Distinguishing Working State by Palm Orientation

Kenta Hayashi
Graduate School/Faculty of Information Science and Electrical Engineering, Kyushu University,
Fukuoka, Japan
hayashi.kenta@arakawa-lab.com

Shingo Kumazoe
School of Electrical Engineering and Computer Science, Kyushu University,
Fukuoka, Japan
kumazoe.shingo.213@s.kyushu-u.ac.jp

Shigemi Ishida
Graduate School/Faculty of Information Science and Electrical Engineering, Kyushu University,
Fukuoka, Japan
ishida@ait.kyushu-u.ac.jp

Yutaka Arakawa
Graduate School/Faculty of Information Science and Electrical Engineering, Kyushu University,
Fukuoka, Japan
arakawa@ait.kyushu-u.ac.jp

***Abstract*—When working from home, self-management becomes of paramount importance due to the absence of a boss or colleagues. As a result, individuals tend to waste time surfing the internet and playing with our smartphones. We propose a wrist-worn sensor-based system that identifies whether a desk worker is working or not for self-management and productivity.**

Our main hypothesis is that the identification of the various tasks that occur during desk work, such as using computers, reading books, manipulating a smartphone, and writing, can be simply distinguished by the direction of the palm. In this paper, to verify our hypothesis, we measure various tasks with the wrist-worn sensor attached to clarify the relationship between hand orientation and each task. At the same time, we develop a machine learning-based classifier to distinguish between the states of 'working' and 'not-working' using the obtained hand orientation data. We performed 10-fold cross-validation and Leave-One-Person-Out validation and we found that it was possible to distinguish whether a desk worker is working or not with an F1-value of 0.8 or higher.

***Index Terms*—Machine learning, Wearable computing, Acceleration, Working or not-working.**

I. Introduction

Japan ranks 20th among the 35 member countries of the OECD and last among the G7 for average productivity per unit time (since 1970, when data is available). In order to increase productivity, it is necessary for workers to fully concentrate and complete their assigned tasks within a limited amount of time, which requires a high degree of self-motivation and self-management. Due to the effect of the current COVID-19 pandemic, working from home has become commonplace. This has a detrimental effect on people with low self-management skills, who become less productive in their home environment due to the absence of a boss or colleagues. We therefore propose in this research a tool that can quantitatively measure the amount of work done by individuals.

Some possible desk worker tasks that can be classed as 'working' include activities such as typing on a laptop or desktop computer, attending online meetings, and making telephone calls. Existing methods in wrist-based activity recognition include Panwar et al. [1] who track the three basic movements of the human forearm in daily life, and Ohnishi et al. [2] who track daily human activities using a wrist-mounted camera. In both these cases, however, activities related to 'working' and 'not-working' during periods of work are not set as identification targets. In addition, Ito et al. [3] classify human activities with a focus on specific tasks performed during work, but does not classify 'not-working' states. In past studies, the activities to be identified while in the 'working' state were defined in advance and training data for machine learning was collected in a controlled laboratory environment. However, when used in real-life situations, there was a variety of activities for which no training data had been collected, such as the 'not-working' state. Therefore, we can expect recognition accuracy to degrade if the model trained in this manner is used on actual test data.

Prior to this study, we noticed by observing individuals in 'working' and 'not-working' situations that there is a relationship between the two states and the orientation of an individual's palm, or 'palm orientation'. We hypothesized that palm orientation could be measured and classified using the acceleration sensor built into a smartwatch, allowing the single-sensor detection and identification of 'working' and 'not-working' states.

In this paper, two participants were asked to perform various operations while wearing a wristwatch-type 3-axis accelerometer; with the data obtained from these experiments being used to verify our hypothesis. We measured the performance of our proposed system using the F1-value metric.

