MULTIMODAL KEY-BINDING BIOCRYPTO-SYSTEM USING LEAST-SQUARE POLYNOMIAL CURVE-FITTING BASED NEW FEATURE-LEVEL FUSION METHOD

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Abstract - In last few years, many works has been proposed using multimodal biometric system because of its high performance as compare to unimodal biometric systems. Most of the Multimodal Biocrypto-System (MBS) have been previously proposed to securely share secret-key over the network, but these systems uses complex signal processing techniques like DFT, SVM, neural network etc. based fusion techniques and relatively low performance. Therefore, we propose simple and effective but mathematically irreversible statistically based new feature level fusion technique using Least-Square Polynomial Curve-Fitting (*LPC*) for the proposed efficient Multimodal Key-Binding Biocrypto-System (*MKBB*). We validate the effectiveness of proposed technique over the fuzzy vault scheme using biometrics fingerprint and iris datasets. This proposed system is implemented to protect the user's cryptographic secret-key and effectively remove the use of public key infrastructure (PKI) system because of its complex certification issuing and distributing management costs, and centralized structure which uses convention network system and shows single point of failure. We also evaluate the overall performance system to successfully retrieval of key with the help of AES-256 algorithm to perform encryption and decryption. The experimentations is done using fingerprint FVC2002DB_1 and Iris CASIA-IrisV1 datasets. The system gives the 99.96% of accuracy, with 99.98% of GAR and 0% FMR.

Keywords: Multimodal Key-Binding Biocrypto-System, fuzzy vault, PKI, AES, feature-level fusion, Least-Square Polynomial Curve-Fitting.

1. Introduction

Most of the organization, who need data privacy are fighting against the security and authentication vulnerabilities of the existing confidentiality and authentication systems due to cryptographic secret-key compromising because end users need to share keys over the internet and have to recorded for remember somewhere in offline line mode or written in diary. One efficient approach to protect cryptographic key is PKI system, which also has many difficulties such as failure of PKI system due network attacks like men-in-the-middle and Denial of service, its complex implementation of certification issuing and distributing management system, and centralized structure with single point of failure [Jiang *et al.* (2019); Shamir (1984)].

The original basic PKI model consists some specific software modules, hardware components, security and privacy related policies with the experts to implement this model. A trusted third party Certificate Authority (CA) provide a digitally signed certificate for each user for its public-private key pair, which are independent from user's identity [Lozupone (2018)]. The PKI model is the client-server based distributed model, so the certificates formation, delivering and cancellation very high complex and time taking, network related issues such as network congestion, attacks over the network. Therefore management of deploying the traditional PKI model is very difficult in exercise. Another problem with the tradition PKI model that must be considered seriously is that, some other vulnerabilities e.g. the malware systems can compromise certificate issuing software and create duplicitous certificate demand or appear as authentic access to core certificate issuing systems to issue certificate. All of these consequences demands a system that can overcome this influence on security systems and determine a trust and protected system for key management [Daniel *et al.* (2019); Lozupone (2018)].Several work already done by

different authors to improve performance and security of traditional PKI [Zhang *et al.*(2019); Kubilay *et al.*(2019); Hiep *et al.*(2010)].

The biocrypto-system (BCS) is the recent technique to protect the cryptographic secret-key and eliminate the use of PKI by merging it with the individual's biometric information i.e. the BCS actually applied the concept of biometric-system with the cryptography-system, it work in two way first to protect key by binding it with biometric and second to generate a key using biometric features [Hiep *et al.*(2010); Tantubay and Bharti (2020); Balakumar and Venkatesan (2012)].

The BCS further classified based on number of biometric data used in the system from different sources like biometric-systems i.e. i) Unimodal biocrypto-system (UBS) and ii) multimodal biocrypto-system (MBS) [Dinca and Hancke (2017); Alaa *et al.*(2017)]. UBS usage a single biometric trait for both key-binding and/or key-generation whereas MBS usages at least two or more biometric trails for the same. The usage of biometrics in UBSs also faces some security challenges because of the noisy sensor data, spoof attacks and intra-class variations error due to the usage of altered secret-keys which requires the additional use of Error Correcting Codes to improve system's performance and overcome errors due to biometric variations. Many studies has been proposed to prove that MBS has a better performance in terms of accuracy and security than UBS, which also restricts the several error and limitations of UBS [Kumar and Kumar (2015); Ilankumaran and Deisy (2018)].

Therefore, MBS bind the user's cryptographic keys with its biometric identities and successfully replace the PKI system and efficiently protect the cryptographic secret-key. The MBS system uses at least two or more biometric data to protect the secret-key in case of key-binding system. The features from biometric images, after pre-processing, are extracted and merged using suitable fusion technique and generates a transformed fused feature template. These fused features are used to successfully bind the secret-key at the encoding phase using fuzzy commitment, fuzzy vault, and etc. key-binding schemes. The secret-key again will only be retrieved successfully if the same biometric images will be input at decoding phase with same fusion technique [Hiep *et al.* (2010); Tantubay and Bharti (2020)].

