Enhanced Way of Biometric Signature Verification

Sri Ramakrishna Vasamsetty, M Raj Kiran Vakkalanka

V1.2 Dept. of CSE, B.V.C College of Engineering and Technology, Odalarevu, AP, India

Abstract
An off-line signature verification system attempts to authenticate the identity of an individual by examining his/her handwritten signature, after it has been successfully extracted from, for example, a cheque, a debit or credit card transaction slip, or any other legal document. The questioned signature is typically compared to a model trained from known positive samples, after which the system attempts to label said signature as genuine or fraudulent. The signature is divided into zones using both the Cartesian and polar coordinate systems and two different histogram features are calculated for each zone: histogram of oriented gradients (HOG) and histogram of local binary patterns (LBP). In this paper, we propose an effective method to perform off-line signature verification based on intelligent techniques. Structural features are extracted from the signature’s contour using the Modified Direction Feature (MDF) and its extended version: the Enhanced MDF (EMDF). Two neural network-based techniques and Support Vector Machines (SVMs) were investigated and compared for the process of signature verification. The results are obtained by modeling the signatures with a Support Vector Machine (SVM) trained with genuine samples and random forgeries, while random and simulated forgeries have been used for testing it.

Keywords
Biometrics, Off-line Signature Verification, Distinguishing Error Rate, Modified Direction Feature, EMDF

I. Introduction
Biometrics can be classified into two broad categories—behavioral (signature verification, keystroke dynamics, etc.) and physiological (iris characteristics, fingerprint, etc.). Handwritten signature is amongst the first few biometrics to be used even before the advent of computers. Signature verification is widely studied and discussed using two approaches [5]. On-line approach uses an electronic tablet and a stylus connected to a computer to extract information about a signature and takes dynamic information like; pressure, velocity, etc whereas in offline approach stable dynamic variations are not used for verification purpose. Offline systems are more applicable and easy to use in comparison with on-line systems in many parts of the world however it is considered more difficult than on-line verification due to the lack of dynamic information. The paper presents a survey of off-line signature verification approaches being followed in different areas.

Signature verification is an authentication method that uses the dynamics of a person’s handwritten signature measure and analyzes the physical activity of signing, such as the stroke order, the pressure applied and the speed. Some systems may also compare visual images of signatures, but the core of a signature biometric system is behavioral, i.e. how it is signed rather than visual, i.e. the image of the signature. Each person has a unique handwritten signature. The way a person signs their name or writes a letter can be used to prove a person’s identity. A pasted bitmap, a copy machine or an expert forger may be able to duplicate what a signature looks like, but it is virtually impossible to duplicate the timing changes in X, Y and Z (pressure). The natural motion of the original signer would be required to repeat the patterns. Even though there will always be slight variations in a person’s handwritten signature, the consistency created by natural motion and practice over time generates a recognizable pattern that makes the handwritten signature suitable for biometric identification. Inspite of being natural and intuitive this technology however has certain advantages as well as disadvantages associated with it. Some of the advantages being [4]:

Advantages
• The signature is the most natural and generally established of all the ways in which we seek to confirm our identity.
• The use of signature verification will minimize the disruption to accepted practices with respect to transactions where personal identity has to be authenticated.
• Measurement of signature characteristics is noninvasive (compare this with other potential techniques such as iris scanning) and has no negative or undesirable health connotations (as might be the case with, say, fingerprint checking, which is often considered to raise civil liberties issues and which, in use, involves direct physical contact with a possibly contaminated surface).

Disadvantages
• There are some inconsistencies to a person’s signature.
• Great variability can be observed in signatures according to country, age, time, habits, psychological or mental state, physical and practical conditions [2].

A handwritten signature is the result of a complex process depending on the psychophysical state of the signer and the conditions under which the signing process occurs [1]. There are two major methods of signature verification. One is an off-line method that uses an optical scanner to obtain handwriting data from a signature written on paper. The other, which is generally more successful, is an on-line method which, with a special device, measures the sequential data, such as handwriting speed and pen pressure. Nevertheless, offline systems have a significant advantage in that they do not require access to special processing systems when the signatures are produced.

