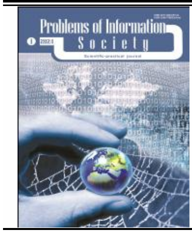

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Criteria for assessing the adequacy of image recognition methods and their verification using examples of artificial series of signals

Ramin Rzayev[1], Azer Kerimov[2], Uzeyir Gurbanli[3], Fuad Salmanov[4]

[1, 2, 3, 4] Institute of Control Systems, Baku, Azerbaijan

[1]raminrza@yahoo.com, [2]a.k.etn00001@gmai.com, [3]uzeyir@sinam.net, [4]fuad.salmanli@sinam.net

[1]*orcid.org/0000-0001-7658-2850*, [2]*orcid.org/0000-0002-1732-2474*, [3]*orcid.org/0009-0007-5489-8687*, [4]*orcid.org/0000-0001-8996-5965*

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ABSTRACT

The article discusses four criteria for assessing the adequacy of the most well-known image recognition methods. Verification of two of these criteria is carried out by empirical analysis using the example of the most well-known signal recognition methods, such as DTW, DDTW, as well as methods based on the Wavelet transform and Fourier transform. Two artificial sets of images are used as recognition objects, formed by uniformly shifting the base image both horizontally and vertically. In general, the goal of this research is to develop a new method for extracting recognition features using the example of the image of the State Emblem of the Republic of Azerbaijan. In the context of this study, a verification of a previously proposed signal recognition algorithm is carried out based on the artificial family of curves, for which the most accessible and acceptable method of displacement is established: horizontally or simultaneously horizontally and vertically.

1. Introduction

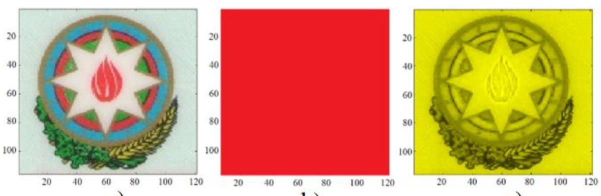
In (Kerimov, 2022), we reviewed some well-known methods of pattern recognition, where their adequacy was tested using the example of the artificial series of regular (one-dimensional) signals generated by sequential uniform horizontal displacement of the selected base signal. In given article, this approach is applied to assessing the adequacy of recognition methods using the example of the artificial series of two-dimensional signals (images) formed by sequential uniform displacement of the selected base image both horizontally to the right and diagonally down. As in works (Rzayev and Kerimov, 2023), the objects of this study are the amplitude recognition method DTW (Dynamic Time Warping), the pattern recognition method DDTW (Derivative Dynamic Time Warping), as well as recognition methods based on the Wavelet Transform (WT) and Fourier Transform (FT). Their adequacy is analysed after linearization of recognized images selected as examples of two-dimensional signals. At the same time, the following question arises: to what extent does a one-dimensional signal adequately reflect the recognized image after its transformation as a two-dimensional signal into a one-dimensional one? Solution to this problem depends on how well the color image is converted into a monochromatic image with the subsequent selection of a recognition feature, as well as on the method of reducing the dimension of the monochromatic analogue of the image. To implement this procedure, the article uses the Maximax method with parallel reduction of the image dimension (Gote et al., 2023; Sui, 2023; Basha, 2022).

2. Recognition Procedure

As is known (Kumar, 2014), extracting characteristic features of images is the initial stage in processing images for their recognition. Different approaches are used to extract features. For example, recently there has been a tendency to extract features using neural networks (Song et al., 2011). However, three well-established basic approaches should be highlighted (Singh, 2023). The first approach involves extracting features by converting a colour image to a grayscale image, and then using the pixel values as features. The second approach involves extracting a feature by finding the average value from three RGB channels. The third approach involves finding the definition of the edge in images for further use of characteristic features. Based on the experience with these approaches, further we use the RGB format to extract features of the images that are interpreted as two-dimensional signals.