The MSB also has a problem of feature fusion of more than one feature of biometric modalities. Most of the existing MSB uses digital signal processing and machine learning based complex fusion techniques at different level, for example Discrete Fourier Transform [Vatsa *et al.* (2010)], SVM [Mehrotra *et al.* (2012)], Gaussian mixture mode [Balaka *et al.* (2018)], Convolutional Neural Network [Alaa *et al.* (2017)], Pulse-Coupled Neural Network [Wang *et al.* (2015)], Discrete wavelets transform [Raghavendra and Busch (2014)], Discrete Cosine Transformation [Tang (2004)], log-Gabor filter and Haar wavelet [Kumar and Passi (2008)].

The following levels of fusion techniques based on different principles are implemented in MBSs i.e. rank-level [Kumar and Kumar (2015)], decision-level [Gudavalli *et al.* (2012)], feature-level [Rathgeb *et al.* (2011); Nagar *et al.* (2012); Lai *et al.* (2019)] and score-level fusion [Nguyen *et al.* (2015); Prakash (2018)]. The fusion must improve the performance and security of the MBS efficient and must leave behind unimodal biocrypto-system. In this proposed work, we propose an MKBB using on new proposed feature-level fusion technique based Least-Square Polynomial Curve-Fitting (*LPC*) and perform AES encryption as well to show the whole working of the system.

The main purpose of the proposed work is to implement an effective and robust new feature-level fusion method for the MKBB to protect the user define secret-key and overcome the use of PKI based secret-key protection.

This research paper is organized as follows, literature review is given in section-2 which has the brief discussion about previous works, section-3 gives the detail of proposed methodology, the experiment implementation and result discussion is shown in section-4, finally section-5 gives the conclusion of the proposed work.

2. Literature Review

In [Vatsa et al. (2010)], the authors propose a score-level fusion technique based quality of features to enhance recognition rate of iris colour image based authentication system. The match score of correlation information of the red, green, and blue channels is applied to Redundant Discrete Wavelet Transform for information association at image level. In score-level fusion technique, the consequential image with the remaining channel is used to enhance recognition rate.

The authors in [Kumar and Passi (2008)], propose a qualified analysis of iris based recognition system using based on Haar wavelet, log-Gabor filter, Fast Fourier Transform, and Discrete Cosine Transform techniques. The CASIA v1, CASIA v3, and IITD Iris databases are used to perform all experimental analysis. The weighted-sum rule are used in both log-Gabor filter and Haar wavelet based on score level. The Haar wavelet is a computationally efficient approach which requires minimum computation time and its combination with log-Gabor filters is create an efficient model. The authors also evaluate the comparative performance of various descriptors with singular training images. The performance of the system is evaluated using one training image on the CASIA and IITD database.

In [Rathgeb *et al.* (2011)] propose a feature level fusion technique to implement fuzzy commitment. The purpose of the suggested feature level fusion technique is to fuse two biometric templates with its binary feature descriptors into a single template of the same size. The presented feature level fusion technique is proposed to stability average reliability through all the biometric templates based on small training set. The proposed technique is more efficient to successfully reduce the use of error correction schemes. The CASIA v3 dataset is used to perform all the experiments and to demonstrate that the performance of proposed fusion technique to overcome the limitations of traditional fuzzy commitment schemes based multimodal-biometric systems.

Authors in [Mehrotra *et al.* (2012)] present the working of multi-unit iris recognition based on Relevance Vector Machines (RVM) to implement score-level fusion technique using diverse classifiers with its applications. The performance analysis is made using the CASIA v4 database and demonstrate the improved performance of RVM with enhanced accuracy as compared to single iris recognition. The presented score-level fusion technique overall enhanced the recognition rate 4%. The computational required time of RVM based fusion techniques is comparatively less than fusion techniques using SVM, with equivalent recognition rate.

In [Murakami *et al.* (2011)] combined the working of Bayes rule based score level fusion and distance based indexing to present an identification technique. The proposed scheme chooses the template of the user based on its posterior probability of being identical. The proposed work is done using two datasets Biosecure DS2 and CASIA v5 Fingerprint dataset to analyse the performance of the proposed work and shows the reduction in identification error rates as compare to unimodal biometrics system.

In [Nagar *et al.* (2012)], present a feature-level fusion technique for multi-biometric cryptosystems to successfully secure the multi-biometric templates using secure-sketch of an individual. The proposed feature-level fusion framework is implemented using the fuzzy vault and fuzzy commitment biocrypto-systems to improve recognition accuracy rate and security of the proposed multibiometric cryptosystems based on real and virtual multi-biometric database, each containing the three most popular biometric modalities, namely, fingerprint, iris, and face. A synthetic multimodal database is assembled using the FVC2002 database for fingerprints, the CASIA v1 database for irises, and the XM2VTS database for faces. The proposed fusion scheme combines a set of biometric features and generates a fused multi-biometric feature template. The proposed system achieve average GAR 99% and 71.5% of both FC and FV scheme using virtual multimodal dataset and real multimodal dataset, respectively. The proposed multibiometric cryptosystem shows overall higher security and recognition rate as compare with unimodal biocrypto-systems.

