An Exercise Recommendation System While Performing Daily Activities Based on Contextual Information

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***Abstract*—Although exercise has positive physical and mental effects, many people worldwide are inactive, and this trend has not improved over the years. One reason for not increasing opportunities for exercise is that people are busy with work and household chores. Thus, we propose incorporating light exercise into daily activities to help people develop exercise habits. In this study, we present an exercise recommendation method based on the contextual information of the user and environment. The results of the offline and online evaluations showed that the recommendation was successfully performed according to the given context and that more than 80 % of the participants judged the recommended exercises as appropriate.**

***Keywords*—recommendation system; context-awareness; wearable sensors; exercise; daily activities.**

I. Introduction

Exercise has physical and mental benefits, preventing diseases such as heart disease, diabetes, and cancer, and delaying the onset of dementia. However, a survey conducted by the World Health Organization (WHO) in 2016 indicated that more than 1.4 billion people worldwide lead sedentary lifestyles–a trend unchanged since 2001 [1]. Moreover, a 2021 Sports Agency poll [2] revealed that the primary reason for not exercising is preoccupation with work or household chores. Notably, the percentage of respondents who answered that they exercised less frequently than they did one year ago exceeded those who answered that they exercised more frequently.

The high cost and the need to make time for gymnasium training are major hurdles to motivation for exercise. There are concerns that self-initiated training may increase the risk of injury owing to incorrect methods or excessive loads. Electrical Myo Simulation (EMS) belts, which stimulate muscles using electricity, have emerged in recent years and can be used even while performing other tasks, and their effectiveness in physical training has been demonstrated [3]. However, repeated use in the same area may cause muscle fatigue and risks muscle damage, without the user knowing. In addition, when used in conjunction with medical electrical devices such as pacemakers, EMS equipment may malfunction, resulting in severe physical damage [4].

To solve these challenges and make exercise a habit, it is desirable to incorporate it into daily life, which can be performed while working or doing housework. In this study, we focused on exercising while working [5] as an exercise method that satisfies this requirement. Exercise relies on muscular strength to obtain beneficial health effects, and exercising while working allows people without sufficient time for traditional exercise to incorporate it into their daily activities at an appropriate intensity with a low risk of injury.

Kobayashi et al. have developed a systematic exercise promotion system in an Internet of Things (IoT) environment, aiming to develop an infrastructure system that can handle various tasks and exercises using exercise recommendation and evaluation during desk work as a case study [6]. The exercise promotion system lowers barriers to exercise for people who do not normally exercise and encourages behavioral changes, such as spontaneously engaging in exercise. Appropriate recommendations that reflect the user's current task and the urgency and possibility of interruption, i.e., the context, are crucial for enabling exercise while working. This appropriate recommendation can be a solution for maintaining motivation. In this study, we added an exercise recommendation function based on user context to an existing exercise promotion system.

The remainder of this paper is organized as follows. Section II examines the related work. Section III presents the basic system configuration and describes the design of the exercise recommendation mechanism, followed by a detection method for user-related contextual information in Section IV. Offline and online experiments are described in Sections V and VI, respectively. Finally, Section VII concludes the paper. This research was conducted with the approval of the Tokyo University of Agriculture and Technology Ethics Review Committee.

II. Related work

A. Reducing the lack of exercise

Consolvo et al. [7] investigated the effectiveness of presenting information on underutilized cell phone background screens and screen savers to increase awareness of exercise in daily life. This study revealed that the abstract display of the user's own activity and physical information on the background screen of a cell phone increased the user's awareness and influenced their behavior. Another study by Klasnja et al. [8] described lessons learned from a study that developed and evaluated two systems aimed at promoting physical activity. These studies have revealed that it is possible to develop systems that effectively motivate behavior by providing support to sustain health maintenance goals, thereby encouraging various

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types of healthy behaviors and promoting social support. Although these studies can sustain motivation to exercise, actual exercise requires conscious time allocation. For non-regular exercisers, barriers to participation may be lower if they can exercise without conscious time allocation. In this study, the system supports exercise while the user is performing work; therefore, there is no need for conscious time allocation for exercise.

Certain studies encourage users to engage in physical activity while working at their desks. Shimizu et al. [9] proposed an exercise system that replaced computer keystrokes with body movements. The proposed system assigns keys to body movements (bending and stretching of knees and ankles) that are equivalent to walking and disables the keys assigned to the original keyboard. These movements can be performed naturally by disabling the keys assigned to the keyboard. Notably, their contribution is akin to our proposed system as users can exercise while performing key input operations. In this study, the proposed system enabled users to perform exercises while performing tasks other than keyboard inputs. Therefore, we aim to recommend appropriate exercises that consider the user's context.

B. Exercise recommendations

Lee et al. [10] proposed an exercise recommendation algorithm that utilizes information on personal tendencies such as eating habits and physical conditions. This algorithm enables the recommendation of highly efficient exercises suitable for everyone. However, before using the proposed algorithm, it is necessary to collect personal information, including sensitive information such as the user's height, weight, and medical history. The exercise events recommended in this study were of moderate intensity; therefore, they can be easily performed by anyone without the need to consider their physical conditions. In addition, the recommendations are remarkably practical because they can be formulated without requiring sensitive information.