The experiments show that the 2nd approach to feature extraction has its drawbacks in the sense that it leads to blurring of the image, for example, as shown in the example of the image of the State Emblem of the Republic of Azerbaijan (AR) (Fig. 1(a) and Fig. 1(b)). Therefore, as an approach to extracting image features, it is proposed to use the maximum value from three RGB channels, which demonstrates its consistency using the example of the State Emblem of the AR recognition (Fig. 1, (c)).

Image segmentation is used to reduce dimensionality. Further, we use image segmentation at scales of 3×3, 4×4, 5×5 and 6×6, which involves dividing the image into squares with sides of length 3, 4, 5 and 6 points, respectively.



a) b) c)

Fig. 1. Feature extraction: a) image of the State Emblem with a size of 100×120 pixels, b) image of the State Emblem using features extracted by the average value from three RGB channels, c) image of the Emblem of the AR using features extracted by the maximum value from three RGB channels.

In a given segment, to select a characteristic feature, we use the rather trivial Maximax method, which involves finding for the given point the maximum value from three RGB channels and, further, the maximum for all points of the segment.

To form the artificial series of images, we selected the State Emblem of the AR with a size of 100×120 pixels as a base image (Fig. 1, a). After segmentation, this image is linearized as shown in Fig. 2.

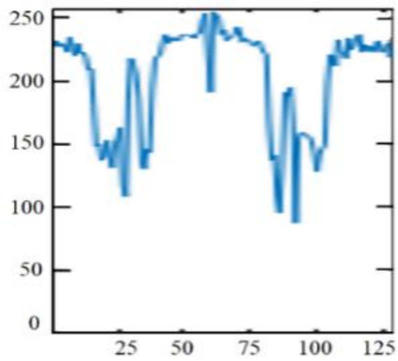


Fig. 2. Linearization of the image of the State Emblem

At the preliminary stage, as a rule, the main recognition features are identified and, on their basis, the appropriate distance norm is selected. Further, the recognition procedure is carried out by comparing the recognized signals with the etalon by calculating pairwise distances between them based on the selected metric. The choice of recognition features depends on the nature of the problem being solved (series of signals to be recognized) and the approach used. However, in all cases, the Euclidean metric is used as the basic norm for the distance between signals. At the same time, for each method the corresponding recognition features are determined.

DTW Amplitude Method. The values of reference points are selected as recognition features (Sakoe, 1978). In particular, if for two arbitrary signals x and y the references are two numerical sequences $f = \{f_1, f_2, \ldots, f_n\}$ and $g = \{g_1, g_2, \ldots, g_m\}$ with lengths n and m, respectively, then the Euclidean metric is chosen as a norm of the distance between them. The minimum distance in the matrix between sequences is determined using the following criterion:

$$\begin{cases} \mathrm{DTW}(f_i, g_j)^2 = d_{ij} + \min\{\mathrm{DTW}(f_i, g_{(j-1)})^2, \\ \qquad \mathrm{DTW}(f_{(i-1)}, g_j)^2, \mathrm{DTW}(f_{(i-1)}, g_{(j-1)})^2\}, \\ \mathrm{DTW}(f_1, g_1)^2 = d_{11}, \\ d_{ij} = (f_i - g_j)^2;\ i = 1 \div n;\ j = 1 \div m. \end{cases} \tag{1}$$

where $\mathrm{DTW}(f_i, g_j)^2$ is the minimum (squared) distance between the sequences f and g.

