Proc. of the 9th Intl. Conf. of Asian Society for Precision Engg. and Nanotechnology (ASPEN 2022)
15–18 November 2022, Singapore. Edited by Nai Mui Ling Sharon and A. Senthil Kumar
doi://10.3850/978-981-18-6021-8_OR-08-0218

Digital Twin-based Cutting Tool Breakage Detection Model using Synthetic Depth Map and Deep Learning

Suhwan Jeong[1], Hyungjung Kim[2], Junghyuk Lee[1], Su-Young Park[1] and Sung-Hoon Ahn[1,2,#]

1 Department of Mechanical Engineering, Seoul National University, Seoul 08826, Republic of Korea
2 Institute of Advanced Machines and Design, Seoul National University, Seoul 08826, Republic of Korea
Corresponding Author / E-mail: ahnsh@snu.ac.kr, TEL: +82-2-880-9074, FAX: +82-2-888-9073

KEYWORDS: Digital twin, Cutting machine, Breakage monitoring, Deep learning, Synthetic image

In many industrial fields, monitoring system using deep learning (DL) algorithms are being used due to their high performances for object recognition based on RGB image. In particular, You Only Look Once (YOLO) is frequently adopted due to the advantage of having fast object recognition speed with a simple process. However, there are some limits to apply 2D RGB image-based monitoring system to machining tools, especially cutting tools. First problem with RGB-based monitoring system is that it is necessary to create a set of images for DL. Cutting tool breakages are irreversible, so it is expensive to produce actual samples for model learning. In particular, cutting tool monitoring, which requires high accuracy, has a large required number of learning images. Second, 2D RGB image may not be sufficient to recognize the breakage of cutting tools of real factory environment. Considering breakage characteristics appears in 3D geometry information rather than RGB data, detecting breakage only with 2D image can be difficult. Also, challenging lighting environment for high accuracy object recognition cannot be established in most of the situation. Therefore, it is necessary to secure a sufficient amount of 3D point set for cutting tool monitoring. This study proposes a cutting tool breakage detection model based on digital twin (DT) environment that generates enough quantity of synthetic depth map. In high fidelity DT environment, the depth map obtained from the cutting tool in a randomly produced situation is similar to that in practice. Virtual point cloud set of a damaged cutting tool, which is difficult to obtain due to a cost problem, is obtained. Then, obtained virtual data set is projected into 2D image and used as learning data for DL based monitoring system. To compose high fidelity DT environment, NVIDIA Omniverse has been used. The resolution and operating distance of the depth camera were set within the Omniverse environment to obtain a virtual depth map exactly matching the depth map obtained by real depth camera. The actual cutting tool model was inserted into the DT environment and various breakage shapes were applied. Defined various breakage shapes are selected, and these are randomly applied to 3D cutting tool CAD shapes to fabricate virtual damaged cutting tools. A 3D model for acquiring virtual data is completed by combining CAD files of damaged cutting tool and entire machine in suitable location within the DT environment. A virtual depth map is acquired using the domain randomization function provided by the Omniverse environment. Normal and damaged model data for various cutting tools are acquired from various angle, moving the virtual depth camera within a limited range. The obtained virtual depth data are used as YOLO learning data. Finally, an integrated real-time cutting tool monitoring system was produced. In the future, creating a monitoring system using a DT environment that consider more diverse physical quantities is intended.

1. Introduction

Monitoring the condition of operating machines is an important issue in the industry, and related research is continuously being conducted. The latest development of artificial intelligence-based machine vision techniques has improved monitoring technologies largely. [1] Especially, 2D RGB image-based monitoring system is being adapted to various machines' operation systems, but some particular cases like a cutting tools have difficulties applying the existing monitoring method.

There are two main problems in applying 2D RGB image-based monitoring methods to the cutting tools. The first problem is the difficulty to make a model training image. It is very difficult to obtain images of many broken cutting tools during milling while breaking normal cutting tools for securing images is very inefficient. Another problem is that RGB image-based monitoring does not reflect many of the characteristics of the cutting tool. The 2D image does not reveal any spiral structure in mm scale at the cutting tool. Also, a challenging lightning environment and specific photographing angle are required to get enough quality RGB images for monitoring. [2] [3]

This study proposes a digital twin-based cutting tool breakage detection system. A digital twin environment to generate synthetic data has been set. Cutting tool breakage has been implemented and a virtual depth map has been generated applying random domain techniques in Nvidia Omniverse. Then, a cutting tool monitoring system that recognizes normal and abnormal cutting tools is proposed. A 3D depth map has been converted to a 2D RGB image and a wall removal algorithm has been applied. YOLO v3 has been chosen for the breakage recognition system. Finally, a monitoring system has been applied to test data to prove the validity of the model trained by synthetic data.

