FUSION OPERATORS FOR MULTI-MODAL BIOMETRIC AUTHENTICATION BASED ON PHYSIOLOGICAL SIGNALS

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ABSTRACT
The transformation of multimodal or multi-sensory data into one representational form is denoted as data fusion. For this purpose the most basic operators, like the sum and the product, have been used together with ordinal operators and the majority voting operator from an early stage of research in many application fields. These include biometrics, which constitutes one of the work presented herein. All these operators have evolved into more advanced ones, particularly through the results of soft-computing and fuzzy operator research. However this state of the art has not flown into the different data fusion application fields. The work presented herein attains the comparison of different soft data fusion operators in a biometric application. Hence we analyze the performance of their application in a multimodal system, which takes into account two modalities based on physiological signals, electroencephalogram (EEG) and electrocardiogram (ECG). The analysis is done by evaluating the performance of five operators on a 29 subjects database. The performance improvement due to the application of a soft data fusion stage is evaluated and demonstrated.

Index Terms— Soft data fusion, fuzzy aggregation operators, biometry, multi-modal biometrics, physiological-based biometrics.

1. INTRODUCTION
Data fusion and integration are terms commonly confused. Both are related to the employment of multi-sensory data in data analysis frameworks like those used in biometrics. In this context different sensory or processing units are capable of generating data related with different biometric traits. The so-called sensory gap, which denote the limitation of a sensor unit to represent just a particular aspect of reality, is overcome by extending the number of sensors, and therefore the gathered reality facets is extended as well. In the case of biometrics the sensory can be extended to the data analysis modules that may work on the same sensor devices, e.g. camera, but that extract different biometric cues, e.g. gait, face. The simultaneous inclusion of these different sensors or the results of their associated analysis modules in a biometric system and, particularly, of the generated data in the data analysis system is denoted as data integration. This is often denoted in the biometry literature as multi-modal biometric systems [1]. Furthermore the transformation of the multimodal classification results into one representational form [2] is denoted as multimodal biometric fusion herein. The application of this concept in a biometric system is expected to improve the performance of the overall biometry recognition system [3][4].

The simplest way of fusing data is putting them in a common reference system, whereby the resulting data dimensionality is the sum of the individual ones, e.g. [5][6]. In this way a general purpose processing or classification algorithm can be used in the larger dimensional feature space. However this configuration results in the disadvantage that pattern recognition systems present more counterintuitive behaviours in large feature spaces than in smaller ones, what has been called the curse of dimensionality in pattern recognition [7]. Beyond this fact, some works emphasise the importance of developing special data fusion algorithms for applications where data fusion is involved [8] in order to take full advantage of this processing stage. This work claims that the most important steps in fusion algorithms is to acquire consistent data sets, co-register them, and develop appropriate data fusion techniques. On the contrary several works makes use of classical fusion operators, e.g. [9][4], or general purpose pattern recognition techniques, e.g. [10], for fusion. These works oversee some existent reviews on fuzzy fusion operators [11][12][13]. We undertake herein a comparison of fusion operators furthering these three reference works w.r.t. the applicability of the results. Thus we do not attain neither a theoretical nor a benchmark problem based comparison, but a comparison within a particular application domain, i.e. biometry. Therefore we compare five different fuzzy operators for the fusion of multi-modal data within a biometric authentication system.

The works described herein have been realized within the ACTIBIO project, a STREP collaborative project supported under the EU 7th Framework Program (Grant agreement number: FP7-ICT-2007-1-215372). ACTIBIO aims at authenticating subjects in a transparent way by monitoring their activities by means of novel biometric modalities.
Particularly one of the novelties of the paper herein is the inclusion of power means and uni-norms in a the performance evaluation with data of a particular application domain.

The biometric system being analyzed herein is devoted to the authentication in an ambient intelligence environment. Hence, it presents the feature of taking into account biometric data fusion operators in an early stage of research [9]. They are still used in schemes including data fusion methodologies together with light modifications and further simple ones like the average operator [16][17]. However all these operators are just the starting point from which more advanced fusion operators have evolved, particularly in the field of soft-computing and fuzzy operator research [2]. Different families of operators were already theoretically compared in [11], i.e. T- and S-norms, means (f-mean, OWA, Choquet Fuzzy Integral), MYCIN operators, the Dempster orthogonal sum, possibility fusion operators, Bayesian based fusion operators, and symmetrical sums. Furthermore [12] makes a comparison of fuzzy aggregation operators versus non-fuzzy ones. It compares on the one hand the weighted majority voting, the minimum, the maximum, the average, the product, and the Nave-Bayes operators, and on the other hand, the fuzzy integral and so-called decision templates in six benchmark pattern recognition problems. She finally states that fuzzy fusion outperforms non-fuzzy operators in these six problems. To the best of our knowledge the work in [13] undertook the last review on fuzzy aggregation from a theoretical point of view. Although not being so complete as [11], it includes some of the most recent developments in the field, e.g. uni-norms and absorbing norms, together with interesting aspects on the topic.