DDTW Recognition Method. The values of the 1st derivatives at reference points are selected as recognition features (Novozhilov, 2016; Keogh, 2017; Santos et al, 2017; Cedro, 2011; Liu, 2019). In the discrete case, the expression $\dot{a}(i) = [a(i) - a(i-1)]/T$ is taken as the 1st order derivative, where $a(i) = a(iT)$, $i = 0, 1, \ldots, N$; T is the sampling period of regular signal a. In particular, if for two arbitrary signals x and y the reference points are the values of the first derivatives p_i and q_i (i=0÷N), respectively, then the Euclidean metric is chosen as the norm of the distance between them in the form

$$D_2(x, y) = \sqrt{\sum_{i=1}^{N} (p_i - q_i)^2} \qquad (2)$$

Wavelet Transform (WT). According to the recognition method using WT, each signal is decomposed into high-frequency and low-frequency components (Zhao et al., 2009; Saraswat et al., 2017). Moreover, each component is characterized by the values of the so-called detailing and approximating coefficients. For example, for the regular signal (Fig. 3 (a)), including 256 reference points, the WT at 4 levels looks as shown in Fig. 3(b).

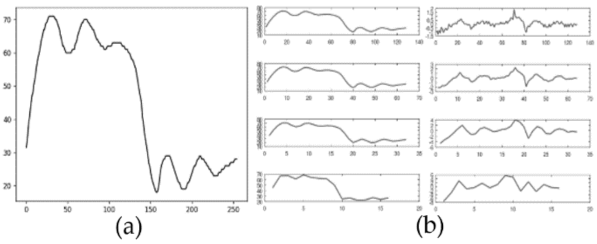


Fig. 3. Regular signal, including 256 samples (a), and its WT at 4 levels (b)

Here, the average values and standard deviations of characteristics (coefficients) in each filter band are selected as recognition features. In the given example, where 4 levels of decomposition are selected (Fig. 3(b)), there are 16 values of recognized features.

Denoting the average values and standard deviations of the coefficients in high-frequency and low-frequency bands as H_{1i}, L_{1i}, H_{2i}, L_{2i}, (i=0÷N), respectively, where N is the number of expansion levels, for two arbitrary signals x and y the Euclidean metric is chosen as following distance norm

$$D_3(x, y) = \sqrt{\sum_{j=1}^{N} (H_{1i} - H_{2i})^2 + \sum_{j=1}^{N} (L_{1i} - L_{2i})^2} \ . \qquad (3)$$

Fourier Transform (FT). The use of FT implies the creation of a spectral image for the recognizable regular signal (Hindarto et al., 2017). In particular, for the signal that includes 256 reference points (Fig. 3(a)), the FT forms the corresponding amplitude spectral image (Fig. 4), including 128 reference points.

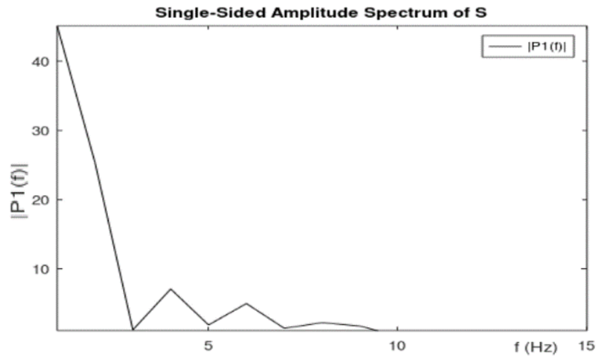


Fig. 4. Amplitude spectrum of signal obtained using FT

Here, variables of the amplitude spectrum are considered as recognition features, which in common form for two signals are denoted by f_{1i} and f_{2i} (i=0÷N), where N is the number of variables. In this case, the Euclidean metric is also used as the norm of the distance between two arbitrary signals x and y in the following form

$$D_4(x, y) = \sqrt{\sum_{i=1}^{N} (f_{1i} - f_{2i})^2} \ . \qquad (4)$$

3. Problem Definition

The application of the above recognition methods is considered using the example of a unified class of regular signals (Kerimov, 2022). An artificial series of curves is chosen as this class of signals, formed by uniformly shifting the curves horizontally relative to the etalon. The analysis of recognition results for the adequacy of these methods is carried out using the following 4 evaluation criteria.

Criterion 1 (C_1 – *uniformity of the method*): as the recognized signals move away, their distances from the etalon should increase uniformly, and not vary unevenly.

