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APPLICATION OF THE HAMMING NETWORK TO THE CLASSIFICATION OF SURFACES AFTER ABRASIVE MACHINING

The use of artificial neural networks for modelling and inference about surface parameters is a more and more often undertaken research topic. Based on the analysis of the ranges of suitability of surface topography parameters, a variety of different parameters can be observed to identify surfaces with different features and different conditions of use. The issues of surface topography analysis and determination of surface condition after abrasive machining are of fundamental importance. Currently, when assessing the surface intended for interaction with the other surface, it is possible to use many surface evaluation parameters. Assigning the machined surface to the appropriate assessment group, especially in automated quality control systems, requires a preliminary surface classification. In this article Hamming's network was used for the surface classification along with modification of Hamming distance.

1. INTRODUCTION

The primary purpose of machining processes is to provide manufactured parts of the required performance characteristics, in accordance with their technological and functional assignment (Fig. 1).
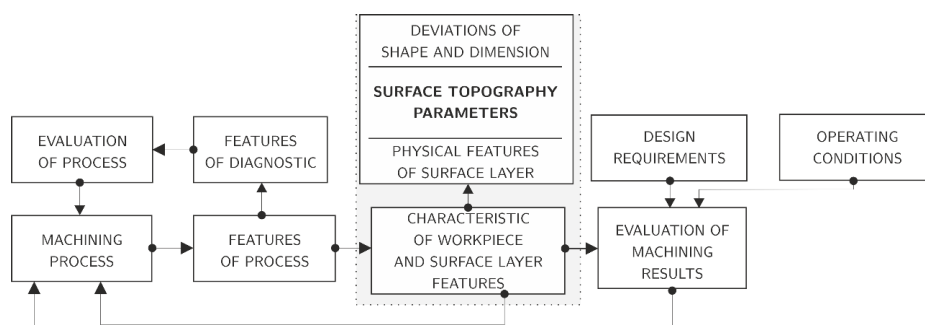

Fig. 1. The importance of surface metrology in providing the expected utilization features of engineering surfaces

Abrasive machining is usually the final operation of the production process [1–3]. The surface features after grinding can be influenced by many factors, among others: abrasive tool features [4-8], characteristics of machined material [9, 10], process kinematics [1, 2], properties of the cutting fluid and parameters the cooling process [11–14]. The geometric structure of the machined surface [10, 15–18] is the result of the overlap and accumulation of many elementary phenomena affecting the process of separating the material by abrasive grains. The variability and complexity of surface topography is a factor that significantly hampers its assessment and causes the result of the assessment to result from the processing of incomplete, uncertain and imprecise information.

Nowadays, in the evaluation of the surface quality intended for the cooperation with the other surfaces, it is possible to apply over three hundred standardized parameters (own calculations). Many parameters are treated selectively, for example considering the type of produced element [19–21]. Other parameters are not taken into account for various reasons, e.g. some parameters describing the surface state in a general way are often strongly correlated [22, 23], and some of them are simply incomprehensible or duplicate the content of information. Moreover, the evaluation of surface topography, for example after micro and nano-finishing, is difficult due to the low measuring range [2]. They often have sizes ranging from a few micrometers to several nanometers in the height of surface irregularities. With such a small range of surface elevation heights, more and more often in its correct description, they start to play their other features, such as the shape and distribution of the peaks and valleys of the surface [24, 25]. The microgeometry assessment here is much more complex and can be considered with different points of view, e.g. through the proper selection of evaluation parameters [20] or by creating new indicators for surface evaluation [26].

The analysis of the entire surface forming process and the methodology of its evaluation indicates that the surface character is different for various abrasive machining processes. The surface structure after grinding contains clear machining marks with underlined peaks and valleys. The surface structure after polishing does not contain expressive traces of machining (is isotropic) with often greater skewness with a large number of flat peaks. Such differentiation indicates that the use of the same set of parameters for such different surfaces is not only difficult, but also simply incorrect.

