Forehead Image Matching Result Analysis

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1 Introduction

In this report, the results of forehead matching using image matching and feature extraction algorithms are shown. Bio-metric authentication using forehead becomes important due to the current pandemic because everyone has to wear a mask and hence, a system which authenticates using forehead wrinkles would be much more convenient. Moreover, the methods used in this report are inexpensive and do not require any complicated equipment to function.

2 Dataset

Students of BITS Pilani, Pilani campus that were enrolled in the Deep Learning course gathered the data. Data was gathered over the course of two sessions, with a minimum of 12 hours between them. Each session resulted in ten photographs, five of which were taken up close and five of which were taken from a distance. The experiment employed 336 pictures from the total data gathered. There were three close-up photos and three far-off images for each of the 28 subjects in each session.

3 Model Pipeline

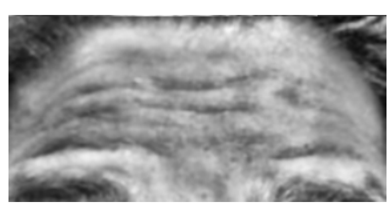
3.1 RoI extraction

The extraction for the region of interest was done manually. The users had to align their forehead in a box while frowning such that their wrinkles are visible. The images were also taken from two poses, one far-off pose and one pose from near the camera. Finally there were 336 RGB RoI extracted images.

3.2 Image Enhancement

CLAHE (Const Limited Adaptive Histogram Equalization) was used to convert the pictures to grayscale. The CLAHE method outperforms the conventional histogram equalization method. CLAHE is a version of adaptive histogram equalization (AHE) that corrects for contrast overamplification. CLAHE works by dividing the image into tiles, which are tiny areas of a picture rather than the full image. To remove the false borders, the nearby tiles are merged using bilinear interpolation. It was found that using CLAHE gave better results than the normal histogram equalization methods, and as a whole these preprocessing techniques gave a better result than using the default RGB images, as wrinkles seemed to be enhanced using these methods.

(a) Before



(b) After

Figure 1: Image after going through enhancement

3.3 Image Matching

SIFT, SURF, ORB, ArcFace, SSIM and AKAZE were the feature extractors employed in this experiment. SIFT, SURF, ORB and AKAZE are used to extract the input picture's local image characteristics. The extracted feature vectors for the two pictures are compared to accomplish image comparison. These matches are found by comparing the feature descriptors of the two pictures in question using the Brute Force method. We use Lowe's ratio test to remove the ambiguous matches. The first image's keypoints are matched with a number of keypoints from the second image. For each keypoint, the two best matches (those with the lowest distance measurement) are preserved. The Lowe's test determines if the two distances are sufficiently dissimilar. If they aren't, the keypoint is removed from the equation and won't be utilised again.

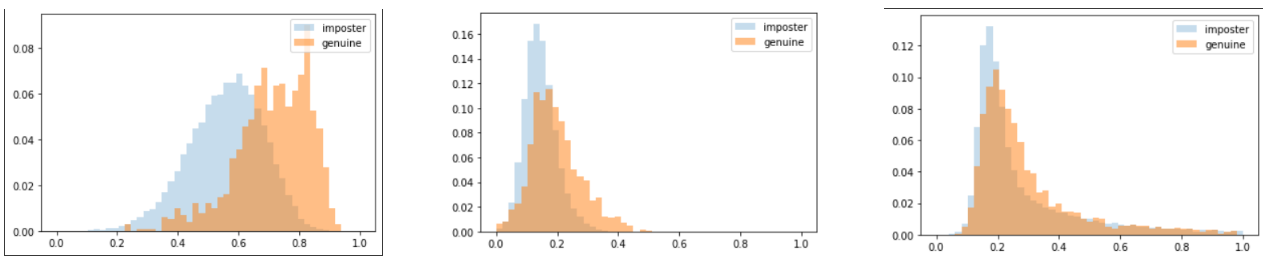
The Structural Similarity Index is an acronym for Structural Similarity Index. It's a statistic that measures how different two pictures are structurally. This measure is based on the picture data rather than the image's characteristics. SSIM is a popular metric that is used for comparing quality of results for image compression and image reconstruction in modern research.

ArcFace is a classification model based on neural networks. It employs a similarity learning method to address distance metric learning in the classification problem by replacing Softmax Loss with Angular Margin Loss. The cosine distance, which is computed by the inner product of two normalised vectors, is used to calculate the distance between faces.

As we will see in further sections, both SSIM and ArcFace far outperformed the other local descriptor based methods.

3.4 Genuine/Imposter Histogram

If the forehead being compared in two photos belongs to the same person, the match is considered to be genuine otherwise it is an imposter match. The photos being compared are from several sessions. It's an imposter match if the two subjects of the matched photos aren't the same. A smaller number of imposter matches is desirable for an authentication system since security is of the essence and we would not want unathourized people having access. For each score, the genuine/imposter histogram is shown against the likelihood of that score occurring. Since there are significantly fewer real matches than imposter matches in *ntimesn* matching, the frequency is not plotted.



