SYNTHESIS OF A RADAR RECOGNITION ALGORITHM WITH
ABILITY TO MEET RELIABILITY OF DECISIONS

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Abstract
This paper is devoted to the variant of synthesis of a radar recognition algorithm with the
ability to meet reliability of decisions. The algorithm is based on the theory of sequential
analysis in combination with flexible change in the level of the classification detail when
the observation time cannot be increased. Compared with one-step algorithms, the proposed
algorithm allows guaranteeing “the posteriori probability of decisions is not smaller than
the set value”. The proposed algorithm can be used in radar target recognition systems.

Keywords: Radar target recognition; sequential analysis; multi-step decision.

1. Introduction
Radar target classes are modeled by a conditional probability density function
(CPDF) of radar portrait (RP) \( p_l(\xi) = p_1(\xi|H_l) \), \( l = 1 \div L \) \( (\xi: \text{RP}; \ H_l: \text{the} \ l-\text{class}
existence hypothesis}; \ L: \text{the number of target’s classes}. \) Here, the identification
features are the discrimination of CPDFs on their shapes or parameters and the one-step
decision algorithm \[1, 4, 7, 9, 10\], is given below:

“If \( k = \arg \max_{l=1+L} \left\{ P_l p_1(\xi|H_l) \right\} \) then \( H^* = H^*_k \).” \hfill (1.a)

In which, \( P_l = P\{H_l\}; l = 1 \div L \): the probability of \( H_l \) (priori probability);
\( H^* = H^*_k; \ k = 1 \div L \): decision on \( k\)-class target existence.

If the priori probability is unknown, the distribution is hypothesized to be
uniform, \( P_l = \frac{1}{L}; l = 1 \div L \) and (1.a) becomes:

“If \( k = \arg \max_{l=1+L} \left\{ p_1(\xi|H_l) \right\} \) then \( H^* = H^*_k \).” \hfill (1.b)

The recognition quality is usually illustrated by a table of conditional decision
probabilities \( P_{k,l} = P\{H^*_k|H_l\}; k,l = 1 \div L \). Based on them, other parameters can be
evaluated, such as average conditional probabilities; a sum of non-conditional
probabilities (true, false decisions); … \[7, 8, 9, 11\].

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Additionally, (1.a) is constrained by the criterion of maximum non-conditional probability; (1.b) is the maximum likelihood criterion which makes the minimum false conditional decision probability [7-12].

Due to the noise interference and the obscure priori information, the quality of radar recognition systems is still poor and unacceptable [7, 8] while a false decision can lead to serious outcomes. Hence, the problem of recognition quality guarantee is important and necessary.

Some methods that try to improve the information collection and reduce the priori inconsistence in radars demanding systematic complication and high price [1, 4, 7-9]. In other words, by results of the limitation of technology those methods only support the recognition improvement in general but cannot satisfy specific practical conditions. Another approach that prolongs the observation cycle to gather a mass of information for classification. Several previous works applied this way, for example, multi-step decisions based on the sequential analysis theorem, however, their results have been limited to the detection problem \((L = 2)\), and the recognition problem \((L > 2)\) needs to be researched further [2, 3, 5, 6, 10, 13]. Besides, the observation cycle cannot be too long; thus, that measure is also unfeasible. In that case, a common solution in most researches is “if the observation cycle has reaches the limited value but no final result returned by the sequential algorithm, then the unsatisfied quality acceptance are informed and the regular one-step decision rule is applied”.

On purpose “guarantee reliability of decisions”, this paper focuses on:
- Synthesizing a sequential (multi-step) algorithm of radar recognition and decision-making solution if the observation cycle is critical.
- Analyzing and evaluating the algorithm quality.

2. Algorithm synthesis

In the radar target recognition, the observation cycle extension is equivalent to the increase in the number of contacts with targets. Call \(\xi_m\) to be RP at the cycle “\(m\)” \((m = 1, 2, \ldots)\), then after the \(n\)-cycle, there are a set of “\(n\)” RPs \([\xi^{(n)}] = [\xi_1, \xi_2, \ldots, \xi_n]\). Generally, due to the large observation cycle compared with the signal fluctuation, the RP can be considered independently and the PDF of the set \([\xi^{(n)}]\) is given by [7-9, 11]:

\[
p_i^{(n)}(\xi^{(n)}) = p_i(\xi^{(n)}/H_i) = \prod_{m=1}^{n} p_i^{(l)}(\xi_m),
\]

where \(p_i^{(l)}(\xi_m) = p(\xi_m/H_i); l = 1 \div L\): CPDF of the \(H_i\)-class of targets at the \(m\)-observation cycle.

