Mean curvature and texture constrained composite weighted random walk algorithm for optic disc segmentation towards glaucoma screening

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Published in Healthcare Technology Letters; Received on 31st May 2017; Revised on 4th August 2017; Accepted on 25th August 2017

Accurate optic disc (OD) segmentation is an important step in obtaining cup-to-disc ratio-based glaucoma screening using fundus imaging. It is a challenging task because of the subtle OD boundary, blood vessel occlusion and intensity inhomogeneity. In this Letter, the authors propose an improved version of the random walk algorithm for OD segmentation to tackle such challenges. The algorithm incorporates the mean curvature and Gabor texture energy features to define the new composite weight function to compute the edge weights. Unlike the deformable model-based OD segmentation techniques, the proposed algorithm remains unaffected by curve initialisation and local energy minima problem. The effectiveness of the proposed method is verified with DRIVE, DIARETDB1, DRISHTI-GS and MESSIDOR database images using the performance measures such as mean absolute distance, overlapping ratio, dice coefficient, sensitivity, specificity and precision. The obtained OD segmentation results and quantitative performance measures show robustness and superiority of the proposed algorithm in handling the complex challenges in OD segmentation.

1. Introduction: Glaucoma is a degenerative and irreversible optic neuropathy, which ranks as the second most disabling and vision impairing disease worldwide [1]. Glaucoma is a silent thief of sight as it is asymptomatic in preliminary stages; hence early diagnosis and treatment is the only way to prevent further retinal damage. Tests such as tonometry, gonioscopy, perimetry are commonly practiced to detect glaucoma. However, these tests are generally time consuming and prone to human errors; therefore computer-aided diagnosis is suitable for large-scale glaucoma screening [2].

There are two approaches for glaucoma detection in the literature such as with segmentation [3–6] and without segmentation [7–15]. In [7–15], the methods use whole image-based features that include higher-order spectral features [7–10], fractal features [11, 12], wavelet-based features [13] and texture features [14] followed by various classification strategies to accurately detect glaucomatous cases. Since this approach does not require explicit segmentation, it is computationally inexpensive. However, the other approach employing segmentation-based reliable features such as cup-to-disc height ratio (CDR), rim area, optic disc (OD) size is also found to be useful for glaucoma screening. The proposed method only concentrates on the OD segmentation procedure which can be used to determine the OD height. The OD height is a prerequisite in computing the CDR-based glaucoma risk index evaluation [16]. To further enhance glaucoma detection accuracy, both approaches can be combined together to design better automated glaucoma detection systems. Moreover, OD segmentation is not only limited to glaucoma detection but also considered to be a fundamental step in diabetic retinopathy detection and localisation of other retinal structures such as fovea and macula [17, 18]. Subtle OD boundary, blood vessel occlusion and intensity inhomogeneity make OD segmentation a challenging task.

OD appears as a bright and relatively circular region, which is partially occluded by the blood vessels as shown in Fig. 1. The approaches adopted for OD segmentation as reported in the literature can be broadly categorised as (i) shape-based template matching, and (ii) deformable model-based methods. In template matching-based methods, the OD is modelled as a circular or elliptical object based on its shape [19–24]. The OD contour is estimated by circular template matching on edge maps using the Hausdorff distance measure [19]. Aquino et al. [20] computed the Hough transform-based circular approximation of the OD using a binary mask of the boundary candidates. Another Hough transform-based OD segmentation approach is also reported in [21]. A circular transformation using evenly-oriented radial line segments of specific length is designed in [22] to capture the circular shape of the OD and the image variation across the OD boundary. The ellipse fitting algorithm with intensity information is utilised to detect the OD contour in [23]. A convex hull in the vicinity of best OD candidate followed by an ellipse fitting approach is suggested in [24]. The shape-based template matching methods have reported several failure cases when an OD shape irregularity is caused by different retinal pathologies.

