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# ON

# ONLINE 3D SIGNATURE VERIFICATION

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# Abstract

Handwritten signature is the most widely accepted biometric to identity verification. The target of research is to present online handwritten signature verification system based on discrete wavelet transform (DWT) features extraction and feed forward back propagation error neural network recognition. Steps for verifying online handwritten signature in this system start with extracting pen position data (*x* and *y* positions) of points that forming the signature. Pen-movement angles are then derived from pen position data.

To enhance the difference between a genuine signature and its forgery, the signature is verified in DWT domain. Low frequency sub-band signals (approximations) of pen-position parameter and pen-movement angle parameter are considered as intrapersonal features. These are used for suppressing variations between different genuine signatures and enhancing the interpersonal variations, hence are given higher scores within total recognition process. Both of pen-position and pen-movement angle features are then associated for obtaining a decision about online handwritten signature verification. A multi-matcher consists of neural networks which use multiple representations and matching for the same input biometric signal is used to verify signature.

## INTRODUCTION -

There exist a number of biometrics methods at present, e.g. signatures, fingerprints, iris, etc. Fingerprints and iris verification require the installation of costly equipments and hence cannot be used at day to day places like banks, etc. There is considerable interest in authentication based on handwritten signature verification system as it is the cheapest way to authenticate a person. Banks and Government bodies recognize signatures as a legal means of authentication. Signature verification technology utilizes the distinctive aspects of the signature to verify the identity of individuals. Criminal experts cannot be employed at every place and hence there has been considerable effort towards developing computerized algorithms that could verify and authenticate the individual’s identity

. A handwritten signature is biologically linked to a specific individual. Modern forensic document examiners commonly compare a suspect signature with several examples of known valid signatures. They look for signs of forgery which include: Signatures written at a speed which is significantly slower than the genuine signatures; frequent change of the grasp of the writing implement; rounded line endings and beginnings; poor line quality with hesitant and shake of the line; retracing and patching; and stops in places where the writing should be free. Compared with other electronic identification methods such as fingerprints scanning and retinal vascular pattern screening, it is easier for people to migrate from using the popular pen- and paper signature to one where the online handwritten signature is captured and verified electronically.

Many times the signatures are not even readable by human beings. Signature verification problem therefore is concerned with determining whether a particular signature truly belongs to a person or not. There are two approaches to signature verification, online and offline differentiated by the way data is acquired. In offline case, signature is obtained on a piece of paper and later scanned. Offline signature verification deals with a 2D static image record of the signature. It is useful in automatic signature verification found on bank checks and documents authentication.

Offline verification techniques are based on limited information available only from shape and structural characteristics of the signature image. A fundamental problem in the field of offline signature recognition is the lack of a significant shape representation or shape factor. In contrast, online signature verification systems are extremely precise. It require the presence of the author during both the acquisition of the reference data and the verification process. This restrict their use to specific applications. Online handwritten signature is usually obtained on an electronic tablet and pen.

