Deep Learning Based System to Extract Agricultural Workers' Physical Timeline Data for Acceleration and Angular Velocity

Shinji Kawakura[1*], Ryosuke Shibasaki[2]

[1] The University of Tokyo/The Research Center for Advanced Science and Technology (RCAST), Bunkyo-ku, Tokyo, 153-8904, Japan.
[2] The University of Tokyo/Center for Spatial Information Science, Kashiwa-shi, Chiba, 277-8568, Japan.

* Corresponding author. Tel.: +81-80-9781-1535; email: s.kawakura@gmail.com, kawakura@motolabo.net
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Abstract: Several physical characteristics of workers can be extracted from physical timeline data to understand acceleration and angular velocity. Although various approaches have been implemented globally for indoor and outdoor agricultural (agri-) working sites, there is room for improvement. In this study, we aim to adapt these approaches particularly for real agri-directors, leaders and managers to improve the quality of tasks and their security levels. Thus, we apply a deep learning-based method and qualitatively demonstrate the classification of physical timeline datasets. To create our dataset, our subjects were six experienced agri-manual workers and six completely inexperienced men. The targeted task was cultivating the semi-crunching position using a simple, Japanese-style hoe. We captured the subjects' acceleration and angular velocity data from an integrated multi-sensor module mounted on a wood lilt 15 cm from the gripping position of the dominant hand. We used Python code and recent distributed libraries for computation. For data classification, we successively executed a Recurrent Neural Network (RNN), which we evaluated using wavelet analyses such as the Fast Fourier Transform (FFT). These methods of analyzing digital data could be of practical use for providing key suggestions to improve daily tasks.

Key words: Deep learning-based classification, characteristic extraction, physical timeline data, acceleration, angular velocity.

1. Introduction

1.1. Background

Stemming from societal and academic needs, there has been increasing interest in machine learning-based analyzing and categorizing methodologies for matrix-formed data, especially targeting agricultural (agri-) workers, managers, technicians, researchers, and unliving targets (e.g., workers, harvests, and agri-tools). Techniques have been improving to a practical level, but investigations into deep learning that targets human body part acceleration and angular velocity data are limited; we could not find any promising past studies concerning angular velocity data.

1.2. Overview of the Study

Existing deep learning-based analysis methods in this field have focused on harvests, weeds, forests, farmers, and other various targets [1]-[3]; however, these are insufficient, particularly for traditional

Japanese workers, for whom there are no current studies. We use timeline matrix-formed datasets with a variety of common Japanese-styled agri-tools. We base our deep learning approach on achievements in the acoustic deep learning fields, where timeline physical data is transformed into WAV formatted sound file data.

1.3. Deep Learning

Recent improvements in analyzing agri-work have considered up-to-date technologies with deep learning approaches to understand how solutions reflect the experience of traditional agri-workers. Generally, deep learning-based systems can pick up on subtleties that a human might fail to notice. Furthermore, such approaches can be used reconstruct data files with missing information. We recently proposed artificial intelligence (AI)-based studies with diverse computers: 1) a non-specific laptop PC and 2) a Raspberry-Pi small Linux computer. We developed a deep learning system with hidden layers to perform Fast Fourier Transform (FFT)-based methodologies using AI computing, focused on program-based applications. Specifically, Recurrent Neural Network (RNN)-based agri-achievements in academic and business fields have already reached sufficient levels for real-world application in agri-fields, and can output a large amount of positive results [4]-[11]. For RNN, we select characteristics that are suitable for analyzing timeline data and sequential digital data. In light of this background and considering future expansions, we developed a numerical matrix-formed data-based deep learning system that utilizes RNN-oriented categorizations to support agri-informatics researchers, manufacturers, managers, and workers.

1.4. Future Perspective

To evaluate these methodologies, we checked not only the validity and precision of the quantitative data, but also the systems' limitations. Agri-informatics researchers and manufacturers will continue to develop diverse techniques to improve agri-worker skills and the utility of existing agri-tools, and to enhance the security level of agri-workers. In future, these results could assist the development of automatic agri-systems and other high-tech agri-systems.

