Classification of Medical Images Using Edge-Based Features and Sparse Representation

M. Srinivas
VIsual learninG and InteLligence (VIGIL) group
Computer Science and Engineering
Indian Institute of Technology Hyderabad
Hyderabad, India
Email: cs10p002@iith.ac.in

C. Krishna Mohan
VIsual learninG and InteLligence (VIGIL) group
Computer Science and Engineering
Indian Institute of Technology Hyderabad
Hyderabad, India
Email: ckm@iith.ac.in

***Abstract*—In this paper, an approach for classification of medical images using edge-based features is proposed. We demonstrate that the edge information extracted from an image by dividing the image into patches and each patch into concentric circular regions provide discriminative information useful for classification of medical images by considering 18 categories of radiological medical images namely, skull, hand, breast, cranium, hip, cervical spin, pelvis, radiocarpaljoint , elbow etc.,. The ability of On-line Dictionary Learning (ODL) to achieve sparse representation of an image is exploited to develop dictionaries for each class using edge-based feature. A low rate of misclassification error for these test images validates the effectiveness of edge-based features and On-line Dictionary Learning models for classification of medical images.**

Keywords*—*Classification, Content based image retrieval, Dictionary Learning, Medical X-ray image, Directions, Sparse representation, ODL, Edge information.

I. Introduction

Digital image retrieval techniques are becoming increasingly important in the field of medical image databases. The increasing dependence on modern medical diagnostic techniques like radiology, histopathology and computerized tomography has led to an explosion in the number of medical images stored in hospitals. Images of various body parts and modalities are becoming an important source of anatomical and functional information for the diagnosis of diseases, medical research and education [1]. However, one cannot utilize the information in these image collections unless they are organized for efficient search and retrieval of data. Effectively and efficiently searching and retrieving of data in these large image collections poses significant technical challenges as the characteristics of the medical images differ from other general purpose images. Some methods have been explored in recent years to automatically classify medical image collections into multiple semantic categories for effective retrieval [2]-[4]. For example, in [3], the automatic categorization of 6231 radiological images into 81 classes is achieved by utilizing a combination of low level global texture features with low resolution scaled images and a K-nearest neighbor (KNN) classifier. Although these approaches demonstrate promising results for medical image classification and retrieval, classification and searching similar images in a large database is still a challenge. Searching similar images in a large image repository on the basis of their visual content is called Content Based Image Retrieval (CBIR) [5]. The traditional text based image classification and retrieval (TBIR) approach has many practical limitations like the images in the collection have to be annotated manually which becomes very difficult as the size of the image collection increases and time consuming. Another important limitation of TBIC and TBIR is inadequacy in representing the image content [6]. Content based image classification and retrieval approaches are proposed to overcome the limitations of text based image classification and retrieval. Digital image retrieval techniques are crucial in the emerging field of medical image databases for clinical decision making process.

Medical image classification is an important task in Content Based Medical Image Retrieval (CBMIR). Automatic medical image classification is a technique for assigning a medical image to an appropriate class among a number of medical image classes. In medical image classification, several methods and algorithms have been presented in the literature [7]-[9]. One approach to content based medical image retrieval is proposed in [7], in which medical images are classified based on body orientation, biological system, anatomical region and image modality. The performance of the classification is evaluated on IRMA database and the best classification result is achieved by using distorted tangent distance in a kernel density classifier. Dictionary learning based clustering method is proposed in [10]. Each image portioned into concentric circular regions around the center, and consider the mean and variance of pixel intensities in each region as components in the feature vector. And dictionary learning based clustering method developed for image retrieval on unlabeled data.

