Movement Analysis of Agricultural Workers' Visual Data by Functions of OpenCV Focusing on Items Related to Human Dynamics

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***Abstract*—Agricultural workers have been pursuing agricultural technical advancements regarding directions, teaching. In this study, the authors have been developing some promising sensing and analyzing systems to solve various agricultural problems, especially by utilizing visual data relating to workers' real motions. The purpose of our prospective research was to prove the utility of our visual analysis system based on the recent OpenCV environment, and to indicate the numerical differences of unique parameters between groups of experienced and inexperienced subjects. The authors have been applying the latest PC program libraries and packages of OpenCV in the analysis. The targeted field was situated in a common outer farm. The targeted work was common tilling (cultivating) using a general hoe. The authors selected time-line analyses and basic statistical analyses, accumulating subjects' fundamental data. Next, the authors performed computations by a wide range of methods concerning human dynamics, physiology, physics and statistics, and made corresponding suggestions in this study and related works. In future, the authors could indicate a range of differences between experienced and inexperienced subject groups from these results. These visual methods of analyzing systems' digital data could be important indicators concerning users' improvement of working movements and habits in outdoor fields.**

***Index Terms*—OpenCV, optical flow analysis, traditional agricultural skills, supporting for workers, time-line visual data**

I. Introduction

In recent years, agricultural workers have been pursuing agricultural technical advancements regarding directions, teaching, and detecting workers' diseases and other physical problems in advance [1]-[6]. Many researchers majoring in agricultural informatics are suggesting various methods for solving these problems. Past existing methods and practical accomplishments have certainly tried to characterize the motion of agricultural workers and machinery (e.g. combine harvesters and trucks) minutely. However, the authors think that past studies and systems were insufficient to analyze human motions realistically and ergonomically, and that those studies hardly connected motions to users' fundamental information and the feelings of workers.

The authors have intensively researched the various body movement fluctuations and vibrations experienced by persons in daily life and work: through sitting in chairs, sitting in vehicles, walking, and while working [7]-[11].

Such whole-body movement fluctuations and vibrations could have adverse effects on health, the efficacy of activities and persons' feelings. An understanding of how the body moves when exposed to the outer world and to vibration is needed [12]-[16]. Consequently, experimental studies of the biodynamic responses to vibration and impact have been conducted to observe body dynamic behavior and to develop scientific models representing specific aspects of body response. Even so, the characteristics and mechanisms of the dynamic responses of the body are not fully understood.

On the other hand, new technologies continue to be developed. Considering these achievements, in this study, the authors have been developing some promising sensing and analyzing systems to solve such problems year by year, especially by utilizing visual data relating to workers' real motions. In addition, for these purposes, the authors have been applying and containing the latest software systems, their various libraries and packages, such as OpenCV series for Visual Studio [3], [10], [17]-[20].

In this study, our targeted field is situated in a common outer farm and the targeted work was common cultivating (tilling) using a hoe. The authors selected time-line analyses and basic statistical analyses, and have also accumulated fundamental data for the subjects (age, years of experience, height and weight), as well as data concerning subjects' fatigue and subjects' work intensity. Next, the authors have made computations by a wide

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range of methods concerning human dynamics, physiology, physics and statistics, and made some suggestions concerning such academic factors in this study and related works. From these results, the authors found the numerical differences between experienced and inexperienced subjects, and thought that these indicators could be useful for agricultural training.

For years, the authors have been developing methodologies for remote observation of workers, in parallel with various wearable electric systems, with the aim of saving workers from sudden and hidden diseases, injuries and other kinds of disorders in rice fields. In the future, these results could tribute to both inner and outer agricultural workers' revising and improving their work habits and safety.

II. Materials and Methods

The authors selected and executed diverse visual data analysis, and surveyed sheet-based questionnaires before and after trials.

A. Target

First, the authors carefully categorized various physical agricultural tasks from various points of view (e.g., their intensities, main postures), and, for the categorization, specifically researched; 1) Work in a sitting position (e.g., cropping onions), 2) Work in a semi-crouching position (e.g., cultivating with a hoe), 3) Work in a standing position (e.g., cutting branches with shears), 4) Work alternating between a sitting and a standing position (e.g., suspending onions on beams in an outhouse) [1], [2], [6]-[9], [17], [21].

Second, the authors selected the action of 2) "cultivating with a hoe" as the targeted task, because the action is common around the world, repetitive, and involves intense full-body movement.

As shown in Fig. 1, the time line of one set was composed of previous set-up time waiting time (10 s), trial time, waiting time (10 s) and post-trial handling time. The authors thought that this duration, the numbers of tasks, and the whole experiment set were appropriate and well balanced considering various farmland managers' opinions.