There are two main approaches for off-line signature verification: static approaches and pseudo dynamic approaches. The static one involves geometric measures of the signature while the pseudo dynamic one tries to estimate dynamic information from the static image [3]. Franco evaluates ink trace characteristics that are affected by the interaction of biomechanical writing and physical ink-deposition processes. In this way, texture analysis of ink trace texture appears as an interesting approach to characterize personal writing. The pixel intensity gives some ink texture information while the pixel position gives some signature shape information. But a signature also contains structures such as spots, line ends, edges and corners that are not represented by the above texture descriptors. So it makes sense to think that a textural descriptor that unifies both statistical and structural signature characteristics will improve the performance of the Automatic Handwriting Signature Verifier (AHSV).

II. Related Works
Although research into signature verification has been carried out for many years, the categorization of forged signatures is
not standardized. Varying skill levels of forgeries are listed as follows:

1. A forged signature can be another person’s genuine signature. Justino et al. categorized this type of forgery as a Random Forgery.
2. A forged signature is produced with the knowledge about the genuine writer’s name only. Hanmandlu et al. categorized this type as a Random Forgery [8]. Justino et al. categorized this type as a Simple Forgery. Weiping et al. categorized this type as a Casual Forgery.
3. A forged signature imitating a genuine signature’s model reasonably well is categorized as a Simulated Forgery by Justino et al.
4. Signatures produced by inexperienced forgers without the knowledge of their spelling after having observed the genuine specimens closely for some time are categorized as Unskilled Forgeries by Hanmandlu et al. [8].
5. Signatures produced by forgers after unrestricted practice by non-professional forgers are categorized as Simple Forgery/ Simulated Simple Forgery by Ferrer et al. [6], and a Targeted Forgery by Huang and Yan [7].
6. Forgeries which are produced by a professional imposter or person who has experience in copying signatures are categorized as Skilled Forgeries by Hanmandlu et al. [8].

It is sensible not to use targeted forgeries to train classifiers as the collection of such forgeries is impractical despite the potential of achieving higher accuracy. Fig. 1, illustrates a general Automated Offline Signature Verification System (AOSVS) that does not use targeted forgeries for training. This research employs a similar system in which an enhanced version of the MDF is integrated in the feature extraction process. In addition, a system that uses targeted forgeries for training is also investigated to evaluate the importance of targeted forgeries quantitatively.

**A. Signature Database**

The gpds SIGNATURE [6] database which is publicly available for all to download at the URL: link http://www.gpds.ulpgc.es/download/index.htm was employed to perform experiments in this research. It contains 160 signature sets of 24 genuine and 30 targeted signatures for each set. For each signer, all genuine specimens were collected in a single day’s writing session. To produce forged signatures, the signers were allowed to practice their forgeries as long as he/she wished with static images of genuine specimens. Each of them imitated 3 signatures of 3 signers in a single day’s writing session. The genuine signature shown to each forger was chosen randomly from the 24 genuine ones. Therefore for each genuine signature there are 30 skilled forgeries made by 10 forgers, using 10 different genuine specimens. Fig. 2 shows some genuine samples and their imitations from the gpdsSIGNATURE database.

![Fig. 2: Genuine and Forged Sample Taken from the GPDS Signature Database](image)

**III. Existing System**

The Existing MDF technique builds upon the DF technique described in Section A. The main difference is in the way the feature vector is created. For MDF, feature vector creation is based on the calculation of transition features from background to foreground pixels in the vertical and horizontal directions. A number of researchers have proposed feature extraction techniques based on transition information, an example may be found here. In MDF, aside from calculating Location Transitions (LTs), the direction value at that location is also stored (Direction Transitions - DTs).

**A. Determining LT Values**

To calculate LT values, it is necessary to scan each row in the image from left-to-right and right-to-left. Likewise, each column in the image must be scanned from top-to-bottom and bottom-to-top. The LT values in each direction are computed as a fraction of the distance traversed across the image. Therefore, as an example, if the transitions were being computed from left-to-right, a transition found close to the left would be assigned a high value compared to a transition computed further to the right (See fig. 3). A maximum value (MAX) was defined to be the largest number of transitions that may be recorded in each direction. Conversely, if there were less than MAX transitions recorded (n for example), then the remaining MAX - n transitions would be assigned values of 0 (to aid in the formation of uniform vectors).

![Fig. 3(a): Processed Signature Single Character Image, (b). Zoned Windows, (c). Input Vector Components](image)
B. Determining DT Values

Once a transition in a particular direction is found, along with storing an LT value, the direction value at that position is also stored (DT). The DT value is calculated by dividing the direction value by a predetermined number, in this case: 10. The value 10 was selected to facilitate the calculation of a decimal value between 0 and 1 (See fig. 3).

