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A Review Paper on Statistical Methods

Mohan Durvey[1], Devshri Satyarthi[2]

[1]Dr. BhimraoAmbedkar Polytechnic College,
Gwalior (M.P), India

[2]Dr. BhimraoAmbedkar Polytechnic College,
Gwalior (M.P), India

Abstract

Today in the world of yield aiming intelligence, trust of people is at tall risk where forgery is repetitive in which fake signature has come into publicity. The fake signature thus needs to be verified using verification techniques. The signature forgery can be classified by either online signature verification or offline signature verification techniques. Offline verifies by performing a match using the two dimensional scanned image of the signature. This paper studies about the various techniques available in offline signature verification.

Keyword: Hidden Markov Model**,**Support Vector Machine**,**Neural Networkand Dynamic Time Warping.

1. INTRODUCTION

Authentication is very important task for human identification in our real life so signature verification plays a main role in society because of its advantages like natural recognized mode, non occurrence of singer for authentication, minimal descriptor of the singer enveloping measurement of the signature quality. Commonly, signature is also a word with which a person use own identity and such be will have a greater personal major than any other word she/he write, it isbased on ownership. The signature is classified that person is genuine and forge. So the signature verification is traditional way of authentication or verification of document, security purpose, cheques etc.

One of the most important threads in signature verification for authentication is the forged signatures. In 1960s first forgery comes in front then after the case need some signature verification system. So the introduce signature verification process for automatic signature verification system.

Signature verification divided into two major categories such as online signature verification and offline signature verification. First is online signature verification captures signee during the writing use device (e.g. camera, digital tablet) other hand offline signature verification once signee written in paper then scanned signee. It store only static information. Offline signature verification is dividing into three types such as random forgery, simple forgery and skilled forgery [2] [3]. Random forgery means any signee she/he not know original signature. Simple forgery means it sees original signee but not many practiced she/he do. Skilled forgery means she/he does many practice then do the signee so it like original signature. In signature verification used many methods for verification of a signature such as Hidden Markov model, Support Vector Machine, Dynamic Time Warping, Neural Network, Pixel Matching Techniques, Histogram Approach and Statistical Method.

2. HIDDEN MARKOV MODEL

Hidden Markov Model (HMM) is developedmathematics behind by L. E. Baum in 1966. HMM is statistical model, in which the state is not directly visible, but output, dependent on the state, is visible. Each state has a probability distribution over the possible output tokens. Therefore the sequence of tokens generated by an HMM gives some information about the sequence of states.

In other word a hidden Markov model (HMM) is one in which you observe a sequence of emissions, but do not know the sequence of states the model went through to generate the emissions. Analyses of hidden Markov models seek to recover the sequence of states from the observed data. Some are drawbacks of HMM such as learning, decoding and evaluation problem occurs during classification.

Signature modelling using HMM's consist of two phases: The first phase is cross-validation procedure used during the learning process and the second phase is verification procedure. The learning phase is to generate an HMM $\lambda = \{A, B, \pi\}$ model that sufficiently characterizes each author signature model from the different writers.Cross-validation procedure is used to find optimal and dynamic solution for define the optimal state number foreach specific signature model. In Verification phase, before theverification of a signature, the signature is transformed into asequence of observe using our feature extraction scheme.The verification process is basically made up of the Forward algorithm[5].In order to define an HMM completely, the following elements are needed.

- A set of N state, (S1...........SN) where qi is the state attime (t).
- A set of K observation symbol, (V1..........Vk) where $O_t$is the observation at time (t)
- A state transition probability matrix ($A = A_{ij}$) where theprobability of transition from state S_i at time (t) to state
- S_j at (t+1) is a:$a_{ij} = P(q_t+1 = S_j / q_t = S_i)$
- A set of output probability distribution B, where foreach state j:$b_j(k) = P(O_t = V_k / q_t = S_i)$
- An initial state distribution:
- $\pi = (\pi_i)$

Where,

$$\pi p = P(q_i = S_i)$$

In discrete models, two factors are important .The first is the number of states to be used and second is the number of transitions among these states. The number of states depends on the signature length hand the best results in terms of learning probability[4].

