공학석사 학위논문

CNN YOLO를 이용한 열화상기반 영상과 점구름 기반 엔드밀 감시 시스템

Point cloud and IR intensity-based end mill state monitoring system using YOLO

2022년 8월

서울대학교 대학원

기계공학부

유 동 걸

CNN YOLO를 이용한 열화상기반 영상과 점구름 기반 엔드밀 감시 시스템

Point cloud and IR intensity-based end mill state monitoring system using YOLO

지도교수 안 성 훈

이 논문을 공학석사 학위논문으로 제출함
2022년 4월

서울대학교 대학원
기계공학부
유 동 걸

유동걸의 공학석사 학위논문을 인준함
2022년 6월

위 원 장 ________ 이윤석 ________ (인)

부위원장 ________ 안성훈 ________ (인)

위 원 ________ 김아영 ________ (인)

Abstract

As adoption of smart−factory system in manufacturing becoming inevitable, autonomous monitoring system in the field of machining has become viral nowadays. Among various methods in autonomous monitoring, vision−based monitoring is the most sought−after. This system uses vision sensors integrated with detection models developed through deep learning. However, the disadvantage of being greatly affected by optical conditions, such as ambient lighting or reflective materials, critically affects the performance in terms of monitoring. Instead of vision sensors, LiDAR, which provides depth map by measuring light returning time using infrared radiation (IR) directly to the object, can be complementary method. The study presents a LiDAR ((Light Detection and Ranging)−based end mill state monitoring system, which renders strengths of both vision and LiDAR detecting. This system uses point cloud and IR intensity data acquired by the LiDAR while object detection algorithm developed based on deep learning is engaged during the detection stage. The point cloud data is used to detect and determine the length of the endmill while the IR intensity is used to detect the wear present on the endmill. Convolutional neural network based You Only Look Once (YOLO) algorithm is selected as an object detection algorithm for real−time monitoring. Also, the quality of point cloud has been improved using data prep−processing method. Finally, it is verified that end mill state has been monitored with high accuracy at the actual machining environment.

Keyword : LiDAR, real−time monitoring, point cloud processing, CNN, computer vision, object segmentation

Student Number : 2020−22094

Table of Contents

List of Figures

List of Tables

Chapter 1. Introduction

1.1. Tool Monitoring in CNC machines

With the arising and development in the field of the artificial intelligence–based vision techniques, machine monitoring in the field of smart factory system embedded manufacturing has been viral during recent years. [1] Machines that are transparent from the outside could be easily monitored using simple vision techniques, but some machines that are surrounded by thick housing such as CNC milling machine cannot be thoroughly monitored from the outside. Vague monitoring techniques using vibration or acoustic based sensors were introduced in the past, however thorough scrutinization was implausible. [2] To monitor the end mill situation, computer vision–dependent monitoring methods were proposed in the past, but the vision–based monitoring systems were not able to monitor during the ongoing operation due to its limits projected by its environmental dependency. [3,4]

Vision monitoring has high accuracy and fast identification speed, but the limitations of cameras have been revealed. Because it only detects ambient light, it is greatly affected by external light condition. Therefore, when using machine vision–based monitoring system in real factories, expensive lighting systems such as backlight lighting or bar lighting should be built. [5]

This study proposes new method to mitigate the limitations of existing vision–based monitoring systems by utilizing the LiDAR. The end mill inside the CNC machine, which showed high limitations in detection in already proposed research, was designated as the observation target. Various point cloud processing techniques were used to improve the monitoring accuracy. Finally, several CNC machines’ operations were recorded in actual factory environment and the evaluation of the monitoring system was carried out.

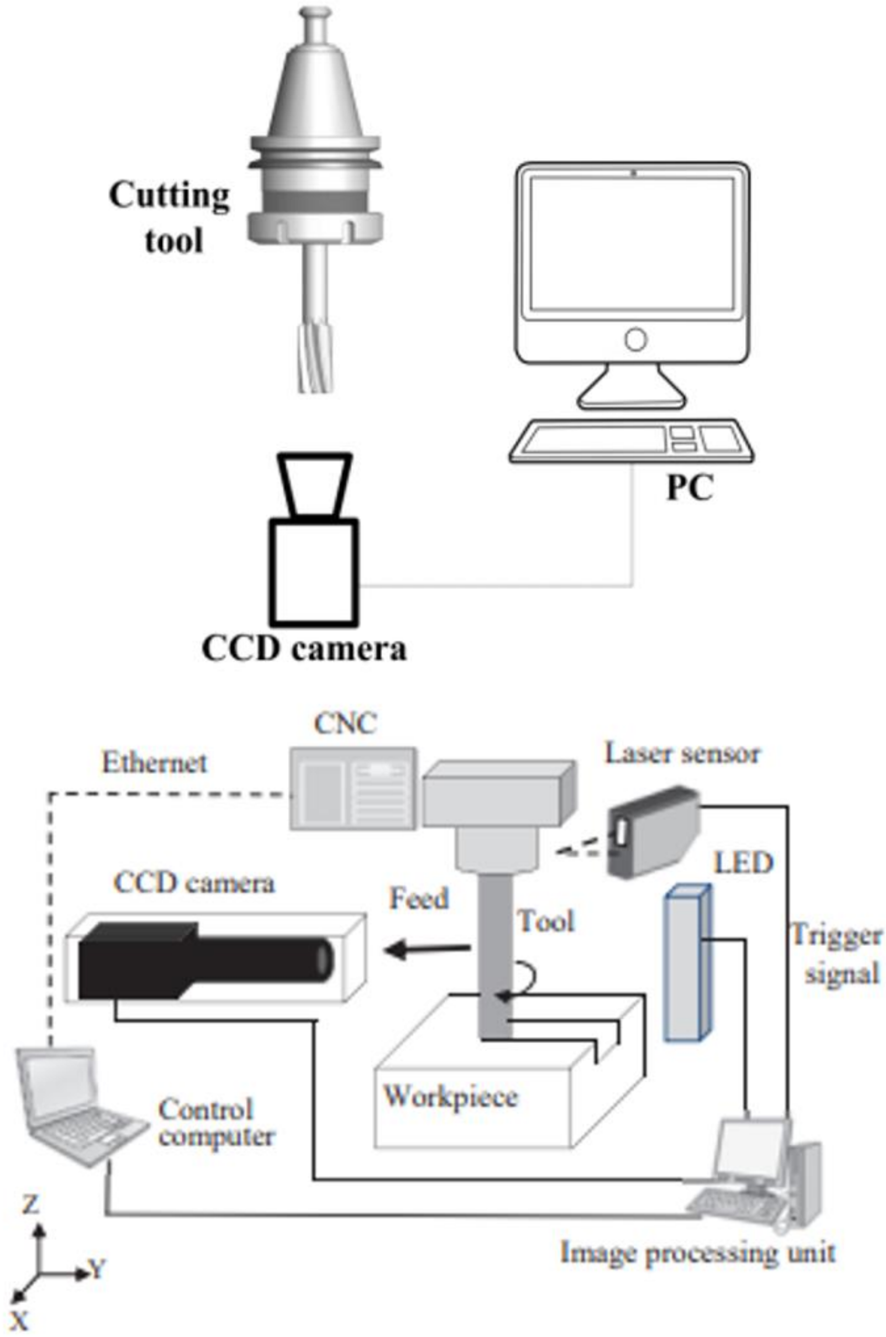

Figure 1.1: Conventional end mill monitoring systems using vision-based sensors. [3, 4]

Table 1. 1 Comparing presented system with existing sensors

	Camera-vision	**Laser scanner**	**High speed camera vision**	**LiDAR (This research)**
Resolution	○○○	○○	○○○	○○
Real-time	○○○	○	○○	○○○
Cost efficiency	○○○	○○	○	○○
Environment independency	○	○○○	○	○○○
Dynamic object detectability	○	○	○○	○○○

※ Number of dots indicate the degree of strength for each monitoring method in each corresponding characteristic. [1,6,7] Each research selected as comparison is about monitoring system.

1.2. LiDAR and point cloud map

LiDAR gathers the point cloud information of the target object by calculating the time difference induced by IR phase change calculation. The point cloud is the coordinate information projected using the distance between the sensor and the target. The LiDAR that was deployed in this study gathers the 3D map of the target and then transforms it into 2D data by QR decomposition. The figure 1.1 projects the example image obtained by the LiDAR.

