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An Approach for Full Reinforcement-based Biometric Score Fusion

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ABSTRACT Multibiometric systems have the potential to mitigate error rates and address certain inherent weaknesses found in unimodal systems. This study introduces an innovative scheme for user recognition in multibiometric systems, centered on a score-level fusion framework. The foundation of this framework lies in the full reinforcement operator (FRO), specifically estimating FRO through generator functions associated with triangular norms (T-norms and T-conorm). The efficiency of the proposed method has been showcased through an extensive set of experiments carried out on four commonly available benchmark databases: all three partitions of the National Institute of Standards and Technology (NIST) databases (Set 1, 2, 3), along with the XM2VTS database. Our method achieves superior accuracy compared to existing methods, reaching 100 % recognition on NIST-Set 1, 93.40 % on NIST-Set 2, and 94.54 % on the more challenging NIST-Set 3. The experimental findings illustrate that score fusion schemes based on FRO not only enhance verification rates when compared to current score-level fusion techniques (such as Asymmetric Aggregation Operators, Minimum, Maximum, T-norms, and Symmetric-Sum) but also offer a swift computational performance.

INDEX TERMS Unidiomatic system, multibiometric system, score-level fusion, full reinforcement operator (FRO).

I. INTRODUCTION

The established methods of authentication are currently facing substantial competition from emerging alternatives. Novel technologies like biometric and multibiometric systems pose challenges to conventional recognition methods. This shift is primarily driven by the significant increase in identity theft and security-related concerns. These technologies rely on unique human attributes, either anatomical (e.g., facial features, fingerprints, iris patterns) or behavioral (e.g., cognitive biometrics, gait, keystroke dynamics) traits [1]. Furthermore, biometric modalities are inherently present in individuals, making them exceptionally challenging to counterfeit or pilfer [2]. Besides, biometric characteristics establish a robust connection between a user and their identity [3]. Furthermore, a system that relies on human attributes is regarded as a better choice in terms of dependability and accuracy [4].

Many researchers contend that unimodal biometric systems, which rely on a single trait, are not sufficiently equipped to tackle challenges such as noisy input data, the limited distinctiveness of the chosen biometric trait, non-universality, low interoperability, and vulnerability to spoofing [5]. These limitations can result in reduced accuracy [5]. Some of the shortcomings associated with unimodal systems can be mitigated by adopting multibiometric systems, which incorporate data from several biometric modalities. Utilizing at least two biometric traits offers several advantages compared to relying on a single modality [6]. Several advantages arise from this approach, including enhancements in overall accuracy, the effective management of universality concerns, and heightened resistance to spoofing attempts. By combining evidence from multiple biometric sources, it becomes significantly more challenging for impostors to simultaneously imitate various physiological and/or behavioral attributes of a genuine user [7]. According to the nature of the biometric information source, a multibiometric recognition can be categorized broadly into several types, such as multimodal (utilizing multiple biometric traits) [8], multi-unit (employing multiple instances of the same kind of biometric data, e.g., both left and right wrist veins in humans) [8], multi-algorithm (applying diverse feature extraction methods on the identical biometric characteristic) [8], multi-sensor (utilizing multiple sensors for capturing the identical biometric trait) [9], and multi-sample (gathering a multitude of samples of the identical biometric characteristic) [9]. To address the limitations observed in prior research on both unimodal and multimodal biometrics, it is imperative to develop contemporary and computationally efficient methods for combining authentication scores.

In this article, we have introduced an innovative approach for integrating biometric scores at the score-level, known as the "full reinforcement operator". This operator is employed to amalgamate scores generated from various sources, and compared to other score fusion techniques like Dempster-Shafer (DS) theory, symmetric-sum, T-norms, weighted sum, and max rules, it shows improved differentiation between genuine and imposter match-scores. Our suggested multibiometric score fusion framework, based on the full reinforcement operator, was rigorously validated in diverse user authentication scenarios, including multiple traits (utilized both the XM2VTS database [31] and the NIST-multimodal database [7]), multiple instances (using the NIST fingerprint database), and multiple algorithms or features (merging output scores from two separate face matchers, NIST face database).

The rest of our paper is organized as follows. Section II delves into the relevant literature concerning the combination of matching scores. In Section III, we offer a detailed explanation about reinforcement in aggregation operators. Section IV presents a concise description of the proposed score fusion technique. Section V is dedicated to discussing the experimental results we have obtained. Finally, Section VI concludes this paper.

II. Related Work

Information fusion contributes significantly in multimodal biometric systems, the key factor behind the success of multimodal biometric is fully related on how we select the fusion schemes to enhance performance. In literature, matching score-level is generally used even though there are many levels of fusion (e.g., decision, features). Moreover, there is a categorization of matching score fusion techniques, which falls into three main groups: classifier-based, density-based, and transformation-based score fusion. Within the transformation-based category, these techniques are broadly separated into a pair of subgroups: fixed and trained score fusion rules. Before implementing either fixed or trained rule-based fusion methods, employing normalization techniques like tanh, or double sigmoid, min-max scaling, z-score standardization (normalization), is crucial to first convert the matched scores into a common domain and to ensure a meaningful integration. Fixed rules, such as symmetric sum, product T-norm, minimum, maximum, and Asym-AOs (Asymmetric Aggregation Operators), do not require any specific learning process. In contrast, trained rules necessitate a learning phase, as seen in techniques like weighted sum.

A. Fixed rule-based score fusion

Following the normalization process, the scores obtained from each matcher are amalgamated using a designated rule, such as minimum, maximum, or multiplication.

For instance, in 2013, Wang et al. [10], created a multimodal biometric system that could recognize faces and irises. To combine the results, they used a score-level fusion method based on the Aczél-Alsina triangular norm (T-norm). The CASIA-Iris-Thousand database, which has dual iris data, and the NVIE face database, which contains both visible and thermal facial photos, are used to test the experiment's vertical databases. Their fusion rule has EER (equal error rate) = $2.98.10^{-4}$, which represents an important improvement than unimodal system. In that very year, Vishi et al. [11], introduced an innovative method for multimodal biometric verification that combines iris and fingerprint characteristics at the score-level. They employed various normalization techniques, including Min-Max, Z-Score, and Hyperbolic Tangent, along with three predefined score fusion methods: Minimum Score, Maximum Score, and Simple Sum. They conducted fusion experiments across four databases, utilizing FP-DB1 and FP-DB2 for fingerprint data and Iris-DB1 and Iris-DB2 for iris data. The authors found that employing the hyperbolic tangent estimator for score normalization and applying the simple sum rule fusion resulted in an Equal Error Rate (EER) of 0.0001 % for the combined fingerprint and iris data. On one hand, better than the unimodal biometric system and on the other hand better than both max and min score fusion rules.

Moeen et al. [12] introduced a score-level fusion technique for person recognition, utilizing the entropy function (Hanman-Anirban). For experimentation, they used the finger-knuckle-print images obtained from (FKP) dataset consisting of left index, left middle, right index and right middle FKP. The findings demonstrate that the suggested method achieves a notable enhancement in performance when compared to individual FKP approaches. They obtained genuine acceptance rate of 99 % with FAR of 0.001 %.

Cheniti et al. [7] proposed score-level fusion of multimodal biometrics using the symmetric sum rule and used T-norm to generate the symmetric sum functions. The provided framework underwent testing on two openly accessible benchmark databases. Specifically, the authors utilized a pair segment of NIST-BSSR1, namely, the NIST- fingerprint database and the NIST-multimodal database. The empirical outcomes demonstrate that the suggested technique surpasses the performance of current methods when applied to both the NIST-multimodal database and the NIST fingerprint database.

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In 2020, Herbadji et al. [8] developed score fusion technique for person authentication using weighted quasi-arithmetic mean. The authors conducted experiments using three publicly accessible datasets: NIST-BSSR1 Fingerprint, NIST-BSSR1 Multimodal, and NIST-BSSR1 Face. In their evaluation of multimodal, multi-unit, and multi-algorithm systems, they demonstrated that the WQAM combining rule they proposed surpasses the earlier suggested score combining method, which relied on fixed techniques like T-norms, trained methods such as support vector machines, and density assessment approaches like likelihood ratio. Table I represents a summary of the contemporary fixed rule-based score fusion.

