International Journal of Applied Engineering Research ISSN 0973-4562 Volume 13, Number 13 (2018) pp. 11279-11284

Performance Evaluation of PPG based multimodal biometric system using modified Min-Max Normalization.

Girish Rao Salanke N S [1], Dr. M V Vijaya Kumar[2], Dr. Andrews Samraj[3]

[1]*Assistant Professor, Department of Computer Science & Engineering, R V College of Engineering, Bangalore, India.*
[2]*Professor, Department of Computer Science & Engineering, Dr Ambedkar Institute of Technology, Bangalore, India.*
[3]*Director, Advance Science and Technology Research Center, Mahendra College of Engineering, Salem, India.*

Abstract

Usage of Photoplethysmograhy (PPG) signal which was limited for clinical purposes is explored for the biometric field by fusing it with a traditional biometric such as fingerprint. A multimodal biometric system is proposed to overcome the limitations of unimodal biometric system. A modified Min-Max Normalization score level fusion is proposed for multimodal biometric system. The paper evaluates the performance of PPG based multimodal biometric approach where in it is observed that the False Acceptance Rate of fingerprint biometric system is reduced from 5.4 % to 3 % and similarly the False Rejection Rate is reduced from 6.7 % to 3.8 % by fusing the PPG component with fingerprint. The proposed method exhibits good identification accuracies when PPG signal is used as one of the biometric trait in a multimodal biometric system.

Keyword: Biometric, PPG signal, Score Fusion, False Acceptance Rate (FAR), False Rejection Rate (FRR), Min-Max Normalization

INTRODUCTION

The traits used in multimodal biometrics[1] have relayed more on traditional biometrics like fusing physiological features such as face with fingerprint, face with palmprint[2], and face with Iris and so on. Most researches in the biometric community have ignored the intrinsic characteristics of the biological signal for their applications. Studies of such signals that can be used for biometrics are very important. Some of the signals that can be considered are ECG, EEG and PPG[3] signals, which exhibit a rich set of features that can be used for identification and verification purpose. The second objective of this work is to propose a new algorithm that is robust to day today as PPG changes due to motion artifact. Since the PPG signal is a time series there is always the question of how long should the PPG is acquired. Considering that enrolment is done only once, subjects will agree to spend some time enrolling themselves into the system however for verification our goal is to minimize the authentication time for the subjects. The final objective of this work is to explore the effectiveness of using the PPG signal in multimodal biometric systems. Since there is no biometric which has 0% False Rejection Rate and all biometrics have their own limitations and disadvantages, multimodal biometric systems uses more than one biometric traits for the sake of improve the performance and making the system robust to spoof attacks.

The main challenge is that to choose appropriate biometrics such that the inherent weaknesses can be offset by overall system design. Therefore in order to further improve the PPG biometric system we propose a multimodal biometric system by fusing PPG and fingerprint. The fingerprint matcher offers high accuracy in terms of authentication however suffers from spoof attacks since a fingerprint trace can be easily taken from any surface that a finger has touched. Finally both modalities can be collected conveniently from subject's fingertips which require less cooperation from subjects unlike other systems.

Multimodal biometrics[4] combines information from different sources as compared to unimodal[5] wherein person recognition is based on a single source of biometric information. Some of the system requirements are not meet in Unimodal biometrics; therefore combining multiple biometrics can overcome the limitations of unimodal biometrics and also improve the performance of the overall system. In multimodal biometrics the sources of information can be from multiple sensors, multiple traits, multiple instances or multiple instances. In multiple sensors the different sensors are used for capturing single biometric trait. For example face images of an individual can be captured using two different sensors. In multiple traits, the system information from different biometric traits are combined to authenticate a subject, for example combing face and fingerprint. In multiple Instances, the systems use multiple instances of a single biometric trait, such as the image of the left and right eye of a subject for a retina recognition system. In multiple Sample, the system uses a single sensor is used to capture multiple samples of a single biometric characteristic of a subject, for example frontal, left and right profiles used in face recognition

The fusion[6] in multimodal biometrics can be done at different levels, such as

a) Feature level fusion
b) Decision level
c) Score level.

In Feature level fusion feature set extracted from multiple data sources are combined to create a new feature set as shown in figure 1. If the features from different biometrics traits are in the same type of measurement than it is recommendable to combine there features vectors into a single new vector.

