Performance Considerations in Implementing Offline Signature Verification System

Charu Jain
Department of CSE
Amity University Haryana

Priti Singh
Department of ECE
Amity University Haryana

Aarti Chugh
Department of CSE
Amity University Haryana

ABSTRACT
Handwritten signatures are widely accepted as a means of document authentication, authorization and personal verification. In modern society where fraud is rampant, there is the need for an automatic Handwritten Signature Verification (HSV) system to complement visual verification. An implementation is a realization of a technical specification or algorithm as a program, software component, or other computer system through programming and deployment. Many approaches are possible to the implementation of a signature verification system [1, 2]. This paper highlights the key performance considerations when planning the implementation of a signature verification system.

Keywords

Handwritten signature verification (HSV), Feature Extraction, False Rejection Rate (FRR)

1. INTRODUCTION
Handwritten signature verification has been extensively studied & implemented. For legality most documents like bank cheques, travel passports and academic certificates need to have authorized handwritten signatures. In general, handwritten signature verification can be categorized into two kinds – on–line verification and off–line verification. On–line verification requires a stylus and an electronic tablet connected to a computer to grab dynamic signature information .Off–line verification, on the other hand, deals with signature information which is in static format.In off–line signature recognition we are having the signature template coming from an imaging device, hence we have only static characteristic of the signatures. The person need not be present at the time of verification. Hence off-line signature verification is convenient in various situations like document verification, banking transactions etc. In the past decade a bunch of solutions has been introduced, to overcome the limitations of off-line signature verification [27] and to compensate for the loss of accuracy. Most of these methods have one in common: they deliver acceptable results but they have problems improving them.
In the off-line case no definite matching exists. These methods can only operate on static image data; therefore they often try to compare global features like size of the signature or similarities of the contour [6]. To get a tractable abstraction of the two dimensional images, these methods often involve some image transformation, like the Hough or Radon transformations [8] or work on the density models of the signatures [11]. Although these methods almost totally ignore the semantic information hidden in the signature, combined with each other they seem to give a good representation of the signature, allowing the researchers to reach Equal Error Rates (EER) between 10% and 15% [3]. The drawback of this methodology is that loosing the semantic information makes it almost impossible to improve the algorithm or to explain the results in detail. Jose L. Camino et al. take another approach [4] they try to guess the pen movements during the signing by starting at the left and bottom most line-end and then following it. There are also other approaches trying to reconstruct the signing process. In [15] stroke and sub-stroke properties are extracted and used as a basis for the comparison. Based on own experience, these latter approaches seem to be the most promising, because their results can be explained (and therefore improved) in a semantically meaningful way. There is also a wide variety of classifiers used to compare the results: Hidden Markov models [14], Support Vector Machines [7], multi-layer perceptions, genetic algorithms, and neural networks [5] are the most widely used solutions.

Sabourin [19] used new approach granulometric size distributions for the definition of local shape descriptors in an attempt to characterize the amount of signal activity exciting each retina on the focus of a superimposed grid. He then used a nearest neighbor and threshold-based classifier to detect random forgeries. A total error rate of 0.02% and 1.0% was reported for the respective classifiers. A database of 800 genuine signatures from 20 writers is used

Zhang [20] have proposed a Kernel Principal Component Self regression (KPCSR) model for off-line signature verification and recognition problems. Developed from the Kernel Principal Component Regression (KPCR), the self-regression model selected a subset of the principal components from the kernel space for the input variables to accurately characterize each person's signature, thus offering good verification and recognition performance. He reported FRR 92% and FAR .5%.

Baltzakis [21] developed a neural network-based system for the detection of random forgeries. The system uses global features, grid features (pixel densities), and texture features (co occurrence matrices) to represent each signature. For each one of these feature sets, a special two-stage perception one-class-one-network (OCON) classification structure is implemented.

Justino [22] used a discrete observation HMM to detect random, casual, and skilled forgeries. A grid segmentation scheme was used to extract three features: a pixel density feature, a pixel distribution feature (extended-shadow-code), and an axial slant feature. Two data sets are used. After optimization first data set was used to detect random, casual, and skilled forgeries in a second data set. The second data set contains the signatures of 60 writers with 40 training signatures, 10 genuine test signatures, 10 casual forgeries, and 10 skilled forgeries per writer. An FRR of 2.83%and an FAR

of 1.44%, 2.50%, and 22.67% are reported for random, casual, and skilled forgeries, respectively.
Fang [23] developed a system that is based on the assumption that the cursive segments of forged signatures are generally less smooth than that of genuine ones. Two approaches are proposed to extract the smoothness feature. An AER of 17.3% is obtained.

