Automatic Recognition of Exudative Maculopathy using Fuzzy C-Means Clustering and Neural Networks

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Abstract. Retinal exudates are typically manifested as spatially random yellow/white patches of varying sizes and shapes. They are a characteristic feature of retinal diseases such as diabetic maculopathy. An automatic method for the detection of exudate regions is introduced comprising image colour normalisation, enhancing the contrast between the objects and background, segmenting the colour retinal image into homogenous regions using Fuzzy C-Means clustering, and classifying the regions into exudates and non-exudates patches using a neural network. Experimental results indicate that we are able to achieve 92% sensitivity and 82% specificity.

1 Introduction

Blindness is a common outcome of diabetic-related eye diseases. When background changes occur in the central retina, the condition is termed diabetic maculopathy, and visual acuity is at risk. Much of the blindness can be prevented if the condition is detected early enough for laser treatment. Unfortunately, because visual loss is often a late symptom of advanced diabetic maculopathy, many patients remain undiagnosed even as their disease is causing severe retinal damage. Hence, there is an urgent need for mass-screening retinal examination for the early detection and treatment of such diseases [1]. Current methods of detection and assessment of diabetic maculopathy is manual, expensive, potentially inconsistent, and require highly trained personnel to facilitate the process by searching large numbers of fundus images. In contrast, a good, automatic method based on modern digital image processing techniques will be faster, will need less, perhaps no human intervention, and will yield consistent results. The aim of our work is to extend the capabilities and productivity of the ophthalmologist and to provide decision support to physicians. We hope to develop a system that will perform our overall aims and objectives including identifying the proportion of the colour retinal image that contains exudates (EXs), and separating them from the other retinal anomalies and pathologies. In this paper, we report a method that first normalises the colours of the retinal image, since this can vary between different races. It then performs local contrast enhancement followed by Fuzzy C-Means (FCM) clustering to highlight salient regions, extracts relevant features, and finally classifies those regions using a multi-layer perceptron neural network.

Most of the work carried out so far in this area consider either Fluorescein Angiogram images [2] or gray level images [3]. The former is time consuming for physicians, inconvenient for patients, costly, and cause non-uniform illumination across the image due to varying amounts of background fluorescence. In the latter, monochrome images of the retina do not always capture all the available information for a more accurate segmentation. Other semi-automated methods for measuring EXs have been developed that need human intervention for defining a threshold, thus reducing the objectivity of the technique [4]. Gardner et al. [5] used artificial neural networks for identification of EXs by classifying whole regions of size 20x20 pixels. In this paper we approach the problem differently and locate EXs at pixel resolution in colour images. We will further compare our work against [5] in Section 3.

2 Proposed Method

Colour retinal images were obtained using a Canon CR6-45 non-mydriatic retinal camera. The image resolution acquired was 760x570 in 24bit RGB. A total of 140 images were classified by an ophthalmologist of which 110 were abnormal and 30 normal. Images were taken with a field of view of 45°. Typically, there is wide variation in the colour of fundus from different patients. This variation is strongly correlated to the person’s skin pigmentation and iris colour. Hence, it is necessary to identify a reference frame and normalise the colours of all other images against it. We performed this colour normalisation step using histogram specification [6]. This modifies the image values through a histogram transformation operator which maps a given intensity distribution \(a(x,y)\) into a desired distribution \(c(x,y)\) using a histogram equalized image \(b(x,y)\) as an intermediate stage. This is applied independently to each individual RGB channel. Figure 1 shows the results on two test images (both of which illustrate varied amounts of bright yellowish EX regions compared to the reference image).

