

# Real Time Workers' Behavior Analyzing System for Productivity Measurement Using Wearable Sensor

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**Abstract:** This paper presents a real time workers' behavior analyzing system using wearable sensors which combine Bluetooth low energy beacon (Beacon) and acceleration sensor to measure production progress and work history data in a cellular manufacturing system. It takes a lot of cost to collect those data on the cellular manufacturing line where workers' work is mainly conducted. For the purpose, we first built an experimental cellular manufacturing line and collected workers' behavioral data. Next, we developed our system and determined analyzing parameters using workers' behavioral data. Finally, we built another experimental cellular manufacturing line, and we measured production progress and work history data from our system. We then compared the result with a conventional visual method using video. The results revealed that our system measured the productivity data in the cellular manufacturing line which does not use a machine, and we could gather production progress and work history data more quickly than the conventional method. We believe that our system will make it possible to increase the efficiency of the supply chain system, to get a quick feedback in daily production, and to improve production.

**Key Words:** behavior analysis, productivity measurement, wearable sensor, cellular manufacturing system.

## 1. Introduction

Since sensors and computers are becoming higher performance and lower price products, a large amount of data can be collected and analyzed in real time. In the manufacturing industry, many ideas have been proposed for improving productivity using these data, such as Industrie 4.0 and Industrial Internet [1]–[4]. To efficiently and stably provide products to customers, many factories build a supply chain system that connects logistics and information [5]. Therefore, each factory has to collect factory data quickly to cooperate with other factory in a supply chain.

Various kinds of data can be collected at the factory. Among the data, production progress and work history data on a manufacturing floor are very important because they influence whole production efficiency indices, which are the quality, the cost, and the delivery. To gather these data, it is necessary to sense materials, machines, and workers, which are constituent elements of the manufacturing floor. However, attaching sensors to materials increases the cost directly, and a machine can not measure the process which does not use the machine. Furthermore, in sensing workers by an engineer's visual method, it requires expertise and takes too much cost. Besides, in sensing workers by a video image analysis, it is difficult to adjust analysis parameters, and it is impossible to measure the data when the worker moves to the blind spot. For these reasons, it is difficult to collect production progress and work history data in a cellular manufacturing system (Fig. 1) that assembles complicated products by workers, and there are much time and effort to improve production efficiency.

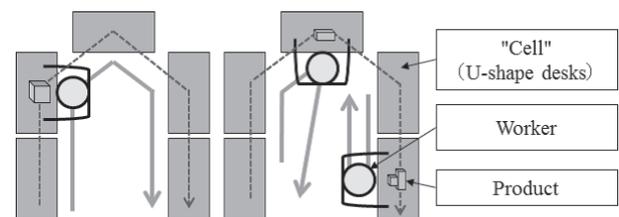


Fig. 1 Cellular manufacturing system.

This paper presents a real time workers' behavior analyzing system using wearable sensors which combine Bluetooth low energy beacon (Beacon) and acceleration sensors to measure production progress and work history data in cellular manufacturing systems. Our system has two analyzing methods of workers' behavior, 1) analyzing workers' position from Beacon's received signal strength index to measure production progress, 2) analyzing workers' movements from acceleration sensor data to measure work history. For that purpose we first built an experimental cellular manufacturing line and collected workers' behavioral data. Next, we developed our system and determined analyzing parameters using the workers' behavioral data. Finally, we built another experimental cellular manufacturing line, and we measured production progress and work history data from our system. We then compared the result with a conventional visual method using video. The results revealed that our system is able to measure the productivity data in the cellular manufacturing line which does not use a machine, and we were able to gather production progress and work history data more quickly than the conventional visual method. We believe that our system will make it possible to increase the efficiency of the supply chain system, to get a quick feedback in daily production, and to improve production.

The rest of the paper is organized as follows: Section 2 discusses the background of the research and related work; Sec-

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tion 3 explains the system configuration; Section 4 describes the experiment's setup of a cellular manufacturing line; Section 5 presents the experimental results of our system and the conventional visual method; Section 6 discusses the results; and Section 7 gives concluding remarks and future work.

