A Biometric Fusion System of Face and Fingerprint for Enhanced Human Identification Using HOG-LBP Approach

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Abstract
This paper presents a biometric fusion system of fingerprint and face images for Ergonomic-Based Enrolment and Verification System. Features from fingerprints and faces are extracted to create a new biometric template with enhanced performance and with an extra level of assurance for identification. A fusion scheme combines the extracted Histogram of gradients (HOG) and local Binary Pattern (LBP) features from a subject's fingerprint and face images. Manhattan Distance is used to compare between the template in the database and the input data. The difference between the database template and the input data determines the decision either to reject or accept. Different "matching score thresholds" were set to evaluate the relationship between False Rejection Ratio and False Acceptance Ratio which is a common measure to determine system performance level. From the experiments and based on the characteristic nature of this HOG-LBP algorithm, a threshold between 75% and 80% is determined to be moderate and close to the EER (Equal Error Rate) point, which is the intersection of the False Accept Rate (FAR) and False Reject Rate (FRR). The system is robust enough to accommodate an increase in the threshold if a high level of system confidence is required.

Keywords: Histogram of gradients, local Binary pattern, face and fingerprint fusion

1.0 INTRODUCTION

There is an increasing use of information technology in voting, crime control and access control management. Single mode biometric systems often get compromised when used for identification, verification, authentication and authorization may due to noisy sensor data, non-universality, spoof attacks, etc or intentional attempt to fool the system (Ross and Jain 2004). In situations where a person's unique identity is of critical importance, a system of fused biometric templates becomes a preferred option as it is likely to give an extra layer of confidence in the task of verification. The need to have a robust multimodal biometric system that can combine at least two biometric features or templates is increasingly becoming a necessity. This research aims to show another viable approach to biometric fusion systems that combines fingerprint and facial images at feature-extraction level. The extracted information from fingerprint sensors and facial image from camera with each modality is stored in vectors based on their modalities. These feature vectors are then combined to create a new template which is the basis for the matching and recognition process. Fusion approaches have been used successfully in large-scale automated fingerprint identification systems (AFIS), which combine multi-biometric data and multiple methods of processing to address some issues faced by the designers, implementers, and operators of biometric systems as explained in (Hicklin *et al.,* 2006).

Biometrics (Biometric recognition) is the scientific cum technological use of distinctive physiological and/or behavioural characteristics or traits for automated human recognition or authentication (Jain *et al.*, 1999, Ross and Jain, 2004). Based on the number of user interfaces or number of biometric features to be acquired from the user, a biometric system is classified into two main categories: unimodal and multimodal biometric system as detailed in (Jain *et al.,* 1999). Essentially, the modality of a biometric system refers to the number of biometric traits it relies on as validation for human recognition. i.e., unimodal and multimodal biometric systems rely on single or multiple biometric traits respectively as evidence for human recognition as in (Monwar and Gavrilova 2009, Panchal and Singh 2013).

It is intuitive to deal with the limitations of unimodal biometric systems by adopting a multimodal approach in which biometric information obtained from multiple traits are combined to provide complementary evidence for very reliable decisions, verification and authentication. There are four levels of fusion namely; sensor level, feature level, score level and decision level. In a multimodal system, each biometric trait is processed in parallel. The processed information is then combined using an appropriate fusion technique. Successive comparison of database template with new input data is often done using an appropriate distance matching algorithm (Dhameliya and Chaudhari, 2013). A biometrics system, irrespective of its category, may be used for enrolment and/or authentication of users as in (Jain *et al.,* 2004, Wayman *et al.,* 2005). In the enrolment mode, the feature extractor commits the digitized biometric features extracted from the captured user data to the system's as templates for future references. In the authentication mode, the matcher attempts to match the extracted feature codes from the user's data with the template(s) stored in the database. Based on the correlations between the input features and the database template(s), the matcher generates a rank score that is used by the decision module to take an appropriate decision for the context in which the system is being used.

Multimodal biometrics systems have been developed in the last few years at different fusion levels where fusion at score and decision levels have been widely studied as found in the multimodal biometric system using rank-level fusion approach (Monwar and Gavrilova, 2009). A Quality based adaptive score fusion approach for multimodal biometric system has been proposed by (Gupta *et al.,* 2020) to address adaptiveness to the dynamic environment and distinguish between spoofing attack and the noisy input image, Normalization and weighting techniques based on genuine-impostor score fusion in multi-biometric systems was proposed by (Kabir *et al.,* 2018) where a weighting technique based on the confidence of the matching scores by considering the mean-to-maximum of genuine scores and mean-to-minimum of impostor scores is explored. A multi-biometric system may have any combination of two or three biometric traits such as iris, fingerprint, palmprint, and ear print and many more.

