Knowledge driven Offline to Online Script Conversion

Sunil Kopparapu, Devanuj, Akhilesh Srivastava, P.V.S. Rao
Cognitive Systems Research Laboratory,
Tata Consultancy Services Limited, Mumbai.

***Abstract*— The problem of offline to online script conversion is a challenging and an ill-posed problem. The interest in offline to online conversion exists because there are a plethora of robust algorithms in online script literature which can not be used on offline scripts. In this paper, we propose a method, based on heuristics, to extract online script information from offline bitmap image. We show the performance of the proposed method on a real sample signature offline image, whose online information is known.**

I. Background

Offline script recognition by computers is well-addressed in literature and still attracts attention from several researchers around the globe [1], [2]. There is rich literature in both online and offline script research. The main difference between online[1] and offline[2] signatures lies in the fact that online signature captures the manner in which the signature was written while the offline signature has no information on how the signature was generated or written. In this paper, we give a brief survey of the offline script literature. Recent surveys by Steinherz et. al [2] for offline script and Lorigo and Govindraju [1] specifically for Arabic offline script show the interest offline script recognition research carries. Rigoli [3] et al, compare the use of Hidden Markov models (HMMs) for both on-line and off-line signature verification. While HMM is a good model to capture second order statistics [3]; the use of HMM for signature verification is questionable. In practice for a given person we can have limited number of signature samples (at maximum three or four) to model the signature through its statistics. Sabourin and Drouhard [5] proposed the use of artificial neural networks (ANN) to model signatures. Neural networks, like, HMMs need a large number of samples to model the signature. Coetzer et. al [7] use discrete radon transform as the parameters to model the signature as HMMs. Leung et al [8] track features and the position of the stroke to verify signatures. Peter et al [12] use wavelet parameters to verify signatures. where Qi et. al [15] set up the problem of signature verification in a multiresolution framework. They process the signature at different resolution and then use the output at different resolutions to verify signatures. Xiao et al [16] use a modified Bayesian network approach to verify signatures. While the approach suggested in each of these references is based either on offline or on online signatures, there have been approaches suggested [17] which tend to take multi-modal cues to verify signatures[3].

[1]Online signature is represented as a set of (x, y) coordinates
[2]bitmap image in one of the several formats (.jpeg, .gif, .pgm, .png, .bmp)

In this paper, we propose a method for deriving online information from offline script. To the best of our knowledge, there is no reported work in literature that deals with procedures to convert an offline script into an online script. The closest work is the work reported by Zimmer and Ling [17] . They propose a hybrid handwritten signature verification system where the on-line reference data acquired through a digitizing tablet serves as the basis for the segmentation process of the corresponding scanned off-line data. Local foci of attention over the image are determined through a self-adjustable learning process in order to pinpoint the feature extraction process. Both local and global primitives are processed and the decision about the authenticity of the specimen is defined through similarity measurements.

In Section II we formulate the problem of deriving online information from offline script, in Section III we give details of the procedure adopted to derive online information followed by experimental results in Section IV and conclusions in Section V.

II. Problem Formulation

The problem that we address in this paper is one of extracting online information from an offline script in the form of a bitmap image. Essentially, we need to derive the way the script was written by looking at the final shape of the script. Clearly, this is an ill-posed problem[4].

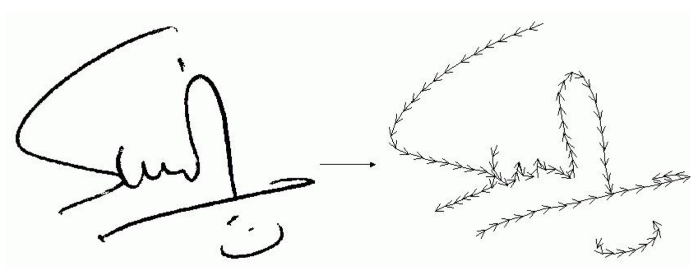

Fig. 1. Offline signature (bitmap image) and the corresponding online signature. Observe that the online signature has information on how the signature was written (shown by arrow direction).

[3]multi-modal approach would require that the same signature be available from different sources simultaneously
[4]in the absence of the actual online signature information there are several ways in which the offline signature could have been generated

Observe that, shown only the bitmap image and in the absence of knowledge about English script, there are several ways in which the signature could have been written. While there is no such ambiguity in determining how the signature was written when online information is available. The problem of offline to online signature conversion is to identify the way the signature was written from the bitmap image[5]. Fig. 1 shows an offline signature and its equivalent online information. The direction of the arrow shows the way the online signature was written. It also captures the number of strokes (four in this case) in the signature (pen-lifts). How ever what is not depicted is the order in which the four segments were written. In this paper we do not address the problem of identifying the order in which the segments were written.

