Signature Verification Techniques: State of Art Survey

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ABSTRACT

Like unique DNA, each person has unique and distinct signature that is being mainly legitimated for purposes such as personal identification and verification of certain documents or legal transactions. In recently, the signatures are being forged for the wrong intent. For the same as of now many techniques have been proposed for the detection/verification of signature forgery. But these signature verifications are inefficient and time consuming for a large number of documents. This paper attempted to present the various approaches that have been proposed yet for signature verification.

Keywords: Signatures, Genuine, Forgery, False Acceptance, Equal Error Rate

1. INTRODUCTION

Our central nervous system coordinates the movements of the hand, fingers, wrist etc makes use of hands bones and muscles while writing or signing. And hence, the handwritten signatures are the products of such complex systems. Signatures contain certain personal traits and thus make it unique. Being unique, signatures are hard to imitate.

Signature has its history since year 1792. Over the years, signature has significance in personal identification and verification of certain documents or legal transactions. But malpractices have led to signature forgeries for wrong intent. For such a scenario first time testimony of signature by experts over a dispute had been asked by a British court. Thus, malpractices in forging signatures have led to signature verification systems which plays important role in identification of signs whether genuine or forgery. We might have signs online, offline or hybrid and hence depending on them different modes of verification are evolved [1].

2. MODES OF SIGNATURE VERIFICATION OPERATION

Quantum of information available leads to accuracy of signature verification; perhaps online systems have resulted in accuracies of signature verifications. Depending on the information available, the system modes are divided into three categories listed below.

a) **Online**: Information is captured run time for example when a person writes using a stylus and tablet, digitizer pen, or touch screens which may produce info through local pressure, acceleration, speed, number of strokes, and order of strokes.

b) **Offline**: In Banks this method can be seen where a cheque is scanned for the signature verification which is static in nature; and depending on the various extraction parameters the signature is verified.

c) **Hybrid**: Instances where both online and offline various parameters are tested for the signature verification [1].

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3. OFFLINE SIGNATURE VERIFICATION METHODOLOGY

The offline signature verification system consists of four stages and the overview of the process as shown below:

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Data Acquisition
  ↓
Preprocessing
  ↓
Feature Extraction
  ↓
Enrollment & Verification
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A. **Data acquisition**: Data (signature) acquired is image means it is available in digital format.

B. **Preprocessing**: After a process of normalization, alignment, thinning and the background noise is elimination a signature template is generated for feature extraction.

C. **Feature Extraction**: Extraction of signature attributes to yield details in the form of an observation data. Any feature can be quantifiable quantity. There are two types of feature classification:
   - **Global Features**: it represents the image as whole. This is less sensitive to some variations and noises so this can used for unskilled forgeries. This is not suitable for high skilled forgeries.
   - **Local Features**: it represents the minutest parts of the image, and it derives the information in detail. This very accurate as compared to global features.

D. **Enrollment and verification**: The extracted information is stored in the knowledge database.

There are various factors to be considered, like the signature attributes change with the person’s mental state. The different features in the training set calculate the decisions threshold. The selection of threshold depends on the application.

3.1. Performance Measures

There must be a performance benchmark of signature detection system to differentiate between the real and the forged signature. There are certain evaluation metrics using which performance is measured. The metrics are False Rejection Rate (FRR), False Acceptance Rate (FAR) and Equal Error Rate (ERR). Theses metrics are evaluated on different systems to get the best system, which can accurately detect the difference between a fake and a real signature. False Error Rate (FRR) is the ratio of original signatures rejected and False Acceptance Rate (FAR) is the ration of fake signatures accepted. FRR is inversely proportional to FAR the means FRR to decrease with increase of FAR [2].

4. METHODS FOR OFFLINE SIGNATURE VERIFICATION

There are plenty of signature verification methods available. They categorized mainly into Template matching (For example, Euclidean Distance, Dynamic Time Warping (DTW), Displacement functions etc.), Statistical (For example, Measures wise-Mahalonobis–distance, Distance Statistics, Membership Functions etc., Neural Networks wise-Multi-Layer Perceptrons (MLP), Feed forwards nets, ARTMAP etc. and Hidden Markov Model wise-Left to right, Ergodic, Ringetc.), Structural (For example, String/ Graph/ Tree Matching, Structural Description Graph Analysis (SDG) etc.)

