AN INTELLIGENT CLASSIFIER FUSION TECHNIQUE FOR IMPROVED MULTIMODAL BIOMETRIC AUTHENTICATION USING MODIFIED DEMPSTER-SHAFER RULE OF COMBINATION

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ABSTRACT
Multimodal biometric technology relatively is a technology developed to overcome those limitations ***imposed by unimodal biometric systems.*** The paradigm consolidates evidence from multiple biometric sources offering considerable improvements in reliability with reasonably overall performance in many applications. Meanwhile, the issue of efficient and effective information fusion of these evidences obtained from different sources remains an obvious concept that attracts research attention. In this research paper, we consider a classical classifier fusion technique, Dempster's rule of combination proposed in Dempster-Shafer Theory (DST) of evidence. DST provides useful computational scheme for integrating accumulative evidences and possesses the potential to update the prior every time a new data is added in the database. However, it has some shortcomings. Dempster Shafer evidence combination has this inability to respond adequately to the fusion of different basic belief assignments (bbas) of evidences, even when the level of conflict between sources is low. It also has this tendency of completely ignoring plausibility in the measure of its belief. To solve these problems, this paper presents a modified Dempster's rule of combination for multimodal biometric authentication which integrates hyperbolic tangent (*tanh*) estimators to overcome the inadequate normalization steps done in the original Dempster's rule of combination. We also adopt a multi-level decision threshold to its measure of belief to model the modified Dempster Shafer rule of combination.

Keywords: Information fusion, Multimodal Biometric Authentication, Normalization technique, Tanh Estimators.

1. INTRODUCTION

Biometric technology has become a foundation of an extensive array of highly secure identification and personal verification solutions, more importantly in the wake of heightened concern about security and rapid advancements in communication and mobility in our environments, [4]; [22]**.** Significant application areas of biometric systems include security monitoring, access control and authentication, border control and immigration, forensic investigation, telemedicine and so on. When a single trait is used in an application it is referred to as unimodal biometric, while combination of two or more traits in an application is referred to as multimodal biometrics, [1]; [3]. Experimental studies however have shown that a biometric system that uses a single biometric trait (unimodal) for recognition has this propensity to contend with problems related to non-universality of the trait, spoof attacks, large intra-class variability, and noisy data. Besides, no single biometric trait can meet all the requirements of every possible application, [9]; [37]**.**

It is believed therefore, that some of the limitations imposed by unimodal biometric systems can be overcome and much higher accuracy achieved by integrating the evidence presented by multiple biometric traits for establishing identity [22]; [33]. However, the issue of efficient and effective information fusion of these evidences obtained from multiple traits remains obvious concepts that attract research attention.

Several different techniques such as sum rule and kernel based technique have been proposed for biometric information fusion at different levels. Most of these techniques rely on heuristic information extracted from the training data and generally these techniques do not update the priors regularly with the presence of new evidences, in the database, which is not pragmatic enough in high security applications [32]. In this research paper, we consider Dempster's rule of combination as proposed in Dempster-Shafer Theory (DST) of evidence, a mathematical theory that provides a useful computational scheme for combining accumulative evidences from multiple sources in artificial intelligence systems.

It has been successfully applied in data fusion and pattern recognition. However, it has some shortcomings. D-S evidence combination can not proceed if the evidence totally collides or conflicts with each other, [13]. Aside famous Zadeh's example on the validity of Dempster's rule of combination, it is shown that for an infinite number of cases Dempster's rule does not respond adequately to combine different sources of evidence even when the level of conflict between sources is low. The problem is not only due to the level of conflict between sources contrariwise to Zadeh's example, but it is due to the inadequate normalization step done in the original Dempster's rule, [11].

To solve these problems, this paper presents a modified Dempster's rule of combination for multimodal biometric authentication which integrates hyperbolic tangent (*tanh*) estimators to overcome the inadequate normalization steps done in the original Dempster's rule of combination. We also adopt a multi-level decision threshold to its measure of belief to model the modified Dempster Shafer rule of combination.