A lot has been reported in the literature on multimodal biometric at feature extraction level using different algorithms. Biometric combinations include face and palmprint (Lee and Bong, 2016), (Rane and Deshpande, 2018), iris and fingerprint (Lahane and Ganorkar,2012), palmprint and fingerprint (Dhameliya and Chaudhari, 2013). In these works, various methods like Gabor, Radon, Ridgelet and Radon-Gabor filters have been used for feature extraction. Authors in (Rahman *et al.,* 2019) proposed a multimodal biometric system using PCA method for face recognition process and used the Daugman method for iris recognition process. Jagadeesan and Duraiswamy, (2010) in their work on secured cryptographic key generation from multimodal biometrics used feature level fusion of fingerprint and iris. The typical tasks addressed are automatic discrimination between subjects, data protection, and access control. Feature-level fusion of face and fingerprint biometrics by Rattani *et al.,* (2007) introduced a scale invariant feature (SIFT) technique for face recognition and minutiae matching technique fingerprint recognition. Recent survey also show investigation on 3-D-based biometrics (Fei *et al.,* 2020).

In general, the overall goal of deploying a multimodal biometric system is to overcome the limitations of unimodal systems such as, non-universality, intra-class variations, noise in sensed biometric data, unacceptable error rates, restricted degree of freedom, etc. (Ross & Jain 2004, Taouche *et al.,* 2014, Jain *et al.,* 1999, Monwar & Gavrilova 2009, Panchal and Singh 2013, Wayman *et al.,* 2005, Jain and Ross 2004, Subbarayudu and Prasad, 2008).

Unarguably, face and fingerprint have a wider usage globally with their applications in passport issuance, access control, crime detection and a lot more. Although a lot has been done in this

research domain, errors due to noise, intra-class variation and illumination remains an open challenge when using the most commonly used biometric i.e. facial images. This is one key area this study addresses.

2.0 MATERIALS AND METHOD

In a multibiometric system, two or more biometrics information are fused to form the signature for the identity of a person. In this work, a multi-modal fusion is performed at feature-extraction level. It is a fusion of two biometrics of a subject namely -fingerprints and face. This work applies descriptors algorithm using combined HOG-LBP to improve the performance of multimodal biometric system (face and fingerprint). Each modality will be subjected to two different algorithms for features extraction and then fuse the processed features. The system is illustrated in Figure1.

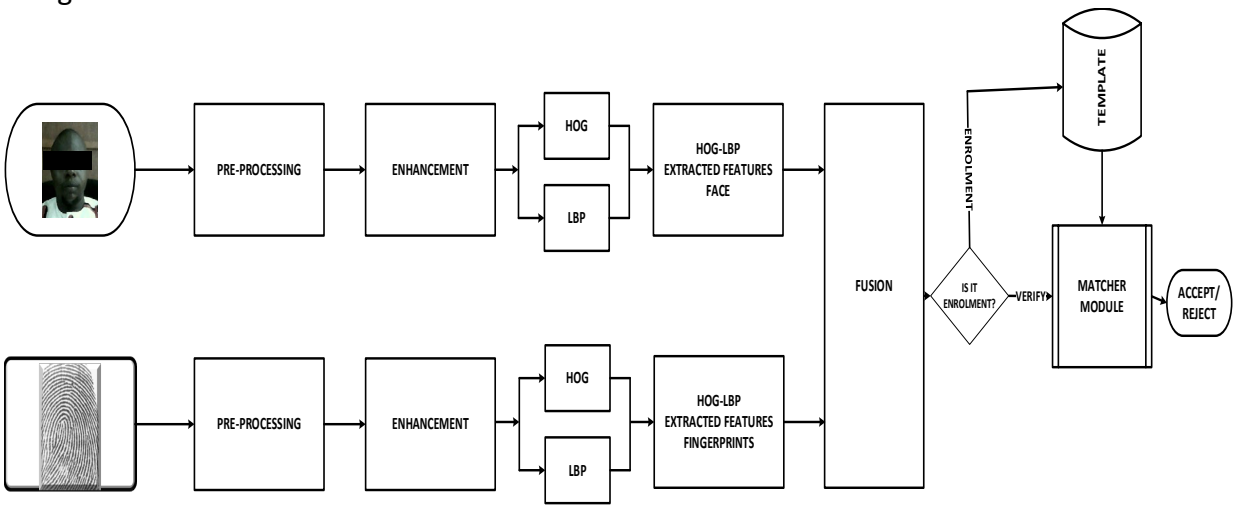


Figure 1: The General framework of biometric fusion system for face and fingerprints using HOG-LBP

