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Artificial bees for multilevel thresholding of iris images

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ABSTRACT

In this paper, a multilevel thresholding based on Artificial Bee Colony metaheuristic is proposed as a pre-segmentation step in the iris detection process. Multilevel thresholding helps in the unification of the iris region and the attenuation of the noise outside and inside the iris region that mainly affects the process of iris segmentation. Since it depends on exhaustive search, multilevel thresholding is time consuming especially if the number of thresholds is not restricted, though it yields convenient results. Two variants of Artificial Bee Colony (ABC) metaheuristic, namely, the basic ABC and the G-best guided ABC in addition to Cuckoo Search (CS) and Particle Swarm Optimisation (PSO) metaheuristics are then used to look for the best thresholds distribution delimiting the components of the iris image for improving the iris detection results. To test our approach, we have opted for the Integro-differential Operator of Daughman and the Masek method for the principal segmentation process on both the standard databases CASIA and UBIRIS. As a result, qualitatively the segmented iris images are enhanced; numerically the iris detection rate improved and became more accurate.

1. Introduction

Iris segmentation is a crucial step in every iris recognition system. It consists of extracting the set of pixels contained in the iris but not the pupil, see Fig. 1. Many algorithms have been proposed in the literature of iris biometrics for accomplishing this task, where we find that the works of Daugman [1] and Wildes [2] are the leading ones.

In the last decades, almost every iris recognition system has exploited these two algorithms for iris segmentation step. As a preprocessing, some of these approaches use a Gaussian filter, allowing noise removal. But, on the whole, the raw input eye image is used. This makes it difficult to depict the iris region; an edge map is needed for the above-mentioned approaches, which is likely to be affected by noise.

Multilevel image thresholding as a segmentation approach has recently emerged as a powerful technique [3]. This method consists of looking for some values of intensities to be used as object delimiters. Having that in an image, pixels belonging to the same object have very near values of intensity and so belong to the same range of values in the image histogram. Thus, looking for these thresholds will allow segmenting the input image. However, the algorithmic complexity, in this approach, increases exponentially as the number of thresholds increases. This makes such an approach less adopted for image segmentation, even if it gives a segmentation of very high quality.

In this perspective, this paper proposes an iris pre-segmentation approach based on the use of a multilevel thresholding step. The latter considerably reduces the number of grey levels in the input image and delimits the iris region in the eye image so well. Being a combinatorial optimisation problem, the multilevel thresholding pre-segmentation task is accomplished by a set of metaheuristics in this work: two variants of the Artificial Bee Colony (ABC) algorithm, namely, the conventional ABC and the G-best guided ABC [4] in addition to two other metaheuristics, namely, CS and PSO for comparison ends.

Consequently, the rest of the paper will be organised as follows. Section 2 presents some basic concepts about iris segmentation, the ABC algorithm and multilevel thresholding. In Section 3, the manner of applying the conventional ABC on iris image multilevel thresholding is detailed. Section 4 presents and discusses the experimental results obtained from applying the proposed approach on some images extracted from both UBIRIS and CASIA reference iris image databases. Finally, Section 5 concludes the paper.

2. Basic concepts

2.1. Iris segmentation

Being the most critical step in any iris biometric system, iris segmentation or localisation can be defined as the isolation of the iris from the captured eye image. Specifically, it refers to the identification of the pupillary and the limbus boundaries of the iris region as

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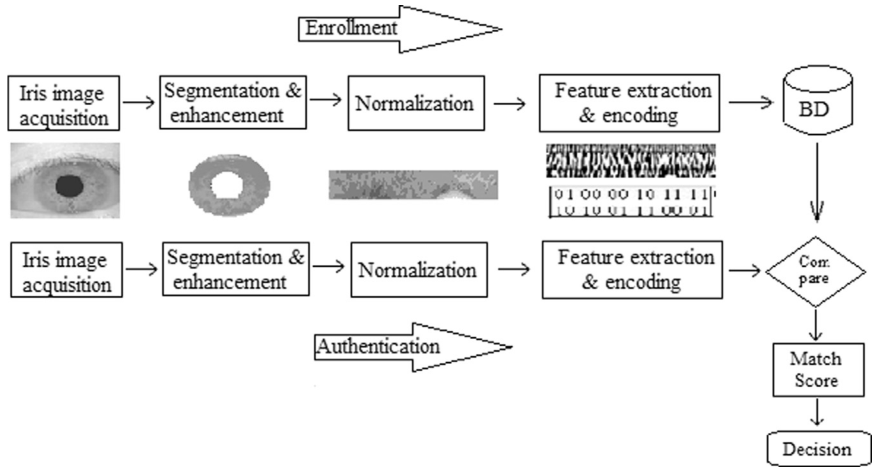

Fig. 1. Iris recognition system.

well as the eyelids and the eyelashes, possibly interrupting the limbus contours.