There are many traditional methods used for offline verification of a signature. The optimized and mostly convenient methods are discussed below.
1. *Zahoor Jan et al. (2015)* proposed a method uses Delaunay Triangulation. End focuses and crossing point focuses are effortlessly separated from which Delaunay triangulation is resolved. After Delaunay triangulation is built then range, relative zone, aggregate number of triangles and distinctive points of triangle is ascertained. From that element vectors are ascertained for every signature and after that by Euclidean separation equation the resultant qualities are coordinated [2].

2. *K S Radhika et al. (2015)* proposed a combine online and logged off signature confirmation method. Online information gathered is the signature procedure caught utilizing a webcam and logged off information gathered are examined signatures. At first both information experiences suitable preprocess steps. At that point highlight extraction is done where elements in view of pen tip following are utilized as a part of instance of online and angle and projection-based components are utilized as a part of instance of offline technique. Later the online and offline system confirms the signature independently lastly their outcomes are consolidated and the signature is checked utilizing SVM [3].

3. *Galbally et al. (2015)* proposed On-line signature acknowledgment through the blend of genuine element information and artificially produced static information. This technique produces engineered static examples from online signatures which intertwines both sorts of information, genuine online and manufactured logged off, keeping in mind the end goal to enhance the execution of online check calculations [4].

4. *Cesar Castanon et al. (2014)* proposed complex system which can be considered among the zones of diagram hypothesis and measurable mechanics. They are suitable for shape acknowledgment because of their properties as invariance to revolution, scale, thickness and commotion. Genuine rate of 85.12% for recognizable proof and 76.11% for confirmation is reported [5].

5. *Nisha Sharma et al. (2014)* proposed a Fuzzy min-max calculation to arrange the signature example and this fluffy min-max calculation absolutely fit to the neural system structure. The neural system center layer work as fuzzified neuron and in light of this the yield can be accurately ordered yet blunder rate rely upon extension coefficients. AER is achieved up to 92% [6].

6. *The-Anh Pham et al. (2014)* proposed a method in which a combination of nearby force based element and worldwide geometry-based element has been demonstrated that they are great components for signature check. The signature incorporating so as to coordinate step has accomplished powerful results the self wrapping highlight to the 2D coordinating step and the utilization of RANSAC to refine the matches [7].

7. *Karrar Neamah et al. (2014)* proposed Discriminative Features Mining for Offline Handwritten Signature Verification. Signature confirmation is a dynamic exploration territory in the field of example acknowledgment. It is utilized to distinguish the specific individual with the assistance of his/her signature’s attributes, for example, pen weight, circles shape, rate of recording and up movement of pen, composing pace, pen weight, state of circles, and so forth keeping in mind the end goal to recognize that individual. Be that as it may, in the whole process, highlights extraction and determination stage is of prime significance. Since a few signatures have comparable strokes, qualities and sizes [8].

8. *Abdi et al. (2014)* proposed a method, for Arabic writing, utilizes the beta-elliptic model to create an engineered grapheme codebook. Results of engineered codebooks performed well in both their crude and diminished size structures. The best distinguishing proof rates were 90.02% for main 1 and 96.35% for main 5, and the best confirmation EER reported 2.1% [9].

9. *Lei Sun et al. (2014)* proposed a method for content recognition from regular scene pictures uses upgraded differentiating extremal area and neural systems to take care of the troublesome issue of programmed content location from characteristic scene pictures [10].
10. *Geetha Ganapathi et al. (2014)* proposed a Fuzzy Hybrid Framework for Offline Signature Verification. Separating gifted imitations from certifiable is an exceptionally troublesome undertaking. This method got an exactness of 88.95%. FRBS based differentiation Intensification and upgrade enhances the exactness to 92.85% and FRFS further improves the precision to 93.99%. With the framework being identified with gifted imitations, it can be reasoned that the fluffy based system forecasts well in unverifiable and vague circumstances as far as exactness and time. Less number of elements makes the framework less computationally extraordinary and this variable is more suitable for ongoing frameworks [11].

11. *Suvarna Joshi et al. (2013)* proposed a method for feature extraction using Discrete Wavelet Transform. It lives up to expectations at worldwide level for extraction of separate signature elements utilizing wavelet change. Wavelet change has been utilized to concentrate highlights from preprocessed signature pictures. Hamming separation has been utilized to figure out separation between test signature example and preparing signature design. Acknowledgment achievement rate for honest to goodness signatures is 95%. FAR of proposed calculation speaks the truth 0.22 [12].

