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Handwritten Signature Recognition, Verification using Neural Network

Doli Yadav¹

MTech Scholar

Department of Computer Science & Engineering
Om Institute of Technology & Management
Hisar, Haryana – India

Shruti Goyal²

Assistant Professor

Department of Computer Science & Engineering
Om Institute of Technology & Management
Hisar, Haryana – India

Abstract: A number of biometric techniques are projected for private identification within the past. Among the vision-based ones area unit face recognition, fingerprint recognition, biometric authentication and membrane scanning. Voice recognition or signature verification area unit the foremost wide better-known among the non-vision primarily based ones. As signatures still play a very important role in monetary, business and legal transactions, actually secured authentication becomes additional and additional crucial. A signature by a certified person is taken into account to be the “seal of approval” and remains the foremost most well-liked means that of authentication. The strategy bestowed during this paper consists of image attractive, geometric feature extraction; Neural Network based Features Extraction and verification. A verification stage includes applying the extracted options of take a look at signature for training which can classify it as a real or solid.

Keywords: FAR, FRR, MATLAB, EIGEN, SIGNATURE.

I. INTRODUCTION

Signatures are most legal and common means for individual’s identity verification. People are familiar with the use of signatures in their daily life. Automatic signature recognition has many applications including credit card validation, security systems, cheques, contracts, etc. There are two types of systems in this field, signature verification systems and signature identification systems [3].

- A signature verification system just decides whether a given signature belongs to a claimed writer or not.
- A signature identification system, on the other hand, has to decide a given signature belongs to which one of a certain number of writers.

In signature verification systems, two common classes of forgeries are considered: casual and skilled. A casual forgery is produced by only knowing the name of the writer, and without access to a sample of the genuine signature. When forger uses his own signature or genuine signature of another writer as a casual forgery, it is called a substitution forgery. So, stylistic differences are common in casual forgeries. In skilled forgeries, the forger has access to a sample of genuine signature and knows the signature very well. Since skilled forgeries are very similar to genuine signatures, some appropriate features for detection of casual forgeries are ineffective in detection of skilled forgeries. The precision of signature verification systems can be expressed by two types of error: the percentage of genuine signatures rejected as forgery which is called False Rejection Rate (FRR) and the percentage of forgery signatures accepted as genuine which is called False Acceptance Rate (FAR). The signature verification is performed in two steps, feature extraction and classification [5][7].

Above fig shows the processing of testing of input signature 1 with the test signature 1.

Perfect Matched
>>

Figure 4: Result of Experiment 1

It's matched and result is "Perfectly Matched".

Experiment 2:

Now we will compare Input Signature 1 with Test Signature 2. It's Different from Original signature.

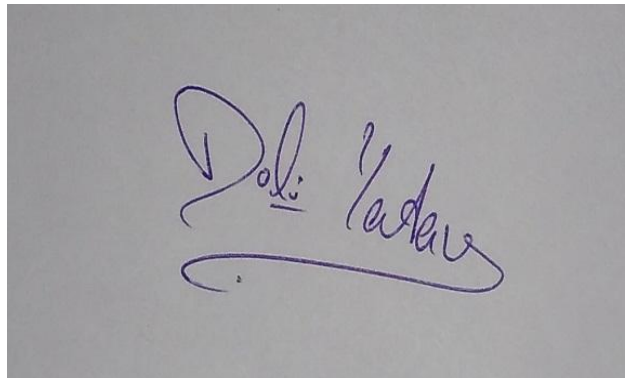


Figure 5: Input reference signature 1

Above figure shows the input image that is used for testing.

Figure 6: Test Signature 2

Above fig shows the processing of testing of input signature 1 with the test signature 2.

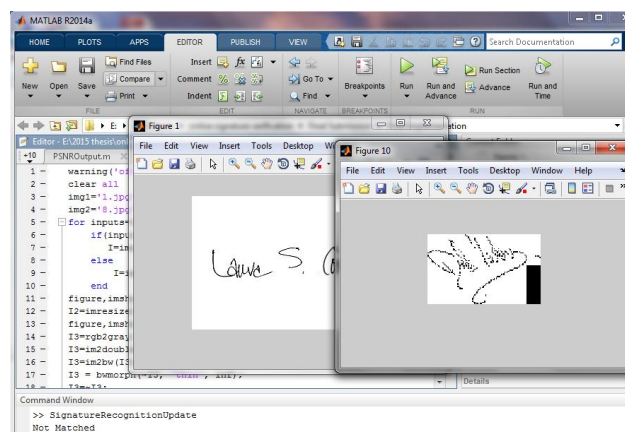


Figure 7: Processing of Test Signature 2

Above fig shows the processing of testing of input signature 1 with the test signature 2.

Not Matched
>>

Figure 8: Result of Experiment 2

It's not matched and result is "Not Matched".

Experiment 3

The above signatures are very less matched because of less percentage matching. Let's see Results of Experiment 3

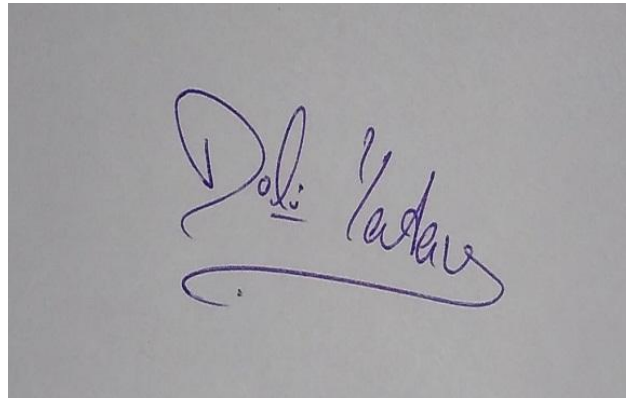


Figure 9: Input reference Image 1

Above figure shows the reference input image that is used for testing.

