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Evaluation of the Multi-Algorithms Targets Recognition Systems

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Abstract **— This paper presents the evaluation's results of the new classes of the target recognition systems – multi-algorithms unimodal systems and multi-algorithms multimodal systems. The structures and the graphs of the systems are described. The mathematical descriptions and the formulas for evaluation of the system's costs depending on the algorithm's recognition probability and the relation between the costs of the algorithm's software and the system's hardware are presented. The approach to determine the cost of a system for an established threshold level of the system's recognition probability is proposed. The relation of the system's cost to the system's recognition probability for different values of the algorithm's recognition probability is evaluated as well as the rating of the target recognition systems based on their recognition probabilities and costs.**

Keywords — algorithm, cost, evaluation, probability, recognition, system, target

I. Introduction

At present, the different kinds of target recognition systems exist, which are characterized by corresponding classification algorithms, technical realization, and applications. The systems for objects and image recognition using computer neural networks are described in [1, 2]. The architectures for automatic target detection on satellite images and military objects classification based on deep transfer learning are presented in [3, 4]. The target tracking and detection systems based on sensor scheduling and resource allocation in distributed and multi-static radars are described in [5, 6, 7]. The systems based on multi-core and multimodal computation are described in [8].

The new classes of systems – multi-algorithms unimodal and multimodal architectures are proposed in [9], where the investigation's results of the systems regarding their recognition probability are presented.

In this paper, there are presented the results of the general evaluation of the multi-algorithms unimodal and multimodal systems. The structure and graphical models of the target recognition systems (TRS) - unimodal, multimodal, multi-algorithms unimodal and multi-algorithms multimodal systems are described in section II.

The evaluation results of the system's costs depending on the relation between the costs of the system's hardware and the algorithm's software, and the algorithm's recognition probability are presented in section III.

The results of the comparative analysis of the recognition probability and costs of different TRS are described in section IV. The approach to determine the cost of a TRS for an established threshold level of the system's recognition probability is proposed. The relation of the system's cost to the system's recognition probability for different values of the algorithm's recognition probability is evaluated. The rating of the different TRS based on their recognition probabilities and costs is evaluated in section V.

II. The Graph Presentation Of The Target Recognition System

In the article [9] the general structure of the target recognition system (TRS) is presented (Figure 1), for which there were developed the graph models of the different kinds of the TRS – unimodal and multimodal systems, multi-algorithms unimodal and multimodal systems (Figure 2). These systems are characterized by a different number of sensors S, processing algorithms A and output decision-making modules D.

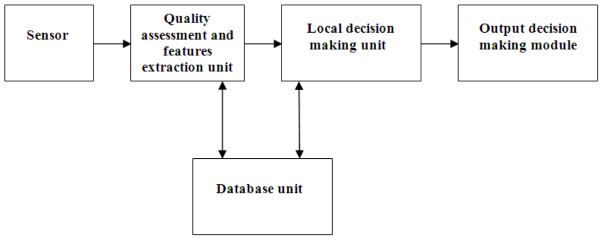
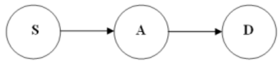
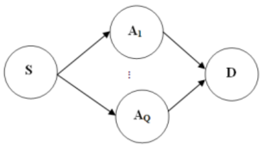


Figure 1. The general structure of the target recognition system

The target recognition processes consist of the following [9]. At the initial stage, the input target's function T(x,y) is generated using the sensor S. At the next stage, the features $F_A=\{f_{Ai}\}$, i=1÷I are extracted from the function T(x,y) following algorithm A. Later, the matrix $D_A=\min\{W[F_A,F_{Aj}]\}$ is determined, where $F_{Aj}=\{f_{Aj}\}$ – features of the reference targets, j=1÷J. And finally, the target is identified in module D.



a)



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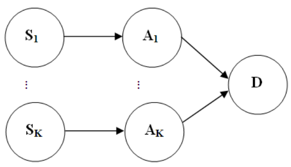

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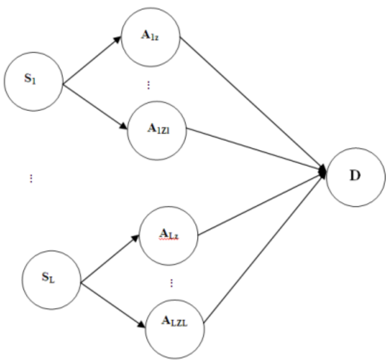

d)

Figure 2. The graph presentation of the target recognition systems:
a) - unimodal system; b) - multimodal system;
c) - multi-algorithms unimodal system;
d) - multi-algorithms multimodal system.