TABLE I: SUMMARY OF CONTEMPORARY FIXED RULE-BASED SCORE FUSION

Method	Year	Fusion Rule	Biometric Traits
[32]	2012	Adaptive weighted	Palmprint
[10]	2013	Aczél-Alsina T-norm	iris and thermal face images
[11]	2013	Sum, max, min rule	iris and fingerprint
[34]	2013	Mean, max, min, median rule	Palm-print-vein
[13]	2014	Mean rule	face and fingerprint
[14]	2015	Max rule	palm-dorsal vein
[12]	2016	Hanman-Anirban entropy function	finger-knuckle-print (left index, left middle, right index and right middle)
[33]	2017	Adaptive weighted	Left and right palmprint
[15]	2017	Dubois and Parad T-norm	left and right wrist vein patterns
[7]	2018	Symmetric sum rule	face and fingerprint
[16]	2019	T-norm	wrist, palm vein images
[8]	2020	Weighted quasi-arithmetic mean	face and fingerprint
[9]	2020	Asym-AO	palmprint, fingerprint, face and ocular left eye

B. Trained rule-based score fusion

Prior to employing the trained rule, it is essential to split the matcher scores into two distinct sets. One of these sets is allocated for the training phase, while the other is reserved for the testing phase. The process of training the rule involves learning and determining the appropriate model parameters, such as identifying the correct weights in the case of weighted sum or product rules. These learned parameters are then applied in the subsequent testing phase.

One of the representative works of trained rules is [17]. Furthermore, in [18], the authors introduced a score fusion technique that integrates belief functions for palmprint, face and iris modalities. The authors employed Gabor filter combined with dimensionality reduction techniques PCA, LDA and KFA to transform matching scores into belief assignments, and they utilized particle swarm optimization (PSO) to determine the weights assigned to the belief assignments of the palmprint, face and iris classifiers. Subsequently, the Dempster-Shafer (DS) theory was applied to combine the masses. While the authors [19] devised an effective score fusion method utilizing the Dezert-Smarandache theory (DSmT). The suggested score fusion framework consists of three main steps: (i) calculation of the generalized basic belief assignment, (ii) fusion of the assigned beliefs using a fusion rule based on DSmT, and (iii) determination of whether to accept or reject a user. A summary of some representative studies in trained rule-based score-level fusion systems is presented in Table II.

TABLE II: SUMMARY OF CONTEMPORARY TRAINED RULE-BASED SCORE FUSION

Method	Year	Fusion Rule	Biometric Traits
[19]	2015	weighted-sum rule	Voice and face
[18]	2019	PSO-DS	Palmprint, iris, face
[20]	2015	weighted-sum rule	Face and iris
[21]	2016	weighted-sum rule	Face and iris
[22]	2017	weighted-sum rule	Face and iris
[23]	2017	Quality-based weights	Voice and face
[24]	2018	DSmT-based rule	Face and Fingerprint
[25]	2019	Backtracking Search, PCR	Iris, finger-vein and fingerprint
[26]	2020	weighted-sum rule	Finger-vein

III. Boosting Aggregation via Reinforcement Strategies

Several attempts have been conducted to find the best score-level fusion technique; moreover, many researchers have claimed that an effective score-level fusion technique should aim to maximize genuine scores while minimizing impostor scores, ultimately leading to an enhanced genuine acceptance rate (GAR) and reduced false acceptance rate (FAR). The only fusion rule that satisfies the required properties, i.e., simultaneously maximizes the genuine scores and minimizes the impostor scores, is called a full reinforcement operator (FRO) [27].

By employing the FRO fusion rule, we can ensure, firstly, that a set of genuine scores work together to strengthen and affirm the fused score, surpassing the individual scores alone. Secondly, a set of impostor scores collaborate to intensify the disconfirming nature of the fused score, surpassing the individual scores alone. To delve into more specific aspects, we need to introduce two closely related methods. The first one is referred to as the upward reinforcement operator (URO) [27]. With this approach, we are describing the tendency where, if the scores used for user identification are all highly favorable (indicating genuine scores), they strengthen each other, resulting in even stronger confirmation that the user falls under the genuine category. Likewise, the downward reinforcement operator (DRO) represents the inclination where, if the scores used for user identification are all low (indicating impostor scores), they strengthen each other, leading to a more pronounced confirmation that the user belongs to the impostor category [27]. Overall, a score fusion rule that displays both URO and DRO is called a full reinforcement operator (FRO) [27].

A score fusion rule W, operating with input scores taken from the unit interval [0,1], is considered to exhibit upward reinforcement exclusively, when its output is greater than the maximum of its individual arguments (input scores). Similarly, a score fusion rule *W*, is said to display downward reinforcement only when its output is lower than the minimum of its individual arguments.

Example 1. Assume a multimodal biometric system is characterized by three score matchers *M1*, M2, M3. Let *W* be a fusion rule. If for the user *x* we have: *M1 (x)* = 0.8, M2 (x) = 0.85, *M3(x)* = 0.9 and if *W* (0.8,0.85,0.9) = 0.91, Then *W* is an upward reinforcement operator (URO).

Example 2. Assume a multimodal biometric system is characterized by three score matchers *M1*, *M2*, *M3*. Let *W* be a fusion rule. If for the user *x* we have: *M1 (x)* = 0.4, *M2 (x)* = 0.3, *M3(x)* = 0.35, and if *W* (0.4,0.3,0.35) = 0.2, Then *W* is a downward reinforcement operator (DRO).

As full reinforcement operators can offer both attributes concurrently, encompassing both the upward and downward reinforcement characteristics, they seem to be a desirable quality to incorporate in score-level fusion techniques. We aim to study if the previously suggested score fusion rules can manifest this property. Because there are ample of fusion rules in the literature, we prefer to begin with T-norms because they confirm their ability to provide a good performance [7], and they are adopted in many studies as a generator to produce some other fusion rules such as symmetric sum [7], Asym-AOs [9]. Additionally, they can represent a broad class of several fusion rules such as min, mean, max, product and average sum.

T-norms, often known as triangular norms, are a class of binary functions that generalize intersection at fuzzy sets. A T-norm is a function T: $[0, 1] \times [0, 1] \rightarrow [0,1]$ that meets the requirements listed below:

i) T is commutative: $T(x, y) = T(y, x)$.
ii) Tassociative : $T\ (x, T\ (y, z)\ =\ T\ (T\ (x, y), z)$.
iii) 1 is an identity operator: $T\ (x, 1) =\ T\ (1, x) = 1$.
iv) $T$is rising in each variable:

$$y \leq\ z\ \Longrightarrow T\ (x, y) \leq T\ (x, z).$$

An indispensable property associated with any T-norm is:

$$T(x_1, \dots, x_n) \leq\ min_i[x_i]$$

From this last property we can say that any biometric score fusion rule base on T-norm exhibits the property of downward reinforcement. Moreover, from the same property we can see that any output of T-norm can never exceed the minimum of the input scores (arguments), therefore, T-norm does not exhibit upward reinforcement. From this investigation we can conclude that T-norm based score-level fusion is very useful when it deals with impostor scores, it indeed reinforces them to a lower value, but it fails to reinforce the genuine scores, unfortunately the T-norm is not full reinforcement operator [27]. As we said above the T-norm is a universal class of numerous score fusion rule like symmetric sum, max, min, product, and Asym-AOs. We can conclude that all these rules are not full reinforcement operator [27].