YaregalAssabie*et al.* [8] based on two approaches for Amharic word recognition in unconstrained handwritten text using HHHs. First approach is builds word models from concatenated features of constituent charters and second method HMM. It is used hierarchy classification for feature deign. In both case the feature s used for training and recognition are a set of primitive strokes and their spatial relationships. It make synthetic dataset of handwritten Amharic document is composed form 177 writers and total of 307 pages were collected. The result expose that feature level concatenation method is more consistent in comparison to HMM-level concatenation technique on the basis of quality and varying sizes of training and test data.

Robert Sabourin*et al.* [29] solve the problem of limited amount of genuine signature samples is addressed by designing a hybrid off-line SV system based on the dynamic selection of generative– discriminative ensembles. It design the generative stage, multiple discrete left-to-right HMMs are trained using a different number of states and code book sizes and allow the system to learn signatures at different levels of perception. In verification, a new dynamic selection strategy based on the K-nearest-oracles (KNORA) algorithm and on Output Profiles selects the most accurate EoCsto classify a given input signature. This SV system is suitable for increment all earning of new signature samples. It is experiment done on two database (Brazilian SV database and GPDS database) apply two scenarios is investigated abundant data and sparse data. It also used five different methods for verification.

Sabri A. Mahmoud *et al.* [30]present the paper on KHATT database using structural/syntactic classifier and updating our results of HMM classifier using 6712 extracted lines of KHATT database. It use statistical feature for feature extraction. It gives 46.13% accuracy.

Dr. S. Adebayo Daramola*et al.* [31] proposed combination of DCT signature features and HMM are incorporated to develop a robust model framework and signature classification algorithm. It gives recognition performance of the system is 99.2%.

K. N. Pushpalatha*et al.* [32]proposedOffline Signature Verification with Random and Skilled Forgery Detection Using Polar Domain Features and Multi Stage Classification-Regression Model. It used random and zernika moment for verification and also take statistical feature. It uses synthetic database 50 samples each from 100 users. It used 1000 signature give FAR is 0.001% and FRR is 0.05%.

Carlos M. Travieso*et al.* [40] the proposal is based on the use of Cepstral coefficients that are transformed by a Hidden MarkovModels (HMM) to be finally classified by Support Vector Machines (SVM). So, this approach uses information from ECG and gives a new point of view regarding the usage of an HMM kernel.It givesmeanaccuracy of 99.2% and use SVUH/UCB sleep apnea Database gives achieved accuracies99.11% and 99.12%, respectively.

3. SUPPORT VECTOR MACHINE

Support Vector Machine (SVM),the algorithm was invented by Vladimir Vapnik and the current standard incarnation was proposed by Corinna Cortes and Vladimir Vapnik. SVM classifier derived from statistical learning process, in which two advantages of SVM when used for image classification problems such as first is ability to work with high dimension data and anther is high generalization performance without the need to add a priori knowledge. SVM not solve to find an optimal hyper plane, find correct classify data pint by separating the points of two classes as much as possible.

In machine learning, support vector machines (SVM) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. SVM designed to divided a set of training images into two different classes $(x_1,y_1),(x_2,y_2)......(x_n,y_n)$ where x_i R^d, d-dimensional feature space and $y_i$in {-1,+1}class label with i=1....n. SVM builds the optimal separating hyper planes based on a kernel function (k). SVM produce very accurate classifiers and less over fitting, robust to noise. But it some drawback that is: svm is a binary classifier. To do a multi-class classification, pair-wise classifications can be used (one class against all others, for all classes) and its computationally expensive, thus runs slow. The problem is svm solve to find an optimal hyper plan that correctly classifies data points by separating the points of two classes as much as possible [7].

Frias-Martinez *et al.* **[7]** Proposed paper based on support vector machines is compared its performance with its traditional classification method is known as multi-layer perceptrons (MLP). A signature recognition system is categorized into two factors: representation and matching. For the testing and training set, two representations of each signature are obtained, one is using the bitmap of the image and anther one that uses a set of charterstic or feature of the signature. For the classification are used global geometric characteristics and Moment based characteristics. It used java NNS (Java Neural Network Simulator. In SVM comparing the training time of the bitmap approach with the characteristic approach for the range of STD where the optimal values are obtained. In testing process characteristic approach compare 33.5 with the 28.8 response time of the bitmap approach for misclassified signature. In MLP both approaches produced a very similar classification rate is 45% correct classification rate and bitmap feature vector a 46.8% correct classification rate. So the summary SVM is 20%increment recognition rate.

