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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 previous 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 nonmonotonic rule can also be an optimum fusion rule.**

***Index Terms*—Adaptive fusion, decision level fusion, multimodal biometrics, particle swarm optimization.**

I. Introduction

The authors in [1] 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

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

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 (1) reduces to

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

An optimization problem employing PSO is formulated to minimize the cost function given in (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 4-bit fusion rule. The term optimum/optimal in this paper refers 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 adaptive multimodal biometric algorithm (AMBM) performance criteria are met.

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

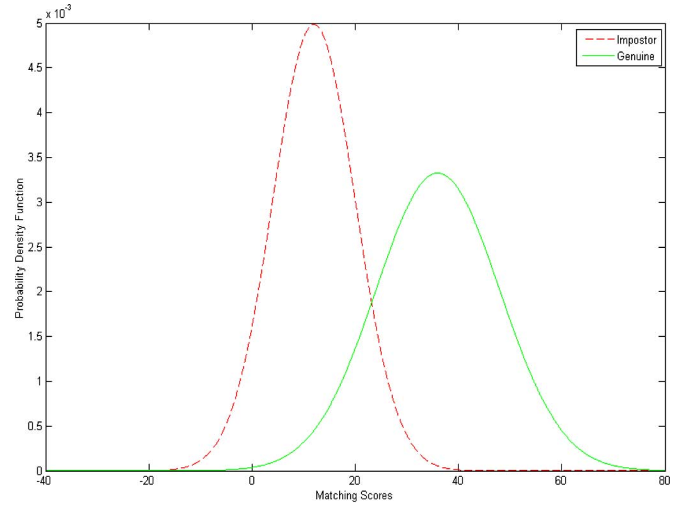

Fig. 1. Score distribution for sensor 1.

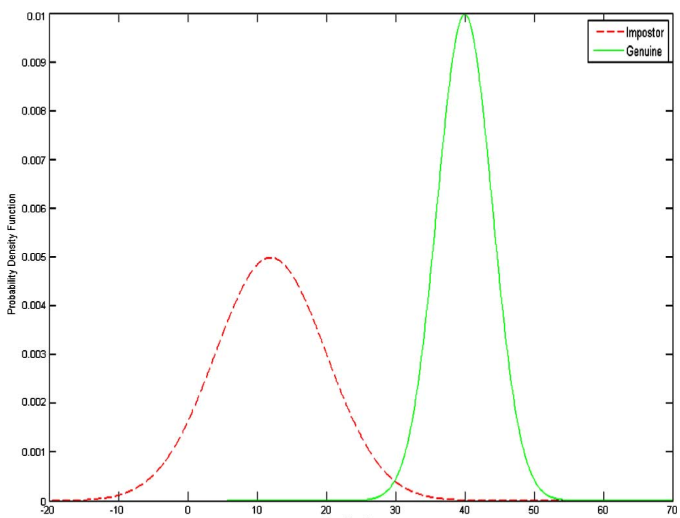

Fig. 2. Score distribution for sensor 2.

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 nonmonotonic 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.

II. Experiments

Figs. 1 and 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, p. 352, Table VI].

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

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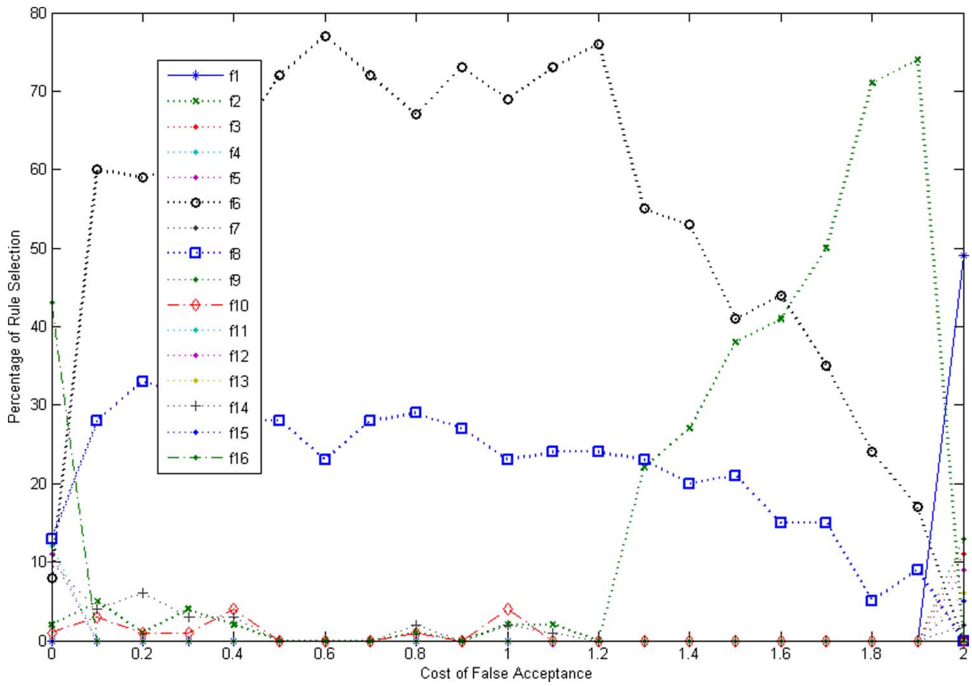

Fig. 3. Probability of selecting fusion rules versus cost of false acceptance.

TABLE I
SELECTION OF OPTIMAL RULES FOR $C_{\mathrm{FA}} = 0$

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

point and a fusion rule. Fig. 3 shows the number of times a rule has been actually selected versus the cost of false acceptance.

It can be observed from Fig. 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, p. 354, Fig. 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 as follows.

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 previous rules give the same cost under these operating conditions.

In addition, the results reported in [1], i.e., Fig. 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 be selected, the individual biometric systems must be operating at $F_{AR_2} = 1, F_{RR_2} = 0$ and F_{AR_1} (or F_{AR_2}) $=1, F_{RR_1}$ (or F_{RR_2}) $= 0$, respectively. However, we find through the experiments that, for $C_{\mathrm{FA}} = 0$, rules f_6 and f_8 are not the only optimal solutions and there are a number of other rules (including nonmonotonic 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 $C_{\mathrm{FA}} = 0$) in our experiments are summarized in Table I.

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

TABLE II
SELECTION OF OPTIMAL RULES FOR $C_{\mathrm{FA}} = 2$

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	$1-F_{AR_1}-F_{AR_2}+F_{AR_1}F_{AR_2}$	$F_{AR_1}(\text{ or } F_{AR_2})=1$	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 Tables I and II 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].

III. Conclusion

We have experimentally demonstrated that a nonmonotonic[1] rule can also be an optimum fusion rule under certain operating conditions, as illustrated in Tables I and II. This is in contrast to the statement in the paper—"an optimum fusion rule for any set of Bayesian costs is monotonic." The 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 $F_{ARi} = 1, F_{RRi} = 0$. The results reported in [1] also indicate that the search space has been limited to only few monotonic rules that can inherently prevent other optimum rules from being selected. Therefore, the experimental results reported in [1, p. 354, Fig. 14] should be replaced/read, as illustrated in Fig. 3 in this paper.

[1] [3, eq. (3.3.11), p. 64] does not hold true as the factor on the left-hand side (LHS) of the equation $P_{Mi}/(1 - P_{Fi})$ becomes indeterminate at $F_{ARi} = 1, F_{RRi} = 0$.

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