Let's shift our focus to the T-conorm aggregation operator, as described in references [15]. This operator has been employed in the field of fuzzy set studies, serving as an extension of disjunction or type aggregation. A T-conorm is a function C: $[0, 1] \times [0, 1] \rightarrow [0,1]$ that satisfies the following properties:

i) C is commutative: $C(x, y) = C(y, x)$.
ii) C is associative: $C\ (x, C\ (y, z)\ =\ C\ (C\ (x, y), z)$.
iii) 0 is an identity operator: $C\ (x, 0) =\ C\ (0, x) = 0$.
iv) C is rising in each variable:

$$y \leq z\ \Longrightarrow C\ (x, y) \leq\ C\ (x, z).$$

An indispensable property associated with any T-conorm is:

$$C(x_1, \dots, x_n) \geq\ max_i[x_i]$$

From this characteristic indicates that the T-conorm functions as an upward reinforcement operator. When all scores are high, the combined value will be equal to or greater than the highest individual score. However, it is worth noting that T-conorm do not function as downward reinforcement operators. In situations where all inputs are low, the result does not fall below the minimum value but instead equals or exceeds the maximum value among the aggregated scores.

Now we see if the mean fusion-rule exhibits the full reinforcement property, we select mean rule-based score fusion for the examination because it represents a general aggregation class to many other score fusion rules such as medium, arithmetic, weighted sum, ordered weighted averaging (OWA) [19] and Weighted quasi-arithmetic mean [8]. A mean operator Z is a mapping $Z: I^n\ \rightarrow\ I$ (I is the unit interval), such that it is:

i) Commutative.
ii) Monotonic.
iii) Idempotent $Z(x_1, \dots, x_n)\ =\ x$.

A substantial and understandable property associated with any kind of mean operator score fusion rule is that its output is always between the max and min of its inputs,

i.e., $min(x_i) \leq\ \ Z(x_1, \dots, x_n) \leq max_i(x_i)$

Due to the aforementioned characteristic, a mean operator score fusion cannot be a URO or DRO, and consequently neither the mean rule nor its subclasses are a FRO [27]. After the examination of three general classes of score fusion rule and their subclasses, we can conclude that all previous fusion score-level fusion rules are not optimized because they fail to exhibit the full reinforcement property. This fact motivates us to introduce a score-level fusion rule based on FRO.

IV. Proposed Full Reinforcement Score Fusion Technique

In this section, we define an innovative technique for score-level fusion that leverages two interconnected methods: upward and downward reinforcement. Initially, we explore the fuzzy models associated with the full reinforcement approach, followed by an explanation of the multibiometric score fusion method based on FRO.

A. Reinforcement from fuzzy models

The above investigation led us to conclude that the majority of score fusion rules previously proposed in the literature do not possess the capabilities of a full reinforcement operator, which motivated us to adopt a score fusion rule based on a full reinforcement operator.

Fuzzy logic theory presents a robust framework for knowledge representation within the domain of intelligent system construction. This framework proves particularly advantageous in a diverse range of applications, including pattern recognition, information retrieval, diagnostic systems, and multi-criteria decision-making [35]. For this reason, we adopt a similar fuzzy logic modeling-based technique of [27]. Initially, it's essential to recall that a T-norm operates as a downward reinforcement operator, while a T-conorm serves as an upward reinforcement operator. Consequently, we can understand that combining both a T-norm and a T-conorm allows us to create the desired operator, with the ability to function as a T-norm when scores are low and as a T-conorm when scores are high. The general form of full reinforcement operator can be formulated in following two distinguishing rules [27]:

Rule 1 (*R1*): When all scores are low, employ a T-norm aggregation.

Rule 2 (*R2*): When all scores are high, utilize a T-conorm aggregation.

Based on the two rules, we can develop a fuzzy logic model. Suppose our score fusion rule comprises n scores, where each score is represented by the variable S_i. Additionally, we define two fuzzy subsets for each S_i on the closed interval: L_i, representing to the "low" notion, and H_i, corresponding to the "high" concept. Furthermore, we introduce two operators: T, representing any T-norm, and C, representing any T-conorm. Let $M(S_i)$ be the full reinforcement operator. Consequently, we can formulate a fuzzy model with a pair of constraints as follows:

R1: If S_1 is L_1 and S_2 is L_2 …. S_n is L_n then $M(S_i)$ is B_1

R2: If S_1 is H_1 and S_2 is H_2 …. S_n is H_n then $M(S_i)$ is B_2

In the context mentioned earlier, both B_1 and B_2 are singleton fuzzy subsets (refer to Eqn. 1, 2), where:

$$B_1 = \left\{\frac{1}{T(S_1, S_2, \dots, S_n)}\right\} \tag{1}$$

$$B_2 = \left\{\frac{1}{C(S_1, S_2, \dots, S_n)}\right\} \tag{2}$$

We observe that in the previously described model, the outcome value depends on the input factors, resembling a Sugeno-Takagi framework. Solving this type of fuzzy system model involves four distinct steps [27], as below:

i) Locate the firing level τ_i of every constraint (refer to Eqn. 3, 4).

ii) Detect the functional output fuzzy membership function of each rule.

iii) Fuse these functional outputs (refer to Eqn. 5).

iv) Crispify the resulting fuzzy set (refer to Eqn. 6).

For rule one the firing level is:

$$\tau_1 = \prod_{i=1}^{n} L_i(S_i) \tag{3}$$

Similarly, for rule two we get:

$$\tau_2 = \prod_{i=1}^{n} H_i(S_i) \tag{4}$$

Combining these two rule-outputs, the system produces:

$$F = \left\{\frac{\tau_1}{T(S_1, S_2, \dots, S_n)}, \frac{\tau_2}{C(S_1, S_2, \dots, S_n)}\right\} \tag{5}$$

Using the center of area method of crispification, we get:

$$M(S_n) = \frac{\tau_1\, T(S_1, S_2, \dots, S_n) + \tau_2\, C(S_1, S_2, \dots, S_n)}{\tau_1 + \tau_2} \tag{6}$$

If we denote:

$$w_1 = \frac{\tau_1}{\tau_1 + \tau_2} \quad , \quad w_2 = \frac{\tau_2}{\tau_1 + \tau_2} \tag{7}$$

Then

$$M(S_n) = w_1 T(S_1, S_2, \dots, S_n) + w_2\, C(S_1, S_2, \dots, S_n) \tag{8}$$

Thus, we see that M (refer to Eqn.8), is obtained as a kind of weighted average of T-norm and T-conorm. However, it is important to emphasize that this approach diverges from a basic weighted average involving a T-norm and a T-conorm, as we have previously demonstrated that such a method does not achieve full reinforcement. Here, the key distinction lies in the fact that the weights (refer to Eqn. 7) are not fixed constants; instead, they are contingent upon the scores S_i.

B. The score fusion method based on FRO

The primary purpose of a biometric system is to perform the detection of patterns or matching. The two main duties of biometric recognition systems are registration and verification. In the registration phase, A biometric sensor, like a fingerprint reader in the case of fingerprint recognition, is used to acquire the biometric attribute. The derived biometric feature is then used to extract salient characteristics, frequently referred to as a "template". It is then entered along with the name of user in a database. When a user requests to be recognized during the recognition or verification phase, they give the system a biometric characteristic. This stage involves extracting features using the biometric trait collected from the sensor, evaluating those features to traits in the enrollment database, and generating a matching score. If the matching score surpasses a predefined threshold, the system classifies the user as genuine; otherwise, it identifies them as impostors.

Figure 1 depicts an architectural representation of the entire procedure of a multibiometric person authentication scheme. This framework combines data from various

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biometric sources using Full Reinforcement Aggregation Operators (FRO).

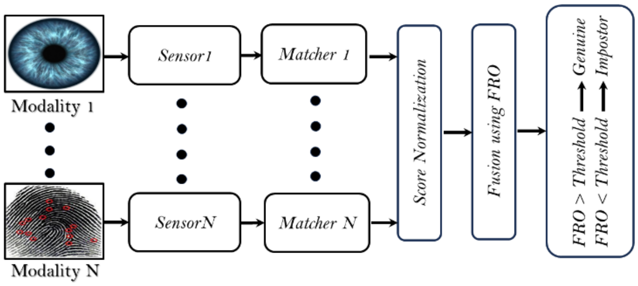

FIGURE 1. Multibiometric person authentication using FRO.