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After normalisation, we applied a local contrast enhancement [7] method to improve both the contrasting attribute of lesions and the overall colour saturation in the image. This operation was performed on the intensity channel of the image only after it was converted to the Hue-Saturation-Intensity (HSI) colour space. The aim is to apply a transformation of the values inside small windows in the image in a way that all values are distributed around the mean and show all possible intensities. Hence, given each pixel \( p \) in the initial image and a small running window \( W \) then the image is filtered as follows to produce the new image \( G \):

\[
G[i, j] = 255 \left[ \frac{\phi_w(p) - \phi_w(Min)}{\phi_w(Max) - \phi_w(Min)} \right]
\]

and the sigmoid function is:

\[
\Phi_w(p) = \left[ 1 + \exp \left( \frac{\mu_w - p}{\sigma_w} \right) \right]^{-1}
\]

The \( \text{Max} \) and \( \text{Min} \) refer to the maximum and minimum intensity values in the whole image, while \( \mu_w \) and \( \sigma_w \) show the mean and standard deviation within each window. This function, produces significant contrast enhancement when \( \sigma_w \) is small, i.e. the contrast is low, and little enhancement when \( \sigma_w \) is large, i.e. contrast is high. Figure 2(a) shows the result of contrast enhancement on image 1(e).

Once the image has been pre-processed as described above, we perform colour segmentation based on a FCM clustering algorithm described in [8]. This method allows pixels to be classified into multiple classes with varying degree of membership, unlike hard segmentation methods that force pixels to belong exclusively to one class. The segmentation consists of two stages, one that clusters the image coarsely followed by the second stage, which performs a finer clustering. The coarse segmentation stage provides an initial segmentation of the image by applying an automatic thresholding technique where the image is divided into a number of regions. The values for the thresholds are generated on the fly by scale-space filtering the histograms of the three colour channels and determining the resulting number of significant peaks. Those pixels not segmented by the coarse segmentation, are further segmented using FCM in the fine segmentation stage to find fuzzy partitioning by minimizing the following squared error objective loss function:

\[
L = \sum_{j=1}^{m} \sum_{i=1}^{n} \mu_j(x_i) \| x_i - c_j \|^2
\]
where \( x_i \) denotes the data vector \((i=1,...,n)\), \( n \) is the total number of pixels, \( c_j \) is the centre of a fuzzy cluster \((j=1,...,m)\), \( m \) is the number of fuzzy clusters known from the coarse segmentation stage, and \( \mu_j(x_i) \) is the fuzzy membership of \( x_i \) to cluster \( j \). The parameter \( b > 1 \) (the weighting exponent) controls the overlap between different fuzzy cluster regions. Performing differentiation and applying the constraint \( \sum_{j=1}^{m} \mu_j(x_i) = 1 \) leads to:

\[
\mu_j(x_i) = \left[ \sum_{k=1}^{m} \left( \frac{d_k}{d_j} \right)^{1/(b-1)} \right]^{-1}, \quad \text{where} \quad d_{ji} = \|x_i - c_j\| \quad \text{and} \quad C_j = \sum_{i=1}^{n} \left[ \mu_j(x_i)^b \right] x_i
\]  

(3)

Here \( d_{ji} \) denotes the Euclidean distance between the data vector and the cluster centre. Equation (2) measures the similarity between the pixel’s attribute vectors and the cluster center of each region. Minimizing this function is based on the suitable selection of values and iterative refinement of (3). In this study the FCM was applied by setting \( b=2 \) and by iterating the algorithm until the change in the norm became less than 0.5 and FCM could distinguish three different clusters. Figure 2(b) shows the result after colour segmentation of the image in 2(a). In Figure 2(c) we have highlighted only the cluster-representing candidate EX regions in the original image. As expected, the EXs have been segmented very well. The characteristics of the FCM are highly suited to our normalised and contrast-enhanced images particularly as the process is parameter-free. Due to the wide variability in the colour appearance of EXs and the retina, sometimes EXs appear so faint that even human experts are not sure about some ambiguous regions. The proposed method is conservative and segments all possible EXs as well as false positives due to its sensitivity. The expert ophthalmologist assisting this project is very satisfied with the detected regions after the segmentation step.

