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Ear Identification Based on Improved Algorithm of ICPSCM

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ABSTRACT
This study presents a brief processing of ear identification and making an improvement of ear recognition via combination of Iterative Closest Point (ICP) algorithm with the Stochastic Clustering Method (SCM). The objective of this study is to enhance the matching template scheme using BPNN based on the ICP algorithm combined SCM method. An effective SLLE (Supervised Locality Linear Embedding) variation for ear recognition was designed based on JAVA programming language. The software provides basic functions for ear identification analysis by using two kinds of algorithm, respectively. In particular, the combined method provides effective identification through BPNN environment condition. Analysis results are expressed realistically through different database. Finally, with the application of ICP and SCM based multilayer neutral network to identify 20 ear images, the experiment results shows 96.12% accuracy.

Key words: Iterative closest point, stochastic clustering method, backpropagation neural network, false reject rate, false accept rate

INTRODUCTION

Many ear recognition algorithms embrace some guide matching techniques. A guide matching method uses pixels, samples, models or textures as pattern. The popularity perform computes the variations between these options and therefore the hold on templates to use correlation or distance measures. The main goal of this approach is to implement and analyze the tool that enables recognition through human ear for authentication or authorization functions. So as to realize this aim, it needs to fastidiously selecting the correct methodology. The necessity for methodologies and techniques to model methods arises primarily from the need to own a group of rules permitting the outline of a process, in order that such a model is understood in a very distinctive method (Abaza and Bourlai, 2013).

Identification of human by ear bioscience is promising as a result of it's a passive identification technique like face recognition. Bioscience identification strategies proven to be terribly economical and a lot of natural and straight forward for users than ancient methods of human identification have been considered (Giraud *et al*., 2014).

In fact, solely bioscience strategies really establish human's information for passive person identification, which may be applied to provide security within the public places. The ear has fascinating properties like form, individuation and permanence. Furthermore, though a powerful disciplined means of continuing doesn't guarantee a decent model for the method being analyzed, the dearth of a structured means of continuing ensures a high chance of failure, particularly with the increasing complexness of the method to be sculptural (Kumar and Chan, 2013). The ICP and SCM are proposed to reconstruct ear surfaces from different scans, to localize points and clustering method to achieve optimal classification planning respectively. The study proposed to determine the pose variations (including different angulations and distances). Probable techniques for pose variation in ear detection are ICP algorithm and for feature extraction area is SCM method.

EAR FEATURE EXTRACTION

Each ear recognition system involves with a feature extraction and a feature vector associated steps. During this survey the proposed approach tend to divide ear recognition into different subclasses particularly maximum line for ear inner approaches. Feature extraction is describing the sequential stages of human ear recognition. The analysis can apply a rather new scale and rotation-invariant detector and descriptor, referred to as SURF that was developed by Bay *et al*. (2008) and Arbab-Zavar and Nixon (2011). Feature extraction is the process to express a set of features, or image characteristics, most efficiently or acquired represent the information that is necessary for analysis.

According to Guyon and Elisseeff (2006) and Clifford *et al*. (2009) feature extraction involves reducing the amount of input required to describe a large set of data. When performing analysis of raw data, one of the major challenges is from the number of contains variables. Analysis with a large number of variables generally requires a large amount of memory in different domain such as biometric feature extractions, biometric data and matching module. The feature extraction conducted to determine the single feature by each image which that called functionality in image process whatever domain.

In order to accomplish this, as proposed by Bay *et al*. (2008) a quantified 3D volume using voxels (Volumetric Picture Elements) will be used. Placing the 3D probe image into this volume, each point of the probe falls into a voxel. Each probe point is then approximated by the voxel center wherein it is placed. For each voxel the closest point in 3D space on the gallery surface is computed ahead of time.

The SURF, is suitable method in theory to similar research and technique, the mean concluder was to focus in matching via feature point, with supportive to increase up the accuracy. Borse *et al*. (2014) and Li (2014) stated that SURF is the most used feature extraction method due to its robustness as it takes advantage of integral image calculation. Because it is strong to use the method for local feature detector as in Fig. 1 a set of test image from noisy pixels has been arranged using Hierarchical models of object recognition (HMAX) to extract features from ear images for robust ear recognition and iterated to generate a set of field lines for image verification.

