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Analysis of Random Walker Algorithm for Iris Image Segmentation

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Abstract: The copiousness and stability of the iris texture make it a healthy and strong biometric trait for unique identification and authentication. The pursuance of an automated iris recognition system is affected by the precision of the segmentation process used to localize the iris structure. Most segmentation models(Edge detection algorithms) in the literature assume that the pupillary, limbic, and eyelid boundaries are circular or elliptical in shape. In this paper we have proposed the idea of introducing Random Walker algorithm, a novel method for performing multilabel, interactive image segmentation in Iris recognition to extract the iris from the surrounding structures. The proposed scheme draws out the iris texture in an iterative fashion and is guided by both local and global properties of the image. The matching accuracy of an iris recognition system is found to improve upon application of the proposed segmentation algorithm. Also a comparative study of different edge detection algorithms is performed along with the introduction of Random Walker algorithm. It is observed that Random Walker is best suited to for Iris segmentation as it establishes the exact inner and outer boundaries surpassing the drawback of consideration of circular shape of the pupil in Iris localization proved through pictorial results. The results obtained are promising and are comparable to the optimal results produced by other edge detection algorithms in literature. The proposed method is studied using PEC database, a benchmarked dataset.

Keywords: *Iris recognition, Iris Segmentation, Interactive Segmentation.*

1. INTRODUCTION

Image Processing is a series of processes viz Image acquisition followed by Image segmentation, Normalization and finally Feature extraction and encoding to uniquely make the resultant image suitable for specific application. In Iris recognition System, the image acquisition is the process to capture a pair of iris images from the subject using a specifically designed sensor. One of the major hurdles for practical applications is getting iris images, of extremely fair quality. As the iris is very small (diameter about 1 cm), it shows numerous and variable texture features under near infrared lighting. The lighting, positioning, and the physical capture of the system are the three main aspects one should consider when designing an image acquisition environment. Usually sequence of images is obtained rather than a single image, while capturing the eye image. Image Segmentation, a significant stage in Iris segmentation is to locate the valid part of the iris for iris biometrics [1], including finding the pupillary and limbic boundaries of the iris, localizing its upper and lower eyelids if they throttle and detecting superimposed occlusions of eyelashes, shadows or reflections.

Iris recognition system consists of several stages which includes Image acquisition as a part of pre-processing followed by segmentation stage which is the most serious and critical one. The goal of

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segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Image segmentation is defined as the process of localizing regions of an image relative to content. In other words its also the process of automatically detecting the pupillary and limbus boundaries of an irisSegmentation partitions an image into distinct regions each pixels with similar attributes. To be meaningful and useful for image analysis and interpretation, the regions should strongly relate to depicted objects or features of interest. The success of image analysis depends on reliability of segmentation, but an accurate partitioning of an image is generally a very challenging problem. However, recent image segmentation approaches have provided interactive methods that implicitly define the segmentation problem relative to a particular task of content localization. This approach to image segmentation requires user guidance of the segmentation algorithm to define the desired content to be extracted.

A realistic interactive segmentation algorithm must provide four qualities:

- Speedy computation,
- Quick editing,
- arbitrary segmentation with suitable interaction,
- Intuitive segmentations.

The random walker algorithm introduced here exhibits all of these mentioned qualities. The random walker algorithm requires the solution of a sparse, symmetric positive-definite system of linear equations which are solved quickly through a variety of methods. The algorithm may perform quick editing by using the preceding solution as the initialization of an iterative matrix solver. An arbitrary segmentation may also be achieved through enough user interaction. The term segmentation in this context is termed to be the neutral segmentation since the image is neutral (i.e., devoid of meaningful content) or highlighting the region of interest.

The remainder of the paper is organized as follows. The works related to the Segmentation algorithms are described in Section II. Section III provides an overview of the proposed idea of the introduction of the segmentation technique i.e Random Walker for Iris recognition. Comparative study of segmentation algorithms along with the matching performance in accordance with the pictorial results due to this novel scheme is reported in Section IV. Section V details the algorithmic results separately.Section VIpresentsconcludes the paper.

