# Grouping Method Using Graph Theory for Agricultural Workers Engaging in Manual Tasks

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***Abstract*—Agricultural directors and managers might employ several grouping methodologies of physical working members to enhance the quality of work and collaborations. In this prospective study, the authors aim to execute and demonstrate the results of a grouping analysis based on the spanning tree method in the field of graph theory. The participants—six experienced agricultural manual workers and six novices—were asked to crop middle-sized root vegetables by hand in a sitting position. The authors handled the data and executed the analyses in VBA. The authors also used Scilab libraries and packages to execute timeline wavelet analyses with accumulated acceleration data obtained from the outdoor agricultural workers' dominant lower arms and the left side of their waists. The authors present qualitative data of the workers' groupings using standard deviations (SD) of the vertical acceleration data. The main index values were SD values of the acceleration data in the dominant frequency zone. After performing the dotting process, the authors successively connected pairs of dots to separate them into two groups. The authors developed several charts and compared them with those from the common and validated analysis of principal components method. These methods could be used to improve the grouping and categorizing for agri-business and related research.**

***Index Terms*—graph theory, grouping method, spanning tree, timeline acceleration data, wavelet analysis**

## I. Introduction

From the viewpoint of research and business, agricultural workers have benefitted for many years from agricultural management technologies involving the direction, teaching, and advanced detection of workers' diseases and physical problems. Researchers in the field of agricultural informatics have proposed various methods for solving these problems, and various methods have been developed that successfully characterize the motion of agricultural workers and their machinery, which have gradually led to increased crop yield [1]-[9]. In this study, our target field was a middle-sized, common outdoor farm, and the target work was cropping root vegetables by hand, without using tools. The authors researched and developed methods for the remote observation of workers, using various wearable technologies, in general outdoor farms, rice fields, and meadows. The authors have also investigated various body movements and vibrations during daily life and in specific workplaces. Such whole-body movements and vibrations can affect workers' health, efficiency of activity, and mood. Consequently, experimental studies of biodynamic responses to vibration and impact have been conducted to observe body dynamics and develop scientific models representing specific aspects of body responses [10]-[13]. However, the characteristics and mechanisms of dynamic body responses are not fully understood. Nevertheless, as new technologies continue to be developed, in this study, the authors develop a promising visual data sensing and analysis system to rapidly solve agricultural management problems. The authors selected timeline wavelet analyses concerning vertical acceleration data, using relative spatial coordinates (X, Y and Z axes), rather than absolute coordinates. Furthermore, the authors developed questionnaires to obtain information relating to the participants. For these purposes, the authors utilized libraries and packages of Scilab (ver. 5.5.2, Scilab Enterprises Inc., France) software for Windows 10 OS, including Scilab Image and Video Processing Toolbox, Scilab Wavelet Toolbox, and its GUI Builder [6]-[8], [11]-[15]. The authors computed our data using various tools and conducted our research from the perspective of human dynamics and physics [16]-[18]. The results of the 3D data and spanning tree-based grouping methodologies showed the most dominant frequency range in these data for later graph theory based analysis. Additionally, the spanning tree-based graph theories' grouping methodologies showed statistically significant features.

## II. Materials and Methods

### A. Targets and Subjects

The authors selected the task of cropping root vegetables that consists of grasping the stems by their

