Effective ATR Algorithms Using Information Fusion Models

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Abstract – *Several types of classifiers have been developed in order to extract the information for the automatic target recognition (ATR). We have noted that these performances are different according to the classifier and the radar target. We propose in this article three approaches of information fusion in order to outperform three radar target classifiers. These three techniques of fusion are the Sugeno's fuzzy integral, the possibility theory and the Dempster-Shafer theory. In this application, we show that the best performance is achieved by the Dempster-Shafer theory.*

Keywords: ! " # " " $$ % & ' (&) * # ' +) ") ,

1 Introduction

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2 Classifiers

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2.1 Multilayer perceptron classifier

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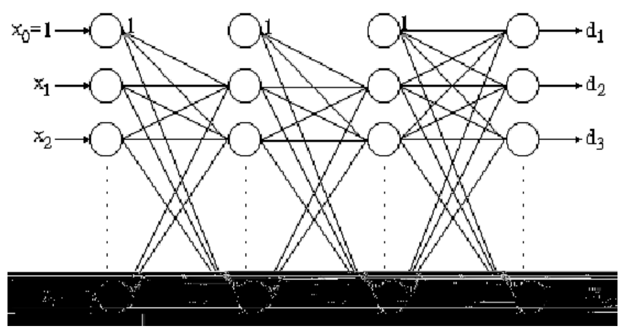

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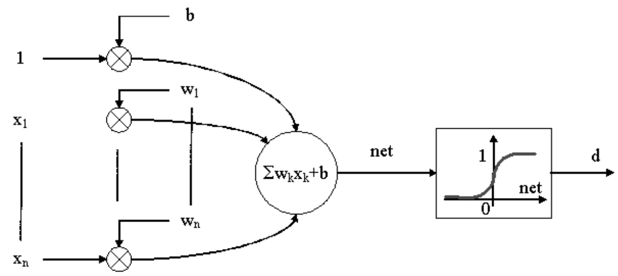

$$\varepsilon = \frac{1}{2}\sum_{j=1}^{m}(d_j - o_j)$$ (1)

o_j

$$\begin{cases} w_{lj}(t+1) = w_{lj}(t) + \eta\delta_j(t)o_l(t) \\ \delta_j = co_j[1-o_j][d_j - o_j] \\ \delta_j = co_j[1-o_j]\sum_l \delta_l w_{lj} \end{cases}$$ ( )

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η

2.2 Fuzzy K Nearest Neighbor Classifier

$V_K(x)$

x

$$K_j(x) = \{x_n | x_n \in C_j \quad x_n \in V_K(x)\}$$ ( )

$$K_k(x) = \#_{j=1\ m}[K_j(x)] \Rightarrow x \in C_k$$ (6)

x

$$u_{jl} = \frac{K_j^{(l)}}{K_F} \quad K_j^{(l)} = \{x_n^{(j)} \wedge x_n^{(j)} \in V_{K_F}(x_t)\}$$ (<)

K_F $K_j^{(t)}$ x_t j x

$$o_j(x) = \sum_{t=1}^{K}\left(u_{jt}\|x-x_t\|^{\delta}\right)\sum_{t=1}^{K}\left(1\|x-x_t\|^{\delta}\right)$$ ( )

K

$$o_k(x) = \#_j\{o_j(x)\} \Rightarrow x \in C_k$$ (@)

2.3 SART classifier

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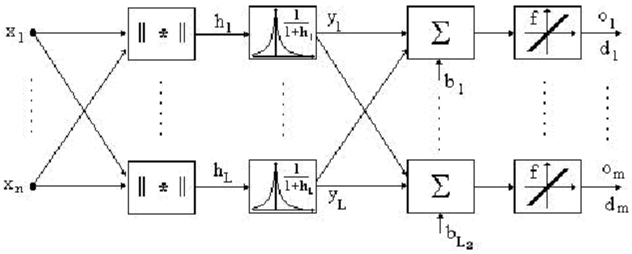

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3 Fusion models

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3.1 Sugeno's fuzzy integral

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$$\begin{aligned} ⨍_Q h(q) \circ g(\cdot) &= \#_{A \subseteq Q} \left[\# \left[\#_{q \in A} h(q) \; g(A) \right] \right] \\ &= \#_{\alpha \in I \; 01} \left[\# \; (\alpha \; g(h_\alpha)) \right] \end{aligned} \quad (\;)$$

4) $h_\alpha = \{ q \mid h(q) > \alpha \}$,
$h(q)$ 2 ") 5 ( ) & " q
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$h(q_0) \geq h(q\;) \geq \cdots \geq h(q_N)$ H ") &&
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$$\chi = ⨍_Q h(q) \circ g(\cdot) = \#_{i=0\,\overline{N}} \left[\# \;\; (h(q_i) \;\; g(A_i)) \right] \quad (\;)$$

4) > $A_i = \{ q_0 \;\; q \;\; \cdots \;\; q_i \}$,
$g(A_i)$ (& & 3 4 %)
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$$\begin{cases} g(A_0) = g(\{q_0\}) = g^0 \\ g(A_i) = g^i + g(A_{i-0}) + \lambda \cdot g^i \cdot g(A_{i-0}) \;\; i = \overline{\;\; N} \end{cases} \quad (0\;)$$

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A. Training stage

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$g_j^i = g_j(\{q_i\})$ ( ) % "
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$$g(Q) = 0 \Rightarrow \lambda + 0 = \prod_{i=0}^{N} (0 + \lambda g_j^i) \quad (00)$$

