Automatic Classification of Muscle Condition based on Ultrasound Image Morphological Differences

Wan M. Hafizah, Joanne Z. E. Soh, Eko Supriyanto and Syed M. Nooh

***Abstract*—**Myofascial Pain Syndrome is a form of chronic muscle pain centered on sensitive points in muscles called trigger points. These points are painful when pressure is applied on them and can produce referred pain, referred tenderness, motor dysfunction and autonomic phenomena. Currently, the location of trigger point is mostly determined through physical examination by clinicians, which is considered unreliable due to the dependency on the clinician's discretion. This study had developed a system that quantifies the location of trigger point using ultrasound images to detect the presence of trigger point. Normal muscle and muscle with trigger point shown morphological difference in ultrasound images, in which, is accentuated through image processing and pattern recognition. Statistical properties of the final signal output were analyzed to determine the most optimum value used for classification. Two parameters were calculated which are the mean and the standard deviation. Upon observation, the value of standard deviation can be used in setting the threshold value for the classifier to differentiate between normal muscle and muscle with trigger point. Based on the results, classifier can be set between 9 to 12 for DUS 100 and 13 to 19 for Aplio MX in order to successfully classify the images. System performance testing shows that this system has high accuracy when detection was performed with the current collection of sample images.

***Keywords*—**moving average filter, myofascial, trigger points, ultrasound.

I. Introduction

CURRENTLY, about 85 percent of the general population is in some way affected by musculoskeletal pain, and one of the frequent syndromes that affect millions of people is myofascial pain syndrome (MPS) [1]. Myofascial pain syndrome is a very common illness, and at least one trigger point is developed by humans' body at some point in their lives. But majority of these people will able to continue on their normal routines as no severe symptoms were developed. However, there are about 14% of the population will develop a chronic form of the syndrome, resulting in persistent pain and discomfort. Myofascial pain syndrome is very common as its incidence can be as high as 54% in women and 45% in men [2]. The most common age at presentation is between 27.5 and 50 years, with preference in sedentary individuals [3]. Previous researches show that myofascial pain syndrome is more common in women compared to men and it increased when age increased.

MPS is a form of chronic muscle pain centered on sensitive points in muscles called trigger points [4-6]. Trigger points, which are located in a taut band of skeletal muscle, are discrete, focal, and hyperirritable [7]. These points are painful when pressure is applied on them and can produce referred pain, referred tenderness, motor dysfunction and autonomic phenomena [8]. Myofascial pain can vary from mild discomfort to incapacitating pain, and it can occur both at rest and during activity [9]. In most cases, referred pain is the main symptom perceived by the patient [10]. Table 1 shows the symptoms of trigger points and their clinical significance. According to Table 1, patient with MPS will have major in local pain which heightens with use, local pain on palpation, referred pain, reproducible pain pattern and 50% pain reduction after treatment and minor in taut bands, local twitch response, reduced extension, non-clinically proven acute malocclusion and muscle tenderness.

Myofascial trigger points are classified as either active or latent. In active form, the pain is continuous, mainly depends on the degree of irritability of the trigger point and if the pressure is directly applied, reduced muscular elasticity, muscle weakness and referred pain can be observed [11]. Active myofascial trigger points play a role in the symptoms of patients with tension headaches, neck pain, forearm and hand pain, low back pain, temporomandibular pain, postural pain, pelvic/urogenital pain syndromes [12-15]. Latent form, by having the same clinical characteristics as active form, is less severe and the pain is induced rather than constant [16]. However, latent form may develop into active form.

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Table 1: Symptomatology of trigger points and their clinical significance [9]

Symptom	Clinical Significance
Taut bands	Minor
Local pain which heightens with use	Major
Local pain on palpation	Major
Referred pain	Major
Reproducible pain pattern	Major
Local twitch response	Minor
Reduced extension	Minor
50% pain reduction after treatment	Major
Non-clinically proven acute malocclusion	Minor
Muscle tenderness	Minor

There are a few methods used to identify and determine the location of trigger points, including physical examination, pain pressure threshold, electromyography, magnetic resonance elastography and ultrasonography. Table 2 shows the comparison of different methods in identifying the trigger points.

Table 2: Comparing the methods to identify trigger points

Methods	Equipments	Parameters
Physical examination	None	Feelings
Pain pressure threshold	Pain algometry	Pressure applied
Electromyography	EMG machine	Electrical activity
Magnetic resonance elastography	MRI	Stiffness
Ultrasonography	Ultrasound machine	Morphology

From previous studies, physical examination and pain pressure threshold depends on few factors that may contributed to the varying reliability of the examination results such as lack of identification of a taut band which is one of the minimum acceptable diagnostic criteria of the trigger point, inexperience of the examiners in assessing trigger points, restriction in the area of examination, incorrect positioning of the patient, incorrect palpation techniques as well as the variation in the amount of force exerted on the palpated point and the duration of force applied [17]. Electromyography is able to indicate increased muscle electrical activity as a result of pain but unable determine the exact location of trigger point [18]. Magnetic Resonance Elastography would be able to show the location of trigger point based on stiffness, though it is an expensive procedure [19, 20].