## 2. Background and Related Work

This section presents the background of the research and related work.

### 2.1 Data Collection Method

Various kinds of data can be collected at the factory, for example, medium-to-long term data such as management strategy results and logistics data, and short-term data such as facility control parameters and production progress [6]. Among these data, production progress and work history data at a manufacturing floor are very important because they influence production efficiency indices, which are the quality, the cost, and the delivery [7]–[10]. To gather data of production progress and work history on the manufacturing floor, it is necessary to sense materials, machines, and workers, which are constituent elements of the manufacturing floor. For sensing materials, barcode or radio frequency identification technology is usually used [11],[12]. For sensing machines, a process log storage is mainly used [13],[14]. For sensing workers, a visual method by an engineer with a stopwatch or a video is conventionally used, and video image analysis has been used recently [15],[16]. These methods are effective. However, in sensing materials, attaching sensors to products increases the cost directly, and therefore it is difficult to implement easily. In sensing machines, it is not possible to measure the production progress and work history data in a process which does not use a machine. Furthermore, sensing workers by an engineer's visual method requires expertise and takes too much cost. Besides, in sensing workers by a video image analysis, it takes time to adjust the analysis parameters, and it is impossible to measure when the worker moves to a blind spot. This paper presents a real time workers' behavior analyzing system using wearable sensors which combine Bluetooth low energy beacon (Beacon) and acceleration sensors to measure production progress and work history data in a cellular manufacturing system.

### 2.2 Data Analysis

Beacon's received signal strength index (RSSI) is widely used for estimating the position of the sensor owner. RSSI has inverse proportion to distance because RSSI is theoretically calculated from Friis' transmission equation as follows:

$$RSSI = TxPower - \log_{10} d, \quad (1)$$

where  $TxPower$  is a pre-measured value with the distance between the sensor and the antenna set to 1 m, and  $d$  is the actual value of the distance between the sensor and the antenna. Sato et al. estimated the position of sensor owner using the actual RSSI and pre-measured RSSI from multiple antennas [17]. Kawamura et al. calculated the distance between a sensor and antennas using maximum likelihood method to estimate the position [18]. Saka et al. created an RSSI database of various fields and compared with an actual value using a particle filter to estimate the position [19]. However, since these methods have measurement errors of several meters, they are diffi-

cult to apply for estimating positions within a small area such as a cell manufacturing line. Thereby, we applied the epsilon-tube method which can extract the peak of the waveform proposed by Murao et al. [20]. Because the workers repeat constant movements in the cell production line, the RSSI data have periodicity.

Acceleration sensors can measure the change of speed in a certain period of time. By wearing the sensor, it is possible to collect the movement of a body part as quantitative data. Many methods have been proposed to identify human motion by analyzing the acceleration data. Nakagawa et al. calculated the jerk which is the differential value of acceleration data and determined the threshold; they specified worker's movements such as moving and stopping [21]. Najafi et al. attached the sensor to the elderly's chest, and analyzed the characteristics of motion such as walking by using a kinematic model and Wavelet transformation from the acceleration and angular velocity of a sensor [22]. Wang et al. attached an acceleration sensor to the tool, and determined the human motion by the support vector machine using the acceleration data [23]. Tontani et al. analyzed the rhythm of motion by preliminarily preparing the waveform of the success pattern of work and judging a worker's sensor data based on dynamic time warping [24]. Murakami et al. applied a topic model which is a natural language processing field technique to the acceleration data and classified ten kinds of movements [25]. In this study, instead of a detailed classification of motion, we first aimed at judging whether a worker moved or not. Therefore, we applied the method of Nakagawa et al., calculated the jerk from acceleration data, and set the threshold to judge a worker's movement.

## 3. System Configuration

This section explains the system configuration, the data collection part of the system, and the data analyzing part in the system.

