Semi-automated Analysis of Tear in Rotator Cuff Ultrasound Images

A diagnostic tool based on image processing and ANN using MATLAB

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Abstract*— Rotator Cuff Tears and injuries are presently being detected using arthroscopy, MRI & Ultrasonography. Since arthroscopy is a surgical procedure and MRI is extremely expensive, Ultrasound is the first option to diagnose Rotator Cuff Tears because of its many advantages over MRI. The main drawback of using this imaging method is that only experienced Radiologists are currently able to conclude any diagnosis from the Ultrasonogram. A diagnostic tool created with the help of medical image processing techniques using Artificial Neural Networks along with GUI when used by a doctor can detect and diagnose Rotator Cuff Tears more easily, quickly and efficiently thereby reducing the discrepancies, complications due to misdiagnosis and workload of Radiologists during diagnosis of Rotator Cuff Tears.

***Keywords*—Ultrasound imaging; Rotator Cuff; shoulder joint; medical image processing; Artificial neural network; MATLAB**

I. INTRODUCTION

Glenohumeral joint or the shoulder joint is an example of ball and socket joint. The head of the humerous fits into the Glenoidal cavity of the Scapula. Rotator Cuff muscles surround the Glenohumeral joint binding the arm to the shoulder. The four tendons which bind the humerous head to the scapula are Subscapularis, Supraspinatus, Infraspinatus and Teres minor. The Rotator Cuff plays an important role in the Glenohumeral joint by providing strength and stability and helps in bringing about a wide range of movements of the shoulder. Rotator cuff plays a major role in stabilizing the shoulder joint. Rotator Cuff Tears can occur from an accumulated damage over time, from an acute injury, abrupt bone protrusions which pierce the muscles/tendons and also due to tendon weakening that occurs from aging process. These tears when untreated can greatly affect the stability and strength of the arm and can cause major joint dysfunction like stiffness, painful and restricted shoulder movements.

Depending on the extent of the severity of the tear in Rotator Cuff, Rotator Cuff Tear is classified into Partial thickness Tear and Full thickness Tear, the latter being classified as Small (<1 cm), Medium (1-3cm), Large (3-5cm) and Massive (>5cm).

Ultrasound is preferred as a diagnostic tool over MRI and X-ray for its non-invasiveness, readiness of use, cost-effectiveness, lack of radiation, and its ability to make dynamic examinations possible. Since only experienced radiologists are able to diagnose Rotator Cuff Tears from ultrasonogram, the prime objective of this paper is to enable easy identification and determination of position and size of Rotator Cuff Tears in Ultrasound image by Orthopedicians as well as Radiologists lacking experience. The marked tear region, location and size of the tear determined by the algorithm form the diagnosis.

II. METHODOLOGY

The proposed methodology includes preprocessing of acquired image, image classification using neural network, identification of tears with presentation of the results and saving the same. Fig. 1 shows proposed methodology.

A. Image Acquisition

A linear array transducer of 10MHz is used for Ultrasound Examination. Patient is seated on a stool. Doctor who performs the ultrasound scan stands in front of the patient or behind the patient such that his shoulder is higher than the patients shoulder and his elbow kept close to the body rather than extending the arm towards the patient. Transducer is held in position and the tendon of interest is scanned in both longitudinal and transverse positions. In order to identify the anatomical structures such as tendons, ligaments, bursae, peripheral nerves and so on in the images, Radiologists use few color differentiating clues that classify the structure to be echogenic, hyperechogenic, isoechoic, hypoechoic and anechoic depending on the strength of the ultrasound waves reflected back on to the receiving transducer.

For the diagnosis of Rotator Cuff, a diagnostic tool is developed with the help of Image Processing Toolbox, Neural Network Toolbox and GUI in MATLAB R2014a.

B. Pre-processing

The US images obtained are of standard resolution in JPG format and are converted into grayscale. The obtained US images included patient information in the image boundaries. Cropping tool in MATLAB was used to remove this information to respect patient's privacy. Cropping also helps to narrow down to the region of interest (ROI). Fig. 2 shows steps in preprocessing.

C. *Image Classification*

Image classification enables classification of the acquired images into Subscapularis- Longitudinal & Transverse and Supraspinatus Longitudinal- Longitudinal & Transverse types.

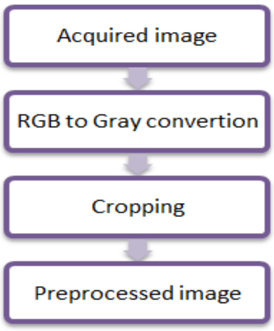

Fig. 2, Steps in preprocessing.

i. Discrete Cosine Transform

On applying DCT, DC values are produced in the top left corner of the image and high frequency components in the bottom right corner of the image.

The definition of the two-dimensional DCT for an input image A and output image B is

$$B_{pq} = \alpha_p \alpha_q \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} A_{mn} \cos\frac{\Pi(2m+1)p}{2M} \cos\frac{\Pi(2n+1)q}{2N} \quad (1)$$

Where $0 \leq p \leq M-1$, $0 \leq q \leq N-1$, M and N are the row and column size of A, respectively.

Here we use DCT to compress the images and obtain feature vectors to be used for classification using artificial neural networks.

ii. Artificial Neural Network

The 'nprtool' in the neural network tool box of MATLAB gives best results when used to classify the images based on the frequency of grayscale images. The nprtool opens the neural network pattern-recognition GUI. It leads through solving a pattern-recognition classification problem using a two-layer feed-forward network with sigmoid output neurons.