Ultrasonography would be able to show the location of trigger point based on the morphology of the muscle, and the cost to undergo this procedure is considerably lower than MRE [21]. Sikdar et al proposed the use of gray-scale echogenicity and color variance imaging based on relative stiffness to differentiate palpable nodules in soft tissue from normal myofascial tissue, and the use of blood flow waveform characteristics to differentiate between active and latent trigger points [22]. Therefore, as a convenient, accessible, and low-risk technique, ultrasonography method can be further developed to effectively detect trigger points.

The main objective of this study is to design a software system that can detect myofascial pain trigger point using ultrasound images of muscles. In order to achieve that, the morphological differences between normal muscle and muscle with trigger point needs to be discovered. It is achieved by processing and analyzing the ultrasound images using the software MATLAB. Based on the differences, an algorithm that will successfully classify the images will be developed.

The rest of the paper is as follows. In section 2, we describe on material and methods that we used in myofascial pain syndrome trigger point detection. In section 3, result and analysis of the study were presented and section 4 shows the conclusion of this study.

II. Materials And Methods

This system was developed based on the concept that normal muscle and muscle with trigger point have morphological differences, and this difference can be portrayed using ultrasound imaging. Based on observation, the muscle layer of normal muscles appears to be flat and parallel to the surface while the muscle layer of muscle with trigger point appears to form a peak at the area of trigger point. Fig. 1 shows the flow chart of the system, consist of image acquisition, image processing, curve detection and image classification.

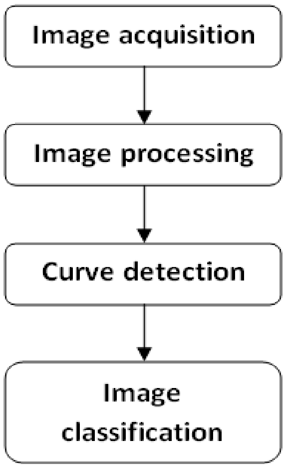

Fig. 1: Flow chart of the system

A. Image Acquisition

Ultrasound imaging was done on 160 subjects, 50 with trigger point and 110 without trigger point. The subjects are in the age range of 20 to 50 years old, and include both the male and female gender. The trigger points are latent trigger points. Images of the shoulder muscles were taken, with the subjects sitting upright in a comfortable position. The transducer head were placed in a way that it is parallel to the direction of the muscle fibers. The pressure exerted on the muscle throughout the scanning was held constant to avoid distortion of muscle layer.

Ultrasound machines used were from two different models, which were Mindray DUS 100 and Toshiba AplioMX. The scanning mode used to capture the images was B- mode. The transducer of the ultrasound machine was of flat head and linear array with frequency 7.5 to 7.6 MHz. Normal upper trapezius muscles taken with the method explained above appeared as a layer that is parallel to the surface. Muscles with trigger point appeared to be curved with a peak forming at the trigger point. The slope of the peak differs for trigger point with different severity. Fig. 2 to Fig. 5 show the normal muscle images as well as the images of muscles with trigger point for both ultrasound machines respectively.