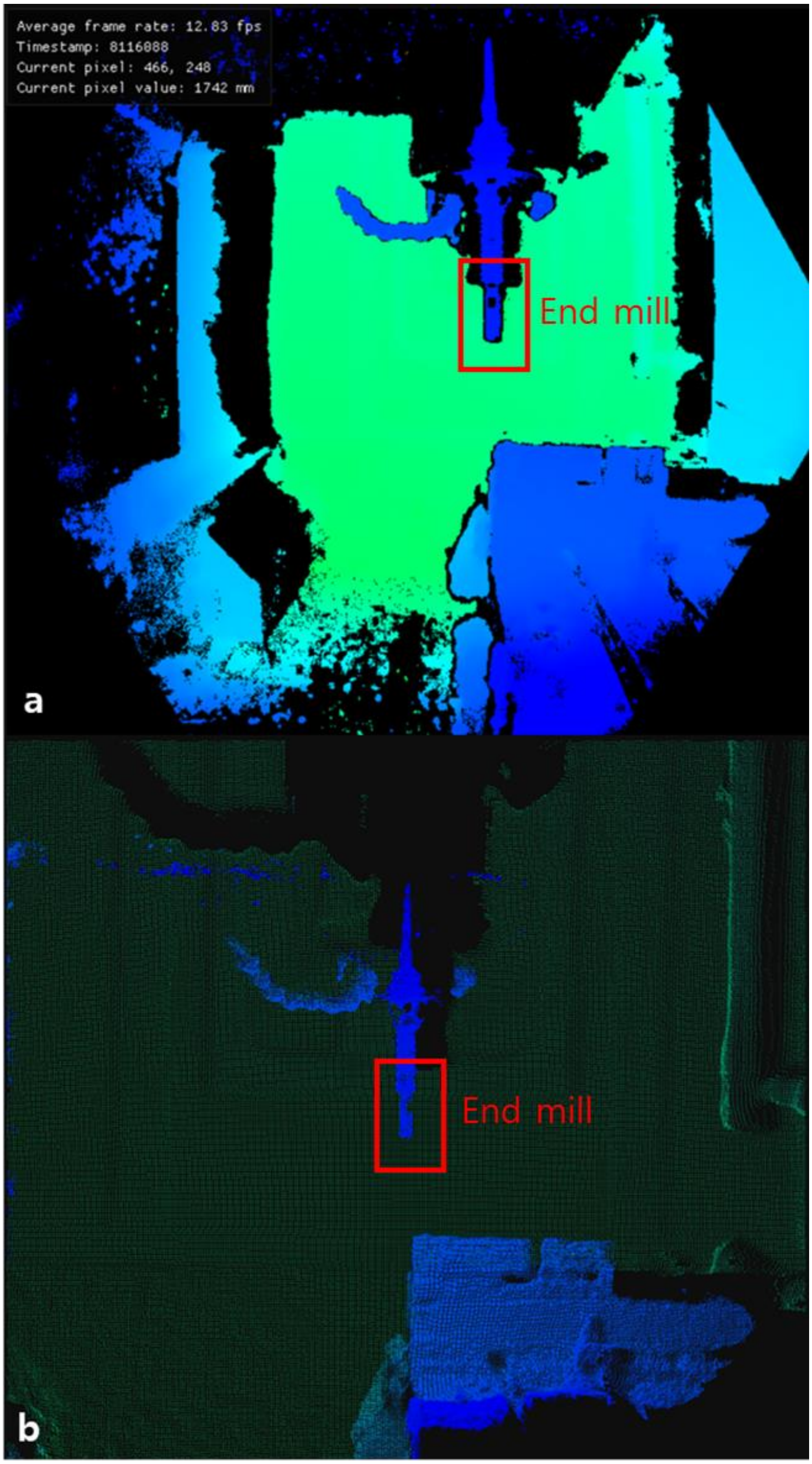

Figure 1.2: Example of LiDAR point cloud visualization (2D (a) & 3D (b)), Red bounding box indicates the tool area

1.3. IR intensity application

Apart from the distance measuring IR, various methods are available using IR. The IR intensity could be a versatile factor that could induce critical information. One of the most popular applications using the IR intensity factor is thermal imaging. [8] For this study, knowing that all matters emit IR energy varying on the surface profile whether it is material related or temperature related, the IR sensor could detect the intensity of the energy and distinguish the different features. Therefore, the surface profile of the working tool could be classified. Throughout the study, the IR intensity profile is to measure the degree of breakage in machining end mills.

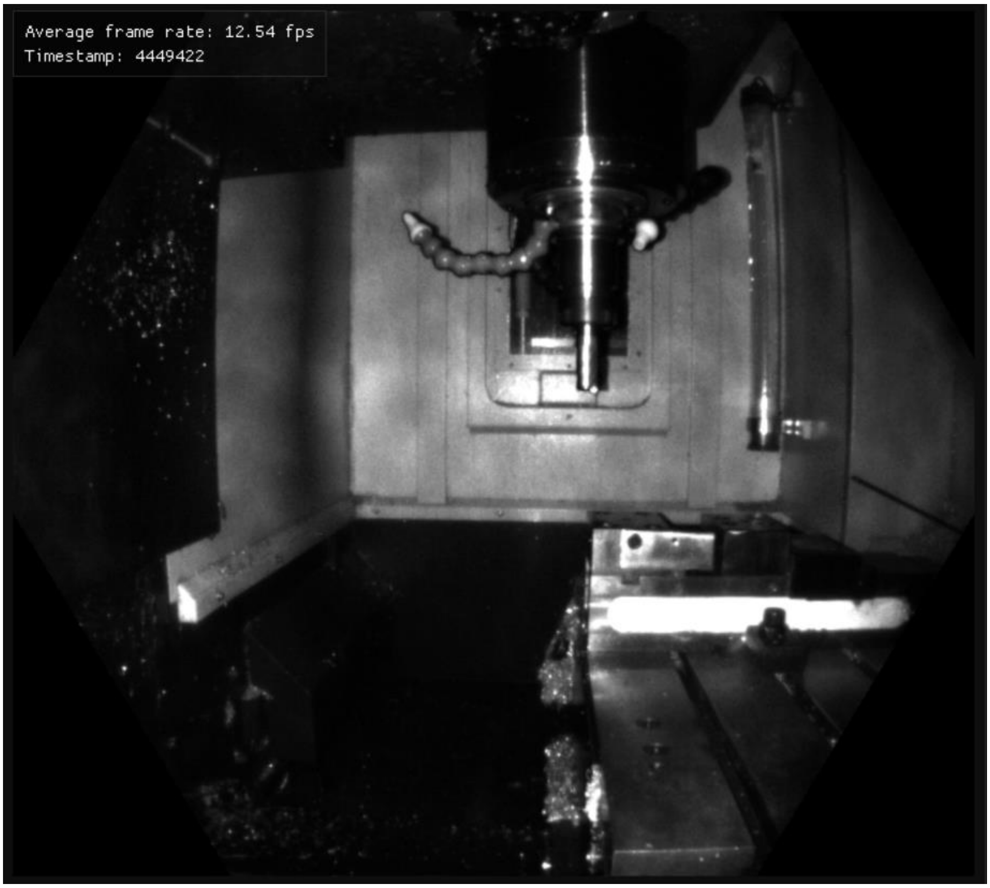

Figure 1.3: Example of IR intensity map obtained by Azure Kinect

Chapter 2. System Modelling

2.1. End mill monitoring system overview

Figure 2.1 projects the overall schematic of tool monitoring system. The objective is to detect the tool by analyzing the point cloud and then classifying the tool condition using the infra-red (IR) intensity. The thorough step is the following. The first step is the data collection step. The Lidar monitors the inside of the CNC machine after its installation. After the collection, noise removal and point cloud accumulation were carried out to raw data. Each improves stability and quality of point cloud. Obtained point cloud data is converted into image format to use as input of YOLO. After sufficient training, overall algorithm performance evaluation is carried out. The final testing stage to evaluate the system was carried out in the actual machining environment that was not included in the training data set to avoid overfitting.

