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Research Article

Efficient Fingerprint Reconstruction System using Novel GAG Method and Modified Otsu Binarization Method

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Abstract: In community security as well as a criminal investigation, like forensic investigation, custom access and law enforcement, the Fingerprint (FP) encompasses a vital function. Utilizing Latent Fingerprint (LFP) samples to perform recognition and reconstruction tasks is often demanding for automated identification systems because of poor quality, distortion, and also partly missing information as of the input samples. To trounce such issues, this paper proposes an efficient Fingerprint Reconstruction System (FRS) utilizing the Gamma CLAHE-Anisotropic Diffusion Gaussian Filter (GAG) together with the Modified Otsu Binarization (MOB) method. First, the GAG method performs the preprocessing step to ameliorate image quality. Next, the significant features like correlation, Stationary Wavelet Transform (SWT), Discrete Cosines Transform (DCT), coherence, edge feature, shape feature, Local Binary Pattern (LBP), along with cluster shade features, are extracted as of the preprocessed image. Subsequently, the Entropy Based-Humming Bird Optimization (E-HBO) does the Feature Selections (FS). After that, the chosen features are given to the Deep Neural Network-Regression (DR) classifier, which classifies the LFP. Next, fingerprint recognition is done utilizing the Euclidean Distance (ED) calculation. Lastly, the novel MOB reconstructs the image. Experiential results exhibit that the FRS proposed attains efficient performance analogized to the existent techniques.

INTRODUCTION

Fingerprints has been extensively included into forensic, civilian, along with numerous commercial applications [19], mainly regarding their originality, stability through life, individuality amidst folks, public acceptance, along with a little threat of invasion. All folks on this planet have a distinct Fingerprint. Usually, FP can well be characterized into three prints: plain (visible) print, roll prints, along with latent (invisible) prints [1]. Contrasted with rolled as well as plain FP, LFP is generally of lower quality overlaid with different non-FP patterns, for example writing letters, lines, or even other LFP. FP encompasses features, which is typically the blend of the ridges with the valleys in the FP. The features of FP, like Orientation Fields (OF), ridge shapes, together with texture information are utilized aimed at matching the equivalent FP. Generally, an Automatic FP Identification System (AFIS) [2] is utilized in FP recognition.

The AFIS generally functions by means of extracting as well as matching FP minutiae. The extraction along with matching's performance enhances with the FP image's quality. A classic AFIS comprises the FP acquisition, the FP pre-processing (like the FP segmentation, the orientation fields estimation, along with enhancement), FP classification, the minutiae detection along with matching. However, it is still a difficult mission to distinguish lower-quality FP, which is debased by different features, like scar, dirt, greasing, along with moisture over the fingertips' surface, as well as to reinstate the noise-contaminated FP ridge structure devoid of introducing false features [10]. Thus, FP image enhancement is an imperative step among FP image acquisition along with FP image feature recognition.

In various instant, the ridges are gone lost or else broken as in an LFP instant. Thus, FP's reconstruction is essential aimed at the production of the orientation field as well as the ridge structures [3]. FP's reconstruction can just be established as triumphant whilst the reconstructed image matches the original FP image centred upon the minutiae points. The FP reconstruction's prime goal is to create the restructured image to look like the original FP image [4]. However, the majority of the reconstruction methods can only produce a partial FP and also some of them are susceptible to create false minutiae [5]. To conquer these problems, MOB centred reconstruction scheme is modelled. The proposed MOB is modelled to effortlessly and correctly execute identifications along with reconstruction in large FP databases.

A comprehensive discussion regarding the methodology propounded is proffered in Section-2; the experiential result is explored in Section-3; the paper is deduced in Section-4.

EFFICIENT FINGERPRINT RECONSTRUCTION SYSTEM

Numerous FP reconstruction methodologies show the requirement aimed at protecting the FP templates [20], enhancing the template's interoperability, together with enhancing fingerprint synthesis. This paper proposed an efficient FRS utilizing the novel GAG and MOB approach.

