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Iris localization using rough entropy and CSA: A soft computing approach

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ABSTRACT

Identification of a person depends on the proper extraction of the iris region. Segmentation, being the first step in iris analysis, constitutes the most important phase in iris localization. Images are often captured in non-ideal conditions, and are incomplete with different kinds of associated uncertainties. Therefore, iris segmentation assumes paramount importance towards its subsequent localization and analysis. A novel soft-computing approach is proposed for the segmentation of iris based on rough entropy, with localization using circular sector analysis (CSA); thereby minimizing uncertainties.

We compare the performance of this algorithm with that by the circular Hough transform, which is state-of-the-art in approximating the iris region although being computationally intensive. The proposed rough entropy based segmentation, followed by CSA for localization of iris, is found to perform more efficiently and accurately in comparison to the state-of-the-art methodologies.

1. Introduction

Biometry [1–4] is the science of establishing human identity based on behavioral or physical characteristics, such as fingerprints, face, iris, voice, gait, etc. Biometric approaches are found to be more reliable than traditional token-based systems (ATM card, credit card, identity card, etc.) or knowledge-based system (password) for identifying individuals. In this context, unlike other measures, the richness and stability of the iris texture makes it a robust biometric trait. The iris is unique to individuals, with even identical twins having different iris patterns, and it remains stable over the life time of individuals [5,6]. Iris recognition system involves modules for iris localization or segmentation, normalization, feature extraction, representation and matching. Localization of iris implies detecting the pupillary and limbic boundaries, with the former differentiating between the pupil and iris regions and the latter distinguishing between the sclera and iris regions. The localization of iris is considered to be an important step in iris recognition, as any inaccuracy can adversely affect its performance caused by inaccurate feature encoding. Image segmentation [7,8] is an essential constituent in a recognition system as it influences the performance of the system through misclassification during authentication.

The integro-differential operator (IDO), widely used in commercial applications, was designed by Daugman [9,5] to find both the boundaries of an iris. It searches over the image with varying radius and center to find circular boundaries across which pixel intensity change is maximum. Pupillary boundary was extracted using multi-valued adaptive threshold [10], while iris boundary was localized by IDO operator by combining Fourier series and radial gradients. In Ref. [11] the contrast of the image was enhanced, followed by thresholding and filling of seeds to isolate the pupil region.

Circular Hough Transform (CHT) was employed on binary images to localize the iris [6]. A fast implementation of CHT is provided in Ref. [12]. Bilinear interpolation and 4-connectivity was employed [13] to fill holes in the image, with the iris boundary being localized by hybrid CHT and image statistics while bi-valued adaptive thresholding enabled pupillary boundary localization. However, these methods and their extensions [14,15] achieved encouraging results in case of ideal iris images captured in controlled environments. In real life, on the other hand, images come from unconstrained environments which can affect their quality. Therefore, segmentation becomes challenging for non-ideal iris images.

A graph-cut framework was used [16] to classify pixels according to their texture and intensity in a non-ideal scenario. Geodesic active contour was also used [17] for the purpose. However, in the

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absence of edge information, the evolving contour became susceptible to getting stuck in local minima. Segmentation involving anisotropic diffusion and morphological operations was designed [18] to detect iris boundaries. Preprocessing by *k*-means clustering to initially estimate the iris region [19] helped reduce the search time of CHT. But CHT based approaches require prior knowledge about approximate ranges of the radii of boundaries. Adaboost-cascade iris detector was employed for estimating iris center and establish a "pulling and pushing" elastic model for segmentation [20]. A variational level set based curve evolution method was developed for iris segmentation [21], with adaptive 2D-Wiener filter being applied to reduce the effect of noise. Identification of the feature set which is less dependent on noise, followed by fuzzy clustering of the position and intensity features, was adopted [22] for segmenting iris images. Hidden Markov Chain (HMC), snail scan and neural network were combined [23] to design an unsupervised iris segmentation model. Histogram of Oriented Gradients with Support Vector Machine (HOG-SVM) was used to localize iris [24], with Grow-Cut segmentation for extracting iris region. Optical correlation based active contour segmentation was developed [25] to detect initial contours for both iris and pupil. Most of the existing iris segmentation approaches encompass complex modules to locate boundaries, thereby resulting in heavy computational burden. Some also require prior domain knowledge for computation [6,14,15]. In this scenario a simple segmentation approach, involving lower computational overhead, is introduced.

Rough sets [26] provide a way of handling uncertainty and incompleteness. They offer an effective strategy to segment images under real life, non-ideal conditions, using the concept of rough entropy [27]. In gray scale images boundaries between object regions are often ill-defined because of spatial ambiguities. This uncertainty can be handled by describing objects as rough sets. This concept promises effective modeling of non-ideal iris images. In the present study, a novel approach is proposed for the fast and accurate segmentation of pupil using rough entropy. A new circular sector analysis helps estimate the circle around the iris. It is found to be as good as CHT (which is supposed to be the most accurate method for iris localization [9]) and even better in some cases. Effectiveness of the model is established on standard data sets available for testing [28–30].