Due to the diversity in match scores, it is necessary to initially convert these various match scores into a single range of [0,1] prior to fusion. In this study, we employed two normalization techniques, specifically the min-max and tanh-estimators, as described here:

$$S' = \frac{S - min(S)}{max(S) - min(S)} \tag{9}$$

Here, S' denotes the adjusted score, and S signifies the match score produced by a particular matcher.

$$S' = \frac{1}{2}\left[\tanh\left(0.01\left(\frac{S-\mu}{\sigma}\right)\right) + 1\right] \tag{10}$$

In this context, S' represents the adjusted score, where S, μ and σ correspond to the input score, mean, and standard deviation of input scores, respectively. These values are determined using the Hampel estimator [7]. After normalizing the match scores using either the min-max method (refer to Eqn. 9) or the tanh-estimators (refer to Eqn. 10), the FRO combines these standardized scores. In this paper, a specific instance of FRO is employed, referred to as the triple $\prod$ combination rule [27]. This operator is created by utilizing the product T-norm and its corresponding dual for T-conorm (refer to Eqn. 11, 12).

$$T = T(S_1, S_2, \dots, S_n) = \prod_{j=1}^{n} S_j \tag{11}$$

$$C = C(S_1, S_2, \dots, S_n) = 1 - \prod_{j=1}^{n} \bar{S}_j \tag{12}$$

$$M(S_1, S_2, \dots, S_n) = \frac{\prod_{j=1}^{n} S_j}{\prod_{j=1}^{n} S_j + \prod_{j=1}^{n} \bar{S}_j} \tag{13}$$

where, T, C, and M correspond to the T-norm, T-conorm, and triple aggregation operator ($\prod$), respectively.

If the combined score surpasses a certain threshold (set empirically), the user is verified as genuine; otherwise, identified as an impostor.

V. Experiments

In this section, we present the performed experiments and results of the proposed score fusion approach, i.e., Full Reinforcement Operator (FRO). More specifically, we have performed experiments using four publicly accessible datasets to evaluate this method's effectiveness in diverse scenarios, including multimodal, multi-unit, and multi-algorithm systems, utilizing four publicly available databases.

A. Experiments Data

The study made use of four databases that are openly accessible, including the three sets of NIST BSSR1 databases (multimode, face, fingerprint) [28], and the XM2VTS database [31].

1) Set 1 (NIST-Multimodal)

Set 1 comprises scores generated from a cohesive group of 517 individuals, incorporating both face and fingerprint data. Each person in this set has one score derived from comparing two right index fingerprints, another from comparing two left index fingerprints, and two additional scores from comparing two facial images. It is important to note that the fingerprint and face images used to generate these scores belong to the same individual, and were captured simultaneously (with documented dates provided for reference).

2) Set 2 (NIST-Fingerprint)

Set 2 consists of fingerprint scores obtained from a unified system applied to images of 6000 individuals. For each individual in this dataset, there is one score obtained by comparing two left index fingerprints and another score from comparing two right index fingerprints.

3) Set 3 (NIST-Face)

Set 3 includes scores derived from two facial recognition systems applied to images of 3000 individuals. In this dataset, each individual is represented by one score obtained by comparing face A with a subsequent face, B, and another score from comparing face A with a different subsequent face, C.

4) XM2VTS Database

The XM2VTS Benchmark database is an expanded version of the m2vts database and has maintained its reputation as one of the most extensive publicly accessible audio-visual speech databases since its inception. It offers approximately 30 hours of unprocessed video footage. In this database, the 295 speakers are divided into 200 clients and 95 impostors. There are two methods for dividing the set used for both training and evaluation, known as Lausanne Protocol I and II, denoted as LP1 and LP2 [29]. The specifics of the Lausanne Protocol can be found in Table III and IV. Facial data undergoes three different feature extraction methods: FH (Face Histogram), DCTs (Discrete Cosine Transform for small images), and DCTb (Discrete Cosine Transform for large images). For speech data, three distinct feature extraction methods are employed: LFCC (Linear Filter-bank

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Cepstral Coefficient), PAC (Phase Auto Correlation MFCC), and SSC (Spectral Sub-band Centroid).

TABLE III: BRIEF EXPLANATION OF LAUSANNE PROTOCOLS I [29]

Lausanne Protocol I				
Set	**Clients/ Impostor**	**Number of subjects**	**Number of recordings per subject**	**Number of scores**
Training set	Clients	200	3	600
Evaluation set	Clients Impostor	200 25	3 8	600 40000
Test set	Clients Impostor	200 70	2 8	400 11200

TABLE IV: BRIEF EXPLANATION OF LAUSANNE PROTOCOLS II [29]

Lausanne Protocol II				
Set	**Clients/ Impostor**	**Number of subjects**	**Number of recordings per subject**	**Number of scores**
Training set	Clients	200	4	800
Evaluation set	Clients Impostor	200 25	2 8	400 40000
Test set	Clients Impostor	200 70	2 8	400 11200

B. *Experiment Protocol for databases*

For the three sets of NIST BSSR1 databases the authentication mode experiments were conducted, and the effectiveness of the proposed fusion method was assessed using Receiver Operating Characteristics (ROC) analysis. The ROC curve is generated by plotting the Genuine Acceptance Rate (GAR) against the False Acceptance Rate (*FAR*). GAR is defined as $(\mathbf{1} - \boldsymbol{FRR})$ [7], where *FRR* (False Rejection Rate) represents the percentage of legitimate individuals that the system mistakenly rejects as impostors, and *FAR* indicates the percentage of impostor individuals that the system incorrectly accepts as client users. Meanwhile, GAR measures the rate at which client users are correctly accepted out of the total number of enrolled individuals.

For XM2VTS Benchmark database, The Half Total Error Rate ($\boldsymbol{HTER}$) is used to compare the performance of the different fusion techniques [29]. It is defined as:

$$\boldsymbol{HTER} = \frac{\boldsymbol{FAR} + \boldsymbol{FRR}}{\mathbf{2}} \qquad (\mathbf{14})$$

It is crucial to highlight that the *FAR* and *FRR* do not exhibit the same level of sensitivity. This discrepancy arises from the presence of more simulated impostor attempts than genuine client attempts. Consequently, the *FRR* experiences more significant fluctuations when erroneously rejecting a genuine client access, whereas the FAR exhibits less dramatic variations accepting an impostor access mistakenly [29].

C. *Experiments Results*

In this section, we present the experimental outcomes obtained from four publicly accessible databases (NIST-multimodal, NIST-Fingerprint, NIST-Face and XM2VTS) involving multimodal, multi-unit, and multi-algorithm biometric systems.

1) Performance of FRO-based fusion on NIST-Set 1

Figure 2 presents an architecture illustrating the entire process of a multimodal person recognition framework utilizing face and fingerprint data. The scores obtained from the face matcher C, face matcher G, as well as the left and right fingerprint scores, undergo normalization using the tanh-estimator normalization technique (refer to Eqn. 10), after which they are integrated using the proposed FRO method.