The procedures of the surface structure evaluation conducted up to now are don't suffice and are far away from modern measuring methods or optimal procedures. Therefore it is possible to define the main goal with which determining the membership of the analysed surface to the determined class, with aim of its further evaluation. To a correct classification of so complex objects is necessary to take into consideration following topics:

- classification criteria - how to set criteria for the classification to meet the needs of surface differentiation considering the conditions of their machining, utilization and functional features?
- classification methods - which classification method should be used to classify a surface with a predetermined utilization goal? What are the limitations of existing methods?
- classification procedure - how to make a surface classification with a minimum number of parameters and assign it to previously defined functional groups, eg surfaces of cooperating parts?

The application of artificial intelligence methods, especially for modelling and inference about surface parameters, is often a research topic [27–31]. For example, using the expert system presented in [32, 33], it is possible to generate surface topography with the expected parameters or even after specific processing. The system is based on a knowledge base containing such sources as standards, measurement data: profiles and surfaces, as well as other data.

The classification can be carried out using recursive networks, among which the Hamming network can be distinguished. Surface classification using the Hamming network [26, 34] requires the following steps:
- Defining a set of various applications and surface utilization conditions;
- Defining a set of parameters with high classification capability that are used to describe surface features;
- Determination of surface patterns based on normalized parameters that are determined for a set of test surfaces;
- Classification using the Hamming network, in which the area to be assessed can be assigned to predefined patterns.

2. SELECTION OF THE PARAMETERS FOR SURFACE EVALUATION

For the needs of the term, whether the surface meets the structural or utilizational requirements, it is necessary to select the parameters describing the topography of the surface. It is obvious that all parameters can not be used to assess surface topography. It is also inappropriate to use one parameter, which often happens in industrial practice.

The basis for the assessment of surface topography are the amplitude parameters, but they do not take into account all surface utilization features. For example, for two surfaces for the same value of the $Sz \cong 1$ parameter, their geometric structure can vary signify-cantly [35].

In this article, the authors propose this methodology for selecting parameters for surface evaluation:
- Determination of degree of cross-correlation in the set of parameters for a surface after various kinds of abrasive machining;
- Evaluation of classification ability of the parameters, based on new indicator W_{clas} [34];
- Determining the small-numerous set of the surface evaluation parameters - with the size of the set corresponding to the number of Miller [36].

The determination of a finished, little numerous set of the parameters for surface evaluation is a not easy task, which should be combination of an expert knowledge and the experiment results. As is shown in [35], in the testing set of surfaces with similar value of parameter Sz [37], the highest classification ability have the parameters which are collected in Table 1.

The number of Miller was set on 7, so to the further calculation will be taken into consideration parameters from P1 to P7.

Table 1. Parameters with the highest classification ability [35]

P1	$Pwh = s\left(\sqrt{P_w}/\sqrt{P_w}_{[h=0.2Sz}\right)$	–	relationship of the standard deviation from the square root of the surface peaks to the average surface of peaks
P2	$S5p$	–	five-point peak height
P3	Sdq	–	root mean square gradient of the scale-limited surface
P4	$Lwjd_{[h=0.2Sz}$	–	number of peaks to the unit of length
P5	Sv	–	maximum pit height
P6	Sp	–	maximum peak height
P7	Vm	–	material volume
P8	Vmp	–	peak material volume of the scale-limited surface
P9	$S10z$	–	ten-point height of surface (S5p+S5v)
P10	$S5v$	–	five-point pit height

