Vertical Off-line Signature Feature Block for Verification

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Abstract: - Handwritten signature image is normally used as a mark of endorsement of written document. Signatures of the same person vary and they can be forged by imposters. Effective feature extraction algorithm is needed in off-line signature verification. Robust features capable of increases interpersonal variation and decreases intra personal variation are required. This work presents robust signature feature that can be used to build effective off-line signature verification system. Signature processing is performed and the preprocessed signature image is vertically divided into sixteen smaller image blocks through the center of gravity. Three features are extracted from these smaller image blocks. Feature vector is formed and are passed to Support Vector Machine (SVM) for training and classification. The proposed signature feature vector increases the accuracy of tested off-line signature verification system.

Key-Words: - Vertical signature image; centre of gravity; Support Vector Machine**.**

1 Introduction

Handwritten signature verification involves authentication of person using signature images written on a paper. Handwritten signature is used all over the world as mean of legal approval of paper document. Many day to day transactions involve the use of signature for authentication. Signature is a behavior biometric tract. The variation that exists in same person signatures makes it difficult to verify signature signed by authentic users. Verification of handwritten signature can be done manually or by computer. Computerized signature verification is different from the manually method. Manual verification of signature is prone to more error and takes longer time than computerized ones. There are two types of computerized signature verification namely off-line and on-line. Off-line signature verification is more difficult to achieve compare to on-line signature verification. In on-line signature verification, availability of dynamic features is added advantage [1][2].

Many researchers had proposed different off-line signature verification systems based on different type of feature extraction methods. In some cases features are extracted from the whole signature image using wavelet transform [3]. On other hand it involves extraction of shape and geometric features from whole signature image [4][5][6][7][8]. Whereas some researchers splitted signature image into smaller sub-images before feature extraction was carried out. In many cases signature are splitted into smaller image of equal size with no foreground pixels [9] [10][11][12][13]. Also it is reported that five geometric features are extracted from signature image which include center of gravity of whole signature and the slope of the line join center of gravity of two sub-signature images of equal size[14][15]. In the past, many features had been extracted from either whole signature image or block signature image. Those features include energy density, angle, pixel mass, normalized area, number of local maxima and directional feature [16][17][18][19]. In this work, three new signature features are extracted from vertical signature image blocks and they are fused together to obtain a robust feature vector. Also unlike the previous works, the proposed feature extraction method put into consideration the image pixel position. Each signature image block is divided into smaller ones through the image center of gravity in consecutive order. Sixteen vertical signature image blocks of different structural sizes are produced .The feature vector generated from these vertical signature image blocks is able to eliminate variation exhibit within person signatures during classification using

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Support Vector Machine. The rest of the paper is organized as follows: Section 2 describes input signature image and preprocessing. Section 3 presents the feature extraction steps, and section 4 describes verification result based on Support Vector Machine. Finally, conclusion is presented in section 5.

2 Input Image Signature Preprocessing

Signature images were collected from 50 people, each person contributed six signature image samples. Users signed their signatures on white paper. Signature image is acquired at 300 dpi. Signature image preprocessing is done via filtering and binarization. The input gray level signature image is passed to gaussian filter . Noise free image is obtained from the output as shown in Fig.1. Thereafter thesholding operation is performed on the filtered gray level signature image to obtain binary image as shown in Fig.2. the binary signature image is thinned to one pixel wide image as shown in Fig.3. Finally the bounded binary signature image is obtained as shown in Fig.4.

Fig.1. Filtered gray level signature image.

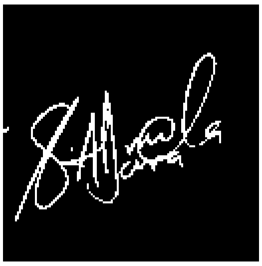

Fig.2. Binary signature image.

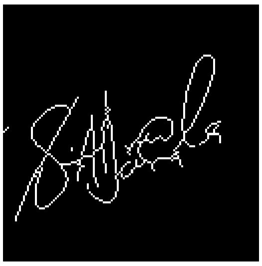

Fig.3. Thinned signature image.

Fig. 4. Bounded signature image.