Criterion 2 (C_2 – *sensitivity*): for a particular recognized signal, the Euclidean distances from the left standing and from the right standing signals should be approximately equal, that is, their ratio should be approximately equal to one. If the standing signals on the left and on the right are symmetrical with respect to this signal, then these distances will be absolutely equal.

Criterion 3 (C_3 – *speed of the method*): as the recognized signals "get closer" to the etalon, the rate of convergence of distance values increases. Here, the rate of convergence of distance values is understood as the difference between the current and next distance values, divided by the next distance value.

Criterion 4 (C_4 – stability): increasing the step of signal shifts cannot improve the satisfaction of recognition methods, that is, the accuracy of the recognition method must remain the same or deteriorate.

The objective of given study is determined by the need to conduct a similar empirical analysis of the adequacy of the listed recognition methods using the example of a series of images (two-dimensional signals) and using evaluation criteria C_2 and C_4.

4. Assessing the Adequacy of Recognition Methods

The image of the State Emblem of the AR with the size of 100×120 pixels (Fig. 1(a)) was selected as the standard two-dimensional signal. Relative to this etalon i_0, the series of images is formed by successive uniform horizontal shift to the right (Kerimov, 2022). Choosing a shift of 2 units as a step h, the artificial series is formed as 4 sequentially horizontally shifted images $I_2=\{i_{20}, i_{21}, i_{22}, i_{23}\}$[1], which is presented in Fig. 5.

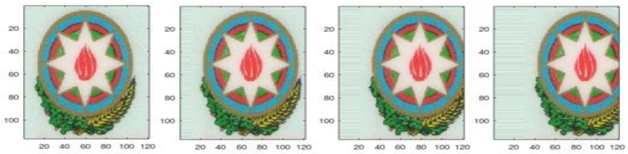


Fig. 5. Artificial series of images I_2

After extracting recognition features and segmentation of images, for example, of size 3×3, the series of images I_2 is transformed into the set presented in Fig. 6.

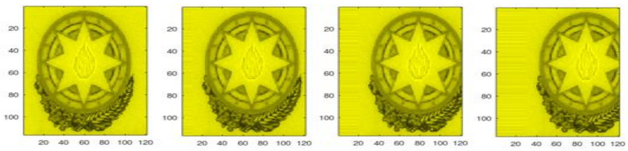


Fig. 6. The series of images i_{2j} (j=0÷3) obtained after feature extraction and segmentation

Fig. 7 shows the set of corresponding one-dimensional (regular) signals $S_2=\{s_{20}, s_{21}, s_{22}, s_{23}\}$ with the total number of reference points RP=1320, which is formed by linearization of images i_{2j}.

[1] The index "2" of the symbol I_2 indicates the length of the horizontal displacement of the curves, i.e. h=2.

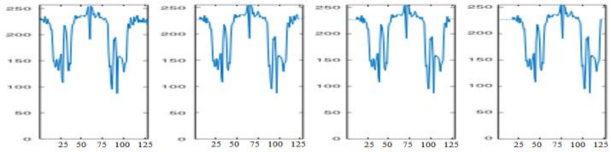


Fig. 7. Series of one-dimensional signals S_2

Taking into account the step length h, which is decisive in the artificial formation of the series of images, for the common case, i.e., for the series of N signals, the following notation are introduced:

- distance between signals as $D_k^h(x,y)$, where k=1 ÷ 4 is the method number;
- for each i=1÷(N-2) the relations between adjacent distances (i.e., between the distances from the right-handed (i+1)-th and from the left-handed (i-1)-th signals to the i-th signal) as $R_{ki}^h = \dfrac{D_k^h(s_i, s_{i+1})}{D_k^h(s_{i-1}, s_i)}$.