II. Related Work

To the best of our knowledge, not-working-state sensing is novel in the field of activity recognition at workplace. Human activity recognition (HAR) has been widely studied and there

doi: 10.1109/LifeTech52111.2021.9391950

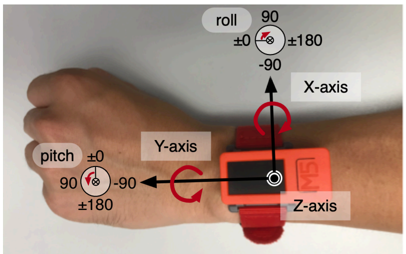


Fig. 1. Wristwatch Type 3-axis Accelerometer

have been many published papers. In this section, we briefly review related work on HAR.

Panwar et al. proposed activity recognition method [1] using wrist-worn accelerometer for the three basic movements of the human forearm in daily life. Ohnishi et al. proposed recognizing method [2] for activities of daily living utilizing a first-person wearable camera. Park et al. proposed a new HAR system via Recurrent Neural Network (RNN) [4] which is one of deep learning algorithms. Hayashi et al. proposed a daily human activity recognition method [5] using a DNN with environmental sound and subject acceleration signals. Activity recognition methods using wireless LAN channel state information (CSI) have also been reported in recent years [6]–[10]. Wang et al. proposed a human activity recognition system named CARM [6], [7], which consists of a CSI speed model that estimates motion or each part of the body, and a CSI activity model that combines the body parts speed information with specific actions by using a hidden Markov model (HMM). Ali et al. proposed keystroke recognition system named WiKey [8], [9] utilizing principal component analysis (PCA) and discrete wavelet transformation (DWT). Zheng et al. proposed a ubiquitous smoking detection system named Smokey [10] that extracts motion from CSI using a foreground detection technology used in the image processing community, and detects continuous smoking activity using autocorrelation.

Previous studies on HAR have also investigated the office work activity recognition method.

Mekruksavanich et al. presented a sitting detection, that also used accelerometer and gyroscope on a smartwatch of office workers [11]. Bonde et al. proposed office activity classifier based on a structural vibration. It monitors vibration data derived from structural objects such as floors, desks, and shelves, that are prevalent in an office environment [12]. Ito et al. proposed activity recognition for office workers where wrist-worn accelerometer was used [3]. In addition, there are studies on behavioral recognition focusing on the posture of office workers [13]–[16].

Although these studies have successfully classified working activities, none of the studies try to detect not-working state. Our aim is to extend these studies to detect not-working state.

III. Proposed System

In Fig. 1, we show how the 3-axis accelerometer is worn on the wrist. We define The fingertip direction as the Y-axis and rightward as X-axis and downward as Z-axis. The X-axis rotation angle is the roll angle, and the Y-axis rotation angle is the pitch angle. In Fig. 2, we show the overview of the proposed system. In our system, 3-axis acceleration data is obtained by the wrist-mounted accelerometer, and the angle data is calculated from the obtained acceleration data. The angle data is then used to determine whether the palm is facing upwards or downwards. The threshold value is that the ratio of the palm facing upwards during working and the ratio of the palm facing downwards during not-working are both 85% or more. We define the palm orientation label as `1` when facing upwards and `0` when facing downwards. We identify the ‘working’ and ‘not-working’ states by inputting the z-axis acceleration value and the palm orientation label as features into the classifier.

In this paper, classification is performed using the Random Forest, Naive Bayes, and Logistic Regression supervised machine learning classifiers.