SPEEDED-UP ROBUST FEATURES (SURF)

As published by Prakash and Gupta (2011), the SURF technique provides a unique talent for matching, description and detection steps; however the picture element intensities are distributed among a scale dependent of neighborhood of every interest purpose detected by the Fast-Hessian. This approach is comparable, but integral pictures employed in conjunction with filters are employed in order to extend lustiness and reduce computation time. Haar wavelets are easy filters which may be accustomed realize gradients within the x and y directions. For quick classification throughout the matching stage, the sign of the trace of Wellington matrix for the underlying interest purpose is enclosed. If the distinction between 2 interest purposes is completely different, the candidate isn't thought of a valuable match.

The proposed ear detection is in the multi-stage method. Figure 2 shows the development of the proposed method. It consists of four stages: Preprocessing, feature extraction, classification and recognition.

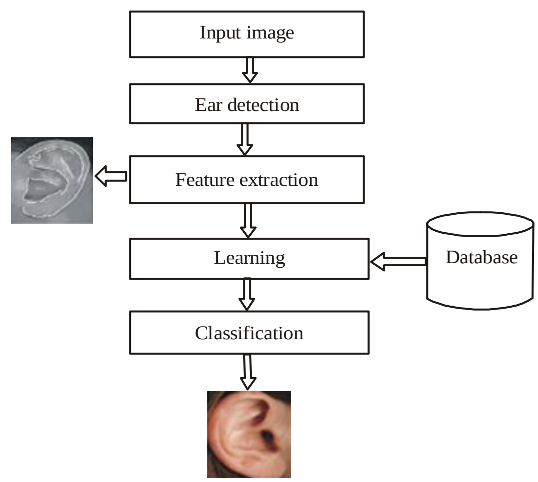

Fig. 1: Ear feature extractions

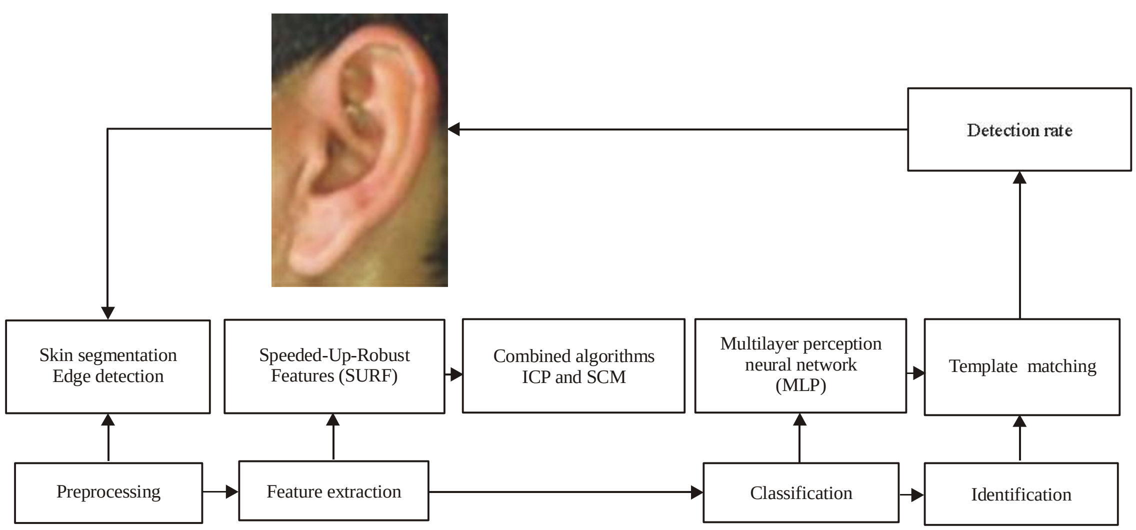

Fig. 2: Block architecture for the proposed ear identification

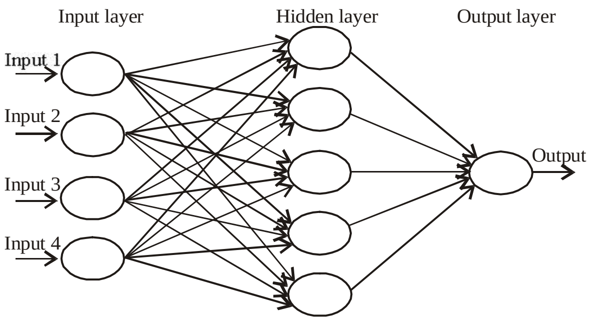

Fig. 3: Back Propagation (BP)

