

ANALYZING AND EVALUATING QUALITY OF THE MULTI-STEP RADAR TARGET RECOGNITION ALGORITHM WITH THE ABILITY TO MEET RELIABILITY OF DECISIONS

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Abstract

The paper presents the issue of improving the efficiency of the radar target recognition by flexibly extending the observation time, giving results of evaluating the quality metrics of “the multi-step recognition algorithm with the ability to meet the reliability of decisions” in the case of recognizing radar targets on Gaussian noise. In the paper, we use the simulation method to determine the probability matrix of conditional true/false recognition and the statistical properties of the required number of observation cycles. The simulation results show that the multi-step algorithm improves the probability of true recognition and allows to meet the reliability of the decisions with the average number of required observation cycles significantly smaller than that in the case of using the conventional one-step algorithm.

Index terms

Radar target recognition, sequential analysis, multi-step decision

1. Introduction

Due to the effect of noise and high uncertainty of posteriori information, the quality metrics of radar target recognition systems are often low and fluctuate strongly according to observation conditions [1], [2], [3], [4]. Meanwhile, making false decisions about target classes to be recognized can lead to serious consequences. Therefore, improving the quality of recognition and ensuring the *reliability of decisions* (RoD) is an important issue that needs to be solved to apply these systems in the radar technique.

Solutions to improve the ability of information collection of the radar system to overcome the uncertainty of posteriori information... often lead to the increase of complexity and cost of the system [1], [3], [4]. On the other hand, because of limitations caused by objective and subjective factors in terms of technology, these solutions only

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contribute to improving the recognition quality in general but do not satisfy the specific requirements of users in reality. With a different approach, the required quality can be achieved by “Extending the observation time to increase the amount of information about the target”. In this way, there are many studies to build multi-step decision-making algorithms based on the sequential analysis theory [5], [6]. However, they have only resolved the detection issues [7], [8], [9]. With the case of recognition, it is required to research and develop further. In order to contribute to the development of the above research direction, the multi-step recognition algorithm (MSRA) with the ability to meet the required RoD was proposed [10]. In which, meeting the RoD is implemented by “extending decision-making time” or “reducing the level of classification detail”. To apply the algorithm to practical applications, it is necessary to analyze in more detail the quality of the recognition decision. In which, we cannot ignore an important parameter, it is “observation time required for decision making”. With this objective, the paper is organized as follows:

- Describe the proposed MSRA with the ability to meet RoD.
- Evaluate algorithm performance.
- Conclusion.

2. Multi-step recognition algorithm with the ability to meet reliability of decisions

The basis for solving the problem of radar target recognition is the “difference” in the type or parameters of the statistical model of each target class needs to be recognized. Statistical models are usually expressed through a set of *conditional probability density functions* (CPDF) of *radar portraits* (RP) that the recognition system can collect. Normally, in radar systems, the observation is done sequentially in cycles. Let ξ_m be the RP created in the m^{th} observation cycle (OC), then after “ n ” OCs, the set of portraits will be obtained $[\xi^{(n)}] = [\xi_1, \xi_2, \dots, \xi_n]$. Since the period of OCs is often much larger than the signal variation time, the RP can be considered independent and the CPDF of the RP set $[\xi^{(n)}]$ is written in the form [3], [10], [4]:

$$p_l^{(n)}([\xi^{(n)}]) = p([\xi^{(n)}]/H_l) = \prod_{m=1}^n p_l^{(1)}(\xi_m), \quad l = 1 \div L \quad (1)$$

where $p_l^{(1)}(\xi_m) = p(\xi_m/H_l)$ is the CPDF of the portrait of H_l class targets obtained in m^{th} OC; $l = 1 \div L$ is the sequence number of the target classes; L is the number of target classes needs to be recognized; H_l is the hypothesis of existing l -class targets.

