Motion Analysis Using Machine Learning for Vocational Training Support

Haruka Kataoka
Graduate Student in Architecture
Polytechnic University
Kodaira-shi, Tokyo
e-mail: m19403@uitec.ac.jp

Masahiro Yokoyama, Masaki Endo, Norikatsu Fujita, Hideyo Tsukazaki
Division of Core Manufacturing
Polytechnic University
Kodaira-shi, Tokyo
e-mail: m-yokoyama@uitec.ac.jp, endo@uitec.ac.jp, fujita@uitec.ac.jp, tukazaki@uitec.ac.jp

Hiroshi Ishikawa
Graduate School of System Design
Tokyo Metropolitan University
Hino-shi, Tokyo
e-mail: ishikawa-hiroshi@tmu.ac.jp

***Abstract*—Recently in the construction industry, because of the declining number of new employees and the aging of skilled workers, carpentry skills have not progressed. One means of transferring these skills smoothly is to train carpenter technicians at vocational skill development facilities. Nevertheless, it is difficult to spend much time at the basic tasks of carpenters, which include sharpening, chiseling, sawing, planing, and nailing, at such facilities. The development of an effective teaching method for carpentry work is desired. Therefore, we constructed a machine learning system to measure and evaluate the movements of unskilled workers. This study uses movements of skilled technicians and a questionnaire survey to evaluate the developed teaching method for tacit knowledge, i.e., intuition or knack, related to planing work.**

Keywords– Big data analysis; Carpenter skill; Component; Motion analysis; Planing work

I. INTRODUCTION

Structural forms of Japanese buildings include wooden structures, steel structures, reinforced concrete structures, and reinforced concrete structures. Among detached houses, according to data compiled by the Ministry of Land, Infrastructure, Transport and Tourism Construction statistics survey report 2018 [1], the percentage of wooden houses among detached houses exceeds 80%. Therefore, the wooden structure shown in Figure 1 represents the mainstream.

In areas where wood suitable for building materials is not available, such as the Middle East, masonry is commonly used to support buildings with walls made of brick or earth. Japanese structures use abundant timber. In addition, buildings are supported by columns and beams. However, the population of Japanese carpenters who produce and maintain wooden houses is declining precipitously. According to the Census Statistics Bureau, Ministry of Internal Affairs and Communications in 1975 [2], and a similar survey conducted in 2015 [3], the construction carpenter technician population has dropped by more than half in 45 years: from 852,745 carpenters in 1975 to only 353,980 carpenters in 2015. Specifically examining the age structure, the proportion of 15–39 year old people responsible for the future of the industry in 1975 was about 60%. By 2015 it had dropped considerably to about 20%.

Figure 1. Japanese wooden house.

The situation described above has come to represent the ordinary state of affairs. Therefore, the architectural carpentry industry must confront challenges hindering the passage of skills to inexperienced workers. One reason for this acute necessity might be that a longer time necessary to acquire full-time construction skills after starting a job engenders a lower retention rate and a higher turnover rate. Therefore, acquiring and passing on skills efficiently and rapidly can contribute greatly to improving the employment rate of young people and to lowering of the turnover rate, in addition to helping to resolve shortages of human resources.

One means of transferring these skills smoothly is to train carpenter technicians at vocational ability development facilities. Vocational training at a vocational ability development facility is intended to develop and improve abilities by enabling students to acquire the necessary knowledge and skills for a profession. Because of recent diversification of employment, vocational development facilities must impart more knowledge and skills. Nevertheless, it is difficult to spend much time at the carpenter's basic work in Japanese architecture, such as sharpening, chiseling, sawing, planing, and nailing. Therefore, an educational method must be developed that can teach carpentry work effectively in a short time.

Planing work, which makes a wood surface smooth and glossy, is often applied to pillars in a Japanese-style room where the pillars are exposed. The planing work emphasized in this study is performed mainly on two pillars, as shown in Figure 1. This skill is particularly important for Japanese carpenters: improperly performed planing work can leave wood splintery and dangerous; also, roughly finished pillars will destroy the unique atmosphere of a Japanese room.

From surveys of technical explanations and research papers published in Japan to date, we have learned the knack of planing work and how to teach related skills. In addition, a questionnaire survey related to planing work was administered to skilled workers to elicit planing work tips from workers. We also analyzed skilled and unskilled workers' behaviors during planing work. Differences were clarified from motion analysis results [4],[5].

