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Offline Signature Verification Using Rotated Local Binary Pattern (RLBP)

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Abstract: Handwritten signature verification is an important technique for many financial, commercial, and forensic applications. Signature verification is considered critical in machine learning and pattern recognition, while a significant work is being done to eliminate the ambiguity involved in the manual authentication process. The signature verification can include two kinds, depending on the input format: (1) online and (2) offline. The capture of dynamic image requires an electronic device with a stylus, which mainly records dynamic information while signing. On the other hand, a scanner or any other form of image devices normally capture the offline signature that produces two-dimensional image. There are different approaches for identification of signatures with many areas of research. In this paper, we propose Rotated Local Binary Pattern (RLBP) for feature extraction for the static signature recognition to identify forgeries. The experiments have been conducted using UTSIG dataset. Performance evaluation is done on the basis of accuracy, computation time, sensitivity, specificity, recall and f1-score.

Keywords: Biometrics; Feature Extraction; RLBP.

I. INTRODUCTION

In a wide range of security applications, biometric technology is most commonly used for data verification. The main purpose of these frameworks is to explain a person's identity based on physiological or personal traits. The first is focused on genetics, including fingerprint, hair color, iris, etc. While second one is about behavioral characteristics including voice and handwritten signature. There are two categories of signature verification system, one is on-line and the second is offline. In online method, dynamic information such as speed and pressure are obtained along with capturing of static signature images using digitizer. While in an offline method, signature is scanned to computer system from a previously signed piece of paper. Signatures are composed of special symbols or characters so usually it is difficult to understand them. The main purpose of signature recognition is to recognize the signer. It is used for official and legal documents such as bank cheques, visa applications, academic certificates, corporations, attendance register monitoring and many more. Processing offline signature approach is a complex task due to unavailability of dynamic features. 2D image is required for offline signature verification and identification. It is also hard to segment signature because of modish and different writing strokes. The obtained signature is also affected by the nature and variety of pens. The signature variation can also occur because of a person's age, illness, geographic location and emotional state. The difficulty in signature verification also arises because of any mark of such element on paper. The signature orientation can be different. We wanted to design a system, which could handle these issues and detect type of forgeries. The proposed technique is addressed in two phases. In first phase, scanned image is processed for segmentation and contrast enhancement. In second phase, features are extracted for further classification.

Luiz G et.al [1] done their investigation in machine learning area by diagnosing risk to offline signature verification. They discussed various threats to the authentication of offline signatures. Several experiments were conducted on four datasets with a handcrafted feature extractor system and CNN.

This [2] study focused on or Binary Robust Invariant Scale Key points (BRISK), a feature detector algorithm for images comparison. The mobile application allows storing of images through a profile list, collecting, and saving substantial signature images that can be matched to another signature image for authenticity. In 2019 Jadhav [3] proposed the handwritten signature verification system by using local binary pattern features and k-nearest neighbor (KNN) classifier. This system worked in different stages which includes pre- processing, local binary pattern (LBP), image conversion, feature extraction, and classification. This system compared the output with another existing system. The hybrid feature removal approach was proposed [4] by using Scale Invariant Feature Transformation (SIFT) and enhanced LBP approach to achieve the robust feature model. A classification study is also presented for the performance measure of the proposed approach. Experimental studies show that the method proposed achieves promising signature verification system performance.

In this system [4] an artificial neural network based on the backpropagation is used for bank cheque recognition and verification. This system verified 400 test signature models with forged and genuine signatures of twenty individuals. This system allowed for judging signature accuracy and attaining more effective outcomes. This paper [5] proposed two descriptors named local binary patterns and binary statistical image features. Which is used to extract the features of signature image. To measure the reliability of the method, experiments were conceded using two datasets. For classification, k-nearest neighbour classifier was used. 97.3% and 96.1% results were obtained using MCYT-75 and GPDS-100 databases respectively. In this paper [6] we have given description about signature recognition methods and have compared all those methods. An innovative technique is introduced [7] for offline verification system. Local features contain signature centroid, slope, angle, and distance are used by the researchers. A genetic algorithm is applied for signature verification. This algorithm identifies features, which are given to SVM for classification.

Paul Maergner [8] proposed a computational graph edit distance method with metric learning and deep neural network for offline signature verification. They showed that combining structural and statistical models leads to significant performance improvements, taking advantage of their additional properties. Li Liu (2018) proposed a Deep Convolutional Siamese Network for offline signature recognition. [9]. Instead of using actual signature image, local features are abstracted and then combining similitudes measures from several regions are used for verification. The experiments were conducted on CEDAR and GPDS datasets. However, Hafemann et al. [10] proposed different strategies for OSV based on using expert forgeries and original signatures.

