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Research Article

MRI of Human Brain Images Classification Based on Dirichlet Laplacian

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Abstract

In [1], 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: Dirichlet Laplacian, MRI, algorithm

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 [2]. 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[3]. 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.

Various techniques for classification of images are in literature [4-7]. Gray level thresholding and morphological features based technique does not provide satisfactory results due to complex brain structure and sudden variations in intensities. Segmentation based schemes [5], fail to work if the abnormalities in the brain are not possible to be segmented spatially. Furthermore, the statistical and geometrical variations in brain images limit the performance of these schemes.

Recently, many authors have turned to eigenvalues and eigenvectors of the Laplace- Beltrami operator as possible tools for shape recognition purposes (Rhoouma, Khabou, Hermi, 2009; Niethammer et al 2009; F. Della Pietra and N. Gavitone, 2014). Indeed, the ratios of the eigenvalues of the Dirichlet Laplace, satisfy the three most important criteria for shape recognition: invariance to translation, rotation and scaling.

Simulation results show that the proposed technique is able to classify between different abnormal classes and provide better classification accuracy compared to the existing state of art techniques.

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.

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2. Eigenvalues of Laplace Operator

Given a bounded planar domain Ω represented by binary image, 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

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

are called the eigenvalues of the *Dirichlet* Laplacian.

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

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

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

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.

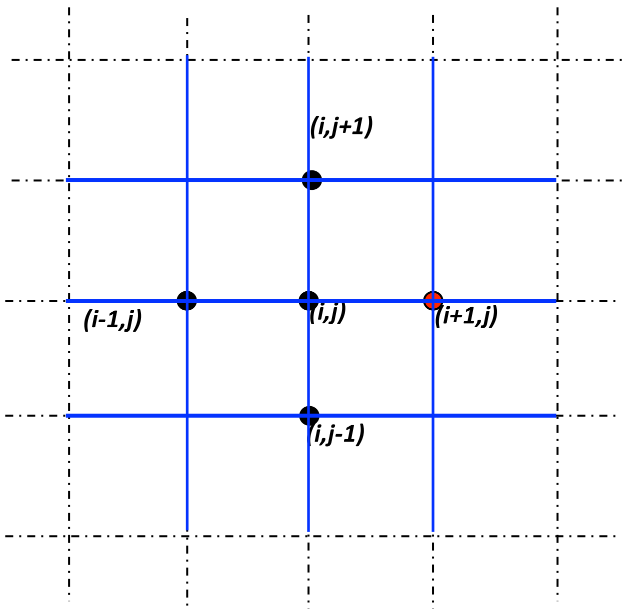


Fig. 1. A rectangular grid used to approximate the solutions of Laplace equation.

3. Feature generation Sets

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

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

Here n counts the number of the desired features to be used for the recognition scheme, and $d_1 < d_2 \leq d_3 \leq \cdots \leq d_n$ 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.

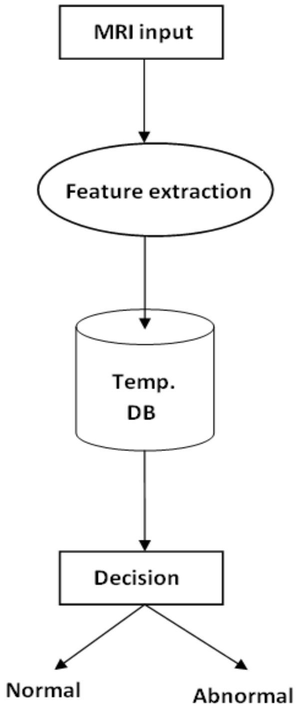


Fig. 2. Schematic diagram of the Proposed System.

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 $F_1^q, F_2^q, \& F_3^q$; $NF_1^q := norm(F_1^q), NF_2^q := norm(F_2^q), \& NF_3^q := norm(F_3^q)$

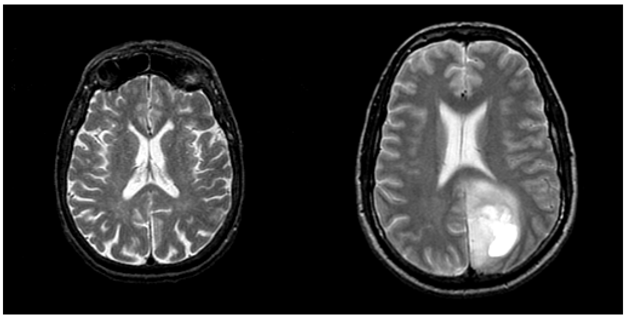
Step 3: For i=1 to no. of images
- i) Calculate $NdF_j^i := (NF_j^i - NF_j^q),\ (j = 1,2,3)$
- ii) Store the values of NdF_j^i in an array A.

