

# Neural Network-based Offline Handwritten Signature Verification System using Hu's Moment Invariant Analysis

Sandeep Patil, Shailendra Dewangan

**Abstract :** *Handwritten signatures are considered as the most natural method of authenticating a person's identity (compared to other biometric and cryptographic forms of authentication). The learning process inherent in Neural Networks (NN) can be applied to the process of verifying handwritten signatures that are electronically captured via a stylus. This paper presents a method for verifying handwritten signatures by using NN architecture. Various static (e.g., area covered, number of elements, height, slant, etc.) [1] and dynamic (e.g., velocity, pen tip pressure, etc.) signature features are extracted and used to train the NN [2]. Several Network topologies are tested and their accuracy is compared.*

*Although the verification process can be thought to as a monolith component, it is recommended to divide it into loosely coupled phases (like preprocessing, feature extraction, feature matching, feature comparison and classification) allowing us to gain a better control over the precision of different components. This paper focuses on classification, the last phase in the process, covering some of the most important general approaches in the field. Each approach is evaluated for applicability in signature verification, identifying their strength and weaknesses. It is shown, that some of these weak points are common between the different approaches and can partially be eliminated with our proposed solutions. To demonstrate this, several local features are introduced and compared using different classification approaches.*

**Keywords -** *Handwritten Signature Verification (HSV), Hu's moment invariants, Neural Networks (NN), offline, Signature Recognition, etc.*

## I. INTRODUCTION

The aim of off-line signature verification is to decide, whether a signature originates from a given signer based on the scanned image of the signature and a few images of the original signatures of the signer. Unlike on-line signature verification, which requires special acquisition hardware and setup, off-line signature verification can be performed after the normal signing process, and is thereby less intrusive and more user friendly. On the other hand, important information like velocity, pressure, up and down strokes is partially lost. In the past decade a bunch of solutions has been introduced

and setup, off-line signature verification can be performed after the normal signing process, and is thereby less intrusive and more user friendly. On the other hand, important information like velocity, pressure, up and down strokes is partially lost. In the past decade a bunch of solutions has been introduced to overcome the limitations of off-line signature verification and to compensate for the loss of accuracy. However when tested against skilled forgeries, even the best systems deliver worse equal error rates than 5%, in contrast with a human expert, who is able to do the distinction with an error rate of 1% [3]. To break this barrier it is essential to identify, understand and compensate for the different sources of error in the algorithms. This paper presents a solution to address the problem of improvement and thereby possibly break the 5% barrier. Typical signature verification approaches consist of 3 main phases. First they extract some features from the images of signatures, then they compare them and finally, they use some kind of classifier to decide whether a given signature is an original or a forgery [4].

This paper concentrates on the final phase of signature verification. In the following section several existing signature verifiers are introduced, with a special emphasis on neural network based classification. Then we summarize the classification problems, occurring when dealing with signatures, and propose solutions for them. In this paper a complete neural network based classification method is introduced to demonstrate, how some of the limitations of off-line signature verification can be overcome. Finally experimental results are presented and used to evaluate the goodness of several different features. Concentrated efforts at applying NNs to HSV have been undertaken for over a decade with varying degrees of success [5].

This paper presents a method for HSV by using NN architecture. Various static signature features (e.g., height, length of signature, number of breaks in signature etc.) are extracted and used to train the NN. Several Network topologies are tested and their accuracy is compared.

## II. METHODOLOGY

This section describes the methodology behind the system development. It discusses the pre-processing performed, the signature database, and the NN features. Signature Recognition Systems need to preprocess the data.

