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A Tool for Robust Offline Signature verification

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Abstract: Hand written signature verification is an important utility in real time applications. It is required to verify identify fake signatures. Many existing techniques are based on the storke pixels and the underlying gray level values. Local Binary Patterns are used to obtain good results in offline signature verification. The experiments were made using GPDS corpus containing offline signatures. The corpus signatures are with uniform white background in invoices or cheques. Ferrero et al. proposed a novel offline signature verification technique that makes use of gray level features. Their technique was tested with offline signatures of various kinds in invoices and checks. In this paper, we implement that technique. We build a prototype application that demonstrates the proof of concept. The empirical results revealed that the prototype is useful in real time applications.

Index Terms – Signature verification, local binary patterns, texture features, and biometrics

I. INTRODUCTION

Identification of humans across the globe is very important for many applications where authentication is mandatory. Biometrics is the science that deals with this for robust deification of humans uniquely across the world. The features in biometrics include hand, hand written signature, voice, face, iris, and fingerprints. Among them hand written signatures plays a very important role in many transactions both private and public in almost every country. The main reason for this is that traditionally hand written signatures are used for identifying humans legally in various monetary transactions. Moreover people are used to this kind of authentication across the globe.

Hand written signature results from a complex process that depends on psycho physical state of the person who signs. To model such complex process many techniques came into existence. These techniques can differentiate forged signatures from genuine ones [1]. One of the methods for offline signature verification uses optical scanner. The other uses special device and works online which is more efficient. There are methods for offline signature verification also. They are also important as they are very useful in many real world applications where humans identify is to be established [2]. For offline signature verification, there are two important approaches. They are known as static and pseudo dynamic approaches. Geometric measures are used in static approaches while dynamic information is required by pseudo-dynamic approaches [3]. For constructing dynamic information there are three different approaches. They are known as mathematical methods, methods pertaining to motor control theory and methods that analyze stroke thickness. The first kind verifies storke production in temporal order. The second kind recovers temporal features while the third kind analyzes thickness of keystrokes.

Higher Pressure Points (HPPs) is the technique proposed by Amar et al. [4] to verify difference in strokes. Both lower and higher pressure points are analyzed by Mitra et al. [5]. Segmentation of gray level values concept is used by Lv et al. [6] which analyzes stroke width distribution. For finding higher pressure points locally radial and angular grid is used in [7]. Ink-trace characteristics are used in [8] and [9] to verify offline handwritten signatures. Texture features like LBP were used by some researchers for biometric identification of hand written signature [10], [11]. There are improvements on LBP in [12], [13] and [14] as they use locational invariants of LBPs. LBP has a drawback as it is sensitive to noise. There was some research on detection of disguised signatures and forged signatures in [15] and [16] respectively. Recently Ferrer et al. [17] presented a novel technique for offline handwritten signature verification based on gray level features.

The remainder of this paper is organized as follows. Section II provides information about corpus containing offline signatures. Section III provides signature verification process. Section IV presents experimental results while section V concludes the paper.

II. OFFLINE SIGNATRE CORPUSES

Two databases which are publicly available are used for

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experiments in this paper. The first one is known as MCYT database [3]. It has signatures from 75 signers. For each signer 15 forged signatures and 15 genuine signatures are taken. The second database is known as the GPDS960GraySignature which has signatures collected from 881 signers. For each signer 24 fake and 24 genuine signatures are present the database. The signatures are present in either checks or invoices. Various gray level models are used for experiments. The blending modes include linear dodge, color, lighten, linear burn, multiply and darken. All the samples have white background. For processing only signature strokes are considered. Outside the signature area is omitted from processing. The samples are as presented in fig. 1.

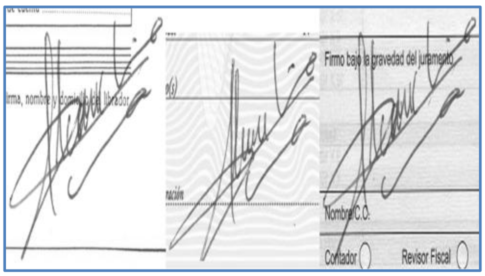

Fig. 1 – Checks with signatures with varied backgrounds

III. SIGNATURE PROCESSING

The signature databases such as GPDS and MCYT are used for processing signatures. They gray level posterized image is obtained using the following equation.

$$I_p(x,y) = \text{round}\left(\text{round}\left(\frac{I(x,y)\cdot n_L}{255}\right)\cdot\frac{255}{n_L}\right)$$

As part of signature verification procedure the signature part has to be segmented. The segmentation is carried out as follows.

$$I_G(x,y) = \begin{cases} I(x,y), & \text{if } I_{\text{NR}}(x,y) = 255 \\ 255, & \text{otherwise.} \end{cases}$$

The segmentation result is shown in fig. 2.

