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# SEGMENTATION OF RETINAL BLOOD VESSELS USING A NOVEL CLUSTERING ALGORITHM

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## ABSTRACT

*In this paper, segmentation of blood vessels from colour retinal images using a novel clustering algorithm and scale-space features is proposed. The proposed clustering algorithm, which we call Nearest Neighbour Clustering Algorithm (NNCA), uses the same concept as* the *K-nearest neighbour (KNN) classifier with the advantage that the algorithm needs no training set and it is completely unsupervised. Results from the proposed clustering algorithm are comparable with the KNN classifier, which does require training set.*

## 1. INTRODUCTION

Automatic segmentation of blood vessels in retinal images is very important in early detection and diagnosis of many eye diseases. It is an important step in screening programs for early detection of diabetic retinopathy [1], registration of retinal images for treatment evaluation [2] (to follow the evaluation of some lesions over time or to compare images obtained under different conditions), generating retinal map for diagnosis and treatment of age-related macular degeneration [3], or locating the optic disc and the fovea [4].

Methods for blood vessels segmentation of retinal images, according to the classification method, can be divided into two groups - supervised and unsupervised methods. Unsupervised methods in the literature comprise the matched filter responses, edge detectors, grouping of edge pixels, model based locally adaptive thresholding, vessel tracking, topology adaptive snakes, and morphology-based techniques [5]. Supervised methods, which require feature vector for each pixel and manually labelled images for training, are the most recent approaches in vessel segmentation and use the neural networks [1], or the $K$-nearest neighbour classifier [5, 6] for classifying image pixels as blood vessel or non-blood vessel pixels. These methods depend on generating a feature vector for every pixel in the image and then using training samples (with known classes) to design a classifier to classify these training samples into their corresponding classes.

Scale-space features such as the gradient magnitude of the image intensity and the ridge strength, both at different scales, are combined with region growing to segment the blood vessels from red-free and fluorescein clinical retinal images [7]. Also, the 1*st* and 2*nd* derivatives - of the green channel image, in $x$ and $y$ directions [6], or with respect to other image coordinates [5] at different scales - are used as features for every pixel in retinal images. Since taking derivatives of discrete images is an ill-posed operation, these are taken at a scale $s$ using the Gaussian scale-space technique [8]. Niemeijer *et al.* [6] proposed a pixel classification method where the *KNN* classifier is used with 31 features to classify the pixels in retinal images to vessel and non-vessel pixels; these features are the green channel image, and the filtered image using the Gaussian and its derivatives at different scale values.

Clustering algorithms such as fuzzy C-means (FCM) clustering have been proposed for vessel tracking [9] and exudates detection [10] in retinal images. Tolias *et al.* [9] proposed a FCM clustering algorithm that is based on the intensity information to track vessels in fundus images. This algorithm is initialised by defining the optic nerve's as a very bright region to be the start point to track image vessels. However, it ignores the possibility of locating abnormalities that have the same properties as the optic nerve. Moreover, vessels of small diameter and low contrast are missed. In [10], retinal exudates are detected by normalising colour channels using local contrast enhancement. Then, a FCM clustering algorithm is used to highlight salient regions and extract relevant features, then those regions are classified using a multi-layer perceptron neural network.

In this paper, we propose to segment retinal blood vessels using a novel clustering algorithm which is based on the nearest neighbours concept that is used in the *KNN* classifier with one main different that our proposed clustering algorithm does not need a training set. For purposes of comparison, results obtained from our proposed *NNCA* are compared with the *KNN* classifier when using the same features and same testing set of images. This paper is organised as follow; the proposed *NNCA* is detailed in section 2 along with the features used in this paper. Experiments and results are demonstrated in section 3. Discussion is presented in section 4 and the paper is summarised in section 5.