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dominant hand, uprooting them and throw them to subjects' right side or left side with no instrument. Incidentally, the categorizations of agricultural motions have been discussed; basically those were based on their several features, for instance, a use or nonuse of the machine, the intensity and the workers' postures. The reason the authors selected the task was it has been inevitable, common and natural motion regardless of the district. Additionally, it is regardless of workers' race and age, and repetitive, consists of low-intensity body movements. The timeline of each set consisted of the waiting time from the previous setup, the trial time, followed by the waiting time again, and post-time (i.e., post-manipulation time). Each trial was comprised of successive 30 cropping motions (around 60 seconds) on the five days with an interval of a few minutes before/after the trial set. Based on the opinions of other relating researchers, farmland managers and past studies, the authors believed that the task's duration time, volumes were appropriate and adequately balanced. Before taking the main measurements, the authors conducted questionnaire-based interviews to obtain information regarding the age, sex, work experience, stature, weight, social position, distinguishing features, dominant hand and their daily lives of each subject. Moreover, the authors used lifestyle and health check sheets written by Japan Association of Industrial Health and other health organizations, and monitored the fatigue and condition of each subject carefully during and after each trial. The authors gathered experienced and inexperienced male workers without remarkable mental or physical characteristics and diseases, and selected six experienced and six inexperienced subjects from this group. All experienced subjects enjoyed walking, and some inexperienced subjects enjoyed moderate tennis or badminton once or twice per week. No subjects reported past serious physical disorders, some of experienced subjects suffered acute lower back pain. The experienced subjects had career lengths ranging 25-60 years (40.8 ± 14.3; average ± standard deviation), were aged 58-74 years old (66.0 ± 8.50), stood at 160-173 cm (162.5 ± 5.5), and weighed 55-85 kg (69.7 ± 9.96). On the other hand, the inexperienced subjects had no experience in agricultural work at all, were 23-25 years old (23.2 ± 1.37), stood at 167-178 cm (170.8 ± 3.34), and weighed 50-78 kg (61.3 ± 7.91). The authors decided that the data were enough in regular, in the range of an average body size for Japanese farmers. The authors thought that they were appropriate subjects in light of various farmland managers whom the authors interviewed in advance of each trial. The authors confirmed again that the selected subjects had met our main criteria of having no serious diseases, peculiar habits, or specific prior careers, especially in sports and martial arts, in preliminary interviews. Five of the experienced subjects were right-handed and one was left-handed, whereas all the inexperienced subjects were right-handed. The questioner sheets' items in investigation papers were subjects' name, affiliation, occupation, age, years of experience, height, weight, a Visual Analogue Scale (VAS) index value, a Borg Rating of Perceived Exertion (RPE) Scale index value, and a lifestyle (Table I). As for VAS and RPE, the authors used to measure worker fatigue and feelings against strength of task. Those items concerning subjects' lifestyle were eight index values and the basic information about a subject's body or a life.

TABLE I. ITEMS IN SURVEY SHEET

| Category | Index | Range of score (point) |
|---|---|---|
| Basic information | Name, affiliation, occupation, stature, weight, pre-existing disease, etc. | These depend on contents |
| Low back pain (LBP) | Experience of Low back pain | No experience of LBP (0), Experience LBP in the past (1), Now having LBP (2) |
| | Frequency in the present workplace | No (0), Sometimes (1), Frequently (2) |
| | Frequency in the past workplace | No (0), Yes (1) |
| Daily successive fatigue | Frequency of continuing fatigue from the previous day | No (0), Rarely (1), Sometimes (2), Always (3) |
| Drinking and smoking habit | Alcohol consumption | No (0), A few times a month or a year (1), Everyday or A few times a week (2) |
| | Tobacco consumption | Nonsmoker (0), Past smoker (1), Smoker (2) |
| Sport habit | During spare time | No (0) Yes (1) |
| | In the past | Non (0), A little in the past (1), Regularly in the past (2) |
| This trials' feeling of fatigue | Indicators in VAS (Visual Analogue Scale) and RPE (Borg RPE Scale) test, and oral, general question | VAS (0～100), RPE (6～20), and open-ended question |
| Usability of the systems | Load of the systems and the tasks, load of the work posture Fatigue of muscles | Five-grade evaluation (0～5) , and open-ended question |

### B. *Experimental Field and Other Settings*

The authors conducted outdoor trials in one outdoor area of farmland during five days when field conditions were as similar as possible, for instance, the amount of insulation, cloud cover, and wind were rather same as enough as possible. The subjects wore uniform clothing; the authors used one of the official working uniforms (no protruding items or accessories). They wore white common working gloves through their experiments (Fig. 1).

Figure 1. Cropping subject wearing wearable measurement system.

### C. Measurement System and Theory of Data Analysis

The authors have adopted and used a common TSND121 multi-sensor (ATR-Promotions Inc., Japan) to obtain diverse physical data (acceleration, angular velocity, earth's magnetism (geomagnetism), air pressure, etc.), and observed the most eminent (dominant) frequency range concerning power spectrums. The multi-sensor was attached on the three points shown in Fig. 2 and Fig. 3 (indicating X, Y, and Z axes) using an original stiff cradle and enough wide elastic bands, concretely, the subjects' chest (over the heart), the right waist, and centrally on the outside of lower arm stably.