In [Alaa *et al.* (2017)] propose multimodal biometric system based on deep learning for both the image of right and left irises of a person, and uses ranking-level fusion technique for fusing the features. They propose a system IrisConvNet based on a combination of Convolutional Neural Network (CNN) and Softmax classifier. All the experiments are analysed using the three datasets SDUMLA-HMT, CASIA-Iris-V3 and IITD iris. The experimental results shows the 100% recognition rate using highest rank identification for all three used databases.

The authors in [Amirthalingam and Radhamani (2016)], present a new framework to generate chaff points using PSO for fuzzy vault based multimodal biometric cryptosystem. In this approach using particle swarm optimization (PSO) algorithm is used to find optimal and best locations to place chaff points. The experimentations are done using two dataset i.e. Yale face and IIT Delhi ear to evaluate and using different performance parameters. The proposed MBS demonstrates 90% of Genuine Acceptance Rate (GAR) as well as recognition rate of person with PSO.

In [Prakash (2018)], author proposes a score-level fusion technique, GPSO, using the hybrid of GA and PSO. In this work, the features of every biometric modality is used as the score weights for optimization. The system uses four CASIA Image Databases i.e. CASIA-Iris, face, palm, finger to evaluate its performance and achieve 0.42% of FAR, 0.79% FRR and 95% of accuracy using the Naive Bayes (NB) classifier based decision rule for authentication.

The authors [Hammad et al. (2018)], propose CNN and Q-Gaussian multi support vector machine (QG-MSVM) based multimodal biometric authentication system, in which features of each biometric traits are extracted using CNN, with two different level fusion algorithms: a feature level fusion and a decision level fusion to enhance the performance and security of unimodal biometric system. The proposed system is evaluated using two datasets PTB and CYBHi database for ECG and two datasets LivDet2015 and FVC2004 database for fingerprint which are openly accessible for experiment usage. The calculated accuracy of proposed multimodal systems are 98.66% for PTB database, 98.97% for CYBHi database, 98.81% for LivDet2015 and 98.20 for FVC2004 database respectively.

3. Proposed Multimodal Key-Binding Biocrypto-System

In this research work, we propose a new efficient Multimodal Key-Binding Biocrypto-System (MKBB) using statistically based new feature-level fusion technique. The proposed system is being implemented using traditional fuzzy vault scheme of key-binding. As the key binding biocrypto-system work in two phases encoding phase and decoding phase. In encoding phase, a user dependent one or more biometric traits, and user defined cryptographic secret-key are taken as input, then the key-binding system hide this secret-key in the biometric features and create a public data known as helper data which stores in database and shared over the Internet. This helper data is very secure and not revealed the important information about the biometric features of the user as well as the secret-key and it very difficult for the attackers to break this helper data. In decoding phase, the user's same biometric traits again taken as input and helper data stored in database are used as the input and retrieve the same secret-key as the output. The same secret-key will be retrieved successfully if the biometric input from the legitimate user and not retrieved otherwise.

In the proposed MKBB, two user's biometric i.e. iris and fingerprint are being used to efficiently protect the secret-key using least-Square Polynomial Curve-Fitting (*LPC*) based new feature-level fusion method. The fusion method plays very important role in biometric multimodal system as well as in biometric-cryptosystems. Efficient fusion method generates the more secure helper data in multimodal system.

3.1. *Least-Square Polynomial Curve-Fitting*

In this research work, we are proposing a new feature-level fusion method using statistical polynomial based curve fitting method known as Least-Square method in short, *LPC,* with mean and standard deviation [Deming (1931)]. It can be formulated as,

$$Y = LPC\left(x, y, d\right)$$

where, Y is vector of $d+1$ coefficients, *x* and *y* are the data set at which coefficients are calculated and *d* is polynomial degree.

Suppose the polynomial *p(x)* of degree *d*, for the data in y [Jaiswal and Khandelwal (2009); Kharab and Guenther (2019)]. The coefficients in *p* are in descending powers, and the length of *p* is $d+1$, then,

$$y_i = p(x_i) = \alpha_1 x_i^{\,d} + \alpha_2 x_i^{\,d-1} + \ldots + \alpha_d x_i + \alpha_{d+1} \quad \text{, where, } i = \{1, 2 \ldots d+1\} \qquad (1)$$

The arithmetic mean for set of $x_1, x_2, \ldots, x_d$ is denoted by $\overline{x}$,

$$\overline{x} = \frac{1}{d}\left(\sum_{i=1}^{d} x_i\right) \qquad (2)$$

The standard deviation (*s*) can be defined as the square root of the variance (*v*). The variance use a normalization factor of d instead of d-1, for a random variable vector x made up of d scalar observations, the variance is defined as,

$$v = \frac{1}{d-1}\sum_{i=1}^{d} \left|x_i - \overline{x}\right|^2$$

$$s = \sqrt{v} = \sqrt{\frac{1}{d-1}\sum_{i=1}^{d} \left|x_i - \overline{x}\right|^2} \qquad (3)$$

Then, the set of coefficients can be calculated using *LPC* as

$$Y = (\gamma_1, \gamma_2, \ldots \gamma_d, \gamma_{d+1}) \qquad (4)$$

where $\gamma_m \mid m = \{1, 2, \ldots, d+1\}$ represents value of mth coefficient.