2.1. One-step recognition algorithm

Assuming that the decision is made after every “ N_{Onc} ” OCs, according to the classical theory, the *one-step recognition algorithm* (OSRA) is implemented based on the

following rule [1], [4], [10]:

$$\text{if } k = \arg \max_{l=1 \div L} \left\{ P_l p_l^{(N_{\text{Onc}})} \left([\xi^{(N_{\text{Onc}})}] \right) \right\} \text{ then } H^{*(N_{\text{Onc}})} = H_k^* \quad (2)$$

where $P_l = P \{H_l\}$, $l = 1 \div L$ is the probability of the appearance of l -class targets; $p_l^{(N_{\text{Onc}})} \left([\xi^{(N_{\text{Onc}})}] \right)$ is CPDF of the set of RPs $[\xi^{(N_{\text{Onc}})}]$ calculated using formula (1); $H^{*(N_{\text{Onc}})}$ is the decision function in the OSRA with the number of accumulated observation cycles N_{Onc} ; H_k^* , $k = 1 \div L$ is the decision of “targets belong to class k ”.

2.2. Multi-steps recognition algorithm

Assume that the requirement for the RoD is:

$$R_k = P \{H_k / H_k^*\} \geq R_k^*, \quad k = 1 \div L \quad (3)$$

where R_k^* , $k = 1 \div L$ the required RoD for the “ k ”-class target.

At n^{th} observation cycle, based on the obtained RPs $[\xi^{(n)}] = [\xi_1, \xi_2, \dots, \xi_n]$, the recognition system forms a set of values “ $P \{H_l / [\xi^{(n)}]\} = \frac{P_l p_l^{(n)}([\xi^{(n)}])}{\sum_{c=1}^L P_c p_c^{(n)}([\xi^{(n)}])}$, $l = 1 \div L$ ” and makes a decision according to the rule:

With $k = \arg \max_{l=1 \div L} \{P \{H_l / [\xi^{(n)}]\}\} :$

$$- \text{ If } P \{H_k / [\xi^{(n)}]\} \geq R_k^* \text{ then } H^{*Mul} = H_k^* \quad (4)$$

$$- \text{ If } P \{H_k / [\xi^{(n)}]\} < R_k^* \text{ then } H^{*Mul} = H_0^* \text{ where } n < N_{\text{max}}$$

and $H^{*Mul} = H_{[k]}^*$ where $n = N_{\text{max}}$

where H^{*Mul} is the decision function of the MSRA; H_k^* is the decision of “the target belongs to class k ” (single decision); H_0^* is the decision of “move to next OC”; N_{max} is the allowed maximum number of OC; $H_{[k]}^*$ is the decision of “the target belongs to the classes of a group, including class k and several other classes” (group decision).

3. Algorithm analysis and evaluation

3.1. Quality metrics and evaluation method

A statistical quality parameter of each recognition algorithm is expressed through a set of *confusion matrix* of the conditional recognition probabilities $P_{k/l} = P \{H_k^* / H_l\}$, $k, l = 1 \div L$. Based on these values, it is possible to determine typical primary quality parameters such as [2], [3], [4], [10]: Probabilities of correct recognition and their

average $D_k = P_{k/k}, k = 1 \div L, D_{TB} = \frac{1}{L} \sum_{k=1}^L P_{k/k}$; Average of the probabilities of wrong recognition for each class and the average cost for all classes $F_k = \frac{1}{L} \sum_{k \neq l, l=1}^L P_{k/l}, k = 1 \div L, F_{TB} = \frac{1}{L} \sum_{k \neq l, l=1}^L F_k$; RoDs and their average: $R_k = \frac{P_k P_{k/k}}{\sum_{l=1}^L P_l P_{k/l}}, k = 1 \div L, R_{TB} = \frac{1}{L} \sum_{k=1}^L R_k$.

