International Journal of Information Processing, 7(3), 34-44, 2013
ISSN : 0973-8215
IK International Publishing House Pvt. Ltd., New Delhi, India

DCT-MLP based approach for Off-line Signature Verification

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In this paper, we propose a transformation based approach for off-line signature verification. The Discrete Cosine Transform (DCT) is used to transform the signature image from spatial domain to frequency domain for compact representation of the signature sample with few coefficients as features. The proposed approach comprises of three major phases: Preprocessing, Feature extraction and Classification. The preprocessed samples are fed into DCT and hence the top-left $M \times N$ coefficients are extracted as the representative features. The Multi-Layer Perceptrons (MLP), a well known classifier is used for classification and the performance is measured through FAR/FRR metrics. Experiments have been conducted on standard signature datasets namely: CEDAR and GPDS-160, and MUKOS, a regional language (Kannada) dataset. The comparative study is also provided with the well known approaches to exhibit the performance of the proposed approach.

Keywords : Discrete Cosine Transform, Multi-Layer Perceptrons, Off-line Signature Verification.

1. INTRODUCTION

For centuries, signatures have served as a reliable and efficient means to detect fraud. Handwritten signature is considered as one of the oldest accepted mode of authenticating a person in many of the business transactions. Even today the signature is still acknowledged as a principal means of authenticating financial and other business transactions. In spite of the technology moving towards paperless offices, usage of paper and signed documents have tremendously increased leading to the growth of fraud through forgery. Automatic signature verification involves aspects from disciplines ranging from human anatomy to engineering, from neuroscience to computer science [1].

There are two major methods of signature verification viz: *On-line method (Dynamic) and Off-line method (Static),* depending on the data acquisition technique and the mode of verification / identification. *On-line signatures* are acquired using the special devices such as graphic tablet, which generates the electronic signals, representing the signature trace during the writing process. On-line signatures are acquired at the instance of its registration beholding the dynamic details *viz*: velocity, acceleration, duration, pen lifts, direction of pen movement, pressure and force applied as the features representing the signature. The other method uses scanners or cameras to obtain handwritten signature on the piece of paper such as the cheques, bank challans, property documents, *etc.*. Here the signature is represented as a grey scale image. Thus, the off-line signatures are the static image of the registered signature and possess global and local features viz: signature image area, height, width, zonal information, important points such as end points, cross points, cusps, loops, and so on. Due to the loss of dynamic information (feature), off-line signatures are difficult to verify/recognize. In other words, the on-line process provides a spatio-temporal representation of the input, where as the off-line process involves analysis of the

the remaining 14 genuine and 24 skilled forged sample features. Similarly 15 genuine sample features along with 15 skilled forge sample features are considered for training in set-2. Now, the testing is carried out with the remaining 9 genuine and 24 skilled forge samples of the respective signers. Both the experimental set-up is repeated five times in order to overcome the effect of the randomness.

From the literature we observed that, Kalera *et al.*, [35], Chen and Shrihari [34] and Kumar *et al.*, [13] have experimented on CEDAR dataset and hence a comparative analysis is given in Table 3.

5.3. Experimentation on GPDS-160 dataset

The Digital Signal Processing Group (GPDS) of the Universidad de Las Palmas de Gran Canaria, has come out with a good scale dataset called GPDS-300 corpus. GPDS-300 is a dataset of 300 signers signature samples with 24 genuine and 30 forge of each, summing to a total of 16200 samples. For our experimentation, a subset of 160 signers, starting from the first signer to 160th signer is extracted from the corpus and named GPDS-160 with 8640 signature samples including both genuine and forge signatures. GPDS-300 corpus is available on [33].

The samples features from all the 8640 signatures from GPDS-160 constitutes the knowledge base. Here, set-1 configuration is initiated with 10 genuine sample features along with 10 skilled forge samples, choosing randomly, to train the MLP classifier. Testing is carried out with the remaining 14 genuine and 30 skilled forged samples. 15 genuine sample features along with 15 skilled forge sample features are randomly chosen to train the MLP classifier in set-2 configuration. The trained network is tested against the remaining 9 genuine and 30 skilled forge samples of the respective signers. The average of five repeated experimental results are tabulated in Table 5. The efficacy of the approach is also exhibited through a comparative analysis with state-of-art approaches on GPDS-160 with varying feature set and classifiers are given in Table 4. The overall performance results on all the three datasets, with both experimental set-up is given in Table 5.

6. CONCLUSION

In this paper, we proposed a frequency domain based approach for off-line signature verification. The merits of DCT that captures the significant information using low-frequency components is exploited in our work and demonstrated its capability for off-line signature verification using MLP classifier. Extensive experimentation on standard datasets including regional language dataset and comparative analysis with the state-of-art approach exhibit the performance and its suitability for off-line signature verification.

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Table 3
Comparative Analysis of Experimental Results Obtained for CEDAR Dataset

Algorithm	Feature Type	Classifier	Accuracy	FAR	FRR
Kalera et al., [35]	Word Shape	PDF	78.50	19.50	22.45
Chen& Shrihari [34]	Zernike Moments	DTW	83.60	16.30	16.60
Kumar et al. [13]	Sign Morphology	SVM	88.41	11.59	11.59
Proposed Algorithm	**DCT Co-efficients**	**MLP**	**93.06**	**6.96**	**7.58**

Table 4
Comperative Analysis of Experimental Result Obtained for GPDS-300/160 Corpus

Algorithm	Feature Type	No. of Features	Classifier Type	Accuracy	FAR	FRR
Ferrar et al., [37]	Geometric features	42*2 + 22*2	SVM HMM	86.65 –	13.12 12.60	15.41 14.10
Vargas et at., [36]	GLCM + LBP	(4+4 *radius)	SVM	87.28	6.17	22.49
Solar et al., [14]	Local interest points	12 * No. of descriptors	Bayseian	84.70	14.20	16.40
Kumar et al., [13]	Surroundedness	29selected	SVM	86.21	13.76	73.76
Nguven [15]	Grid based	(12*6*4)*No. of grids	SVM	86.32	13.68	14.18
Proposed Algorithm	**DCT Co-efficients**	**100**	**MLP**	**91.45**	**8.55**	**10.36**

Table 5
Summarised Experimental Results : DCT-MLP Approach

Dataset /Metric	**Set-1**		**Set-2**	
	FAR	**FRR**	**FAR**	**FRR**
CEDAR	8.42	8.69	6.96	7.58
GPDS-160	9.83	11.62	8.55	10.36
MUKOS	7.04	9.62	4.18	10.49

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