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An ear biometric system based on artificial bees and the scale invariant feature transform

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ABSTRACT

Ear recognition is a new biometric technology that competes with well-known biometric modalities such as fingerprint, face and iris. However, this modality suffers from common image acquisition problems, such as change in illumination, poor contrast, noise and pose variation. Using a 3D ear models reduce rotation, scale variation and translation-related problems, but they are computationally expensive. This paper presents a new architecture of ear biometrics that aims at solving the acquisition problems of 2D ear images. The proposed system uses a new ear image contrast enhancement approach based on the gray-level mapping technique, and uses an artificial bee colony (ABC) algorithm as an optimizer. This technique permits getting better-contrasted 2D ear images. In the feature extraction stage, the scale invariant feature transform (SIFT) is used. For the matching phase, the Euclidean distance is adopted. The proposed approach was tested on three reference ear image databases: IIT Delhi, USTB 1 and USTB 2, and compared with traditional ear image contrast enhancement approaches, histogram equalization (HE) and contrast limited adaptive histogram equalization (CLAHE). The obtained results show that the proposed approach outperforms traditional ear image contrast enhancement techniques, and increases the amount of detail in the ear image, and consequently improves the recognition rate.

1. Introduction

Biometric authentication allows the automatic recognition of a person based on his physiological or behavioral characteristics (Jain, Bolle, & Pankanti, 1999; 2004; 2006). Biometrics is widely used in many official and commercial identification systems, especially those involving automatic access control. Important properties of biometric systems include: accuracy, cost, and non invasive identification methods of the measured characteristics. The most common modalities used in biometrics are face, iris and fingerprint. However, these modalities suffer from some drawbacks. For instance, the face can be affected by age, health conditions and facial expressions; the iris is an intrusive modality, in addition to its high cost; and the fingerprint can be affected by some medicine, burns or ink on fingers (Fadi, Nuaimi, & Maamri, 2012).

Human ear recognition is a new biometric technology. The French criminologist Bertillon (1890) was the first to suggest that people can be identified by the shape of their outer ear. A bit later, the American police officer Iannarelli (1989) proposed the first ear recognition system based on 12 features. Iannareli experimentally found that 10,000 ears were different even in identical twins (Iannarelli, 1964). Ear biometrics has been used in many governmental systems such as forensics, security and law enforcement applications (Islam, Bennamoun, Owens, & Davies, 2012). In fact, the ear has attracted the interest of biometrics community because of the following advantages. First, it has small size which allows speeding up the recognition task and increasing its efficiency. Second, the ear has a uniform distribution of colors which ensures that pertinent information be conserved when converting it into a gray scale image (Abate, Nappi, & Riccio, 2006). Third, the ear does not need much collaboration from the user, it can even be captured without his knowledge from far distances (Prakash & Gupta, 2013). Hence, ear biometrics is a good choice because it offers a good compromise between accuracy and cost.

Ear biometrics has been used in many governmental and commercial applications, such as forensics and security. For instance, in the United States, an ear classification system based on manual measurements (Iannarelli, 1989) has been in use for more than 40 years. Also, the United States Immigration and Naturalization Service (INS) gives a specifications that indicates that the right ear should be visible. During crime scene investigation, earmarks are

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often used for identification in the absence of valid fingerprints (Chen & Bhanu, 2005; Yuan, Mu, & Xu, 2005). Moreover, ear biometrics has been widely used in the European community. We cite, for example, the project of forensic ear identification (FearID), that was initiated by nine institutes from Italy, the UK, and the Netherlands in 2006, in order to study the efficiency of ear biometrics. This researches came to the conclusion that ear prints can be used as evidence in a semi-automated systems (Pflug & Busch, 2012). Besides, the German criminal police uses ear biometrics and other appearance-based properties in order to collect evidence for the identity of suspects from surveillance camera images (Pflug & Busch, 2012).

2D models of ear biometrics still suffer from acquisition problems yet to be solved; such as change in illumination, poor contrast, noise and pose variation. A possible solution to overcome these problems is using the 3D model of ear biometrics. 3D representation of ear images can be adapted to any rotation, scale and translation. Furthermore, the depth information contained in 3D models can be used for enhancing the accuracy of ear recognition systems. Unfortunately, most 3D ear recognition systems tend to be computationally very expensive (Pflug & Busch, 2012).

To solve the acquisition problems of 2D ear images, many preprocessing approaches have been applied. Filtering approaches have proven to be efficient for image denoizing and deblurring, while contrast enhancement has generally been treated by histogram equalization-based approaches such as the histogram equalization (HE) and contrast limited adaptive histogram equalization (CLAHE) techniques. Though, these techniques are likely to increase the contrast of background noise, decrease useful signal and over-enhance the image, due to the fact that they fail in preserving minor gray levels (Wang, Chang, & Shen, 2008), which would increase noise in the image. Besides, using exhaustive approaches for histogram equalization is an algorithmically complex task.

