A Multiple Algorithm Approach to Textural Features Extraction in Offline Signature Recognition

Jide Kehinde Adeniyi[1(✉)], Tinuke Omolewa Oladele[2], Noah Oluwatobi Akande[1], Roseline Oluwaseun Ogundokun[1], and Tunde Taiwo Adeniyi[3]

[1] Department of Computer Science, Landmark University, Omu-Aran, Kwara State, Nigeria
{adeniyi.jide,akande.noah, ogundokun.roseline}@lmu.edu.ng

[2] Department of Computer Science, University of Ilorin, Ilorin, Kwara State, Nigeria
oladele.to@unilorin.edu.ng

[3] National Assembly, Abuja, Nigeria
Adekitos2@gmail.com

Abstract. Signature is a biometric trait that has piqued the interest of researchers. This is due to its high rate of acceptability. Offline signature in particular, has been around for a while and hence its suitability as a biometric trait. This paper proposes an offline signature recognition system using a multiple algorithm approach. The system accepts handwritten signature, filters the signature and crops the signature region. The Local Binary Pattern (LBP) of the signature image is then obtained. After this, Grey Level Co-occurrence Matrix (GLCM) is applied. Statistical features are then extracted. The difference in the stored features and the extracted features was obtained. The output is compared with a threshold for discrimination. This research aims at improving the performance of offline signature recognition using its textural features. The designed system gave an FRR and FAR of 8.6%, 4.6% respectively for MYCT signature database and 8.8%, 5.2% for GPDS signature database.

Keywords: Offline signature · Local binary patter · Grey level co-occurrence matrix · False acceptance ratio · False rejectance ratio

1 Introduction

Individual identification in the past used to be performed with the aid of password, PIN (Personal Identification Number) and so on) [13]. However, issues arising from forgetfulness, theft amongst others has led to the need for a better way of identification [9, 13]. Biometrics emerged to alleviate some of the challenges of the traditional identification methods. Biometrics is the use of an individual's characteristics (Physical or behavioural) for identification. There are several biometric traits, however, they are generally grouped into three (3) categories [5]. These categories are Physiological,

M. Themistocleous et al. (Eds.): EMCIS 2020, LNBIP 402, pp. 541–552, 2020.
https://doi.org/10.1007/978-3-030-63396-7_36

behavioural and Chemical [5, 8]. A Physical biometric trait uses a physical characteristic of an individual for recognition, some examples include iris, palmprint, hand geometry, and so on. Chemical biometrics uses a chemical characteristic for identification, and an example is body odour. Behavioural characteristics uses an individual's behavioural characteristics for identification [17]. Amongst the behavioural biometrics is the Signature. [6] defines signature as the legal mark of an individual. While signature's biometric performance is low compared to some of its peers, its acceptance is high [7, 8]. Its uses ranges from bank transactions to document validation [9]. Signature can be replicated falsely by others and this is termed signature forgery. Signature forgery can either be random (without prior knowledge of the signature), unskilled (with less practice of the forged signature) and skilled (with proper practice of the signature being forged). Random signature forgery is the easiest to identify while skilled forgery is the most difficult to identify [18].

Signature recognition can either be online or offline. Online signature are individual signatures obtained on digital tablets. Data are obtained as the user writes on the tablet. Offline signatures are obtained from hardcopy scanned (or snapped) into the computer [20, 22]. Online signature performs better than offline signatures because of the various features extracted during the signing process (such as co-ordinates, pressure, pen angle and others) [5, 20]. However, Offline signature is still more widely used than Online signature [22]. Hence the need to improve this biometric method. Several approaches have been proposed for offline signature; however, most approaches have been limited to the co-ordinates, edges and curvature of the signature [5, 8, 9]. Recent trends in offline signature is examining the use of textural features for signature recognition. Hence, this paper presents a texture-based offline signature recognition system.

