SKULL RECOGNITION USING SIFT FEATURES

M. Chitra Devi[1] , Dr. M. Pushpa Rani[2]

[1] PhD Research Scholar in Computer Science, Mother Teresa Women's University, (India)

[2] Professor & Head, Dept. of Computer Science, Mother Teresa Women's University, (India)

ABSTRACT

Now-a-days, security is a major fretfulness in the world. Biometrics is very helpful and it's easy to implement for security purpose. Many algorithms and techniques have been proposed to recognize the human using behavioural and physiological characteristics. This paper aims to apply the Scale Invariant Feature Transform approach in the context of man identification with skull based matching. This method contains three major steps: The first step identifies Euclidean distance between the test sample and all training samples. The second step counts the numbers of well matched pairs of SIFT features between each candidate chosen in the first step and the test sample, then chooses several samples from candidates with the greater number of well matched pairs. The third step calculates the similarity between the test sample and each class that includes training samples chosen in second step, and chooses a class with the highest similarity to be the recognition result.

Keywords: Biometrics, Skull Recognition, SIFT Technique

I. INTRODUCTION

Biometric is a powerful tool for reliable automated person identification and there exist several established biometrics-based identification techniques including fingerprint, geometry methods, speaker identification, face recognition and iris identification [1]. These techniques have been broadly applied to access system, security system and other occasion needing identity witnesses.

Skull based human recognition is an advanced research in Biometrics. In recent years, the applications about security issues such as individual identification, access control and security application attract much important. For the convenience of users, a skull recognition system is suitable rather than a traditional personal password or an ID card, and has better interaction between human beings and machines. It is still a difficult problem because Because of the high cost and great difficulties in the skull imitation, the research on the skull recognition technology becomes important. Besides, the structure of human skull is very complicated, with exclusive size and shape for each individual, containing abundant information. So the recognition system based the skull is feasible and significant.

At present, the researches on skull mostly belong to three aspects [2]. The first is used for clinical diagnosis and medicinal treatment [3-5]. The second is for human origin, geological distribution, ethnic characteristic, and so on [6-8]. The third is for the identity recognition or identification with the help of computers. To the third class, one of the methods is to choose some symbol features based on the 2-D skull Image; the second is to reconstruct 3-D or 2-D face image from the skull utilizing certain methods and technology, then calculate the similarity degree between the image and the picture ready.

The skull images we obtained may have different orientations mostly, which will badly influence the recognition in some algorithms. So we must find a method that is not sensitive to the skull deflection. There are some similarities between the skull and the face recognition. This paper proposes a new approach based on Scale Invariant Feature Transform (SIFT) [9] to identify the Skull.

II. REVIEW OF LITERATURE

SIFT is firstly developed by D. Lowe in 1999 [10], the main idea of SIFT is to extract features from images to match the reliable features between different parts of the same object. The extracted features are invariant to scale and orientation, and are very distinctive of the image.

In 2006, A. Mohamed [12] proposed SIFT for face recognition process and compared with well-established face recognition algorithms, namely Eigenfaces and Fisher faces. The results how the lead of SIFT over these two methods, specially using smaller training sets. Reference [15] presented presents a novel human face identification approach.

In 2008, F. Alhwarin et al. [13], proposed an improvement on the original SIFT algorithm by producing more reliable feature matching for the object recognition purposes. This is done by splitting the features extracted from both the test and the model object image into several sub groups before they are matched.

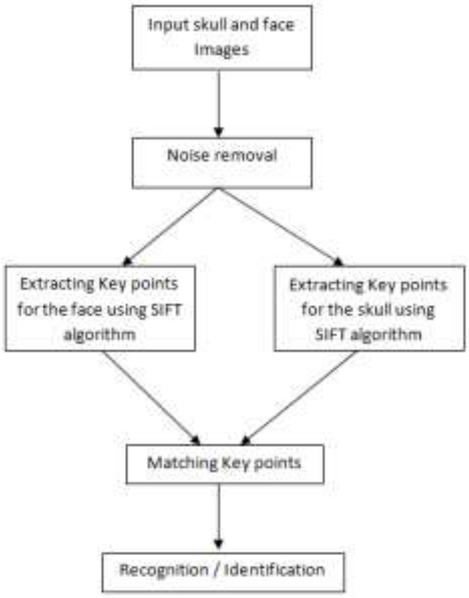
They also proposed in [14] a new method for fast SIFT feature matching and the experimental results show that the feature matching can be speeded up by 1250 times with respect to exhaustive search without lose of accuracy.