For script belonging to the same set[6], it is possible to traverse the signature using rules based on heuristics. These derived rules would primarily be based on the knowledge of how people write that script (left to right, top to bottom, etc) in that particular language. A large portion of such rules would be based primarily on the language in which the signature is written in addition to heuristics.

III. Offline to Online Conversion

The bitmap offline signature image consists of the actual signature (the written part) and the background (the paper on which the signature was signed). The primary idea of our methodology is to intelligently traverse the written part in the bitmap image signature. We assume the script/signature to form a path/road and the traversal scheme being a truck driver who is trying to stay on the path. The driver of the vehicle steers the truck along the signature path so as to stay on the path all the time.

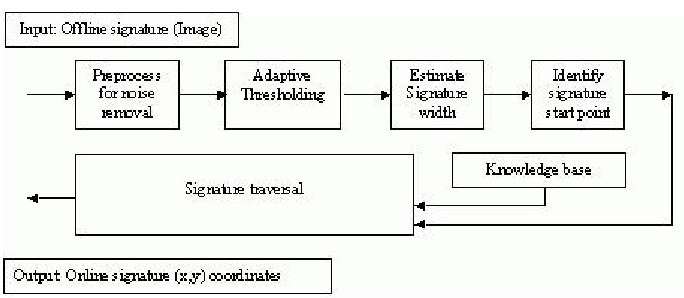

Fig. 2. Block diagram of the offline to online conversion process

Block diagram of the complete offline to online conversion process is shown in Fig. 2. The offline signature is obtained by scanning a signature on a paper with the help of a scanner. The original offline bitmap signature images are normally 8 bit which results in any of the pixel in the image taking a value between 0 and 255, namely, 256 (2^8) gray pixel intensity levels. The first step in the offline to online signature conversion is to preprocess the bitmap image using some basic image processing to remove any noise that might have cropped up in the scanning process. We use a 5×5 median filter to remove noise. This gray level image is binarized using dynamic thresholding method. The threshold is determined by observing that the histogram plot of the gray level image would largely be a two hump plot. We take the two highest peaks[7] in the pixel- intensity histogram of the bitmap and record the corresponding intensities. The binarizing threshold is set at the intensity that lies at the middle of the two intensities. The actual signature traversal[8] is carried out on the binary image.

The binarised image is then traversed using the truck driver steering his truck on the signature. The traversal process that we have adopted is influenced by the way a truck driver steers the truck when driving the truck on a road. The start of the road or the signature is determined by scanning the bitmap image from top to bottom and from left to right (probably one would adopt another strategy if one were to look at script in a different language). The first road pixel becomes the start point of the truck. Now the strategy adopted by truck driver is to steering the truck such that the truck stays on and in the middle of the road. We assume the written part of the signature to be the road to be traversed. We construct a virtual truck[9] with two wheels, which sense if the truck is going off the road (see Fig. 3) by determining the ration of the road pixels under each of the wheels. When the truck is tending to get off the road (namely the number of road pixels under the left and right truck are not approximately same) it steers itself so that the number of pixels under both the left and the right wheel are same and hence stays on the middle of the road. This allows the virtual truck to traverse the signature. The places of intersection in the signature, where two paths cross each other, both the paths become available for the truck to steer itself. In such situations, we direct the truck to proceed in the direction in which it has been moving.

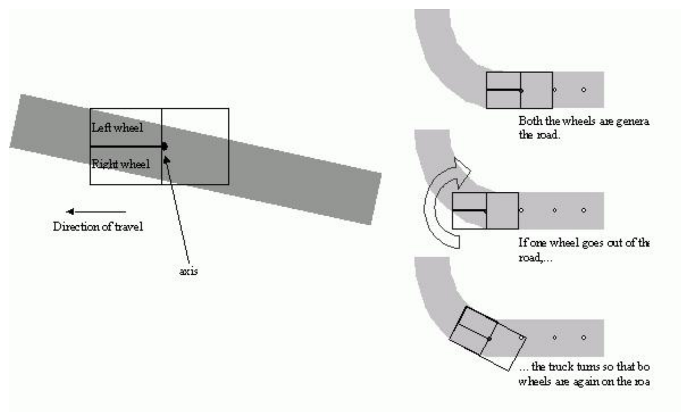

Fig. 3. Construction of a virtual truck and the virtual truck steering itself to stay in the middle of the road when it is tending to get off the road.

[5]We assume that one is aware of the way script is written; essentially the language in which the signature is written.

[6]Same language, English for instance

[7]one peak is due to the foreground and the other peak is due to the background

[8]which enables conversion to online signature

[9]The size of the virtual truck is different for different signature traversal. The size of the truck is a function of the width of the signature.