2.1. NORMALIZATION OF THE PARAMETERS TO EVALUATION OF THE SURFACE TOPOGRAPHY

Normalization of parameters was carried out using the theory of fuzzy sets [38]. Normalized values of parameters form the basis for determining the membership of the surface being assessed. The range of normalized parameter values can be in the range [−1, 1], [−1, 0] or also [0, 1]. Parameter normalization makes an independent parameter value from the reference point (initial value). As a basis for normalization of a specific parameter, eg to the range [0, 1], the membership function shown in Fig. 2 can be assumed.
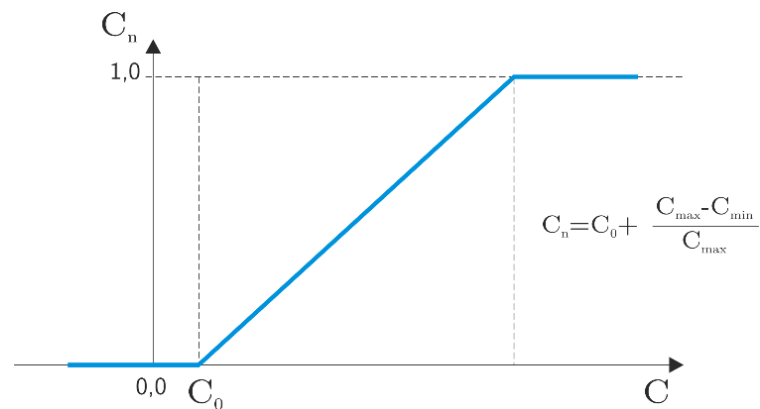

$$C_n = C_0 + \frac{C_{max} - C_{min}}{C_{max}}$$

Fig. 2. Schema of parameters normalization procedure using a fuzzy logic sets

2.2. PATTERNS OF THE SURFACE

The definition of a surface class may include the method of machining, its purpose of utilization, as well as other conditions depending on the needs. In this work, the abrasive machining method was used as the criterion for class definition:

- C1 – surfaces after grinding, machined with the use of grinding wheels with small grains size - surfaces characterizing small distances between the tool marks (narrow width of the motifs),

- C2 – surfaces after grinding, machined with the use of grinding wheels with a high porosity - surfaces with a large distances between the tool marks (large width of the motifs),
- C3 – surfaces after rough grinding,
- C4 – surfaces after finishing grinding - surfaces with the medium density of motifs,
- C5 – surfaces after microfinishing, with the use of the microfinishing films,
- C6 – surfaces after honing,
- C7 – surfaces after lapping,
- C8 – surfaces after polishing.

An example surface pattern of a specific class, e.g. C1, containing binary values corresponding to the range of normalized values of selected parameters is shown in the Fig. 3.
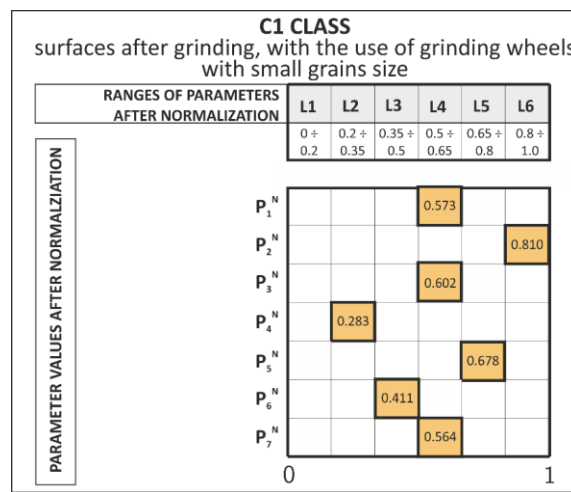

Fig. 3. Surface pattern corresponding to class C1

To determining binary patterns for individual classes of the surface, is necessary to extract the most often appearing values of the parameters (modal value), taking into account parameters with the highest classification ability (Table 2).

Table 2. The modal value of the parameters with the highest classification ability for earlier defined classes of surfaces

		The modal value of parameters						
		P1 [-]	P2 [µm]	P3 [-]	P4 [-]	P5 [µm]	P6 [µm]	P7 [µm³/µm²]
Class of the surface	C1	0.601	0.678	0.468	533	0.610	0.428	0.484
	C2	0.944	0.664	0.536	612	0.687	0.640	0.636
	C3	0.475	0.251	0.437	479	0.611	0.426	0.370
	C4	0.261	0.222	0.347	312	0.454	0.427	0.308
	C5	0.265	0.192	0.167	973	0.440	0.433	0.396
	C6	0.690	0.323	0.361	165	0.556	0.420	0.386
	C7	0.199	0.241	0.210	1797	0.318	0.297	0.164
	C8	0.256	0.249	0.161	35	0.381	0.367	0.173

The values of parameters (Table 2) need to be normalized, e.g. according to the described above methodology. The normalized parameters constitute patterns for each of the classes (Table 3).