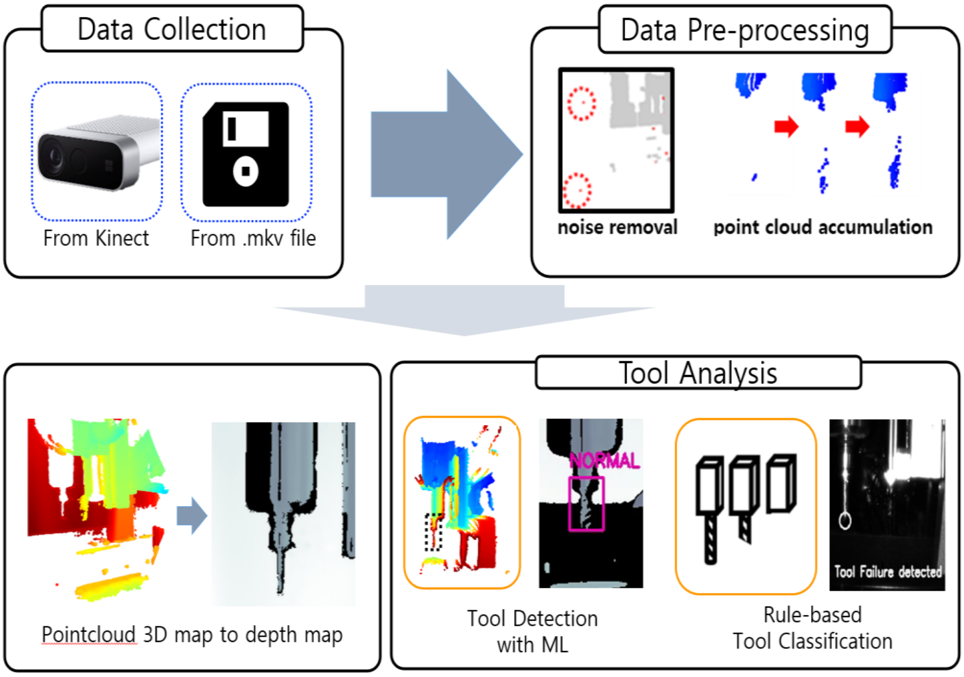

Figure 2.1 Schematic of proposed end mill monitoring system

2.2. Hardware setup

The radius of the tool to be monitored was set from 6 mm to 18 mm. Azure Kinect DK was selected as the operating LiDAR for this study by synthesizing various restrictions. [9] It has a resolution of 1 mm, which was high enough to distinguish each spiral of end mill. The overall spec of the LiDAR is listed in the Table 2.1. Maximum operating fps was 30, and specified measuring distance was 0.25 m to 2.21 m, which is suitable for general CNC machine.

As shown in figure 2.3, packaging was carried out to protect LiDAR from harsh environments such as chips and coolant engagement during milling operation inside the CNC machine. The installation was carried out by using neodymium magnet installed docking mount on the ferrous metal wall of the CNC machine.

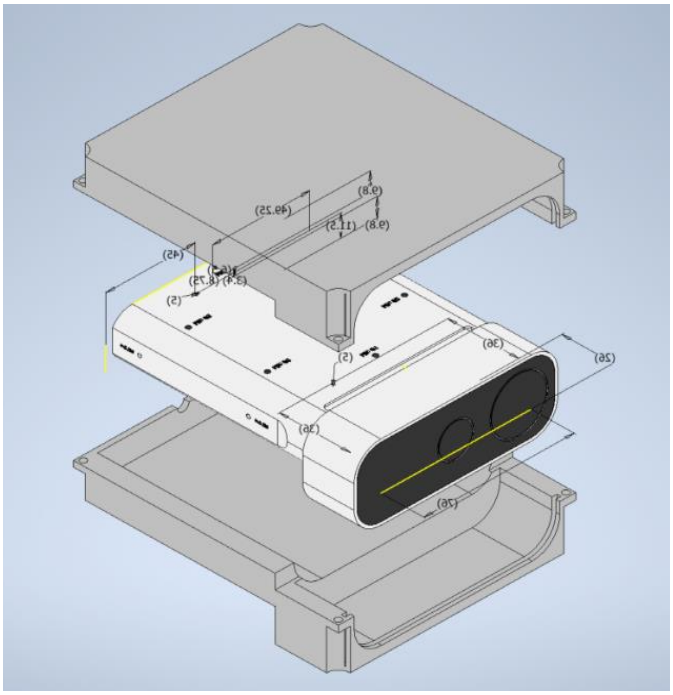

Figure 2.2: CAD of LiDAR housing

Figure 2.3: Azure Kinect DK with housing installed

Table 2.1 Azure Kinect specification

Specification	Value
Name	Azure Kinect DK
Size	103 x 39 x 126 mm
Weight	440 g
Color camera resolution	3840 x 2160
Depth camera resolution	1024 x 1024
Field of view (depth image)	120 º x 120 º
Specified measuring distance	0.25 – 2.21 m
Operating fps (frames per second)	5, 15, 30

Figure 2.4: Attachment of packaged LIDAR into HSM−560A CNC

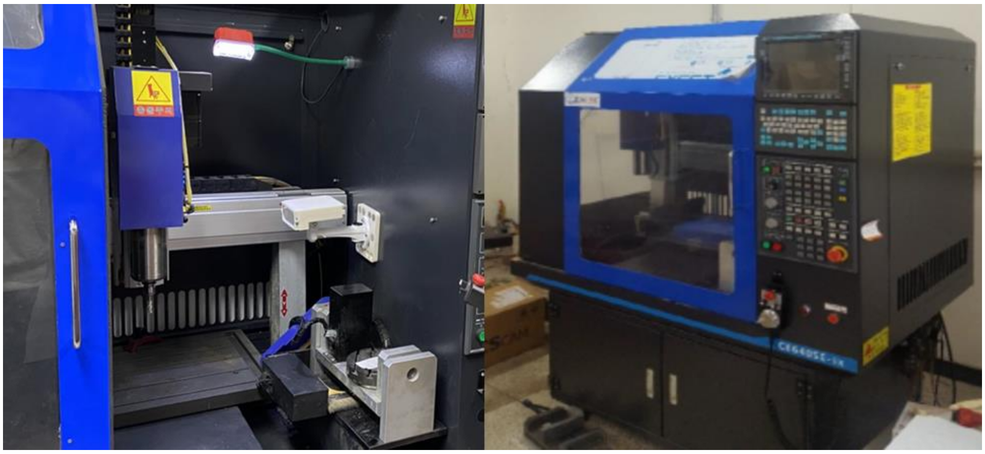

Figure 2.5: Attachment of packaged LIDAR into CE6405E−5X CNC

2.3. End mill failure modelling

The condition of cutting tools is of particular importance for an efficient milling process in any metal cutting process to achieve optimal performance. Tool failure is the major issue, and the reason tool condition monitoring system (TCMs) is needed. [10,11] Among many monitoring methods such as vibration monitoring, acoustic emission and temperature monitoring, this paper presents a TCMs based on IR intensity.

Tool failure involves features such as abrasive tool wear, tool wear based on microfracture and tool breakage. This study focuses on tool breakage which LiDAR is predicted to be suitable to detect due to its proper

For the experimental setup, a tool breakage modelling was carried out. Figure 2.5 shows a type of tool breakage categorized by type of tool tooth damage has been done on the tool. For this study to be a firmly controlled study, the breakage caused by both horizontal and vertical wear had to be manifested. Therefore, isosceles shape right corner on the tip of the endmill was removed according to the cross-sectional area. Figure 2.6 shows the CAD file and the prototype of the isosceles shaped area removal. The machining method of the removal was carried out using wire EDM. Throughout this study, the machined parameter for fracture would be mentioned as ‘fracture index’.

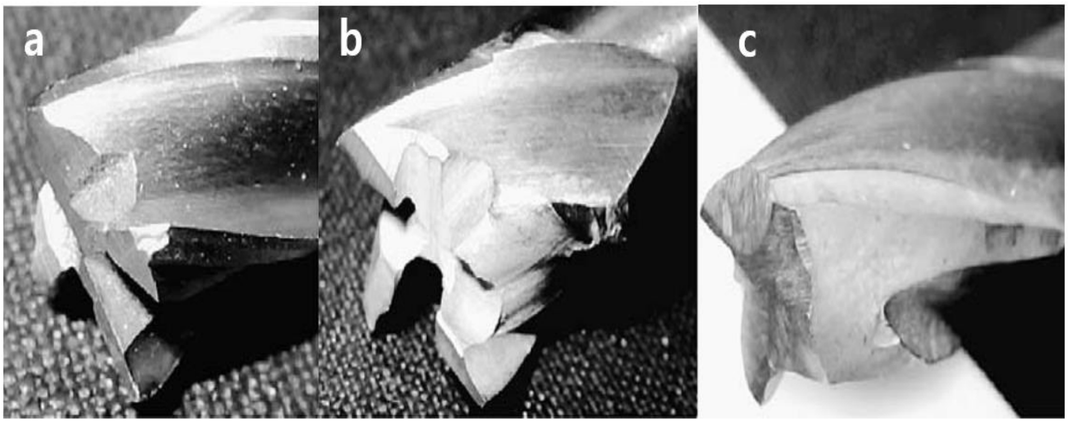

Figure 2.6: Typical examples of end mill tooth breakage: (a) tip breakage, (b) complete breakage of a single tooth, (c) two teeth breakage. [11]

