NEURAL NETWORK BASED QUALITY INCREASE OF SURFACE ROUGHNESS RESULTS IN FREE FORM MACHINING

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Abstract

This paper concerns with free form surface reorganization and assessment of free form model complexity, grouping particular surface geometrical properties within patch boundaries, using self organized Kohonen neural network (SOKN). Neural network proved itself as an adequate tool for considering all topological non-linearities appearing in free form surfaces. Coordinate values of point cloud distributed at a particular surface were used as a surface propertie's descriptor, which was led into SOKN where repersentative neurons for curvature, slope and spatial surface properties were established. On a basis of this approach, surface patch boundaries were reorganized in such a manner that finish machining strategies gave best possible surface roughness results. The patch boundaries were constructed regarding to the Gaussian and mean curvature, in order to achieve smooth transition between patches, and in this way preserve or even improve desired curve and surface continuities, (C2 and G2). It is shown that by reorganization of boundaries considering curvature, slope and spatial point distribution, the surface quality of machined free form surface is improved. Approach was experimentaly verified on 22 free form surface models which were reorganized by SOKN and machined with finish milling tool-path strategies. Results showed rather good improvement of mean surface roughness profile Ra for reorganized surfaces, when comparing to unorganized free form surfaces.

Keywords: Neural network (NN), Self organized Kohonen neural network (SOKN), free form surface, CAM, index of surface complexity (ISC)

Presenting Author's biography

Marjan Korošec. He received his Master degree in 1997 in Faculty of Mechanical engineering - Ljubljana in an area of of Automation of production systems. From 1998 to 1999 he was employed as an assistant in metal cutting Laboratory in Faculty of Mechanical Engineering in Ljubljana. From 1999 to 2001 he was a leader of research and development group in tool – shop company Saturnus – Ljubljana. From 2001 to 2003 he was an independent entrepreneur in an area of representation of CAD/CAM systems and solutions of environmental problematics. He received his Ph.D. degree in 2003 in Faculty of Mechanical Engineering Maribor, in an area of intelligent machining He works as an assistant in Laboratory for Computer added design – Lecad in Faculty of Mechanical engineering Ljubljana.

1 Introduction

In a last time many research effort has been made in an area of recognizing, extracting and optimal feature machining of 3D free form surfaces. Available free form surface recognition methods are mostly focused on recognition of geometrically simple machined objects, attempting to classify surfaces into planar regions, spherical regions, or surfaces of revolution. [1] The most common approach is based on signs of Gaussian and mean curvature, because this allows four surface types: convex, concave, and two types of saddle regions. Some methods also consider umbilic regions (those are regions in which the two principal curvatures are equal), and direction of surface normals in particular points. But these type of methods are not sufficient to classify free form surfaces for later machining features. Nowadays the purpose of automatic feature recognition techniques is mostly to generate feature recognition rules and hints from feature examples in accordance to a given feature taxonomy. There are also some automatic methods that combine the advantages of inductive and deductive techniques and are called hybrid, but they all work mainly on volume models. In this sphere one can also find the rule based approach, which relies on pattern recognition. [15] There exists also feature recognition technique based on the hint based approach which is mainly used for recognition of interacting features. [16, 17] The biggest lack of this methods is dificulty to define rules for all conceivable feature configuration or expand an existing rule while maintaining its consistency. As a lack of these informations, features are not well concatenated which has a reflection in a bad later finish machining results.

Because all geometric and technological properties of complex free form surface are changing continuously and relations between them are mostly non-linear, it is hard to predict them, and this is also one of the reasons why SOKN is beeing used to overbridge this problems. [2] The SOKN based on point cloud inputs enables dynamically free form surface boundaries reorganization and therefore contributes to improved surface roughness results in finishing tool path strategies.

2 Neural network approach

General neural network approach employs two types of algorithms to train the network, supervised and unsupervised learning. Aplications of supervised learning are reported in [18,19] The NN is trained to recognize some geometrical and topological patterns that are specific for a given feature. So there must be available a set of predefined set of feature classes. The benefit of this approach is that system could be growing and extending easily with adding new features into training data base. At the same time it should be noted that NN deals only with numerical inputs, that are not always sufficient to represent geometrical and topological data stored in CAD models. Usually NN approach demands desired data file of features which must be prepared before training the network. Of course because of tiresome procedure of effectively recognizing free form features it is very hard to establish the appropriate desired file. To overcome this problem, the Kohonen structure of self organized NN is often used. [3] In this way the problem is elegant overcome by inputting strewed point cloud data directly into NN, which represents geometrical and topological free form surface properties.