2. RELATED WORK

The main aim of the process of Iris segmentation is to segment the iris region from the rest of the image of eyes. There are different approaches in iris image segmentation process such as Daugman Integro Differential Operator [2]. Daugman presented the first approach to computational iris recognition, including iris localization. An integro differential operator is proposed for locating the inner and outer boundaries of an iris. Widles et al. [3] proposed an iris recognition system in which iris localization is completed by detecting edges in iris images followed by use of a circular Hough transform to localize iris boundariesand Active Contours Model [4]. Camus and Wildes (2004) described an algorithm for segmenting iris in a closed image. But when dealing with noisy data, the algorithm’s accuracy deteriorates significantly [5]. The intelligent scissors algorithm [6] treats the image as a graph where each pixel is associated with a node and a connectivity structure is imposed. This technique requires the user to place points along the boundary of the desired object to segment the regions of interest. The graph cuts [7], [8] technique has been developed as a method for interactive, seeded, segmentation. As with intelligent scissors, graph cuts views the image as a graph, weighted to reflect intensity changes.

A Hough transform-based method is used to segment the iris. Also, the upper and lower boundaries of the eyelid are approximated using parabolic curves. Matching is done using the normalized correlation between the test and training images. Masak and Kovesi proposed their segmentation technique based on Edge detection and hough transform where ID-Log Gabor filters is the encoding technique employed and hamming distance was calculated in the algorithm. Hamming distance is then used as a measure to determine the proximity of two iris codes. Adding to Edge detection and hough transform segmentation techniques Ma et al.[9], Lim et al. [10] proposed segmentation algorithms based on different encoding techniques namely Circular symmetric Gabor filters and 2-D Haar Wavelet Transforms respectively.

3. IRIS SEGEMENTATION USING RANDOM WALKER ALGORITHM

Updating segmentation results in real-time based on repeated user input is a reliable way to guarantee accuracy, paramount in medical imaging applications, while making efficient use of an expert's time. The random walker algorithm with priors is a robust method able to find a globally optimal probabilistic segmentation with an intuitive method for user input.

In our approach, we consider an image as a pure distinct object, a graph with a fixed number of vertices and edges. Each edge is assigned a real-valued weight corresponding to the likelihood that a random walker will cross that edge (e.g., a weight of zero means that the walker may not move along that edge). The advantage of formulating the problem on a graph is that purely conjunctional operators may be used that incur no discretization errors or ambiguities. Ignoring of the dimensions of the data, we will use the term pixel throughout this paper to refer to the basic picture element in the context of its intensity values. In contrast, the term node will be used in the context of a graph in the discussion.

Fortunately, it has been already established [11], [12] that the probability a random walker first reaches a seed point exactly equals the solution to the Dirichlet problem [13] with boundary conditions at the locations of the seed points and the seed point in question fixed to unity while the others are set to zero[14]. The development of a fully discrete calculus [15] has allowed for the connection between random walks on graphs [16] and discrete potential theory [17] to be made completely explicit [12].

The solution to the combinatorial Dirichlet problem on an arbitrary graph is given exactly by the distribution of electric potentials on the nodes of an electrical circuit with resistors representing the inverse of the weights (i.e., the weights represent conductance) and the "boundary conditions" given by voltage sources fixing the electric potential at the "boundary nodes".

The random walker is a semi-supervised segmentation algorithm, because it needs the user to mark seed regions. These are in the form of random marks in regions that the user wants to belong to different segments. Once it has that information, the algorithm labels every unlabelled pixel. For every unlabelled pixel xx (Highest probability)it initializes a random walker that is free to go anywhere in the image (constrained by the 4-connected pixel grid). Probabilities are calculated for the random walker first touching each seed region.

