A sophisticated edge detection method for muscle biopsy image analysis

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Abstract: Muscle biopsy image morphometric analysis provides valuable diagnostic information to expert clinicians. Subsequently, there is an indispensable need to support muscle fiber morphometry with computer-aided automated systems that require no user interaction. The first step towards producing such a system is the automated border detection of muscle fibers. The objective of this work is to investigate the potential performance of edge detection algorithms, as well as any optimal combination of them, towards automated identification of regions of interest in a muscle biopsy image. Finally, a sophisticated edge detection model is proposed, that seems to closely resemble actual fibers boundaries and can be a reliable base for an accurate and effective segmentation of muscle biopsy images.

Key-words: Muscle, Fiber, Image, Edge Detection, Boundaries

1 Introduction

Muscle biopsy image analysis can provide essential diagnostic information for the assessment of neuromuscular disease [1]. However, muscle fiber measurement and size estimation, in most published studies on quantitative muscle fibre analysis, is performed manually using manual morphometric programs. Hence, the whole process is rather tedious, time consuming and subjective [2,3].

Despite the indispensable need for computer-aided automated systems to support muscle fiber morphometry, most papers related to this research field describe semi-automatic methods that require user interaction. There are few research efforts aiming to provide a fully automated system that is accurate and effective [3-6].

The first step towards producing such a system is the automated border detection of muscle fibers [7]. Therefore there is a need for automation of muscle fibers boundaries mapping using optimal edge detection techniques. When muscle fibers are separated successfully from non-fibers material (i.e. vessels, connective tissue etc), automated measurement of actual muscle fibers and multiple morphometric parameters can easily been attained .

Edges characterize boundaries. Edge detection is an essential part of the process of recognizing objects in a digitized image [8]. This process detects boundaries between objects and the background in the image. Edge detecting reduces the amount of data, filters out useless information but preserves important structural properties in an image. Once the edges of objects are detected other techniques can be used to proceed with feature extraction and object segmentation [8-10].

The objective of this work is the comparison of edge detection algorithms towards automated identification of regions of interest in a muscle biopsy image. In the following sections, the potential performance of each algorithm as well as any optimal combinations of them is investigated. Finally, an edge detection model is described in detail that seems to closely resemble actual fiber boundaries.

2 Standard Edge Detection

There are many different methods for edge detection, but most of them may be grouped into two categories [8,10].

Many edge-detection operators are based upon the 1st derivative of the intensity - this gives us the intensity gradient of the original data. Using this information we can search an image for peaks in the intensity gradient (Sobel, Roberts, Cross, Prewitt, Canny). Some other edge-detection operators are based upon the 2nd derivative of the intensity. This is essentially the rate of change in intensity gradient. In the ideal continuous case, detection of zero-crossings in the second derivative captures local maxima in the gradient (Laplacian - Gaussian second derivative filter - SDGD filter) [8,13]

The goal of this study is to locate the more effective edge detection method towards separating the regions of interest in digitized muscle biopsy images. In the following paragraphs, a comparison of different edge detection algorithms performance as well as various combinations of them is presented in detail.

3 Implementation and comparison of edge detection algorithms

For edge based segmentation purposes, Sobel and Laplace algorithms have been implemented in C language. Comparison of algorithms performance is made on an RGB image of a dystrophic muscle biopsy sample (cryostat section, HE,x20 objective) that had been found in a relevant paper [3]

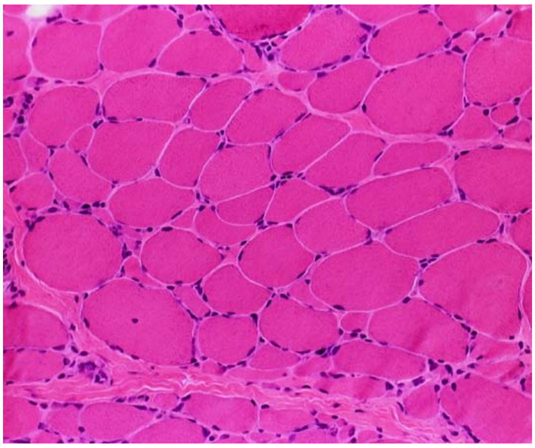


Figure 1: Initial input RGB muscle biopsy image [3]