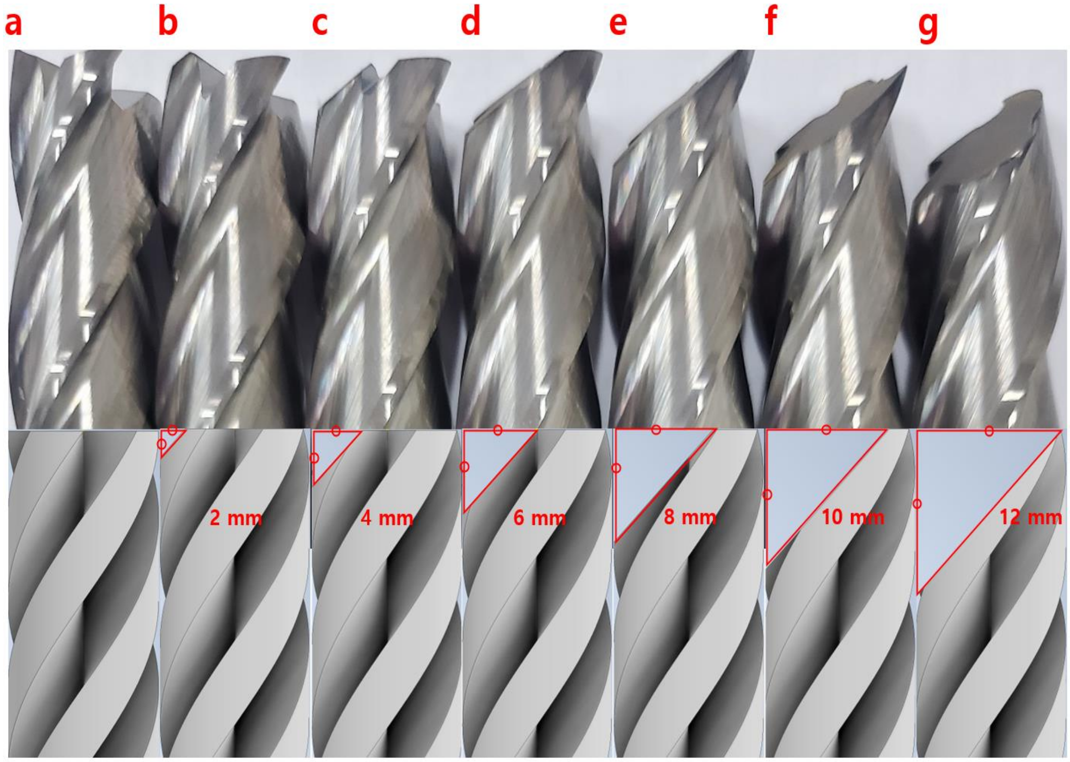

Figure 2.7: Tool breakage simulation by wire Electrical discharge machining (EDM). Isosceles shaped part on the side cross-section of the tool being removed orthogonally according to the cross-sectional area. a) reference tool. b) 2 mm c) 4 mm d) 6 mm e) 8 mm f) 10 mm g) 12 mm isosceles shape removed.

2.4. YOLO setup

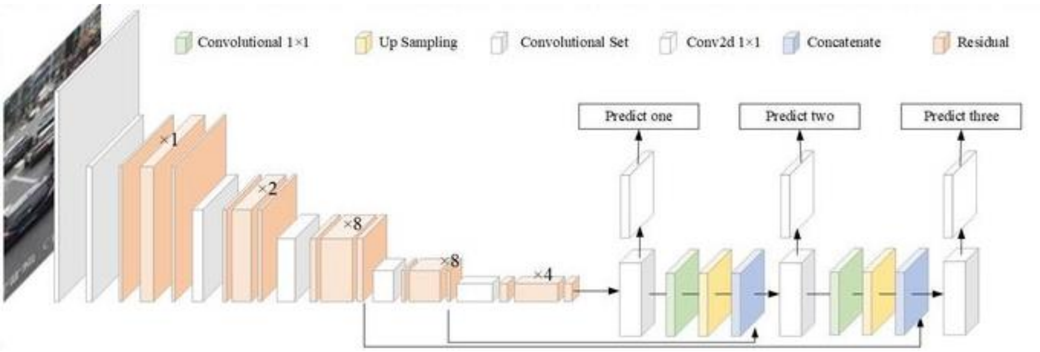

Figure 2.7: YOLO v3 architecture. It uses backbone architecture (Darknet 53). [12]

YOLO version 3 (darknet) was selected as an object detection algorithm. Other CNN based detection algorithm such as R-CNN (Region with Convolutional Neural Network), can only process seven frames per second. [13] YOLO can secure up to 45 fps, which seems proper to carry out a real time monitoring system for this study.

Chapter 3. Data Processing

3.1. Confidence score

To evaluate the monitoring system, confidence score was used as a performance measure. The meaning of confidence score is as follows. IOU stands for intersection over union.

$$Confidence\ score = \Pr(Object) * IOU_{pred}^{thruth} \tag{1}$$

Successful detection could be stated if confidence score exceeds a certain threshold. Therefore, confidence score was used to evaluate the performance of the detection system. Throughout the study, confidence score is also used to evaluate the performance of noise removal and point cloud accumulation method.

3.2. Noise removal

Even if all the conditions remain the same, the reflection of IR is not constant and might create an outlying point cloud data due to the uncertain characteristics of the LiDAR. So additional process to delete temporarily observed noise points is necessary.

Points generated due to noise are characterized by the existing positions which are totally solitary and lack of continuity. If a point is stationed solitarily and not around the surroundings, the point is to be declared as a noise. Therefore, an algorithm development that recognizes and removes the points when a specific point's depth information has big difference with surrounding points had been carried out. Figure 3.1 shows the schematic of how the noise removal is performed. The threshold that measures the degree of solitude for the point’s position has been set using heuristic measures. Since data generation in all processes was performed in the form of a python based numpy array, almost real-time processing was possible and did not hinder other processes.

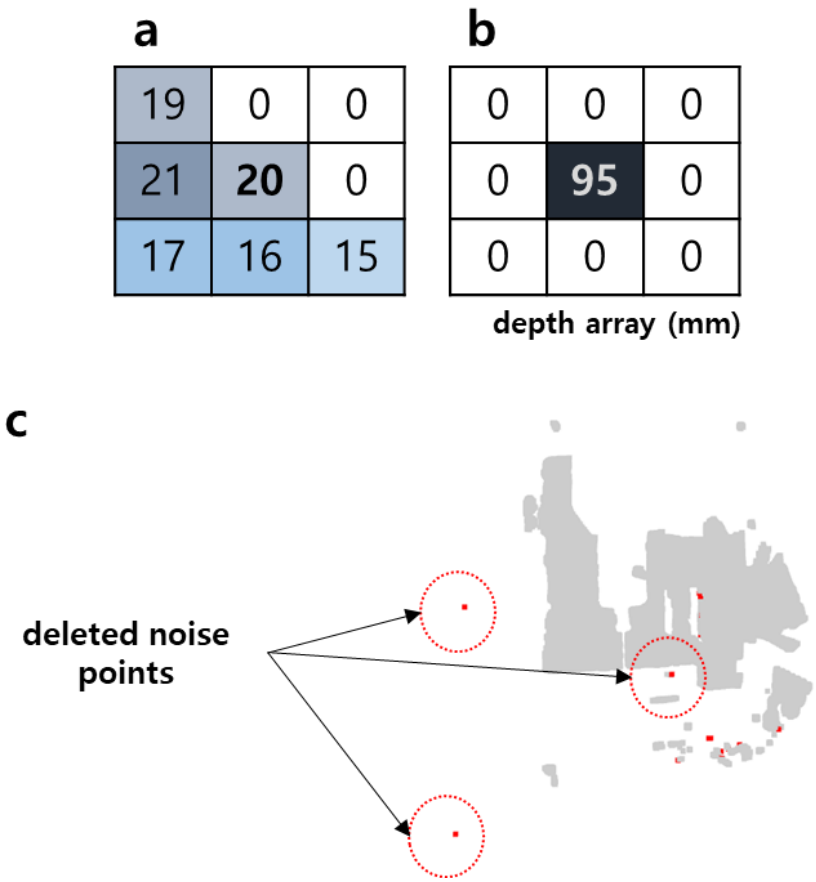

Figure 3.1: (a) Example of normal pixel and abnormal pixel.