2. FUSION TECHNIQUES IN BIOMETRIC SYSTEMS

Many researchers have combined the outputs of two or more classifiers in biometric systems and several different techniques such as rule based, statistical methods and machine learning procedures (e.g k-Nearest Neighbor, multi layer perceptron, decision trees, support vector machine e.tc.) have been proposed for biometric information fusion, [2]; [29]. [32]; [35]. The sum rule, logistic regression and non-linear multi layer perceptron (MLP) technique representing each of the techniques mentioned above are discussed below:

2.1 Linear summation (Simple Summation Rule)

A simple summation rule is the most popular combination scheme for combining score values from multiple systems. The scores from different systems is however required to be standandized. The standandaization is learned from development dataset by estimating distributions score values from each system. The scores are then translated and scaled to have zero mean and unit variance, [36]. The simple sum rule adds the scores of each classifier to calculate the fused score. This can be expressed in the equation stated below:

$$S = \sum_{i=1}^{N} si \qquad \text{Equation (1)}$$

Where Si is the score from the ith classifier, assuming N classifiers.

2.2 Logistic Regression

Another linear combination method is the Logistic Regression that assigns weights to each verification system. In this method, the weight ωi given to the i-th system correspond to the difference of the means of the distributions for client and impostor scores for the i–th system.

The system performs better when the distributions relative to the clients and impostors are more separated and when their variance is smaller.

In this case, the combination of two verification systems, S^{ij} for the test j, can be defined as a weighted sum rule (see equation 2 below):

$$S^{ij} = \sum_{i=1}^{j=2} \omega i \, S^{ij} \qquad \text{Equation (2)}$$

2.3 Multi Layer Perceptron

Multi Layer Perceptrons (MLP), a non-linear method can also be used to fuse the scores from two verification systems. The two scores are to be considered as input features for the MLP classifier which is trained with client and impostor score samples on the development set. The MLP parameters, number of hidden units, and input size, although not fully optimized, were to be experimentally tuned to reach acceptable performances for the different systems. The MLPs used may have one input layer, one hidden layer with 5 neurons, and one output layer. Hidden and output layers are computational layers to be used with a double sigmoid as activation function (see equation 3 below):

$$s' = \frac{1}{1 + \exp\left(-2\left(\frac{s-t}{r}\right)\right)} \qquad \text{Equation (3)}$$

$r = r_1$, if $s < t$

$r = r_2$, otherwise

Another technique which is widely studied in classical classifier fusion but less addressed in biometrics is the Dempster's rule of combination from the original conception of Dempster-Shafer theory (DST), [30]. The overview of this technique is discussed in section below.

3. OVERVIEW OF DEMPSTER RULE OF COMBINATION

Dempster–Shafer Rule od Combination as proposed in Dempster Shafer Theory (DST) is a mathematical theory of evidence that provides a useful computational scheme for combining information from multiple sources, [7]; [26]. It is a powerful tool for combining accumulative evidences and changing priors in the presence of new evidences. The evidence theory has been successfully applied in artificial intelligence systems, data fusion and pattern recognition, [13]. The evidence theory was first introduced by Dempster in the 1960s, and later developed by Shafer in 1976, and since then it has been widely discussed and used, [13]; [18]; [19]; [21]; [23]; [28]; [30]. The measures of its belief are derived from the combined basic assignments and combines the multiple belief functions through their basic probability assignments (*m*). These belief functions are defined on the same frame of discernment, but are based on independent arguments or bodies of evidence, [25].

The idea of Dempster-Shafer theory is based on two ideas:

(i) Obtaining degrees of belief for a subject, and

(ii) Combining such degrees of belief using Dempster's rule of combination based on independent items of evidence, [7]; [27]; [28].

3.1 Formal Definition:

Here, the main concepts of the D-S theory are briefly recalled and some basic notation introduced. Let $\Theta = \{ \Theta i, i = 1,\ldots n\}$ denote a finite set of mutually exclusive and exhaustive proposition or possible states of a system under consideration commonly known as frame of discernment, where n denotes the set cardinality. The power set of Θ , denoted as 2^{Θ} , represents the set of all subsets of Θ, including Θ itself, [19], i.e: $2^{\Theta} = \{\emptyset , \{a\}, \{b\}, \Theta\}$. The basic belief assignment (bba) m (belief masses) on Θ is defined as a function from 2^{Θ} to [0, 1], [26]; [30] satisfying:

$$\sum_{x \in \theta} m(x) = 1, m(\phi) = 0 \qquad \text{Equation (4)}$$

The traditional interpretation of this is that each subset in the power set is called focal element and each element is assigned a belief mass by the theory of evidence. The Dempster-Shafer theory of evidence use a number in the interval [0,1] to indicate the degree of evidence supporting a proposition. For instance, a bba m can be equivalently represented by a belief function $\longrightarrow$ bel: 2^{Θ} [0, 1], defined as:

$$bel(x) = \sum_{\theta \neq y \varepsilon x} m(y), \forall x \varepsilon \theta \qquad \text{Equation (5)}$$

Shafer further introduced a rule to combine these belief functions called Dempster's rule of combination as discussed in section 3.2 below.