It includes a series of operations to get the results. The major steps are as follows :

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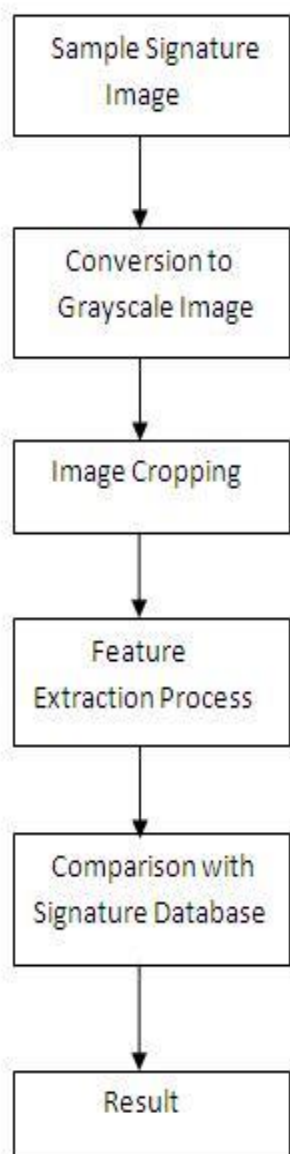
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A. *Data Acquisition* :The signatures to be processed by the system should be in the digital image format (Figure 1). We need to scan the signatures from the document for the verification purpose. Data acquisition is required to acquire the signature of the user which can be based on a variety of input tools.

Data acquisition process is a process where the real time inputs of signature from the digitizing tablet and the special pen are read into the CPU for processing and to store the signature in to the database. The digitizing tablet is sending the real time inputs to the CPU for further processing and storage.



**Figure 1. Simplified workflow for a typical Signature Recognition System**

A total of 660 genuine signatures were collected from a population of 66 human subjects which included 25 women and 41 men’s and seven of them are left handed writers. The process flow of signature recognition system is shown in figure. Our main task is to recognizing the

signature with good feature recognition techniques which provide good results on the signature recognition dataset.

B. *Signature Pre-processing* : We have to normalize the signature, resize it to proper dimensions, remove the background noise, and thin the signature. This yields a signature template which can be used for extracting the features. Therefore minimal signature pre-processing is required [6]. Other areas of handwriting analysis require large amounts of pre-processing such as slant correction, rotation correction and size normalization to reduce variations in the handwriting. However, in HSV most of the subtle nuances of the writing such as size and slant are indicative of the signer’s natural style, removal of which would deny the HSV system of useful information. The only pre-processing performed is rotation normalization. This procedure involves extracting the baseline points from the signature (i.e., the bottoms of all non-descended characters). Linear regression is used to best fit a straight line through the baseline points.

C. *Feature Extraction* : The features extracted from signatures or handwriting play a vital role in the success of any feature based HSV system. They are the most important aspect, exceeding the choice of model or comparison means. If a poorly constructed feature set is used with little insight into the writer’s natural style, then no amount of modeling or analysis is going to result in a successful system. Further, it is

necessary to have multiple, meaningful features in the input vector to guarantee useful learning by the NN. The initial decisions as to which features to incorporate, in order to maximize the accuracy, involved a combination of studying other publications in the area (what other researchers have found useful or useless) and intuitively considering which other features might be most applicable. The intuitive approach was based on study of the handwriting process, forensic analysis of handwriting by humans and examination of features that are most useful to humans in deciding whether a particular handwriting sample is produced by some author. The properties of “useful” features must satisfy the following three requirements : (1) The writer must be able to write in a standard, consistent way (i.e., not unnaturally fast or slow in order to produce a particular feature); (2) The writer must be somewhat separable from other writers based on the feature; and (3) The features must be environment invariant (remain consistent irrespective of what is being written).

The third point is more relevant to the process of writer identification than HSV, as a person’s signature is most often a fixed text. It is relevant to HSV, however, in the sense that the features should remain stable irrespective of the environment in which the signature is being performed (e.g., the pen’s weight, the pen tip’s friction, etc.) [7]. What follows now is a description of each of the features that are extracted from a given signature, as well as their significance and method of calculation. Each of these features acts as a single input to the NN.

In this paper we have considered total five different features of signature. Out of these five features following features the most important feature under our consideration for the process of signature verification, is Hu's Moment Invariant.