2.1 Self-organized Neural networks

Self organized feature maps introduced by Kohonen were inspired by the meaningful organization of neurons in the cerebral cortex of the brain. Soma cells comprising a mental-level map are usually distributed over the entire nervous system. That's why self organized feature maps in a sense emulate the mental-level maps by evolving the intrinsic status of constituent neurons in response to outside stimuli. This network has a strong self-organizing ability which is used to predefine or organize many kinds of unordered data structures, like point cloud received with coordinate measuring machines, or with projection operation inside CAD systems. [4]

2.2 Arhitecture of Kohonen self organized neural network

The SOKN is structured as a two-layer network, consisting of one input layer and one output layer. Neurons on this layers are arranged into a 2-D array in which they are interconnected to each other. The number of output nodes is always a compromise between accuracy and effectiveness, mostly determined in a heuristic manner. The graphic presentation and the training procedure of SOKN is shown in Figure 1. [5]

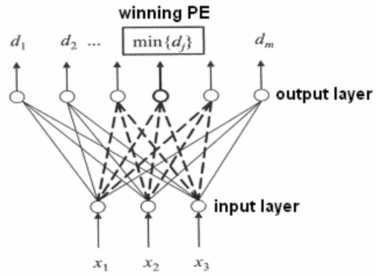


Fig. 1 The structure of the Kohonen neural network

The network uses so called soft competition map, where both the winning PE and its neighbours join in a learning process and they also participate on sharing winning input vectors. [6] Opposite to this kind of learning exists hard competition, where the winner neuron takes it all. The process of competition is initiated by some input stimuli within the output layer. In soft competition the winning share is distributed around the neighbouring neurons according to Gaussian distribution. As a result clusters of responses can be established. In our case clusters of strewed cloud points written in (x,y,z) manner are established. The collection of clusters forms what we call a feature map. The training procedure is the following: [7]

Initialize the weights w_j^s, (s = 1,2,3, j = 1,…,m). Let the training time t = 1

Present new input values (x_1, x_2, x_3), which are the coordinates of a randomly selected input point

Compute the Euclidian distance of all output nodes to the input point:

$$d_j = \sum_{s=1}^{3} \left(x_{si0} - w_j^s\right)^2, \quad j=1,\ldots,m \tag{1}$$

Compute the neighborhood $N(t) = (j_0, j_1, \ldots, j_k)$ of the winning node

Update the weights of the nodes in the neighbourhood for $\forall j \in N(t)$ by the following equation:

$$w_j^s(t+1) = w_j^s(t) + \eta(t)(x_{si_0} - w_j^s(t)) \tag{2}$$

where $\eta(t)$ is a gain term decreasing in time

Let $t = t+1$. Repeat all upper steps so many times, until the network is finally trained

The gain term which is decreasing in time is defined as Gaussian function, written in following form:

$$\eta(t) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}t^2} \tag{3}$$

SOKN is actually used three times. The first NN will be used for spatial presentation of geometric properties of particular free form surface. The coordinates of point cloud (x,y,z) are feed into input layer.

The second neural network is used for presentation of topological properties of free form surface. The Gaussian curvatures calculated in each point, are fed into the input layer.

The third NN is used for presentation of properties responsible for tangent and smooth surface patch connections. The slope gradient calculated in each point is fed into input layer.

Number of nodes in input layer is three, and every node in the second layer has three conections to which three weights are assigned. These weights are considered as spatial weight coordinates (x,y,z) of a particular point. The nodes in second layer are ordered in quadri-lateral grid, thus the corresponding spatial points Q_i also form a grid, which is not absolutely fixed, because the weights are changing all the time, but the topology of the moving grid is the same as of the quadrilateral (nodes) grid.

