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MICROMECHANICS AS A TESTBED FOR EVALUATION OF ARTIFICIAL INTELLIGENCE METHODS IN MANUFACTURING

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Методы искусственного интеллекта (ИИ) могут использоваться для улучшения систем автоматизации в производственных процессах. Однако применение этих методов в промышленности не получило широкого распространения из-за высокой стоимости экспериментов с системами ИИ в обычных производственных системах. Для снижения стоимости экспериментов в этой области нами разработано специальное микромеханическое оборудование, аналогичное обычному механическому оборудованию, но гораздо меньших размеров и, следовательно, более низкой стоимости. Это оборудование может быть использовано для оценки различных методов ИИ простым и недорогим способом. Методы, которые показывают хорошие результаты, могут быть переданы в промышленность путем соответствующего масштабирования. Кратко описаны прототипы микрооборудования, имеющих низкую стоимость, и некоторых методов ИИ, которые могут быть оценены с такими прототипами.

Методи штучного інтелекту (ШІ) можуть використовуватися для поліпшення систем автоматизації у виробничих процесах. Однак застосування цих методів у промисловості не набуло широкого поширення через високу вартість експериментів з системами ШІ у звичайних виробничих системах. Для зниження вартості експериментів у цій галузі нами розроблено спеціальне мікромеханічне обладнання, аналогічне звичайному механічному обладнанню, але набагато менших розмірів і, отже, більш низької вартості. Це обладнання може бути використано для оцінки різних методів ШІ простим і недорогим способом. Методи, які показують хороші результати, можуть бути передані в промисловість шляхом відповідного масштабування. Ця Коротко описано прототипи мікрооборудованія, що мають низьку вартість, та деяких методів ШІ, які можуть бути оцінені з такими прототипами.

INTRODUCTION

Many Artificial Intelligence methods were proposed in the 40–60s of 20th century. Among them very interesting approach was proposed by Canadian researcher D.O. Hebb [1]. D.O. Hebb supposed that the neurons of human brain form the assemblies during the learning process. Each assembly can correspond to an object, property or concept of external world. The neurons of an assembly have many excitatory connections, so if any part of the assembly is excited, all the other neurons of this assembly are excited due to excitatory connections. Such behavior of the neural assemblies permitted explanation of associative processes that occurs in the brain. The problem was to ensure the stability of this assembly neural network. At the first time D.O. Hebb and his progeny P. Milner could not solve it.

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In 1965 N.M. Amosov [2] proposed his interpretation of human brain functioning. All the objects, relations, concepts, etc. were presented in his interpretation as i-models (information models) that had the level of activity similar to excitation level of Hebbian neural assembly. In the process of thinking the activity of i-models was changed because i-models were connected with excitatory and inhibitory connections. To ensure the stability of the whole network N.M. Amosov proposed special System of Reinforcement and Inhibition (SRI) that found the most active i-model and increased its activity level decreasing activity level of other i-models. After short time period the activity of selected i-model decreases due to tiredness, and SRI finds new most active i-model repeating the process of reinforcement and inhibition. This scheme allowed creation of associative chains that can be observed in the process of associative thinking of real mind.

N.M. Amosov continued his investigations in this area and published the results in different books (see for example [2–8]).

In the department of Biological cybernetics of Cybernetics Institute of Academy of Sciences of Ukraine headed by N.M. Amosov we always tried to encounter practical applications of his investigations. We made some prototypes of mobile robots that were controlled with "i-model" networks, we developed some special neuro-computers for simulation of these networks and so on. However, computers and electronics of that time were not sufficiently developed for this purpose. At present we continue some of the works of this type in UNAM (National Autonomous University of Mexico) using new technical possibilities.