3.2 Application of Dempster's Rule of Combination

The traditional interpretation of Dempster's rule is that it fuses separate argument beliefs from independent sources into a single belief, [19]. It is an associative and commutative operation that maps a pair of belief functions defined both on the same space say Ω into a new belief function on Ω'. For instance, let bel_1 and bel_2 be two belief functions on Ω, with m_1 and m_2 as their related basic belief assignments (bba's). The combination (called the joint $m_{1,2}$) is calculated from the aggregation of two bba's m_1 and m_2 , [10]; [31]. A and B are used here for computing new belief function for the focal element C. Their bel_1 and bel_2 is defined through its related bba m_1 and m_2 where:

$$m1,2(C) = \frac{\sum_{A \cap B = C} m1(A) X m2(B), \forall C \in \Omega}{1 - K} \qquad \text{Equation (6)}$$

$$\sum_{A \cap B = \theta} m1(A) X m2(B) \qquad \text{Equation (7)}$$

According to the theory, the denominator is a normalization factor. In particular, if it is null, it means that there is a total conflict between the sources, and aggregation is then impossible. The use of this rule is thus valid only when the sources are sufficiently in agreement, [11]; [31]; [38].

The same result in equation (7) above can be conveniently represented with the commonality function as stated in equation (8):

3.3 Limitations of Dempter's Rule of Combination

Analyzed below are the identified shortcomings of Dempster rule of combination:

(i) Inability to respond adequately to the fusion of different basic belief assignments (bba's) of evidences obtained from multiple sources in certain context. This is as a result of inadequate normalization step done in the original Dempster's rule, even when the level of conflict between sources is low. [11].

(ii) In addition, the Dempster's rule of combination has the tendency of completely ignoring plausibility and attributing any associated with the divergence to be zero, [15]; [21]. Figure 1 below shows a graphical representation of defined measures of belief A (*bel(A))* and plausibility of A (*pl(A)*). *Bel (A) and Pl (A)* represent belief A and plausibility of A respectively. The difference between *pl(A) - bel(A)* describes the evidential interval range, which represents the uncertainty concerning the set A. Based on the evidence, a numeric value between [0,1] is assigned to each focal length. The value 0 indicates no belief in a proposition, the value 1 indicates total belief, and any values between these two limits indicate partial beliefs. Although this is a potentially valuable tool for the evaluation of risk and reliability in engineering applications. However, in certain contexts this operation can yield counterintuitive results, [7]; [21].

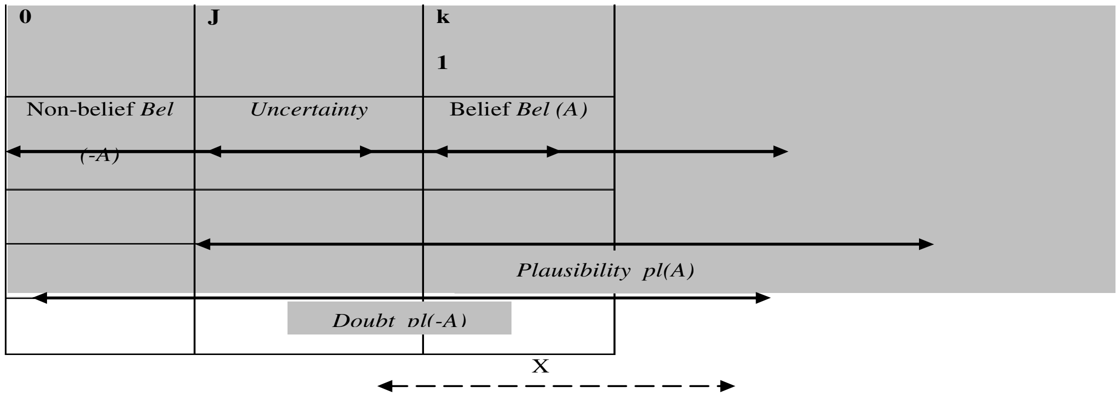

Figure 1: Measures of Belief and Plausibility (Haralick and Shapiro, 1993)