157 training images were used to train a two-layer feed-forward network, with sigmoid hidden and softmax output neuron,to classify images into Longitudinal and Transverse sections of Supraspinatus and Subscapularis muscles/tendons.

The network was trained with scaled conjugate gradient backpropagation. Feature vectors used contain 104 elements and the net contained 25 hidden neurons and 4 output neurons. Of 157 samples 109 are used for training, 24 each for validation and testing. 93.0% positive result was got for training, validation and testing using "nprtool".

D. *Application Of Mask*

To identify the muscle / tendon in the ultrasound image, the user is asked to mark the Region of Interest (ROI) as the size of the muscle/tendon varies from person to person. Binary mask is later applied to isolate the ROI.

E. *Speckle Noise reduction*

Ultrasound images suffer from speckle noise and is removed by using three filters namely Wiener, Median and Gaussian which improved the image quality as shown in Fig 4.

i. Wiener filter

Wiener filter is a non linear filter. Wiener low pass filter filters a degraded grayscale image by constant power additive noise. Wiener filter in frequency domain is given by;

$$W(f1, f2) = \frac{H^*(f1,f2)\, Sxx\,(f1,f2)}{|H(f1,f2)|^2\, Sxx(f1,f2) + Snn(f1,f2)} \quad (2)$$

Where Sxx(f1, f2) and Snn(f1,f2) are power spectra of the original image & the additive noise respectively & H(f1, f2) is the blurring filter [10,12].

ii. Median Filter

Median filter is a nonlinear filter used to reduce salt and pepper noise as well as speckle noise.

iii. Gaussian Filter

Gaussian Low-pass filter is used to remove the speckle noise in ultrasound images [10]. Gaussian filtering is used to blur images and remove noise in detail. It is given by;

$$g(x) = \frac{1}{\sigma\sqrt{2\pi}}\, e^{-x^2/2\sigma^2} \quad (3)$$

Where σ is the distribution standard deviation and degree of smoothing.

F. *Thresholding*

The simplest method of image segmentation is thresholding. By using thresholding binary images can be obtained from grayscale images. Local thresholding is used to obtain the object i.e. the tear.

G. *Edge detection*

The purpose of edge detection is to identify areas of an image where a large change in intensity occurs. Edge detection method is used for segmentation and also identification of objects in a scene. Sobel edge detector is used here.

H. *Diagnosis & final output*

The algorithm classifies the image based on the muscle/tendon and axis along which it was imaged. The final output image shows the tear (if present) with its boundary marked in black. Diagnosis is given based on the size of tear (small, medium, large and massive) which is determined by the number of pixels inside the region of tear.

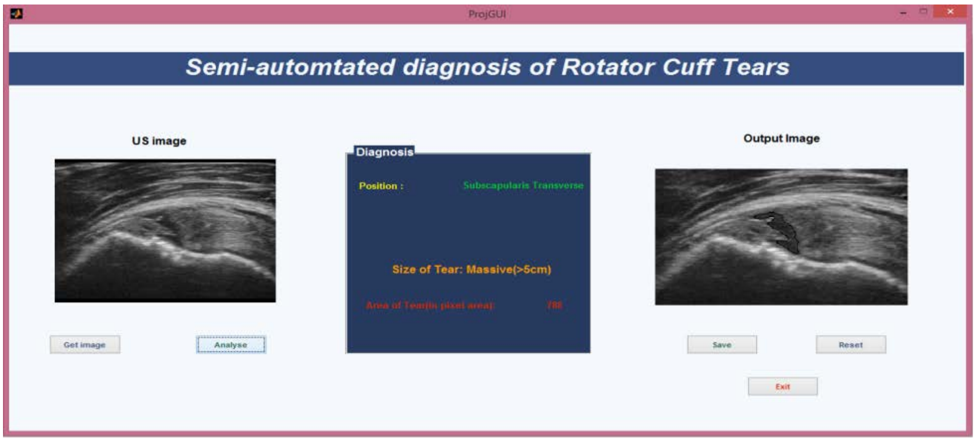

Fig. 5, Diagnosis as observed on the GUI

I. GUI incorporation

GUI incorporation allows the user to "Get image" from a database and load it, "Analyse" the loaded image, observe the diagnosis in the "output image" section, "Save" the diagnosis and tear boundary marked image, "Reset" the tool for new image and "Exit" from the entire procedure.

III. Results

i. A total of 309 images were used for testing.

ii. 256 of 309 images were diagnosed accurately by the algorithm with respect to both transducer position and presence/absence of tear.

iii. 290 of 309 images were classified properly with respect to transducer position in which 34 of the images showed improper tear detection.

iv. 12 of 309 images were misclassified with respect to transducer position, but, tear detection was correct.

v. 7 were misdiagnosed due to both misclassification with respect to transducer position and improper tear detection.

IV. Conclusion

The proposed method of semi-automated diagnosis of rotator cuff tears; where the objective of diagnosing Rotator Cuff Tears is achieved by determining the presence of the tear(s), obtaining the area of the tear(s) in terms of pixel unit and the location of the tear(s) is determined by the image classification procedure used to classify the images based on the tendon/muscle imaged and the axis along which it was imaged; can reduce such discrepancies and workload of radiologists. It can also be an aid to Orthopedicians to diagnose Rotator Cuff tears when experienced Radiologists are inaccessible.

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