Resistance of Scale-Invariant Feature Transform (SIFT) Against Rotation and Noise

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Abstract

In most nations throughout the world, signatures have long been the primary indicator of authenticity and authorization in financial and legal operations, so there is a lot of demand for the development of real- time signature verification systems, especially offline signature verification. One of the problems that arise in offline signature verification is writing signatures with different scales and rotations because someone is not always consistent when writing their signature, thus significantly affecting the level of accuracy in offline signature verification. In addition, the existence of a signature that has a very high level of similarity between one individual and another and changes in lighting intensity and noise in thesignature data can also affect the accuracy level of signature verification testing. In this subject, a number of strategies have been developed, however, the feature extraction methodology has a considerable impact on the verification performance. Here, we describe a Scale Invariant Feature Transform (SIFT) feature extraction algorithm to address this issue and produce a robust feature model that is noise, scaling, androtation resistant. A categorization study is also given in order to evaluate the effectiveness of the suggested strategy. Experimental research demonstrates that the suggested method for offline signatureverification systems achieves promising performance.

Keywords: SIFT, SVM, handwriting signature

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1 Introduction

A person's handwriting style is much influenced by the factors that characterize that person; one form of handwriting is a signature. In most nations throughout the world, signatures have long been utilized as the primary criterion of authentication and authorization in financial and legal operations. This is becoming a typical occurrence in daily life. Although the community has employed signature verification, the use of computer-based signature verification in biometrics is currently primarily restricted to academic research. Regardless of the meaning of the handwriting, the signature verification method seeks to extract handwritten information to confirm the author's identity. The signature verification system is essentially separated into online and offline categories based on the data collecting technique. (Al-banhawy et al., 2020; Sigari et al., 2012; Zhou et al., 2021).

The online category makes use of the subject-specific pen movement dynamics of the signature, which are captured by the digital tablet or instrumented pen in real-time and allow for the extraction of more features. Additional data can be obtained when creating a signature, such as time, pen pressure up and down, and azimuth. The offline signature refers to a signature that is written on paper, then transferred to a computer via a camera or scanner to create a signature image, which is then confirmed based on the image attributes. Due to the lack of constant dynamic properties and the difficulties in isolating specific features from static pictures,

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offline signature verification systems are typically thought to be more difficult than online signature verification systems.

Based on the differences in the patterns of the originaland fraudulent signatures, signature verification determines if an observed signature is authentic or fake. Most of the research efforts in this area have examined the detection of simple and random (unprofessional) signature forgery. Random forgery of signatures is carried out without knowing the name of the signer and the form of the signature. A simple signature forgery is carried out based on knowledge of the original signature but the imitation that is made the level of similarity is still far away (Al-banhawy et al., 2020). For example, forgery of signatures based on his memory of the original signature.Professional signature forgeries, as opposed to random and straightforward forgeries, are made by those who are familiar with the original sample signature and then makean effort to make the copy as accurate as possible.

The signature verification process is carried out by comparing the tested signature with all signatures in the defined dataset. The similarity value obtained can beinterpreted as the proximity of the signature. The foundation of many traditional approaches of signature verification is the assignment of a semantically interpretable distance metric. Next, decide if the difference between the test signature and the reference signature is acceptable by setting a threshold that dependson the signer. Several studies have used general classifier techniques to verify signatures, including Support VectorMachine (SVM) (Kumar & Bhatia, 2021; Soleymanpou etal., 2010), k-Nearest Neighbour (kNN) (Desai et al., 2021; Harakannanavar et al., 2021; Hezil et al., 2018), andMultilayer Perceptron (MLP) (Kaur & Kumar, 2021; Rabbi et al., 2019).

Extraction of a feature representation that can be used to separate each person's signature from a collection of signature images, in addition to distance calculation, is a crucial step in developing an offline signature verificationsystem. There have been several feature representations produced, which may be generally divided into global or local methods (Lee et al., 2005; Qi & Hunt, 1994). A global approach is used to characterize the entire signature. The most popular example of a global approach is Principal Component Analysis (PCA). The reason PCAis referred to as a global technique is that it gathers the fundamental signature properties that apply to the whole signature, including different geometric aspects like signature area, signature height to width ratio, and maximum horizontal or vertical histograms. The section of the signature used to characterize the precise geometrical and topological properties of the local segment are known as the local approximation. At the stroke and sub-stroke levels, the local approach may be inferred using examples of stroke segment samples, sub- stroke descriptors, and local shape descriptors (Zhang, 2010). The local approach is widely accepted to include more precise and complete characteristics of the signaturesample. Typically, a single technique (geometric, local, global, statistical, etc.) is used, or a combination of various approaches. Despite all these developments, offline signature verification results fall well short of expectations in terms of accuracy and resilience. So, for offline signature verification systems, research on the effective encoding of signature picture characteristics is still a key area of study.