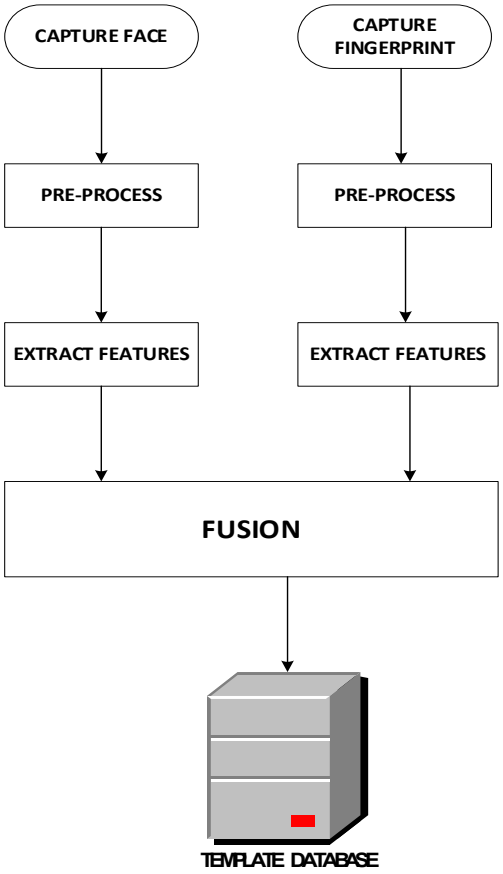


Figure 2: Enrolment Sub-System

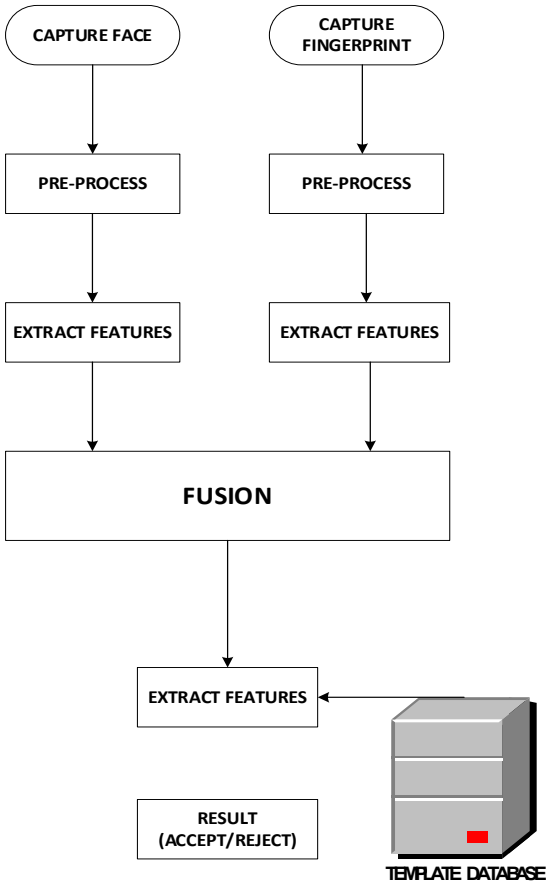


Figure 3: Verification Sub-System

The operational follow is depicted for enrolment and verification in Figure 2 and Figure 3. respectively.

A. *Techniques*

Local Binary Pattern (LBP) is combined with the Histogram of Oriented Gradients (HOG) descriptor using OpenCV tools in MATLAB to implement this project. Some pre-processing operations were employed to improve the quality of both face and fingerprint images before features are extracted.

B. *Pre-processing*

Wiener filtering is employed to improve the legibility of the fingerprint and remove noise in facial image without altering their ridges structures. The filter is based on local statistics estimated from a local neighbour η of size 3×3 of each pixel and is given by the following equation as obtainable in (Jagadeesan and Duraiswamy, 2010).

$$w(n_1, n_2) = \mu + \frac{\sigma^2 - v^2}{\sigma^2}(I(n_1, n_2) - \mu) \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

where v^2 is the noise variance, μ and σ^2 are local mean and variance and I represents the gray level intensity in $n_1, n_2 \in \eta$.

This approach often produces better results than linear filtering. The adaptive filter is more selective than a comparable linear filter, preserving edges and other high-frequency parts of an image.

i. *Facial Image*

Viola-Jones algorithm as experimented in (Viola and Jones ,2001) which is made available as a tool in MATLAB 2017 Release is applied on every input image to detect the facial structure part and then crop out the detected area.

ii. *Fingerprint Image*

The fingerprints image is filtered to remove noise and then by using histogram equalization for enhancing the contrast of an image. It flattens and stretches the dynamic range of the image's histogram resulting in overall contrast improvement of the fingerprint image. The Histogram Equalization equation is given below as experimented in (Sepasian *et al.,* 2008).

$$s_k = T(r_k) = \sum_{j=1}^{k} P_r\left(r_j\right) = \sum_{j=1}^{k} \frac{n_j}{n} \quad . \ . \ . \ . \ . \ . \ . \ . \ . \qquad (2)$$

Where s_k is the intensity value in the processed image corresponding to intensity r_k in the input image, and

$P_r(r_j) = 1,2,3, \ldots, L$ is the input fingerprint image intensity level.

iii.HOG-LBP Technique

This combines HOG-LBP is an algorithm that combines shape and texture analysis or representation for HOG and LBP respectively.

iv. *Local Binary Pattern*

Local Binary Pattern (LBP) has been found to be computationally efficient texture descriptor with tolerance against illumination changes. LBP was introduced by (Ojala *et al.,* 1996). The LBP operator is structural and statistical texture descriptor in terms of the characteristics of the local structure, so that it is very efficient for texture analysis as experimented by (Nagaraja and Prabhakar, 2015)

Brief Steps in LBP Implementation

a. Identify all pixels with luminance less than centre pixel luminance
b. Remaining pixels are greater than or equal to centre pixel luminance
c. Next, Binarize results

It labels the pixels of an image by using the 3x3 neighbourhood of each pixel with the centre value as a threshold and the result as a binary number. The LBP code for the centre pixel is then produced by concatenating the eight ones or zeros to a binary code.