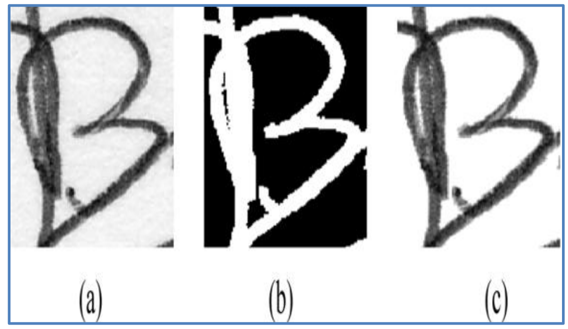

Fig. 2 Result of segmentation

As seen in fig. 2, the original mage with 256 gray levels is shown in (a). Fig. 2 (b) represents noise-reduced and baized image while fig. 2 (c) represents a segmented image with white background. More details about the offline handwritten signature verification can be found in [17].

IV. EXPERIMENTAL RESULTS

The prototype application is built using Microsoft .NET platform. C# programming language is used to implement the functionality of the application. The environment used to build and test the application includes a PC with 4 GB RAM, Core 2 Dual processor running Windows 7 operating system. Visual Studio 2010 is used for rapid application development. The experimental results are presented below.

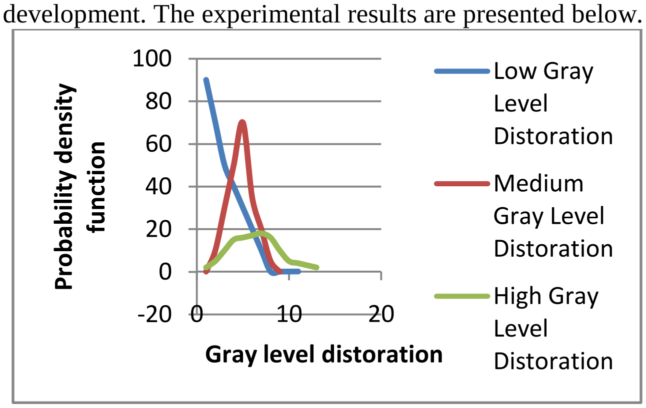

Fig. 3 – Distribution of signature gray level distortion for each database

As can be seen in fig. 3 the horizontal axis represents gray level distortion while the vertical axis represents probability density function. The result shown in graph represents low, medium and high gray level distortion distribution.

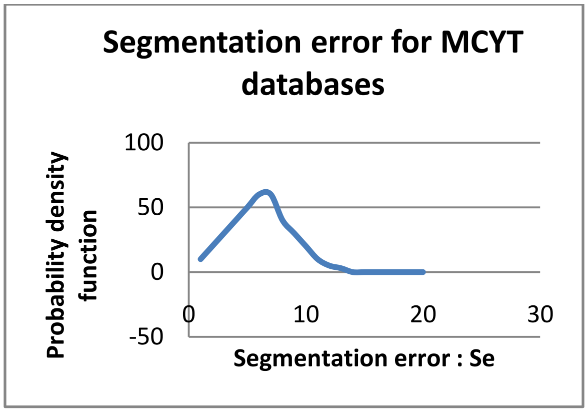

Fig. 4 – Distribution of automatic segmentation error

As can be seen in fig. 4 the horizontal axis represents segmentation error while the vertical axis represents probability density function. The result shown in graph represents distribution of segmentation error.