2. Method

2.1. Subject and Target

For the visual data used in this study, we captured and aggregated original pictures from non-specific outdoor farmlands for test data. The target subjects were agri-workers with 1–5 years' experience (Table 1). Prior to the data collection, we consulted agri-managers and workers to mitigate the difficulties in handling dozens of samples in farmlands. Following consultations with Japanese farmers, we focused on agri-workers using a traditional Japanese hoe, which is the most familiar agri-tool in traditional Japanese small- to middle-sized outdoor farms after consultation with real farmers [12], [13]. First, we accumulated four categories of datasets (Fig. 1). "Cultivating a field using a hoe" (pictures captured workers cultivating agri-fields using a traditional Japanese hoe in the semi-standing posture in an outdoor farmland; (Figs. 2–5): experienced subjects aged 25–60 years old ($n = 6$), completely inexperienced subjects aged 25–60 years old ($n = 6$). In this study, we used the vertical acceleration value in the vertical direction (x-direction in Fig. 2) and the angular velocity data (the direction rotating around the y-direction presented in Fig. 3). We output the accuracy values concerning classifications of hoe acceleration data from experienced and inexperienced subjects, and of hoe angular velocity data from experienced and inexperienced subjects.

2.2. Field

Based on consultations with farmers about future practical applications, particularly in diverse Asian countries, we examined agri-workers using agri-tools in traditional Japanese, not very trimmed, and small-to middle-sized outdoor farms.

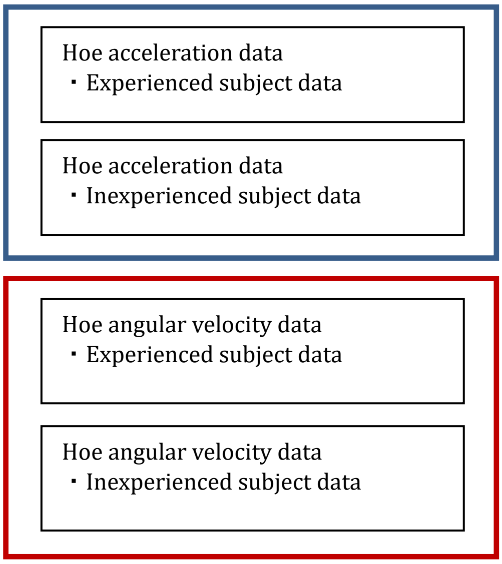

Fig. 1. Target data set categorizing.

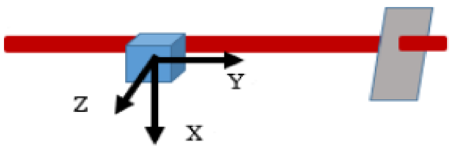

Fig. 2. The three-axes of the acceleration sensor module attached to a hoe.

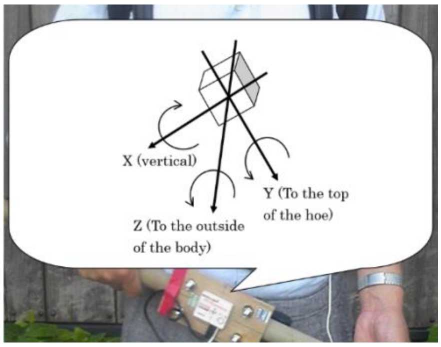

Fig. 3. The Three-axes of the angular velocity sensor module attached to a hoe.

Fig. 4. A subject equipped with measuring modules and knapsack with laptop PC connecting to various modules.

Fig. 5. A subject cultivating with a hoe.

Table 1. Basic Information Related to Subjects (Range, Average (Ave), Standard Deviation (SD), Average Z Value (Z), Coefficient of Variation (CV) and Description

Index	Experienced Group (n = 6)	Inexperienced Group (n=6)
Experience (year)	25–60 (Average (Ave) 40.8, Standard Deviation (SD) 14.3, Average Z value (Z) -1.73* 10^{-16}, Coefficient of Variation (CV) 2.61)	None
Age (year)	58–74 (Ave 66, SD 8.50, Z 0* 10^{-15}, CV 34.9)	23–26 (Ave, 24.2, SD 1.07, Z -1.15 * 10^{-15}, CV 4.42)
Stature (cm)	160–173 (Ave 162.5, SD 5.5, Z 0* 10^{-15}, CV 3.39)	170–180 (Ave 174.8, SD 3.34, Z -2.85* 10^{-15}, CV 1.91)
Weight (kg)	55–85 (Ave 69.7, SD 9.96, Z -1.73* 10^{-16}, CV 14.3)	58–28 (Ave 67.3, SD 7.91, Z 5.92* 10^{-16}, CV 11.7)
Dominant hand	Right (n=5), Left (n=1)	Right (all subjects)
Past serious physical disorder	None (Some had acute low back pain)	None
Fitness habits	Walking	None or tennis or badminton (once or twice per week)