In the representation above, *j* and *k* are two elements of [0,1] such that $j \leq k$: The interval [1,k] represents the belief *Bel (A)* in event A. [0,j] is the non-belief in X, i.e the degree with which we believe in the negation of A, *Bel (-A).* Between these two extremes, is the interval X which represent uncertainty on the occurrence of event A, this means that we can not choose between A and the negation of A, hence the need to adopt a threshold decision as presented in section 4.

3.5 Related Works

Several different techniques have been proposed for biometric information fusion at different levels. Earliest efforts in combining multiple biometrics for person recognition can be traced back to mid nineties, [5]; [6]; [20]; [22]. In all these works, the common practice was to combine the matching scores obtained from the unimodal systems by using simple sum rules, statistical methods, or machine learning procedures. The ***problem related to non-universality of trait, spoof attacks, large intra-class variability, and noisy data imposed by unimodal biometric*** was not addressed.

With respect to the two early theoretical frameworks for combining different machine experts as described by [6] and [20], the former was from a risk analysis perspective, and the later from statistical pattern recognition point of view. Both of them concluded under some mild conditions that may not hold in practice that weighted average is a good way of conciliating the different opinions provided by the unimodal systems in the form of similarity scores. In all these works, the approach definitely improves performance of biometric system but reduces the system's throughput because of its computational complexity.

Teoh *et al,* 2004 presented a match score fusion algorithm to fuse the information of face and voice using theoretic evidence of k-NN classifiers based on DS theory [34]. Although authors have used Dempster Shafer theory, but they did not address the weakness and inconsistency of the Dempter Shafer rule of evidence.

Other researchers have proposed alternative rules of combination to palliate the weakness of Dempster's rule in order to provide acceptable results especially in highly conflicting situations. Chinmay *et al,* 2001, presented a novel implementation of the Dempster-Shafer theory for use in condition monitoring and fault diagnosis applications [8]. The approach was based on predictive rates, and it is intuitively sensible. The authors demonstrated the effectiveness of this approach in a case study involving the detection of static thermostatic valve faults in a diesel engine cooling system. The use of the predictive rates was found much more effective than the traditional Dempster-Shafer implementation. However, the authors addressed different issues entirely from biometric system; hence the issue of normalization factor was not addressed.

Guan *et al*, 2005 proposed an improved Dempster-Shafer Algorithm for resolving conflicting evidences, in which they verifies and modifies the conflicting evidences [13]. Experiments show that this method improves performance and rationality of the combination results satisfying practical situation. Yet the evidences highly conflict with one another. Florea *et al*, 2007 presented and discussed two combination rules for evidence theory: (1) the class of adaptive combination rules (ACR) with its particular case the symmetric adaptive combination rule (SACR) and (2) the proportional conflict redistribution rule (PCR), [12]. These two new combination rules were only able to cope with the problem of conflicting information. In the work, the potential problem of inadequate normalization steps and its nconsistency in handling plausibility was not addressed.

Our work is different from those presented above. In the sense that, a modified Dempster's rule of combination is presented to overcome the problem of inadequate normalization steps done in the original Dempster's rule and to circumvent its inconsistency in handling plausibility in the measure of its belief. Specifically, the modified technique integrates hyperbolic tangent (tanh) estimators into the conventional algorithm and employ a multilevel decision threshold based fusion strategy to overcome the identified problems respectively.

3.6 Need for Score Normalization in Multimodal Biometric Systems

Score normalization generally refers to changing the scale parameters of the matching score distributions at the outputs of the individual matchers, so that the matching scores of different matchers are transformed into a common domain. In Multimodal biometric systems, score normalization is needed to transform the scores generated by different matchers into a common domain (common numerical range), prior combining the scores since the matching scores output by the various modalities are heterogeneous, [17]. For example, one matcher may output a distance (dissimilarity) measure while another may output a proximity (similarity) measure. In addition, the matching scores at the output of the matchers may follow different statistical distributions.

