



An Improved Geo-Textural Based Feature Extraction Vector for offline Signature Verification

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

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Abstract

In the field of pattern recognition, automatic handwritten signature verification is of the essence. The uniqueness of each person's signature makes it a preferred choice of human biometrics. However, the unavoidable side-effect is that they can be misused to feign data authenticity. In this paper, we present an improved feature extraction vector for offline signature verification system by combining features of grey level occurrence matrix (GLCM) and properties of image regions. In evaluating the performance of the proposed scheme, the resultant feature vector is tested on a support vector machine (SVM) with varying kernel functions. However, to keep the parameters of the kernel functions optimized, the sequential minimal optimization (SMO) and the least square method was used. Results of the study explained that the radial basis function (RBF) coupled with SMO best support the improved featured vector proposed.

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1 Introduction

In the field of pattern recognition, automatic handwritten signature recognition has received considerable attention to be used for human biometric [1, 2, 3]. Enormous studies in the domain of computer science have been carried out in respect of the identification and verification of persons. In this study area, characteristics of biometric that are quantifiable can be measured both physiological and behavioral. For instance, the fingerprint, DNA, and iris of the eye are classified as physiological while signature, handwriting, gait, and voice are categorized as behavioral and all these constitute biometrics [4]. It is well known that every person's signature is unique in terms of its behavioral property and this fact has yielded a great community acceptance of its use as biometric for identification and authentication [5, 6]. In the light of its popularity, several negative cases of the ease to forge them are recorded motivating the need for an enhanced system for recognition. This system can either be dynamic or static depending on the structure of the input data [7]. In this case, the process of recognition is defined as finding or identifying the owner of the signature whereas the process of verification is to determine whether a signature is forged or genuine. The forged signature comes in various forms and are tagged as one of the following: skilled forgeries [8], deliberate forgeries [9], disguise [10], random or impostor signatures [11], and simulated or highly skilled forgeries [12]. A forgery is classified as skilled if the signature is signed by an individual who has done several practices given the genuine one. In simple forgery, the signer has very little knowledge of the genuine signature whereas, in random forgery, the signer has no knowledge regarding the signature or the name of the signature owner [13].

In the analysis and verification of static signatures, Zois et al. [14] presented a grid-based template matching scheme. In their study, the fine geometric structure of the signature is efficiently encoded with the grid template and partitioned into subsets. Using a five-by-five pixel window binary mask shape for lattice-shaped probing structures, features are extracted to detect the ordered transitions. Evaluating the performance of the verification approach on four different datasets of signatures using the Spearman ranking test reveals a strong correlation between complexities. This study continues to prove that the chances of a signature being correctly classified improve significantly when there is an exhibition of a higher quality of genuine samples by signature owners. Following the work of [4], the point of gravity center and the orientation of the skeleton were combined to extract accurate feature patterns for static signature recognition which resulted in success. Using the writer-independent parameters, [15] proposed the use of one-class support vector (OC-SVM). In their approach, only original signatures are taken into account while the forgery is observed as counterexamples for designing the HSVS system. This approach is very effective for accurate classification on a large sample; however, there is inaccuracy in the training of the OC-SVM model which affects performance on an insufficient dataset. It is recommended that there is the need for the modification of the decision function used in the OC-SVM which is achieved by carefully adjusting the optimal threshold through the combination of various distance metrics used in the OC-SVM kernel. In [16], a new online HSV system was proposed to function on low-end mobile devices and reported on the outcome of the experimental evaluation of the system on the various dynamic handwritten signature datasets. Finally, with the work of [17], a review of research works and methodologies were presented in the domain of handwritten signature verification. It is at this point clear that the many works proposed in the literature by various authors have a fundamental issue with optimal feature extraction for offline and online signature verification. In this work, an improved feature extraction vector is proposed using a blend of GLCM and region properties to increase verification accuracy.