Intuitively, objects with complex shapes and huge sizes require larger numbers of clusters and surface patches to approximate the free form surface shape. In this paper the number of patches depends on object size and object complexity, which is assessed with the index of surface complexity (ISC) in the following equation: [10]

$$ISC = \left\{a \cdot \left[\sum gaussian\_curvature\right] + b \cdot \left[\sum slope\_gradient\right]\right\}^{\frac{\max R}{\min R}} \cdot \left(\frac{S}{V}\right)^{\frac{a\max}{a\min}}$$

coeficient a = f (workpiece hardness, surface roughness)

coeficient b = f (geometrical tolerance, final machining tolerance)

Find the winning node as the

S/V ……relation between area of machined surface and volume of removed material

maxR/minR……relation between maximum and minimum tool radius used for finishing

a_{max}/a_{min}……relation between maximum and minimum height of cut

The importance of particular components in equation (4) and their influences on results were established with the help of usual backpropagated multilayer neural network, which performed the sensitivity test, using gradient descent learning algorithm. This test showed influence (contribution) of every equation member on NN weight changes during training. On a basis of sensitivity test results and trials, the equation (4) was formed.

Next is presented the calculation of ISC for free form surface from figure 2.

a = 0.1 to 0.5 (hardness < 42HRc) and 0.5 to 1 (42HRc < hardness < 52HRc)

b = 1 for final finish machining, for the rest operations b< 1

ISC = $(0{,}25 \ . \ 37{,}66 \ 10^{-2} + 1 \ . \ 92{,}74)^{1.26} \ . \ 0{,}0476$ = 16,19

Relation between number of neurons and ISC is shown in Table 1.b

ISC	Number of neurons on output layer	Machining description
0 ÷ 7,5	0 - 5	very easy to machine

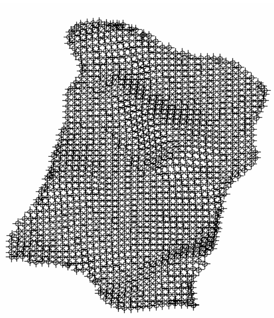
7,5 ÷ 15	6 - 10	easy machining
15 ÷ 22,5	11 - 15	usually machining
22,5 ÷ 30	16 - 20	relative complex
30 ÷ 37,5	21 - 30	complex machining
37,5 ÷ 45	31 - 40	very complex machining

Table 1: Index of surface complexity depends on number of neurons in output layer

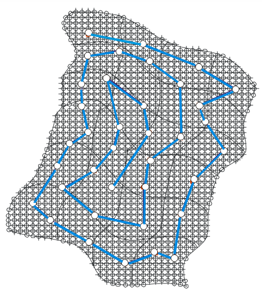
3 Example of free form surface reorganization, using Kohonen map

3.1 Spatial form shape presentation of free form surface

A model of projected points shown on figure 2a., written in (x,y,z) ASCII format is fed into input layer of Kohonen neural network. The SOKN substitutes the whole number of projected points with clusters, each containing the winning neuron and sub neurons, which shares the winning share, according to the Gaussian distribution. If the winning neurons are connected in anti clock wise direction, then a kind of string is formed as shown in figure 2b., and the shape of this string is now significant for this particular surface and describes all spatial properties of this free form surface.



a)



b)

Fig 2. Projected point cloud in free form surface (a) and winning neurons organized in a string form (b)

Organization, arrangement and number of winning neurons on a surface, is possible to link with the ISC, and respectively in the next step with the quality of machined surface. Relation is shown in figure 3. 1342 projected points from figure 2a, are reduced to 37 PE, maintaining complete geometrical relations from the input layer. Kohonen map found 37 central neurons, which completely describe the spatial shape properties of the surface. So these center areas should be considered when the milling path strategy will be chosen, and when the main technological parameters will be established. Because some central neuron areas were partly covered among themselves, or the same points were delivered to the different neuron centers, only one point was left in such a case, and it was added to the central neuron, which covered a larger area.

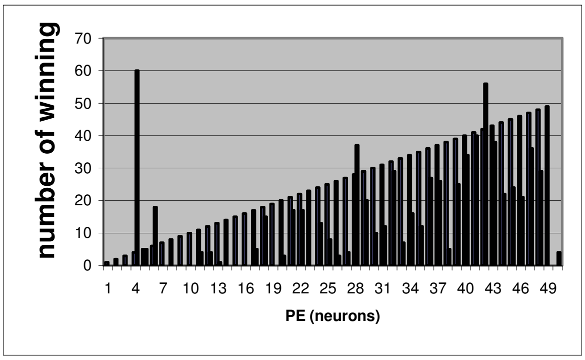


Figure 3. Frequency of winning for 37 neurons

It is obvious from figure 3., that the neuron number 4 which has won 60 times, neuron number 28 which won 37 times and neuron number 42 which won 56 times, are the absolute favorites. From 49 neurons used on the output layer of SOKN, only 37 were reported to get at least one victory or more, while 12 neurons never won. Neurons who never won, are called death neurons, which emerged because there was too many neurons on the output axon. But after they are identified and excluded, they became harmless.