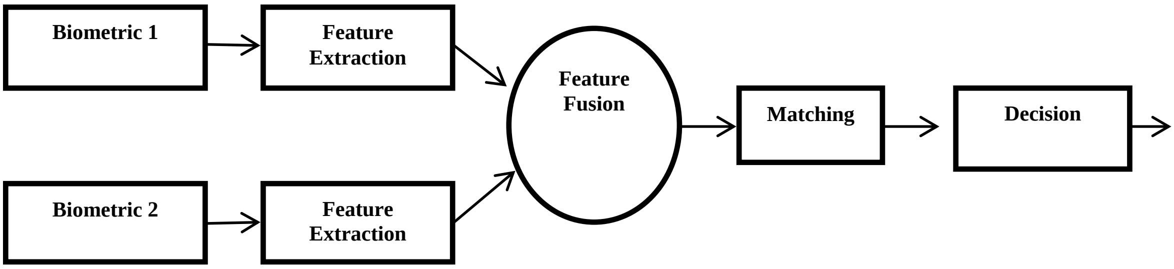

Figure 1. Feature Level Fusion

In Decision level fusion, the decision is independent of the other biometric trait and then the decisions are combined into a single decision as shown in figure 2 .The AND and OR are the major rules used in decision level fusion.

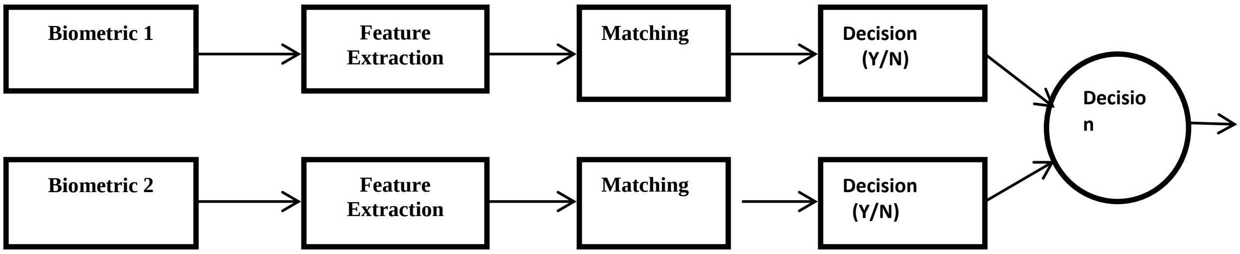

Figure 2. Decision Level Fusion

In Score level fusion[7], the match scores generated by different biometric systems are combined, where match score is a measure of similarity between the input and template biometric feature vectors as shown in figure 3. This level of fusion is the most commonly used technique in multimodal biometrics due to the fact that it is relatively easy to generate and combine the match scores of different biometric traits.

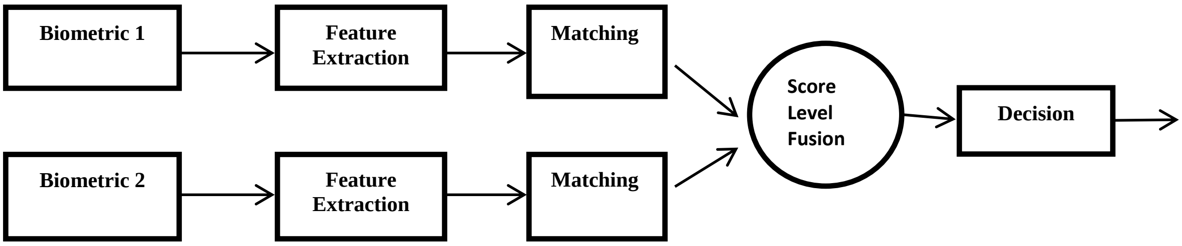

Figure 3. Score Level Fusion

PPG signals provide a non-invasive and accurate methodology to obtain valuable physiological information such as blood oxygen saturation, heart rate and blood flow. The blood in human body is being pumped from the heart to all parts in the body by blood vessels called arteries. Blood pressure is the force of blood pushing against the walls of the arteries. Each time the heart beats it pumps out a considerable volume of blood to the arteries. Systolic pressure which is the highest blood pressure occurs when heart is in pumping motion. Diastolic pressure is lowest blood pressure when heart is in resting. Since blood pressures are an indirect measurement of heart beats and the blood pressure tends to change according to the time and emotion. For instance, blood pressure will rise when a subject is awaken and excited. The unit for measurement of blood pressure is in mmHg and the notation will be systolic followed by diastolic pressure. The PPG signals reflect the change in blood volume caused by blood vessel expansion and contraction, which can be detected by photodiode if external light is illuminated into tissue[8].