2 Preliminary Concepts and Methods

2.1 Image Preprocessing

In signing a signature, persons exhibit varying variations in terms on pressure, posture and even the kind of object used [18, 19, 20, 21]. There is, therefore, the need for image normalization which required the concept of image preprocessing in this context as the first phase of the recognition process. The main aim of the preprocessing is to standardize the signature image and make it ready for feature extraction as well as improving the quality of the image. The series of operations performed chronologically on the signature image is as outlined as follows: binarization[22, 23, 24], background elimination[25, 26], edge detection[27] and skeletonization[28, 29]. Stepping into the details of these operations, the grayscale signature image in its raw state is converted into black and white during the binarization process to make feature extraction much easier. The background of each binarized image is eliminated. The edge detection operation is then used to compute the boundaries of objects within images by detecting discontinuities in the image brightness. Finally, the skeletonization process is performed to obtain the skeleton of the 2-D binary image of which the required feature can be extracted with ease.

2.2 Feature Extraction

One of the most essential part in signature recognition system is the ability for select accurate sets of features. In this section, two groups of features are estimated namely GLCM properties and region properties [30, 31, 32, 33, 34, 35, 36].

2.2.1 Gray-Level Co-occurrence Matrix (GLCM)

The statistical method used to examine texture and pixels spatial relationships is the gray-level co-occurrence matrix (GLCM). In this matrix, statistical features such as contrast, energy, correlation, and homogeneity are computed. These features are defined as follows given the following notations:
 $p_{ij} = (i, j)^{th}$ entry in GLCM

N_g = Number of distinct gray levels in the image

1. Contrast

This is the difference between the highest and the lowest values of the adjacent set of pixels. It is also known as variance or inertia, and it is estimated as:

$$\text{Contrast (con)} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} |i - j|^2 p_{ij} \quad (2.1)$$

2. Correlation

This is the measure of the linear dependency, and it ranges from -1 to 1. This value is zero (0) for a constant image and its computational formulation is given by:

$$\text{Correlation (cor)} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{(i - \mu_i)(j - \mu_j)p_{ij}}{\sigma_i \sigma_j} \quad (2.2)$$

where μ_i and σ_i is the mean and standard deviation of p_{ij} rows, and μ_j and σ_j are the means and standard deviations of p_{ij} columns respectively.

3. Energy

Energy also referred to as Uniformity or Angular second moment measures the uniformity

of the texture. This is given by:

$$\text{Energy (ene)} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} p_{ij}^2 \quad (2.3)$$

4. Homogeneity

This measures the closeness of the distribution of elements in the GLCM to the diagonal of the GLCM. It is also referred to as the Inverse Difference Moment, and it is measured mathematically as:

$$\text{Homogeneity (hom)} = \sum_{i=1}^{N_g} \sum_{j=1}^{N_g} \frac{p_{ij}}{1 + |i - j|} \quad (2.4)$$

2.2.2 Region Properties

Apart from the statistical properties of an image, images also exhibit other properties based on their region. Several such properties exist; however, in this study, only twelve of them are extracted based on their relevance and significant contribution to the proposed feature vector.

1. Area

The area measures the extent of any two-dimensional figure in a plane. It is given by the integral function:

$$f(x) = \int_a^b f(x) dx \quad (2.5)$$

where a and b are the two values on the horizontal axis such that $b \geq a$. In image analysis, this is a scalar value representing the total number of pixels in the region of interest.

2. Bounding Box

This represents the smallest rectangle containing the region. Given an object representation with the set of points

$$\begin{aligned} Q_0 &= (x_0, y_0, z_0) \\ Q_1 &= (x_1, y_1, z_1) \\ &\vdots \\ Q_n &= (x_n, y_n, z_n) \end{aligned} \quad (2.6)$$

then the bounding box of the object can be established by defining it to be

$$\begin{aligned} \min(x_i) \leq x &\leq \max(x_i) & 0 \leq i \leq n \\ \min(y_i) \leq y &\leq \max(y_i) & 0 \leq i \leq n \\ \min(z_i) \leq z &\leq \max(z_i) & 0 \leq i \leq n \end{aligned} \quad (2.7)$$

3. Centroid

The centroid or geometric center of a plane figure is the arithmetic mean position of all the points in the shape. This defines the region's center of mass of an image. The centroid of a finite set of k points x_1, x_2, \dots, x_k in R^n is

$$C = \frac{x_1 + x_2 + \dots + x_k}{k} \quad (2.8)$$

4. Convex Hull

Given any set of points in the Euclidean space say X , we define the convex hull as the smallest convex set that contains X . Mathematically, we have Equation (2.9).

