An integrated approach on verification of signatures using multiple classifiers (SVM and Decision Tree): A multi-classification approach

Upasna Jindal 1, Surjeet Dalal 1,*, G. Rajesh 2, Najm Us Sama 3, N. Z. Jhanjhi 4, Mamoona Humayun 5

1Department of CSE, SRM University, Delhi-NCR, Sonipat, Haryana, India
2Department of IT, MIT Campus, Anna University, Chennai, Tamil Nadu, India
3Department of Science, Deanship of Common First Year, Jouf University, Sakaka, Saudi Arabia
4School of Computer Science and Engineering, SCE, Taylor's University, Jaya, Malaysia
5Department of Information Systems, College of Computer and Information Sciences, Jouf University, Sakakah, Saudi Arabia

1.1. Digital signature vs handwritten signature

Online, signatures are taken using a digitizer having a stylus, and dynamic features are captured while writing in space provider to the person (Kiani et al., 2009). In comparison, offline signatures are quite different, collected using pen paper, open space given to the signer, and features collected are static in nature. Considering previous research on the system, online signatures are more accurate than offline (Swain et al., 2020; Saeed et al., 2020). One major factor which affects the total performance is noise. Higher the noise lowers down performance. In other terms, the performance of the verification system depends on the factor of noise available in the input signatures. The key objective of the signature verification system (SVS) is to discriminate the human signatures into the defined classes either genuine/original or forged. Every time when the person signs there are certain variations that come in that, due to some stress, environmental conditions ad any other physical trait. This term can be called Inter/Intra personal variations.

• Forgery classification

Further forgery is also having some classes such as Random, Skilled, and Unskilled depending upon the presentation (Kiani et al., 2009):

• Random: Where signer knows the presentation of signature.
• Skilled: Where signer knows name and representation of the signature.
• Unskilled: Where signer does not know name and signature.
• Signature verification system (Guru and Prakash, 2008; Vargas et al., 2009; Jarad et al., 2014)
In this system, the signature image is normalized and checks whether the image matches the original image or not. For security purposes, SVS can be used, such as verification for assessing entry applications and password substitutions. Signature verification has four stages namely acquisition and preprocessing, feature extraction, classification, and verification. Signature verification system block diagram given in Fig. 1.

![Signature verification system diagram](image)

**Fig. 1:** Signature verification system

- Phases and their description in the signature verification system

  Step 1: Signature images collected via a pen-paper or any digital device. Pre-processing phase makes the signature image prepared for the next phase i.e., feature extraction. This stage also includes binarization, rotation, scaling, thinning, cropping, and many others. **Fig. 2** explains the steps involved in the pre-processing. How signature image becomes clean and clear for next step.

  Step 2: Feature Extraction: This section is the main part of the signature verification. It is called respiratory of the system, where features are classified into two local and global, both the classes have their own set of features, which needs to extract while calculating the forgery factor from the signature image. Local and global features are their sub-division is described in the below **Fig. 3**.

  Step 3: Classification: Classification plays a vital role in the verification process, where the signature image is trained using single or multiple classifiers. Most of the researchers have given different learning approaches to train the input. Some of the classifiers which are used for the process are listed below in **Fig. 4**.

![Pre-processing phase diagram](image)

**Fig. 2:** Pre-processing phase
Fig. 3: Classification of local and global features

Fig. 4: Represents the types of classifiers

Step 4: Verification: In this step, a certain decision comes in the form of scores, which are further matched with the original score of the signature. It is accomplished by some distance measure and decision rules e.g., Euclidean distance, Mahalanobis measure, etc. Previously authors have calculated the False Acceptance Rate (FAR), False rejection rate (FRR), Equal error rate (EER), and other terms as result. The formula for calculating the distance is mentioned below:

1. Euclidean Distance: Defines the average distance between the two points of signature.

Consider two images $I, J$ where points in the images are:

$I=[I_1, I_2, I_3, ..., I_n]$ and $J=[J_1, J_2, J_3, J_n]$

$D=\sqrt{\sum_{m=1}^{n}(I_m - J_m)^2}$.

2. Mahabalonis Distance: To calculate the covariance between two feature vectors and maintain the matrix (Qiao et al., 2011).