Each inexperienced subject participated in three trial sets. Each trial comprised 30 swings and the length of each one trial was about one minute. Sets of three trials were conducted successively for the different subjects, on the same day. There was an interval of a few minutes between sets. Before the trials, the authors interviewed the subjects about their daily lives.

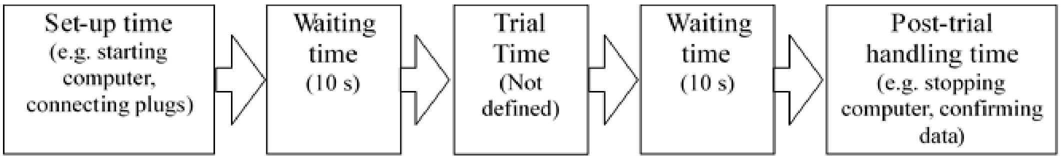

Figure 1. Time line concerning each trial.

B. Subject

The authors selected 12 subjects – six in the "inexperienced" group and six in the "experienced" group – and retrieved subjects' age, years' experience in agricultural work, height, weight, social position, distinguishing features, sex etc. and from the original survey sheets (see Table I).

The authors gathered male experienced and inexperienced workers without any remarkable mental or physical characteristics. In other words, they were of average body size for Japanese farmers. The main criteria of not having any serious diseases, peculiar habits, or specific prior careers (especially in sports and martial arts) were confirmed by preliminary interviews.

TABLE I. Basic Information Related to Subjects (Range, Average (Ave), Standard Deviation (S.D.), Average, Z Value (Z), Coefficient of Variation (CV) and Description)

Index	Inexperienced Group (N=6).	Experienced Group (N = 6)
Experience (year)	None	25–60 (Average (Ave)=40.8, Standard Deviation (S.D.)=14.3, Average Z value (Z)=-1.73×10^{-16}, Coefficient of Variation (CV)=2.61)
Age (year)	23–26 (Ave=24.2, S.D.=1.07, Z=-1.15×10^{-15}, CV=4.42)	58–74 (Ave=66, S.D.=8.50, Z=2.05×10^{-15}, CV=34.9)
Stature (cm)	170–180 (Ave 174.8, S.D. 3.34, Z -2.85×10^{-15}, CV=1.91)	160–173 (Ave=162.5, S.D.=5.5, Z=8.88×10^{-15}, CV=3.39)
Weight (kg)	58–28 (Ave=67.3, S.D.=7.91, Z=5.92×10^{-16}, CV=11.7)	55–85 (Ave=69.7, S.D.=9.96, Z=-1.73×10^{-16}, CV=14.3)
Dominant hand	Right (all subjects)	Right (N=5), Left (N=1)
Past serious physical disorders	None	None (Some had acute low back pain)
Fitness habits	None or tennis or badminton (once or twice per week)	Walking

The length of experienced workers' careers was from 25 to 60 years, which was recognized as generally sufficient by many of the farmland managers who the authors interviewed. Experienced workers' standard deviation (S.D.) values concerning each index were higher than those of inexperienced workers.

The complexity of the human body's structure, difficulties in taking measurements and differences in responses within and between individuals have impeded understanding of various physical data. In such studies, researchers have been measuring the motion and position of various bones, not muscles; that is why the authors have focused on the right crest of subjects' iliac bones in this research.

Both the left and right iliac crests have been sensed and tracked in a wide range of studies. The crest (top) of the ilium (the iliac crest) is thought of as the superior border of the wing of ilium. Furthermore, it is the margin of the greater pelvis. The ilium stretches from the anterior superior iliac spine to the posterior superior iliac spine. Behind the anterior superior iliac spine, it divides into an outer and inner lip separated by the central zone. The outer lip bulges laterally into the iliac tubercle. Concerning previous research relating to the iliac, Matsumoto [14] measured the vibration at six locations on the surface of the first and eighth thoracic vertebrae, the fourth lumbar vertebra, the left and right iliac crests, and the knee of the left leg.

C. Hoe, Field, and Other Settings

There are various hoe types that are available for purchase all over the world. These differ among districts, climates and agricultural styles. The main differences are the weight, length and form of the metal head and the haft. After adequate research, the authors selected the Kairyo-Kuwa hoe, because this hoe is one of the popular types used in the in the Kantou region where the study was conducted.

The specifications of the hoe include the weight (1.65 kg), the total length (1200 mm) and the head size (120 mm × 425 mm). The haft was made from light wood. The point where subjects grasped the hoe with their dominant hand was 300 mm from the head of the hoe. Subjects could grasp the tool anywhere with their other (non-dominant) hand. The authors used one area of farmland, consolidated the other field settings (the amount of insulation, cloud and wind) as much as possible, and selected five days in November and December, 2013 to perform trials. Furthermore subjects' clothes were made uniform to facilitate the unification of the conditions concerning successive visual data analysis; they wore a light blue jumper (jacket), gray pants, white cotton work gloves and black high boots.