$$\text{Conv}(A) = \left\{ \sum_{i=1}^{|A|} \alpha_i x_i \mid \forall i : \alpha_i \geq 0 \wedge \sum_{i=1}^{|A|} \alpha_i = 1 \right\} \quad (2.9)$$

5. Minor Axis Length, Major Axis Length and Eccentricity

The Minor Axis Length : is the length (in pixels) of the minor axis of the ellipse that has the same normalized second central moments as the region while the Major Axis Length is the scalar value specifying the length (in pixels) of the major axis of the ellipse that has the same normalized second central moments as the region. The eccentricity, on the other hand, determines the ratio of the distance between the foci of the ellipse and its major axis length. This property has a range of 0 to 1 where 0 and 1 are degenerate cases; thus an ellipse with an eccentricity of 0 is a circle, while an ellipse with an eccentricity of 1 is a line segment. Given Equation (2.10) as an ellipse

$$\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} = 1. \quad (2.10)$$

where (h,k) is the center of the ellipse and (x,y) being any arbitrary point in the x-y plane, we represent the major axis as:

$$a = r_{min} + r_{max} \quad (2.11)$$

and the minor axis as

$$b = 2\sqrt{r_{min}r_{max}} \quad (2.12)$$

where r_{max} and r_{min} are the maximum and minimum distances from the focus to the endpoints of the ellipse. Given the definition, the eccentricity of the ellipse is formulated as

$$e = \sqrt{1 - \frac{b^2}{a^2}} \quad (2.13)$$

6. EquivDiameter

This parameter specifies the diameter of a circle with the same area as the region and is computed as:

$$\sqrt{\frac{4 * Area}{\pi}} \quad (2.14)$$

7. Euler Number

This specifies the number of objects in the image minus the number of holes in those objects. The Euler Number is given by

$$E = N - H \quad (2.15)$$

where N is the number of regions of the image (number of connected components of the object) and H is the number of holes in the image (isolated regions of the background of the image).

With these region properties including Extent, Extrema, Orientation, Solidity, ConvexArea, and Perimeter, the mean and variance are computed giving a sum of twenty-eight features of the region properties. Adding these to the GLCM features gives a total of thirty-two features extracted from each signature image. These extracted features are then passed to a classifier. In this study, the support vector machine is used as detailed below.

2.3 Support Vector Machine (SVM) Classifier

One major tool that is used purposely for both classification and predictive regression is the support vector machine (SVM)[37, 38, 39, 40, 41]. To maximize the accuracy of any prediction with low computational complexity, this machine learning based theory is used. Having different objects with a different class of memberships, the SVM seeks to draw a decision plane between these set of objects and classify them. For any two given classes, the SVM classifies the data points by providing the best hyperplane that separates one class from the other. In practice, the hyperplane with the greatest margin between the two classes is considered the best hyperplane. The nearest data points to the separating hyperplane which is assumed to be linear represent the support vectors. Unfortunately, not all data are linearly separable hence the need to modify the decision function using kernel tricks.

2.3.1 Kernel Functions

For a non-linear separable set of training data, kernel functions are used by implicitly mapping the non-linear separable input space into a linear separable feature space, where the linear classifiers can be applied[42, 43, 44, 45, 46]. The kernels transform the input data into the required form by finding the inner product between two points in a suitable feature space. Some common kernels used with SVM are:

1. Polynomial kernel:

Training samples that are similar in the feature space are represented by the polynomial kernel over polynomials of the input space (original variables), and this allows learning of non-linear datasets. It is formulated as:

$$K(X_i, X_j) = (X_i \cdot X_j + c)^d \quad (2.16)$$

where X_i and X_j are vectors of the training samples, d is the degree of the polynomial and $c \geq 0$ is a free parameter trading off the influence of higher-order versus lower-order terms in the polynomial.

2. Gaussian radial basis function (RBF):

Given any two samples X_i and X_j , the Gaussian radial basis function (RBF), representing the feature vectors in some input space, is defined as

$$K(X_i, X_j) = \exp(-\gamma \|X_i - X_j\|^2) \quad (2.17)$$

where $\|X_i - X_j\|^2$ is the squared Euclidean distance between the two feature vectors X_i and X_j and $\gamma > 0$.

