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Human ear classification using BRISK feature detection method

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Abstract - Human ear has been identified as an unique biometric trait for recognition because of excellent characteristics it possesses in addition to being a passive biometric trait. Ear biometrics has gained a lot of popularity because it has various advantages over other biometric traits. Human ear can be used alone or in hybrid manner for a higher performing biometric system. After applying robust feature detection and extraction classification is done. In this paper using Binary Robust Invariant Scalable Key-points (BRISK) features are detected and for extraction the Histogram of Oriented Gradients is performed (HOG). Using Support vector machine as classification technique, recognition rate is calculated.

Key Words:Biometrics, identification, BRISK, SVM, feature detection, classification

1.INTRODUCTION

Biometric verification techniques are gaining worldwide attention as they are proved to be more efficient, they are more convenient and are natural methods for identification. There are various physiological traits like iris, fingerprint, DNA and behavioural biometric traits like gestures, keystrokes used but ear biometrics are now achieving importance. This because of various factors that are taken into consideration. The most important being that the ear is the most stable human anatomical feature as proved by Iannarelli [1]. The ear shape and features remain considerably same during the human life as compared to the face. Also, facial expressions change due to various human emotions. Application of cosmetics and eye glass also hampers face detection. So human ear as a biometric feature seems a great example of passive biometric system. Size of the ear is also an additional advantage. That's because size of the ear is ideal to capture. The ear size is larger than iris and fingerprints but is also smaller than the face. Hence easy to capture.Iannarelli (1989) [1] stated that the human ear is an also a distinctive feature for each individual. He divided the ear into eight parts and took twelve measurements around the ear as shown in the Figure 1 and calculated the distances by placing a compass over an enlarged image. The geometric method proposed by Burge and Burger [3] was based on Voronoi diagrams of the detected ear edges. But the edges detected from the ear have shown considerable variation even in presence of relatively small changes in camera-to-ear orientation or lighting. Hurley and Carter [4] described various methods for identification mixing results from different neural classifiers. Nixon and Carter (2000a, 2000b) have conducted researches based on force field transforms. The method used by Choras (2005) [5] was based on the new co-ordinate system in the centroid. Middendorff et al. (2007) [6] emphasized that the type of data 2D or 3D, the type ofrecognition algorithm performed on each data, the output of that algorithm, the fusion typeperformed to combine them can improve the performance of a biometric system. Kisku et al. (2009) [7] proposed a hybrid recognition system consisting ear and fingerprints based on Scale Invariant Feature Transform (SIFT). Another research in ear biometric by Zhou et al. (2001) [8] involves a robust technique 2D ear recognition using colour SIFT features.

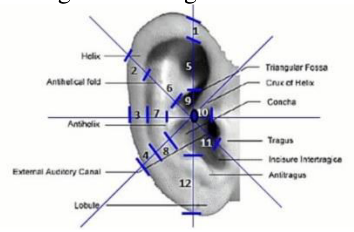

Fig -1: Steps for the ear biometric system

2. METHODOLOGY

Figure 2 shows the steps implemented for the biometric identification system based on the ear images.

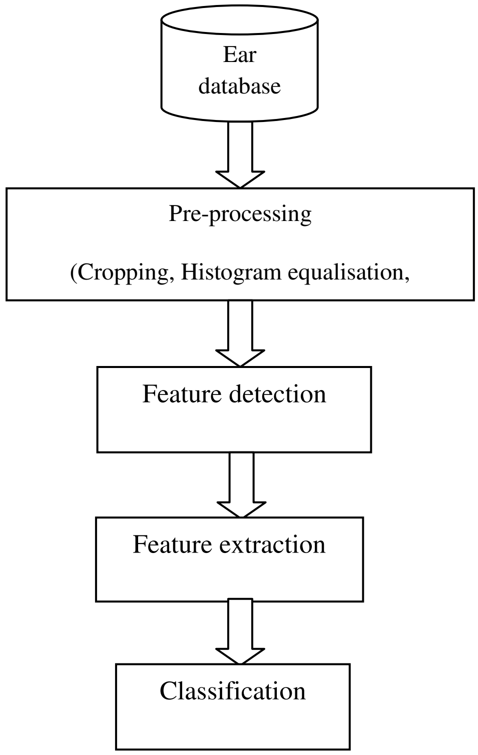

Fig -2: Steps for the ear biometric system

Pre-processing:

First step in implementing the biometric system is to pre-process the input ear images. Pre-processing is mainly done to fragment the ear portion. First the image in cropped into suitable dimensions were all the details that are required are present. The next step is to perform histogram equalization for contrast enhancement. During the acquisition phase a lot of noise in added to the input images in form of illuminations,unwanted signals, variations. To reduce this unwanted substances gaussian filtering is done.