METHODOLOGY

The traditional biometric used to fuse with PPG signal selected was fingerprint as it has good feature set used for identification. The main steps involved in the finger print biometric are

a. Fingerprint Enhancement
b. Feature extraction using minutiae
c. Matching

The enhancement basically has two operations namely binarization and thinning. Binarization is a process of converting a pixel image to a binary image. First the image is converted into grayscale and then a threshold gets applied. The threshold can either be set fixed or adaptive using any existing clustering algorithm. The clustering algorithm first counts the appearance of each tone of in the image and tries to find a good center. Figure 4 show the output of binarization. The main objective of thinning is to find the ridges of one pixel width. It is an iterative to erode away the foreground pixels until they are one pixel. Each iteration examines the neighbourhood of each pixel and checks whether the pixel can be deleted or not. Figure 5 shows the thinned image of the binarized fingerprint.

In the feature extraction stage the minutiae are detected by using 3x3 masks as shown in figure 6. Masking helps in eliminating the false detected minutiae points. After the extraction of minutiae, they are stored in a template containing the following information: [X, Y, θ], where X and Y are the minutiae position and θ is the minutiae direction (angle). During the enrolment process the extracted template is stored in the database and the same will be used as the reference template during the matching process.

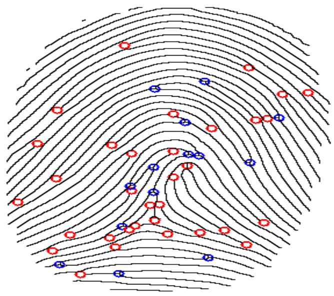

Figure 4. Binarized Fingerprint **Figure 5.** Thinned Fingerprint **Figure 6.** Minutiae points

In the matching process, the numbers of matched minutiae are found by aligning the queried image with the referenced template. Two minutiae points are considered to be matched, if the distance and the direction difference between them are smaller than a given threshold. Therefore the correct alignment of the fingerprint is very much important to maximize the number of matched minutiae. To align the fingerprints correctly we use a segment between a pair of minutiae in the given template. The segment is created as shown in the figure 7

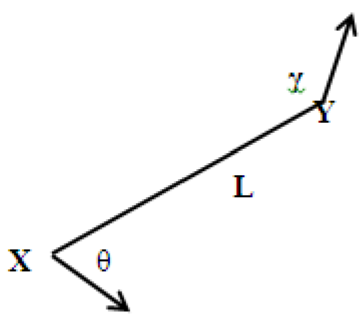

Figure 7. Segment between 2 minutiae points

Each segment has the following information: segment length (L) and the segment angles (θ and γ).The segment is constructed for both the templates(reference and the quereied). Let L_r and L_q be the segment lengths and θ_r, θ_q, γ_r, γ_q be the segment angles for the reference dand the quereied one. Two segments are considered same when the following conditions are meet

$| L_r - L_q | < L\tau$ and $| \theta_r - \theta_q | < \theta\tau$ and $| \gamma_r - \gamma_q | < \gamma\tau$ where τ is the threshold . Using the above the matching score is constructed based on which the final decision is taken. The fingerprint biometric system is very dominant mainly because its easy to use and higher level of accuracy .So we observe that fingerprint biometric is vastly used in forensic investigations, police case and also in the registration of the land records. The main drawbacks of finger print are

1. Large variation of the quality of fingerprint over the population as it depends on age, performance deterioration over the time
2. Has poor public reputation since it has strong relationship with criminals as it associated with forensic applications.
3. Inability to enroll users in some special cases.

For authentication the system will primarily try to authenticate the user using its fingerprint, if the subject is rejected then that's the final decision of the overall system, however the accepted subjects will be given to the PPG matcher. If the subject is accepted in accepted in this stage then that is the final decision for that subject. The remaining rejected subjects will be given to the combination of the PPG and Fingerprint multimodal biometric system which fuses the two at the score level to make the final decision. In order to fuse the score we have normalized them to have a dynamic range of one. For the fingerprint scores, a linear function and for PPG scores a piecewise linear function are used. After normalising the scores, each score is weighted and the sum of the two weighted scores is considered as the final score. The score fusion is based on the subject weighting fusion technique where it assigns weights to individual matchers that are generally different for distinct subjects.