These specific outfits were chosen for subjects because they are similar to one of the official working uniforms at the Graduate School of Agricultural and Life Sciences at The University of Tokyo in terms of color and shape, and the authors were considering some future collaborations with the School. These outfits do not contain any protruding items or accessories.

D. System and Theory of Visual Data Analysis

The authors selected and used a common, nonspecific medium-spec digital video camera – the Canon 410f IXY – rather than one of the specialized high-speed cameras used in the fields of human dynamics and sports sciences. The sampling rate for this camera was 20 fps with manual mode input. The distance from fixed camera to the subject in a static position (not walking) was 3.5 meters.

The authors supposed that those settings were the middle course and were reasonable for general agricultural workers, directors and managers to obtain time series of visual data for diverse analyses concerning outdoor experiments with certainty thinking of past studies [5], [20], [22], [23].

The authors did not select visual data capturing libraries and program codes of OpenCV to obtain visual data because of the possibility of a negative impact on the accuracy of the recording. The authors are aware that various studies have utilized these features, but the authors did not have complete confidence in the methods at the time of the study, which is why the authors decided to put them to use only for the analyses after visual data processing described later. The authors analyzed the visual data (AVI format) using original programs written in Visual Basic 2010 (Microsoft Corporation).

The theories of image analysis are discussed below [17]-[19].

1) The method of calculation of area

In the field of Optical Flow-based image analysis, an analyst defines the values of picture's area and center of gravity as per the equations below.

Area:

$$A = \sum_x \sum_y I(x, y) \quad (1)$$

I: One fundamental unit in image source file

2) The method of calculation for center of gravity

Center of gravity:

$$x_g = \frac{1}{A} \sum_x \sum_y x \quad I(x, y) \quad (2)$$

$$y_g = \frac{1}{A} \sum_x \sum_y y \quad I(x, y) \quad (3)$$

3) The method of calculation for moment

Moment:

The formula concerning the $(p + q)$th order moment of picture $(f(i,j))$ in the coordinate (i,j) is defined.

$$m_{pq} = \sum_i \sum_j i^p \, j^q \, f(i,j) \quad (4)$$

Concerning binary pictures, 0th order moment (m_{00}, $p = 0$, $q = 0$) means the pictures' area. In addition, the coordinate (m_{10}/m_{00}, m_{01}/m_{00}) means the center of gravity $G(i_G, j_G)$, the moment around this $G(i_G, j_G)$ means the center of gravity moment (M_{pq}).

$$M_{pq} = \sum_i \sum_j (i - i_G)^p \, (j - j_G)^2 \, f(i,j) \quad (5)$$

On the other hand, the second-order moment is called as the moment of inertia, and an analyst can define the second-order gravity point moment as per (6) concerning the picture $f(i,j)$. In this case, an analyst sets (p=2, q=0) or (p=0, q=2).

$$M_f = \sum_i \sum_j \{(i - i_G)^2 + (j - j_G)^2\} f(i,j) = M_{02} + M_{20} \quad (6)$$

In (7), when an analyst defines the second-order moments based on the X-axis or Y-axis as μ_{02} or μ_{20} while setting the center of gravity as the original point, the analyst can define the second-order moment as the per (7).

$$\mu_2 = \mu_{02} + \mu_{20} = \sum_i \sum_j j^2 f(i,j) + \sum_i \sum_j i^2 f(i,j) \quad (7)$$

4) The method of calculation for main shaft and its angle from X-axis

An analyst uses the equation of line that penetrates the origin of the graph (in short, the main shaft). The analyst also defines and calculates the angle θ; that is the elevation angle from the X-axis to the line. Additionally, the analyst outputs the second-order moment around this line. The principal axis of inertia, θ, is a specific angle when the value of the second-order moment becomes a minimum in this area.

$$j = i \tan\theta \quad (8)$$

$$\theta = \frac{1}{2}\tan^{-1}\left\{\frac{2\mu_{11}}{\mu_{20} - \mu_{02}}\right\} \quad (9)$$

The value of θ is one of the characteristic indicators of what angle the main axis of the figure penetrates (Fig. 2).

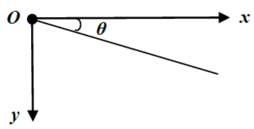

Figure 2. Definition of θ in this study

5) Shi-Tomasi method and Harris method

The authors selected Shi and Tomasi's method and the function "cvGoodFeaturesToTrack" in the library of OpenCV to execute automatic searching for characteristic points in directed pictures. On another front, the Harris method and operator are not used by analysts in this study, because of these characteristics. However, an analyst can easily use the Harris method in OpenCV-based programs to change parameters. The main reason why the authors selected the Shi and Tomasi method is explained later in this section.