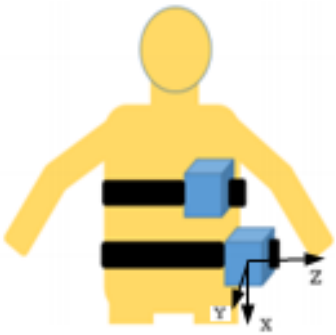


Figure 2. Location of sensor modules on subjects' 1) left side of waist and 2) front of breast, and the relative coordinate axis.

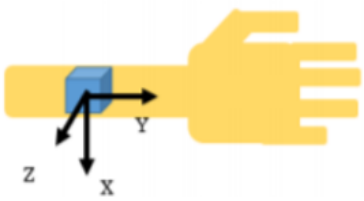


Figure 3. Location of the sensor modules on subjects' dominant lower arm, and the relative coordinate axis.

However, the authors selected only the acceleration data from the waist and lower arm and ignored other acceleration, angular velocity, air pressure and geomagnetic data, as the authors believed that acceleration would be the most dynamic and characteristic variable for agricultural performance. The authors assumed that these experimental settings were practical for use by general agricultural workers, directors, and managers to obtain time-series of visual data for diverse analyses of outdoor experiments with reference to past studies.

### D. Theory of Wavelet Data Analysis

The authors did not use the visual data capturing libraries and program codes from Scilab (ver. 5.5.2) and OpenCV series to obtain visual data. The authors were aware that various studies have utilized these features. The authors decided to use these features only for analyses after visual data processing as described later. Instead, the authors analyzed timeline 3-axis acceleration data sets (G) using original programs written in Scilab before analysis based on spanning tree based method in the field of graph theory. The theories of image analysis, particularly Continuous Wavelet Transformation (CWT), have been discussed as follows. In the field of mother wavelet-based image analysis, CWT is defined by equation (1) and is used to divide a continuous time function into wavelets. Unlike Fourier transformation, continuous wavelet transformation is capable of constructing a time-frequency representation of a signal that offers excellent time and frequency localization. The continuous wavelet transform of a function $x(t)$ at a scale ($a > 0$) $a \in R^{+}$, the time span of wavelet (in short, the value of $1/a$ means the frequency), and translational value $b \in R$is expressed by the following (1):

$$(T^{wav} f)(a,b) := \int dx |a|^{-1/2} f(x) \overline{\psi\left(\frac{x-b}{a}\right)} \quad (1)$$

$a$ represents the scale, $b$ represents the translation, and $f\psi(x)$ represents the function of the mother wavelet, where a continuous function in both the time and the frequency domain is called the mother wavelet. The over line represents operation of the complex conjugate. The main purpose of the mother wavelet is to provide a source function to generate the daughter wavelets, which are translated and scaled versions of the mother wavelet. The function $\psi(x)$ and the value *coef* of complex Morlet wavelet (*cmor*) is defined by (2) and (3).

$$\psi(x) = \sqrt{\pi f_b}\, e^{2i\pi f_c x}\, e^{-\frac{x^2}{f_b}} \quad (2)$$

$$coef = cwt(x, scales, wname) \quad (3)$$

The $\psi(x)$ depends on $f_b$, which refers to bandwidth, and $f_c$, which is a wavelet center frequency. The authors used the cwt function in Scilab (equation (3)) to obtain an overview of the main properties of this family by typing wave-type information (in this case, '*cmor*' was the *wname* used in equation (3)) from the Scilab command line. In equation (3), $x$ refers to numerical input data (double-type vector data), scales refer to vector scale (accuracy of analysis), *wname* refers the type of wavelet analyzed, and *coef* refers to the coefficient of successive wavelet transformation.

### E. Theory of Graph Theory Based Data Analysis

Experimental parameters must be input before this analysis can be conducted in Scilab (Fig. 4). Therefore, after starting these programs, the authors observed and recorded features and matrix-formed numerical data from the wavelet analyses. Fig. 5 showed the chart for graph

theory based analysis and one program written in Microsoft (MS) Excel VBA (Visual Basic for Applications) considering the viewing and calculation of vertical hoe acceleration data in Scilab.

[Main function]
・Declaring and reading (inputting) of data
・Setting of significant parameters (e.g., frequency, spectrum, scale roughness) as matrix variables
・Closing the source files
・Setting the graph view windows (ON/OFF of graph drawing functions, maximum and minimum values of the axis, etc.)
・Declaring of the wavelet function types (e.g., Haar function, complex Morlet function)
・Setting read sequential data into 3-dimentional frames (*X*, *Y* and *Z* axis)
・Viewing of the graph view windows
・Executing functions to draw graphs for both original data and data generated by the wavelet analysis
・Plotting the calculated data using the wavelet function
・Escaping from the main function

Figure 4. Chart for the calculation and viewing of wavelet analysis 3D wave formed data from subjects' arm and waist acceleration data in Scilab.