In order that the truck is able to traverse a signature accurately, the two wheels of the truck should be as close to the corresponding two edges of the signature. The thickness of different signatures is not uniform because of different writing material used. This requires that the size of the truck be a function of the thickness of the signature. The size of the truck is dependent on the average width of the signature. The average signature width is calculated (see Fig. 4) as the normalized average of highest three sectional widths with respect to the x-axis. Suppose there are n sectional widths estimated in a signature image. and let X_i be the sectional width of the i^{th} section. Without loss of generality we can assume that X_i is arranged in the increasing order of widths for increasing i. The average width of the signature is calculated as

$$\frac{\sum_{i=n-3}^{n} X_i \times i}{\sum_{i=n-3}^{n} X_i} \quad (1)$$

Note: The sectional width can be looked upon as the distance of an uninterrupted stretch of signature (foreground pixels) if one travels along a line parallel to x-axis. For example, the sectional width is the number of pixels between the first point where the foreground changes to background and the next immediate instance when the background changes to foreground (see Fig. 4).

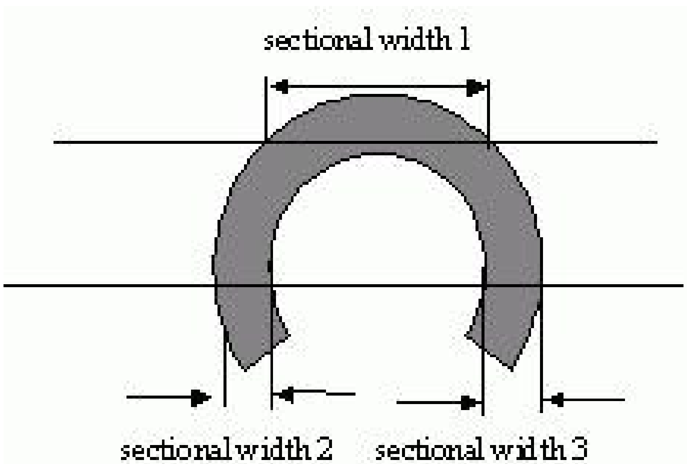

Fig. 4. Determining the average width of the signature. The average width of the signature is used to determine the size of the conceptual truck used to traverse the signature.

IV. Experimental Results

We tested the robustness of the developed scheme by capturing online signature from CrossPad[10]. The CrossPad in addition to capturing the online signature in the form of (x, y) coordinates also supports the capture of the same image in the form of a bitmap image. We used the bitmap signature image as input to our offline to online conversion system and cross check the generated online data with the online (x, y) information given by the CrossPad. Fig. 5 shows one of the offline signatures on which we tested our scheme[11]

Notice that there are three major steps involved in the process of offline to online conversion. Initially, the bitmap image is binarized (bi-gray value image), the truck dimension are estimated from the average width of the signature (using 1) and then using heuristics (Section III) the truck is made to traverse the signature bitmap. The whole process is captured in Fig. 4 for a sample signature image. We compare the obtained online information with the actual online data in terms of the number of strokes (pen lifts) and the direction of traversal. The trace of each segment was same as that captured in the online information from CrossPad. Nevertheless, as discussed earlier the segments were not traversed in the same order in which the signature was written. The segment three (the long line in the signature) was traced as segment two. More work is being carried out in this regard as part of our ongoing research.

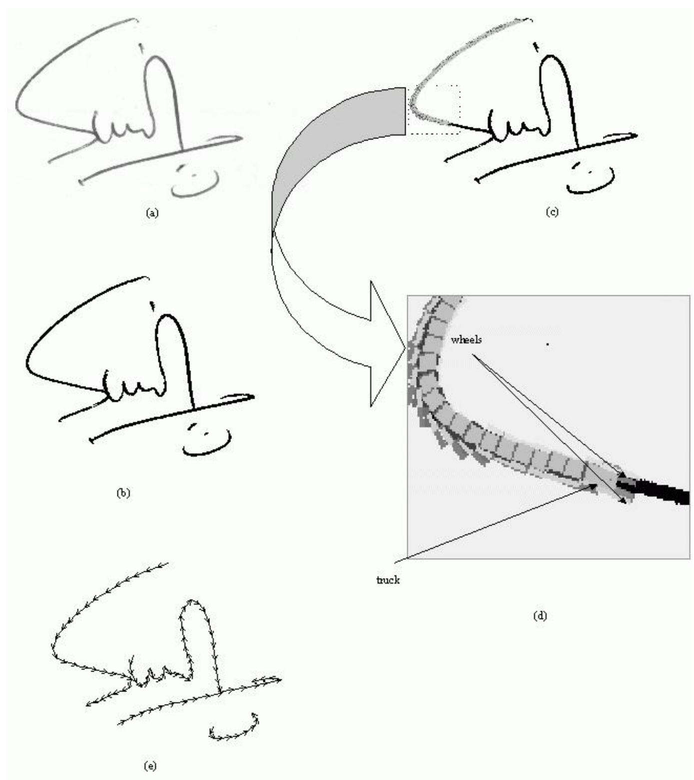

Fig. 5. Process of extracting online information from the offline signature bitmap for a sample signature. (a) Original bitmap image (256 gray levels), (b) binarized image (2 gray levels), (c) initial traversal, (d) expanded view of initial traversal, (e) fully traversed image.

