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Facial Identification using Haar Cascading with BRISK

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***Abstract*— A swift and efficient facial identification system is a well-known discipline of computer vision applications and thus forms a pivotal part of image processing. Despite the advantages of existing methods, there is still a great demand for modifications in these algorithms in order to close to lacks of proposed methods. In this proposed work, the image is pre-processed with Contrast-limited Adaptive Histogram Equalization and faces are detected with Haar-Cascading (Viola-Jones algorithm). Then face identification is done using BRISK (Binary Robust Invariant Scalable Key-points) descriptor. Experimental results demonstrate that the proposed methodology achieves better facial identification even under various challenging conditions compared with the existing BRISK.**

Keywords— Facial Identification, Facial Recognition, Feature Extraction, BRISK, Viola-Jones, Image Processing, FAST.

I. Introduction

Facial identification system has a pervasive effect in a wide number of image processing applications. A growing need of facial identification in access and security, criminal identification and IoT applications is paving the way for technological strides in this field.

Facial identification applications' ubiquitous nature is propelling the need for better algorithms and techniques. Facial Detection forms an integral part of biometrics and has a pivotal role in security mechanisms. Thus, robust and swift facial detection is of paramount importance and there is little or no room for error in these applications. The conformation of different facial identification and facial recognition algorithms forms the algorithm of facial detection. Thus, a careful consideration of time complexity and effectiveness of combination of both algorithms is the key to build the robust method.

To match images that evolved by some transformations, distortions due to noise, compression and affine transformations, researchers have proposed a lot of robust feature detectors and descriptors techniques. In object recognition, the well-known detectors and descriptors that receiving most citations are ORB, SIFT, SURF, BRISK, BRIEF and FAST. Since there is a trade-off between robust feature detection and execution-time, yet a fastest one that yields best results in all conditions has not been developed yet. Our main aim is to increase the efficiency of BRISK for face identification by preserving its swiftness.

II. Related work

Automatic facial recognition or identification has always been a problem of interest for Computer Scientists. Through the concept of early machine learning techniques, a simple facial recognition system was devised and implemented [1]. This system proposed by W.K. Taylor dates back to 1967 and was a relatively simple implementation. With the rapid advancements in facial recognition, the systems being developed have become faster and more efficient. These systems according to X. Tian now have multiple applications across diverse fields and are used extensively and efficiently for human benefits [2]. Facial identification is done through a sequence of steps which are: facial detection, feature point extraction and lastly facial recognition [4].

Facial detection has also been an active area of research, the initial attempts to automate this process had begun from the late 1970s [3]. by Erik Hjelmås proposed that Facial detection methods can be divided into two basic sub-categories: Machine learning and feature based methods [3]. One of the most famous feature based face detection algorithms was made by Viola and Jones in the year 2001. They used Haar based features for facial detection and segmentation [5]. Our proposed methodology also makes use of the Viola Jones algorithm for facial detection. Following the research by S. Jida Histogram based techniques have also been deployed to serve in the process of facial detection [6]. Machine learning based facial detection is commonly performed using neural networks model [7,8].

One of the first algorithms for feature point extraction is SIFT (Scale-Invariant Feature Transform) and has been used widely in generating accurate and robust features in images. As proposed by D. G. Lowe, SIFT is scale invariant and blur invariant [9]. Modifications were made to SIFT by H. Bay and team and various techniques were devised, one of them being SURF (Speeded-up Robust Features) [10]. Performance evaluation of SIFT and SURF was done by N.Y. Khan and it was found out that SIFT was more accurate in cases of image blurring [11]. Other descriptors such as BRIEF (Binary Robust Independent Elementary Features) [13], FAST (Features from Accelerated Segment Test) [18], ORB (Oriented FAST and Rotated BRIEF) [12], were also devised and studied by various authors. Each of these algorithms solved different problems associated to feature extraction. In 1994, Local Binary Patterns was proposed by T. Ojala on the basis of the Kullback discrimination of sample and prototype distributions [14]. It's commonly known as LBP and is used in many image processing applications that involve an aspect of facial recognition and identification [15,16,21].

BRISK [17] proposed by S. Leutenegger utilizes an accelerated version of FAST (Features from Accelerated Segment Test) algorithm, also known as AGAST (Adaptive & Generic Accelerated Segment Test). BRISK is widely used for real time operations such as video processing and high-speed image processing systems as stated by M. Zhou [19,20]. Due to its efficiency BRISK has also been applied for mobile image processing applications [22]. BRISK's efficiency and robustness makes it a very promising descriptor to include in facial identification and thus, it was chosen for the same in our proposed method.