[Main class]
・Declaring the valuables
・Declaring, reading and closing of data input in MS Excel's calls
・Inputting of data into arrays
・Initializing the class-table
・Declaring the main loop
・Declaring, calling and executing the function sub classes
・Escaping from the main function

[Sub class 1]
・Inputting data into MS Excel's cells sequentially
・Indicating the end row of the data for the next handling

[Sub class 2]
・Calculating the distance of each data in MS Excel's calls for the graph theory based grouping methods

[Sub class 3]
・Calculating the distance of each groups of aforementioned data with the graph theory based method and input those values into MS Excel's cells

[Sub class 4]
・Selecting the minimum distance calculated in Sub class 3

[Sub class 5]
・Inputting the grouping pattern give the minimum distance calculated in Sub class 4 into MS Excel's calls

[Sub class 6]
・Resetting all tables written about each classes appropriately

Figure 5. Chart of the main program calculate the distances between two subject groups separated according to spanning tree theory in the field of graph theory.

Those data defined as $x_{ik}$, $x_{jk}$ ($i$, $j$: row number, k: column number). The Euclid distance between two norm data (two dots) of a feature amount vector is written in equation (4) below. However, the authors thought the calculative quantity, and selected the approximate value as shown in equation (5) because of the difficulty of the calculations and the volumes of numbers. The authors judged that it was one enough adequate adopted value in this case.

$$|x_p, x_q| = \sqrt{\sum_{k=0}^{m-1} (x_{pk} - x_{qk})^2} \tag{4}$$

$$|x_p, x_q| = \sum_{k=0}^{m-1} |x_{pk} - x_{qk}| \tag{5}$$

The authors decided to use the power value in the most eminent (strongest) frequency band eminent as a result of a wavelet analyses for calculations. What is more, the authors drew graphs using those standard-deviation values. The authors depicted some scatter charts that the SD (Standard Deviation) values of dominant lower arm's acceleration set in the horizontal axis, SD values of the right side of waist's acceleration set in the vertical axis. In the field of human dynamics (kinematics), the aforementioned SD have been utilized as one of the most valid, convincing indicators (items). Utilizing such theories besides spanning tree method, the authors tried to separate the aforementioned subjects into two groups. In general, in the case of using graph theory or various methods including the spanning tree based method concerning graph theory, researchers often use the maximum or minimum values because of the characteristics. As for the formatting of the equations, the authors set the assembly of the index numbers in group *A*'s members as $\alpha$, as for group *B*'s members as $\beta$. The authors define the distance *d* between these two groups in the aforementioned scattered charts as the equation (6) below. Relating to the distance *d*, the authors successively chose the minimum one line which connects between the members of each class α and β, and drew them. After those handlings, all dots of twelve subjects were certainly included in these two groups' nets.

$$d(A,B) = \min_{i\in\alpha, j\in\beta} \sum_{k=0}^{l} |x_{ik} - x_{jk}| \qquad (6)$$

Additionally, in this research, the authors selected the aforementioned the analysis of principal component, executed the computation processes, and compared the scattered charts and the aforementioned spanning tree based charts for the sake of confirm and estimate the validities and accuracies of graph theory based methods. The results from the analysis of principal component are visually precise as for indications and grasps. Moreover, in other academic fields (e.g., social science, commercial science) and other researches, the method has been dominant widely, and the authors also use it. In carrying out those computational operations, the authors adopted "Add-in of Excel for multi-variable analysis" which is a default add-in of Microsoft Excel. This Excel and add-in program are widely spread and comparatively compatible with other Microsoft systems.

The authors judged that those systems' features are important for the spread of similar systems in future. Those formulas are (7) to (9) as follows. When the numbers of dimensions of the principle components are two, X and Y show the data group, W shows weight (dignity), those indexes show the data number and *e* shows these errors. The techniques determine the weight W so that the sum total of the square of $e_1$ and $e_2$ will be smallest.

$$Z = w_1 x + w_2 y \qquad (7)$$

$$Z_1 = w_1 x_1 + w_2 y_1 + e_1 \qquad (8)$$

$$Z_2 = w_1 x_2 + w_2 y_2 + e_2 \qquad (9)$$

## III. Results

The authors discussed about the results of this study were statistically analyzed [19]-[21]. First, the authors showed a set of methods for this study's trial, secondary, the authors analyzed data in the Scilab platform for Windows 10 OS that was handled by the program as previously described.