A number of methods have been proposed to address the shape irregularity of OD based on various deformable models [3–6, 25–28]. Xu et al. [3] detected the OD contour by improving the original snake algorithm in two aspects: knowledge-based clustering and smoothing. Joshi et al. [4] applied active contour model with energy function that includes multi-dimensional features such as intensity, colour and texture. An anchored active contour which was initialised by Hough circle fitted to the edges of the binarised distance map is applied to the OD boundary extraction in [5]. Mittapalli and Kande [6] proposed an active contour model for OD segmentation which incorporates the image information from multiple image channels. An automatic OD boundary detection technique based on morphology and active contour model is proposed in [25]. Wong et al. [26] proposed a variational level-set model followed by ellipse fitting operation to obtain the smooth OD boundary. A local deformable model with variable edge-strength dependent stiffness for OD segmentation is used in [27]. Dai et al. [28] proposed a PCA-based shape energy which constrains the curve evolution in OD segmentation.

In deformable model-based OD segmentation, the boundary localisation is sensitive to curve initialisation. The curve evolution stops at a local energy minimum if proper initialisation is not undertaken. Various types of local information are used in the level set energy functional to address this problem. The main limitation of the level set methods is that they often require specification of several parameters and it is tedious to tune them, especially when the desired contour does not correspond to a local energy minimum. The above challenges provide space to explore and apply graph-based random walk (RW) segmentation paradigm...
The RW provides accurate segmentation output even at weak boundaries in the presence of intensity irregularity. In addition, it avoids the trapping at local minima in deformable models and small cut problem in graph cuts. RW-based segmentation was applied successfully in biomedical images such as left ventricle segmentation in cardiac magnetic resonance images and tumour segmentation in brain and liver images.

In this Letter, we propose a new curvature and texture constrained RW (CTCRW) algorithm for OD segmentation in fundus images. Here, we propose a graph-based RW algorithm with a modified weight function which is new for OD segmentation. A new composite RW weight function is defined by incorporating mean curvature, Gabor texture energy features with multiple orientations and intensity features. The distinctive curvature and texture information of OD enable the segmentation process to tackle the misleading interference such as noise, weak boundaries in the OD segmentation procedure.

The remaining of this letter is organised as follows: Section 2 describes the details of the proposed CTCRW-based segmentation method. The results are provided in Section 3. In Section 4, the effectiveness of the proposed CTCRW algorithm is tested and validated by comparing the accurate OD segmentation performance on a wide variety of fundus images taken from DRIVE, DIARETDB1, DRISHTI-GS and MESSIDOR databases. Finally, Section 5 presents the concluding remarks.

2. Methods: This section describes the proposed CTCRW algorithm for accurate OD segmentation. The schematic representation of the proposed OD segmentation algorithm is illustrated in Fig. 2. In the first step, blood vessel inpainting and intensity adjustment is performed. The mean curvature feature, Gabor energy texture feature and intensity features are then extracted and used to compute the weights for the proposed CTCRW algorithm. After selecting the background and foreground seed pixels, the solution to combinatorial Dirichlet problem minimisation is computed to get the probability of unmarked pixels belonging to the seed pixels. Finally, the segmentation decision is obtained by retaining the maximum probability value at each pixel.

2.1. Pre-processing: The OD segmentation process starts with the grey-scale image \( I \) created by a weighted combination of red (\( I_r \)) and green (\( I_g \)) channels of the RGB fundus image to enhance the contrast across the OD boundary [22]

\[
I = \alpha I_r + (1 - \alpha)I_g,
\]

where \( \alpha = 0.6 \) (1)

The OD segmentation performance degrades due to blood vessel obstruction in and around the OD region. Hence, the blood vessels are extracted using the binary Hausdorff symmetry measure based seeded region growing and then inpainted. This is followed by the intensity adjustment using median filtering at each pixel around the OD centre that is detected based on the symmetry property of retinal blood vessels. A sample pre-processed image is shown in Fig. 3.

2.2. RW for segmentation: In RW-based segmentation, an image is treated as a graph with fixed number of vertices and edges. A real-valued weight is assigned to each edge in the graph which corresponds to the likelihood that a random walker will cross that edge [29].

A graph \( G = (V, E) \) constitutes of vertices \( v \in V \) and edges \( e \in E \), where \( E \subseteq V \times V \). An edge connecting two vertices \( v_i \) and \( v_j \) is represented by \( e_{ij} \). In a weighted graph, each edge \( e_{ij} \) is assigned to a weight \( w_{ij} \). The degree \( d_i \) of the vertex \( v_i \) is the summation of all the incident edge weights

\[
d_i = \sum_j w_{ij}. \quad (2)
\]

In classical RW [29], the edge weights are represented by a Gaussian function that maps a change in image intensities to the edge weights

\[
w_{ij} = \exp\left(-\beta (I_i - I_j)^2\right) \quad (3)
\]

where \( I_i \) and \( I_j \) represent the image intensities at pixels \( i \) and \( j \), respectively, and \( \beta \) represents the free parameter of RW algorithm.

