International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJIRMPS)
Volume 1, Issue 2, December 2013

shape-based texture features extracted from wavelet-transformed images. The neural network classifier is constructed for the features using the back-propagation learning algorithm. Among the various texture features, the diagonal moment was the most effective. Hong bao Cao, Hong-Wen Deng, and Yu-Ping Wang etld[4] Segmentation of M-FISH Images for Improved Classification of Chromosomes With an Adaptive Fuzzy C-means Clustering Algorithm An adaptive fuzzy c-means algorithm was developed and applied to the segmentation and classification of multicolour fluorescence in situ hybridization (M-FISH) images, which can be used to detect chromosomal abnormalities for cancer and genetic disease diagnosis. The algorithm improves the classical fuzzy c-means algorithm (FCM) by the use of a gain field, which models and corrects intensity in homogeneities caused by a microscope imaging system, flairs of targets (chromosomes), and uneven hybridization of DNA. Other than directly simulating the in homogeneously distributed intensities over the image, the gain field regulates centers of each intensity cluster. Sai Yang and Chunxia Zhao etld[5] A Fusing Algorithm of Bag-Of-Features Model and Fisher Linear Discriminative Analysis in Image Classification A fusing image classification algorithm is presented, which uses Bag-Of-Features model (BOF) as images' initial semantic features, and subsequently employs Fisher linear discriminative analysis (FLDA) algorithm to get its distribution in a linear optimal subspace as images' final features. Lastly images are classified by K nearest neighbour algorithm. The experimental results indicate that the image classification algorithm combining BOW and FLDA has more powerful classification performances. In order to further improve the middle-level semantic describing performance, we propose compressing the BOF distribution of images distributing loosely in high-dimensional space to a low-dimensional space by using FLDA, the images are classified in this space by KNN algorithm. Ajay Kumar Singh, ShamikTiwari& V.P. Shuklaetld[6] Wavelet based Multi Class image classification using Neural Network, A feature extraction and classification of multiclass images by using Haar wavelet transform and back propagation neural network. The wavelet features are extracted from original texture images and corresponding complementary images. The features are made up of different combinations of sub-band images, which offer better discriminating strategy for image classification and enhance the classification rate. Liping Jing Chao Zhang Michael K. Ng etld[3] SNMFCA: Supervised NMF-based Image Classification and Annotation A novel supervised nonnegative matrix factorization based framework for both image classification and annotation (SNMFCA). The framework consists of two phrases: training and prediction. In the training phrase, two supervised nonnegative matrix factorizations for image descriptors and annotation terms are combined together to identify the latent image bases, and represent the training images in the bases space. These latent bases can capture the representation of the images in terms of both descriptors and annotation terms. Based on the new representation of training images, classifiers can be learnt and built.Sancho McCann David G. Lowe etld[7] Local Naive Bayes Nearest Neighbor for Image Classification An improvement to the NBNN image classification algorithm that increases classification accuracy and improves its ability to scale to large numbers of object classes. The key observation is that only the classes represented in the local neighbourhood of a descriptor contribute significantly and reliably to their posterior probability estimates. LexiaoTian, DequanZheng, Conghui Zhu etld[8] Research on Image Classification Based on a Combination of Text and Visual Features A text-image co-occurrence data become available on the web, mining on those data is playing an increasingly important role in web applications. Utilizing description information to help image classification and propose a novel image classification method focusing on text-image co-occurrence data. In general, there are three main steps in our system: feature extraction, training classifiers and classifier fusion. Shaohua Wan etld[9] Image Annotation Using the Simple Decision Tree Automatic image annotation is an important but highly challenging problem in semantic-based image retrieval. In this paper, they formulate image annotation as a supervised learning image classification problem under region-based image annotation framework. In region-based image annotation, keywords are usually associated with individual regions in the training data set.

III. PROPOSED APPROACH

A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin. If a function 'h' satisfies the property $h(\boldsymbol{x})=h(\|\boldsymbol{x}\|)$, then it is a radial function. Their characteristic feature is that their response decreases (or increases) monotonically with distance from a central point. The centre, the distance scale, and the precise shape of the radial function are parameters of the model, all fixed if it is linear [25]. A typical radial function is the Gaussian which, in the case of a scalar input, is

$$h(x)= \exp((-(x-c)^2)/(r^2)) \qquad (1)$$

Its parameters are its centre c and its radius r.