III. EVALUATION OF THE SYSTEM'S COST

Let's estimate the system's cost considering the components of the system – the Sensor and Algorithm, where the costs of the Sensor and Algorithm are C_S and C_A respectively, with relation $C_A = zC_S$, and $1 \geq z > 1$.

In this case, the cost of the unimodal system (UMS) can be estimated in the next mode:

$$C_{UMS}=C_S+C_A=(1+z)C_S \tag{1}$$

The cost of the multimodal system (MMS) can be estimated as:

$$C_{MMS}=\sum_{k=1}^{K}(C_{Sk}+C_{Ak})=\sum_{k=1}^{K}(C_{Sk}+z_kC_{Sk})=\sum_{k=1}^{K}(1+z_k)C_{Sk}, \tag{2}$$

where K is the number of the sensors equal to the number of the algorithms.

The cost of the multi-algorithms unimodal system (MAUMS) will be:

$$C_{MAUMS}=C_S+\sum_{q=1}^{Q}C_{Aq}=C_S+\sum_{q=1}^{Q}(z_qC_S), \tag{3}$$

where Q is the number of the algorithms.

The cost of the multi-algorithms multimodal system (MAMMS) can be evaluated as:

$$C_{MAMMS}=\sum_{l=1}^{L}\{C_{Sl}+\sum_{z=1}^{Zl}(z_{lz}C_{Sl})\}, \tag{4}$$

where L is the number of the sensors; Zl is the number of the algorithms referring to the sensor.

The cost evaluation of the TRS is carried out according to the formulas (1) - (4). The results are presented in Table 1 and in Figure 3, where z is the ratio of the cost of the algorithm's software C_A to the cost of the system's hardware C_S: $z = C_A/C_S$.

TABLE 1. THE COSTS OF THE SYSTEMS, UNITS

z	UMS-1A1S	MMS-1A2S	MMS-1A3S	MAUMS-2A1S	MAUMS-3A1S	MAMMS-2A2S	MAMMS-3A2S	MAMMS-2A3S	MAMMS-3A3S
0.50	1.50	3.00	4.50	2.00	2.50	4.00	5.00	6.00	7.50
0.75	1.75	3.50	5.25	2.50	3.25	5.00	6.50	7.50	9.75
1.00	2.00	4.00	6.00	3.00	4.00	6.00	8.00	9.00	12.00
1.25	2.25	4.50	6.75	3.50	4.75	7.00	9.50	10.50	14.25
1.50	2.50	5.00	7.50	4.00	5.50	8.00	11.00	12.00	16.50
1.75	2.75	5.50	8.25	4.50	6.25	9.00	12.50	13.50	18.75
2.00	3.00	6.00	9.00	5.00	7.00	10.00	14.00	15.00	21.00

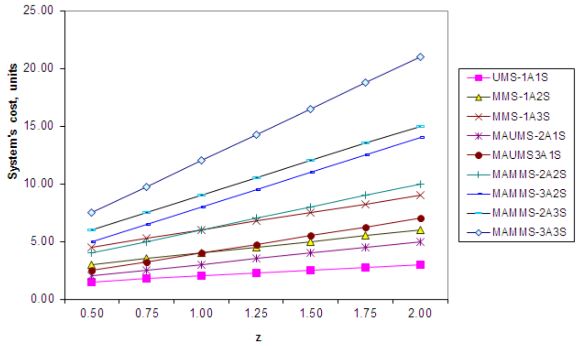

Figure 3. The cost of the systems depending on z – the ratio of the costs of the algorithm's software to the system's hardware

The results show that the cheapest is the system UMS. The most expensive are the systems MAMMS-3A3S, MAMMS-2A3S, and MAMMS-3A2S. For z >1.0 the system MAMMS-2A2S is more expensive than system MMS-1A3S and the system MAUMS-3A1S is more expensive than system MMS-1A2S. The systems MAUMS-2A1S and MAUMS-3A1S (for z<1.0) are cheaper in comparison with systems of classes MMS and MAMMS.