3 Vertical Feature Extraction Block Algorithm.

Signature feature extraction technique describes in this section produce feature vector that is able to represent signature of different people notwithstanding the level of variation within the signatures of the same person. The feature extraction steps are stated as follows:

Step 1: Determine the centre of gravity of the whole bounded signature images using (1). Perform vertical splitting on the whole bounded signature image through point $\bar{x}$ and $\bar{y}$ to obtain two signature images block1 and block2 as shown in Fig.5

Step 2: Determine the centre of gravity of each of the signature images block 1 and block 2 using (1). Perform vertical splitting on signature image block1 and block2 through their $\bar{x}$ and $\bar{y}$ points respectively. Four smaller signature images: block1a, block1b, block2a and block2b are formed as shown in Fig. 6.

Step 3: Determine the centre of gravity of each of signature images block 1a, block 1b, block 2a and block 2b using (1). Perform vertical splitting on signature images: block 1a, block 1b, block 2a and block 2b through their $\bar{x}$ and $\bar{y}$ points respectively. Eight smaller signature images: block 1a1, block1a2, block1b1, block1b2, block2a1, block2a2, block2b1 and block2b2 are formed as shown in Fig. 7.

Step4: Determine the centre of gravity of each of the signature images: block1a1, block1a2, block1b1, block1b2, block2a1, block2a2, block2b1 and block2b2 using (1). Perform vertical splitting on signature images: block1a1, block1a2, block1b1, block1b2, block2a1, block2a2, block2b1 and block2b2 through their $\bar{x}$ and $\bar{y}$ points respectively. Sixteen smaller signature images: B1, B2,B3,B4,B5,B6,B7,B8,B9,B10,B11,B12,B13,B14, B15 and B16 are formed as shown in Fig. 8.

Step5: Extract three features from each of the sixteen vertical blocks. Calculate the deviation of the centroid of connected pixels. Calculate the city-block distance. Calculate signature image block size.

Step6: Concatenate the three set features from each of the sixteen blocks to obtain feature vector of 48 elements.

$$\bar{x} = \frac{1}{N}\sum_{i=1}^{N} x(i),$$

$$\bar{y} = \frac{1}{N}\sum_{j=1}^{N} y(j). \qquad (1)$$

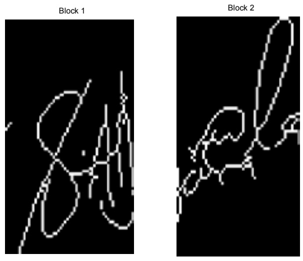

Fig.5. Two vertical signature image blocks

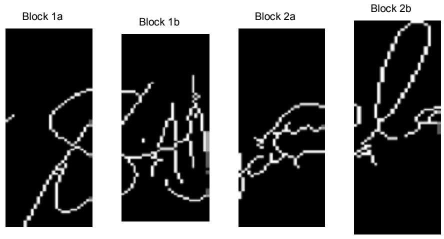

Fig.6. Four vertical signature image blocks.

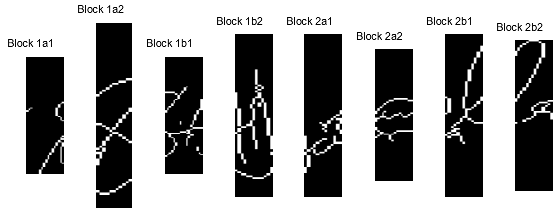

Fig.7. Eight vertical signature image blocks.

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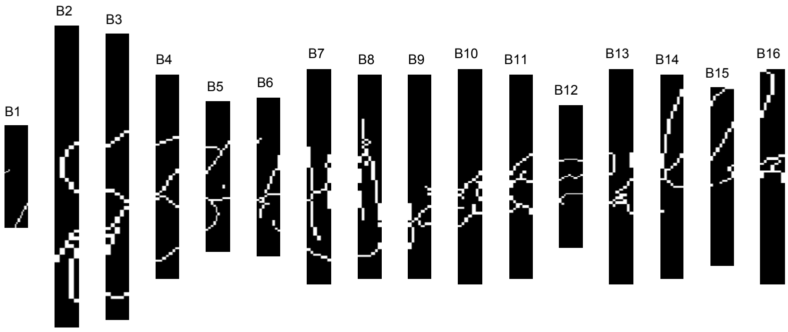

Fig.8. Sixteen vertical signature image blocks

4 Signature Verification Results Using Support Vector Machine.

Support Vector Machine (SVM) has the capacity to train and test features derived from signature images. It classify images into two major classes. These two classes are separated by large margin called optimal hyper plane. The support feature vectors are the subset of the training feature vectors that lie on the margin [20]. SVM trains signature image based on the feature vectors that comes from all registered users. The verification of test signature image is obtained by classifying each of user test signature image as belong to any of the two classes.