DEVELOPMENT OF MICROMECHANICAL EQUIPMENT

The main idea of low cost micromechanical equipment manufacturing is the following: each new micro device should be manufactured by micro machine tools and micro assembly devices which have the sizes that are comparable to the sizes of the work pieces to be manufactured. For example, if a new micro device contains a shaft with diameter 0.2 mm and length 0.8 mm then this shaft is to be manufactured with a lathe that has overall size of 4 mm × 4 mm × 4 mm. In most cases a lathe of this size will automatically have tolerances that coincide with the specifications of the shaft. The main errors of machine tools that originate from thermal expansions, vibrations, elastic deformations, etc. are proportional to the machine tool sizes [9]. Therefore, if we manufacture a micro shaft with a lathe of size 250 times smaller than the size of a conventional lathe then we can also decrease the tolerances 250 times. The low end conventional lathe of size 1000 mm × 1000 mm × 1000 mm has tolerances of about 0.05 mm. Therefore, our micro lathe should have tolerances of about 0.0002 mm. That is sufficient for most applications of micro shafts. A low end conventional lathe has a low cost. Our micro lathe should have an even lower cost due to low consumption of materials, work area and energy.

To examine the possibility of production of micro machine tools with low cost components we have developed two prototypes of micro machine tools with the cost of the components less than $100 [10–12]. One of these prototypes is presented in Fig. 1.

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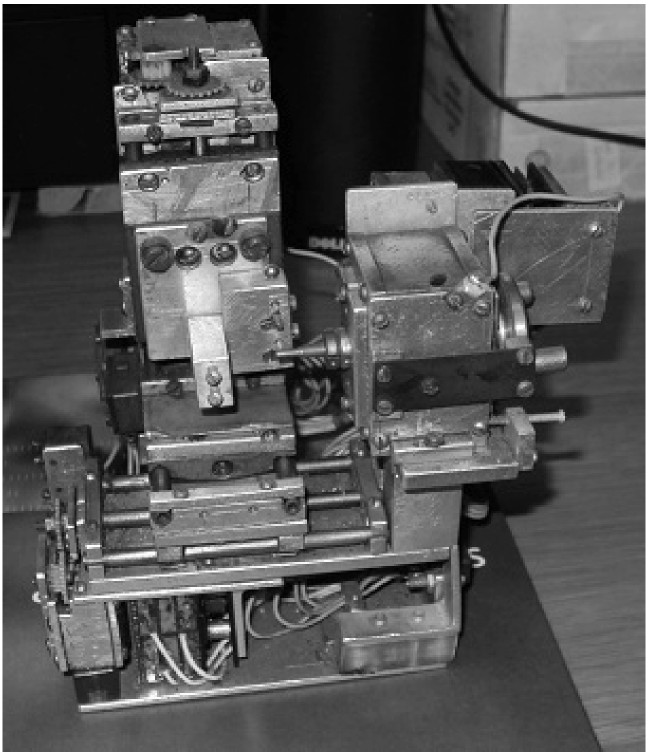

Fig.1. Prototype of micro machine tool

The experiments with these prototypes have proved their ability to manufacture micro work pieces similar to the ones produced with an expensive Japanese micro lathe. Japanese researchers turned the brass needle with diameter 0.05mm to show the possibility of micro turning [13]. They used a micro lathe which has expensive components with a total cost of more than a thousand dollars. We repeated their results (Fig. 2) our with a micro machine tool which has low cost components with a total cost of less than a hundred dollars.

Fig. 2. Brass needle with diameter of 50μm and examples of work pieces manufactured with the first micro machine tool prototype

The first one is the shaft of 0.05 mm diameter. Other two are examples manufactured by our micro machine tool to show its possibilities. The first work piece is a gear with a worm that can be used in micro transmissions. The second work piece is a screw that can be used in gas filters of “micro cyclone” type.

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To obtain high precision in low cost microequipment we use adaptive algorithms based on computer vision systems. The first problem that we dealt with was the problem of micro assembly. To introduce a pin into a hole it is necessary to place them with close tolerances. Low cost microequipment does not permit such collocation without adaptive algorithms. A neural network image recognition system was developed to recognize the mutual pin-hole position.

The different types of neural networks are used in industrial electronics to investigate and built the control systems [14], to compensate the disturbance and friction in hard disk drives [15], to diagnose the faults for interior permanent-magnet synchronous motor drives [16], to construct and investigate an adaptive speed controller [17].

