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KLASYFIKACJA RUCHÓW ROBOTA PRZEMYSŁOWEGO NA PODSTAWIE DANYCH Z MONITORINGU DRGAŃ Z WYKORZYSTANIEM SIECI NEURONOWEJ LSTM

Streszczenie: Niniejszy artykuł koncentruje się na problemie zastosowania sieci neuronowych LSTM do klasyfikacji parametrów ruchu robota przemysłowego FANUC na podstawie zmierzonych sygnatur drgań. W artykule przedstawiono perspektywy wykorzystania sieci neuronowych LSTM do diagnostyki wibroakustycznej i zadań predykcyjnych w przemyśle.

Słowa kluczowe: LSTM Sieć neuronowa, wibrodiagnostyka, FANUC, konserwacja predykcyjna

CLASSIFICATION OF INDUSTRIAL ROBOT MOVEMENTS BASED ON VIBRATION MONITORING DATA USING LSTM NEURAL NETWORK

Summary: The present paper focuses on the problem of applying LSTM neural networks to classify the motion parameters of a FANUC industrial robot based on measured vibration signatures. The paper hints at the perspectives of using LSTM neural networks for vibrodiagnostics and predictive maintenance tasks in the industry.

Keywords: LSTM neural network, vibrodiagnostics, FANUC, predictive maintenance

1. Introduction

At present set high demands on the productivity and efficiency of production and all its components. Reducing downtimes and optimizing all production processes to reduce machine shutdowns are effective ways to improve production productivity.

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At the same time, continuous operation in harsh conditions leads to deterioration and degradation of components and also increases the probability of failure of any device. In this case, industrial robots are not an exception.

Traditional maintenance strategies based on scheduled inspections often fail to detect incipient failures or abnormalities, resulting in unplanned downtime and increased maintenance costs. That is why proactive measures are required to ensure continuous performance.

Condition monitoring is an effective tool for obtaining data on the current status of equipment without directly interfering with the production process. An attractive parameter that can be easily measured in condition monitoring is vibration signatures. By analysing vibration patterns, anomalies such as mechanical deterioration, misalignment, or component failures can be detected long before they develop into critical problems [1, 2]. That's why vibrodiagnostics has become a powerful predictive maintenance tool that offers a real-time view of the mechanical condition of industrial robots.

At the same time, in addition to traditional statistical methods for evaluating and processing these signals, methods, and algorithms that are based on artificial intelligence are gaining popularity because of their ability to track and evaluate non-linear dependencies of the parameters being analysed. Moreover, these methods provide not only sufficient data on the equipment but also an estimate of the possible causes of failures [3].

The present paper deals with the classification of FANUC industrial robot motion parameters based on measured vibration signatures using the LSTM neural network to apply the obtained knowledge for predictive maintenance tasks.

2. Technical diagnostics

Technical diagnostics is defined as the process of determining the current state of the equipment to detect faults in its operation, mainly by objective evaluation of the measurement results of certain technical parameters using measurement technology [4]. In addition, technical diagnostics is an important part of any production process. The complexity of the design and control of modern production equipment places high demands on the qualifications of the operating personnel and thus increases the level of responsibility placed on the production process. This can also be seen as an increase in costs and losses caused by operational errors and machine downtime.

Vibrodiagnostics is a method of technical diagnostics based on the measurement of vibrations caused by the movements of machine parts, the collision of machine parts with each other, and the misalignment of rotating machine components. Vibration provides information on the condition of the machine, the dynamic stresses on the machine, and the effects of the environment [1, 2]. Each piece of equipment in production has individual waveforms of vibration, and it is the change in these waveforms typically indicates the occurrence of a failure or excessive deterioration of one of the components of the equipment [2].