Following the aforementioned works we undertake a comparison of five soft data fusion operators. They have been selected after analyzing theoretically their level curves. This small subset of soft data fusion operators seem to present a diversity that makes them worth being compared. They present different degrees of softness [2].

2.1. Power or Generalized Mean

The mean is one of the most well-know fusion operators. It is used in statistics for finding the central location of a probability distribution. This is attained through the application of the arithmetic mean. There are other mean operators like the geometric mean or the harmonic mean. Moreover a parametric generalization of all these expressions has been proposed [18], which is known as the power or generalized mean. It presents the following expression

\[ z = \left( \frac{1}{n} \sum_{i=1}^{n} x_i^m \right)^{1/m}, \]

whose value depends on the real-valued parameter m, e.g. for m=1 results in the arithmetic mean and for m=2 is denoted as the quadratic mean.

2.2. Yager S-norm

T- and S-norms, whose fundamentals were introduced in [19], are aggregation operators related with the concept of statistical metrical spaces [20]. T- and S-norms were adopted in fuzzy systems for operating with fuzzy membership functions [21]. The Yager S-norm has been selected herein after a preliminary study taking the diversity of operators to be analyzed into consideration. This S-norm presents the following expression:

\[ z = \min\left\{ 1, (x_1^p + x_2^p)^{1/p} \right\}, \]

where \( p \in [0, \infty] \).
2.3. Weighted Sum

The weighted sum is an operator used in different application domains, e.g. descriptive statistics, neural networks. It is a further generalization of the arithmetic mean. In this case the generalization is done by weighting the input values, i.e.

$$z = \sum_{i=1}^{n} w_i x_i.$$  

(3)

Usually the sum of the weights is normalized to sum up 1, which ensures working in the unit hypercube.

2.4. Uninorm based on Yager norms

Uni-norms were introduced in [22]. Uni-norms generalize T- and S-norms by introducing an arbitrary neutral element denoted as $e$ [13] defined in $[0, 1]$ such that $U(x, e) = x$. There exist a mathematical expression to map T- and S-norms into Uni-norms. The mapping $U \rightarrow T, S$ holds for the unit hypercube, whereas $T, S \rightarrow U$, only for the spaces $[0, e]^2$ and $[e, 1]^2$. In the other subspaces the uninorm shows a compensating behavior, i.e. the result value is between minimum and maximum. There is a particular type of uni-norms denoted as representable among which we can find the operators used in well-known fusion paradigms of expert systems, like MYCIN and PROSPECTOR [23]. The work in [24] presents the concept of absorbing norm, which in some sense is dual to this of uni-norm. They present a so-called absorbing element $a$, whereby $A(x, a) = a$.

One can see uni-norms and absorbing-norms as two different ways of combining T- and S-norms in the unit hypercube. Thus in the uni-norms the subspace $[0, e] \times [0, e]$ is occupied by a T-norm, whereas $[e, 1] \times [e, 1]$ by a S-norm. In the remaining two spaces there is a compensatory operator, although this is not a condition of the operator. The only condition is that the resulting operator must be commutative and associative.

Since the T-norm with the largest value is the minimum and the S-norm with the smallest one is the maximum [11], no the T- and S-norm can be placed in the U and A quadrants. Moreover these two quadrants have to be filled by compromise operators like means or min/max itself. In the works described herein we have selected a uninorm based on the Yager T- and S-norms, and on the arithmetic mean in the U-quadrant after realizing a theoretical analysis of the operators to be analyzed as already mentioned.

2.5. Ordered Weighted Averaging

A generalization of the average, where the weighting is established after sorting the input data, was proposed in [25] and denoted as Ordered Weighted Averaging (OWA). The OWA presents the following expression:

$$z = \sum_{i=1}^{n} w_{(i)} x_{(i)},$$  

(4)

where $w_{(i)}$ are the weights of the operator. The bracketed subindices state for a sorting operation that is applied on $x_i$ before aggregating their values, e.g. (1) state for the largest $x_i$, $(n)$ for the lowest one. The operator definition results in a unique weighting set, but that is applied to different channels on each canonical region of the unit hypercube [2].

3. APPLICATION DOMAIN AND METHODOLOGY

The operators mentioned in the former section have been tested with a data set acquired within an ambient intelligence facility. Hence up to 29 subjects go through a data acquisition protocol within two different scenarios denoted as workplace and office. In the first one the subject walks in the workplace, whereas in the second one a sitting subject realizes different office related activities, e.g. answering the phone, watching a video, typing a document on the computer. As a consequence different modalities are applied to the different activities, i.e. a modality like gait can not be extracted when the subject is sitting. For a preliminary analysis we have selected the activity of watching a video, where the subjects are authenticated herein through the Electroencephalogram (EEG) and Electrocardiogram (ECG) modalities [14].