### 3.1 System Overview

The overview of our system is shown in Fig. 2. This system aims to measure production progress and work history data by analyzing workers' behavior data collected by wearable sensors in the cell manufacturing line where workers' work is mainly conducted. This system is composed of two parts, data collection part and data analysis part. The data collection part stores workers' behavioral data collected by using wearable sensors. The data analysis part extracts production progress and work history data by analyzing these data. Moreover, the data analysis part has two analyzing methods of workers' behavior; one is analyzing workers' position from RSSI data to measure production progress, and another is analyzing workers' movements from acceleration sensor data to measure work history.

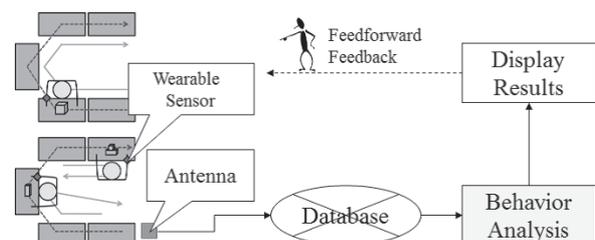


Fig. 2 System overview.

### 3.2 Data Collection Part

A worker wears wearable sensors to collect the behavioral data. In this research, the wearable sensor is the StickNFind series of Basis Innovation Inc. (Fig. 3).

This sensor is a composite device that can measure Beacon, three-axis acceleration, temperature and power consumption. We stored the data to the database server through the antenna made by the same company as the sensor. Workers wear the sensors to the left chest, the front waist, and the right foot. When performing motion analysis, sensors are often attached to the wrist, but we excluded this arrangement from this study because workers in the cellular manufacturing line sometimes dislike wearing on the wrist to prevent parts breakage due to contact and to avoid work speed's decrement.

### 3.3 Data Analysis Part

The process flow of the data analysis part is shown in Fig. 4. The data analysis part performs two analyzing methods of workers' behavior. One is analyzing the RSSI data collected by the wearable sensors, extracting the time at which the worker arrived at the production start position in the cellular manufacturing line, and measuring the production cycle time for each

product from the difference of arrival times. The other is analyzing three-axis acceleration data to estimate the movement (move or stop) of the worker, and when the number of movement while producing one product is different than predetermined one, it determines that abnormal work has happened. This system is made by JAVA and capable of analyzing the loading data while confirming whether or not the data is updated by using parallel processing. In Fig. 4, the variables  $F$ ,  $d$ ,  $r$ , and  $a$  are flags for deciding whether to make the corresponding threads sleep or execute respectively.

Now we describe the process flow. When the main thread starts, we first set the global flag  $F=1$ , then we build several execution threads, such as a data loading thread, a Beacon analysis thread, an acceleration analysis thread, and other simulation threads. Each constructed thread continues to move while  $F=1$ , but is basically in the sleep state and is controlled to be executed through by the flag when processing is required. The data loading thread checks the database server at regular intervals. When the database is updated and the Beacon analysis thread is not executed, the data loading thread stores the data and allows other analysis threads to refer the data. The Beacon analysis thread is executed when the data loading thread stores data, analyzes the RSSI of Beacon from the stored data, estimates the workers' position, extracts the time at which the worker arrived at the production start position in the cellular manufacturing line, and measures the production cycle time for each product from the difference of arrival times. When measuring a new production cycle time, the data loading thread also delivers the data to the acceleration analysis thread. The acceleration analysis thread executes when the Beacon analysis thread measures a new production cycle time. The acceleration analysis thread analyzes the number of movements and the number of stops from the worker's acceleration data, and estimates whether abnormal work has happened while the product



Fig. 3 A wearable sensor (right) and an antenna (left).