The result obtained from this work is better compare to the one obtained in [9] and [15]. Fig. 9 and Fig. 10 show the examples of stem feature plot of verified signature images that matched with users' signatures. The implementation of the work is carried out using MATLAB 2012a platform [21] [22].

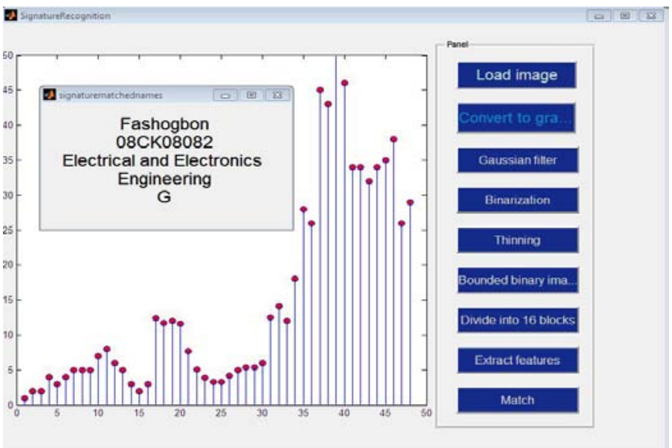

Fig. 9: Stem plot of test feature for user1.

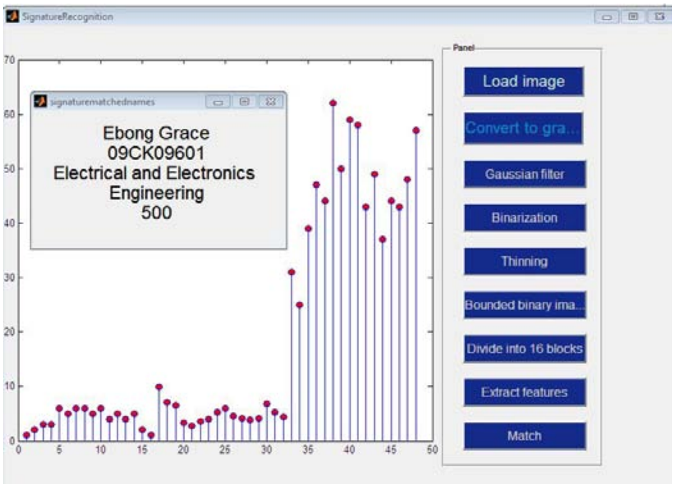

Fig. 10: Stem plot of test feature for user2.

5 Conclusion

In this work, robust features are extracted from vertical signature image blocks for off-line signature verification. Splitting of signature image into smaller ones using center of gravity on consecutive order is able capture the variation that exist within signature images of the same person. It also gave way to obtain predominate features that describe signature completely. Test signature images matched corresponding genuine users' signature images correctly. Further work is to test the strength of the feature vector in widen inter- personal variation for skilled forged signatures.

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References

[1] Hemanta Saikia and Kanak Chandra Sarma, Approaches and Issues in Offline Signature Verification System, *International Journal of Computer Applications*, Volume 42, No.16, March 2012, pp45-52.

[2] Vitthal K. Bhosale, Dr. Anil R. Karwankar, Automatic Static Signature Verification Systems: A Review, *International Journal Of Computational Engineering Research*, Vol. 3 Issue2, 2013, pp8-12.

[3] M. H. Sigari, M. R. Pourshahabi & H. R. Pourreza, Offline Handwritten Signature Identification and Verification Using Multi-Resolution Gabor Wavelet, *International Journal of Biometrics and Bioinformatics* , Volume (5) , Issue (4) , 2011, pp 234-248.