The tests are done in order to attain 3 goals. First the optimal parameter set of the operators mentioned in Sec. 2 for each subject will be selected. Second, the optimal fusion operator for each subject will be established. This will be achieved by comparing the performance of the operators when being parameterized with their optimal parameter set. Lastly, the robustness with respect to a change in the subject of the operators will be analyzed.

Given the ground truth of subject authentication, the validation criteria is the Area Under the Curve (AUC), which is computed as the area of the Receiver Operating Curve, which relates the True Positive Rate (TPR) and the False Positive Rate (FPR). The AUC can be computed as the integral value of the TPR w.r.t. FPR. For a complete review of the utilization of the ROC in performance assessment the reader is referred to [26]. The optimal parameter set for each operator is computed through an extensive search over the parameter space. Therefore the AUC of the ROC for each parameter set of the operator being optimized is computed. The parameter set delivering a maximal AUC is select as the optimal one for the corresponding operator. This is achieved thanks to the vectorial algorithmical structure of the fusion operator implementation.

When characterizing the robustness of a particular fusion operator we will use the average and the variance of the AUC over subjects. Then we take as the most robust parameter the
one with the maximal minimal performance over parameter values. Here the minimal expected performance over parameter values is computed as the mean value of the average AUC over subjects minus the variance of the AUC over subjects.

4. PERFORMANCE EVALUATION ON PRELIMINARY RESULTS

As described in the former section, the optimal parameter set has been computed for each of the fusion operators being evaluated. As mentioned in the former section this achieved by an extensive search in the parameter space. An example of the results attained in such a procedure is shown in Fig. 2.

![Fig. 2](image)

**Fig. 2.** Example of the compensatory behavior of the power mean operator on subject 3 classification scores (x-axis) when being optimally parameterized. True Positives, i.e. authentications of subject 3, are placed in the samples around the interval [650, 900]. The remaining ones correspond to results of impostor tests. In this case the power mean operator decreases the value on all the samples, but in such a way that TP maintain the maximal value.

![Fig. 1](image)

**Fig. 1.** Example of the extensive search procedure in the parameterization of the weighted sum operator with subject 4 data. No all parameter results are shown for the sake of clarity. The ROCs (color coded) and its corresponding AUCs are computed. Parameters deliver several ROCs from optimal (red) to worst one (black).

Once obtained the optimal parameter set in terms of AUC, we attain the comparison of the performance for each subject. First is worth illustrating what is the goal of the fusion application. For this purpose the result of the fusion application is shown for a subject data in the sample domain (see Fig. ??). As it can be observed the operator attains the maximization of the detection probability in the True Positive samples and its minimization in the False Positive ones. This is attained compensating the values on these two types of samples.

The performance evaluation however is done on hand of the ROCs. An exemplary subset of these results can be observed in Fig. 4. As it can be observed in this figure the performance of the fusion operator improves the performance of any individual modality. However we can distinguish among different types of improvement. In the cases where one of the modalities presents an optimal performance, i.e. its AUC is close to 1, the application of the fusion operator tends to reproduce the behavior of this modality (see Figs. 3a, and b). If the performance of one of the modalities is much worse than the other, even approaching the performance of random guessing, either we obtain a light improvement (see Fig. 3c) or reproduce the performance trend mentioned in the former case (see Fig. 3d).

The improvement is more clear in those cases where the performances of both modalities are commensurable (see Fig. 4). If the maximal FPR is similar, but the TPR differs, we can improve the performance in two different manners. An improvement in terms of TPR (see Fig. 4a) can be obtained in case the TPR is not large enough. Otherwise, i.e. TPR is large enough, the improvement is achieved in terms of FPR (see Fig. 4b, c, and d).

One further result of this test is the selection of the fusion operators to be used. As it can be observed in the different figures (see Fig. 4), the difference in terms of performance of the different fusion operators is not significant. This means that the selection of one or other will not alter significantly the final performance of the system. It is worth mentioning that the selection of the optimal parameter set is an important intermediate step in order to obtain this result.

Once we have selected the optimal parameter set for each
fusion operator, we evaluate their robustness with respect to a change in the subject. For this purpose we compute the average performance in terms of AUC over the different subjects. We compare the average AUC when the operators are parameterized optimally for each subject with the average AUC when the operators are parameterized with their most robust parameter set. The obtained comparison is given in Table 1. The most parameter set is obtained by comparing the average AUC over the different subjects for different values. These values (which can be observed in the third column of Table 1) with a maximal difference between the average AUC over subjects and their variance are selected as most robust for each operator.