The RW algorithm is initialised by assigning \( K \) seeds indicating regions belonging to \( K \) objects in the image. The RW algorithm labels each unmarked pixel by computing the probabilities of its first arrival at one among the \( K \) seed points. A solution using the minimisation of the combinatorial Dirichlet problem with boundary conditions is established to optimally compute the probability values.

2.3. Proposed CTCRW algorithm: In this subsection, we present the CTCRW algorithm in details. The CTCRW algorithm uses the mean curvature and Gabor texture energy features as constraints in the proposed RW weight computation. In classical RW, \( w_{ij} \) is a function of pixel intensities in (3). However, irrespective of the pathological variations in OD shape, the curvature value is more at the OD boundaries and the texture of OD region is different than the background. Therefore, in addition to pixel intensities, the mean curvature and texture features could achieve improved performance as compared to classical RW. Furthermore, the curvature and texture information in CTCRW is dynamically derived from the image itself such that the requirement of any prior shape training is avoided. The CTCRW algorithm constitutes of mainly three steps: (i) seed initialisation, (ii) assignment of the
The mean curvature is an extrinsic measure of curvature that comes from differential geometry and that locally describes the curvature of an embedded surface [34]. The mean curvature $H$ of an image $I$ is given by

$$H = \frac{(1+I_x^2)I_{xx} + 2I_xI_yI_{xy} + (1+I_y^2)I_{yy}}{2(1+I_x^2+I_y^2)^{3/2}}. \quad (4)$$

Gabor filter is a linear filter used for texture analysis, which analyses the specific frequency content in the image in specific directions in a localised region. A two-dimensional (2D) Gabor filter mask comprises of Gaussian modulated sinusoidal wave used for localised and oriented frequency analysis [35]. A 2D

$$g(x, y) = \exp\left(-\frac{(x-x_0)^2+(y-y_0)^2}{2\sigma^2}\right) \sin\left(\frac{2\pi}{\lambda} (x \cos \theta - y \sin \theta)\right). \quad (5)$$

For $g(x, y)$ computation, the wavelength $\lambda$ and standard deviation $\sigma$ are considered as 1.414 and 0.1, respectively, in 12 equidistant orientations ($0, 15, 30, 45, ..., 180$) in this method (Fig. 5). The Gabor energy is computed by convolving $g(i,j)$ with the image $I(x, y)$.

$$T_{\theta} = I(x, y) \times g_{\theta}(i,j), \quad \theta_{\theta} = [0^\circ, 15^\circ, ..., 180^\circ] \quad (6)$$

After computing the mean curvature and Gabor texture energy values at different angles, the composite weight of the edge connecting two nodes is found using the following equation:

$$w_{ij} = c_1 \exp\left(-\beta_1(I_x^2-I_x^2)\right) + c_2 \exp\left(-\beta_2(H_y^2-H_y^2)\right) + c_3 \exp\left(-\beta_3 \sum (T_{\theta_{\theta}} - T_{\theta_{\theta}})^2\right) \quad (7)$$

**Labeling of unmarked pixels:** The probability of each unmarked pixel belonging to a seed point is computed by solving the combinatorial Dirichlet problem. The final segmentation decision is obtained by retaining the maximum probability value ($\nu_u$) at each vertex $v_u$ (unmarked pixel)

$$\text{Label}_{\nu_u} = \max (\nu_u), \quad \forall v_u \in V_u \quad (8)$$

The maximum probability at each unmarked pixel is shown in Fig. 4b and the contour of the segmented region is shown in Fig. 6.

**3. Results:** The validation of the proposed CTCRW algorithm is carried out on DRIVE [36], DIARETDB1 [37], DRISHTI-GS [38] and MESSIDOR [39] databases having colour and pathological artefacts variability. The DRIVE database contains 40 colour fundus images including 7 pathological images. The images are captured using 8 bits per colour plane at $564 \times 584$ pixels and $45^\circ$ FOV (field of view). The DIARETDB1 dataset consists of 89 colour
images with 84 of them containing at least one indication of lesion. The images are captured with a digital fundus camera at 50° FOV and had a size of 1500 × 1152 pixels. DRISHTI-GS consists of a total of 101 images out of which 70 images have signs of glaucoma. The images are taken with 30° FOV and of dimensions 2986 × 1944 pixels. MESSIDOR database [39] comprises of 1200 retinal images captured using 8 bits per colour plane at different resolutions of 1440 × 960, 2240 × 1488 or 2304 × 1536 pixels.

