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3D ear recognition using local salience and principal manifold

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ABSTRACT

As an emerging class of biometrics, human ear has drawn significant attention in recent years. In this paper, we propose a novel 3D ear shape matching and recognition system. First, we propose a novel method for computing saliency value of each point on 3D ear point clouds, which is based on the Gaussian-weighted average of the mean curvature and can be used to sort the keypoints accordingly. Then we propose the optimal selection of the salient key points using the Poisson Disk Sampling. Finally, we fit a surface to the neighborhood of each salient keypoint using the quadratic principal manifold method, establishing the local feature descriptor of each salient keypoint. The experimental results on ear shape matching show that, compared with other similar methods, the proposed system has higher approximation precision on shape feature detection and higher matching accuracy on the ear recognition.

1. Introduction

Biometrics deal with the automatic recognition of a person based on his or her physiological or behavioral characteristics. Compared with traditional identification methods, biometrics offer far better accuracy and stability. Ear, a new class of biometrics, has received significant attention recently due to its non-intrusive collection, rich set of features and stable structure, which is age-invariant (from 7 to 70 years old) [1]. Furthermore, although larger than fingerprint, ear is smaller in data storage size than face and is not affected by variations in facial expression.

The anatomical structure of human ear is mainly composed of helix, antihelix, Lobe, antitragus, tragus, concha and crus of helix. Although the distinctive features of ear can sufficiently exhibit individual uniqueness, they also make fast and accurate detection and recognition of ear very challenging. Traditional human ear recognition system is based on three components: Ear Detection, Feature Extraction and Ear Recognition. As the first phase, real-time ear detection focuses on isolating human ear from the background, an input profile face image. The next step is to represent the relevant data by appropriate features and design effective classifiers. Based on the type of data used, current ear recognition approaches can be classified as 2D, 3D and multimodal 2D & 3D. Most of the existing work focuses on 2D intensity images, as 2D data are easier and less expensive to acquire. 2D ear recognition, however, has numerous inherent problems such as sensitivity to illumination and pose. 3D data offer more flexibility to address these issues in 2D data.

In this paper, we present an improved human recognition system using the 3D ear biometric. The specific contributions of this paper are as follows:

(1) We present a highly desirable keypoint distribution based on saliency value and Poisson-Disk exclusion strategy, which balances the significance and uniformity of keypoint distribution.

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(2) We improve the local 3D features proposed in [2] by fitting a surface to the neighborhood of each salient keypoint using the quadratic principal manifold method. This surface fitting scheme takes into account the ambiguity of the neighboring surface patches and can get multi-valued quadratic surface under the same resolution, which leads to the local features of each keypoint and describes the local shape in a highly accurate way.

The rest of the paper is organized as follows: In Section 2, we introduce the state-of-the-art methods on ear recognition using both 2D and 3D data. In Section 3, we give the overview of the proposed system. In Section 4, we explain the new keypoint identification method on 3D ear and extract the local features based on principal surface fitting, with a higher fitting precision than the GRIDFIT method employed in [2]. The feature compression and matching schemes are also given in this section. In Section 5, we evaluate and discuss the performance of the proposed approaches and make a comparison with previous works. Finally, in Section 6, we provide the conclusion and discuss future work.

2. Related work

Current ear recognition systems have exploited both 2D ear image and 3D ear model for human recognition. In this section, we will briefly review several recent ear recognition techniques in 2D and 3D respectively.

2.1. Ear recognition on 2D image

Ear recognition in 2D can be categorized into holistic and feature-based matching algorithms [3].

The holistic matching algorithms basically extract global features from the entire ear. In 2008, Xie et al. first obtained the lower dimensional representation of ear data using a Local Liner Embedding (LLE) algorithm and then adopted Linear Discriminant Analysis (LDA) to resolve the problem of human ear classification [4]. Experimentally they showed their technique has better recognition performance for multi-pose ear recognition but they did not explain how they performed the detection and normalization steps. In 2009, Nanni et al. mapped the normalized human ears into color spaces and extracted a set of Gabor features from each space, which assisted to solve the imaging condition problems and the combination of Gabor filters and local binary patterns might achieve substantial improvement in performance [5]. In 2010, Bustard et al. treated the ear as a planar surface that was registered to a gallery using a homography transform calculated from Scale Invariant Feature Transform (SIFT) matches [6]. The technique was robust to background in terms of occlusion and pose variation.

The local feature-based matching algorithms extract local feature or region and match these features or their local statistics for recognition. In 2007, Nanni et al. extracted features from the convolution of each sub-window with a bank of Gabor Filters and applied Laplacian EigenMaps to the features to reduce dimension [7]. Then they employed the Sequential Forward Floating Selection (SFFS) to filter out the best matcher which had been trained in accordance with the features. But the application of Laplacian EigenMaps may lose information excessively. In 2010, Yazdanpanah et al. constructed a region covariance matrix by using bi-orthogonal and Gabor wavelet features as an efficient and robust ear descriptor, which is robust to illumination and pose variation [8]. The same year, Yuan et al. extracted the features for segmented ear regions using Neighborhood Preserving Embedding and the most discriminative region was selected according to the recognition rate [9]. Their algorithm could avoid the occlusion problem but also had a drawback when dealing with the multi-pose problem.

2.2. Ear recognition on 3D model

Ear recognition using 3D or range data can improve performance especially in conditions of illumination variation and orientation variation.

A comprehensive survey of ear biometrics using 3D shape is presented by Bhanu and Chen [10]. In 2007, Yan et al. automated segmentation of the ear in a profile view image by detecting ear pit and consider two approaches for 3D shape matching: point-to-point and point-to-surface matching schemes [11]. Their algorithm achieved a rank-one recognition rate of 97.8% using 1386 probes from UND database and might still benefit from additional feature classifiers. In the same year, Chen et al. used a model-based (template matching) technique to locate ear helix and antihelix in side face range image, and a modified Iterative Closest Point (ICP) algorithm with two ear representation (helix/antihelix and local surface patch representation) for ear recognition [12]. They achieved a promising recognition rate on UCR database and the UND collection F database. Due to the high dimensionality of the local surface patch representation, in their later work [13], they employed an embedding algorithm to map the feature vector to a low-dimensional space and Support Vector Machine (SVM) for ranking all model-test to generate a short list of candidate models for verification, achieving a linear time complexity. In 2010, Zeng et al. proposed an automatic 3D reconstruction method based on binocular stereo vision [14]. They employed Scale Invariant Feature Transform (SIFT) feature based approach to compute seed matches and the adapted match propagation algorithm with epipolar geometry constraint to obtain quasi-dense correspondence points. The absence of pre-processing of this algorithm could reduce the complexity of the recognition time. In 2011, Islam et al. employed AdaBoost-based ear detection approach to locate the ear parts in 2D color and 3D range image, and fast 3D local feature matching and fine matching via the ICP algorithm to obtain an ear biometric system [2]. They used PCA-based and random selection method to detect points that are stable and distinctive (also known as keypoints). Then the 3D features were extracted by fitting a surface to the neighborhoods of keypoints and sampling it on a uniform grid. The features were used to construct a rejection classifier to extract a small region with feature-rich points. But the random