The false positives non-EX areas are segmented wrongly due to cluster overlapping, non-uniformity of colour distribution, and noise in our retinal images. The optic disk is segmented as fragmented EX regions due to the similarity of its colour to yellowish EX regions. At present we can ignore the falsely detected optic disk regions when we present our results to the ophthalmologist since it is already such a prominent and easily recognised part of the image. In future, we will automatically detect and segment the optic disk.

(a) After contrast enhancement  (b) Segmented image after FCM  (c) Candidate EXs in white

Figure 2. Various processing stages for Figure 1(c)

Next, the remaining segmented objects are classified as EX/non-EX regions by training and testing a neural network. After a comparative study examining different possible feature sets we selected 10 to segment the feature space into two disjoint classes, EX and non-EX (Table 1). These features correspond to the information sought by ophthalmologists when diagnosing such images. They were automatically measured and recorded on each FCM segmented region.

We trained a fully connected multiplayer neural network with a 10-N-1 architecture [9] for our final classification. The input nodes correspond to the size of the feature vector, and a single output unit was used for a probabilistic EXs and non-EX decision. Inputs were normalized to have zero mean and unit variance across the entire training and test data set.
Table 1. The feature set used for training the neural network

<table>
<thead>
<tr>
<th>Feature</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Size</td>
</tr>
<tr>
<td>2-7</td>
<td>Colour (RGB inside and around the region)</td>
</tr>
<tr>
<td>8</td>
<td>Average Intensity</td>
</tr>
<tr>
<td>9</td>
<td>Edge Sharpness</td>
</tr>
<tr>
<td>10</td>
<td>Standard Deviation of Intensity</td>
</tr>
</tbody>
</table>

3 Results and Discussion

In this work we tried different numbers of hidden units between 1 and 30, finding 5 hidden units to be optimal during the training stage. Two different learning methods were experimented with: back propagation and scaled conjugate gradient. The latter was found to perform slightly better than the standard back propagation but at the expense of increased training time. We used 42 colour retinal images (of our original 140 image set) containing 4037 objects for training and testing the neural network. Each object was labelled by an ophthalmologist as an EX or non-EX region. The data was split randomly into 74% for training and 26% for testing, hence the training set was 3000 candidates, of which 1205 were labelled as EX. The remaining 1037 objects (of which 417 were labelled as EXs) were used as an independent testing set. Ten-fold cross validation was used with the training and validation data, so we always had 300 objects as a validation, within these 10 iterations. In the testing stage, our results gave a sensitivity of 92% and specificity 82%, where sensitivity is the ratio of true positive decisions against the number of positive cases and specificity is the ratio of true negative decisions against the total number of negative cases. These results are directly comparable to those obtained by [5] who also used a neural network with a sensitivity of 93.1%. However, this figure is the result of their identification of exudates by classifying regular regions of size 20x20 pixels. This involved training their network on patches that were ‘bad’ if one or more pixels in the 20x20 patch were exudates or ‘good’ if no pixels were affected. Furthermore, this approach is weakened since not all of an exudates region may appear within a square patch. In our method the 92% sensitivity is the classification result of training the network on actual independent, randomly shaped EX and non-EX region. Also, our more localised results facilitate a more accurate monitoring of the disease over time. Additionally, the network training in [5] took 2 to 3 weeks, whereas ours requires about an hour. We can also increase our sensitivity and specificity results by changing the threshold on the network output.

The objectives of our study are to investigate methods for automated analysis of colour retinal images for the purpose of detecting and classifying early lesions related to diabetic maculopathy. The results are very good so far and show that automated identification of EX lesions on the basis of colour information is certainly of practical use to ophthalmologists. In this work we used only one-third of our images in the dataset for training the network and the performance should be improved by using more. Our future work will involve the identification of retinal image pathologies like microaneurysms and haemorrhages and the main retinal parts such as blood vessels, macula and optic disk, with the final aim of establishing a cost-effective mass screening system for diabetic maculopathy.

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4 References