Table 3. The normalized values of parameters with the highest classification ability for earlier defined classes of surfaces

		The normalized values of parameters						
		$P1^N$	$P2^N$	$P3^N$	$P4^N$	$P5^N$	$P6^N$	$P7^N$
Class of the surface	C1	0.573	0.810	0.602	0.283	0.678	0.411	0.564
	C2	0.970	0.791	0.712	0.116	0.805	0.773	0.784
	C3	0.426	0.198	0.551	0.429	0.681	0.407	0.398
	C4	0.178	0.156	0.403	0.577	0.422	0.409	0.307
	C5	0.183	0.113	0.110	0.597	0.399	0.419	0.435
	C6	0.676	0.301	0.427	0.176	0.589	0.398	0.421
	C7	0.107	0.183	0.179	0.890	0.198	0.187	0.097
	C8	0.173	0.195	0.100	0.169	0.301	0.307	0.110

The set of binary patterns defined for predefined classes is shown in the Fig. 4.
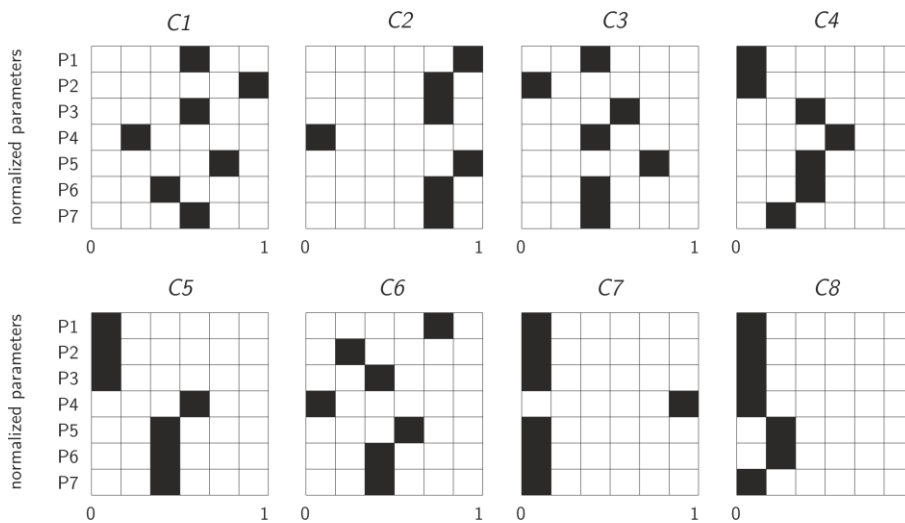