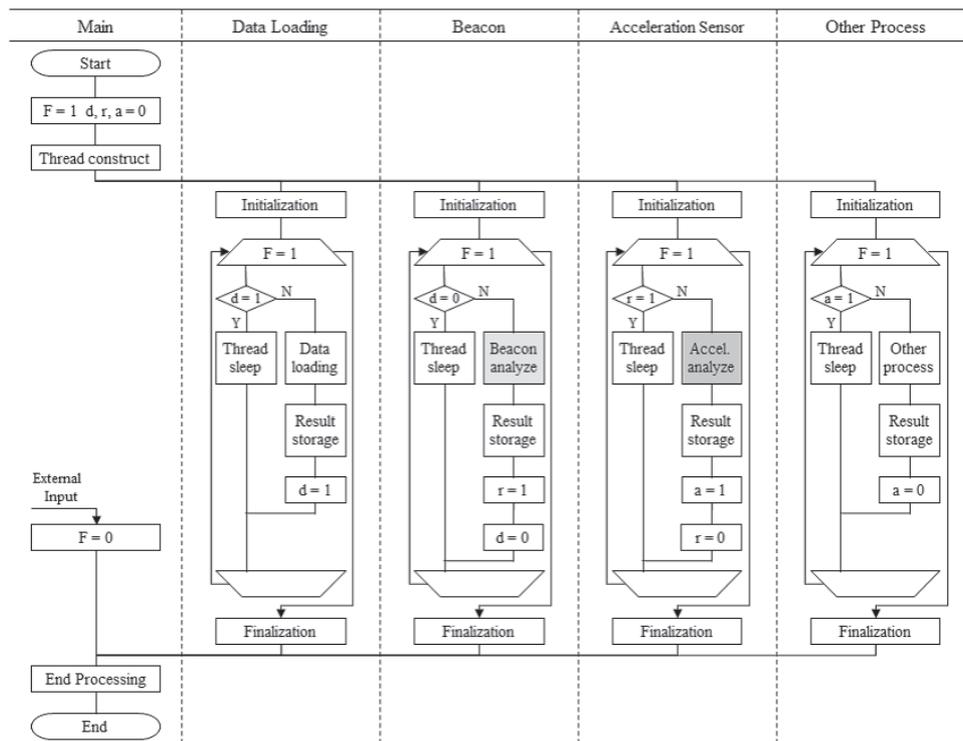


Fig. 4 A process flow of data analysis part in our system.

is manufactured. When other analysis threads exist, the acceleration analysis thread stores the data. The other analysis thread is used for other analysis of extracting production progress and work history data. For example, it can implement the dynamic scheduling which considers the production progress and the agent-based simulation to estimate the resource redistribution using these data. Finally, when an instruction to terminate the analysis is input,  $F$  is changed to 0, and all the threads enter finalization mode and stop.

### 3.3.1 RSSI analysis

In the RSSI analysis process, to measure the production progress, noise removal and analysis are performed on the data received from the data loading thread. In this study, a moving average filter (MAF) is used as noise removal [26]. An MAF replaces the corresponding data with the average value of  $2m+1$  data including in the front and back  $m$  data ranges. This is because the cycle of the RSSI waveform is the same as the manufacturing time of one product and this cycle is longer than observation noise, so it is possible to expect improvement of analytical accuracy by using a moving average filter with strong noise removal power. In this study, the epsilon-tube method is used for analysis (Fig. 5). In the epsilon-tube method, the average value is calculated with past  $k$  RSSI value in the data. Next, the epsilon tube is defined as the range between the average plus and minus  $E$  for some  $E > 0$ . The peak waveform is defined as the period outside the epsilon tube. This method is easier to calculate than the Fourier transform method and wavelet transform method. This study focused on the cellular manufacturing line where workers move between several desks to manufacture products. In the cellular manufacturing line, we set the antenna at the starting point of the manufacturing. As such, the worker starts at the location closest the antenna and moves farther from it. The next time the worker starts another manufacturing process, they return to the antenna location. Thus, the RSSI has periodicity of the highest value at the starting point of the manufacturing, and we can measure the start time of the manufacturing each product by extracting the upper peak of the RSSI value.