EXPERIMENT AND RESULTS

The experiment was initial conducted for fingerprint identification with 25 subjects and henceforth the fingerprint database consists of 25 legitimate subjects (S_1 to S_25) and each subject provided his finger (right thumb) 10 times (25x10 = 250 images in total). Let's assume, that single image is sufficient for template creation. The rest of his images we use to verify the fingerprint and we receive 9 genuine scores. All images of other subjects can be used as impostors and we have 240 impostor scores. The template generation for all images and all subjects and in total we have 225 genuine scores and 6000 impostor scores. These scores are usually used to generate ROC curves to choose the best threshold, with a threshold of 0.7 it was observed that 325 impostor scores exceed the threshold and 15 genuine scores fall below the threshold. The FAR and FRR was calculated as

$$\text{FAR} = \frac{\textit{imposter scores excedding the threshold}}{\textit{all imposter scores}} = \frac{325}{6000} = 0.054$$

$$\text{FRR} = \frac{\textit{genuine scores below the threshole}}{\textit{all genuine scores}} = \frac{15}{225} = 0.067$$

FAR was found to be 5.4 % and FRR was found to be 6.7%. If the database is scaled for more subjects then the FRR will be automatically more. One solution to decrease the FAR is to fuse the fingerprint biometric system with the other biometric trait. The proposed system is to extract the features of fingerprint and PPG signal and fuse their scores as shown in figure 8. One of the main challenges here is to evaluate the rejected subject once again by fusing both the biometric trait and to minimize the False Acceptance Rate and False Rejection Rate.

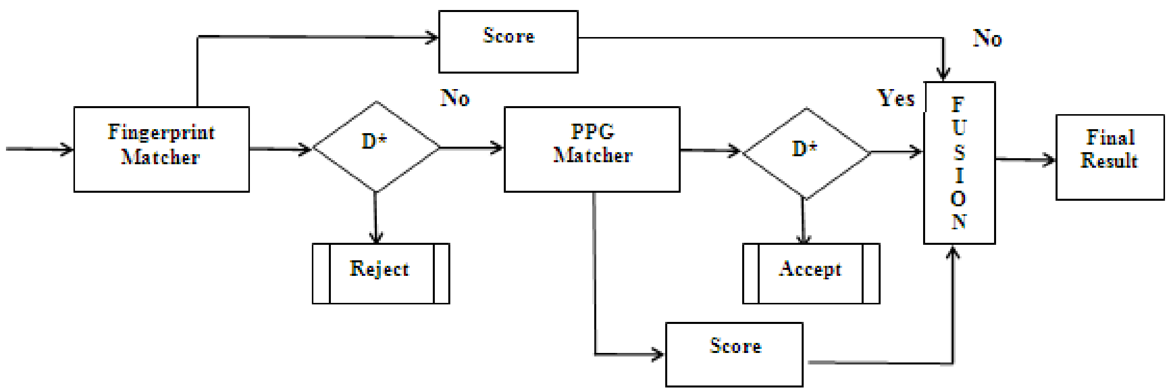

Figure 8. The Proposed multimodal biometric System

(D* - Decision)

The PPG signals were collected from Physionet, which is an online public database with the sampling rates of 125 Hz. The motion atrifact PPG signal is pre-processed to remove the noise by Fourier series analysis. Further the Semi Discrete Decomposition[8,9]. The fisrt p features from the feature set F were used as features for matching purpose. The values of q's differ from subject to subject but finally when normalised, the values will result to uniqueness. Here the reduced feature vector can be represented as

$F = [\, a_1, a_2, \ldots\ldots a_p]$

i.e $\sum_{i=1}^{p} Fi = 1.$

For the classification, We first generate a matching score by the selected feature compared with the stored template. For each PPG signal, the Euclidean's distance is calculated and is compared with the set of samples stored in the system is computed. The template resulting in the smallest distance is considered to be the match.