(b) Deleted areas through noise removal algorithm.

3.3. Point cloud accumulation

The biggest weakness of data acquired through LiDAR is that the data is not stable and appears intermittently. This problem was more evident when measuring the moving and rotating objects. If the data from various continuous frames is combined, the intermittence and unstableness could be mitigated. For this case, an approach has been made to compile information from multiple frames to accumulate depth map of each frame. Unlike RGB information, depth maps exist as independent points that can be easily combined. Figure 3.2 shows the process of improving the quality of the depth map viewed as an actual viewer by accumulating the points of several frame.

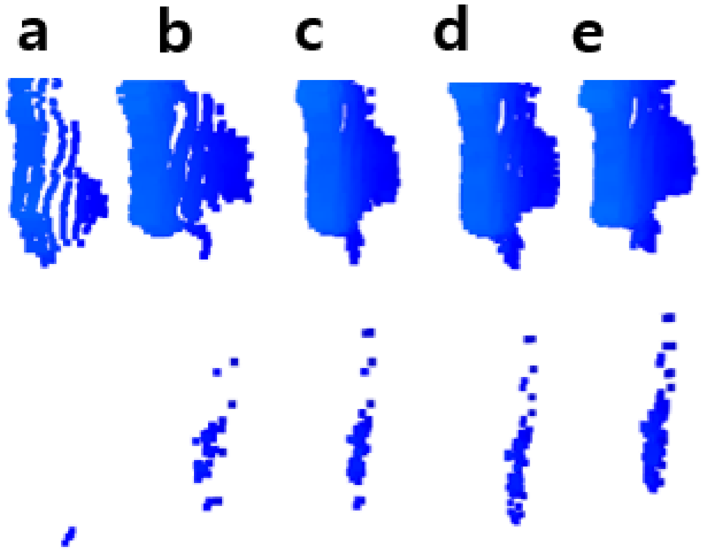

Figure 3.2: Accumulated frame points near the tool.

(a) Raw frame. (b) 5 frames accumulated. (c) 10 frames accumulated.

(d) 15 frames accumulated. (e) 20 frames accumulated.

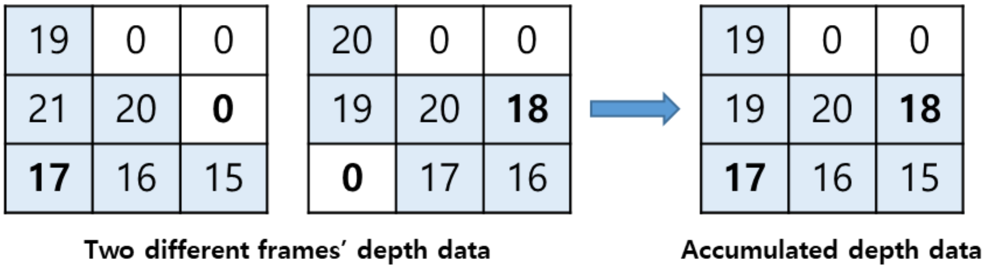

Figure 3.3: Schematic of point cloud accumulation is carried out.

Figure 3.4 shows schematic of point cloud accumulation. Point cloud accumulation also does not significantly affect the real−time operation of the system because the operation is performed not in the form of image but in the form of numpy based array directly. Point cloud accumulation algorithm is specifically effective for moving or rotating CNC machines. Even in CNC machines that run with a goal of high cutting speed, the tool's moving speed is up to 1m per second, and the target CNC machines travel up to 20cm over tenth of a second. This can mean that frames with different spindle position might be accumulated which would result in losing the original shape of the tool. However, this could be mitigated by adjusting the overlapping number and sampling rate of the LiDAR (maximum 30 frames per second).

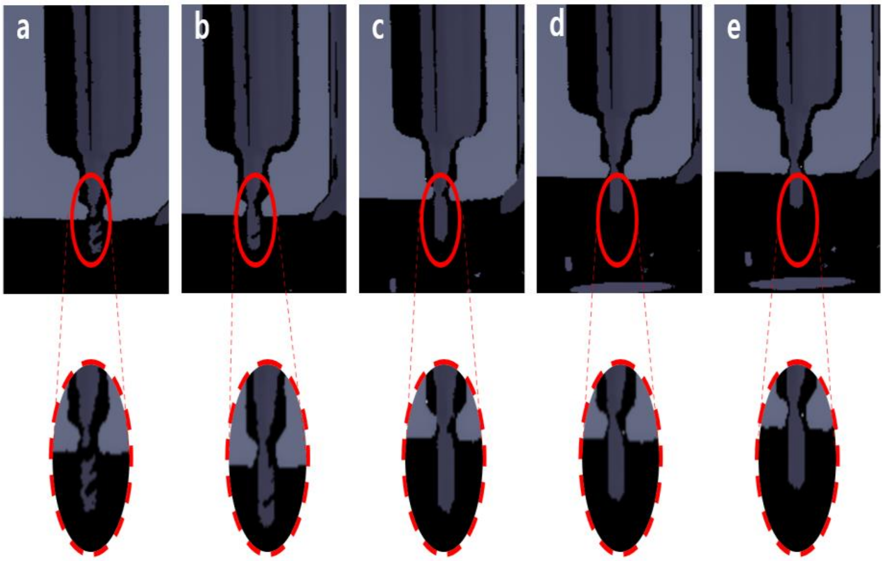

Figure 3.4: Depth map result when point cloud accumulation was applied during CNC machining process.

(a) Raw frame. (b) 5 frames accumulated. (c) 10 frames accumulated. (d) 15 frames accumulated. (e) 20 frames accumulated

3.4. IR intensity monitoring

For the tool breakage monitoring during the machining process, the previous approaches using sensors that yield ultra-high sampling rates such as the highspeed camera were introduced. [14] However, the sensor itself could be considered redundant due to the high installation costs due to the high price of sensors. In this research IR monitoring device Azure Kinect is used to monitor the tool breakage using IR intensity map which projects the IR intensity profile through a grayscale contour with 16-bit resolution. Pricewise Azure Kinect is user friendly due to its price (1/10th of conventional highspeed camera). The IR map projects the geometrical and material based on the characteristics of the target object. Therefore, as shown in figure 3.5, when the tool is rotating in high speed, the IR intensity value is expected to differ on the area of tool breakage compared to the non-damaged reference end mill.