2.1 Vibration sensing

Different sensors and encoders are used for sensing vibration data of individual parts of the equipment. Sensors often differ in sensitivity, measuring range, data sensing principle, sensed magnitude, and other parameters.
To select suitable sensors, it is necessary to specify the requirements in accordance with the task to be solved, the design of the equipment to be monitored, the possibility of sensor placement, the surrounding environment, etc.
The most commonly used sensors for vibrodiagnostics are:
- Deflection (path) sensors
- Speed sensors
- Acceleration sensors (accelerometers)

2.2 The causes of vibrations

Vibrations are generated during the operation of every machine and equipment, even if their technical condition is suitable. Vibration is caused by the operation of the machine, the inhomogeneity of the individual components, and the final precision of the manufacture and assembly of the individual components [1].
However, the fault manifests itself by adding its vibration signal to the normal condition. In this case, the essence of fault detection is to separate the fault signal from the normal operation of the equipment. This signal is amplified at the time of the fault pattern and is amplified as the fault grows. In addition to the fault signal itself, adverse vibrations can subsequently lead to more rapid fault development in other parts of the equipment [1]. The main causes of adverse vibration include:
- Imbalance of rotating components
- Mechanical deterioration or damage to machine parts
- Mechanical loosening of connections
- Defects in gears or electric motors
- Change in size and shape of components due to thermal stresses
- Excessive loading

Technical diagnostics act as a preventive tool to avoid breakdowns, relying on serviceability prognosis methods. The purpose of technical diagnostics is to determine the current state of the equipment or system being investigated. That is to say, to obtain the necessary amount of data on the condition of the equipment to establish the correct diagnosis for the deployment of preventive actions to maintain the operable condition of the equipment.

3. Artificial intelligence for vibrodiagnostics tasks

Machine learning technologies and artificial intelligence are finding applications in several areas of industry, and the field of predictive maintenance (PdM) is no exception. Artificial intelligence in predictive maintenance can adjust routine maintenance activities to the needs of individual equipment, contributing to the determination of dependencies between individual parameters in multi-parametric diagnostics and the analysis of historical data. Furthermore, artificial intelligence facilities are applied in predictive tasks for the determination of the lifetime forecast of a production system[5].

By deploying condition monitoring, sensors, data analysis, and machine learning algorithms, PdM can provide real-time information on the performance of various system components. By collecting and analyzing data on the vibrations generated, early detection of equipment warning signs is possible, allowing the remaining lifetime of the equipment to be predicted and, based on this, alerting those responsible to the necessity of performing maintenance.

Artificial neural networks are a widespread method of artificial intelligence nowadays. The ability of neural networks to learn from the data presented to them is a key feature that allows them to approximate arbitrary functions and reveal dependencies between data. The ability to generalize knowledge allows neural networks to respond correctly even to unknown input data. Due to this feature, neural networks are widely applied to solve tasks based on classification, regression, cluster analysis, and prediction problems [6].

4. Motivation for the experiment

Industrial robots are an indispensable tool in today's manufacturing, increasing accuracy, efficiency, and productivity in a variety of industries. The initial goal of deploying industrial robots was to reduce the proportion of human labor in performing tasks in hazardous and harmful environments, but in modern manufacturing, the application area of industrial robots is much more extensive than just handling heavy products and also includes applications requiring high precision, such as machining, measuring, welding, etc.

In precision applications, it is important to maintain stable values for the performance criteria of the industrial robot. Therefore, early identification of changes in these parameters can prevent the occurrence of collision situations or the production of non-conforming products.

One of the possibilities is the continuous monitoring and identification of changes in these parameters in an unacceptable range, which allows the introduction of preventive measures before a fault state occurs.

For monitoring tasks, the principles of vibrodiagnostics are often used as there are proven methods for identifying faults of various types in the frequency spectrum. At the same time, artificial neural networks can learn in real-time from sensed data and take into account hidden non-linear dependencies between monitored parameters.

Hence, the objective of the proposed experiment is to verify the ability of the LSTM neural network to identify and classify the change in motion parameters (velocity) of the end effector of a Fanuc LR Mate 200iC industrial robot based on vibration sensing using an ADXL345 3-axial accelerometer.