$M=\frac{1}{n}\sum_{i=1}^{n}(x_i - m)(x_i - n)^T$.

$M$ is the mean value, $i$ is the input image, $n$ be the set of signature images.
3. Decision Score: Calculating the score where

\[
\text{Score}(S; \text{ID}) = \sum_{m=1}^{M} \left( F(X|\text{Ref S}_{\text{IDm}}, S)|\text{Meas}_{\text{IDm}}; \theta) \right)
\]

\(M\) is the set of signatures; \(\text{Ref S}\) is the reference signature trained using classifiers.

The above three measures support the process to find out the forgery factory from signatures.

2. Research motivation

Our main aim is to develop a secure system that helps us to find the forged signature out of a set of signatures, whether online or offline, and the main challenge is a skilled forgery, where chances of forgery are very high as compared to others. Signatures are broadly classified into global, local, and transitional features. Global features describe the entire signature including length, width, height, etc. whereas local features consider small of signature and extract detailed information from it. Verification of the system depends on two steps: Extraction and classification. More extraction, better classification will produce a high rate of accuracy and increase performance.

2.1. Classifiers used to calculate forgery factor using different datasets offline and online signature

Based on the previous approaches, Table 1 shows that the features extracted, their classifiers used to find out forgery and accuracy obtained. Most of the researchers have used already available data of signatures and created their own set. An experiment was done on various datasets of signatures. Some of the authors used their own data set.

| Author, Type, Year | Classifiers | Dataset | Accuracy |
|--------------------|-------------|---------|----------|
| Oliveira et al. (2007) offline | Hidden Markov Models | 60 writers included 30 training signatures, 10 casual forgeries, 10 original, and 10 skilled forged | FAR 2.83% FRR 2.50%, 1.44%, and 22.67% was obtained for casual, random, and skilled forgeries 26.7% of EER achieved for Skill forgeries and 5.6% EER for random forgeries |
| Abuaiba (2007) Offline/Online | Graph Matching Problem | MCYT-100 signature includes 100 signers, 25 genuine and 25 forgeries | EER=0.12% |
| Quan and Liu (2007) Online | HMM/ANN using time delay NN, Localtime function position, and pressure | MCYT-100 signature includes 100 signers, 25 genuine and 25 forgeries | FAR: 14.58% achieved |
| Nirmalathas et al. (2008) Offline | Singular Value Decomposition (SVD) numerical tool | Forgeries dataset of 100 signatures, contains 20 genuine signatures | EER achieved is less than 2.37% from the previous |
| Yanikoglu and Kholmatov (2009) Online | Fast Fourier Transform (FFT), Pen up duration | SUSIG-Visual subcorpus, MCYT-100 | Equal Error 6.2% and 12.1% on skilled forgeries |
| Soleymapour et al. (2010) Offline | SVM using counter let transform, Directional features | 10 genuine signatures skilled forgery (Persian, Turkish) | Error 4.5% |
| Qiao et al. (2011) Online | Dynamic time warping (DTW), Mahabalonis Distance, positions, pressure, azimuth, angle, and inclination angle | MVCY-100 biometric database | Equal error rate 5.23% |
| Sreraj and Idicula (2011) Offline/Online | Likelihood ratios and applied methods used by Forensic Handwriting Examiners (FHEs) | SVC 2004, Bio Secure, SigComp 2009 (Chinese and Dutch) | Accuracy: 90% Dutch signatures |
| Kour et al. (2011) Online | Genetic Algorithm-Support Vector Machine (GA-SVM), Time function features | SVC 2004 | Accuracy 83% |
| Kruthi and Shet (2014) Offline/Online | Global Features, SVM | Own dataset 336 Signatures with different pens | Accuracy 72.2% |
| Bharadwaja (2015) Offline/Online | Global features, Euclidean Distance with a global threshold | 30 original signatures and 35 forged (online and offline) | FAR in offline 11.4% FAR online 8.57% |
| Zulkarnain et al. (2015) Offline | Global Features added new features, Hipotensuric distance, SVM | GPDS-960 Total of 23049 genuine and 28800 forgeries signatures | Accuracy: 87.5% |
| Cpałka et al. (2016) Offline | Initial, middle, and final time moments, DTW | SVC-2004, MCYT-100 | FAR: 3.36% FRR: 3.33% |
| Lai et al. (2017) Online | Features related to scaling, rotation, length normalized | 100 persons, with 25 genuine and random forgeries respectively | EER: 2.37% |
| Sharif et al. (2018) Offline | Global aspect ratio, area of signature, pure width, pure height, and normalized actual signature height, Local centroid, slope, angle, and distance | CEDAR, MCYT, and GPDS synthetic. | AER: 5G: 6.67% 10G: 5.96% 12G: 5.0% |
| Maergner et al. (2019) Offline | Key point graphs with approximated graph edit distance and ink-ball models | GPDS 100 | EER: 4.17% FAR: 3.94% |
3. Proposed work

