# A Fusion Methodology of AKAZE and Neural Network for Fingerprint Recognition

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***Abstract*—In recent years, biometric information has become essential to the maintenance of data confidentiality. In particular, fingerprints have become the most reliable biometrics system for individual human identification based on finger image characteristics. A good quality fingerprint should have at least 25 to 90 minutiae. An unclear image will result in poor recognition. In this work, we propose a novel methodology to improve fingerprint recognition. We represent the fingerprint feature using the AKAZE features. The KAZE features use nonlinear diffusion to perform local blurring on the image data while preserving the object boundaries and removing the noise. The heuristic method for calculating the matching rate is replaced with a neural network that distinguishes various data types with fewer rules. Experiments have been performed to validate the proposed method using an instance of the FVC2002 database. The proposed method has achieved adequate results for the biometric evaluation. The values of EER are less than 1.5%, with the highest success rate recorded in DB2 having an EER of 1.01%.**

***Keywords*—AKAZE feature, neural network, fingerprint recognition**

## I. INTRODUCTION

Biometrics have been effectively used in data accuracy preservation over the last decade. The biometric process depends on the physical, chemical, and behavioral characteristics of a person. Biometric features are used as authentication or identification methods, such as in the exchange of networked computer services, payment or credit cards [1]. Fingerprint has become the most reliable biometrics system for individual human identification based on finger image characteristics. Our comparison of fingerprints with the other biometric traits also agrees with this observation. The fingerprint is more distinctive, permanent, and with higher acceptability than other biometric traits like face, signature, speech, etc. [2].

A fingerprint comprises grooves, furrows, and minutiae obtained by an ink impression on paper or sensors. The configuration is permanent and unchangeable for an individual. Saliency and suitability are the properties of a good fingerprint [3]. Saliency consists of the model containing specific information. Suitability aims to represent image features effectively, as well as store images and assist in image matching. A good fingerprint image should have at least 25 to 90 minutiae [4]. If the image is not clear, the recognition will be poor.

Many research works have been done to improve the detection of minutiae features. For example, a fingerprint can be recognized by region and shape features [5], [6]. However, this approach depends on the spacing and orientation of the features. Similar analysis has been proposed for multiple minutiae features by combining the secondary features, namely the minutiae triplets. This method contains local domain and global transformation invariants [7], [8]. Nonetheless, those methods must ensure the number of minutia and the clarity of fingerprint objects.

The fingerprint features can also be represented as a pore descriptor. The pore information can be derived from the ridges or valleys, which appear as dark or bright lines, whereas the pores appear as bright blobs on the ridges. The pattern can be analyzed using a 2D Gaussian filter or blob detection. More advanced pore extraction approaches often incorporate deep learning approaches. First, the coordinates of the pores in the images are labeled as a dataset. A CNN is then applied to learn the pattern of the pore images. Finally, the descriptor that stores the pore information is provided [9], [10]. The Daisy descriptor and the Pore Valley descriptor are two frequently used descriptors [11]. Nonetheless, the pore-based method works well only within the range of 1000 dpi and cannot be implemented in a low-cost system.

Others have tried to use local feature-based methods such as ORB, SIFT, SURF, or even AKAZE for more advanced approaches [12]– [14]. These approaches preserve the noise, scale and image orientation. Local feature-based approaches detect sub-images with limited locations and orientations. The AKAZE features use nonlinear diffusion to perform blurring adapted locally to the image data, thus preserving the object boundaries and removing the noise. It has been shown that the repeatability and the discriminability of KAZE features are better than the SIFT and SURF features. Nevertheless, the KAZE features are computationally expensive due to the Additive Operator Splitting (AOS) schemes for solving nonlinear diffusion equations [15]– [17].

AKAZE has been used as a feature representation for fingerprint recognition. It achieves adequate results compared to the SIFT method. However, this method still uses a heuristic approach in generating matching rates [13]. So it is necessary to do trial and error in determining the best weight for each image subset. the heuristic approach also has a weakness in providing confidence values in image matching. This can be proven by the value of FRR@FAR 1/50000 which will be carried out in this work.

In this work, we propose new strategies for fingerprint recognition that use the AKAZE features for representation. These features are selected because they use nonlinear diffusion to blur the image data, maintain object boundaries, and remove noise. It can maintain the fingerprint image's noise, scale, and orientation. Furthermore, we proposed the neural network (NN) approach to replace the heuristic method for calculating the matching rate as a decision scoring method. The neural network also distinguishes various data types without adding many rules to the system [18].

The paper is organized as follows. Section 2 outlines the background of this work, Section 3 describes the proposed approach, including the overview of the system, feature extraction, feature matching, and decision scoring. Section 4 discusses the results and Section 5 provides the conclusions of this work.