2. Virtual depth map generation

2.1 Random cutting tool breakage modeling

To generate a synthetic damaged cutting tool depth map, a damaged virtual cutting tool has been created. The actual cutting tool that has been the basis for creating virtual tools is a 4 flute flat-Φ10 end mill. The original cad file of the same shape as the actual shape has been firstly imported.

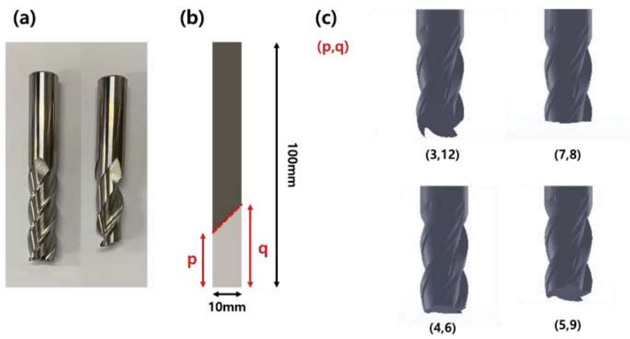

Fig. 1 Actual cutting tool and cutting tool modeling. (a) Actual normal and broken Φ10 cutting tool. (b) A mathematical model for random tool breakage implementation. Two factors, p and q, that detect breakage shape have been selected randomly. (c) Four randomly generated abnormal cutting tools.

As shown in figure 1 (b), a simple mathematical model of cutting tool breakage has been presented. The protruding cut has been applied based on two factors, *p* and *q* that decide the cross-section of the breakage shape. In consideration of the actual length of the spiral section of the cutting tool, the factors *p* and *q* have been determined as random integers between 2 and 15 mm. As a result, four virtual abnormal cutting tools have been generated as shown in figure 1 (c).

2.2 Random domain-based depth map generation

Virtual data that is similar to the depth map that can be obtained by the depth camera in the actual monitoring process should be obtained. In order to consider the depth information of the wallpaper, the CAD file of the actual CNC milling machine has been imported into the Omniverse environment, as shown in Figure 2 (a). Then virtual depth camera in the Omniverse has been installed. To satisfy high-fidelity conditions, the resolution and photographing conditions have been set as the same as the actual depth camera model (Azure Kinect DK). [4] One original normal cutting tool and 4 generated abnormal cutting tool CAD models have been fitted to CNC milling machine in sequence.

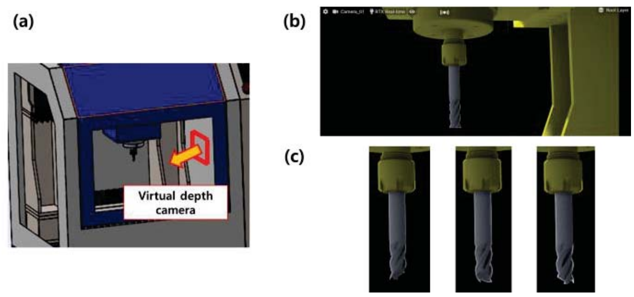

Fig. 2 (a) CAD file of the actual CNC milling machine. Virtual depth camera has been attached in an appropriate location. (b) Overall field of view (FoV) image of virtual depth camera. (c) 3 synthetic depth map of same cutting tool. Generated cutting tools in random cutting tool breakage implementation have been used.

Controlling the orientation of attached cutting tool, random domain-based depth map generating has been conducted. The rotation angle through x-axis has been randomly determined between 0 and 360 degree. Omniverse's virtual depth camera and image processing process have been connected so that synthetic depth maps can be quickly stored in real time. Through this process, 100 synthetic depth maps for each cutting tool breakage case have been generated.