A huge amount of work and a great deal of time are necessary to compare motion analysis results manually. Conducting training efficiently requires rapid analysis of training data and provision of feedback promptly to trainees. Therefore, for this study, we are examining improvement of training efficiency using a system that analyzes and visualizes big data related to skills that can be acquired during training. As described herein, we summarize the possibility of training effects by machine learning in the field of vocational training based on analysis using k-means method for planing work training data.

The remainder of the paper is organized as follows. Section II presents earlier research related to this topic. In Section III, we propose a K-means analytical method using data collected for planing work. Section IV presents a description of experimentally obtained results for our proposed method and a discussion of the results. Section V is a summary of the study contributions and expectations for future work.

II. RELATED WORK

Chen et al. conducted a series of studies specifically examining motion analysis related to carpentry skills [6]–[8]. The studies and the results are described below.

In one study [6], Chen et al. analyzed the same planing work as that examined in this study. They specifically reported details of measurement results of one of the four skilled workers. Results indicated that the posture during work should be "half-body"(diagonally opposite to the planing material). Half body is a posture similar to that shown in Figure 2, which portrays the posture with one leg before a half step from a standing position.

Figure 2. Half body (diagonally opposite to the planing material).

They were able to classify planing work into four basic forms: a providing planing motion, a cutting motion produced by rapid closing of the elbow, a cutting motion resulting from a large backward movement, and sudden stopping of the planing motion.

Chen et al. used a motion capture system to analyze sawing operations [7]. The report describes comparison of the sawing behaviors of skilled and unskilled persons. Results highlight their differences during work in terms of the forehead position, right arm movement, and saw speed. However, that report presented an analysis of few data. Its results are therefore regarded as being less generalizable. Features common to skilled people and those common to unskilled people were not described. Moreover, the analysis of measured values used no objective method such as an analytical statistical method or a clustering method.

Research using a Kinect™ device (Microsoft Corp.) for motion analysis includes one study described by Kurebayashi et al. [8] with a developed system that can animate skeletal information measured using Kinect™. Furthermore, the system was used for a junior high school class: evaluations of the students' feelings of use were assessed, showing high evaluations. Nevertheless, classification and organization of student motions were not performed using data obtained from this system.

As described above, several behavioral analyses related to carpentry skills have been conducted, but results of only a few test subjects have been presented. Moreover, no objective method has been applied for data analysis. An earlier report [9] explaining various methods used to analyze big data is helpful for selecting an analytical method for big data obtained from many subjects, as in this study. Therefore, this study examines whether a difference between skilled and unskilled workers can be extracted by application of the K-means method, a clustering method, to results obtained from numerous test subjects.

III. Our Proposed Method

This section presents a description of a method for analyzing data with machine learning using training data from planing work.

A. Data collection

In the experiment, the subject completed eight consecutive planing work bouts over the entire length of the work material. The subject's movements were measured using a Kinect™ sensor. In addition, the force generated during the work was measured using a strain gauge load cell (capacity 500 N). Figure 3 portrays the positional relation and axes for Kinect™ and the test subject.

Kinect™ is prone to misrecognize skeletal information when measuring from a perspective that includes overlapping of body parts (e.g., the position information of the right and left elbows is switched). Therefore, Kinect™ was installed to give a perspective by which the body parts overlap to the least extent possible during operations, thereby mitigating misrecognition. The relation between the load direction and the axis during the planing operation is designated as the X axis; the pulling force is along the Y axis, with pushing force also occurring along the horizontal axis. The Z axis shows pushing force in the vertical direction.

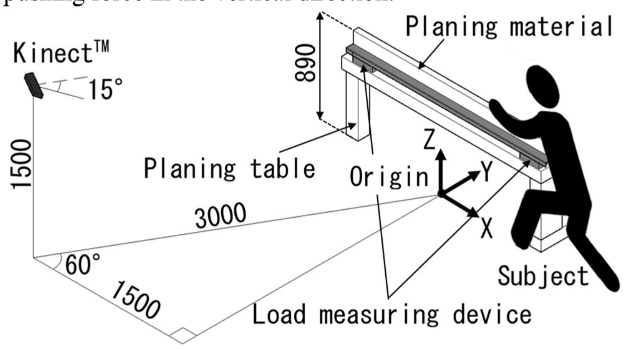

Figure 3. Kinect™ and the subject's positional relation and axes (unit: mm).