Due to these reasons, score normalization is essential to transform the scores of the individual matchers into a common domain prior to combining them. More to this, for a good normalization scheme, the estimates of the location and scale parameters of the matching score distribution must be robust and efficient, [16]; [17]. Robustness refers to insensitivity to the presence of outliers. Efficiency refers to the proximity of the obtained estimate to the optimal estimate when the distribution of the data is known. Huber, (1981) explains the concepts of robustness and efficiency of statistical procedures. He also elucidate the need for statistical procedures that have both these desirable characteristics. Although many techniques can be used for score normalization, the challenge lies in identifying a technique that is both robust and efficient, [16].

3.7 Need for Hyperbolic Targent (*tanh*) Estimators Normalization Scheme

According to Jain et al, 2005, experiments revealed that the min–max, *z*-score and tanh normalization schemes resulted in better recognition performance compared to other methods, [17]. However, experiments further revealed that the min-max and z-score normalization techniques are sensitive to outliers in the data, highlighting the need for a robust and efficient normalization procedure like the tanh normalization scheme. The characteristics of the different normalization techniques is tabulated in table 1 below.

Table 1: Summary of Normalization Techniques

Normalization Technique	Robustness	Efficiency
Min-max	No	N/A
Decimal scaling	No	N/A
z-score	No	High
Median and MAD	Yes	Moderate
Double sigmoid	Yes	High
tanh-estimators	Yes	High
Biweight estimators	Yes	High

Source: (Jain et al, 2005)

The tanh-estimators introduced by Hampel et al (1986) is given in equation 10 below,

4. ANALYSIS OF THE MODIFIED DEMPSTER'S RULE OF COMBINATION

The modified Dempter's rule of combination is developed to overcome the limitations of Dempster's rule of evidence as discussed in section 3.3 by integrating a tanh estimator normalization scheme into the original Dempster's rule of combination to model the modified Dempster's rule of combination as shown in equation (9).

From equation *(8),* The modified Dempster's rule of combination is represented as m(C)' such that

$$m(C)' = \sum_{A \cap B = C} ns(A)\, X ns\,(B), \forall\, C\, \varepsilon \Omega$$

Equation (9)

Where,

$$ns = \frac{1}{2}\left\{ tanh\left(0.01\left(\frac{sk - \mu GH}{\sigma GH}\right)\right) + 1\right\} \quad \text{Equation (10)}$$

such

ns	=	Normalized score
s_k	=	number of samples,
μGH	=	Arithmetic mean,
σGH	=	Standard deviation,

m_1 represent bba of evidence A and
m_2 represent bba of evidence B,

Further, mass of each evidence or classifier is combined recursively using equation (11),

$$mfinal = m_1 \oplus m_2 \oplus m_3 \qquad \text{Equation (11)}$$

Where $\oplus$ shows the Dempster rule of combination. Final result is obtained by applying multi-level threshold value *t* to *mfinal* as stated in equation 12 below.

$$Result = \begin{cases} Accept, & if \quad mfinal \geq t_1\ OR\ t_2 \\ Reject, & otherwise \end{cases}$$

Equation (12)

where t1 = threshold value for level 1,
t2 = threshold value for level 2.

Level 1 and level 2 are user-centric based on choice of modalities.

5. SUMMARY

Multimodal biometric technology indeed offers considerable improvements in reliability with reasonably overall performance in many applications over unimodal biometric system. But the issue of developing an intelligent fusion technique that can efficiently and effectively fuse these evidences obtained from different sources can not be over emphasized. In this work, we review a classical classifier fusion technique; Dempster's rule of combination proposed in Dempster-Shafer Theory (DST) of evidence and analysed its shortcomings. An intelligent classifier fusion for improved multimodal biometric authentication is presented using modified Dempster Shafer rule of combination.

The modified technique integrates hyperbolic tangent ($tanh$) estimators to overcome the inadequate normalization steps done in the original Dempster's rule of combination, adopt a multi-level decision threshold to its measure of belief to model the modified technique and appropriate the effect of completely ignoring plausibility in the measure of its belief. The research work is believed to produce an intelligent classical classifier fusion technique to overcome the identified shorcomings of Dempster's rule in this work, improve reliability, accuracy, verification time, reduce error rates and consequently improve the overall performance of multimodal biometric authentication. Further and comprehensive evaluation of this work is ongoing and is based on comparative application in selected and relevant case studies.

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