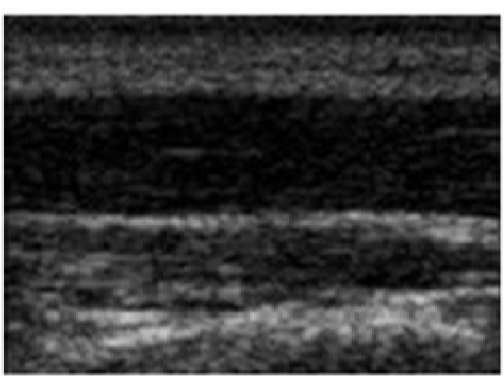

Fig. 2: Images of normal muscle for DUS 100

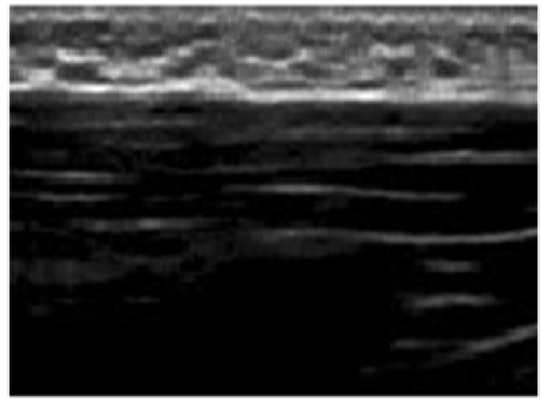

Fig. 3: Images of normal muscle for AplioMX

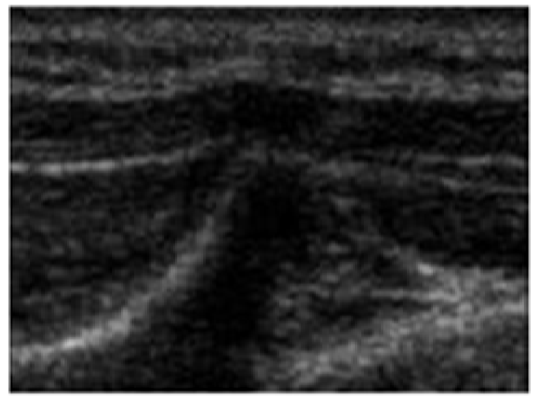

Fig. 4: Image of muscle with trigger point for DUS 100

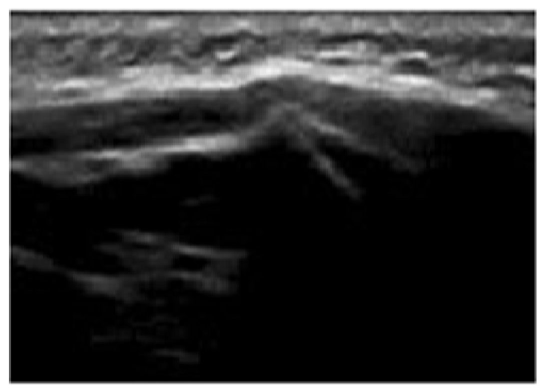

Fig. 5: Image of muscle with trigger point for Aplio MX

B. Image Processing

Image processing was done on the ultrasound images obtained in order to extract the relevant parameter for detection. Ultimately, the purpose of image processing in this project was to obtain the upper boundary of the muscle layer, which is the line representing the shape of muscle layer. Image processing is done using MATLAB Image Processing Toolbox. Fig. 6 shows the flow chart of image processing applied to the muscle images with and without trigger points consist of loading the image into MATLAB, cropping the image, converting the gray scale image to binary image, eliminating the isolated pixel group and lastly boundary detection.

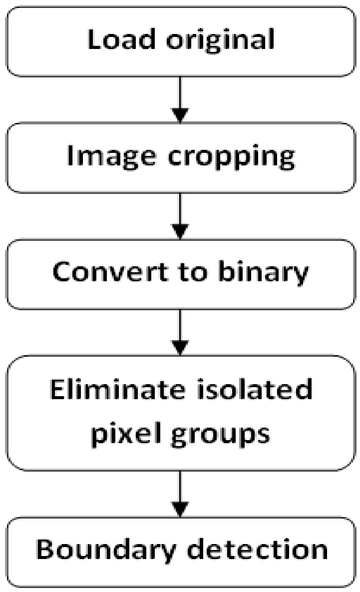

Fig. 6: Flow chart of image processing

1. Convert to Binary Image

Binary image is the image that contains two values for its pixel which is 0 and 1. The value 1 represents the white color and the value 0 represent the black color. Before binary conversion, the image is cropped to retain only the upper portion of the muscles layer and tissue above it. The fascia, fat, and skin layer, which are at the higher layer, has lighter intensity compared to the muscle layer. By applying the threshold method, the upper layer will be converted to white, while the lower layer will be black in color, representing the background.

Thresholding was applied to convert the gray scale ultrasound image to binary image. Suppose an image A (i,j) is composed of light objects on a dark background, in a way the object and background pixel have intensity levels grouped into two distinct groups. One way to extract the objects is to select a threshold value T that separates these groups. Below is the equation for thresholding the image.

$$BW = \begin{cases} 1, & if\ f(x,y) > T \\ 0, & if\ f(x,y) < T \end{cases} \tag{1}$$

2. Eliminate Isolated Pixel

For eliminating the isolated pixel groups, morphological processing was applied by using dilation operator [23-27]. Dilation is an operation that thickens object in a binary image where the white pixel is expanded to surrounding pixels and makes the area of the white object bigger. The specific manner and content of this thickening is controlled by a shape referred as structuring elements. Computationally, structuring elements are represented with a matrix of 0s and 1s. Mathematically, dilation is defined in terms of set operations. The dilation of A by structuring element of E, is denoted by $A \oplus E$ is defined as

$$A \oplus E = \left\{ z \middle| \left(\hat{E}\right)_z \cap A \neq \Phi \right\} \tag{2}$$

