A Robust Biometric Template Protection Scheme using Fuzzy Vault Cryptography

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Abstract

Biometric authentication systems have transformed identity management by providing secure, reliable, and user-friendly verification methods. Unlike traditional systems that rely on passwords or tokens, biometric authentication utilizes unique physiological and behavioral traits, such as fingerprints, iris patterns, or voice. This eliminates the risks associated with forgotten passwords or stolen credentials. If compromised, biometric templates cannot be easily revoked or replaced, making them valuable attack targets. This project explores advanced biometric template protection mechanisms, focusing on the Fuzzy Vault scheme. The Fuzzy Vault is a cryptographic method that binds a secret, such as a cryptographic key, to biometric features. Only authorized users with valid biometric data can access the secured information. By incorporating error tolerance, the scheme accounts for natural variations in biometric data, ensuring usability while maintaining security. Through a comprehensive evaluation, this project demonstrates how the Fuzzy Vault scheme can protect biometric data, prevent unauthorized access, enhance privacy, and reinforce the reliability of modern authentication systems.

Keywords: Biometric security, template protection, fuzzy vault, fingerprint recognition.

1 Introduction

Biometric authentication systems utilize distinct physical and behavioural attributes, including fingerprints, iris scans, facial recognition, and voice patterns, to confirm an individual's identity. Biometric authentication systems utilize distinct physical and behavioral attributes, including fingerprints, iris scans, facial recognition, and voice patterns, to confirm an individual's identity. These technologies are being widely integrated into various sectors such as finance, healthcare, mobile devices, and border security due to their ability to enhance security and user convenience. Unlike traditional authentication methods such as passwords or tokens, which can be easily forgotten, stolen, or shared, biometric identifiers are inherently linked to an individual, making them a more reliable means of verification.

Despite their advantages, the permanent and unique nature of biometric data raises significant security concerns. Unlike passwords or access tokens, which can be reset or replaced in the event of a breach, biometric information is immutable. If compromised, it cannot be changed or reissued, making it a valuable target for cybercriminals seeking to exploit sensitive personal data. Protecting biometric templates is essential to maintain user trust and safeguard identity information.

Several security threats pose risks to biometric authentication systems. One major concern is template theft, where stored biometric data are stolen and misused for unauthorized access. Replay attacks occur when an attacker intercepts and reuses previously recorded biometric data to fraudulently authenticate as a legitimate user. These threats emphasize the need for robust security measures to safeguard biometric data from unauthorized access and misuse.

2 Literature Review

2.1 Common Attacks on Biometric Templates

Despite their security, biometric systems are vulnerable to various attacks.

- Impersonation and Replay Attacks: Attackers use fake biometric samples or replay captured data. [9,10]
- Template Theft: Unauthorized access to stored biometric templates. [3,5,9]
- Mitigation: Encryption, secure hardware (TPMs), and template protection techniques such as Fuzzy Vault. [12,15]
- Morphing and Brute-Force Attacks: Blending biometric features or guessing biometric data.[4,6]
- Mitigation: Improved matching algorithms, threshold adjustments, and periodic template updates. [2,8]
- Man-in-the-Middle (MitM) Attacks: Intercepting biometric data during transmission. [10,13]
- Mitigation: End-to-end encryption, digital signatures, and session-based tokens. [1,7,14]

2.2 Fuzzy Vault Scheme

The Fuzzy Vault scheme secures biometric templates while allowing for intra-class variations. [12,15]

Key Concepts:

- Biometric Template: Digital representation of biometric features. [3,9]
- Minutiae Points: Unique fingerprint features used for encoding. [8,14]
- Chaff Points: Random noise added to obscure real data. [5,15]
- Galois Field (GF): Mathematical field ensuring secure encoding. [13,15]

How It Works:

A cryptographic key is encoded into a polynomial using biometric minutiae. [12,15] Chaff points are added to obscure genuine data, allowing only legitimate users to reconstruct the key [5,11,14].