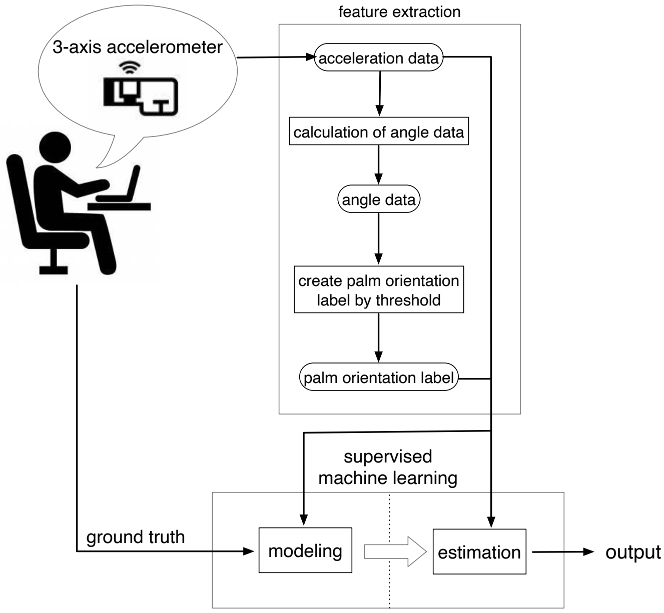


Fig. 2. System Overview

TABLE I
Classification of Activities

Working	Typing, writing, online meetings
Not-working	Reading a book, operating a smartphone, eating, playing a video game

IV. Results

A. Experiment

In Fig. 5, we show the experiment scenery. We used an M5StickC development board as our wristwatch-type 3-axis accelerometer. The sampling rate was set to 10Hz. We utilized mobile batteries to power these accelerometers continuously for a long time.