Next, the isolated groups of pixels which are the small objects are eliminated. A limit of pixel must be set, and pixel groups with less number of pixels than this limit will be eliminated. In other words, all connected components that have fewer than P pixels is removed. This step is to produce two distinct and solid layers, with the white layer being on top and the black layer being at the bottom. The equation to remove small objects is:

$$BW = \begin{cases} M, & if\ area(M) > P \\ 0, & if\ area(M) < P \end{cases} \tag{3}$$

3. Boundary Detection

The boundary or edge detection is the process of identifying and locating sharp discontinuities in an image. The discontinuities are abrupt changes in pixel intensity which characterize boundaries of objects in a scene. There are many ways to perform edge detection and the most may be grouped into two categories, gradient and Laplacian. Gradient method detects the edges by looking for the maximum and minimum in the first derivative of the image while Laplacian method searches for zero-crossings in the second derivative of the image to find edges.

Prewitt filter, one of the gradient-based algorithms is very sensitive to noise. On the other hand, Canny algorithm performed depends heavily on the adjustable parameters, σ, which is the standard deviation for the Gaussian filter, and the threshold values, 'T1' and 'T2'. Bigger value of σ will lead to the larger the size of the Gaussian filter. Smaller values of σ imply a smaller Gaussian filter which limits the amount of blurring, maintaining finer edges in the image. Canny edge detection algorithm was chosen for this study for boundary detection as Canny's edge detection algorithm performs better than all other operators. Table 3 below shows some advantages and disadvantages of different kind of edge detection methods [28-30].

Table 3: Some advantages and disadvantages of edge detectors

Operators	Advantages	Disadvantages
Classical (Sobel, Prewitt, Kirsch)	Simplicity, detection of edges and their orientations	Sensitivity to noise, inaccurate
Zero Crossing (Laplacian, Second directional derivative)	Detection of edges and their orientations, Having fixed characteristics in all directions	Responding to some of the existing edges, Sensitivity to Noise
Laplacian of Gaussian(LoG) (Marr-Hildreth)	Finding the correct places of edges, Testing wider area around the pixel	Malfunctioning at the corners, curves and where the gray level intensity function varies. Not finding the orientation of edge because of using the Laplacian filter
Gaussian(Canny, Shen-Castan)	Using probability for finding error rate, Localization and response. Improving signal to noise ratio, Better detection specially in noise conditions	Complex Computations, False zero crossing, Time consuming

C. *Curve Detection*

After the line of the muscle layer is obtained in the image, it will be converted into a one-dimensional signal representation. Next, this signal will undergo signal processing such as filtering with moving average filter and squaring in order to be successfully classified. Fig. 7 shows the algorithm for curve detection. The muscle line produced after the image processing is still stored in the format of an image. Signal representation for this muscle line can be obtained by obtaining the coordinate of the line. A 'for' loop is used for that purpose. Then, moving average filter (MAF) was applied on the signal in order to make the signal more smooth and reduce the effect of outliers. The size of the filter window is set to 10, in order to maintain the localized slope of the signal. The equation for MAF is as follows:

$$MAF = \frac{1}{N}\sum_{n=1}^{i}(X_n + \ldots + X_{(n+N)}) \quad (4)$$

After that, the signal is subtracted with its minimum value to bring the signal down to the x-axis (y=0), and obtain the relative height of the signal. Subsequently, each value of the signal will be squared to accentuate the curve of the signal. The equation is as follow:

$$X_2 = X - \min(X) \quad (5)$$

$$Output = X^2 \quad (6)$$

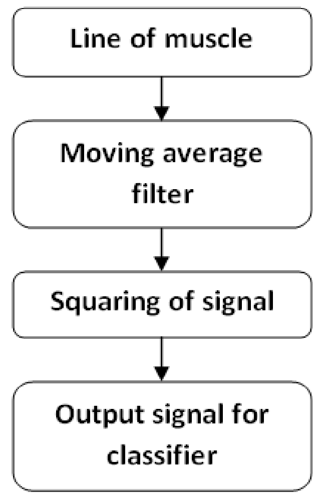

Fig. 7: Algorithm for curve detection

D. *Image Classification*

The signals after the curve detection were categorized by using a classifier. A threshold value was set based on the data collected. Signals with values exceeding the threshold will be detected as muscle with trigger point. On the contrary, signals that do not exceed the threshold value will be considered as muscle with no trigger point. The classification process was done to both images from DUS 100 and AplioMX ultrasound machines.

III. Results and Analysis

A. *Image Representation*

Based on the methods and processes described in the previous section, the system is tested with ultrasound images collected throughout the implementation of the study. The results can be seen in following Fig. 8 – Fig. 11. Fig. 8 shows the output of image processing consist of binary image conversion, isolated pixels elimination as well as boundary detection for normal muscle without trigger points while Fig. 9 shows the output of image processing consist of binary image conversion, isolated pixels elimination as well as boundary detection for muscle with trigger points.