The work material was Japanese cypress material of 50 mm width and 105 mm depth. The material length was 2000 mm. The plane used for measurements was a replaceable blade-type intermediate finish plane. The plane blade adjustment was left to the working subject. Table 1 presents characteristics of five skilled workers (group J) and 10 unskilled persons (group M). The author conducted motion analysis for them at a laboratory of Polytechnic University.

Group J in this study mainly comprises artisans who have won prizes in the Skill Grand Prix. All were first-class technicians. Skills Grand Prix is a tournament for those with level 1 technical skills, especially those with outstanding skills. Group M members were 10 unskilled people: 5 third-year students and 5 fourth-year students from a Japanese polytechnic university studying architecture in 2018.

TABLE I. Characteristics of Skilled and Unskilled Persons

No.	Height (cm)	Dominant hand	Dominant eye	Age	Carpentry experience (year)	Teaching history (year)	Remarks
J1	165	Right	Right	62	45	35	Skill Grand Prix 1st place
J2	165	Right	Right	72	55	40	Skill Grand Prix 1st place
J3	161	Right	Right	67	49	28	In-house training school instructor
J4	177	Right	Right	38	23	18	Skill Grand Prix 2nd place
J5	172	Right	Right	39	16	10	Certified training school instructor
M1	178	Right	Right	21	4	0	PTU, Arch, major 4th year
M2	177	Right	Right	22	4	0	PTU, Arch. major 4th year
M3	173	Right	Right	21	3	0	PTU, Arch. major 3rd year
M4	174	Right	Right	22	4	0	PTU, Arch. major 4th year
M5	165	Right	Right	21	3	0	PTU, Arch. major 3rd year
M6	180	Right	Right	20	3	0	PTU, Arch. major 3rd year
M7	170	Right	Right	21	3	0	PTU, Arch. major 3rd year
M8	168	Right	Right	20	3	0	PTU, Arch. major 3rd year
M9	178	Right	Right	22	4	0	PTU, Arch. major 4th year
M10	177	Right	Right	22	4	0	PTU, Arch. major 4th year

B. Preprocessing

We used software (MATLAB; The MathWorks Inc.) to analyze skeleton position data measured using Kinect™ at 0.03 s intervals. Table 2 presents data for one subject that were processed. Table 2 presents XYZ-axis values for 20 points of skeletal position data during planing work obtained from one shooting: the first column shows waist X axis data; the second shows waist Y axis data; and so on.

TABLE II. Data Example (Before Processing)

Time (s)	Waist X-axis (mm)	Waist Y-axis (mm)	Waist Z-axis (mm)	Spine X-axis (mm)	Spine Y-axis (mm)
0.03	-40.239	-762.46	1057.8	-37.527	-757.54
0.06	-40.121	-762.30	1057.8	-37.435	-757.48
0.09	-39.452	-760.96	1058.0	-36.798	-756.52
0.12	-37.735	-757.84	1057.9	-34.922	-753.77

Time (s)	Waist X-axis (mm)	Waist Y-axis (mm)	Waist Z-axis (mm)	Spine X-axis (mm)	Spine Y-axis (mm)
0.15	-35.893	-754.11	1058.5	-32.863	-750.72
0.18	-32.994	-750.87	1057.8	-29.517	-748.11
0.21	-29.873	-747.39	1056.8	-26.216	-745.33
0.24	-27.388	-743.58	1055.5	-23.721	-742.15
0.27	-25.869	-740.55	1055.5	-21.958	-739.66

Among the data for 20 points of skeletal position information in Table 2, skeleton position information of the head, shoulder, waist, and left hand, which has been emphasized in earlier studies, is the subject of analyses in this study. Using these data groups, the data were processed into a machine-learning format for analysis using the k-means method. Table 3 presents an example of a dataset obtained by processing information related to the head, shoulder, waist, and left hand for each subject.

TABLE III. DATA EXAMPLE (PROCESSING FOR CLUSTER ANALYSIS)

J1, 1st experiment, 2nd plane	J1, 1st experiment, 3rd plane	…	J1, 1st experiment, 7th plane	J1 2nd experiment, 2nd plane	…
-382.37	-410.78	…	-306.42	-352.84	…
-377.42	-399.05	…	-308.62	-357.03	…
-376.92	-396.86	…	-299.68	-357.81	…
-364.65	-394.47	…	-299.32	-356.31	…
-363.17	-389.36	…	-298.31	-349.42	…
-360.46	-385.36	…	-291.69	-328.33	…
-364.44	-369.31	…	-289.85	-333.24	…
-355.89	-364.90	…	-284.37	-337.13	…
-351.41	-348.89	…	-279.63	-334.60	…

Data in Table 2 include those of eight consecutive planing works. Therefore, the data in Table 3 are divided into those of six planing works excluding the first and last planing work pieces. The time-series data of the location information for each planing work of each subject are arranged in one column as one dataset. A dataset for each XYZ axis value comprises head, shoulder, waist, and left hand data. Therefore, 12 datasets are handled as one-dimensional data.