3. Multilayer Perceptron (MLP) kernel:

The Multilayer Perceptron (MLP) kernel which is also known as the Hyperbolic Tangent Kernel or the Sigmoid Kernel is formulated as

$$K(X_i, X_j) = \tanh(\alpha X_i \cdot X_j + c) \quad (2.18)$$

for some $\alpha > 0$ and $c < 0$

2.4 Parameter Estimation

From the kernel function defined, there is the need to estimate the various parameters that explain the kernel function more appropriately given the dataset. In this study, two methods are considered that is: Sequential Minimal Optimization[47] and the Least Square [48] as explained in detail the following subsection.

2.4.1 Sequential Minimal Optimization (SMO)

In this procedure, the SMO seeks to divide the optimization problem into a series of smaller possible sub-problems and solved analytically. By illustration, consider a given dataset $(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)$ where the input vector is x_i and $y_i \in \{-1, +1\}$ a binary label that corresponds to each x . The SVM is trained to solve this Quadratic Programming (QP) problem expressed below;

$$\max W(\alpha) = \sum_{i=1}^m \alpha_i - \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m y^{(i)} y^{(j)} K(x_i, x_j) \alpha_i \alpha_j, \quad (2.19)$$

subject to the constraints:

$$0 \leq \alpha_i \leq C, \quad \text{for } i = 1, 2, 3, \dots, m, \quad (2.20)$$

$$\sum_{i=1}^m y^{(i)} \alpha_i = 0 \quad (2.21)$$

where $K(x_i, x_j)$ is a kernel function, C , a hyperparameter and α been the Lagrange multipliers. Since the constraints are linearly equal and involves the Lagrange multipliers α , the least possible problem has two of such multipliers. The constraints for the two multipliers α_1 and α_2 is therefore reduced to:

$$0 \leq \alpha_1, \alpha_2 \leq C, \quad (2.22)$$

$$y^{(1)} \alpha_1 + y^{(2)} \alpha_2 = k \quad (2.23)$$

which is solved analytically and k is the negative of the sum over the rest of the terms in the equality constraint, and this has a fixed value for each iteration.

2.4.2 Least Squares Optimisation (LS)

Consider a given dataset $(x_1, y_1), (x_2, y_2), (x_3, y_3), \dots, (x_n, y_n)$ where the input vector is x_i and $y_i \in \{-1, +1\}$ a binary label that corresponds to each x . The SVM satisfies the following conditions as:

$$\begin{aligned} w^T \varphi(x_i) + b &\geq 1, \quad \text{for } y_i = 1 \\ w^T \varphi(x_i) + b &\leq -1, \quad \text{for } y_i = -1 \end{aligned} \quad (2.24)$$

Rewriting Equation (2.24) into a single equation we have the following:

$$y_i(w^T \varphi(x_i) + b) \geq 1, \quad i = 1, 2, \dots, n \quad (2.25)$$

where $\varphi(x_i)$ is the nonlinear function that maps the original input space into a higher dimensional feature space. In instances where the hyperplane that separates the two data does not exists, a slack variable ξ_i is introduced such that the optimization problem becomes:

$$\min Q(w, \xi_i) = \frac{1}{2} w^T w + c \sum_{i=1}^n \xi_i \quad (2.26)$$

subject to:

$$\begin{aligned} y_i(w^T \varphi(x_i) + b) &\geq 1 - \xi_i, \quad i = 1, 2, \dots, n \\ \xi_i &\geq 0, \quad i = 1, 2, \dots, n \end{aligned} \quad (2.27)$$

For the Least squares SVM classifiers, the minimization problem is reformulated as:

$$\min Q(w, b, e) = \frac{\mu}{2} w^T w + \frac{\gamma}{2} \sum_{i=1}^n e_i^2 \quad (2.28)$$

which is subject to the inequality constraints

$$y_i(w^T \varphi(x_i) + b) \geq 1 - e_i, \quad i = 1, 2, \dots, n \quad (2.29)$$

with $e_i = (y_i - (w^T \varphi(x_i) + b))$ where both μ and γ are considered as hyper-parameters which tunes the amount of regularization versus the sum of squared error.