In the MSRAs, in addition to the parameters mentioned above, it is necessary to pay attention to the observation time required to ensure requirements quality criteria. Specifically, with the algorithm (4), it is the number of OCs (symbolized by N_{Mul}) necessary for the decisions to have the required reliability (3). It can be seen that, in (5), the decision to stop or continue the observation depends on $P\{H_k / [\xi^{(n)}]\}, k = 1 \div L$ are functions of a set of random values $[\xi^{(n)}]$. Thus, N_{Mul} is a discrete random value, its variation law is expressed through the probability mass function and other parameters such as mean, variance... Notice that, when evaluating the statistical properties of N_{Mul} , it is necessary to exclude group decisions (remove the limit on the maximum number of OCs: $N_{max} = \infty$). In addition, the comparison of the MSRA (4) and the OSRA (2) should be performed under the same reliability requirement that the decisions need to satisfy (3).

Note that, if $L = 2$ (corresponding to two hypotheses of the detection problem: “ H_1 – target presence”, “ H_2 – target absence”) and $P_1 = P_2$, then (4) can be transformed to the same form as the generalized Wald sequential probability ratio test [8]:

$$\begin{aligned} H^* = H_1^* \quad \text{if} \quad L^{(n)} = \frac{p_1^{(n)}([\xi^{(n)}])}{p_2^{(n)}([\xi^{(n)}])} \geq L_1^{*AP} = \frac{R_1^*}{1 - R_1^*} \\ H^* = H_2^* \quad \text{if} \quad L^{(n)} \leq L_2^{*AP} = \frac{1 - R_2^*}{R_2^*} \end{aligned} \quad (5)$$

In [6], the authors developed an algorithm of sequential detection of targets in multichannel systems with the ability to fix the false-alarm rate and the rate of missed detections at specified levels. This sequential detection procedure is asymptotically optimal in the sense of minimizing the expected sample size (number of observation cycles) when the probabilities of erroneous decisions are small. It has been rigorously demonstrated by both theoretical analysis and simulation. In the case of $L > 2$, it is difficult to prove the optimality. Therefore, we only limit the evaluation of the algorithm (4) according to the key recognition quality metrics given above by simulation.

3.2. Simulation procedure

In order to comprehensively evaluate the recognition algorithm, it is necessary to investigate its quality metrics according to many parameters (observation conditions as

well as parameters of the algorithm) [1], [4]. Due to the limited capacity, the paper only focuses on the main goal of analyzing MSRA in terms of “Assuring reliability - Observation time” in the condition of variable noise levels, providing evaluation results of its advantages and disadvantages compared to the OSRA operating under similar conditions. The selection of simulation conditions is carried out towards the common radar target identification problem in practice: the number of layers needed and capable of discriminating is not too large. The recognition is processed after interference has been removed, remaining only Gaussian noise in RPs [3], [4], [9]. With the above goal, the parameters of the observation conditions and the algorithm are selected as follows.

Parameters of the observation conditions:

- Target classes need to be recognized: the amount of $L = 5$ with the same appearance probability.
- Type of the portrait: the power portrait with five levels “0; 3; 5; 9; 11” [dB] (represent five target classes: very small, small, medium, large, and very large).
- Type of noise: Gaussian noise with spectral density $\sigma_0^2 = 0 \div (-24)$ [dB].

Parameters of the algorithm:

- The reliability requirement of decisions:

$$R_k = P \{H_k/H_k^*\} \geq R_k^* = R^* = 0.78, \quad k = 1 \div L \quad (6)$$

- The maximum number of OCs in the MSRA (5): $N_{\max} = \infty$.
- The number of OCs in the OSRA (2): $N_{\text{Onc}} = 10$.

Simulation procedure:

With each set of parameters mentioned above, simulate algorithms (2) and (4) with N_{St} iterations (N_{St} is chosen large enough to ensure the required accuracy). The data obtained from the simulation is used to estimate the *confusion matrix* $P_{k/l}$; $k, l = 1 \div L$ and the statistical parameters of N_{Mul} (the conditional mean $Nk_{Mul} = \overline{N_{Mul}/H_K}$, $k = 1 \div L$, and their average $NTB_{Mul} = \frac{1}{L} \sum_{k=1}^L Nk_{Mul}$). From here, we can calculate and investigate different quality metrics. The main results are presented in the next section.