The block diagram of the proposed FP reconstruction system is proposed in *Figure 1.*

Input Data

Initially, the input LFP image is taken as of the LFP dataset. The input dataset is mathematically expressed as:

$$\mathrm{F_k} = \{\mathrm{F_1}, \mathrm{F_2}, \mathrm{F_3} \dots \dots \mathrm{F_n}\} \quad (1)$$

where, F_k implies the LFP dataset and F_n symbolizes the n-number of FP images as of the dataset.

Pre-processing

Here, pre-processing is performed on the input image for image enhancement and also eradicating spurious minutiae on the FP image utilizing a novel GAG technique. The GAG is an amalgamation of the Gamma- CLAHE technique with the Anisotropic Diffusion-Gaussian (ADG) filter. Thus, this technique is labelled as GAG. In the proposed work, the GAG pre-processed technique encompasses four steps: image contrast enhancement, Local Ridges Orientation (LRO) estimation, frequency estimation and filtering, which is elucidated as follows:

Image contrast enhancement

This is a necessary step in the pre-processing part. Contrast enhancement ameliorates the image's quality via augmenting the luminance variation betwixt the foregrounds and the backgrounds. In the proposed technique, the Contrasts Limited Histograms Equalizations (CLAHE) [6] is utilized. The CLAHE technique regulates the image's intensity values by utilizing a nonlinear method to augment the contrast for every image's pixels. A variation of the contrast limited method termed adaptive histograms clip (AHC) [7] can as well be implemented, which automatically regulates the optimal clipping level in CLAHE together with the enhancement parameter in local contrasts enhancement. And therefore, the proposed technique attains optimum contrast enhancement intended for the inputted images. The customized gray levels for CLAHE technique with Uniform Distribution is mathematically rendered as:

$$\mathrm{C(f)} = \frac{P(f) - P(f)_{min}}{mXn - P(f)_{min}}(G_L - 1) \quad (2)$$

wherein, C(f) signifies the CLAHE function of the n -number of FP images; P(f) implies the cumulative probabilities distribution, $P(f)_{min}$ denotes the cumulative distributions function's minimal non-zero value; m X n renders the image's number of pixels wherein m signifies the width and n implies the resized image's height; G_L states the number of grey levels utilized. In this CLAHE, the luminous intensity is bad; so as to shun this, the proposed one deploys the Gamma cantered CLAHE that is called Gamma-CLAHE [21]. Gamma correction [8] has been utilized to regulate an image's luminance. The Gamma is resultant as of:

$$i_n = G(\alpha)(i_0)^{1/\gamma} \quad (3)$$

wherein, i_n implies the new intensity value; i_0 signifies the C(f)'s old intensity value, G(α) state the gray stretch parameter employed to linearly scale the result to be in the [0, 255] image in addition to implies the positive constant. In the proposed work, the luminance is altered centered on the gamma value. The contrast-ameliorated image is equated as:

$$\vec{F}_k = \{\vec{F}_1, \vec{F}_2, \vec{F}_3 \dots . \vec{F}_n\} \quad (4)$$

wherein, $\vec{F}_k$ signifies the Gamma-CLAHE implemented LFP image dataset, $\vec{F}_n$ symbolizes the Gamma-CLAHE implemented -number of LFP images.

Local Ridge Orientation (LRO) Estimation

Ridges orientation [9] is explicated as the procedure of attaining the ridges' angle all through the image. It is certainly utilized for describing, detecting, along with matching FP features, like minutiae along with singular points. Primary, the FP image is partitioned into non-ridge and as well ridge regions. Next, segment the ridge areas centred upon the estimated ridge orientation's correctness. The local orientation is calculated from the filtered vector field by utilizing the subsequent formula:

$$O(i,j) = \frac{1}{2} tan^{-1} \frac{\psi'_y(i,j)}{\psi'_x(i,j)} \quad (5)$$

where, O(i,j) is the local orientation of image; mathematically, it signifies the direction which is orthogonal to the leading direction of the Fourier spectrums of w X w and $\psi'_y(i,j)$ and $\psi'_x(i,j)$ represents continuous vector field.