2.3. Data Sensing and Accumulating

Fig. 6 presents the formatted timeline of the processes concerning data sensing and accumulating: 1) Time of various previous settings (several dozen minutes), 2) waiting time (10 s), 3) trial time (30 swings), 4) waiting time (10 s), and 5) time for various post-handling processes (several minutes).

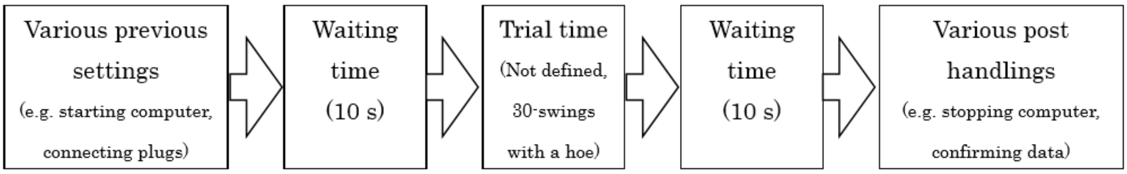

Fig. 6. Timeline of the processes concerning data sensing and accumulating.

2.4. Computing

The flowchart shown in Fig. 7 demonstrates the flow of computing in this study.

We used distributed API and a program written in Visual Basic to input and saved datasets; we obtained using the integrated sensor ATR-121 (ATP Promotion Inc., Japan) in Figs 8-9. As shown in Figs. 10-14, we computed using two systems:

1) For the "Learning Part" and "Classification Part," we computed in Linux OS (Ubuntu 18.04) in Raspberry Pi 3 B+ Computer connected to a laptop computer, and 2) other basic computing was executed in Python 3.6 language with PyTorch. We used these open systems for our approach. However, owing to the

study's characteristics, we used originally obtained data rather than open, distributed datasets. The steps of the training and evaluating programs are as follows:

(A) For the data training program,

(1) Importing Pytorch, Numpy, Scipy, and Chainer;

(2) defining (setting) the RNN-based classes;

(3) defining a method to standardize data shapes;

(4) defining the FFT-based analyses method; and

(5) defining and executing the main class with the aforementioned factors.

(B) For the data evaluating program,

(1) Importing PyTorch, Numpy, Scipy, and Chainer;

(2) defining the RNN-based classes;

(3) defining a method to standardize the data shapes;

(4) defining the FFT-based analyses method;

(5) judging and classifying WAV files; and

(6) defining and executing the main class with the aforementioned factors.

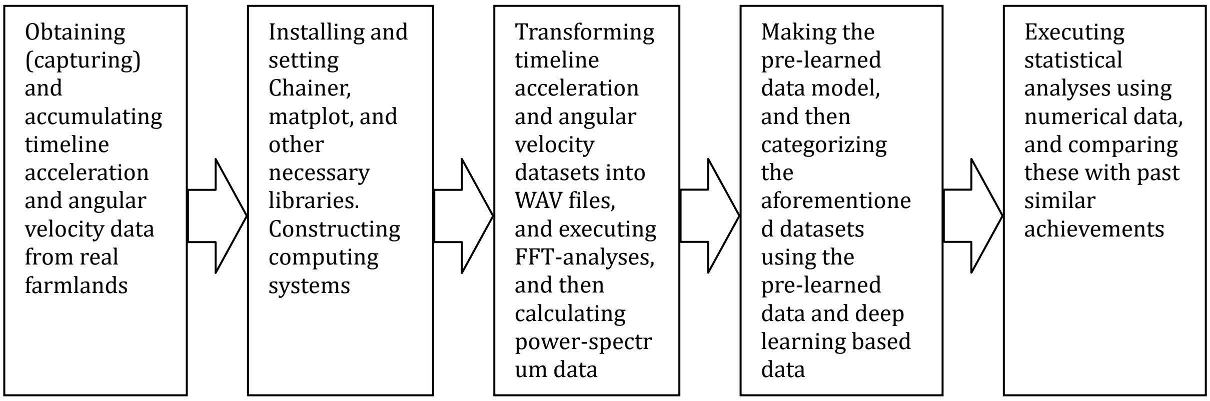

Fig. 7. Flow of computing.