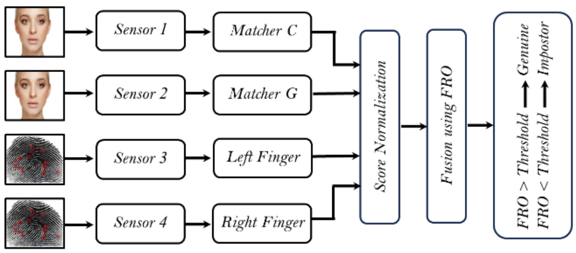

FIGURE 2. **FRO-based scores integration using NIST- Set 1.**

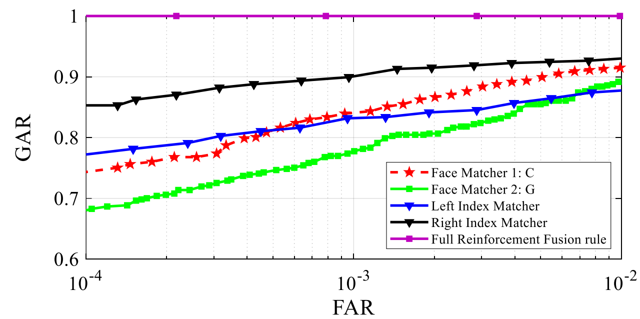

FIGURE 3. **Assessment of ROC curves of different unimodal systems with score-level Fusion for NIST-Set 1 database.**

In Figure 3, we can observe the Receiver Operating Characteristic (ROC) curves for each individual modality as well as the combined modalities using the Full Reinforcement Operator (FRO) method. These results are based on data from the NIST-multimodal database. At a False Acceptance Rate (*FAR*) of $\mathbf{10^{-4}}$, the Genuine Acceptance Rates (GARs), which are calculated as (1-FRR) [7], are 74.3% for face matcher C, 68% for face matcher G, 77.2% for the left fingerprint, and 85.3% for the right fingerprint. However, at $\mathbf{10^{-4}}$ *FAR* operating point, GAR of 100% is attained with the FRO produced by the products T-norm and T-conorm. As indicated in Table V, various symmetric sum S-sums produced through many T-norm rules (probabilistic, Yager, and Hamacher [7]) are employed for merging scores on the NIST- set1 database. Additionally, the study reports the results achieved through combining scores using the likelihood ratio (LR) and Support Vector Machine (SVM) techniques proposed in [17], both of which necessitate learning and training.

TABLE V: EVALUATION OF FUSION USING DIFFERENT APPROACHES ON NIST-SET 1 DATABASE

Combining approach at FAR = 0.01 %	GAR (%)
Entropy using Hamacher T-norm p = 0.01) [12]	96.7
Entropy using Frank T-norm p = 0.01) [12]	96.62
LR-based fusion [17]	99.1
SVM [17]	98.8
Adaptive weighted [33]	97.5
Min rule [34]	78
Max rule [34]	91.7
S-sum using min rule [7]	93.2
S-sum using max rule [7]	93.3
S-sum with Schweizer & Sklar T-norm with p = 0.9 [7]	99.8
S-sum with Yager T-norm with p = 1.2 [7]	99.8
S-sum with Hamacher T-norm [7]	95
S-sum using probabilistic T-norm [7]	97
Asym-AO2 using Aczel-Alsina [9]	94
Asym-AO1 using Aczel-Alsina [9]	96.17
Asym-AO2 using Algebric T-norm [9]	96.90
Asym-AO1 using Algebric product T-norm [9]	96.5
Asym-AO2 using Hamacher T-norm [9]	97.55
Asym-AO1 using Hamacher T-norm [9]	97.50
Proposed Full Reinforcement Fusion Rule (FRO)	**100**

Furthermore, the study showcases results for fusion using the Entropy-with-Frank and Entropy-with-Hamacher T-norms [7]. Table V clearly illustrates that the FRO, generated by both T-norm and T-conorm, outperforms the performance of score-level fusion methods previously documented in the literature.

2) Performance FRO on NIST-Set 2

Figure 4 depicts an architecture that illustrates the complete process of a multi-unit person recognition framework based on left and right index finger data. The input scores of the left and right index fingers for this dataset are normalized using the min-max method as in Eqn. 9. The combination order is not important because we fused the two matched scores here using the commutative property. Using the FRO produced by both products (T-norm and T-conorm) on the NIST-Set 2 database. Figure 5 shows the ROCs of individual modalities and of fused modalities. The left index finger and right index finger had GARs of 75.5% and 83.5%, respectively, at FAR = $\mathbf{10^{-4}}$. However, using the same FAR operating point and the FRO produced by both products (T-norm and T-conorm), a GAR of 93.40% is attained. Table VI shows that various S-sums produced using (probabilistic, Yager and Hamacher T-norms) are likewise utilized for score-level fusion on the NIST-Set 2 database. For comparison, the outcomes of combining scores utilizing the LR and SVM learning-based approaches are also provided [17]. Table VI shows that the adopted FRO performs better than the score-level fusion rules that is currently used in the literature.

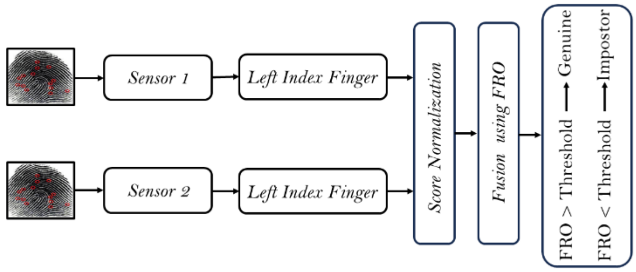

FIGURE 4. *FRO based scores integration using NIST-Set 2.*

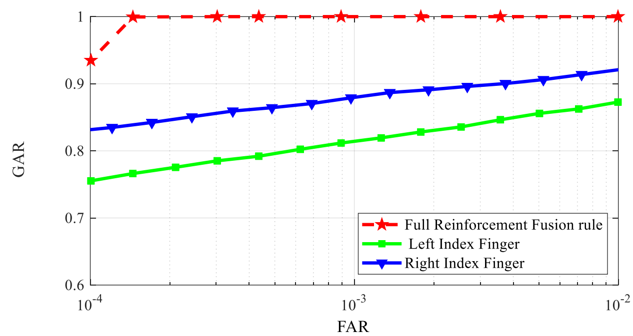

FIGURE 5. Performance of FRO score-level Fusion for NIST-Set 2.

TABLE VI: EVALUATION OF FUSION USING DIFFERENT APPROACHES ON NIST-SET 2 DATABASE

Combining approach at FAR = 0.01 %	GAR (%)
SVM [17]	91.40
S-sum generated using max rule [17]	90.75
Adaptive weighted [33]	90.87
Max rule [34]	90.30
Min rule [34]	79.60
LR-based fusion [17]	91.40
Entropy (using Frank T-norm) [12]	87.42
Entropy (using Hamacher T-norm) [12]	85.42
WQAM using cos(s)r with r = 11 [8]	91.60
S-sum generated by probabilistic T-norm [17]	89
S-sum generated by Hamacher T-norm [17]	75.5
S-sum generated by Yager T-norm with p = 10.3 [17]	90
S-sum generated by Schweizer & Sklar T-norm [17]	89
S-sum generated by max rule [17]	90.75
S-sum generated by min rule [17]	82.5
Proposed Full Reinforcement Fusion Rule (FRO)	**93.40**

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3) Performance of FRO on NIST-Set3

In this section, we provide the results of a multi-algorithm biometric system score fusion technique based on FRO. Figure 6 illustrates the design of a framework for face-based multi-algorithm person recognition. The two face-matching algorithms (Macher C and Machar G) used by this system. We specifically experimented on the NIST-face database, where 3000 subjects have similarity scores. The genuine match-score is 6000 (3000×2), but the impostor match-score is 17,994,000 (6000×2999). The two match-scores of face matcher C and face matcher G were standardized by tanh-estimators normalization technique as in Eqn. 10. Figure 7 displays the ROC curves for separate biometric algorithms when combined with our suggested score-level fusion technique. At the operating point where the FAR is set to $\mathbf{10^{-4}}$, we observe GARs of 63.0%, 72.1%, and 94.54% for the C face matcher, G face matcher, and the multi-algorithm approach using FRO, respectively. Table VII provides a summary of the authentication rates achieved based on FRO using both product T-norm and product T-conorm functions, as well as other fusion techniques proposed previously, such as SVM, LR, S-sum produced by Hamacher T-norm, S-sum using max rule, Hamacher T-norm, Frank T-norm, sum rule, min rule, and max rule.