Sobel and Laplace algorithms[8,10] use their masks to perform 2D discrete convolution with the actual image according to the following formulae:

$$f * g(m,n) = \sum_{m',n'} f(m-m', n-n')\, g(m',n')$$

3.1 Sobel-based Edge Detection

The Sobel operator performs a 2-D spatial gradient measurement on an image. It is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The Sobel edge detector uses a pair of 3x3 convolution masks, one estimating the gradient in the x-direction (columns) and the other estimating the gradient in the y-direction (rows) [8,10]. The actual Sobel masks are shown below

$$S_X = \frac{1}{8}\begin{bmatrix} 1 & 0 & -1 \\ 2 & 0 & -2 \\ 1 & 0 & -1 \end{bmatrix} \quad S_Y = \frac{1}{8}\begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix}$$

This operator places an emphasis on pixels that are closer to the middle of the masks. The performance of this operator on the initial muscle biopsy image is shown in figure 2A

The Sobel operator produced a number of gaps in the muscle fiber boundaries and thick edges as it is outlined within the coloured circles on Fig 2A.

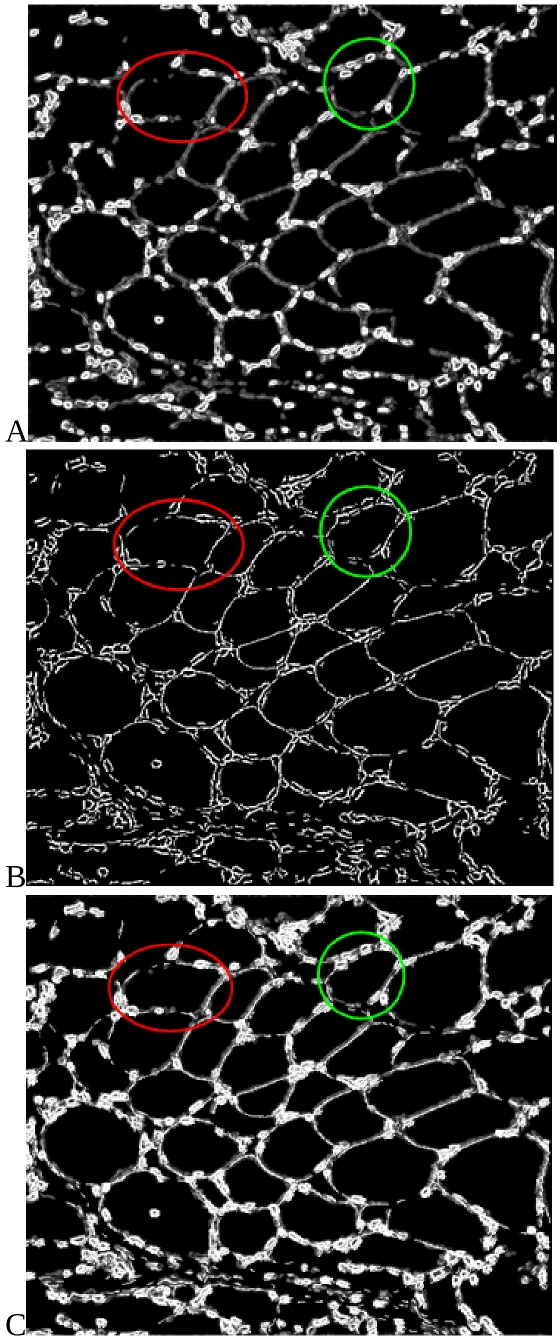


Figure 2: Output comparison of edge detection algorithms on the initial input RGB image: (A) edges obtained by the Sobel operator, (B) edges obtained by

the Laplacian operator (C) edges obtained after bitwise logical OR between A and B images

3.2 Laplace-based edge detection

The 5x5 Laplacian used is a convoluted mask to approximate the second derivative, unlike the Sobel method which approximates the gradient [8,10,11].. And instead of 2 3x3 Sobel masks, one for the x and y direction, Laplace uses 1 5x5 mask for the 2nd derivative in both the x and y directions [10,11]:

$$\nabla^2 = \begin{bmatrix} -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & 24 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 \\ -1 & -1 & -1 & -1 & -1 \end{bmatrix}$$

The performance of this operator is shown in figure 2B.The resulting edge map obtained from performing the Laplacian operator on the input image detects thin edges and a number of gaps in the defined edges (Fig. 2B).