This study focuses on the problem of writing signatures with different scales and rotations because they significantly affect the level of accuracy in offline signature verification. The existence of a signature that hasa very high level of similarity between one individual and another and changes in lighting intensity and noise in thesignature data can also affect the accuracy level of signature verification testing. Several attempts have beenmade to minimize this. One attempt involves using the Scale Invariant Feature Transform (SIFT), a feature extraction technique that is invariant to scale and rotation(Lowe, 2004).

In computer vision, the SIFT algorithm is used to findand characterize the little details in the picture. The local feature is more effective in distinguishing between genuine and fake signatures because it can recognize the signature image with simple modifications (Ahlawat et al., 2014). SIFT is very resistant to image scaling, rotation, and shifting the angle of view. SIFT can withstand variations in both noise and light intensity (Wang et al., 2022).

The advantages of SIFT that are resistant to rotation, and noise make SIFT proposed in this study to extract offline signature image features and will then be classifiedusing SVM. The original offline signature that had been rotated to be categorized was entered in this study's SIFT resistance test scenario against rotation. The initial offline signature, which was stamped, was entered in order to testthe shift's tolerance to noise.

2 Related Work

The advancements in feature extraction and signature verification system approaches are covered in this section. As said earlier, the feature extraction process is an essential component of any application based on computer vision. The last few years have seen the presentation of several studies aimed at providing effective feature extraction to improve classification and detection performance. Verification methods for handwritten signatures are a frequently used example of a form of biometric authentication. In some countries, such as Indonesia, China, Arabic, and Japan, official letters are written in the native language of the country. Pal et al. research's has shown the effectiveness of an offline approach for verifying signatures. (Pal et al., 2013). This service focuses on authenticating signatures written in Western characters in addition to the offline signature verification method. This work employs SVM classifiers, Zernike moment features, and gradient features for verification.

Research Song et al. explore signature verification techniques by determining whether the original signature has been forged or not (Song et al., 2017). Song et al. performing significant feature extraction can result inbetter feature perception, which can then be used in further analysis. Signature verification is significantly affectednot only by the feature extraction process but also by feature selection. The foundation for signature verification can be improved by selecting reliable and authenticfeatures. In order to recreate reliable spectral qualities, Song et al. created a system based on spectrum information. In this system, the spectral information isverified and chosen dynamically. Additionally, spectrum decom-position and information extraction are accomplished with effectiveness using wavelet packet decomposition. Dynamic feature extraction improves theperformance of tested online and offline signature verification systems. In the same way, A dynamic feature extraction framework for a handwritten signatureverification system has been developed by Zalasiński et al.(Zalasiński et al., 2015). This is accomplished by creating a reliable signature sharing system that takes into consideration both the horizontal and vertical parts and isthen used to the identity verification procedure. The traditional signature verification system needs a lot of characteristics to finish the job, but because the input reference is so little, the training processes are ineffective.The characteristics of each person have their own distinctive pattern, which can be identified using a computer vision-based system. In this approach, signature verification is done by extracting the identifying features.

An offline signature verification model was created by Ferrer et al. utilizing rotation-invariant LBP features combined with GLCM features (Ferrer et al., 2013). In this work, a unique technique has been designed that is able to perform well in identifying text in images with complex backgrounds and layouts, such as checks and invoices. In this study, a reliable model for feature extraction was built. This model is capable of generating useful features and leading to improved classification performance.

Rivard et al. offer an innovative method for author- independent offline signature verification (Rivard et al., 2013). In this research, many feature extraction processes are carried out, each of which serves to determine which features are relevant. In addition, a dichotomous transformation is carried out with the aim of achieving an efficient classification performance. The most important conclusion is that the improvement strategy was successfully adopted, which allows automatic feature selection while the training process is being carried out. This study improved the system while also solving the reference signature-based verification issue. The usage ofonline signatures can be hampered by a number of performance problems, some of which can be resolved by integrating special features into the system. In their study, Iranmanesh et al. describe a novel technique for use in systems that verify online signatures (Iranmanesh et al., 2014). The study also focuses on expert forgery, which can be processed by traditional procedures in the same way as authentic signatures. Studies have revealed that artificial intelligence has a strong tendency to learn patterns from given complex scenarios. Therefore, the multilayer perceptron approach was used in this study by considering the PCA properties.