3.3. Simulation results

3.3.1. Evaluation results in terms of “Assuring reliability – Observation time”

The analysis of the ability to ensure the reliability (5) and the number of OCs in OSRA and OSRA is implemented through the two main results: - With the OSRA: The dependence of RoD on the noise level σ_0^2 and the number of OCs N_{Onc} . Investigation

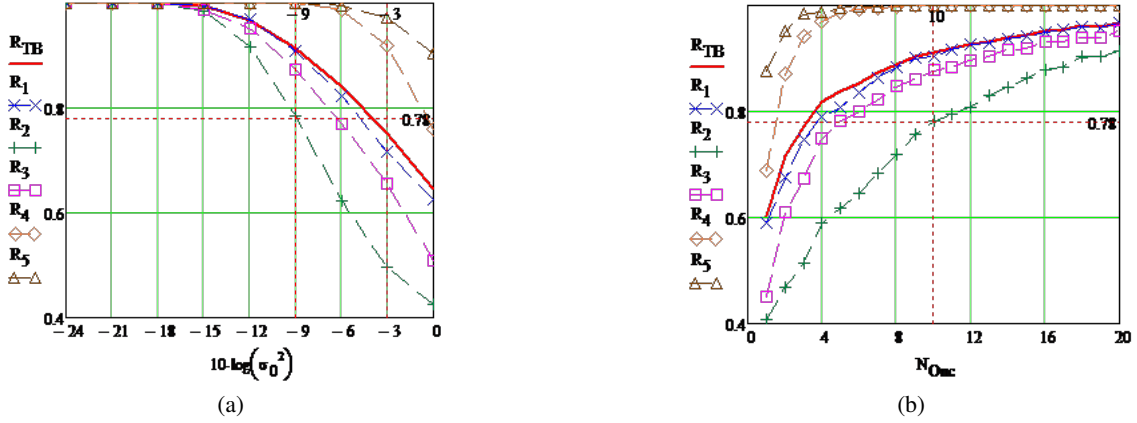


Fig. 1. The dependence of "RoD" of the OSRA on the noise level and the number of OCs.
 (a) - $\sigma_0^2 = var$, $N_{Onc} = 10$; (b) - $N_{Onc} = var$, $\sigma_0^2 = -9$ [dB].

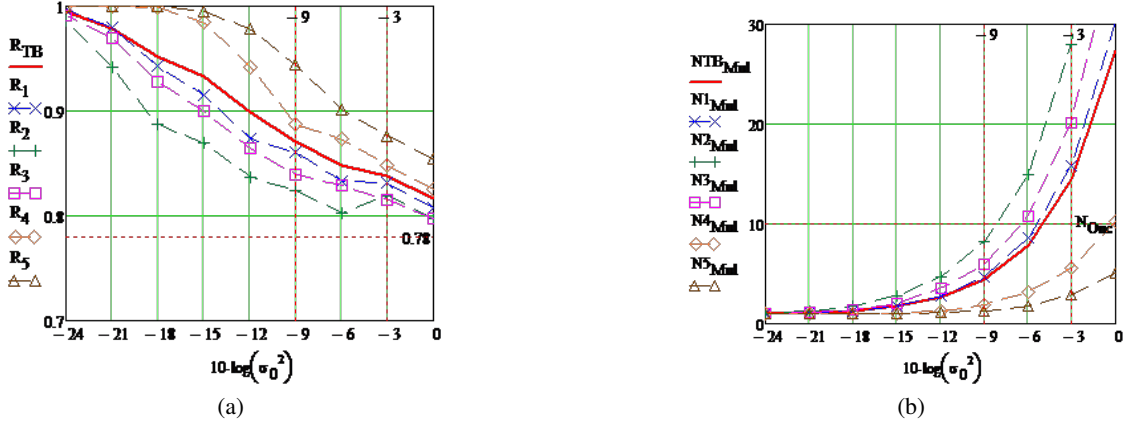


Fig. 2. The dependence of "RoD" (a) and "average number of OCs" (b) on the noise level ($\sigma_0^2 = var$) in the MSRA.