Fig -3: Cropped image

Fig -4: Histogram equalized image

Fig -5: Gaussian filtered image

Feature detection:

A feature detection algorithm detects ideal feature points also called as interest points or key points in an input image. Features are generally detected as corners, blobs, lines, edges etc. The features which are detected are described in different ways on the basis of distinctive patterns owned by their neighboring pixels. In this paper Binary Robust Invariant Scalable Key-points (BRISK) are detected.

Binary Robust Invariant Scalable Key-points (BRISK) were ppt forward by S. Leutenegger et al [9] in 2011. BRISK is a corner detector and detects corners using AGAST algorithm and filters them using FAST corner scores. All this while searching for maxima in the scale space pyramid. In BRISK framework scale space pyramid is used which consists of n octaves c_i and nintra-octaves $d_i$for i = {0,1, …, n-1} and here n taken as 4. The octaves are established gradually half-sampling the original image (c_0). Each intra-octave $d_i$is down sampled and placed between layers c_i and c_{i+1} as shown in figure 6. The first intra octave d_0 is formed by down sampling the original image c_0. By a factor of 1.5 whereas the remaining intra-octave layers are obtained by consecutive half sampling. Hence, if t denotes the scale then $t(c_i) = 2^i$ and $t(d_i) = 2^i \cdot 1.5$.

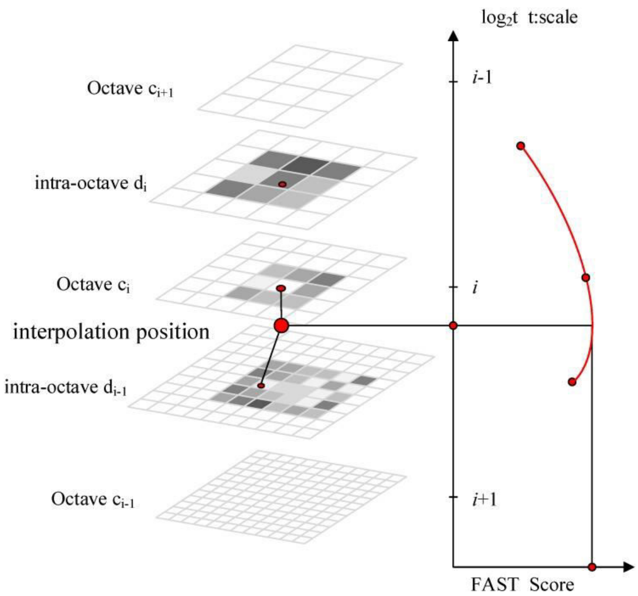

Fig -6: Scale space pyramid for BRISK key-point [9]

In Figure 6, an interest point is identified in octave c_i by examining the 8 neighbouring scores in c_i as well as score patches in the immediate neighbours layers above and below. The position of the key point is then re-interpolated between patch maxima closet to the determined scale [9].

In BRISK the FAST 9-16 detector is applied on the octaves and intra-octaves separately using the same threshold *T.* After that the points affiliated to these regions are subjected to non-maxima suppression. The key point in question needs to fulfil maximum condition with respect to the 8 neighbour. FAST scores *s.* The fast score *s* is the maximum threshold for considering a point as corner. Also, the scores in the above and below layers are supposed to low. After checking inside the equally sized square patches: the side length of 2 pixels in layers is chosen with the suspected maximum. Then some interpolation is applied at the boundaries of patch as shown in Figure 6.