Ridge Frequency Estimation

The evaluation of ridge frequency is one fundamental precondition in the improvement of Fingerprint images. The ridge frequency of F_k is mathematically written as:

$$F(i,j) = \sum_{u=-\frac{\psi}{2}}^{u=\frac{\psi}{2}} \sum_{v=-\frac{\psi}{2}}^{v=\frac{\psi}{2}} W(u,v)\psi_y(i - uw, j - vw) \quad (6)$$

Here, F(i,j) signifies each block's local ridges frequency that is stated as the frequency of the ridge along with furrow structures within a local neighbour.

Filtering

An Anisotropic Diffusion Gaussian (ADG) [10] is changed to the equivalent frequency, along with orientation can effectively eradicate the unwanted noise and protect the true ridge together with furrow structures. This filter renders superior performance by eliminating noise whilst preserving image details. In the ADG filter, the Edge Stopping function (ESF) [22] is not equipped to effortlessly eradicate unwanted noise. To efficiently protect the ridges along with valleys, this paper employs the Gaussian [26] for ESF in the ADG filter. The ADG filter is written as:

$$\vec{F}_k^{(t+1)} \simeq \vec{F}_k + \frac{\delta}{|\lambda_i|} \sum_{j \in \lambda_i} J(\Delta G_\sigma * (\vec{F}_k)^t_{i.j}) \quad (7)$$

wherein, $\vec{F}_k^{(t)}$ implies as the contrast-enhanced image at instant t, δ implies a scalar associated with the diffusion rate, λ_i implies the compilation of adjacent pixels of i and J(.) signifies the ESF. $(\vec{F}_k)_{i.j}^t$ signifies the magnitude of the frame directional gradient as of pixel i to j at instant t, G_σ referred as the Gaussian filter (GF) of scale σ and $\vec{F}_k^{(t+1)}$signifies the filtered image. That is, the local gradients (parameter of ESF) are computed utilizing a smoothed adaptation of the image in each iteration. This ADF filter the image to plainly separate out ridges along with valleys, and therefore, lessen the probability of spurious minutiae. This method efficiently eradicates the unwanted noise and conserves the true ridge along with furrow structures.

Feature Extraction (FE)

The chief features [11], like correlation [23], Stationary Wavelet Transform (SWT) [25], Discrete Cosines Transform (DCT) [24], coherence, edge feature, shape feature [27], Local Binary Pattern (LBP) [28], along with cluster shade features, are extricated as of the pre-processed image.