The objective of our research is to design a robust integrated signature verification system. We have already studied different types of forgeries present in online and offline signatures. For this, a database containing skill level forgeries has been used. However, the proposed system will try to identify unique features from the signatures of a person. Thus deliberate or fake inputs may cause lower down verification rates. By using a support vector machine we can produce a better classification. The one major disadvantage of the SVM classifier is that more the input slows down the results.

To overcome the complexity of SVM, an addition of decision tree function produced better results previously, the hybrid SVM model was proposed embed C4.5 algorithm of a decision tree into the SVM and resulting in a more accurate and efficient hybrid classifier. Then we introduced the modified DT-SVM (Maergner et al., 2019; Blankers et al., 2009) algorithm addition of a new method, Probability-based Distance as Splitting Criterion, in which we use the distances in the frequency distribution of the instances. Thus, the modified DT-SVM provides better performance over the previous decision tree, and SVM (Ferrer et al., 2005) in comparison with the Computational Complexity and overall Accuracy. We have emphasized reducing input space using new splitting criteria. The proposed algorithm will show better performance from previous research.

i. Input signature: The input signatures are collected from persons where each signature has its own x-y coordinates, which are calculated from the pen up and pen down points. Every single point has is stored in the database. Representation of the signature can be done in the form of conservative coordinates i.e., x-y coordinates. Coordinates will be saved in the system in the .txt file Database for online and offline signatures are separate. Fig. 5 depicts the illustration of our proposed system i.e., integrated signature verification Fig. 5.

![Diagram](image-url)

**Fig. 5:** Graphical illustration of the proposed system (ISV)

ii. Mathematical formulation: Signature Sample. Let \( \lambda = \lambda(i) \) Where \( \lambda \in \Psi \) be an input signature. \( \Psi^{(g)} \) is the no. of genuine signature, \( \Psi^{(f)} \) is the no. of a forged signature. \( \{\lambda_i^{(g)} + \lambda_i^{(f)} \in \Lambda\} \), where i, j be the location of the pixels of the input signature.

\[
i = [1,2,3 .... n], \quad j = [1,2,3,4 .... m]
\]

The output of the signature image is produced in terms of the forgery factory. The input signature is initially scaled and calculate length Ls, and, find its velocity vector \( \vec{V}_{\text{new}} \) directly comparable with each sample signature \( \lambda(i) \), rotate in a clockwise direction to produce new velocity vector \( \vec{V}_{\text{new}} \lambda(i) \) having initial direction \( \vec{V}_{\text{new}} \lambda(i) \). An indication that the new signature is forged (Bharadwaja, 2015) is then provided by large values of the 'forgery index':
 Forgery Index then normalized (λnew) to range lies either 0 or 1, and we assume it, to be small for original input signatures. In terms of λnew theory testing, is a test statistic, for the null hypothesis that the new signature is original.

iii. Pre-processing: Pre-processing (Sheng et al., 2005) is another important phase of the verification system, to improve the overall accuracy and reduce the computational needs of the feature extraction phase. The main purpose of this phase is to make the standardized form of signature and prepare for the next phase i.e., feature extraction. It primarily includes the following steps Noise, conversion, resizing, thinning, normalization, transformation, and smoothing. All these are to avoid the developed system falsifying the original signature.

Size normalization is done by scaling each character, each node, and every point of direction both horizontally and vertically.

\[ x_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} W \]
\[ y_i = \frac{y_i - y_{min}}{y_{max} - y_{min}} H \]

where \( x_i \) and \( y_i \) denote the point of original signatures is the corresponding point after the transformation:

\[ x_{min} = \min_i (x_i^o), x_{max} = \max_i (x_i^o) \]
\[ y_{min} = \min_i (y_i^o), y_{max} = \max_i (y_i^o) \]

where \( W \) and \( H \) are the width and height of the normalized signature respectively.