The random walker needs to be influenced by the underlying image, otherwise the segmentation would be the same for all images provided they have the same seed. So they add a cost for walking from one pixel to another which is

$$w_{ij} = \exp\left(-\beta\left(g_i - g_j\right)^2\right)$$

where β is a free parameter. The trick of the algorithm lies in finding an efficient way to solve this large problem, because initializing a random walker for each unlabelled pixel and letting it walk freely till it reaches a seed is computationally prohibitive. They formulate this as solving a Dirichlet problem. In their formulation this ultimately boils down to solving a large linear system of equations.

Algorithm can be viewed in three aspects:

1. Generating the graph weights
2. Establishing the system of equations to solve the problem
3. Practical details of implementation

Generating Edge weights:

In order to represent the image structure by the random walkers basis we should define a function that maps the change in image intensities to edge weights. It also uses a function that maximizes the entropy resulting weights. The function that we used to satisfy the above need is Typical Gaussian Weighting function, It is given as

$$w_{ij} = \exp\left(-\beta\left(g_i - g_j\right)^2\right) \tag{1}$$

Calculation of Probabilities and System of Equations:

The Dirichlet integral may be defined as;

$$D[u] = \frac{1}{2}\int_{\Omega} |\nabla_u|^2 \, d\Omega \tag{2}$$

A harmonic function is one that satisfies the Laplace equation. It is represented as;

$$\nabla^2 u = 0 \tag{3}$$

The problem of finding a harmonic function subject to its boundary values is called the Dirichlet problem. The harmonic function that satisfies the boundary conditions minimizes the Dirichlet integral, since the Laplace equation is the Euler-Lagrange equation for the Dirichlet integral.

The combinatorial Dirichlet problem has the same solution as the desired random walker probabilities. Denote the probabilities assumed at the node v_i, for each label, s, by x_i^s. Define the set of labels for the seed points as a function $q(v_j) = s$, for sllv_j belongs to Vm, $0 < s \Leftarrow K$. Define the $|Vm| \times 1$ vector for each label, s, at node v_j belongs to Vm as

$$m_j^s = 1 \text{ if } Q(vj) = s \tag{4}$$

$$m_j^s = 0 \text{ if } Q(vj) \; ! = s \tag{5}$$

Therefore, for label s, the solution to the combinatorial Dirichlet problem may be found by solving

$$L_U x^S = -B^T m^S \tag{6}$$

for one label or

$$L_U x^S = -B^T M \tag{7}$$

for all labels, where X has K columns taken by each xs and M has columns given by each ms. Since the probabilities at any node will sum to unity, i.e.,

$$\sum_s x_i^s = 1, \forall v_i \in V, \tag{8}$$

only $K - 1$ sparse linear systems must be solved, where K is the total number of labels.

Practical Implementation:

1. Map the image intensities to edge weights in the Lattice.
2. Obtain a set, *Vm*, of marked pixels with K Labels, either interactively or automatically.
3. Solve Each label for probabilities for computational efficiency.
4. Obtain a final segmentation by assigning to each node, $v_{i,}$ the label corresponding to $\max_s(x_i^s)$.

Algorithm Random Walk

1. Using (1), map the image intensities to edge weights in the lattice.
2. Obtain a set, VM, of marked (labelled) pixels with K labels, either interactively or automatically.
3. Solve (7) outright for the potentials or solve (6) for each label except the final one, f (for computational efficiency).
4. Set $xf\ i = 1 - Ps < f\ xs\ i$.
5. Obtain a final segmentation by assigning to each node, *vi*, the label corresponding to maxs (*xs i*).

4. COMPARITIVE STUDY OF SEGMENTATION ALGORITHMS

A comparative study of all the edge detection algorithms have been done and the algorithmic results are shown in below figure 1.Segmentation results obtained through random walker has established that the iris segmentation accuracy was increased when the rough pupil centre was identified using this segmentation algorithm.

In addition, the comparison results shown pictorially revealed that the random walker algorithm used to segment iris outperformed on some state-of-the-art iris segmentation methods considering segmentation accuracy as the parameter.