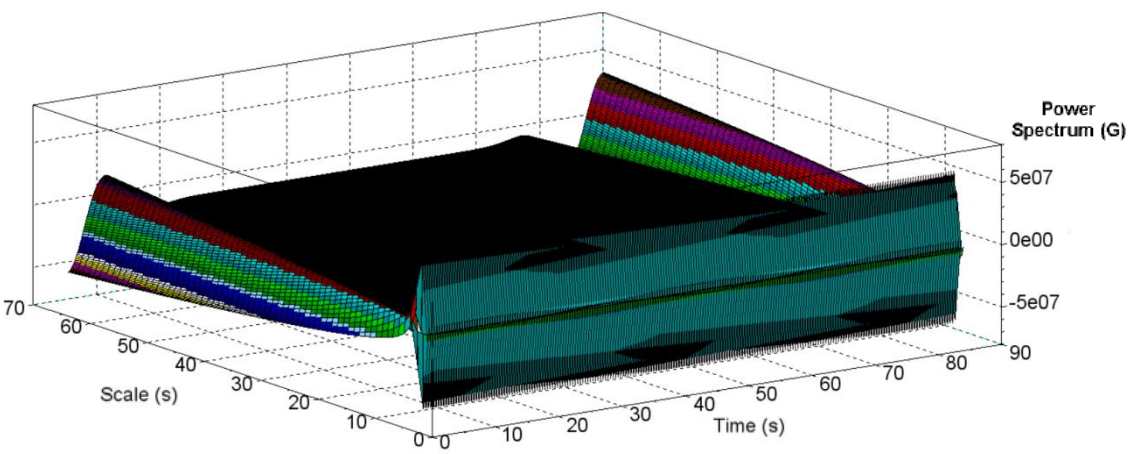


Figure 6. Average timeline graph of arm acceleration generated by experienced subjects cropping in a sitting position.

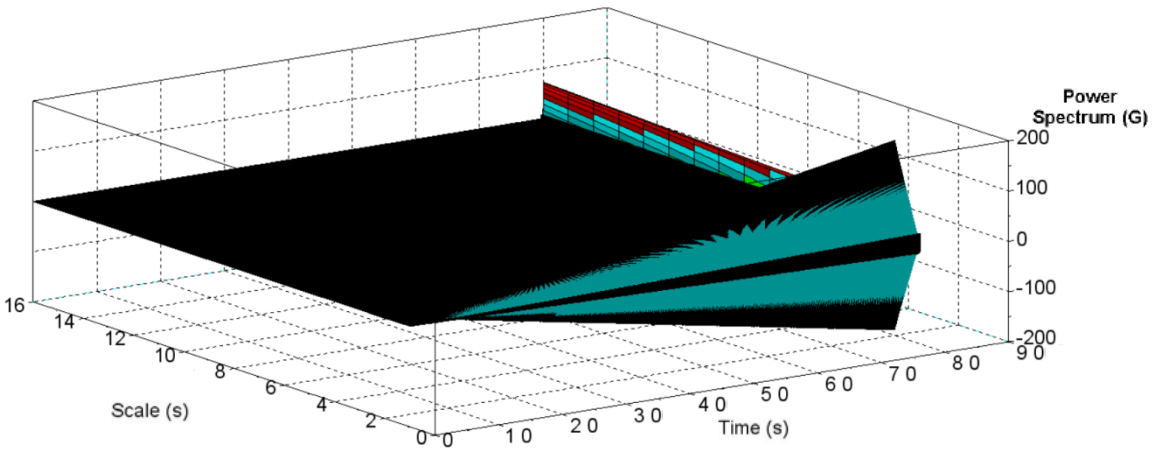


Figure 7. Average timeline graph of waist acceleration generated by experienced subjects cropping in a sitting position.

