Optical Flow–Based Study Related to Outdoor Tree Pruning Using OpenCV Utilities and Captured Visual Data

Shinji Kawakura
Department of Information Technology and Human Factors, National Institute of Advanced Industrial Science and Technology, Tsukuba, Japan
Email: s.kawakura@gmail.com

Ryosuke Shibasaki
Center for Spatial Information Science, The University of Tokyo, Meguro, Japan
Email: shiba@csis.u-tokyo.ac.jp

***Abstract*—We construct and use wearable sensing systems and various cameras to analyze the characteristics of the motions of trained workers and beginners (sometimes including semi-beginners) in non-specific agricultural jobs, and the differences between them. In recent sequential studies, we developed multitudinous, coverall analysis systems to address various agricultural challenges. We have been contributing to them with investigations verifying the accuracy and utility of our kinematic direct sensing and semi-original program-based visual analysis systems for workers and trainers engaged in the pruning of tree branches using special small saws. Pruning tasks include cutting tree branches and forming shapes to improve ventilation for efficient nourishment and promotion of tree growth. Other purposes of these tasks are to make the trees appear beautiful and to prevent illnesses and breeding of noxious insects. The research analysis is based on nine selected optical flow (OF)–based numerical items (features) used in many other scientific fields. These are extracted from OF vectors calculated from the differences between two successive frames of the obtained digital visual data. The targeted experimental field is situated in the Graduate School of Agriculture of the University of Tokyo in Japan, where the targeted trees are common and adequate for the trials. The targeted task of pruning tree branches is one of the most common movements worldwide, which is why our measurements and proposed indicators are expected to be useful in the future in agricultural fields, especially in developing countries and trend agricultural schools.**

***Index Terms*—tree pruning, visual data analysis, OpenCV, optical flow–based factors, wearable sensing modules**

I. Introduction

In many countries, agricultural informatics societies are attempting to improve agricultural practices and the field of agricultural informatics is growing in proportion with the expansion and complication of its methodologies. There are many methods that have successfully characterized the motion of agricultural workers and their machinery, which have gradually led to increased agricultural worker efficiency [1]–[11]. However, there are still modern problems related to the critical shortage of young beginners interested in agriculture and the lack of transmission of traditional methods from skilled, experienced workers to beginners and inexperienced workers.

In past studies, there has been no research concerning the pruning of plum tree branches using special small saws. The task of pruning involves cutting the branches of trees and forming shapes to improve ventilation for efficient nourishment and promotion of the tree growth. This is not only to make the trees appear beautiful, but also to prevent illnesses and the breeding of noxious insects.

The main aim of this study is to improve the physical motions of workers in this type of agricultural labor. Therefore, we aimed to utilize electronic technologies, index data obtained from visual data, and provide concrete data feedback to support workers and trainers. In particular, we obtained both immediate and distant time-line data and analyzed them. Additionally, we obtained sheet-based questionnaires before and after trials.

Experimental studies of the bio-dynamic features (e.g., body vibrations, straight-forward motions, etc.) and responses relating to visual data have been conducted to optimize body dynamics and to develop scientific models representing specific aspects of body movements [10]–[16]. However, the characteristics and mechanisms of dynamic body responses have not yet been fully understood or acquired; nevertheless, new technologies are in development. In light of this, we have suggested a promising, direct, distant (not immediate) measurement method relating to visual data [17], [18]. To solve these physical problems, we have utilized various libraries and packages in the OpenCV series [19]–[21].

II. Materials and Methods

A. System Design, Creation, and Testing

Firstly, we reviewed past industrial goods, patents, and academic papers, and discussed their findings relating to

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agricultural informatics with actual workers and farmland managers simultaneously. What became evident was that past studies and policies have proved insufficient when considering the aforementioned problems.

With this consideration, after testing various scales in terms of measurement range, we designed systems to measure and analyze acceleration data, angular velocity data, and very close (3.5 m away from a subject) visual data to obtain comprehensive whole body motions. We attached two non-specific digital video cameras (Canon IXY 410F, Canon Inc., Japan) to obtain motion data of users on the solid tripod stand from the subjects' front and left sides. In light of the information above, we executed a number of indoor experiments to estimate their utility and suitability.