It has been noticed that the resulting gaps after applying Sobel and Laplace operators are spotted either at different positions or at the same place but with different type of representation (Fig. 2A & 2B). To refine the edge detection results, a bitwise logical OR is applied between the images that have resulted from Sobel and Laplace operators. This way an attempt is made to take in account the edges that have been detected from both algorithms and to define better myofiber boundaries. The outcome of this operation is represented in Figure 2C. This attempt reduces the number of gaps but there are still some boundaries that are not complete and accurate.

3.3 Modified Laplacian -based Edge Detection

The next experiment was to modify the mask of Laplace operator by changing the values of the table and apply the altered mask to the initial image. After several tests, the best visual result that gave more acceptable boundaries of region of interest is shown below:

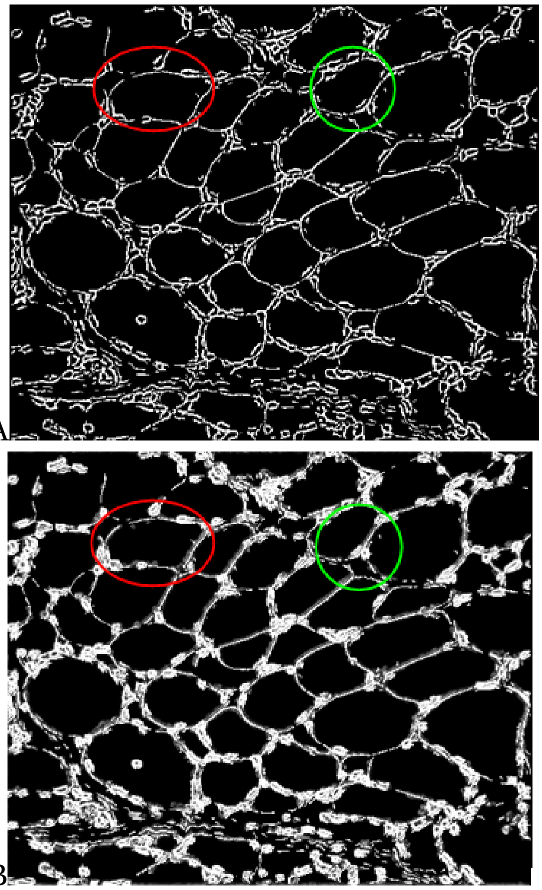
$$.\nabla^2 = \begin{matrix} -2 & -2 & -2 & -2 & -2 \\ -2 & -1 & -1 & -1 & -2 \\ -2 & -1 & 40 & -1 & -2 \\ -2 & -1 & -1 & -1 & -2 \\ -2 & -2 & -2 & -2 & -2 \end{matrix}$$

The performance of modified Laplacian-based operator (it will be referred as Laplace -2,-1, for the next sections) is outlined in Figure 3A.

A visual assessment of the outcome result is that the produced number of gaps on the edges is lower, and the overall muscle fibers boundaries detection is more accurate compare to the result after Laplace based operation.

In order to refine the edge detection results, the above mentioned method by using a bitwise logical OR is applied between the images that have resulted from Sobel-based and modified Laplacian-based operators. The outcome of this operation is represented in Figure 3B. The output image seems to have reduced number of gaps compared to the image from image on Fig 2C. Nevertheless, there are still some gabs and boundaries that are not completely and accurately defined.

