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Signature Verification

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Abstract:Signature verification is a unique method to identify the person which is used word-wide. To reduce the cost of online verification process, I have utilized the on-line registration and off-line verification process to reduce cost. It utilizes Neural- Networks to identify the various parameters to identify and train the model system. It has resulted in low cost and accurate off-line model for verification process.

Keywords: Biometric, Signature, Verification, Neural Network, It uses two cameras (webcam) with XGT Serial Digitizing tablet,

I. INTRODUCTION

Signature is a socially accepted authentication method and is widely used as proof of identity in our daily life. Signature verification techniques utilize many different characteristics of an individual's signature in order to identify that individual. The advantages of using such an authentication techniques are:

i. Signatures are widely accepted by society as a form of identification and verification.
ii. Information required is not sensitive.
iii. Forging of one's signature does not mean a long-life loss of that one's identity.

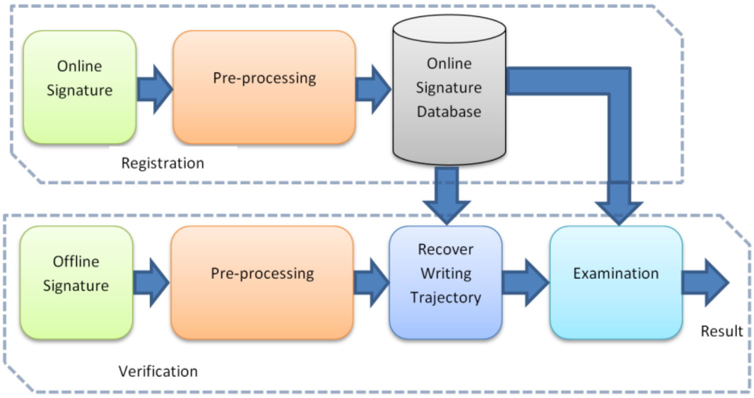
The basic idea is to investigate a signature verification technique which is not costly to develop, is reliable even if the individual is under different emotions, user friendly in terms of configuration, and robust against imposters.
The signatures are processed to extract features that are used for verification in two stages called enrollment and verification.The features have to be small enough to be stored in a smart card and do not require complex techniques. There are two types of features, i.e., static and dynamic features.Static features are those, which are extracted from signatures that are recorded as an image whereas dynamic features are extracted from signatures that are acquired in real time.

II. TECHNIQUE IMPLEMENTED

2 features used to differentiate signature type are:

1) Global features: It is extracted from the whole signature andit includes block codes, Wavelet and Fourier series, etc.
2) Local features:It calculates the geometrical and topological characteristics of local segments, such as position, tangent direction, and curvature.

The global features deliver limited information for signature verification while local features provide rich descriptions of writing shapes but the extraction is hard problem in comparison of global features.
The local features based approaches are more popular in online verification than in the offline process. This is because it is much easier to calculate 1D sequence than in 2D image. This fact inspires me to consider recovering writing trajectories from offline signature images. Then local features can be calculated and aligned more efficiently and effectively by using recovered trajectories. Similar idea had been adopted by Lee and Pan, where they proposed local tracing algorithms to find the dynamic information of signatures. However, as pointed out in, the local tracing methods are sensitive to noise and writing variance and it is difficult to design tracing algorithms which can be applied to variant writing styles. In fact, direct recovery of writing trajectory is still an open problem in handwriting research. To circumvent this difficulty, I used an approach that uses online signatures in the registration phase. I thought this approach based on the observation that registration needs to be done only once and it has to be done in person in-situ (such as in a bank) where an online device is easily available. In the verification phase, the procedure is exactly the same as an offline system thus is convenient to use. In my algorithm, I take advantage of the online registration data to recover writing trajectory of an offline input signature image and make the verification decision based on the recovered trajectory. The system diagram is shown below.



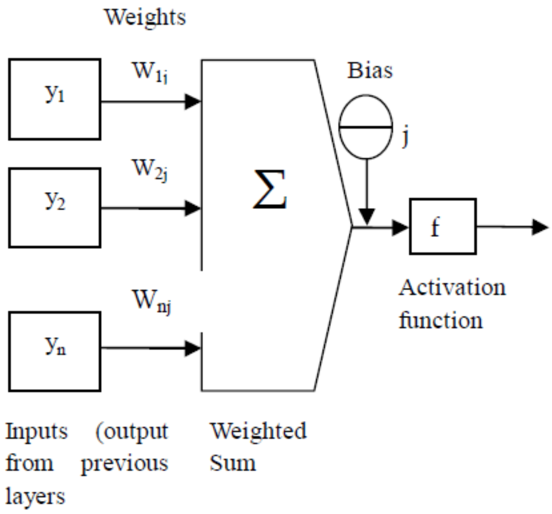
A. Neural Network- based Handwritten Signature Verification

Neural networks (NNs) have been a fundamental partof computerised pattern recognition tasks for more thanhalf a century, and continue to be used in a very broadrange of problem domains. The two main reasons fortheir widespread usage are:

1) Power (the sophisticated techniques used in NNs allow a capability of modelling quite complex functions).
2) Ease of use (as NNs learn by example it is only necessary for a user to gather a highly representative data set and then invoke training algorithms to learn the underlying structure of the data).