Many approaches have been proposed in this respect. Daugman [1] proposed the Integro-Differential Operator (IDO), which is a process that behaves as a circular edge detector that searches iteratively for approximating the iris boundaries as perfect circles. The main drawback of this approach is that it does not work properly in the presence of noise, in the case of images generated under non-ideal conditions [5,6]. In fact, this is the case of everyday biometric systems.

Another widely used segmentation algorithm is that of Wildes [2], who suggested a histogram-based model-fitting approach accomplished by the implementation of the Hough transform for iris boundaries localization. The Hough transform should be applied on an edge map of the input image generated through a gradient-based edge detector. This approach suffers from the fact that it requires large storage spaces and so costs high computation time [7].

Other methods have been proposed in the literature for approximation of the iris boundaries: either light variations of the Daugman ID Operator or a blend of Wildes' edge detection and the Hough transform [8]. More details about some of these variants can be found in [9–13].

Another interesting approach for iris image segmentation is that of Shah and Ross [14], who proposed the geodesic active contours, a model based on the relation between active contours and the computation of geodesics. The principle here is to randomly initialize a curve from within the iris. This curve is evolved under the influence of the geometric properties of the iris boundaries till a stop condition is met [14].

Recently, the authors in [15,16] proposed a new model for iris boundaries detection based on variational level sets. This approach uses partial equations to numerically solve the evolution of the curves that define the iris boundaries which are first approximated using elliptical models, and then refined using geometric active contours with variational formulation.

Although active contours are known to be very efficient with respect to segmentation quality, they suffer from the intrinsic complexity of computation. Also, the localisation of initial snakes in the model generally needs human intervention, in order to put initial snake points as close as possible to the iris edge. This is not practical in real-life biometrics, where it is highly recommended that human intervention be minimal.

In (2007), Daugman [17] suggested the use of Fourier-based approximation series for iris boundaries detection, an approximation that verifies both the completeness and the closure of the detected boundaries.

It should be pointed that the three last approaches look for determining the precise iris boundaries opposing the first two ones that search for approximating the iris with a circle or an ellipse. It is clear that the latter type offers a reduced computational complexity, while the former offers better results with regard to segmentation quality.

2.2. Artificial Bee Colony

The Artificial Bee Colony (ABC) algorithm is a swarm based meta-heuristic that was first introduced by Karaboga and Basturk in 2005 [18] for numerical optimisation. It was inspired by the intelligent foraging behaviour of natural honeybees. In a natural bee swarm, the food search is collectively performed by three kinds of honeybees: the employed bees, the onlookers and the scouts [19].

The employed bees search food around the food sources, they memorise, and they share information about the found food sources with the onlookers via the *waggle dance*. The onlookers select the good food sources and search around them to find better food sources. The scouts tend to randomly search for new food sources [4].

Inspired by this natural behaviour, the artificial version of the bee swarm behaves as follows. The population in an Artificial Bee Colony is subdivided into three sub-groups: employed bees, onlookers and scouts. The number of employed bees is equal to the number of onlookers and to that of the whole population of solutions [20]. These artificial bees fly around in a multidimensional search space and choose food sources which are possible solutions to the optimisation problem in question. The employed and onlooker bees search depends on their self-experience and that of their mates, while the scouts search is random, without any experience. The associated nectar amount to each food source corresponds to the fitness fit_i of the new associated solution.

For minimization problems, the nectar amount is calculated using the formula in Eq. (1), where f_i is the fitness value of the current solution [18,19].

$$fit_i = \begin{cases} 1/(1+f_i) & \text{if } f_i \geq 0, \\ 1+abs(f_i) & \text{if } f_i < 0 \end{cases} \quad (1)$$

The ABC algorithm follows an iterative process whereby the concerned bees move towards better solutions by means of neighbour search mechanism, abandoning poor solutions. After an initialization phase, the ABC algorithm cyclically repeats, till meeting a stop condition, three basic stages: the employed bee stage, the onlooker stage and the scout stage [19,4,20].