Various steps in the process of iris recognition involve different levels of difficulty. The first step in this process is imaging. The present study focuses on images from non-cooperative environments, where acquiring perfect images is always difficult. Here the first problem concerns the quality of the image, while the other refers to the occlusion of the iris with eyelids. In order to localize the iris, in this scenario, the concept of rough entropy is applied to segment the pupil area by minimizing the gray level and spatial ambiguity. This is followed by necessary post-processing to eliminate the artefacts. A new circular sector analysis (CSA) approach is proposed to meaningfully estimate the iris region with only a partial unoccluded (visible) area. It has been demonstrated that the proposed method is computationally efficient with accurate localization, as compared to state-of-the-art methods in literature.

The rest of the article is organized as follows. Section 2 provides a brief description of rough entropy. Section 3 introduces the proposed method for detection of pupil and iris, using rough entropy and circular sector analysis (CSA). Experimental details, results, and discussion, are presented in Section 4. Finally Section 5 concludes the article.

2. Rough segmentation

Rough set theory was proposed by Pawlak in 1991 [26]. A rough set is an approximation of a crisp set in terms of its lower and upper approximations. Let $S = \langle U, A \rangle$ be an information system. Let $Z \subseteq U$ be a set, which can be approximated using the attributes contained in $C \subseteq A$. The lower and upper approximations are defined as $C\underline{Z} = \{y \in U : [y]_C \subseteq Z\}$ and $C\bar{Z} = \{y \in U : [y]_C \cap Z \neq \phi\}$, where $[y]_C$ indicates the equivalence class of the object $y \in U$ relative to equivalence relation. Roughness of a set Z can be defined as

$$R_\alpha = 1 - \frac{|C\underline{Z}|}{|C\bar{Z}|}, \text{ where } 0 \le R_\alpha \le 1. \tag{1}$$

Pal et al. [27] proposed an application of rough sets in image segmentation. It is often observed that in gray scale images, object boundaries are not well-defined due to low contrast. In such cases segmentation becomes very difficult. To circumvent this issue they considered an object as a rough set with upper and lower approximations.

Let the image I of size $M \times N$ and level L be considered as the universe U, and be partitioned into non-overlapping windows of size $m \times n$. Each window represents a granule G. Let gray level intervals 0 to T and $T+1$ to $L-1$ be two properties characterizing the background and object, respectively (here object is in the brighter part). Hence the object and background can be considered as two rough sets, and represented as follows.

The lower and upper approximations of the object are expressed as

$$\begin{aligned} \underline{O}_T &= \left\{ \bigcup_i G_i | P_j > T, \forall j = 1, \ldots, mn \text{ and } P_j \text{ is a pixel belonging to } G_i \right\}, \\ \bar{O}_T &= \left\{ \bigcup_i G_i, \exists j, j = 1, \ldots, mn \mid P_j > T, \text{ where } P_j \text{ is a pixel in } G_i \right\}. \end{aligned} \tag{2}$$

The lower and upper approximations of the background are given by

$$\begin{aligned} \underline{B}_T &= \left\{ \bigcup_i G_i | P_j \le T, \forall j = 1, \ldots, mn \text{ and pixel } P_j \text{ belongs to } G_i \right\}, \\ \bar{B}_T &= \left\{ \bigcup_i G_i, \exists j, j = 1, \ldots, mn \mid P_j \le T, \text{ where pixel } P_j \text{ is in } G_i \right\}. \end{aligned} \tag{3}$$

Therefore, the roughness of object O_T and background B_T are defined as

$$R_{O_T} = 1 - \frac{|\underline{O}_T|}{|\bar{O}_T|} \quad \text{and} \quad R_{B_T} = 1 - \frac{|\underline{B}_T|}{|\bar{B}_T|}, \tag{4}$$

where $|\underline{O}_T|$, $|\bar{O}_T|$, $|\underline{B}_T|$ and $|\bar{B}_T|$ denote the cardinalities of sets $\underline{O}_T$, $\bar{O}_T$, $\underline{B}_T$, $\bar{B}_T$, respectively.

The uncertainty which arises from the ill-defined object-background boundary can be quantified in terms of an entropy measure, called rough entropy (RE_T). Therefore, for a given granule size, the roughness of the object and background can be minimized as much as possible by maximizing the rough entropy. Hence, the threshold (T^*) for object background separation is obtained from the maximum RE_T. We have [27]

$$RE_T = -e/2[R_{O_T}\log_e(R_{O_T}) + R_{B_T}\log_e(R_{B_T})] \tag{5}$$

and

$$T^* = \underset{T}{\operatorname{argmax}} RE_T, \tag{6}$$

to segment the region of interest (ROI).