Ferrer, Alonso, and Travieso [24], used Offline Geometric Parameters for Automatic Signature Verification Using Fixed-Point Arithmetic. They used set of geometric signature features for offline automatic signature verification based on the description of the signature envelope and the interior stroke distribution in polar and Cartesian coordinates. The feature set was calculated using 16 bits fixed-point arithmetic and tested with different classifiers, such as hidden Markov models, Euclidean distance classifier etc. FRR reported was 2.12% and FAR was 3.13%.

Kekre and Pinge used template matching approach in [25]. The signature was segmented in predefined shape templates, in all 40 different templates were considered for feature extraction. They used neural network classifier. Two separate algorithms were used. Total 10 users database was used for testing: algorithm 1 reported FAR 20% and algorithm 2 reported FAR 0%.

For various approaches used in implementing offline signature verification system [18] can be used as reference.

2. METHODOLOGY

The algorithm used for the implementation of offline signature verification systems [26] consist of four major modules:

2.1 Data Management

This module handles the various aspects of database management like creation, modification, deletion and training for a signature instance. The information regarding a particular signature is stored in the database as a feature vector.

2.2 Preprocessing and Noise Removal

Preprocessing in both offline generally involves removing noises like spurious pixels (in case of offline) or signals (in case of online), space standardization and normalization, skeletonization, converting a gray scale image to a binary image, extraction of the high pressure region images, etc.

2.3 Feature Extraction and Parameter Calculations

Features can be classified into two types-- global and local features, where global features are characteristics, which identify or describe the signature as a whole (e.g. width and height of individual signature components, width to height ratio, total area of black pixels in the binary and high pressure region (HPR) images etc.) and local features are confined to a limited portion (e.g. a grid) of the signature.

2.4 Learning and Classification

The learning phase is mainly based on a single comparison algorithm, which is able to calculate the distance function between signature pairs. The classification phase is able to make a decision, whether to accept or reject the tested signature.

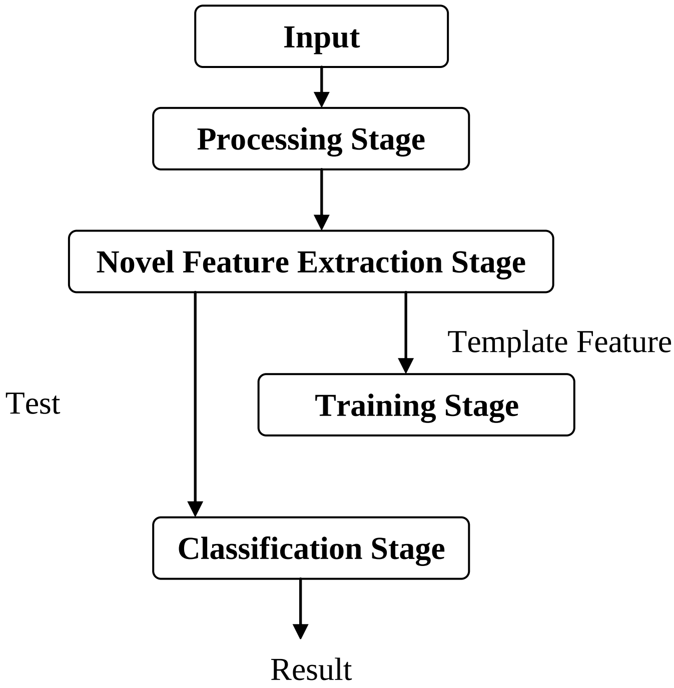

Fig 1: Methodology for Signature Verification

3. PERFORMANCE ISSUES

Signature verifier systems are getting more and more complex day by day. Various issues which must be addressed if practical success is to be achieved are:

3.1 Data Management

The handwritten original signatures of the customer are scanned and stored on disk. Size of database is an important consideration. There are two options: One is to store image in database itself and other is to store path of the scanned images in the database along with some identification number for reference. In both cases, image size and format should be similar for every input image. In most of the observed systems the scanned images of the signatures are assumed to be already present, therefore the acquisition phase is usually not a part of the system diagrams or description though it is necessary to mention how database of images is to be maintained. Of course, there are several other important features like resolution, color depth or information on image size and format but these are rarely mentioned in the most papers. Various problems are also associated with scanning e.g. we might get less critical information due to some technical problem.

3.2 Preprocessing and Noise Removal

The preprocessing phase is a sequence of image transformations creating the best possible input for the feature extraction algorithms. Some of the preprocessing steps, like noise filtering, rotation normalization, position normalization induce minimal information loss, while others, like binarization, morphological closing or size normalization can cause the loss of valuable information.