For quantitative performance evaluation of the proposed algorithm, the following performance measures are taken into consideration. The mean absolute distance (MAD) between the detected OD boundary $I_D$ and the groundtruth $I_G$ is defined as

$$\text{MAD}(D, G) = \frac{1}{2} \left( \frac{1}{n} \sum_{i=1}^{n} d(d_i, G) + \frac{1}{m} \sum_{j=1}^{m} d(g_j, D) \right)$$  \hspace{1cm} (9)

where $D$ and $G$ are represented as the sets of contour points, i.e. $D = \{d_1, d_2, \ldots, d_n\}$ and $G = \{g_1, g_2, \ldots, g_m\}$ in $I_D$ and $I_G$, respectively. Furthermore, $d(d_i, G)$ is the distance of point $d_i$ to its closest point in $G$.

The other parameters such as overlapping ratio (OR), dice coefficient (DC), sensitivity (SN), specificity (SP) and precision (PR) values are derived from true positive (TP), false positive (FP), true negative (TN) and false negative (FN) rates as follows:

$$\text{OR} = \frac{\text{area}(G_R \cap D_R)}{\text{area}(G_R \cup D_R)} \hspace{1cm} (10)$$

$$\text{DC} = \frac{2 \times (G_R \cap D_R)}{G_R \cup D_R + G_R \cap D_R} \hspace{1cm} (11)$$

$$\text{SN} = \frac{TP}{TP + FN} \hspace{1cm} (12)$$

$$\text{SP} = \frac{TN}{TN + FP} \hspace{1cm} (13)$$

$$\text{PR} = \frac{TP}{TP + FP} \hspace{1cm} (14)$$

where $G_R$ and $D_R$ correspond to the groundtruth and segmented OD regions, respectively.

The performance of the CTCRW algorithm for OD segmentation is first compared with the classical RW [29] and its recent variations applied on medical images [30, 31]. In order to make an unbiased performance comparison, the preprocessing and seed initialisation process are kept identical for each method. In [30], the distance transform of the fitted circle to the initial contour is used in the weighting function to incorporate the circular shape information of the left ventricle during segmentation. An extra penalty term is utilised in the weighting function of [31] which penalises the dispersion of Gaussian-filtered intensities. The segmentation algorithms in [30, 31] are referred as RWDT (RW with distance transform) and RWP (RW with penalty function) here.

The visual comparison of all these methods is shown in Fig. 7 and the quantitative parameters are given in Table 1. From Fig. 7 and Table 1, it is observed that the proposed algorithm achieves better segmentation performance in terms of MAD (1.46) and OR (0.93) values. This indicates better detection accuracy with an improved match between the groundtruth and proposed segmented outputs. The proposed CTCRW algorithm achieves an improved performance as it incorporates mean curvature and Gabor texture energy features to compute the edge weights. Few more segmentation results are shown in Fig. 8.

### Table 1: Quantitative parameters

| Method          | MAD  | OR  | DC  |
|-----------------|------|-----|-----|
| classical RW    | 4.51 | 0.92| 0.96|
| RWDT [30]       | 5.75 | 0.75| 0.86|
| RWP [31]        | 6.33 | 0.73| 0.84|
| proposed CTCRW | 1.46 | 0.93| 0.96|

![Fig. 7 Detected OD boundary](image)

**Fig. 8 OD segmentation results**

(a–d) First column: colour fundus images and second column: overlapped OD boundaries (black: groundtruth, red: detected contour)
4. Discussion: The proposed CTCRW algorithm for OD segmentation incorporates mean curvature, Gabor texture energy features with multiple orientations in the RW weight formulation. Both curvature and texture features of OD are different than the pathological structures like myelinated nerve fibre and peripapillary atrophy. In addition to that, the intensity adjustment around the OD centre in the preprocessing step and careful selection of $K$ number of foreground and background seeds add robustness to the proposed method.