These two methods are mathematically similar. When an analyst focuses on the characteristic points that are easy to distinguish from nearby pixels and shifts the targeted picture in the analyzing area slightly, the analyst detects and memorizes the points where the sum of squared difference (SSD) becomes bigger than for other points. An analyst defines SSD as shown in (11) when an analyst shifts the picture by Δv (sufficiently small) in the window W where the center is point p.

$$S(p) = X\, q \in W\, (I(q) - I(q + \Delta v))^2 \quad (10)$$

$$SSD = S_{(p)} = \sum_{q \in W}^{n} \left(I(q) - I(q + \Delta v)\right)^2 \quad (11)$$

Furthermore, if an analyst executes Taylor developing and primary approximation about the pixels of the shifted picture, the analyst can express $I(q + \Delta v)$ as (12) using $I(q)$'s partial differential based on the X-axis and Y-axis ($Ix(q)$ and $Iy(q)$, respectively).

$$I(q + \Delta v) \fallingdotseq I(q) + [I_x(q) \quad I_y(q)]\Delta v \quad (12)$$

Following this, the analyst can combine these two equations into one and express $S(p)$ as shown in (13).

$$S_{(p)} = \Delta v^{\mathrm{T}} \begin{bmatrix} \sum_W I_x^2 & \sum_W I_x I_y \\ \sum_W I_x I_y & \sum_W I_y^2 \end{bmatrix} \Delta v = \Delta v^{\mathrm{T}} H_{(p)} \Delta v \quad (13)$$

The matrix $H(p)$ presents the features of luminance distribution around point p. In the theories of Harris and Shi and Tomasi, the feature amount M from the characteristic value of matrix in (13) is defined as per (14), and is used for detecting the feature points.

$$M = min(\lambda_1, \lambda_2) \quad (14)$$

On the other hand, in the theory of Harris, an analyst can define the characteristic value of the matrix in (13) as λ_1 and λ_2, with κ as one parameter. When both λ_1 and λ_2 are sufficiently large, the analyst can define the appropriate feature points as one. Then, the Harris operator can detect the specific points that make the value of M in (15) sufficiently large.

$$M = \lambda_1 \cdot \lambda_2 - \kappa(\lambda_1 + \lambda_2)^2 = det(H) - \kappa\, trace^2\,(H) \quad (15)$$

The main reason why the authors selected the Shi and Tomasi method for corner detection is related to its precision and burden (time and effort). Concerning the Harris operator, the program simply judges the corners from the balance between the value of M and threshold κ. However, in almost all cases, analysts must obtain the value of κ by performing a sufficient number of experiments. In general, the range of κ becomes 0.04 to 0.15. However, these trials are quite tentative and experimental, so in practical cases, analysts should select the safer method.

6) The theory of Kanade and Optical Flow

The authors selected the Kanade method and Optical Flow to execute both automatic and manual searching for characteristic points in directed pictures. These are currently distinguished, strong methods in this scientific field. The outline is: 1) Presumption of Optical Flow vectors by least squares method; 2) Recognition of the differences between the real values and the estimated solutions; and 3) Access the estimated solutions to the real values by hill climbing method (Fig. 3).

Concerning summarization of the flow of the Kanade method; first, an analyst creates a smoothing filter and covers (wraps) pictures H and I with it, prunes pixels, and make the new pictures H_1 and I_1 such that the resolution is 1/2 (the number of pixels is 1/4; the pixel size is doubled). The analyst then repeats these procedures to make H_2, I_2, H_3, I_3 ... H_n.

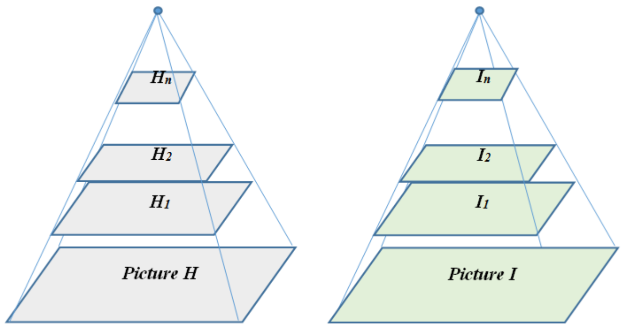

Figure 3. Gaussian pyramids

The analyst continues to create the “pyramids of picture” based on H and I until the pixel size becomes larger than the maximum amount of “travel distance” concerning pixels in these pictures. Second, as was the case in prior processing, the analyst sets the approximate solutions of travel distance as $u = 0$ and $v = 0$, and the rank (level) of pictures as $i = n$ according to all pixels, respectively. Third, the analyst calculates each of the values due to the aforementioned methods as one “loop of procession”.