## 2. METHOD

### 2.1 The Proposed Clustering Algorithm (*NNCA*)

The proposed *NNCA* is a modified version of the *KNN* classifier, and it can be divided into two stages for creating $N_C$ clusters. First stage is to randomly select $N$ pixels. Then non-overlapping clusters are created from these $N$ pixels, each of maximun size $K_{init}$ pixels (the choice of $K_{init}$ ensures that more than $N_C$ clusters are generated here). Afterwards an iterative control strategy is applied to update the clusters and their memberships by increasing the number of neighbours untill $N_C$ non-overlapping clusters are created. Second stage is to cluster the remaining pixels. For each

**Algorithm 1** Nearest Neighbour Clustering Algorithm

**Input** (data, $N$, $K_{init}$, $Nc$, $K$)
where:
* $N$ is the number of random pixels to be clustered.
* $K_{init}$ is the nearest neighbour pixels from $N$.
* $Nc$ is the user defined number of clusters.
* $K$ is the number of nearest clustered pixels.

# Step 1: Create $N_C$ non-overlapped clusters
# (a) Create initial clusters:
* Initially, all the $N$ pixels are unclustered.
let $M = 1$
**For** $i = 1$ to $N$
**IF** ( pixel $i$ is unclustered )
- Assign $i$ and its unclustered neighbours (from $N$) of the $K_{init}$ nearest neighbours to cluster # $M$.
- $M = M + 1$
**End IF**
**End For**

# (b) Merge clusters:
* **DO**
- $K_{init} = K_{init} + 1$
- Assign each clustered pixel to the common cluster of the $K_{init}$ nearest neighbours.
- Update the number of clusters $\rightarrow M$
**WHILE** ( $M > Nc$)

# Step 2: Find the nearest $K$ neighbours for each remaining pixel
- Assign each unclustered pixel to the common cluster of the $K$ nearest clustered pixels.
-Use Eq. 2 to find hard partition and Eq. 3 to find soft partition.

**Output** ( Hard partition vector, Soft partition matrix)

unclustered pixel $q$, $K$ nearest clustered pixels are found. Then, the cluster to which most of these $K$ clustered pixels belong is deemed to be one to which the pixel $q$ belongs to.

Our proposed *NNCA* is detailed in Algorithm 1. Let each pixel $x$ be described by the feature vector:

$$< a_1(x)\, a_2(x), \ldots\ldots, a_n(x) >$$

where $a_r(x)$ is used to denote the values of the $r_{th}$ attribute of data point $x$. If we consider two pixels $x_i$ and $x_j$, then the distance between them is defined as $d(x_i, x_j)$, which is expressed in Equation 1.

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n} (a_r(x_i) - a_r(x_j))^2} \qquad (1)$$

A fuzzy clustering, where all pixels are allowed to belong to all clusters with different degrees of membership, is achieved by obtaining the mean value of the $K$ nearest neighbours for each pixel in the retinal image. Therefore, hard partition as well as soft partition can be obtained. For an image pixel $x_q$ to be clustered, let $x_1 \ldots x_K$ denote the nearest $K$ clustered pixels to $x_q$ and $C(x_i) \in \{1, \ldots, Nc\}$ is the cluster index for pixel $x_i$. Hard partition for $x_q$ is:

$$C(x_q) = arg\ Max_{n \in C} \sum_{r=1}^{K} (n == C(x_r)), \qquad (2)$$

Figure 1: Colour sub-image with blood vessels clustered using *NNCA*.

and soft partition is:

$$C(x_q) = \frac{\sum_{r=1}^{K} C(x_r)}{K} \qquad (3)$$

Figure 1 shows the result for clustering blood vessels for a sub image from a colour retinal image.