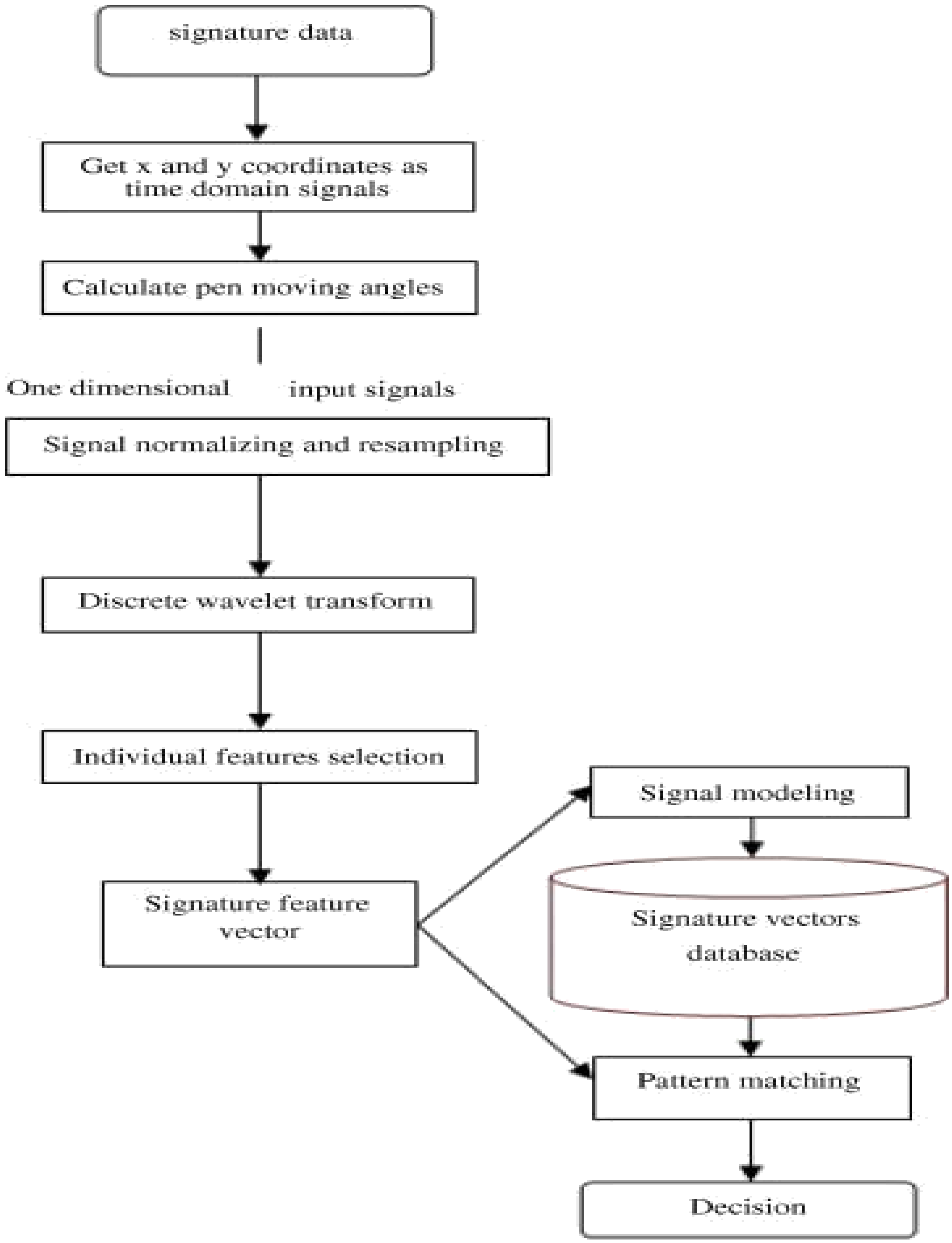
Online signature verification track down path and other time-variable sequence variables using specially designed tablets or other devices during the act of signing. Automatic online signature verification is an interesting intellectual challenge with many practical applications. This technology examines the behavioral components of the signature such as: stroke order, speed, and pressure, as opposed to comparing visual images of signatures. Unlike traditional signature comparison technologies, online signature verification measures the physical activity of signing. The target of this research is to present online handwritten signature verification system based on DWT features extraction and neural network classification

## Proposed system description

The proposed online handwritten signature recognition system consists mainly of three phases: Signal modeling, feature extraction, and feature matching. The *x* and *y* positions of signature points are extracted and each is represented as 1D time domain signal. Pen moving angles are derived from pen position data points. It is then used as the third time domain signal. These signals are then normalized and resampled. This is to overcome the problem of different sizing and different number of points exists in every signature even for the same user.

Discrete wavelet transform is used to extract features from these signals. Sub-band decomposition is used to extract intrapersonal features from the DWT features to enhance signature individuality. The extracted feature vectors are used to train back propagation neural networks bank that are used within multi matcher as a classifier. In the testing phase, signals which were captured from a signature of unknown person are subjected to feature extraction. The resulting features are inputted to the bank of the trained neural networks of multi matcher.