### 3.3.2 Acceleration analysis

In the acceleration analysis process, to measure whether the abnormal work is occurring, noise removal and analysis is performed on the data received from the Beacon analysis thread. The abnormal work of this study is defined as movement other than assembly and carriage of products. Abnormal work includes, for example, skipping the desk by forgetting a process and picking up dropped parts on the floor. To evaluate whether abnormal work is occurring, we extract the number of worker's movements from acceleration data and compare with the number of movements of a standard work for each product. In this study, a Savitzky-Golay filter (SGF) is used for noise re-

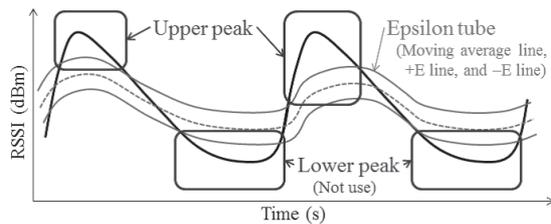


Fig. 5 Epsilon tube method.

moval [26]. An SGF replaces the corresponding data with the value of the polynomial of degree  $O$  calculated from  $2n+1$  data including in the front and back  $n$  data ranges. An SGF has the merit that noise can be eliminated while preserving high frequency components to some extent, but there is a disadvantage that noise removal performance is lower than an MAF. Because the movement in the cellular manufacturing line is limited in a short period of time, the acceleration data include high frequency components. Therefore, an SGF was considered to be more suitable than an MAF. In this study, we calculated the jerk and we set the threshold for analysis. Additionally, the horizontal vector of the acceleration is extracted and calculated from the waist sensor. The horizontal vector is calculated by dividing the vertical vector measured beforehand from the vector of the measured three-axis acceleration. Because the movement between the desks in the cellular manufacturing line is an only movement in the horizontal direction, it is expected that improvement in accuracy can be expected by extracting the horizontal component. The sensor of the ankle is not applied because the direction of the wearable sensor is changed when the foot moves.

## 4. Experimental Setup

This section explains the setting of one experiment for parameter setting and the setting of two experiments for system evaluation.

### 4.1 First Experiment

Three types of products were prepared using Lego blocks (Fig. 6). Each product is designed to be manufactured in about one minute. One worker manufactured a total of 30 pieces of 10 products for each product while walking in a desk arranged in a U-shape as shown in Fig. 7. The subjects were five people, all of whom made an experiment after learning how to move in cell production and how to manufacture each product. In the experiment, in addition to data collection using a wearable sensor, we took workers' situation with a video camera. After the experiment, we obtained production progress and work history data by the visual method using the video data. In this study, we treated the video camera result as a true value. Using the data obtained in this experiment, we searched for analytical parameters that can obtain high accuracy in our system. From the reference, we set the parameter ranges to be searched as in Table 1.

### 4.2 Second Experiment

In the second experiment, same as the first experiment, one worker manufactured product while walking in a desk arranged in a U-shape. However, different from the first experiment, the product was used only one type, "Car", and each worker manufactured 50 cars. The subjects were six people, all of whom



Fig. 6 Three kind of experimental product using LEGO block.

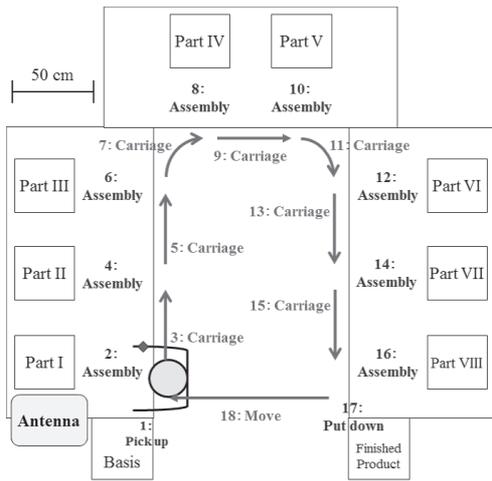


Fig. 7 Experimental cellular manufacturing line by one worker.

Table 1 The range of analyzing parameter.

Method	Variable	Parameter
MAF	Range $m$	5, 10
Epsilon-tube	Range $k$	10, 20
Epsilon-tube	Epsilon $E$	1-10
SGF	Range $n$	5, 10
SGF	Degree $o$	2
Jerk Threshold	Waist	0.01-0.20
Jerk Threshold	Ankle	0.01-0.20

made an experiment after learning how to move in cell production and how to manufacture each product. Same as the first experiment, in addition to data collection using a wearable sensor, we took workers' situation with a video camera, and we obtained production progress and work history data by the visual method using the video data.