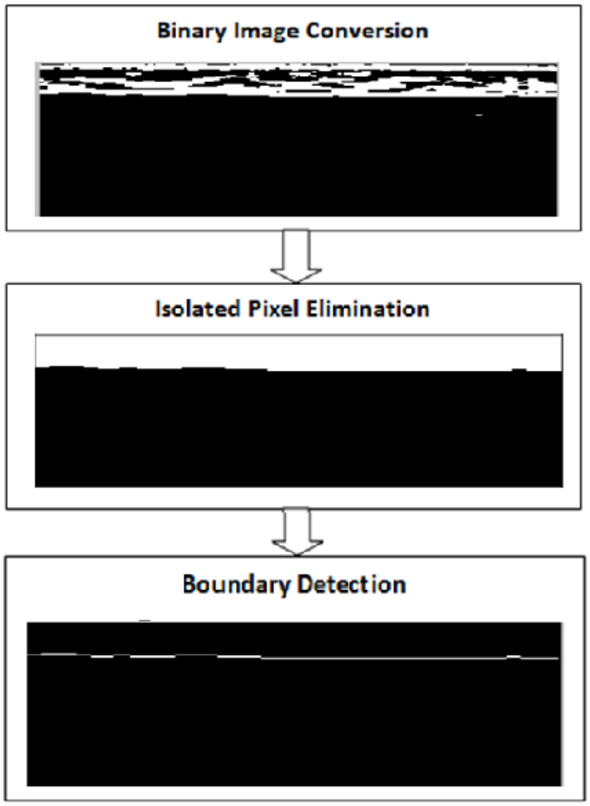

Fig. 8: Output after image processing for normal muscle

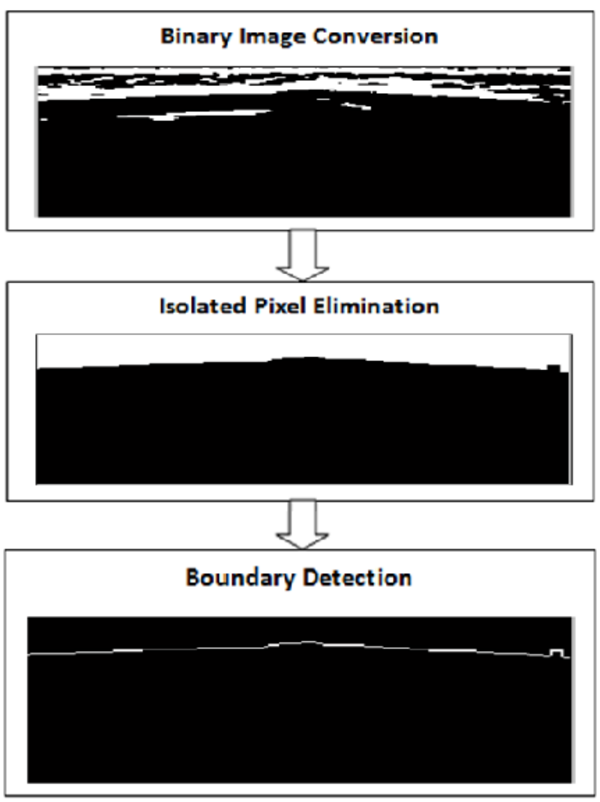

Fig. 9: Output after image processing for muscle with trigger points

Fig. 10 shows the resulting output signal for ultrasound image of muscle without trigger point captured using Toshiba Aplio MX while Fig. 11 shows the resulting output signal for image of muscle with trigger point. From the Fig. 10 and Fig. 11, we can see that the output signal of normal muscle without trigger point is more linear without obvious peaks. In the other hand, the muscle with trigger point gives an output signal with high peak.

