Abstract—Neural network techniques have been demonstrated to be successful at segmenting the retinal vasculature in fundus images; however, occasionally there are cases where a haemorrhage is misclassified as a vessel. The combination of the output from the neural network and information gained from the application of a tracking algorithm, based upon a matched filter, is shown to be a promising technique in reducing misclassifications.

Index Terms—Haemorrhage, fundus imaging, Neural Network, Tracking algorithm.

I. INTRODUCTION

A Background
A large body of work exists where image processing techniques have been applied successfully to the problem of recognition and quantification of features on adult fundus images[1-11]. A majority of that work has been applied to images of patients exhibiting symptoms of diabetic retinopathy[12,13]. The main challenge of this work is to separate normal components of the retina such as the optic disc and vascular network from the abnormal pathologies such as exudates, haemorrhages and cotton wool spots. Identification techniques range from application of filters[1] to those which employ artificial intelligence[3].

A technique that uses Neural Networks[3] has been demonstrated to be a successful method for segmenting the network of vessels seen in adult retinal images that exhibit the condition diabetic retinopathy. One area where the Neural Network technique falls short of an ideal performance is where pathologies such as haemorrhages are of a similar size. This situation is illustrated by Figs. 1 and 2. Fig. 1 shows a fundus image with an area containing a haemorrhage circled in black. Fig. 2 shows a segmentation of the vascular system from the recognition algorithm based on neural networks[3]. The haemorrhage identified in the top image has been recognized as part of the vascular network (the area is shown circled in red).

B Previous Work
A brief overview of Image Processing techniques applied to adult retinal images is given in this section. In order to detect abnormalities on a retinal image, it is important first, to detect the main retinal components in a normal image, such as the...
retinal vessels, the optic disc and the fovea. Automatic methods to detect vessels in retinal images have used two-dimensional matched filters, and piecewise threshold probing of a matched filter. Martinez-Perez et al. employed scale space analysis for the measurement and quantification of retinal vascular tree morphology. Srinthanaothin et al. has developed a range of algorithms for the detection of the vessels, optic disc and the fovea based upon a combination of image processing techniques and artificial neural networks. Features on the retina have also been detected using fractal geometry. Exploratory or tracking algorithms, similar to the type described in this paper, work by exploiting local image properties to trace the vasculature starting from an initial point either specified manually or detected automatically.

The majority of the work on the detection of abnormalities in retinal images has focused on addressing the problem of diabetic retinopathy, which requires the detection of features such as exudates, microaneurysms and cotton wool spots. Ranges of techniques have been applied to this problem ranging from neural networks to rule based systems. In addition automated tortuosity and engorgement measures of adult retinal vessels have been developed.

II. METHOD

A. Neural network and tracking techniques

The neural network method has been fully reported. It is based upon a multi-perceptron back propagation technique that receives a feature vector based upon the intensity and texture of an image. The technique uses principal component analysis to reduce the data set before input to the neural network. The output of the neural network is a segmented binary image, an example of this output is shown in Fig. 2. The segmented binary image shows a good match to the vascular network of the original image of Fig. 1. The tracking method implemented in this work was originally developed for use on infant retinal images exhibiting the condition retinopathy of prematurity. It derives information from a matched filter image. The two-dimensional matched filter method is based on the observations of three properties of the blood vessels. The three properties are:

- Since the blood vessels usually have small curvatures, the anti-parallel pairs are approximated by piecewise linear segments,
- The shape of the blood vessels are approximated by a gaussian curve given in the following equation

\[
f(x, y) = A \left(1 - k \exp\left(-\frac{x^2}{2\sigma^2}\right)\right)
\]

where \(x\) is the perpendicular distance between the point \((x, y)\) and the straight line passing through the centre of the blood vessel in a direction along its length, \(\sigma\) gives the spread of the intensity profile, \(A\) the amplitude factor is given by the grey level intensity of the local background, and \(k\) is a measure of reflectance of the blood vessel relative to its neighborhood.
- Despite the progressive decrease in the width of a vessel, the width is generally in the range of 2-10 pixels.

The tracking method operates by examining the matched filter image and exploits local image properties. The tracker begins by finding a maximum value of the intensity in the matched filter image. By examining a small area around that maximum value, the tracker will identify the angle at which the matched filter response is strongest. The pixels on the image in that direction will be flagged as part of the track and the tracker then moves along to the end of the track and repeats the process. Once the output of the matched filter falls below a particular threshold in any direction, the tracker will terminate.

B. Combination of techniques to reduce misclassification of hemorrhages.

This section describes how the segmented binary image output of the neural network technique is examined. Candidate vessels are identified based upon their size, as possible haemorrhages. The vessel tracker is then run on a small local area surrounding this possible haemorrhage. Finally, after considering output from the tracker, a decision is made about if the candidate is a haemorrhage or a vessel.

It is important to examine the neural network output for areas where a haemorrhage may have been mistaken for a vessel. This is because the purpose of the vessel classification is to identify normal areas of the image that can then be subtracted from the image before pathology classification takes place. If haemorrhages are misclassified as vessels, they will be removed from the image before pathology recognition even takes place.

An example of the misclassification of a haemorrhage as a vessel is shown by the areas circled in Figs. 1 and 2. The steps followed to decide if a haemorrhage has been misclassified as a vessel can be summarized:

1) From the binary-segmented output image produced using the neural network technique, identify vessel classifications on the image likely to be approximately the size of a haemorrhage. This information is readily available because the output of the neural network is already analyzed with respect to the size of connected components, this is so that components of the neural network output that are considered too small to represent vessels can be rejected from the final output image by applying a threshold. The vessel output circled in Fig. 2 represents an area identified on the basis of size.