An X-ray image categorization and retrieval method using patch-based visual word representations is proposed in [11]. The feature extraction process is based on local patch representation of the image content and a bag-of-features approach for defining image categories, with a kernel based SVM classifier. The method is especially effective in discriminating orientation and body regions in X-ray images, and in medical visual retrieval. In [12], wavelet features extracted from an image provide discrimination useful for classification of different sensors (modalities) based medical images. And with the help of On-Line dictionary learning and sparse representation methods are used for classification approach. In [13], a descriptor was proposed which combines local features with global shape features. The descriptor combines edge of whole image with edge density of sub-images and it is known as the Edge Density Histogram Descriptor (EDHD). The image retrieval and classification is then done based on euclidean distance and with the help of support vector machines. A learning based classification framework based on local binary pattern(LBP) feature is proposed in [14]. Local binary pattern is extracted from each image in database with the help of an LBP operator which labels image pixels by thresholding neighborhood of each pixel with the center value and considers the results as a binary number, which is then classified using a maximum margin SVM. Moreover, a merging technique is applied on the overlapped classes. These overlapped classes are detected in merging scheme with the help of measures such as correctness rate of each class, similarity of imaging body organ and misclassification ratio. In [15] adaptive learning based heartbeat classification method is proposed. To reduce inter-patient and intra-patient variations in heartbeat cycles feature normalization techniques and for effective representation of the data time and frequency domains based new feature extraction methods are proposed. In [16], multiple features are used for medical image indexing and retrieval. In this approach, combines the edge and patch based feature extraction methods. And based on similarity measure retrieve similar type of images.

Sparse representation has received a lot of attention from the research in signal and image processing. Sparse coding involves the representation of an image as a linear combination of some atoms in a dictionary [17]. It is a powerful tool for efficiently representing data. This is mainly due to the fact that signals and images of interest tend to enjoy the property of being sparse in some dictionary. These dictionaries are often learned directly from the training data. Several algorithms like On-Line Dictionary Learning (ODL) [18], K-SVD [19] and Method of Optimal Directions (MOD) [20] have been developed to process training data. Sparse representation is used to match the input query image with the appropriate class.

In this paper, we propose a classification method for Image Retrieval in Medical Applications (IRMA) database [21] using on-line dictionary learning approach. Learned dictionaries are used to represent datasets in sparse model of IRMA medical images. Dictionaries are designed to represent each class. For a given N number of classes, we design N dictionaries to represent the classes. Each image associated with a dictionary provides the best sparsest representation. For every image in the given set of images $\{\mathbf{y}_i\}_{i=1}^{n}$, ODL is used to seek the dictionary D that has the sparsest representation for the image. We define $l(\hat{\mathbf{D}}, \hat{\Phi})$ as the optimal value of the l_1-lasso sparse coding problem [22]. This is accomplished by solving the following optimization problem:

$$l(\hat{\mathbf{D}}, \hat{\Phi}) = \arg\min_{\mathbf{D},\Phi} \frac{1}{N} \sum_{i=1}^{N} \frac{1}{2} \|\mathbf{Y}_i - \mathbf{D}\Phi_i\|_2^2$$

$$subject\ to\ \ \|\Phi_i\|_1 \leq \lambda, \qquad (1)$$

where Y is the matrix whose columns are y_i and λ is the sparsity parameter. D denotes the learned dictionary, Φ represents the sparse representation vectors, N denotes the number of classes and Y represents the training database. The ODL algorithm alternates between sparse coding and dictionary update steps. Several efficient pursuit algorithms have been proposed in the literature for sparse coding [20],[23]. The simplest one is the l_1-lasso algorithm [22]. Main advantage with ODL algorithm is its computational speed as it uses l_1-lasso algorithm for sparse representation. In sparse coding step, dictionary D is fixed and representation vectors $\mathbf{\Phi_i}$ are identified for each example y_i. Then, the dictionary is updated atom by atom in an efficient way.

The rest of the paper is organized as follows. Section 2 presents the proposed method. Experiments of content based medical image classification application are described in detail in section 3. Finally, we draw the conclusions in section 4.

II. Medical Image classification using ODL algorithm

The present work provides a method for medical image classification using the framework of dictionary learning. There are many advantages to this approach. Firstly, the edge and patch based feature extraction method proposed to classify the data. Secondly, the entire dataset is represented with the help of fixed small size of dictionary which greatly reduces computational time. Moreover, performance improves because of the uniform dictionary size irrespective of number of training images.