An analyst can calculate the value of Δu and Δv concerning H_i and I_i, the values of travel distance $((u,v) = (u'+\Delta u,\ \ v'+\Delta v))$ for each pixel, and the approximate values of travel distance (u',v') concerning the one-rank higher picture (H_{i-1}, I_{i-1}) about the resolution by the methods below. An analyst newly sets the pixel-point $(2u,2v)$ (the number of this picture’s pixels is $(x/2 \times y/2)$). Both x and y are odd numbers. The approximate traveling distance is $I = (u',v')$.

According to other pixels, the analyst defines the average values of travel as (u',v') concerning only pixels that those four sides’ (upper, lower, right and left sides) pixels are odd numbers. In short, it is a twin linear complement. Next, the analyst subtracts one from the current i’s number (in the program code, $i = i_{-1}$) and then repeats the procedures until the value of i reaches zero. The analyst further sets the values of u and v based on $u' = 2u$ and $v' = 2v$, sets the values of Δu and Δv based on $u'' = 2(u' + 2\Delta u)$ and $v'' = 2(v' + 2\Delta v)$, and repeat these sequences from “i = n” to “i = 0” in the program while decreasing the value of i one by one ($i = i_{-1}$).

7) Motion template

An analyst can successively update the motion history image and process obtained visual data for various motion analysis and object tracking tasks by “moving silhouette” contained in OpenCV.

For clarification, the authors describe this feature and its peripheral functions citing the information in the web site of opencv.org (http://opencv.org/). First, the authors elected to use a function named “updateMotionHistory” of the C++ version.

By estimating and indicating these arguments, we can handle these functions flexibly. The arguments are: (1) silhouette – silhouette mask that has non-zero pixels where the motion occurs; (2) mhi – motion history image that is updated by the function (single-channel, 32-bit floating-point); (3) timestamp – current time in milliseconds or other units; and (4) duration – maximal duration of the motion track in the same units as timestamp).

The function updates the motion history image as follows:

$$\mathtt{mhi}(x,y) = \begin{cases} \mathtt{timestamp} & \text{if } \mathtt{silhouette}(x,y) \neq 0 \\ 0 & \text{if } \mathtt{silhouette}(x,y) = 0 \text{ and } \mathtt{mhi} < (\mathtt{timestamp} - \mathtt{duration}) \\ \mathtt{mhi}(x,y) & \text{otherwise} \end{cases} \tag{16}$$

Equation (16) shows that mhi pixels where the motion occurs are set to the current “timestamp”, while the pixels where the motion happened last time a long time ago are cleared.

The function, together with two important functions – “calcMotionGradient” and “calcGlobalOrientation” – implements a motion templates technique.

8) Methodology of computer-based visual data analysis

The authors selected and executed 1) calculation and drawing of the main shaft of subject; 2) manual setting and chasing the characteristic point of subjects; and 3) automatic setting and chasing of the characteristic point. Next, the authors analyzed each time-line numerical data by significant mathematical (mainly statistical) methodologies. The target was the test subjects who were tilling with a hoe in all cases.

On the other hand, the authors cannot trace the position of any points on the heads or arms of subjects, because those movements were too quick and wide, and the programs used did not have the ability to capture them sufficiently. For the authors to trace head and arm movement accurately, the authors must set up and use a specialized high-speed camera (such as those used in the sports science field) and more high-spec, latest libraries of OpenCV.

a) Calculation and drawing the main shaft

The authors calculated and drew the main shaft of tilling subjects in each frame of obtained visual data.

b) Manual setting and automatic chasing of the characteristic point

We set the characteristic point – the right crest of iliac bone – by manually clicking with a mouse, and chased the indicated point automatically by our original program (described later).

c) Automatic setting and chasing the characteristic point

We set 24 characteristic points by our original program automatically. We then erased 23 points except for one point on the right crest of iliac bone, by manually clicking with a mouse. The program chased remained one point automatically.

Fig. 4 and Fig. 5 show the construction of original programs. The flow chart in Fig. 4 was concerning the analysis of main axis and characteristic points on the video data.

[Pre-processing]
・Initial declarations of header and library files

[Main function]
・Declaration of variable numbers
・Declaration, obtaining and setting of video data
・Obtaining the initial frame of visual data from the video data
・Obtaining the value of input data's size
・Keeping and initializing resources for video data

[Main loop]
・Changing the first frame into binary-colored (monochrome) data
・Calculation the differences of brightness concerning dots between current frame and the previous frame
・Changing the differences into binary-colored data
・Obtaining, recording and arranging the history of visual data's frame
・Calculation and drawing the line of the main shaft of the binary-colored objectives in this video data utilizing the history of visual data's frame and current direction data
・Resister current frame as the next loop's "the previous frame"
・Escaping the main loop if user input any commands to quit the program indicated in advance

[Post-processing]
・Release the resources for various data concerning window and captured images, etc.