A formal LBP operator can be described as:

$$LBP(x_c, y_c) = \sum_{P=0}^{P-1} 2^P \times s(i_p - i_c) \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \qquad (3)$$

With (x_c, y_c) as central pixel with intensity $i_c \ and \ i_p$ being the intensity of the neighbour pixel. s is the sign function defined as;

$$s(x) = \begin{cases} 1 & if\ x \geq 0 \\ 0 & if\ x < 0 \end{cases} \ \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \qquad (4)$$

Where, P is the number of neighbourhoods

v. *Histogram of Oriented Gradient*

The histogram of oriented gradients (HOG) is a feature descriptor used in computer vision and image processing for the purpose of object detection. It was proposed by (Dalal and Triggs, 2005).

Brief Steps in HOG Implementation

1. Compute gradients in the region to be described

2. Put them in bins according to orientation
3. Group the cells into large blocks
4. Normalize each block
5. Train classifiers to decide if these are parts of a human

HOG feature is an excellent descriptor, which calculates the gradient magnitude and the gradient direction of the local image. mage gradients are basically the change in pixel values in x and y directions of the image. Mathematically, it is the linear sum of the x and y derivatives of an image. The gradient amplitude of the input image both in the horizontal and vertical direction with a 1-D mask template, i.e., $[-1\ 0\ 1]$.

$$H_x(x,y) = I(x+1,y) - I(x-1,y) \quad \ldots\ldots\ldots \quad (5)$$

$$H_y(x,y) = I(x,y+1) - I(x,y-1) \ldots\ \ldots\ldots \quad (6)$$

where $I(x,y)$ is pixel value of the point (x,y), $H_x(x,y)$ and $H_y(x,y)$ denote the horizontal gradient amplitude and vertical gradient amplitude respectively.

Gradient amplitude of the pixel (x,y):

$$H(x,y) = \sqrt{H_x(x,y)^2 + H_y(x,y)^2} \ldots\ldots\ldots \quad (7)$$

Gradient direction of the pixel (x,y):

$$\theta(x,y) = \tan^{-1}\left(\frac{H_y(x,y)}{H_x(x,y)}\right)$$

$$v' = \frac{v}{\sqrt{||v||_2^2 + \epsilon^2}} \quad \ldots\ldots\ldots\ldots\ldots \quad (8)$$

Where, v is a non-normalized vector containing all histograms in a given block and ϵ is a small constant.

vi. *Fusion*

Extracted HOG features and LBP features of each biometric are fused. The extracted HOG features, returns a 1-by-N vector or matrix. The features encode local shape information from regions or from point locations within an image while LBP feature vector, returned as a 1-by-N vector of length N representing the number of features. LBP features encode local texture information. Because of huge number column vectors often produced by HOG during features extraction unlike LBP simple matrix concatenation is not always applicable because of curse of dimensionality. Therefore, for this work statistical analysis was carried out on 1-by-N vectors of both HOG and LBP extracted features using mean and variance.

The feature vector of HOG can be represented as,

$$H = [h_1, h_2, h_3 \ldots\ldots\ldots\ldots h_D]$$

The feature vector of LBP can be represented as,

$$L = [L_1, L_2, L_3 \ldots\ldots\ldots\ldots L_N]$$

Where D >>> N,

For HOG mean computation

$$Hm = \frac{1}{D}\sum_{i=1}^{D} h_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \quad (8)$$

Compute Standard deviation for HOG

$$Hstad = \sqrt{\frac{1}{D-1}\sum_{i=1}^{D}|h_i - Hm|^2} \ldots\ldots\ldots\ldots\ldots\ldots \quad (9)$$

Similarly,
Compute LBP mean computation

$$Lm = \frac{1}{N}\sum_{i=1}^{N} L_i \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (10)$$

Compute Standard deviation for LBP

$$Lstad = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N}|L_i - Lm|^2} \ldots\ldots\ldots\ldots \quad (11)$$

HOG-LBP is easily combined after the above computation. Each result from the above will be concatenated as 1 by N vector for each biometric

$$Fingerprint = F1 = [Hm \ \ Hstad \ \ Lm \ \ Lstad]$$
$$Face = F2 = [Hm \ \ Hstad \ \ Lm \ \ Lstad]$$

By applying simple concatenation method of two vectors of equal dimension.

$$F = [\mathrm{F1} \ \ \mathrm{F2}] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. \quad (12)$$

