Adaptive SIFT/SURF Algorithm for Off-line signature Recognition.

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Abstract

Signature recognition is the process of verifying a writer's identity by checking the signature against samples previously stored in the database. Several techniques such as the distance-based and statistical classifiers used for feature extraction on a signature image are not invariant to scaling and rotation and the Scale invariant feature transform (SIFT) though invariant to scaling and rotation cannot cater for intra-class variation (Transposition) among set of genuine signature images.

This paper proposed a SIFT-SURF algorithm which is used for enhanced offline signature recognition. The SIFT-SURF algorithm computes integral image; obtains hessian data and interest point for each computed integral image; applied neuro-scaling PCA based radial basis function neural network to compute the optimal features for each signature image to come up with an algorithm that is invariant to scaling and rotation as well as reliably match transposition among genuine samples of a signature image.

It was experimentally found that the newly developed adaptive SIFT-SURF algorithm performed better in times of computational time, scaling, rotation and transposition as compared to the existing SIFT.

Keywords- *SIFT, HSV, ADAPTIVE SIFT-SURF, SIGNATURE, NEURAL NETWORK.*

1. Introduction

Biometric means are not based on the possession of materials (as the case of key magnetic card or badge) or the knowledge of some information (as the case of password, key phrases) [1]. Biometrics can be classified into two types; Physiological and behavioural. Physiological biometrics measure some physical features of the subject like fingerprints, iris, hand and finger geometry which are stable over time. Behavioural biometrics measure user actions such as the act of speaking, writing and walking which are affected by health, age and physiological factors [2],[3] A signature is a behavioural biometric characterised by behavioural trait that a writer learns and acquires over period of time and becomes his unique identity [4],[2].

Of the various biometrics, signature- based recognition has the advantage that its analysis requires no invasive measurement and is widely accepted since signature has long been established as the most diffuse means for personal verification in our daily life, including commercial applications, banking transactions and automatic fund transfers [5]. In recent times, the need for an automatic handwritten signature recognition system in complementing visual verification is important due to the rampage of fraud.

A signature recognition system should be able to verify between genuine signatures which are related to Intra-personal variability. Intra-personal variation is variation among the signature of the same person [6] [7].

Various distance-based and statistical classifier such as Neural Network, Artificial Neural Network, Support vector machine, Contour features, Hidden markov model, Graph matching have been used to extract features on signature images but to the best of my knowledge from literatures we have not seen those that are invariant to scaling and rotation. However, SIFT which is invariant to scaling and rotation cannot reliably match transposition (intra-class variation) among samples of a genuine image.

2. Related Works

Various works have been done in the area of signature recognition system. [8] presented an offline signature recognition system based on graph matching which was aimed at evaluating the similarities of two graphs involving a deformation measure and mapping functions between point sets on the signature, the graph method performs better than many other methods and obtained high accuracy. The high accuracy derived in this method is hinged on the fact that the method matches extremes. [9] developed a system to detect skilled forgeries. The system emphasized on the extraction of critical regions which are more prone to mistakes and matched them following a modular graph-matching approach, an accuracy of 98.68% was achieved for the system [10], [11],[12] also developed an offline signature verification system with HMM to detect random simple and skilled forgeries.

[13] proposed an offline signature verification and recognition system with Neural Network. In their approach they used a different way apart from the conventional way of writing an algorithm to solve a computer problem. They developed a system that was able to recognise handwritten signatures and verify its authenticity by using the concept of neutrons in human brain which is familiar with medical practitioners. The system was developed, tested and found suitable for its purpose and results were presented in dynamic images. All these techniques are not invariant to scaling and rotation.

[14], [15] developed an algorithm (SIFT) for extracting robust and stable features from an image which is invariant to scaling and rotation. It uses 4 steps to extract set of descriptors from an image which are the scale-space extrema detection, accurate keypoint localisation, orientation assignment and keypoint description. [16] Used SIFT on face images to develop a face recognition system and the result was excellent when compared to other affore mentioned methods in terms of scaling and rotation.