Concretely, Fig. 6 and Fig. 7 were 3-axis charts (time (s), scale of wavelet analysis (s) and power spectrum (G)) of vertical acceleration data respectively, the 3D frames processed; the 3D views of the wavelet power spectrum timeline from six experienced and six inexperienced subjects respectively. Those data were the nearest them to an average values in the group. In Fig. 6, the most power-dense areas occurred at 0.35-2.55 Hz; the authors supposed that the range was similar for past kinematic studies' data relating to dairy chores (e.g. cleaning with a common cleaner, cooking), close to full-body motions in this academic field. In contrast, about Fig. 7, it showed in the range of 0.04-0.55 Hz. It was exquisite differences in the power spectrum characteristics between the lower arm and the waist's one. The value of wavelet scale was set at 64 and 16 respectively for its characteristics and accuracy; for instance, a value of 32 was considered too rough, whereas a value of 128 was considered too dense and the Scilab version could not show the graph clearly in the latter case. After then, the authors grouped the scatter chart's data based on the spanning tree method in the graph theory field. In detail, the authors combined 12 subjects' plotted data on the graph step by step with the program written in VBA in Microsoft Excel 2013.

The authors used the aforementioned calculated, drawn scatter graph-data in Fig. 8 and Fig. 9. The former was just one dot graph, the latter was connected dots graph. Additionally, for the sake of contrasting the result from 1) the spanning tree analysis based data to 2) the group questioner sheets' data, the Fig. 10 and Fig. 11 was scattered graph of the standardized result from the analyses of the aforementioned analysis of principal component. The one set of a dot graph and a connected dots graph from the results of the aforementioned computer software.

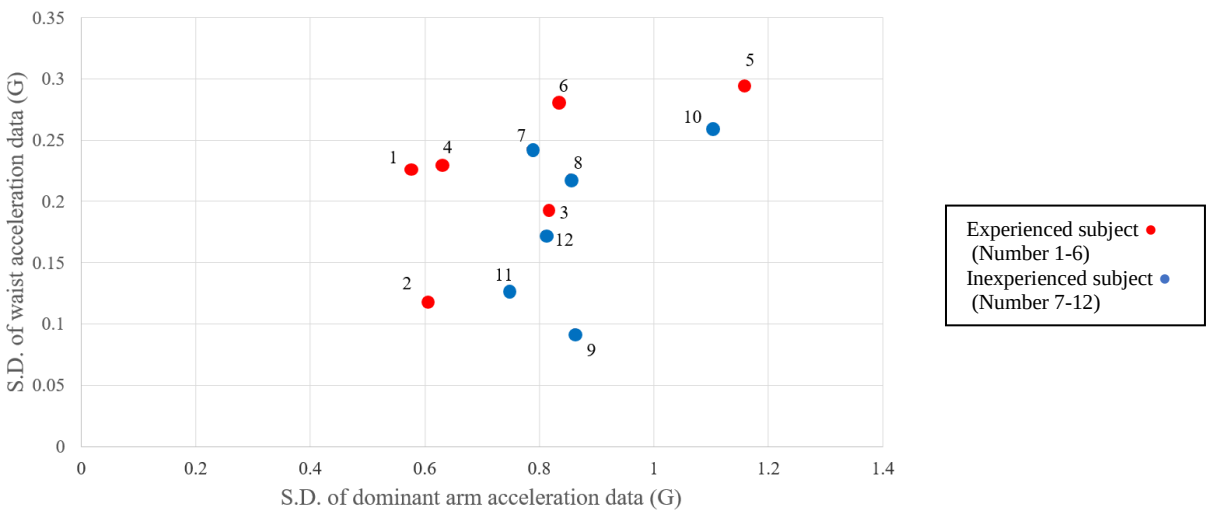


Figure 8. SD values of the biggest wave (including the biggest amplitude) in the range of most dominant frequency range resulted from the wavelet analysis of X-axis (Fig. 6 and Fig. 7) acceleration data obtained from subjects' dominant arm and waist concerning experienced and inexperienced subject group.