To overcome these contrast enhancement limitations, Hashemi et al. (2010) proposed an approach that uses a genetic algorithm to look for the optimal mapping of gray levels to substitute the gray levels of the input image, in order to offer better contrast for the image, this technique is known as *'the gray-level mapping technique'*. Draa and Bouaziz (2014) proposed an approach based on the artificial bee colony algorithm to image contrast enhancement using the gray-level mapping technique. This ABC-based approach gave promising results, which motivated us to apply it for contrast enhancement of ear images as a preprocessing step of our ear biometric system.

In this paper, a new architecture for ear biometrics is proposed. In the preprocessing stage, the technique for ear image contrast enhancement based on gray-level mapping using the artificial bee colony (ABC) algorithm is used in order to present more natural 2D ear images, with higher-detail content, and so to improve the recognition rate of the system. In the feature extraction stage, the scale invariant feature transform (SIFT) is applied, to extract the most discriminant features. Finally, the Euclidean distance is used in the matching stage.

The rest of this paper is organized as follows. Basic concepts related to image enhancement, the artificial bee colony and the scale invariant feature transform are presented in Section 2. In Section 3, a review of previous works related to ear biometrics is given. Section 4 presents the proposed 2D ear recognition system. in Section 5, the experimental results obtained from applying the proposed architecture on three reference ear image databases are presented and compared to the results offered by two other systems based on classical approaches of ear images contrast enhancement. Finally, some conclusions and future directions of research are drawn up in Section 6.

2. Basic concepts

In this section, we present basic concepts related to image contrast enhancement, the artificial bee colony algorithm and the scale invariant feature transform.

2.1. Image contrast enhancement

Image enhancement aims at improving the quality of an image by increasing the contrast and removing noise and blur from it (Preethi & Rajeswari, 2010). In the literature, many techniques for improving image contrast have been proposed. The most common techniques for accomplishing this task are briefly presented in the following.

Histogram equalization (HE) is a technique for adjusting image intensities in order to enhance its contrast. It operates by dividing the image histogram into classes containing equal numbers of pixels. The transformation used in histogram equalization is non linear. For continuous images, histogram equalization is relatively simple to complete and gives good results. However; for discrete images, things become different; usually, several minor gray levels would merge into only one gray level. More importantly, the details included in minor gray levels would be lost after applying histogram equalization, although the equalization itself is supposed to make details clearer after enhancement (Wang et al., 2008). So, HE cannot adapt to local light conditions because it uses only global image histogram information over the whole image (Kim & Cha, 2009). In addition, and due to the flattering property of HE, it might produce an over-enhancement (Somasundaram & Kalavathi, 2011), resulting in an unnatural output image (Kim & Cha, 2009), it may also increase the contrast of background noise, while decreasing useful contrast.

Sometimes the overall histogram of an image may have a wide distribution while the histogram of local regions is highly skewed towards one end of the gray spectrum. In such cases, it is often desirable to enhance the contrast of these local regions, because global histogram equalization is ineffective in such cases (Solomon & Breckon, 2011). This can be achieved by contrast limited adaptive histogram equalization (CLAHE; Zuiderveld, 1994) which is an extension to the traditional histogram equalization (HE) technique. CLAHE enhances the contrast by dividing an image into multiple non-overlapping regions and performing histogram equalization for each region separately. Then, these regions are recombined to get the entire enhanced image (Prakash & Gupta, 2013). Though its efficiency, the CLAHE technique has the disadvantage to enhance not only the image, but also the noise present in the image (Haller, 2011).

There are many other variants of histogram equalization such as dynamic histogram equalization (Abdullah-Al-Wadud, Kabir, Dewan, & Chae, 2007), brightness preserving bi-histogram equalization (Kim, 1997) and the recursive mean separate histogram decomposition (Chen & Ramli, 2003).

2.2. Artificial bee colony algorithm

Recently, bio-inspired optimization algorithms have proven their efficiency in different domains such as transportation (Karaboga & Gorkemli, 2011) and image processing (Cuevas, Echauri, Zaldivar, & Prez, 2013). Among the most known metaheuristics, we cite the particle swarm optimization (PSO) algorithm (Eberhat, Shi, & Kennedy, 2001; Kennedy & Eberhart, 1995), the genetic algorithm (GA; Holland, 1992; Tang, Man, Kwong, & He, 1996), ant colony optimization (ACO; Zhiwei, Zhaobao, Xin, & Xiaogang, 2006) and bacterial foraging (BF; Sathya & Kayalvizhi, 2011a; 2011b; 2011c). In 2005, Karaboga invented a new optimization algorithm inspired by the intelligent foraging behavior of bees