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MRI of Human Brain Images Classification Based on Dirichlet Laplacian

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Abstract

In [2], Dirichlet Laplacian(DL) was used to develop a three generic and robust set of features that are size-, translation-, and rotation-invariant that showed to be tolerant to boundary noise and deformation. The prescribed technique was applied to develop an efficient algorithm to classify the magnetic resonance images (MRI) and distinguish between the normal and abnormal images.

Keywords: *MRI human brain images, brain images classification, features extraction.*

1. Introduction

Magnetic resonance imaging (MRI) is often the medical imaging method of choice when soft tissue delineation is necessary. This is especially true for any attempt to classify brain tissues, the most important advantage of MR imaging is that it is non-invasive technique [1]. The use of computer technology in medical decision support is now widespread and pervasive across a wide range of medical area, such a cancer research, gastroenterology, heart diseases, brain tumors, …etc[4]. Fully automatic normal and diseased human brain classification can be obtained from magnetic resonance images; which is a great importance for research and clinical studies.

It was shown that the eigenvalues of the Dirichlet Laplacian is a reliable feature descriptor for shapes. In brief, let Ω be bounded planar domain, the sequence of eigenvalues $0 < \lambda_1 < \lambda_2 \leq \lambda_3 \cdots \leq \lambda_k \leq \cdots \to \infty$ of the partial differential equation $\Delta u + \lambda u = 0$ in Ω with appropriate conditions on its boundary $\partial\Omega$, where Δ is the Laplacian operator. It was shown that features based on the eigenvalues of the Dirichlet Laplacian can be successfully used to represent and classify synthetic and natural images. In pattern recognition problems, it is often desirable to extract features from an input image that are translation, rotation, and size-invariant. A good set of features should also be consistent within particular class, have a good class separation capability, and tolerate noise/variability within a particular class. The three feature sets $F_1(\Omega)$, $F_2(\Omega)$, and $F_3(\Omega)$, are based on the ratios of eigenvalues of the Dirichlet Laplacian operator. They are rotation, translation, and size-invariant, and are shown to be tolerant of boundary deformation and to possess good class separation capability. In this context, we build a retrieval system that query the binary images database and do the match in a high accuracy.

2. Eigenvalues of Laplace Operator

Given a bounded planar domain Ω represented by binary image, the sequence of eigenvalues

$0 < \lambda_1 < \lambda_2 \le \lambda_3 \cdots \le \lambda_k \le \cdots \to \infty$ of the partial differential equation

$$\begin{cases} \Delta u + \lambda u = 0 \quad \text{in} \quad \Omega \\ \partial u / \partial n = 0 \end{cases} \tag{1}$$

are called the eigenvalues of the *Dirichlet* Laplacian.

Various techniques were used to simulate equation (1) [2].

In this paper, finite difference scheme used to simulate the model to get

$$\frac{u_{i+1,j} + u_{i,j+1} + u_{i-1,j} + u_{i,j-1} - 4u_{i,j}}{h^2} = -\lambda u_{i,j}. \tag{2}$$

Here the domain is divided into squares of side h, u_{ij} is the value of the eigenfunction corresponding to λ at the gird point (ih, jh) not at the boundary.

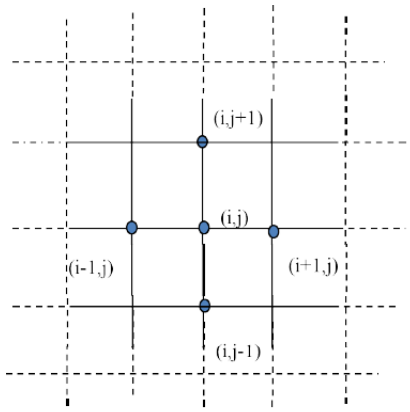


Figure 1: A rectangular grid used to approximate the solutions of Laplace equation.

3. Feature Generation Sets

For a given binary image Ω the following three feature sets based on the above described eigenvalues

$$\begin{aligned} F_1(\Omega) &:= \left\{ \left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_1}{\lambda_3}, \frac{\lambda_1}{\lambda_4}, \cdots, \frac{\lambda_1}{\lambda_n} \right) \right\}, \\ F_2(\Omega) &:= \left\{ \left(\frac{\lambda_1}{\lambda_2}, \frac{\lambda_2}{\lambda_3}, \frac{\lambda_3}{\lambda_4}, \cdots, \frac{\lambda_{n-1}}{\lambda_n} \right) \right\}, \\ F_3(\Omega) &:= \left\{ \left(\frac{\lambda_1}{\lambda_2} - \frac{d_1}{d_2}, \frac{\lambda_1}{\lambda_3} - \frac{d_1}{d_3}, \frac{\lambda_1}{\lambda_4} - \frac{d_1}{d_4}, \cdots, \frac{\lambda_1}{\lambda_n} - \frac{d_1}{d_n} \right) \right\}. \end{aligned}$$

Here n counts the number of the desired features

to be used for the recognition scheme, and $d_1 < d_2 \le d_3 \le \cdots \le d_n$ are the first n eigenvalues (counting multiplicity) of a disk.