2 Related Work

Offline Signature recognition has been an area of interest for a while with researchers exploring this biometric method so as to increase its accuracy. Researchers have focused on the binarization of offline signatures so as to extract features from this biometric. This section examines some of the approaches to signature recognition. [13] examined both Offline and Online signature recognition respectively. For the Offline signature, filtering was performed to reduce noise in the signature image. Binarization and thinning were both done to make the signature image compact. For the Online signature, preprocessing was not necessary as data were obtained as the user writes on the digital tablet. The stroke co-ordinates were used as features for the Offline signature while the co-ordinates, pressure of pen and time to complete signature were used as features for Online signatures. The PCA was used to extract relevant features from the feature set and Manhattan Distance (MD) was used for matching.

A classification method to detect forged signatures from the authentic signature was presented [10]. In this approach, binarization was the first step performed. Smoothing is performed to remove unconnected pixels from the signature image. To avoid variation in image thickness, thinning was performed. The last step in the preprocessing stage crops out the actual signature area. Global features, slant features and textural features were collected from the binary image. Fine random forest model was used for classification.

An approach consisting of four major steps was proposed by [18]. These steps are: preprocessing, features extraction, features selection and feature verification. Median filter was used for noise removal. Otsu method and morphological operations were used to segment the signature image. Global features (width, height and area of signature) and Local features (slope, signature centroid, angle and distance) were extracted. Genetic algorithm was used for the feature selection, and the support vector machine performs the verification.

[9] used Local Binary Pattern (LBP) and Binary Statistical Image Features (BSIF) for Offline features extraction. Kernel Neural Network was used classification. In their Offline signature verification system, the signature image is converted to its binary representation before the LBP and BSIF is applied.

[6] examined Online signature verification using Dynamic Time Warping for features extraction. Smoothing, rotation and normalization were performed as preprocessing steps. Coordinate, pressure, altitude and azimuth were extracted during the signature capture.

From the reviewed literature, LBP has been credited with its ability to extract image features even under varying pixel intensities. Combining this trait with a statistical function that has the ability to produce a global representation of the features extracted would certainly improve the recognition rate of this biometric trait.

3 Proposed Method

The proposed method is examined in this section. The proposed method is made up of the following steps: Acquisition, Preprocessing, Features extraction, Matching. The system can undergo two stages and they are the Enrolment stage and Recognition stage. The features extracted from an individual's signature is saved as a template in the enrolment stage while the recognition stage states whether a signature is genuine or not. Figure 1 depicts the block diagram of the system.

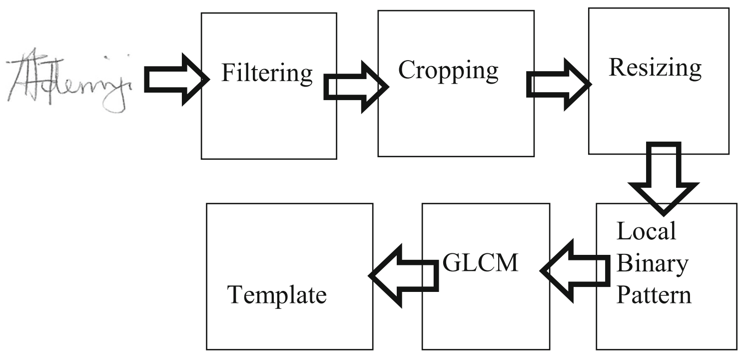

Fig. 1. Block diagram of the system

The first step is the acquisition of signature image after which is preprocessing. Preprocessing is the second step in this system and it is primarily aimed at preparing the signature image for features extraction. The steps involved in preprocessing the signature image in this system are filtering, cropping and resizing.

3.1 Signature Image Filtering

Gaussian Filter was applied to remove noise from the signature images. The blurred image is obtained from the original image using the Eq. 1 [13]:

$$G(a, b; \sigma) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{a^2 + b2}{2\sigma^2}\right)} \tag{1}$$

with a as the distance horizontally, b being the distance vertically and $\boldsymbol{\sigma}$ is the standard deviation ($\boldsymbol{\sigma}^2$ the variance).