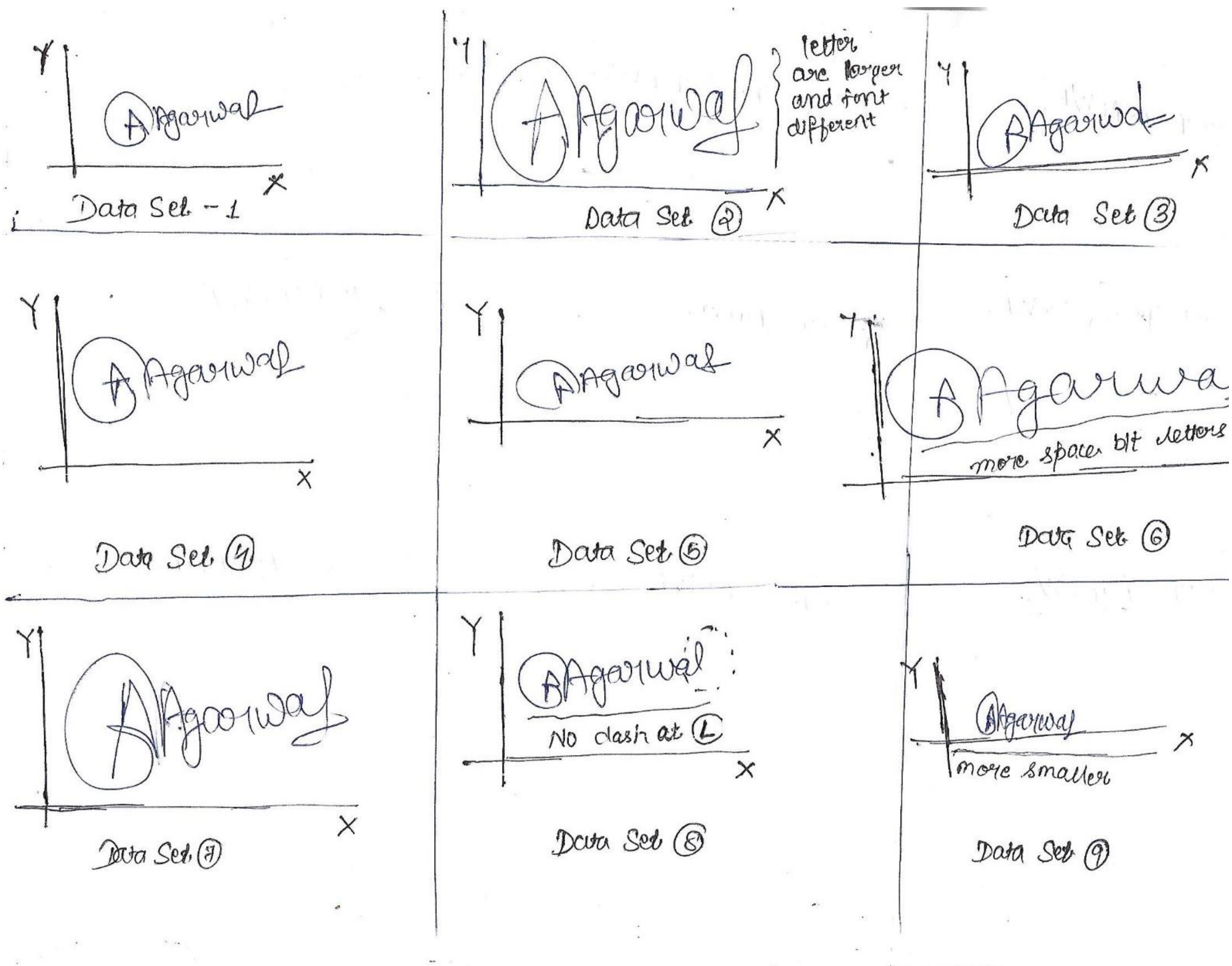
The resultant outputs are allowing the unknown signature to be identified if it is a genuine handwritten signature or not. To summarize, two algorithms are of critical importance to handwritten identification system. The first is feature extraction process (obtained from discriminatory information). The second is classification process (using the features to determine the correct signal, which corresponds to the correct handwritten signature). The proposed handwritten signature verification system is shown.