According to current academic trends and past results, our methodology is adequate in the agri-informatics field.

Fig. 8. Hoe connected to sensors and laptop PC.

Fig. 9. Integrated sensor: ATR-121.

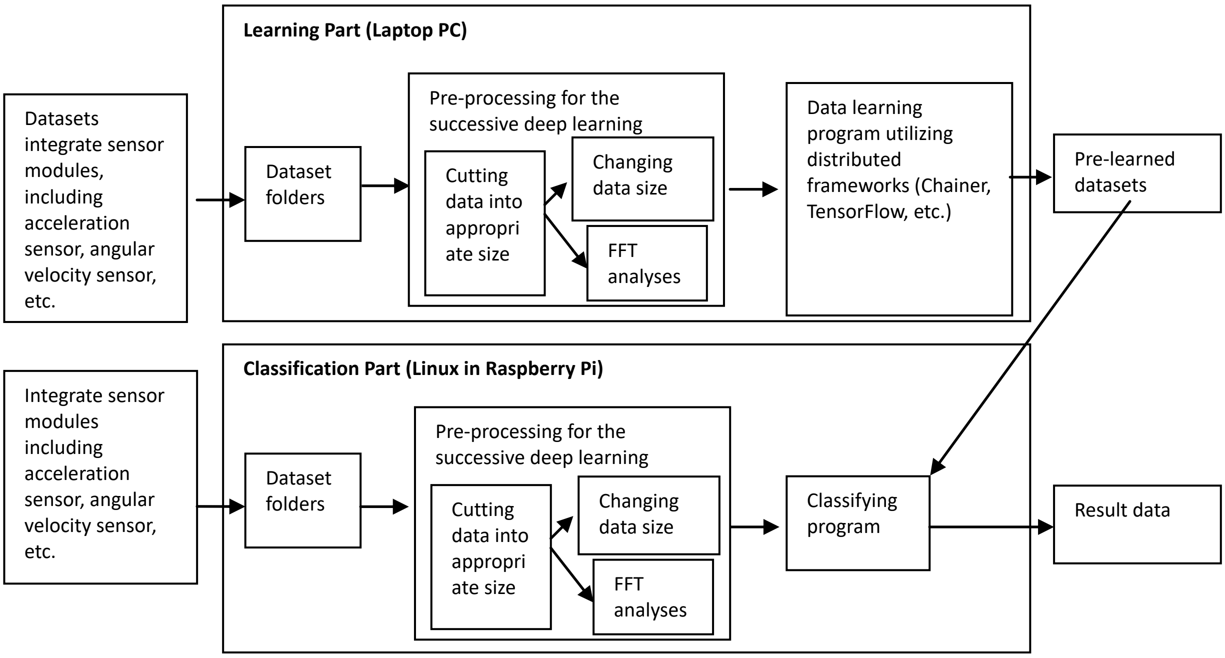

Fig. 10. Flowchart of deep learning-based executions.

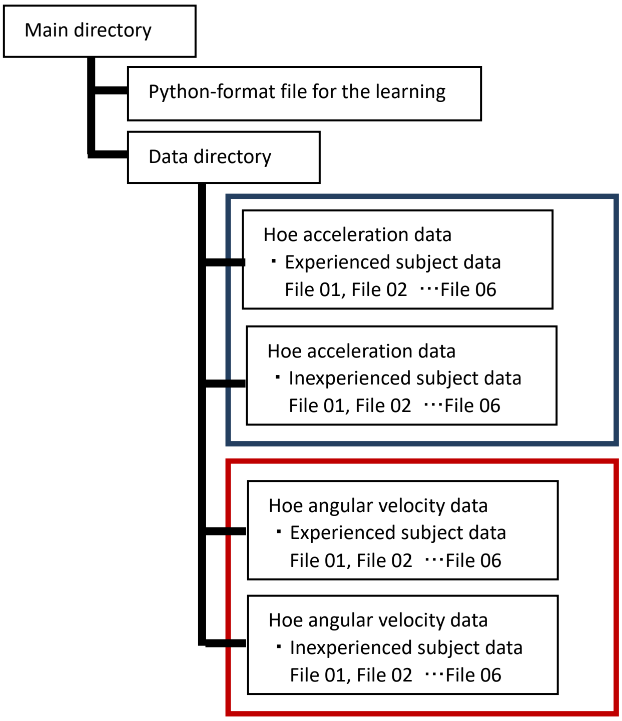

Fig. 11. Classification of the transformed WAV files from acceleration and angular velocity data.