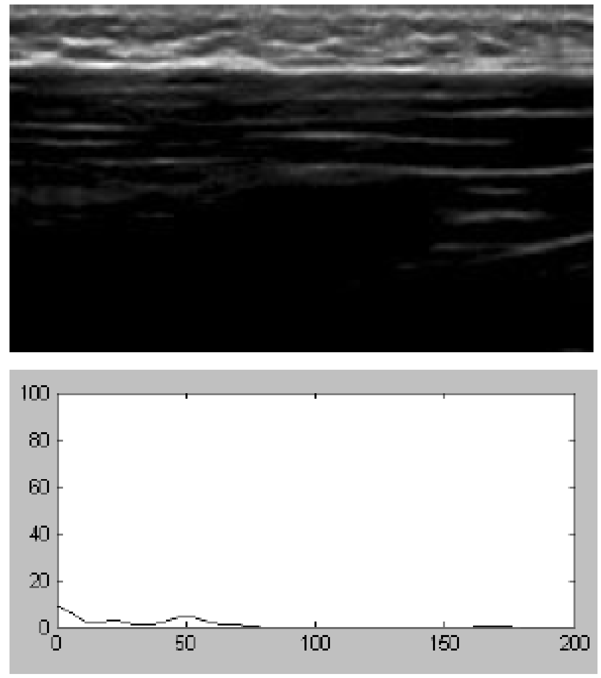

Fig. 10: Ultrasound image and output signal of muscle without trigger point

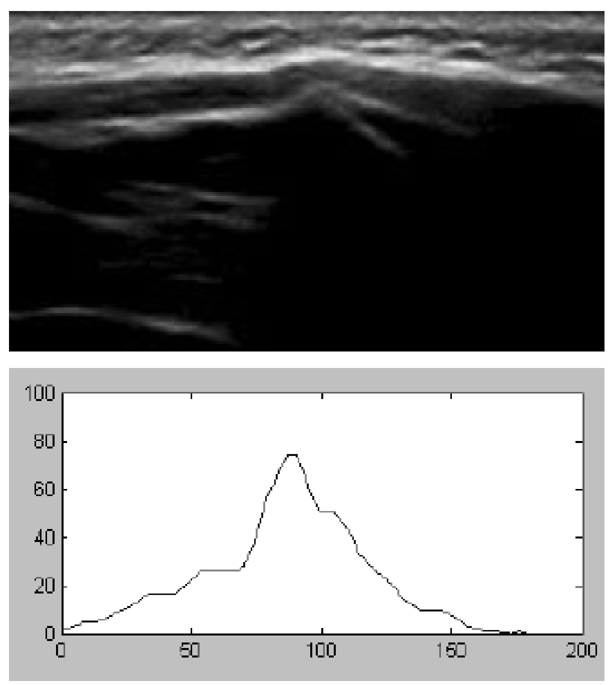

Fig. 11: Ultrasound image and output signal of muscle with trigger point

B. *Statistical Analysis*

The statistical properties of the signal representation for the muscle layer after curve detection algorithm were analyzed in order to set an optimum threshold value for the classifier. Properties evaluated are the mean of the signal and the standard deviation for each image. There were two types of ultrasound machine used in this study which was the low cost Mindray DUS 100 and the high cost Toshiba Aplio MX. Therefore, due to the different resolution and quality of ultrasound images, image from different ultrasound machine were analyzed separately.

Table 4, Fig. 12 and Fig. 13 show the mean and standard deviation for signal representation of muscles for Mindray DUS 100. Upon observation from Table 4 and Fig. 12, the mean value is inconsistent with the condition of muscles, as both normal muscle and muscle with trigger points have high values and therefore, classification between normal muscle and muscle with trigger point cannot be made. This situation might be due to the effect of outliers caused by noise in the ultrasound images, since the image is captured using low cost ultrasound machine.

As seen in the Table 4 and Fig. 13, the standard deviation values for muscles with trigger point are relatively higher compared to the standard deviation value for normal muscle. Therefore, the value of standard deviation can be used in setting the threshold value for the classifier to differentiate between normal muscle and muscle with trigger point and based on the result, the threshold value for the classifier can be set between 9 to 12.

Table 4: Mean and standard deviation for signal representation of muscles (Mindray DUS 100)

Image	Condition of Muscle	Mean	Standard Deviation
01	Normal	19.6075	7.9739
02	Normal	18.8255	7.1256
03	Normal	5.7211	3.1374
04	Normal	2.6797	3.2713
05	Trigger point	12.2683	16.9532
06	Trigger point	9.2745	13.6313
07	Normal	3.9248	2.2358
08	Normal	2.6308	2.7501

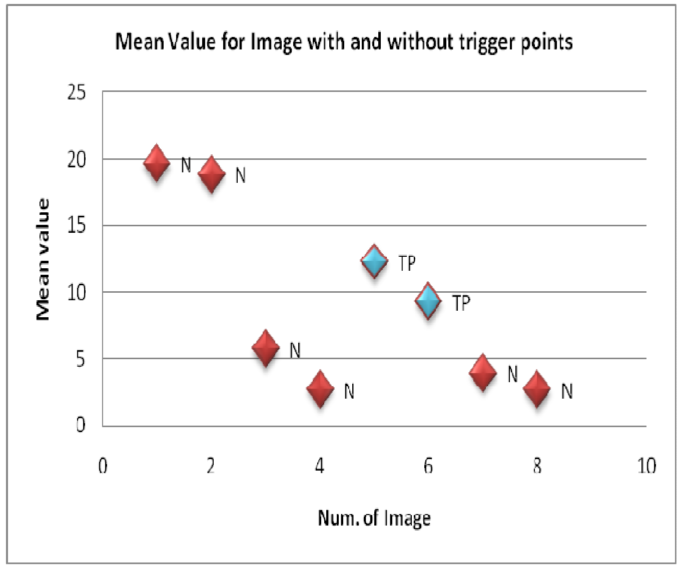

Fig. 12: Mean value for image with (TP) and without (N) trigger points for DUS 100