(a) ArcFace (b) SSIM (c) SIFT

Figure 2: Genuine/Imposter histogram

3.5 Calculation of metrics

Thresholds for each value from 0 to 1 inclusive, with a step size of 0.0001 were used to check the performance of each algorithm. For each threshold, the FAR (False Acceptance Rate), the FRR (False Rejection Rate) and CRR (Correct Rejection Rate) were calculated. Using those values, EER was also calculated which gave a threshold to the system for rejection and acceptance. The given metrics were calculated for each algorithm.

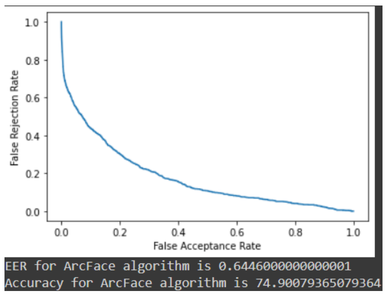
$$\text{CRR} = \frac{TP+TN}{TP+TN+FP+FN} = \frac{\text{No. of matches correctly recognized}}{\text{Total no. of matches}} \quad (1)$$

$$\text{FAR} = \frac{FP}{FP+TN} = \frac{\text{No. of incorrect matches recognized}}{\text{Total no. of imposter attempts}} \quad (2)$$

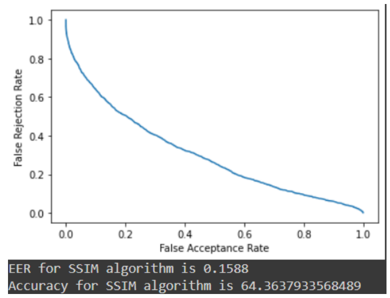
$$\text{FRR} = \frac{FN}{FN+TP} = \frac{\text{No. of correct matches recognized}}{\text{Total no. of genuine attempts}} \quad (3)$$

$$\text{Accuracy} = 100 \text{ - } \frac{FRR+FAR}{2} \quad (4)$$

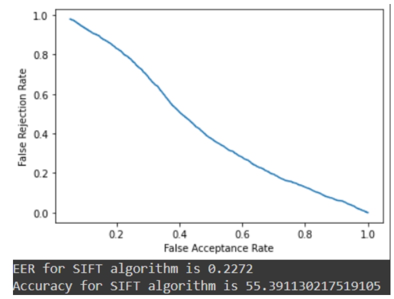
After calculating these metrics, the ROC (receiver operating characteristic) curves for each algorithm were plotted. An ROC curve has the FAR on the x-axis and FRR on the y-axis.



(a) ArcFace ROC



(b) SSIM ROC



(c) SIFT ROC

Figure 3: ROC curves

3.6 Result Analysis

Feature Extractor/ Image Matching Algorithms	EER	Accuracy
SIFT	0.2272	55.39
SURF	0.1288	58.38
ArcFace	**0.6446**	**74.90**
ORB	0.2400	54.21
AKAZE	0.2642	54.72
SSIM	0.1588	64.36

Table 1: Summary of results

With the supplied data, ArcFace performs the best. The findings are good since it extracted face characteristics from the image using pre-trained weights and parameters. The similarity scores were calculated by finding the cosine similarity between the embeddings given by the ArcFace model on the two images. Due to the similarity in location and illumination of the photos examined, SSIM also worked well. SSIM is unreliable with shifting camera angles, illumination, contrast, and other factors since it does not extract features and instead compares the picture data as is. The lighting and contrast of the comparison photos were similar because we applied suitable image improvements. The absence of features retrieved by the feature extractor is the cause of the excessive number of 0s in the ORB and AKAZE histograms. This is owing to the dataset's existence of fuzzy pictures. For all of the feature extractors, the Contrast Limited Adaptive Histogram Equalization produced somewhat better results than standard equalisation. Figure 4 shows the ROC curves of the extractors utilised in the experiment for comparison.

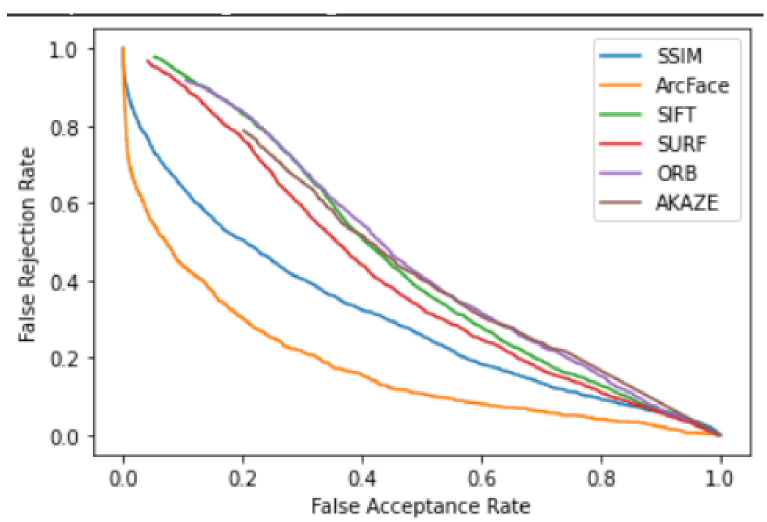


Figure 4: ROC curves for different algorithms