For preprocessing, data are standardized: the average of each column data becomes 0. The time series of the data were also checked: abnormal behaviors (values that should have increased had decreased, etc.) were excluded from time series data for the corresponding single-cutting operation.

The time required for a planing work piece differs every time. Therefore, the number of lines of motion data obtained in time-series differs for each planing work piece. Therefore, the number of rows in the dataset must be unified. Based on the planing operation with the longest planing work time, the blank after the other planing work was filled entirely with zeros.

C. *Analytical method*

Collecting large amounts of data has become easier because of improvements in computer processing speed and communication infrastructure. Furthermore, big data are analyzed and used in various fields. Performing this big data analysis manually would be very expensive and impractical. For this reason, machine learning, which can automatically obtain accurate results from large amounts of data in a shorter time than humans could reasonably achieve, is often used. Machine learning can resolve difficulties by inferring patterns from large amounts of data. Therefore, for this study, we decided to conduct analyses using the K-means algorithm, a method of unsupervised learning, as the first experiment to explore training effects using machine learning in the vocational training field. There are two reasons that the k-means method was chosen as the machine learning technique. The first being simple clustering technique. The second is to explain many data in a short time. The author chose it because this k-means method meets both requirements for the purpose of this article.

Equation (1) presents evaluation function f of the k-means algorithm. Data X are divided into arbitrary K clusters by finding the center of the cluster that minimizes Equation (1).

$$f = \sum_{X_j \in X} \min_{i \in X} \left\| X_j - c_i \right\| \tag{1}$$

Where X_j, $j \in \{1,\ldots,n\}$ represents each datum; n denotes the total number of data. Also, c_i signifies the cluster center i^i $n\{1,\ldots,k\}$. The k-means method performs clustering by obtaining a cluster center that minimizes the distance between each data point and the nearest cluster center.

IV. EXPERIMENTS

As described herein, we try to discriminate between movements of skilled and untrained persons based on acquisition of motion data. In doing so, we aim to clarify unique behaviors that are typical of skilled workers.

A. *Preliminary analysis*

First, cluster analysis was applied to divide the data into two by k-means using 12 datasets of XYZ axes of the head, shoulder, waist, and left hand shown in Section III.B as one matrix. A value of k was chosen as 2 is because it confirms the usefulness of the k-means method. In addition, one can see if clustering can be categorized broadly into skilled and unskilled people. The reason for choosing the head, shoulder, waist, and left hand is that they were also chosen in earlier studies [5]. One can ascertain the characteristics of the posture of the subject with planing work. Results show simple classification according to the length of time needed for the work. Work speed is an effective index for evaluating work movements, but specific movements common to skilled workers have not been clarified. Therefore, to exclude information related to work speed and to compare detailed movements in the planing work of the respective subjects, results demonstrated the necessity of conducting analyses using positional information aligned within a certain time interval.

B. Experiment method

This study specifically examines movements in the first few seconds of planing work and during the first few seconds before the end of the movement. Specifically examining the start and end of planing, they have their own movements. Therefore, the skill levels are easier to understand than during planing. To organize the time-series data of the obtained motion, the interval from the start to 2.25 s (initial interval) and the interval from 2.25 s before the end to the end time (final interval) were set. The reason to set the time to 2.25 s is the necessary amount of data to identify work trends. Then, the 75 time-series position information data included in each section were made into one matrix. The data were divided into two clusters using k-means.

C. Experiment results for interval

The experimentally obtained results for the initial interval presented in section IV.B are described in IV.C.1). Experimentally obtained results for the final interval are described in IV.C.2).

1) Experiment results of the initial interval

The analysis specifically examined movement for 2.25 s from the start of movement. Data were divided into two by k-means for a matrix containing all data in the X-axis, Y-axis, and Z-axis directions (including the head, shoulder, waist, and left hand). Results show rough classification by skilled and unskilled persons. Figure 4 presents classification results for each planing work by skilled and unskilled workers obtained using location information in the initial interval.