3.2. *Encoding Phase of proposed MKBB*

The working of complete encoding phase of proposed MKBB is demonstrated in Fig.1. In the proposed multimodal encoding phase, features from iris and fingerprints are extracted and applied as input to the proposed new feature-level fusion method which employs the polynomial curve fitting method to fuse these features and produce a set of fused template which further used in fuzzy vault encoding scheme. The polynomial is constructed using the cryptographic secret-key as its coefficients. The genuine points are now generated by polynomial projection over the set of fused value and create a fuzzy vault by merging the chaff points, which are randomly generated.

In this research work, a complete Advanced Encryption Standard (AES) cryptography is implemented to verify secret-key retrieval as well as the performance of the proposed MKBB system. The user defined secret-key which is used in encoding phase for binding is also apply in encryption phase of the AES to produce the cipher text of the given plaintext.

The generated Vault and ciphertext is stored in the database or share with the other user over the internet for further used in decoding phase.

3.2.1. Working of Proposed Encoding Phase

In most of the iris based authentication system, the iris template suffers by some serious noise elements such as eyelid, eyelashes and etc. which may affect the genuine feature extraction from iris template. Due to this reason, in proposed work, some certain part of the iris that is the side part of it is selected as shown in Fig. 2. This selected part is then encoded in binary then converted in set of decimal values (η_e).

The detailed working of the proposed encoding phase is shown by the following steps:

Step 1: The iris image is taken as input, after pre-processing and normalized it select the concern part, which is most probably noise free as display in Fig. 2.

Step 2: Encode the selected part in binary codes (I_B), in our case it the part is selected in order to generate 256-bits of code for each image of the dataset.

Step 3: Make the 16 parts of I_B, each part consists a group of 16-bits, then convert each group in from binary code to a set of 16-decimal values (η_e)by using such formula,

$$I_B = \{t_1, t_2 ... t_{16}\}$$

$$\eta_e = BinToDec(t_{1:16}) \quad \textit{where, e=\{1,2,…16\}}$$

Step 4: Now the other biometric image is taken i.e. fingerprint as input and extract the feature points i.e. minutiae points, which gives set of coordinates (x, y). Find the set of unique x-coordinates,