Olivier Chapelle*et al.* [9] Proposed on introduced SVM using high dimensional histograms for image classification problems. Some major drawbacks of this representation are its large size and its lack of invariance with respect to translations. Feature extract by global and low level feature. The color histogram technique is a very simple and low-level method. For a color space, it works on the hue-saturation-value (HSV) space, which is in bisection with the red–green–blue (RGB) space. The Corel stock photo collection consists of a set of photographs. SVM kernels workwith two Corel tasks, namely Corel14 and Corel7. In the cases of the RBF kernels, the values were selected heuristically. RBF kernels reduce the Gaussian RBF error rate from around 30% down to 15–20%. It compares the kernel design with input remapping and show that non-Gaussian RBF kernels with exponential decay rates that are less than quadratic can lead to remarkable SVM. Error rates as low as 11% for the classification of 14 Corel categories and 16% for a more generic set of objects.

Le Hoang Thai *et al.* [10] in this paper work on image classification using SVM and ANN. The k-NN classifier, a conventional non-parametric, calculates the distance between the feature vector of the input image (unknown class image) and the feature vector of training image dataset**.**There are various types of features for image classification’s aim as follow: color and shape features, statistical features of pixels, and transform coefficient features. this paper is combining two areas are ANN and SVM applying for image classification after that it convert into novel combination model. This feature vector is the input of ANN for image classification based on a sub-space. In this paper, SVM and ANN are used to identify optimal weights.SVM need to be trained first, the parameter of SVM is adjusted to suitable for the training data in the specific problem.The training dataset contains 322 matrixes of images of Roman numerals. The average classification rate is 86%.

Xiaojun Wang *et al.* **[**11] proposed a different image denoising approach for snowing model which is stable and reliable over a wider range of noise distributions. Snowing model is iteratively smooth the various image noises while preserving the important image structures such as edges and lines.The LS-SVM works on Gaussian noise while the weighted LS-SVM works on the outliers and non-Gaussian noise. An adaptive weighted least squares support vector machine (LS-SVM) is proposed to realize the snowing model. To solve a nonlinear problem in the original space, the support vector machine (SVM) is applied to map the data into a higher dimensional space (possibly of infinite dimension) and the task is more tractable.In the natural snowing process, the snow deposits adaptively on the ground surface.It can obtain a robust estimate based upon the proposed LS-SVM solutions using an iteratively reweighting approach.The snowing approach performs relatively well in the presence of bipolar impulse noise (Type I).The Bi-Shrink approach is even in cases of high noise level.The RKHS method performs better than the snowing method in case of bipolar impulse noise (Type I) with high level noise.Compared with BM3D and RKHS, the snowing method provides similar performance in terms of PSNR and gives some better visually quality. This contra the high performance of the adaptive weighted LS-SVM applied in the proposed snowing method.

SubhransuMaji*et al.* [38] introduce novel features based on multi-level histograms of oriented edge energy and present experiments on various detection datasets.It present an algorithm for IKSVM classification with time complexity O(n logm) and space complexity O(mn). It used INRIA datasetan approximate IKSVM classifier based on these features has the current best performance, with a miss rate 13% lower at 10^{-6} False Positive Per Window than the linear SVM detector of Dalal&Triggs.

4. DYNAMIC TIME WARPING

In time series analysis, dynamic time warping (DTW) is an algorithm for measuring similarity between two temporal sequences which may contrast in time or speed. For example, similarities in walking patterns could be detected using DTW, even if one person was walking faster than the other, or if there were accelerations and decelerations during the course of an observation. DTW has been applied to temporal sequences of video, audio and graphics data — indeed, any data which can be turned into a linear sequence can be analyzed with DTW. In other words say DTW is a method that calculates an optimal match between two given sequences (e.g. time series) with certain restrictions. The sequences are “warped” on in the time dimension to determine a measure of their similarity independent of certain non-linear variations in the time dimension [12].

InanGüler*et al.*[13] based on different approaches of offline signature verification using optimal DTW algorithm. It is mainly deal with parametric approaches. It is used MCYT bimodal database and result perform by performance measure based on signature similarity is nearly 80.05%.