B. Subject, Field, and Experimental Settings

The trial's timeline consisted of the waiting time from the previous setup, the waiting time, the trial time (in the time span, the numbers of branches cut by one subject were five to nine), and post-processing time. Based on the opinions of real farmland managers and a search of past studies, these time spans and volumes of tasks were judged to be well-balanced trials. Sets of three trials were conducted successively on the same day with an interval of a few minutes between each set. Before taking the main measurements, to monitor the subjects' fatigue and condition, we conducted questionnaire-based interviews to obtain information, in addition to using lifestyle and health check sheets used across Japan.

We gathered two experienced male workers and two male complete beginners; they had no remarkable mental or physical characteristics or diseases (Fig. 1 and Fig. 2). Two of those subjects (one skilled and one beginner) did not have an average body size for Japanese farmers; however, based on the difficulty of gathering subjects in the agricultural informatics field, we conducted experiments regardless. The skilled workers had career lengths of 11 and 13 years, were 34 and 41 years old, stood at 164 and 173 cm, and weighed 71 and 73 kg, respectively. The inexperienced subjects had no experience in agricultural work at all, were 24 and 34 years old, stood at 178 and 172 cm, and weighed 65 and 63 kg, respectively. All four were right-handed, and no subjects reported past serious physical disorders. The analysis of the various physical data was impeded by the complexity of the structure of the human body, difficulties in taking measurements, and inter-individual differences in responses.

Figure 1. A skilled subject pruning plum tree branches with a saw on the left side of the capturing camera.

Figure 2. A skilled subject pruning plum tree branches with a saw in front of the capturing camera.

C. System and Theory for Analyses

We assume that these experimental settings would be useful for general agricultural workers, directors, and managers to obtain time-series visual data for various analyses of outdoor experiments, with reference to past studies [1], [2], [5], [6], [9], [11], [17]–[21]. To avoid the possibility of a negative impact on the accuracy of the recordings, we did not use the visual data capturing libraries and program codes from the OpenCV series (especially from versions 2.2 to 2.4) to obtain visual data. We were aware that various past studies have utilized these features, but we did not have complete confidence in the methods at the time of the study. Therefore, we decided to use these features only for analysis after visual data processing, as described later.

As for the agricultural materials, various small, special saws are available for purchase worldwide. The basic specifications of these saws differ across districts, climates, and agricultural styles, with the main differences lying in the form of the metal head and the haft, and not so much in the weight. We selected one saw type (U-M Industry Inc., Japan), because it was popular enough in the Kantou region in Japan where our research was conducted. The saw weighed 717 g and had dimensions of 648 mm × 152 mm × 38 mm. The haft was made from a stiff wood. The subjects grasped the saw with their dominant hand and the branches with the other hand.

The targeted experimental field was situated in the Graduate School of Agriculture of the University of Tokyo (Nishi-Tokyo-shi, Tokyo, Japan). In our opinion, the targeted trees were common and adequate for the trials. During the period of the experiment, we conducted outdoor trials in one outdoor area of farmland on days when field conditions (e.g., the amount of insulation, cloud cover, and wind) were as similar as possible. The experienced subjects wore working uniform clothing from the Graduate School of Agricultural and Life Sciences at the University of Tokyo (with no protruding items or accessories), keeping in mind future collaborations and similar experiments with the school.

Considering the results of Nagata and Toyosawa [19], [20], we analyzed visual data using programs written in

Microsoft Visual C++ (in particular, we used versions 2010 to 2015) to calculate, output, and accumulate matrix CSV (comma separated values) formatted data, using various general OpenCV packages including libraries and classes [19]–[21]. Furthermore, we employed a method based on the sum of squared differences, because the methodology targeted only moving objects and did not use stationary ones (e.g., background sceneries).

For the mathematical theory, the sum of the squares of differences in pixel values between two sequential frames is minimized as follows:

$$SSD(i,j) = \sum_{\alpha}\sum_{\beta}\left[\mathrm{t}(\alpha,\beta) - \mathrm{f}(\mathrm{i}+\alpha,\ \mathrm{j}+\beta)\right]^2 \tag{1}$$

where i and j are the numbers of differences in pixels and α and β are the numbers of the currently calculated pixels. All numbers are integers.