The fusion component will be 1 by N vector, where N is 8 i.e.
The overall general fusion computation is

$$Fusion = F = [F_1 \ \ F_2 \ \ F_3 \ \ F_4 \ \ F_5 \ \ F_6 \ \ F_7 \ \ F_8] \ldots\ldots\ldots\ldots\ldots.. \quad (13)$$

vii. *Matching*
Comparison is done between the database template and the test fused images by using Manhattan Distance. In this approach the difference between the template in database which is F vector from Ftest Vector.
From equation, let $F_k(x_i)$ denotes template on the database and $F_k(x_j)$ denotes Ftest.
Therefore, the difference between two instances x_i and x_j can be defined as

$$f(x_i, x_j) = \sum_{k=1}^{n}\left|F_k(x_i) - F_k(x_j)\right| \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (14)$$

A threshold is set for each value of $f(x_i, x_j)$ i.e. if $f(x_1, x_1)$ falls within the threshold, assign 1 otherwise 0. At the end of the computation, 8 bits are generated. The percentage of '1s' in the 8 bits will determine Accept/ Reject.

3.0 RESULTS AND DISCUSSION

To overcome the problems of inaccuracy of unimodal biometric system, a novel combination of HOG-LBP is proposed for fusion at feature extraction level of face and fingerprints images for multimodal biometric recognition system. Seventy subjects were enrolled. Identity verification

with the same subject was also carried out. Identity verification with the same subject with different cloth and background was tested to determine the system accuracy. Finally, Impostor was tested to determine vulnerability.

i. Subject Enrolment

Figure 4 to Figure 8 shows the internal working process of the system during enrolment as well as verification.

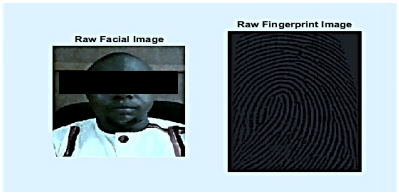


Figure 4: The Capture Page of Face and Fingerprint

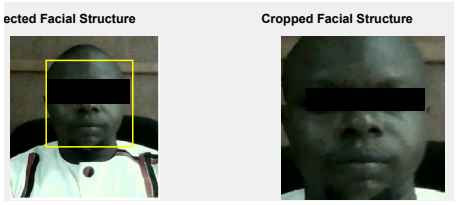


Figure 5: The Face Detection using Viola-Jone Algorithm

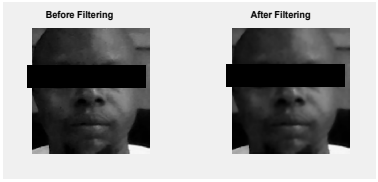


Figure 6. Filtering Image Using Wiener Filter

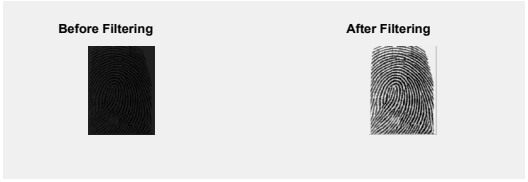
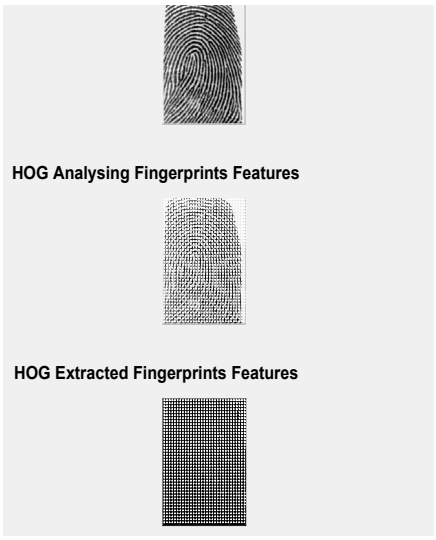
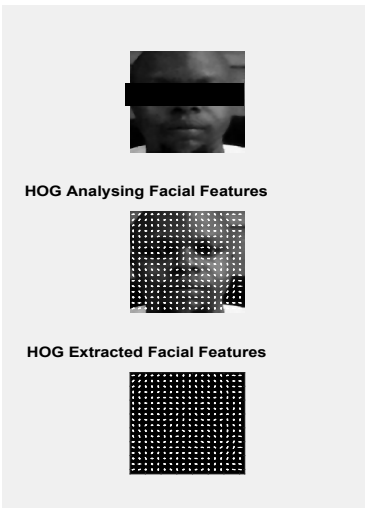


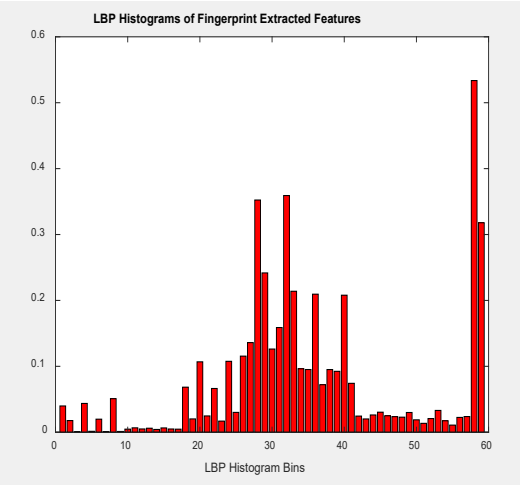
Figure 7. Filtering and Enhancement Fingerprint Image Using Wiener Filter and Histogram Equalization