3.3Feature Extraction

The most common approach to the design of automatic signature verification systems till now is based on the extraction of a feature set which is claimed in some way to be of universal applicability across the community of potential signers. Most of the existing statistical and distance based classifiers deals with geometric and structural features of the signatures and they do not cater for scale, rotation, transformation and affine variation. However, the difficulties associated with the inherent variability of signature data i.e. the signatures of one person can vary considerably. The differing requirements of different task domains and operational conditions, and so on, an alternative approach has been to seek a system structure which can more easily be optimized with respect to a particular set of individual signatures.

3.3 System evaluation

A major problem in the evaluation of automatic signature verification systems is the lack of availability of a generally accessible, large scale and objective database of sample signatures. Reported trials are generally based on closed user groups or small numbers of samples, or are conducted essentially under laboratory conditions, often with questionable validity. Hence, there should be appropriate system evaluation.

3.4 Maintainability and Compatibility

The system should manage the changes effectively i.e. easy to be maintained. Any changes in hardware and software should be acceptable by signature verification system. The system must be compatible with all the operating systems and the underlying database. Understanding the volumes, the number of users, and the availability and disaster-recovery requirements will ensure the system is designed correctly. For example, access from offshore processing sites requires that the system be available for longer periods than would otherwise be the case. Inability to support "off-shore" processing due to limited availability is one of the important implementation issues of these systems.

3.5 Results

The effectiveness of a system is most commonly described with its "false rejection rate" (FRR, Type I error or false non-match rate), its "false acceptance rate" (FAR, Type II error or false match rate), and the "equal error rate." (EER) The false rejection rate is the percentage of original signatures the system rejects. The false acceptance rate is the percentage of forgeries the system accepts as original, and the equal error rate is the point at which the two factors intercept. Authors sometimes refer to the "average error rate" (AER), which has no clear meaning. In some cases it is used as a synonym for ERR, in other cases it is simply calculated as an average of FAR and FRR (which we should note can be a good approximation for EER). There are also papers, where AER is used to describe really the average of some error measures.

Again, we would like to emphasize the importance of applicability. In forensic and financial applications the goal is often not to reach a low EER, but to get an acceptable FRR at a FAR level near 0. In our opinion this should be also considered as an important parameter to note, because it would make comparison between industrial founded research and pure scientific researches easier. All in all it can be stated that algorithms are improving at a really slow, but observable rate. Currently the best off-line signature verifiers work at an EER around 9%.

3.6 Threshold

The verification process may then be defined as the evaluation of a discriminant function with respect to a test sample which can be compared against a selected threshold value. The acceptability/ non acceptability are determined by whether or not the discriminant value falls above or below the chosen threshold value. Clearly, the choice of threshold defines the limits of acceptability required for a sample to be considered genuine., and will be very important in establishing the nature of the trade-off which can be achieved between the practical requirement to keep the number of false rejections encountered as low as possible while simultaneously maintaining as high a degree of robustness as possible in relation to attempted forgery compromise.

4. CONCLUSION

In a real situation, the choice of the best algorithm for the implementation of a signature verification system that is able to cope with all types of signatures is a very difficult task. Implementations are often narrowly focused that is they are limited to specific market sectors (such as business accounts) or processes (such as check-signature verification). Most systems offer limited capability for integration with other systems, including workflow solutions, fraud detection and customer information. Although the basic problem is relatively easy to define, its solution presents many difficulties in practice, and if acceptable performance is to be achieved for real tasks, then a number of fundamental issues must be addressed. Off-line signature recognition systems need to be designed very carefully to achieve the implementation that is suitable in every aspect. Our work in this field is to come up with a solution that is more generalized and efficient to support multiple applications.

5. REFERENCES

[1] Plamondon, R. and Lorette, G.: Automatic signature verification and writer identification: the state of the art, Pattern Recognition, 22, 1 07- 13 1, 1989

[2] Leclerc, F. and Plamondon, R.: Automatic signature verification - the state of the art 1989-1993, Int. J. Patt. Rec. & Art. Int., 8,643-659, 1994.

[3] H B kekre, V A Bharadi, "Specialized Global Features for Off-line Signature Recognition", 7th Annual National Conference on Biometrics RFID and Emerging Technologies for Automatic Identification, VPM Polytechnic, Thane, January 2009.

[4] H B Kekre, V A Bharadi, "Signature Recognition using Cluster Based Global Features", IEEE International Conference (IACC 2009), Thapar University, Patiala-Punjab, India. March 2009,

[5] H. Baltzakis, N. Papamarkos, "A new signature verification technique based on a two-stage neural network classifier", Engineering Applications of Artificial Intelligence 14 (2001).