The proposed CBMIR framework, First, the features are extracted from the images of the each training dataset. A dictionary is generated for each class using the ODL algorithm. Then, given test data is compared with the existing dictionaries to identify the dictionary with the sparest representation using l_1 lasso algorithm. Finally, test data is assigned to the class associated with the sparsest dictionary. Fig. 1(a) shows some of sample IRMA medical images.

A. Feature Extraction

The performance of a CBIR system depends on the representation of an image as a feature vector. Generally, content based medical image classification and retrieval techniques use fundamental visual features like images color, shape and texture yielding vectors with thousands of features. But using these features directly, one cannot retrieve similar images easily. In the proposed method, we consider two type of feature extraction methods to represent the content of medical images. In the first method, edge based feature extraction is used to extract edge information of the medical images. Since, medical images of different body parts contains different shapes and different edge information, medical images can be easily be classified based on the edge features.

In this paper, Canny edge [24] detection method is used for finding the edges of the images shown in Fig. 1(b). This feature extraction method is more suitable for medical image databases. In the second method, patch based feature extraction method is used on edge images. An edge image is divided into equal size of patches as shown in Fig. 1 (c). Each patch of the image is partitioned into concentric circular regions of equal area as shown in Fig. 1(d).

The mean and variance of pixel intensity in each circular region become a component of the feature vector using equations (2) and (3), where P is the number of pixels in each region, m is the mean of pixels intensity values and S is the variance of pixels intensity values in each region. This

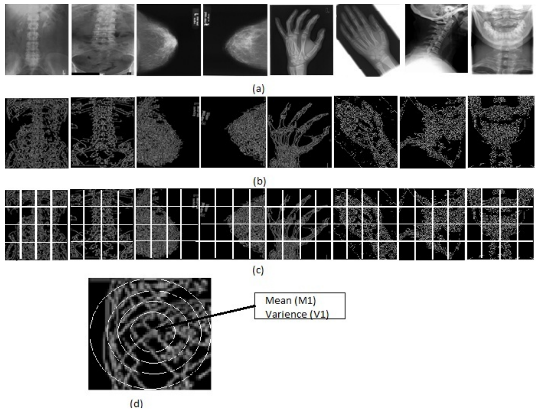

Fig. 1. Includes (a) samples of the IRMA medical images. (b) Coressponding edge images (c) Images are divided into equal size of patches.(d) A patch is divided into concentric circular regions.

approach accomplishes the best representation of the contents of an image.

$$m = \frac{1}{P}\sum_{k=1}^{P}(y_k) \tag{2}$$

$$S = \sum_{k=1}^{P}(y_k - m)(y_k - m)^t, \tag{3}$$

The procedure for feature extraction is as follows:
1. Edge information extracted from medical images.
2. Each edge image is divided into 16 equally sized (50×50) patches.
3. Patch of the every image is partitioned into 4 concentric circular regions, such that each circular region has the same number of pixels as the other regions.
4. Calculate mean and variance of each circular region are used as components for the feature vector. The size of the feature vector for each image is 128×1 (we have 16 patches, each patch has 4 circular regions and calculate the mean and variance of the pixels for each region, so we get a feature vector of size $16 \times 4 \times 2$).

B. Proposed Method

In this proposed method, we introduce a sparsity based medical image classification by representing the test data as a sparse linear combination of training data from a dictionary. In this paper, class $C = [C_1, \ldots, C_N]$ consists of training samples collected directly from the image of interest. In the proposed sparsity model, images belonging to the same class are assumed to lie approximately in a low dimensional subspace. Given N training classes, the p^{th} class has K_p training images $\{\mathbf{y}_i^N\}$ i=1,..., K_p. Let b be an image belonging to the p^{th} class, then it is represented as a linear combination of these training samples:

$$b = \mathbf{D}^p \Phi^p, \tag{4}$$

where D^p is $m \times K^p$ a dictionary whose columns are the training samples in the p^{th} class and Φ^p is a sparse vector. Proposed method consists of two steps:

1) *Dictionary Construction:* Construct the dictionary for each class of training images using on-line dictionary learning algorithm [18]. Then, the dictionaries $D = [D_1, \ldots, D_N]$ are computed using the equation:

$$(\hat{\mathbf{D}}_i, \hat{\Phi}_i) = \arg\min_{\mathbf{D}_i, \Phi_i} \frac{1}{N}\sum_{i=1}^{N}\frac{1}{2}\|\mathbf{C}_i - \mathbf{D}_i\Phi_i\|_2^2 + \lambda\|\Phi_i\|_1, \tag{5}$$

satisfying $\mathbf{C}_i = \hat{\mathbf{D}}_i\hat{\Phi}_i, \quad i = 1, 2, \ldots, N.$

2) *Classification:* In this classification process, the sparse vector Φ for given test image is found in the test dataset $B = [b_1, \ldots, b_l]$. Using the dictionaries of training samples $D = [D_1, \ldots, D_N]$, the sparse representation Φ satisfying $D\Phi$=B is obtained by solving the following optimization problem:

$$\begin{aligned} \Phi^j &= \arg\min_{\Phi} \tfrac{1}{2}\|\mathbf{b_j} - \mathbf{D}\Phi_j\|_2^2 \quad \text{subject to} \|\Phi_j\|_1 \le T_1, \\ and\ \hat{i} &= \arg\min_i \|\mathbf{b_j} - \mathbf{D}\delta_i(\Phi^j)\|_2^2 \quad j = 1, \cdots, t, \end{aligned} \tag{6}$$

where δ_i is a characteristic function that selects the coefficients. Then b_j is assigned to C_i associated with the i^{th} dictionary. It means, finding the sparesest dictionary for a given test data using l_1 -lasso algorithm. Then, test data is assigned to the class associated with this sparsest dictionary.

III. Experimental Results

Experiments are carried out on IRMA medical database, in which each image is of size 200×200 pixels. Majority of medical images are generally grayscale images such as X-ray, CT, etc. Fig.1(a) shows some of the sample ImageCLEF images of IRMA database. For classification of medical images, 5400 sample images of skull, breast, chest, hand etc., spanning 44 different classes with different orientations are used. The main problem in classifying medical radiological images is high inter class overlap and intra class variability in some of the classes [6]. For tackling this problem, different merging techniques are applied [6]. We devised a merging technique where different orientations of the same shaped image are merged into a single class, which reduces the number of classes from 44 to 18. Moreover, the proposed method works for images with various orientations. So, merging different orientations of the same body part image into one class. Each class consists of 300 training and 50 testing images, and experiments are run through 5-fold cross validation. The best results obtained from these experiments are presented in Table 1.

The proposed method gives best classification results of 98.5% as compared to other image classification techniques such as Linear Discriminative Analysis (LDA), Kernel SVM, Neural Network (NN), KNN (K-Nearest Neighbor) and Bayes Classifier (BC). Linear discriminant analysis classifier and Bayes classifier give the classification performance results of 77% and 74% respectively. Neural network classifier is tested with different number of hidden layers. Among these, classification performance is maximized at 82% when using 50 hidden layers. KNN gives best performance results of 88.1% with K=5. When K value increases, the KNN classification

Table. 1 Comparing Performance (%) results of each class with different classifiers.

Classifiers/ Classes	NN	K-SVM	BC	ODL	KNN	LDA
C1	76	88	82	90	88	86
C2	94	94	76	100	98	28
C3	54	78	88	100	76	60
C4	68	88	44	100	78	44
C5	84	98	80	100	92	96
C6	80	100	60	92	78	100
C7	94	94	96	100	94	90
C8	100	100	100	100	100	100
C9	70	80	44	100	74	44
C10	88	100	88	100	100	100
C11	74	82	54	92	64	48
C12	80	96	74	100	86	96
C13	74	100	52	100	94	74
C14	92	96	78	100	92	70
C15	94	96	84	100	88	90
C16	98	98	92	100	98	98
C17	64	96	72	100	90	56
C18	98	100	64	100	96	100
Average	82	94	74	**98.5**	88.1	77

performance results decrease. The performance results of KNN with different K values are shown in Fig.2.

Kernel SVM gives highest performance results of 94% using polynomial kernel function. Further, KSVM was explored with different types of kernels namely, linear, polynomial, RBF and sigmoid. The best classification results among all classes with various kernels is shown in Fig.3.