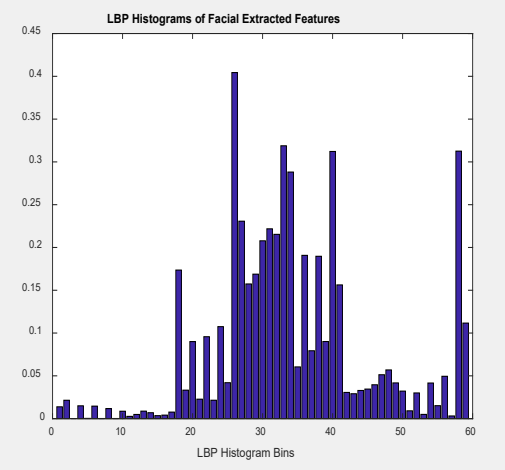


(a)



(b)





(c) (d)

Figure 8: Features Extraction HOG((a) & (b)) and LBP ((c) &(d))

A. *Identity Verification*

All the internal working process of the system that was depicted from Figure 4 to Figure 8 will be equally undergone during verification.

i. Identity Verification with The Same Subject

As shown in Figure. 9, the subject was verified in the same cloth, background and illumination, the accuracy was 100%.

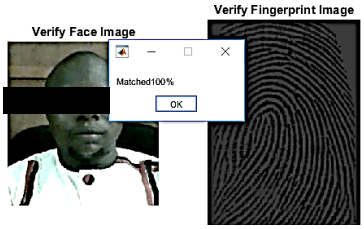


Figure 9. Verification with same subject condition

ii. Identity Verification with The Same Subject with Different Cloth, Background, Posture and Illumination

The subject is the same as the enrolee in the database but undergoing verification with different conditions like background, cloth, illumination level and posture as shown in Figure 10.
The system was able to achieve 74% accuracy to match with the template on the database.

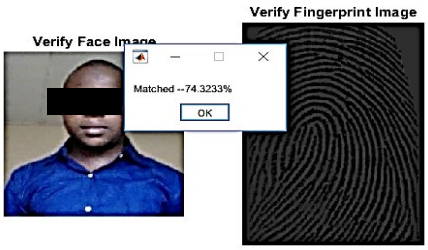


Figure 10: Verification of the Same Subject with Different Conditions

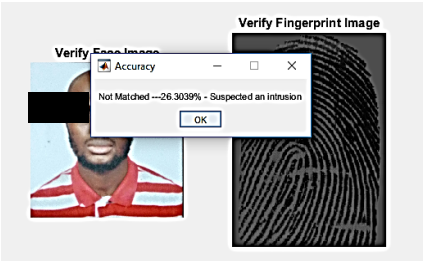


Figure 11: Verification of another subject as an impostor

Table 1. Feature extraction details

The experimental results are as follows:

a. Genuine Attempt

i. Result of Identity Verification with The Same Subject Condition

The matcher graph shows no variation between template in the database and subject as shown Figure 12.

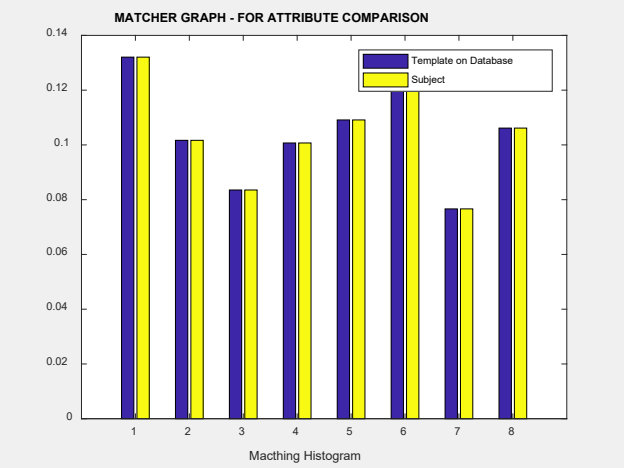


Figure 12: Matcher Graph for the same subject condition

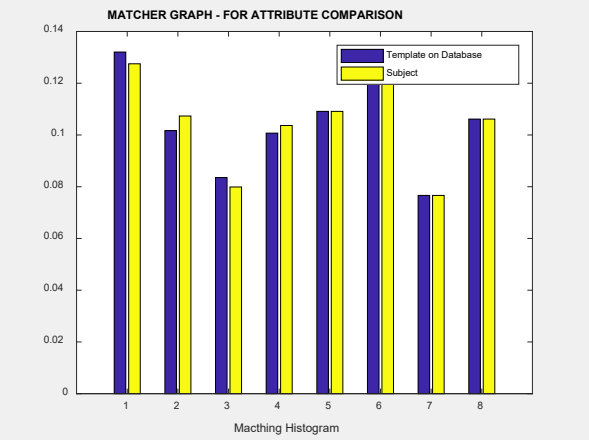


Figure 13: Verification of the Same Subject with Different Conditions

ii. Result of Identity Verification with The Same Subject with Different Cloth, Background, Posture and Illumination.