For fusing the fingerprint and the PPG signal, the normalised score level fusion is used .The normalization of scores is based on the Min–Max normalization[9]. In Min-Max normalization, the matching scores are mapped within the interval [0-1]. The normalised score for a raw matching score of max(x) and min(x) is calculated as given in Eq. (1)

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

Where max(x) and min(x) is the maximum and minimum values of the raw matching scores. In a multimodal biometric system if the normalised score for both the biometric system are in the same scale or in the same order, as in case of fingerprint and palmprint or even with face and fingerprint the min-max normalization is more suitable. As in our case both the biometric traits are not correlated as one is a signal and the other one is an image, min-max normalization is very hard to apply because the Min-Max normalization is not robust because this method is highly sensitive and volatile to high value data used for estimation. So to overcome this drawback we propose a modified Min-max normalization, where we retain the original distribution of matching scores except for a scaling factor and all the high scores are normalized. Consider an example, let the range of the first score be [20, 85] and the range of the second score be [35, 100], then it is recommended to use the raw scores instead of the normalized scores because the range of the first and the second score are almost same. Consider another example, wherein the range of the first score is [20, 85] and the range of the second score is [0.25, 0.75], here the first score set should be normalized as the first score is almost 100% more than the second score set. The normalization can be done using the formula

$$x' = \frac{x - \min(x)}{\mathrm{mean}(x*) + std(x*) - \min(x)} \quad (2)$$

In Eq. (2), x denotes all the raw scores of genuine and imposer scores and x* denotes the only the genuine scores. The value of the mean of genuine scores distribution is added by its standard deviation instead of the maximum value of all raw scores in order to reduce the effect of high scores at the right-tail of genuine scores distribution as mentioned in Eq. (1).

The normalized scores from a particular subject for both biometric trait, fingerprint as a_1 and PPG signal as a_2 is calculated and then the fused score fs is evaluated using the formula

$$fs = w_1 a_1 + w_2 a_2 \quad (3)$$

where w_1 and w_2 are the weight which is assigned to the first and the second biometric trait. Eq. (3) gets simplied to Eq. (4) on assuming both the biometric traits having equal weights.

$$fs = a_1 + a_2 \quad (4)$$

Further, the fused score fs will be compared to threshold t which was pre specified. We declare a person to be genuine if fs is greater than or equal to t, otherwise, we declare the subject as an impostor.

Figure 9 shows the ROC of fused Fingerprint and PPG by applying the Min-Max normalization. It is observed that the FAR and FRR of the fused biometric traits is marginal less when compared to fingerprint. Figure 10 shows the ROC on applying the modified Min-max normalization; here we observe the performance of the system is increased to a larger extent by reducing FAR by 2 % and FRR to 3% when compared to fingerprint.

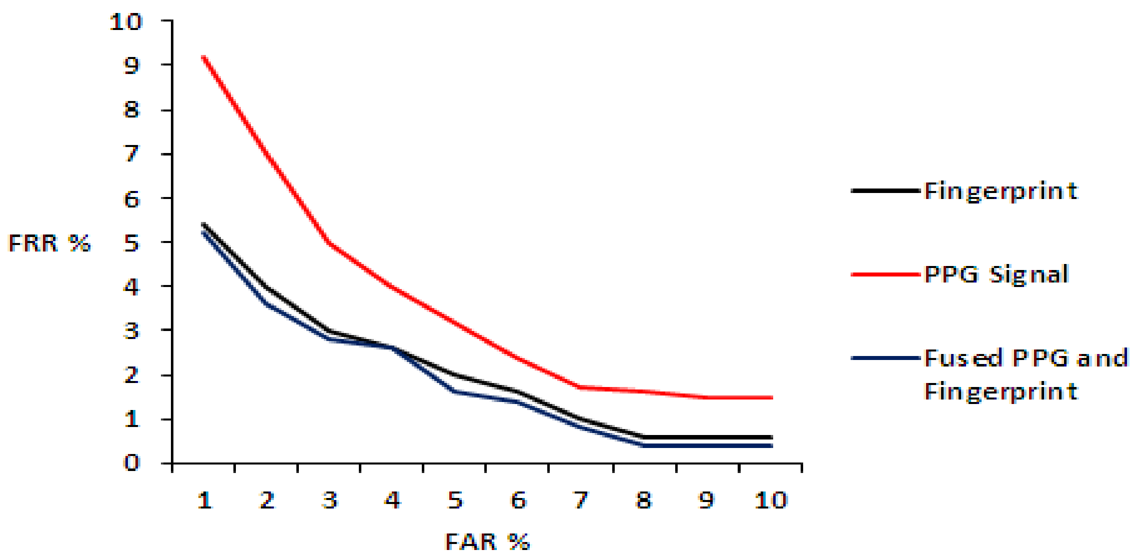

Figure 9. ROC curve of Fingerprint, PPG Signal and Fused PPG and Fingerprint with Min-Max Normalization.