Ramanathan et al. [11] design a system for signature recognition based on Histogram Oriented Gradient features with a linear SVM classifier. In each cycle, a small modification is made to the image, and a new point is defined as the distance from the new image to SVM hyperplane. This approach allowed the authors to create images that processed by HOG and SVM classification with negligible noise. In [12] 70% accuracy was achieved by using Efficient Fuzzy Kohonen Clustering Networks (EFKCN) and [13] proposed histogram of oriented gradients. The system provided recognition rate of 96.87% with 4 training sample per individual. In [14] for enhanced signature verification SURF and SIFT algorithms are used and their performance was compared. The accuracy of 98.75% has been achieved using SIFT with SVM-RBF kernel system while accuracy of 96.25% has been achieved using SURF with SVM-RBF kernel. [15],[16] proposed a supervised learning approach with convolution Siamese network for verifying individuals offline signatures. In this work, features are extracted by using Histogram of Oriented Gradients (HOG). Here a feature vector was represented [17] and in [18] a variant of local binary pattern called Block wise Binary Pattern (BBP) was suggested. In this method, different features like Skewness, Eccentricity and Kurtosis are extracted by transforming the image into (200x200) binary pixel image. Then by using backpropagation technique, these features are used to train neural network. [19] [20].

II. PROPOSED METHODOLOGY

In the proposed method, a novel approach called Rotated Local binary pattern (RLBP) is proposed to extract unique structural features from the signature. The given approach comprises of three major steps: preprocessing, feature extraction and classification. We selected Accuracy, Sensitivity and Specificity as the metrics for evaluation. The proposed method for offline signature verification works in two phases; initially the image is preprocessed, then features are extracted. The signature recognition can be done by support vector machine. Proposed system design is shown in Fig. 1

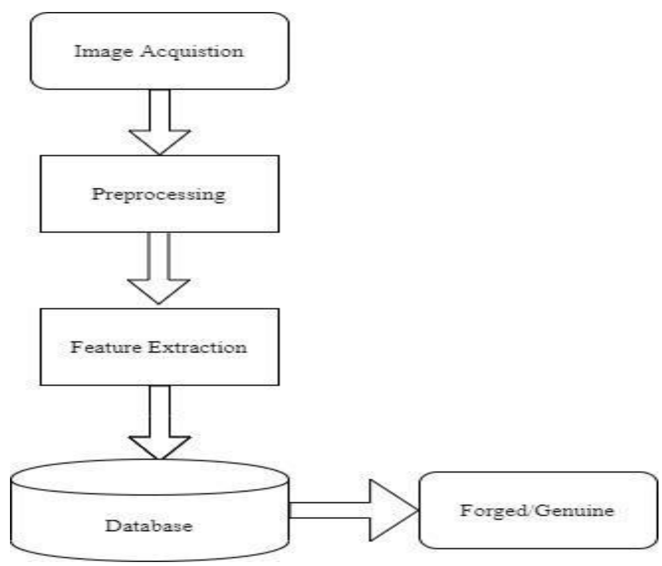


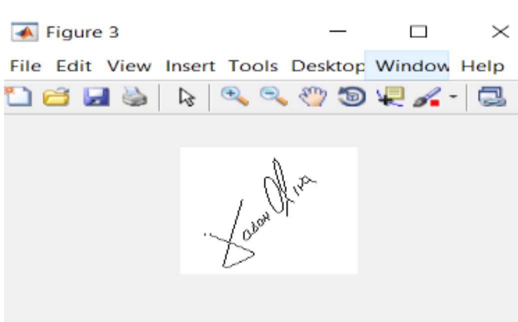
Figure 1. Block Diagram of Proposed Approach

A. *Image Acquisition*

For offline signature verification system, input image is acquired through any digital device such as camera, or scanner etc. These devices convert given image into digital form. Now the issue is to recognize signatures from this available image. Sometimes it is hard because the scanned image may have other patterns and noise. Therefore, it is important to identify the proper region of interest. When the signature region had been recognized it has to assist for finding out the precise position of signature in scanned image. There are number of restrictions in the data acquisition phase. In case of too long signatures, it may be difficult to determine the unique data points for the recognition system.

