International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 03 - Issue 02 || February 2017 || PP. 01-13

ASSESSING POSTURE AND MOVEMENT OF BEGINNER FARMER WITH WEARABLE SENSORS

Riki tatsuta[1], DihnThi Dong Phuong[1], Yusuke Kajiwara[2], Hiromitsu Shimakawa[2]

[1]*(Graduate School of Information Science and Engineering, Ritsumeikan University/Shiga, Japan),*
[2]*(College of Information Science and Engineering, Ritsumeikan University/Shiga, Japan)*

Abstract: New farmers need technical guidance to improve working efficiency because they are lacking in experience. Agricultural experts put much effort to provide guidance for beginner farmers. However, continuing to give guidance is difficult because it is a large burden on the experts. This study proposes a system which contributes to transferring a deft motion of experts to improve the working efficiency of beginners in farm works. The system promotes beginners to assess their own farming works without an expert. The beginners can confirm whether their own works are proper works. An experiment has suggested that machine learning is an effective way to achieve a model to discriminate the proper farming works using posture and movement magnitude of each body part.

Keywords: Agriculture, farming works, physical behavior, machine learning, acceleration sensor, wearable sensor

1 INTRODUCTION

In recent years, many corporations enter the agricultural business actively in Japan by amending Agricultural Land Act. However, they have serious problems in human resource development. According to Japan Agricultural Corporations Association, agricultural corporations have pointed out their issues as follows: 37.0% of them try to strengthen their ability of human resource development, 24.6% work on the improvement of executive management, and 23.3% worry about development of successors [1]. The issues come from the fact that almost all new employees of the agricultural corporations have no experience [2]. Most of agricultural corporations full of beginner farmers have dropped the efficiency in their farming works, because their new employees frequently made big losses [2]. The corporations must improve their working efficiency of beginner farmers.

In order to improve the efficiency, agricultural experts teach their know-how to new employees in many agricultural corporations. One of the know-how is a criterion for decision in farming works. An expert makes a decision based on his/her experience and intuition. For example, when an expert sprinkles water, he/she checks the moisture of the soil and then adjusts the amount of the watering. An expert could express the know-how in words, because he/she memorizes the know-how in their mind. If an expert makes a manual about the know-how, beginners can follow the expert's know-how through the manual.

In the meantime, the know-how also includes deft motions obtained from a long-term experience. A deft motion reduces fatigue, because it helps to avoid unnecessary motion. It also helps to improve working efficiency. Since most experts work with deft motions unconsciously, it is difficult to verbalize the motion. Even if an expert verbalizes his/her motion, a beginner may not be able to understand it. For example, suppose an expert supervise a beginner, saying, "You should bend your arms to 50 degrees and move your hand in the direction of 6 o'clock". It is hard for the beginner to understand the advice. It is necessary to provide an easy guidance for beginners to understand, so that they can acquire a deft motion from an expert. The acquisition of a deft motion drastically improves working efficiency in the agricultural corporation.

In this research, we propose a system, which makes beginners master deft motion to improve the working efficiency in farming works by utilizing acceleration sensors. To master deft motion, beginners need to assess their own farming works. The assessment process would make beginners be conscious of their wrong movement, which may lead them to modify the wrong movement to the right one. The proposed method assesses the movement in farming works. Using this system regularly, beginners can master a deft motion quickly. It contributes to improve their working efficiency.

This paper is organized as follows. Section 2 introduces existing works. Section 3 explains our method to assess beginner's works. In Section 4, we show the experiment and its results. In Section 5, the paper discusses the result. Finally, Section 6 summarizes our work.The introduction of the paper should explain the nature of the problem, previous work, purpose, and the contribution of the paper. The contents of each section may be provided to understand easily about the paper.

2 RELATED WORKS

On-the-Job Training (OJT) is one of the methods to transfer a deft motion from experts to beginners. In most of the cases, beginners receive instructions on agricultural know-how from experts in OJT. However, experts must build well-considered plans for the training. It is a big burden for the experts. The shortage of experts and the big burdens prevent agricultural corporations from implementing the training.

Several studies proposed some methods to build a manual for transferring the knowledge and criteria to support beginners. Nanseki et al. suggested a system to share agricultural knowledge with farmers using a recorded video how experts work, including their working environments [3]. This system helps beginners to learn work procedures. Dimitriad et al. and Sekiguchi et al. extracted criteria for decision in farming works, which are based on expert's experience and intuition regarding to working contents, growing conditions, and environmental information [4][5].

The studies on a deft motion in farming work are fewer than studies on other know-how. Kawakura et al. calculated the difference in motion between experts and beginners using acceleration sensors and videos [6][7]. However, the study did not investigate whether the difference relates to a deft motion or not. The study neither verified the possibility to discover the difference using data in actual environments. No one has successfully developed a system which makes beginners master a deft motion without imposing stress on experts. Previous researches, which make workers master a deft motion, converted tacit knowledge into explicit knowledge in the works, where monotonic movement is repeated [8][9].

An acceleration sensor is expected to work well in the extraction of the explicit knowledge, because it can accurately record actual movement of body parts. However, there is no study to extract explicit knowledge in farming using acceleration sensors.

3 EVALUATION METHOD OF FARMING WORK FOCUSING ON PHYSICAL BEHAVIOR

3.1 SELF-ASSESSMENT OF FARMING WORKS

We aim at developing a system to make a beginner master a deft motion without imposing extra works on experts. To master a deft motion quickly, beginners need to evaluate their work accurately. The beginners generally lack knowledge and experiences on farming works. In order to evaluate farming works of beginners accurately, they need to point out their problems. On the contrary, the number of experts who engage in agricultural work have declined recently. It is hard for them to spare their time to train beginners because of their own farming works. We need a method to assess farming works of beginners simply instead of experts. We have proposed a system which assesses farming works of beginners simply using an acceleration sensors and machine learning processes.