12. *Indrajit Bhattacharya et al. (2013)* proposed a method utilizing pixel coordinating procedure. Signature confirmation machine is executed to give a basic, sheltered, quick biometric behavioral security framework. By utilizing a few mathematical statements from co-ordinate geometry makes this system quicker than different strategies. The shading coordinating method makes it more secure. The Interface of this application is exceptionally basic which makes it easy to use and simple [13].

13. *Srikanta Pal et al. (2013)* proposed a method in which diverse components like inclination highlight, water repository highlight, circle highlight, angle proportion etc was utilized, and Support Vector Machines were as a classifier. Capacity to decrease normal blunder rate 4.81% is reported more when script distinguishing proof system is utilized [14].

14. *Sabri Mahmoud et al. (2013)* proposed an Arabic offline written by hand content database. The structures were filtered at 200, 300, and 600 dpi resolutions. A formal confirmation method is actualized to adjust the written by hand content to its ground truth at the structure, section and line levels. The checked ground truth database contains metadata portraying the composed content at the page, passage, and line levels in content and XML positions. Classifiers such as Concealed Signature Models (HMM) and new syntactic classifier were used [15].

15. *Marianela Parodi et al. (2013)* proposed Legendre polynomials based component extraction for online signature confirmation. In this method, highlight blends connected with the most usually utilized time capacities identified with the signature procedure are broke down, keeping in mind the end goal to give some knowledge on their real discriminative force for online signature confirmation. Two cutting edge classifiers, in particular, Support Vector Machines and Random Forests are utilized as a part of the confirmation tests [16].

16. *Rajesh. Bawa et al. [2013].* In this technique, characteristic scene pictures are divided for content in light of edge examination and morphological administrators. The pictures are changed over to dim scale and Canny edges are recognized. The edge picture is morphologically widened and broke down to evacuate edges comparing to non-text regions. At that point, the picture is binarized utilizing the mean and standard deviation estimations of edge pixels. The subsequent picture is post-prepared to fill the crevices and smoothen the content strokes [17].

17. *G. Pirlo et al. (2013)* proposed a method based on optical stream. Neighborhood strength in static signatures was broke down by optical stream examination. Moreover, the signature check execution accomplished with this methodology was found to yield results like those of the best methodologies in the writing [18].
18. *Eskander et al.* (2013) proposed Fuzzy Vault framework. A boosting highlight choice method is proposed for selecting a reduced and discriminant client particular element representation from countless extractions. Exactness of around 97% is reported [19].

19. *Shrikant Pal et al.* (2012) proposed a method uses Gabor filter based features. Support Vector Machine is processed as a classifier. AER of 97.05% is reported [20].

20. *Srikanta Pal et al.* (2012) proposed method for Hindi signatures. Support Vector Machine, gradient and Zernike moment features are considered for the signature verification. Accuracy of 7.42% FRR and 4.28% FAR is reported [21].

21. *K. Tselios et al.* (2012) proposed a feature extraction method which extracts features of signature image such as strokes, lines and arcs after many image partitioning. SVM and RBF are used as a classifier [22].

22. *Miguel Ferrer et al.* (2012) proposed a method based on gray level features which gauges dark level components power when it is bended by an intricate foundation furthermore to propose more steady elements [23].

23. *Marianela Parodi et al.* (2011) proposed a method considers roundabout matrix extraction. Graphometric highlights for the roundabout framework are characterized by adjusting comparative elements accessible for rectangular networks, and the property of revolution invariance of the Discrete Fourier Transform (DFT) is utilized as a part of request to accomplish power against pivot. Bolster Vector Machine (SVM) based classifier plan is utilized for arrangement errands. This confirmation framework has an execution equivalent to comparable condition of-craftsmanship signature check frameworks with the extra point of interest of being strong against pivot of the signatures [24].

24. *Luana Batista et al.* (2011) proposed methods to be specific OP-UNION and OP-ELIMINATE, both in light of the K-closest prophets. Tests performed by utilizing certifiable SV information, included real examples, and arbitrary, straightforward and talented frauds, show that the proposed techniques accomplish a fundamentally more elevated amount of execution [25].

25. *Minal Tomar et al.* (2011) proposed an intelligent network using Chain Code method. The proposed Chain-Code strategy is difficult to actualize and in addition gives acceptable execution for constrained preparing test moreover [26].

26. *PM Mhatre et al.* [2011] proposed strategy depends on offline check of mark by two unique calculations. Before extricating distinctive components from the signature, some preprocessing of the sign is finished. In preprocessing, the sign is shading standardized and scaled into a standard configuration. The primary calculation depends on discrete cosine change and it mulls over all the Discrete Cosine Transform (DCT) coefficients while discovering match between test sign and sign put away in the database. The second calculation is enhanced adaptation of the first calculation; it considers just noteworthy DCT coefficients while coordinating. Both the calculations use Euclidean separation classifier for contrasting test sign and database. The calculations have demonstrated promising results while managing random forgeries; likewise it gives great acknowledgment rates [27].