[4] Paigwar Shikha and Shukla Shailja, Neural Network Based Offline Signature Recognition and Verification System, *Research Journal of Engineering Sciences*, Vol. 2(2), 2013, pp11-15.

[5] Miguel A. Ferrer, Carlos M. Travieso, Jesus B. Alonso, Jesus F. Vargas, Offline Signature Verification Based on Pseudo-Cepstral Coefficients, *10th International Conference on Document Analysis and Recognition*, 2009, pp126-130.

[6] Meenu Bhatia Off-Line Hand Written Signature Verification using Neural Network, *International Journal of Application or Innovation in Engineering & Management*, Volume 2, Issue 5, 2013, pp108-116.

[7] Priya Metri , Ashwinder Kaur, Handwritten Signature Verification using Instance Based Learning, *International Journal of Computer Trends and Technology*, March to April Issue1, 2011,pp1-4.

[8] Gulzar A. Khuwaja and Mohammad S. Laghari, Offline Handwritten Signature Recognition, *World Academy of Science, Engineering and Technology* 59, 2011, pp1300-1303.

[9] S. Daramola and S. Ibiyemi, Novel Feature Extraction Technique for Off-line Signature Verification, *International Journal of Engineering Science and Technology* Vol. 2(7), 2010, pp 3137 - 3143 .

[10] Prashanth C. R. and K. B. Raja, Off-line Signature Verification Based on Angular Features *International Journal of Modeling and Optimization*, Vol. 2, No. 4, 2012, pp477-481.

[11] Rahul Verma, D.S. Rao, Offline Signature Verification and Identification Using Angle Feature and Pixel Density Feature And Both Method Together, *International Journal of Soft Computing and Engineering*, Volume-2, Issue-4, 2013, pp740-746.

[12] Minal Tomar and Pratibha Singh, A Directional Feature with Energy based Offline Signature Verification Network, *International Journal on Soft Computing*, Vol.2, No.1, 2011, pp 48-57.

[1 [13] Mandeep Kaur Randhawa, A.K Sharma, R.K Sharma, Off-line Signature Verification System Using Fusion of Novel Diagonal and Statistical Zone based Features, *International Journal of Emerging Technologies in Computational and Applied Sciences*, 2(1) 2012, pp106-111.

[14] Banshider Majhi, Y Santhosh Reddy, D Prasanna Babu, Novel Features for Off-line Signature Verification, *International Journal of Computers, Communications & Control*, Vol. I, No. 1, 2006, pp. 17-24.

[15] Amit Kishore Shukla Shreyas Singh, Offline Signature Verification System Using A set Of Simple Shape Based Geometric Features, *International Journal of Computer Trends and Technology* volume4, Issue4, 2013, pp511-514.

[16] K.Harika1, T.Chandra Sekhara Reddy A Tool for Robust Offline Signature, *International Journal of Advanced Research in Computer and Communication Engineering*, Vol. 2, Issue 9, 2013, pp3417-3420.

[17] Anu Rathi, Divya Rathi, Parmanand Astya, Offline handwritten Signature Verification by using Pixel based Method, *International Journal of Engineering Research technology* Vol. 1 Issue 7, 2012, pp1-4.

[18] Sanjay N. Gunjal, Manoj Lipton, Robust Offline Signature Verification Based on Polygon Matching Technique, *International Journal of Emerging Technology and Advanced Engineering* Volume 1, Issue 1, 2011, pp79-86.

[19] Manoj Kumar, Signature Verification Using Neural Network, *International Journal on Computer Science and Engineering* , Vol. 4, No. 09, 2012, pp1498-1504.

[20] Mandeep Kaur Randhawa A.K. Sharma R.K Sharma, Off-line Signature Verification based on Hu's Moment Invariants and Zone Features using

Support Vector Machine, *International Journal of Latest Trends in Engineering and Technology*, Vol.1, issue3, 2012, pp16-23.

[21] Kritika Raghuwanshi Niketa Dubey, Riju Nema Rishabh Sharma, Signature Verification through MATLAB Using Image Processing, *International Journal Emerging Trends Electonics and Computer Science*, volume 2, issue4, 2013, pp203-206.

[22] www.mathworks.com.

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