B. *Preprocessing*

After image acquisition preprocessing has been an important step to improve the image quality. It enhanced the accuracy and reduced the computation time. The input images are preprocessed for removing non informational data. Preprocessing stage also included the conversion of RGB image into grey scale one, removing background noise, image resizing and normalizing the intensity. In signature recognition, color has no importance therefore scanned image is converted into binary image using Otsu method. It is used to convert the 3D color image into 2D binary image having intensity 0TH-255. It is also found image intensity dynamically. After binarization, image is resized to 256×256. Then median filter is applied for noise removal. It is a linear filtering technique in which pixel value is replaced with the median of its neighboring pixel values. These values are used to calculate median, called window. This window slides over each pixel. These windows are distinct in shapes. Each window has varying number of pixels. These varies from case to case e.g., in box like shape there may be 3×3, 5×5 or 7×7 group of pixels, each have different results. The following Fig. 2 shows preprocessing steps.



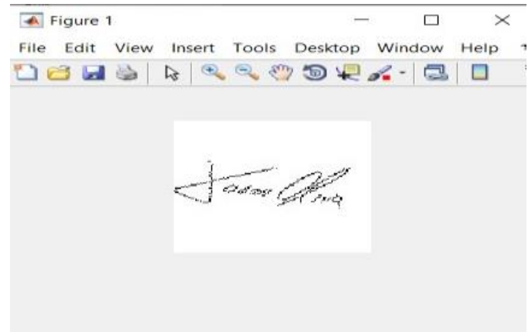


Figure 2. Preprocessing Steps

C. *Rotated Local Binary Pattern*

Here we performed detail steps involved in feature extraction using Rotated Local Binary Pattern (RLBP) [21]. RLBP Operator is obtained by circular moving LBP operator weights. This applied a difference in magnitude to find notable direction in the region. The prominent direction represented highest difference of neighboring pixels from central pixel. The operator of RLBP calculated the pixel based binary patterns in the neighbourhood. The final values of these operators varied because the weights in the RLBP operator are circulated. It has high discriminative power and computational complexity. In a circular neighbor, RLBP is used for deciding a dominant direction, and the descriptor is calculated for its reference. The weights correlated with the adjacent pixels in this dominant direction are circularly modified. The Rotated Local Binary Pattern (RLBP) of the features is calculated as:

$$\mathrm{RLBP} = \sum_{\mathrm{P}=0}^{\mathrm{P}-1} S\,(gp - gc).\,2\,mod\,(p - D, P) \qquad (1)$$

where mod is the modulus operation. In the above equation the term $2^{\mathrm{mod}\,(p-D,\,P)}$ depends on dominant direction D. The weight of the dominant direction is circularly modified. The change results in an invariance of rotation because weights depend not on a predetermined structure, but on the neighbourhood. In Figure. 3 It may be seen that for original and rotated images the weight corresponding to the dominant position is the same, though these pixels are at different position. Therefore, in this case the RLBP values obtained in two different rotated regions are identical.

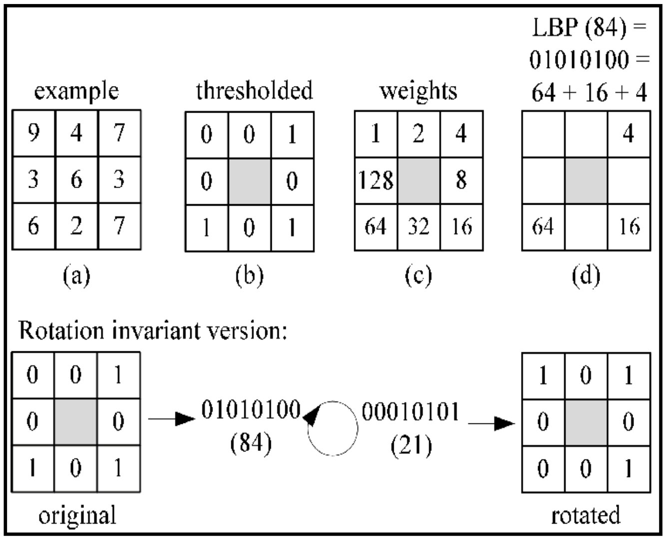


Figure 3. RLBP Computation

D. Support Vector Machine (SVM)

SVM has gained significant consideration in the area of pattern recognition. it is used to check the performance of descriptor and was developed from Statistical Learning Theory (Vapnik & Chervonenkis) [22]. SVM is known as a possible and effective method to identify classification issues. It has perfect accuracy and consistency in various design [23]. It is a supervised machine learning algorithm that examines data for classification and regression analysis. It can use different kernel types. One important advantage of SVM classification is that it is effective on datasets with many features, only a few cases can be identified during the training process. In the proposed approach, extracted features from different descriptor fed to SVM for identifying fake and original signatures. The SVM classifier [24] for a given training set of N-semantic class images is calculated in a given class as,

$$\{(x_i\ ,\ y_i)\}_{i=1}^{m}\ y_i\ =\ \{+1,\ -1\} \qquad (2)$$

where xi and yi are considered as corresponding labels and inputs. The images from positive class are categorized as +1 and images from other classes are categorized as -1.