Xu et al. investigate the application of artificial intelligence and this technique in signature verification systems. (Xu et al., 2011). According to this method, character representation is performed by utilizing feature vectors. In addition, a feature selection technique that provides effective features for training model formation has been introduced here. This process has been carried out as part of the overall design. The neural network is used in the creation of the template, and then threshold- based verification is shown at the end. Thumwarin et al. explore the signature verification process using a limited impulse response mechanism (Thumwarin et al., 2013). This technique uses time-frequency characterization to draw out dynamic characteristics. The midpoint parameter is initially extracted, which aids in reducing the degree ofvariance in handwritten characters. Based on the identification of handwriting behavior, this study examines characteristics, handwriting movement pressure, and area pressure values in order to assess handwriting behavior. In addition, this study also contains a dynamic feature analysis method based on FIR and wavelet coefficients.

Emrich et al. create a novel method for handwriting verification feature extraction and categorization (Emerich et al., 2010). For feature extraction purposes, an approach based on wavelet decomposition is used. The feature is then processed to facilitate classification by an SVM. Ansari et al. created a decision-based approach for signature verification using fuzzy logic. (Ansari et al., 2014). Signature verification is done through the use of form features and dynamic feature extraction methodology in this study. For the purpose of feature extraction, a unique technique has been devised. In contrast to the previous method, this approach first involves segmenting the signature data into different parts, followed by an operation involving feature extraction.

Gruber et al. present a new approach to the creation of a signature verification system (Gruber et al., 2010). In this study, the SVM classifier and identification techniquewith the longest sequence were used to determine the level of signature similarity. This method concentrates on regional signal variations and takes those variations into account when trying to extract features. This method usesa graphics tablet for pen tip coordinate analysis, which results in varying signal strength.

Refer reference (Mohammadi & Faez, 2012), explorecontemporary strategies for signature verification and identification systems. The author of this paper did research and discovered that applying dynamic time wrapping and the Euclidean distance computation significantly improves performance for similaritymeasurement. As long as the time length of the twoestimated signals is the same, this is something that can bedone. This technique uses the input signal's time length to determine the signature. The patterns are then classified as authentic or false signatures. In order to maximize the distance between authentic and false signatures, this article introduces a novel method that determines the similarity index between two signatures. The categorization may be incorrect if there is not enough separation between the original and phony signature spacing. This section discusses the most recent methods for both online and offline signature verification systems. The investigation's findings support the assertion that the feature extraction procedure is a crucial stage in determining performance criteria. Although the system performs flawlessly when it comes to verifying signatures, there are still some difficult problems. For instance, this system's erroneous acceptance rate may result in a decline in security performance. Conventional systems have issues with complexity and might not perform as well as expected in cases involving extremely complicated images. However, the majority of these issues are caused by the feature extraction process, hence it is vital to develop trustworthy feature extraction methods.

3 Research Methodology

The offline signature verification technique consists of several steps. First of all, create a signature database. Furthermore, pre-processing and feature extraction is performed on digital images using texture descriptors and geometric features. This study uses SIFT to perform feature extraction according to the research focus, namely the different scaling and rotation problems in offline signature verification. After feature extraction from the signature image, the comparison algorithm is implemented. Finally, the performance of this offline signature verification technique was evaluated using the Confusion Matrix.

3.1 SIFT

Referring to the research of Wang et al. that the image local feature description operator known as SIFT is based on rotation, space scaling, image invariant scaling, and even radiation conversion (Wang et al., 2022). The feature point assessment stages, feature vector construction, and feature match search, each of which is optimized depending on a particular scenario, can all be combined inthe same way using SIFT. It is also possible to match the features of two photos with minor changes. Following are the steps of SIFT based on reference.

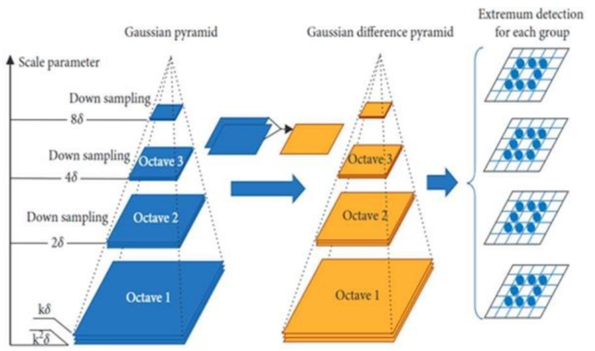


Figure 1: Gaussian pyramid.