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

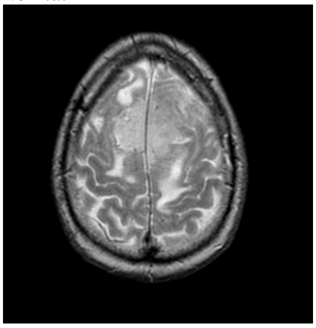
Step 5: display normal or abnormal brain images.

6. Simulation

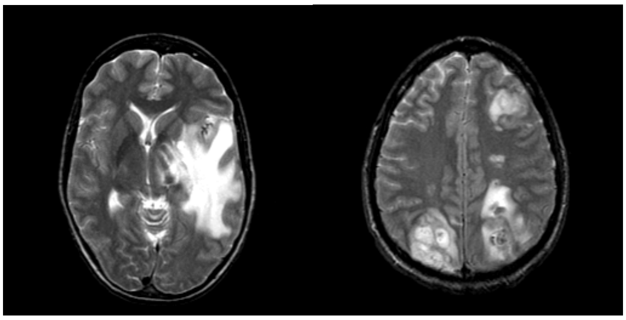
In this section, the proposed technique has been implemented on a real human brain MRI dataset. The input dataset consists of total 70 images which in turn contain 10 normal images and 60 abnormal images used for classification. The MRI images are all 256x256 pixel. These images collected from Harvard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



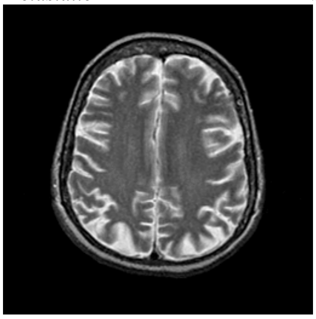
Normal *Glioma*



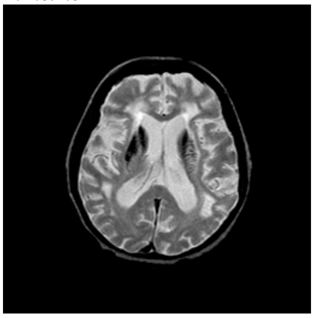
Meningioma



Metastatic *Sarcoma*



Alzheimer



Cerebral calcinosis

Fig. 3. Sample of the human brain MRI data.

7. Experimental results

Algorithm(1) implemented using Matlab version 8.0; GUI figure 4 containing all necessary input parameters like image resolution, pop-up menu to choose query image in addition to in/out image display with names.

Running the program on DB images to store the three feature sets, namely F_1, F_2, and F_3 with their norms for each image and similarly for the query image to get the minimum norm that corresponds to the retrieved image.

Our experiment done with the change of image resolution; 256, 64, and 32 yet we get excellent results at zero noise density (absence of noise) for resolutions 256 and 64 while for 32, the image is not recognized as shown in figure (5).

Next experimentation was conducted on Alzheimer's MR images of resolution 64 with noise (of type salt and pepper) add to the input images; 0.01, 0.05, 0.1, 0.2 and 0.22 yet we get excellent results till 0.2 while at noise 0.22, the image is not recognized as shown in figure (6).

Odd case happened when we increased the noise density as shown in figure (6e) (noise =0.21) which gives incorrect classification.