Figure 4. Flow chart of program for calculation, viewing and accumulating of the result data concerning the main shaft output from the time-line binary-colored (monochrome) video data by the motion template

[Pre-processing]
・Initial declarations of header and library files
・Declaration of variable numbers and functions concerning frame for video data, visual data and characteristic points

[Main function]
・Declaration of another numbers and functions concerning frame for video data, visual data and characteristic points
・Setting and showing one window to demonstrate current handling visual data
・Appearing the common window to show visual data
・Declaration of "mouse events" to manipulate the procedures in this program
・Keeping resources for video data
・Keeping various resources related this procedure after obtaining one piece of picture's frame
・Declaration of requirements and conditions concerning escaping (quitting) the repetitive algorithms in the main loop below

[Main loop]
・Changing the video data into binary-colored (monochrome) data
・Calculation concerning characteristic points by Kanade's pyramid method if there are any characteristic points in the changed video data
・Drawing characteristic points in the currently handled frame
・Quit this program's successive procedures by inputting of commands indicated in advance after handlings and data are cleared

[Post-processing]
・Release the resources for various data concerning aforementioned window and captured images, etc.

[Declaration of the functions]
・Declaration of the function to delete unnecessary dots
・Declaration of the function to set new characteristic points by clicking of mouse, and to add the coordinated data with making these accuracy higher (with deleting the points looking as unnecessary dots if there are any close dots around them)
・Declaration the function for auto-detecting of characteristic points (with detecting corners' edge and making these accuracy higher)

Figure 5. Flow chart of the program for calculation, showing and accumulation of data relating to the characteristic points output from the time-line binary-colored (monochrome) video data by Optical Flow-based methods

E. Other Fundamental Data

Some interview sheets have been made by and used by Japan Association of Industrial Health and other health organizations. These are considered reliable. The authors asked about fatigue after each trial, subjects' fitness habits, smoking habits and their backache to make sure subjects condition.

III. Results

The authors took the analyzed results of this study and discussed them statistically and successively [24]-[33].

First, we show one set of typical binarized subject pictures in visual data that was handled by the previously-described program. Fig. 6 is typical of one of the frames processed, taking differences of pixels between successive two binarized frames by one function concerning motion template, and calculating the coordinates of both the top and the end of the main shaft, and drawing it as one straight, red line on the execution window in our environment of Visual Studio 2010 (Fig. 7).

Figure 6. Binarized and shown video data on Visual C++ program environment by OpenCV libraries

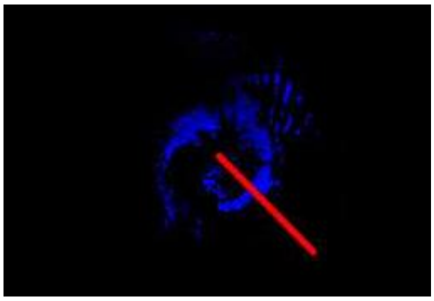

Figure 7. Differences of pixels between successive two binarized frames by one function concerning motion template, and drawn the main shaft by one red line on Visual C++ program environment by OpenCV libraries

Next, the authors used another program. One of them was used to indicate, mark and erase the aforementioned characteristic points by mouse-clicking.

The authors selected the crest of subjects' iliac bone as one point for tracing in this trial (Fig. 8). The other program was for automatic indication and marking of characteristic points by programs' algorithms (Fig. 9). Furthermore, in this program, the authors can erase inappropriately-selected points by clicking the mouse (Fig. 10). Not to mention, the user can input the features and accuracy of characteristic points that the programs have selected automatically.

After the authors started this program, the operator erased marked points except for one point on the crest of the subjects' iliac bone manually one by one, and then accumulated those sequential time-line data concerning those coordinate values of X-axis and Y-axis of the one point (in two-dimensional geometry).

The areas of subjects and the hoe in each binarized frame look appear to indicate their dynamism and their motion characteristics. However, the other elements (e.g. length and degree of circularity) did not show their motion characteristics significantly, assuming only their physical attributes.

Figure 8. One characteristic point directed, showed and tracked manually by OpenCV-based programs written in Visual C++

Figure 9. Characteristic points directed, showed and tracked automatically by OpenCV-based programs written in Visual C++

Figure 10. One characteristic point on a subject's right side top of iliac bone showed and tracked automatically by OpenCV-based programs written in Visual C++

After basic trials, the authors defined some major indicators (the targeted figures' area (Fig. 11), center of gravity (Fig. 12), moment of main shaft (Fig. 13), angle of main shaft (Fig. 14), coordinate values of manually set characteristic points (Fig. 15) and coordinate values of automatically set characteristic points (Fig. 16)).