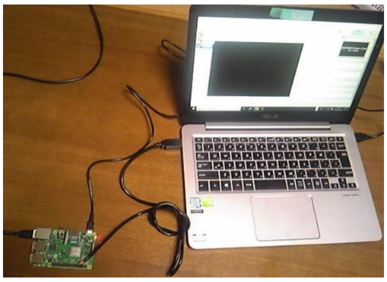

Fig. 12. Raspberry Pi connected to a laptop computer.

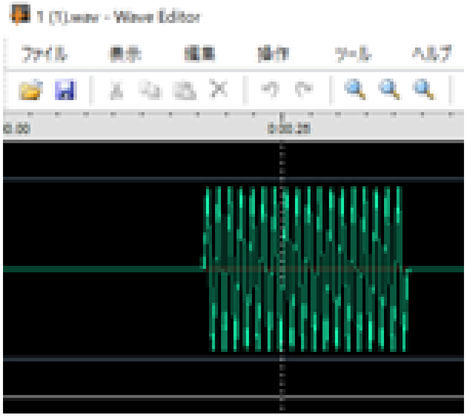

Fig. 13. An example of a transformed time WAV from acceleration and angular velocity data.

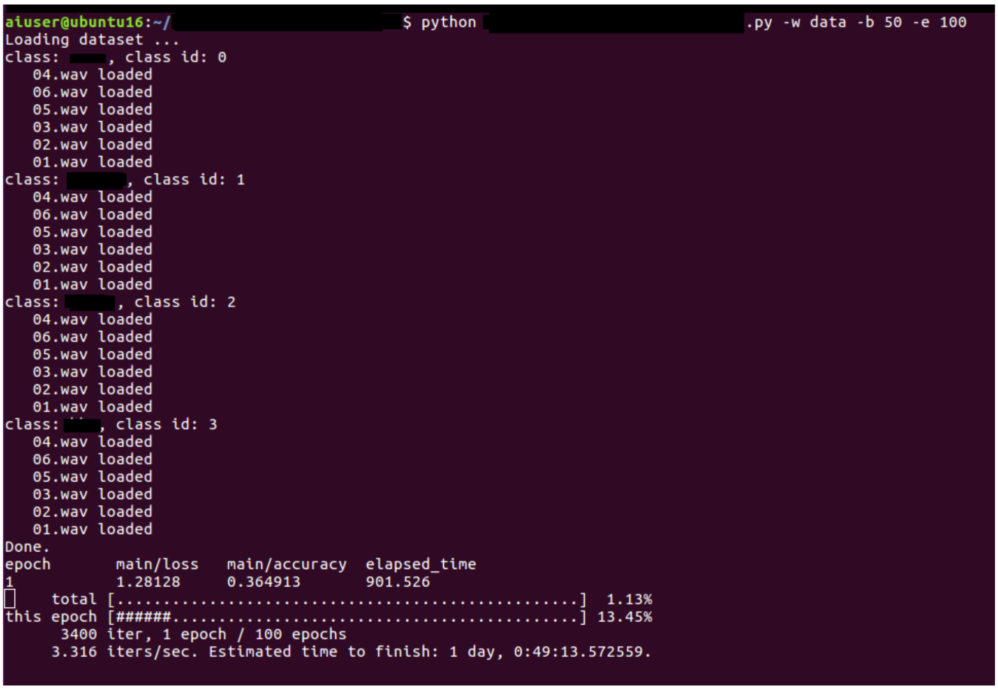

Fig. 14. An example of deep learning-based classification processes.

3. Result

Table 2 presents the matrix-formed numerical data for the trials considering past studies utilizing deep learning-based data analyses [14]-[17]. The items in the rows of "Elapsed time," "Loss," and "Validation Accuracy" are average values (n = 5); we set these epoch periods and elapse times in light of past similar achievements.