3.2 OVERVIEW OF PROPOSED METHOD

No system has been developed to assess farming works instead of experts. In this research, we made an interview to find out the points related to a deft motion. The points are

- posture, and
- efficient movement

The proposed method assesses farming works from features related to the points. The points are factors to master a deft motion. This paper refers to each item of assessment in farming works as a work assessment item. The work assessment item focuses on posture and efficient movement. The proposed method gets a work assessment item through an interview with an expert. Efficient movement would improve the speed and the accuracy of farming works. The fixing bad posture in farming works of beginners would suppress deterioration of working efficiency by fatigue. Fig.1 shows the overview of the method.

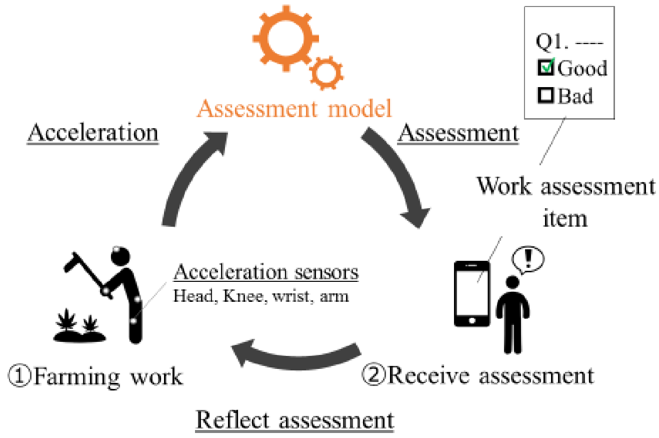

Fig.1 System overview

The proposed method assesses farming works from physical behavior of a user. This method uses acceleration sensors to obtain physical behavior. An acceleration sensor, which is compact and light, are easy to install on a user's body.

3.3 WHAT IS ASSESSED?

This paper proposes a method to judge automatically whether users unfamiliar to farming works take deft motions like experts. This paper refers to a criterion which assesses farming works from physical behavior as an assessment model. The assessment model tells a user if farming works are appropriate. The user can confirm his or her own farming works through the assessment model. The proposed method enables users to attain deft motions quickly. The method to construct an assessment model is shown in Fig.2.

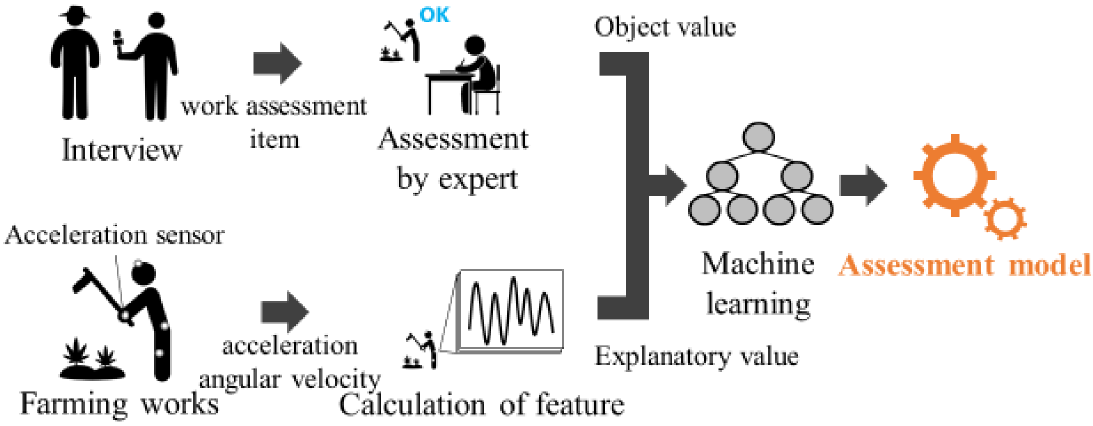

Fig.2The proposed method to construct an assessment model

The model constructing procedure is below.

1. An acceleration sensor grasps user's acceleration of each body part during farming works.
2. The method calculates features on posture and efficient motion from the acceleration.
3. The method gets work assessment items through an interview with an expert.
4. An expert assesses user's farming works based on the work assessment items.
5. This method constructs an assessment model using machine learning.

A new user's evaluation is calculated with the assessment model which takes the acceleration while farming work.

The method to calculate features related to posture and efficiency motion is shown in Fig.3.

International Journal of Latest Research in Engineering and Technology (IJLRET)
ISSN: 2454-5031
www.ijlret.com || Volume 03 - Issue 02 || February 2017 || PP. 01-13

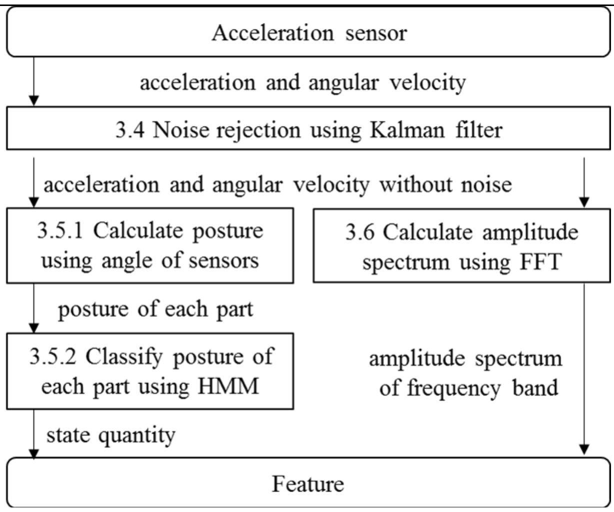

Fig.3The method to calculate features related to posture and efficiency motion

The step 3.5 is the method for posture. The step 3.6 is the method for efficient movement. The features are calculated according to the following procedure.

3.4 The proposed method reduces noises of acceleration and angular velocity using Kalman filter.

3.5.1 The method calculates the inclination angle of a sensor from acceleration.

3.5.2 The method classifies the state of each body parts using the angle of the sensors. It also calculates the frequency of each state.