2.5 Performance Evaluation of Proposed Features

The parameters used in measuring the performance of the system are the False Acceptance Rate (FAR) and False Rejection Rate (FRR)[49]. The False Acceptance Rate (FAR) measures the probability that the biometric security system will falsely accept an unauthorized person accessing the system. This is usually referred to as the Type - II error. The lower its value, the better and vice-versa. The False Rejection Rate (FRR) on the other hand measures the probability that the biometric security system will falsely reject an authorized person accessing the system. Again, this is also referred to as Type - I error similarly, the lower the FRR, the better and vice-versa.

3 Proposed Framework

This section presents the proposed framework for the verification of an offline signature. As shown in Fig. 1., the GPDS image dataset is partitioned into two sets (training and test) with each set pre-processed while geometric and textual are being extracted to for the train and test feature vector respectively. The train feature vector is then trained to generate models which are evaluated using the test feature vector with the best performing model that well explain the dataset selected.

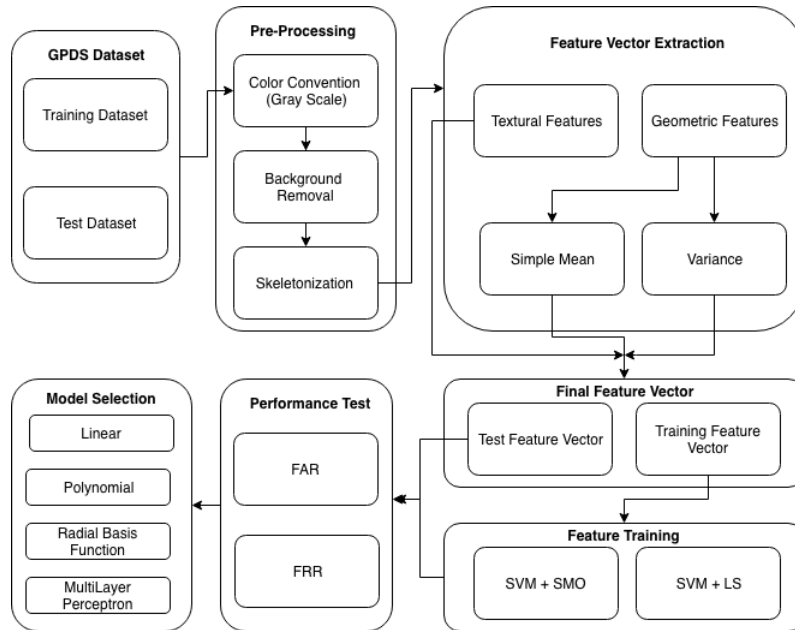


Fig. 1. Proposed Framework

4 Results

4.1 Dataset Selection

This study used the Grupo de Procesado Digital de Senales (GPDS) dataset to evaluate the proposed framework [46]. This is to help make a valid conclusion since most published research in this field make use of this dataset and hence serving as a standard for analysis. The dataset consists of signatures from 4000 individuals, each having 24 genuine signatures and 30 forged signatures. Fig. 2. shows three genuine and three forged signatures from three distinct individuals.

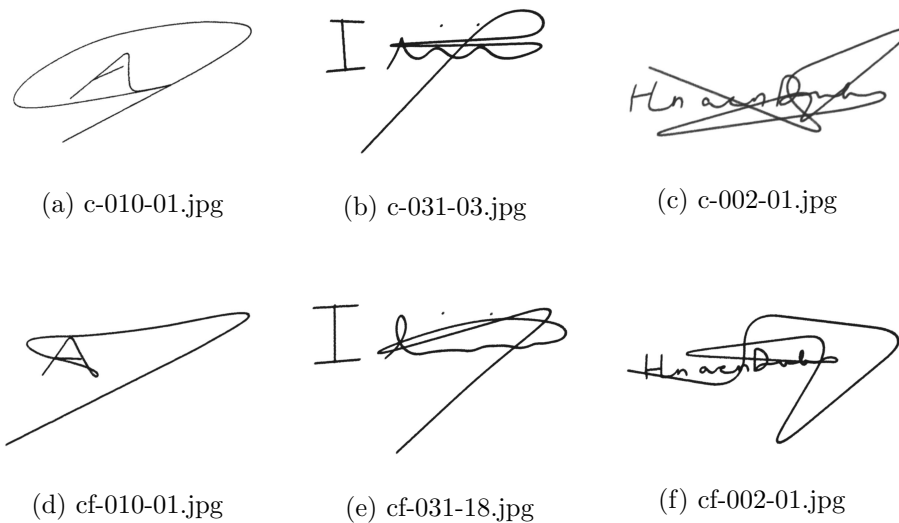


Fig. 2. Three sample images each of genuine and forged signatures

4.2 System Requirement

The proposed method was implemented on a system with the following features as a proof of concept:

1. machine brand: Lenovo thinkpad x270
2. memory: 16GB
3. processor: intel i7, 2.4GHz
4. operating system: Ubuntu 16.04LTS
5. application: MATLAB 2016a

4.3 Experimental Result

In this article, the support vector machine (SVM) was used to train the extracted feature vectors. Since SVM is parametric by definition, it is important that these parameters are fine tune optimally to explain the given dataset. The key parameters here are the choice of the Kernel function and the optimization scheme for the parameter fitting. In the case of the Kernel function, options such as linear, quadratic, polynomial, radial basis function and multilayer perceptron were considered. Each of these options also comes with some set of parameters which require fine tuning. After

varying these local parameters and observing their influence on the overall performance Table 1 and Table 2 was obtain. Table 1 was obtained with the use of Sequential Minimal Optimisation method while Table 2 was obtained using the Least Square methods. For a better appreciation

Table 1: FAR and FRR Values using SMO Method

| Kernel Function | FAR | FRR |
|-----------------|-------|-------|
| Linear | 18.33 | 43.96 |
| Quadratic | 17.78 | 0.07 |
| Polynomial | 14.78 | 0 |
| RBF | 2.50 | 0.14 |
| MLP | 2.67 | 97.71 |

Table 2: FAR and FRR Values using Least Square Method

| Kernel Function | FAR | FRR |
|-----------------|-------|-------|
| Linear | 5.82 | 89.92 |
| Quadratic | 11.44 | 45.44 |
| Polynomial | 7.49 | 0.69 |
| RBF | 2.29 | 0.75 |
| MLP | 0.71 | 97.78 |

of the feature engineering method proposed, we compare our method to other four current existing methods using the same dataset and performance measure. Results from the comparison are shown in Table 3.

Table 3: Experimental results obtained for GPDS dataset. A comparative analysis

| Proposed by | Feature | FAR | FRR |
|-------------------|--------------------------|------|-------|
| [50] | GLCM | 6.17 | 22.49 |
| [15] | Curvelet Transform | 19.4 | 12.5 |
| [51] | Pattern Spectra | 8.94 | 8.59 |
| [52] | Feature Learning | 3.53 | 3.94 |
| proposed approach | GLCM + Region Properties | 2.50 | 0.14 |

4.4 Discussion

Theoretically, it is expected that the performance metric (FAR and FRR) will be zero indicating error intolerance of signature verification. However, in practice, this is usually not feasible due to several factors. From the experimental results shown, one may think the polynomial function of the SMO method will make a good model since it has a zero value for FRR. Unfortunately, this is not the case as it has a higher value of FAR. This implies the need for a trade-off between FRR and FAR. Using this concept, one may now settle on the RBF model for both methods (SMO and LS) but the question of which method to hold-on to becomes necessary. Here, the error margin

between the two methods is evaluated. This gives a value of 0.21 (2.50 - 2.29) for FAR comparison and 0.61 (0.75 - 0.14) for FRR comparison. Clearly, 0.61 is relatively higher than 0.21. Hence the best model that will explain the given dataset using our proposed method is the RFB with SMO optimizer.

5 Conclusion

In conclusion, an improved geo-textural based feature extraction vector is proposed and trained with Support Vector Machine. Methods such as Sequential Minimal Optimisation and Least Square was used with five learning models (Linear, Quadratic, Polynomial, Radial Basis Function and Multilayer Perceptron). The results show that SVM with the RBF model and SMO method performs well on the data sample with a FAR value of 2.50 and FRR value of 0.14. Besides the proposed method also outperform the existing methods quite significantly make it a choice to be considered in real time implementation.

Competing Interests

Authors have declared that no competing interests exist.

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