These indicators and the definitions of the optical flow (OF)–based analysis are given below (see Table I and (2)–(3)):

$$ave = \frac{1}{N}\sum_{i=1}^{N} s(i) \tag{2}$$

$$var = \frac{1}{N}\sum_{i=1}^{N} s(i)^2 - ave^2 \tag{3}$$

By inserting ave from (2) into (3), we obtain:

$$mean0 = \frac{1}{N}\sum_{i=1}^{N} \left|\mathrm{s(i) - ave}\right| \tag{4}$$

$$mean1 = \frac{1}{12}\sum_{i=1}^{12} \mathrm{m}_j \tag{5}$$

$$diff = \frac{1}{N}\sum_{i=1}^{N} \left|\mathrm{s(t,\ i) - s(t+1,\ i)}\right| \tag{6}$$

where i, j, and t are the numbers of the current calculating vector; s(i) is the length of the vector; and m(i) is the mean value. All numbers are integers. In previous similar studies, in many cases researchers have shown that the three items, ave, var, and diff, are likely to be the most significant and dominant [20]. Additionally, we checked the significance of the three values through outdoor experiments concerning tilling and cropping motions.

TABLE I. INDICATORS OF VISUAL DATA ANALYSIS

Index	Code	Description
Average	ave	OF average absolute length of speed vectors
Variance	var	Variance of the speed vector length
Median	med	Median of the absolute value of the speed vector length
Mean value 0	mean0	Average of the variance of the speed vector length, deleting bad effects from “pans” of camera work
Mean value 1	mean1	Average of the variance of each of the 12 blocks separated on the screen of the speed vector length, deleting bad effects from the back and forth movements of users
Max value 0	max0	The maximum vector length in the frame
Max value 1	max1	The top 1.5% value of max0
Max value 2	max2	The top 10% value of max0
Second-order differential	diff	Difference in accelerations of speed vectors between two successive frames

III. RESULTS

The nine factors in Table I were statistically analyzed with a focus on the average values, and the output data are discussed.

First, we show in Fig. 3 a set of analyzed data in Visual C++, including OpenCV header files and libraries for the Windows 10 operating system, that was handled by the program as previously described. Fig. 3 shows the differences between the aforementioned experienced and inexperienced groups.

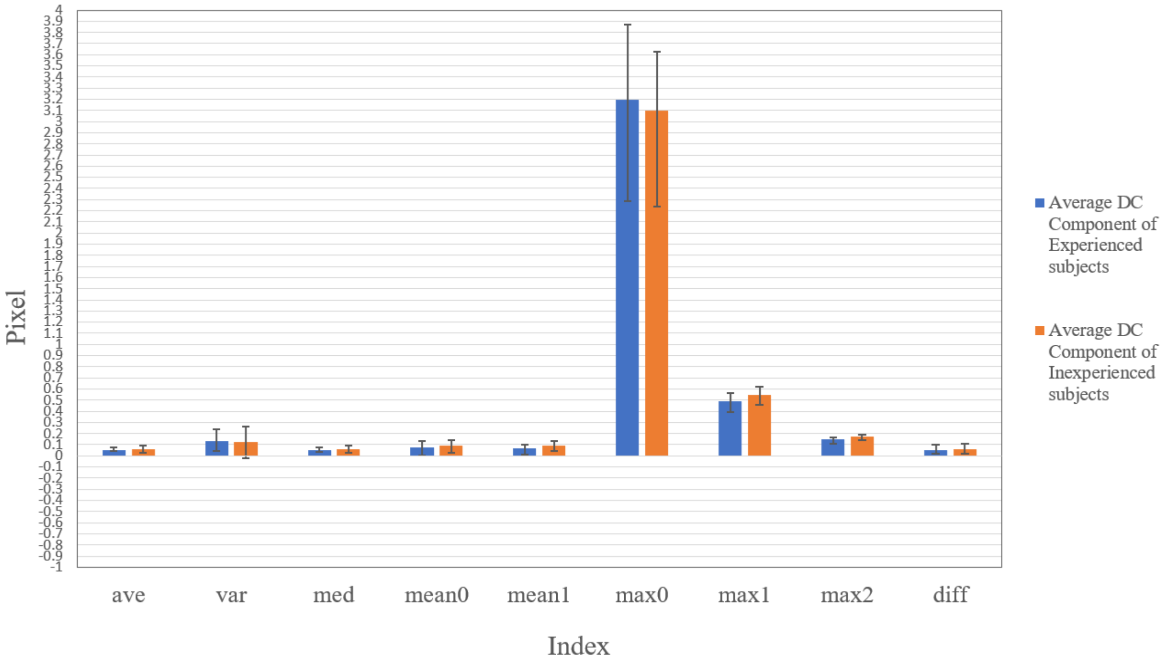

Figure 3. Comparison of the DC (direct component) and S.D. (standard deviation) values of nine indicators relating to the results of the OF–based visual analyses between the average data of the two groups of subjects.