To investigate the performance of this system we created an image database that contains 441 images with different mutual positions of pin and hole. For this purpose we developed the prototype [18, 19]. In our system we used one web camera and four light sources. The shadows from the light sources (Fig. 3) permit us to obtain the 3-D position of the pin relative to the hole. We used a neural classifier LIRA (Limited Receptive Area) to recognize this position [20]. The input for our neural classifier is an image that is a combination of four images of one pin-hole position that correspond to different light sources. This image was processed and the contours were extracted (Fig. 4). The output of the neural classifier gives the *X* and *Y* coordinates of pin-hole position.

If the position is recognized with a precision of 0.1mm then the recognition rate is sufficiently high: 99.5% for the *X* coordinate and 89.9% for the *Y* coordinate.

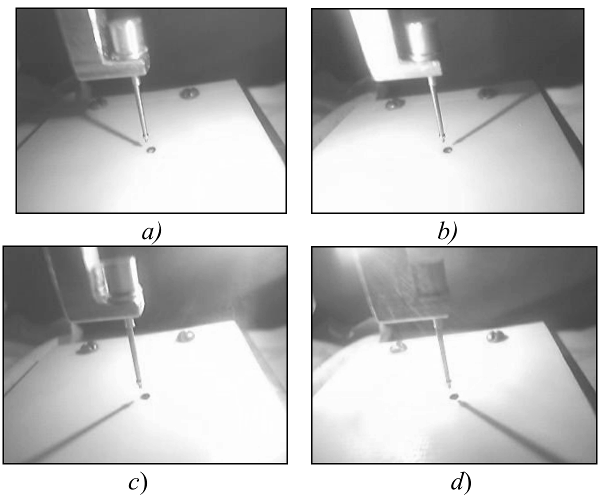

Fig. 3. Examples of images obtained with four light sources

Another task where we used neural networks was the task of shape recognition [21]. Low cost microequipment does not permit precise allocation of the cutters in the CNC lathe. The errors of cutter allocation cause erroneous shapes of manufactured work pieces. Examples of such erroneous shapes are presented in Fig. 5.

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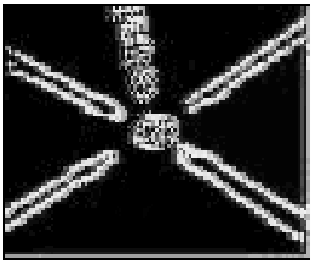

Fig. 4. Example of the LIRA neural classifier input image

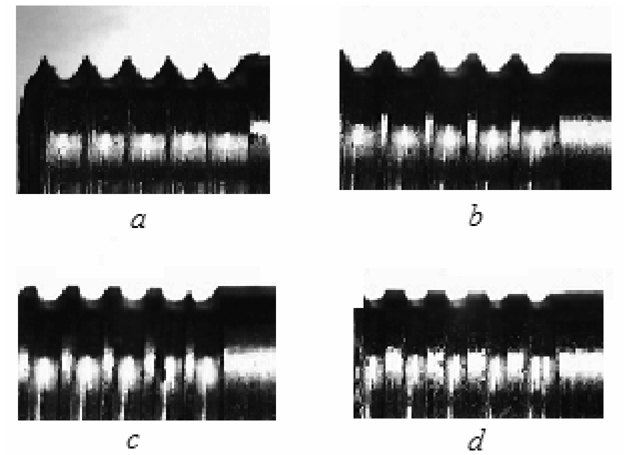

Fig. 5. Examples of initial images

Two cutters are used to manufacture the screws shown in Fig. 5. One cutter is used for the outer diameter treatment and the other cutter is used for the thread treatment. If the relative position of the cutters is not correct, then the thread can have an erroneous shape (Fig. 5, *a*, *c*, *d*). It is difficult to estimate the relative position of the cutters directly. That is why we propose to estimate the correctness of the relative position of the cutters by the shape of the first screw that is manufactured with the lathe. If the distance between the second cutter and the screw axis is smaller than necessary then the shape of the thread will be as the one presented in Fig. 5, *a*. If this distance is larger than necessary then the shape of the thread will be as the one presented in Fig. 5, *c*, *d*. We manufactured 40 screws with diameter 3 mm with the CNC-lathe. Ten screws were produced with the correct position of the thread cutter (Fig. 5, *b*). Thirty screws were produced with erroneous positions of the cutter. Ten of them (Fig. 5, *a*) had the distance between the cutter and the screw axis 0.1 mm smaller than was necessary. Ten screws (Fig. 5, *c*) were produced with the distance 0.1 mm larger than necessary and the remaining ten (Fig. 5, *d*) were produced with the distance 0.2 mm larger than necessary. We created an image database of these screws using a web camera mounted on an optical microscope. Five randomly selected images from each group of screws were used for neural classifier training and the other five were used for neural classifier testing.