ISSN: 2349-7300
ISO 9001:2008 Certified
International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJIRMPS)
Volume 1, Issue 2, December 2013

A Gaussian RBF monotonically decreases with distance from the centre. In contrast, a multiquadric RBF which, in the case of scalar input monotonically increases with distance from the centre. Gaussian-like RBFs are local (give a significant response only in a neighborhood near the centre) and are more commonly used than multiquadric-type RBFs which have a global Response. Radial functions are simply a class of functions. In principle, they could be employed in any sort of model (linear or nonlinear) and any sort of network (single-layer or multi-layer). RBF networks have traditionally been associated with radial functions in a single-layer network. In the Figure 1, the input layer carries the outputs of FLD function. The distance between these values and centre values are found and summed to form linear combination before the neurons of the hidden layer. These neurons are said to contain the radial basis function with exponential form. The outputs of the RBF activation function is further processed according to specific Requirements.

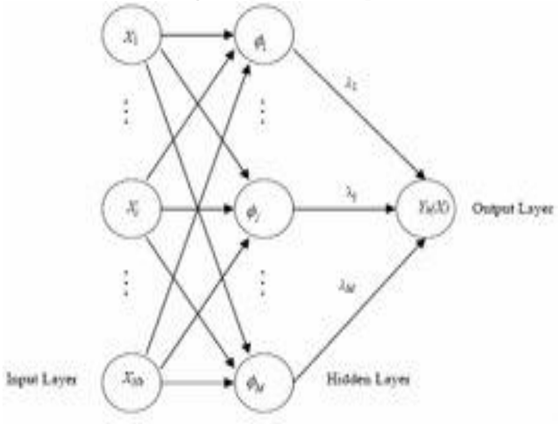


Fig. 1.Structure of Radial Basis Function Neural Network.

In order to specify the middle layer of an RBF we have to decide the number of neurons of the layer and their kernel functions which are usually Gaussian functions. In this paper we use a Gaussian function as a kernel function. A Gaussian function is specified by its center and width. The simplest and most general method to decide the middle layer neurons is to create a neuron for each training pattern. However the method is usually not practical since in most applications there are a large number of training patterns and the dimension of the input space is fairly large. Therefore it is usual and practical to first cluster the training patterns to a reasonable number of groups by using a clustering algorithm such as K-means or SOFM and then to assign a neuron to each cluster. A simple way, though not always effective, is to choose a relatively small number of patterns randomly among the training patterns and create only that many neurons. A clustering algorithm is a kind of an unsupervised learning algorithm and is used when the class of each training pattern is not known. But an RBFN is a supervised learning network. And we know at least the class of each training pattern. So we'd better take advantage of the information of these class memberships when we cluster the training patterns. Namely we cluster the training patterns class by class instead of the entire patterns at the same time (Moody and Darken, 1989; Musavi et al., 1992). In this way we can reduce at least the total computation time required to cluster the entire training patterns since the number of patterns of each class is usually far less than that of the entire patterns. We use an one-pass clustering algorithm called APC-III (Hwang and Bang, 1994). APC-III is similar to RCE (Reilly et al., 1982) but different in that APC-III has a constant radius while RCE has a variable radius. First of all we decide the radius $R0$ of clusters. Therefore APC-III creates many clusters if the radius is small and few clusters if it is large. We set $R0$ to the mean minimum distance between the training patterns multiplied by a:

$$Ro = \alpha \frac{1}{P} \sum_{i=1}^{P} \min(\|Xi - Xj\|) \qquad (2)$$

Where P is the number of the training patterns. If the number of the training patterns is too large, we may well use a subset of them to obtain an approximate $R0$ instead of the exact $R0$. This will speed up the calculation of $R0$. This is not true with K-means and SOFM clustering algorithms. Furthermore APC-III tends to create an

ISSN: 2349-7300
ISO 9001:2008 Certified
International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJIRMPS)
Volume 1, Issue 2, December 2013

appropriate number of clusters since it determines the radius of a cluster based on the distribution of the training patterns. This fact makes APC-III to perform as good as the regular multi-pass clustering algorithms.