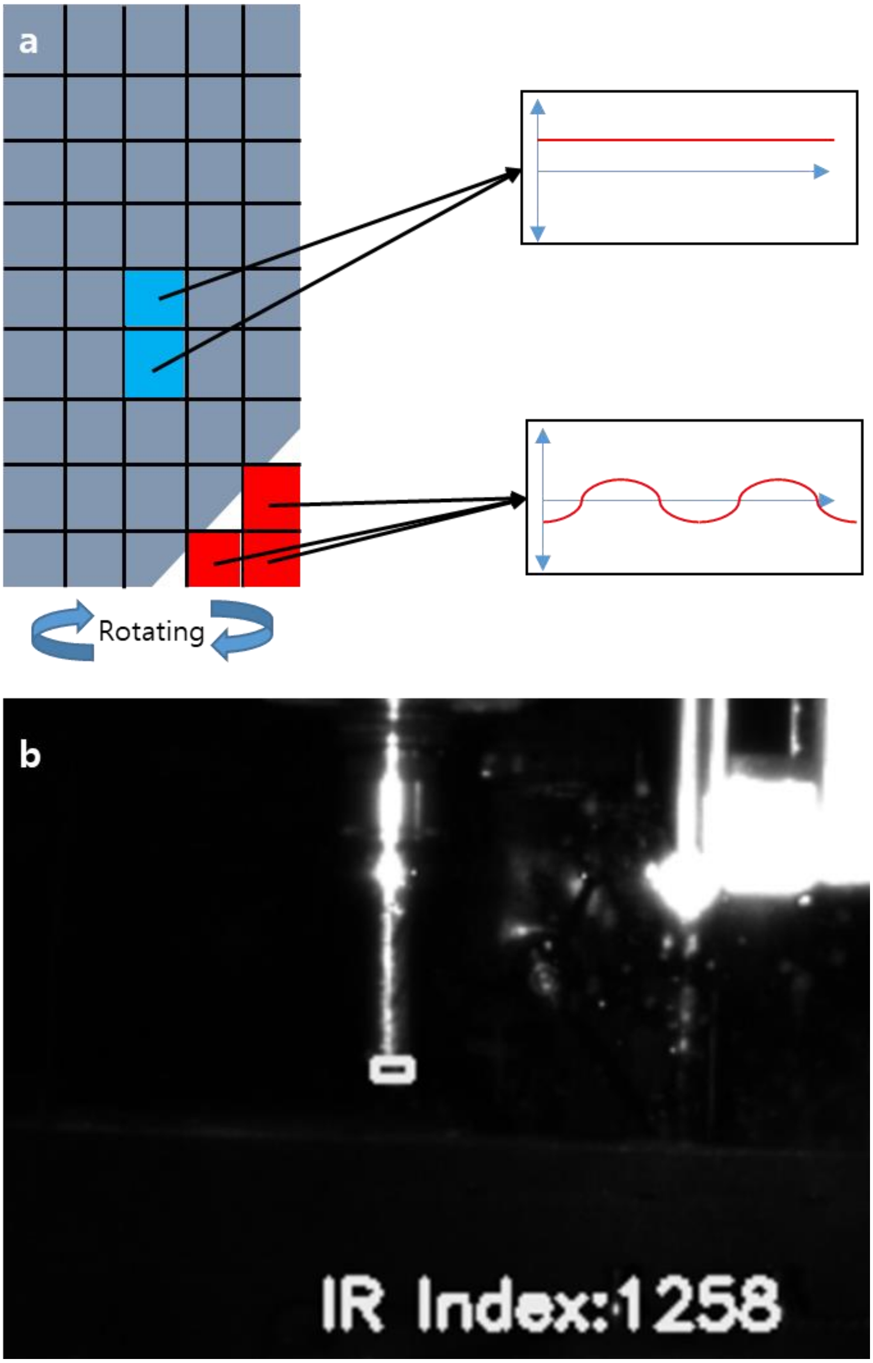

Figure 3.5: IR intensity sampling. a) Schematic of difference in IR intensity between normal and fractured regions. b) sampled IR index on certain pixel.

Chapter 4. Experiments and discussion

4.1. Data gathering

Data acquisition was carried out from 2 different CNC machine models (CE6405E−5X, HSM−560A). End mills with various diameters (Φ 6 − Φ 18) were observed for performance evaluation. Figure 4.1 shows the overall test bed setting. Each tool was recorded at 30 fps and each frame was stored in the form of a .mkv file. The rotation speed of the tool was fixed into two values. (1000 rpm, 3000 rpm)

Both IR intensity map and the point cloud data were collected. The point cloud maps were inspected before running through noise removal process and point accumulation process to inspect the suitability for detection process. The points that were missing on each frame due to noise and features exerted during rotation, were compensated using two previously mentioned data processing methods.

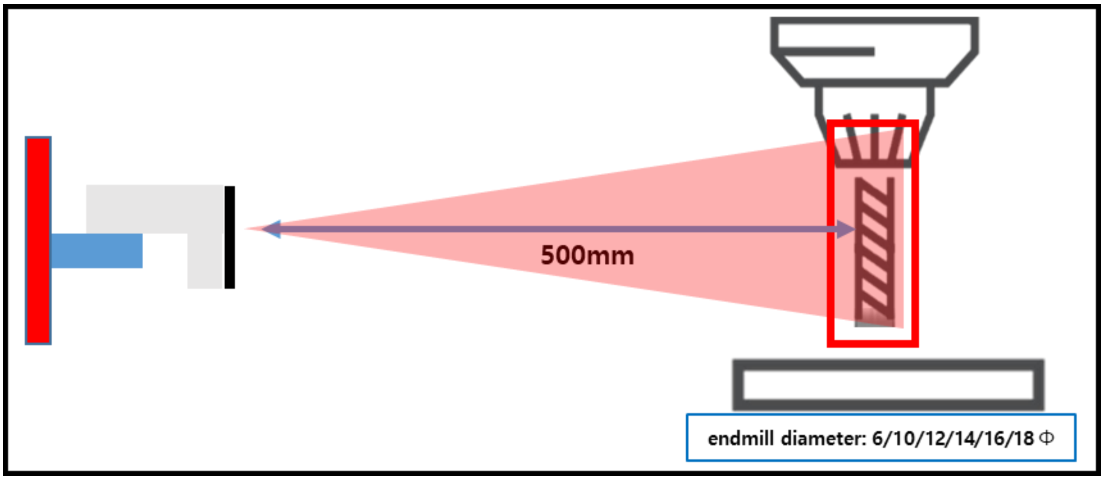

Figure 4.1: End mill point cloud gathering experiment.

4.2. Training

Φ 6, Φ 10, Φ 12 tool data from CE6405E−5X CNC machine and Φ 14, Φ 16, Φ 18 tool of HSM−560A CNC machine have been chosen for training set. Each case contains 20 different point cloud, and ratio of test set and validation set is 7:3. Epoch was 4,000 times and figure 4.2 (c) shows loss value relative to the iteration number. The loss function was set to cross entropy loss function showing to project high decay.

The training was carried out using graphic card model NVIDIA Quadro RTX 5000−max with Intel Xeon W−10886M using CUDA based processors enabling graphic card architecture to compute tensor format structures. The training progress took 10 hours to iterate 4000 epochs of feed forward processes and loss function update using gradient descending method.

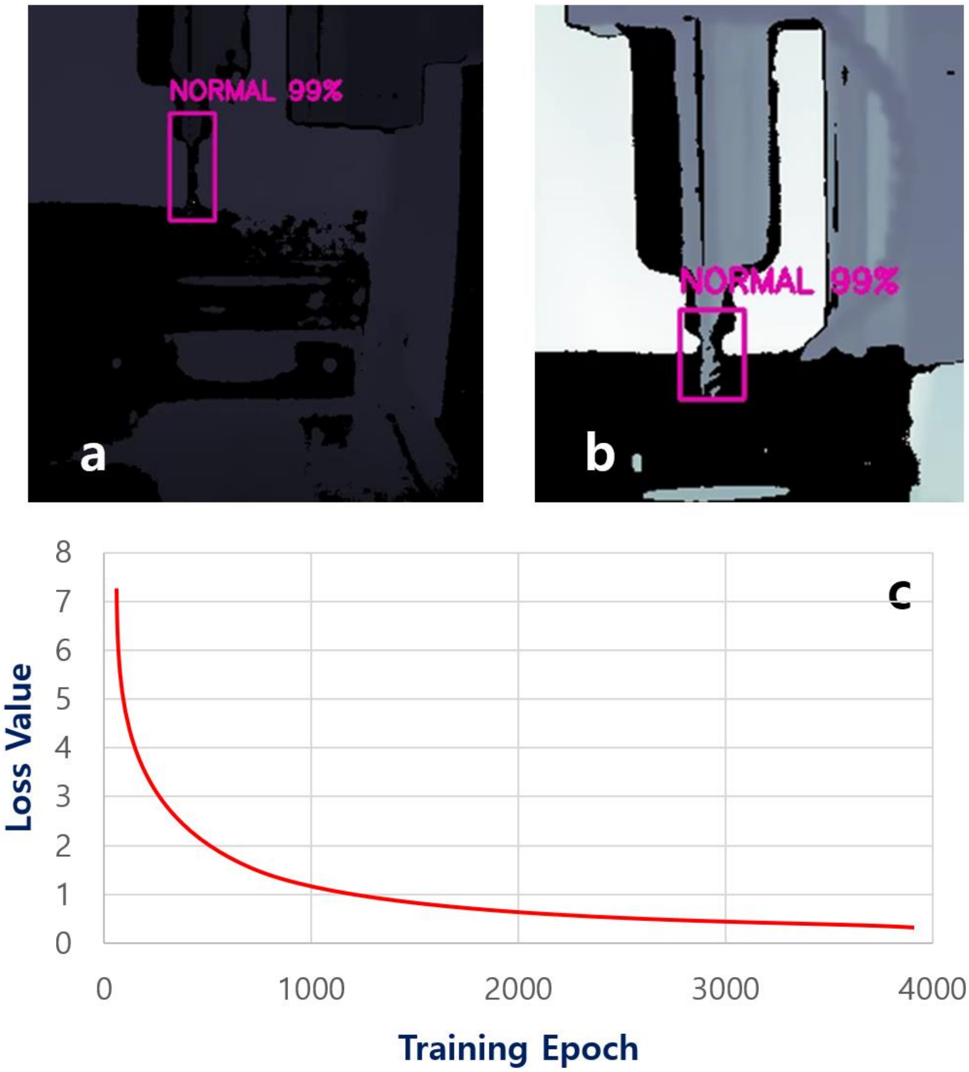

Figure 4.2: (a) Φ 6 end mill validation. (b) Φ 10 end mill validation. (c) Training model loss reduction by iteration

4.3. Results

4.3.1 Tool detection

After the training process, weights file was collected to run the real time monitoring. The monitoring showed successful detection rate meaning that all the detection yielded a detected bounding box around the tool area and the confidence score. For all the stationary rotating end mills with diameter from Φ 6 to Φ 18 showed over 95% detection success rate with average confidence score of 0.95. Figure 4.3 shows the monitoring done on stationary Φ 18 rotating endmill. The confidence score of all the detected tools in each frame. However non-stationary moving end mill detection showed lower confidence score before applying the noise removal and point cloud accumulation.