27. *Luana Batista et al.* (2010) proposed a two-classifier framework; first, an arrangement of delegate HMMs prepared with diverse number of states – was utilized to create comparability measures to shape new element vectors. And second, these vectors were info to one or more SVMs keeping in mind the end goal to give the last grouping [28].

by the individuals who might pretend the recognizable proof or aim of a person. This utilizes an arrangement of straightforward shape based geometric elements such as Area, Center of gravity, Eccentricity, Kurtosis and Skewness. At that point fake neural system classifier was utilized to confirm and group the signatures: correct or manufactured, and an arrangement proportion of around 93% was gotten under a limit of 90% [29].

29. D K Bhole et al. (2010) proposed method which uses Graph Matching and Cross Validation Approach. In this the signatures are compared using graph matching. In order to measure the dissimilarity between them, Euclidean distance is calculated. This scheme forms the CGMOSV algorithm. Signature database selection is done by cross validation approach [30].

30. Vu Nguyen et al. (2009) proposed a method which uses MDF and SVM produced result of AER 17.25%. The random forgeries of the False Acceptance Rate (FAR) were also kept as low as 0.08% [31].

31. Danjun Pu et al. (2009) proposed A Machine Learning Approach to Off-Line Signature Verification Using Bayesian Inference. We make a 3-stride, essayist free approach: 1) Determine the earlier parameter dispersions for method for both “honest to goodness versus authentic” and “fabrication versus known” classes utilizing a separation metric. 2) Enroll authentic and falsification signatures for a specific essayist and ascertain both the back class probabilities for both classes. 3) When assessing an addressed signature, focus the probabilities for every class and pick the class with greater likelihood. By utilizing this methodology, execution over different ways to deal with the same issue is drastically enhanced, particularly when the quantity of accessible signatures for enlistment is little [32].

32. Tal Steinherz et al. (2009) proposed a method based on loop modeling and contour analysis. Various loop resolution scenarios, including axial loop understanding and collapsed loop recovery have been considered which shows excellent results [33].

33. B. Schafer et al. (2009) proposed a method based on combination of features. The features taken are aspect ratio, centroid features, 4 surface features, 6 surface features, number of edge points, transition features, etc. AER 84.10% is reported [34].

34. C. R. Prashanth et al. (2009) proposed a method based on Standard Scores Correlation. In the system 2 features are extracted. They are: feature points from vertical splitting and horizontal splitting. The signature image is divided into 2 parts, left and right, by splitting the image with a vertical line passing through its geometric center. Now the horizontal line is used to split the image into top and bottom parts by passing it through the image’s geometric center [35].

35. Abdelkarim Elbaati et al. (2009) proposed a method in which reiteration of a fragment will be concentrated on in an optional calculation with the goal not to hamper GA operations. The methods utilized as a part of GA are the choice, hybrid and the change. The wellness capacity worth relies on upon right-left bearing (Arabic composing), the fragments reiteration and rakish deviation on the impediment’s intersection stroke [36].

36. Ramachandra A. C. et al. [2009] proposed a authentication method uses Cross-validated Graph Matching algorithm. Some of the measures for calculating the similarity between two signatures are: constructing a bipartite graph, obtaining complete matching in graph and calculating Euclidean distance by Hungarian method [37].

37. Cheng-Lin Liu (2008) et al. proposed method named Class-specific feature polynomial classifier (CFPC), is a type of polynomial classifier which gives high classification accuracy in spaces of high dimensional feature. But the disadvantage is having high computational cost [38].
38. *Sargur Srihari et al. (2008)* proposed a method based on Bayesian Approach. This method validates signatures genuinity by utilizing a non-parametric Bayesian approach. The methodology yields enhanced execution over other non-parametric non-Bayesian approaches [39].

39. *Miyoshi T. et al. (2008)* proposed the Simplified polynomial network (SPN) classifier. It was quite successful in reducing the complexity of polynomial network but degraded a little of classification accuracy. With the help of certain experiments, it was found that SPN works better than CFPC [40].

40. *Jing Wen et al. (2007)* proposed Rotation Invariant Approach. Turn issue is one of the real challenges to recognize signature designs in logged off talented signature confirmation which is handled using Ring-Peripheral components. On a fundamental level, Ring-Peripheral elements have the capacity to depict inside and outside structure of signatures with distinctive stage shift [41].