MULTILAYER NEURAL NETWORK (MLNN)

Back Propagation (BP) is used in general purpose function approximations (Bengio and LeCun, 2007). The outputs of the BP focused in this thesis as shown in Fig. 3 was interpreted as the sufficient statistics of the associate member of the exponential family which was based on conditional input (X), inducing a distribution over the output space target (Y) (Santini *et al.*, 1995). Meanwhile the nonlinear initiations were calculated based on BP model as conditional distribution p(Y, X) as shown in Fig. 3.

Ear classification and identification are implemented based on the proposed MNN method being used in ear identification technique.

FEATURE MATCHING

The correspondence between two features is calculated as the root mean square distance between corresponding points generated when the feature is created and aligned to the geometry axes in the ear. The Root Mean Square (RMS) distance is computed from each investigation feature location to all the ear feature locations.

Matching image features which are placed more than a threshold values are discarded to escape matching in quite different areas of the cropped ear. The image feature that matches to the minimum distance is measured as the corresponding image feature for that particular review feature. The root mean of the distances for all the coordinated probe and image features is used as a relationship measure.

IMPROVED FEATURE CLASSIFICATION

Previous analysis within the literature review has instructed the employment of ears as a biometric for human identification. Researchers have supported that the character of the ear and also the look of the outer of humans could be a distinctive address and comparatively unchanged throughout the long period of a private human (Burge and Burger, 2005). The planned equation based mostly is predicated on SCM and ICP based feature extraction, wherever the interactive feature extraction depends on the full distribution points and also the corresponding alignment error of the center of mass coordinates for contour array. The purpose of the new approach for integrated ICP and SCM feature to be strong to correspondences parameter to tune the most match distance to gift in most variants of ICP.

The performance of the analyses depends on the evaluated points at numerous stages of the conversion victimization speed sturdy feature (SURF) analysis. The SURF features are administrated on increased pictures to achieve the sets of native options for every increased image.

The ICP is an efficient algorithm for defining the rigid body objects in given image data. However, alone ICP has some drawback which prevents boosted ear identification performance. Therefore, the ICP algorithm has been combined with SCM algorithm for better results and faster completion time of the data set process. Some of the drawback occurred in ICP algorithm is listed below (Besl and McKay, 1992):

- It is much computationally relevant to recognize the nearest point for each object points in iteration
- It only promises converge to local minima point
- It is not converging fast enough

For some shapes, there are algorithm conflictions which avoid working properly. However, this is considered as a minor and rare problem.

Some equation of the developed strategies, that is impressed during this analysis proposal are explicit in details. Associate in nursing approach to figure ear options of breast recognition, that are related to Multilayer Neural Network look, were used for diagnostic ear recognition estimation.

EAR IDENTIFICATION

Extracting ear from images is one of the most essential tasks to identify the person. In addition to this concept, the strength of following systems greatly depends on the detection of targets and error free. A new combination perception of biometrics and integrative closest points based upon ear surface matching scheme with features was introduced for use in the development of ear identification systems. Figure 4 shows the idea of ear identification process.

The idea of the ear identification method, which combines the result from ear matching based on neural classifiers using the target of outer ear points, information acquired from ear profile and shape and macro features extracted density. Subsequently, the ear position is extracted from the input image; the ear identification process is initiated based on integrative closest points.

The template method requires a suitable schema as the format of the target database. The proposed system uses three databases which are IITK, WPUTED and USTB databases. A template which suits the most in the common points of the databases used is generated. In the conceptual method, human ears can be one of the four different shapes as listed in the points below (Kisku *et al.*, 2009).