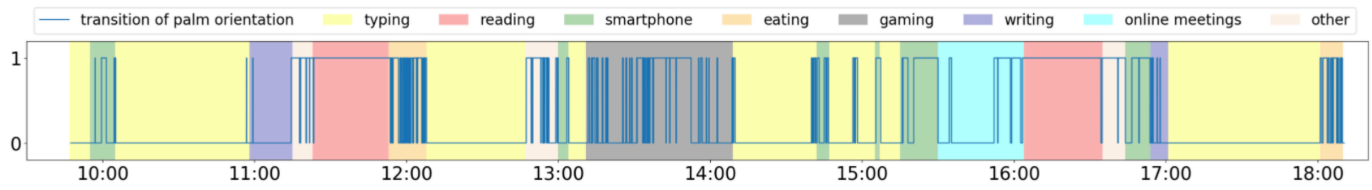


Fig. 3. The transition during the day of right palm orientation

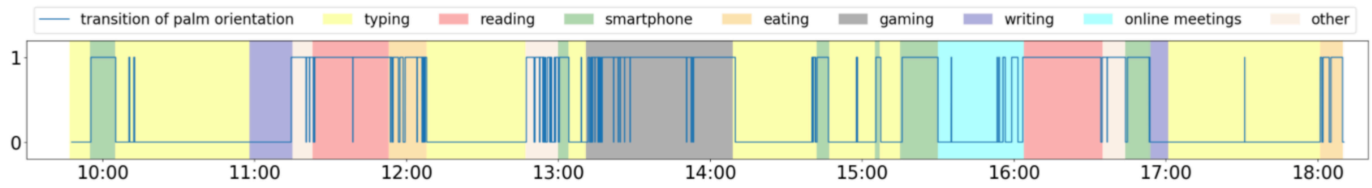


Fig. 4. The transition during the day of left palm orientation

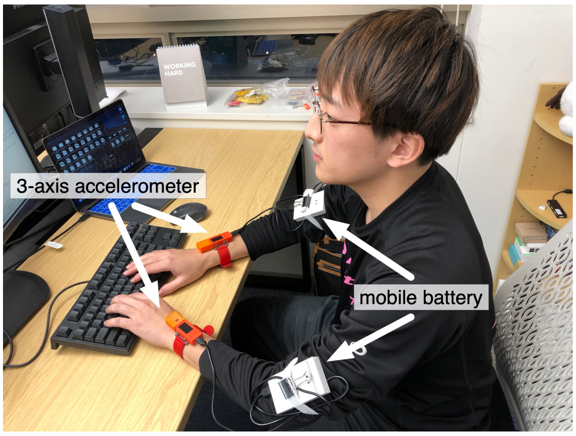
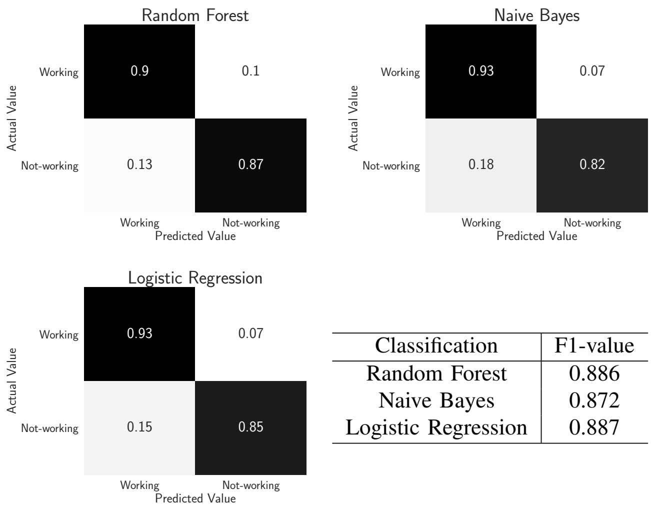


Fig. 5. Experiment Scenery



Classification	F1-value
Random Forest	0.886
Naive Bayes	0.872
Logistic Regression	0.887

Fig. 6. F1-value of 10-fold Cross-Validation using Dominant Wrist Data

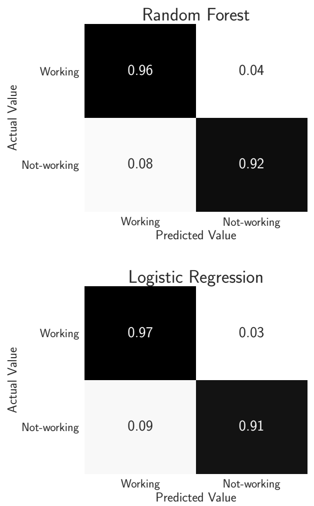
We asked the first subject for working 9 hours in our experimental environment: a university laboratory. At that time, we asked the subject wear accelerometers on both wrists. The movements occurred around a desk during this period were roughly classified into 7 categories: typing, reading a book (reading), writing, operating a smartphone (smartphone), eating, playing a video game (gaming), and attending online meetings.

In order to establish the threshold for determining palm orientation, the second subject performed each of the 7 activities for a duration of 2 minutes with accelerometers placed on both wrists. We categorized each of the activities listed above as either ‘working’ or ‘not-working’. The categories are shown in Table I.

B. Evaluation

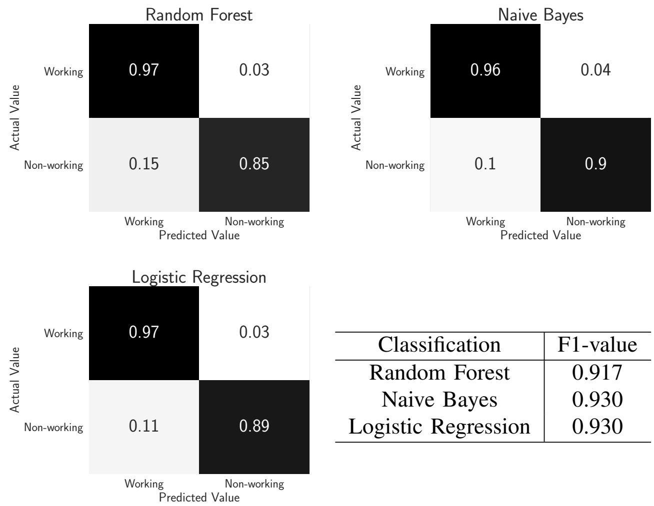
Both Figs. 3 and 4 show how the left and right hand palm orientations transition throughout the day. Other includes activity unrelated to desk work such as walking or shopping which is not target in this research. Using data obtained from the sensor attached to the dominant wrist, it was determined that the palm faced upwards 94.3% of the time when ‘working’, and faced downwards 66.4% of the time when ‘not-working’. In the same manner, data obtained from the sensor attached to the non-dominant wrist allowed us to determine that the palm faced upwards 96.9% of the time when ‘working’, and faced downwards 88.9% of the time when ‘not-working’.