Feature extraction:

Histogram of oriented gradients (HOG) is proved to be a powerful feature extractor. This extraction method was proposed by Dalal and Triggs [10]. Histogram of Oriented Gradients (HOG) are successfully and congently used where illumination variations are major. Here each detection window is divided is divided into cells of 8 × 8 pixels.

HOG feature extractor involves five steps, which are the gradient computation, orientation binning, histogram computation, histogram normalization and concatenation of local histograms. Consider a cell image I and gradient computation filters $h_x = [-1,0,1]$ and $h_y=[-1,0,1]^T$ [10]. Let $g_x$and g_y be the gradient calculated by

$$g_x = I * h_x \quad (1)$$

$$g_y = I * h_y \quad (2)$$

Here * is convolution. The magnitude at each pixel (*i,j*) is calculated based on the above two gradients.

$$G(i,j) = \sqrt{g_x(i.j)^2 + g_y(i.j)^2} (3)$$

and the dominant gradient orientation at each pixel (*i,j*) can be calculated as

$$\theta(i,j) = \arctan\left(\frac{g_y(i,j)}{g_x(i,j)}\right) (4)$$

Cell consists of the accumulation of vote in orientation of bins. The orientation bins can either be "signed" with even space over 0 to 180 degrees or "unsigned" gradient over 0 to 360 degrees. For simulations 8 × 8, HOG cells and 9 bin histograms are used as shown Figure 7.

Classification:
Support vector machine (SVM) is one of the most powerful and successful statistical classification technique. The support vector machines are supervised learning models with its associated learning algorithms that analyze data and recognize the patterns.

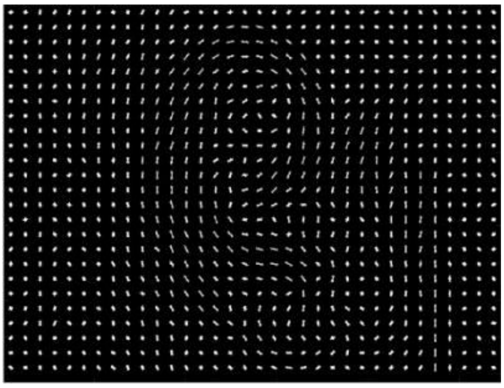

Fig -7: 8×8 cell size of ear image

3. SIMULATION RESULTS

The IIT Delhi ear database is used which is provided by the Hong Kong Polytechnicuniversity(*https://www4.comp.polyu.edu.hk/~csajaykr/myhome/database_request/ear/).* Sample of ear database images is shown in Figure 8.The database comprises of 493 grayscale images of 125 subjects. The number of images used per subject varies between 3 to 6. For the simulation purpose images of 35 subjects are used. Thedatabase is further divided into training set and testing set to calculate the accuracy. The number of images in training set varies from 3 to 4 per person and the number of images in testing set varies from 1 to 2 per person. Matlab-2018 has been used for performing the simulation in this paper. Specifications of computer system used are: Intel (R) Core (TM) i5-4200U CPU @ 1.60 Hz, 4GB RAM.

After pre-processing feature detection is performed using BRISK technique. The number of detected BRISK features are 74 as shown in figure 9.

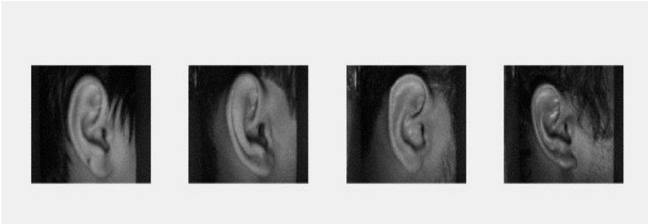

Fig -8: Sample from ear database

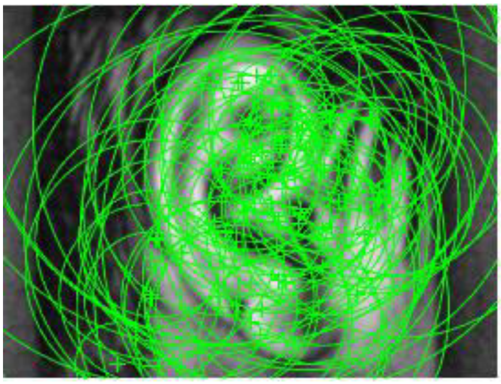

Fig -9: Detected BRISK features

The detected BRISK features are then fed into feature extraction technique using the Histogram of Oriented Gradients (HOG). HOG is the feature descriptor used to detect objects in computer vision and image processing. this method counts occurrences of gradient orientation in localized portions of a picture – region of interest. This feature is important to coach and test the algorithm which is employed to acknowledge the ear. For simulations 8 × 8, HOG cells and 9 bin histograms are used as shown figure 7.