3.6 The method calculates amplitude spectrum using fast Fourier transform (FFT).

This study focuses on harvesting operation as a farming work. It is difficult for a machine to harvest crops without damaging crops. Farmer usually harvest fragile crops with their own hands. Harvesting operation is a common process for almost all crops. Every kind of crops has its best season to harvest. Since it is hard to sell a crop which is outside of the season, farmers care the season. Farmers need to finish harvesting operations during the harvest season. They should work efficiently during harvesting. The working efficiency depends on deft motion. These are the reason why we focus on manual harvesting operations which easily affect working efficiency.

3.4 POSITION OF SENSORS AND NOISE REJECTION USING KALMAN FILTER

This method obtains physical behavior using an acceleration sensor shown in Fig.3. The user harvests crops in various motions and postures. For example, the user repeats standing and siting one after another. The user moves his/her head up and down to find crops and uses both arms to pick up crops. An expert assesses the farming work based on these motions and postures of the user. The system needs to obtain these motions and postures. We should attach the sensor in the position so as not to prevent the user's work. In the proposed method, acceleration sensors are attached on his/her head, knee, wrist and both arms, as it is shown in Fig.4.

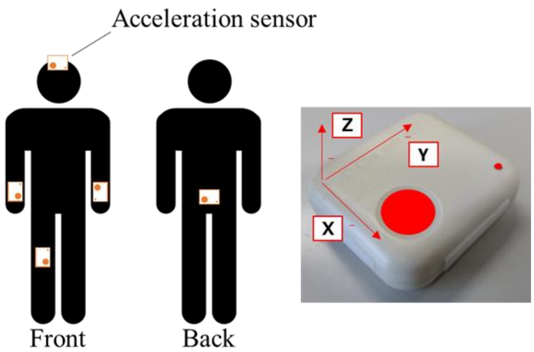

Fig.4 Acceleration sensor and its position

3.5.1 CALCULATING POSTUREUSING ANGLE OF SENSORS

This method calculates an inclination angle of a sensor to obtain the user's physical behavior. The inclination angle of a sensor attached on the user's body depends on the user's physical behavior. For example, when the user raises his/her head to find crops, the inclination angle of a sensor attached on the head changes. It is assumed that the method can obtain various physical behavior from the inclination angle. This proposed method calculates inclination angle of sensors on each part. The inclination angle is obtained through the conversion of the acceleration. Let θ_x, θ_y, θ_z represent the angle of the sensor based on the x-axis, based on the y-axis, and the z-axis, respectively. We denote the angle of the sensor $\theta_x, \theta_y, \theta_z$ at time of $t$as $\theta_{x_t}, \theta_{y_t}, \theta_{z_t}$.

$$\theta_{x_t} = \tan^{-1}\left\{\frac{A_{x_t}}{\sqrt{A_{y_t}^2 + A_{z_t}^2}}\right\}$$
$$\theta_{y_t} = \tan^{-1}\left\{\frac{A_{y_t}}{\sqrt{A_{x_t}^2 + A_{z_t}^2}}\right\}$$
$$\theta_{z_t} = \tan^{-1}\left\{\frac{A_{z_t}}{\sqrt{A_{x_t}^2 + A_{y_t}^2}}\right\}$$

3.5.2 CLASSIFY POSTURE OF EACH PART USING HMM

It is assumed that the user repeats similar physical behavior in farming works. For example, the user raises his/her head to find crops. The user uses both arms to pick up crops. The user puts the crops into a basket. The physical behavior cycle is assumed to be common to most users. To evaluate user's farming work, an expert examines the common physical behavior cycle. For example, to pick up crops with both hands, the user bends down. An expert evaluates the user's farming work based on the frequency of such physical behavior. The proposed method classifies the state of each body part using $\theta_{x_t}, \theta_{y_t}, \theta_{z_t}$. It is expected that the behavior which corresponding to a deft motion is obtained from the frequency of occurrence and state quantity. The method uses the Hidden Marcov Model (HMM) to classify states [11]. We use the Baum-Welch algorithm to build the HMM. The Baum-Welch determines parameters to maximize the likelihood of training data. We use the Viterbi algorithm for the output of the HMM. The Viterbi algorithm estimates state quantity which has the highest likelihood.

3.6 CALCULATE AMPLITUDE SPECTRUM USING FFT

An expert repeats an efficient movement many times during farming works. Such repeated movement includes a distinctive frequency band. Therefore, the proposed method calculates amplitude spectrum using FFT. The amplitude spectrum represents the power in a specific frequency band. The power in a specific amplitude spectrum increases if the same movement is repeated. We assume the efficient movement appears as a feature of the amplitude spectrum. The value of the acceleration sensor includes information on the direction of the action. The information on the direction of the action depends on the relative position of the harvest crop against the farmer. Since the position of the harvest crop is diverse, various actions may happen for one behavior, depending on the position of the harvest crop. The information on the direction of the action could be noisy. The proposed method uses the norm of acceleration and angular velocity. It removes information on the direction of the action. The method obtains a value independent of the environment.

3.7 ASSESSMENT MODEL CONSTRUCTED WITH MACHINE LEARNING

This method constructs the assessment model with the Random Forest (RF), which is one of machine learning algorithm [12]. RF computes multiple decision trees produced with training data. It predicts the class, taking the majority of decisions in each of the individual trees. The RF classifies physical behavior with two phases: identification and learning. In the identification phase, it evaluates the user's farming work from features of the amplitude spectrum presented in Section 3.5 and 3.6. In the learning phase, it creates an assessment model from a pair of features and assessment results based on the work assessment item. The proposed method constructs two models for the efficiency movement and the posture. To achieve it, an expert needs to assess farming work of several users. To obtain training data, an expert needs to work with sensors attached. The work might be a burden for the expert. However, in the identification phase, the proposed method can evaluate the user's work using only the acceleration of each body part of the user during his/her working. The burden on the expert in the proposed method is much smaller than the ones in other methods.

