

Semantic Image Retrieval in Magnetic Resonance Brain Volumes

S.AvinashVarma¹, M.Mohan², N.Naga Sandeep³, R.Nithish Kumar⁴
^{1,2,3,4} *Department of Computer Science and Engineering*

Abstract- In the area of neurology often need to retrieve multimodal magnetic resonance (MR) images of the brain to study disease progression and to correlate observations across multiple subjects. Given a 2-D MR query slice, the technique identifies the 3-D volume among multiple subjects in the database, associates the query slice with a specific region of the brain, and retrieves the matching slice within this region in the identified volumes. The proposed technique is capable of retrieving an image in multimodal and noisy scenarios. In this study, support vector machines (SVM) are used for identifying 3-D MR volume and for performing semantic classification of the human brain into various semantic regions.

1. INTRODUCTION

Content Based Image Retrieval (CBIR) is an important research area in the field of multimedia information retrieval. The application of CBIR in the medical domain has been attempted before; however the use of CBIR in medical diagnostics is a daunting task. The goals of medical information systems have often been defined as the delivery of the needed information at the right time, at the right place to the right persons in order to ensure efficient and high quality of patient care processes and protocols. CBIR technology has been reported in a wide range of medical specializations including cytological images, CT brain scans, mammograms, dermatological images, high-resolution computed tomography scans, and thorax radiographies. Due to the requirement of very high accuracy, the utilization of CBIR in medical diagnostics is very challenging. In order to achieve a higher degree of accuracy in the presence of misalignments, an image registration based retrieval framework is developed. Additionally, to speed-up the retrieval system, a 2-D dyadic wavelet transform is proposed. Further improvement in speed is achieved by semantically classifying of the human

brain into various “Semantic Regions”, using an SVM based machine learning approach. A new and fast identification system is proposed for identifying a 3D volume given a 2D image slice. To this end, we used SVM output probabilities for ranking and identification of patient volumes. The proposed retrieval

algorithms provide medical practitioners with the ability to retrieve 2D MR brain images accurately and monitor the disease progression in various lobes of the human brain, with the capability to monitor the disease progression in multiple patients simultaneously. Additionally, the proposed semantic classification scheme can be extremely useful for semantic based categorization, clustering and annotation of images in MR brain databases.

2 EXISTING SYSTEM

The presence of an impressive amount of research in the area of CBIR, its acceptance for mainstream and practical applications is quite limited. For example, many researchers proposed CBIR systems where the image database consists of images belonging to a heterogeneous mixture of man-made objects and natural scenes while ignoring the practical uses of such systems. Furthermore, the intended use of CBIR systems is important in addressing the problem of “Semantic Gap”. Indeed, the requirements for the semantics in an image retrieval system for pathological applications are quite different from those intended for training and education. Moreover, many researchers have underestimated the level of accuracy required for a useful and practical image retrieval system. The Existing systems used imprecise segmentation and feature extraction techniques, which are not suitable for precise matching requirements of the image retrieval in this application domain. This dissertation uses Multiscale

representation for image retrieval, which is robust against noise and MR in homogeneity. In order to achieve a higher degree of accuracy in the presence of misalignments, an image registration based retrieval framework is developed.

3 PROPOSED SYSTEM

The Proposed System implements a new technique for retrieving 2-D MR images (slices) in 3-D brain volumes. Given a 2-D MR query slice, the technique identifies the 3-D volume among multiple subjects in the database, associates the query slice with a specific region of the brain, and retrieves the matching slice within this region in the identified volumes. The proposed technique is capable of retrieving an image in multimodal and noisy scenarios. The support vector machines (SVM) are used for identifying 3-D MR volume and for performing semantic classification of the human brain into various semantic regions. The wavelet transform magnitude of the incoming query image with 4 levels of decompositions is computed, which is followed by the feature extraction process. A multiclass SVM normally predicts class outputs; however, in the process of identification, some measure of similarity is needed to rank the results. Next, the semantic classification is performed using a trained SVM model as shown in the figure.

4. MODULE DESCRIPTION

4.1 Multiscale Edge Representation and Decomposition:

The Multiscale edge representation of a 2-D signal provides characterization of singularity in an image, namely, Lipschitz exponents. This representation is efficiently computed at dyadic scales using separable low-pass and high-pass filters. In order to compute the decompositions at coarse scale, filters are upsampled instead of subsampling the image itself.

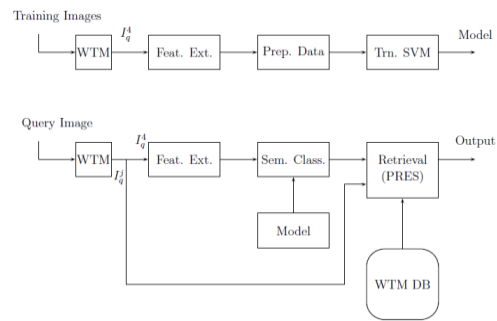
4.2. Feature Extraction in Multiscale domain:

The feature set consists of gray scale values of $M2j$ $f(x, y)$, sample circularly, starting from the outermost circle. This scheme samples the wavelet transform magnitude more densely near the center that is a desirable property for MR brain images because the shape of ventricle significantly determines various areas of the Brain. The two components of this feature map are the angular and the radial intervals. The angular interval is at $2\pi/48$ rad and the radial interval is 5 mm. Finally, each WTM produces a feature vector of $48 \times 18 = 864$ tuple. This is achieved by automatically detecting the center of the

object by thresholding the incoming image and averaging the rows and columns positions separately.