3.2 Signature Image Cropping

After the noise in the image is removed, cropping is performed so as to rid the image of unwanted pixels (background) surrounding the signature. The algorithm used to crop out the signature area is as follows:

Input: An array of the grey value of an image.

a. Start
b. Locate the coordinate of the first non-white pixel (x, y), moving from left to right, beginning at the top.
c. Locate the coordinate of the first non-white pixel (x, y), moving from left to right, beginning at the bottom.
d. Locate the coordinate of the first non-white pixel (x, y), moving from top to bottom, beginning from the left.
e. Locate the coordinate of the first non-white pixel (x, y), moving from top to bottom, beginning from the right.
f. Copy pixels within the boundary specified by the pixels obtained from step b, c, d and e above.
g. end

3.3 Signature Image Resizing

The images are resized to 100 by 80. There are several methods for resizing. However, bicubic interpolation was used in this system because it examines 16 data points in the neighbourhood of the interpolation region. This improves its result because more pixels are examined compared to cubic interpolation [13].

Bicubic interpolation uses an up-sampling distance Z to estimate pixels not known for the interpolation process as shown in Fig. 2 [13].

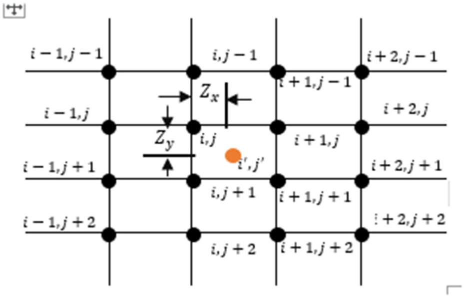

Fig. 2. Sample pixels of an image

At (i', j') in Fig. 2, the interpolated pixel is obtained with Eq. 2 below.

$$f_{i'j'} = \begin{bmatrix} f_{i-1,j-1} & f_{i,j-1} & f_{i+1,j-1} & f_{i+2,j-1} \\ f_{i-1,j} & f_{i,j} & f_{i+1,j} & f_{i+2,j} \\ f_{i-1,j+1} & f_{i,j+1} & f_{i+1,j+1} & f_{i+2,j+1} \\ f_{i-1,j+2} & f_{i,j+2} & f_{i+1,j+2} & f_{i+2,j+2} \end{bmatrix} \begin{bmatrix} W_{-1}Z_x \\ W_0 Z_x \\ W_1 Z_x \\ W_2 Z_x \end{bmatrix} \begin{bmatrix} W_{-1}Z_y & W_0 Z_y & W_1 Z_y & W_2 Z_y \end{bmatrix} \quad (2)$$

where $Z_y = j' - j, Z_x = i' - i$ and $f_{i,j}$ means the pixel at (i,j). For weights $W_{-1}(Z), W_0(Z), W_1(Z), W_2(Z)$, they are given as

$$W_{-1}(Z) = \frac{-Z^3 + 2Z^2 - Z}{2} \quad (3)$$

$$W_0(Z) = \frac{3Z^3 + 5Z^2 - 2}{2} \quad (4)$$

$$W_1(Z) = \frac{-3Z^3 + 4Z^2 + Z}{2} \quad (5)$$

$$W_2(Z) = \frac{Z^3 - Z^2}{2} \quad (6)$$

4 Features Extraction

For features extraction, the local binary pattern and grey level co-occurrence matrix is proposed. The local binary pattern is a grey image features extraction method that is resistance to changes in intensity. This is proposed so as reduce the effect of the colour of the pen used.

4.1 Local Binary Pattern

Local binary pattern (LBP) is a textural feature extraction method that uses the grey version of an image. It examines a pixel, uses it as threshold for categorizing its neighbours as 1 or 0 and computes the decimal value of the binary representation of the neighbouring pixels in a clockwise manner [11, 15]. This is shown in Fig. 3. If the centre pixel is greater than any neighbouring pixel, the pixel is set to 0. If the center pixel is less than or equal to the neighbouring pixel is set to 1.