A



B

Figure 3: Output comparison of edge detection algorithms on the initial input RGB image: (A) edges obtained by the Laplacian-based operator with mask -2,-1 (B) edges obtained after bitwise logical OR between image after Sobel operation and outcome image after Laplacian-based operator with mask -2,-1

3.4 MC algorithm-based Edge Detection

For this application, a better edge detection result with fewer gaps and holes is desired. Following this spirit, a smoothing operator will be applied to the initial image and a color based edge detection algorithm will be employed.

A smoothing algorithm is applied in order to reduce noise and to prepare images for further image processing acts [13]. The most common linear smoothing algorithm is the mean filter. The Mean is used to soften an image by averaging surrounding pixel values. Mean filtering is usually thought of as a convolution filter and it is based around a kernel [12, 13].. In the proposed approach a Simple 3x3 mean rectangular filter is defined by:

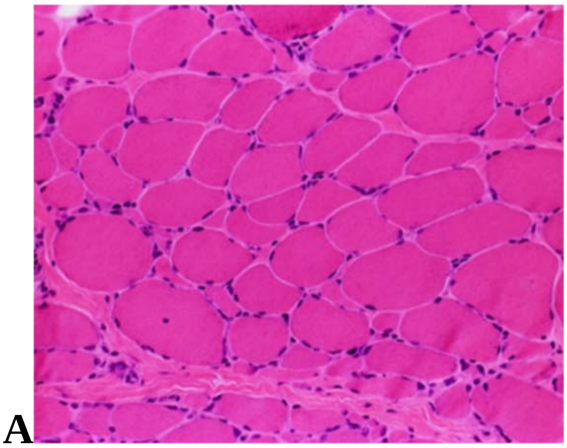
$$C=\frac{1}{K}\cdot\begin{bmatrix}1 & 1 & 1\\ 1 & 1 & 1\\ 1 & 1 & 1\end{bmatrix}; \ k = 9$$

The output image, after applying the smoothing algorithm to the initial muscle biopsy image is shown in Fig 4A.

The next step in the proposed approach, is to employ a simple algorithm (it will be referred as MC algorithm) based on mode color value of the resulted smoothed image [7,12]. For each pixel the most frequent RGB color is estimated, which is the mode RGB color of the image. Then a +-10% fault tolerance is defined.

Finally pixels that belong in the predefined color value range are represented as black and the remaining pixels as white on the output image.

The resulting image is shown in Fig 4B. Visual assessment of boundaries detection (outlined in the coloured circles on the image) show a number of gaps and a rather different estimation of muscle fibers edges in comparison to the resulted image of Fig 3B.



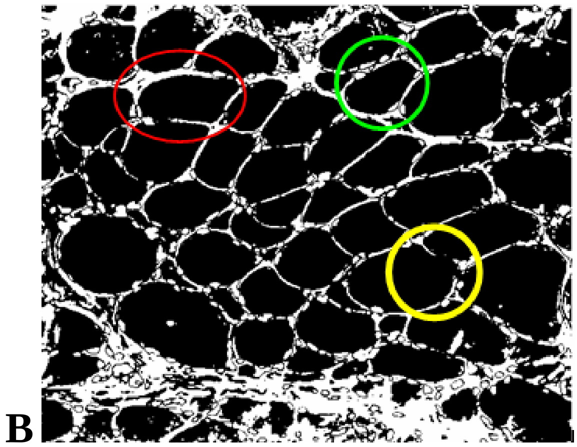


Figure 4: Output comparison of edge detection algorithms on the initial input RGB image: (A) output image after smoothing operation of the initial input RGB image (B) edges obtained by the MC algorithm

4 Proposed edge detection method

The ultimate goal of this work is to define the most accurate myofibers boundaries of the initial picture, in order to have better results to the segmentation of the image, which is the next step. A more sophisticated edge detection technique is required to achieve this target. Hence it has been decided to combine, by using a “bitwise logical OR” operation, the resulted images of previous implemented edge detectors. A flow diagram of the proposed edge detection model is presented in Figure 5.