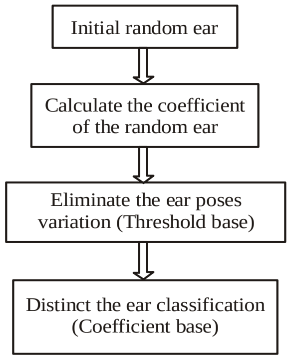

Fig. 4: Ear identification process

FRR AND FAR ERROR EVALUATION CRITERIA

Automated ways of recognizing a private ear supported measurable frame characteristics. However, different biological characteristics exhibit each strengths and weaknesses, such as fingerprints may result in high recognition rates however, so as to be measured accurately it needs controlled conditions and also the subjects have to be compelled to move hand and glove with a finger print machine. In applications wherever remote recognition is critical face and ear biometry are additional convenient to be measured. The ear biometric particularly has bound advantages: Ears are comparatively static in size and structure over every individual's person life and in contrast to human faces, they're unaffected by facial expressions (Yan and Bowyer, 2005).

This study addressed the limitations by planning an ear detection methodology based that supported the proposed framework. The most benefit of the methodology is procedure time, False Accept Rate (FAR), False Reject Rate (FRR) and Equal Error Rate (EER). In typical ear detection methods the procedure time and rate for coaching is the threshold value obtained by BPNN.

DATA COLLECTION

The study has considered three databases, namely Indian Institute of Technology, Kanpur (IIT Kanpur) database, University of Science and Technology Beijing (USTB) database. To validate the results for more accuracy, the West Pomeranian University of Technology Ear Database (WPUTED) used to analyze the proposed combination of SCM with ICP systems.

Theoretically, database designers had consensus on the necessity of reliability requirements as a part of non-functional requirements in the image detection development process. The major principle of dataset reliability requirements is a consideration for available solutions when a failure or error occurs. According to the ear functional requirements, the proposed process must be reliable in terms of result accurateness and must perform well from its ancestors as what

Table 1: Distribution of dataset

		Experiments		
Name of database	Total image	Set 1	Set 2	Set 3
USTB	500	200	150	150
IIT Kanpur	500	200	150	150
WPUTED	500	150	200	150

this is scheduled. The system must be verified very well with appropriate and correct training collections therefore; a valid report can be defined for system reliability in testing stage.

Additionally, the complicated datasets contain images of many types and content the precise need in ear detection. Table 1 shows the distribution of the dataset in each experiment used in the research.

RESULTS AND SIMULATIONS

Figure 5 shows the stochastic clustering algorithm and ear biometric based field feature proposed for ear recognition development in digital image processing based neural network techniques.

In order to apply the ear classification, features of the input and the database images must be extracted. The most likely area is then can be found for a particular point by taking the most closed value to the one. The task of the entire MNN process can be shown in sub processes for WPUTED in Fig. 6.

To better visualize and implementation, the proposed method applied a texture map. As a first step the system need a simple parameterization of the mesh analysis. The system offers a couple of parameterization tools to use the simple independent right-triangle packing approach for its robustness. This creates a surface made entirely of right triangles as shown in ear design shape. Figure 7 shows the point matching and structure form for generating transformation by minimizing RMS (Root Mean Square) error between matched points.

Experimental results illustrated that the ear detection accuracy was defined overall for FRR and FAR for ICP algorithm. After the algorithm have been tested the FRR, FAR, recognition rate for ICP associated with SCM Algorithm has been defined in Fig. 8 as higher recognition rate. The most advantage of the planned technique is that it will operate in all type of ear shape.

DISCUSSION

The recognition process is output of the developed algorithm. In normal case, a stable match is the one closest to perfect match which is strongly trusted. The recognition process is not a single process but stages of processes. It is hierarchal structure makes the recognition invalid if the previous stages fails to perform well. This failure comes along until the recognition process. This study has been demonstrated with screenshots and detailed explanations. The results of the implementation phase together with FAR and FRR illustrations. Detailed comparisons of the databases used in the study have been provided as well. Additionally, the contribution of the research explained the template matching and validated with ear identification through WPUTED