In 2013, Tong Liu et al. [16] proposed a face recognition system based on SIFT feature and its distribution on feature space. The proposed method gave a higher face recognition rate than other methods included matching and total feature based methods in three famous databases.

Scale Invariant Feature Transform (SIFT) proposed by D. Lowe [11] became popular in face recognition. One interesting thing about the SIFT is its capability to capture the main gray level features of an objects view by means of local patterns extracted from a scale-space decomposition of an image [12].

III. SCALE INVARIANT FEATURE TRANSFORM TECHNIQUE

In the 2004 David Lowe presented a method to extract distinctive invariant features from images [11]. He named them Scale Invariant Feature Transform (SIFT). This particular type of features are invariant to image scale and rotation, and are shown to provide robust matching across a a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. They are well localized in both the spatial and frequency domains, reducing the probability of disruption by occlusion, clutter, or noise. Large numbers of features can be extracted from typical images with efficient algorithms. A typical image of size 500x500 pixels will give rise to about 2000 stable features (although this number depends on both image content and choices of various parameters). In addition, the features are highly distinctive, which allows a single feature to be correctly matched with high probability against a large database of features, providing a basis for object and scene recognition. The cost of extracting these features is minimized by taking a cascade filtering approach, in which the more expensive operations are applied only at locations that pass an initial test.



Following are the major stages of computation used to generate the set of image features:

STEP1. Choose N \candidates" based on the Euclidean distance. We define $X = \{x11; \cdots ; xij ; \cdots \}$ as a test sample, $Y = \{y11; \cdots yij ; \cdots \}$ as a training sample, where xij and yij are the pixels at position (i.j) of the test and training samples respectively. Let $B = \{Y1; Y2; : : :\}$ denote the training set. Let $D(X;Yk)$ be the Euclidean distance between a test sample X and a training sample Yk.

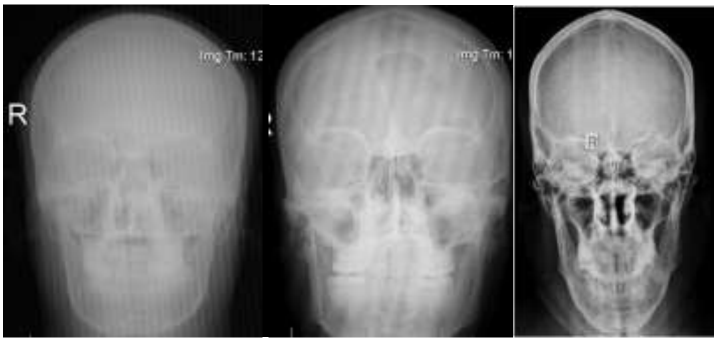
$$D(X,Y_k) \sqrt{\sum_{I=1,\, j=1}^{I=H,\, j=W} (x_{ij}-y_{ij})^2}$$

H and W are the height and width of a test sample respectively. The training samples should have the same size as the test sample. We sort the whole training samples in the ascending order of Euclidean distance, and then choose N training samples with smaller distance as “candidates” set C.

$$C = \{(Y1:::YN)|D(X; Y1) \leq D(X; Y2) \leq : : : \leq D(X; YN) \leq D(X; YN+1)\}$$