3.2 Gaussian curvature presentation of free form surface

The benefit of presentation of curvature map with SOKN is mainly in very smart forming of point curvature clusters, which can give us a very good review of cluster interlacement and therefore describes zones which are very important and favourable for forming patch boundaries at later machining strategies inside CAM system. Areas which are recognized with SOKN as particulary significant according to their curvature changes, and ave very strong influence on a radial and tangential acceleration of milling tool. [8,10]

The Gaussian curvature which is considered in point M, is defined as:

$$K = \frac{1}{R_1 . R_2} \quad \text{where} \qquad (5)$$

R_1,R_2…..maximum and minimum main curve radius of normal cross-section of surface in point M. General three different cases are distinguished on a free form model:

K>0, R_1 in R_2 have the same sign, it means that the entire surface is located on the same side of tangential plane. These points are called eliptical points, and the form of surface is spherical.

K<0, R_1 in R_2 have different sign, it means that tangent plane in point M intersects the surface. The surface has a form of saddle and is very inconvenient for machining, because the embrace angle of milling tool increases or respectively changes during the machining process.

K=0, R_1 in $R_2 = \infty$, These points are called parabolic valley points.

After all Gaussian curvature cluster values were uncoded from curvature space into spatial space, the curvature clusters with their boundaries formed with Kohonen neural network were formed as shown in figure 4. The cluster areas are already settled up, after the redundant zones which made unions and which also included duplicated winning neurons are left out. The borders of neighbourhoods and location of winning neurons were established with the help of Hinton diagram inside Neurosolution software, after the positions in Hinton diagram are decoded. The central neurons are shown exactly, since the individual cluster borders are known, because for every central neuron 8 neighbourhood neurons could be found, and for every neighbourhood neuron, 8 new border neurons are detected. Therefore central neuron boundaries could be made, as shown in figure 4. [9]

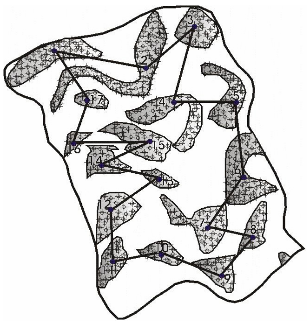


Fig 4. Curvature clusters with their central neurons formed with Kohonen neural network

There are 17 curvature clusters formed on this particular surface, with their winning neuron shown as line junctions on figure 4. The shape of every cluster area is formed according to a winning distribution of the central neuron. When all central winning neurons or processing elements (PE) are connected together with a straight lines, the charcteristic string is formed, as shown in figure 4. The shape of band string could be used for later surface curvature properties description, and for comparison of these properties between different surfaces.

Also in this case it was found that there exists a strong relation between the number of neurons in output layer and ISC (index of surface complexity). [10]

3.3 Analysis extended to more comprehensive free form surface data base

To achieve more reliable results considering average profile of surface roughness Ra in reorganized surfaces, all procedure was checked on 22 free form models, including point cloud model from figure 2., which serves as an example for detail explanation of procedure.

The same algorithm which was shown in chapter 3.1 and 3.2 was performed on 21 free form surfaces, taken from tool-shoop company which produced dies and inserts for injection moulding tools in car industry. Relations for clustering curvature properties to neuron number in SOKN is shown in figure 5.

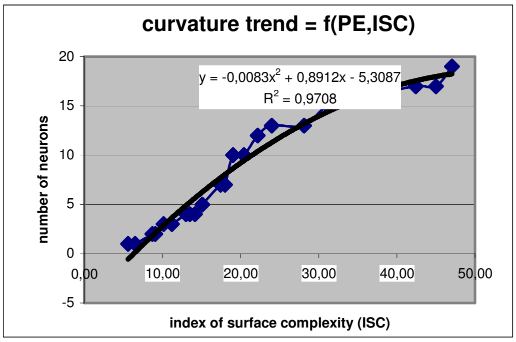


Fig 5. Trend of curve for number of neurons on output layer in dependence of ISC (index of surface complexity) for 22 free form models

It is noticed that for different free form surface models, also different trends of curves are gained. The curvature trend curve in figure 5. is significant for our 22 models which were used in presented case. When the other group of models is used, then curve with another trend would appear. So on a basis of these curve trends, the hardness or easiness for machining could be concluded in advance, which is very useful information for department of production planning in any tool-shop company. Going one step further, the comparison for different families of free form surfaces could be made when comparing trend of these curves. It was also found in [11,13] that the number of neurons and the value of ISC is in relation with the number of milling tool-path strategies when finish operation is performed.