## II. BACKGROUND STUDY

### A. AKAZE FEATURE

Multiscale image processing has been widely used to extract image information by detecting interesting features at different scale levels. The features of an image are obtained by filtering the original image with an appropriate Gaussian scale-space function. However, feature extraction from images using the SIFT and SURF methods, which use the Gaussian kernel space, is only successful for images with uniform object intensity distributions.

Nonlinear scale-space approaches solve feature extraction by improving the Gaussian scale-space. Moreover, nonlinear diffusion typically reduces the noise and improves the contour images. The AKAZE features adhere to this principle by using nonlinear diffusion processes in the image domain. These approaches are described by nonlinear differential equations (PDEs) [16], [17]. The classical nonlinear diffusion equations given in equation (1).

$$\frac{\partial L}{\partial t} = \mathrm{div}\,(c\,(x,y,t)\,)\,\cdot\,\nabla L \qquad (1)$$

Where $div$ is the divergence operators, $\nabla$ is the gradient operators, $L$ is the image luminance, $c$ is the conductivity function, and $t$ is the scale parameter.

The system detects points of interest, and the features are found by computing the scale-normalized determinant of the hessian in multiscale space [17]. The scale of the differential operators must be normalized since the amplitude of the spatial derivatives decreases with the scale, as shown in equation (2).

$$L_{Hessian} = \sigma^2\,(L_{xx}\,L_{yy} - L_{xy}^2\,) \qquad (2)$$

Where $Lxx$ $Lyy$ is the second-order horizontal and vertical derivatives and $L2_{xy}$ is the second-order cross derivative.

After finding the features, they are described by a feature descriptor. The Modified-Local Difference Binary (M-LDB) descriptor uses the gradient and intensity information from the nonlinear scale space. Figure 1 shows the result of the LDB feature extraction. The average intensity Iavg and the first-order gradients, dx and dy of grid cells within an image field, are used by the feature descriptor. The average intensity and gradients provide a more comprehensive description than other binary descriptors. The descriptor then uses a multiple-gridding strategy to encode the structure at different spatial granularities. Coarse grids can cancel high-frequency noise, while fine grids capture detailed local patterns to increase the discriminability. Finally, the LDB descriptor uses a modified AdaBoost method to select a set of salient bits.

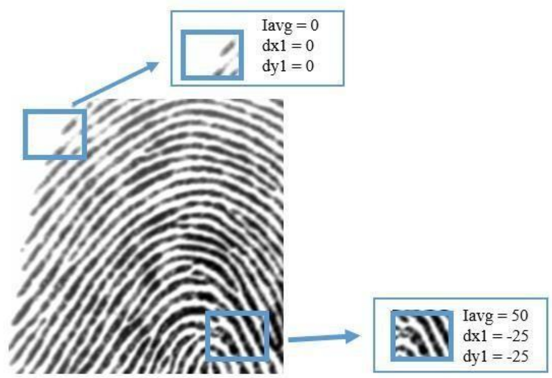


Fig. 1 Illustration of the LDB extraction

### B. NEURAL NETWORK

This work uses a neural network algorithm for decision-scoring. Neural networks have been shown to classify recognized nonlinear inputs into a match or a non-match label. Generally, a neural network is designed based on the workings of the human brain for a particular task or function of interest

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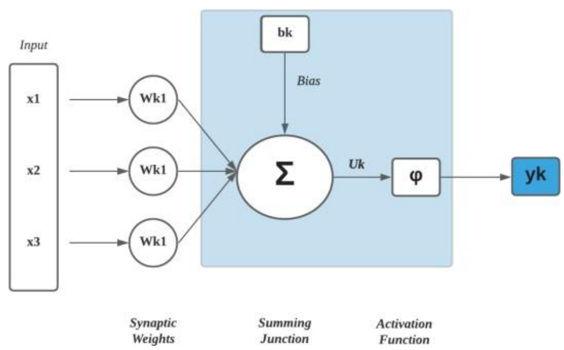



Fig. 2 A basic neural network model.

Figure 2 shows the basic model of the neural network. It consists of three neuron inputs, one hidden layer, and one neuron output. The bias $b_k$ affects the increasing and decreasing of the activation function's net input [19]. Each neuron $k$ can be expressed based on equations (3) and (4).

$$u_k = \sum w_{ki} x_i, \qquad (3)$$

$$y_k = \varphi\,(u_k + b_k), \qquad (4)$$

Where $x1, \ldots, xn$ are the input signals, $wk1, \ldots, wkn$ are the synaptic weights of neuron $k$, $u_k$ is the linear combiner output due to the input signals, $b_k$ is the bias, $\varphi(.)$ is the activation function, and $y_k$ is the output signal of the neuron.