### 4.3 Third Experiment

In the third experiment, different from the first and second experiments, two workers manufactured products while walking in a desk arranged in a U-shape (Fig. 8). The worker in charge of the first half of the cellular manufacturing line assembled the product. On the other hand, the worker in charge of the second half of the cellular manufacturing line disassembled the product. The second worker was able to start work when the first worker delivered the product. The product was used only one type, "Car", and each worker manufactured 50 cars. The subjects were six subjects of three pairs, all of whom made an experiment after learning how to move in cell production and how to manufacture each product. Same as the other experiments, in addition to data collection using a wearable sensor, we took workers' situation with a video camera, and we obtained production progress and work history data by the visual method using the video data.

## 5. Experimental Result

This section shows the result of the experiments.

### 5.1 First Experiment

Table 2 shows the most accurate parameters. Table 3 shows the analyzing results using the most accurate parameters. In Table 3, the collection rate shows the ratio of the number of products whose production time was measured by Beacon analysis, out of the total 150 products produced by subjects. The mea-

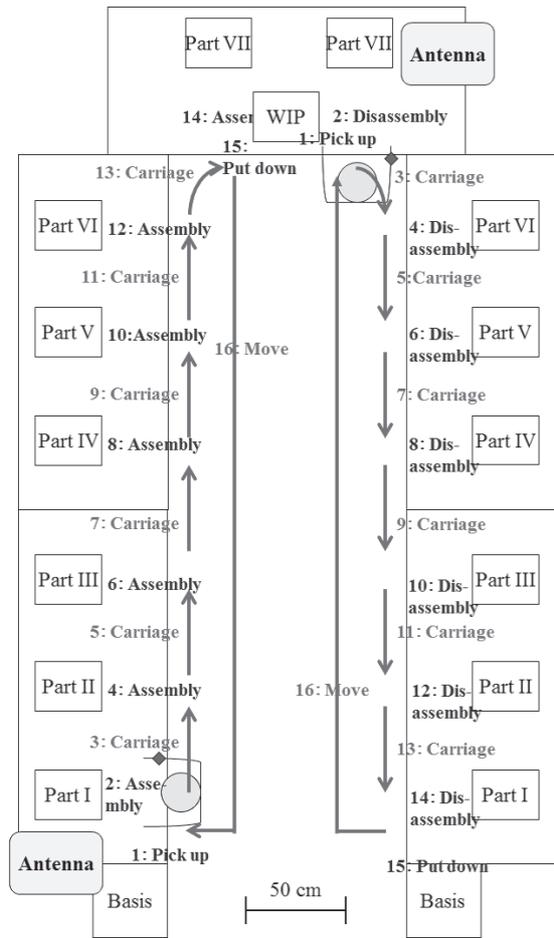


Fig. 8 Experimental cellular manufacturing line by two workers.

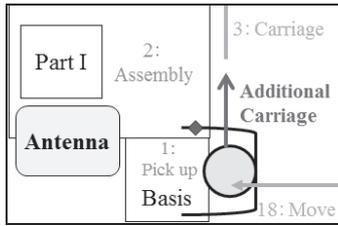
Table 2 The most accurate analyzing parameter.

Method	Variable	Parameter
MAF	Range $m$	10
Epsilon-tube	Range $k$	20
Epsilon-tube	Epsilon $E$	3
SGF	Range $n$	10
SGF	Degree $o$	2
Jerk Threshold	Waist	0.01
Jerk Threshold	Ankle	0.12

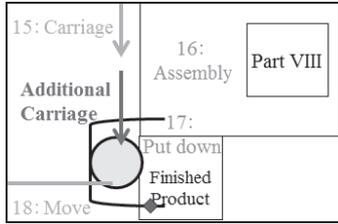
Table 3 The result of first experiment.