Fig. 4. Sample of binary patterns of the surface classes

3. CLASSIFICATION OF THE SURFACE AFTER ABRASIVE MACHINING USING THE HAMMING NETWORK

The Hamming network is a three-layer recurrent network and its structure is based on the Hopfield network [39]. The classification using the Hamming network consists in minimizing the Hamming distance of the input vector from the coded vectors (learning patterns). Classification of bipolar n-bit input vectors x, resulting in those patterns that are closest to the input signal. The general scheme of Hamming's neural network is shown in Fig. 5.
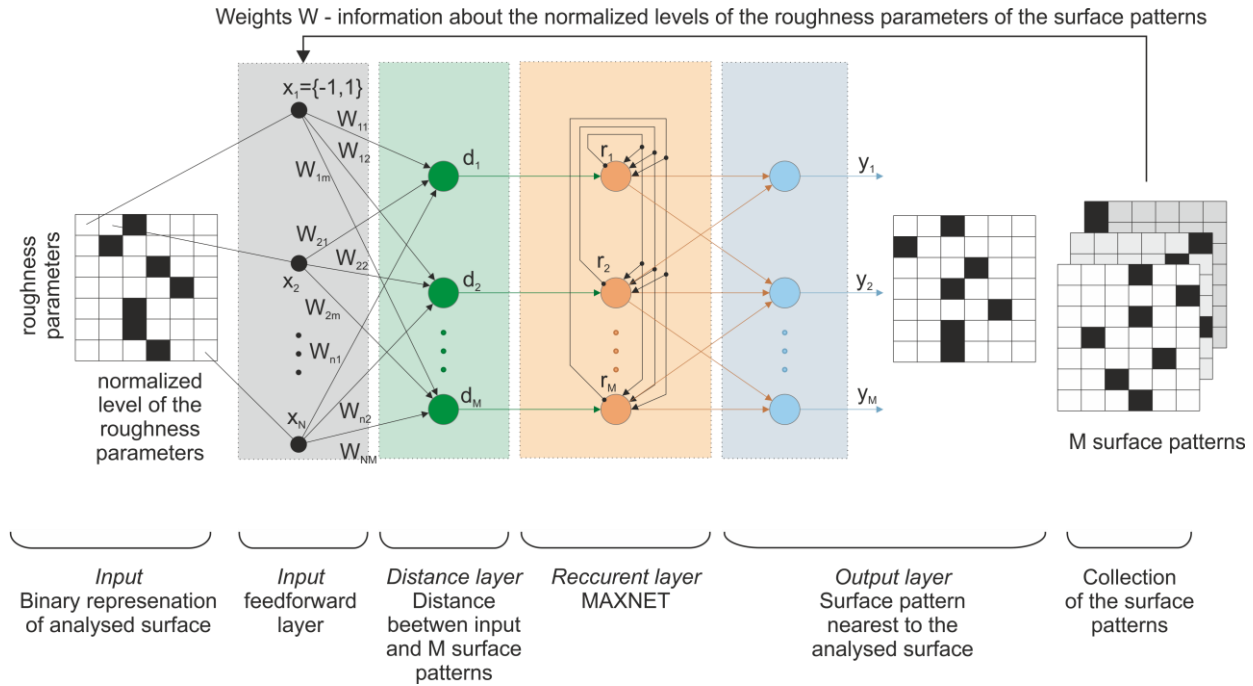
Fig. 5. The general scheme of the Hamming neural network to the classification of surface topography

The algorithm of determination of surface membership to the defined classes, runs in the several stages. First from them, is determination of typical parameter values of surfaces for chosen class:

$$x = [a_{s1} \cdots a_{sm}] \tag{1}$$

As typical are use an average parameters from the entire test set of the surfaces after the defined abrasive machining, which are presented in the matrix form:

$$P^{n \times m} = \begin{Bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{Bmatrix} = \begin{bmatrix} a_{p11} & a_{p12} & a_{p13} & a_{p14} & a_{p15} & a_{p16} & a_{p17} \\ a_{p21} & a_{p22} & a_{p23} & a_{p24} & a_{p25} & a_{p26} & a_{p27} \\ & & & \vdots & & & \\ a_{pn1} & a_{p12} & a_{p13} & a_{p14} & a_{p15} & a_{p16} & a_{pn7} \end{bmatrix} \tag{2}$$

where: n – number of patterns, m – number of parameters (7 parameters were assumed), x – the input vector of parameters for the chosen class of the surfaces, a_{pi} – parameter values of the surface after determined machining.

The second stage is implementation of normalization, of the typical parameters collection to the value from range $\langle -1, +1 \rangle$:

$$P \to T \in \langle -1, +1 \rangle \tag{3}$$

The normalized values of parameters present the input of the first layer of the Hamming network. The distance d between input signal and patterns is measured by using a Hamming distance [37, 39], that specifies the number of bits that differ the input signal from the patterns. The second layer called MAXNET is a recurrent layer, which suppress all

outputs besides these, which were the strongest in the first layer. The weights of neurons in MAXNET layer are constant. The initiation of weights in MAXNET layer aims to strengthen the signal of some neuron and the weakening of others. Neurons in this layer are working in the WTA system (Winner Takes All). The output of the first layer initiates the states in the second layer. The input vector x is deleted and it is starting iterative process in the MAXNET layer. This process continues to the moment, in which remained only nonzero neurons. The neurons with the nonzero values in the output signal represent the class, which may be an approximation of the input vector. The third layer, which is one-way layer, is a representation of the output vector associated with the input vector. Weights of the neurons in this layer are determined based on the input vector.