Therefore, following the completion of the above, four vectors would be present for each set of feature values (eight vectors in total). For both LT and DT values, two vectors would have dimensions MAX × NC (where NC represents the Number of Columns/width of the character) and the remaining two would be MAX × NR (where NR represents the Number of Rows/height of the character).

A further re-sampling of the above vectors was necessary to ensure that the NC/NR dimensions were normalized in size. This was achieved through local averaging. The target size upon re-scaling was set to a value of 5. Therefore, for a particular LT or DT value vector, windows of appropriate dimensions were calculated by determining an appropriate divisor of NC/NR, and the average of the LT/DT values contained in each window were stored in a resampled 5 × 5 matrix (as shown in fig. 4, for vectors obtained from a left-to-right direction traversal). This was repeated for each of the remaining transition value vectors so that a final 120 or 160 element feature vector could be formed using the following formula:

\[ \text{nrFeatures} \times \text{nrTransitions} \times \text{nrVectors} \times \text{resampled Matrix Height (Width)} \]

where:

\( \text{nrFeatures} = 2, \text{nrTransitions} = 3 \text{ or } 4, \text{nrVectors} = 4 \) and

\( \text{resampledMatrixHeight(width)} = 5. \)

The Modified Direction Feature (MDF) [9] utilizes the location of transitions from background to foreground pixels in the vertical and horizontal directions of the boundary representation of an object. For each transition, the Location of the Transition (LT) and the Direction Transition (DT) values are stored (as illustrated in Figure 5). An LT is calculated by taking the ratio between the position where a transition occurs and the distance across the entire image in a particular direction, whilst the DT is obtained by examining the stroke direction of an object’s boundary at the position where a transition occurs. Finally, a local averaging process is applied to the LT and DT values obtained in each of the four possible traversal directions to reduce the feature vector size.

Fig. 5: The Extraction of LT and DT Values Along the Left to Right Direction

IV. Proposed System

Additional geometric features examined in this research are the Ratio, Length, Centroid, tri Surface, Best-Fit, and the Sixfold-Surface feature [10]. The Ratio is a global feature that considers the proportion of the height and the width of the image of the signature as shown in fig. 6(a). To obtain the Sixfold-Surface feature set, the signature image is first divided into three equal parts vertically. The centre of gravity is then calculated for each part to determine a horizontally separating line for each part. These separating lines divide each component into two domains. Six feature values are finally calculated by dividing the surface covered by the signature in a particular domain by the domain’s area.

The triSurface is similar to the Sixfold-Surface feature except that the parts are not divided further into domains by horizontal separating lines. In order to obtain an approximation for the signature’s skew for the Best-Fit feature, a linear regression was applied to the minima and the maxima point sets of the signature to determine top and bottom best-fit lines. The angles created by these two lines with the horizontal formed the first two features after normalization. The signature surface area enclosed between these two lines became the third feature.

Fig. 6: Extra Features Extracted for EMDF

The Centroid feature relates to the dominant angle of the signature’s pixel distribution. To determine the Centroid feature, the signature image is first divided into two equal parts. The position of the centre of gravity of each part is then determined. The angle which is created by the line that crosses these two points and
the horizontal line (see fig. 6(e)) is then normalized for use in the feature vector. The Length feature provides a contribution to the feature vector using the width of the signature following a normalization process.

A. Classifiers

Two types of neural networks, the MLP trained using Resilient Back propagation and the Radial Basis Function network, were employed as classifiers in this research. Besides the main purpose of comparing the performance of classifiers in the absence of targeted forgeries in the training process, it is also of interest to see how the involvement of targeted forgeries in the training process would affect verification accuracy.

Another type of classifier, which was also investigated in this research is the Support Vector Machine (SVM), the relatively new statistical learning technique developed by Vapnik. They implemented the idea of mapping the input vectors into a high-dimensional feature space through some nonlinear mapping. In such space, the optimal separating hyperplane is then searched. It is also based on a structural risk minimization principle (SRM). Two main objectives of the SRM induction principle are to control the empirical risk on the training samples and to control the capacity of the decision functions used to obtain that risk value.