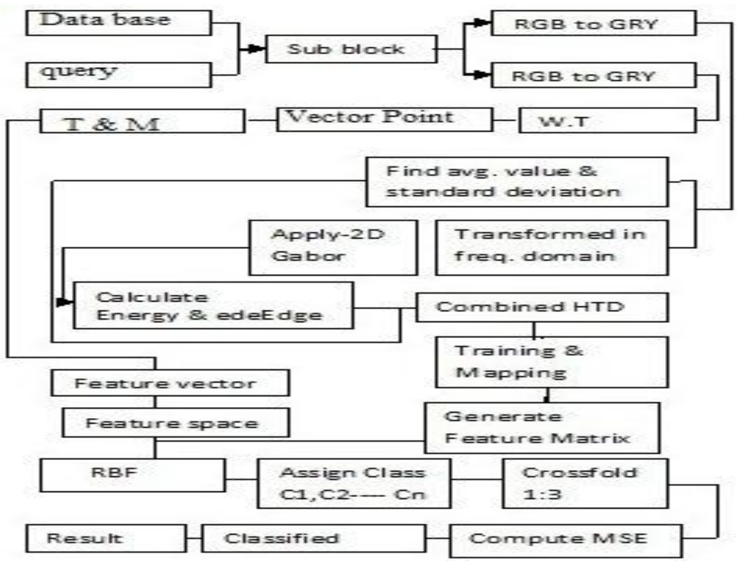
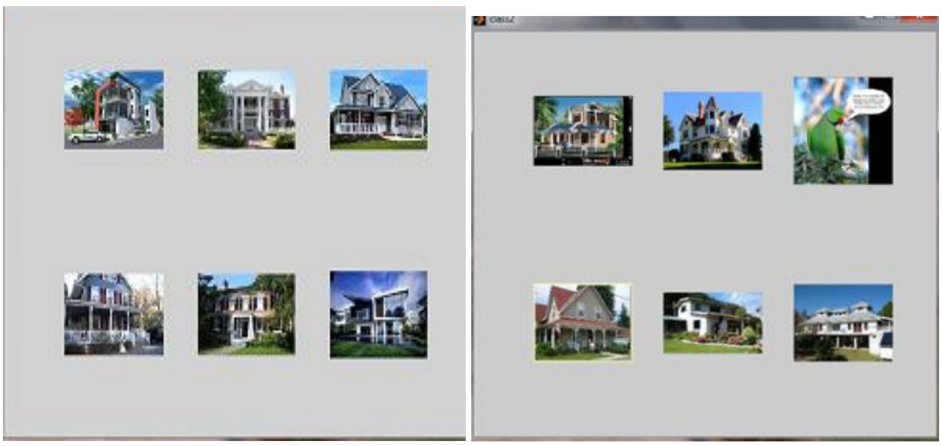


Fig.2Block diagram of proposed method

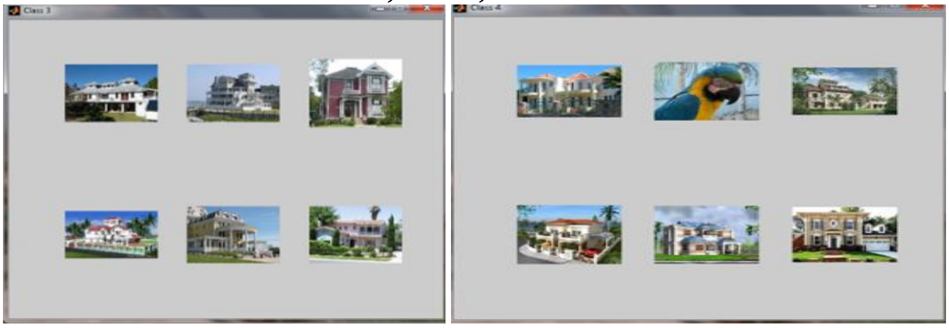
IV. EXPERIMENTAL RESULT ANALYSIS

To evaluate the performance of proposed method of content based image classification we have use MATLAB software 7.8.0 with a variety of image dataset used for experimental task. The image data set is very famous image data set for research purpose for image retrieval. We have used 1000 500 content images and grouped them into a set of 250 images. In our result we have used total 500 content images and they are subdivided into five datasets. Then we have performed an image classification method on each dataset using SVM-DAG and SVM-RBF. Our some content images is given below as

Fig. 3 shows data base and input image class



IJIRMPS
ISSN: 2349-7300
ISO 9001:2008 Certified
International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences (IJIRMPS)
Volume 1, Issue 2, December 2013



Fig, 4 shows the windows of multi class in data set houses, using SVM-RBF for input house.