V. Conclusion

In this paper, we have proposed a heuristics based technique to convert an offline signature to an online signature by extracting the trace information of the signature from the offline bitmap image. The motivation for offline to online

[10] IBM manufactured online signature capturing device

[11] We have tested the scheme on several signature images. We will give more experimental results on different offline images in the final paper

conversion comes from the fact that algorithms for online signature verification are more robust than the offline signature verification systems. This is true primarily because of the extra trace information that is absent in the offline bitmap images. The knowledge driven offline to online conversion algorithm described in this paper is able to robustly trace the signature in the bitmap image to produce an online image. It is proposed that the derived online information from the offline image be used to perform computer signature verification using several of the online signature verification algorithms proposed in literature.

REFERENCES

[1] Liana M. Lorigo, Venu Govindaraju, "Offline Arabic Handwriting Recognition: A Survey," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 28, no. 5, pp. 712-724, May, 2006.

[2] T. Steinherz, E. Rivlin, and N. Intrator. Off-line cursive script word recognition: A survey. *International Journal of Document Analysis and Recognition*, 2(2):90–110, 1999

[3] G. Rigoli, A. Kosmala, "A Systematic Comparison Between on-line and off-line Methods for Signature Verification with Hidden Markov Models, *14th International conference on pattern recognition*, vol. II Australia (1998), 1755-1757.

[4] A. A. Kholmatov, Biometric Identity Verification Using On-Line & Off-Line Signature Verification, Master of Science Thesis, Graduate School of Engineering and Natural Sciences, Sabanci University 2003

[5] Sabourin, R., and J.P. Drouhard, Off-line signature verification using directional PDF and neural networks, *Proceedings 11th International Conference on Pattern Recognition*, Vol 2, pp. 321-325, 1992.

[6] W. Nelson and E. Kishon, "Use of Dynamic Features for Signature Verification", *Proc IEEE Int Conf on Systems, Man, and Cybernetics*, Charlottesville, pp. 201-205, 1991.

[7] J. Coetzer, B. M. Herbst, and J. A. du Preez, "Offline Signature Verification Using the discrete Radon Transform and A Hidden Markov Model", *EURASIP Journal on Applied Signal Processing* 2004:4, pp 559-571, 2004.

[8] C.H. Leung, Y.Y. Tang, P.C.K. Kwok, K.W. Tse, Y.K. Wong, "Off-line signature verification by the tracking of feature and stroke positions," *Pattern Recognition*, vol. 36, no. 1, pp. 91-101, January 2003.

[9] B. Fang, C.H. Leung, Y.Y. Tang, "Reduction of Class Statistics Estimation Error for Small Training Sample Size in Off-line Signature Verification," *IEEE Transactions on Systems, Man, and Cybernetics* (C), 2004.

[10] B. Fang, C.H. Leung, Y.Y. Tang, "Off-line signature verification with generated training samples," *in Proc. of SPIE Vol. 4929 Optical Information Processing Technology*, Shanghai, China, October 14-18, 2002, pp. 388-397.

[11] B. Fang, "Tracking of feature and stroke positions for off-line signature verification," *in Proceedings. ICIP' 2002*, Rochester, New York, September 2002, vol. 3, pp. 965-968.

[12] Peter Shaohua Denga, Hong-Yuan Mark Liaob, Chin Wen Hoc and Hsiao-Rong Tyand, Wavelet-Based Off-Line Handwritten Signature Verification, *Computer Vision and Image Understanding*, Volume 76, Issue 3, December 1999, Pages 173-190

[13] Mizukami, Y., Yoshimura, M., Miike, H., Yoshimura, I., An off-line signature verification system using an extracted displacement function, *PRL(23)*, No. 13, November 2002, pp. 1569-1577.

[14] Fang, B., Leung, C.H., Tang, Y.Y., Tse, K.W., Kwok, P.C.K., Wong, Y.K., Off-line signature verification by the tracking of feature and stroke positions, *PR (36)*, No. 1, January 2003, pp. 91-101.

[15] Qi, Y.Y., Hunt, B.R., A Multiresolution Approach to Computer Verification of Handwritten Signatures, *IP (4)*, No. 6, June 1995, pp. 870-874.

[16] Xiao, X, Leedham, G, Signature verification using a modified Bayesian network, *PR (35)*, No. 5, May 2002, pp. 983-995.

[17] Zimmer, A., Ling, L.L, A hybrid on/off line handwritten signature verification system, *ICDAR03*, pp. 424-428, 2003.