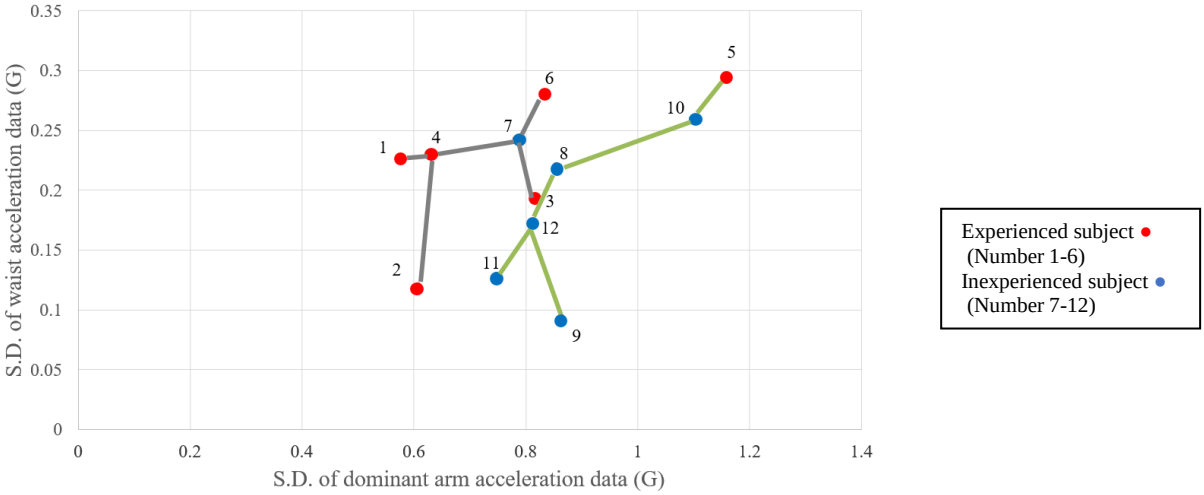


Figure 9. SD values of the biggest wave (including the biggest amplitude) in the range of most dominant frequency range resulted from the wavelet analysis of X-axis (Fig. 6 and Fig. 7) acceleration data obtained from subjects' dominant arm and waist concerning experienced and inexperienced subject group (10 connection lines included).

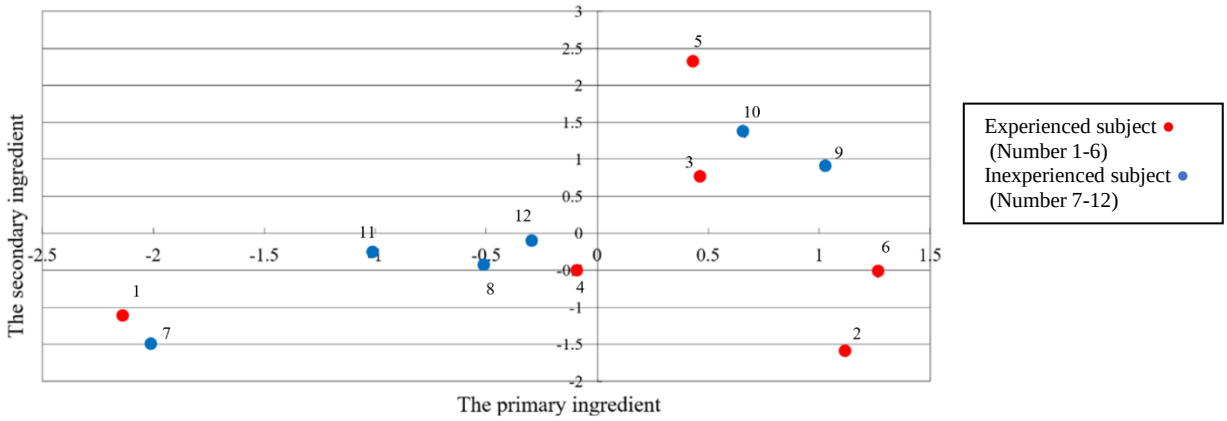


Figure 10. Scattered graph of the standardized result from the analyses principal component using various basic factors.