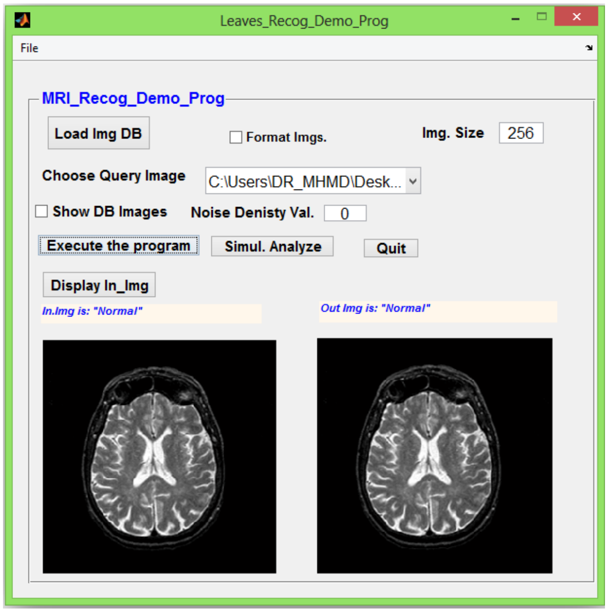
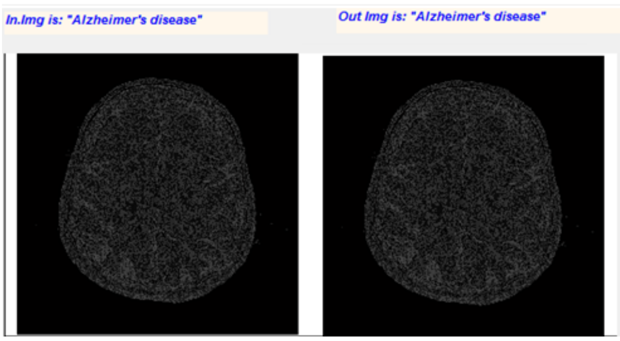
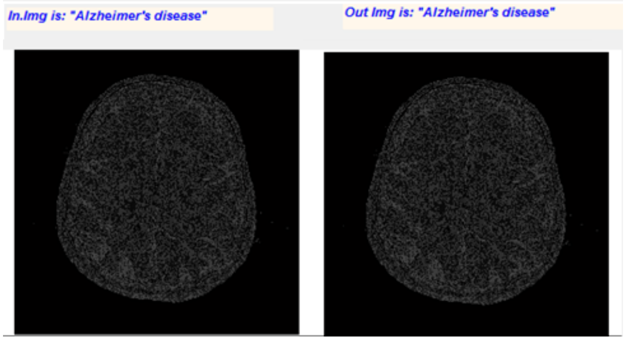


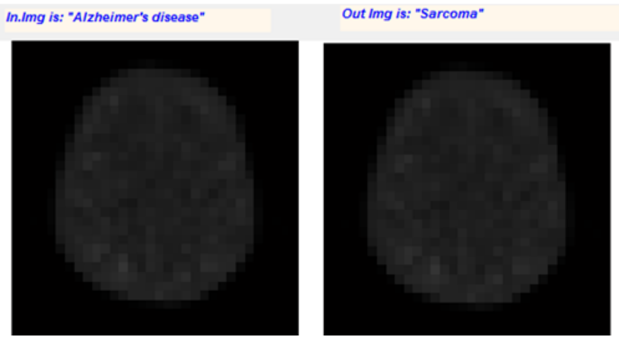
Fig. 4. Program excution window with synthetics of momal MRI. (the GUI have fields: image size, Noise intensity val., Display of input and output images)



5a. Image size 256

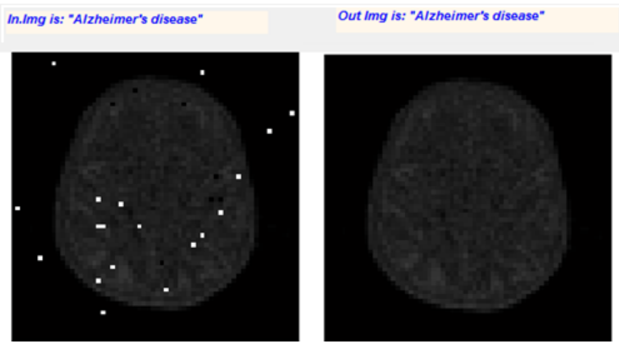


5b. Image size 64

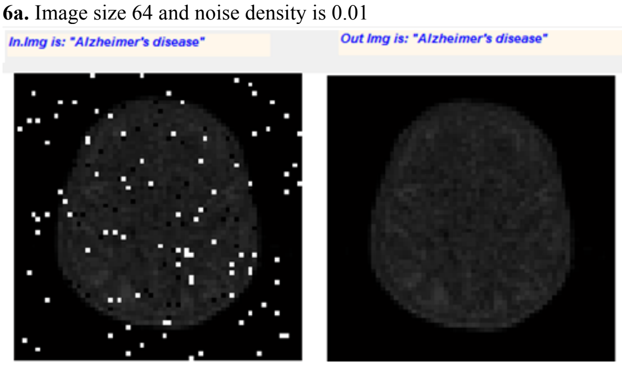


5c. Image size 32

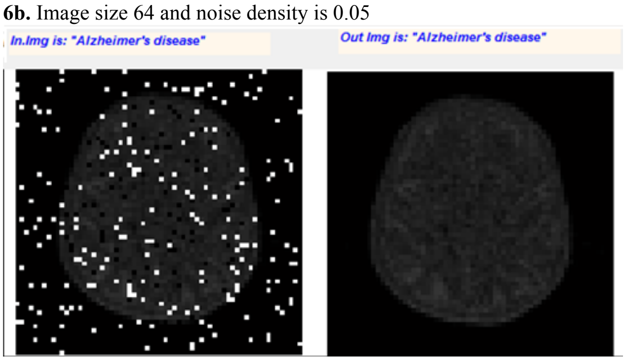
Fig. 5. Experiments conducted on Alzheimer's MRI without noise at different resolution.