4 EXPERIMENT

4.1 EXPERIMENT OVERVIEW

An experiment was conducted to assess the user's farming work based on work assessment item using the user's behavior. We use a 3-D wireless hybrid sensor WAA-010 manufactured by Wireless technology

Corp. The sampling interval was set to 50ms. Subjects were five males who did not have farming experience and one male who was an expert. Each of them wore acceleration sensors on his head, knees, waist and wrists of both arms. We conducted the experiment at a farm of Takashima, Shiga in Japan. In this experiment, we harvested blueberries. Blueberries are too fragile to be harvested with machines. Even an expert harvests it using his hands without a machine. Each of subjects wore a basket on the neck to store the crops. To make the beginner subjects get used to harvesting operation, the expert showed model operations. The beginner subjects harvested blueberries until they gain confidence to take behavior similar to the model ones. We recorded the acceleration for 20 minutes as one set, to prevent subjects from getting tired with too long works. The beginner subjects conducted the set twice. After the each set, an expert assessed farming work of subjects based on the work assessment item. The scale of grading was two grades: “good” and “to be improved”. We formed a work assessment item through an interview with the expert. A work assessment item is as follows.

- Posture
  e_1:stretching the spine
  e_2:taking a comfortable posture
  e_3:looking up blueberries, kneeling down under them
- Efficiency movement
  e_4:leaning closer to the trunk of a tree
  e_5: holding a branch with many blueberries with one hand to keep it close to his body
  e_6:keeping dense branches away witF-measureh one hand

The example of physical behavior related to the work assessment items is shown in Fig.5 and 6.

Fig.5 Example of physical behavior (e_1 *and* e_2)

Fig.6 Example of physical behavior (e_4)

In Fig.5, the expert straightens his spine and get kneels down on the ground. On the other hand, the beginner bended his body. If the beginner keeps this posture, he will easily get tired. In Fig.6, the expert leans closer to the trunk (red line) of a tree. On the other hand, the beginner keeps away from the trunk and reaches his arm out to search blueberries. Taking such unreasonable posture for a long time would also make him exhausted. We used statistical analysis tool R for analysis. We used the functions of depmix and randomForest in the R environment. We left all the parameters default. We selected the number of states so that the unbiased variance of intra-group variability changes most in each states, when we consider states in the physical behavior shown in Section 3.6. To verify the performance of the proposed method, we took the 11-fold cross-validation. We used one data set as test set, while ten data sets as training set. We used the random forest (RF) algorithm to create a discriminator. We evaluated the accuracy with the F-measure (F), which was calculated with the precision (p) and the recall (r), as follows.

$$F = \frac{2 \cdot p \cdot r}{p + r}$$

4.2 Results

In this experiment, we regarded the result of assessment of data set, which obtained from the expert in farming work, as “good”. The assessment for the others was determined by the expert. Table 1 denotes the result. We divided states so that unbiased variance of intra-group variability changed most in each states. In this experiment, the number of states was 2 and 4 to classify the motion of the head and that of the others, respectively.

Table 1 Result

		e1	e2	e3	e4	e5	e6
F-measure		0.769	0.833	0.833	0.941	0.545	0.400
Recall		0.500	0.800	0.800	0.889	0.600	0.400
Precision		0.750	0.800	0.667	1.000	0.500	0.400

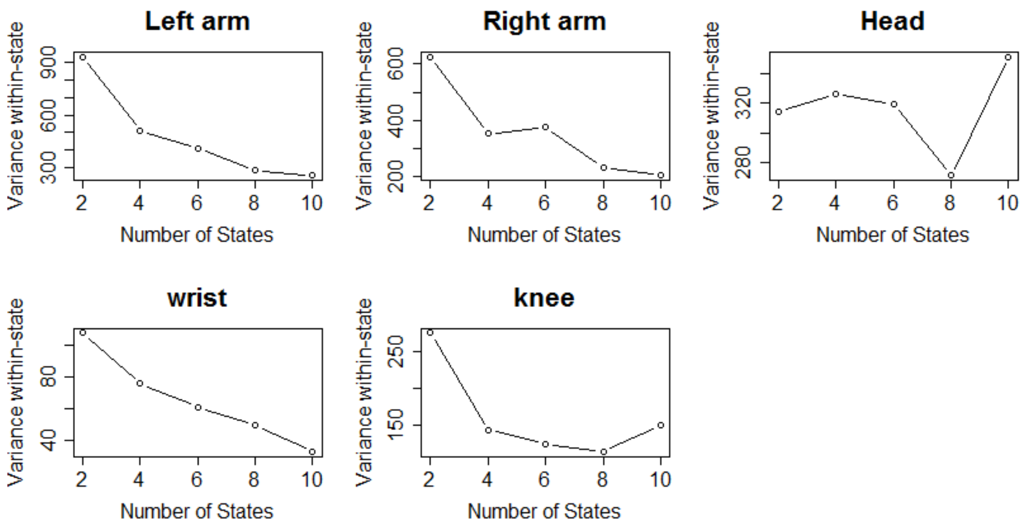

Fig.7 Variance of within n-state

5 DISCUSSION

The F-measure other than e6 exceeded 0.5. The values are higher than those of judgement given randomly. However, this result shows the system is likely to misidentify, which makes a user receiving an incorrect assessment confused. This study assumes that the user use this system periodically. It is less likely to repeat misidentification many times for the work assessment items whose F-measure exceeds 0.7. For those work assessment items, comprehensive judgement of the received assessment makes the user to find his/her own problems. However, the proposed method needs improvement of the accuracy for the other items.

5.1 ANALYZING FEATURES USING VARIABLE SIGNIFICANCE

The result suggests the proposed method can reproduce the assessment by experts. We consider why the proposed method can reproduce the assessment. We focus on the difference between the feature of group $G_e(good)$ and group $G_e(bad)$. Group $G_{e1}(good)$ represents users who received "good" as assessment of $e1$, while $G_{e1}(bad)$ represents users who received " to be improved" as assessment of $e1$. We find differences in their features using the importance of variables. We consider the relation between the variables of high importance and the work assessment item. We use the Gini coefficient as a measure of the importance. In this experiment, 11 models were constructed for each work assessment item by cross validation. Among these models, we pick up only the model which gave the same assessment as expected. For each variable, we sum up the Gini coefficients obtained from each of the models. In this study, we use the calculated value as the measure of the importance. Table 2 shows variables of high importance for e1, e2, e3 in descending order.