41. *Javier Galbally et al. (2007)* proposed a feature selection using Genetic Algorithm with binary coding, to find a suboptimal subset of features that reduces the verification error rate of the system [42].

42. *Umapada Pal et al. [2007]* used the Modified Quadratic Discriminant Function (MQDF) to recognize Bangla handwritten characters based on the directional information obtained from the arc tangent of the gradient [43].

43. *Julian Fierrez et al. (2007)* proposed an On-Line signature verification method takes fusion of local and global Information. Classifier Hidden Markov Model is used [44].

44. *Shih-Yin Ooi et al. (2007)* proposed a method based on concept of writer signs which has similarity among signature samples, with small distortion and scale variability. Following the experimentation, EER of 1.1% on database of random forgery is obtained while casual forgery on EER 1.2% and skilled forgery on EER 2.1% [45].

45. *Umapada Pal et al. (2006)* proposed a method for South Indian scripts in which a quadratic classifier is used. For highlight calculation, the jumping box of a character is fragmented into pieces, and the directional elements are figured in every square. These pieces are then down-tested by a Gaussian channel, and the components acquired from the down-inspected squares are encouraged to an adjusted quadratic classifier for acknowledgment. Precision acknowledgment from 90.34% to 96.73% is reported [46].

46. *Vladimir Pervouchine et al. (2006)* proposed a method extracts features from vector skeletons of Grapheme which are separated by a uniquely created skeletonisation calculation. A helpful neural system was utilized as a classifier and a hereditary calculation was utilized to hunt down ideal capabilities. Results demonstrated that utilization of the vector skeletonisation permits both extraction of more auxiliary components and change the element extraction exactness 94% [47].

47. *Armand et al. (2006)* developed a system uses Modified Direction Feature such as Direction Feature (DF) and Transition Feature (TF). In DF, replacing foreground pixels by their direction values does the extraction of direction features. By using the TF technique, locations of transitions are recorded having values between 0 and 1 in a binary image. Two Neural Network classifiers are utilized to order the signatures. A database totaling 2106 marks is utilized and the most noteworthy precision got was 91.12% [48].

48. *Banshider Majhi et al. (2006)* proposed system utilizes geometric community for highlight extraction. For order Euclidean separation model is utilized. Threshold choice depends on like normal and standard deviation. FAR of 16 % for gifted imitations and FRR of 14 % is acquired [49].

49. *Buddhika Jayasekara et al. (2006)* proposed a fluffy rationale and hereditary calculation approaches. It comprises of two stages; the fluffy induction framework preparing utilizing Genetic Approach
(GA) and the signature acknowledgment. Signature acknowledgment rate of around 90% was gotten and took care of the arbitrary imitations with 77% precision and gifted frauds with 70% exactness however the framework execution profoundly relies on upon the fluffy surmising framework capacities and in this way depends on the fluffy principle base [50].

50. Miguel Ferrer et al. (2005) proposed a method which uses signature envelope and the interior stroke distribution in polar and Cartesian coordinates. Classifiers such as Hidden Markov models, Support Vector machines, and Euclidean distance have been tested and calculated using 16 bits fixed-point arithmetic [51].

51. E. Ozgunduz et al. (2005) The features extracted to represent the signatures are global geometric features, direction features and grid features. Experiments were conducted to compare SVM and Advanced Neural Network (ANN). An FRR of 0.02% and an FAR of 0.11% are obtained by combining SVM with Radial Basis Function (RBF). ANN gave an FRR of 0.22% and an FAR of 0.16% [52].

52. Abdelkarim EL Baati et al. (2005) proposed Recovery of Temporal Information from logged off Arabic Handwritten. A scope of a window grants to distinguish intersection and spreading of strokes and a suitable calculation licenses to take care of the fleeting’s issue request in these equivocal zones. At last, another calculation grants to recognize the beginning stage of the following and to take after the following so as to reconstitute the request in which it has been composed. The speculative of evaluation demonstrates that an awful recognition of the beginning stage or equivocal zone translation acted specifically on exhibitions of the framework. Hence the procedure’s change of location of the beginning stage and additionally this of the uncertain zone understanding expands the framework’s exhibitions that can reach 100% [53].

53. Emli-Mari Nel et al. (2005) proposed Pen Trajectories of static signatures uses Hidden Markov Models. Dynamic version of the static image is available, that is mostly obtained during a registration process done earlier. Then derive the hidden Markov model from the static image to match it to the dynamic part of the image resulting in the estimated pen trajectory of the static image [54].