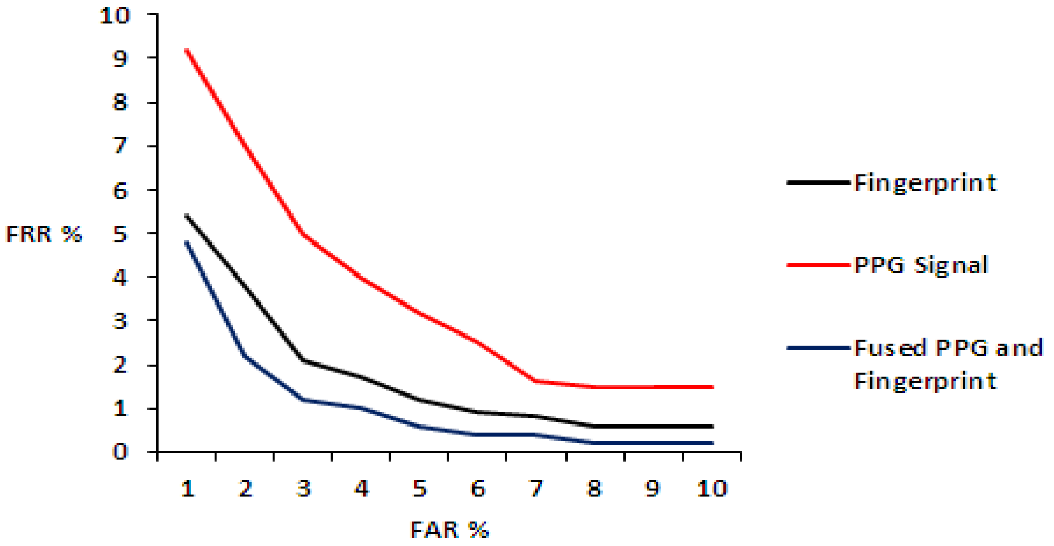

Figure 10. ROC curve of Fingerprint, PPG Signal and Fused PPG and Fingerprint with modified Min-Max Normalization

CONCLUSION

Based on the result obtained, it can be recommended that a biological signal like PPG signal has a good set of features that can be used for person's identification. Further the classification approach suggests that the proposed method gives classification accuracy as high to 98%. Therefore it can be conclude that PPG signal can be used in developing an efficient multimodal biometric system.

REFERENCES

[1] Arun Ross, Anil K. Jain. *"MULTIMODAL BIOMETRICS: AN OVERVIEW"*. Proc. of 12th European Signal Processing Conference (EUSIPCO), (Vienna, Austria), pp. 1221-1224, Sepember 2004.

[2] Yong-Fang Yao, Xiao-Yuan Jing, Hau-San Wong, *"Face and palmprint feature level fusion for single sample biometrics recognition"*, Neurocomputing, Volume 70, Isuues 7-9, pp 1582-1586,March 2010,doi: 10.1016/ j.neucom. 2006.08.009.

[3] Singh M, Spiti G, "*Correlation studies of PPG finger pulse profiles for Biometric system",* Int J Inf Technol Knowl Manage. 2012; 5:1–3.

[4] Yunhong Wang, Tieniu Tan, Anil K. Jain,"*Combining Face and Iris Biometrics for Identity Verification*", Proceedings of the 4th international conference on Audio- and video-based biometric person authentication.ages 805-813, Springer-Verlag Berlin, Heidelberg ©2003, ISBN:3-540-40302-7.

[5] Jain AK, Arun R, Salil P*" An introduction to biometric recognition*", IEEE Transactions on Circuits and Systems for Video Technology. 2004; 14(1):4–20.

[6] A. Ross, A. K. Jain, "*Information fusion in biometrics*", Pattern Recognition Letters, vol. 24, pp. 2115–2125, Sep 2003.

[7] Mingxing He, Shi-Jinn Horng, *"Performance evaluation of score level fusion in multimodal biometric systems*", Pattern Recognition, Volume 43, Issue 5, May 2010, doi: 10.1016/j.patcpg. 2009.11.018.

[8] Girish Rao Salanke N S., A Samraj. N. Maheswari" *Enhancement in the design of biometric identification system based on photoplethysmography data*", IEEE International Conference on Green High Performance Computing (ICGHPC); 2013.

[9] Siti Nurfarah Ain Mohd Azam,Khairul Azami Sidek," *Time Variability Analysis of Photoplethysmogram Biometric Identification System*", Indian Journal of Science and Technology, Vol 9(28), DOI: 10.17485/ijst/2016 /v9i28/97731, July 2016.