4. THE PROBLEM OF SURFACE CLASSIFICATION USING THE HAMMING DISTANCE

The surface classification after abrasive machining to the above-defined classes was made on the example of the surface (Fig. 6) of Ti6Al4V titanium alloy ground using an grinding wheel with 99A aluminium oxide grains with a nominal grain size of about 36 µm.
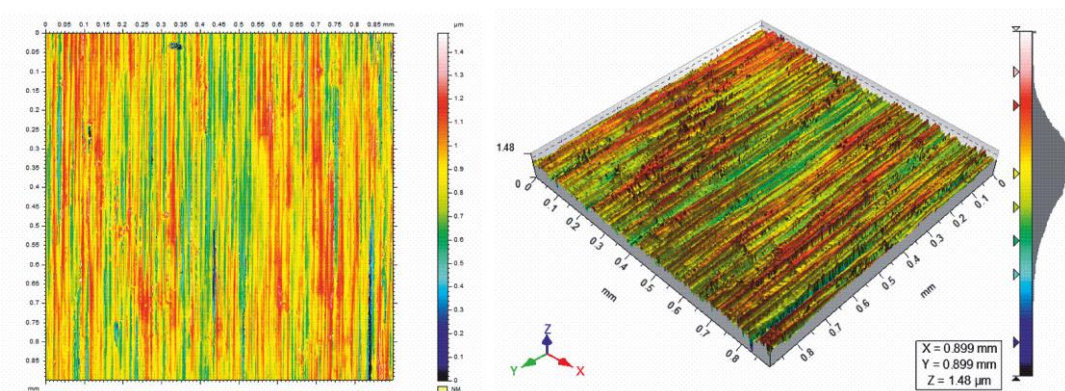

Fig. 6. Topography of the analysed surface

The first stage of proceeding in the surface classification is to determine the values of parameters from P1 to P7. The values of the selected parameters describing the surface topography are given below:

$$x = [0.47 \quad 0.3 \quad 0.45 \quad 890 \quad 0.44 \quad 0.41 \quad 0.52] \tag{4}$$

The second step is to normalize the set of parameters to a value in the range $P \rightarrow T \in \langle -1, +1 \rangle$, that give resultant vector of normalized values:

$$x = [0.42 \quad 0.27 \quad 0.57 \quad 0.77 \quad 0.41 \quad 0.39 \quad 0.61] \tag{5}$$

Based on the above, one can define a binary pattern of surface features (Fig. 7).
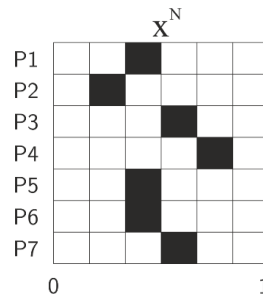
Fig. 7. Binary pattern of the analysed surface

The normalized values of the input parameters $\{x_n\}$, are the input on first layer of the neural network Hamming. The result of the first layer network is the Hamming distance between binary pattern of the evaluated surface and binary patterns of previously defined classes (C1–C8):

$$d = [8 \quad 14 \quad 8 \quad 10 \quad 10 \quad 10 \quad 14 \quad 14] \tag{6}$$

