ISSN: 2321-7782 (Online)
Impact Factor: 6.047
Volume 4, Issue 6, June 2016
International Journal of Advance Research in Computer Science and Management Studies
Research Article / Survey Paper / Case Study
Available online at: www.ijarcsms.com

Content MRI Brain Image Retrieval using Shape Descriptors and Relevance Vector Machine (RVM)

Dhara Arun Bhai Parmar
CE Department,
SPBPEC, SIT, Linch, Mehsana
Gujarat – India

Abstract: Growth of huge amount of uploading and downloading of images and videos on internet needs help of a better way of retrieving. Similar manner the different areas like hospitals, offices, schools, colleges, social networking cites etc also has to withstand the users requests of file(s) as per user's requirements. Here, the scenario for a hospital has been considered where a strong, reliable system for retrieval is mandatory as patient's life is at stake. So, for the retrieval of the Brain MR Images from the data available with them, Content based retrieval of images technique is used through which similar kind of images to the query/requested image provided by the user from all the images will be extracted.

Keywords: FD (Fourier Descriptor), Relevance Vector Machine (RVM), KNN (K-nearest neighbor).

I. INTRODUCTION

Content-based image retrieval (CBIR), also known as query by image content (QBIC) and content-based visual information retrieval (CBVIR) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based image retrieval is opposed to concept-based approaches.[1] For efficient services in all fields such as government, academics, hospitals, crime prevention, engineering, architecture, journalism, fashion and graphic design images are being used. Due to the popularity of these types of digital images database becomes huge, and to search and retrieve required image from the huge database it becomes difficult and time consuming. To solve these problems traditionally text-based retrieval is used. In a computer system for browsing, searching and retrieving images from the huge database of digital images retrieval system is used. To search images, a user provides query terms of keyword and the system will return images similar to the query.[2]

The query image bestowed to our criticism is the magnetic resonance brain images, which provides good disparity between the soft tissues of brain. In this paper the features of brain images extract by descriptor of shape based on region . Depending on those features, the feature vector is evaluated and given as the index for further classification of brain images under tumor or not tumor classes. The significant part of this diagnosis is to a relevance vector machine (RVM) for classification and determining the presence tumor or not tumor followed by KNN (K-nearest neighbor) [1] that retrieves the most similar images in the database for classifying brain images according to its characteristics.

II. PROPOSED SYSTEM

The main aim of our system is, to identify the similar type of images from the brain MR images set. This will be performed in stages, 1. Extracting the features from the images, 2. Classifying the images as tumorous and non-tumorous and after that 3. Retrieval of similar images. The primary objective of first stage is formation of feature vector which would be given input to the next stage. In the next stage, the primary objective is to bifurcate the images in two categorizes , 1. Tumor image or 2. Non Tumor image. After the bifurcation, the similar images are retrieved. This is the primary objective of the last stage. Using a distance measure the similar images to query images are identified and retrieved.

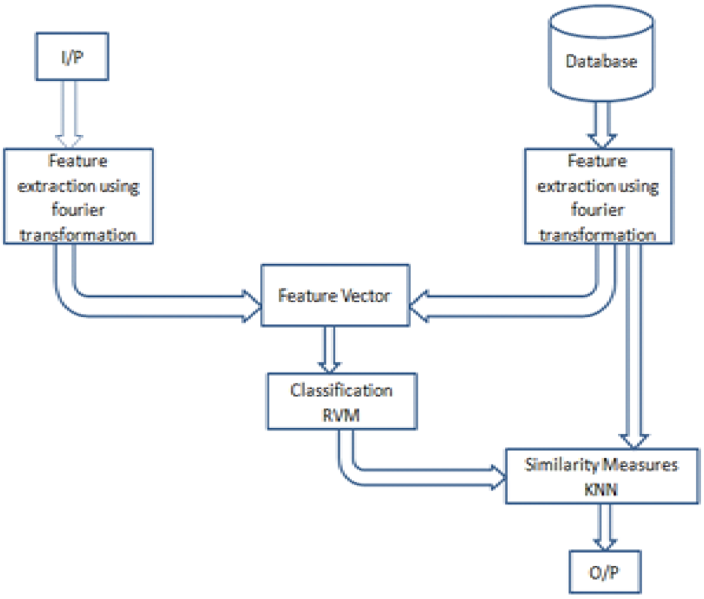

Figure 1: System Flow Diagram

The proposed method is based on the following techniques: Fourier Descriptors, Relevance Vector Machine and KNN. It consists of three stages: (1)feature extraction stage, (2) classification stage, and (3) similarity test stage. The proposed technique for MRI image retrieval is illustrated in Figure 1. In the following sections, we illustrate how the proposed method is applied. A review of basic fundamentals of RVM, Fourier Descriptors, and KNN are introduced.