	1st Exp.
Production cycle time collection ratio (%)	96.0
Production cycle time MAE (s)	2.8
Work accuracy (%)	66.7
Total accuracy (%)	64.0
Sampling rate (data/s)	4.7

surement error of the cycle time is a value obtained by calculating the mean absolute error (MAE) with the true value as a percentage. The system classified the process into either "Normal" or "Abnormal". "Normal" is regarded as the product produced without any abnormality such as component falling at the time of production. "Abnormal" is regarded as the product produced with abnormality. The work accuracy is regarded as the ratio between the sum of (1) the number of actual "Normal" from inside the system's classified "Normal" and (2) the number of actual "Abnormal" from inside the system's classified "Abnormal", against the number of products whose production time



(a) The additional carry with the basis pick up.



(b) The additional carry with the product put down.

Fig. 9 The additional carriage from the first experiment.

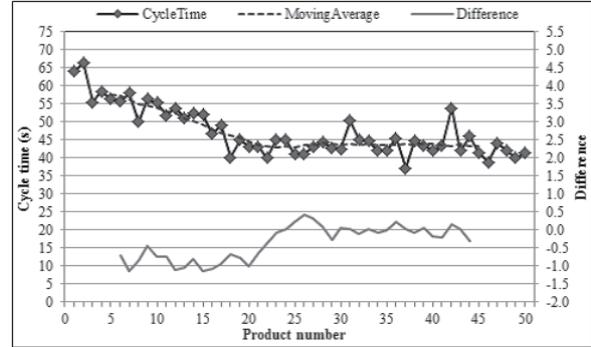
was measured by Beacon analysis. In the first experiment, the number of movement in standard work is eight. However, from the observation of the first experiment, many workers made additional movements between “1: Pick up of Basis” and “2: Assembly of Part I” and between “16: Assembly of Part VIII” and “17: Put down of Finished Product” (Fig. 9). These additional movements are part of the carriage, therefore we do not consider these as abnormal works. Therefore, the number of movements in standard work may increase by two. Moreover, the start of the each production is “1: pick up of the basis” in Fig. 7, but due to analytical error there is a possibility to include the last movement of the previous product. Therefore, the basic number of movements of workers may be further increased by one. Thereby, in the first experiment, the range of the basic number of movements was modified to the range of 8 to 11. In the second experiment where a worker’s movement is same as the first experiment, the range of basic number of movements was modified to the range of 8 to 11. In the third experiment which the number of movements in standard work is 7, the range of basic number of movements was modified to the range of 7 to 10. The total accuracy indicates the ratio of the sum of (1) the number of actual “normal” from inside the system’s classified “normal” and (2) the number of actual “abnormal” from inside the system’s classified “abnormal”, against the total 150 products produced by subjects. The sampling rate shows how much data was collected per second from one sensor.

**5.2 Second and Third Experiments**

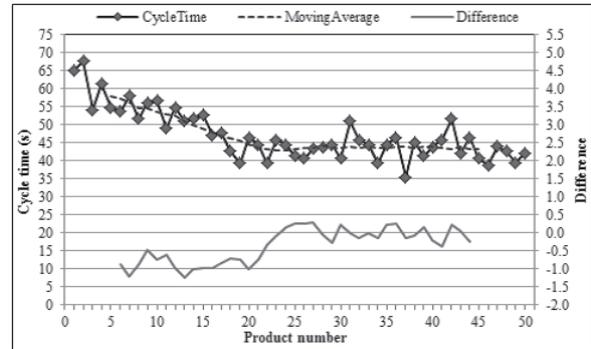
Table 4 shows the result of the second experiment and third experiment which used the most accurate parameter set from the first experiment. In both experiments, the accuracy was calculated with the total number of products produced by the subjects, i.e., 300. The sampling rate of the first experiment was different from those of the second and third experiments because a trouble occurred and the setting was reset by updating the application of the antenna. Actually, it should be the same setting as the first experiment. In Table 4, the calculation time indicates the time taken to obtain cycle time after the produc-

Table 4 The result of the second and third experiment.

	2nd Exp.	3rd Exp.
Production cycle time collection ratio (%)	90.0	78.7
Production cycle time MAE (s)	3.7	9.2
Abnormal work accuracy (%)	67.4	67.4
Total accuracy (%)	60.7	53.0
Sampling rate (data/s)	1.7	1.6
Calculation time (s)	13.54	13.72



(a) The result of the visual method.