3. Methodology

This section of the paper discusses the approach to the signature recognition system using adaptive SIFT/SURF features and it follows thus: Image pre-processing, feature extraction and template creation which are all in the enrolment phase. The recognition phase involved matching a test set for a known writer against the already stored template in the database for the same writer.

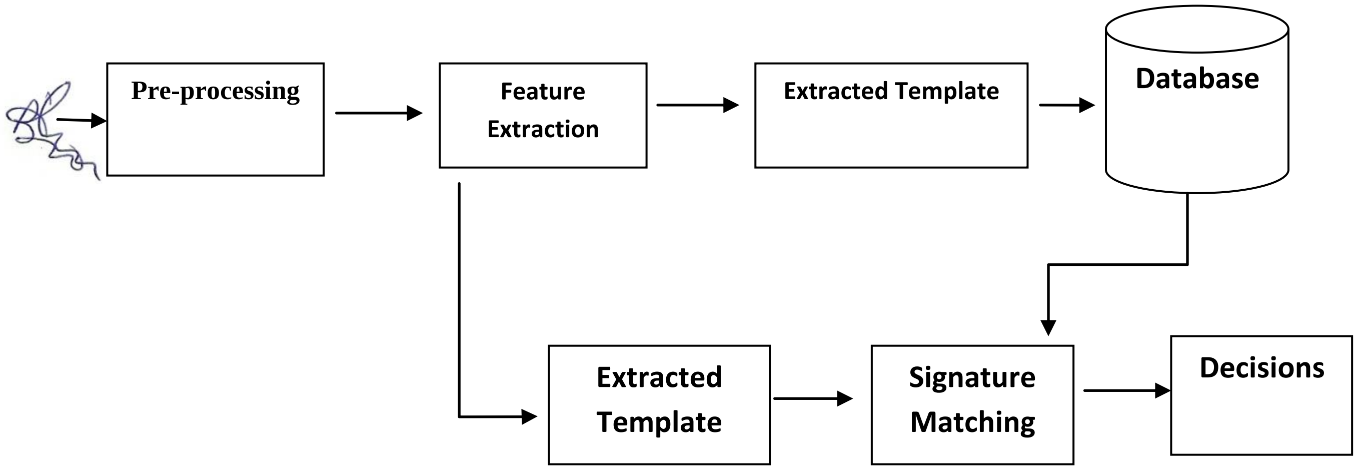

Figure 1: Generic model of Adaptive SIFT/SURRF

3.1 Model Explanation

The images used were signatures which were extracted from documents through scanning and cropping. Signature images were stored in portable network graphic (PNG) format. These images were converted to grey scale for further processing.

In this work, robust feature is extracted using adaptive SIFT-SURF algorithm. This involved identifying stable shape descriptors from the pre-processed signature image.
The feature extraction algorithm is stated below:

1. Computation of the Hessian. Building the Hessian of the output layer by get the image coordinates
2. Building the Hessian of the hidden layer
3. Extraction of the interest points
4. Computation of the Laplacian.
5. Computation of the *priori* outputs response
6. Extrapolating for the extremum:
7. Validation of the extremum of the *posteriori* Hessian estimate:
8. Extraction of the output response using the Hessian data results.
9. Image integration using the *Box Integral* algorithm
10. Create possible regions of the interest points using the descriptor algorithm
11. Obtain the complete description of the point.
12. Obtain the orientation for the prescribed image points.
13. Display results with mappings and feature extractions compared with original image.
14. Apply the "*parfor*" to reduce computational load

Snippet for the Adaptive SIFT/SURF Algorithm

This feature extraction process was done for the ten signatures captured for each known writer and later stored in an array in the Database.

Only the signatures and arbitrary writer IDs were used. For each known writer, a sample of 10 signatures was taken to cater for intra-personal variations.

A template was generated as a MATLAB file and stored. The template has the following:

1. Writer ID.
2. The Euclidean distances between key points.
3. Intra-class thresholds: The minimum and maximum among key points. The range on maximum and minimum intra -class distance given by ± 0.05.