88
The fundamental of the multi-steps decision algorithm is to divide the whole dynamic of $[\xi(n)]$ into “$L+1$” separated regions $[\xi(n)]_i^i$; $i = 0 \div L$ and make decision in [2, 6, 13]:

“With $i = 0 \div L$, if $[\xi(n)] \in [\xi(n)]_i^i$ then $H_i^{(n)} = H_i^{(n)}$.” (3)

in which $H_i^{(n)}$: decision at the $n$-cycle; $H_{k(l)}^{(n)}$, $k,l = 1 \div L$: decision “targets belonging to the class $H_{k(l)}^{(n)}$”; $H_0^{(n)} = H_i^{(n+1)}$: decision “prolongs the observation cycle”.

Apart from the decision $H_0^{(n)}$, the reliability of decisions $H_k^{(n)}$, $k = 1 \div L$ is the posteriori probability $P\{H_k / H_k^{(n)}\}$ which satisfy the condition:

$$P\{H_k / H_k^{(n)}\} = \frac{P_k P_k^{(n)} \left[ \xi(n) \right]}{\sum_{l=1}^{L} P_l P_l^{(n)} \left[ \xi(n) \right]} \geq P_k^r; \quad k = 1 \div L,$$ (4)

where $P_k^r; \quad k = 1 \div L$: the required reliability of the decision $H_k^{(n)}$; $P_k^{(n)} = P\{H_k^{(n)} / H_l\}$; $k,l = 1 \div L$: conditional decision probability at the “$n$”-cycle.

2.1. Multi-steps recognition algorithm

Suppose that the set $[\xi(n)]$ is obtained after “$n$” observation cycles. At this time, the posteriori probability of target classes is given by the formula:

$$P\{H_l / [\xi(n)]\} = \frac{P_l P_l^{(n)} \left[ \xi(n) \right]}{\sum_{l=1}^{L} P_l P_l^{(n)} \left[ \xi(n) \right]} \geq 1 \div L.$$ (5)

Thus, the decision selection in $H_l^{(n)}; l = 1 \div L$ can be carried out by the posteriori probability maximum:

“If $k = \arg \max \left\{ P\{H_l / [\xi(n)]\} \right\} = \arg \max \left\{ P_l P_l^{(n)} \left[ \xi(n) \right] \right\}$ then $H_l^{(n)} = H_k^{(n)}$.” (6)

Next, check the reliability of the decision if it is satisfactory then this decision is final and vice versa switch to the adjacent cycle. Hence, the multi-steps decision algorithm can be described as below:

“If $k = \arg \max \left\{ P\{H_l / [\xi(n)]\} \right\}$ then $H_l^{(n)} = H_k^{(n)}$ when $P\{H_k / [\xi(n)]\} \geq P_k^r$ and $H_l^{(n)} = H_0^{(n)}$ when $P\{H_k / [\xi(n)]\} < P_k^r$.” (7)

The recognition program of the algorithm (7) comprises $L$ processing channels.
corresponding to $L$ target classes. A channel is responsible for a target class to calculate the posteriori probability through the expression (5). The final decision is based on the maximum of all the channels.

### 2.2. Decision-making solution in critical cycle

If the observation cycle reaches the critical point in the time extension ($n = N_{\text{max}}$) while the algorithm (7) has not returned a decision, then the level of the classification detail should be reduced. Accordingly, a decision $H^{(N_{\text{max}})} = H^{(N_{\text{max}})}_{[k]} = \{H^{(N_{\text{max}})}_l, l \in [I^{(N_{\text{max}})}_k]\}$ - targets in a group of classes $[I^{(N_{\text{max}})}_k]$ is made instead of seeking a target class based on the maximum of a processing channel $H^{(N_{\text{max}})} = H^{(N_{\text{max}})}_k$. The elements in the group $[I^{(N_{\text{max}})}_k]$ have to qualify the reliability with the minimum number of classes $L^{(N_{\text{max}})}$. Here, the reliability of decision $H^{(N_{\text{max}})}_k$ is a sum of posteriori probabilities:

$$P \left\{ \sum_{l \in [I^{(N_{\text{max}})}_k]} H_l \right\} \left[ \xi^{(N_{\text{max}})} \right] = \sum_{l \in [I^{(N_{\text{max}})}_k]} P \left\{ H_l \left[ \xi^{(N_{\text{max}})} \right] \right\}. \quad (8)$$