$$y(x)\ =\ w^T\ \varphi x\ +\ b \qquad (3)$$

where ϕ(.) represents the non-linear mapping, which is used to map the input vector into higher dimensional feature space, b is the bias and w is a weight vector of the same dimension as that of the input vector. SVM assumes the linearly separable case as:

$$\begin{Bmatrix} w^T x_i + b \geq +1 if\,(y_i = +1) \\ w^T x_i + b \leq -1 if\,(y_i = -1) \end{Bmatrix} \qquad (4)$$

III. RESULT AND DISCUSSION

A. UTSIG Dataset

A number of signature datasets are available to check the performance of verification system. In our study we have selected UTSIG dataset. A Persian Offline Signature Dataset comprises of 115 classes and contained 8280 images in total. There are 27 genuine signatures, 42 skilled forgeries made by 6 forgers and 3 opposite hand signatures from each class. In comparison with other public data sets, Persian offline signature dataset has more samples, classes and forgers. UTSIG has more classes, samples and forgers as compared to other public datasets. In data collection process authors considered different variables including signing times, writing tool, signature size and observable samples for forgers. When analyzing carefully the key features of offline signature data sets, they note that the number of branch and end points of Persian signatures is reduced. They propose and evaluate four different settings for UTSIG training and testing.

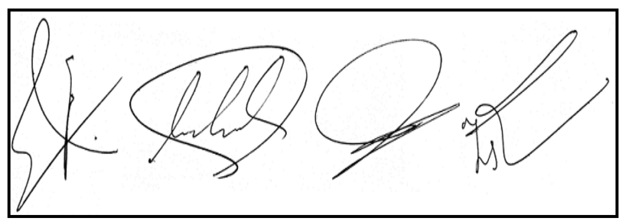


Figure 4. UTSIG Signature Samples

The proposed method is evaluated on the basis of different performance metrics such as accuracy, sensitivity, specificity, recall and f1-score. The below table explains performance evaluation for UTSIG using Rotated Local Binary Pattern. In our experiments, we find the highest accuracy 99.172%. It also described recall, sensitivity and f-score accomplished by our proposed method. The given method achieves 99.58% specificity which means most of signatures features were identified correctly. We also detect 52.38% recall which shows some of the features are false positive.

TABLE I. PERFORMANCE EVALUATION

DATASET	**Accuracy**	**Sensitivity**	**Specificity**
UTSIG	99.172	52.388	99.582

IV. COMPARATIVE ANALYSIS

The accuracy of proposed system was compared to other systems in order to confirm the efficiency of proposed model. The experiments were performed on UTSIG dataset for signature verification. In the proposed work handcrafted features such as RLBP is compared in terms of accuracy, sensitivity and specificity. These results are difficult to compare directly because they are affected by the type or number of signatures used during construction and evaluation of the classifier. Table II shows the accuracies of proposed method together with other state of the art methods.

TABLE II. COMPARISON OF PROPOSED METHOD WITH THE STATE-OF-THE-ART

UTSIG DATASET	
Method	**Accuracy/AER**
Deep multitask metric learning+ HOG [25]	17.6
Fixed Point Arithmetic [26]	29.7
HCC [27]	92.42%
Proposed	**99.172%**

V. CONCLUSION AND FUTURE WORK

In this paper, distinctive machine learning and image processing approaches are used for human signature verification. This technique frequently identifies shape and size of signature. At first the images are pre-processed with the usage of median filter and OTSU method then the rotated local binary pattern algorithm is used to extract the features. From the comparison analysis we observe that the performance metrics produce a trade-off between accuracy and time. After experiments and result evaluation it is concluded that the proposed method is accurate, efficient and easy to implement. For the future work, more descriptors can be put into experiment. The computation time for signature verification increases as database increases. Therefore, some newly proposed methodologies like neural networks and deep learning can be used in future.