*Hu's Moment Invariant* : Hu's introduced seven moment invariants [8] in 1962.

$$M_1 = \eta_{20} + \eta_{02}, \quad (1)$$

$$M_2 = (\eta_{20} - \eta_{02})^2 + 4\eta_{11}^2, \quad (2)$$

$$M_3 = (\eta_{30} - 3\eta_{12})^2 + (3\eta_{21} - \eta_{03})^2, \quad (3)$$

$$M_4 = (\eta_{30} - 3\eta_{12})^2 + (\eta_{21} + \eta_{03})^2, \quad (4)$$

$$M_5 = (\eta_{30} - 3\eta_{12})(\eta_{12} + \eta_{30})^2 [(\eta_{12} + \eta_{30})^2 - 3(\eta_{21} + \eta_{03})^2]$$

These moments are of finite order, therefore, unlike the centralized moments they do not comprise a complete set of image descriptors. The result is a set of absolute orthogonal (i.e. rotation) moment invariants, which can be used for scale, position, and rotation invariant pattern identification. These were used in a simple pattern recognition experiment to successfully identify various typed characters. This moment invariant is used for signature verification in [9]. Moments and functions of moments have been extensively employed as invariant global features of images in pattern recognition. For object recognition, regardless of orientation, size and position, feature vectors are computed with the help of nonlinear moment invariant functions. Representations of objects using two-dimensional images that are taken from different angles of view are the main features leading us to our objective. Few more important features of a signature that we have taken under our consideration, are as followings :

(a) *Horizontal Length*: This is the horizontal distance measured (Figure 2) between the two most extreme points in the x direction (often simply the distance between the first



Figure 2. Horizontal Length of Signature

The non-orthogonal centralized moments are translation invariant and can be normalized with respect to changes in scale. However, to enable invariance to rotation they require reformulation. Hu described two different methods for producing rotation invariant moments. These moments having the desirable properties of being invariant under image scaling, translation, rotation,

and shear in which can be defined by following equations (Equation 1 to 7),

$$+ (3\eta_{21} - \eta_{03})(\eta_{21} + \eta_{03}) [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2], \quad (5)$$

$$M_6 = (\eta_{20} - \eta_{02}) [(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2] + 4\eta_{11}(\eta_{30} + \eta_{12})(\eta_{21} + \eta_{03}), \quad (6)$$

$$M_7 = (3\eta_{21} - \eta_{03})(\eta_{30} + \eta_{12})^2 [(\eta_{12} + \eta_{30})^2 - 3(\eta_{21} + \eta_{03})^2] - (\eta_{30} + 3\eta_{12})(\eta_{21} + \eta_{03}) [3(\eta_{30} + \eta_{12})^2 - (\eta_{21} + \eta_{03})^2], \quad (7)$$

point captured and the last point captured) [10]. Any fragments such as 't' crossings or 'i' dotting are excluded (such fragments far less stable and individual traits such as extravagant 't' crossings can cause high variability with this feature). The horizontal length tends to remain stable with a practiced word and particularly with a signature, irrespective of the presence of a bounding box, horizontal line or even with no line present.

(b) *Maximum Height*: This is the distance between the lowest points in a word (the lowest descender's depth) and the highest point in a word (the highest ascender's height) (Figure 3). This calculation ignores 'i' dotting and 't' crossings or other such

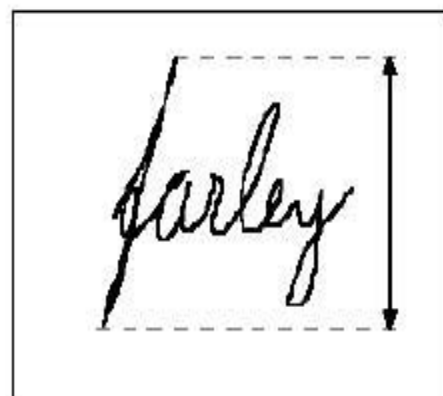


Figure 3. Maximum Height of Signature

artifacts occurring in the handwriting. Also removed from consideration is the final trailing stroke in a signature in examination of the trailing strokes in different signatures produced by the same signer, this stroke's height was found to be by far the most variable [12]. The maximum height feature using the remaining captured points reflects, to some extent, the "flair" with which the author writes and the maximum distance typically traversed by the pen tip. This feature remains reasonably stable across several written samples.

(c) *Aspect Ratio*: This is the ratio of the writing length to the writing height. It remains invariant to scaling. If the user signs in a different size, the height and length will be altered proportionally to retain the aspect ratio.