Considering the initial reliability of single decisions, we give a condition for the group decision:

$$P^{(N_{\text{max}})}_k = \sum_{l \in [I^{(N_{\text{max}})}_k]} P \left\{ H_l \left[ \xi^{(N_{\text{max}})} \right] \right\} \geq \max \left\{ P^{*}_l ; l \in [I^{(N_{\text{max}})}_k] \right\} = P^{*}_{[k]} \quad (9)$$

The determination of classes in group decisions $[I^{(N_{\text{max}})}_k]$ according to (9) is as the following process:

1) $k = \arg \max \left\{ P \left\{ H_l \left[ \xi^{(N_{\text{max}})} \right] \right\} ; P \left\{ H_k \left[ \xi^{(N_{\text{max}})} \right] \right\} < P^{*}_{[k]} \right\} ;$

2) $H^{(N_{\text{max}})}_{[k]} = \{H^{(N_{\text{max}})}_k\}$; Put “$k$” into the group $[I^{(N_{\text{max}})}_k]$;

3) $l = \arg \max \left\{ P \left\{ H_l \left[ \xi^{(N_{\text{max}})} \right] \right\} \right\} ;$

4) Add the class “$l$” into the group $[I^{(N_{\text{max}})}_k]$;

5) If $\sum_{l \in [I^{(N_{\text{max}})}_k]} P \left\{ H_l \left[ \xi^{(N_{\text{max}})} \right] \right\} < \max \left\{ P^{*}_l ; l \in [I^{(N_{\text{max}})}_k] \right\}$ then jump backward into the step (3);

6) $H^{(N_{\text{max}})}_{[k]} = \{H^{(N_{\text{max}})}_l, l \in [I^{(N_{\text{max}})}_k]\}.$
Hence, the multi-steps recognition algorithm with decision-making solution in critical cycle has a following form:

\[
\text{"With } k = \arg \max_{l=1+L} \left\{ P\{H_l / [\xi^{(n)}]\} \right\} : \quad (10) \]

If \( P\{H_k / [\xi^{(n)}]\} \geq P_k^{(n)} \) then \( H^{(n)} = H_k^{(n)} \) (single decision);

If \( P\{H_k / [\xi^{(n)}]\} < P_k^{(n)} \) then \( H^{(n)} = H_{[1]}^{(N_{\max})} = [H_i^{(N_{\max})}; l \in [l^{(N_{\max})}]] \) when \( n = N_{\max} \) (group decision)" or \( H^{(n)} = H_0^{(n)} \) when \( n < N_{\max} \).

Here, \( P\{H_l / [\xi^{(n)}]\} \) is calculated by (5) and (2); the group term \([l^{(N_{\max})}]\) is defined by the above 6-steps process.

In order to implement the algorithm (10) in classic radar target recognition systems with the one-step decision rule (1), some function blocks should be added:

- A processing channel needs a storage of observation cycles and a calculator of conditional probability density function - formula (2);
- A calculator of posterior probability for target classes - formula (5);
- A decision-making element - algorithm (10).

3. Algorithm analysis and evaluation

3.1. Quality analysis of single decisions

If omitting the observation time extension, then the single decision making in (10) complies the criterion "maximum posteriori probability for the set \([\xi^{(n)}] \)"

\[
\text{"If } k = \arg \max_{l=1+L} \left\{ P\{H_l / [\xi^{(n)}]\} \right\} = \arg \max_{l=1+L} \left\{ P_l P_i^{(n)} ([\xi^{(n)}]) \right\} \text{ then } H^{(n)} = H_k^{(n)} \text{.} \quad (11.a) \]

Therefore, this is optimized through "minimum sum of non-conditional probability"

\[
F_{VDK}^{(n)} = \sum_{l=k}^{L} P\{H_l / H_k^{(n)}\} = \sum_{l=k}^{L} P\{H_l\} P\{H_k^{(n)} / H_l\} = \sum_{l=k}^{L} P_l P_k^{(n)} \rightarrow \min .
\]

where \( P_k^{(n)} = P\{H_k^{(n)} / H_l\} \) : decision probability of target class "\( k \)" at the observation cycle "\( n \)" in the existence of target class "\( l \)".