From the experimental results, we found that the feature vector selected from the multiple features and on-line dictionary based classifiers class gives the best performance among all the other classifier methods.

Over the years, various works have been done by taking different number of images from the IRMA medical database. In [7], best classification error rate of 8.0% was achieved for a set of 1617 images from IRMA database. Database consisting of 9100 medical x-ray images of 40 classes are considered in [6]. It provides accuracy rate of 90.83% on 25 merged classes in the first level. Next, if correct classes were considered within the best three matches, then the performance values increase to 97.9%. In [3], medical images are classified into 80 classes describing the image direction and modality. In this, 6231 training images are used for classification of medical images and 85.5% correctness is obtained. In [8], for a database consisting of 5000 medical images of 20 classes, classification accuracy of 81.96% is achieved. In [9], an evaluation on a dataset of 1500 images of IRMA database achieved a classification rate of 97.5% in a 17-class classification problem. Fesharaki et al. [25] used the IRMA database for medical image classification. Database includes 4937 X-ray images belonging to 28 different classes. Classes are separated based on the angle of photography and the anatomical area and an accuracy rate of 82.87% was achieved.

IV. Conclusion

We have presented an approach for classification of X-ray images using edge-based features. We have exploited

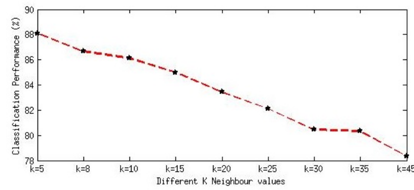

Fig. 2. KNN classifier performance results using different K values.

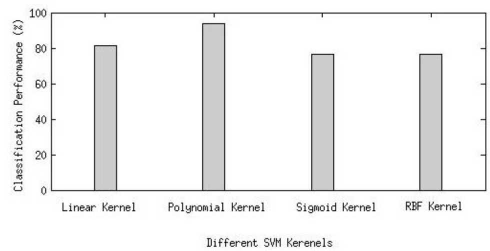

Fig. 3. Different type of SVM kernels performance results.

the ability of ODL to achieve sparse representation of an image, to develop dictionaries for each class using edge-based feature. Other classifiers, namely, Kernel SVM, NN, LDA, KNN and Bayes were also examined. The X-ray images database containing 18 categories, namely, skull, hand, breast, cranium, hip, cervical spin, pelvis, radiocarpaljoint, elbow etc.,. was used for training and testing the models. Experimental results indicate that the edge-based feature can provide useful information for discriminating the classes. These edge-based features along with on-line dictionary learning and sparse representation based classification gives the best possible classification performance till date. Preliminary computational results are promising and have the potential for practical image classification. The proposed method has achieved best performance of 98.5%. The experimental results suggest that the proposed method is better than other well known classification algorithms.

Acknowledgement

We would like to thank Dr. T.M. Deserno, Department of Medical Informatics, RWTH Aachen, Germany for making the original IRMA Database available for research purposes.

References

[1] H. D. Tagare, C. Jafe, J. Duncan. Medical Image Databases: A Content Based Retrieval Approach. JAmer. Medical. Informat.Assoc. 1997; 4(3):184-198.

[2] A. Mojsilovis, J. Gomes. Semantic based image categorization browsing and retrieval in medical image databases. In: Proc. IEEE Int. Conf. Image Process 2002; (3): 145-148.

[3] T. M. Lehmann, M. O. Guld, T. Deselaers, D. Keysers, H. Schubert, K. Spitzer, H. Ney, B. B. Wein. Automatic categorization of medical images for content-based retrieval and data mining. Comput.Med.Imag. Graph 2005; (29): 143-155.

[4] F. Florea, H. 'Muller, A. Rogozan, A. Geissbuhler, S. Darmoni. Medical image categorization with MedIC and MedGIFT. In: Proc. Med. Inf. Eur. Maastricht, Netherlands: 3-11.

[5] A. W. M. Smeulder, M. Worring, S. Santini, A. Gupta, R. Jain. Content based image retrieval at the end of the early years. IEEE Trans. Pattern Analysis Machine Intell 2000; 22(12):1349-1380.