IV. Systems' Costs Evaluation Depending on the Algorithm's Recognition Probability

In many cases it is important to evaluate the cost of the system C_S depending on the algorithm's recognition probability p_A. Let the parameters z and p_A are changing in the diapasons $\{z_{min} \div z_{max}\}$ and $\{p_{Amin} \div p_{Amax}\}$, respectively. In this case, parameter z can be calculated via p_A in the next mode:

$$z = (p_A - p_{Amin})w + z_{min}, \qquad (5)$$

where $w = (z_{max} - z_{min})/(p_{Amax} - p_{Amin})$.

After the substitution of the value of z from formula (9) in the formulas (1) - (4), will be obtained:

$$C_{UMS}=[1+(p_A-p_{Amin})w+z_{min}]C_S \qquad (6)$$

$$C_{MMS}=\sum_{k=1}^{K}\{[1+(p_{Ak}-p_{Akmin})w_k+z_{kmin}]C_{Sk}\} \qquad (7)$$

$$C_{MAUMS}=C_S+\sum_{q=1}^{Q}[(p_{Aq}-p_{Aqmin})w_q+z_{qmin}C_S] \qquad (8)$$

$$C_{MAMMS}=\sum_{l=1}^{L}\{C_S+\sum_{z=1}^{Zl}[(p_{Alz}-p_{Alzmin})w_{lz}+z_{lzmin}C_{Sl}]\} \qquad (9)$$

Table 2 and Figure 4 consist of the data regarding the costs of the systems depending on the algorithm's recognition probability.

TABLE 2. The Costs Of The Systems Depending On The Algorithm's Recognition Probability

p_A	UMS-1A1S	MMS-1A2S	MMS-1A3S	MAUMS-2A1S	MAUMS-3A1S	MAMMS-2A2S	MAMMS-3A2S	MAMMS-2A3S	MAMMS-3A3S
0.50	1.50	3.00	4.50	2.00	2.50	4.00	5.00	6.00	7.50
0.55	1.67	3.33	5.00	2.33	3.00	4.67	6.00	7.00	9.00
0.60	1.83	3.67	5.50	2.67	3.50	5.33	7.00	8.00	10.50
0.65	2.00	4.00	6.00	3.00	4.00	6.00	8.00	9.00	12.00
0.70	2.17	4.33	6.50	3.33	4.50	6.67	9.00	10.00	13.50
0.75	2.33	4.67	7.00	3.67	5.00	7.33	10.00	11.00	15.00
0.80	2.50	5.00	7.50	4.00	5.50	8.00	11.00	12.00	16.50
0.85	2.67	5.33	8.00	4.33	6.00	8.67	12.00	13.00	18.00
0.90	2.83	5.67	8.50	4.67	6.50	9.33	13.00	14.00	19.50
0.95	3.00	6.00	9.00	5.00	7.00	10.00	14.00	15.00	21.00

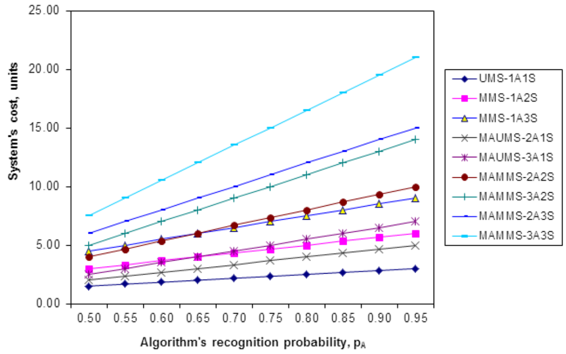

Figure 4. The costs of the systems depending on the algorithm's recognition probability

The analysis shows that system UMS-1A1S is of the lowest cost. The system MAUMS-2A1S is cheaper than MAUMS-3A1S and other systems of classes MMS and MAMMS. For p_A<0.65 the system MAMMS-2A2S is cheaper than the system MMS-1A3S, and the system MAUMS-3A1S is cheaper than the system MMS-1A2S.

In some cases, there appears the necessity to determine the cost C_S of a TRS for an established threshold level of the system's recognition probability P_{ST}. The proposed approach includes the next stages. At the first stage, for the established value of P_{ST} the maximum value of the algorithm's recognition probability p_{AM} is determined, as is demonstrated in [9]. In the next stage, using the formulas (6)÷(9) the costs of the systems are estimated.

Table 3 consists of the data regarding the values of p_{AM}, z, and costs of the different systems for P_{ST} = 0.99.