## III. OUR APPROACH

The emphasis of this work is on the performance and evaluation of the matching process. Therefore, we intend to develop a fingerprint recognition system with satisfactory accuracy and sensitivity to detect impostor and genuine results.

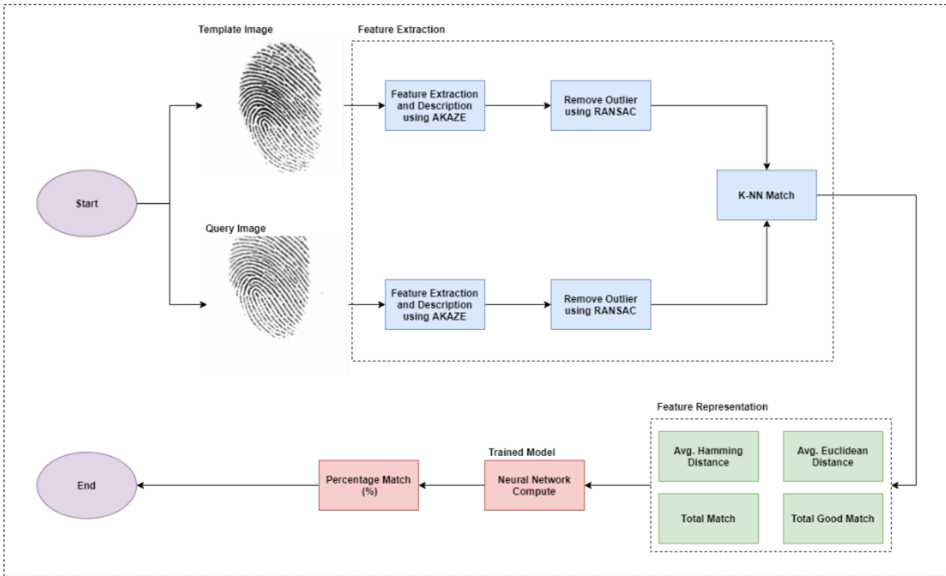



Fig. 3. The general design of the proposed system.

There are several stages in image identification. Figure 3 describes the general design of the proposed system. The first stage includes feature extraction and description using AKAZE features. In the second stage, we combine the brute force and RANSAC approaches for matching. It has been shown that the combination overcomes the issues for matching based on point-based features and prevents outliers. In the final stage, we use a neural network for decision scoring. The neural network correctly evaluates and assigns the result into two classes (matching and non-matching).

The system incorporates two processes, training, and testing, for fingerprint recognition. The model is initially trained according to the features from the neural network. The trained model is then used for testing.

As an evaluation, this work analyzes the method using EER and FRR@FAR 1/50000. EER is used to determine threshold values for false acceptance rate and false rejection rate. Meanwhile, FRR@FAR 1/50000 determines the sensitivity regarding the balance of impostor and genuine result. So this work focuses not only on the error rate obtained but also on the level of sensitivity between the acceptance rate and the rejection rate.

## IV. RESULTS AND DISCUSSIONS

Several experiments have been conducted to evaluate the proposed system. First, we have experimented with different types of datasets to determine the performance of the proposed method for the recognition of specific image sets. Secondly, we have compared the proposed approach with other approaches. Finally, several algorithms have been selected for comparison based on [20]. Here are other approaches for comparison:

- **Minutiae triplets** are a minutiae representation that contains information such as the orientation, angle and position of each minutia with respect to its neighbors [7].
- **Finger ConvNet** is a deep learning recognition methodthat combines feature extraction and decision making [21].

The FVC2002 database, including DB1, DB2, and DB3 is used in the experiments. Each dataset consists of 800 images (100 fingers ID x 8 impressions). So, the total comparison of impostor is 4950 (100 * 99 / 2) and genuine is 2800 (100 * 8 * 7 / 2) [22].

### A. *PERFORMANCE ANALYSIS WITH DIFFERENT DATASETS*

Our approach needs to be proven for a different type of dataset. This experiment can be used as a reference for analysis in comparison to other approaches. Table 1 shows the evaluation results summarized by the EER (*Equal Error Rate*) and AUC (*Area Under The ROC Curve*). The EER determines the threshold values for the false acceptance rate and the false rejection rate. The AUC determines the robustness of the approach in the differentiation of each class. It is described in the ROC (*Receiver Operating Characteristic*) curve.