III. Feature Extraction

Shape is the contours and shapes of objects represented in the image. The process of extracting shapes often goes like this: First we find the contours in the image, then we segment the image into the different contours and index these. Finding contours can be obtained by using *chain codes* which is an algorithm that "walks" around the edge of *regions*, creating a set of straight lines around the region. A region could for instance be an area of similar color or an area that is in some way different from the rest of the image. These lines can be further simplified with *polygon approximation* which makes the lines less jagged[6]. Further we can capture the essence of the shape using Fourier Descriptors. The shapes can be indexed by simple statistical moments, such as the mean and variance. Shape features are classified in to two types: boundary/contour descriptors and region descriptors.[7][8][9][10] Further they are classified as (a) Structural and (b) global. The global boundary descriptors include various signatures, Fourier descriptors and wavelet descriptors[7] as shown in Figure 2.

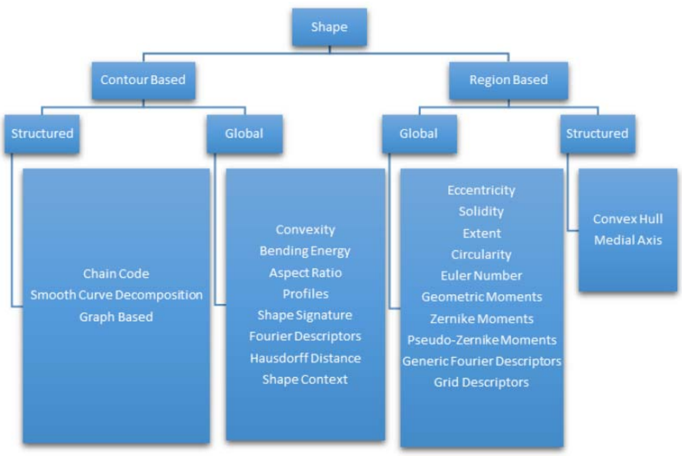

Figure 2: Classification of Contour & Region based shape descriptors [3]

Fourier Descriptors

The Fourier transformed coefficients form the Fourier descriptors of the shape. These descriptors represent the shape of the object in a frequency domain. The lower frequency descriptors contain information about the general features of the shape, and the higher frequency descriptors contain information about finer details of the shape. The dimensions of the Fourier descriptors used for indexing shapes are significantly reduced.[4]

FD is obtained by applying Fourier transform on a shape signature. In the first step of the derivation of FD, the boundary coordinates $(x(u),y(u));u=0,1,2,\ldots N-1$ are obtained, where represents total number of boundary points. For establishing the translation invariance, radial distance between the boundary points $(x(u),y(u))$ and the centroid $(X\mathrm{c},Y\mathrm{c})$ of the shape is represented as [5]:

$$r(u) = \sqrt{(x(u)-x_c)^2 + (y(u)-y_c)^2}$$

$$where\ x_c = \frac{1}{N}\sum_{u=0}^{N-1} x(u)\,, y_c = \frac{1}{N}\sum_{u=0}^{N-1} y(u)$$

The discrete Fourier transform of *r(u)* is given as:

$$a_n = \frac{1}{N}\sum_{u=0}^{N-1} r(u)\exp\left(\frac{-j2\pi u}{N}\right), \qquad n = 0,1,\ldots,N-1$$

The coefficients a_n are called the Fourier descriptors of the shape, and denoted as FD_n. The rotation invariance is achieved by considering only the magnitude and scale invariance is done as follows [5]:

$$F = \left[\frac{|FD_1|}{|FD_0|}, \frac{|FD_2|}{|FD_0|}, \ldots, \frac{|FD_{N/2}|}{|FD_0|}\right]$$

IV. Classification

Relevance Vector Machine

The ‘relevance vector machine' (RVM) is a model identical to the popular and state-of-the-art `support vector machine' (SVM)’s functional form. We demonstrate that by exploiting a probabilistic Bayesian learning framework, we can derive accurate prediction models which typically utilise dramatically fewer basis functions than a comparable SVM while offering a number of additional advantages. These include the benefits of probabilistic predictions, automatic estimation of `nuisance' parameters, and the facility to utilize arbitrary basis functions (e.g. non-`Mercer' kernels). [11]

Relevance vector machine (RVM) is a special case of a sparse linear model, where the basis functions are formed by a kernel function φ centred at the different training points:

$$y(x) = \sum_{i=1}^{N} w_i \emptyset(x - x_i)$$

While this model is similar in form to the support vector machines (SVM), the kernel function here does not need to satisfy the Mercer’s condition, which requires φ to be a continuous symmetric kernel of a positive integral operator.[12]

V. Similarity measure

K-Nearest Neighbour

K-Nearest Neighbour (KNN) technique is the simplest technique that provides good accuracy. The KNN algorithm is based on a distance function and a voting function in K-Nearest Neighbour’s, the metric employed is the Euclidean distance, Hamming distance, Minkowski distance. The KNN has higher accuracy and stability for MRI data than other common statistical classifiers.[14]

KNN on MRI images:

1) Euclidian distance: This is used as distance function due to its simplicity.