(d) *Number of "pen-ups"*: This indicates the number of times the pen is lifted while signing after the first contact with the tablet and excluding the final pen-lift [11]. This is highly stable and almost never changes in an established signature. This can be a difficult feature for a forger to discern from an off-line copy of the signature.

*D. Training of Database of Signatures* : The extracted features are stored in to database. The human signature is dependent on varying factors, the signature characteristics change with the psychological or mental condition of a person, physical and practical condition like tip of the pen used for signature, signatures taken at different times, aging etc. We have to consider a high degree of intra-class variation because two signatures from a same person are never same [13]. Our system should consider this variation and at the same time the system should possess high degree of accuracy to detect forged signatures.

We train the system using a training set of signature obtained from a person. Designing of a classifier is a separate area of research. The decision thresholds required for the classification are calculated by considering the variation of features among the training set. Separate set of thresholds (user Specific) is calculated for each person enrolled, some system also use common threshold form all users [14].

III. EXPERIMENTAL SET-UP

We have designed a multi algorithmic signature recognition system which takes into account the conventional features as discussed above as well as it combines some of the prominent feature extraction mechanisms with newly

The experimental results are categorized in Table II. However it is not sufficient to verify the validity of a signature only by comparing the physical image of it.

Table II : The result of Experiments

Percentage of similarity	Description
0-70%	The sample signature is not similar to the original one.

proposed cluster based global features to develop an off-line signature recognition system [11]. The performance of system depends on how accurately the system can classify between the genuine and fraud signatures. The forgeries involved in handwritten signatures have been categorized based on their characteristic features.

Table I shows the values of fluctuation for seven moment invariants on different resolution from 60x60 to 330x330. We can see that the fluctuation decreases as the image spatial resolution increases. The fluctuation almost comes up to 1921.1% when the resolution is only 60x60, but rapidly decreases to 1.1% when the resolution is 270x270. The fluctuation obviously decreases as the resolution increases until to the threshold. However, the fluctuation does not monotonically decrease any more when the resolution greater than 270x270.

Table I. Fluctuation of Moment Invariants on Different Resolution of Images

Image Resolution	M1	M2	M3	M4	M5	M6	M7
60x60	18.7	3.9	10.7	19.8	11.5	28.6	19.21
90x90	13.3	2.6	73.0.9	14.5	11.18	19.4	84.2
120x120	10.7	1.9	43.6.0	10.9	94.7.6	14.0	51.7.4
150x150	7.4	1.3	32.8.0	86.3	53.2.0	98.9	30.2.1
180x180	4.5	8.2	15.9.2	51.5	23.7.3	57.7	14.0.0
210x210	3.2	5.6	88.1	36.2	17.9.3	38.9	75.5
240x240	1.1	1.9	21.4	12.3	46.2	12.8	19.7
270x270	0.2	0.3	1.8	0.4	2.9	0.5	1.1
300x300	0.2	0.5	1.4	0.3	2.0	0.5	1.3
330x330	0.1	0.3	1.9	0.2	1.2	0.2	1.7

70-99%	The sample signature is similar to the original one.
100%	The sample signature is the original one.

This fact should be considered that a person's signature is not the same from time to time and it is different from one occasion to another. As it is shown in Fig. 4, with the increase of similarity false reject rate (FRR) is increased but false acceptance rate (FAR) is decreased [14] [15]. The results of our examination show that in this method, the best value for the percent of signature similarity is nearly 80.05 (SS≈80%). In this point we obtain the minimum error rate (MinErrRate = min(FAR, FRR)). If we consider average error rate (AER) are as following:

$$AER = (FAR + FRR) / 2 \quad (8)$$

AER will be the smallest amount in  $SS \in [75,85]$ . On the other hand, we have the best performance of the system

in  $(75\% \leq SS \leq 85\%)$  [16]. In this interval, we have the minimum value for AER (see Figure 4). Where the value of the FAR and the FRR meet one another, the point is called equal error rate (EER) as it is shown in Figure 4. As a matter of fact, getting the best performance, we should consider  $75\% \leq SS \leq 85\%$ . The fundamental result of this study is obtaining the average of minimum errors not in the maximum surface similarity. In other words, if the correctness of a signature is its high similarity to the original one, the correct signatures will be rejected because of minor differences and this trend will decrease the efficiency of the system.