The best result in shape recognition obtained with the neural classifier PCNC (Permutation Coding Neural Classifier) was 92.5% [21].

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The third task was the recognition of mechanically treated metal surface textures. This problem is crucial for systems of surface quality inspection and systems that have to recognize position and orientation of complex work pieces in the task of assembly of micromechanical devices.

To test the LIRA neural classifier based recognition system we created a specific image database of four texture types that correspond to metal surfaces after: milling, polishing with sandpaper, turning with lathe and polishing with file (Fig. 6). 20 grayscale images were taken for each class.

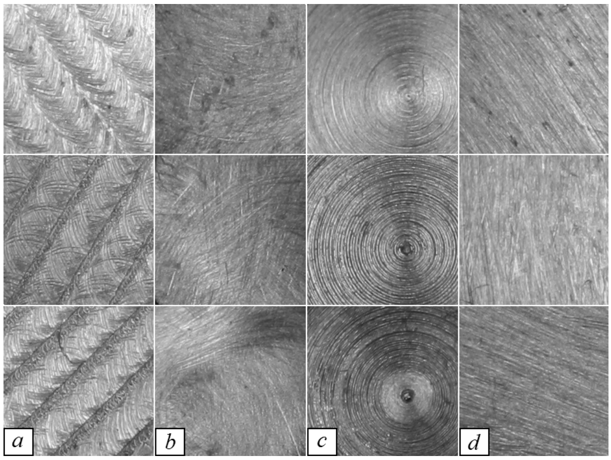

Fig. 6. Examples of metal surfaces (columns) after: *a* — milling, *b* — polishing with sandpaper, *c* — turning with lathe, *d* — polishing with file

We randomly divided these 20 images in half into the training and test sets. It can be seen that different lighting conditions greatly affect the grayscale properties of the images. The textures may also be arbitrarily oriented and not centered perfectly. Metal surfaces may have minor defects and dust. All these image properties correspond to the conditions of a real industrial environment and make the texture recognition task more complicated. The promising recognition rate of 99.7% was obtained in this task.

ASSEMBLY NEURAL NETWORKS

At present we are working on more sophisticated systems to control the cutting process. We intend to analyze the potential of distributed knowledge representation (DKR) to solve some problems of adaptive cutting with micromachine tools.

Distributed knowledge representation was proposed in the famous book of D.O. Hebb “The Organization of Behavior. A Neuropsychological Theory” [1]. The simplest technical realization of this type of knowledge representation was made by K. Steinbuch, D.J. Willshaw and others [22, 23]. In 1978 V. Braitenberg [24] described mechanisms that permit the realization of DKR as a neural assembly structure. Further development of DKR was made in the works of G. Palm [25] and his colleagues [26]. In these works each concept is represented not by a specific symbol (or identifier) but by a specific vector $V(\nu_1, \ldots, \nu_N)$ which represents the activity of neurons $A(a_1, \ldots, a_N)$. The matrix M of connections between neurons A is

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to be created in order to obtain an associative memory. To store some concept in the associative memory it is necessary to increase the weights of connections between the neurons that have high activity. After this operation such neurons form a subset of the set of all neurons. This subset is termed a neural assembly. A neural assembly has the property to become active as a whole when its part becomes active. This assembly corresponds to the concept to be memorized. To examine if a concept is stored in the memory it is necessary to obtain the following product:

$$V^{*} = V M \,. \tag{1}$$

If vectors V^{*} and V are strongly correlated then vector V is stored in memory and if they are weakly correlated then vector V is not stored in the memory. Several DKR systems that use only vectors but not the connection matrices were developed by Plate [27, 28]. We believe that systems that use connection matrices are more flexible and therefore we use these systems in our work.