The subject is the same as the enrolee in the database but undergoing verification with different conditions like background, cloth, illumination level and posture as shown in Figure 10. Ten different subjects were experimented with relatively similar conditions. The system was able to achieve average of 74% accuracy to match with the template on the database. The matcher graph in Figure 13 reveals further while the accuracy dropped to 74% in matching. The histograms 5 to 8 in Figure 13 show no variation while 3 and 4 show slight variation from each other. Histogram 1and 2 more conspicuously a little wide variation from each other.

B. Result of Impostor Attempt

Having passed through the internal working process and failed to match with the attributes of template by falling within 70% - 100% matching score pass. Such a subject will be considered as an impostor as shown in Figure 4.7(a-c). Twenty different subjects were tested. The matcher graph in Figure 14 exposes the huge variation or outliers between the biometric template on database and the impostor.

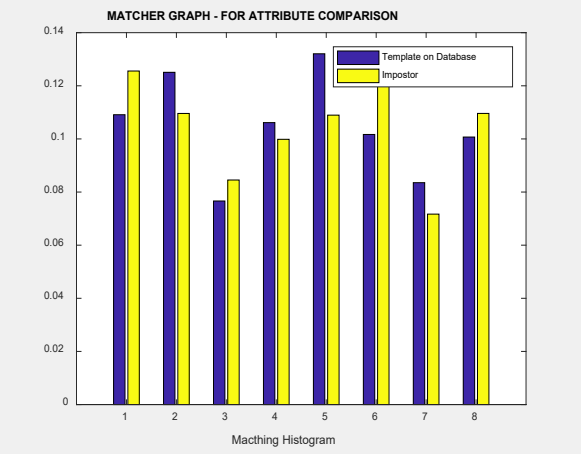


Figure 14: Matcher Graph Verification of Another Subject as An Impostor

B. *Performance*

Evaluation

Seventy subjects were enrolled as stated in experimental setup with their face and fingerprint. Twenty different subjects as impostors were tested against each individual on the database which generated $70\ x\ 20 = 1400\ \ impostor\ scores$ while genuine attempts were made using 10 subjects against database which generated $70\ x\ 10 = 700\ scores$.

As depicted in the Table 2; at different thresholds set, genuine attempts for ten subjects produce average match score (accuracy) at each threshold. The same is applicable to impostor attempts of twenty different subjects. Threshold for this fusion biometric system is based on the differential limit set between database template and tested template.

Table 2: Features Matching Accuracy Result

Threshold Attempt	Average match score at threshold set 90% and above	Average match score at threshold set between 80% and 89%	Average match score at threshold set between 70% and 79%
Genuine	67.5%	77.5%	96.5%
Impostor	0.5%	20.5%	43.5%

At threshold set between 70% and 79%, the True Acceptance Rate (TAR) is high with accuracy of 96.5% but the system is slightly prone to imposition.

As shown in the Table 3; for different "matching score thresholds", the relationship between False Rejection Rate and False Acceptance Rate relationship was also established which is a common measure to determine the performance level of any biometric system either unimodal or multimodal system. In this project, at 90% and above threshold, it puts the presented sample under strict examination. This is necessary when a high level of system confidence is required. At this threshold percentage of FRR increased with this algorithm.

Table 3: Performance Measure

THRESHOLD	FRR (%)	FAR (%)
T>=90	3.5	0.1
90>T>79	2.5	0.75
80>T>=70	1.65	1.85

At 80% and above threshold, the sample presented is subjected to less strict examination unlike 90%. Based on the characteristic nature of this algorithm with a novel combination of HOG-LBP, 70% and 79% threshold to be moderate and is close to EER (Equal Error Rate) point, which is the intersection of the FAR and FRR.

There is no unusual computational processing requirement for this system. The device specification for this work is an 8GB RAM, Intel Core i3 CPU @ 1.7GHz with Windows Pro 64 bit. From the computational complexity, it takes an average of 15.47 seconds to execute matching of 10 subjects individually and it takes an average 10.56 seconds for enrolment of 10 subjects individually. Definitely, a system of higher specifications will work faster but If the database is more populated the time for execution of matching may increase.

4.0 CONCLUSION

This study applies the HOG-LBP framework to two commonly used biometrics namely face and fingerprint for person identification. Each biometric modality is subjected to both descriptor algorithms independently for features extraction step and then fused together to create a new biometric template in a manner different from other applications of the HOG-LBP approach. The method makes for a more robust algorithm that is robust to take care of the problem of noisy signals, intra-class variation and illumination differences of facial images which have been key challenges in similar works. The study demonstrates that LBP is robust to illumination changes which is often cited as a challenge in the literature. Further research will develop better dimensionality reduction techniques for the features extracted by the HOG-LBP algorithms due to the differences in the independent feature dimension spaces. This will improve the efficiency of the system little or no loss of features information at the at fusion level.