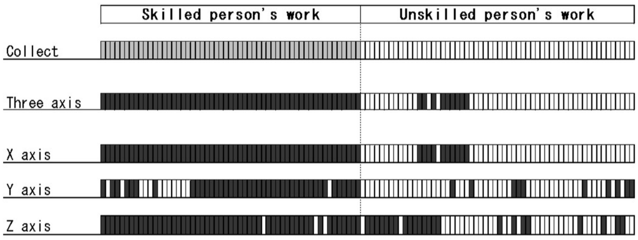

Figure 4. Results of clustering by skeletal position in the initial interval.

In addition, to ascertain which of the three directions is most effective for clustering, we divided the datasets in the X-axis, Y-axis, and Z-axis directions and applied cluster analysis using each dataset to ascertain key factors for classification. As shown in Figure 4, results show that the movement in the X-axis direction had an effect. Therefore, the head, shoulder, waist, and left hand were clustered into two clusters using the k-means method to find out which part of the X-axis movement most affected clustering. As shown in Figure 5, all factors affecting the head, shoulder, waist, and left hand were confirmed as influential.

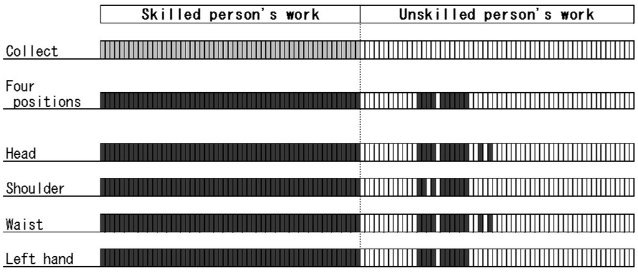

Figure 5. Results of clustering by skeletal position in the X-axis direction at the initial interval.

2) Experiment result of the final interval

These analyses specifically addressed the period of 2.25 s of movement until the end of movement. Data were divided into two parts using k-means for a matrix containing all data in the X-axis, Y-axis, and Z-axis directions (including the head, shoulder, waist, and left hand). As described in IV.C.1), results show rough classification of skilled and untrained work. Figure 6 shows how planing work by a skilled person and by an unskilled person is classifiable using position information in the final interval.

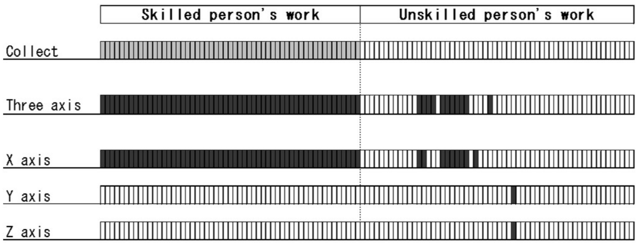

Figure 6. Results of clustering by skeletal position in the final interval.

In addition, to ascertain which of the three directions is most effective for clustering, after dividing the datasets in the X-axis, Y-axis, and Z-axis directions to ascertain key factors for classification, we applied cluster analysis using each dataset. Figure 7 presents experimentally obtained results for X. As in IV.C.1), results demonstrated that movement in the X-axis direction was affected. Therefore, the head, shoulder, waist, and left hand were clustered into two clusters by the k-means method to ascertain which part of the X-axis movement most affected clustering. On the X-axis, all head, shoulder, waist, and left hand effects were confirmed.

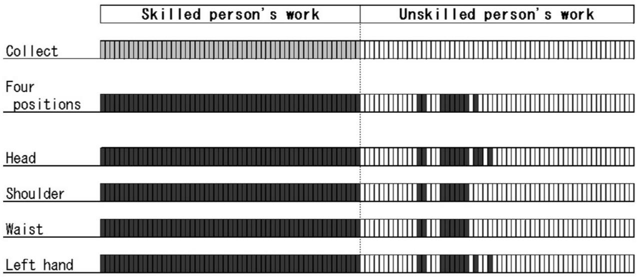

Figure 7. Results of clustering by skeletal position in the X-axis direction at the final interval.

Results presented above show that a feature exists in movement in the X-axis direction in the initial interval and final interval. To examine the factors that led to this analysis, we examined the video during the experiment and the raw data of the head, shoulder, waist, and left hand. Furthermore, all elements of the head, shoulder, waist, and left hand are affected. This effect might be attributable to the number of pauses used by skilled and unskilled persons during one bout of planing work. Skilled persons use a large forward-leaning posture because the pauses during planing work are few: 0–2 times. This tendency was also observed for unskilled workers clustered in the same group as skilled workers. However, unskilled workers in different groups tend to use a slightly forward-leaning posture because they pause several times (1–6 times) during planing work. Therefore, cluster analysis revealed differences between efficient work with few stops and work with numerous stops.