Figure 4. A sample of the analysis window of OF–based analysis.

Fig. 4 shows an example of the 2D frame processing as it relates to common manual agricultural work. The physical movement data of the subjects and the saw shown indicates the dynamism and quality of the task.

IV. Discussion

We obtained the aforementioned data with the contributions of agricultural scientists, engineers, workers, and managers. From the data in Fig. 4, we could not confirm any mathematically meaningful differences and variations, not only in the raw time-line physical data (e.g., acceleration data and angular velocity data), but also in mathematically defined indicators (items) from the captured visual data. The averaged data expressed did not have any significant differences concerning the direct component (DC) and standard deviation (S.D.) values of the nine indicators between the two subject groups, which could be because the data values were from typically non-specific traditional motions within a semi-standing position. Furthermore, it could be because we could not gather enough subjects for experimental reasons. In contrast to past similar research results, ave, var, and diff did not indicate clear differences.

All the same, we confirmed subtle differences and numerical trends in this study. For instance, as for S.D. values, those of inexperienced subjects have the inclination to be higher than those of experienced subjects. Those trends were suggesting 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

We have developed methods for both surface and distant observations of agricultural workers. In this study, using Visual C++–based semi-original programs including OpenCV libraries and header files, we constructed and described measurement and assessment systems and data for use in common outdoor tree pruning work sites.

In particular, we have gathered a variety of numerical data relating to worker skill and performance in a common pruning task. By focusing on traditional agricultural skills and relating the non-specific tasks of experienced subjects, we verified their usefulness. However, mathematically differences were not found.

The proposed system has various future applications, in that it can be used with the latest informatics, electronics, statistics, and human dynamics to contribute to the improvement of agricultural practices. It might aid inexperienced workers in achieving diverse competencies and furthering their agricultural skills.

In the future, our results may allow researchers in the fields of human dynamics, agricultural personnel, and engineering for various agricultural systems to achieve high-level results with specific instructions. However, we must seek further confirmation, especially concerning the durability, precision, and long-term performance of our system. In particular, future studies should investigate other parameters, such as different program settings, trial settings, agricultural tools, and field conditions.

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Shinji Kawakura was born in Toyama Pref., Japan on July 14, 1978. Ph.D. in Environmentology, University of Tokyo, 2015, Bunkyo-ku, Tokyo, Japan. B.A. in Control System Engineering, Tokyo Institute of Technology, 2003, Meguro-ku, Tokyo, Japan. M.A. in Human-Factor Engineering, Tokyo Institute of Technology, 2005, Meguro-ku, Tokyo, Japan.
Career: Systems engineering, research for private companies. Development and verification of sensing systems for outdoor agricultural workers.
Dr. Kawakura, associate researcher at the National Institute of Advanced Industrial Science and Technology/Department of Information Technology and Human Factors, Tsukuba, Japan. Committee member of ICEAE and ICBIP.

Ryosuke Shibasaki was born in Fukuoka. Pref. Japan on March 1, 1958. Doctorate in Engineering, University of Tokyo, 1987, Bunkyo-ku, Tokyo, Japan. B.A. in Engineering, University of Tokyo, 1980, Bunkyo-ku, Tokyo, Japan. M.A. in Engineering, University of Tokyo, 1982, Bunkyo-ku, Tokyo, Japan.
Career: 3D mapping of urban spaces, measurement and monitoring of the movement and behavior of human and moving objects in urban spaces, modeling context of human behavior and its application to context-aware services.
Dr. Shibasaki, professor at the Center for Spatial Information Science, University of Tokyo, Kashiwa-shi, Chiba, Japan, and at the Department of Socio-Cultural and Socio-Physical Environmental Studies, University of Tokyo, Bunkyo-ku, Tokyo, Japan.