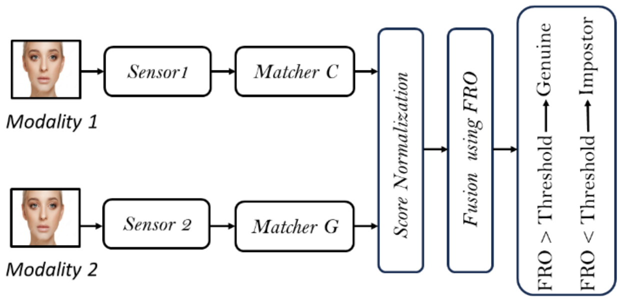

FIGURE 6. **FRO based scores integration using NIST-Set 3.**

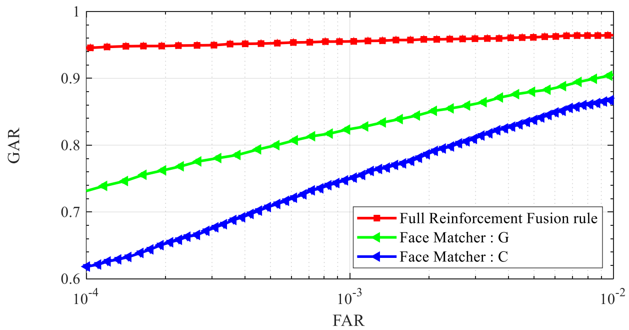

FIGURE 7. **Comparison of ROC curves of individual modality with score-level Fusion for NIST-Set 3.**

TABLE VII: EVALUATION OF FUSION USING DIFFERENT APPROACHES ON NIST-SET 3 DATABASE

Combining approach at FAR = 0.01 %	**GAR (%)**
Asym-AO2 using Aczel-Alsina [9]	76.20
Asym-AO1 using Aczel-Alsina [9]	76.23
Asym-AO2 using Algebric product [9]	76.27
Asym-AO1 using Algebric product [9]	76.00
Asym-AO2 using Hamacher [9]	76.10
Asym-AO1 using Hamacher [9]	76.20
Adaptive weighted [33]	85.29
Max rule [34]	71.50
Min rule [34]	73.15
Sum rule [17]	75.75
Product T-norm [30]	75.85
Hamacher T-norm [30]	75.90
Frank T-norm with p = 1.3 [30]	75.80
S-sum using Max rule [7]	76.00
S-sum using Hamacher T-norm [7]	75.75
SVM [17]	77.3
LR-based fusion [17]	77.2
Proposed Full Reinforcement Fusion Rule (FRO)	94.54

4) Performance of FRO on XM2VTS Database

The experimental findings on the XM2VTS databases utilizing Lausanne Protocol I and II are presented in this section, via modalities (multimodal biometric), extractor (multi-algorithm), and classifiers (multi-unit biometric system).

For Lausanne Protocol I, we have employed all 15 possible configurations (via modalities). Additionally, we have used 6 combinations via extractor, and 2 combinations employing various classifiers. We also utilized the DS theory, the Likelihood ratio-based (LR) combining method, and the sum rule for comparisons. The HTER (refer to Eqn. 14) is employed to assess and contrast the effectiveness of various combining methods.

The outcomes in Table VIII, provide a contrast between the suggested combining method (FRO) utilizing product T-norm and product T-conorm with DS theory (using a sigmoid function), the LR combing rule, and the sum operator. From the same Table, it is evident that across the 15 configurations of the baseline systems (via modalities), the FRO combining rule surpasses the basic sum rule headed by Z-score and Max-Min normalization in 15 and 12 configurations, respectively. Nevertheless, the basic sum rule headed by Tanh normalization exceeds the FRO combining rule in three configurations. Likewise, we can see that the projected combining method outperforms the DS theory and LR approach in 15 and 12 configurations, respectively. Moreover, we can determine from Table VIII that over the six configurations (via extractor), the proposed FRO combining approach surpasses the basic sum rule preceded by Z-score, Max-Min, and tanh normalization in 6, 5, and 6 configurations, respectively. Nevertheless, the LR-based

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TABLE VIII: ASSESSING THE HTER (%) DIFFERENCES BETWEEN THE FRO-BASED FUSION, DS THEORY-BASED FUSION, THE BASIC SUM RULE, AND LR- BASED FUSION FOR THE LAUSANNE PROTOCOL I

Sl.	Fusion candidates via modalities		Proposed FRO	DS theory [31]	Basic sum rule [31]			LR-based fusion [31]
					Z-score	Min-Max	Tanh	
1.	(FH, MLP)	(LFCC, GMM)	0.595	**0.433**	0.75	0.862	0.737	1.108
2.	(FH, MLP)	(PAC, GMM)	**1.018**	1.500	1.13	1.161	1.026	1.441
3.	(FH, MLP)	(SSC, GMM)	**0.531**	0.693	0.88	1.072	0.778	1.339
4.	(DCTs,GMM)	(LFCC, GMM)	**0.433**	0.542	0.56	0.492	0.583	0.574
5.	(DCTs,GMM)	(PAC, GMM)	**1.409**	1.421	1.46	1.417	1.476	1.417
6.	(DCTs,GMM)	(SSC, GMM)	1.152	1.348	1.14	1.218	**1.132**	1.201
7.	(DCTb,GMM)	(LFCC, GMM)	0.493	**0.436**	0.53	0.503	0.467	0.499
8.	(DCTb,GMM)	(PAC, GMM)	1.399	2.734	1.17	**1.093**	1.661	1.106
9.	(DCTb,GMM)	(SSC, GMM)	0.828	1.385	0.77	**0.720**	0.733	0.764
10.	(DCTs,MLP)	(LFCC, GMM)	0.845	0.589	0.81	0.972	0.728	**0.193**
11.	(DCTs,MLP)	(PAC, GMM)	1.360	2.436	1.19	1.413	**0.822**	1.982
12.	(DCTs,MLP)	(SSC, GMM)	1.343	1.056	1.32	1.594	**1.036**	1.721
13.	(DCTb,MLP)	(LFCC, GMM)	**2.428**	2.542	2.61	3.278	2.874	2.693
14.	(DCTb,MLP)	(PAC, GMM)	**2.525**	2.875	3.63	4.121	2.623	3.547
15.	(DCTb,MLP)	(SSC, GMM)	2.994	**1.864**	2.83	4.329	2.058	3.722
Sl.	Fusion candidates via extractors		Proposed FRO	DS theory	Basic sum rule			LR-based fusion
					Z-score	Min-Max	Tanh	
1.	(FH,MLP)	(DCTs,GMM)	**0.970**	1.283	1.280	1.750	1.743	1.581
2.	(FH,MLP)	(DCTb,GMM)	**1.624**	1.854	1.153	1.735	1.740	1.723
3.	(FH,MLP)	(DCTs,MLP)	1.537	**1.492**	1.510	1.516	1.522	1.573
4.	(FH,MLP)	(DCTb,MLP)	1.598	1.609	1.969	1.726	1.711	**1.578**
5.	(LFCC,GMM)	(SSC,GMM)	1.363	1.013	1.497	**0.878**	1.141	1.615
6.	(PAC,GMM)	(SSC,GMM)	4.202	4.215	4.225	4.244	4.828	**3.964**
Sl.	Fusion candidates via classifiers		Proposed FRO	DS theory	Basic sum rule			LR-based fusion
					Z-score	Min-Max	Tanh	
1.	(DCTs,GMM)	(DCTs,MLP)	**1.654**	1.873	2.390	3.359	3.357	1.928
2.	(DCTb,GMM)	(DCTb,MLP)	**2.541**	3.356	3.061	3.102	3.402	3.203

Note: The numbers presented in **bold** fonts indicate the top-performing values within each row [31].