TABLE 3. The Costs Of The Systems At The Threshold Level Of The Systems Recognition Probability P_{ST}=0.99

	UMS	MMS-1A2S	MMS-1A3S	MAUMS-2A1S	MAUMS-3A1S	MAMMS-2A2S	MAMMS-3A2S	MAMMS-2A3S	MAMMS-3A3S
p_{AM}	-	0.9	0.8	0.9	0.8	0.7	0.55	0.55	0.5
z	-	1.83	1.5	1.83	1.5	1.17	0.67	0.67	0.5
C_S	-	5.67	7.50	4.67	5.50	6.67	6.00	7.00	7.50

One of the important parameters of the TRS is the relation of the system's cost to the system's recognition probability $E_{CP}=C_S/P_S$ for different values of p_A. Table 4 and Figure 5 consist of the data regarding the values of E_{CP}.

TABLE 4. THE RELATION OF THE SYSTEM'S COST TO THE SYSTEM'S RECOGNITION PROBABILITY

p_A	UMS-1A1S	MMS-1A2S	MMS-1A3S	MAUMS-2A1S	MAUMS-3A1S	MAMMS-2A2S	MAMMS-3A2S	MAMMS-2A3S	MAMMS-3A3S
0.50	3.00	4.00	5.14	2.67	2.86	4.27	5.08	6.10	7.51
0.55	3.04	4.18	5.50	2.92	3.30	4.87	6.05	7.06	9.01
0.60	3.05	4.37	5.88	3.18	3.74	5.47	7.03	8.03	10.50
0.65	3.08	4.56	6.27	3.42	4.18	6.09	8.01	9.02	12.00
0.70	3.10	4.76	6.68	3.66	4.62	6.72	9.01	10.01	13.50
0.75	3.11	4.98	7.11	3.91	5.08	7.36	10.00	11.00	15.00
0.80	3.13	5.21	7.56	4.17	5.54	8.01	11.00	12.00	16.50
0.85	3.14	5.45	8.03	4.43	6.02	8.67	12.00	13.00	18.00
0.90	3.14	5.73	8.51	4.72	6.51	9.33	13.00	14.00	19.50
0.95	3.16	6.02	9.00	5.01	7.00	10.00	14.00	15.00	21.00

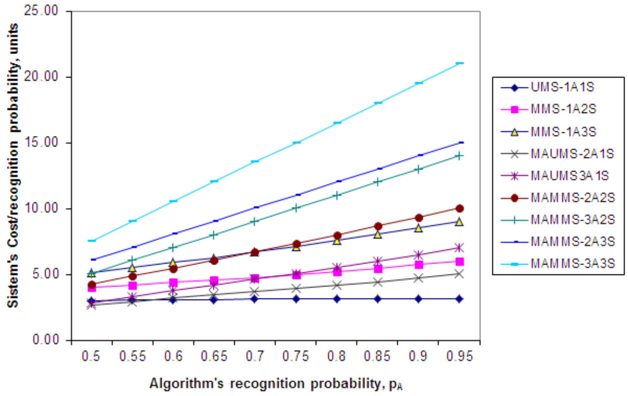

Figure 5. The relation of the system's cost to the system's recognition probability depending on algorithm's recognition probability

The results show that for $p_A<0.55$ the system MAUMS-2A1S is more efficient than other systems. For $p_A>0.7$ the system MAUMS-3A1S is more efficient than the system MMS-1A2S and the system MAMMS-2A2S is more efficient than the system MMS-3S. The system MAMMS-3A2S is more efficient in comparison with the system MAMMS-2A3S.

V. RATING OF THE TARGET RECOGNITION SYSTEMS

On the bases of the data from Tables 1, 4 was determined the rating of the systems based on their recognition probabilities P_S, costs C_S, and relation C_S/P_S. The results are presented in Table 5 and Figure 6.