Hamming distance does not always allow to the distinguishing of the class to which the analysed surface may belong (Fig. 8).
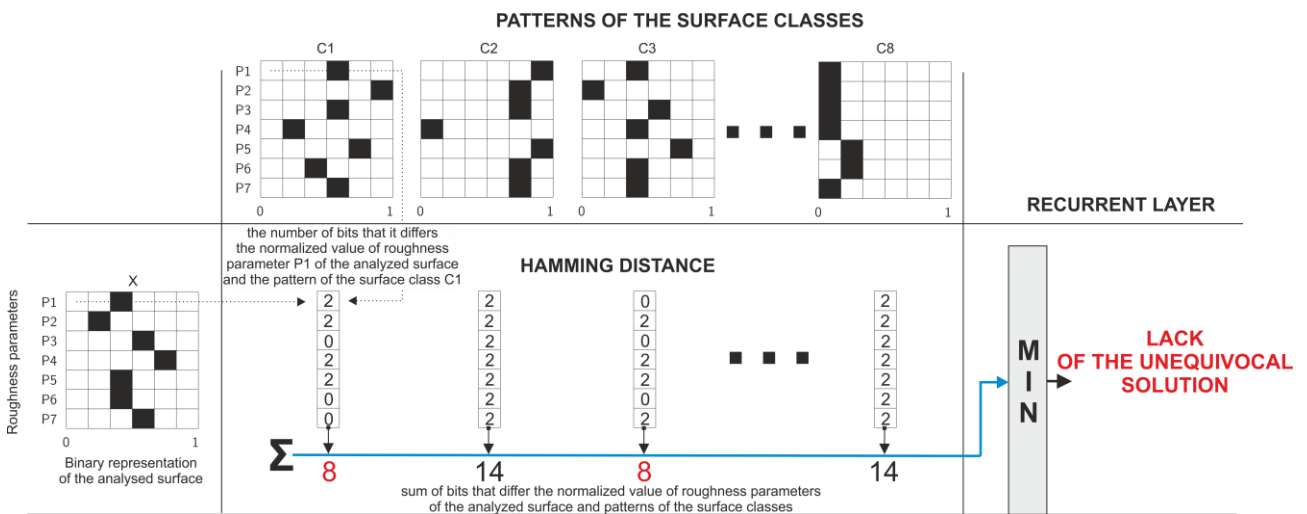

Fig. 8. Visualization of the problem to the determination of the Hamming distance, between the evaluated surface and the surface pattern classes

This is due to the fact that the Hamming distance is information about the number of compatible bits between the pattern definition and the input signal. In the case of non-compliance, the degree of discrepancy between the parameter values is not taken into account. The Hamming distance does not take into account the levels of individual normalized parameters, and thus the Hamming distance is independent of the number of levels used.

The location of the levels of a given parameter is an important information in determining the difference between the analysed surface pattern and the design classes. This is an important factor affecting the quality of classification. For example, if the parameter in

one of the classes is on the first level and in the second class, the same parameter is on the sixth level; this is a significant difference, indicating a significant diversity of these surfaces.

4.1. MODIFICATION OF THE HAMMING DISTANCE MEASURE

Taking into account the above conclusions, the Hamming distance measure was modified, taking into account the differences in the levels of a given normalized parameter. In order to present a new distance determination algorithm that replaces the Hamming distance, the binary surface pattern shown in Figure 7 was used.

Algorithm is as follows:
1. In the first step, the level (L1–L6) of the given input parameter describing the analysed surface is determined:

$$p = \begin{bmatrix} 3 & 2 & 4 & 5 & 3 & 3 & 4 \end{bmatrix} \tag{7}$$

The parameter levels for predefined classes are defined in a similar way:

$$cp = \begin{bmatrix} 4 & 6 & 4 & 2 & 5 & 3 & 4 \\ 6 & 5 & 5 & 1 & 6 & 5 & 5 \\ 3 & 1 & 4 & 3 & 5 & 3 & 3 \\ 1 & 1 & 3 & 4 & 3 & 3 & 2 \\ 1 & 1 & 1 & 4 & 3 & 3 & 3 \\ 5 & 2 & 3 & 1 & 4 & 3 & 3 \\ 1 & 1 & 1 & 6 & 1 & 1 & 1 \\ 1 & 1 & 1 & 1 & 2 & 2 & 1 \end{bmatrix} \tag{8}$$

2. Then, the absolute differences between the level of a given parameter for the analysed surface and previously defined classes are determined:

$$reldist = |cp - p| = \begin{bmatrix} 1 & 4 & 0 & 3 & 2 & 0 & 0 \\ 3 & 3 & 1 & 4 & 3 & 2 & 1 \\ 0 & 1 & 0 & 2 & 2 & 0 & 1 \\ 2 & 1 & 1 & 1 & 0 & 0 & 2 \\ 2 & 1 & 3 & 1 & 0 & 0 & 1 \\ 2 & 0 & 1 & 4 & 1 & 0 & 1 \\ 2 & 1 & 3 & 1 & 2 & 2 & 3 \\ 2 & 1 & 3 & 4 & 1 & 1 & 3 \end{bmatrix} \tag{9}$$