4. System Description

Figure(2) shows schematic diagram of the proposed system; where the MR image input and the corresponding features are extracted and compared to the whole data base of the system and finally the decision is outputted ether it is normal case or abnormal one.

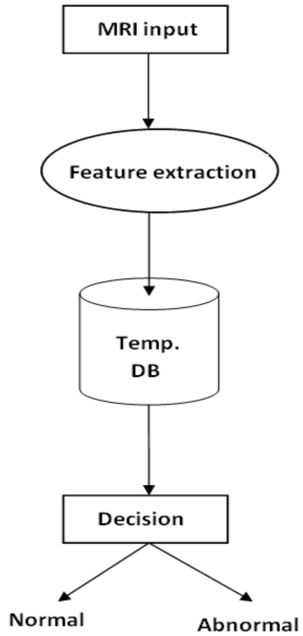


Figure 2: Schematic diagram of the Proposed System

5. Implementation

Algorithm 1:

Input: 256x256 brain images

Output: normal or abnormal brain.

Step 1:

a) Store the images $(i = 1, \cdots, n)$ in a Database(*IDB*)
b) Evaluate $F_1^i, F_2^i, \& F_3^i$ for each image of the *IDB*
c) Calculate the norms of $F_1^i, F_2^i, \& F_3^i$; $NF_1^i := norm(F_1^i), NF_2^i := norm(F_2^i), \&$ $NF_3^i := norm(F_3^i)$

Step 2: Let the query image q, repeat b) and c) as in the former step; step 1; to calculate the norms of $F_1^q, F_2^q, \& F_3^q$; $NF_1^q := norm(F_1^q), NF_2^q := norm(F_2^q), \&$ $NF_3^q := norm(F_3^q)$

Step 3: For i=1 to no. of images

i) Calculate $NdF_j^i := (NF_j^i - NF_j^q),\ (j = 1, 2, 3)$
ii) Store the values of NdF_j^i in an array A .

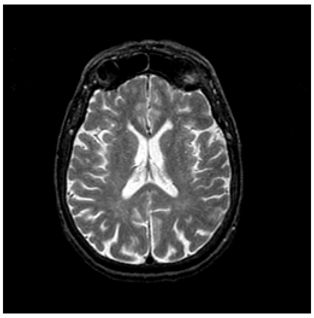
Step 4: Find $min(A)$ and the corresponding index ; which is the index of the retrieved image.

Step 5: display normal or abnormal brain images

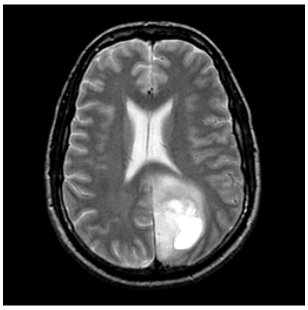
5. Simulation

In this section, the proposed technique has been implemented on a real human brain MRI dataset. The input dataset consists of total 70 images which in turn contain 10 normal images and 60 abnormal images used for classification. The MRI images are all 256x256 pixel.

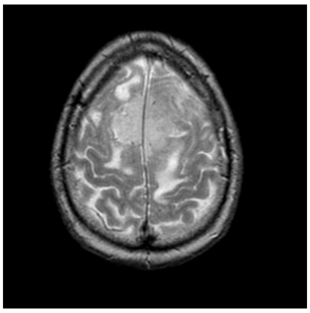
These images collected from Harvard Medical school website (http://www.med.harvard.edu/aanlib/home.html). Figure (3) shows some samples from the used data for normal and pathological brain.



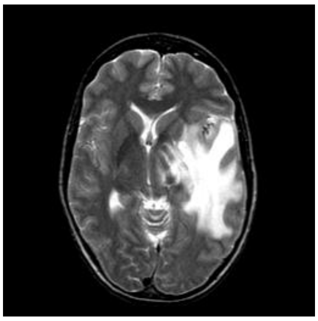
Normal



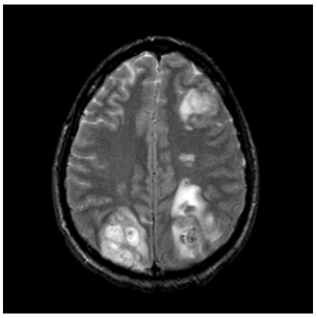
Glioma



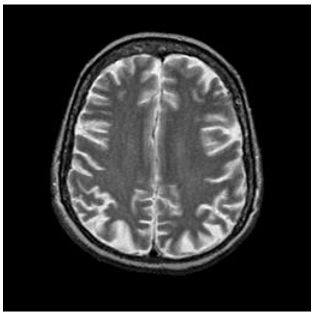
Meningioma



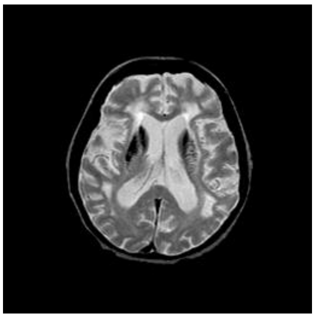
Metastatic



Sarcoma



Alzheimer



Cerebral calcinosis

Figure 3: Sample of the human brain MRI data.