In the accepted notation, we formulate the satisfiability of methods for compliance with criteria C_2 and C_4 as follows:

- the adequacy of the recognition method for compliance with criterion C_2 is assessed based on the value of the maximum deviation, formulated as $G_k^h = \max_{i=1\div 5}\{1-R_{ki}^h\},\ k=1\div 4$;
- the adequacy of the recognition method for compliance with criterion C_4 is assessed based on the fulfilment of the condition $R_{ki}^{h_1} < R_{ki}^{h_2}$ when $h_1<h_2$, where h_1 and h_2 are the steps of curve displacements (for example, horizontally) in two different series of recognized signals; i=1÷(N-2); k=1÷4.

Thus, the results of pairwise comparison of regular signals from the series under consideration $S_2=\{s_{20}, s_{21}, s_{22}, s_{23}\}$ (N=4) using metrics (1) – (4) are presented in the following corresponding Tables 1–4.

Table 1. Pairwise comparisons of signals from the S_2 series using metric (1)

	s_{20}	s_{21}	s_{22}	s_{23}
s_{20}	0	717.46	1109.7	1335.1
s_{21}	717.46	0	957.89	1230.4
s_{22}	1109.7	957.89	0	947.95
s_{23}	1335.1	1230.4	947.95	0

Table 2. Pairwise comparisons of signals from the S_2 series using metric (2)

	s_{20}	s_{21}	s_{22}	s_{23}
s_{20}	0	703.57	794.74	780.8
s_{21}	703.57	0	824.8	797.97
s_{22}	794.74	824.8	0	824.38
s_{23}	780.8	797.97	824.38	0

Table 3. Pairwise comparisons of signals from the S_2 series using metric (3)

	s_{20}	s_{21}	s_{22}	s_{23}
s_{20}	0	3.1023	8.6571	15.278
s_{21}	3.1023	0	6.1876	13.907
s_{22}	8.6571	6.1876	0	10.35
s_{23}	15.278	13.907	10.35	0

Table 4. Pairwise comparisons of signals from the S_2 series using metric (4)

	s_{20}	s_{21}	s_{22}	s_{23}
s_{20}	0	0.72204	1.4483	4.2199
s_{21}	0.72204	0	1.2511	4.1472
s_{22}	1.4483	1.2511	0	3.9514
s_{23}	4.2199	4.1472	3.9514	0

Analysis of the results presented in Tables 1–4 for compliance of signal recognition methods with the criteria C_k (k=1÷4) demonstrate the following.

DDTW method does not satisfy criterion C_1 (Table 2) sufficiently. For example, for signals s_{20} and s_{21} after the corresponding values of 794.74 and 824.8, there are a decrease to the values of 780.8 and 797.97, accordingly, which contradicts the condition of criterion C_1. At the same time, the remaining three methods satisfy criterion C_1.

To evaluate the recognition methods for their satisfaction with criterion C_4, by analogy with the construction of the series S_2 another artificial series of curves is formed. That is, for the series of images I_4={i_{40}, i_{41}, i_{42}, i_{43}}, constructed by shifting images horizontally to the right with the step length of 4 units, after extracting characteristic features, segmentation of size 3×3 and linearization, the artificial series of one-dimensional curves S_4={s_{40}, s_{41}, s_{42}, s_{43}} is obtained. Further, based on the values of the maximum deviations $G_k^{h_1}$ and $G_k^{h_2}$ (h_1=2, h_2=4) (Tables 5 and 6), the coefficients u_k are calculated using the formula

$$u_k = \frac{G_k^{h_1}}{G_k^{h_2}},\ k=1\div4, \tag{5}$$

which, in the context of criterion C_4, reflect "degradation" from the application of D_k norms in the process of recognizing signals from artificial series S_2 and S_4. In this case, the degradation coefficient u_k reflects the degree of satisfaction of the k-th recognition method to criterion C_4.

Table 5 presents the values of the maximum deviations G_k^2 and G_k^4, as well as the values of the degradation coefficient u_k calculated for two series S_2 and S_4, formed by segmenting images of size 3×3 and with the total number of reference points RP=1320.