[6] Almudena Gilperez, Fernando Alonso-Fernandez, Susana Pecharroman, Julian Fierrez, Javier Ortega-Garcia, "Off-line Signature Verification Using Contour Features", Biometric Recognition Group – ATVS, 2008.

[7] Martinez L.E., Travieso C.M., Alonso J.B., Ferrer M.A., Parametrization of a Forgery handwritten signature verification system using SVM, IEEE, vol. 2, no. 3, pp. 193_196, 2004.

[8] Cajote R.D., Guevara, R.C.L., Global word shape processing using polarradii graphs for off-line handwriting recognition, IEEE, no. 7, 2004.

[9] Miguel A. Ferrer, Jesu´s B. Alonso, and Carlos M. Travieso.: Offline Geometric Parameters for Automatic Signature Verification Using Fixed- Point Arithmetic. IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 27, no. 6, June 2005 p 993-997.

[10] Robert Sabourin, J.-P. Drouhard, Etienne Sum Wah: Shape Matrices as a Mixed Shape Factor for Off-line Signature Verification. Fourth International Conference Document Analysis and Recognition (ICDAR'97), pp. 661.

[11] H. A. Sofien Touj, Najoua Ben Amara, Global feature extraction of offline arabic handwriting, IEEE SMC, vol. 2, no. 4, 2003.

[12] Jalal Mahmud and Chowdhury Mofizur Rahman: On the Power of Feature Analyzer for Signature Verification. Proceedings of the Digital Imaging Computing: Techniques and Applications (DICTA 2005).

[13] Bence Kővári: The Development of Off-Line Signature Verification Methods, Comparative Study. Proceedings of microCAD, International Scientific Conference, 2007

[14] Camino J.L., Travieso C.M., Morales C.R., Ferrer M.A., Signature classification by Hidden Markov model, IEEE, no. 5, 1999.

[15] Jinhong K. Guo, David Doermann, Azriel Rosenfeld: Off-Line Skilled Forgery Detection Using Stroke and Sub-stroke Properties. Proceedings of the International Conference on Pattern Recognition (ICPR'00)

[16] A. El-Yacoubi, M. Gilloux, R. Sabourin, C.y. Suen, An HMM-based approach for off-line unconstrained handwritten word modeling and recognition, IEEE, no. 6, 1999.

[17] Stephane Armand, Michael Blumenstein and Vallipuram Muthukkumarasamy: Off-line Signature Verification Based on the Modified Direction Feature. The 18th International Conference on Pattern Recognition (ICPR'06), 2006.

[18] Charu Jain, Priti Singh, Aarti Chugh: Panoramic View of Offline Signature Verification: A Survey .Proceedings of the National Conference on Convergence of Emerging Technologies, 2011.

[19] R. Sabourin, G. Genest, F.J. Preteux, "Off-line signature verification local granulometric size distributions", IEEE Trans. Pattern Anal. Mach. Intell. 19 (9) (1997) 976-988.

[20] Bai-ling Zhang, "Off-line Signature Recognition and Verification by Kernel Principal Component Self regression", (ICMLA'06), 0- 7695-2735-3/06, 2006, 4 – 6.

[21] H. Baltzakis, N. Papamarkos, "A new signature verification technique based on a two-stage neural network classifier", Engineering Applications of Artificial Intelligence 14 (2001) 95±103.

[22] J Edson, R. Justino, F. Bortolozzi and R. Sabourin, "The Interpersonal and Intrapersonal Variability Influences on Off-line Signature Verification Using HMM", Proc. XV Brazilian Symp. Computer Graphics and Image Processing, 2002, pp. 197-202,Oct.2002.

[23] B. Fang, C.H. Leung, Y.Y. Tang, P.C.K. Kwok, K.W. Tse, Y.K. Wong, "Offline signature verification with generated training samples", IEEE Proc, Image Signal Process. 149 (2) (2002) 85-90.

[24] Miguel A. Ferrer, Jesu´s, B. Alonso, and Carlos M. Travieso, "Offline Geometric Parameters for Automatic Signature Verification Using Fixed-Point Arithmetic", IEEE transactions on pattern analysis and machine intelligence, vol. 27, no. 6, June 2005

[25] S. Pinge, H. Kekre, " Signature Identification using Neural Networks", Proceedings of National Conference on Image Processing 2005 (NCIP2005), Organized by TSEC, Mumbai, pp 31-39

[26] Charu Jain, Priti Singh, Aarti Chugh: An Optimal Approach to Offline Signature Verification System using GMM, Proceedings of International Conference on Science and Engineering (ICSE 2011).

[27]Yazan M. Al-Omari, Siti Norul Huda Sheikh, Khairuddin," State-of-the art in offline verification system", Proceedings of International Conference on Pattern Analysis and Intelligent Robotics, June 2011.