3.4 Clustering with Voronoi tesselation, using winning neurons (PE's)

An unsupervised technique that groups data according to similarity (which also implies considering what is dissimilar) is called Voronoi tessellation. This operation is also commonly called clustering in pattern recognition. From the point of view of the input space, clustering is dividing the space in local regions, each of which is associated with an output neuron (PE). The input space is divided as a honeycomb. The weights of each PE represent points in the input space called prototype vectors. If we join prototype vectors by a line, its perpendicular bisector will meet other bisectors forming a division that resembles a honeycomb, shown in figure 7. So the Voronoi diagram is used to differentiate between clusters in the input space on a basis of winning neurons (PE), determined by Kohonen NN. Each PE in figure 6. corresponds to a cluster or region of input space, where it is the closest to all the points in that particular region. Honeycomb in figure 6. is formed for curvature clusters which are shown in figure 4.

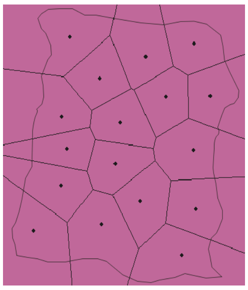


Fig 6. Patches, made by Voronoi tessellation, with their center neurons for Gaussian curvatures, for surface model from figure 2.

Clustering is therefore a continuous-to-discrete transformation. The ultimate requirement of this process is to have a set of clusters that minimizes the distance between the centers of each cluster and the input that falls into each cluster. [9,12]

Slope gradient presentation of free form surface with Kohonen neural network

The slope gradient (tangent) was calculated in every single point, and values were fed into input layer of Kohonen neural network. Topology of neural network is the same as in former case. As a result, seven winning neurons were established, and the other were found to be dead neurons, without winning any competition. Figure 7. presents 7 winning neurons, which have attracted in their neighbourhood similar values for slope gradient, on a (x,y) working plane. The values extend from minimum slope = -0.8574 to maximum slope = 0.7713.

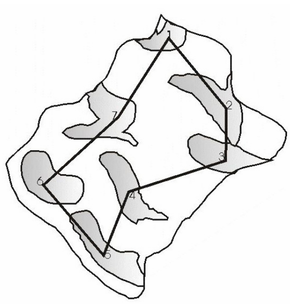


Fig 7. Clusters of slope gradients formed with Kohonen neural network, shown in spatial space, for sample model presented in figure 2.

It was shown in [12,13], that slope gradient areas have significant influence on a feedrate of milling tool.

3.5.1 Analysis of slope gradient clusters

All informations about the particular free form surface organized with Kohonen neural network, and data needed to efectively represent the free form surface are now coded and reduced, and as such very suitable for manipulation and storing a large amounts of geometrical data considering investigated surfaces. It is also reasonable to form the millimg patch boundaries in similar shape, like the clusters boundaries, because in this case the transition from one patch to another can easily satisfy the C_1 and C_2 continuities. So patch boundaries can be reorganized in a way to be very suitable for NURBS machining. This access was shown in former contribution [12] . As in curvature clusters, also in this case a relation between number of neurons and ISC can be recorded. To get more reliable results, this relationship was plotted for the entire group of all 22 free form surface models as in case of curvature investigation. Results are shown in figure 8.

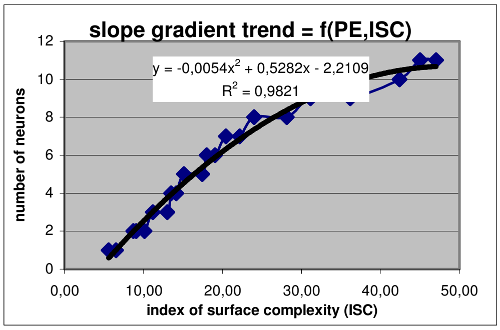


Fig 8. Trend of curve for number of neurons on output layer in dependence of ISC (index of surface complexity) for 22 free form models

After computing the ISC, it can be concluded on necessary number of neurons in Kohonen output layer, in dependence from curvature or slope gradient in particular free form surface model.