If "\( n=1 \)" then (11.a) is not different from the one-step algorithm along with the criterion (1.a). Obviously, if "\( n \)" increases then the sum of false probabilities \( F_{VDK}^{(n)} \) decreases. The reason is that the amount of information for the recognition is accumulated in observation cycles (the algorithm employs CPDF of all the sets \([\xi^{(n)}]\) .
When the priori probability is obscure, set $P_l = \frac{1}{L}$; $l = 1 \div L$ and (11.a) becomes:

“If $k = \arg\max_{l=1+L} \left\{ P_l^{(n)} \left[ \xi_l^{(n)} \right] \right\} = \arg\max_{l=1+L} \left\{ \prod_{m=1}^{n} p_i^{(l)}(\xi_m) \right\}$ then $H^{(n)} = H_l^{(n)}$.”  

(11.b)

This is the criterion “maximum likelihood function”; the optimization means “minimum average of false conditional recognition probability”:

$$F_{TB}^{(n)} = \frac{1}{L} \sum_{k=1}^{L} P \left\{ H_k^{(n)} / H_l \right\} = \frac{1}{L} \sum_{k,l=1}^{L} P^{(n)}_{k/l} \to \min.$$  

If “$n=1$” then (11.b) is not different from (1.1). Apparently, if “$n$” increases then the sum of false probabilities $F_{TB}^{(n)}$ decreases. Here, the information accumulation over observation cycles is explained as follows:

Suppose that at the first cycle ($n=1$), priori probabilities are equivalently considered: $P \left\{ H_l \right\}_{n=1}^{n} = P_i^{(1)} = \frac{1}{L}; i = 1 \div L$, in the next cycles ($n \geq 2$) the priori probabilities are taken to be the posteriori probabilities in the previous cycles $P \left\{ H_l \right\}_{n=1}^{n} = P_l^{(n)} = P \left\{ H_l / \xi_{n-1} \right\}$; therefore, we have a formula:

$$P \left\{ H_l / \xi_{n} \right\} = \frac{P_l^{(n)} p_i^{(1)}(\xi_{n})}{\sum_{c=1}^{L} P_c^{(n)} P_c^{(1)}(\xi_{n})} = \frac{1}{\prod_{m=1}^{n} P_l^{(1)}(\xi_m)} \cdot \frac{\prod_{m=1}^{n} P_l^{(1)}(\xi_m)}{\sum_{c=1}^{L} \sum_{m=1}^{n} P_c^{(m)} P_c^{(1)}(\xi_m)}.$$  

Thus, the algorithm (11.b) is equivalent to:

“If $k = \arg\max_{l=1+L} \left\{ P \left\{ H_l / \xi_{n} \right\} \right\} = \arg\max_{l=1+L} \left\{ P_l^{(n)} p_i^{(1)}(\xi_{n}) \right\}$ then $H^{(n)} = H_k^{(n)}$.”  

(12)

It can be seen that (12) is the one-step algorithm with the criterion “maximum posteriori probability - for $\xi_{n}$ received at the decision moment”. Here, the information acquisition at the previous cycles is presented by the posteriori probability $P \left\{ H_l / \xi_{n-1} \right\}$ and applied for the priori probabilities $P_l^{(n)}$ for the decision-making in the next cycle.

3.2. Evaluation of required reliability

3.2.1. For single decisions

Assume that at the $n$-cycle, the system makes the decision $H_l^{(n)} = H_k^{(n)}$; $k = 1 \div M$. According to the algorithm (2), this is equivalent to $\xi_l^{(n)} = \xi_{k}^{(n)}$. If that,
from (10), we have:

\[
P\{H_k / \text{HS}_n\} = \frac{P_k P_k^{(n)}(\text{HS}_n)}{\sum_{i=1}^{L} P_i P_i^{(n)}(\text{HS}_n)} \geq P_k^* ; \quad P_k P_k^{(n)}(\text{HS}_n) \geq \sum_{i=1}^{L} P_i P_i^{(n)}(\text{HS}_n).
\]  