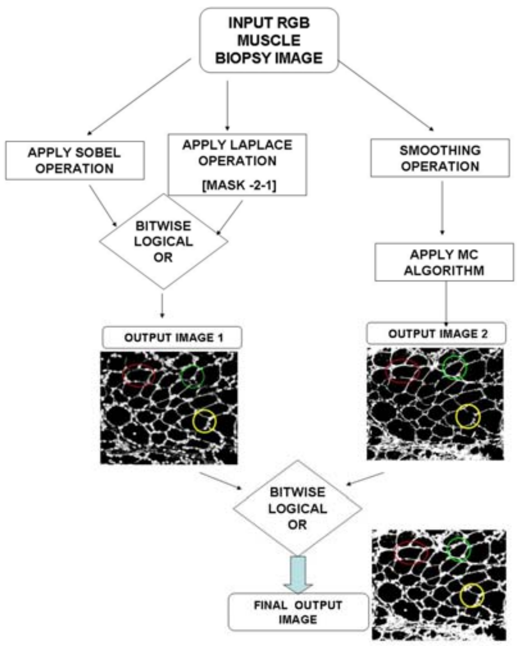
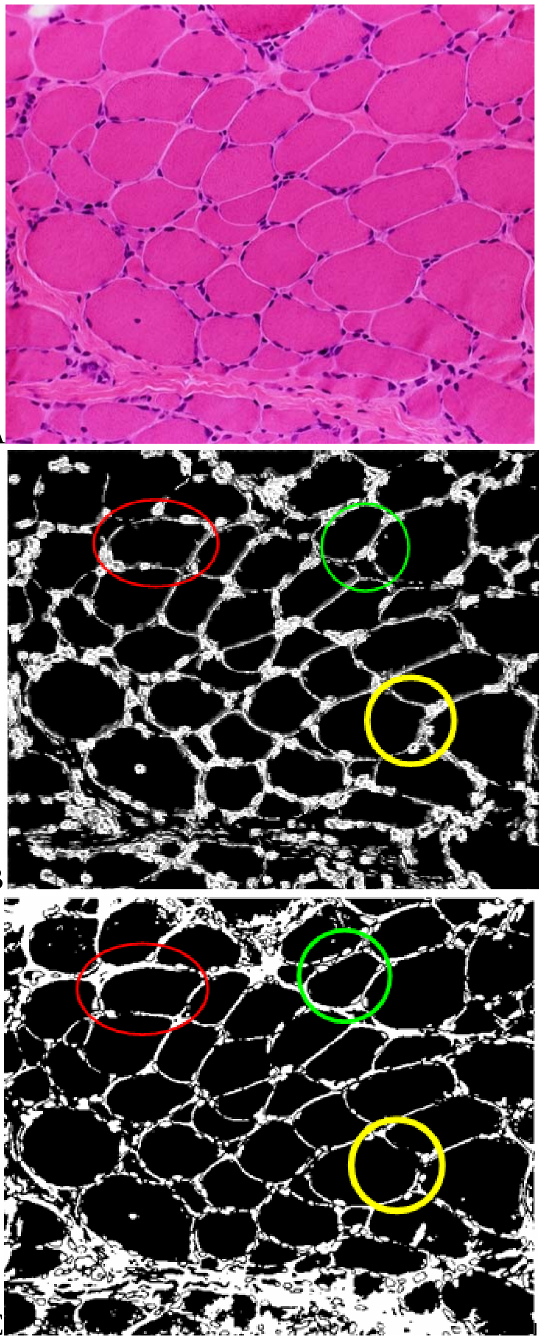


Figure 5: Flow diagram of the proposed edge detection approach

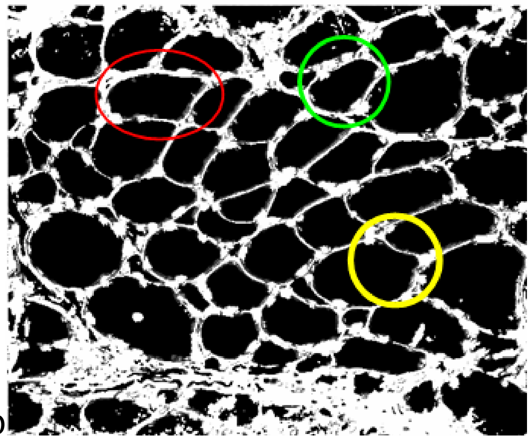
The output comparison of the resulted images according to the proposed method is outlined in Figure 6. The final image (Fig 6D) has significantly better quality results in muscle fiber edge detection, compared to the resulted images before logical OR. By blending the results of both methods, the gaps that have been noticed with previous method are filled and their number is reduced.