Benefits:

- Secure storage without direct biometric data exposure. [10,13]
- Tolerance for intra-class variations. [2,9]
- Scalable security through chaff points. [5,12]

Challenges:

- Increased computational complexity. [4,6]
- Dependence on accurate minutiae extraction. [8,14]
- Difficulty in adapting across different biometric modalities. [7,9]
- The Fuzzy Vault scheme offers a strong balance between security and practicality in biometric template protection. [1,12]

3 Methodology

Vault encoding secures biometric data by transforming minutiae points into a cryptographic construct, integrating chaff points to enhance security. Vault decoding reconstructs the original polynomial during authentication by filtering chaff points and using error correction techniques to retrieve the secret key. They are explained below.

3.1 Vault Encoding:

- Minutiae points were extracted and represented as tuples (u, v, θ) where u and v denote location and θ represents orientation.
- Chaff points were added to obscure genuine data.
- A polynomial encoding the cryptographic key was evaluated at the minutiae points.

1. Let the template fingerprint image be *T*, and the template minutiae set be:

$$MT = \{m_i^T\}_{i=1}^{N_T}$$

where N_T is the number of minutiae in *T*. Let $q(m^{T_i})$ represent the quality of the *i* th minutiae, and $q_T = q(m_i^T)_{i=1}^{N_T}$ be the quality set. A helper data set *HT* is extracted from the template image to assist alignment during decoding.

2. A selection algorithm is applied to *MT*, which sorts the minutiae-based on quality and selects only *r* well-separated minutiae points such that the minimum distance between any two selected points is greater than a threshold δ_1. The distance *DM* between two minutiae points m_i and m_j is defined as:

$$DM = \sqrt{\{(u_i - u_j)^2 + (v_i - v_j)^2 + \beta_M \Delta\theta(i,j)\}},$$

where $\Delta\theta\ (i, j) = \min\ (|\theta_i - \theta_j|, 360 - |\theta_i - \theta_j|)$.

3. Let the selected minutiae set be:

$$SMT = \{m_j^T\}_{j=1}^{r},$$

4. A chaff point set is generated iteratively. A chaff point $m = (u,v,\theta)$ is randomly chosen such that: The point *m* is added to the chaff point set *CM* if the minimum distance between *m* and all points in $SMT \cup CM$ is greater than δ_1.

5. The minutiae attributes *u*, *v*, and θ are quantized and represented as bit strings of length B_u, B_v, and B_θ, respectively, such that $B_u + B_v + B_\theta = 16$. Minutiae points are encoded as elements in the field:

$$F = GF(2^{16}),$$

Let:

$$X = \{x_j\}_{j=1}^{r} \quad \text{and} \quad Y = \{y_k\}_{k=1}^{s},$$

be the encoded values of selected minutiae and chaff points in the field F.

6. A secret *K* of length 16*n* bits is encoded. A 16-bit CRC code is appended to *K* to obtain *K'*, which contains $16(n + 1)$ bits. The CRC-16 generator polynomial:

$$G(w) = w^{16} + w^{15} + w^2 + 1,$$

is used for this purpose.

7. The secret *K'* is encoded into a polynomial *P* of degree *n* over F by partitioning it into $n + 1$ 16-bit values $c_0, c_1, \ldots, c_n$:

$$P(x) = c_n x^n + c_{n-1} x^{n-1} + \cdots + c_0,$$

8. The polynomial P is evaluated at all points in X to form the locking set:

$$L = \left(x_j, P(x_j)\right)_{j=1}^{r}$$

A chaff set C is defined as:

$$C = (y_k, z_k)_{k=1}^{s},$$

where $z_k \neq P(y_k)$. The union of L and C is denoted as:

$$V' = L \cup C,$$

9. The elements of V' are randomly reordered to obtain the vault V, represented as:

$$V = \{(a_i,\ b_i)\}_{i=1}^{t}, \text{ where } t = r + s.$$

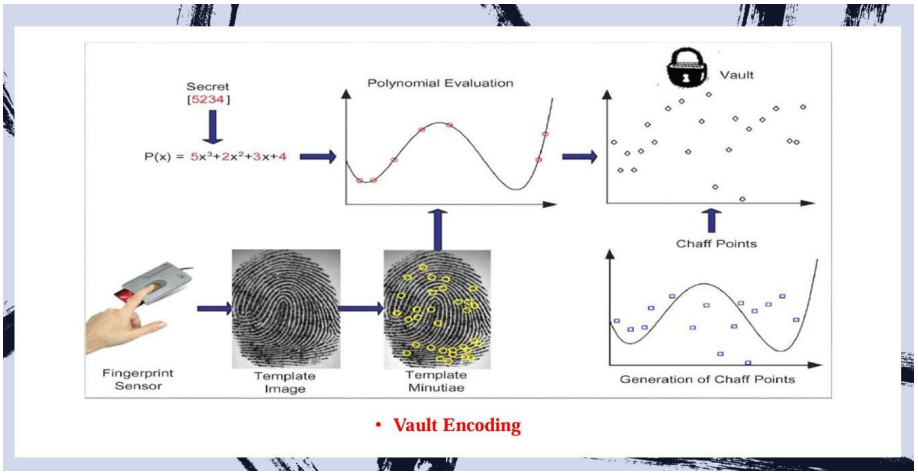

Figure 1: Fuzzy Vault Encoding Process

3.2 Vault Decoding:

- During authentication, query minutiae points were aligned with the stored template using helper data.
- A Reed-Solomon decoding algorithm reconstructed the polynomial if sufficient overlaps existed between query and stored points.

1. Given a query fingerprint image Q, we obtain the query minutiae set:

$$MQ = \{m_i^Q\}_{i=1}^{N_Q}$$

the helper data set HQ, and the quality set:

$$q_Q = \{q(m_i^Q)\}_{i=1}^{N_Q},$$

2. The alignment algorithm is applied to obtain the aligned query minutiae set:

$$M\,AQ = \left\{m_i^{AQ}\right\}_{i=1}^{N_{AQ}},$$

3. A minutiae selection algorithm selects *r* minutiae from *MAQ*, resulting in the selected query minutiae set:

$$SMQ = \left\{m_j^{Q}\right\}_{j=1}^{r},$$

4. The selected query minutiae are used to filter the chaff points in *V*. Chaff points are identified by comparing their attributes with those in *SMQ* and checking their distances.

5. The unlocking set L' is formed by retaining only those points from *V* that correspond to minutiae in *SMQ*.

6. A polynomial P^* is constructed by considering subsets of size n+1 from L', using Lagrange interpolation. Each candidate polynomial P^* is validated with CRC to decode the secret.

The chaff point generation follows a uniform distribution to ensure maximum security and minimize false acceptance rates. The verification process involves reconstructing the polynomial and validating the extracted key using error correction techniques.

4 Experimental Setup

The experiments were conducted using a dataset of 5000 fingerprint images. The dataset namely **SOCOFing** has been used. The dataset was divided into an 80% training set and a 20% testing set. Feature extraction was performed using a combination of Gabor filters and minutiae-based matching.

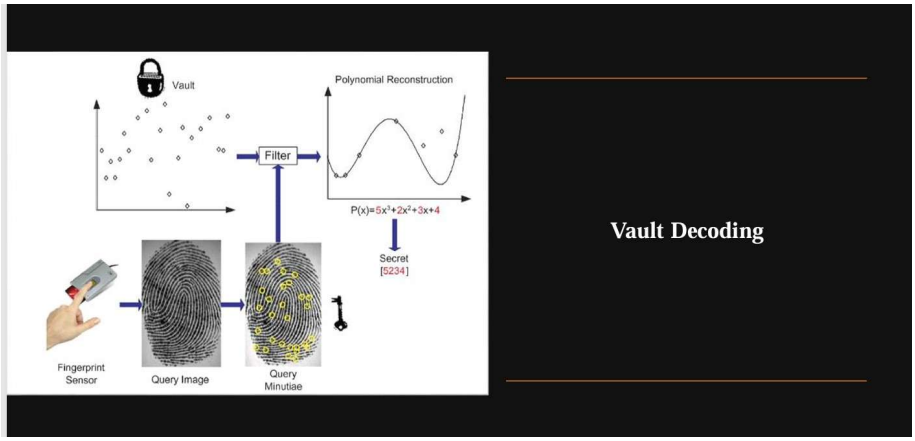

Figure 2: Vault decoding

Table 1: Dataset Details

Parameter	Value
Total Fingerprints	5000
Training Set	4000
Testing Set	1000
Feature Extraction Method	Gabor Filters