PiyushShanker*et al.* [14] based on Dynamic Time Warping Algorithm for signature verification system. The effectiveness of two types of pre-processing techniques was investigated – Maximum Length Vertical Projection method (MLVP) and Minimum Length Horizontal Projection method (MLHP).In the DTW algorithm to find an optimal match among two sequences of feature vectors and modified DTW algorithm for automated signature verification. Classification based on threshold. In the training phase, the thresholds on the dissimilarity measures for each of the signatures are computed. On threshold value is 1.88 to distinguish casual forgery and original sign about EER is 2% and skilled forgery detection accuracy is about 65%.

HemantaSaikia*et al.* [15] it a survey paper on various approaches and issues related to offline signature verification systems**.** Type of operations in Pre-processing, Feature Extraction and Classification depend on the signature pattern. Features extracted for off-line signature verification can be broadly divided into three main categories: Global, local and geometric features. The major approaches to off-line signature verification Systems for classification are the Template Matching approach, Statistical approach, Structural or Syntactic approach, Spectrum Analysis approach and Neural Networks approach. Signature verification occur some issues and also two major problems. Some general characteristics of genuine signatures and forgeries are: Enlargement of characters, Tendency of curves to become angles, retouching, retouching, hesitation, punctuation, differing pressure, sudden endings, etc. A human expert is able to identify skilled forgeries with an error rate of 1%.The major problem associated with signature verification is the availability of limited data.

Se-Hoon Kim et al. [16] based on Off-Line Verification System of the Handwrite Signature or Text, Using a Dynamic Programming. In which calculate the similarity of signatures. It works both charter and word. Statistical feature extract by using labelling algorithm of projection profile after apply DTW is to use a dynamic programming to calculate similarity, then analyse features by calculate mean and covariance matrix another feature analyse then the Mahalanobis distance it calculating similarity. It is give very better result as compare other.

Jayadevan R, et al. [17]based on DTW is used to segment the signature into a fixed number of components and computes a component-wise dissimilarity measure. It used static hand print signature using DTW. Statistical feature extract feature. DWT is used for matching similarity by calculate different cost. The total dissimilarity between the vectors is proposed as a product of the area and the different cost. This is based on dynamic programming. The matching between the two vectors is done and a path is found using a rectangular grid is open and close boundary. It is work on GPSD database. It calculates score of the database find FAR, FRR, EER and TER. It minimise TER of 44.07% of proposed work.

5. NEURAL NETWORK

In machine learning and related fields, artificial neural networks (ANNs) are computational models inspired by an animal's central nervous systems (in particular the brain) which is capable of machine learning as well as pattern recognition. Artificial neural networks are generally presented as systems of interconnected "neurons" which can compute values from inputs.

For example, a neural network for handwriting recognition is defined by a set of input neurons which may be activated by the pixels of an input image. After being weighted and transformed by a function (determined by the network's designer), the activations of these neurons are then passed on to other neurons. This process is repeated until finally, an output neuron is activated [18].

Ali Karouni*et al.* [19] Based on offline signature verification by a series of simple shape based geometric features recognition usingNeural Networks. It used geometrical feature based on the shape and dimensions such as area, centre of gravity, eccentricity, kurtosis and skewness.ANN trained and creates a given input/ target data training pattern. It is use 100 signature for test, and fixed threshold of 90% a FAR of 1.6% and a FRR of 3%. If it selects a high threshold variance then the FRR is reduced but at the same time the FAR also increases and vice-versa. It is achieved 93% in classification.

BenceKovari*et. al.* [20] it measure physiological features of a person using normal distribution N (μ_i σ_i^2) and calculateaccuracy of the system. It uses Baselines and Loops for verification process and also take fourteen shape descriptors for calculated during feature extraction process(perimeter, area, form factor, maximum diameter, maximum diameter angle, roundness, inscribed circle diameter, extent, compactness, bounding circle, moment axis angle, convexity, solidity, and aspect ratio) and it classification process used multiple feature properties (normal distribution of feature properties of original signatures, Distribution of feature properties in forged signatures, Notation, Separation of original and forged features properties , Single feature property, Multiple feature properties) with the help of different test therefore baseline use Shapiro-Wilk test and Lilliefors test, also loops use Shapiro-Wilk test and Lilliefors test . It is perform on low sample sizes.So if the first value of baselines were absent, the normality tests failed in 20% in the case of Shapiro-Wilk test and in 22% of the case in Lilliefors test. Visual inspection gives that 90% of the errors determine.