During comparative study, the algorithm was observed to be the efficient in its recognition performance than those of segmentation algorithms already present in the literature. Also the recognition performance results showed that the random walker algorithm used for iris segmentation method attained the higher discriminating capabilities.

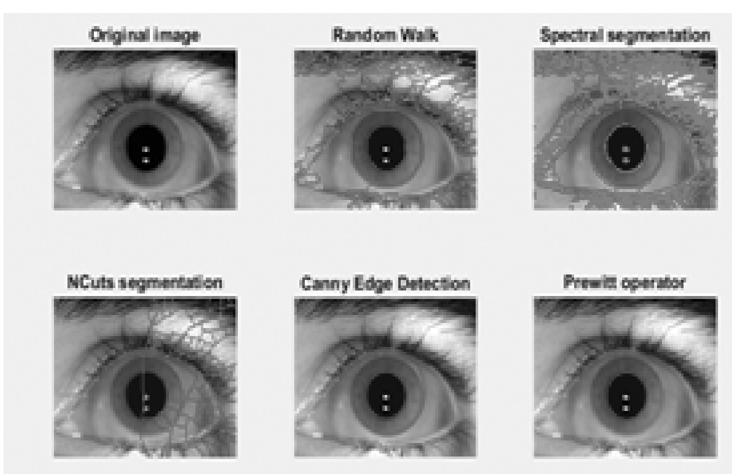

Figure 1: Results of comparative study of different segmentation algorithms

Table 1
Performances of various segmentation algorithms

Segmentation Technique	*Status of Recognition*
Prewitt Operator	Not recognized
NCuts Segmentation	Not recognised
Spectral Segmentation	Recognized but over segmentation
Canny Edge Detection	Recognized but isn't appropriate
Random Walker	Recognized clearly

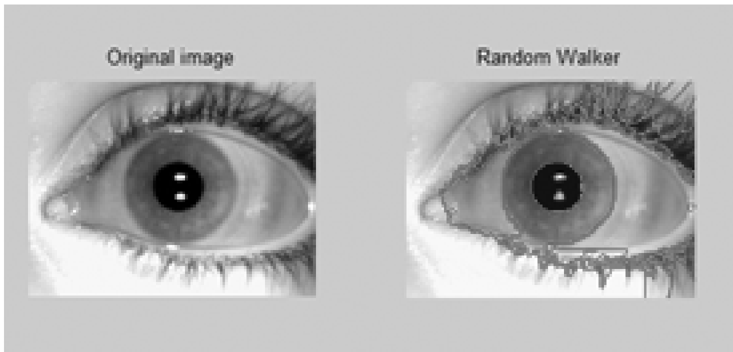

Figure 2:Original image and Resultant image after segmentation using Random Walker.

Figure 2 shows the segmentation results on an iris image. Grayscale images were only considered to experiment for ease of projecting clarity in publication. But colour images could be easily handled by modifying the aspect to reflect colour changes in the place of intensity changes. In each segmentation, the value of the one free parameter, â in (1), was kept constant, despite the different characteristics of the images.

The figure 2 also shows the results of applying the segmentation algorithm to an iris image. The result after the application of this algorithm is that the segmentation results are generally stable to perturbations of the seed locations.

5. CONCLUSION

A new-fangled algorithm based on a small set of pre-labelled pixels for image segmentationhas been experimented in this paper. The pre-labelled pixels mentioned in the algorithm may be generated automaticallyor either given interactively or for a specific purpose. The functioning of the algorithm is carried in a way by accrediting each unseeded pixel to the label of the seed point. The seed point to which assignment must be done is established from the fact that a random walker initiating from that pixel would be most likely to reach first, given that it is tendentious to avoid crossing object boundaries (i.e., intensity gradients). The Random walker is devised on a general graph and the image segmentation is achieved on the basis of separation of quantities which are defined specifically at the nodes (say potentials) and no restriction is adopted on the dimension or the topology of the graph. In this paper we have demonstrated this approach on real iris images and inferred that it provides a quality, unique solutions of iris segmentation that is robust.

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