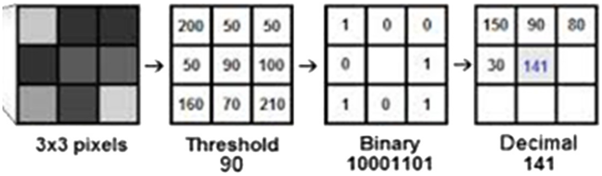

Fig. 3. Figure showing the operation of LBP

Hence, the LBP of a given pixel is denoted as [16, 19]:

$$LBP_A(i,j) = \sum_{h=0}^{A-1} s(g_h - g_c)2^h \tag{7}$$

$$s(k) = \begin{cases} 1, k \geq 0 \\ 0, k < 0 \end{cases} \tag{8}$$

Where i, j is the location of the pixel at the centre, A are the 8 neighbouring pixels, g_c is the grey value of the center pixel, g_h is the grey value of the neighbouring pixel, $s(k)$ is a sign function of a sequence k defined in Eq. (8). The feature vector LBP_A is a histogram of 2^A Local Binary Pattern of image pixels.

4.2 Grey Level Co-occurrence Matrix

Grey Level Co-occurrence Matrix (GLCM) is used for analyzing textural information of an image [1]. It is a statistical technique that give detailed descriptions about spatial relationship of pixels [1, 2]. It examines the relationship between two pixels at a time, and is sometimes termed the reference and neighbour pixel. The separation is made by the second order statistics [3, 4, 21]. Second order means they consider the relationship between groups of two pixels in the original image. First order texture measures are statistics calculated from the original source (image), like variance, and do not consider relationship between pixels. It is computed using the displacement and orientation between surrounding pixels [12, 17].

Let P be a normalized symmetric GLCM. Let μ_x, μ_y, σ_x and σ_y be the means and standard deviations of P_x and P_y respectively, of the partial probability density functions. Let $P_{x+y}(i)$ be the probability of co-occurrence matrix coordinates summing to $x+y$. The features used in this research include [4, 17]:

Contrast: This is also known as "sum of square variance" or "inertia". It is obtained using equation [1, 3]:

$$Contrast = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}(i-j)^2 \tag{9}$$

Dissimilarity: Unlike contrast, dissimilarity weight increases linearly [1]

$$Dissimilarity = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}(i-j) \tag{10}$$

Homogeneity:

$$Homogeneity = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}(i-j) \tag{11}$$

Angular Second Moment:

$$ASM = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}^2 \tag{12}$$

Energy: This is the square root of the Angular Second Moment (ASM)

$$Energy = \sqrt{\sum\nolimits_{i,j=0}^{N-1} P_{i,j}^2} \tag{13}$$

Entropy:

$$Entropy = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}\left(-\log P_{i,j}\right) \tag{14}$$

Correlation Texture Measure: This computes the linear dependency of a grey level with those of its neighbors.

$$Entropy = \sum\nolimits_{i,j=0}^{N-1} P_{i,j}\left[\frac{(i-\mu_i)\left(j-\mu_j\right)}{\sqrt{\left(\sigma_i^2\right)\left(\sigma_j^2\right)}}\right] \tag{15}$$

Where variance (μ) and standard deviation σ is $\mu_i = \sum_{i,j=0}^{N-1} i\left(P_{i,j}\right)$,

$$\mu_j = \sum_{i,j=0}^{N-1} j\left(P_{i,j}\right),$$
$$\sigma_i^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_i)^2,$$
$$\sigma_j^2 = \sum_{i,j=0}^{N-1} P_{i,j}(i-\mu_j)^2,$$
$$\sigma_i = \sqrt{\sigma_j^2},$$

$$\sigma_j = \sqrt{\sigma_j^2}$$

5 Matching

The system made use of Euclidean distance for matching. The Euclidean distance of the GLCM features extracted from the enrolled signature image and the features extracted for the verification process is used for matching. The obtained value is compared with the stated threshold for verification. The Euclidean distance is expressed in Eq. 16 [23, 24]:

$$\mathrm{d}_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{16}$$

For two samples $X_i = (X_{i1}, X_{i2}, \ldots, X_{in})^T$ and $X_i = \left(X_{j1}, X_{j2}, \ldots, X_{jn}\right)^T$.