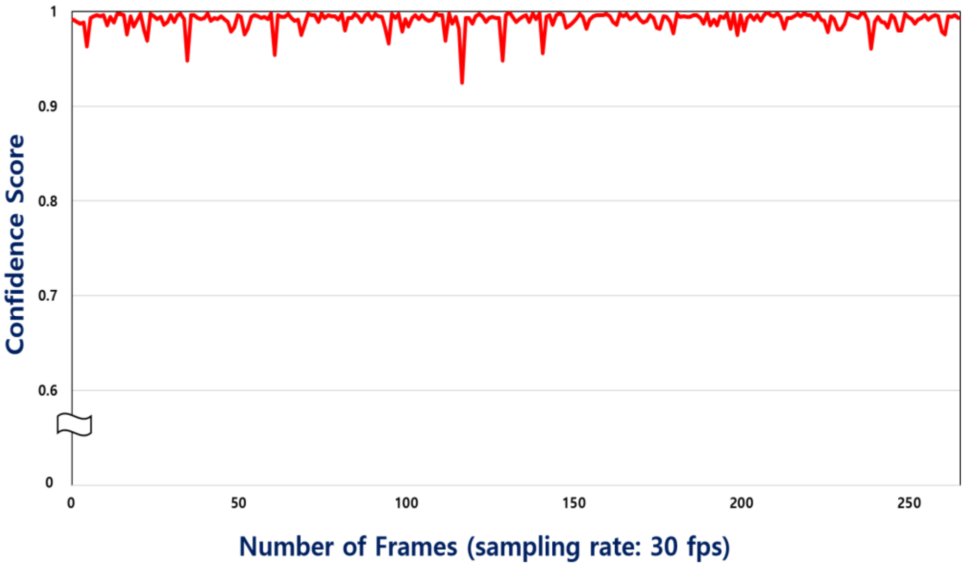

Figure 4.3: Confidence score during the detection for Φ 18−rotating−tool

Figure 4.4 explains how point cloud accumulation works in a positive direction in monitoring. During the real time monitoring stage, the 15 frames were accumulated during the process which showed increase in confidence score from 0.729 to 0.887 meaning over 15% increase in performance. During the machining process where tool was removed from the sensor field of view, the minor errors only occurred during 2 frames which could be considered trivial.

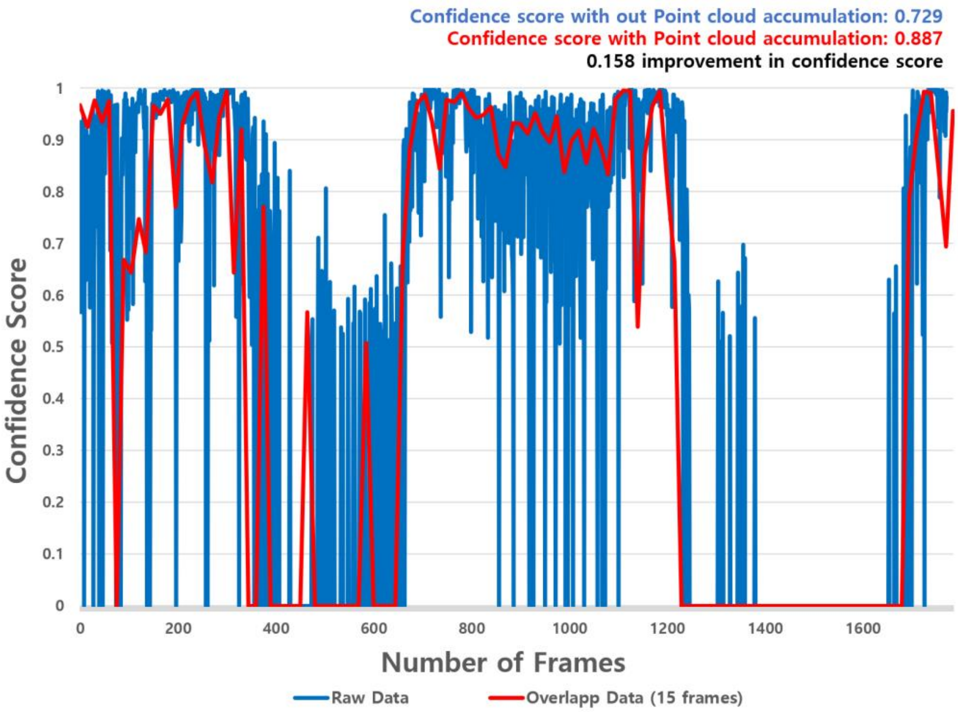

Figure 4.4: Confidence score change of HSM−560A−Φ 18−rotating−stationary end mill.

.

4.3.2 Tool condition monitoring using IR index

When the end mill coordinates were extracted from the detection process, the grid search for IR intensity was carried out. As it is shown in the figure 4.5, the IR value of the fractured region showed periodic fluctuation. The fracture end mills with fracture index of 6 mm, 8 mm, 10 mm, and 12 mm showed distinguishable fluctuation which enabled the extract the threshold IR intensity value for the fracture criterion. However, the endmills with 2 mm and 4 mm showed no fluctuation in the values due to the lack of resolution of the LiDAR.

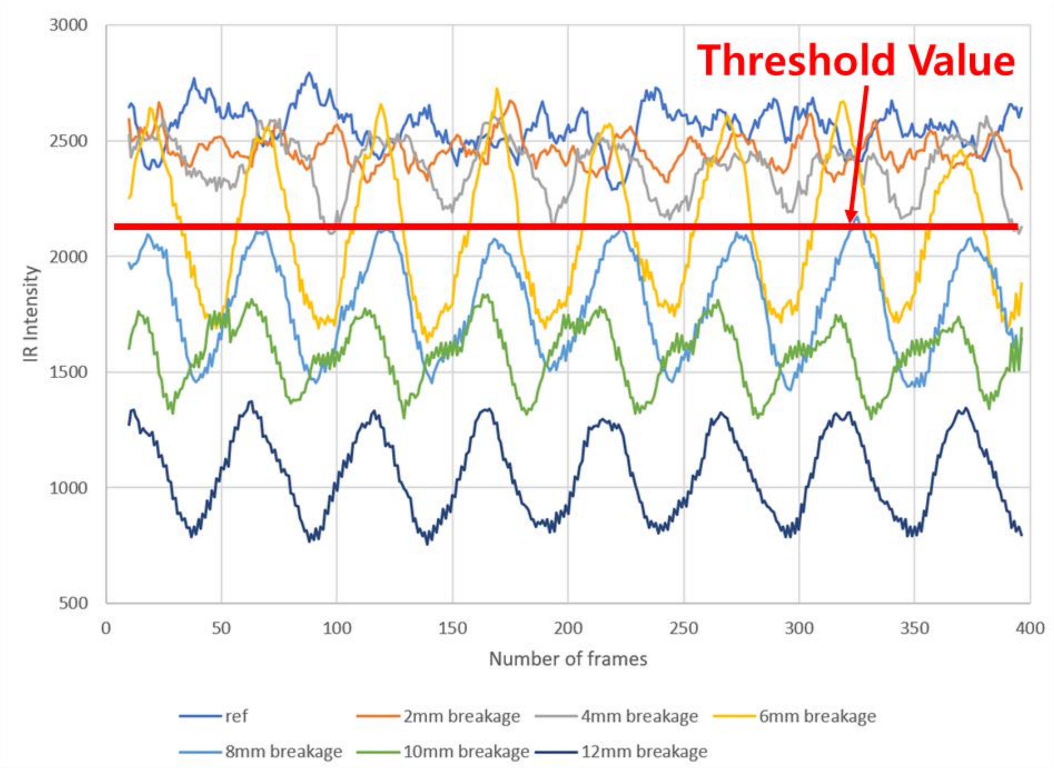

Figure 4.5: IR Intensity graph on frame based (sampling rate: 30 fps for 15 seconds).