Table 2. Data of the Deep Learning-Based Classifications

Item	Acceleration Data (Training Data)	Acceleration Data (Evaluation Data)	Angular Velocity Data (Training Data)	Angular Velocity Data (Evaluation Data)
Epoch (epoch)	100	100	100	100
Batch size	50	50	50	50
Loss (%)	33.3	35.0	23.9	21.1
Validation Accuracy (%)	75.2	39.0	82.5	64.7

4. Discussion

Table 2 in Section 3 presents the quantitative features of the aforementioned four cases. For the datasets of training data concerning acceleration and angular velocity, we observed that the range of loss was from 23.9 % to 33.3 %, and for the range of evaluation data was from 21.1 % to 35.0 %. On the other side, for the datasets of training data concerning acceleration and angular velocity, we observed that the range of validation accuracy was from 75.2 % to 82.5 %, and for the range of evaluation data was from 39.0 % to 64.7 %. Specifically, relating to the system's construction, we cannot extrapolate results to different combinations of people, tools, and other factors. Additionally, we could not definitely determine whether the two groups' datasets were adequate for evaluation.

5. Conclusion and Future Task

In this study, we constructed and demonstrated a novel deep learning-based data system for analyzing and classifying timeline acceleration and angular velocity data for cultivating movements with a hoe in outdoor agri-sites. We expect categorization of the angular velocity data to be especially promising for practical use. In the future, we will check the accuracy and appropriateness of the proposed system for other computing patterns. Previous works have presented accuracy-based data to some extent, and our next studies will provide further progressions for the varieties of categorizing and analyzing agri-targets (mainly manual agri-workers and machines) and background conditions. Practically speaking, we will present the results and consultation to agri-system developers, not only for agri-workers and managers, but also for security guards. We hope that these promising methodologies will be widely applied to real agri-working sites to promote productivity. Future users could automatically or semi-automatically apply our approaches to classify a wide variety of digital matrix-formed data. In the long term, we aim to check and improve the system durability, long-term performance, and other methodological mixing patterns. Additionally, these methods could be utilized for agri-arm robots for harvesting vegetables and eliminating weeds.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Shinji KAWAKURA and Ryosuke SHIBASAKI made the plan; Shinji KAWAKURA conducted the research, analyzed the data and wrote the paper; Shinji KAWAKURA and Ryosuke SHIBASAKI had approved the final version.

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Shinji Kawakura is research assistant professor at The Research Center for Advanced Science and Technology (RCAST), the University of Tokyo, received the Ph.D. in environmentology, the University of Tokyo, 2015. (Meguro-ku, Tokyo, Japan).

He was born on July 14, 1978. He got the B.A in control system engineering, Tokyo Institute of Technology, 2003. He got the M.A. in human-factors engineering, Tokyo Institute of Technology, 2005; the Ph.D. in environmentology, University of Tokyo, 2015, Bunkyo-ku, Tokyo, Japan.

Past career: system engineering, researching for private companies, development and verification of wearable sensing systems with real-time spoken commands for outdoor agricultural workers.

Career: Systems engineering, research for private companies, development and verification of sensing systems for outdoor agri-workers.

Dr. Kawakura is with the Department of Technology Management for Innovation at the University of Tokyo/Bunkyo-ku, Tokyo, Japan. Committee member of ICEAE and ICBIP.

Ryosuke Shibasaki is with the Department of Socio-Cultural and Socio-Physical Environmental Studies, The University of Tokyo/Kashiwa-shi, Chiba, Japan.

He is a professor at the Center for Spatial Information Science, University of Tokyo.

He got the Dr. in engineering, the University of Tokyo, 1987, Bunkyo-ku, Tokyo, Japan; the B.A in engineering, the University of Tokyo, 1980, Bunkyo-ku, Tokyo, Japan; the M.A. in engineering, the University of Tokyo, 1982, Bunkyo-ku, Tokyo, Japan.

Career: 3D mapping of urban space, measurement and monitoring of the movement and behavior of human and moving objects in urban space, modeling context of human behavior and its application to context-aware services.

Dr. Shibasaki is professor at the Center for Spatial Information Science, the University of Tokyo, Kashiwa-shi, Chiba, Japan. and at the Department of Socio-Cultural and Socio-Physical Environmental Studies, the University of Tokyo, Bunkyo-ku, Tokyo, Japan.