6 Experimental Result

For evaluating the performance of the method suggested above, online database of signatures and manually collected signatures were used. Repetitive collection was used for the enrollment process. Repetitive collection here entails extracting the GLCM features multiple times (5 times in this system) and averaging the results of each GLCM feature. MYCT and GPDS offline signature database were used. For the evaluation of the performance of the system, the False Acceptance Ration (FAR), False Rejectance Ratio (FRR) and the Accuracy of the system were used. FAR is the ratio of falsely accepted signature and the total false signature submitted. FRR is the ratio of genuine signature rejected and the total genuine signature submitted. Both FAR and FRR are usually represented in percentage. Accuracy is also used in some researches because it is obtained from both the FAR and the FRR and it is given in Eq. 17 [13].

Figure 4 shows the Equal Error Rate (EER) of the system. It is a graph of the thresholds against their FAR and FRR. It usually denotes the optimal threshold for which both the FAR and the FRR are fairly represented. It is used in obtaining the threshold for the system. The threshold at which the FAR and FRR crosses each other is the threshold at which both are low (without one being extremely high and the other very low).

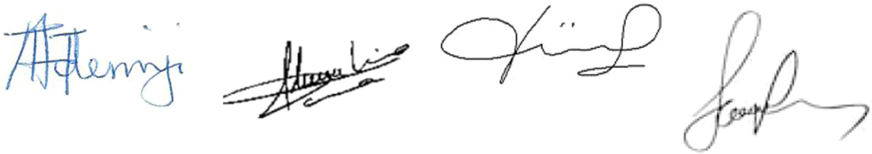

Fig. 4. Handwritten signature samples

$$Accuracy = 100 - \frac{(FAR + FRR)}{2} \quad (17)$$

The prototype of the system was developed using Matblab R2015a on an intel core i7 laptop with a processor of 2.20 GHz and a RAM of 4 GB.

6.1 MYCT Dataset

MYCT is a publicly available database of biometric images, that is widely used for biometric system testing. Ministerio de Ciencia y Tecnologı´a, Spanish Ministry of Science and Technology was partially responsible for funding the biometric image collection from four academic institutions [14]. After testing this system, a FAR of 4.6% and an FRR of 8.6% was obtained.

6.2 GPDS Dataset

GPDS (Digital Signal Processing Group) is group at the University of las Palmas de Gran Canaria that specializes in research related to biometrics, one- and two-dimensional pattern recognition and behaviour characterization through audio and video. They have available signature database for signature biometric system testing. It consists of 4000 sets of signature images, each with 30 forged and 24 genuine. After testing the system with randomly selected forged images and genuine images, a FAR of 5.8% and an FRR of 8.8%. Some Handwritten signature samples used are shown Fig. 4:

Table 1 summarizes the FAR, FRR and accuracy of the system and Fig. 5 shows the Equal Error Rate graph of the system.

A comparison of the obtained result with other relevant papers is shown in Table 2.

Table 1. Result obtained from testing the system.

Database	FAR (%)	FRR (%)	Accuracy
MYCT	4.6	8.6	93.3
GPDS	5.2	8.8	92.7

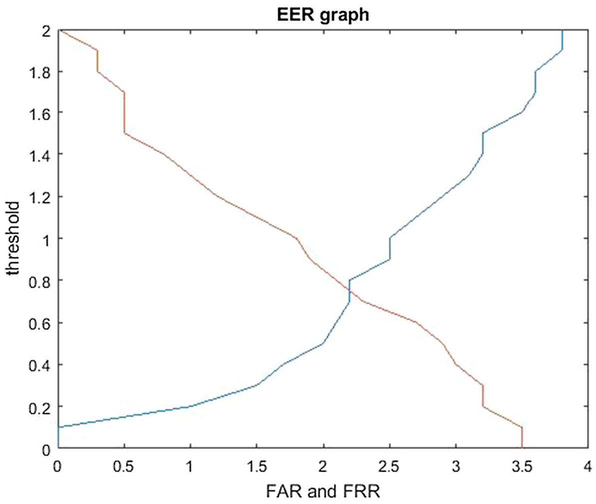

Fig. 5. The Equal Error Rate (EER) graph of the system

Table 2. Comparison of result with existing results in the literature.