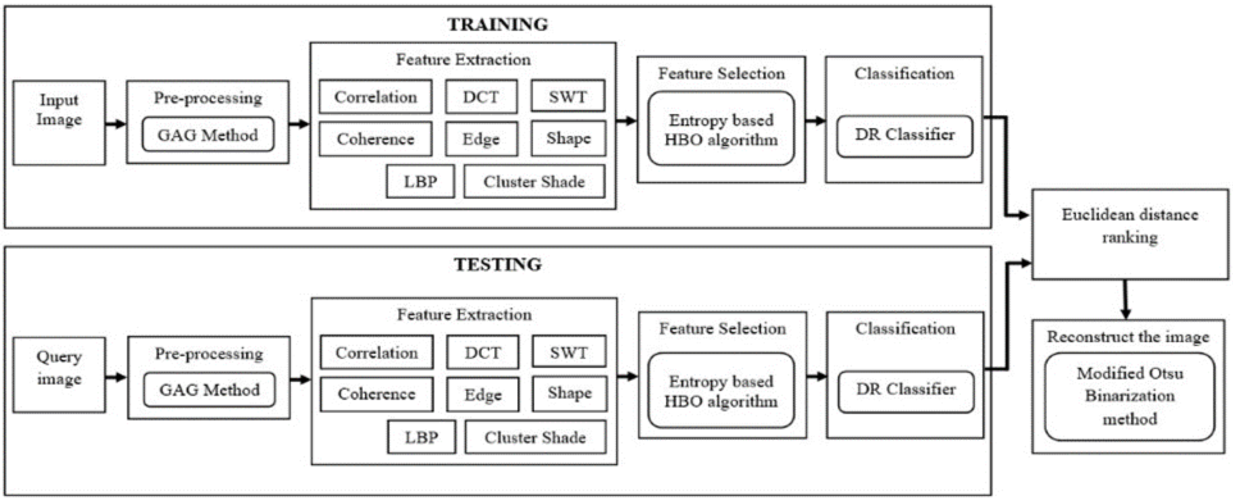

Fig 1: Block diagram of the proposed FRS

Feature Selection (FS) using Entropy-based HBO

After FE, the features required are elected as of the features taken out employing the Entropy-centric Humming Bird Optimization (Entropy-based HBO) algorithm [12]. The normal HBO algorithm utilizes Levy flights (non-Gaussian random walk) [13], which creates over selection; hence, it broadly explores the search space more. For overcoming this difficulty, this approach employs the Entropy function in place of levy flights. Hence, this optimization is termed as `Entropy-based HBO'. HBO is generally inspired with the foraging activities of hummingbirds [29]. The proposed algorithm undergoes self-searching phase and guide-searching phase. With such phases, the algorithm`s exploitation as well as exploration abilities could be balanced. In HBO, the food resources' quality indicates the fitness functions' values, and the finest food resource specifies the optimum solution [12]. The formula for HBO initialization is:

$$H_i = u_b - rand(u_b - l_b) \tag{8}$$

where, H_i is the position of the i^{th} humming bird (i ϵ 1,2, 3....n), N denotes the population size, u_b and l_b represents the Upper and lower bounds of the variables in the search space, respectively and rand is the Random value in between [0, 1]. Consider H_i^t is the i^{th} hummingbird in t^{th} generation, which is expressed as follows:

$$H_i^t = H_{i,1}^t, H_{i,2}^t \ \dots \ H_{i,d}^t \tag{9}$$

Here, d denotes the dimension. When hummingbird i continually discovers better sources of food, the individual's position is updated grounded on its former gradient information. The updated position of hummingbird could be attained via the succeeding formula:

$$H_i^{t+1} = H_i^t + rand.\left(H_{i,1}^t - H_{i,1}^{t-1}\right) \tag{10}$$

$H_{i,1}^t$ and $H_{i,1}^{t-1}$ signifies the i^{th}-hummingbird's positions at the t^{th} and $(t\text{-}1)^{th}$ generations, respectively. When hummingbird i searches continually, but fails to find better results ($H_{i,1}^t = H_{i,1}^{t-1}$), it means that the current area is not worth continued exploitation. In this scenario, the hummingbird would arbitrarily vary the search direction and this is performed centred on Levy flights. But in the proposed work, the search direction is altered grounded on the entropy value to avert over-selection. The new position of the hummingbirds in self-searching phase is created by executing the entropy model [14] as:

$$E(H) = \sum_{i=0}^{n} H_i \, log_2 H_i \tag{11}$$

Guided searching phase can be implemented as in [12]. At last, the selected feature set is indicated as:

$$F(s)_k = \{F(S)_1, F(S)_2, F(S)_3 \dots \dots F(S)_n\} \tag{12}$$

where, $F(S)_k$ is the selected feature set and $F(S)_n$ is the n - number of selected features.

Classification using DR Classifier

Here, the features $F(S)_k$ attained from FS are inputted to the DR classifier to successfully classify the pattern of the FP image. Normally, the FP pattern has the succeeding types, such as loops, whorls, and arches. In the proposed technique, the Deep learning neural Network-Regression activation (DR) classifier [30] which is the modified version of Artificial Neural Network (ANN) is implemented for classification. The conventional ANN utilizes just one hidden layer (HL), and it wouldn't bring a precise outcome, and also its training time is high on account of backpropagation. For overcoming these problems, the proposed method utilizes a deep learning concept since it utilizes more than three HLs. The normal Activation Function is enough for one HL, but as previously mentioned the proposed methodology utilizes innumerable HLs [15]. So, for an effectual classification, the proposed work utilizes R_{AF}, which increments the layer's margin and diminishes the error, and also it is proficient in learning and executing much intricate operations aimed at more number of HLs. Regression function gauges a relation in between a dependent variable and 1 or more independent variables.