The re-sampling step is a fraction of the total arc length \( L \). Below equations shows data points in the signature.

\[ d_i = \sqrt{(x_i - x_{i+1})^2 + (y_i - y_{i+1})^2} \]
\[ L = \sum_{i=1}^{n-1} d_i \]
\[ \Delta S = \frac{L}{n_i} \]

Noise Removal: Given Fig. 6 is the example of a signature taken from the database for the pre-processing. For noise removal, a modified canny edge algorithm is defined, where the Sobel detection operator is used to detect the edges of the image (Mathur et al., 2016; Gao et al., 2010; Sheng et al., 2005; Vincent and Folorunso, 2009). As in the canny edge used Gaussian filter, which loses informational edges only isolated edges appeared. In our system, both the static and dynamic are available in the signature. To improve the edge detection modified canny edge algorithm was used.

\[ \lambda_{new} = \frac{1}{m} \min_{i = 1..n, j = 1..m} \theta(i,j) = \int_{\Delta} \gamma_{Ki}(t) dt, \]  

Where \( \theta(i,j) \) denotes the angle Vnew (\( \lambda_{old} \), \( \Delta \)).

Step 1: An input signatures \( I \), where \( I \geq 0 \). Step 2: Convert image \( I \) (grayscale image) into \( I_b \), i.e binary image, Step 3: Morphological operation on \( I_b \), (If \( I_b < 0 \)) then go to

Step 4: After a normalized operation, \( I_b \) converts to \( I_b^* \), Image is normalized, Step 5: Apply noise removal Canny edge using Sobel filter (Shokhan, 2014), Step 6: Calculate the Error from \( I_b \), Step 7: Conversion of image \( I_b \) to image \( I_{new} \).

iv. Feature extraction: Feature extraction technique (Sharif et al., 2018) is respiratory of the verification process, and different extract attributes and characteristics from the given image and create a matrix for further purpose. Feature Extraction is broadly divided into three main categories: Global, Local and Geometrical.

Further, our system has two phases: Training and Testing. In the training phase, we applied a support vector machine and then classified the image. Output is displayed in the form of a feature matrix. In the testing phase, we applied a modified SVM-DT algorithm which is the proposed algorithm. For Decision function mapping with support vector machine (Shao et al., 2013; Zuo and Jia, 2016; Boonchuay et al., 2017; Nazari and Kang, 2015) where \( F(I) \) represents the decision function of the new signature image. \( K \) belongs to the \( I \), \( I_x \) coordinates i.e., the kernel function to define the feature matrix.

\[ F(i) = \sum_{i=1}^{m} \alpha_i K(I_i, I_x) + b \]

The split function is used to calculate the feature space where \( cur \_value \) denotes the current value of the features extracted from the original and forged signature.

if \( cur \_value \) > Split Criteria then
return \( \sqrt{Split \ Criteria} \)

Distances in features of the signature need to be calculated using the Frequency distributions function which is used to map the balance between unbalanced and balanced datasets of signatures.

The previously defined Bhattacharyya Coefficient is given below (Zuo and Jia, 2016).

P1 and P2 define the probability distribution distance of two signatures:

\[ P(P_1, P_2) = \int_{0}^{\infty} \int_{0}^{\infty} \frac{\partial P_1}{\partial x} \frac{\partial P_2}{\partial y} dx dy. \]

Derived distance using Bhattacharyya Coefficient in Eq. 13:

\[ h_{df}(P_1, P_2) = \]
\[ 2 \left[ 1 - \int_{\ln}^{\ln} \sqrt{\frac{dx}{dv}} \sqrt{\frac{dx}{dv}} \, dv \right] = \int_{\ln}^{\ln} \left( \frac{dx}{dv} - \frac{dx}{dv} \right)^2 \, dv. \quad (13) \]

While integrating two classifiers, problems raise in their mapping because we have both balanced and unbalanced data. For mapping these data, we add The Bhattacharyya coefficient in the proposed algorithm using Probability-based Distance as Spitting Criterion.