Table 2Gini coefficient（Top 5）

	$e1$	$e2$	$e3$
1	RA_{s2}	LA_{s3}	LA_{s3}
2	LA_{s3}	RA_{s2}	RA_{s2}
3	K_{s1}	RA_{s3}	W_{s4}
4	RA_{s1}	LA_{s4}	W_{s1}
5	W_{s1}	K_{s3}	W_{s3}

In the table, LA_s is the left arm, RA_s is the right arm, H_s is head, W_s is wrist, $K_s$is knee of state. $s_n$represents each state. The mean and variance of angles in each state of each body parts are shown in Table 3 to Table 7.

Table 3 Mean and variance of angles in each state of the left arm

	x		y		z	
	$mean$	var	$mean$	var	$mean$	var
LA_{s1}	-47.563	16.601	-9.644	29.159	4.893	30.192
LA_{s2}	16.209	20.851	-4.358	37.848	43.665	22.922
LA_{s3}	60.673	11.888	5.43	21.576	-1.355	21.56
LA_{s4}	26.35	11.637	19.338	17.16	-51.729	13.337

Table 4 Mean and variance of angles in each state of the right arm

	x		y		z	
	$mean$	var	$mean$	var	$mean$	var
RA_{s1}	14.645	24.744	4.35	28.053	50.729	17.783
RA_{s2}	65.396	10.208	-4.467	18.976	4.276	17.022
RA_{s3}	21.092	24.794	-50.691	12.494	12.488	19.458
RA_{s4}	40.346	11.968	-19.883	17.529	-37.758	13.209

Table 5 Mean and variance of angles in each state of the head

	x		y		z	
	$mean$	var	$mean$	var	$mean$	var
H_{s1}	-52.112	11.184	1.087	17.331	3.537	34.258
H_{s2}	-75.288	6.096	-0.187	9.181	0.569	12.915

Table 6 Mean and variance of angles in each state of the wrist

	x		y		z	
	$mean$	var	$mean$	var	$mean$	var
W_{s1}	-79.665	1.893	1.193	6.602	-0.838	8.023
W_{s2}	-85.152	1.89	0.074	3.529	-0.269	3.824
W_{s3}	-74.071	2.724	7.85	5.553	-2.077	12.736
W_{s4}	-62.313	9.52	0.115	10.701	18.961	19.025

Table 7 Mean and variance of angles in each state of the knee

	x		y		z	
	$mean$	var	$mean$	var	$mean$	var
K_{s1}	1.624	16.285	11.727	16.408	65.526	10.396
K_{s2}	7.976	6.896	66.388	4.937	-20.675	5.797
K_{s3}	-0.394	18.544	55.98	12.076	22.964	18.228
K_{s4}	0.115	8.156	79.406	4.604	-1.308	8.031

5.1.1 E1: LOOKING UP BLUEBERRIES, KNEELING UNDER THEM

RA_{s2}, LA_{s3}, K_{s1}, RA_{s1}, W_{s1} are variables of high importance from Table3 on $e1$. The group mean of the state quantity is shown in Fig.8.

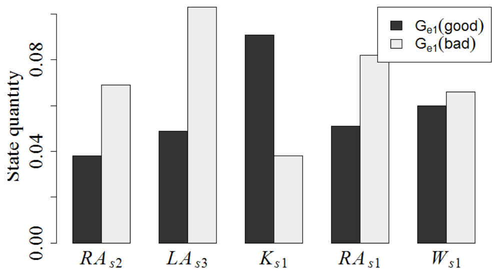

Fig.8 Group mean of state quantity

The state quantity of RA_{s2},LA_{s3},RA_{s1} in $G_1(bad)$ is higher than that of $G_1(good)$. The posture of RA_{s2},LA_{s3} is the posture in which the arm does not tilt up and down and the palm of the hand is facing sideways. $RA_{s1}$is the posture in which the arm is not tilted up and down and the palm of the hand is facing downward. These states show the user harvests blueberries in lower position than the user's shoulder. The difference between the state quantities of W_{s1} is little. The state quantity of K_{s1} in $G_{e1}(good)$ is higher than that of $G_{e1}(bad)$. K_{s1} is the posture in which the knees are bent. It shows the user kneels down. Therefore, $G_{e1}(good)$ works longer than $G_1(bad)$ in a low posture.

5.1.2 E2: STRETCHING THE SPINE

LA_{s3},RA_{s2},RA_{s3},LA_{s4},K_{s3} are variables of ahigh importance from Table3 on $e2$. The group mean of the state quantity is shown in Fig.9.

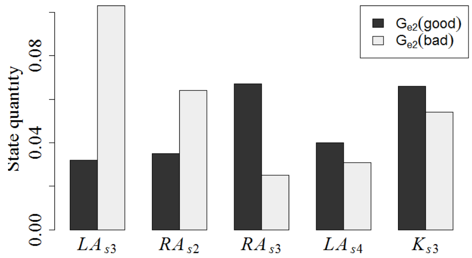

Fig.9 Group mean of state quantity

The state quantity of LA_{s3} and RA_{s2} in $G_{e2}(bad)$ is higher than that of $G_2(good)$. The difference between the state quantities of LA_{s4} and K_{s3} is little. The state quantity of RA_{s3} in $G_{e2}(good)$ is higher than $G_2(bad)$. $RA_{s3}$is a posture where the user raises the right arm. This state shows the user harvests blueberries of high position in a low posture. Meanwhile, this state quantity of $G_{e2}(bad)$ is very low. Therefore $G_{e2}(good)$ works in a low posture longer than $G_2(bad)$.

5.1.3 E3: TAKING A COMFORTABLE POSTURE

LA_{s3},RA_{s2},W_{s4},W_{s1},W_{s3} are variables of high importance from Table3 on $e3$. The group mean of the state quantity is shown in Fig.10.

