Comments on "An Adaptive Multimodal Biometric Management Algorithm"

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Abstract – *We note that there are some discrepancies in the results reported in the above titled paper. Our experiments indicate that the authors have considered only a subset of all possible fusion rules, contradicting the statement that all possible rules have been considered. Moreover, the authors state that only monotonic rules can be optimal and therefore all other rules can be ignored. However, our experimental results examining all possible rules demonstrate that a non monotonic rule can also be an optimum fusion rule.*

1. Introduction

In the paper [1], the authors propose an algorithm based on Particle Swarm Optimization (PSO) to optimally combine the individual biometric sensor decisions. The proposed algorithm selects the fusion rule and sensor operating points that minimize a given cost function. The cost function, formulated in terms of global false acceptance and rejection rates, is defined as:

$$E = C_{FA}(F_{AR_a} - F_{AR_d}) + (2 - C_{FA})(F_{RR_a} - F_{RR_d}) \quad (1)$$

where C_{FA} is the cost of falsely accepting an impostor. F_{AR_a} (F_{RR_a}) and F_{AR_d} (F_{RR_d}) are the achieved and desired global false acceptance (rejection) rates. Enforcing the most stringent condition to achieve false acceptance rate of zero while ensuring zero false rejection ($F_{AR_d} = 0$ and $F_{RR_d} = 0$), the cost function (Equation 1) reduces to:

$$E = C_{FA}(F_{AR_a}) + (2 - C_{FA})(F_{RR_a}) \quad (2)$$

An optimization problem, employing PSO is formulated to minimize the cost function given in equation (1). Each particle of PSO algorithm is defined as,

$$X_m = \{F_{AR_{1m}}, F_{AR_{2m}}, f_m\} \quad (3)$$

where the first two dimensions are false acceptance rates of individual unimodal biometric systems and the last dimension is the four bit fusion rule. The term optimum/optimal in this paper refer to the converged solutions given by the PSO. This terminology has been borrowed from [1] where the authors refer all PSO solutions (multiple solutions with approximately equal PSO costs, but not the same) as optimum as long as the AMBM performance criteria are met.

The authors in [1] claim that the proposed adaptive multimodal biometric algorithm (AMBM) comprehensively considers all fusion rules and all possible operating points of the individual sensors ([1], pp. 344, paragraph 5). However, we find that there are some discrepancies in the reported results. Our observations are summarized as follows:

1. The experimental results presented in [1] show that the AMBM algorithm considers only the monotonic rules. The results are quite contradictory to the claims in [1], *i.e.*, 'algorithm considers all fusion rules'.
2. We find that some of the non monotonic rules perform as good as monotonic rules and therefore these rules cannot be ignored by the algorithm.

We carried out the experiments under the same conditions, using the same parameter values and data reported in their paper.

2. Experiments

Figure 1 and figure 2 show the genuine and impostor score distributions for individual biometric systems. These distributions are assumed to be Gaussian, with parameters described in the paper ([1], pp. 352, Table VI).

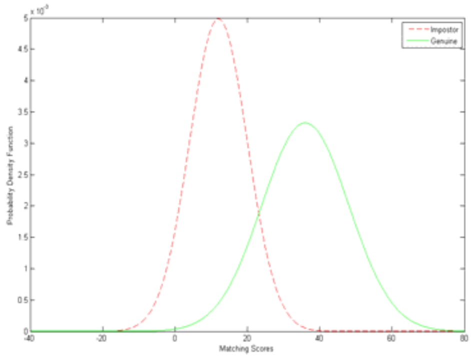

Figure 1: Score distribution for sensor 1

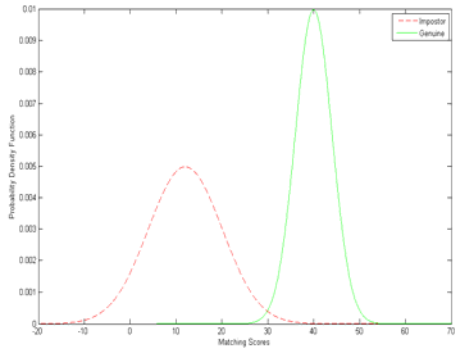

Figure 2: Score distribution for sensor 2

For every cost of false acceptance (C_{FA}) from 0 to 2, in steps of 0.1, the AMBM algorithm is run 100 times to select an optimal operating point and a fusion rule. Figure 3 shows the number of times a rule has been actually selected versus the cost of false acceptance.