M.Taylan Das et al. [21] proposed SV tool box with a new algorithm for PSO-NN Application, feature extraction method used for distinctive feature of handwritten signature for new division technique then applied automatic apply statistical feature calculate, then apply PSO algorithm for the learning process and compare by traditional MDF with new MDF-CTLSF (centroid, tri-surface, length,six-fold-surface and best fit feature). It used GPDS database 44 sample, 20 for training, 4 for testing. Its compute verification rate for RBP is 88.64% with 1.16% error rate using a single NN. In second one is the RBF 88.77% verification rate and 1.22% error rate.

Meenu Bhatia*et al.*[22] Presents a method of off line handwritten signature verification using neural network approach. The method uses features extracted from pre-processed signature images. The extracted features are used to train a neural network using error back propagation training algorithm. The network could classify all genuine and forged signatures correctly. When the network was presented with signature samples from database different than the ones used in training phase, out of 600 such signatures (300 genuine and 300 forged) it could recognize 596 signatures correctly. Hence, the correct classification rate of the system is 98.66% in generalization. Our recognition system exhibited 100% success rate by identifying correctly all the signatures that it was trained for. However, it exhibited poor performance when it was presented with signatures that it was not trained for earlier.

Alan McCabe*et al***.** [33] presents a method for HSV by using NN architecture. Various static (e.g., height, slant, etc.) and dynamic (e.g., velocity, pen tip pressure, etc.) signature features are extracted and used to train the NN. Several Network topologies are tested and their accuracy is compared. The resulting system performs reasonably well with an overall error rate of 3.3% being reported for the best case.

MadasuHanmandlu*et al.* [34] proposed automatic off-line signature verification and forgery detection system based on fuzzy modelling. This system uses the Takagi–Sugeno (TS) model incorporated with structural parameters to take account of local variations in the characteristics of the signature. It is used synthetic database and tested on genuine, skilled signature, unskilled signature and random signatures.

6. PIXEL MATCHING TECHNIQUES

Pixel-based techniques it is detect statistical anomalies introduced at the pixel level. The basic idea of the pixel based data hitting method is to use pixel coordinate (x, y) and surrounded by a predefined locality set (x, y) such that f (x, y)=Sb, where f is the drawing out function and Sb, is the message digit in array notational structure to be covered.

For example, the two binary images, assuming that are same resolution and same orientation of object in the images, the most sensitive for similarity comparison between the images will be to do an exact pixel by pixel matching. It is like overlaying two shapes one on top of the other and seeing how many part of image fit into each other. The part of the image that is in excess is an indicator of how different the given image.

Indrajit Bhattacharya *et al.* [28] proposed an offline signature verification and recognition system by pixel matching technique. It is used statistical measure for feature extract and for verification uses SVM, ANN get result and compare PMT. The best result gives PMT as compare to both methods.

Abu Shamim Mohammad Arif*et al.* [35]proposed method based on peak and curve matching. It can perform peak detection, such as threshold peak detection and curve-fitting-based peak detection. False Acceptance Rate (FAR) and False Rejection Rate (FRR) are 1.38 % and 13.75% respectively.

Ashwin C S *et al.* [36] proposed offline signatures by taking a boundary of the entire signature and do the pixel comparison. Detection process is done after data acquisition and pre processing. It used synthetic database, the experimental result shows that 50% of accurate matching with the existing one from the database.

Deepak Tiwari*et al.* [37] proposed an intelligent neural network that work on the feature like pixel density method, directional method and mix both method together .and compared both the result and which of the best. For the proposed system the features which are extracted are the pixel density of the signature and the directional feature of the signature.

7. STATISTICAL METHODS

In offline signature verification play an important role of statistical methods. Statistical methods is used for probabilistic description and classification of (different parts of) the images and for their quality estimation. Statistical parametersuse characterizes the content of an image and its texture. Statistical method categorizes into three types such as first-order (one pixel), second-order (two pixels) and higher-order (three or more pixels) statistics. The first-order statistics calculate approximately properties (e.g. average and variance) of individual pixel values and ignoring the spatial interaction between image pixels, whereas second- order and higher order statistics calculate approximately properties of two or more pixel values going on at specific locations relative to each other. So, first order measures are statistics calculated from the original image values like variance, mean, standard deviation etc. and do not consider pixel neighbourhood relationships.

Histogram based approach is based on the intensity value concentrations on all or part of an image represented as a histogram. Common features include moments such as mean, variance, dispersion, mean square value or average energy, entropy, skewness and kurtosis. Images can also be represented with high-order statistical parameters computed from co-occurrence or run-length matrices or from frequential approaches [1].