V. CONCLUSION

The purpose of this study was to construct a system to analyze and visualize big data related to training that can be acquired during vocational training. Then we conducted experiments to evaluate planing work to improve training efficiency, and found the possibility. The experiments specifically examined the initial interval and final interval, and included application of cluster analysis using k-means with position information obtained for four skeletal locations: the head, shoulder, waist, and left hand. Results show clustering of results by skilled and unskilled people. These results confirmed that applying simple machine learning such as k-means to planing work training data can engender useful analysis. This study used only four skeleton positions for analytical information. For that reason, only analysis that is related closely to the number of stops during planing is possible. In the past, analyses that were performed manually could be performed quickly using machine learning. The present study assessed clusters of skilled and unskilled people. Future studies, by performing clustering among unskilled people, are expected to provide optimal skill instruction for individual groups. Therefore, in this paper, we were able to analyze only the number of stops during planing. Future studies will use analytical methods to generate posture data from the measured three-axis data assess methods to analyze data for the load applied to the work material during planing work operations. Promoting this research can improve training effects in the field of vocational training by producing a continuous support system using machine learning.

ACKNOWLEDGMENTS

This work was supported by JSPS KAKENHI Grants No. 18K13254, 16K00157, 26350221, 15H02920, and 19K15248.

Figures 1 and 2 were from Professor Emeritus Shinichiro Matsudome of the Polytechnic University. The author acknowledges that contribution and appreciates it earnestly.

REFERENCES

[1] Ministry of Land, Infrastructure, Transport and Tourism Construction statistics survey report, total for 2018. [Online]. Available from: http://www.mlit.go.jp/sogoseisaku/jouhouka/sosei_jouhouka_tk4_000002.html/ [retrieved: 12,2019]

[2] Statistics Bureau, Ministry of Internal Affairs and Communications. Census 1971: Extraction details National result table number 18. [Online]. Available from: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200521&bunya_l=02&tstat=000001037125&cycle=0&tclass1=000001037140&stat_infid=000007915263&result_page=1&second=1&second2=1/ [retrieved: 12,2019]

[3] Statistics Bureau, Ministry of Internal Affairs and Communications. Census 2015: Extraction details National result table number 9. [Online]. Available from: https://www.e-stat.go.jp/stat-search/files?page=1&layout=datalist&toukei=00200521&tstat=000001080615&cycle=0&tclass1=000001104855&tclass2=000001108965&stat_infid=000031643878&cycle_facet=tclass1%3Acycle&second2=1/ [retrieved: 12,2019]

[4] H. Tsukazaki, M. Tamai, K. Kondo, H. Maekawa, and S. Matsudome, “A study on the behavior analysis of carpenter skills.” Summaries of Technical Papers of Annual Meeting. Architectural Institute of Japan, pp.59-60, 2016.

[5] H. Kataoka, H. Tsukazaki, M. Sadanari, H. Maekawa, T. Sahata, K. Nishiguchi et al. “A study of the behavior analysis of carpenter skills – Instruction method of planing work.” Summaries of Technical Papers of Annual Meeting. Architectural Institute of Japan, pp.147-148, 2019.

[6] G. Chen, A. Yamashita, K. Shibaki, and C. Tanaka, “Three-dimensional analyses of the work motion using woodworking tools I: Basic from of planing motion of skilled Japanese woodworkers.” Mokuzai Gakkaishi Vol.48, No.2, The Japan Wood Research Society, pp.80-88, 2002.

[7] G. Chen, A. Yamashita, K. Shibaki, and C. Tanaka, “Three-dimensional analysis of the work motion using woodworking tools II: Comparison on the sawing motions of the skilled and no-skilled woodworker.” Mokuzai Gakkaishi Vol.49, No.3, The Japan Wood Research Society, pp.171-178, 2003.

[8] S. Kurebayashi, K. Kobayashi, D. Takayama, K. Eguchi, and S. Kanemune, “The Development of Basic Motion-Analysis Using the Sensor KINECT.” Bulletin of the Japan Society of Industrial and Technical Education Vol.55, No.3, pp.213-220, 2013.

[9] H. Ishikawa, Social Big Data Mining. CRC Press, March 2015.