Fig.5 shows the multiclass of Dataset 2 parrot classification using SVM-RBF

Fig.6 shows the multiclass of Dataset 5 includes images of horse

Table 1 shows the comparative result of SVM-DAG and SVM-RBF

Data set	Method	Precision (%)	Recall (%)
Data set 1	SVM DAG	86.23	80.21
	SVM RBF	90	83.60
Data set 2	SVM DAG	90	91

	SVM RBF	93	96.06
Data set 3	SVM DAG	83.33	79.81
	SVM RBF	80	79
Data set 4	SVM DAG	83.33	76.83

V .CONCLUSION

RBF-SVM reduces the semantic gap and enhances the performance of image classification. However, directly using SVM scheme has two main drawbacks. First, it treats the core point and outlier equally, although this assumption is not appropriate since all outlier share a common concept, while each core point differs in diverse concepts. Second, it does not take into account the unlabeled samples, although they are very helpful in constructing a good classifier. In this dissertation, we have explored unclassified region data on multi-class classification. . We have designed RBF-SVM to alleviate the two drawbacks in the traditional SVM. Here RBF play a role of feature sampling technique. The sampling of the feature technique reduced the unclassified region of multi-class classification.DAG based support Vector machine perform a better classification in compression of another binary multi-class classification. DAG applied a graph portion technique for the mapping of feature data. The mapping space of feature data mapped correctly automatically improved the voting process of classification. But DAG suffered a little bit problems with mapping of space data into feature selection process. Performance of result evaluation shows that our RBF-SVM is better classifier in compression of DVM-Dag.

REFERENCES

[1] SooBeom Park, Jae Won Lee, Sang Kyoon Kim “Content-based image classification using a neural network” in 2003 Elsevier.

[2] Wei-jiu Zhang, Li Mao, Wen-boXu ” Automatic Image Classification Using the Classification Ant-Colony Algorithm” in International Conference on Environmental Science and Information Application Technology 2009.

[3] Liping Jing, Chao Zhang and Michael K. Ng “SNMFCA: Supervised NMF-based Image Classification and Annotation” in IEEE 2011.

[4] Hongbao Cao, Hong-Wen Deng, and Yu-Ping Wang “Segmentation of M-FISH Images for Improved Classification of Chromosomes With an Adaptive Fuzzy C-means Clustering Algorithm” in IEEE TRANSACTIONS ON FUZZY SYSTEMS, VOL. 20, NO. 1, FEBRUARY 2012.

[5] Sai Yang and Chunxia Zhao “A Fusing Algorithm of Bag-Of-Features Model and Fisher Linear Discriminative Analysis in Image Classification” in IEEE International Conference on Information Science and Technology 2012.

[6] Ajay Kumar Singh, ShamikTiwariand V.P. Shukla “Wavelet based Multi Class image classification using Neural Network” in International Journal of Computer Applications (0975 – 8887) Volume 37– No.4, January 2012.

[7] Sancho McCann and David G. Lowe “Local Naive Bayes Nearest Neighbour for Image Classification” in IEEE 2012.

[8] LexiaoTian, Dequan Zheng and Conghui Zhu “Research on Image Classification Based on a Combination of Text and Visual Features” in Eighth International Conference on Fuzzy Systems and Knowledge Discovery 2011.

[9] ShaohuaWan ” Image Annotation Using the Simple Decision Tree” in International Conference on Management of e-Commerce and e-Government 2011.

[10] Shang Liu and Xiao Bai “Discriminative Features for Image Classification and Retrieval” in Sixth International Conference on Image and Graphics 2011.

[11] Saurabh Agrawal, Nishchal K Verma , Prateek Tamrakar and Pradip Sircar “Content Based Color Image Classification using SVM” in Eighth International Conference on Information Technology: New Generations 2011.