$$X_u \mid x_u \neq x_{u+1}, \forall u = \{1, 2, ...16\} \qquad (5)$$

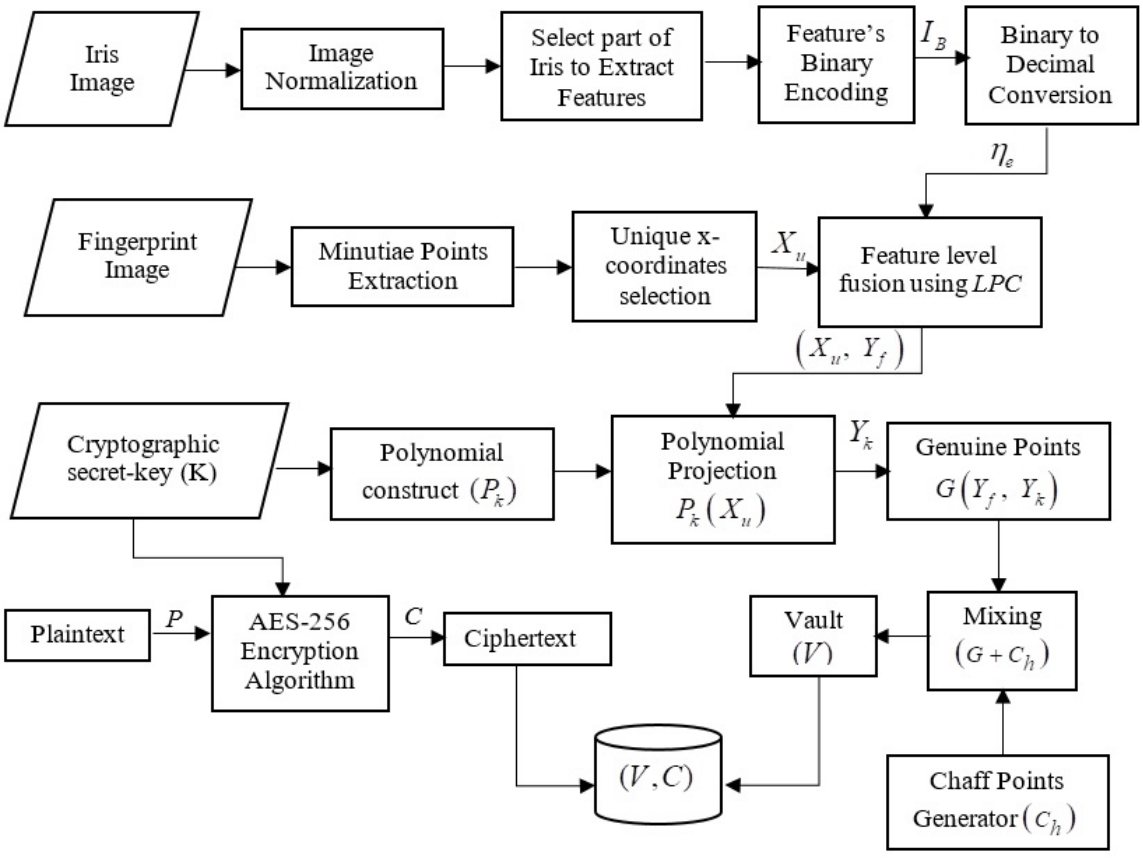

Fig.1. Encoding phase of proposed MKBB using New *LPC* Feature-level fusion method

Step 5: The proposed feature-level fusion method based on *LPC* from Eq. (1) and Eq. (4) is applied using feature sets minutiae points (X_u) from fingerprint and set of decimal value (η_e) from iris are used as input, and produce the set of values (Y_f) as output.

$$Y_f = LPC\left(X_u, \eta_e, d\right) = (\gamma_1, \gamma_2, ...\gamma_d, \gamma_{d+1}) \quad (6)$$

Finally, the set of fused features is formed as $\left(X_u,\ Y_f\right)$ using Eq. (5) and Eq. (6).

Step 6: Now user defined cryptographic secret-key (K) is taken and generates a polynomial (P_k) with coefficients as key-value. Calculate its projection over the X_u, as $P_k\left(X_u\right)$. The output of the polynomial projection is Y_k, then form set of Genuine Points as $G\left(Y_f,\ Y_k\right)$.

Step 7: The random Chaff Points Generator is used to create the noise points (C_h) to protect the genuine points. The chaff points are mixed with genuine points then shuffle to create helper data known as Vault (*V*) and store in database.

Step 8: Now AES-256 encryption algorithm is implemented to using secret-key (*K*) and plaintext (*P*) as input then generates ciphertext (*C*) and share over the Internet to end user or store in database for further use in decryption.

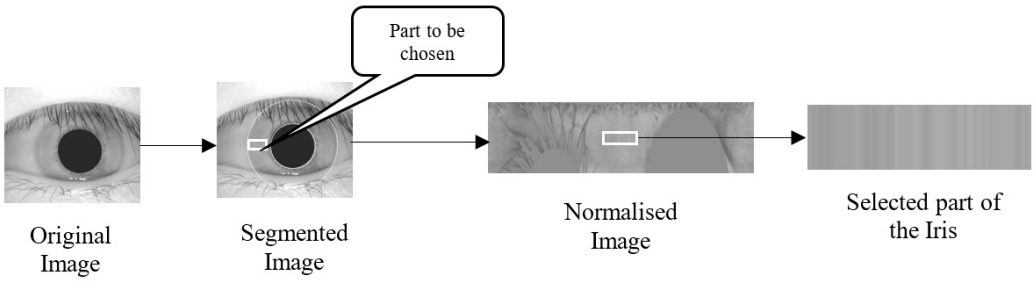

Fig. 2. Selected Iris image in proposed system (CASIA-IrisV1 databases)

3.3. *Decoding Phase of proposed MKBB*

The decoding phase perform to retrieve the secret-key which is bind in encoding phase. The encoding phase of proposed MKBB is shown in Fig. 3, which describes its complete working. In this phase, again the query biometrics are taken as input, same as encoding phase, then extract feature and fused as done in encoding phase. These fused feature are used to retrieve set of genuine points from the vault which is stored in database. Now reconstruct the polynomial using the extracted genuine points and find the secret-key as its coefficients, verify this retrieved secret-key by applying AES-256 decryption.

3.3.1. Working of Proposed Decoding Phase

In proposed decoding phase of MKBB, again a select the part of query iris image which is most probably noise free, as discusses in encoding phase and Fig. 2. The detailed working of the proposed decoding phase is shown by the following steps:

Step 1: The query iris image is taken as input, process it as step-1 of encoding phase. Then encode the selected part in binary codes ($\hat{I}_B$), it is again 256-bits of code.

Step 2: Again make the 16 groups of $\hat{I}_B$, and convert each group in decimal values ($\hat{\eta}_e$), which makes a set of 16 decimal values as,

$$\hat{I}_B = \{t_1, t_2 ... t_{16}\}$$

$$\hat{\eta}_e = BinToDec(t_{1:16}), \quad where\ e=\{1,2,...16\}$$

Step 3: Now extract the minutiae points of query fingerprint, which again gives set of coordinates ($\hat{x}, \hat{y}$). Find the set of unique $\hat{x}$-coordinates,

$$\hat{X}_u \mid \hat{x}_u \neq \hat{x}_{u+1}, \forall u = \{1, 2, ...16\} \quad (7)$$

Step 4: Again, apply the proposed fusion method, as applied in step-5 of encoding phase, using feature sets minutiae points ($\hat{X}_u$) from fingerprint and set of decimal value ($\hat{\eta}_e$) from iris are used as input, and produce the set of values ($\hat{Y}_f$) as output.

$$\hat{Y}_f = LPC\left(\hat{X}_u, \hat{\eta}_e, d\right) = (\hat{\gamma}_1, \hat{\gamma}_2, \ldots \hat{\gamma}_d, \hat{\gamma}_{d+1}) \quad (8)$$

Again create a set of query fused features as $\left(\hat{X}_u,\ \hat{Y}_f\right)$ using Eq. (7) and Eq. (8).