REFERENCES

Dalal, N., Triggs, B. (2005). Histograms of oriented gradients for human detection. In *2005 IEEE computer society conference on computer vision and pattern recognition (cvpr'05)* (vol. 1, pp. 886-893). IEEE.

Dhameliya, M. D., Chaudhari, J. P. (2013). A multimodal biometric recognition system based on fusion of palmprint and fingerprint. *International journal of Engineering trends and technology*, *4*(5), 1908-1911.

Fei L., Zhang B., Jia W., J. Wen and Zhang D (2020), "Feature Extraction for 3-D Palmprint Recognition: A Survey," in *IEEE Transactions on Instrumentation and Measurement*, vol. 69, no. 3, pp. 645-656.

Gupta, K., Walia, G.S., Sharma, K. (2020) Quality based adaptive score fusion approach for multimodal biometric system. Appl Intell 50, 1086–1099.

Hicklin, A., Ulery, B., Watson, C. (2006). A brief introduction to biometric fusion. *Study, Department of the Interior, National Institute of Standards and Technology, Washington: NIST*.

Jagadeesan, A., Duraiswamy, K. (2010). Secured cryptographic key generation from multimodal biometrics: feature level fusion of fingerprint and iris. *arXiv preprint arXiv:1003.1458*.

Jain, A. K., Hong, L., Kulkarni, Y. (1999). A multimodal biometric system using fingerprint, face and speech. In *2nd Int'l Conf. AVBPA* (Vol. 10).

Kabir W., Ahmad M. O. and Swamy M. N. S (2018, August) "Normalization and Weighting Techniques Based on Genuine-Impostor Score Fusion in Multi-Biometric Systems," in IEEE Transactions on Information Forensics and Security, vol. 13, no. 8, pp. 1989-2000.

Lahane, P. U., Ganorkar, S. R. (2012). Fusion of Iris & Fingerprint Biometric for Security Purpose. *International Journal of Scientific & Engineering Research*, *3*(8), 1-5.

Lee, T. Z., Bong, D. B. (2016). Face and palmprint multimodal biometric system based on bit-plane decomposition approach. In *2016 IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW)* (pp. 1-2). IEEE.

Monwar, M. M., Gavrilova, M. L. (2009). Multimodal biometric system using rank-level fusion approach. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, *39*(4), 867-878.

Nagaraja, S., Prabhakar, C. J. (2015). Low-level features for image retrieval based on extraction of directional binary patterns and its oriented gradients histogram. *Computer Applications: An International Journal (CAIJ)*, *2*(1).

Ojala, T., Pietikainen, M., Harwood, D. (1996). A comparative study of texture measures with classification based

on featured distributions. *Pattern recognition*, *29*(1), 51-59.

Panchal, T., Singh, A. (2013). Multimodal biometric system. *International Journal of Advanced Research in Computer Science and Software Engineering*, *3*(5), 1360-1363.

Rahman M. Z., Rahman M. H. H and Majumdar M. M. R, (2019) "Distinguishing a Person by Face and Iris Using Fusion Approach," *2019 International Conference on Sustainable Technologies for Industry 4.0 (STI)*, Dhaka, Bangladesh, pp. 1-5

Rane M. E. and. Deshpande P. P, (2018) "Multimodal Biometric Recognition System Using Feature Level Fusion," 2018 Fourth International Conference on Computing Communication Control and Automation (ICCUBEA), Pune, India, pp. 1-5.

Rattani, A., Kisku, D. R., Bicego, M. and Tistarelli, M. (2007) "Feature Level Fusion of Face and Fingerprint Biometrics," *2007 First IEEE International Conference on Biometrics: Theory, Applications, and Systems*, Crystal City, VA, pp. 1-6,

Ross, A., Jain, A. K. (2004). Multimodal Biometrics: an overview. In *2004 12th European Signal Processing Conference* (pp. 1221-1224). IEEE.

Sepasian, M., Balachandran, W., Mares, C. (2008). Image enhancement for fingerprint minutiae- based algorithms using CLAHE, standard deviation analysis and sliding neighborhood. In *Proceedings of the World congress on Engineering and Computer Science* (pp. 22-24).

Subbarayudu, V., Prasad, M. (2008). Multimodal Biometric System. *In Emerging Trends in Engineering and Technology. ICETET'08. First International Conference on (pp. 635-640).* IEEE.

Taouche, C., Batouche, M. C., Berkane, M., Taleb-Ahmed, A. (2014). Multimodal biometric systems. In *2014 International Conference on Multimedia Computing and Systems (ICMCS)* (pp. 301-308). IEEE.

Viola, P., Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In *Proceedings of the 2001 IEEE computer society conference on computer vision and pattern recognition. CVPR 2001* (Vol. 1, pp. I-I). IEEE

Wayman, J., Jain, A., Maltoni, D., Maio, D. (2005). An introduction to biometric authentication systems. In *Biometric Systems* (pp. 1-20). Springer, London.