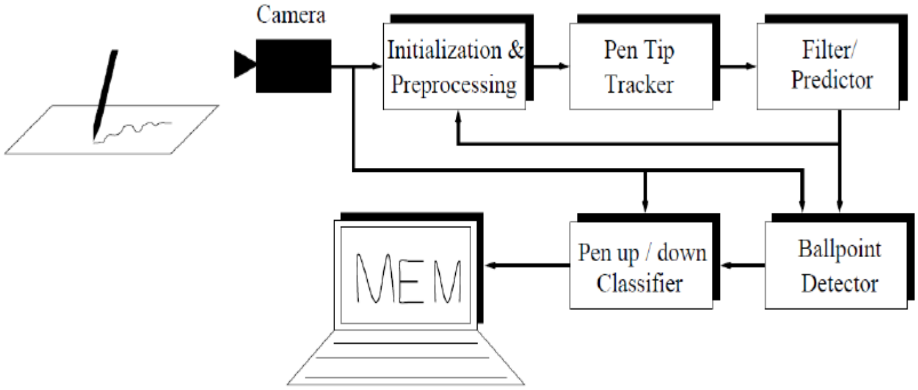
The Handwritten Signature Verification (HSV) process parallels this learning mechanism. There are many ways to structure the NN training, buta very simple approach is to firstly extract a feature setrepresenting the signature, with several samples from different signers.The second step is for the NN to learn the relationshipbetween a signature and its class (either "forgery" or "genuine"). Once this relationship has been learned, thenetwork can be presented with test signatures that canbe classified as belonging to a particular signer. NNstherefore are highly suited to modelling global aspects ofhandwritten signatures.Concentrated efforts at applying NNs to HSV have beenundertaken for over a decade with varying degrees ofsuccess. The main attractions include:

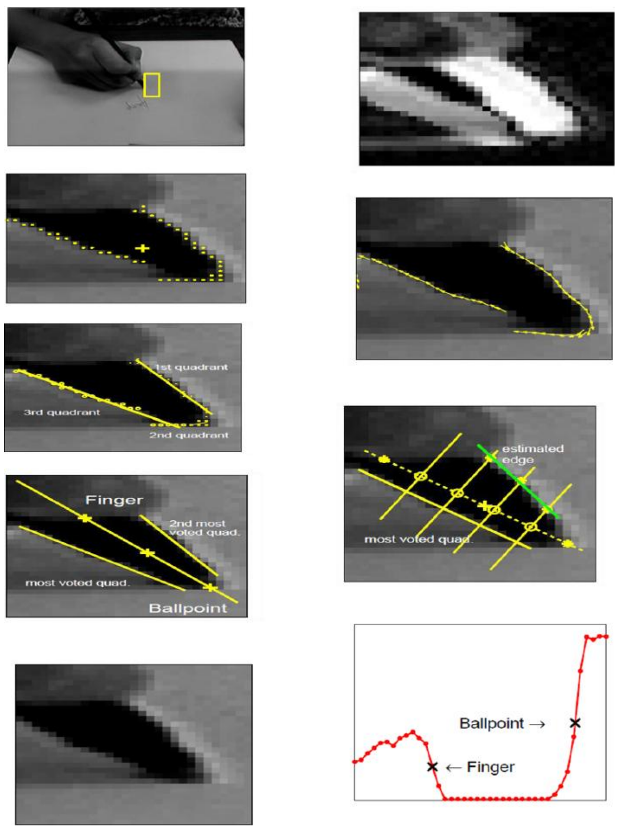
1) Expressiveness: NNs are an attribute-based representation and are well-suited for continuous inputs and outputs. The class of multi-layer networks as a whole can represent any desired function of a set of attributes, and signatures can be readily modelled as a function of a set of attributes.
2) Ability to generalise: NNs are an excellent generalization tool (under normal conditions) and are a useful means of coping with the diversity and variations inherent in handwritten signatures.
3) Sensitivity to noise: NNs are designed to simply find the best fit through the input points within the constraints of the network topology (using nonlinear regression). As a result, NNs are very tolerant of noise in the input data.
4) Graceful degradation: NNs tend to display graceful degradation rather than a sharp drop-off in performance as conditions worsen.
5) Execution speed: The NN training phase can take a large amount of time. In HSV this training is a one-off cost undertaken off-line (i.e., rarely performed while a user waits for verification results).