(b) The result of our system.

Fig. 10 The time series result of one worker in 2nd experiment.

tion of one product. This time included the data loading time, RSSI analysis time, and acceleration analysis time. Our system can measure them automatically. Thus, the measurement cost is significantly lower than the visual method. However, if it takes a long time to analyze the data, its usefulness will decrease. The measurement time of the visual method was about 30 s per a product. Since our system took only approximately 13 s to complete, therefore it is much more effective than the visual method.

Figure 10 is a time-series graph of the cycle time of one worker in the second experiment by the visual method and our system. The moving average and the value difference of the cycles are also shown in the graph. In Fig. 10, the worker decreases the cycle time at around the 25th product compared with the production start. Thereafter, the worker manufactured the product almost in the same cycle time.

**6. Discussion**

The collection rate of production cycle time by analyzing RSSI data exceeded 90% in the second experiment, but decreased to 78.7% in the third experiment. This is because the movement of workers in the third experiment is different from that of the first experiment in which parameters were determined. Therefore, for deploying to different cellular manufac-

turing lines and factories, the learning method which dynamically improves the parameter to RSSI analysis is necessary. In all the experiments, the abnormal work accuracy by analyzing acceleration data was not good. This is considered to be the limit of the method using the jerk that judges with fixed criteria, although the movement of each person is different. Thereby, it is necessary for acceleration analysis to consider time-series such as the machine learning and the wavelet method.

On the other hand, the calculation time has been significantly shortened compared with the conventional visual method, and it seems that it contributes greatly to the efficiency of data collection. It is expected that the merit of this system will be further improved by improving accuracy in the future. Furthermore, in Fig. 10, a decrease of the cycle time seems to indicate the effect of proficiency of the worker. The ability to display such time-series results in real time is an advantage of using our system. Moreover, the motion will be slowed by worker fatigue and the accuracy of the work will be deteriorated [27],[28]. From Fig. 10, in the second half of the experiment, the worker manufactured the product almost in the same cycle time. Even other workers, we could not see the cycle time nor the accuracy of the work was deteriorated. Therefore, the effect of fatigue could not be confirmed in this experiment. However, we believe that it is highly possible to observe the effects of fatigue in real time by collecting the data with our system for a long time.

## 7. Conclusion Remarks and Future Work

This paper has presented the real time workers' behavior analyzing system using wearable sensors which combine Bluetooth low energy beacon (Beacon) and acceleration sensors to measure production progress and work history data in a cellular manufacturing system. Our system has two analyzing methods of workers' behavior, 1) analyzing a workers' position from Beacon's received signal strength index to measure production progress, 2) analyzing workers' movements from acceleration sensor data to measure work history. For the purpose, we first built an experimental cellular manufacturing line and collected the workers' behavioral data. Next, we developed our system and determined analyzing parameters using the workers' behavioral data. Finally, we built another experimental cellular manufacturing line, and we measured production progress and work history data from our system. We then compared the result with a conventional visual method using video. The results revealed that our system is able to measure the productivity data in the cellular manufacturing line which does not use a machine, and we were able to gather production progress and work history data more quickly than the conventional visual method.

There are three items for future work. The first is to improve the measurement accuracy of the RSSI analysis and acceleration analysis by using the machine learning method which dynamically improves the parameter to the RSSI analysis, and the machine learning and the wavelet method which consider the time-series for acceleration analysis. The second is to use the other process thread by implementing dynamic scheduling and agent-based simulation to improve the efficiency of supply chain systems by immediately using the data to measure. The third is to make it possible to analyze items other than the production record and work history using Beacon and acceleration data, for example, the estimation of workers' fatigue from the

collected data. The fatigue is estimated from the movement speed of the worker and the magnitude of the body shake, and the threshold of fatigue at which the working accuracy deteriorates is clarified. Accordingly, it becomes possible to prevent in advance those serious accidents due to errors of work and planning delays due to slowing of motion.

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