(13)

Take the integration for the two sides in the range \([\text{HS}_n]^i\) and substitute \(\int_{\text{HS}_n} p_i^{(n)}(\text{HS}_n) d(\text{HS}_n) = P\{H_k^{(n)} / H_i\} = P_{k/l}\) into that, we have:

\[
P\{H_k / H_k^{(n)}\} = \frac{P_k P_{k/l}^{(n)}}{\sum_{i=1}^{L} P_i P_{i/l}^{(n)}} \geq P_k^*.
\]  

(14)

Thus, the condition (4) is always satisfied with each decision \(H_k^{(n)} ; k = 1+M\).

3.2.2. For group decisions

Suppose that at the cycle \(n = N_{\text{max}}\), the system makes a group decision \(H^{(N_{\text{max}})} = H_{[k]}^{(N_{\text{max}})}\). Set \([\xi^{(N_{\text{max}})}]_{[k]}\) to be a decision region \(H^{(N_{\text{max}})}_{[k]}\), according to (10), along with the process of class determination in a group decision we have:

If \([\xi^{(N_{\text{max}})}]_{[k]}\) then:

\[
\sum_{l \in [l]^{(N_{\text{max}})}} P\{H_l / [\xi^{(N_{\text{max}})}]_{[k]}\} = \sum_{l \in [l]^{(N_{\text{max}})}} \frac{P_k P_k^{(N_{\text{max}})}([\xi^{(N_{\text{max}})}])}{\sum_{m=1}^{L} P_m P_m^{(N_{\text{max}})}([\xi^{(N_{\text{max}})}])} \geq \max \{P_l^* ; l \in [l]^{(N_{\text{max}})}\} = P_k^*.
\]  

(15)

Take the integration for the two sides in the range \([\xi^{(N_{\text{max}})}]_{[k]}\), transform the expression and replace \([\xi^{(N_{\text{max}})}]_{[k]}\) to be \(H_{[k]}^{(N_{\text{max}})}\), we have:

\[
\sum_{l \in [l]^{(N_{\text{max}})}} P\{H_l / H_{[k]}^{(N_{\text{max}})}\} = P\left(\sum_{l \in [l]^{(N_{\text{max}})}} H_l / H_{[k]}^{(N_{\text{max}})}\right) \geq P_{[k]}^* = \max \{P_l^* ; l \in [l]^{(N_{\text{max}})}\}.
\]

Thus, the reliability of a group decision is not smaller than the required value of the posteriori probability all over the classes in the group.
4. Conclusion

In this paper, a radar recognition algorithm with the ability to meet the reliability of decisions has been synthesized. The analysis results show that:

- Compared with conventional multi-step algorithms, the synthesized algorithm allows group decision-making to ensure the reliability of decisions when the observation time cannot prolong. However, if the observation time is not limited, then the conventional multi-step algorithm is capable of quality assurance without reducing the level of the classification detail.

- Compared with one-step algorithms, the synthesized algorithm not only raises the recognition quality in general but also allows guaranteeing the reliability of decisions. The solution for this is the observation time extension or detailed classification reduction.

- The algorithm is applicable for classic recognition systems by adding a small number of hardware resources.

References


TỔNG HỢP THUẬT TOÁN NHẬN DẠNG MỤC TIÊU RA ĐA VỚI KHẢ NĂNG ĐÁP ỨNG ĐỐ TIN CẢY CỦA CÁC QUYẾT ĐỊNH

Tóm tắt: Bài báo trình bày phương án tổng hợp thuật toán nhận dạng mục tiêu ra đa với khả năng đáp ứng độ tin cậy của các quyết định. Thuật toán được xây dựng trên cơ sở lý thuyết phân tích lân lượt kết hợp với việc thay đổi mức chi tiết phân lớp một cách linh hoạt khi không thể kéo dài thời gian quan sát. So với các thuật toán nhận dạng một bước đã có, thuật toán đề xuất cho phép đảm bảo xác suất hậu nghiệm của các quyết định dựa ra luôn lớn hơn giá trị cho trước. Thuật toán này có thể áp dụng trong những hệ thống nhận dạng mục tiêu ra đa.

Từ khóa: Nhận dạng mục tiêu ra đa; phân tích lân lượt; ra quyết định nhiều bước.

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