In the recognition stage, samples of rotated and scaled images are used to determine the recognition ability of the proposed system. The recognition performance of the proposed system was compared to that of [15] in terms of scaling, rotation, transposition and computational time and results observed were presented thus;

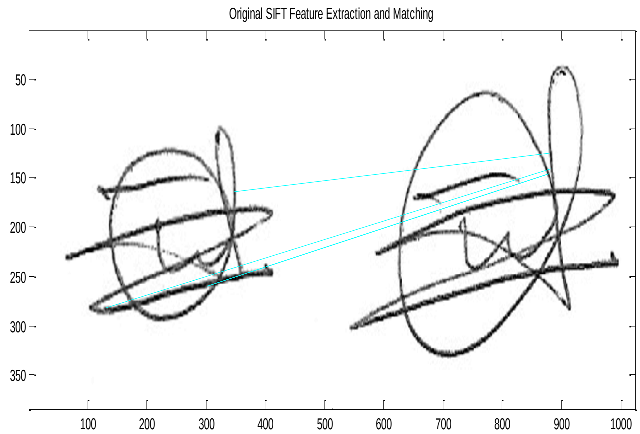

Figure 2 A sample of a scaled signature of a known writer

Figure 2 shows samples of scaled signatures of a known writer. The signature to the right is 2.34 times bigger compared to that on the left. Original SIFT algorithm was used to extract features from it.

It was observed that the SIFT algorithm could not reliably match because the images are not exactly the same but they are samples of genuine signatures of a particular writer presented at different magnification.

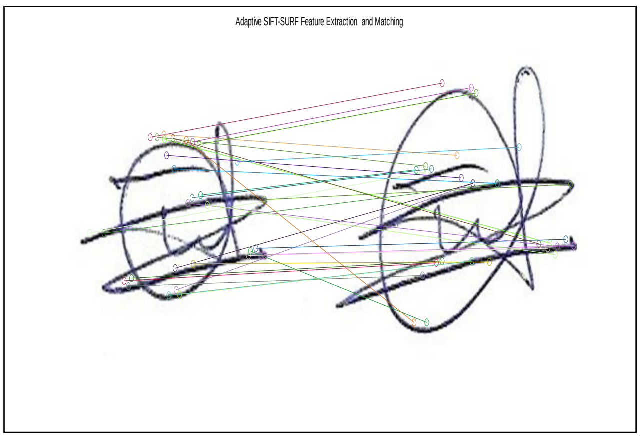

Figure 3: Sample of scaled signature of a known writer using Adaptive SIFT-SURF algorithm

Figure 3 shows the same signatures as in figure 2 but this time the Adaptive SIFT-SURF algorithm is been used to extract features from it.

The result shows the Adaptive SIFT-SURF algorithm can reliably match intra-class variation among genuine samples of a known writer's signature as compared to the SIFT algorithm which could only match a few key points

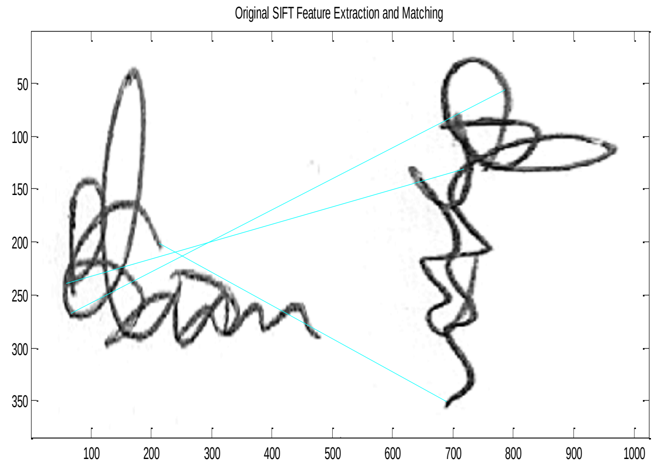

Figure 4 Sample of signatures rotated at a different angle using SIFT algorithm

From figure 4 above, the algorithm could only match three few key points when rotated at angle 180^0 and this is because the signature images are not exactly the same but they are from the same writer showing that the SIFT algorithm though invariant to rotation cannot cater for intra-class variation among samples of genuine signature images