results in two specific cases " $\sigma_0^2 = var$, $N_{Onc} = 10$ " and " $N_{Onc} = var$, $\sigma_0^2 = -9$ [dB]" are shown in Fig. 1.

- With the MSRA: The dependence of RoD and "average number of OCs" on the noise level. The results are shown in Fig. 2.

Discussion:

- With N_{Onc} , the RoD of the OSRA only meets the requirement [9] with the noise level $\sigma_0^2 = -9$ [dB] (see Fig. 1-a). With a constant noise level, when N_{Onc} increases, the RoD increases (see Fig. 1-b). However, as the number of cycles N_{Onc} used in the OSRA is always fixed in advance, it is impossible to guarantee the RoD when the observation conditions change.

Table 1. Simulation results at the noise level of $\sigma_0^2 = -3$ [dB]

	Target class order “k”	1	2	3	4	5	Ave. value	Ref. figure
For the OSRA	RoDs - R_k	0.716	0.495	0.655	0.919	0.972	0.751	Fig. 1-a.
	Number of OCs - N_{Onc}			10			10	
For the MSRA	RoDs - R_k	0.832	0.819	0.815	0.848	0.877	0.838	Fig. 2-a.
	Number of OCs - $N_{k_{Mul}}$	15.8	27.9	20.1	5.6	2.9	14.5	Fig. 2-b.

- The MSRA always meets the requirement (5) in the whole variation range of the noise level. Similar to the OSRA, the RoD in the MSRA tends to decrease as the noise level increases. However, its slope gradually decreases as approaching the required value of the reliability (see Fig. 2-a).

- As the noise level increases, the average number of OCs of the MSRA (N_{TBMul}) also increases. At a noise level value of $\sigma_0^2 = -9$ [dB] (the maximum noise level that the OSRA with $N_{Onc} = 10$ can satisfy the requirement (5)), we have $N_{TBMul} \cong 4.5 \ll N_{Onc} = 10$. In addition, it is noticed that $N_{TBMul} \cong N_{Onc} = 10$ occurs at a noise level of $\sigma_0^2 \cong -5$ [dB], about 4 [dB] higher than the maximum noise level at which the OSRA can still meet the requirement (5) (see Fig. 2-b).

- Simulation results at the noise level of are given in Table 1.

It can be seen that, due to the constant number of OCs, the RoDs in the OSRA has a large distinction: for easy-to-identify targets, the RoD is higher than the required value ($R_k > R^* = 0.78$ with $k = 4, 5$), for difficult-to-identify targets, the RoD is lower than the required value ($R_k < R^* = 0.78$ with $k = 1, 2, 3$). In the MSRA, the RoDs tends to be more uniform and always meet the required value ($R_k \geq R^* = 0.78$ with $k = 1 \div 5$). The reason is flexibility in adjusting the number of OCs: for easy-to-identify targets, using fewer OCs ($N_{k_{Mul}} < N_{Onc}$ with $k = 4, 5$), for difficult-to-detect targets, using more OCs ($N_{k_{Mul}} > N_{Onc}$ with $k = 4, 5$). Considering the mean value (in general), at the noise level $\sigma_0^2 = -3$ [dB], the MSRA gives the average RoDs $R_{TB} \cong 0.838$ with the average number of OCs $N_{TBMul} \cong 14$. Compared with the OSRA ($R_{TB} \cong 0.751$; $N_{Onc} = 10$), it improves the RoDs by approximately 0.09 by extending about 4,5 OCs.