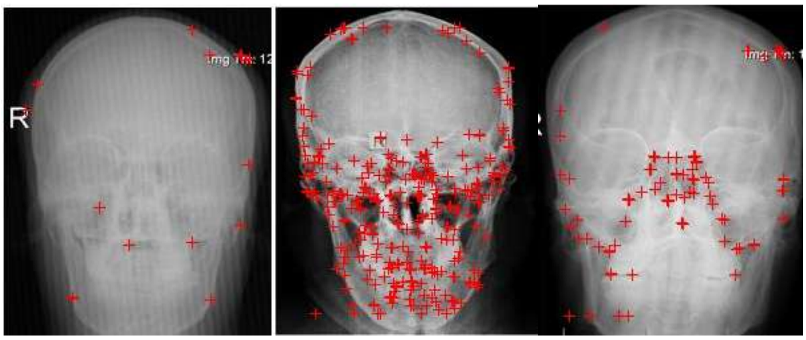
Where $N \leq n$, n is the number of training samples in training set B.

(a) Test Sample



(b) 3 sample skull images

(c) 3 Sample Face Images



(c) Images with SIFT Features

STEP2. Choose P new \candidates" based on SIFT features. In this step, we choose P new "candidates" from *C* based on the number of well matched pairs of SIFT features. First of all, we define the criterion of well matched pair of SIFT features. We build a KD-tree [42] using the descriptors of SIFT features in a training sample. And then, for each descriptor *a* in the test sample, we employ Best-Bin-First search algorithm to find out *k* nearest nodes $b1; b2; : : : bk$ in the KD-tree (usually k= 2), which are sorted in descending order. Let $d1,d2$ respectively be the distances between *a* and $b1$, *a* and $b2$. We then calculate the ratio of $d1; d2$:

$$ratio = d1/d2$$

If $ratio < Threshold$ (defined manually), we define *a* and $b1$ are a well matched pair of SIFT features. Fig.3 shows the effect of *Threshold* on the recognition accuracy. When *Threshold* is below a certain value, the recognition accuracy increases rapidly and reaches the highest while *Threshold* is 0.5. Thus, we fix it as 0.5 in our method.

In this step, we count the number of well matched pairs of SIFT features between the test sample and each "candidate" in *C*, and sort the "candidate" samples in descending order. Then we choose *P* samples from *C* with the greater number of well matched pairs

as the new "candidates" set $C' = \{C'1; C'2; \cdots ; C'P\}$.

(a) Corresponding FP Between Face and skull1

(b)Corresponding FP Between Face and skull2

(C) Corresponding FP Between Face and skull3

STEP3. Calculate the average similarity between classes. Let M_i be a class with the same class label as new "candidates" $c'_i \in C'$, e_{ij} the angle of SIFT feature descriptors between a test sample and the j-th training sample in M_i, and $\bar{e}_i$ be the average angle between the test sample and each class M_i.

$$e_{ij} = \cos^{-1}\left(\frac{f_{test} \cdot f_{ij}}{\|f_{test}\| \cdot \|f_{ij}\|}\right)$$

$$\bar{e}_i = \frac{\sum_{J=1}^{L} e_{ij}}{L}$$

Where f_{test} and f_{ij} are the descriptors of the test sample and the j-th training sample in M_i respectively, and L is the number of training samples in M_i. In our method, we describe the similarity of a test sample and the class M_i by using e_i and choose the class with the minimum angle as the recognition result. To get high recognition accuracy, we adjust some parameters involved in our method by using a small validation set. The parameters mainly include the numbers N,P of "candidates" chosen in the first two steps and the *Threshold* used to count the number of well matched pair of SIFT.

The Face Image Matched With Skull3

Matlab was used to implement the SIFT matching algorithms. In an attempt to assess the significant number of SIFT features required for reliable matching of face and skull images, several experiments were performed using only a subset of the extracted SIFT features in the matching process.

Clearly, the accuracy increases rapidly with increasing the number of SIFT features used and then starts to saturate. This can considerably decrease the run time for SIFT matching process, as the number of matching operations is O(n2) where n is the number of features to be matched.

V. CONCLUSIONS

Skull is the most complex and important component among human skeletons. It includes large amount of information about human beings, and skull varies with different individual. So biological recognition based on the skull feature is feasible. The SIFT is applied to the problem of the skull recognition in the paper. The SIFT modelling of human skulls appears to be an encouraging method for skull recognition under a wider range of image orientations.

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