2) Hamming distance: This method detects edges in the image. The Hamming distance is a metric on the vector space of the words of length n, as it fulfils the conditions of non-negativity, identity of indiscernible and symmetry .It can be shown by complete induction that it satisfies the triangle inequality.

3) Minkowski distance: This is a metric on Euclidean space which can be considered as a generalization of both the Euclidean distance and the Manhattan distance.

4) Cosine similarity: This detects intense parts of the tumour.

VI. PERFORMANCE MEASURE

Precision: Precision and recall are basic measures used in evaluating the effectiveness of an information retrieval system. Precision is the ratio of the number of relevant records retrieved to the total number of irrelevant and relevant records retrieved (Baeza-Yates, & Ribeiro-Neto, 1999). It indicates the subject score assigned to each of the top five images in this experiment. The formula is expressed as follows[13]:

$$p = \frac{\sum_{i=1}^{n} S_i}{N}$$

where *Si* is the score assigned to the *i*th hit, *N* is the number of top hits retrieved.

Recall: Recall is the ratio of the number of relevant records retrieved to the total number of relevant records in the database (Baeza-Yates & Ribeiro-Neto, 1999). It is defined as follows[13]:

$$R = \frac{R_n}{T_n}$$

where *Rn* is the number of retrieved relevant hits, and *Tn* is the total number of relevant images in the database.

VII. RESULTS

First applying the fourier transformation on the image. The images are converted to fourier descriptors by fourier transformation. Then the resultant descriptors are given for classes bifurcation. By using classification the efficiency would be increased. After this the query image is given for checking the similar images from the data available. Figure 3 shows the output for the proposed system.