The quantitative evaluation parameters computed on complete DRIVE, DRISHTI-GS, DIARETDB1 and MESSIDOR databases are provided in Tables 2–5, respectively. The proposed CTCRW algorithm has MAD values 4.63, 13.03, 7.3 and 2.95 in DRIVE, DRISHTI-GS, DIARETDB1 and MESSIDOR, respectively, which is better than that of classical RW, RWDT and RWP. It signifies that the detected OD contour is nearer to the groundtruth as compared to other methods. It is also observed from Tables 2–5 that the CTCRW algorithm achieves better OR, DC, SN values compared to other methods. It is also observed from Tables 2–5 that the CTCRW algorithm achieves better performance than Roychowdhury et al. [31], 12.59 0.7367 0.8347 0.9166 0.9765 0.8105.

Furthermore, Table 6 shows the performance comparisons between the proposed CTCRW approach and state-of-the-art OD segmentation methods. The original results are obtained from the respective papers for this comparison. The proposed CTCRW algorithm achieves OR value of 0.8467 in DRIVE and 0.8841 in DRISHTI-GS database. The RWDT depends on the circularity criteria; therefore does not perform accurate segmentation where OD is not circular. In RWP, Gaussian filter kernel is used to reduce the responsiveness of the variation of intensities. However, it is unable to detect the correct OD boundary in the presence of peripapillary atrophy around OD. In such challenging scenario, the final OD contours by RWDT and RWP segmentation moves away from the groundtruth.

### Table 2 OD segmentation performance in DRIVE database

| Method | MAD | OR  | DC  | PR  | SP  | SN  |
|--------|-----|-----|-----|-----|-----|-----|
| classical RW [29] | 9.89 | 0.8063 | 0.8927 | 0.8964 | 0.9985 | 0.8871 |
| RWDT [30] | 18.47 | 0.5901 | 0.7101 | 0.6136 | 0.9600 | 0.9706 |
| RWP [31] | 12.06 | 0.6118 | 0.7446 | 0.7207 | 0.9884 | 0.8560 |
| proposed CTCRW | 4.63 | 0.8467 | 0.9070 | 0.9257 | 0.9983 | 0.9167 |

### Table 3 OD segmentation performance in DRISHTI-GS database

| Method | MAD | OR  | DC  | PR  | SP  | SN  |
|--------|-----|-----|-----|-----|-----|-----|
| classical RW [29] | 15.05 | 0.8583 | 0.9222 | 0.9472 | 0.9983 | 0.9041 |
| RWDT [30] | 17.40 | 0.7477 | 0.8535 | 0.9751 | 0.9993 | 0.7658 |
| RWP [31] | 18.09 | 0.7370 | 0.8421 | 0.9668 | 0.9989 | 0.7633 |
| proposed CTCRW | 13.03 | 0.9040 | 0.9496 | 0.9441 | 0.9966 | 0.9552 |

### Table 4 OD segmentation performance in DIARETDB1 database

| Method | MAD | OR  | DC  | PR  | SP  | SN  |
|--------|-----|-----|-----|-----|-----|-----|
| classical RW [29] | 10.08 | 0.8206 | 0.8891 | 0.9029 | 0.9764 | 0.9116 |
| RWDT [30] | 11.07 | 0.7344 | 0.8362 | 0.9540 | 0.9910 | 0.7737 |
| RWP [31] | 12.59 | 0.7367 | 0.8347 | 0.9166 | 0.9765 | 0.8105 |
| proposed CTCRW | 7.30 | 0.8841 | 0.9385 | 0.9574 | 0.9980 | 0.9203 |

### Table 5 OD segmentation performance in MESSIDOR database

| Method | MAD | OR  | DC  | PR  | SP  | SN  |
|--------|-----|-----|-----|-----|-----|-----|
| classical RW [29] | 5.88 | 0.7056 | 0.8161 | 0.9091 | 0.9987 | 0.7888 |
| RWDT [30] | 7.37 | 0.6511 | 0.7822 | 0.9876 | 0.9999 | 0.6580 |
| RWP [31] | 10.42 | 0.6388 | 0.7575 | 0.7783 | 0.9843 | 0.8434 |
| proposed CTCRW | 2.95 | 0.8588 | 0.9218 | 0.9360 | 0.9994 | 0.9168 |