Step 5: Extract the genuine points from vault (*V*), which is created in encoding phase, using the set of query fused features as $\left(\hat{X}_u,\ \hat{Y}_f\right)$, the created set of genuine points is $\hat{G}\left(\hat{Y}_f,\ \hat{Y}_k\right)$.

Step 6: Reconstruct the polynomial $(\hat{P}_k)$ of *d*-degree using the set of extracted values of $\hat{Y}_k$ and find value of coefficients set that represents retrieved secret-key $\hat{K}$ of 16-digits.

Step 7: To verify the uniqueness of the retrieved secret-key, perform the AES-256 decryption algorithm. Take the ciphertext *C*, which is created in encoding phase, and retrieved key $\hat{K}$ as the input. The output of the decryption algorithm will be plaintext $\hat{P}$.

Step 8: Finally, check the plaintext $\hat{P}$ is as original plaintext P , which is used in encryption algorithm, if the generated plaintext is original that means secret-key is retrieved successfully, otherwise not.

There may be two cases, if the secret-key is not retrieved successfully:

(i) The inputs of query biometrics in decoding phase are from the illegitimate person, due to which system unable to match the features points and extract the original secret-key.

(ii) If case one if false that means system performance is poor and system unable to retrieve the secret-key efficiently.

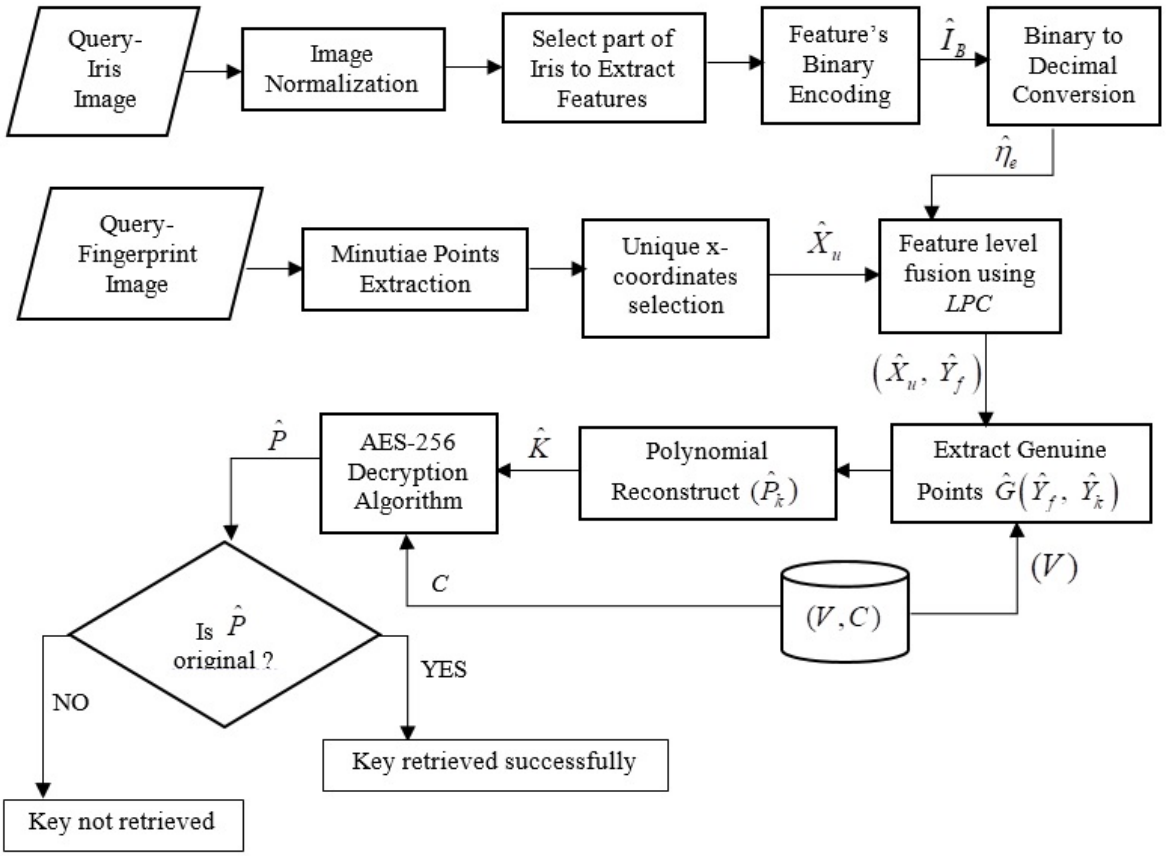

Fig. 3. Decoding phase of proposed MKBB using New *LPC* Feature-level fusion method

4. Experiment and Result Analysis

The proposed MKBB based on new feature-level fusion method is evaluated using two biometric datasets [Nagar et al. (2012):

(1) FVC2002_ Db1_a fingerprint dataset which is provided by the Biometric System Lab of University of Bologna, Pattern Recognition and Image Processing Lab of Michigan State University and U.S. National Biometric Test Center of San Jose State University, which consists 800 images of 100-persons, 8-images each person.