54. Fang et al. (2003) proposed two methods which recognize skilled forgeries.

Fang’s first method calculates one dimensional projection profiles for each signature in both the horizontal and vertical plains to optimally match with reference signature database using dynamic time warping technique.

Fang’s second method matches the each signature stroke segments of a two-dimensional to optimally match with reference signature database using elastic matching algorithm [55].

55. C. Quek et al. (2002) proposed a system which mainly detects random forgeries. Signature features such as global baseline features, pressure features and slant features were experimented. This experiment obtained EERs 22.4% [56].

56. Y. Mizukami et al. (2002) proposed displacement extraction method. In this method, the sum of the squared Euclidean distance between two signatures is extracted for a signature. A database with 20 writers is used with 10 genuine signatures and 10 skilled forgeries per writer. An AER of 24.9% is obtained [57].

57. Balazs Kegl et al. (2002) proposed Piecewise Linear Skeletonization Using Principal Curves which calculates to discover piecewise direct skeletons of transcribed characters by utilizing chief bends. The system’s advancement was propelled by the clear closeness between the meaning of foremost bends and the average hub. The focal fitting-and-smoothing venture of the calculation is an expansion of the polygonal line calculation which approximates essential bends of information sets by piecewise
straight bends. The polygonal line calculation is reached out to discover main diagrams and supplemented with two stages particular to the errand of skeletonization: an instatement system to catch the rough topology of the character, and a gathering of rebuilding operations to enhance the auxiliary nature of the skeleton delivered by the introduction strategy. The outcomes show that the proposed calculation discovers a smooth average pivot of the colossal dominant part of a wide mixture of character layouts and considerably enhances the pixel savvy skeleton got by customary diminishing techniques [58].

58. F. R. Rahman et al. [2002] had proposed a method to verify handwritten Bengali characters. Matra, upper part, disjoint sections, vertical line and double vertical line are the features were extracted [59].

59. J. K. Guo et al. (2002) proposed establishing a local correspondence between the model and test signature method. The test signature is divided into consecutive stroke segment and is compared with the stroke segment of the model. The sets of geometric properties of sub strokes are compared to determine the cost of the match. The least invariant features of the least invariant sub-strokes are given the largest weights, thus emphasizing features that are highly writer dependent. The information which is writer dependent embedded at sub-stroke level and the unballistic motion and tremor information in each stroke segment is examined by using the local correspondence between the model and a test signature. Here the matching is done through DTW. The same genuine signatures that are used for training are also used for testing obtained when only skilled forgeries are considered an FRR of 6% and an FAR of 11.5% is obtained and when only casual forgeries are considered an FRR of 2% and an FAR of 3.3% is obtained [60].

60. Xiao et al. (2002) investigate the feasibility of using a modified Bayesian network for off-line signature verification. For each signature, top and bottom profiles are calculated. It is assumed that the signature strokes are represented by black pixels. The top profile is calculated as follows: a minimum rectangular bounding box, which embraces the signature image, is used to define the signature area. This box is then scanned vertically line by line, from top to bottom and from left to right until a black pixel is encountered. The scan line (up to the encountered black pixel) is then filled with black pixels. The bottom profile is obtained in a similar way. The length from the beginning of the scan line to the encountered black pixel is called the run length of the profile at that point. These profiles are then subdivided into smaller components at the positions where the run lengths of two adjacent points change significantly. For each component certain attributes are extracted. These attributes include the length of the component, the run length of each scan line in the component, etc. They use a small database that consists of the signatures of eight writers. Between 10 and 20 signatures are collected for each writer and 60% of these signatures are used for training. An FRR of 20% and an FAR of 14% are reported. Although the test set contains some skilled forgeries, this paper is not clear on the quality of the other forgeries [61].

61. J.A. Sanchez et al. (2001) proposed a feature extraction method uses both global (Polar coordinates) and local features (points located inside the envelope). Hidden Markov Model classifier is processed. AER 95.15% is reported [62].

62. Baltzakis et al. (2001) proposed a system which mainly detects random forgeries. It used neural network approach and this applied on global features, grid features and texture features of each signature. The database contained 500 genuine test signatures and 57 000 random forgeries. An average False Rejection Ration (FRR) and FAR of 3% and 9.8% respectively was reported [63].