3. Cutting tool breakage monitoring system

3.1 Depth map conversion

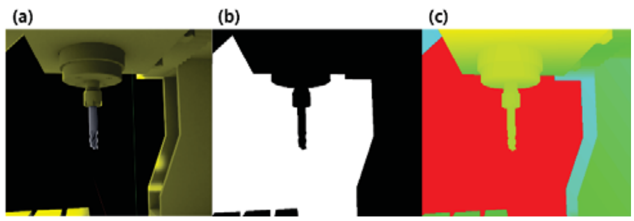

Fig. 3 Resultant changes due to data processing in the same frame. (a) Raw synthetic point cloud data. (b) 2D converted data. It looks like one channel information because it contains too far away points such as walls. (c) As a result, it is possible to obtain a large amount of RGB images, in which cutting tool is clearly distinguished, that are suitable for use as YOLO input

To use existing image-based object recognition algorithm, 3D depth map has been converted to 2D RGB image. Depth information has been converted to RGB information based on a suitable scale. Based on wave length of each color, Hue value can be decided. Depth information is transformed according to a series of formulas based on hue values. [5]

In the conversion process, wall deleting algorithm has been applied to improve the quality of the depth map. A suitable threshold has been set based on the point with the longest distance.

3.2 Object detection algorithm

YOLO v3 was selected as an object detection algorithm. YOLO can secure up to 45 fps [6], so it is suitable algorithm for final cutting machine breakage detection monitoring. The monitoring system has two classes, normal and abnormal. Based on existing research [7], a YOLO learning environment suitable for monitoring has been set up. Filters were 21, batch was 64, subdivision was 32, width and height were 416, 608, respectively.

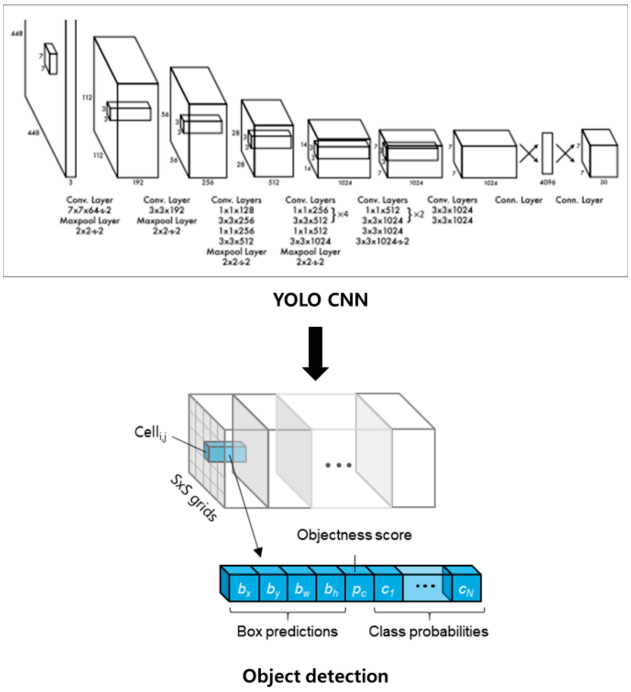

Fig. 4 Full architecture of monitoring system that includes YOLO v3 architecture. YOLO v3 uses backbone architecture (Darknet 53).

4. Experiments and evaluation

4.1 Training

In this section, a training procedure is explained. 2D RGB image that has been obtained by virtual depth map generating and depth map converting to RGB has been used for training model. Φ10 cutting tool have been chosen for entire system target.

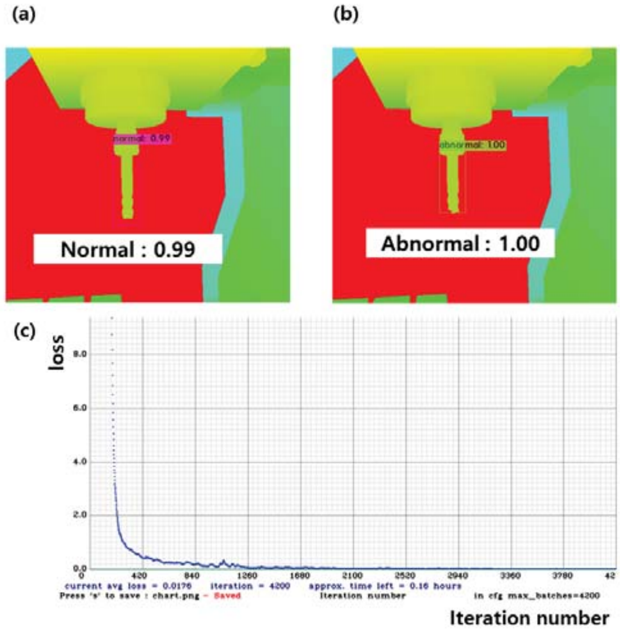

Fig. 5 Training for Φ10 cutting tool validation. (a) Normal cutting tool training with 0.99 confidence score. (b) Abnormal cutting tool training with 1.00 confidence score. (c) Loss vs iteration number graph while training. Total iteration number is 4200 and loss goes under 0.2 at 1260 iterations.