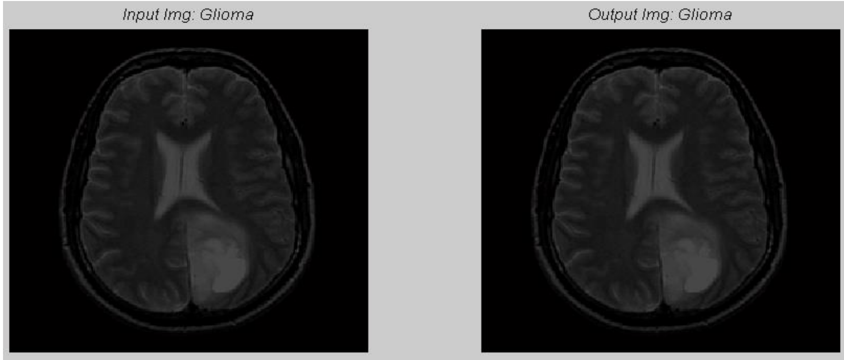


Figure 4:Abnormal case(Gliomia)

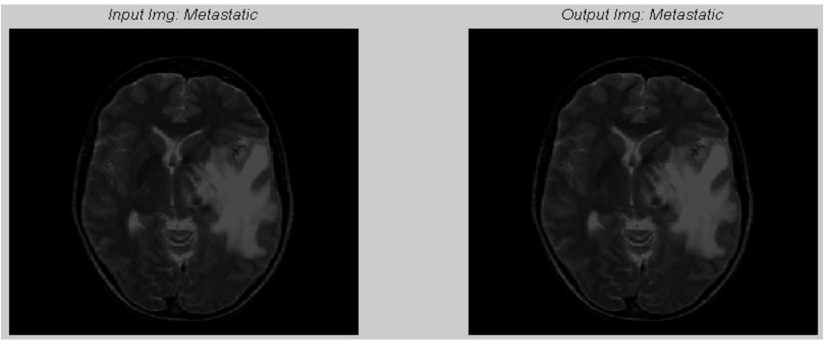


Figure 5:Abnormal case(Metastatic)

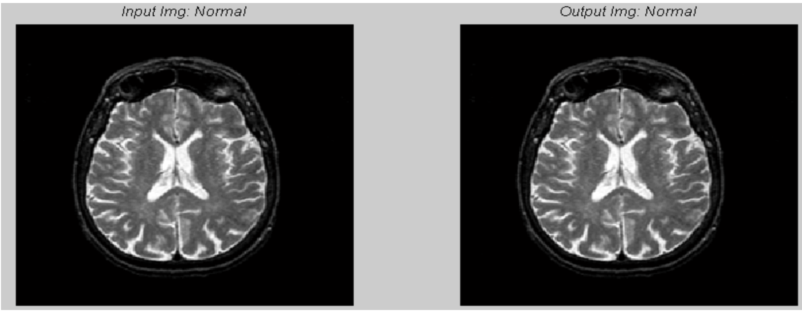


Figure 6:Normal case

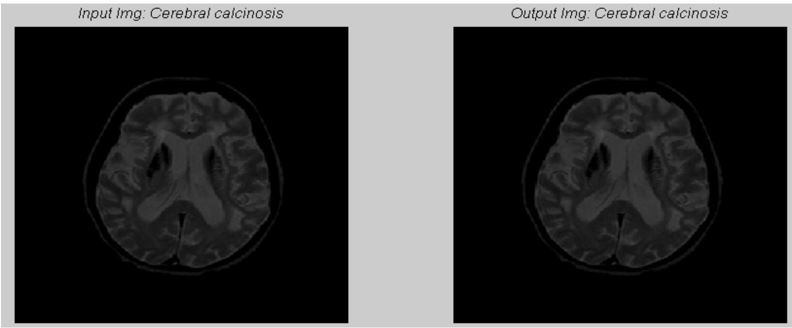


Figure 7: Abnormal case(Cerebral calcinosis)

6. Conclusion

In this paper an application of classification of human brain MRI was developed as a result of the efficient three-feature sets of Dirichlet Laplacian. The algorithm developed showed a high accuracy and sensitivity for the brain images which can be implemented in a telemedicine system that have many benefits.

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