3. The final step is to determine the total distance value *dist*, between the surface pattern and the individual classes. Sums are counted in the horizontal direction (the sum of the row):

$$dist = \begin{bmatrix} 10 & 17 & 6 & 7 & 8 & 9 & 14 & 15 \end{bmatrix} \tag{10}$$

As can be seen, compared to the Hamming distance, in the case of a new distance measure, there are few cases of ambiguity description, which suggests that the new measure

properly will be support the classification process (Fig. 9), which is realized in the second layer of the Hamming neural network (MAXNET).
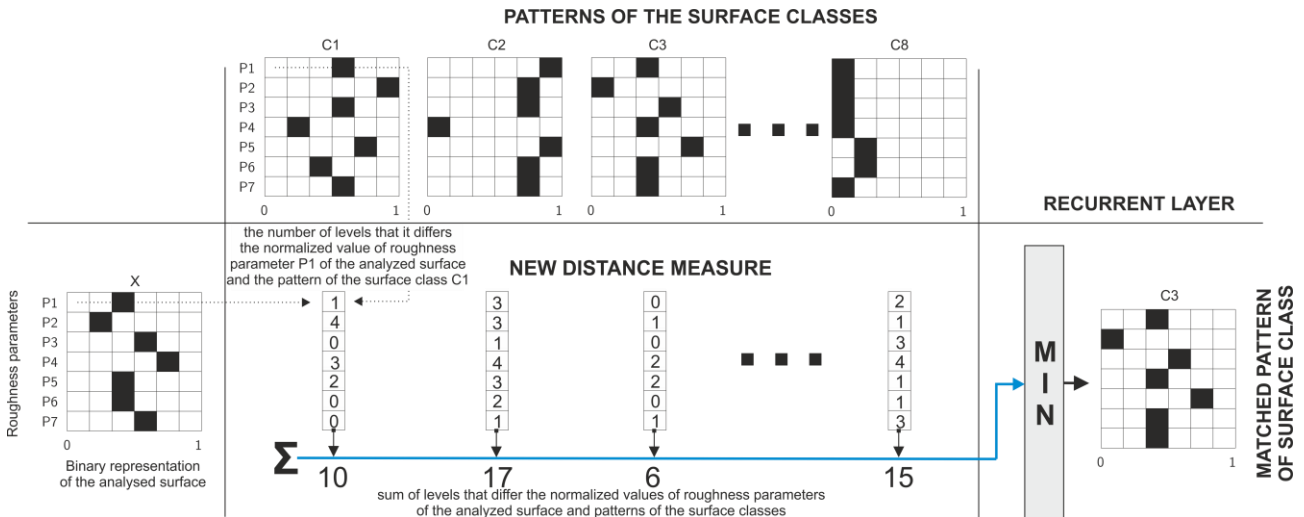

Fig. 9. Visualization of the new distance measure, between the evaluated surface and the surface pattern classes

5. SUMMARY AND CONCLUSIONS

The assessment of surface topography is a complex problem. It is particularly difficult to assess the surface after abrasive processes, the nature of which is highly stochastic compared to the deterministic surface structure, eg after turning or after milling. In industrial practice, the entire analysis of technical surfaces is carried out in accordance with one methodology and one parameter. The most commonly used parameter is Ra (arithmetic average of the surface profile values). This methodology is based on standardization documents and internal standards of companies that may be different for different countries and continents.

Approximately 300 different parameters can be used for surface evaluation. This significantly hinders the proper selection of parameters allowing for the description of the surface in relation to its application. This type of assessment can only be made using a complementary set of parameters with a low redundancy factor.

This paper uses the Hamming network to classify surfaces after abrasive machining. The modified Hamming measure was used to determine the distance, in the parameter space assumed to be complementary, between the analysed surface and previously defined patterns. The use of a modified distance function enables effective classification of the analysed surface. It should be noted, however, that the choice of the number of levels of a given surface evaluation parameter requires the user's knowledge and experience.

Using the Hamming network as a surface classifier seems to be a good direction in the development of new decision support systems. Such a system, used in the design of quality control systems, would lead to a clear choice of surfaces with assumed functional characteristics.

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