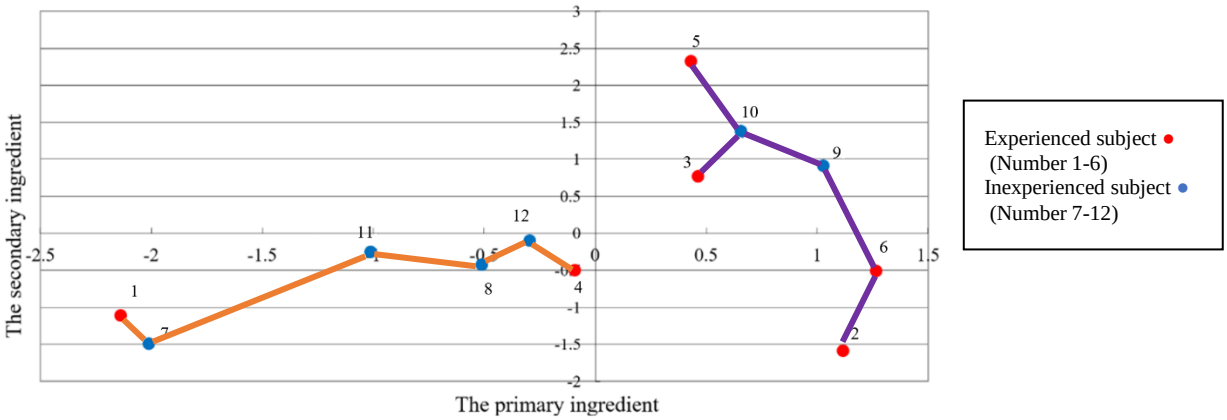


Figure 11. Scattered graph of the standardized result from the analyses principal component using various basic factors (10 connection lines included).

## IV. Discussion

In this study, the authors accumulated and analyzed the aforementioned standard deviation (SD) values of acceleration data from subjects at the non-specific agricultural farms. After that, the authors grouped subjects mathematically for the contributions of agricultural managements and leaderships. Additionally, the authors executed the standard the analyses of principal component using survey sheets' data. As for these raw acceleration, angular velocity and visual data, in many past researches, the authors already confirmed and grasped the features, and indicated numerical them visually. Generally, these data from subjects showed contrasts and distinctions between spanning tree method and the principal component analysis method visually and quantitatively.

In light of the result from 2D power spectrum analysis using Scilab, those power spectrums' areas were rather in narrow spans, whereas the values of the powers in themselves were not so condensed. In Fig. 6, it was difficult to comment on the small waves at scale values 60-64 (s) because the changings of the amplitude were rather mellow and slight, the small-sized to middle-sized heaves (not big vibrations) for them were different at scale values 10–64 (s) (in this case, the most appropriate scale value was 64). In Fig. 7, it was difficult to comment on the extremely small waves at scale values 15-16 (s). In this case, the most appropriate scale for the analyses for us was 16 (s) when the scale value was 64 (s), the graph looked like just a flat board, on the other hand, when the scale value was 8 (s), the authors couldn't observed the graph as one set of valid waves for the analyses. In Fig. 8-Fig. 11, as for the contrast of scattered charts between spanning tree-based methods and analyses of principal components, the authors observed various apparent, significant differences between those two methods.

Anyways, there were some similarities concerning pivotal points, however, not concerning those connecting lines in those chats. For instance, the similar tendencies of scattering were seen relating to the Fig. 9 and Fig. 11 members. For instance, the dots of No. 5 and 10 were rather close and far from other dots, No. 4, 8, 11, 12 were rather near to the center of the scattered dots. Furthermore, those tendencies seemed to have no relation with their career (experienced years) and age. Considering those results, especially as for the spanning tree based grouping methodology in itself could be one valid tools to separate agricultural employees efficiently with using a not complicated sensors and computer programs. Therefore, the authors believed that the aforementioned theories and computing methods the authors selected could be utilized and be a practical management tools for actual agricultural teaching fields. The authors confirmed and suggested that these systems may benefit not only agricultural users, but also other manual workers in other fields, such as carpenters and traditional craftsmen.

## V. Conclusion and Future Tasks

In the successive projects and other relative works, the authors have developed methods for both near and distant observations of agricultural workers engaging in copping tasks. In parts of them, the authors have been developing wide range of sensor modules and analysis systems including aforementioned wavelet analysis methods and other wave form analysis for use at agricultural work sites, and the other sites using diverse programs and peripheral software.

In this study, the authors already obtained meaningful results using our graph theory's spanning tree based grouping methods, especially regarding the presentation of separated subject groups and gradual changes of them constricting with the result from the analyses of principal component. However, the authors have not reported enough quantitative grouped sample data and grouped graphs that showed significant differences between existing calculating (algorism) patterns and methods.

Furthermore, these trials were still in one challenging preliminary phase, not in a practical phase yet. The authors have been seeking for further confirmation concerning those variety, validity, durability, precision, and long-term reliance of our methods and systems in the later phases.

Futures studies should also investigate different parameters, such as different computational settings, trial timelines, agricultural tools, and field conditions. Those systems have been suggesting new grouping methodologies for providing promising algorism for full-body workers' patterning and estimating their works' quality but also clustering them computationally. Those could be useful not only for chasing and for recording their improvements for several dozen of years, but also, for agri-business managements, instructions and trainings.

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