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Method for Automatically Recognizing Various Operation Statuses of Legacy Machines

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Abstract

Monitoring the operation status of machine tools using IoT is widely carried out in order to improve productivity. However, at manufacturing sites, a lot of legacy machines, which are old and lack the capability of sending data on their operation status to networks, are still in use because the average useful life of machine tools is more than 20 years. Therefore, we developed method for recognizing the operation status of machine tools using a spindle motor current acquired by a current sensor. Because this current is in proportion to the spindle torque, a conventional method recognises the operation status when the current amplitude is above a threshold value. However, in a high-mix low-volume factory, the threshold value must be reset frequently because a drill and the cutting process change per order so the spindle torque varies. In contrast, we propose an automatic recognition method that can learn the variance in spindle motor current by unsupervised learning and with labelling scheme based on prior knowledge. We applied the proposed method to eight kinds of machine tools in a real factory, and the accuracy rate of the operation status estimation was more than 80% for all the machines. This result shows that all machine tools could be monitored by using this method.

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Keywords: Unsupervised learning; IoT; Legacy machine

1. Introduction

In recent years, forms of manufacturing that hitherto have not considered ICT (information and communication technology) and the IoT (Internet of Things) are being debated around the world. For example, in Germany, industry, government, and academia are cooperating in accord with the Industrie4.0 initiative [1], and on the national level, projects aiming to boost competitiveness by revitalizing manufacturing industries are pushing ahead.

Example targets affording rejuvenation by applying the IoT include upgrading manufacturing control by using advanced track-record collection of on-site dynamic status. To meet such targets, information concerning work transitions between workers, machinery, and manufactured goods—respectively referred to as “3Ms” (standing for “man”, “machine”, and “materials”)—must be collected and stored more rigorously [2]. However, monitoring the status of the second “M”, namely, machines, has conventionally been achieved by collecting and recording contact signals of machine tools, and information corresponding to status of on/off power switches and signal towers of machinery (namely, “operating” or “shutoff”) is monitored. In the case of mass-production systems, although actual operational status of machines can be presumed from the NC (numerical control) program, in the case of non-mass-production systems, processing factors may change during the process flow. Consequently, precisely comprehending the progress of a process necessitates comprehending the actual cutting state. However, even if the signal tower of a machine indicates “in operation,” it is impossible to judge whether the machine is in actual operation or just in idling state. As a result, it is possible to compile data on operating times of machines, but it is impossible to grasp the state of progress of the machining operation in detail. Furthermore, at manufacturing sites, so-called “legacy” equipment (with average serviceable lifetimes exceeding

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twenty years) that is incompatible with networks is still being used, and retrofitting such legacy equipment to make it IoT compatible presents big problems.

The aim of the present study is to devise a means of accurately monitoring the operational status of existing machines by simply attaching a monitoring device to the machine in question. As the target machine, a metal-processing machine tool was selected, and a sensing technology for estimating the operational status of that machine tool from its current-waveform pattern—in the form of an add-on current sensor placed in the power line of the machine tool—was developed.

2. Related works

Related works on technologies for monitoring operational status on equipment by sensing power-line current of machine tools are reviewed in the following. The spindle motor (which rotates the cutting tool for processing metal) is controlled by a control board within the motor. Whether a machine tool is in cutting status or idling status is determined according to whether the cutting tool is either contacting or not contacting the workpiece, and the processing load and spindle-motor load vary according to the status the machine tool. Since drive current of the spindle motor is proportional cutting load [3,4], if the drive current of the spindle motor in an actual machine tool is measured, as shown in Figure 1, the current amplitude varies in accord with the change in processing status. In comparison with other sensors (such as ones for sound and vibration), a drive-current sensor has the advantages of being simple to install at low cost as well as being less susceptible to the influences of noise in the work place, and a number of technologies for monitoring machine-tool status on the basis of current measurements have been proposed [5,6]. The target of current monitoring is mainly monitoring the status of cutting-tool wear and detecting defects during machining. As methods for estimating machine-tool status, supervised learning, such as fuzzy classification [7, 8], neural networks [9,10], and support vector machines [11], is mainly used. Moreover, operating status can be estimated from a threshold of current amplitude, and machining status has been predicted from the change in current amplitude by Bedini et al. [12].

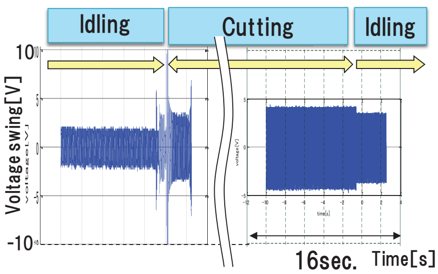

Fig. 1. Voltage waveform of machining process.

3. Method for recognizing operation statuses

Problems concerning conventional methods and solutions to those problems are described in the following section.

3.1. Problem statement

In the case of manufacturing plants that make low volumes of a large variety of products, mainly in the manner of made-to-order production, conventional methods for estimating machine-processing status have to account for the characteristic that the work (i.e., workpiece) and machining process as well as the kind and number of tools used in that process differ according to each order. Consequently, feature values (such as current amplitude expressed during processing) also vary according to order. In addition to that situation, machining load varies in accord with variations in the wear condition of the cutting tool during machining, processing factors, and so on. As a result, feature values of electrical current vary frequently owing to tool changes and variations in processing conditions (such as rotation speed) even during machining of a single workpiece.

Fuzzy classification is a means of estimating machining status by using a knowledge base, and it requires that a current model for each status is extracted beforehand. As for supervised learning, preliminarily learning using labeled data (i.e., training data) is necessary. Moreover, as for threshold methods, appropriate threshold values must be preliminarily set. For those reasons, it is known that technologies for estimating the operational status of equipment (like machine tools) by applying the principles of fuzzy classification and supervised learning as well as by using threshold methods are not applicable to small-volume large-variety plants (in which feature values of sensor data change frequently during processing).

3.2. Approach

As for solving the above-described problems, since drive-current amplitude is proportional to cutting load, when the drive current of an actual spindle motor is monitored, the current amplitude varies according to processing status correlated in order of magnitude as "stop < idling ≦ cutting," and the correlation is constant even if equipment and processes change. It can thus be considered that it is possible to automatically estimate operating status of a cutting tool, even if the feature values change, by clustering feature values by using unsupervised learning (without learning data and setting of threshold values) and by applying labeling rules on the basis of the constant correlation mentioned above.

The present study, which targets small-volume large-variety plants, targeted enabling visualization of the operating status of all kinds of machine tools in a plant containing legacy equipment (at target status-estimation accuracy of ≧80%) by means of automatically estimating operational status even when processes and tools are changed. The results of an investigation on the estimation method for enabling the targeted monitoring of equipment status are presented in the following section.