The proposed method used Contrast limited adaptive histogram equalization. Contrast limited adaptive histogram equalization as proposed by Zuiderveld K, proved to be a great prospect for image equalization [25]. This is achieved through the use of clip limit which provides necessary clipping before the cumulative distribution function of the neighbourhood is calculated as shown by M. Pizer [26].

III. Proposed Methodology

In this proposed work, the image is pre-processed with Contrast-limited Adaptive Histogram Equalization (CLAHE) along with Haar-Cascading (Viola-Jones algorithm) face detection method followed by BRISK (Binary Robust Invariant Scalable Key-points) descriptor to increase the efficiency of facial identification.

CLAHE normalizes the grey-level pixels of the input images and Haar-Cascading helps to identify the region of the face and mask is created with respect to this region followed by applying BRISK for feature matching and extraction. The proposed method exploits the salient features of BRISK descriptor to generate key-point in less computational time than other descriptors while maintaining the description quality. The binary nature of BRISK makes the process of key-point matching a rapid process.

Elimination of futile part of images by applying CLAHE and Haar Cascading further helps the BRISK algorithm to work on specific area i.e. ROI (region of interest), thus reducing the overall time taken to recognize the face. Thus, our approach includes Haar-Cascading complementing the BRISK descriptor to obtain fruitful results. A significant improvement of identifying images with different expressions and minor altercations in face is successfully achieved than simply using BRISK descriptor.

Our proposed methodology can be divided into the following three steps:

A. Pre-processing

The first step was to convert the colour images to its grayscale variant for further processing. While performing preliminary experimentation without any significant pre-processing it was found out that, its robustness particularly over people of colour was quite poor. Haar Cascading method was particularly failing to capture ROI of few images of people of colour over dark backgrounds. Contrast enhancement techniques were chosen to mitigate such problem and to increase the robustness of the system. Contrast Limited Adaptive Histogram Equalization was chosen over the other variations of Adaptive histogram equalization due to its nature of not amplifying the noise contrast unlike the others. The tile size and clip limit to be used varies from images to images, thus rigorous experimentations were performed to determine these two factors. CLAHE improved the quality of system by enhancing the number of features detected during the extraction phase. An increased number of feature points increased the number of in-liners or matches thus, helping in improving the performance of the proposed algorithm.

B. Face Detection

Face detection is the next phase of our proposed methodology. We have utilized the Viola Jones algorithm to facilitate us in this process. The Viola Jones algorithm is an efficient and robust algorithm that is extensively used for facial detection. This algorithm is able to detect faces in images by matching the similar properties found in faces using Haar based features. Haar Cascading is a machine learning based approach where a cascade function is trained from a lot of positive and negative images.

The Viola Jones algorithm works using the AdaBoost machine learning algorithm. The way in which it trains itself has been underlined below:

1. The first step is to initialize a set of positive and negative images based on the classification we are set to perform.
2. Following this, initial weights need to be set up accordingly. The formula for calculating the same takes into account the number of positive and negative test samples that we have.

$$w_{1,i} = \frac{1}{2m}, \frac{1}{2l} \tag{1}$$

Here m and l are the number of positive and negative samples.

3. Iteratively these weights (t=1 to T) are then normalized with the help of a probability distribution.

$$w_{t,i} \leftarrow \frac{w_{t,i}}{\sum_{j=1}^{n} w_{t,j}} \tag{2}$$

4. In each iteration a classifier is trained for a specific feature and the error is calculated in correspondence to the weight.

5. The classifier with the least error is value is chosen.

$$\varepsilon_t = \min_{f,p,\theta} \sum w_i |h(x_i, f, p, \theta) - y_i| \tag{3}$$

6. The weights are updated. Here $e_i = 0$ if the example is classified correctly otherwise it is 1.

$$w_{t+1,i} = w_{t,i}\beta^{1-e_i} \tag{4}$$

where we have:

$$\beta_t = \frac{\varepsilon_t}{1-\varepsilon_t}$$

7. Steps 3-6 are repeated for a number of iterations based on the requirement and specifications.

Once that the classifiers are trained efficiently, accurate results are obtained. These classifiers are cascaded together to obtain a proper algorithm that is able to detect features as per the need. This approach is used to segment the face from the remaining part image. In our work we have made use of Viola Jones pre trained features that include frontal face, frontal face eyes, frontal face smile and profile face. If required we can train more features as per the database our operation has to take place on. In our research such training was not needed.

This approach is used to segment the face from the remaining part image. Once the facial area has been detected, a mask is generated as per the facial position. With the use of CLAHE in the previous step, it was observed that a more accurate mask is obtained. This mask is important as it signifies the location of the face that has been detected within the image, which helps in preserving the ROI and provides input for further facial recognition.