4. Implementation and result analysis

In our research, two different experiments were carried out. One for the testing phase and the other training phase. The first experiment was conducted on the training phase of the system where signature features are extracted. The second experiment is applied in the testing phase using the proposed algorithm SVM-DT features of captured signature data. A performance evaluation is done for each phase. The proposed integrated signature verification system includes a database of original signatures which contains all the information of the features. The set of features are captured at the time of feature extraction further it will compare with the set of features of the forgery signature to verify the status of the signature. For comparison of such feature set, we propose an algorithm that has multiple classifiers Support Vector Machine and Decision Tree (SVM-DT) are applied. Given Fig. 7 shows some sample signatures collected from the dataset.

![Fig. 7: Sample signature set for the verification purpose](image)

In this system, set of total 1036 signatures we have taken. Out of these, 192 were trained and 47 were tested using the proposed algorithm DT-SVM. Using the proposed algorithm, the system displayed the false acceptance rate and false rejection rate for both global and local features. The results are very promising and decrease the rate of forgery. The verification results of the SVM and DT-SVM methods are given in Table 2. Fig. 8 shows a graphical representation of the implementation of the verification system and Fig. 9 shows the confusion matrix of the integrated signature verification system.

| Classifiers                  | Dataset             | Features extracted       | FAR and FRR | Accuracy |
|------------------------------|---------------------|--------------------------|-------------|----------|
| Support vector Machine       | 336 Set signatures  | Global                   | -           | 72.2%    |
| GA- Support vector Machine (Kour et al., 2011) | SCV 2004 | Time function features   | -           | 83%      |
| DTW (Cpalka et al., 2016)   | MCYT, Biosecure     | Initial, Middle, and final Time moments | FAR 3.33% | 96.6%    |
| Proposed Algorithm           | 192 Set signatures  | Global and Local         | FRR 3.6%   |          |
|                              |                     |                          | FRR 2.28%  |          |

![Fig. 8: Graphical representation of the implementation of the verification system](image)
4.1. Characteristics of performance analysis

In this section, we have calculated certain True positive, False Negative, and precision values of the signature dataset which is implemented on two different datasets of the training and testing phase (Tables 3 and 4).

Table 3: Characteristics of the training dataset

| Class represent | True Positive | False Negative | Precision | F-Measures |
|-----------------|---------------|----------------|-----------|------------|
| Original Signatures | 0.983         | 0.540          | 0.915     | 0.998      |
| Forged Signatures  | 1.0           | 0.016          | 0.995     | 0.979      |
| Weighted          | 0.965         | 0.008          | 0.953     | 0.973      |

Table 4: Characteristics of the testing dataset

| Class represent | True Positive | False Negative | Precision | F-Measures |
|-----------------|---------------|----------------|-----------|------------|
| Original Signatures | 0.999         | 0.512          | 0.943     | 0.996      |
| Forged Signatures  | 1.0           | 0.023          | 0.988     | 0.996      |
| Weighted          | 0.989         | 0.058          | 0.996     | 0.998      |

4.2. ROC curve

In the integrated signature verification, we have plotted the receiver operating characteristics curve to illustrate the performance of our proposed system. It is the graphical representation of the results where x and y axis will represent the true positive rate and false positive rate respectively. In the given curve, there are three different signature sets represented in different classes 1, class 1, and class 2. Figs. 10, 11, and 12 of the ROC curve are generated at different threshold values.
In the end, it is clear that combining two classifiers gives better and more accurate results and reliability than the previously used classifiers. The main of our research is to show the reduction in the error rate from the signature image and find out the forgery rate from the signature. From the above section 5, certain scores of the signature have been generated. Experiment analysis is done using the machine learning tool.

5. Results

As expected, the Accuracy results of the integrated systems are much better than previous systems. The accuracy achieved 96.6%. Use of single classifiers, the systems are not able to compute within the variability of a person. Generally expected to yield better results when presented with more classifiers for the reference signatures.

6. Conclusion and future scope

This paper presents a brief survey of various features and methods for the classification of the set features from the signature image. These approaches are studied according to their different stages, and the performance evaluation based on FRR, and FAR is given. In addition, they can be analyzed for efficiency to get a better result. There is a need to develop one general system in future work to classify every style of signature and to enhance performance.

Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.
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