B. Classification stage

0. & &) ' $o_j^i = h_j(q_i)_{\; j=\overline{0\,m} \;\; i=\overline{0\,N}}$ ") N
& " ' %) m & ,
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$$\chi_j = \#_{i=0\,\overline{N}} \left[\# \;\; (o_j^i \;\; g_j(A_i)) \right] \quad (0\;)$$

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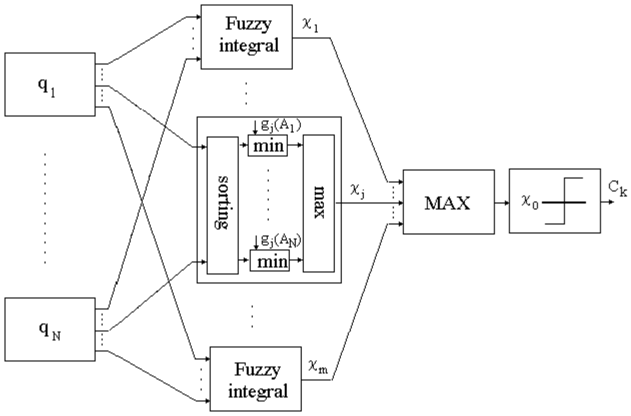

3.2 Possibility theory

$$\pi : D \to [0,1] \qquad \sup_{x \in D} \pi(x) = 1$$

$$\forall A \in 2^{D} \quad \Pi(A) = \sup_{x \in A} \pi(x)$$

$$\forall A \subseteq D \quad N(A) = 1 - \Pi\left(A^{C}\right)$$

$$x \in C_k \quad \text{if} \quad \mu_k(x) = \max_{i=1..N} \mu_i(x)$$

3.3 Dempster-Shafer theory

$$\sum_{A \subseteq D} m(A) = 1$$

$$\begin{cases} m_j^i\left(\{C_i\}\right)(x) = \alpha_{ij} R_j p(q_j|C_i) / \left(1 + R_j p(q_j|C_i)\right) \\ m_j^i\left(\{C_i\}^c\right)(x) = \alpha_{ij} / \left(1 + R_j p(q_j|C_i)\right) \\ m_j^i(D)(x) = 1 - \alpha_{ij} \end{cases}$$

$$m(.) = \oplus_{i=1..N}\left(\oplus_{j=1..m} m_j^i(.)\right)$$

$$K = \sum_{B_1 \cap B_2 \cap \dots \cap B_N = \emptyset} \prod_{i=1}^{N} m_i(B_i) > 0$$

$$m(A) = \sum_{B_0 \cap B \cap ... \cap B_N = A \neq \emptyset} \prod_{i=0}^{N} m_i(B_i) \quad (0)$$

$$m(\emptyset) = K$$

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4 Database and simulation results

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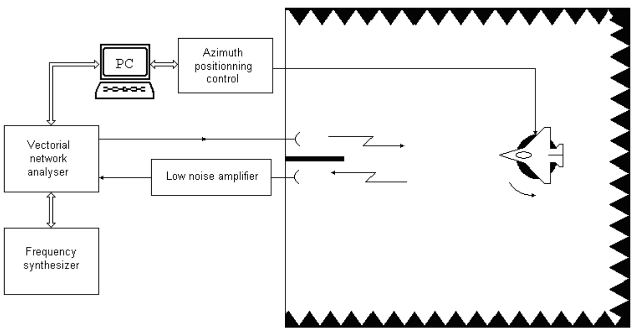

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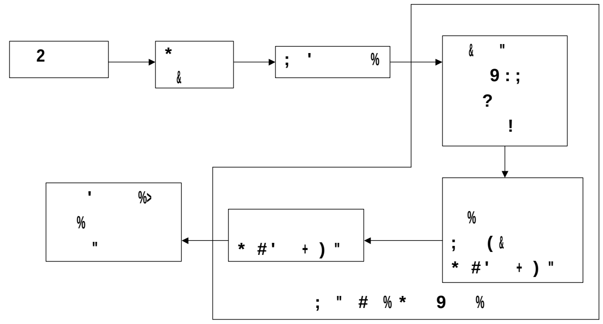

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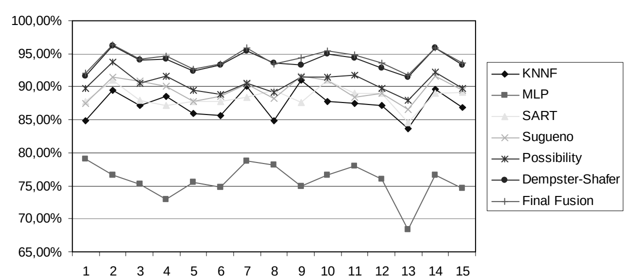

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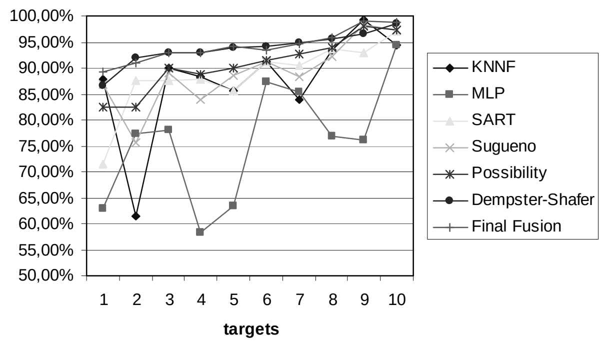

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5 Conclusions and future works

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