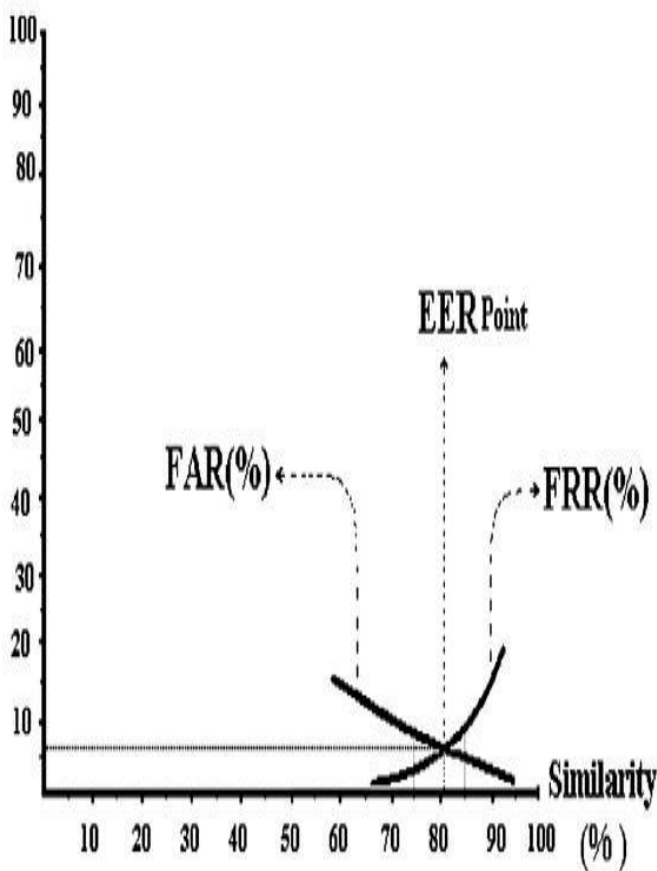


Figure 4. The best value of signature similarity percentage.

The method is tested using genuine and forgery signature produced, an equal error rate (EER) of 25.1% and 5.5% was archived for skilled and random forgeries, respectively. Figure 6 displays relationship among FRR, FAR for random forgeries (FAR-random), and FAR for skilled forgeries (FAR-skilled). It is natural to notice that the FAR-random curve is lower than the FAR-skilled curve, since in random forgeries the signer has no previous knowledge and/or training on the signature she/he is forging.

In a study two types of classifiers, a nearest neighbor and a threshold classifier are used for offline signature verification