In this work we use a binary vector V where the components of this vector are equal to either 0 or 1. Another property of vector V is the following: the number of components that are equal to 1 (unit components) is considerably smaller than the number of components that are equal to 0 (zero components). Since sometimes this type of vector is termed rare we term vector V as a rare binary code of the concept. Such codes have many advantages. It was shown that the storage capacity (the number of different vectors that can be stored in associative memory) of rare vectors is much larger than the storage capacity of the vectors that have approximately the same number of unit and zero components. For example, the number of vectors stored in the Hopfield neural network is approximately $0.14N$, where N is the number of neurons. The vectors of the Hopfield neural network have approximately equal numbers of unit and zero components. If vector V has $Log\ N$ unit components then the storage capacity increases up to $0.5N^2 / Log$. This is a large storage capacity but such vectors are sensitive to the noise. To obtain more stable codes of the concepts it is necessary to use rare binary codes that have more than $Log\ N$ unit components. We performed experiments to estimate the number of unit components needed to assure the stable concept coding and to obtain large storage capacity.

To test the storage capacity of associative memory we performed the following experiments. We randomly create Q neural assemblies coded in the form of the binary vectors. Each binary vector contains N components (the size of the neural network). m components are equal to 1 and N-m components are equal to 0, that is m is the size of the neural assembly. We stored all these vectors in associative memory creating the matrix M of connections between the neurons. After that we tested the capacity of associative memory to restore stored vectors with the following vector restoring procedure:

1) Randomly select $0.5m$ of unit components of initial binary vector and set them equal to 0. Randomly select $0.5m$ of zero components and set them equal to 1. These operations correspond to 50% noise.

2) Multiply this binary vector by the matrix of neuron connections M to obtain non binary excitations of the neurons (neuron inputs).

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3) Create the binary vector of neuron outputs in the following way: select $1.1m$ of the most excited neurons and set their outputs equal to 1; the outputs of the rest of the neurons set equal to 0.

4) Repeat five times steps 2 and 3.

5) Compare the resulting binary vector with the initial binary vector. If positions of $0.9m$ of unit components in the resulting binary vector coincide with the positions of unit components in the initial binary vector, then we say that the noisy initial binary vector is restored correctly, otherwise we say that it is not restored.

We performed experiments with different values of parameters Q and m. We say that the experiment is successful if more than $0.999Q$ of initial vectors are restored correctly.

The results of these experiments are presented in Tab. 1.

TABLE 1

The number of assemblies successfully restored from associative memory

Size of neural network *N*	**Assembly size, *m***					
	10	**20**	**40**	**80**	**120**	**160**
6000	0	2000	6000	3500	1500	800
12000	0	24000	20000	20000	10000	6000
24000	4000	14000	80000	95000	60000	34000

In these experiments the size of the neural network was set equal to 6 000, 12 000 and 24 000 neurons. The optimal number of unit components in the binary vector without noise (in accordance with [26]) was calculated for $N = 24\,000$ in the as follows: $\log_2(24\,000) = 14.55$, $\log_2(12\,000) = 13.55$, $\log_2(6\,000) = 12.55$. Optimal size of noisy vectors (Tab. 1) for $N = 24\,000$ is equal to 80.

ASSEMBLY REPRESENTATION OF OBJECTS AND THEIR PROPERTIES

Each object in the assembly neural network can be represented with its own neural assembly coded in the form of the binary vector. The interrelation between the neural assembly and its binary code V is the following: all the components of vector V that correspond to the neurons that belong to the current neural assembly are set equal to 1 while the rest of the components of vector V are set equal to 0.

For example, let a micro shaft be described with a binary vector V_{shaft}, a micro screw — with a different binary vector V_{screw}. Let the length of the micro work piece be represented with different vectors V_{long}, V_{medium}, V_{short} and the diameter of the micro work piece be represented by vectors V_{thick}, V_{thin}. To describe the micro object we have to combine the name of the object with its properties. In terms of our example, to obtain the vector V_{object1} that corresponds to the object 1 which is a long thin shaft we perform the following operations:

First, we calculate

$$V^*_{\text{object1}} = V_{\text{shaft}} \cup V_{\text{long}} \cup V_{\text{thin}} \tag{2}$$

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where V^*_{object1} is a raw binary vector that corresponds to the object 1, $\bigcup$ is a bitwise disjunction of binary vectors.