B. Registration

I used two cameras (webcam) with XGT Serial Digitizing tablet (It consists of an opaque tablet and a cordless non-inking pressure sensitive pen) for online signature registration system. The XGT has 6 X 8 inch effective writing area and capture samples at the rate of 205 points per second. The system consists of two low cost webcams. The input online signature data obtained by time series images, which are acquired through webcam by pen tip tracking, while the signature is being written. The pen tip tracking is obtained by sequential Monte Carlo method. We are taking two camera positions one at left side and another at front side (90° apart). The time series images are obtained by webcam. The online signature data obtained from images captured by webcam by pen trip tacking with XGT is then pre-processed and some features are extracted. The extracted features enrolled as reference data. Basically extracted features include strokes, trajectory of signature and hand movement while in pen-up state (that is undetectable by forgers using written signature) etc.





C. *Extracted features*

The features extracted from signatures or handwritingplay a vital role in the success of any feature-based Hand Signature Verification (HSV) system. They are the most important aspect, exceedingthe choice of model or comparison means. If a poorlyconstructed feature set is used with little insight into the writer's natural style, then no amount of modelling oranalysis is going to result in a successful system. Further,it is necessary to have multiple, meaningful features in theinput vector to guarantee useful learning by the Neural Network (NN).The properties of "useful" features must satisfy thefollowing 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.
3) The features must be environment invariant (remain consistent irrespective of what is being written).

Each ofthese features acts as a single input to the NN is as follows:

1. Signature Duration
2. Pen-Down Ratio

3. Horizontal Length
4. Aspect Ratio
5. Number of “pen-ups”
6. Cursivity
7. Top Heaviness
8. Horizontal Dispersion
9. Curvature
10. Maximum Height
11. Average Velocity
12. Standard Deviation of the Velocity
13. Average Absolute Acceleration
14. Standard Deviation of the Absolute Acceleration
15. Maximum Acceleration
16. Maximum Deceleration
17. Handwriting Slant Using All Points
18. Mean Pen-Tip Pressure

D. Verification process

For Verification process, I have used the Neural Network (NN) in MatLab, with Image Processing Toolbox. It included different training algorithms,different training sets and the use of forgeries (both skilledand zero-effort) in the training set. The experimentationand error rates apply to a MLP (Multi-Layer Perceptron) structure with one hiddenlayer unless otherwise specified.

The first training aspect under consideration is thealgorithms to perform the actual weight adjustments. The available training algorithms are:

1) Back-propagation: This is the most widely used algorithm in NN training due to its efficiency, simplicity and performance. Back-propagation has been used successfully in many different environments, and results in the highest classification accuracy compared to the other implemented algorithms.
2) Conjugate Gradient Descent: This is the major alternative to back-propagation but is not as widely used in HSV. The conjugate gradient descent algorithm converged much faster during training than back-propagation. Unfortunately, due to the fact that this training algorithm is suited to more complex networks (with several hundred weights), the resulting error rate was somewhat worse than networks trained via back-propagation.
3) Levenberg-Marquardt: The classification accuracy of the Levenberg-Marquardt training algorithm was slightly better than that obtained using conjugate gradient descent but not as good as back-propagation. However, the training process was exceedingly slow, which may be a problem in a large, dynamic database.

The back-propagation algorithm seems to be superiorin this HSV environment. Although it didn’t converge asquickly as conjugate gradient descent, the classificationaccuracy was superior to the other two approaches andtraining error rates continue to improve after severalhundred epochs. The actual “wall clock time” required fortraining to complete using back-propagation is typicallybetween thirty seconds and two minutes. This trainingtime is not prohibitively slow as it is generally a one-offcost and is not performed while the user waits.

As the training is unsupervised, a stopping condition isneeded to ensure that training time is finite and that theresulting network is not under- or over-trained. Experimentswere conducted using heuristic approaches withdifferent limitations and slightly different rules.

III. CONCLUSION AND FUTURE WORK

This thesis presents a method for verifying hand written signatures by using NN architecture. Various static and dynamic signature features are extracted and used totrain the NN.

I analysed online signature verification by tracking the pen tip and use of XGT Serial Digitizing tablet. The XGT Serial Digitizing tablet is a costly hardware, but needs to be used only once per person, which can be likeithas to be done in person in-situ (such as in a bank).I evaluated the best placement for webcams. It was confirmed that the webcam should be placed to the side of the hand for best results.

The data base used for the verification was not large. Thus, this technique should be verified with large database.

It is observed that in several cases where the system lost its track of the pen tip when the user wrote with an extremely fast stroke and the images of the pen tip were blurred at that time. This problem can be solved by an approach that finds blurred images by using sequential marginal likelihood with sequential Monte Carlo marginalization, and re-estimates the pen tip positions.

Another interesting future work could be to incorporate a multimodal technique combining other biometric data acquired from webcams (Like Retina Scan, Finger Prints, Face Recognition and Body Language etc; all with webcams) or combing the signature data obtained from cameras placed at different positions.

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