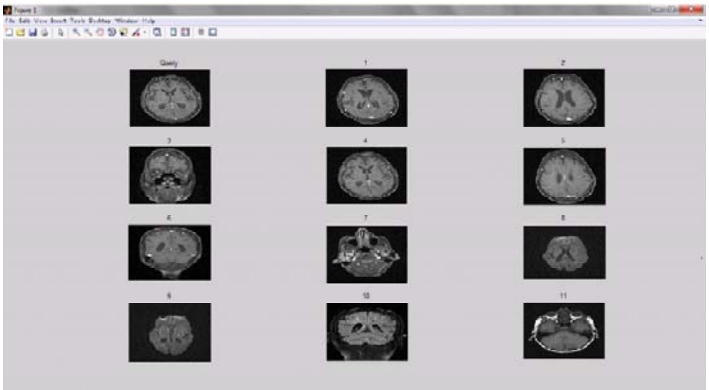

Figure 3: Proposed system's output for CBIR of images

- The results of performance analysis for precision and recall

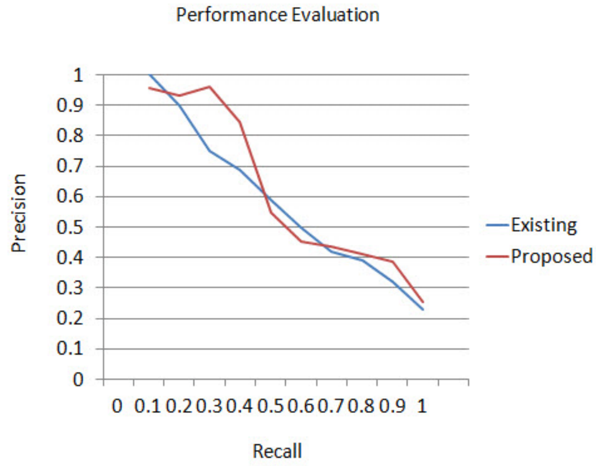

Figure 4 : Performance Evaluation of the proposed method with existing

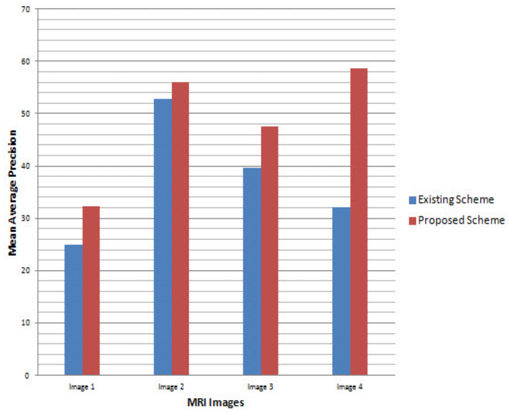

Figure 5 : Mean Average Precision graph

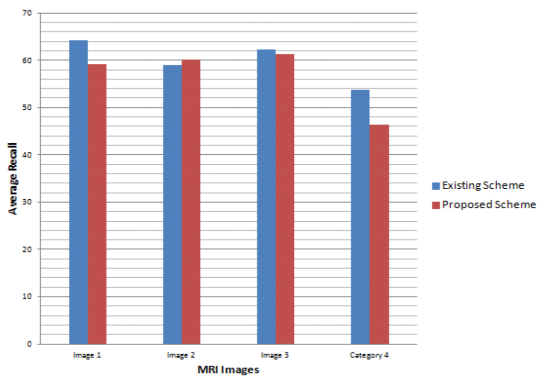

Figure 6 : Mean Average Recall graph

VIII. Conclusion

In this study we proposed a method for an effective way of building CBIR system that assists medical image diagnosis in clinical domain, this system is based on two different steps. In the First step, after feature extraction by Fourier Descriptors images are classified in tumor and and not-tumorous category using RVM, then the second step where similarity measure is carried out by KNN where Euclidean Distance is used for searching the relevant images and at last similar images are retrieved.

According to the experimental results, the proposed System is efficient for retrieval of the human brain MR database, and similar image.

References

1. S. SUBITHA & S. SUJATHA, “SURVEY PAPER ON VARIOUS METHODS IN CONTENT BASED INFORMATION RETRIEVAL”, IJRET, Vol. 1, Issue 3, Aug 2013, 109-120.
2. Anuradha Shitole and Uma Godase, “Survey on Content Based Image Retrieval”, International Journal of Computer-Aided Technologies (IJCAT), Vol.1,No.1,April 2014
3. Jamil Ahmad, Muhammad Sajjad, Irfan Mehmood, Seungmin Rho, Sung Wook Baik, “Describing Colors, Textures and Shapes for Content Based Image Retrieval – A Survey”, JOURNAL OF PLATFORM TECHNOLOGY VOL. 2, NO. 4, DECEMBER 2014
4. Dengsheng Zhang,Guojun Lu, Gippsland, “A Comparative Study on Shape Retrieval Using Fourier Descriptors with Different Shape Signatures”
5. Chandan Singh,Pooja, “An Effective Image Retrieval System using Region and Contour based Feature”, International Conference on Recent Advances and Future Trends in Information Technology (iRAFIT2012) Proceedings published in International Journal of Computer Applications® (IJCA)
6. R.C. Gonzalez & R.E Woods, “Digital Image Processing” chapter, 2. ed., 2002
7. Yogita Mistry, Dr.D.T. Ingole, “Survey on Content Based Image Retrieval Systems”, IJIRCCE, Vol. 1, Issue 8, October 2013, ISSN 2320-9798
8. A.Ranjidha, A.Ramesh Kumar, M.Saranya, “SURVEY ON MEDICAL IMAGE RETRIEVAL BASED ON SHAPE FEATURES AND RELEVANCE VECTOR MACHINE CLASSIFICATION”, International Journal of Emerging Trends & Technology in Computer Science (IJETTCS), Volume 2, Issue 3, May – June 2013, ISSN 2278-6856
9. Aiswarya.V, T. Senthil Kumar, “ SURVEY ON CONTENT BASED IMAGE RETRIEVAL TECHNIQUES”, IJRET, Volume: 03 Special Issue: 07, May-2014, eISSN: 2319-1163 | pISSN: 2321-7308
10. Maytham Safar, Cyrus Shahabi and Xiaoming Sun, “Image Retrieval By Shape: A Comparative Study”, Proceedings of IEEE International Conference on Multimedia and Exposition ICME 2000, U.S.A
11. Michael E. Tipping, “Sparse Bayesian Learning and the Relevance Vector Machine”, Journal of Machine Learning Research 1 (2001) 211{244
12. Dimitris G. Tzikas , Liyang Wei , Aristidis Likas , Yongyi Yang , and Nikolas P. Galatsanos, “A TUTORIAL ON RELEVANCE VECTOR MACHINES FOR REGRESSION AND CLASSIFICATION WITH APPLICATIONS”
13. Chia-Hung Wei,Chang-Tsun Li,Roland Wilson, “A Content-Based Approach to Medical Image Database Retrieval”, Chapter IX, Wei, Li, and Wilson
14. D. Manju et al, “Comparison Study of Segmentation Techniques for Brain Tumour Detection” , International Journal of Computer Science and Mobile Computing Vol.2 Issue. 11, November- 2013, pg. 261-26.