Table 5. Compliance of recognition methods with criterion C_4: segmentation 3×3 and RP=1320

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.3351	0.071754	0.21413
DDTW	2	0.17231	0.094958	0.55109
WT	3	0.99451	3.416	3.4349
FT	4	2.1583	6.3377	2.9364

The results of the calculations, summarized in Table 5, demonstrate that the DTW and DDTW methods do not satisfy criterion C_4, since the corresponding values of the degradation coefficients $u_{DTW}=u_1$=0.21413 and $u_{DDTW}=u_2$=0.55109 do not satisfy the requirement of criterion C_4: $u\geq1$. At the same time, methods based on the use of WT and FT, with the degradation coefficients $u_{WT}=u_3$=3.4349 and $u_{FT}=u_4$=2.9364, fully satisfy criterion C_4.

A reasonable question arises: is there a relationship between the degradation coefficients u_k, on the one hand, and the choice of the image segmentation size and the number of RP of one-dimensional signals, on the other? To answer this question, recognition methods are assessed for their satisfaction with criterion C_4 using examples of series S_2 and S_4 obtained after segmentation of images of size 4×4, and when choosing the total number of RP as 750 after linearization. The indicators of such assessment are summarized in Table 6.

Table 6. Compliance of recognition methods with criterion C_4: segmentation 4×4 and RP=750

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.34213	0.09752	0.28504
DDTW	2	0.17764	0.093837	0.52824
WT	3	0.94748	1.8539	1.9567
FT	4	4.6926	6.0321	1.2854

Similar calculations were carried out for the cases of segmentation of initial images of sizes 5×5 and 6×6, and the corresponding selection of the total number of RP as 480 and 320. The calculation results are summarized in the following Tables 7 and 8.

Table 7. Compliance of recognition methods with criterion C_4: segmentation 5×5 and RP=480

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.3843	0.13055	0.33971
DDTW	2	0.19179	0.10122	0.52776
WT	3	1.6899	2.9287	1.7331
FT	4	3.2625	4.6875	1.4368

Table 8. Compliance of recognition methods with criterion C_4: segmentation 6×6 and RP=320

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.41412	0.13093	0.3162
DDTW	2	0.25728	0.14579	0.5667
WT	3	1.5013	2.5125	1.6735
FT	4	3.4445	2.957	0.8585

The values of degradation coefficients reflecting the degree of satisfaction of criterion C_4 of the considered recognition methods using examples of artificial series of regular curves S_2 and S_4, formed after segmentation of images of sizes 3×3, 4×4, 5×5, 6×6, and when choosing the number of RP after linearization such as 1320, 750, 480 and 320 are summarized in Table 9. For the DTW and DDTW methods, the dynamics of changes in the degradation coefficients are presented in Fig. 8.

Table 9. Values of degradation coefficients reflecting the satisfaction degree of methods relative to criterion C_4

Method	Degradation coefficients u_k			
	Segmentation and RP			
	3×3, RP=1320	4×4, RP=750	5×5, RP=480	S 6×6, RP=320
DTW	0.21413	0.28504	0.33971	0.3162
DDTW	0.55109	0.52824	0.52776	0.5667
WT	3.4349	1.9567	1.7331	1.6735
FT	2.9364	1.2854	1.4368	0.8585

The dynamics of changes in the degradation coefficients, as indicators of the satisfaction of the DTW and DDTW methods relative to criterion C_4, demonstrate that with an increase in the segmentation size and, accordingly, a decrease in the number of RP, the value of the degradation coefficient gradually increases, verging towards 1 from below, which confirms the presence of its dependence on the selected number references after linearization of images. This tendency can be explained by the fact that relatively trivial DTW and DDTW methods are not effective enough when recognizing signals with the large number of RP, which is confirmed by the corresponding values of the degradation coefficients. In particular, this feature of the DTW and DDTW methods was not identified in (Kerimov, 2022), where the small number RP=256 were considered.