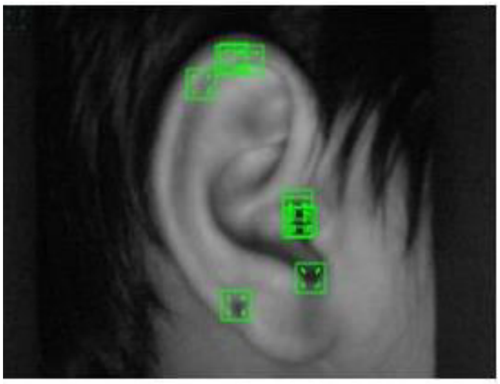

Fig -10: Extracted HOG features

In the last step (classification) support vector machine is employed for verification. SVM classifier is employed to calculate the accuracy of the system. From the confusion matrix of the tested ears average class accuracy is obtained for SVM classifiers. The Y-axis of the confusion matrix corresponds to the anticipated class (Output Class) and also the X-axis corresponds to truth class (Target Class). The diagonal cells correspond to observations that are correctly classified. The off-diagonal cells correspond to incorrectly classified observations. Figure 12 shows the plot of the confusion matrix for BRISK detector using HOG extractor and SVM classifier. The obtained accuracy is 62.79% for BRISK detector where out of 86 ear images 54 have been correctly classified as shown in Table 1.

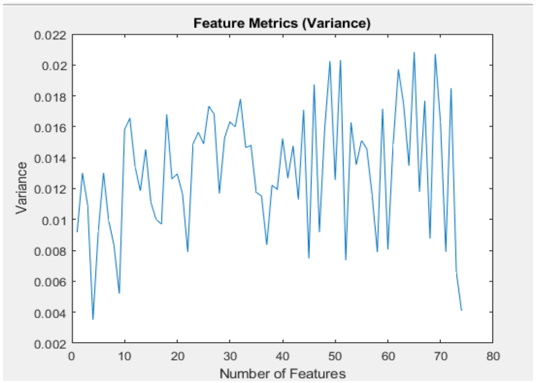

Fig -11: Variance calculated

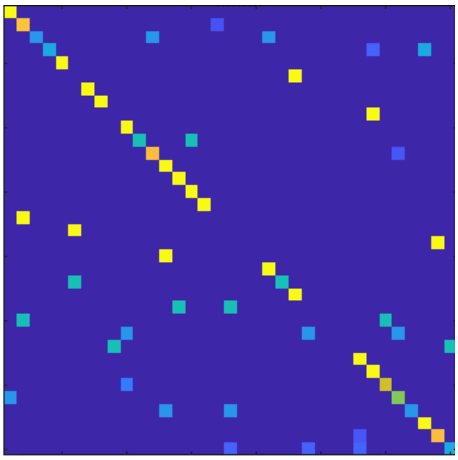

Fig -12: Confusion plot of BRISK-HOG

Table -1: Number of detected BRSIK features

Detector used	No. of features detected	Detected images/Total images	Recognized rate
BRISK	74	54/86	62.79%

4. CONCLUSIONS

In this paper ear classification is performed using BRISK-HOG detector extractor pair. BRISK is a novel method for key point detection. BRISK is a corner detector and is scale independent. BRISK is also invariant to rotation. BRISK identification is based upon identifying the direction of the features. In the proposed system ear is unimodal biometric trait which extract unique feature and give recognition accuracy of 62.79%.

The simulation is tested with offline images. Future work will be to make the system more accurate and to construct a system which deals with video surveillance and which can classify humans with online images. Also, to work with large number of features and different extractors and a large dataset. Future work will also include working with ear images that have occlusions like earrings, covered with hair.

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