The R_{AF} is a sort of radial basis function, which is grounded on a standard statistical approach termed kernel regression. The regression-centric neural network has excellent performances on learning speed together with approximation ability. In addition, it is rapid learning and it merges to the optimum regression surface when the number of sample data increases. When such sample data is less, the DR still has a good forecasting outcome.

The input features $F(S)_k$ are accepted by the Input Layers (IL). The features are passed on to the HL and no other computation is done at its nodes. In an IL, each feature in $F(S)_k$ is initially assigned with their respective weight value as:

$$(Wv)_l = \{w_1, w_2, w_3 \ldots\ldots w_n\} \tag{13}$$

Here, $(Wv)_l$ is the corresponding weight value of F(S)k. The input features and their individual weight values are inputted to the HL. In the HL, the input entered via the IL are multiplied, and then, they are totally summed, which is expressed as:

$$H_i = \sum_{i=1}^{n} F(S)_k \,(Wv)_l \tag{14}$$

Here, h_i denotes the HL's input value. After giving input to the HL, the R_{AF} is determined.

$$R_{AF} = \frac{\int_{-\infty}^{\infty} F(S)_k . f\big((Wv)_l\, F(S)_k\big). dF(S)_k}{\int_{-\infty}^{\infty} f\big((Wv)_l\, F(S)_k\big). dF(S)_k} \tag{15}$$

Here, $((Wv)_l), F(S)_k)$ is the Joint probability density function of $F(S)_k$ and $(Wv)_l$. Subsequently, the HL's output is computed as:

$$h_0 = B_s + \sum_{s=1,f=1}^{n} R_{AF}. F(S)_k. (Wv)_l \tag{16}$$

where, h_0 is the Output of the HL and B_s is the Bias function. The last output decision of the DLNN is centred on the biases and weights of the past layers prevalent within the network structure. The proposed DR's end output is equated as:

$$\overrightarrow{O_t} = B_s \sum_{f=1}^{n} ((h_0)_{l+1} - (h_0)_l). K_r\, ((Wv)_{l+1}, (Wv)_l \tag{17}$$

K_r denotes the weight value's kernel function; l represents the Hidden Layer and $\overrightarrow{O_t}$ is the Output unit.

Grounded on "17", the proposed DR classifier precisely classifies and found the patterns of the Fingerprint whether it is loop or arch pattern or whorl. All the afore-mentioned phases like pre-processing, FE, FS, and classification are also done in the Query Image (QI). In the proposed work, the mentioned QI is a culprit's Fingerprint image.

Euclidean Distance (ED) Ranking

Here, this Euclidean Distance ranking method [16] gauges the similarity or dissimilarity between the classified Input Image and Classified Query Image, which has one or multiple attributes. Consider the input image as p and QI as q. The Euclidean Distance *ED(p, q)* between p and q could be evaluated as:

$$D(p,q) = \sqrt{\sum_{i=1}^{n} (p_i - q_i)^2} \tag{18}$$

where, n is the number of dimensions, q_i is the Query Image and p_i is the input image as of the database. *ED(p,i)* gauges the numerical difference for each corresponding attribute of image p and q. The image that is having the lowest ED with the QI is regarded as a culprit's Fingerprint. So, grounded on the *ED(p,i),* the culprit's Fingerprint image as of the input image has been recognized. The Euclidean Distance is applied between all the input images in the dataset and the Query Image.

Image Reconstruction using MOB

In this proposed work, the MOB [17] approach is employed for culprits FP image reconstruction. The general Otsu Binarization (OB) method utilizes the average sample value and derivation for computing dispersion and the location, which renders poor thresholding outcomes. For resolving this issue, a median centric OB is proposed in the work.