Table 1: Robustness Evaluation of operators w.r.t. a change in subject. Performance measures of the different evaluated fusion operators (FOP) when comparing the performance with their optimal parameter set (PS) and with their most robust parameter set. The comparison is done in terms of the obtained AUC. \( \bar{AUC} \): Average AUC over subjects. \( \sigma_{AUC} \): Standard deviation of AUC over subjects.

<table>
<thead>
<tr>
<th>FOP</th>
<th>performance</th>
<th>PS</th>
<th>( \bar{AUC} )</th>
<th>( \sigma_{AUC} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>power</td>
<td>optimal</td>
<td>-</td>
<td>0.7914</td>
<td>0.2471</td>
</tr>
<tr>
<td>mean</td>
<td>most robust</td>
<td>2</td>
<td>0.7756</td>
<td>0.0574</td>
</tr>
<tr>
<td>weighted sum</td>
<td>optimal</td>
<td>-</td>
<td>0.7907</td>
<td>0.2469</td>
</tr>
<tr>
<td></td>
<td>most robust</td>
<td>0.9, 0.1</td>
<td>0.7831</td>
<td>0.0587</td>
</tr>
<tr>
<td>Yager</td>
<td>optimal</td>
<td>-</td>
<td>0.7378</td>
<td>0.1859</td>
</tr>
<tr>
<td>S-norm</td>
<td>most robust</td>
<td>121</td>
<td>0.7334</td>
<td>0.0332</td>
</tr>
<tr>
<td>Uni-norm</td>
<td>optimal</td>
<td>-</td>
<td>0.7788</td>
<td>0.249</td>
</tr>
<tr>
<td></td>
<td>most robust</td>
<td>0.9, 0.1</td>
<td>0.7766</td>
<td>0.0594</td>
</tr>
<tr>
<td>OWA</td>
<td>optimal</td>
<td>-</td>
<td>0.7714</td>
<td>0.2471</td>
</tr>
<tr>
<td></td>
<td>most robust</td>
<td>0.9, 0.1</td>
<td>0.7756</td>
<td>0.0574</td>
</tr>
</tbody>
</table>

As it can be observed the performance of the optimal parameter set and this of the most robust one does not differ more than 2% for any of the analyzed operators. This demonstrates the robustness of soft data fusion operators with respect to a change in the subject. One further interesting point is that the performance variance is smaller when applying the most robust parameter set. This fact can be explained easily from a numerical point of view, since the most robust parameter set selection has taken into account the variance with respect to a change of subject. Furthermore this makes the system performance more stable over a change of the subject.

Lastly it is worth commenting on the most robust parameter. Although all fusion operators present a similar performance, as formerly mentioned, the weighted sum demonstrates to be the one with the most robust behavior with respect to a change in the subject. In this context we point out the fact that the obtained weights reflect the importance of both modalities in the performance of the final authentication. Furthermore the OWA is however the operator with a minimal difference between its average performance of the optimal parameter sets, and this of the most robust parameter set.

5. CONCLUSIONS AND FUTURE WORK

We have demonstrated the performance improvement that can be achieved through the application of soft data fusion operators in a system of multi-modal biometric authentication. The fusion behavior of the five analyzed operators only differs lightly, at least on the preliminary results evaluated herein. Moreover the improvement depends both qualitatively and quantitatively on the relationship between the performances of the individual modalities.

One further result of the undertaken performance evaluation refers to the robustness of the operators with respect in a change of the subject being analyzed. Hence all the analyzed operators allow a robust parameterization. Therefore they can be used with a unique parameter set for all the analyzed subject set without downplaying its performance significantly. In this context it is worth pointing out the robustness of the weighted sum and the ordered weighted averaging (OWA) operators. Their difference in performance with respect to this of other operators is however small enough, to consider an equivalent behavior among the outperforming ones.

Future research works will take into account the extension of the results herein with respect to an increment in the number of modalities included in the system. Moreover we will evaluate the stability of the results presented herein when the subject being authenticated goes through different activities.

6. REFERENCES


subject 2 ROCs for different fusion operators

(a) Results 3

subject 1 ROCs for different fusion operators

(a) Result 4

subject 3 ROCs for different fusion operators

(b) Result 4

subject 6 ROCs for different fusion operators

(b) Result 4

subject 14 ROCs for different fusion operators

(c) Result 1

subject 9 ROCs for different fusion operators

(c) Result 4

subject 20 ROCs for different fusion operators

(d) Result 4

subject 14 ROCs for different fusion operators

(d) Result 4

Fig. 3. Example of placing a figure with experimental results.

Fig. 4. Example of placing a figure with experimental results.