5. Collection and processing of experimental data

During the measurement, the accelerometer was placed on the robot's end of robot's arm and the Arduino UNO programmable board for communication with the PC was attached to the robot's J4 joint. For data acquisition, it was decided to place the accelerometer on the end effector of the robot since the changes in the monitored parameter are most evident when the accelerometer itself moves. The orientation of the accelerometer concerning the robot's world coordinate system is shown in Fig. 1.

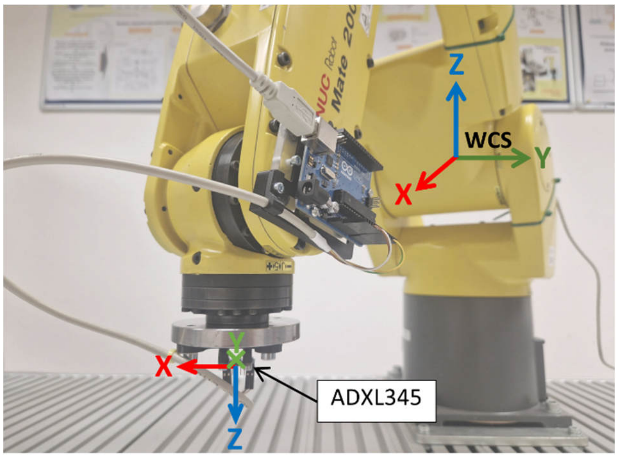

Figure 1. Location of accelerometer ADXL345

The measurement process itself consisted of a linear motion between points A and B (Fig. 2), at four velocity values: 100%, 75%, 50%, and 25% of the maximum linear velocity of 4000 mm/s, which can be defined in the robot program.

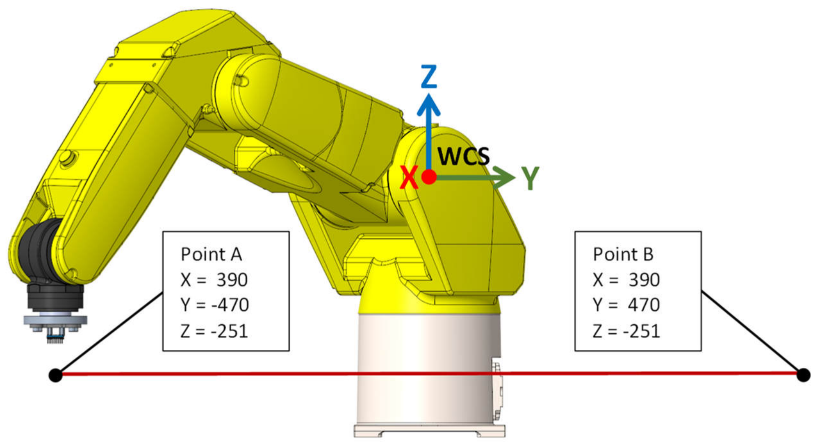

Figure 2. Location of the measurement path in the workspace of the industrial robot

For each velocity value, 60 repetitions were performed, recording acceleration values in all three axes and both directions of motion (from point A to point B and back). The length of the linear path (940 mm) and its location in the robot workspace follows from experiments carried out in the past [7], in connection with the issue of the influence of the robot calibration on its accuracy. All measurement conditions are listed in Table 1

Table 1. Measurement conditions

Position of measured path (X; Y; Z) relative to the WCS	380; -470; -251
Path length	940 mm
Coordinates of TCP (X; Y; Z)	0; 0; 74.65
Speed of TCP (mm/s)	4 000
Number of repetitions	× 60 for speed 100%; 75%; 50%; 25%
Running-in period before measurement (h)	2

The datasets for training and testing the subsequently designed neural network consist of 528 samples, each of which is represented by a matrix of size 3xN, where 3 represents the number of axes in which the vibration data were taken (X, Y, and Z axes) and N is the number of measurements in each axis for a particular sequence. The length of the sequence is varied for each sample in such a way that it contains the entire period for a single robot movement (from point A to point B or in the opposite direction). Each input sequence is assigned a categorical variable that represents the class to which each sequence belongs. The output classes are "Velocity 100%", "Velocity 75%", "Velocity 50%" and "Velocity 25%".