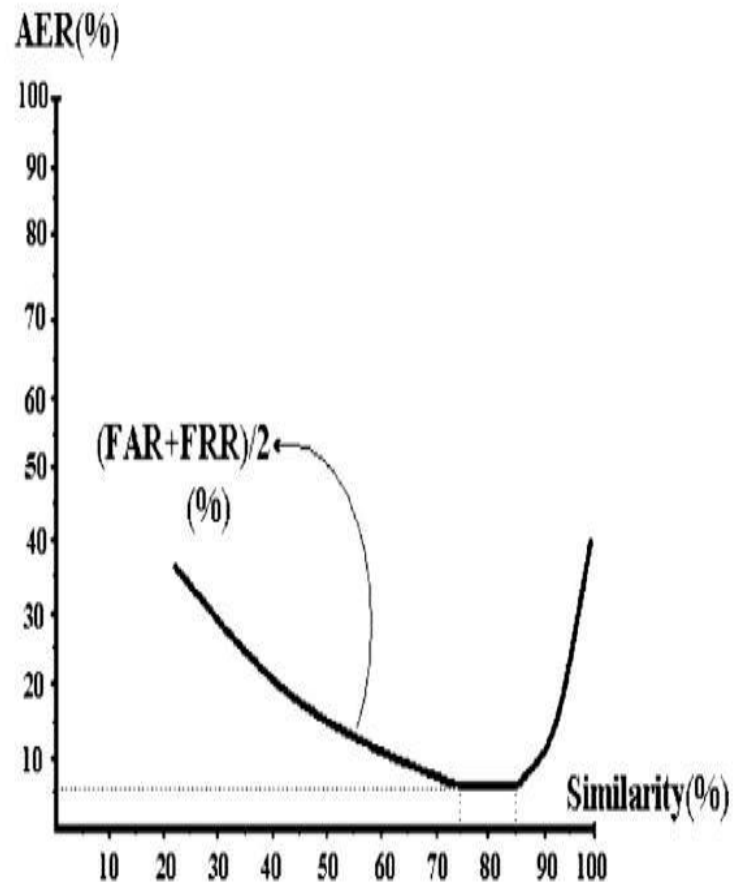


Figure 5. Interval of the best performance.

[14]. These classifiers show a total error rate below 2% and 1% respectively in the context of random forgeries. These rates are better than ours which is 5.5%. For skilled forgeries, the FAR of our algorithm is similar to those of other researchers. From the results, it is obvious that the problem of signature verification becomes more difficult when passing from random to skilled forgeries.

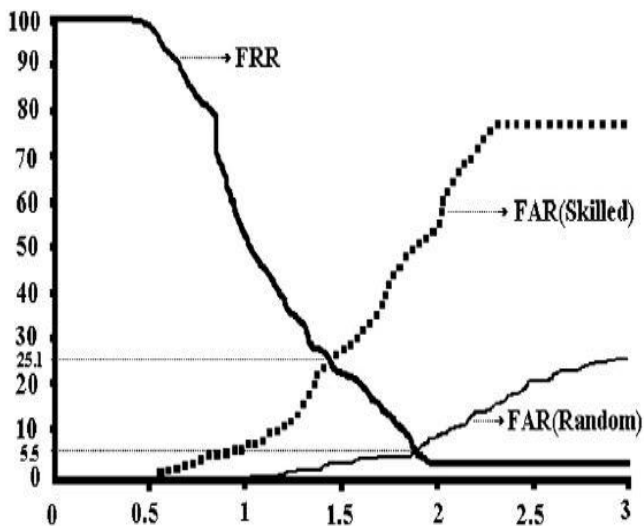


Figure 6. Relationship among FRR and FAR

#### IV. CONCLUSION

As discussed in Section III (Experimental Set-up & Results), we can reach the conclusion, that with the higher resolution of images, the fluctuation is lower. However, the computation of moment invariants will increase when the resolution increases [17]. As a consequence, the research of relationship between the resolution of images and computation is necessary. This paper has presented an analysis of fluctuation of Hu's moment invariants on image scaling and rotation. Our findings may be summarized as follows: (1) The moment invariants change as images scale or rotate, because images are not continuous function or polluted by noise; (2) The fluctuation decreases when the spatial resolution of images threshold; (3) The computation increases quickly as resolution increases.

The proposed algorithm can be used as an effective signature verification system. The algorithm proposed was successfully made rotation invariant by the rotation of the image. The error rejection rate can further be improved by using better techniques for rotation, blurring and thinning. Using these algorithm random and simple forgeries can be easily detected. A great number of skilled forgeries can also be removed.

It uses a compact and memory efficient storage of feature points which reduces memory overhead and results in faster comparisons of the data to be verified.

From the experimental studies, we find that the choice of image spatial resolution is very important to keep invariant features. To decrease the fluctuation of moment invariants, the image spatial resolution must be higher than the threshold of scaling and rotation [18]. However, the resolution cannot be too high, because the computation will remarkably increase as the resolution increases. Therefore, the choice of resolution must balance computation and resolution on the real application increases.

#### FUTURE WORK :

Future development of software is possible and in fact is very useful in order to increase its efficiency and flexibility in use. Matlab is powerful software when comes to mathematical operations but it uses a lot of vectors and matrix [19]. These matrices and vectors uses too much memory, hard disk and slow down the processor unit of the computer hence, coding can be done in c, c++, java etc. The character recognition system that is developed is only able to recognize the single/isolated character. Further research is needed to develop a system that recognizes the connected/joined characters [20].

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