A decision function of an SVM has the form of:

\[ f(x) = \text{sign}(w \cdot x + b) \]

Given a set of training vectors \( S \) with \( l \) pairs \((x_i, y_i)\) of samples:

\[ S_i = \{(x_1, y_1), \ldots, (x_l, y_l)\} \quad x_i \in \mathbb{R}^n, \quad y_i \in \{-1, +1\} \]

Each of these samples belongs to either two classes, \( W_1 \) \((y_i = +1)\) or \( W_2 \) \((y_i = -1)\). SVM finds the hyperplane with the maximum Euclidian distance from the training set. According to the SRM principle, there will be only one optimal hyperplane (fig. 7) with the maximal margin \( \delta \) defined as the distances from the hyperplane to the closest points of the two classes. Dealing with non-separable training sets, the \( i \)th misclassified sample is assigned with a slack variable \( \xi_i \) representing the magnitude of the classification error.

\[ \text{Minimise}_{w, b} \quad \frac{1}{2} w \cdot w + C \sum \xi_i \]

\[ \text{Subject to} \quad \sum \xi_i = 1 - y_i \cdot (w \cdot x_i + b), i = 1, \ldots, l, \]

\[ \xi_i \geq 0, i = 1, \ldots, l. \]

\( C \) is the regularization constant determining the trade-off between the empirical error and the complexity term. The parameters are experimentally chosen by the user. A large \( C \) means a higher penalty for misclassifications. The choice of kernel varies among classification problems and feature extraction techniques. With respect to the off-line signature verification problem, Ferrer et al. and Lv et al. reported their best results were achieved with the RBF [6] kernel whilst Justino et al. achieved their best results with the linear kernel. In this research, three types of kernel were investigated: linear kernel, polynomial kernel, and RBF kernel. All the experiments with SVM in this research were conducted using SVMlight version 6.01 created by Joachims [12].

B. Histogram Analysis

As mentioned earlier, we used three types of kernel, linear, polynomial, and RBF, in our experiments with SVM. Kernel parameters were experimentally chosen and the best configurations were used for comparison purposes. It is observed that the RBF kernel had produced the best results. Figure 8 shows the results of classifiers using different settings and the MDF-R feature set. The results show that the use of targeted forgeries sufficiently assists the classifiers to provide better verification accuracy. For all the settings, SVM produced the better results as compared to RBF and RBP. The best results were obtained with Setting IV with the DER as low as 11.89%.

Following the introduction of targeted forgeries into the training process, it is noted that the performance of RBF was significantly improved (from 22.87% with Setting II down to 12.72% with Setting IV). The FARR rates in experiments with SVM were also well under 1% (0.16% with Setting II) and are comparable to FARR rates reported by Justino et al. and Ferrer et al. [6]. Taking this type of error into account, the proposed system is comparable to that of Ferrer et al. [6]. Meanwhile, a direct comparison to the research proposed by Justino et al. is not feasible as the definition of forgeries and their collection process were not identical to that proposed in this research.

Fig. 9, summarizes results employing the MDF-R plus extra features (MDF-R-CTLFS). The results achieved with the SVM classifier approximate to those achieved using the MDF-R feature set. Using the RBP classifier, the enhanced MDF feature set
assisted in reducing the DER significantly. The best result (DER: 9.21%) employing the MDF-R-CTLFS feature set was achieved with Setting IV using the RBF classifier.

Fig. 9: A Comparison Amongst Classifiers With Different Settings Using the MDF-R-CTLFS Feature Set

V. Conclusion
This research compared the performance of RBF, RBP neural networks, and SVM as classifiers in an AOSVS employing an enhanced MDF technique under two specific conditions. One condition is the distribution of samples used for training and the other is the use of targeted forgeries in the training process. Under both conditions, the results obtained using SVM were more favorable than RBF and RBP. Further work will involve the investigation of other machine learning techniques as well as the addition of rotation invariant geometric global features for enhancing the verification process.

References

Mr. Sri Ramakrishna Vasamsetty, well known Author and Excellent Teacher Received M.TECH (CSE) UCEK, JNTU KAKINADA (CSE). B.TECH(CSE) SVH COLLEGE OF ENGINEERING 1999-2003 He Working as Faculty ASSOCIATE PROFESSOR IN CSE B.V.C College of Engineering & Technology. His area of Interest includes Digital Image processing and AI. He has vast Teaching experience in various engineering colleges. To his credit couple of publications both National & International conferences /journals., His area of Interest includes Digital Image processing and AI. he has guided many projects for Engineering Students.

Mr. Rajkiran Vakkalanka is a student of B.V.C College of Engineering & Technology, odalarevu. Presently, he is pursuing M.Tech (C.S.E) From this college and he received B.Tech (C.S.E) from BVC College of Engineering (JNTUK) in the year 2010. His area of interest includes Computer Networks and Object oriented Programming languages in Computer Applications.