Each case contains 40 different depth map converted-RGB images. Total 200 pictures have been chosen for training set and 40 pictures have been used for validation set. Epoch was 4,200 times and figure 4 shows training process and loss value relative to the iteration number.

4.2 Results

The system evaluation has been conducted using normal cutting tools and abnormal cutting tools where the tool has been destroyed in various forms. The test set also used raw 3D point cloud obtaining by randomly positioning tools. In normal tool cases, 40 frames have been set. In abnormal tool cases, 40 frames have been set for each breakage shape, so total of 160 frames have been used for evaluation.

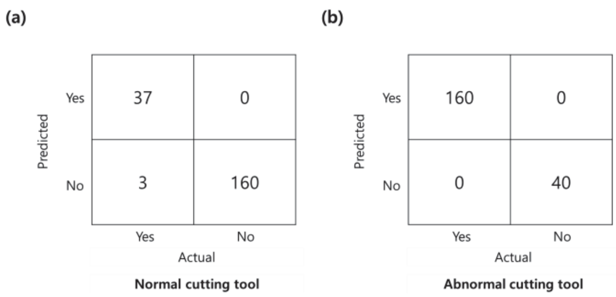

Fig. 6 Confusion matrix for cutting tool monitoring system. (a)

Normal cutting tool monitoring system sometimes does not recognize the actual normal cutting tool. (b) Abnormal cutting tool monitoring system operated successfully for every test set.

The precision value of normal cutting tool monitoring system is 92.5%, while abnormal cutting tool monitoring system has 100% precision value. Recall value of both system are 100%, so it can be seen that there is no confusion between different objects.

5. Conclusion

In this study, the 2D RGB image-based object recognition algorithm has been applied to the 3D depth map. Cutting tool inside the CNC milling machine, which is difficult to be detected by the existing 2D RGB image-based monitoring system, can be observed.

A virtual depth map has been generated for model training. The random shape of cutting tool breakage has been implemented. The actual CNC milling machine's point cloud has consisted of background information, and breakage has been defined by simple mathematical factors. By using domain randomization, a virtual depth map of cutting tools with different orientations has been generated.

Based on the achieved synthetic depth map, RGB images for model training have been gained. Wall deleting algorithm has been applied for quality improvement. YOLO architecture has been built with appropriate factors.

Finally, the entire monitoring model has been trained and applied to the test set. The system monitored a normal cutting tool with a 92.5% precision value while it detected an abnormal cutting tool with a 100% precision value. The only false detection case is the failure to recognize the normal cutting tool. The normal cutting tool has a symmetrical structure, unlike the abnormal cutting tool with a random breakage shape. It will also be solved if different types of normal cutting tools are learned.

ACKNOWLEDGEMENT

This work was supported by the National Research Foundation of Korea (NRF) grant funded by Korea government (MSIT) (No. NRF-2021R1A4A2001824 and No. NRF-2021R1C1C2008026)

REFERENCES

1. Kim, Hyungjung, et al. "Image-based failure detection for material extrusion process using a convolutional neural network." The International Journal of Advanced Manufacturing Technology 111.5 (2020): 1291-1302.
2. Klancnik, S., et al. "Computer vision-based approach to end mill tool monitoring." International Journal of Simulation Modelling 14.4 (2015): 571-583.
3. Cong Hoan, Nguyen, et al. "Design and Implementation of a Monitoring System Using Optical Camera Communication for a Smart Factory." Applied Sciences 9.23 (2019): 5103.
4. Tölgyessy, Michal, et al. "Evaluation of the azure Kinect and its comparison to Kinect V1 and Kinect V2." Sensors 21.2 (2021): 413.
5. Chernov, Vladimir, Jarmo Alander, and Vladimir Bochko. "Integer-based accurate conversion between RGB and HSV color spaces." Computers & Electrical Engineering 46 (2015): 328-337.
6. Lee, Yong-Hwan, and Youngseop Kim. "Comparison of CNN and YOLO for Object Detection." Journal of the semiconductor & display technology 19.1 (2020): 85-92.
7. Redmon, Joseph, and Ali Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).