6. Proposed neural network

For the experiment, it was decided to use the so-called LSTM (Long Short Term Memory) neural network. It aims to learn to recognize and assign to a single class the change of motion parameters (velocity) of the end effector of the Fanuc LR Mate 200iC industrial robot based on the labeled sequential accelerometer data.
LSTM neural network is a type of neural network which have been designed to work with long-term dependencies. In the LSTM architecture, each neuron in the hidden layers is replaced by a memory cell. LSTM memory cells consist of different neural networks called gates. The gates control the interaction between memory blocks and decide which data to store or forget during training [8]. The process of data processing using recurrent LSTM cells is as follows:

- Input Gate: The input gate determines how much new input information is stored in the memory cell. It takes into account the current input and the previous hidden state. The input gate calculates a value between 0 and 1 for each element in the input, indicating the importance of that element for updating the cell state.
- Forgetting gate: this gate determines which information is not important and should be discarded from the memory cell. It takes into account the current input and the previous hidden state. Similar to the input gate, it calculates a value between 0 and 1 for each element in the input, which indicates the degree of importance of retaining the existing information.
- Cell state update: The state of the cell is stored in the LSTM memory. It is updated using the input and forgets gates. The cell state is updated by multiplying the value of the forget gate with the previous cell state and adding the product of the input gate value and the new input.

The structure of the proposed neural network is shown in Fig. 3.

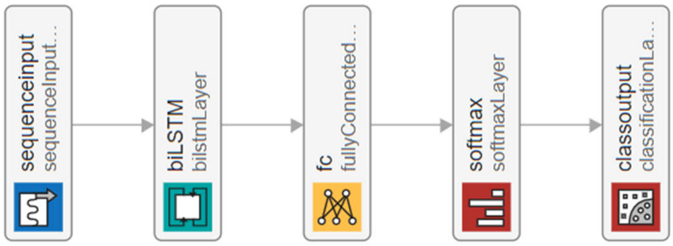

Figure 3. Proposed LSTM neural network

The neural network consists of a three-dimensional sequential input layer, followed by a hidden BiLSTM layer that contains 400 memory cells. The term BiLSTM means that each memory cell inherently is represented by two unidirectional LSTM cells, one of which processes the signal, in the forward direction, and the other - in the reverse direction. The use of the BiLSTM layer allows the proposed model to better understand and process data in both directions and thus achieve better results.
BiLSTM is followed by a fully connected layer which contains 4 neurons and prepares the output. Next follows a layer with SoftMax activation function that normalizes the output of the network to the probability distribution of the predicted output classes. The last layer is the classification layer, which arranges the input sequence data into a particular class based on the probability distribution of the sequence belonging to a particular class.

7. Network training and validation

For model training, a supervised learning method was used, which means that each input sequence was assigned a certain class (one of the possible movement speeds of the robot end effector). The collected data was distributed as follows: 80% of the data (384 labeled samples) was used for training the model and 20% of the data (144 samples), the classes for which are known.
The training was performed using the Adam optimization algorithm and was completed in 29 seconds after reaching the maximum specified number of epochs. The training progress is shown in Fig. 4.
After training the model, it was necessary to evaluate the accuracy of the model on validation data, i.e., data that were not part of the model training. In this way, it is possible to determine whether the trained model can generalize the sensed data to classify the measured vibration signatures. Subsequently, to evaluate the performance of the model, the accuracy of the model class prediction was expressed and a confusion matrix was constructed.
For classification tasks, the accuracy is the ratio of the number of correct predictions to the total number of predictions made by the model. Accuracy indicates the probability with which an object will be furnished to the correct class.