TABLE I
PERFORMANCE COMPARISON BETWEEN NEURAL NETWORK AND HEURISTIC APPROACH.

| Data sets | Evaluation Results: EER (%) | Evaluation Results: AUC (%) |
|---|---|---|
| DB1 | 1.41 | 99.93 |
| DB2 | 1.01 | 99.96 |
| DB3 | 1.56 | 99.90 |

As shown in Table I, the results of the proposed approach have consistent reliabilities and balances across all three image sets. For all three image sets, the EER values are less than 2%. Furthermore, the EER for DB2 is lower than for DB1 and DB3. The DB2 image set has more evenly distributed differences in the finger ID image than DB1 and DB3.

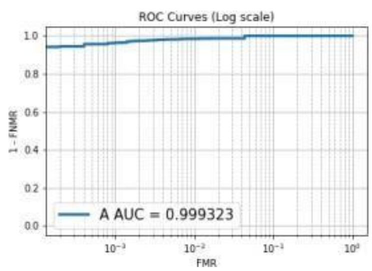
This research provides efficient and reliable fingerprint pattern recognition. The AKAZE method has a vital role in accurately describing fingerprint features and image noise. Furthermore, the neural network can adequately map the input features such as the average Hamming distance, average

Euclidean distance, total match, and total good match with output percentage.

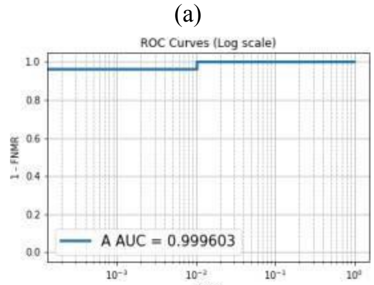
In addition, we compared our proposed method with a heuristic method to produce a matching rate. Table II showed that the EER value was slightly the same, but with the approach using neural networks, the sensitivity between the acceptant rate and the rejection rate was higher than the heuristic method. This is proven in the evaluation of FRR@FAR 1/500000.

TABLE II
PERFORMANCE COMPARISON BETWEEN NEURAL NETWORK AND HEURISTIC APPROACH.

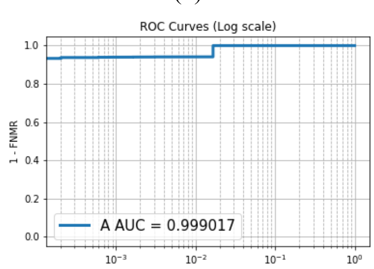
| Data sets | Evaluation Results | |
|---|---|---|
| | EER (%) | FRR@FAR 1/50000 (%) |
| Neural Network Approach | | |
| DB1 | 1.41 | 5.82 |
| DB2 | 1.01 | 3.85 |
| DB3 | 1.56 | 6.71 |
| Heuristic Approach | | |
| DB1 | 2.78 | 18.79 |
| DB2 | 2.50 | 24.75 |
| DB3 | 2.98 | 21.01 |




(a)




(b)




(c)

Fig. 4. The ROC curves for the FVC2002 fingerprint database

The results for all data sets also exhibit a reasonably good trade-off between the sensitivity and specificity with AUC values of over 99%. Furthermore, there is also a reasonably good balance between the FAR and 1-FAR as shown by the ROC curve in Figure 4.

### B. *PERFORMANCE ANALYSIS WITH DIFFERENT APPROACHES*

We have evaluated the matching results with different approaches. The proposed method is compared to existing methods to assess the robustness of the method. Table 2 shows the comparative results based on the EER values.

TABLE III
COMPARISON OF DIFFERENT APPROACHES.

| Approaches | EER Evaluation | | |
|---|---|---|---|
| | DB1 (%) | DB2 (%) | DB3 (%) |
| Minutiae triplets [7] | 1.00 | 2.07 | 6.11 |
| Finger ConvNet [21] | 1.79 | 2.35 | 4.31 |
| Proposed approach | 1.41 | 1.01 | 1.56 |

As shown in Table III, the proposed method provides relatively stable performances when tested across different datasets. All of the tested approaches have similar EER values for DB1, which has good clarity and low noise content. However, all tested approaches have higher EER values for DB3 due to the lack of saturation in the DB3 images.

## V. CONCLUSION AND FUTURE WORK

In this work, we have proposed a methodology for fingerprint recognition using the AKAZE features in conjunction with a neural network. Evaluations and comparisons have been performed to determine the performance of the proposed approach with respect to existing approaches. Evaluations have shown that the proposed approach has performed reliably for different datasets. Furthermore, the EER values have demonstrated that the proposed method distinguishes false images from genuine images and reduces the variance of the match score. The proposed approach has also performed competitively when compared to existing approaches.

In the future, we aim to improve the method by reducing the number of stages and integrate it with deep learning for more effective fingerprint recognition.

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