A

B

C



D

Figure 6: Output comparison of edge detection algorithms (A) the initial input RGB image (B) edges obtained after bitwise logical OR between the 2 output images after Sobel operator and the Laplacian operator with mask -2,-1, (C) edges obtained after smoothing operation on the initial input RGB image and MC algorithm (D) final output image- edges obtained after bitwise logical OR between the 2 output images B and C

A preliminary attempt has been made to proceed with segmentation of the image and measure the muscle fibers, based on the edges that detected according to the proposed method. As it can been seen in Figure 7, the first results are quite satisfactory according to an expert clinician opinion.

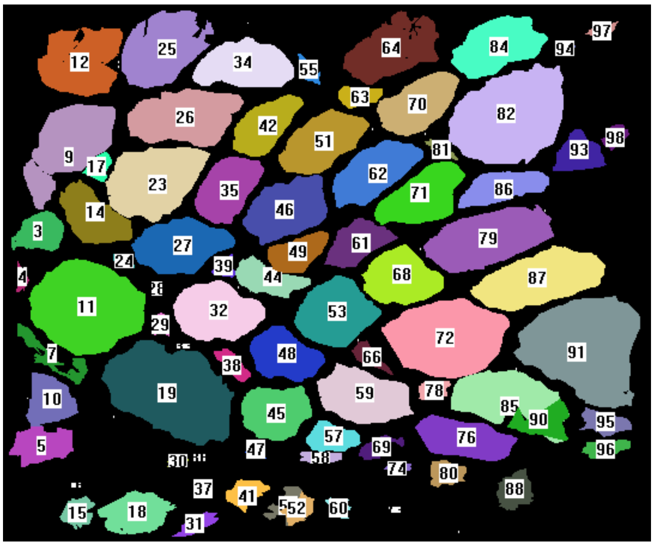


Figure 7: Defining muscle fiber material

5 Conclusions

The main goal of this work was to provide automated and effective border detection of muscle fibers in digitized muscle biopsy images. The initial approach to solving the edge detection problem in this application was to compare the performance of standard edge detection algorithms like Sobel and Laplace. The results obtained with the Sobel operator and the Laplacian operator, are rather acceptable. It has been noticed that there had different boundaries detection results and also a number of gaps but in different positions.

The next thought was to apply a "logical bitwise OR" between the resulted images of the above mentioned methods in order to benefit from the advantages of both methods. As the outcome result was not still satisfactory, Laplacian mask has been modified to succeed even better result in detecting actual fibers boundaries, and the same procedure was followed. Although the outcome result was better with less gaps there was still place for improvement. A different edge detection method has been applied to the initial image. After smoothing operation based on a simple mean filter, edge detection has been accomplished based on MC algorithm and the use of mode color value. This method resulted also to rather good detection of actual muscle fiber boundaries but there were still gaps and undefined edges.

For this application, a better edge detection result with fewer gaps is desired. Subsequently, a more sophisticated edge detection model was presented in detail. The proposed model combines different edge detectors using "bitwise logic OR" operations between resulted images. In the final output image, automatic border detection of muscle fibers seems to closely resemble actual fiber boundaries. Furthermore, detected borders are similar to those obtained manually by an expert. It is believed that this edge detection model can be a reliable base for an accurate and effective segmentation of muscle biopsy images. Future proceeds of this work include the completion of segmentation of muscle biopsy image and the automated measurement of actual muscle fibers and morphometric parameters. Moreover, it is anticipated to evaluate the overall method using a significant number of muscle biopsy images and compare the outcome results with morthometrics analysis results obtained from experts clinicians manually.

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