### 2.2 Feature Extraction

In a previous work [11], a set of 3 features, in conjunction with the *KNN* classifier, have been proposed to segment retinal blood vessels. These features are the green channel intensity, the local maxima of the gradient magnitude, and the local maxima of the largest eigenvalue. Fig. 2 shows a sub-image with the intensity information for a blood vessel section is plotted along with the gradient magnitude, the ridge strength and the largest eigenvalue. From the graphs, it is clear that the green channel has a higher contrast than the red channel image, gradient magnitude gives two peaks at

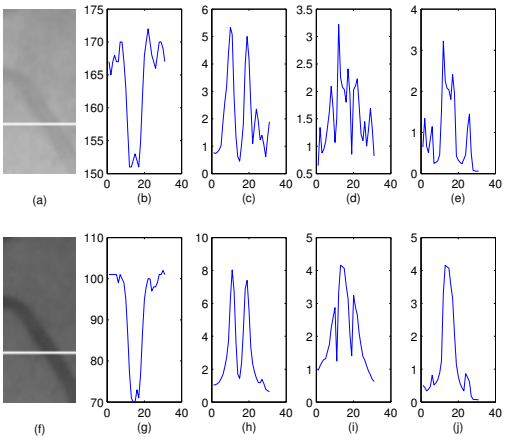



Figure 2: Sub-image with colour and scale-space features. (a, b, c, d, e) sub-image and its intensity along a horizontal line crossing a blood vessel, gradient magnitude, ridge strength, and largest eigenvalue from red channel image, (f, g, h, i, j) the same but for sub-image from the green channel image.

the parallel edges of the blood vessels, and finally the largest eigenvalue is better than the ridge strength in determining the centerlines of the blood vessels when processing colour fundus images.

**The Gradient Magnitude (maximum over scales)**

The gradient magnitude is calculated as:

$$|\bigtriangledown L| = \sqrt{L_x^2 + L_y^2} \quad (4)$$

$$L_x = I(x,y) \otimes sG_x$$

$$L_y = I(x,y) \otimes sG_y \quad (5)$$

where $L_x$ and $L_y$ are the first derivative of the image in the $x$ and $y$ directions, $G_x$ and $G_y$ are the Gaussian derivatives in the $x$ and $y$ directions, and $s$ is the scale parameter [8]. The gradient magnitude of the image intensity is calculated at different scales [7], then the local maxima of the gradient magnitude $\gamma$ is calculated as:

$$\gamma = \max_s \left[ \frac{|\bigtriangledown L(s)|}{s} \right] \quad (6)$$

**The Largest Eigenvalue (maximum over scales)**

The eigenvalues (the large eigenvalue, $\lambda_+$, and the small eigenvalue, $\lambda_-$) of the Hessian, the matrix of the second order derivatives, of the intensity image $I(x,y)$ are calculated as [7]:

$$\lambda_+ = \frac{L_{xx} + L_{yy} + \alpha}{2} \quad (7)$$

$$\lambda_- = \frac{L_{xx} + L_{yy} - \alpha}{2} \quad (8)$$

where $\alpha = \sqrt{(L_{xx} - L_{yy})^2 + 4L_{xy}^2}$

Then, the local maxima of the largest eigenvalue $\lambda_{max}$ is calculated as :

$$\lambda_{max} = \max_s \left[ \frac{\lambda_+(s)}{s} \right] \quad (9)$$

## 3. EXPERIMENTS AND RESULTS

### 3.1 Experiments

In our experiments, retinal blood vessels are segmented using the proposed clustering algorithm in conjunction with the pre-defined set of features. The performance is measured by calculating the false positive rates (FPR) and the true positive rates (TPR), these rates are defined in the same way as in [12]. To evaluate the performance of our proposed algorithm, a set of 20 images publicly available [13] are used, where 10 are normal and 10 contain pathology. For purposes of comparison, the performance of our proposed clustering algorithm is compared with the *KNN* classifier when using the same feature vector.

For the *KNN* classifiers, two sets are required; one for training and the other for testing, so the dataset is randomly divided into two sets of images, each contains 5 normal and 5 abnormal images. The training set contains large number of training samples, which is the main problem with this type of classifiers. To overcome such a problem, random number of pixels are chosen from the field of view (FOV) of each image in the training set. The targets for these training samples are available from the manually segmented images. The testing set contains 10 images to test the performance of the classifier. The value of $K = 60$ is used and each feature is normalised to zero mean and unit standard deviation.