Second, we perform the binding procedure [29, 30] for binary vector V^*_{object1}. Let $\neg V^*_{\text{object1}}$ be the bitwise negation of vector V^*_{object1} and $C_\lrcorner$ be a vector C shifted to the right by one bit with the last bit transferred to the first bit (cyclic shift). In the set of equations (3) we present the binding procedure. To perform this procedure we assign the value of vector V^*_{object1} to the new vector C, and then we make a cyclic shift of vector C and perform bitwise conjunction (&) with negation of vector V^*_{object1}, assigning the result to vector C. We perform this operation R times and assign the resulting vector to vector V_{object1}.

$$\begin{aligned} &C = V^*_{\text{object1}};\\ &C = (C_\lrcorner)\&(\neg V^*_{\text{object1}}),\\ &\ldots \qquad (R \text{ times})\\ &C = (C_\lrcorner)\&(\neg V^*_{\text{object1}}).\\ &V_{\text{object1}} = C; \end{aligned} \tag{3}$$

The first purpose of the binding procedure is to reduce the number of active neurons in the neural assembly, thus increasing the computation speed. The second purpose of this procedure is to bind the properties of the object to its name. This property is useful for recognition of the object with its properties. There are many different algorithms proposed for the binding procedure.

This type of representation permits us to create the measure of the property. For example, if the shaft is neither very thick nor thin, we can form the assembly that would consist of λm neurons that belong to the assembly "thick" and $(1-\lambda)m$ neurons that belong to the assembly "thin", where λ is taken within the range $(0,1)$. Such representation is similar to fuzzy representation but it is not the same.

It is possible to use this method of concept representation to associate the cause with the effect. In this case we can develop a neural network system for prediction of behavior of a micromechanical device. This prediction can be used to avoid defects in different processes of material treatment. In the following section we present an example of a mechanical problem that can be solved using this prediction.

RESONANCE AVOIDANCE

Mechanical treatment of metal surfaces frequently suffers from resonant oscillations of either work piece or cutting tool. These oscillations result in a decrease of both surface quality and work piece precision. The resonant oscillations appear when the rigidity of the system Machine tool — Tool — Work piece is insufficient. In Fig. 7, *a* an example of the work piece that was manufactured without resonant oscillations is presented. For comparison, an example of the work piece that was manufactured with resonant oscillations is presented in Fig. 7, *b*.

Reliable prediction of resonant oscillations is crucial for optimal control of cutting processes under resonant oscillation conditions. Many factors affect the appearance of resonance oscillations, and this fact makes assembly neural networks

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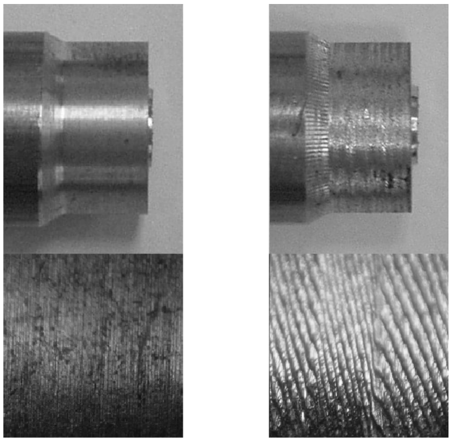
the perfect candidate for their prediction due to the ability to associate the cause with the effect.



a *b*

Fig. 7. Example of the work piece and its surface: *a* — without resonant oscillations, *b* — with resonant oscillations

CONCLUSION

Several neural network algorithms were proposed to improve automation systems in manufacturing processes. These algorithms were tested with specific micromechanical equipment, similar to conventional mechanical equipment, but of much smaller sizes and therefore of lower cost. We consider this equipment a good testbed for examination of the AI algorithms that can be used to increase the level of automation of manufacturing processes. One of the problems we intend to examine is the prediction of resonant oscillations in the process of turning and avoidance of resonance vibrations using assembly neural networks.

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