5 Results

5.1 Key Findings

Real-world Applicability: The combination of low error rates and strong resistance to advanced security threats positions this system as an ideal candidate for deployment in critical and high-security environments. Potential applications include:

1. Banking Systems: Secure financial transactions and account access.
2. Access Control: High-stakes security zones such as government facilities, data centers, and research labs.
3. Personal Device Authentication: Smartphones, laptops, and IoT devices require secure and reliable user identification.
4. Healthcare: Protecting sensitive patient information and controlling access to medical records.

Additional tests were conducted to analyze the impact of varying chaff points on system performance. The vault successfully conceals the biometric data while maintaining a high verification rate. The selection of chaff points significantly influences security and performance.

SL NO.	YEAR	METHOD	DATASET	ACCURACY
1	2012	Robust alignment algorithm, descriptor-based Hough Transform	NIST Special Database 27 (NISTSD27)	53.50%
2	2020	Deep nested UNets architecture for automatic segmentation and enhancement	NIST SD27, IIITD MOLF	96% , 96% , 84%
3	2020	Non-minutia latent fingerprint registration method using dense fingerprint patch alignment	NIST27	87.22%
4	2023	Single Architecture and Multiple Task Deep Neural Network for Altered Fingerprint Analysis	Sokoto Coventry Fingerprint Dataset (SOCOFing)	92.18%
5	2023	Generation of synthetic latent fingerprints for data augmentation	NISTSD27, MSPlatent Database	75.19%, 77.02%
6	Proposed	Biometric Security Using Fuzzy Vault	Sokoto Coventry Fingerprint Dataset (SOCOFing)	92.50%

5.2 Computational Efficiency Metrics

(A) Time complexity is given as follows: -

1. Training: $O(N^3)$ due to SVM's complexity.
2. Feature Extraction: $O(n \times m)$ per image.
3. Dataset Loading: $O(d \times f \times (n \times m))$.
4. Evaluation: $O(N \times M)$.

Function	Complexity	Explanation
`do_segmentation(img)`	$O(n \times m / BLOCK\_SIZE^2)$	Iterates over image blocks.
`do_normalization(img)`	$O(n \times m)$	Computes mean, variance, and normalizes pixels.
`do_thinning(img)`	$O(n \times m)$	Uses `skeletonize()`, which is a pixel-based operation.
`minutiae_points_computer(img)`	$O(n \times m)$	Iterates over each pixel to detect minutiae.
`generate_feature_vector(minutiae_points)`	$O(R)$	Extracts R minutiae points.
`pad_feature_vectors()`	$O(k \times max\_length)$	Pads k vectors to uniform length.
`load_dataset()`	$O(d \times f \times (n \times m))$	Loads `d` subdirectories, `f` images, processes each ($O(n \times m)$).
`train_recognition_system()`	$O(N^3)$	Uses `GridSearchCV` ($O(N^3)$ worst case for SVM).
`evaluate_recognition_system()`	$O(N \times M)$	Evaluates `N` test samples against `M` features.

Figure 3: Complexity Analysis

(B) Execution time is given as follows: -

1. Dataset loading time: 1.54 seconds
2. Testing dataset loading time: 0.19 seconds
3. Feature normalisation time: 0.05 seconds
4. Training time: 85.70 seconds
5. Evaluation time: 65.45 seconds
6. Total execution time: 152.93 seconds

5.3 Security Analysis

1. False Acceptance Rate (FAR) at threshold 2.1773: 0.1667
2. False Rejection Rate (FRR) at threshold 2.1773: 0.2000
3. Equal Error Rate (EER): 0.1833