Gaussian Difference pyramid (DOG) are frequently used to place SIFT accurately, however, their DOG values are susceptible to edges and noise (Figure 1). The positioning and size of feature points were precisely changed through additional multi-quadratic procedures fitting for local extremum points. Additionally, the Taylorequation for the local extreme value of the point D(a0, b0,α0) in the space-scale function D(a, b, α) is shown as equation (1).

The key point deviation is represented by D (a0, b0, α0), and the value of D(a, b, α) at the local extreme of the figure is represented by D(a0, b0, α0), when the key point is deviated by E = $(a, b, \alpha)^T$. In order to determine the precise location of the extreme E, as illustrated in the equation (2), the derivative of equation (1) must be calculated to get zD (E)/E = 0.

The key point should be deleted if another monitoringpoint is positioned extremely near to it and the divergence e from the interpolation center is more than 0.5 in both directions. The techniques described above allow the determination of the reference direction of the local imagecharacteristics. In addition, Gaussian images created from feature point scale values are used to obtain the closest match to the scale values. The possible expressions of the computational procedure are as equation (3).

The gradient modulus and gradient direction of the picture gradation around radius 31.5 and the feature pointas the center are estimated using the finite difference technique of calculation. The gradient gradI (a, b) of the feature point is represented by equation (4) to (6). Equations (4) to (6) also express the modulus of thegradient and the direction of the gradient, respectively.

The values of the gradient modality and the gradient directional of the pixels in the environment are then collected based on the histogram after all of the gradient feature points of the Gaussian image have been formed. Figure 2 displays the procedure.

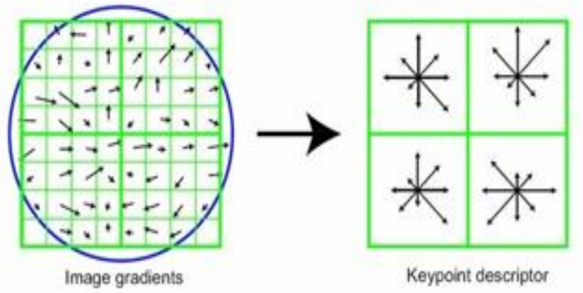


Figure 2: Histogram of gradient orientation.

$$D(a,b,\alpha) = D(a_0,b_0,\alpha_0) + \frac{\partial D^T}{\partial E}E + \frac{1}{2}E^T\frac{\partial^2 D}{\partial E^2}E. \quad (1)$$

$$\hat{E} = \frac{\partial^2 D^{-1}\partial D}{\partial E^2\partial E}. \quad (2)$$

$$L(a,b,\alpha) = G(a,b,\alpha).I(a,b). \quad (3)$$

$$gra\ dI(a,b) = \left(\frac{\partial I}{\partial a},\frac{\partial I}{\partial b}\right), \quad (4)$$

$$n(a,b) = \sqrt{\left(L(a+1,b) - L(a-1,b)\right)^2 + \left(L(a,b+1) - L(a,b-1)\right)^2}, \quad (5)$$

$$\theta(a,b) = \tan^{-1}\left[\frac{L(a,b+1) - L(a,b-1)}{L(a+1,b) - L(a-1,b)}\right] \quad (6)$$

3.2 Research Subject

The respondents involved were 8 people, each of whom wrote 100 signatures. A total of 50 signatures were stamped and another 50 were without a stamp. The number of training data for each respondent is 70 signatures and test data for each respondent is 30 signatures and also added fake signature data for each respondent made by professionals as test data.

4 Experimental Results

Results from the experiments are published below, along with a description of the suggested techniques. This studydemonstrates the feature extraction technique's potential to enhance offline signature verification systems' functionality. This whole experiment uses Python. The signature data used are 800 signatures from 8 respondents. Each respondent has 100 signatures with 50 signatures affixed with a stamp and 50 other signatures without a stamp. This is intended to see the consistency of the signatures of each respondent.

Figure 3 illustrates the stages of the overall calculation process. This model starts from the colour segmentation pre-processing stage shown in Figure 3(b) and continues with the dilation process (Figure 3(c)). The final result ofthe pre-processing can be seen in Figure 3(d). The application of SIFT feature extraction is the subsequent stage, which is represented in Figures 3(e) to 3(g), and the outcome of the SIFT feature extraction process is displayed in Figure 3. (h). The following step is matching areas with coloured circles in the supplied image. Important point matching reveals the importance of key points that were retrieved throughout the matching procedure.