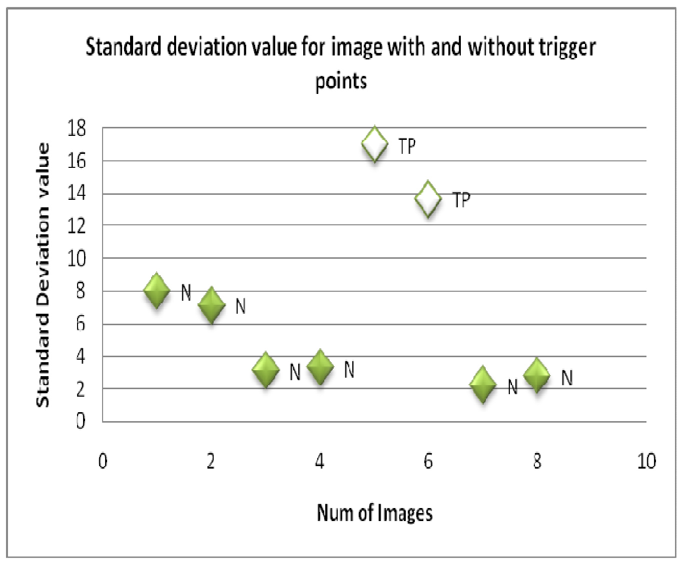

Fig. 13: Standard deviation value for image with (TP) and without (N) trigger points for DUS 100

Table 5, Fig. 14 and Fig. 15 show the mean and standard deviation for signal representation of muscles for Toshiba Aplio MX. As can be seen in the Table 5, the values of mean and standard deviation for muscle with trigger point are relatively higher compared to the normal muscle and therefore both values of standard deviation can be used in setting the threshold value for the classifier to differentiate between normal muscle and muscle with trigger point. This condition might be due to the quality of the images as Toshiba Aplio MX is a high cost ultrasound machine compared to Mindray DUS 100.

Table 5: Mean and standard deviation for signal representation of muscles (Toshiba Aplio MX)

Image	Condition of Muscle	Mean	Standard Deviation
01	Normal	1.5478	1.1914
02	Normal	1.0328	1.6481
03	Trigger point	37.3856	25.1892
04	Normal	11.5344	10.4919
05	Normal	12.5099	11.1172
06	Trigger point	26.8823	20.1710
07	Normal	8.8225	6.5713
08	Trigger point	22.8192	20.6081

Based on Fig. 14 and Fig. 15, if the threshold value is set based on mean value, the classifier can be set between 14 to 21 to successfully classify the images and if the threshold value is set based on standard deviation value, the classifier can be set between 13 to 19 to successfully classify the images. However, in order to accommodate both models of ultrasound machine, the value of standard deviation is selected for classification.

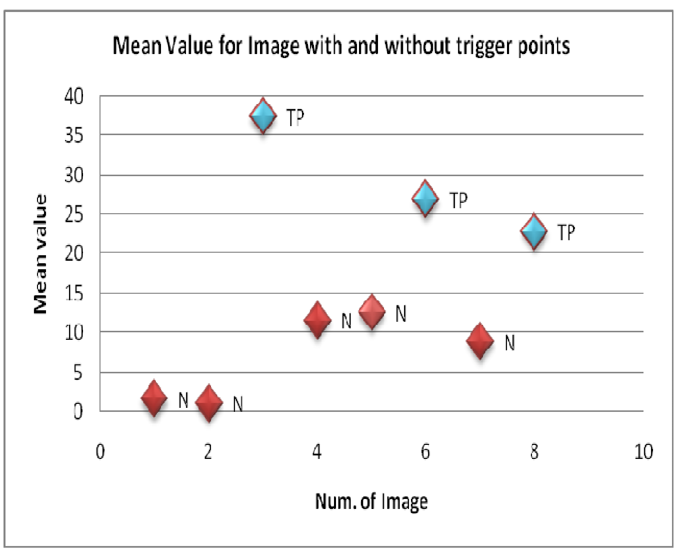

Fig. 14: Mean value for image with (TP) and without (N) trigger points for Aplio MX