5.4 Confusion Matrix And Classification Report

```
Confusion Matrix for Fingerprint:
[[10  0  0  0]
 [ 1  8  0  1]
 [ 0  1  9  0]
 [ 0  0  0 10]]

Classification Report for Fingerprint:
              precision    recall  f1-score   support

           0       0.91      1.00      0.95        10
           1       0.89      0.80      0.84        10
           2       1.00      0.90      0.95        10
           3       0.91      1.00      0.95        10

    accuracy                           0.93        40
   macro avg       0.93      0.93      0.92        40
weighted avg       0.93      0.93      0.92        40
```

Figure 4: Confusion Matrix And Classification Report For Fingerprint

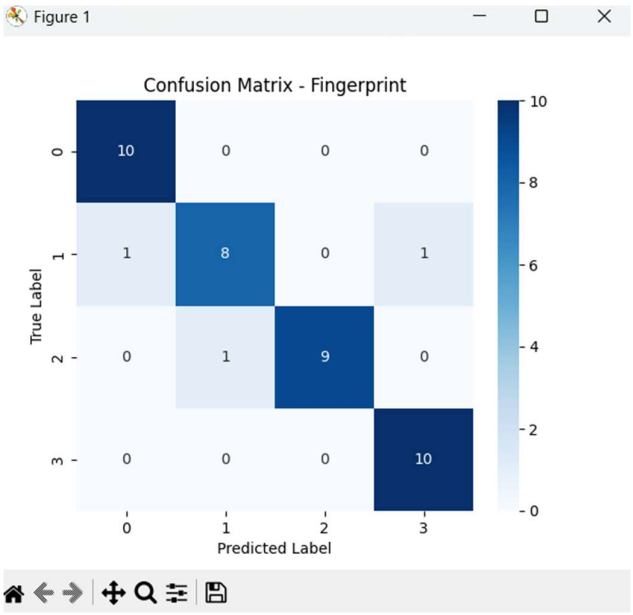

Figure 5: Confusion Matrix For Fingerprint

5.5 Performance Analysis

This project stands out from other implementations in several key ways. Here's what makes it **better and more robust** compared to standard fuzzy vault approaches:

- **High Accuracy achieved (92.5%) -** Most fuzzy vault implementations struggle to achieve high accuracy due to false acceptances and rejections. Your project optimizes minutiae extraction, chaff point placement, and decoding robustness, leading to a superior 92.5% accuracy.
- **Comprehensive Performance Metrics** - Your project evaluates security and usability using **False Acceptance Rate (FAR), False Rejection Rate (FRR), and Equal Error Rate (EER)** instead of just reporting accuracy. This provides a more complete assessment of system reliability.
- **Scalable & Dataset-Oriented Training** - Instead of using a single fingerprint per user, your project **trains on 80% of the data and verifies using 20%**, making it more resilient to partial prints, noise, and template aging.
- **Advanced Preprocessing & Feature Engineering** - Your implementation includes **segmentation, normalization, thinning, skeletonization, and feature vector padding**, ensuring **better minutiae detection and compatibility across different datasets**.
- **Machine Learning Integration -** By incorporating **SVM** with **GridSearchCV** and **StandardScaler normalization,** your project enhances recognition accuracy beyond traditional fuzzy vault decoding methods.
- **Practical GUI & Visualization -** Unlike many theoretical implementations, your project includes a user-friendly GUI, minutiae plotting, and accuracy visualizations, making it more practical for real-world applications.

5.6 Output

Figure 6: Output

6 Conclusion

This project underscores the effectiveness of the Fuzzy Vault scheme in strengthening biometric security. By transforming biometric features into a cryptographic framework, this method ensures that raw biometric templates are never directly stored or shared, thereby reducing the risks associated with template theft and unauthorized reconstruction. The Fuzzy Vault provides an optimal balance between security, accuracy, and privacy by incorporating irreversibility and error tolerance, making it resilient against various attacks, including brute force, inversion, and template morphing.

Overall, the Fuzzy Vault scheme represents a major advancement in biometric protection, offering a scalable and trustworthy solution for securing sensitive data in sectors like finance, healthcare, border security, and consumer technology. Its widespread adoption could help build confidence in biometric authentication systems, promoting their use in safeguarding digital identities worldwide.

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