4 Surface roughness results of machined free form surfaces, reorganized via SOKN

Presented in figure 9. is comparison of average mean surface roughness profile Ra, for all 22 free form surfaces machined by proposed reorganized boundaries, and Ra for surfaces machined in a conventional manner. Whole family of 22 free form surfaces is prepared in such a manner, that it covers complete ISC index range, as presented in Table 1. The ISC index is explained in greater detail in reference [12]. All free form surfaces were machined with free form milling path strategies in three different CAM systems, using a 42 HRC steel material. Finishing operation was performed in 5 axis

Mikron UCP 1000 CNC machine, using 4 to 8mm diameter ball mill cuters. Results of Ra against ISC range is shown in figure 9a and 9b. Milling tool-path finishing strategies were formed by following the so called string from figure 4., using "finish projection machining" considering the form of string, directly on a patches obtained by Voronoi diagram. It is also possible to perform "surface finishing" tool-path strategy on Voronoi patches, but patches should be machined in successive order, following the curvature cluster string for every of 22 free form surfaces. This task could be easily done in every modern CAM system, which allows to define its own tool-path motion, by projection of particular polyline or spline directly on a free form surface.

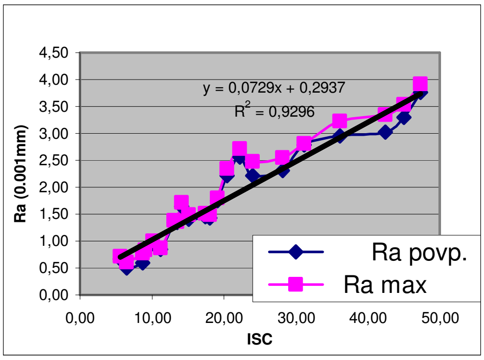


Fig 9a.: Average value of Ra for all 22 models (Ra = 1,81 µm)

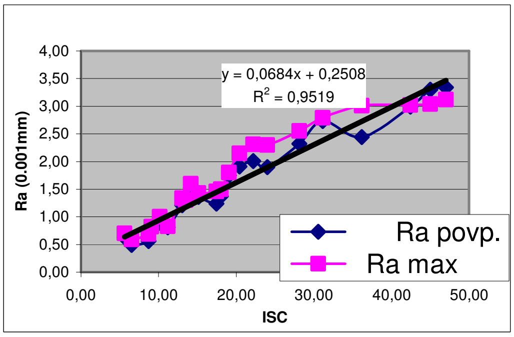


Fig 9b.: Average value of Ra for all 22 models with reorganized patch boundaries via SOKN (Ra = 1,42 µm)

It is noticeable how Ra is growing according to raised ISC. It was shown on a tool-shop floor, that ISC interacts also with applied feed rate during free form machining. Models reorganized by SOKN shows surface roughness profile results improved for about 20% to 25%. It must be pointed out, that this holds only for finishing milling path strategies, where at semifinish the sourface roughness it is not important as primary goal. On a basis of clustering of spatial point clouds with SOKN, boundary patches are constructed, whose machining parameters are much more stabile and consistent, and therefore give better surface roughness results. It is also possible to determine an optimal entry and exit cutting tool points, considering regions established with SOKN, which also contributes to better quality of machined surface. Detailed research is still going on, and interaction results of ISC with other technological parameters like cutting speed, cutting depth etc. will be shown in future papers.

5 Conclusions and further research work

It was shown how the free form surfaces and their main topological and geometrical properties can be interpreted through Kohonen maps.. Boundaries of the patches on a surface can be optimized according to the optimal technological parameters, when the areas obtained with clustering in Kohonen maps are considered. It was also shown that surface roughness mean profile Ra is improved almost for about 25% when using reorganized boundaries on a basis of SOKN. The other benefit which was not shown in this paper is that once the central neurons (PE) and curvature trends are known, it is also possible to go in opposite direction, therefore infer on and determine the complete spatial, slope and curvature point clouds. So it is usable for surface properties presentation as well as for data compression of very complex free form surfaces, which otherwise are very hard to transform into CAM features.

The influence of the winning neurons in a spatial, slope gradient and curvature Kohonen maps on a milling tool-path strategy inside CAM system and their influence on a main technological parameters should be further investigated. The form in which Kohonen maps present all crucial surface properties is also very suitable for using it as an input to the other type of neural network topologies, otherwise it is very hard to present surface shape as an input into neural network. In these directions further research work will be proceeded.

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