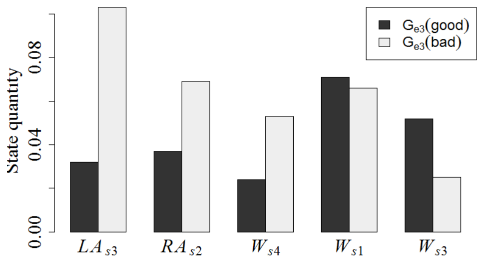

Fig.10 Group mean of state quantity

The state quantity of LA_{s3}, RA_{s2}, W_{s4} in $G_{e3}(bad)$ is higher than that of $G_3(good)$.$W_{s4}$is the posture in which the waist is bend down most in each state. Therefore, $G_{e3}(bad)$ works in a posture in which the waist is bent for a long time.The difference between the state quantities of W_{s1} is little. The state quantity of W_{s3} in $G_{e3}(good)$ is higher than that in $G_3(bad)$. $W_{s3}$is a posture in which stretching the spine than W_{s4}.Therefore, $G_3(good)$ works in a posture in which stretching the spine for a long time.When a user knee the ground, it is easy to take a posture stretching the spine. Thus, it is assumed that the features appeared on waist.

5.1.4 E4: LEANING CLOSER TO THE TRUNK OF A TREE

The work assessment item of $e4$ and $e5$ related to efficient movement. The proposed method uses the amplitude spectrum(As). It is assumed that the difference in the amplitude spectrum of each group appears in the rough frequency band. The difference of each group does not appear even if we focus on variables of high importance. We focus on each body part with the variable of high importance. We consider the differences in features of each group among each body part. Table 7 shows the mean of the variables of high importance among the parts relating to $e4$. The importance of all body part is high. We use the standard deviation and the mean value of the amplitude spectrum presented in Section 3.6 as the difference in features of each group. It is shown in Fig.11 to 20.

Table 8 mean of high importance variables of each body parts

LA	RA	H	W	K
0.192	0.208	0.195	0.206	0.197

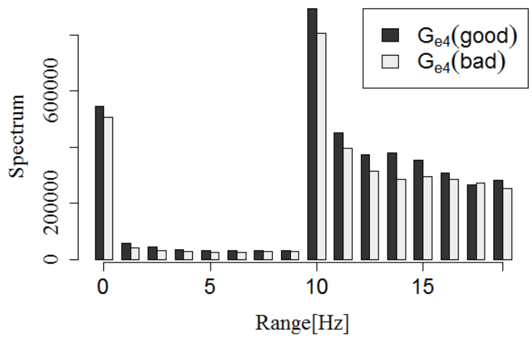

Fig.11 Group mean of As (*LA*)

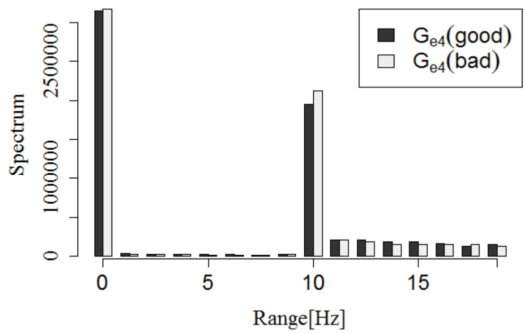

Fig.12 Group Sd of As (*LA*)

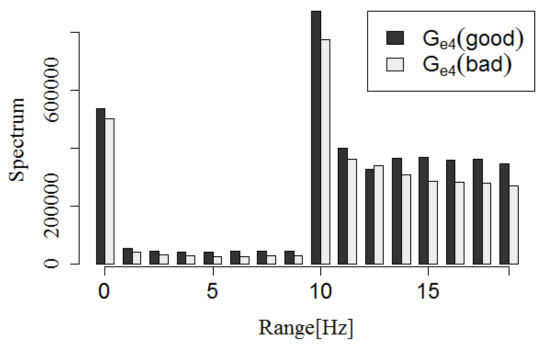

Fig.13 Group mean of As (*RA*)

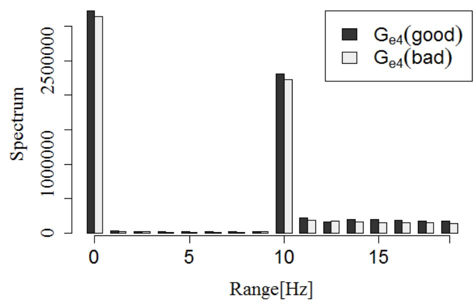

Fig.14 Group Sd of As (*RA*)

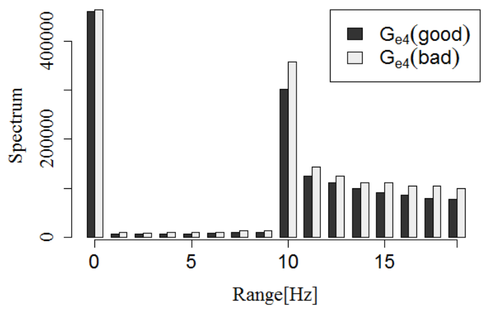

Fig.15 Group mean of As (*H*)

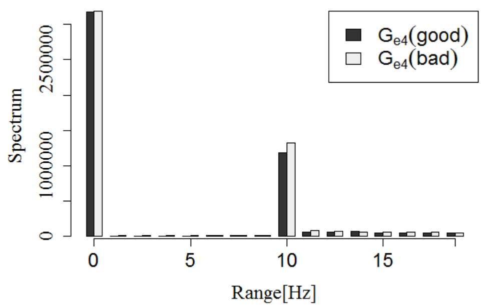

Fig.16 Group Sd of As (*H*)

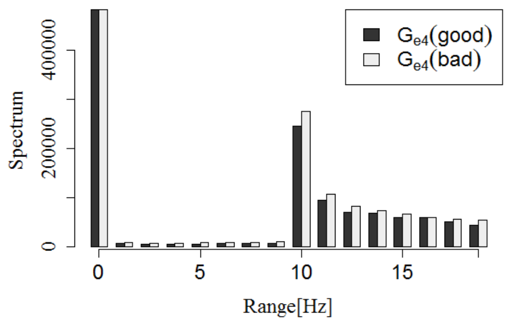

Fig.17 Group mean of As (*W*)