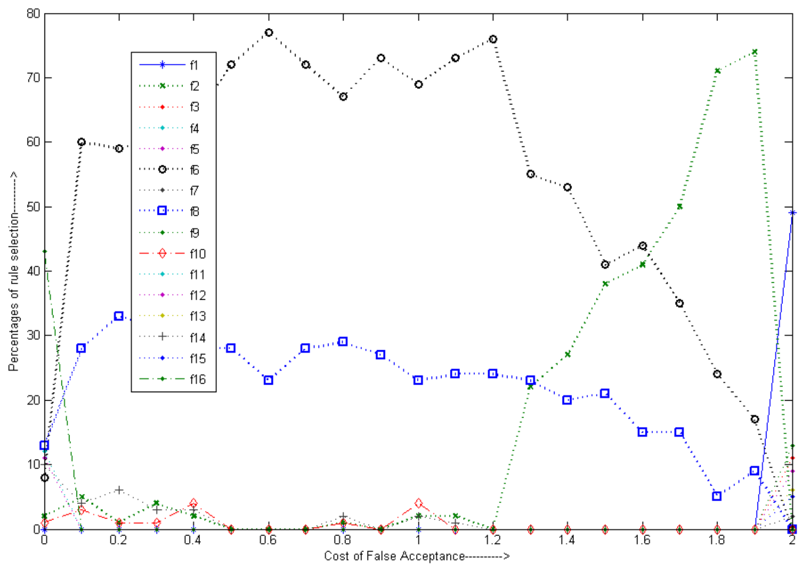

Figure 3: Probability of selecting fusion rules versus cost of false acceptance

It can be observed from Figure 3 that in the range of C_{FA} from 0 to 1.2, the five different rules, namely f_8, f_6, f_{14}, f_2 and f_{10} are selected. However, rules f_{10} and f_{14} have never been selected in the reported experimental results in ([1], pp. 354, Figure 14). This is unlikely as the rules f_6, f_{14} and f_{10} are equally good and can give the same minimum cost for a particular set of operating points. This is illustrated below:

For rule f_6:

global $F_{AR} = F_{AR_2}$, and global $F_{RR} = F_{RR_2}$

For rule f_{14}:

global $F_{AR} = 1 - F_{AR_1}(1 - F_{AR_2})$, and global $F_{RR} = F_{RR_2}(1 - F_{RR_1})$

For rule f_{10}:

global $F_{AR} = (1 - F_{AR_1})(1 - F_{AR_2}) + F_{AR_1} F_{AR_2}$, and global $F_{RR} = F_{RR_2}(1 - F_{RR_1}) + F_{RR_1}(1 - F_{RR_2})$

Therefore, when $F_{AR_1} = 1$ and $F_{RR_1} = 0$, rules f_{14} and f_{10} result in global error rates $F_{AR} = F_{AR_2}$, $F_{RR} = F_{RR_2}$ and as a result, all of the above rules give the same cost under these operating conditions.

In addition, the results reported in [1], *i.e.*, Figure 14, show that rules f_6 and f_8 are the optimal solutions when C_{FA} is 0. Under these conditions, for rules f_6 and f_8 to selected, the individual biometric systems must be operating at $F_{AR_2} = 1, F_{RR_2} = 0$ and $F_{AR_1}(\text{ or } F_{AR_2}) = 1,\ F_{RR_1}(\text{ or } F_{RR_2}) = 0$ respectively. However, we find through the experiments that, for $C_{FA} = 0$, rules f_6 and f_8 are not the only optimal solutions and there are a number of other rules (including non monotonic ones) that result in the same minimum PSO cost and therefore they should have appeared in the results reported by the authors.

Optimal rules selected (for $C_{FA} = 0$) in our experiments are summarized in Table 1.