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REFERENCES

[1] G. Luiz. Hafemann, R.Sabourin, S.Luiz Oliveira “Characterizing and Evaluating Adversarial Examples for Offline Handwritten Signature Verification” IEEE, 2019. 14, No.08.

[2] M. Christina Aragon, R. Castillo, J. Agustin and I. Benedict Aguilar” Utilization of Feature Detector Algorithms in a Mobile Signature Detector Application” March 16–19, 2019

[3] T. Jadhav "Handwritten Signature Verification using Local Binary Pattern Features and KNN". 2019. 6 no. 4: p. 579-586.

[4] V. Tambade, P. Varma, A. Sonawale "Bank Cheque Signature Verification System". 2018. 1. no. 9.: p. 265-267.

[5] H. Hedjaz, R. Djemili and H. Bourouba ne “Signature recognition using binary features and KNN”. 2018. 10. No. 1.

[6] P.Henali , D. Pooja and A. Damani “Review on Offline Signature Recognition and Verification Techniques”. 2018. 179-No.153.

[7] M. Sharif, M. Attique Khan, M. Faisal, M. Yasmin, and S. L. Fernandes., "A framework for offline signature verification system: Best features selection approach,". 2018.

[8] P. Maergner, V.P. Michele Alberti, M. Liwicki, Kaspar Riesen, R. Ingold, and A. Fischer “Offline Signature Verification by Combining Graph Edit Distance and Triplet Networks” 17 0ct, 2018.

[9] L. Liu, L. Huang, F. Yin, Y. Chen., “Off-line Signature Verification using a Region Based Metric Learning Network”. 2018.

[10] L. Gustavo Hafemann, R. Sabourin and L. S. Oliveira., "Learning features for offline handwritten signature verification using deep convolutional neural networks," Pattern Recognition. 2017. 70: p. 163-176.

[11] A. Ramanathan, “Adversarial attacks on computer vision algorithms using natural perturbations,” 2017: p. 1-6.

[12] D. Suryani, R. Chindra., “Offline Signature Recognition and Verification System using Efficient Fuzzy Kohonen Clustering Network (EFKCN) Algorithm” 2017.

[13] P. Pallavi, and B. Almeida “Offline Signature Recognition System using Histogram of Oriented Gradients”. 2017.

[14] T. Abdilbaree Nasser and D. Nuran Dougu “Signature recognition by using SIFT and SURF with SVM basic on RBF for voting online” 2017.

[15] T. Longjam and R. Dakshina Kisku “A Supervised Manipuri Offline Signature Verification System with Global and Local Features” 2017.

[16] D. Sounak , J. Ignacio Toledoa, K. Suman, G. Josep Llad, Umapada Pal “SigNet: Convolutional Siamese Network for Writer Independent Offline Signature Verification”. 2017.

[17] M. Taúk Õran, Z. Gülru ÇamZ “Offline Signature Identification via HOG Features and Artificial Neural Networks”. 2017.

[18] B. H Shekara, P. Bharathi, S. Kumar, “Blockwise binary pattern: a robust and an efficient approach for offline signature verification”. 2017. XLII-2/W4.

[19] M. Trikha, Maitreyee Dutta, M. Singhal “Signature Verification using Normalized Static Features and Neural Network Classification,”. 2016. 6 No. 6: p. 2665.

[20] M. Singhal, D. Maitreyee and M. Dutta., “Time Independent Signature Verification using Normalized Weighted Coefficients,”. 2016. 6 No. 06: p. 2658.

[21] M. Rakesh, O. Karen. Egiazarian, “Rotated Local Binary Pattern (RLBP): Rotation invariant texture descriptor”.

[22] N. Vladimir. Vapnik “An overview of statistical learning theory,”. vol. 10 No. 05: p. 988-999.

[23] W. Xiang-Yang, C. Jing-Wei - n, Hong –Ying Yang "A new integrated SVM classifiers for relevance feedback content-based image retrieval using EM parameter estimation.". Appl. Soft Computer., 2011: p. 2787-2804.

[24] S. Zoran, T. Yasufumi, H. Kaoru.. "Geneticalgorithm-based relevance feedback for image retrieval using local similarity patterns". Inf. Process Manager. 2003

[25] A. Soleimani, Babak. N. Arabi, and K. Fouladi, "Deep Multitask Metric Learning for Offline Signature Verification". Pattern Recognition Letters, 2016. vol.80

[26] R. Ashraf Abdel Raouf, "Handwritten Signature Verification using Haar Cascade Classifier Approach" 2018