(2) CASIA-IrisV1 iris dataset which is provided freely by the Institute of Automation (IA) and Chinese Academy of Sciences (CAS) for the researchers, which includes 756 images from 108 eyes, 7 images for each eye, taken in two sessions.

In our experiment, the 1st fingerprint image of each 100-person is taken in consideration with pair of 1st iris image of first session of only 100-persons are taken to implement proposed system and evaluate the performance. The proposed MKBB system based on fingerprint and iris images is evaluated using the following evaluation parameters:

4.1. *False Matching Rate (FMR)*

The FMR shows the rate of recognize of non-authorized persons which are recognized incorrectly. The FMR is formulated as follows:

$$FMR = \frac{No.\ of\ \ illegitimate\ input\ falsely\ recognized}{Total\ no.\ of\ \ inputs} \times 100$$

4.2. *False Non-Matching Rate (FNMR)*

The FNMR shows the rate of not recognize of authorized persons which are not recognize incorrectly. The FNMR is formulated as follows,

$$FNMR = \frac{No.\ of\ \ legitimate\ inputs\ falsely\ not\ recognized}{Total\ no.\ of\ \ inputs} \times 100$$

4.3. *Genuine Acceptance Rate (GAR)*

The GAR shows the rate of truly recognition of the persons which are matched by the system. The value of GAR is calculated using the False Non-Matching Rate and formulated as follows,

$$GAR\ \ =\ \ (1 - FNMR) \times 100$$

4.4. *Accuracy*

The accuracy shows the robustness of the systems in terms of successful attempts against total number of attempts. The accuracy of the system is formulated as follows,

$$Accuracy\ \ = \frac{Total\ no.\ of\ \ successful\ outputs\ of\ \ the\ system}{Total\ no.\ of\ \ outputs\ of\ \ the\ system} \times 100$$

In encoding phase of proposed MKBB system, pair of fingerprint and iris images is being consider from a person and performing the proposed *LPC* based new feature-level fusion method. The parameters used in our proposed work are shown in table 1.

Table 1. List of parameters with its values

Parameters	Values
Iris binary codes (I_B)	256-bits
Set of Decimal values (η_e)	16
Set of unique minutiae points (X_u)	16
Degree of Polynomial (d)	15
Set of fused feature (Y_f)	16
Size of cryptographic secret-key (K)	16-digits
No. of genuine points (G)	16
No. of chaff points (C_h)	160

The accuracy is calculated using the *100-times* performing the experiment with pair of *100-images* with 10-thousand randomly generated different secret-key of 16-digits. Total 10-thousand times key binding in encoding phase and 10-thousand times key retrieving in decoding phase decoding performed to calculate the accuracy. The 99.96% average accuracy is achieved for the proposed system, the comparison shown in Table 2, demonstrate that proposed MKBB with new proposed fusion method is more efficient than the other systems.

To calculate the GAR, the 100- pair of fingerprint-iris images with 100 randomly of 16-digits generated secret-keys are used in encoding phase to bind to secret-key. The same pair of images are used in retrieving the secret-keys. The proposed MKBB system shows the 99.98% of GAR and 0.02% of FNMR, given by the Table 3.

Table 2. Performance evaluation of multi-biometric and Multi-biocrypto systems in Accuracy

Authors	System	Biometrics Dataset	Fusion Level	Fusion Technique	Accuracy %
Gawande *et al.* (2013)	Multi Biometric	CASIA Iris & real Fingerprint	Feature level	Mahalanobis Distance Technique	94
Eskandari *et al.* (2017)	Multi Biometric	CASIA IrisV3 & ORL Face	Hybrid Feature-level & Score-level	Features Concatenated	93.62
Hammad *et al.* (2018)	Multi Biometric	PTB & CYBHi for ECG and LivDet2015 & FVC 2004 for Fingerprint	Feature level	Features Concatenated	99.37
				Features Addition	99.68
Proposed MKBB	Multimodal Biocrypto-System	FVC2002 Fingerprints, CASIAv1 Iris	Feature level	Least-Square Polynomial Curve-Fitting	99.96