63. Edson Justino et al. (2001) proposed method in which a signature image is divided into cells using a grid segmentation method in order to extract features such as pixel density, pixel distribution and axial slant. Using 100 writer signature profiles, FRR of 2.83% and False Accept Ratio (FAR) of 1.44%, 2.50% and 22.67% are obtained for random, casual and skilled forgeries respectively [64].
64. Edson Justino et al. (2000) proposed a system utilizes Hough transform change to find strokes of lines of a sign. The Hough change is utilized to extract the parameterized Hough space from signature as extraordinary trade signature highlight of signatures. Back Propagation Neural Network is utilized as an instrument to inexact the execution. The framework has demonstrated acknowledgment rate of 95.24% [65].

65. M. A. Ismail et al. (2000) explored the use of fuzzy concepts for the verification of Arabic signatures. They used local features to form a primary feature set, including central line features, corner line features, central circle features, corner curve features and critical point features. They used a data set that contained the signatures of 22 writers, from each writer 6 training signatures, 4 genuine signatures and 5 skilled forgeries were taken. An average of 98% overall verification confidence was achieved [66].

66. El-Yacoubi et al. (2000) proposed a system which mainly detects random forgeries using Hidden Markov Model (HMM) and cross validation principle. In this, a signature image is divided into local square cells by superimposing a grid over it. For each of these cells, pixel density is calculated, which represents local feature of each cell. A feature vector contains a column of cells and thus such feature vectors represent each signature image. A system is built to which a training set of a particular writer’s signature is fed. The cross-validation principle uses a subset of this training set for validation purposes. The other writers’ training sets are used for detecting imposter signatures as this system only tries to detect random forgeries. Using database of 40 writers signature and 60 writers signature, twice the experiment is performed which produced AERs of 0.46% and 0.91% respectively [67].

67. M. A. Ismail et al. (2000) A database is taken and 2400 signature images are stored in it. Chain code feature extraction is utilized to speak to a limit by an associated arrangement of straight-line sections of indicated length and heading. 7 distinct sorts of separation measure were utilized taking into account feature vectors got from Eigen-marks. The most astounding precision of 96.2% is gotten with the Manhattan separation measure [68].

68. Yoshiharu Kato et al. (2000) proposed Recovery of Drawing Order from Single-Stroke Handwriting Images. The issue is an augmentation of the unicursal figure issue and permits a script to incorporate two fold-followed lines. The technique depends on chart traversal and comprises of two stages. In the first stage, investigate the chart built from the skeletal picture and name the diagram by deciding the sort of every edge. In the second stage, follow the chart from the begin vertex to the end vertex by alluding to the naming data. There is no compelling reason to ascertain the neighborhood or worldwide smoothness of the arch aside from the extraordinary recognition twofold followed lines [69].

69. Kaewkongka et al. (1999) proposed method that uses the Hough transform to extract the feature/parameterized Hough space of a signature. The performance of the system is tested using back propagation Neural Network. A set of 70 signatures from different writers were considered which yielded AER 95.24% [70].

70. P. S. Deng et al. (1999) proposed a system that uses Closed Contour tracing algorithm where the signature edges are represented using many closed contours. Closed contours of signature curvature information are decomposed using wavelet transformations into multiresolution signal. Zero-crossings of the curvature data is used as a feature for matching. A statistical measurement is used to determine which closed contour and its frequency data is most stable and discriminating. To control accuracy of the feature extraction process the optimal threshold value is calculated. DTW is used for matching. The experiments are conducted on two sets independently. The first has all the English signatures and the second set has all the Chinese signatures. For each experiment 25 writers
are used with 10 skilled forgeries, 10 casual forgeries, 10 training test signatures and 10 genuine test signatures. FRR of 5.6% and FARs of 21.2% (skilled forgeries) and 0% (casual forgeries) for the English data set is reported and for the Chinese data set an FRR of 6.0% and FARs of 13.5% (skilled forgeries) and 0% (casual forgeries) is reported [71].

71. *G. Rigoll et al. (1998)* proposed a method which considers an angle between 2 strokes of consecutive sample points of a signature (Offline) & sliding bitmap (online) is used and then difference between maximum and minimum coordinates is calculated. 99.0% and 98.10% accuracy is reported for the on-line and off-line verification systems respectively [72].

72. *L. C. Bastos et al. (1997)* developed a structural approach for detecting random forgeries. The writing trace of each signature was subdivided into conic sections, like straight lines, ellipses and hyperbolae. They used a database of 120 signatures from six writers that is twenty signatures per writer. Similarly indices that vary between 86.3% and 97.3% were reported for the individual writers [73].