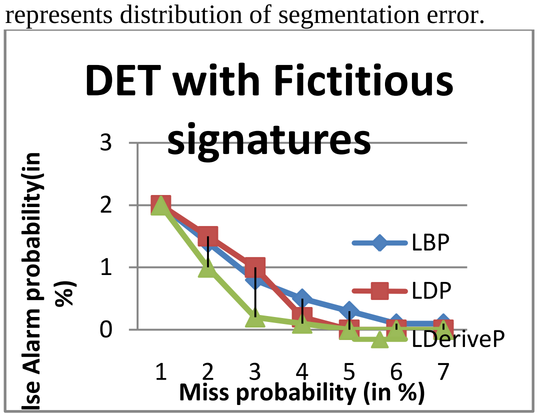

Fig. 5 – Plots LBP, LDP, and LDerivP

As can be seen in fig. 5 the horizontal axis represents miss probability in % while the vertical axis represents false alarm probability in %. The result shows DET with fictitious signatures.

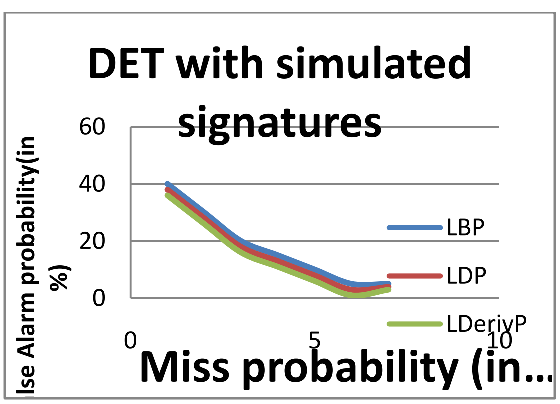

Fig. 6 – Plots LBP, LDP, and LDerivP

As can be seen in fig. 6 the horizontal axis represents miss probability in % while the vertical axis represents false alarm probability in %. The result shows DET with simulated signatures.

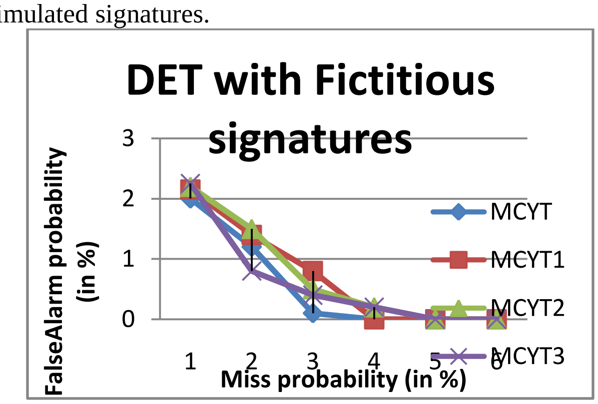

Fig. 7 – Plots for LDerivP features with various datasets

As can be seen in fig. 7 the horizontal axis represents miss probability in % while the vertical axis represents false alarm probability in %. The result shows DET with fictitious signatures of various databases.

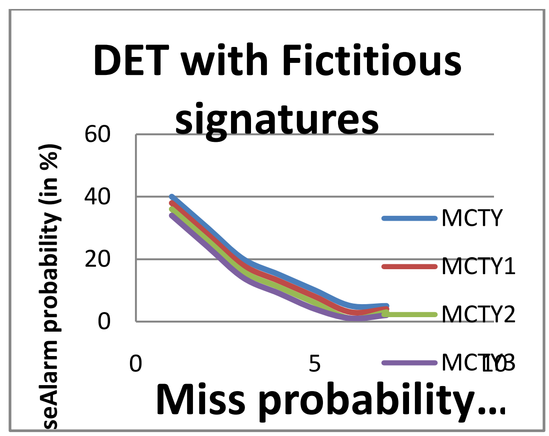

Fig. 8 – Plots for LDerivP features with various datasets

As can be seen in fig. 8 the horizontal axis represents miss probability in % while the vertical axis represents false alarm probability in %. The result shows DET with simulated signatures of various databases.

V. CONCLUSION

In this paper we implemented the offline signature verification technique presented by Ferrer et al. [17]. The technique uses histograms of various patterns such as local derivative, local directional and local binary. Different classifiers were built to evaluate those parameters. The classifiers used include SVM, NN. Histogram oriented kernels and RBF were used to evaluate the functionality of

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SVM. The aim of the technique is to verify offline hand written signatures. A corpus of offline hand written signatures are used for experiments. We built prototype applications for demonstrating the proof of concept. The prototype is tested with real time offline signatures. Experiments are made using both invoices and checks for signature verification automatically. The empirical results revel that the proposed technique is very useful and can be incorporated in real time applications for offline signature verification accurately.