signature data
Get x and y coordinates as time domain signals
Calculate pen moving angles
One dimensional input signals
Signal normalizing and resampling
Discrete wavelet transform
Individual features selection
Signature feature vector
Signal modeling
Signature vectors database
Pattern matching
Decision

## WORK DONE SO FAR ……

In this paper, we present a neural network based recognition of offline handwritten signatures system that is trained with low-resolution scanned signature images. The objective is to eliminate bulk storage requirements. We used neural networks because of their adaptive nature of learning by example in solving problems. This feature makes such computational models very appealing for a wide variety of application domains including pattern recognition. The neural network approach has long been in use for pattern recognition. The classifier performance is evaluated using a locally developed database comprising English handwritten signatures. The handwritten signatures are recognized based on features extracted with an adaptive learning vector quantization (LVQ) neural network compact architecture. The images are scanned for this purpose using a resolution of 200 dp.

## DATA SET




**DATA SETS AT VARIOUS PLACES TYPES ---**

**ORIGINAL DATA SET --**

Now, we would make use of classifier to match the most suitable sample image to our owned stored ORIGINAL data set signature ,
For that we make use of LVQ classifier.

Since comparion of signature directly to dataset , leds to various errors and wrong results , therefore we need to carry out various transformations before comparing and taking decisions.

So. Some of the observed errors and their solutions-

1. **To overcome the SIZE factor (signature).** –
   You can see in data set 9 v/s data set 2, as both varies each other in terms of size and somewhat density between the letters, so to overcome that we took out the vector of each small subsection of image and compare with that with our original dataset.
   This way we eliminate the size factor and correct decision making.

2. **<u>To overcome the density factor (Unwanted space between letters).</u>**

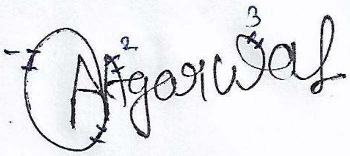
   Here , same way we eliminate the density factor so that we carry out the identification process correct in any situation.

The answer to above difficulties , we would refer a solution is -
In our purposed algorithm we, make use of sizeable vector at very very small subsections of our target image , so that we could observe any change regarding curvature whether maxima or minima ,and compare that curvature with our original dataset , this way we could eliminate the both the listed difficulties above.

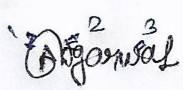
SAMPLE DATASET --


H ⟶ small subsection of original data set.

I data set 2 v/s data set 9




1,2,3
subsection vectors
are compared to same

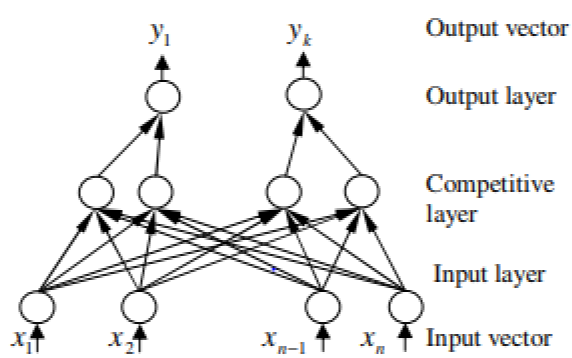


1, 2, 3
Subsection vectors

So, we are making use of vectors to compare the different.

## LVQ CLASSIFIER

LVQ (learning vector quantization) is a supervised classifier that was first studied by Kohonen. To classify an input vector, it must be compared with all prototypes. The Euclidean distance metric is used to select the closest vector to the input vector. And the input vector is classified to the same class as the nearest prototype.