73. *Oliveira et al. (1997)* This system uses Receiver Operating Characteristic curves. The classifier that is used is Support Vector Machine (SVM) and they got recognition rate of 91.80% [74].

74. *M. Yoshimura et al. (1997)* proposed the projection of frequency of the black pixels on the X-axis they apply Dynamic Time Warping for Japanese signature verification. Here the average ERR is approximately 12.9% [75].

75. *Robert McLaughlin et al. (1996)* proposed Randomized Hough Transform: better Ellipses Detection. Standard techniques for oval location are moderate and memory escalated; exhibited on both engineered pictures and straightforward certifiable pictures. It is observed to be quick, memory efficient and precise with pictures containing numerous ovals and clamor [76].

76. *Nouboud et al. (1994)* they use Dynamic Time Warping to compare the curve. The curve is obtained from the signature’s envelope [77].

77. Robert Sabourin from 1993 to 1997:

The first system (Sabourin, Cheriet, and Genest (1993)) used an extended-shadow-code representation method. Two experiments, that use a k nearest neighbor’s classifier and a minimum distance classifier respectively, are conducted on the above-mentioned database. When 10 training signatures are used for each writer, an Average Error Rate (AER) of 0.77% is obtained [78].

The second system (Sabourin, Drouhard, and Wah (1997)) used a shape matrix representation and a minimum distance classifier. A best AER of 0.84% is reported [79].

The third system (Sabourin, Genest, and Preteux (1997)) used distributions of local shape descriptors to characterize the amount of signal activity exciting each retina on the focus of superimposed grid. The system then used a nearest neighbor and threshold based classifier. AERs achieved are 0.02% and 1.0% for classifiers respectively [80].

78. *Cardot et al. (1994)* used a global approach to eliminate random forgeries. They used the envelope and geometric parameters (mean stroke direction, moments of inertia and scale) of a signature. Their database consisted of 6000 signatures. An FRR of 5% and an FAR of 2% were achieved [81].

79. *Shapiro et al. (1993)* they use Dynamic Time Warping and compare the projections of image at different angles. On this basis the signature can be recouped from the projections [82].

80. *Sabourin et al. (1992)* use a Neural Network, with the PDF of the stroke directions serving as a global characteristics vector. Their database consisted of 800 signatures from 20 writers and other writers genuine signatures were treated as random forgeries. An FRR of 1.75% and an FAR of 9% were achieved [83].
81. Wilkinson et al. (1990) used Dynamic Time Warping for the detection of casual forgeries. Assuming that the slant angle, the curvature and the total length is same among different samples of signature. Each signature is represented by a histogram. They use a database of 500 genuine signatures and 306 casual forgeries from nine individuals, and sampled them over a period of 18 months. Then the authors reported the ERR of approximately 7% [84].

82. Mighell et al. (1989) used a neural network that uses back proportion for learning and to detect random forgeries. They used a training set consisting of 10 genuine signatures and 10 forgeries and a test set that consists of 70 genuine signatures and 56 forgeries. The genuine signature belonged to the same user and Equal Error Ratio of 2% is reported [85].

5. DISCUSSION/CONCLUSION

Each person is uniquely identified by his/her handwritten signature. It’s been very long now; signatures have become legal and widely accepted in the systems. But recently, the signatures are being forged for the wrong intent and this has sprunged up offline/online signature verification methods. Research is being carried out on the signatures as well as the regional languages. The domain of signature verification is now not limited for teaching faculty but has become commercially important especially in Bank CTS (Cheque Truncation System). This paper attempted to present the various approaches that have been proposed yet for signature verification.

REFERENCES


[8] Karrar Neamah Dzulkifli Mohamad Tanzila Saba and Amjad Rehman: Discriminative Features Mining for Offline Handwritten Signature Verification, Published in Journal 3D Research of ACM Volume 5 Issue 1, March 2014 Article No. 2.


[12] Suvarna Joshi and Dr Abhay Kumar: Feature Extraction Using DWT with Application to Offline Signature Identification,


[81] Cardot, H., Revenu, M., Victorri, B., and Revillet: A Static Signature Verification System Based on a Cooperative Neural

[82] Shapiro, V.A. and Bakalov, I.S.: Static Signature Verification as a Dynamic Programming Problem. Proceedings of the
Sixth International Conference on Handwriting and Drawing, pp. 219-221, 1993.


Verification. Advances in Neural Information Processing Systems 1, Touretzky, D.S., editor, Morgan Kaufman Publications,