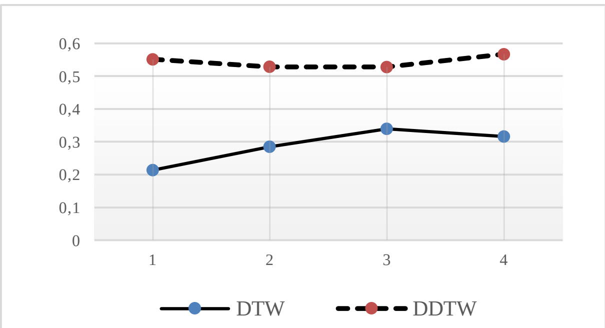


Fig. 8. Dynamics of change in the u_k

Regarding recognition methods using WT and FT, it should be noted that they are highly satisfactory in terms of compliance with criterion C_4 in the presence of a larger number of RP. This is confirmed by the corresponding values of the degradation coefficients u_3 and u_4 presented in Table 9.

Further, the question arises: is there a dependence of the degradation coefficients u_k on the method of artificial formation of image series, i.e., on the way the images are moved? To answer this question, we form new image series $P_2=\{p_{20}, p_{21}, p_{22}, p_{23}\}$ by sequentially shifting the base image from left to right down the hypotenuse, i.e., simultaneously one step to the right and one step down (Fig. 9).

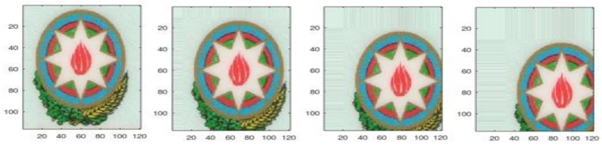


Fig. 9. Artificial series of images P_2

After feature extraction and segmentation, for example, in size 3×3, the series of 4 images is formed (Fig. 10), simultaneously shifted 2 steps to the right and 2 steps down.

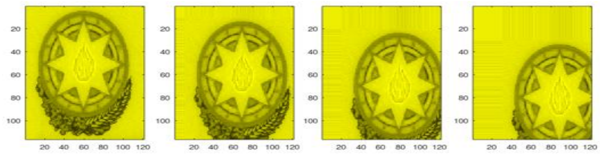


Fig. 10. The series of images p_{2j} (j=0÷3) obtained after feature extraction and segmentation

Fig. 11 shows the set of corresponding regular signals $Q_2=\{q_{20}, q_{21}, q_{22}, q_{23}\}$ with the total number of RP=1320, formed as a result of linearization of images p_{2j} (j=0÷3).

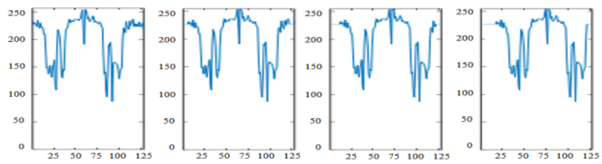


Fig. 11. Set of one-dimensional signals S_2

By analogy with the empirical analysis of the four recognition methods under consideration, carried out on the basis of two artificial series of images formed by uniformly shifting the curves horizontally, the degradation coefficients are calculated for the fulfillment of criterion C_4. The following Tables 10-13 present the degradation coefficients calculated for four scenarios: 1) 3×3 segmentation, RP=1320; 2) segmentation 4×4, RP=750; 3) segmentation 5×5, RP=480; 4) segmentation 6×6, RP=320. In this case, along with

Q_2, the series of curves Q_4 is considered, obtained after linearization of images simultaneously shifted 4 steps to the right and 4 steps down.