We determined the label of ‘working’ or ‘not-working’ via both 10-fold cross-validation and Leave-One-Person-Out (LOPO) cross-validation. We used the mode value of the palm orientation label calculated over a 10 second period, along with the z-axis acceleration value as features in our classifiers. The results of 10-fold cross-validation are shown in Figs. 6 and 7. We used the data obtained in the actual environment for the 10-fold cross-validation. The results of LOPO cross-validation are shown in Figs. 8 and 9. For the LOPO cross-validation, we used the data obtained in the controlled environment as training data for creating the models, and the data measured during the actual working period for testing the models. From the results, it can be see that the estimation accuracy is higher



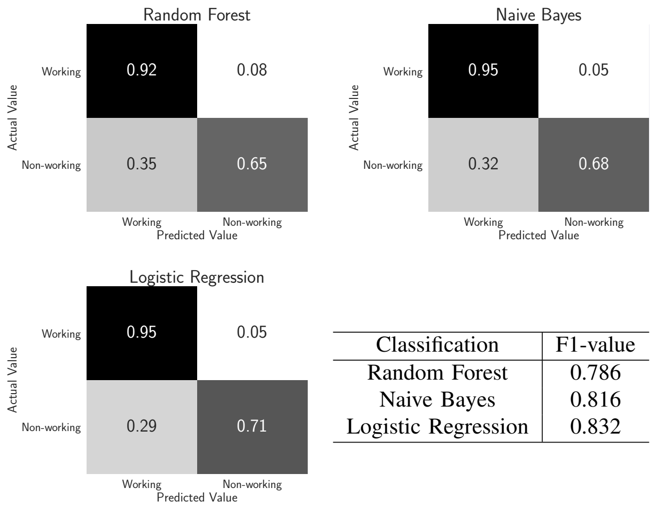
Classification	F1-value
Random Forest	0.939
Naive Bayes	0.938
Logistic Regression	0.939

Fig. 7. F1-value of 10-fold Cross-Validation using Non-dominant Wrist Data



Classification	F1-value
Random Forest	0.917
Naive Bayes	0.930
Logistic Regression	0.930

Fig. 9. F1-value of Leave-One-Person-Out Cross-Validation using Non-dominant Wrist Data



Classification	F1-value
Random Forest	0.786
Naive Bayes	0.816
Logistic Regression	0.832

Fig. 8. F1-value of Leave-One-Person-Out Cross-Validation using Dominant Wrist Data

when the non-dominant wrist data is used than when the dominant wrist data is used.

The obtained results show that the system is of high generality.

V. Conclusion

In this paper, we proposed a wrist-worn sensor-based system capable of distinguishing whether a worker is working or not. Our results indicate that using knowledge of the non-dominant hand's palm orientation it is possible to determine which activity is being performed with an F1-value of over 0.8. It is possible to estimate by the movement of the non-dominant hand, which is generally the arm that wears the wristwatch, so it was found that it is a highly practical method that can be implemented as a function of a smartwatch. We have shown that by continually monitoring palm orientation information, we are able to visualize the amount of work performed over a given time period.

Acknowledgment

This work was supported in part by JSPS KAKENHI Grant Numbers JP18H03233.

References

[1] M. Panwar, S. R. Dyuthi, K. C. Prakash, D. Biswas, A. Acharyya *et al.*, "CNN based approach for activity recognition using a wrist-worn accelerometer," in *Proc. IEEE EMBC*, pp. 2438–2441, July 2017.