### Table 6 Performance comparison of the proposed OD segmentation with state-of-the-art methods

| Methods | Approach | Database (number of images) | Performance measures |
|---------|----------|-----------------------------|----------------------|
| Aquino et al. [20] | model-based method | MESSIDOR (1200) | MAD | OR  | DC  | PR  | SP  | SN  |
| Roychowdhury et al. [24] | convex hull at best OD candidate ellipse fitting | DRIVE (40) | 5.01 | 0.8067 | 0.8780 |
| | | DIARETDB0 (130) | 4.91 | 0.7761 | 0.8660 |
| | | DIARETDB1 (89) | 4.82 | 0.8022 | 0.8815 |
| | | STARE (81) | 9.13 | 0.7286 | 0.8380 |
| | | MESSIDOR (1200) | 3.93 | 0.8373 | 0.9043 |
| Joshi et al. [4] | active contour with intensity and texture feature | DRISHTI-GS (101) | 11.1 | — | — |
| Mittappali and Kande [6] | active contour using different image channels | local database (59) | 10.11 | — | — |
| Dai et al. [28] | shape energy constrained curve evolution | DRIONS (110) | 2.42 | 0.9081 |
| Welser et al. [40] | adaptive morphological approach | MESSIDOR (1200) | 2.25 | 0.9100 |
| Salazar-Gonzalez et al. [41] | Markov random field with compensation factor | DRIVE (40) | 5.74 | 0.4147 |
| Diaz-Pernil et al. [42] | implementation using parallel architecture | DIARETDB1 (89) | 8.31 | 0.4365 |
| | | DRIVE (40) | 3.39 | 0.8240 | 0.9819 |
| | | DIARETDB1 (89) | 6.55 | 0.7850 | 0.8750 |
| | | MESSIDOR (1200) | 8.43 | 0.8400 |
| Muramatsu et al. [43] | fuzzy C-mean, active contour and artificial neural network | local test set 1 (98) | 0.8820 |
| | | local test set 2 (30) | 0.8710 |
| proposed method | CTCRW | DRIVE (40) | 4.63 | 0.8467 | 0.9167 |
| | | DRISHTI-GS (101) | 13.03 | 0.9040 | 0.9552 |
| | | DIARETDB1 (89) | 7.30 | 0.8841 | 0.9203 |
| | | MESSIDOR (1200) | 2.95 | 0.8588 | 0.9168 |
et al. [24] in terms of MAD, OR and SN values, whereas Dai et al. [28] report slightly higher performance in terms of MAD and OR. The proposed CTCRW algorithm segments the OD more accurately. However, accurate OD centre detection is an additional requirement for successful execution of the proposed segmentation algorithm.

The computation of the probabilities of random walkers first reaching a seed point starting from each pixel is computationally complex. However, it has been established that the minimisation of combinatorial Dirichlet problem makes the RW algorithm simple, convenient and computationally efficient. The proposed CTCRW method is implemented in MATLAB environment on an Intel desktop processor (core i7 CPU, 3-40 GHz). The average computational time per each image for CTCRW is 19.44 s, which is marginally higher than the time of 16.30 s by the classical RW algorithm. In contrast, the processing time of 18.59 and 21.71 s is required for RWDT and RWP-based OD segmentation, respectively. The proposed algorithm has achieved better performance at the cost of few more seconds to compute mean curvature and Gabor texture energy features.

The optimal parameter ($\beta_1$, $\beta_2$, and $\beta_3$) selection in proposed RW is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results. The values is an important task. The parameters are experimentally chosen to optimise the performance of the segmentation results. The values of the free parameters $\beta_1$, $\beta_2$, and $\beta_3$ are chosen as 90, 250 and 90, respectively. To show the parameter SN on result accuracy, Varying $a$ optimise the performance of the segmentation results.

5. Conclusion: Glaucoma is an irreversible optic neuropathy, which leads to blindness if remains untreated. Early detection and diagnosis of glaucoma can only prevent further vision loss. Monitoring the shape changes in the OD is crucial for indicating the progression of glaucoma. This letter contributes an efficient and fully automated system for the glaucoma using Gabor transformation and correntropy features. Knowledge-based System, 2012, 33, pp. 73–82.

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6. Funding and declaration of interests: This work was not funded by any organisation. The authors of this Letter do not have any conflict of interest with any other people or organisations that could inappropriately influence their work.

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