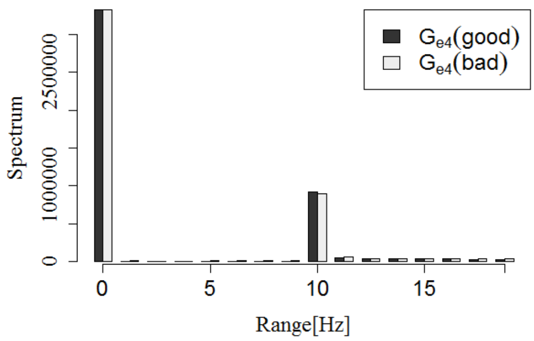

Fig.18 Group Sd of As (*W*)

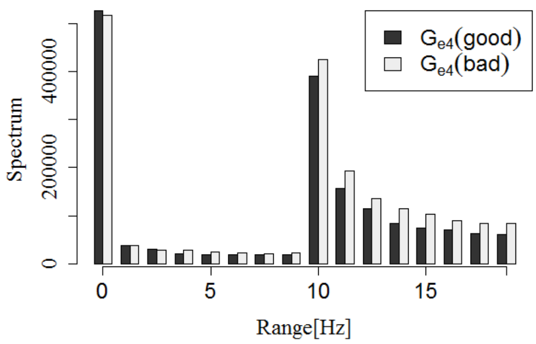

Fig.19 Group mean of As (K)

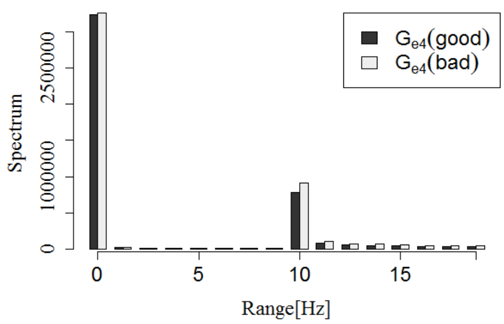

Fig.20 Group Sd of As (K)

According to Fig.11 and 13, $G_{e4}(good)$ has higher amplitude in the high frequency band of both arms than $G_{e4}(bad)$. It is implied that their arms repeat small movements frequently. In addition, the amplitude of the low frequency band of the right arm is also high. Thus, users in $G_{e4}(good)$ move the right arm quickly. According to Fig.15, 17 and 19, $G_{e4}(good)$ has a lower amplitude in the almost frequency band of head, knee and wrist than $G_{e4}(bad)$. The amplitude spectrum increases for the above three parts by walking. Therefore, $G_{e4}(good)$ does not walk so much. $G_{e4}(good)$leans closer the tree trunk. They do not change standing position frequently.

5.1.5 E5: HOLDING A BRANCH WITH MANY BLUEBERRIES WITH ONE HAND TO KEEP IT CLOSE TO HIS BODY

Table 9 shows the mean of the variables of high importance among each parts relating to $e5$. The importance of arms is high. Therefore, we consider the features of both arms relating to $e5$. The standard deviation and the mean value of the amplitude spectrum presented in Section 3.6 is shown in Fig.21 to 24.

Table 9 mean of high importance variables of each body parts

LA	RA	H	W	K
0.284	0.312	0.131	0.126	0.144

According to Fig.21 and 23, $G_{e5}(good)$ has a higher amplitude in the all frequency band of both arms than $G_{e4}(bad)$. The movement of holding a branch with many blueberries with one hand to keep it close to his body is big and slow. Almost users harvest with small movements through dropping blueberries into the basket after this movement. It is assumed that the high amplitude of the low frequency band at $G_{e5}(good)$ is due to the former movement. It is assumed that the high amplitude spectrum of the high frequency band at $G_{e5}(good)$ is due to the later movement.

5.2 APPLICABILITY TO OTHER AGRICULTURAL WORK

In this section, we consider the reason why the F-measure of $e6$ is quite poor. $e6$is “keeping dense branches away with one hand”. The proposed method focus on the feature of the amplitude spectrum presented in Section 3.6 as the efficiency movement. The movement repeated many times appears as a feature in the spectrum. The frequency of movement related to $e6$ depends on the condition of blueberry trees. However, there were many blueberry trees with branches crowded in this experimental environment. Therefore, the movement of $e6$ appears as a feature of the amplitude spectrum. However, the accuracy of identification of $e6$ is low. It is assumed that the proposed method could not capture the feature related to $e6$. One of the reasons is that the features related to e5 and e6 are similar. We discussed the important feature of $e5$ is the small movement of both arms. The cause is one arm rests while holding a branch. However, this movement can also occur in $e6$. Most users keep arms holding the branches. Therefore, it assumed that similar feature appears from the movement related to these items. It is considered that the feature of e6 is mixed with the feature of e5, and the frequency of movement satisfying e6 is lowered. In order to avoid it, a method to deal with the difference is necessary. The position of the arms is different between them. The user's arm is located near user's body because the user moves the grabbed branch close to the user. It is assumed that the feature difference between e5 and e6 can be calculated by grasping the position of the arms. To calculate position of the arms, it is necessary to use motion sensor that can detect the position of each body parts.