[2] K. Ohnishi, A. Kanehira, A. Kanezaki, T. Harada, "Recognizing activities of daily living with a wrist-mounted camera," in *Proc. IEEE CVPR*, pp.3103–3111, June–July 2016.

[3] M. Ito, M. Miki, S. Murano, "Construction of desk work behavior analysis system for office workers based on wrist acceleration (inJapanese)," *IPSJ Kansai Branch Conference Proc.*, vol. 2019, 2019.

[4] S. Park, J.Park, M.Al-Masci, M.Al-Antari, M. Z. Uddin, *et al.*, "A depth camera-based human activity recognition via deep learning recurrent neural network for health and social care services," *Procedia Computer Science*, vol. 100, pp. 78-84, 2016.

[5] T. Hayashi. M. Nishida, N. Kitaoka, K. Takeda, "Daily activity recognition based on DNN using environmental sound and acceleration signals," in *2015 23rd European Signal Processing Conference (EUSIPCO).*, IEEE, 2015, pp. 2306-2310.

[6] W. Wang, A. X. Liu, M. Shahzad, K. Ling, S. Lu, "Understanding and Modeling of WiFi Signal Based Human Activity Recognition," Sep. 2015, pp.65-76.

[7] W. Wang, A. X. Liu, M. Shahzad, K. Ling, S. Lu, "Device-Free Human Activity Recognition Using Commercial WiFi Devices," *IEEE J. Sel. Areas Com-mun.*, vol. 35, no. 5, pp. 1118-1131, May 2017.

[8] K. Ali, A. X. Liu, W. Wang, M. Shahzad, "Keystroke recognition using WiFisignals," Sep. 2015, pp. 90–102.

[9] K. Ali, A. X. Liu, W. Wang, M. Shahzad, "Recognizing keystrokes using WiFidevices," *IEEE J. Sel. Areas Commun.*, vol. 35, no. 5, pp. 1175–1190, May 2017.

[10] X. Zheng, J. Wang, L. Shangguan, Z. Zhou, Y. Liu, "Smokey: Ubiquitous smokingdetection with commercial WiFi infrastructures," Jul. 2016, pp. 1–9.

[11] S. Mekruksavanich, N. Hnoobom, and A. Jitpattanakul, "Smartwatch-based sitting detection with human activity recognition for office workers syndrome," in *International ECTI Northern Section Conference on Electrical, Electronics, Computer and Telecommunications Engineering (ECTI-NCON)*, Feb. 2018, pp. 160-164. [Online]. Available: https://doi.org/10.1109/ECTI-NCON.2018.8378302

[12] A. Bonde, S. Pan, M. Mirshekari, C. Ruiz, H. Y. Noh *et al.*, "OAC: Overlapping Office Activity Classification through IoT-Sensed Structural Vibration," in *Proc. 2020 IEEE/ACM 5th Int. Conf. Internet-of-Things Design and Implementation (IoTDI)*, Apr, pp. 216-222.

[13] Y. Otoda, T. Mizumoto, Y. Arakawa, C. Nakajima, M. Kohana, *et al.*, "Census: Continuous posture sensing chair for office workers," in *2018 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 1-2.

[14] T. Mizumoto, Y. Otoda, C. Nakajima, M. Kohana, M. Uenishi, *et al.*, "Design and Implementation of Sensor-Embedded Chair for Continuous Sitting Posture Recognition," *IEICE TRANSACTIONS on Information and Systems*, vol. 103, no. 5,pp. 1067–1077, 2020.

[15] Y. Umetsu, Y. Nakamura, Y. Arakawa, M. Fujimoto, H. Suwa, "Ehaas: Energy harvesters asa sensor for place recognition on wearables," in *2019 IEEE InternationalConference on Pervasive Computing and Communications (PerCom)*, pp. 1–10

[16] Y. Arakawa, "Sensing and changing human behavior for workplacewellness,"Journal of information processing, vol. 27, pp. 614–623, 2019.