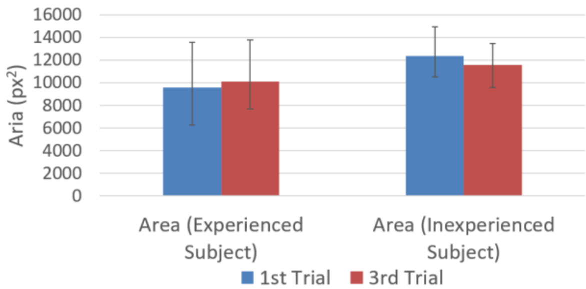

Figure 11. Time-line chart of targeted area from experienced and inexperienced subjects' data

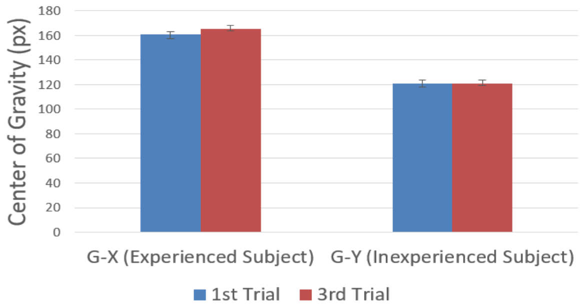

Figure 12. Time-line chart of targeted subjects' center of gravity (coordinate values X and Y) from experienced and inexperienced subjects' data

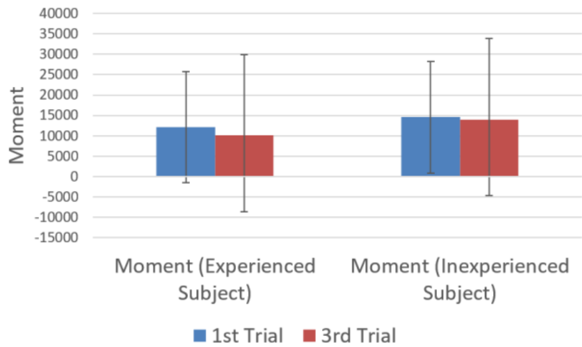

Figure 13. Time-line chart of targeted subjects' moment of main shaft from experienced and inexperienced subjects' data

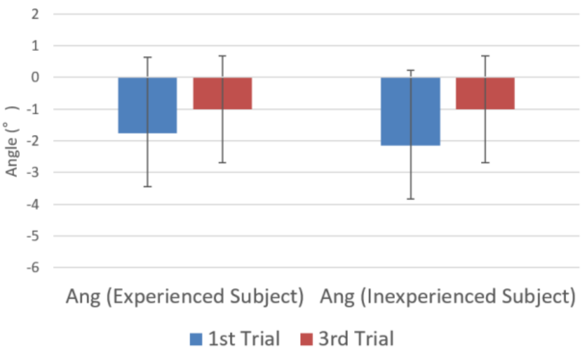

Figure 14. Time-line chart of targeted subjects' angle of main shaft from experienced and inexperienced subjects' data

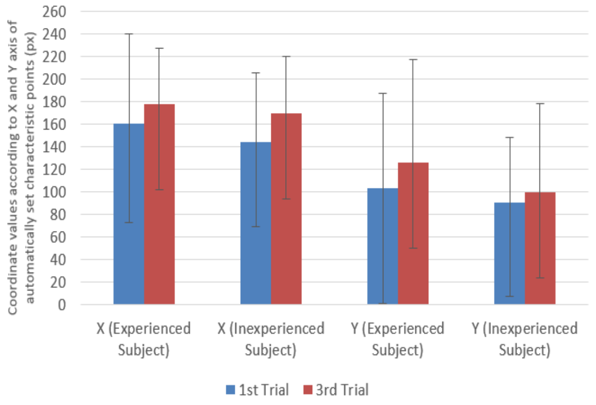

Figure 15. Time-line chart concerning coordinate values according to X and Y axis of manually set characteristic points (the right crest of the iliac bone) of experienced and inexperienced subjects' data in the frame of program