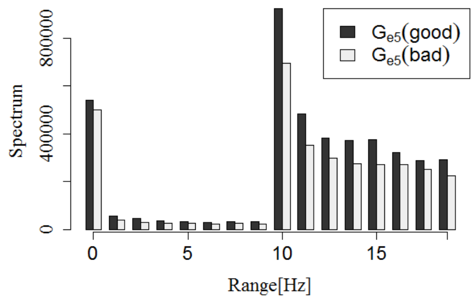

Fig.21 Group mean of As (*LA*)

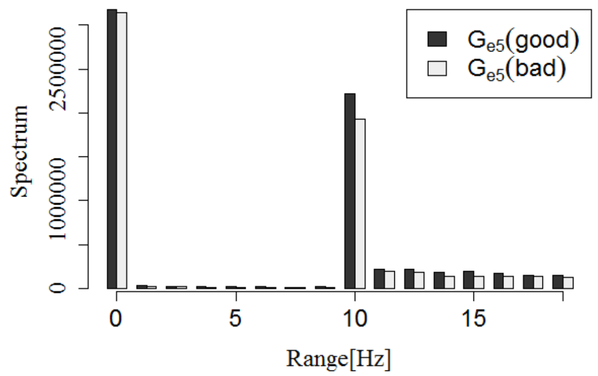

Fig.22 Group Sd of As (*LA*)

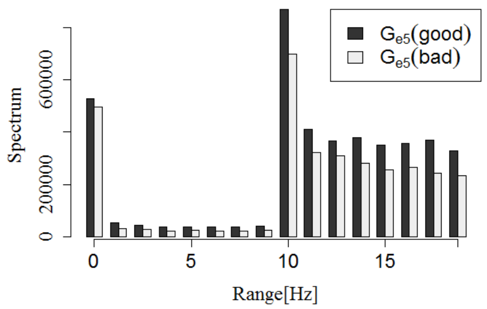

Fig.23 Group mean of As (*RA*)

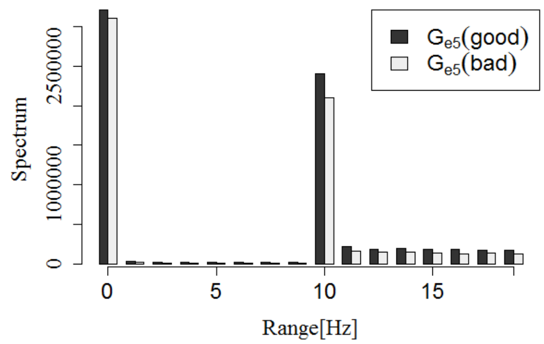

Fig.24 Group Sd of As (*RA*)

5.3 Applicability to other agricultural work

We discussed the problems about the burden on experts by OJT in Section 2. The burden on experts by this system is shown below.

- Getting work assessment item through an interview with the expert.
- Farming work with an acceleration sensor.
- The certain number of assessment of farming works.

The expert does not need to do the above works after building the system. Thus, this system can give guidance to beginners without the burden on experts like OJT. Since the acceleration sensor is inexpensive, it is easy to introduce. In addition, the sensor is small and light weight. Therefore, it is a small burden for the user. In this study, we indicated the harvesting work could reproduce the expert's assessment from the acceleration sensor. In order to apply this system to other farming works, it is necessary to satisfy the following conditions.

- We can get work assessment item.
- The expert can assess farming work by looking at the movement of workers
- Both of good and bad works appear in movement.

This method reproduces the assessment of experts. Therefore, experts require having work assessment item and assessment criteria in farming works. In order to construct a work assessment model, the expert must assess the farming works by looking at the movement of workers. The proposed method focuses on the movement during farming works. Therefore, the method cannot be applied if there is no relation between the assessment criteria and the movement.

6 CONCLUSION

In this paper, we have proposed a method to make beginner farmers master a deft motion assessing farming works from calculated physical behavior. To visualize the behavior, we used acceleration sensors. Experimental results suggest that farming works can be assessed based on a machine learning technique using state quantity and movement spectrum of each body part. In future works, we aim to find effective features for work assessment items we failed to identify in the experiment.

REFERENCES

[1] Japan Agricultural Corporations Association (2012) agricultural corporations report 2011 Survey results about actual conditions of agricultural corporations, p26

[2] Teruaki NANSEKI, Yoshitaka FUJII (2015) "Transmission of Agriculture Technology and Skill : Farming Visualization and Support System by ICT", The Food Agricultural and Resource Economics Society of Japan, 66(2):893-87.

[3] T. Nanseki, Y. Fujii, and T. Ezoe, "Development of a Farming visualization system 'FVS-PC Viewer': Support for agricultural skills succession," Agricultural Information Research, vol. 22, no. 4, pp. 201-211, 2013.

[4] Dimitriadis, Savvas, and Christos Goumopoulos. "Applying machine learning to extract new knowledge in precision agriculture applications."Informatics, 2008. PCI'08. Panhellenic Conference on. IEEE, 2008.

[5] H. Sekiguchi, et.al., Data Mining to Extract Greenhouse Sidewall Control Rules for Raising Rice Seedlings, Japanese Society of Agricultural Informatics, 22(4), 212-227, 2013

[6] Shinji Kawakura and RyosukeShibasaki, "Statistical Analysis of Index Values Extracted from Outdoor Agricultural Workers Motion Data," Journal of Advanced Agricultural Technologies, Vol. 1, No. 1, pp. 69-74, June 2014. Doi: 10.12720/joaat.1.1.69-74

[7] Shinji Kawakura and RyosukeShibasaki, "Various Advanced Statistical Analyses of Index Values Extracted from Outdoor Agricultural Workers Motion Data," Engineering and Technology Nutrition and Food Sciences,1(2014),7,p122-129,2014/07/14

[8] Yu Enokibori and Kenji Mase, "Reproduction of Expert's Subjective Skill-Level Evaluation with Wearable Acceleration and Gyroscope Sensors on Metal-Filing," Transactions of the Japanese Society for Artificial Intelligence, vol. 28, issue 4, pp.391-399, Sep. 2013.

[9] Kojima, K., Mase, K., Tokai, S., Kawamoto, T., &Fujii, T. (2009). On-body multi-sensor analysis of metal filing performance for manufacturing skill training. In *IEEE International Symposium on Wearable Computing (ISWC2009), Advances in Wearable Computing 2009* (pp. 21-28).

[10] Kalman, Rudolph Emil. "A new approach to linear filtering and prediction problems." *Journal of basic Engineering* 82.1 (1960): 35-45.

[11] J. Mannil, M. M. Bidmeshki and R Jafari: Rejection of irrelevant human actions in real-time hidden Markov model based recognition systems for wearable computers; WH '11 Proceedings of the 2nd Conference on Wireless Health, No. 8 (2011)

[12] Breiman, L.: Random Forests, Journal of Machine Learning, Vol.45, pp.5–32 (2001).