Paper		FAR (%)	FRR (%)	Acc. (%)
Chandra and Maheshkar [25]	**MYCT**	8.76	9.83	93.84
	GPDS	7.36	8.84	90.56
Jadhav [27]	**GPDS**	1.92	13.79	85.66
Pushpalatha et al. [26]	**GPDS**	9.34	4.9	88.34
Proposed	**MYCT**	**4.6**	**8.2**	**93.3**
	GPDS	**5.2**	**8.8**	**92.7**

7 Conclusion

This work presented the design of a textural features extraction method for signature recognition using a multi-algorithmic approach. The signature used for testing were obtained from MYCT handwritten signature databased and GPDS handwritten signature database. The obtained images were preprocessed by removing noises from them, cropping out the actual signature area and resizing the signature image. Gaussian filter was used for noise removal and resizing was performed using bicubic interpolation. The Local Binary Pattern of the image was generated and the Grey Level Co-occurrence Matrix was computed. A number of statistical properties of the Grey Level Co-occurrence Matrix were computed. The Manhattan distance was applied to the difference obtained from the test signature and the store template. The obtained result is then compared with the system threshold so as to verify whether the signature is genuine or not. The results obtained after testing the system showed that the textural feature extracted from signature images using the fusion LBP and the GLCM is better than those obtained from using only LBP or GLCM. Hence, the use of a statistical method for feature selection (GLCM) after applying LBP for features extraction gives a better feature set than when LBP is used alone. For future research, a look at the fusion of textural features, curvature features and stroke co-ordinates-based features to improve the performance of this biometric trait is a viable direction.

References

1. Aferi, F.D., Purboyo, T.W., Saputra, R.E.: Cotton texture segmentation based on image texture analysis using gray level co-occurrence matrix (GLCM) and Euclidean distance. Int. J. Appl. Eng. Res. **13**(1), 449–455 (2018)
2. Gade, A.A., Vyavahare, A.J.: Feature extraction using GLCM for dietary assessment application. Int. J. Multimedia Image Process. (IJMIP) **8**, 2 (2018)
3. Hall-Beyer, M.: GLCM Texture: A Tutorial v. 3.0, March 2017. University of Calgari (2017). https://doi.org/10.11575/prism/33280
4. Josuttes, A., Zhang, T., Vail, S., Pozniak, C.: Parkin, I.: Classification of crop lodging with gray level co-occurrence matrix. In: IEEE Winter Conference on Applications of Computer Vision (2018). https://doi.org/10.1109/WACV.2018.00034
5. Masoudnia, S., Mersa, O., Araabi, B.N., Vahabie, A., Sadeghi, M.A., Ahmada-badi, M.N.: Multi-representational learning for offline signature verification using multi-loss snapshot ensemble of CNNs. Expert Syst. Appl. (2019). https://doi.org/10.1016/j.eswa.2019.03.040
6. Patil, B.V., Patil, P.: An efficient DTW algorithm for online signature verification. In: International Conference on Advances in Communication and Computing Technology (ICACCT) (2018)
7. Rateria A., Agarwal S.: Offline signature verification through machine learning. In: UPCON 2018 5th IEEE Uttar Pradesh Section International Conference on Electrical, Computer and Electronics (2018)
8. Diaz, M., Ferrer, M.A., Impedovo, D., Malik, M.I., Pirlo, G., Plamondon, R.: A perspective analysis of handwritten signature technology. ACM Comput. Surv. **51**(6) (2019)
9. Hezil, H., Djemili, R., Bourouba, H.: Signature recognition using binary features and KNN. Int. J. Biometrics **10**(1) (2018)
10. Jayaraman, M., Gadwala, S.B.: Writer-independent offline signature verification system. In: Balas, V.E., Sharma, N., Chakrabarti, A. (eds.) Data Management, Analytics and Innovation. AISC, vol. 839, pp. 213–223. Springer, Singapore (2019). https://doi.org/10.1007/978-981-13-1274-8_17
11. Kumra, S., Rao, T.: A novel design for a palm prints enabled bio-metric system. IOSR J. Comput. Eng. (IOSRJCE) **7**(3), 1–8 (2012)
12. Mohebian, R., Riahi, M.A., Yousefi, O.: Detection of channel by seismic texture analysis using grey level cooccurrence matrix based attributes. J. Geophys. Eng. **15**(5), 1953–1962 (2018). https://doi.org/10.1088/1742-2140/aac099
13. Olabode O., Adeniyi J.K., Akinyede, R.O., Oluwadare S.A.: A signature identification system with principal component analysis and Stentiford thinning algorithms. Int. J. Comput. Technol. **14**(9) (2015)
14. Ortega-Garcia J., et al.: Biometrics on the internet MCYT baseline corpus: a bimodal biometric database. IEE Proc.-Vis. Image Sig. Process. **150**(6) (2003). https://doi.org/10.1049/ip-vis:20031078