C. Feature Extraction & Matching

Now that the pre-processing and facial detection phases are over, facial identification is the final step. BRISK algorithm is used for feature point extraction and matching. BRISK is a robust and fast algorithm that can be used for various object recognition applications. BRISK uses AGAST as the descriptor for feature extraction [17]. AGAST is a modification of FAST and is proven to be quicker than the already efficient FAST approach. BRISK does scale space key point detection. In this technique, BRISK estimate the scale of each and every key point in the continuous scale space. AGAST is applied on the layers of the scale space which is divided into octaves to boost efficiency and running speed. The BRISK descriptor is composed by concatenating the results of simple brightness tests into one binary string. Rotational invariance is obtained in BRISK by identifying the characteristic direction of each and every keypoint which is important in order to achieve general robustness. BRISK uses AGAST as the descriptor for facial recognition. It is applied on the mask of the image which is generated by Haar. Since the mask helps in restricting the area for feature point detection and matching, it ensures that feature points of the facial region only get extracted and no extra points are obtained. These feature points are extracted and matched with other images present in the dataset. These matches help in the formation of a polygon using the feature points. The polygon signifies the visual position of a face if it has been correctly identified. The area of the polynomial should lie in a particular range to be able to confidently say that the face has been identified. Based on the matches made, it is decided whether the face present in the test image has been identified or not.

The following schematic diagrammatically explains the algorithm of proposed methodology:

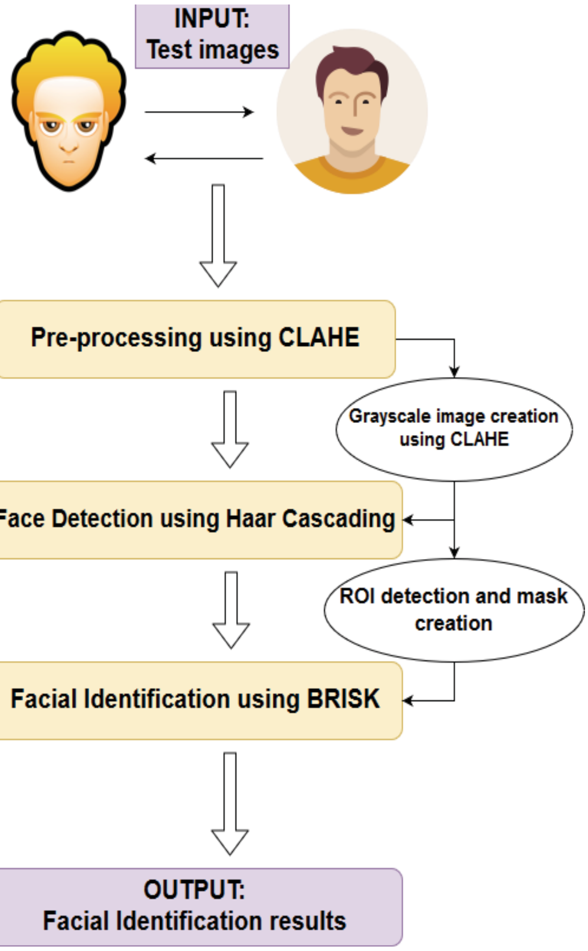


Fig. 1. Flow of proposed model

IV. Experimental Results and Discussion

A. Determining Clip Limit and Tile Size for CLAHE

CLAHE's quality and image enhancement are determined by 2 factors namely, clip limit and the Tile size. The tile size is basically the non-overlapping blocks to which the image has to be divided and for which the histogram is calculated. While clip limit is the thresholding factor with respect to which the histograms of each blocks has to be clipped. It limits the noise amplification by clipping the histogram at predefined value before the cumulative frequency distribution is computed. Image enhancement using CLAHE is determined by these two factors and usually is done using trial and error basis. Instead the parameters of set of images belonging to one dataset is calculated by finding the point of maximum curvature of clip limit vs entropy graph [27]. For each tile size, clip limit vs entropy graph is computed and compared based on the entropy and the best one is chosen.