TABLE IX: ASSESSING THE HTER (%) DIFFERENCES BETWEEN THE FRO-BASED FUSION, DS THEORY-BASED FUSION, THE BASIC SUM RULE, AND LR- BASED FUSION FOR THE LAUSANNE PROTOCOL II

Sl.	Fusion candidates via modalities		Proposed FRO	DS theory [31]	Basic sum rule [31]			LR-based fusion [31]
					Z-score	Min-Max	Tanh	
1.	(FH, MLP)	(LFCC, GMM)	**0.595**	0.793	0.688	1.459	1.298	1.245
2.	(FH, MLP)	(PAC, GMM)	1.762	1.362	**1.144**	1.626	1.527	1.674
3.	(FH, MLP)	(SSC, GMM)	**0.665**	0.691	0.981	1.615	1.339	1.339
4.	(DCTb,GMM)	(LFCC, GMM)	**0.109**	0.534	0.133	0.250	0.126	0.342
5.	(DCTb,GMM)	(PAC, GMM)	**0.141**	1.212	0.175	0.504	1.220	1.487
6.	(DCTb,GMM)	(SSC, GMM)	0.342	1.258	**0.177**	0.445	1.223	1.207
Sl.	Fusion candidates via extractors		Proposed FRO	DS theory	Basic sum rule			LR-based fusion
					Z-score	Min-Max	Tanh	
1.	(FH, MLP)	(DCTs,GMM)	**0.970**	1.163	0.962	1.486	1.485	1.481
2.	(FH, MLP)	(DCTb,GMM)	1.624	1.736	0.828	1.105	**1.101**	1.420
3.	(FH, MLP)	(DCTs,MLP)	**1.437**	1.455	2.891	2.978	3.033	2.762

Note: The numbers presented in **bold** fonts indicate the top-performing values within each row [31].

fusion surpasses the FRO based-fusion in two combinations. Also, the proposed FRO based-fusion outperforms the DS theory in 5 configurations. Finally, we can see from Table VIII that over the two combinations (via classifiers), the proposed fusion method outperforms all other score fusion strategies. For Lausanne Protocol II, we have employed all six possible configurations of face and speech classifiers (via modalities). Additionally, we have used three combinations via extractor. We also utilized the DS theory, Likelihood ratio technique, and sum rule for the purpose of making comparisons. The HTER is employed to assess and contrast the effectiveness of various fusion methods (refer to Eqn. 14). The outcomes in Table IX provide an assessment between the adopted fusion technique (FRO) using product T-norm and product T-conorm with DS theory (using sigmoid function), the basic sum rule, and the LR fusion rule. From the same Table, it is evident that across the 6 configurations (via modalities), the FRO outperforms the basic sum rule preceded by tanh and Min-Max normalization in all configuration. But the basic sum rule preceded by Z-score normalization surpasses the FRO based-fusion in 2 configurations. Moreover, we can discern from Table IX that over the 3 configurations (via extractor), the proposed FRO based fusion outperforms the simple sum rule preceded by Z-score, Min-Max, DS theory, and LR-based fusion in all configurations. However, the basic sum rule preceded by tanh normalization surpasses the FRO based- fusion in one configuration ((FH, MLP), (DCTb, GMM)).

VI. CONCLUSION

In this paper, we introduce an innovative score fusion method for a system that uses multiple biometrics traits, that relies on the complete reinforcement operator (FRO). This FRO does not necessitate any form of learning or training, which simplifies our system, enhances its efficiency, and reduces computational costs.

Experiments were conducted using three distinct subsets of the NIST-BSSR1 dataset (set 1, set 2, set 3) in addition to the XM2VTS database. The outcomes obtained from NIST-multimodal biometric tests demonstrated exceptional performance of our proposed score-level fusion method, which utilizes product T-norm and product T-conorm. Specifically, it attains a high Genuine Acceptance Rate (GAR) of 100% at a False Acceptance Rate (FAR) of 0.01%. This performance surpasses that of individual modalities and outperforms various conventional score-level fusion methods, including S-sum, Entropy, Asym-AOs, Yager T-norm, Product T-norm, Sum, LR-based method, and SVM. In the context of NIST fingerprint data, our suggested score-level fusion technique achieves superior performance, with a GAR of 92.8% at a FAR of 0.01%, surpassing the performance of all previously employed methods. For the last subset of NIST-BSSR1 (NIST-face database), the proposed score-level fusion technique achieves superior performance, with a GAR of 92.8% at a FAR of 0.01%, surpassing the performance of all previously used approaches.

The test of the approach on the publicly available scores of the XM2VTS Benchmark gives better performance (HTER) compared to various conventional existing approaches, including DS theory, LR-based, sum rule using tanh normalization, sum rule using min-max normalization, and sum rule preceded by Z-score.

To summarize, our experimental findings unequivocally demonstrate the superiority of the proposed framework when compared to existing methods like DS theory and SVM. Nevertheless, a more extensive evaluation, including mobile authentication databases, is imperative and will be pursued in future research. Additionally, we aim to assess the model's resistance against counterfeiting attempts in our upcoming endeavors.

REFERENCES

[1] Z. Wahid, A. H. Bari, F. Anzum, and M. L. Gavrilova, "Human Micro-Expression: A Novel Social Behavioral Biometric for Person Identification," *IEEE Access*, vol. 11, pp. 57481–57493, 2023, doi: 10.1109/ACCESS.2023.3283932.

[2] S. Basheer, K. K. Nagwanshi, S. Bhatia, S. Dubey, and G. R. Sinha, "FESD: An Approach for Biometric Human Footprint Matching Using Fuzzy Ensemble Learning," *IEEE Access*, vol. 9, pp. 26641–26663, 2021, doi: 10.1109/ACCESS.2021.3057931.

[3] A. Benabdallah and A. Djebbari, "Biometric Individual Authentication System using High Performance ECG Fiducial Features," in *2022 5th International Symposium on Informatics and its Applications (ISIA)*, M'sila, Algeria: IEEE, Nov. 2022, pp. 1–6. doi: 10.1109/ISIA55826.2022.9993496.

[4] P. Sivakumar, B. R. Rathnam, S. Divakar, M. A. Teja, and R. R. Prasad, "A Secure and Compact Multimodal Biometric Authentication Scheme using Deep Hashing," in *2021 IEEE International Conference on Intelligent Systems, Smart and Green Technologies (ICISSGT)*, Visakhapatnam, India: IEEE, Nov. 2021, pp. 27–31. doi: 10.1109/ICISSGT52025.2021.00017.

[5] M. Rukhiran, S. Wong-In, and P. Netinant, "IoT-Based Biometric Recognition Systems in Education for Identity Verification Services: Quality Assessment Approach," *IEEE Access*, vol. 11, pp. 22767–22787, 2023, doi: 10.1109/ACCESS.2023.3253024.

[6] T. Ahmed, S. Samima, M. Zuhair, H. Ghayvat, M. A. Khan, and N. Kumar, "*FIMBISAE*: A Multimodal Biometric Secured Data Access Framework for Internet of Medical Things Ecosystem," *IEEE Internet Things J.*, vol. 10, no. 7, pp. 6259–6270, Apr. 2023, doi: 10.1109/JIOT.2022.3225518.

[7] M. Cheniti, N. Boukezzoula, and Z. Akhtar, "Symmetric sum-based biometric score fusion," *IET Biom.*, vol. 7, no. 5, pp. 391–395, Sep. 2018, doi: 10.1049/iet-bmt.2017.0015.

[8] H. Abderrahmane, G. Noubeil, Z. Lahcene, Z. Akhtar, and D. Dasgupta, "Weighted quasi-arithmetic mean based score level fusion for multi-biometric systems," *IET Biom.*, vol. 9, no. 3, pp. 91–99, May 2020, doi: 10.1049/iet-bmt.2018.5265.

[9] A. Herbadji *et al.*, "Combining Multiple Biometric Traits Using Asymmetric Aggregation Operators for Improved Person Recognition," *Symmetry*, vol. 12, no. 3, p. 444, Mar. 2020, doi: 10.3390/sym12030444.

[10] Ning Wang, second Li Lu, therd Ge Gao, Fanglin Wang, and Shi Li, "Multibiometrics Fusion using Acz él-Alsina Triangular Norm," *KSII Trans. Internet Inf. Syst.*, vol. 8, no. 7, Jul. 2014, doi: 10.3837/tiis.2014.07.012.

[11] K. Vishi and S. Y. Yayilgan, "Multimodal Biometric Authentication Using Fingerprint and Iris Recognition in Identity Management," in *2013 Ninth International Conference on Intelligent Information Hiding and Multimedia Signal Processing*, Beijing, China: IEEE, Oct. 2013, pp. 334–341. doi: 10.1109/IIH-MSP.2013.91.