Table 10. Compliance of recognition methods with criterion C_4: segmentation 3×3 and RP=1320

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.30481	0.14003	0.45941
DDTW	2	0.1321	0.083589	0.63277
WT	3	1.6132	2.3027	1.4274
FT	4	0.44596	0.47647	1.0684

Table 11. Compliance of recognition methods with criterion C_4: segmentation 4×4 and RP=750

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.33283	0.1715	0.51528
DDTW	2	0.12096	0.10248	0.84722
WT	3	0.36324	0.52341	1.4409
FT	4	0.48782	0.79146	1.6224

Table 12. Compliance of recognition methods with criterion C_4: segmentation 5×5 and RP=480

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.40747	0.18713	0.45924
DDTW	2	0.19786	0.063437	0.32061
WT	3	0.77575	0.49956	0.64396
FT	4	0.74637	1.1979	2

Table 13. Compliance of recognition methods with criterion C_4: segmentation 6×6 and RP=320

Method	k	G_k^2	G_k^4	u_k
DTW	1	0.49603	0.30228	0.6094
DDTW	2	0.27316	0.25313	0.92666
WT	3	2.0691	0.84003	0.40599
FT	4	0.77204	1.3843	1.793

The values of degradation coefficients reflecting the degree of satisfaction of criterion C_4 of the considered recognition methods using examples of artificial series of regular curves Q_2 and Q_4, formed after segmentation of images of sizes 3×3, 4×4, 5×5, 6×6, and when choosing the number of RP after linearization such as 1320, 750, 480 and 320 are summarized Table 14. For the DTW and DDTW methods, the dynamics of changes in the degradation coefficients are presented in Fig. 12.

Table 14. Values of degradation coefficients reflecting the satisfaction degree of methods relative to C_4

Method	Degradation coefficients u_k			
	Segmentation and RP			
	3×3, RP=1320	4×4, RP=750	5×5, RP=480	6×6, RP=320
DTW	0.45941	0.51528	0.45924	0.6094
DDTW	0.63277	0.84722	0.32061	0.92666
WT	1.4274	1.4409	0.64396	0.40599
FT	1.0684	1.6224	2	1.793

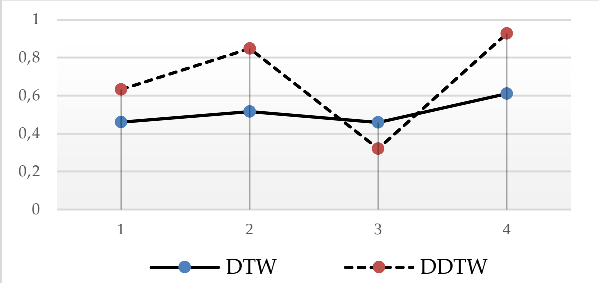


Fig. 12. Dynamics of change in the u_k

A comparative analysis of the data from Tables 9 and 14 shows that the values of the degradation coefficients u_{DTW} and u_{DDTW}, as indicators of their satisfaction with criterion C_4, on the series of images formed by successive simultaneous shifts to the right and downwards quickly move towards 1 (for example, for the DDTW method to the value of 0.92666) than on the series of images formed by successive horizontal shift to the right.

5. Conclusion

The article declared 4 criteria for assessing the adequacy of pattern recognition methods, two of which, namely criteria C_2 and C_4, were tested to evaluate the four most well-known methods using examples of artificial image series constructed by uniform displacement by equal steps, both horizontally and diagonally. The calculations performed using the C_4 criterion once again confirmed the priority of recognition methods based on WT and FT over the simpler methods DTW and DDTW. This was the basis for considering criterion C_4 as quite relevant.

An empirical analysis carried out using four recognition methods using the example of the image of the State Emblem of the Republic of Azerbaijan confirmed the consistency of the approach to image recognition based on the recognition of the corresponding one-dimensional signals using procedures for extracting recognition features and image segmentation. The author's algorithm for comparing recognition methods showed its greatest "convexity" using the example of an artificial family of one-dimensional signals obtained by simultaneously shifting curves relative to the etalon by equal distances horizontally and vertically.

The advantage of the approach proposed in the article was that the processes of transforming a color image into a monochromatic one, extracting recognition features and segmentation were performed in parallel, and this led to high-speed operation on a computer. At the same time, no difficulties were identified when implementing this approach. In addition, the author's recognition algorithm based on artificial families of curves used in the article made it possible to determine the best image displacement for evaluating recognition methods.

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