3.3.2. Evaluation based on the true or false recognition probability

To evaluate the quality metrics of MSRA more fully, following the analysis under the aspect of “Assuring reliability - Observation time” in the previous section, we will compare MSRA with OSRA according to two sets of primary quality parameters given in Section 3.3.1, they are the probabilities of true and false recognition: D_k ($k = 1 \div 5$), D_{TB} and F_k ($k = 1 \div 5$), F_{TB} . The results of evaluating these parameters when the noise level varies are shown in Fig. 3 (for the OSRA) and Fig. 4 (for the MSRA).

Discussions:

- As the noise level increases, the average probability of the true (false) recognition increases (decreases) for both algorithms. However, the rate of increase and decrease of these probabilities in the MSRA is significantly smaller than that in the OSRA. The difference is more pronounced in the strong noise region, where the probabilities of

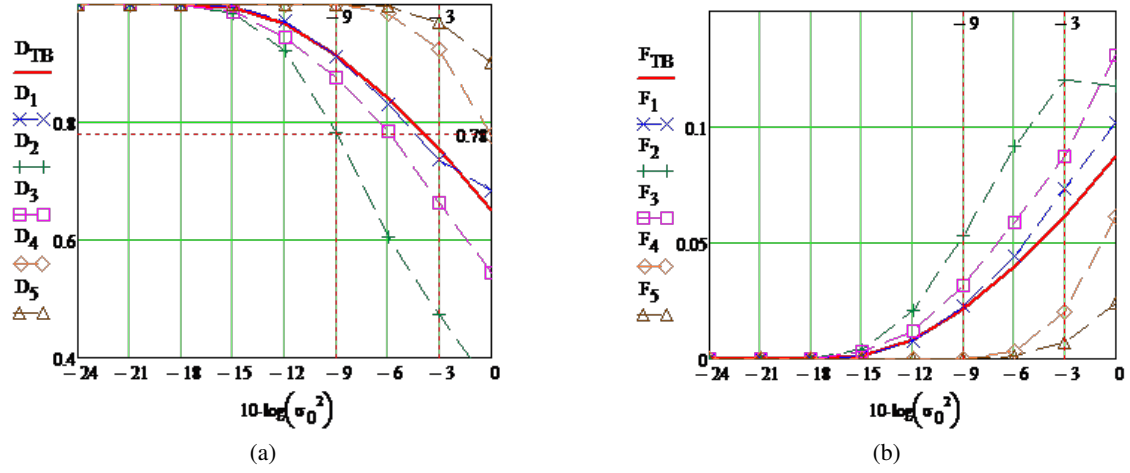


Fig. 3. The dependence of the probability of true (a) and false (b) recognition of the OSRA on the noise level $\sigma_0^2 = \text{var}$ and $N_{\text{Onc}} = 10$.