RESULTS AND DISCUSSION

The proposed algorithms performance is estimated on the Latent Fingerprint dataset of IIITD [18]. As of this dataset, 76 percentage of images are employed in favour of training and 24 percentage of images in favour of testing.

Performance analysis of DR classifier

Here, the proposed DRs performance is estimated utilizing the metrics mentioned in *Table 1.*

Performance analysis of E-HBO

The proposed E-HBO technique that is used in Feature Selection is contrasted to the existing PSO and HBO techniques, in respect of Fitness Value (FV) in *Figure 2*. The FV is assessed for 10 to 100 iterations. From the above performance analysis, the outcomes inferred that the proposed technique is robust for FP detection and FP reconstruction.

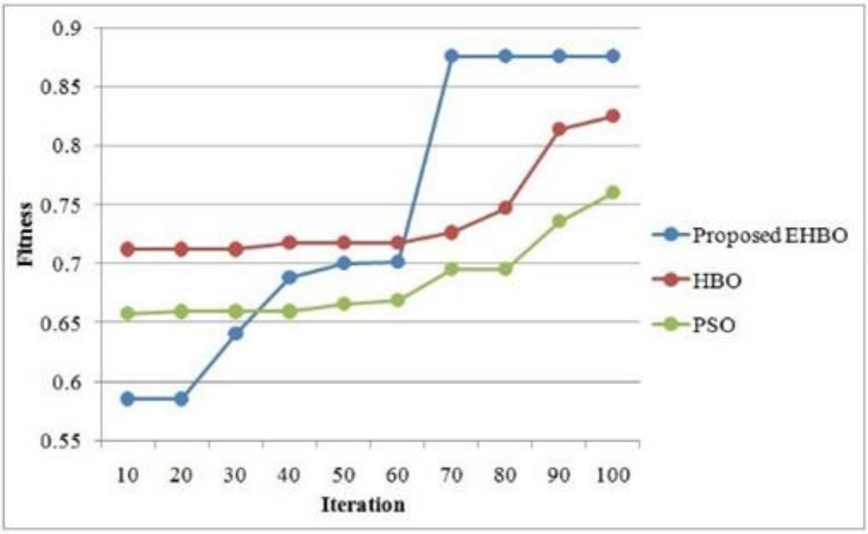

Fig 2: Fitness comparison of E-HBO with existing algorithms

Table 1: Performance of the proposed DR-classifier with the existing classifiers

Matrices	**DR Classifier**	**Existing ANN**	**Existing SVM**	**Existing KNN**
Precision	0.8441	0.5303	0.5064	0.7012
Recall	0.8441	0.4545	0.5064	0.7012
F-Measure	0.8441	0.4895	0.5064	0.7012
Sensitivity	0.8441	0.4545	0.5064	0.7012
Specificity	0.8441	0.7987	0.7532	0.8506
Accuracy	0.8441	0.6839	0.6709	0.8008

CONCLUSION

For authentication, minutiae are employed as an attribute by most of the FP systems. These features are conserved in a database. Nevertheless, these databases are observed to be insecure as the damages caused to them are irreparable. Therefore, securing FP in the database is highly significant. Thus, by employing WDBS-VSS along with GMRFS, an effectual FP reconstruction system is proposed here. Securing FPIs along with reconstructing user FPs effectually for authentication is the intention of this work. The proposed methodology's outputs are analogized with the prevailing methodologies for performance evaluation. The latent FP database is wielded to conduct experiments. The experiential outcomes displayed that a better performance is offered by the proposed model by obtaining a higher accuracy and lower MSE of 97.9892 and 0.122057, respectively. In proportion to the experiential outcomes along with performance evaluation, it is evident that in correlation with the prevailing methodologies, enhanced performance is acquired by the proposed scheme. The work will be advanced by focusing on the additional possible reconstruction of FPIs with enhanced algorithms in the approaching future.

CONFLICT OF INTEREST

Authors declare that no competing interests exist.

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