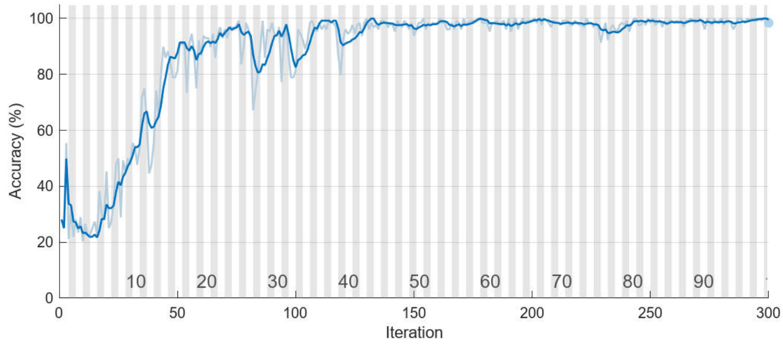

Figure 4. Training progress plot

The confusion matrix is a specific tool for judging the performance of a machine-learning model that is designed for classification tasks. Confusion matrix is a table that contains 4 possible states of predicted classes - True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). The confusion matrix is shown in Fig. 5.

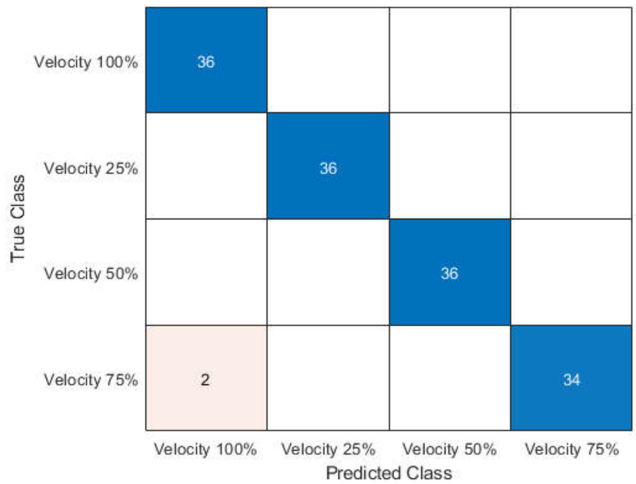

Figure 5. Confusion matrix

The size of the error matrix depends on the number of classes into which the trained model sorts the validation data. On the diagonal of the error matrix are the correct predictions of the trained model (marked in blue). In each cell of the matrix outside the diagonal, there are misclassified samples.

8. Results and discussion

As can be seen in Fig. 5, the proposed neural network model was able to correctly predict the class of 142 samples out of 144 samples. Confusion matrix also shows that the trained qualifier best identifies the categories of data corresponding to 100%, 50%, and 25% speeds. Two samples from the class "Velocity 75%" were incorrectly furnished to the class "Velocity 100%". The resulting accuracy is calculated using equation (1), where TP is total number of true positive classes predictions, TN is total number of negative classes predictions and Total is the total amount of tested samples.

$$Accuracy = \frac{TP + TN}{Total} \tag{1}$$

The resulting accuracy in this case is 0.9861, which is considered to be a very good result and indicates a nearly 99% probability that the submitted vibration sequence will be arranged into the correct class.

9. Conclusion

In the proposed experiment, the proposed LSTM neural network model showed a resulting classification accuracy of 98.61%. Thus, by using LSTM neural networks, it is possible to classify the sensed vibratory motion signatures of the end effector of an industrial robot into four defined classes with an accuracy greater than 98%.
The above results show that the proposed LSTM neural network model is effective for classifying the motion parameters of an industrial robot based on the measured vibration signatures. The results also indicate the prospect of using this model for the tasks of technical diagnostics and predictive maintenance such as detection and classification of anomalous states of the investigated equipment.
Due to the success of the LSTM neural network in processing and classification of vibration signals, it is planned to focus the following research on further optimization of the model and its application in real industrial environments.

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