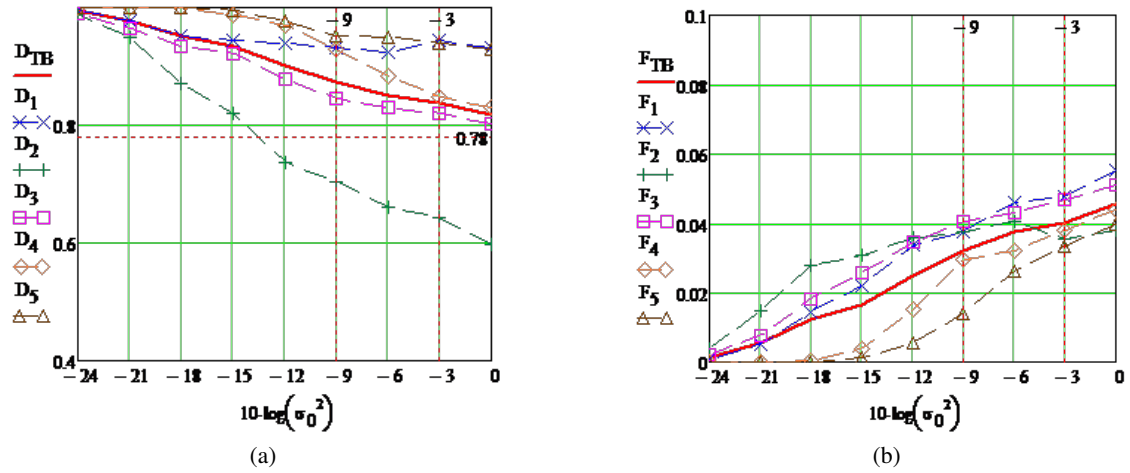


Fig. 4. The dependence of the probability of true (a) and false (b) recognition of the MSRA on the noise level $\sigma_0^2 = \text{var}$.

the true (and false) recognition in the MSRA tend to be closer to each other. This is explained as when the noise increases, the MSRA will extend the observation time flexibly to ensure reliability with the smallest number of OCs.

- Considering the average recognition quality parameters (D_{TB} và F_{TB}), at the noise level $\sigma_0^2 \cong -5$ [dB] (the level where $N_{\text{Onc}} = \text{NTB}_{\text{Mul}}$) two algorithms have the same quality. With the noise level $\sigma_0^2 \leq -5$ [dB], the OSRA proves higher quality (due to $N_{\text{Onc}} > \text{NTB}_{\text{Mul}}$) and when $\sigma_0^2 \geq -5$ [dB] - worse quality (due to $N_{\text{Onc}} < \text{NTB}_{\text{Mul}}$).

4. Conclusion

In this paper, the analysis of quality of the MSRA in the radar technique has been presented, the primary recognition quality parameters of the algorithm have been verified by simulation. The results show that:

- Accumulation through OCs increases the overall recognition quality metrics. The MSRA ensures the RoD when the noise level varies by flexibly changing the observation time. Under the same noise level and the required RoD, the average number of OCs of the MSRA is significantly smaller than that required for the OSRA.
- Due to the randomness of the number of OCs used in the MSRA, the observation time may be extended. This drawback can be overcome by the solution of making group decisions as proposed in [3].
- The number of OCs is an important parameter of the MSRA. Its statistical properties depend on many different factors and should be completely evaluated for each specific recognition task. Due to the limitation of capacity, in this paper, we only present some key results in typical conditions.

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PHÂN TÍCH ĐÁNH GIÁ CHẤT LƯỢNG THUẬT TOÁN NHẬN DẠNG MỤC TIÊU RA ĐA NHIỀU BƯỚC VỚI KHẢ NĂNG ĐÁP ỨNG ĐỘ TIN CẬY CỦA CÁC QUYẾT ĐỊNH

Nguyễn Hoàng Nguyên, Hoàng Minh Thiện, Lưu Văn Tuấn, Phạm Cao Đại

Tóm tắt

Bài báo đề cập đến vấn đề nâng cao hiệu quả của quá trình nhận dạng mục tiêu ra đa theo hướng linh hoạt kéo dài thời gian quan sát, đưa ra kết quả khảo sát đánh giá các chỉ tiêu chất lượng của “thuật toán nhận dạng nhiều bước với khả năng đáp ứng độ tin cậy của các quyết định” trong trường hợp nhận dạng mục tiêu trên nền tạp Gauss. Ở đây chúng tôi sử dụng phương pháp mô phỏng để xác định ma trận xác suất nhận dạng đúng, sai có điều kiện và tính chất thống kê của số chu kỳ quan sát cần thiết. Kết quả mô phỏng cho thấy, thuật toán nhiều bước góp phần nâng cao xác suất nhận dạng đúng và cho phép đáp ứng độ tin cậy của các quyết định với trung bình số chu kỳ quan sát cần thiết nhỏ hơn đáng kể so với trường hợp sử dụng thuật toán một bước kinh điển.