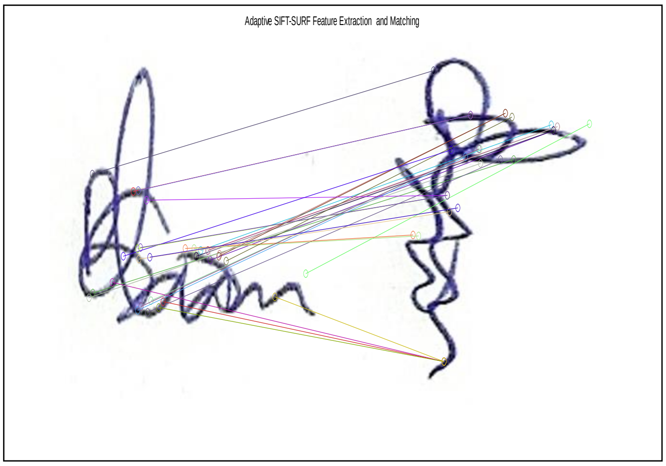

Figure 5 Sample of the same signature as in figure 4 using Adaptive SIFT-SURF algorithm

The algorithm performed better than the Original SIFT as it could match twenty-three key points when the image was rotated at angle 180^0 showing it can reliably match intra-class variation among the genuine samples of a known writer's signature.

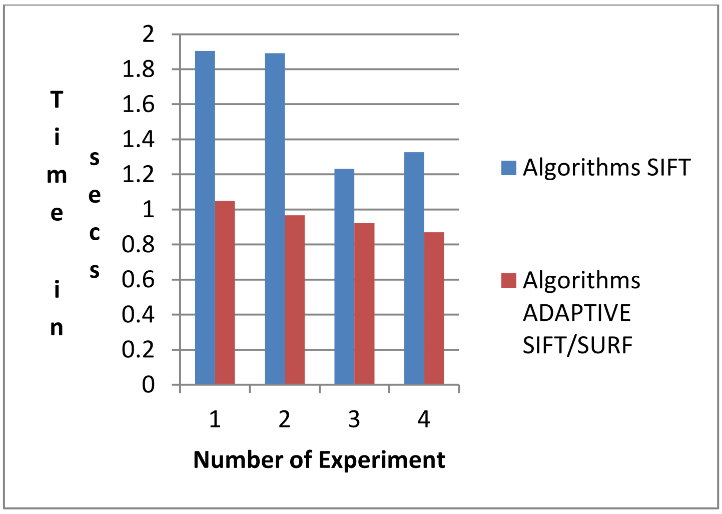

Figure 6: Comparative analysis of computational time

Figure 6 presents a graphical illustration of how Adaptive SIFT/SURF outperforms the original SIFT in terms of computational time when extracting robust features from signature images.

From the first experiment (1 in the number of experiment as shown in figure 6), it is observed that it took the original SIFT algorithm 1.9secs while the Adaptive SIFT/SURF takes 1.1Secs in extracting the same robust features from the same image. Likewise, experiment 2, 3, 4 takes 1.9, 1.25 and 1.35 for original SIFT and 0.9, 0.8 and 0.7 for Adaptive SIFT/SURF respectively.

4. Conclusion

This paper focused on building a fast and robust feature extraction algorithm for signature that is invariant to scaling, rotation and transposition (Intra-class variation).

From the research carried out, it was observed that the new algorithm Adaptive SIFT/SURF performed better in matching intra-class variations of genuine samples of images. Adaptive SIFT/SURF outperformed SIFT with criteria such as scaling, rotation, computational time and transposition.

5. Future Works

Since it has been identified that it is possible to have a robust feature extracting system that will be invariant to different scaling, rotation and transposition as well as fast in extracting these robust feature, there is a need to ensure that this new algorithm is totally invariant to illumination changes when exploring on other image based biometrics such as face, fingerprint, iris recognition.

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