Table 1: Selection of optimal rules for $C_{FA} = 0$

Rule	Monotonic/Non monotonic	Global FRR (F_{RR})	Operating Point	Cost(Eq.1) at operating point	Number of times selected
f_2	Monotonic	$F_{RR_1} + F_{RR_2} - F_{RR_1} F_{RR_2}$	$F_{RR_1}, F_{RR_2} = 0$	0	2
f_4	Monotonic	F_{RR_1}	$F_{RR_1} = 0$	0	12
f_6	Monotonic	F_{RR_2}	$F_{RR_2} = 0$	0	8
f_8	Monotonic	$F_{RR_1} F_{RR_2}$	F_{RR_1} (or $F_{RR_2}) = 0$	0	13
f_{10}	Non monotonic	$F_{RR_1} + F_{RR_2} - 2F_{RR_1} F_{RR_2}$	$F_{RR_1}, F_{RR_2} = 0$	0	1
f_{12}	Non monotonic	$F_{RR_1}(1 - F_{RR2})$	$F_{RR_1} = 0$	0	12
f_{14}	Non monotonic	$F_{RR_2}(1 - F_{RR_1})$	$F_{RR_2} = 0$	0	10
f_{16}	Monotonic	0	NA	0	43

Similarly, for $C_{FA} = 2$, we obtain a number of optimal rules satisfying the performance criteria, where as there is only one rule, f_1 appearing in the authors' results. These rules are summarized in Table 2.

Table 2: Selection of optimal rules for $C_{FA} = 2$

Rule	Monotonic/Non monotonic	Global FAR (F_{AR})	Operating Point	Cost(Eq.1) at operating point	Number of times selected
f_1	Monotonic	0	NA	0	49
f_3	Non monotonic	$F_{AR_1}(1 - F_{AR_2})$	$F_{AR_2} = 1$	0	11
f_5	Non monotonic	$F_{AR_2}(1 - F_{AR_1})$	$F_{AR_1} = 1$	0	9
f_7	Non monotonic	$F_{AR_1} + F_{AR_2} - 2F_{AR_1} F_{AR_2}$	$F_{AR_1}, F_{AR_2} = 1$	0	2
f_9	Non monotonic	$1 - F_{AR_1} - F_{AR_2} + F_{AR_1} F_{AR_2}$	F_{AR_1} (or $F_{AR_2}) = 1$	0	13
f_{11}	Non monotonic	$1 - F_{AR_2}$	$F_{AR_2} = 1$	0	5
f_{13}	Non monotonic	$1 - F_{AR_1}$	$F_{AR_1} = 1$	0	6
f_{15}	Non monotonic	$1 - F_{AR_1} F_{AR_2}$	$F_{AR_1}, F_{AR_2} = 1$	0	5

While selection of all the rules in Table 1 and Table 2 cannot be guaranteed (especially the ones with very low number of selections, due to stringent conditions on operating points) on repeated runs of the simulation, complete absence of these rules as in [1] cannot be justified. Most of them did appear consistently in our experiments.

The program files used to achieve our experimental results are now publicly available [2].

3. Conclusions

We have experimentally demonstrated that a non monotonic rule can also be an optimum fusion rule, under certain operating conditions as illustrated in Table 1 and 2. This is in contrast to the statement in the paper - "an optimum fusion rule for any set of Bayesian costs is monotonic". Authors state that this result has been proven in [3]. However, the proof in [3] does not consider the case when any of the individual sensor operating point is $F_{AR_i} = 1, F_{RR_i} = 0$ *. The results reported in [1] also indicate that the search space has been limited to only few monotonic rules which can inherently prevent other optimum rules from being selected. Therefore the experimental results reported in [1] (figure 14, pp. 354) should be replaced/read as illustrated in figure 3 in this paper.

References

[1] K. Veeramachaneni, L. A. Osadciw, P. K. Varshney, "An Adaptive Multimodal Biometric Management Algorithm," *IEEE Trans. Sys. Man & Cybern*., *Part-C*, vol. 35, no. 3, pp. 344-356, Aug. 2005.
[2] http://www.comp.polyu.edu.hk/~csajaykr/comments_ambm.rar
[3] P. K. Varshney, *Distributed Detection and Data Fusion*. New York: Springer, 1997.

* Equation 3.3.11 (page 64) in [3] does not hold true as the factor in the L.H.S of the equation, $\frac{P_{Mi}}{1-P_{Fi}}$ becomes indeterminate at $F_{AR_i} = 1, F_{RR_i} = 0$.