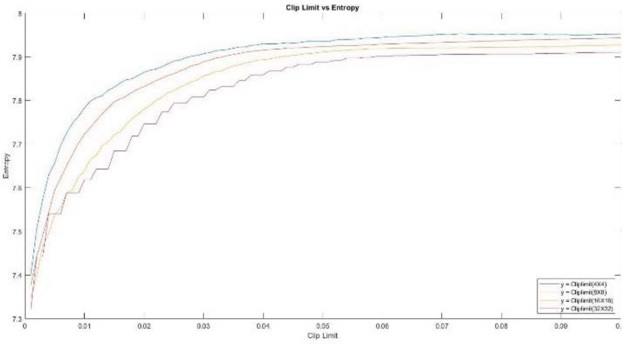


Fig. 2. Clip Limit Vs Entropy Graph

The original experimentation was done on the datasets namely "Head Pose Image Dataset" [23] and "Ljubljana CVL Face Dataset" [24]. The Colorferet dataset was chosen for further experimentation and a random image was chosen from the sample [28,29]. The clip limit vs entropy curve of that image was calculated for each tile size from 4X4 till 32X32 (See Image 2). As evident from the graph the entropy for 4X4 is substantially greater than the rest for all values of clip limit thus, 4X4 is chosen as the Tile size for further experimentation. Since the Clip Limit vs Entropy curve is not a monotonic curve, it is fitted using the following equation (5) [27]:

$$F(x) = a_1 e^{-\lambda_1 x} + a_2 e^{-\lambda_2 x} \quad (5)$$

The abovementioned curve (5) was fitted using the lsqcurvefit() function of MATLAB suite, where a_1, a_2, λ_1 and λ_2 are the coefficient of Function F(x) and their values are:

TABLE I.

Variable	Value
a_1	78.3775
a_2	-70.6163
λ_1	-1.8639
λ_2	-2.0219

The equation for the curvature of a given function is given by the following equation (6):

$$\kappa(x) = \frac{|F''(x)|}{\left(1+ F'(x)^2\right)^{3/2}} \quad (6)$$

The point of maximum curvature is at the maxima of K(x), so the critical points of K'(x) will provide us the point of maximum curvature i.e. the ideal value of clip limit. Through rigorous mathematical calculations the point of maximum curvature is approximately at clip limit (or x)= 0.15. This clip limit along with the tile size of [4X4] will be used for further set of experiments.

TABLE II. THE VISUAL REPRESENTATION OF EFFECT OF CLIP LIMIT AND TILE SIZE

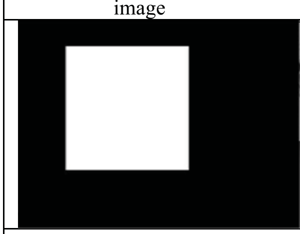
Clip Limit	Image A (Tile Size = [4x4])	Image B(Tile Size = [4x4])
Original Image		
0.01		
0.15		
0.35		
0.89		
2.003		

B. Experiment on Face Dataset 1

Our proposed methodology was subjected to a total of 76 images compiled from 2 different sets of datasets namely "Head Pose Image Dataset" [23] and "Ljubljana CVL Face Dataset" [24]. The Head Pose Image Dataset has a resolution of 72 dpi (384X288 pixels) and the Ljubljana CVL Face Dataset has a resolution of 96 dpi (640X480 pixels). We chose 42 images from Head Pose Image Dataset i.e. 15 sets of images(people) while we chose 24 images(people) i.e. 12 sets of images(people) all in .jpeg format. The images have varied expressions and minor variations in clothing, hair style or accessories such as spectacles. The Ljubljana CVL Face Dataset mainly focuses on the facial expressions while the Head Pose Image Dataset focuses one facial orientation and minor variations. The optimal value of clip limit was applied for the Contrast Limited Adaptive Histogram Equalization. The optimal limit after experiments shown in section 5.1- 'Determining clip limit and tile size for CLAHE' was determined to be 0.15. The default value for threshold and octave for BRISK were chosen for experimentation [17].

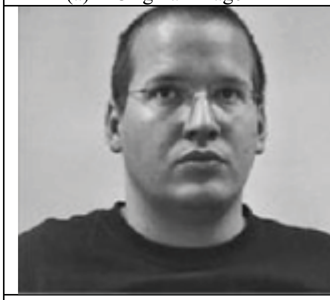
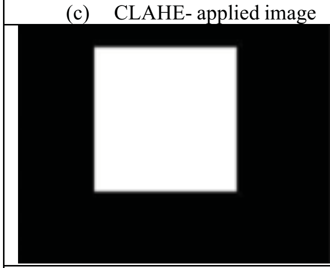
A comprehensive study on facial datasets revealed that our proposed methodology is invariant to the orientation of face in a particular range i.e. the proposed methodology works and is capable of identifying faces in a range of [-15, 15] degrees in the X and the Y-axis i.e. both horizontally and vertically as well as for faces with different expressions and faces with spectacles on..