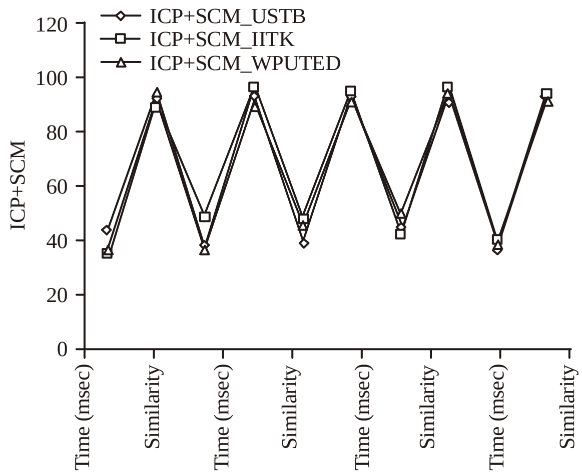

Fig. 5: Ear average detection time using ICP and SCM

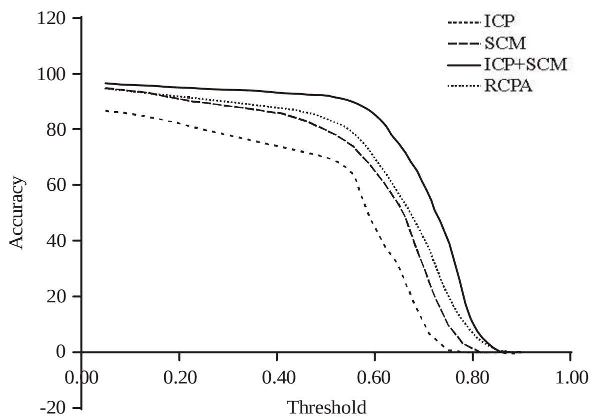

Fig. 6: Ear detection accuracy based WPUTED data base

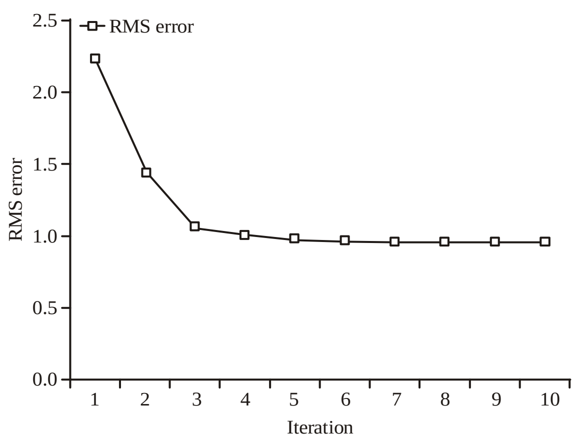

Fig. 7: RMS error curve for ICPSCM

database. Ear identification software is developed based on iterative closest point and stochastic clustering method system model and integrated with multilayer neural networks for ear identification.

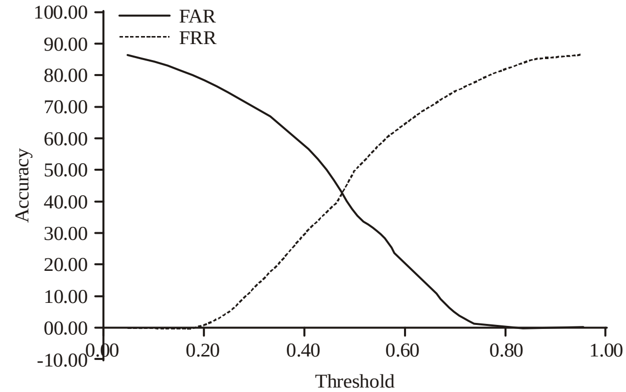

Fig. 8: FRR and FAR for ICPSCM algorithm

CONCLUSION

This study stated the technical aspects and results of the proposed method. The ear extraction and ear recognition stages are explained and elaborated in details with feature based ear identification samples and references. This study is being reference for the development stage where actual system implementation is carried out. The proposed methods and results stated in this study conferred that SCM technique matching with associate degree ICP-based approach has robust potential method for ear detection algorithms with less error and more accuracy. The number of the ear form taken from different database utilized in the probe representations was adjusted to fit into the proposed method.

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