REFERENCES

[1] D. Impedovo and G. Pirlo, "Automatic signature verification: The state of the art," *IEEE Trans. Syst. Man Cybern.—Part C: Applications Rev.*, vol. 38, no. 5, pp. 609–635, Sep. 2008.
[2] W. Hou, X. Ye, and K. Wang, "A survey of off-line signature ver-ification," in *Proc. Int. Conf. Intelligent Mechatronics Automation*, Chengdu, China, Aug. 2004, pp. 536–541.
[3] J. Fierrez-Aguilar, N. Alonso-Hermira, G. Moreno-Marquez, and J. Or-tega-Garcia, "An off-line signature verification system based on fusion of local and global information," in *Proc. Workshop Biometric Authen-tication, Springer LNCS-3087*, May 2004, pp. 298–306.
[4] M. Ammar, Y. Yoshida, and T. Fukumura, "A new effective approach for automatic off-line verification of signatures by using pressure fea-tures," in *Proc. 8th Int. Conf. Pattern Recognition*, 1986, pp. 566–569.
[5] A. Mitra, P. Kumar, and C. Ardil, "Automatic authentication of hand-written documents via low density pixel measurements," *Int. J. Com-putational Intell.*, vol. 2, no. 44, pp. 219–223, 2005.
[6] H. Lv, W. Wang, C. Wang, and Q. Zhuo, "Off-line Chinese signature verification based on support vector machine," *Pattern Recognition Lett.*, vol. 26, pp. 2390–2399, 2005.
[7] J. Vargas, M. Ferrer, C. Travieso, and J. Alonso, "Off-line signature verification based on high pressure polar distribution," in *Proc. Int. Conf. Frontiers of Handwriting Recognition 2008*, Montreal, Canada, 2008.
[8] K. Franke and S. Rose, "Ink-deposition model: The relation of writing and ink deposition processes," in *Proc. Ninth Int. Workshop IEEE Com-puter Soc. Frontiers in Handwriting Recognition*, Washington, DC, 2004, pp. 73–178.
[9] K. Franke, O. Bünnemeyer, and T. Sy, "Ink texture analysis for writer identification," in *Proc. Eighth Int. Workshop IEEE Computer Soc. Frontiers in Handwriting Recognition*, Washington, DC, 2002, pp. 268–273.
[10] T. Mäenpää and M. Pietikäinen, , C. H. Chen and P. S. P. Wang, Eds., "Handbook of pattern recognition and computer vision," in *Texture Analysis With Local Binary Patterns*, 3rd ed. Singapore: World Sci-entific, 2005, pp. 197–216.
[11] T. Ahonen, A. Hadid, and M. Pietikainen, "Face description with local binary patterns: Application to face recognition," *IEEE Trans. Pattern Anal. Machine Intell.*, vol. 28, no. 12, pp. 2037–2041, Dec. 2006.
[12] S. Liao, M. W. K. Law, and A. C. S. Chung, "Dominant local binary patterns for texture classification," *IEEE Trans. Image Process.*, vol. 18, no. 5, pp. 1107–1118, May 2009.
[13] Z. Guo, L. Zhang, and D. Zhang, "A completed modeling of local bi-nary pattern operator for texture classification," *IEEE Trans. Image Process.*, vol. 19, no. 6, pp. 1657–1663, Jun. 2010.
[14] J. F. Vargas, M. A. Ferrer, C. M. Travieso, and J. B. Alonso, "Off-line signature verification based on grey level information using texture features," *Pattern Recognition*, vol. 44, no. 2, pp. 375–385, Feb. 2011.
[15]. M. Liwicki, C. E. van den Heuvel, B. Found, and M. I. Malik, "Forensic signature verification competition 4nsigcomp2010—Detection of sim-ulated and disguised signatures," in *Proc. 12th Int. Conf. Frontiers in Handwriting Recognition*, Kolkata, India, Nov. 16–18, 2010, pp. 715–720.
[16] O. Hilton, "Can the forger be identified from his handwriting?," *J. Criminal Law, Criminology, Police Sci.*, vol. 43, pp. 547–555, 1952.
[17]. Miguel A. Ferrer, J. Francisco Vargas, Aythami Morales, and Aarón Ordóñez, "Robustness of Offline Signature Verification Based on Gray Level Features". IEEE TRANSACTIONS ON INFORMATION FORENSICS AND SECURITY, VOL. 7, NO. 3, JUNE 2012

BIOGRAPHIES

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