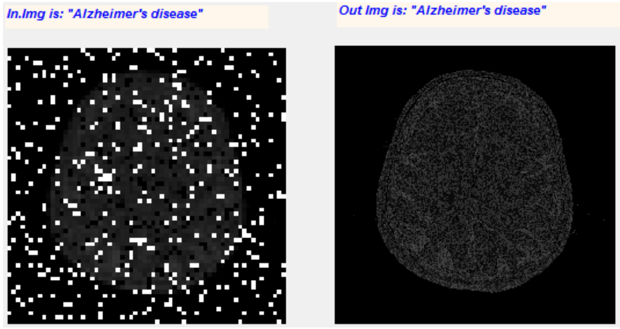
6a. Image size 64 and noise density is 0.01



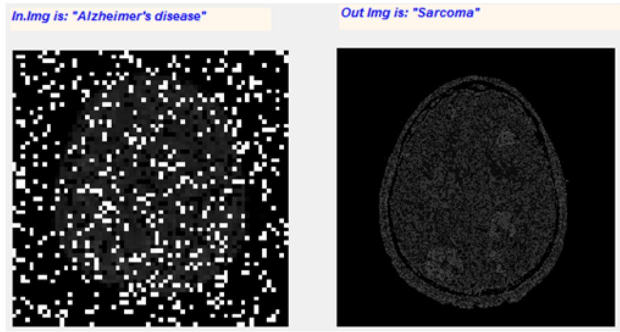
6b. Image size 64 and noise density is 0.05



6c. Image size 64 and noise density is 0.1



6d. Image size 64 and noise density is 0.2



6e. Image size 64 and noise density is 0.22

Fig. 6. Experiments conducted on Alzheimer's MRI with noise at 64-resolution.

Additional results are presented below for recognize other abnormal MRIs at size 64 in the absence of noise, Fig. 7

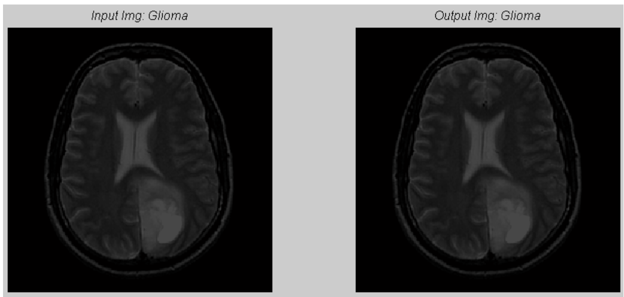


Fig. 7a. Abnormal case(Gliomia)

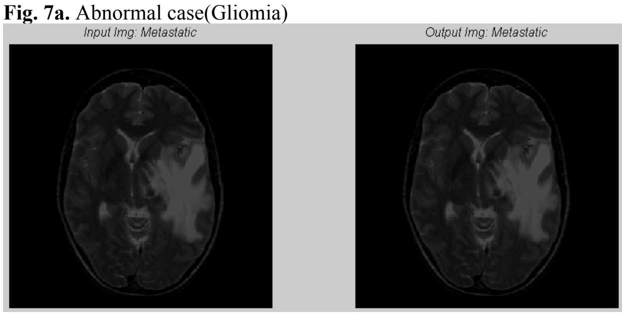


Fig. 7b. Abnormal case(Metastatic)

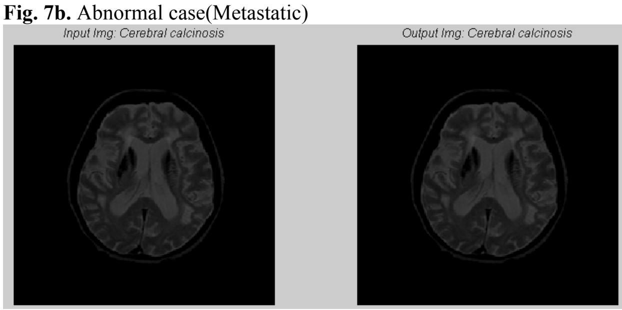


Fig. 7c. Abnormal case(Cerebral calcinosis).

8. 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. Simulation results show that the proposed technique is able to classify between different abnormal classes and provide better classification accuracy compared to the existing state of art techniques.

Although change of size and adding noise to the query image, the result is still excellent, which means that our algorithm can be beneficial for telemedicine with unsuitable circumstances.

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