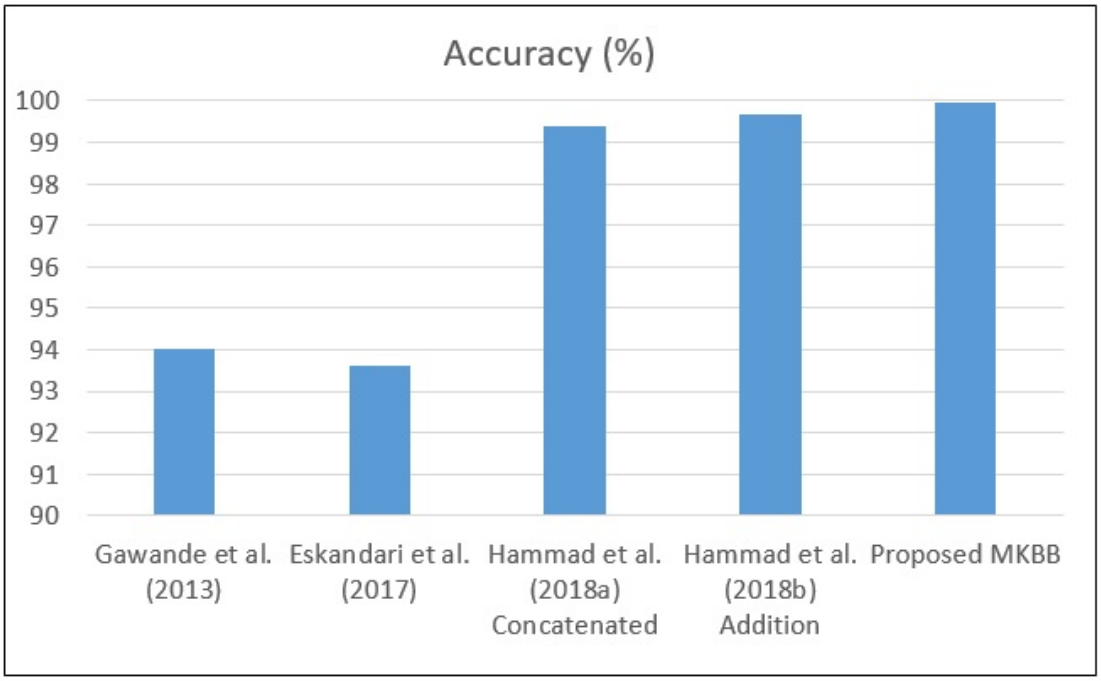

Fig. 4. Accuracy comparison of proposed work with previous works

Table 3. Performance evaluation of Uni and Multimodal-biocrypto systems in FMR, FNMR and GAR

Authors	Scheme	System	Biometric Dataset	Polynomial Degree	FMR %	FNMR %	GAR %
Lai *et al.* (2019)	Symmetric Keyring Encryption (SKE)	Uni-Biocrypto-System	FVC 2002 DB1 Fingerprint	12	2	38	62
				14	0	38	62
				16	0	52	48
			LFW Face	12	0	10	90
				14	0	12	88
				16	0	13	87
Nagar *et al*. (2012)	Fuzzy Vault	Multi-Biocrypto-System	FVC2002 Fingerprints, CASIA v1 Irises & XM2VTS Faces	13	0	1	99 (Virtual DB)
						32	68(Real DB)
	Fuzzy Commitment					1	99 (Virtual DB)
						25	75 (Real DB)
Heena *et al.*(2018)	Secure Sketch	Multi-Biocrypto-System	FVC 2004 Fingerprint, CASIA iris & Face	--	17	0	100
Proposed MKBB	Fuzzy Vault	Multi-Biocrypto-System	FVC2002 Fingerprints, CASIAv1 Iris	15	0	0.02	99.98

The FMR is now calculated by performing the encoding phase using 100-pair of 1st fingerprint image of each person from fingerprint dataset and 1st iris image of session one of each person, to bind the secret-key which are generated randomly. In decoding phase of the proposed system, 2nd fingerprint image of each person from the same fingerprint dataset and 2nd iris image of one session is used to retrieve the secret-key, the system demonstrate the 0% of FMR, that means no illegitimate person can retrieve the secret-key. The performance evaluations shown in Table 3, because in [Heena *et al.* (2018)] has the highest rate of recognition which is 100% but its false acceptance rate is also very high 17%, therefore, the overall performance of proposed MKBB, in terms of GAR and FMR, is relatively better from all other previous works.

In all the cases of Accuracy, GAR and FMR calculation, the AES-256 encryption and decryption in encoding and decoding phase respectively also implemented parallel to verify the retrieved secret-key in all cases. The AES with its largest key size, that is 256-bits, is used to show that the proposed system is efficient for long key size also, as well as to demonstrate it is efficient to remove the need of third party based PKI system to protect the secret-key.

5. Conclusion

The results of proposed Least-Square Polynomial Curve-Fitting (*LPC*) based feature-level fusion method is has better performance than complex fusion techniques. The performance results shows that the proposed MKBB using *LPC* fusion is efficient and robust in terms of accuracy and recognition rate (GAR) which are 99.96% and 99.98% respectively. Thus, the proposed MKBB is efficient to protect cryptographic secret-key and can effectively overcome the use of third party based PKI system. The proposed work can be extended to enhance the security of Multimodal Biocrypto-systems in future.

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