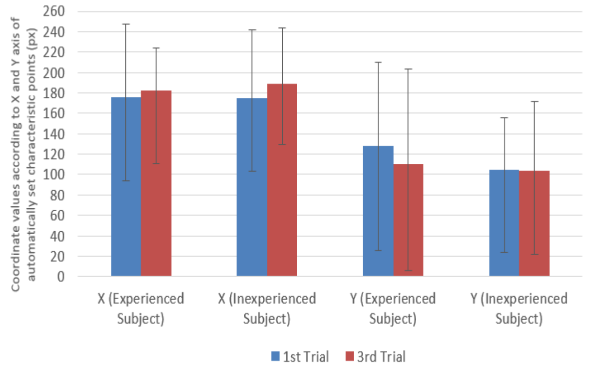

Figure 16. Time-line chart concerning coordinate values according to X and Y axis of automatically set characteristic points (the right crest of the iliac bone) of experienced and inexperienced subjects' data in the frame of program

IV. Discussion

In this study, considering the contributions to agricultural workers, the authors obtained significant data. Experienced and inexperienced workers have obvious differences concerning both limb and body movements, and the authors can check these differences from video data and analyzed numeric data. Experienced workers movements are generally smoother and more natural than those of inexperienced workers. Experienced workers' natural, unselfconscious working motions must be more effective and energy-efficient.

Concretely, the time series of experienced workers' arms shows that they are likely to rise quicker and more sharply than inexperienced workers' arms. Furthermore, they do not look hesitant when conducting successive actions.

As for keeping in a semi-crouching position, in particular, the area and the center of gravity were limited in some way, however, the reason for these limitations were unclear. Inexperienced subjects' values of area were likely to be larger than those of experienced workers. The data concerning the inexperienced workers' center of gravity in Fig. 12 became closer to the values for experienced workers.

As for physical tilling up forms in a semi-crouching position, the coordinates of center of gravity and the angle of main shaft did not change between experienced and inexperienced subjects. The authors thought that those indicators are difficult to utilize for actual agricultural teaching fields.

Concerning the changing ranges of coordinates of inexperienced subjects' waist (iliac bone), it is difficult to comment. However, the automatically-set characteristic points and manually–set points were rather similar. The feature was observed as one most important point related to skill–lecturing for inexperienced workers.

The authors confirmed and insist that there are some benefits of these systems for users, and that the values of area and moment seemed to be important.

As a general tendency, experienced subjects' performances are smoother and more stable as we mentioned, and concretely speaking, the time series data relating to waist characteristic points are calmer but the risings among the time series of graph lines concerning main shafts are more emergent and sharper than those of inexperienced subjects. In addition, the swings of the hoe are faster and more acute. Concerning the experienced subject group's postures, judging from their visual data, the changing about both acceleration and angler rate were generally more gradual and smooth, not sudden, moving as needed. However, there were not prominent, significant differences or other exquisite, apparent differences between two groups.

On the other hand, inexperienced group members were likely to become anemically. The authors think that this was probably due to their fatigue and idleness. Inexperienced subjects' group were likely to do careless work, which might be due to their fatigue, however, inexperienced workers could be effective if they are only deployed for short periods of time.

V. Conclusion and Future Tasks

In this study, the authors constructed novel OpenCV-based visual analysis systems for use at agricultural work sites, demonstrated these availabilities, and presented various types of extracted numerical data relating to worker tilling movements using a common hoe. Through these procedures, the authors obtained meaningful results, especially relating to the presentation of successive drawing and tracking the main subjects' shaft, the point of the crest of iliac bone, and characteristic points set manually and automatically.

Additionally, the authors indicated numerical data and graphs and showed significant differences between inexperienced and experienced workers and their features both quantitatively and qualitatively. These findings closely resembled past results noted by other researchers and agricultural personnel. The aforementioned facts require researchers, agricultural personnel and engineers of diverse agricultural systems to achieve enough high-level agricultural educations including concrete and minute directions.

By focusing on traditional agricultural skills and focusing on daily tasks of experienced subjects, the authors verified the usefulness of our system to inexperienced workers to improve their agricultural work competency. However, these trials are still in a challenging and a preliminary phase. In the future, the authors wish to seek further confirmation concerning the variety, validity, durability, precision and long-term performance of their systems. For instance, increasing the number of shafts, bones and characteristic points to be analyzed is expected. Other methodological settings (e.g. different kinds of trial timelines, other agricultural tools, field conditions) should be investigated in future studies, too. Furthermore, diverse FFT (Fast Fourier Transformation)-analysis would be certainly helpful in such scientific fields.

For years, the authors have been developing methodologies of distant observation of agricultural worker, in parallel with various wearable electric systems. These visual analyzing systems' digital data could be important indicators and checkers concerning users' improvement and brush-up of working movements, with the aim of saving workers from sudden and hidden diseases and injuries in rice fields.

Additionally, the authors hope that these promising methodologies will be applied to real working sites in a broad and practical manner, and they must cover worker contributions and traditional skills and prevent users from suffering common injuries (e.g. back pain, broken bones) comprehensively.

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