[12] S. Moeen, M. Uddin, and J. Grover, “Score Level Fusion of Multimodal Biometrics based on Entropy Function,” *Int. J. Comput. Appl.*, vol. 142, no. 9, pp. 28–33, May 2016, doi: 10.5120/ijca2016909912.

[13] Y. Zheng, “Using Score Fusion for Improving the Performance of Multispectral Face Recognition,” in *Signal and Image Processing for Biometrics*, vol. 292, J. Scharcanski, H. Proença, and E. Du, Eds., in Lecture Notes in Electrical Engineering, vol. 292. , Berlin, Heidelberg: Springer Berlin Heidelberg, 2014, pp. 107–128. doi: 10.1007/978-3-642-54080-6_5.

[14] P. Gupta and P. Gupta, “Multi-modal fusion of palm-dorsa vein pattern for accurate personal authentication,” *Knowl.-Based Syst.*, vol. 81, pp. 117–130, Jun. 2015, doi: 10.1016/j.knosys.2015.03.007.

[15] C. Mohamed, Z. Akhtar, B. N. Eddine, and T. H. Falk, “Combining left and right wrist vein images for personal verification,” in *2017 Seventh International Conference on Image Processing Theory, Tools and Applications (IPTA)*, Montreal, QC: IEEE, Nov. 2017, pp. 1–6. doi: 10.1109/IPTA.2017.8310109.

[16] A. Herbadji, N. Guermat, L. Ziet, M. Cheniti, and D. Herbadji, “Personal authentication based on wrist and palm vein images,” *Int. J. Biom.*, vol. 11, no. 4, p. 309, 2019, doi: 10.1504/IJBM.2019.102860.

[17] K. Nandakumar, Yi Chen, S. C. Dass, and A. K. Jain, “Likelihood Ratio-Based Biometric Score Fusion,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 30, no. 2, pp. 342–347, Feb. 2008, doi: 10.1109/TPAMI.2007.70796.

[18] A. Boucetta and K. E. Melkemi, “Score Level Fusion of Palmprint, Face and Iris Using Adaptive PSO:,” Int. J. Appl. Metaheuristic Comput., vol. 10, no. 3, pp. 175–194, Jul. 2019, doi:10.4018/IJAMC.2019070109.

[19] F. S. Assaad and G. Serpen, “Transformation based Score Fusion Algorithm for Multi-modal Biometric User Authentication through Ensemble Classification,” *Procedia Comput. Sci.*, vol. 61, pp. 410–415, 2015, doi: 10.1016/j.procs.2015.09.175.

[20] V. Azom, A. Adewumi, and J.-R. Tapamo, “Face and Iris biometrics person identification using hybrid fusion at feature and score-level,” in *2015 Pattern Recognition Association of South Africa and Robotics and Mechatronics International Conference (PRASA-RobMech)*, Port Elizabeth, South Africa: IEEE, Nov. 2015, pp. 207–212. doi: 10.1109/RoboMech.2015.7359524.

[21] O. Sharifi and M. Eskandari, “Optimal Face-Iris Multimodal Fusion Scheme,” *Symmetry*, vol. 8, no. 6, p. 48, Jun. 2016, doi: 10.3390/sym8060048.

[22] A. Matin, F. Mahmud, T. Ahmed, and M. S. Ejaz, “Weighted score level fusion of iris and face to identify an individual,” in *2017 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, Cox’s Bazar, Bangladesh: IEEE, Feb. 2017, pp. 1–4. doi: 10.1109/ECACE.2017.7912868.

[23] S. Artabaz, L. Sliman, H. N. Dellys, K. Benatchba, and M. Koudil, “Multibiometrics Enhancement Using Quality Measurement in Score Level Fusion,” in *Intelligent Systems Design and Applications*, vol. 557, A. M. Madureira, A. Abraham, D. Gamboa, and P. Novais, Eds., in Advances in Intelligent Systems and Computing, vol. 557. , Cham: Springer International Publishing, 2017, pp. 260–267. doi: 10.1007/978-3-319-53480-0_26.

[24] R. Sharma, S. Das, and P. Joshi, “Score-level fusion using generalized extreme value distribution and DSmT, for multi-biometric systems,” *IET Biom.*, vol. 7, no. 5, pp. 474–481, Sep. 2018, doi: 10.1049/iet-bmt.2017.0076.

[25] G. S. Walia, T. Singh, K. Singh, and N. Verma, “Robust multimodal biometric system based on optimal score level fusion model,” *Expert Syst. Appl.*, vol. 116, pp. 364–376, Feb. 2019, doi: 10.1016/j.eswa.2018.08.036.

[26] J. H. Teng, T. S. Ong, T. Connie, K. Sonai Muthu Anbananthen, and P. P. Min, “Optimized Score Level Fusion for Multi-Instance Finger Vein Recognition,” *Algorithms*, vol. 15, no. 5, p. 161, May 2022, doi: 10.3390/a15050161.

[27] R. R. Yager and A. Rybalov, “Full reinforcement operators in aggregation techniques,” *IEEE Trans. Syst. Man Cybern. Part B Cybern.*, vol. 28, no. 6, pp. 757–769, Dec. 1998, doi: 10.1109/3477.735386.

[28] “NIST Biometric Scores Set (BSSR1),” *NIST*, Jan. 2017, Accessed: Sep. 25, 2023. [Online]. Available: https://www.nist.gov/itl/iad/image-group/nist-biometric-scores-set-bssr1

[29] N. Poh and S. Bengio, “Database, protocols and tools for evaluating score-level fusion algorithms in biometric authentication,” *Pattern Recognit.*, vol. 39, no. 2, pp. 223–233, Feb. 2006, doi: 10.1016/j.patcog.2005.06.011.

[30] M. Hanmandlu, J. Grover, A. Gureja, and H. M. Gupta, “Score level fusion of multimodal biometrics using triangular norms,” *Pattern Recognit. Lett.*, vol. 32, no. 14, pp. 1843–1850, Oct. 2011, doi: 10.1016/j.patrec.2011.06.029.

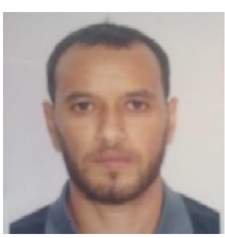
[31] S. Artabaz, L. Sliman, K. Benatchba, and M. Koudil, “Optimized multi-biometric enhancement analysis,” IET Biom., vol. 10, no. 3, pp. 326–341, May 2021, doi: 10.1049/bme2.12026..

[32] L. Leng and J. Zhang, “PalmHash Code vs. PalmPhasor Code,” Neurocomputing, vol. 108, pp. 1–12, May 2013, doi: 10.1016/j.neucom.2012.08.028.

[33] L. Leng, M. Li, L. Leng, and A. B. J. Teoh, “Conjugate 2DPalmHash code for secure palm-print-vein verification,” in 2013 6th International Congress on Image and Signal Processing (CISP), Hangzhou, China: IEEE, Dec. 2013, pp. 1705–1710. doi: 10.1109/CISP.2013.6743951.

[34] L. Leng, M. Li, C. Kim, and X. Bi, “Dual-source discrimination power analysis for multi-instance contactless palmprint recognition,” Multimed. Tools Appl., vol. 76, no. 1, pp. 333–354, Jan. 2017, doi: 10.1007/s11042-015-3058-7.

[35] P. A. Ejegwa, S. Wen, Y. Feng, W. Zhang, and N. Tang, “Novel Pythagorean Fuzzy Correlation Measures Via Pythagorean Fuzzy Deviation, Variance, and Covariance With Applications to Pattern Recognition and Career Placement,” IEEE Trans. Fuzzy Syst., vol. 30, no. 6, pp. 1660–1668, Jun. 2022, doi: 10.1109/TFUZZ.2021.3063794.



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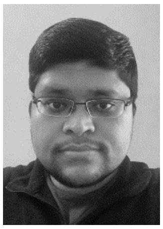

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