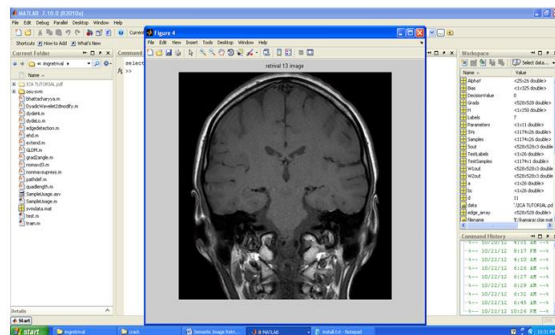
4.3.SVM-based semantic classification:

The support vector machines (SVM) are used for identifying 3-D MR volume and for performing semantic classification of the human brain into various semantic regions. The wavelet transform magnitude of the incoming query image with 4 levels of decompositions is computed, which is followed by the feature extraction process. A multiclass SVM normally predicts class outputs; however, in the process of identification, some measure of similarity is needed to rank the results. Next, the semantic classification is performed using a trained SVM model as shown in the figure.



4.4. Bhattacharyya distance:

The Bhattacharyya distance, is applied for semantics based learning .Bhattacharyya distance for statistical similarity is used where concept probabilities are determined for the combined color and texture feature vector by using multi-class SVM classifier. A support vector machine constructs a hyperplane (or a set of hyperplanes) in a hyper dimensional space, which is used for classification and regression tasks. A good separation is achieved by the hyperplane which has the largest distance to the nearest training data points of any given class because the larger the margin the lower the generalization error of the classifier.



Bhattacharyya.m

```
function d=bhattacharyya(X1,X2)
% BHATTACHARYYA Bhattacharyya distance
between two Gaussian classes
%
% d = bhattacharyya(X1,X2) returns the
Bhattacharyya distance between X1 and X2.
%
% Inputs: X1 and X2 are n x m matrices represent
two sets which have n
% samples and m variables.
%
% Output: d is the Bhattacharyya distance between
these two sets of data.
%
% Example :
% {
N=100;
M=10;
e1=2;
e2=5;
c1=3;
c2=7;
X1 = c1*randn(N,M)+e1;
X2 = c2*randn(N,M)+e2;
d = bhattacharyya(X1,X2);
% }

%Check inputs and output
error(nargchk(2,2,nargin));
error(nargoutchk(0,1,nargout));

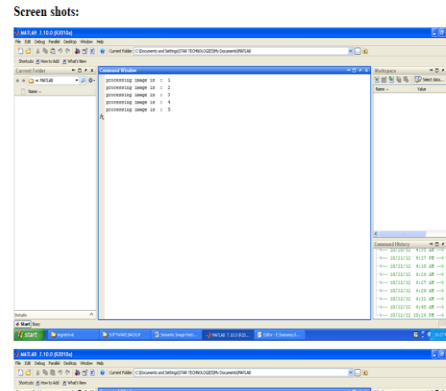
[n,m]=size(X1);
% check dimension
% assert(isequal(size(X2),[n m]),'Dimension of X1
and X2 mismatch. ');
assert(size(X2,2)==m,'Dimension of X1 and X2
mismatch. ');

mu1=mean(X1);
C1=cov(X1);
mu2=mean(X2);
C2=cov(X2);
C=(C1+C2)/2;
dmu=(mu1-mu2)/chol(C);
try

d=0.125*dmu*dmu'+0.5*log(det(C/chol(C1*C2)));
```

catch

```
d=0.125*dmu*dmu'+0.5*log(abs(det(C/sqrtm(C1*C2
)))));
warning('MATLAB:divideByZero','Data are
almost linear dependent. The results may not be
accurate. ');
end
%
d=0.125*dmu*dmu'+0.25*log(det((C1+C2)/2)^2/(det
(C1)*det(C2)));
```



5 .CONCLUSION

The problem of identification of 3-D MR volume, semantic classification and retrieval in multiple volumes given a 2-D query slice. The retrieval scheme is based on three stages.

In the first stage, an SVM-based technique for identifying a 3-D volume using an incoming 2-D query image; in the second stage, SVM-based, semantic classification technique is proposed for classifying the incoming 2-D query image into one of the semantic regions.

The semantic regions are inspired by the lobes of the human brain. The proposed semantic classification scheme can be extremely useful for semantic-based categorization, clustering, and annotation of images in medical databases.

REFERENCES

[1] A. Winter and R. Haux, "A three-level graph-based model for the management of hospital information systems," *Methods Inf. Med.*, vol. 34, pp. 378–396, 1995.

- [2] M. Mattie, L. Staib, E. Stratmann, H. Tagare, J. Duncan, and P. Miller, "Pathmaster: Content-based cell image retrieval using automated feature extraction," *J. Amer. Med. Informat. Assoc.*, vol. 7, pp. 404–415, 2000.
- [3] Y. Liu and F. Dellaert, "Classification-driven medical image retrieval," presented at the ARPA Image Understanding Workshop, New Orleans, LA, 1997.
- [4] I. El-Naqa, Y. Yang, N. P. Galatsanos, R. M. Nishikawa, and M. N. Wernick, "Asimilarity learning approach to content-based image retrieval: Application to digital mammography," *IEEE Trans. Med. Imag.*, vol. 23, no. 10, pp. 1233–1244, Oct. 2004.
- [5] G. Quellec, M. Lamard, G. Cazuguel, B. Cochener, and C. Roux, "Wavelet optimization for content-based image retrieval in medical databases," *Med. Image Anal.*, vol. 14, pp. 227–241, 2010.
- [6] L. H. Tang, R. Hanka, H. H. S. Ip, and R. Lam, "Extraction of semantic features of histological images for content-based retrieval of images," in *Proc. Int. Soc. Opt. Eng.*, vol. 3662, SPIE, 1999, pp. 360–368.