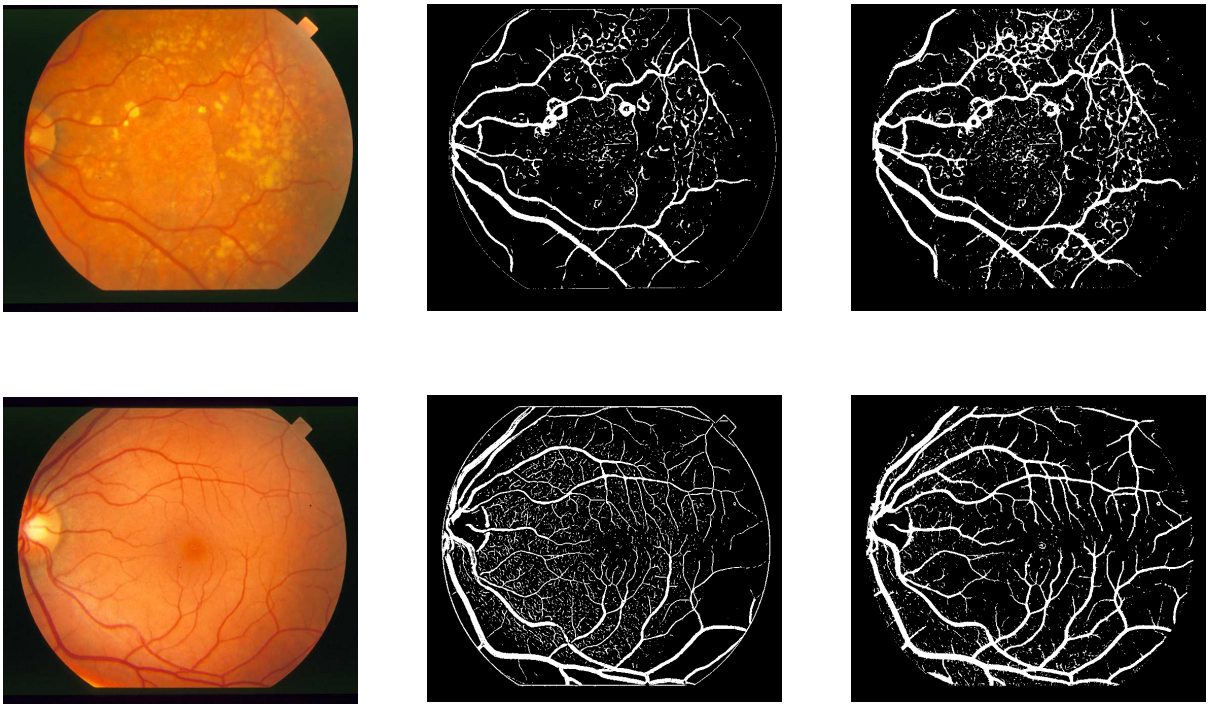
### 3.2 Experimental Results

Figure 3(a and b) shows two examples; abnormal (top) and normal (bottom) images and their results after blood vessels segmentation using the proposed clustering algorithm. On the whole, when using 20 images, average sensitivity of 77% is achieved at average specificity of 90% as summarised in Table 1. These values are calculated using the retinal field of view only.

Table 1: *NNCA* results (average from 20 images)

| Image type | Specificity % | Sensitivity % |
|---|---|---|
| Normal | 92.30% | 81.42% |
| Abnormal | 87.61% | 72.13% |
| All | 89.95% | 76.77% |

Figure 3(b and c) compares results from the *NNCA* with the *KNN* classifier. When comparing with the *KNN* classifier; the same set of images (10 images for testing), also, the hard decision from the *KNN* classifier are used and result from this comparison are summarised in Table 2. Average sensitivity of 80.54% is achieved at average specificity of 89.45% from our *NNCA* compared with average sensitivity



(a) (b) (c)

Figure 3: (a) Colour images, (b) output from the *NNCA* (hard decision), and (c) output from the *KNN* classifier (hard decision).