15. Priya, T.V., Sanchez, G.V., Raajan, N.R.: Facial recognition system using local binary pattern (LBP). Int. J. Pure Appl. Math. **119**(15), 1895–1899 (2018)
16. Rachapalli, D.R., Kalluri, H.K.: Texture driven hierarchical fusion for multi-biometric system. Int. J. Eng. Technol. **7**(4), 33–37 (2018)
17. Rajapaksa S., et al.: Modified texture features from histogram and gray level co-occurence matrix of facial data for ethnicity detection. In: IEEE 2018 5th International Multi-Topic ICT Conference (IMTIC) (2018). https://doi.org/10.1109/IMTIC.2018.8467231
18. Sharif, M., Khan, M.A., Faisal, M., Yasmin, M., Fernandes, S.L.: A framework for offline signature verification system: best features selection approach. Pattern Recogn. Lett. (2018). https://doi.org/10.1016/j.patrec.2018.01.021
19. Singh, S., Kaur, A.: Off-line signature verification using sub uniform local binary patterns and support vector machine. In: International Conference on Chemical Engineering and Advanced Computational Technologies (ICCEACT 2014) (2014). https://doi.org/10.15242/iie.e1114033
20. Sthapak, S., Khopade, M., Kashid, C.: Artificial neural network based signature recognition & verification. Int. J. Emerg. Technol. Adv. Eng. **3**(8) (2013)
21. Valentin, P., Kounalakis, T., Nalpantidis, L.: Weld classification using gray level co-occurrence matrix and local binary patterns. In: IEEE International Conference on Imaging Systems and Techniques (IST) (2018). https://doi.org/10.1109/IST.2018.8577092
22. Yadav, D., Saxena, C.: Offline signature recognition and verification using PCA and neural network approach. Int. J. Sci. Res. Dev. **3**(9) (2015)
23. Pandit, S., Gupta, S.: A comparative study on distance measuring approaches for clustering. Int. J. Res. Comput. Sci. **2**(1) (2011)
24. Zhang, Y., Xu, Y., Bao, H.: Offline handwritten signature recognition method based on multifeatures. J. Converg. Inf. Tech. (JCIT), **8**(5) (2013)
25. Chandra, S., Maheshkar, S.: Static signature verification based on texture analysis using support vector machine. Int. J. Multimedia Data Eng. Manag. **8**(2) (2017). https://doi.org/10.4018/ijmdem.2017040103
26. Pushpalatha, K.N., Gautam, A.K., Raviteja, K.V., Shruthi, P., Srikrishna, A.R., Yuvaraj, P.: Signature verification using directional and textural features. In: IEEE 2013 International Conference on Circuits, Controls and Communications (CCUBE) (2013). https://doi.org/10.1109/ccube.2013.6718560
27. Jadhav, T.: Handwritten signature verification using local binary pattern features and KNN. Int. Res. J. Eng. Technol. (IRJET) **6**(4) (2019)