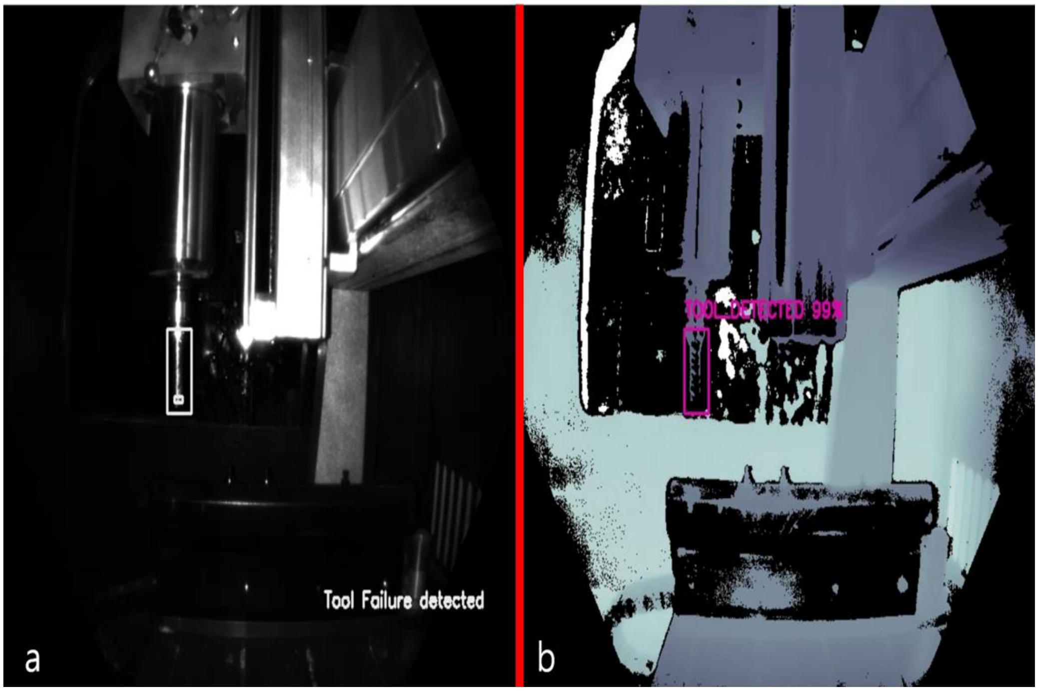

Figure 4.6: Real time monitoring of the system. a) IR intensity−based tool condition monitoring b) YOLO−based tool detection.

Chapter 5. Conclusion

In this study, the object detection algorithm was applied to point cloud data and the IR intensity data which were acquired by LiDAR. The end mill in the CNC machine, which was difficult to be monitored by vision-based monitoring system, was observed.

The preliminary step of detection and recognition was carried out using the YOLO v3 model imbedded with the point cloud data. After the point cloud data collection, each frame was labelled and ran through training process for the YOLO algorithm.

YOLO parameters were imbedded on the sensor after the training, which allowed the end mill detection process. The coordinate of the endmill was extracted during the detection, then allowed the grid search for end mill condition monitoring

The expected behavior of fractured region was projection in fluctuation in IR intensity values. For the test bed set up and hardware set up, the end mill fracture was simulated and prototyped by wire EDM process of the conventional Φ 12 end mills. As expected, the IR profile of the fractured area showed periodic fluctuation and was able to extract the fracture criteria that enabled the fracture detection of end mills with fracture indices of 6 mm, 8 mm, 10 mm, and 12 mm. The end mill with 2 mm and 4 mm fracture indices were not able to be detected due to the low resolution of the LiDAR. It is expected to be detected using high resolution LiDAR with more IR channels.

Finally, the entire system has been applied to real industrial site. System monitored end mill with 30 fps of sampling rate and showed over 95 % success rate in detection and fracture detection for 450 frames which is 15 seconds of machining time.

Reference

[1] D. Zuehlke, "Smartfactory–from vision to reality in factory technologies," IFAC Proceedings Volumes **41**, 14101–14108 (2008).

[2] J. Kim, H. Lee, S. Jeong, and S.−H. Ahn, "Sound−based remote real−time multidevice operational monitoring system using a convolutional neural network (cnn)," Journal of Manufacturing Systems **58**, 431–441 (2021).

[3] S. Klancnik, M. Ficko, J. Balic, and I. Pahole, "Computer vision−based approach to end mill tool monitoring," International Journal of Simulation Modelling **14**, 571–583 (2015).

[4] S. Yoshimitsu, D. Iwashita, K. Shimana, Y. Kobaru, and S. Yamashita, "Monitoring of cutting state in end−milling based on measurement of tool behavior using ccd image," International Journal of Automation Technology **13**, 133–140 (2019).

[5] N. Cong Hoan, N. Van Hoa, V. Thanh Luan, and Y. M. Jang, "Design and implementation of a monitoring system using optical camera communication for a smart factory," Applied Sciences **9**, 5103 (2019).

[6] J. Sivanandan, E. Liscio, and P. Eng. "Assessing structured light 3D scanning using Artec Eva for injury documentation during autopsy." J Assoc Crime Scene Reconstr **21**, 5−14 (2017).

[7] SE. Reutebuch, HE. Andersen, and Robert J. McGaughey. "Light detection and ranging (LIDAR): an emerging tool for multiple resource inventory." Journal of forestry **103.6**, 286−292 (2005).

[8] X. Chen and L. Hao. "Application analysis of infrared thermal imaging technology in intelligent manufacturing field." Journal of Physics: Conference Series. Vol. 1693. No. 1. IOP Publishing (2020).

[9] S. Berezvai, D. Bachrathy, and G. Stepan. "High-speed camera measurements in the mechanical analysis of machining." Procedia CIRP **77**, 155-158 (2018).

[10] D.E.D Snr. "Sensor signals for tool-wear monitoring in metal cutting operations—a review of methods." International Journal of Machine Tools and Manufacture **40.8**, 1073-1098 (2000).

[11] I. Yesilyurt. "End mill breakage detection using mean frequency analysis of scalogram." International Journal of Machine Tools & Manufacture **46**, 450–458 (2006).

[12] J. Redmon and A. Farhadi. "Yolov3: An incremental improvement." arXiv preprint arXiv:1804.02767 (2018).

[13] Y.H. Lee and Y. Kim, "Comparison of cnn and yolo for object detection," Journal of the semiconductor & display technology **19**, 85–92 (2020).

[14] M. Tölgyessy, M. Dekan, L. Chovanec, and P. Hubinsk y, "Evaluation of the azure kinect and its comparison to kinect v1 and kinect v2," Sensors **21**, 413 (2021).

초록

제조 분야에서 스마트 팩토리 시스템의 도입으로 인해 가공 과정의 무인 모니터링 시스템이 필연적으로 도입되고 있다. 무인 모니터링의 다양한 방법 중 비전 기반 모니터링이 가장 많이 쓰이고 있다. 해당 비전 기반 시스템의 경우 딥 러닝을 통해 개발된 감지 모델과 통합된 비전 센서를 사용한다. 하지만 주변 조명이나 반사 물질과 같은 광학적 조건에 크게 영향을 받는 단점은 모니터링 측면에서 성능에 치명적인 영향을 미치기에 이를 보완하는 대안이 필요하다. 이 연구에서는 비전 센서 대신 적외선(IR)을 물체에 직접 조사하여 빛의 왕복 시간을 측정하여 깊이 정보를 측정하는 LiDAR를 이용하여 비전 센서의 한계를 보완하는 시스템을 소개한다. 또한 비전과 LiDAR 감지의 장점을 모두 제공하는 LiDAR 기반 엔드밀 상태 모니터링 시스템을 제시한다. 이 시스템은 LiDAR에서 획득한 점 구름 정보 및 IR 강도 데이터를 사용하며, 딥 러닝을 기반으로 개발된 객체 감지 알고리즘은 감지 단계와 엔드밀의 길이를 감지하고 측정하는 데 사용되며 IR 강도는 엔드밀에 존재하는 마모 혹은 파손 정보를 감지하는 데 사용된다. 실시간 모니터링을 위한 객체 감지 알고리즘으로 YOLO(You Only Look Once) 알고리즘을 기반으로 하는 컨볼루션 신경망이 선택되었으며 데이터 전처리를 통해 포인트 클라우드의 품질을 향상시켰다. 마지막으로 실제 가공 환경에서 엔드밀 상태를 높은 정확도로 모니터링하는 과정을 진행하였다.

주요어 : LiDAR, real-time monitoring, point cloud processing, CNN, computer vision, object segmentation

학　번 : 2020-22094