Jing Wen*et.al.*[23]This paper based two models for rotation invariant structure feature to rectify theproblem: Mahalanobis Distance –based model and ring Hidden Markov Model (HMM). In this paper, it focuses on ring HMM model**.**It motivates to design the following RPF to deal with the rotation problem. The ring peripheral features (RPF) or transformation-ring-projection (TRP) are use feature extracted (global shape features based on the projection of the signature and local grid features), then sets the threshold decision for optimal results.The proposed methods were evaluated on a self-made signature database which consists of 1320 genuine signatures and 1320 skilled forgeries. These signatures gathered from 55 volunteers who contributed 24 signatures, 12 other persons were recruited for providing forgeries, and each person imitated two signatures for each of the 55 subjects after practice for a while. It compares self-made database with MCYT database for offline signature.

J.F. Vargas *et.al.*[24] In the paper focus on feature based on grey level information from images containing handwritten signature, especially for ink distribution along traces delineating the signature. Textural analysis methodology used for rotation and luminance invariance. This method executes on global image level and calculates the grey level variations in the image by the use of statistical texture features. Using histogram eliminates the power of different writing ink pens through the signers. Least squares support vector machines (LS-SVM) reformulations to standard SVMs, which lead to solving indefinite linear (KKT) systems. It is used MCYT and GPDS database for processing and it gave very good results; it is processed using grey level information that achieved EER is 16.27% and 12.82% in the performance. It is simple and low computational cost segmentation algorithm.

Rajesh Kumar*et. al.* [25] proposed based on the surroundedness property use for skilled forgery verification. It extractsthe feature information like connectivity among pixels, curvilinear nature of strokes and local density of black pixels that can adequately describe the signature .It is use four statistical measure. To measure surroundedness at a distance r, the circle of radius r is determined using Chebyshev distance which is a special case of Minkowski distance. The proposed feature is a special case of colour correlogram where only one colour (black) is considered. Some statistical features are: entropy, first order moment, second and third order moment for calculates frequency distribution. For analysis of feature selection techniques may be divided into two categories: Filter and Wrapper methods. It is compare performances of MLP with various feature selection techniques. Experiments are carried out on two databases, GPDS300 corpus and CEDAR. In this paper, always measure accuracy of the proposed system at equal error rate (EER), which is nothing but (100-EER). For CEDAR and GPDS300 databases, to get accuracy of ERR are 91.67 % and 86.24 % respectively.

Kai Huang*et al*. [26] based on the combine the static image pixel features and pseudo-dynamic structural feature. It introduced directional frontier feature of a signature image is transformed from pixels into a set of stroke like DF-curve. It is used two models: Pixel feature based signature model and Structural feature model. The structural distance metric is formulated to organize whenever an input signature image consider as the genuine samples. The functional distances between related strokes are computed in the detailed verification with the aid of B-spline curves. It consist 8904 signature images. These images train neural network for the verification process. Approximately 20% of the total input signatures are examined by the structural matching algorithm for original is FAR is 84.9%, FRR is 2.2% and forgery FAR is 3.6%, FRR is 76.6%. In the second classification, it can show accept rate for genuine signature is 68.8% and 23.2% for forgery while it can show reject rate for genuine is 31.2% and 76.8% for forgery. In the combined classifier, it can show accept rate for genuine signature is 93.7% and 8.2% for forgery while it can show reject rate for genuine is 6.3% and 91.8% for forgery.

Bai ling Zhang *et al*. [39] introduces a simple and efficient approach called Kernel Principal Component Self-regression (KPCSR) that can be applied to off-line signature recognition and verification. The technique is based on first performing Kernel Principal Component Analysis (KPCA) in the kernel space and then applying self-regression from the extracted features (kernel principal components). Using a benchmarking signature database gpds, experimental results have supported the effectiveness of the proposed model. And the performance of KPCSR based signature recognition scheme has also been substantiated by experiments.

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AUTHOR

Mohan Dhurveyreceived the B.E. degree in Computer Science Engineering from Jiwaji University in 2000, respectively. During 2000 to 2008, he stayed in software at MEK INFO Hyderabad, Training Officer at ITI Jobat M.P. and Lecture in Dr.BRA Polytechnic college Gwalior M.P