2) A small patch (100x100 pixels) surrounding this vessel classification is extracted from the image and is shown in Fig. 3(a).

3) Apply the matched filter technique to the area shown in Fig. 3(a). The output of the magnitude of the matched filter is shown in Fig. 3(b) and the angular information from the matched filter is shown by Fig. 3(c). Both these images summarize information that will be used by the tracker.
4) Find first maximum value within the magnitude image of the matched filter shown in Fig. 3(b). This is shown as the black dot in Fig. 3(d).

5) Run tracker using the maximum value identified as its start point. The tracker path is shown in Fig. 3(d). Pixels that are tracked are then flagged and not included in subsequent steps.

6) Repeat steps 4 and 5 a second time. The result of the second application of the filter is shown in Fig. 3(e).

The tracked outputs (Figs 3(d) and (e) are then compared with the small circular area identified as a possible haemorrhage and shown as part of the 100x100 pixel area in Fig. 3(f). If the tracker outputs and suspected haemorrhage do not overlap, as is the case in this example, then the vessel classification is changed to be a possible haemorrhage. If the tracker outputs and the suspected haemorrhage do overlap (shown in a second example in the next section) then the vessel classification is left as a vessel. The overlap is defined to take account of the difference in vessel definitions between the two systems.

Number1 is the total number of pixels of the suspected haemorrhage defined by the neural network system.

Number2 = total number of matched tracker and neural network pixels. Define a Ratio to be (Number2/Number1)*100. If the Ratio = 0%, then the suspected haemorrhage is reclassified as a haemorrhage. If Ratio > 0%, then the suspected haemorrhage is left as a vessel.

III. RESULTS

The results of the application of the method to decide if a vessel classification of small overall area (as identified in Figs. 1 and 2) is a haemorrhage or a vessel is shown in Figs. 3(a) to (f). Because the tracked vessels and neural network recognition of the haemorrhage do not overlap at all, the suspected haemorrhage is confirmed to be a haemorrhage.

Figs. 3(a) to (f) show different information on the same 100x100 pixel area of the lens. Fig. 3(a) shows the raw image with a haemorrhage surrounded by two vessels. Fig. 3(b) shows the magnitude image of the matched filter application. Fig. 3(c) shows the angular image of the matched filter application. Figs. 3(d) and (e) show the first and second maximum values of the magnitude image (shown as a black dot) and the tracked output as white lines. Fig. 3(f) shows the neural network binary segmented image output.

A further example of the system where a suspected haemorrhage is actually a vessel is shown in Figs. 4 and 5. The suspected haemorrhage is circled in red in Fig. 5.

The results of the application of the method to decide if a vessel classification of small overall area is a haemorrhage or a vessel is shown in Figs. 4(a) to (f). Because the tracked vessels and neural network recognition of the suspected haemorrhage do overlap at, the suspected haemorrhage is confirmed to be a vessel.

Figs. 6(a) to (f) show different information on the same 100x100 pixel area of the lens. Fig. 6(a) shows the raw image of one strong clearly defined vessel and one less defined vessel. Fig. 6(b) shows the magnitude image of the matched filter application. Fig. 6(c) shows the angular image of the matched filter application. Figs. 6(d) and (e) show the first and second maximum values of the magnitude image (shown as a black dot) and the tracked output...
The results on a total of six suspected haemorrhages (three are actual haemorrhages and three are vessels) are summarized in Table 1. On a small data set, the combined method of neural network and tracking recognition is shown by the results in this table to be a promising area of investigation for reducing the uncertainty of small size vessel outputs.

<table>
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<tr>
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<th>Haemorrhage judged by system</th>
<th>Vessel judged by system</th>
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<tbody>
<tr>
<td>Haemorrhage judged by clinician</td>
<td>2</td>
<td>1</td>
</tr>
<tr>
<td>Vessel judged by clinician</td>
<td>1</td>
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Table 1: Summary of results on six suspected haemorrhage areas

IV. DISCUSSION AND CONCLUSION

Two methods of vessel detection have been combined in this work to help correct misclassification of haemorrhages. The overhead in terms of speed of the algorithm is not high, because the second tracker method is only applied to a small area of the original image.

Table 1 shows two out of six cases where the systems produced an incorrect classification. The first case where an actual haemorrhage was judged to be a vessel by the system was an area where a haemorrhage and vessel were in close proximity to each other. Adjustment of the ratio to compare pixels of the neural network and tracker may help to refine the method in this case. The second case where a vessel was judged to be a haemorrhage was an area where the vessel was very faint and surrounded by background noise and so was missed by the tracker entirely. These types of very faint vessels present a problem to both the tracker and neural network recognition system.

The data set the method has been applied to is very small. Before expansion of the data set, the following issues should be investigated: a study is required to estimate the standard size of haemorrhages in a larger data set so that suspect haemorrhage cases can be accurately identified; further investigation into adjustment of the ratio to compare pixels in the output images of the neural network and the tracker should be made to account for cases where vessels are in close proximity to haemorrhages.

The work described in this paper shows that application of a tracking algorithm combined with the neural network is a promising area of investigation to help to correct the misclassification of vessels as pathologies. This is an important initial step in enabling the accuracy of pathologies recognition for diabetic retinopathy to be increased. The method exploits the insensitivity of the matched filter and tracking method to haemorrhage shapes that are more rounded than vessels.