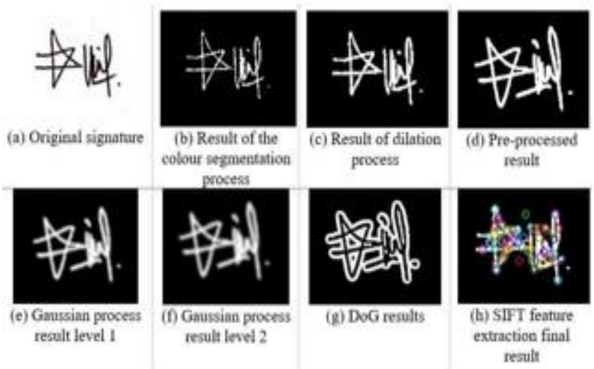


Figure 3: Proposed process steps.

The next step is experimental verification of the effect of the feature extraction approach used on the signature verification system. Classification performance analysis is run to measure performance. Table 1 presents the classification performance based on the feature extraction approach used for the original offline signature image thathas been rotated 180 degrees. The experiment was carried out as a whole by inputting the original signature image that had been rotated 15, 30, 45, 90 and 180 degrees and the system identified the rotated offline signature image as the original signature.

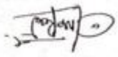
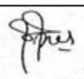
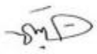
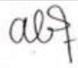
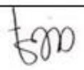
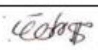
Subject	Original Signature	180^0 Rota-tion	Results
Respondent 1			Success
Respondent 2			Success
Respondent 3			Success
Respondent 4			Success
Respondent 5			Success
Respondent 6			Success
Respondent 7			Success
Respondent 8			Success

Table 1: Original offline signature verification results with 180-degree rotation.

The proposed approach shows that it has good performance in recognizing the original offline signature that has been rotated with various rotation angles as the original signature. The result is that 100% original rotated offline signatures are recognized correctly. The accuracy of the system in order to be more accountable in this study is determined by using a confusion matrix.

$$CA = \frac{TP+TN}{TP+TN+FP+FN} \quad (7)$$

The following presents a confusion matrix based on the experiments that have been carried out.

Table 2: Test results for signature verification without astamp.

Subject	Confusion Matrix				
	TP	FN	TN	FP	CA
Respondent 1	20	0	4	0	100%
Respondent 2	19	1	4	0	95.83%
Respondent 3	19	1	3	1	91.66%
Respondent 4	18	2	4	0	91.66%
Respondent 5	20	0	4	0	100%
Respondent 6	20	0	3	1	95.83%
Respondent 7	19	1	3	1	91.66%
Respondent 8	19	1	3	1	91.66%

The average accuracy of the offline signature verification test without a stamp obtained is 94.79%.

Table 3: The results of the signature verification test witha stamp.

Subject	Confusion Matrix				
	TP	FN	TN	FP	CA
Respondent 1	10	0	3	1	92.86%
Respondent 2	9	1	4	0	92.86%
Respondent 3	8	2	3	1	78.57%
Respondent 4	8	2	4	0	85.71%
Respondent 5	9	1	3	1	85.71%
Respondent 6	7	3	3	1	71.43%
Respondent 7	9	1	2	2	78.57%
Respondent 8	9	1	3	1	85.71%

The average accuracy in offline signature verification tests with stamps obtained is 83.93%.

Table 4: The results of the signature verification test withall test data.

Subject	Confusion Matrix				
	TP	FN	TN	FP	CA
Respondent 1	30	0	7	1	97.36%
Respondent 2	28	2	8	0	94.74%
Respondent 3	27	3	6	2	86.84%
Respondent 4	26	4	8	0	89.47%
Respondent 5	29	1	7	1	94.74%
Respondent 6	27	3	6	2	86.84%
Respondent 7	28	2	5	3	86.84%
Respondent 8	28	2	6	2	89.47%

The average accuracy of the offline signature verification test for all test data obtained is 90.79%.

The suggested method proves that it can achieve the required performance in the rotational or noisy offline signature verification process and can be adapted for real- time offline signature verification systems.

5 Conclusion

Offline signature verification systems are widely utilizedin many industries to prevent misuse of signatures, both government and private. It is vital to develop effective methods to analyze the signature pattern because people are not always consistent when signing documents, which can lead to variances in their signature pattern. Here, we demonstrate SIFT feature extraction, which is used to analyze signature patterns. By integrating an invariant rotation feature during orientation calculations, the SIFT feature extraction method was enhanced based on the model utilized. A feature vector is then created, and SVMis used to process it in order to generate training and testing analyses. Finally, experimental research demonstrates that the suggested strategy works effectively for the offline signature verification system.

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