TABLE III. CONTRAST-LIMITED ADAPTIVE HISTOGRAM EQUALIZATION FOLLOWED BY DETECTING REGION OF INTEREST (ROI) DETECTION AND MASK CREATION USING HAAR CASCADING FOR BASE IMAGE

	
(a) Original image	(b) Grayscale image
	
(c) CLAHE-applied image	(d) Face detection
	
(e) Generated mask	(f) Detected ROI

As per "Table III", Original Image consisting of person with 0° tilt is input, its equivalent contrast limited adaptive histogram equalized grayscale image is generated (c) as part of pre-processing stage. Haar Cascading is applied on generated image (c) to create a mask as shown in (e).

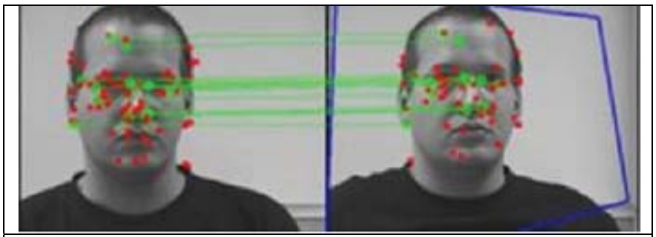
TABLE IV. CONTRAST-LIMITED ADAPTIVE HISTOGRAM EQUALIZATION FOLLOWED BY DETECTING REGION OF INTEREST (ROI) DETECTION AND MASK CREATION USING HAAR CASCADING FOR 15 DEGREES TILTED FACE

	
(a) Original image	(b) Grayscale image
	
(c) CLAHE- applied image	(d) Face detection
	
(e) Generated mask	(f) Detected ROI

Similarly, for "Table IV", Original Image (with a tilt in 15°) is input, its equivalent contrast limited adaptive histogram equalized grayscale image is generated (c) as part of pre-processing stage. Haar Cascading is applied on generated image (c) to create a mask as shown in (e).

"Table V" below shows the images by applying BRISK on the target image and the respective identified dataset image.

TABLE V. FEATURE EXTRACTION & MATCHING ON IMAGES FROM DATASET[1][2]



(a) Match visualisation

(b) Extracted image after identification

The cases depicted over "Table VI" below clearly show how the CLAHE-based BRISK methodology outperforms the original BRISK. The proposed methodology can clearly match faces with multiple variation in faces and clothing and accessories.

TABLE VI. TABLE SHOWING DETAILS OF SUCCESS OF PROPOSED METHOD OVER BRISK

Image1	**Image2**	**Method and Variation**	**Match Summary**	**Homograph summary**	**Result**
 Without Spectacles	 With Spectacles	BRISK only	10/10	Not enough	No
		Proposed BRISK Method	116 / 121	15 / 116	Yes
 With Spectacles	 Without Spectacles and Black shirt	BRISK only	139 / 139	11 / 139	No
		Proposed BRISK Method	151 / 151	10 / 151	Yes
 No Smile	 Smiling	BRISK only	119 /119	10 /139	No
		Proposed BRISK Method	80/80	12/80	Yes

The test cases outputs are classified as true positive, true negative, false positive and false negative and the graph is drawn for the facial identification using (a) BRISK and (b) Proposed methodology.

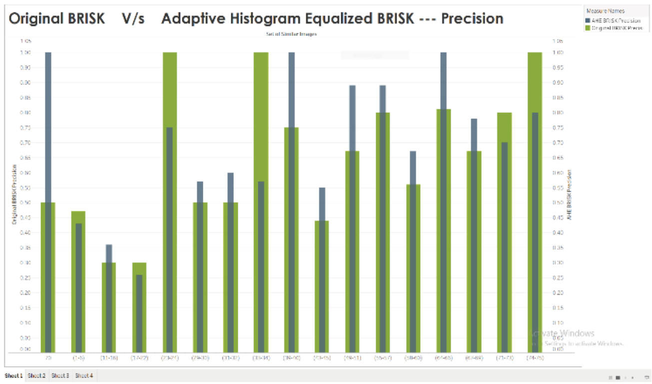


Fig. 3. "Original BRISK" Vs "BRISK with Proposed Methodology"

V. CONCLUSION & FUTURE ENHANCEMENTS

Proposed methodology aims at providing efficient facial identification with a minute trade-off in execution speed, we observed that our methodology yields precise and more accurate results than original BRISK when there are changes in images (a) Facial expressions (b) Clothing (c) With and without spectacles between the target image and dataset images. In future, the research work may concentrate to identify the faces when there is a rotational change greater than 15 degrees in X and Y axis. In future, we wish to proceed this idea by conducting research on other detectors and descriptors like ORB and BRIEF.

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