The LVQ classifier consists of an input layer, a hidden competitive layer, which learns to classify input vectors into subclasses and an output layer, which transforms the competitive layer's classes into target classifications defined by the user. Only the winning neuron of the hidden layer has an output of one and other neurons have outputs of zero. The weight vectors of the hidden layer neurons are the prototypes, the number of which is usually fixed before training begins. The number of hidden neurons depends upon the complexity of the input-output relationship and significantly affects the results of classifier testing. Selection of the number of hidden neurons must be carefully made, as it highly depends on the encompassed variability in the input patterns. Extensive experiments are performed to conduct the suitable number.

For a training set containing *n* input signatures, each of these images is labeled as being one of *k* classes. The learning phase starts by initiating the weight vectors of neurons in the hidden layer. Then, the input vectors are presented randomly to the network. For each input vector $X_j$ , a winner neuron

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$W_i$ is chosen to adjust its weight vector:

$$|X_j - W_i| \le |X_j - W_k| \text{ , for all } k \ne i \quad \text{——(1)}$$

The weight vector $W_i\,(t)$ is updated to the next step $t+1$ as follows:

$$\Rightarrow W_i\,(t+1) = W_i\,(t) + \alpha\,(X_j - W_i(t)) \quad \text{——(2)}$$

if $X_j$ and $W_i$ belong to same class

$$\Rightarrow W_i\,(t+1) = W_i\,(t) - (X_j - W_i\,(t)) \quad \text{——(3)}$$

if $X_j$ and $W_i$ belongs to different classes

where $0 \le \alpha \le 1$ is the learning rate, which may be kept constant during training or may be decreasing monotonically with time for better convergence. Otherwise, do not change the weights. The training algorithm is stopped after reaching a pre-specified error limit. During the test phase, the distance of an input vector to each processing element of the hidden layer is computed and again the nearest element is declared as the winner.

## SIGNATURE DATABASE PREPROCESSING

A typical biometric system has three distinct phases. These are biometric data acquisition, feature extraction, and decision-making. The first step, the acquisition phase, is extremely important. If high quality images are not obtained, the next phase cannot operate reliably. In fact, most difficulties in accurately identifying an individual can be traced back to the image acquisition phase.

In our data base we have collected , 9 sample signatures +1 original signature of a person.

This way we have a data base of about 10 persons to compare.

Also the signature of a person depends on emotional, health and attitude of person. So, we making that concept in account also.

The whole set of scanned handwritten signatures is re-sampled as 200×100 pixels and converted to 8-bit 256 gray level images. To reduce the image size, a low pass filter is applied to the image before interpolation using the nearest (Euclidean distance) neighbor interpolation method.

# ALGORITHM

The most challenging step in the design of a pattern recognition system is the selection of a suitable base model that constitutes its building blocks. The next step is the features selection and extraction method.

## Neural Classifiers

In machine-based detection, a gallery of patterns is first enrolled in the system and coded for subsequent searching. A probe pattern is then obtained and compared with each coded image in the gallery, detection is noted down when a suitable match occurs. The challenge of such a system is to perform detection of the pattern despite transformations; area of the image, changes in lighting conditions, common problems of machine vision, and changes due to an individual’s emotion, health, state of mind, writing posture, fatigue, etc. The need is, thus, to find appropriate codings for signatures which can be derived from a number of images and to determine in what way, and how well, two such codings shall match before the signatures are declared the same.

# CONCLUSION

In modern pattern recognition systems all the stages of pattern recognition could be performed by a single scheme such as neural networks and genetic algorithms which has the inherent capabilities of noise filtering, data reduction, feature extraction and classification. The advantage of using neural networks is that they can extract the most discriminative and representative set of features.

We have presented a learning vector quantization neural network architecture based on varying parameters and eliminating redundant hidden layer units or blind neurons that learns the correlation of patterns and recognizes handwritten signatures.

# FUTURE GOALS –

We just have purposed the idea and work behind this project .

In future we make sure that we implement the same and eliminate the upcoming errors to make it scalable for the future use.

Also we would further include the signature in various languages such as hindi, Bengali, telugu.

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