TABLE 5. THE RATING OF THE SYSTEMS

	UMS-1A1S	MMS-1A2S	MMS-1A3S	MAUMS-2A1S	MAUMS-3A1S	MAMMS-2A2S	MAMMS-3A2S	MAMMS-2A3S	MAMMS-3A3S
Systems' recognition probability P_S	6	5	4	5	4	3	2	2	1
Systems' cost C_S	1	4 for $p_A>0.7$	6 for $p_A>0.7$	2	3 for $p_A<0.7$	5 for $p_A<0.7$	7	8	9
Relation C_S/P_S	2 for $p_A>0.55$	4 for $p_A>0.7$	6 for $p_A>0.7$	1 for $p_A<0.55$	3 for $p_A<0.7$	5 for $p_A<0.7$	7	8	9
Total nr of points, S	9	13	16	8	10	13	16	18	19
General rating	2	4	5	1	3	4	5	6	7
Total nr of points for P_S and C_S	7	9	10	7	7	8	9	10	10
General rating for P_S and C_S	2	4	5	1	3	4	5	6	7

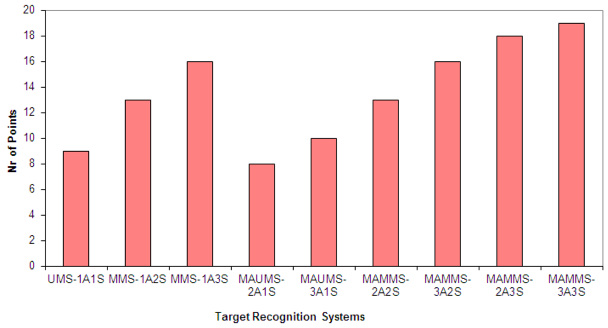

Figure 6. General rating of the systems

The data show that the highest general rating has the system MAUMS-2A1S – multi-algorithms unimodal system regarding system's recognition probability P_S, system's cost C_S and relation C_S/P_S. The same rating is observed if are taken into account only the parameters P_S and C_S (Table 5, last 2 rows).

CONCLUSIONS

As a result of the research, the mathematical models there were obtained for estimation of the system's cost according to the relation between the costs of the algorithm's software and system hardware and the algorithm's recognition probability.

The approach to determine the cost of a target recognition system for an established threshold level of the system's recognition probability is proposed.

The evaluation of the relation of the system's cost to the system's recognition probability for different values of the algorithm's recognition probability is made, where the effectiveness of different systems is determined.

The rating of the different target recognition systems based on their recognition probabilities and costs is evaluated. It is established that the highest general rating has the system MAUMS-2A1S – multi algorithms unimodal system, in which are realized 2 recognition algorithms.

The proposed theory allows the design of new target recognition systems according to the predetermined recognition probability and cost.

REFERENCES

[1]. M.Hussain, J.Bird, D.Faria. "A study on CNN transfer learning for image classification". In: 18th Annual UK Workshop on Computational Intelligence (UKCI), Nottingham, 2018.

[2]. J.Jagruti, A.Mehzabeen. "Object recognition using CNN". International Journal of Advanced Research, Ideas, and Innovations in Technology. Vol. 4, Issue 2, 2018, pp. 1987-1991.

[3]. M.Khan, A.Yousaf, N.Javed et all. "Automatic Target Detection in Satellite Images using Deep Learning". In: Journal of Space Technology, Vol 7, No 1, 2017.

[4]. D.El-Din, A.Hassanein, E.Hassanien. "An Automatic Detection of Military Objects and Terrorism Classification System Based on Deep Transfer Learning". Proceedings of the International

Conference on Artificial Intelligence and Computer Vision (AICV2020), 2020, pp. 594-603.
[5]. O.Kechagias-Stamatis, N.Aouf, G.Gray et all. "Local feature-based automatic target recognition for future 3D active homing seeker missiles". Aerospace science and technology. Volume 73, 2018, pp. 309-317.
[6]. K.Polyzos, E. Dermatas. "Design of Automatic Target Recognition system based on multi-static passive RADAR". University for Business and Technology International Conference, October 2018. DOI: 10.33107/ubt-ic.2018.89.
[7]. A.Uribe-Hurtado, M.Orozco-Alzate. "Acceleration of Dissimilarity-Based Classification Algorithms Using Multi-core Computation". Proc. Intern. Conf. on Practical Applications of Agents and Multi-Agent Systems PAAMS 2017, pp. 231-233, 2017.
[8]. E.Kannan. "Multimodal Authentication for High-End Security". International Journal on Computer Science and Engineering, vol. 3, no. 2, 2011, pp. 687 – 692.
[9]. V.Perju. Multiple classification algorithms unimodal and multimodal target recognition systems. Journal of Engineering Science Vol. XXVIII, no. 3, 2021, pp. 87 – 95. ISSN 2587-3474/ eISSN 2587-3482. https://doi.org/10.52326/jes.utm.2021.28(3).07.