Table 2: *NNCA* and *KNN* results (average from 10 images (testing set))

| Image type | *NNCA* Specificity % | *NNCA* Sensitivity % | *KNN* Specificity % | *KNN* Sensitivity % |
|---|---|---|---|---|
| Normal | 91.70% | 83.43% | 93.57% | 88.60% |
| Abnormal | 87.21% | 77.66% | 91.93% | 82.34% |
| All | 89.45% | 80.54% | 92.72% | 85.47% |

Table 3: *NNCA* results when using one feature only (average from 20 images)

| Image type | Specificity % | Sensitivity % |
|---|---|---|
| Normal | 94.97% | 81.02% |
| Abnormal | 93.53% | 71.77% |
| All | 93.11% | 76.39% |

of 85.47% at average specificity of 92.72% from the *KNN* classifier.

On average, the *KNN* classifier performs better than our proposed *NNCA* because of the use of a training set that helps in the classification of pixels to vessels and non-vessel pixels. Results from our proposed *NNCA* are 5% less than the *KNN* classifier as it is completely unsupervised. For supervised classifiers; generating a training set required manually segmented images provided by an ophtholmologist or a trained person at least and the classifier should be trained for each and every dataset (as images were captured using different camera types, FOV's degree, and resolution). However, the performance of our clustering algorithm can be enhanced by adding new features that allow more accurate clustering for image pixels, such as: colour features, texture features, or even directional features. Also the performance can be enhanced when clustering pixels to more than 2 clusters, i.e. to extend the non-vessels cluster to background, bright abnormal regions, and dark abnormal regions. Further investigations are under way to introduce another set of features to help in obtaining more accurate clustering results. Table 3 shows results when using the maximum eigenvalue as the only feature to cluster pixels which indicate an improvement in the specificity values than using the previous set of three features.

## 4. DISCUSSION

One of the main problems with supervised classifiers is the need for a training set and a feature vector in order to classify data points (in our case, image pixels) to their corresponding classes. There is no doubt that the performance of the classifier is affected by the choice of the feature vector and the

training set. The processing time increased with the increase of the feature vector's size. The number of samples used for training is an important issue to be considered as well as training samples itself, therefore the choice of the training set affects the classifier performance directly.

In this application, where retinal blood vessels segmentation is our main task, generating a training set was not an easy job to do. First, there are 423500 pixels/image with more than 25% dark background pixels and the dataset consists of 20 images some of them of bad quality (very bright or saturated images). Second, the property of multiple object classes of varying colour/reflectance [14] and - sometimes - there is a similarity between feature vectors for vessel and non-vessel pixels from different images.

Two of the advantageous aspects of our proposed algorithm are that there is no need for a training set and it achieves results as a hard decision which can be directly used in further analysis of the blood vessels network. For soft classification or soft segmentation, FPR and TPR are calculated when the image is thresholded different threshold values which gives the ROC curve. In this case, there is a need to decide the optimum threshold value to be used for each image. On the other hand, hard segmentation, gives a 1 or 0 value to each image pixel to decide is it a blood vessel or not, and in this case there is only one FPR corresponding to a single TPR to describe the performance of the method.

In our proposed nearest neighbour clustering algorithm (*NNCA*):

- We combine concepts of supervised and unsupervised methods where a feature vector is generated for each pixel in the image, then image pixels are clustered depending on these features without using a training set.
- For the twenty images in the dataset, average sensitivity and specificity of 77% and 90% are achieved respectively when using three features, and 76% and 93% respectively when using only one feature (the maximum eigenvalue).
- When comparing with the *KNN* classifier, using the same set of images in the testing set, the *KNN* classifier performs better than our proposed clustering algorithm because of using the training set. To overcome such a drawback, other set of features should be considered to allow the algorithm to perform better and image pixels should be clustered to more than 2 clusters.

## 5. CONCLUSIONS

In this paper, we have proposed a novel clustering algorithm to be used in segmentation of retinal blood vessels. This is used to cluster pixels of retinal images into those belonging to blood vessels and others not belonging to blood vessels, based on feature vectors. Experimental results show that the proposed algorithm offers comparable performance as the *KNN* classifier but with the advantage that it is completely unsupervised and needs no training set.

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