[6] H. Pourghassem, H. Ghassemian. Content based medical image classification using a new hierarchical merging scheme. Computerized Medical Imaging and Graphics 2008; 32(8), 651-661.

[7] D. Keysers, J. Dahmen, H. Ney, B. B. Wein, T. M. Lehmann. Statistical frame work for model based image retrieval in medical applications. J Electronic Image 2003; 12(1): 59-68.

[8] M. M. Rahman, P. Bhattacharya, B. C. Desai. A frame work for medical image retrieval using machine learning and statistical similarity matching techniques with relevance feedback. IEEE Trans. Inf Technology Biomed 2007; 11(1): 58-69.

[9] H. Greenspan, A. T. Pinhas. Medical image categorization and retrieval for PACS using the GMM-KL frame work. IEEE Trans. Inf Technology Biomed 2007; 11(2): 190-202.

[10] M. Srinivas, R. Ramu Naidu, C. S. Sastry, Mohan, C Krishna. Content Based Medical Image Retrieval Using Dictionary Learning.Neurocomputing (2015), Vol.168, : 880-895.

[11] U. Avni et al., X-ray image categorization and retrieval using patch-based visual words representation. In Proc. IEEE Int. Symp. Biomed. Image 2009; 1(2): 350-353.

[12] Srinivas, M and Mohan, C Krishna. Medical images modality classification using multi-scale dictionary learning. 19th International Conference on Digital Signal Processing (DSP), 2014, pp. 621–625, 2014.

[13] Fu. Li-dong, Z. Yi-fei. Medical image retrieval and classification based on morphological shape feature. In Proc. IEEE Int. Conf. Intelligent Networks and Intelligent systems 2010; 116-119.

[14] M. R. Zare, M. Awedh, A. Mueen, W. C. Seng. Medical scheme based classification of medical X-ray images. In Proc. IEEE Int. Conf. Computational Intelligence, Modeling and Simulation 2011; 253-258.

[15] M. Srinivas, Tony Basil, C. Krishna Mohan. "Adaptive learning based heartbeat classification." Bio-medical materials and engineering (2015), Vol.26.1-2 : 49-55.

[16] M. Srinivas, C. Krishna Mohan. Medical Image Indexing and Retrieval Using Multiple Features. In Proceedings of CIIT conference 2013; Elsevier.

[17] I. Ramirez, P. Sprechmann, Guillermo. Spiro. Classification and Clustering via Dictionary Learning with Structured Incoherence and Shared Features. In IEEE Int. Conf. Computer Vision and Pattern Recognition (CVPR) 2010; 3501-3508.

[18] J. Mairal, F. Bach, J. Ponce, G. Sapiro. Online dictionary learning for sparse coding. In Proceedings of the 26th Annual International Conference on Machine Learning ICML 2009; 689-696.

[19] M. Aharon, M. Elad, A. M. Bruckstein. The K-SVD: An Algorithm for Designing of Over complete Dictionaries for Sparse Representation. IEEE Trans. Signal Process 2006; 54(11): 4311-4322.

[20] K. Engan, S. Aase, J. Hakon-Husoy. Method of optimal directions for frame design. In Proc. IEEE Int. Conf. Acoust., Speech, Signal Process 1999; (5): 2443-2446.

[21] www.irma-project.org.

[22] H. Lee, A. Battle, R. Raina, A. Y. Ng. Efficient sparse coding algorithms. In Proc. Advances in Neural Information Processing Systems 2007; (19): 801-808.

[23] S. Mallat, Z. Zhang. Matching Pursuits with Time Frequency Dictionaries. IEEE Trans. Signal Processing 1993; 41(12): 3397-3415.

[24] J. Canny. A computational approach to edge detection. IEEE Trans. Pattern Analysis and Machine Intelligence 1986; 8(6): 679-698.

[25] N. J. Fesharaki, H. Pourghassem. Medical X-ray Images Classification Based on Shape Features and Bayesian Rule. In Proc. IEEE Int. Conf. Computational Intelligence and Communication Networks 2012; 369-373.