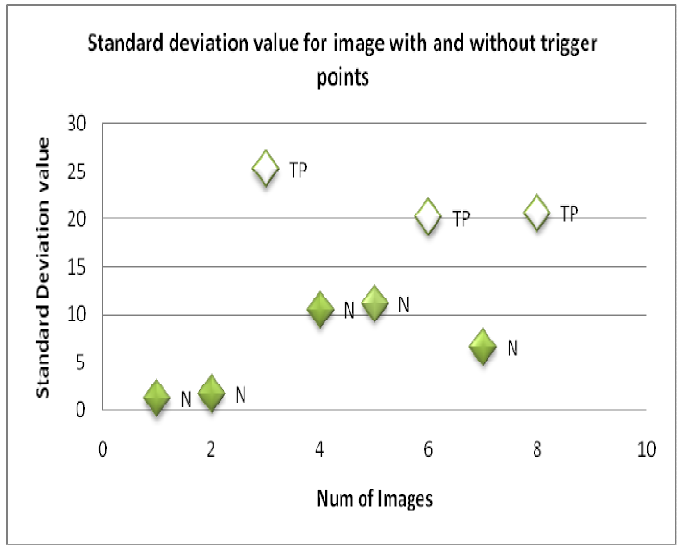

Fig. 15: Standard deviation value for image with (TP) and without (N) trigger points for Aplio MX

C. System Performance Testing

Fig. 16 and Table 6 show the accuracy of the system. It is tested with ultrasound images captured from both ultrasound machines Mindray DUS 100 and Toshiba Aplio MX. For Mindray DUS 100, 60 normal muscle images and 20 muscles with trigger points images were taken and for Toshiba Aplio MX, 50 normal muscle images and 30 muscle with trigger points images were taken.

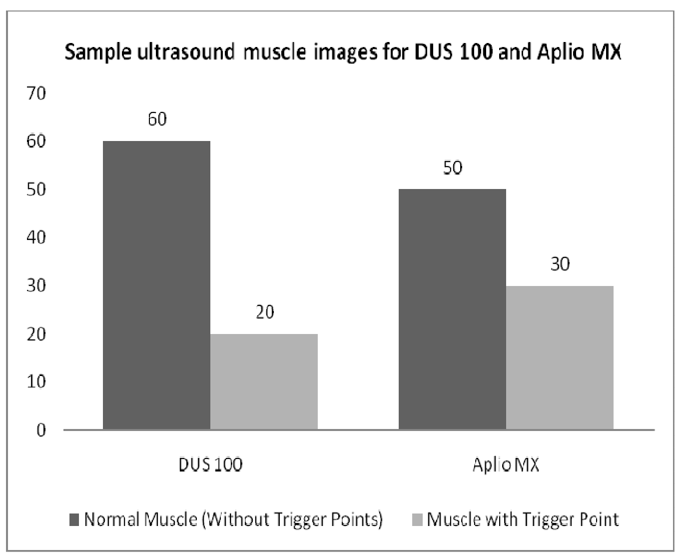

Fig. 16: Sample of ultrasound muscle images for DUS 100 and Aplio MX

Table 6: System performance testing

Machine	Number of Images		Correct	Incorrect	Accuracy (%)
	N	TP			
DUS 100	**60**	**20**	**80**	**0**	**100%**
Aplio MX	**50**	**30**	**80**	**0**	**100%**

As can be seen, the accuracy of the system is high, which recorded 100% for both machines. This is due to the fact that this system is developed based on the current collection of ultrasound images. The contrast and quality of the images from the same model of machine are similar to each other, causing the present values to be suitable for every image. Furthermore, the sample size (160 images) enables the setting of values that are highly specialized to detect images for current collection. Different contrast setting of ultrasound machine will cause error in detection, since the values used in image processing and also the classifier will be different.

IV. Conclusion

A system that is able to detect the trigger point of Myofascial Pain Syndrome has been developed. This system could be useful in assisting physical therapists to accurately locate the trigger point, in complement to the current situation in which physical therapists use physical examination to locate trigger points.

Detection was done by using ultrasound images of the muscle, and classification of images was based on the morphological differences between normal muscle and muscle with trigger point. The morphological difference observed was the contour of the muscle layer, where normal muscle appeared flat and muscles with trigger point appeared to peak at the area of trigger point.

The morphological difference in ultrasound images, in which, was accentuated through image and signal processing. Methods used in image processing include morphological operations such as thresholding, dilation and boundary detection. As for signal detection, moving average filter and mathematical functions were applied to the signal.

Statistical properties of the final signal output indicate that the standard deviation (SD) for the signal was suitable to be used to recognize the trigger point pattern. Threshold value for the classifier was thus set according to the value of standard deviation. For DUS100 images the SD threshold value was set between 9 to 12 while for Aplio MX the SD threshold value was set between 13 to 19. This system performed with high accuracy (100%) with the current collection of sample ultrasound images.

Compared to the conventional way of identifying trigger point with physical examination, this method of detection using ultrasound images is more reliable since quantitative data can be obtained. The condition of the muscle itself will be portrayed with the ultrasound imaging. However, the system developed was highly dependent on the quality of ultrasound images and the method of image processing used.

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