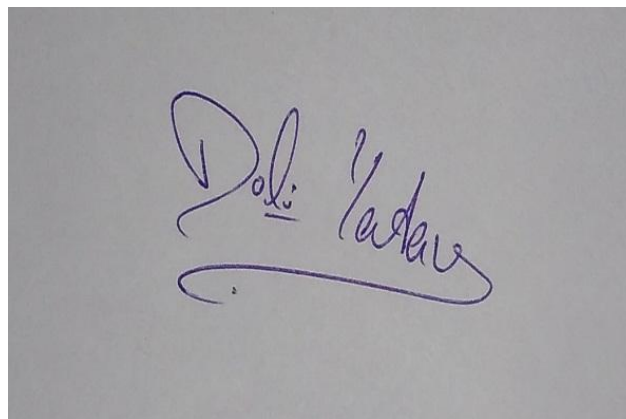


Figure 10: Test Image 3

Above fig shows the test signature 3 for testing with the test image.

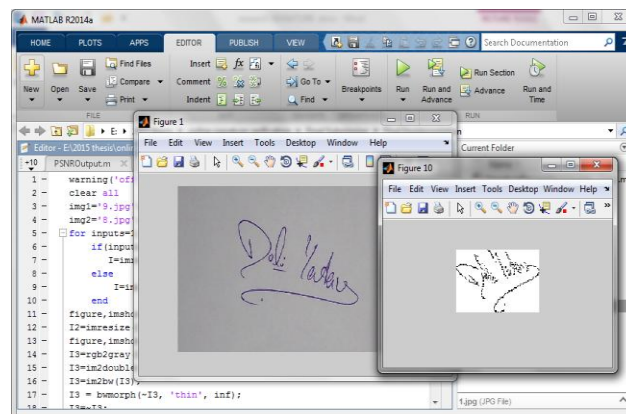


Figure 11: Processing of Test Signature 3

Very Less Matched
>>

Figure 12: Result of Experiment 3

III. ALGORITHM

Algorithm is used for solving the problem step by step which can be implemented with help of programming in any language.

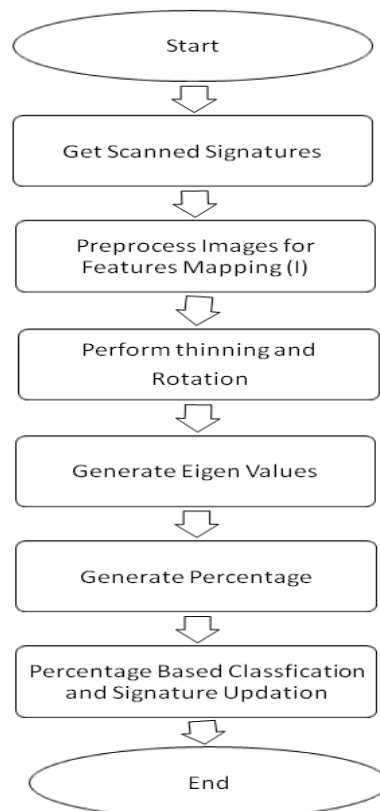


Figure13: Flow Chart

- Start
 - Get Input and Verification Scanned Signature Images (I)
 - Preprocess Images for Features Mapping (I)
 - Generate Black and White Image of Image Set (I)
 - Process the thinning of Signature
 - Process Rotation and Generate angle of Rotation.
 - Generate Eigen Values for Generate the Signature
 - Parameters and Training.
 - If(Successful) then
 - Move to Next Step
- Else Move to Step 3.
- Calculate Percentage of Input and Mapping Signature Images.
 - Set $O = \text{Percentage}$
 - Classify the Images based on Output Percentage O and Update Signature.
 - If $O > 80$ && $O < 91$
- Then 'Mostly Matched'

- Else If $O > 90$

Then 'Perfect Matched'

Else If $O > 70$ & $O < 81$

Then Signature Need to Update. Do You Want to Update

If Yes, Signature Updated

Else 'Update It'.

- If $O > 49$ & $O < 71$

Then 'Very Less Matched'

- Stop

IV. CONCLUSION

The strategy uses options extracted from preprocessed signature pictures. The extracted options are accustomed train a rule. The rule may classify all real and cast signatures properly supported the options. Once the network was given with signature samples from information totally different than those utilized in coaching part, it may acknowledge signatures properly. Our recognition system exhibited shows success rate by characteristic properly all the signatures that it had been trained for. However, it exhibited poor performance once it had been given with signatures that it had been not trained for earlier. we tend to failed to take into account this a "high risk" case as a result of recognition step is often followed by verification step and these types of false positives will be simply caught by the verification system. Usually the failure to recognize/verify a signature was attributable to poor image quality and high similarity between a pair of signatures. Recognition and verification ability of the system will be multiplied by exploitation further options within the input file set. This study aims to cut back to a minimum the cases of forgery in business dealing.

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Author(s) Profile



Ms Doli Yadav, is currently pursuing her MTech (CSE) from Om Institute of Technology & Management, Hisar. She is completed BTech (CSE).



Ms Shruti Goyal, is currently lecturer in CSE Department, in Om Institute of Technology & Management, Hisar. She is completed MTech (CSE).