Zhao et al. [11] proposed an exercise recommendation system that included gamification-based exercise promotion. This system can yield personalized exercise recommendations based on the information obtained from user questionnaires. However, the system recommends exercises during breaks, considering only the time and location of the user. In this study, we differentiated our system by recommending exercises that could be performed simultaneously without interfering with the user's work.

Yong et al. [12] designed an IoT-based fitness system. The system consists of equipment installed in gyms and wearable devices that measure and record the amount of exercise performed by fitness users using the equipment and other user activity data. The system can also calculate the cosine similarity between users based on the data of users' scores, indicating their level of interest in the equipment installed in the fitness club and can present recommendations to similar users. However, a user evaluation of the proposed system has not been conducted. Based on user evaluations, in addition to offline evaluations, the recommendation system can be evaluated more accurately.

III. Exercise facilitation system for exercising while working

A. System Overview

Figure 1 depicts the major system components. First, the system detects the user's state based on data obtained from the equipment and location (Figure 1 A). If the system detects that the user is performing a less urgent task that can be interrupted, an exercise recommendation process is invoked (Figure 1 B). The type of exercise, that is, item, is determined by referring to the rule using the contextual information obtained from the user and the environment, such as the objects being used and the places frequented by the user (Figure 1 C). The information to be presented to the user includes an image of the exercise category and the goal, ensuring that the necessary information is conveyed in a concise manner. Subsequently, the generated information is presented to the user via a push notification to their smartphone at a time that does not interrupt the current task (Figure 1 F). Once the user accepts and follows the recommendation, the duration and form of the exercise are evaluated based on the information collected on wearable sensors and the sensor-augmented objects (Figure 1 D). In accordance with the evaluation, a feedback message, including a chart of the exercise duration, is forwarded to the user's device through the same push-type mechanism as the recommendation process (Figure 1 E, F).

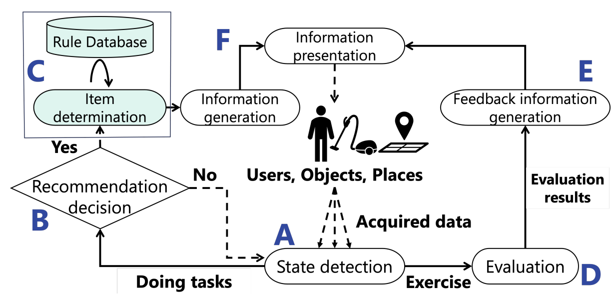

Figure 1. The flow of exercise facilitation system while doing daily activities.

In the event that objects or places are used and frequented by an unspecific number of people, a user identification function can be added to enable individual exercise recommendations, feedback, and management of the exercise results using the user's device. Even in the absence of a user identification function, the installation of a display device on or near objects enables on-the-spot exercise recommendations and feedback.

User context is used in two aspects: the determination of recommendation items and the timing of recommendations. In this study, we focused on the item selection aspect (Figure 1 C), which is described in detail in Sections III-B and IV. In contrast, context processing for timing determination is outside the scope of this study.

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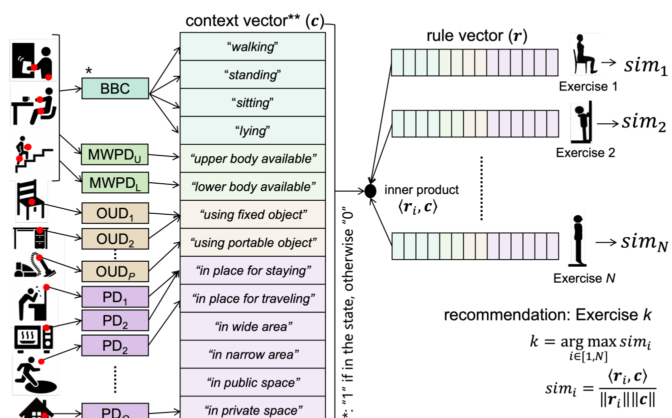
TABLE I: CATEGORIES OF CONTEXTUAL INFORMATION AND SPECIFIC VALUES OR EXAMPLES IN EACH SUB-CATEGORY, AND INFORMATION TO BE INFERRED FROM THE CONTEXTUAL INFORMATION.

Main-category	Sub-category	Elements in sub-category	Information to be inferred
User	Basic behavior	Sitting (SIT), Standing (STD), Walking (WLK), Lying (LYN)	Performable exercise
	Main working part	Upper body (UB), Lower body (LB)	Interruptibility to current task
Environment	Object in use	Fixed (FIX), e.g., chair, Portable (POT), e.g., vacuum cleaner	Performable exercise and interruptibility to current task
	Characteristics of place	Stay (STY), e.g., in front of a microwave, Travel (TRV), e.g., Corridor Wide (WID), e.g., Space to spread hands Narrow (NRW), e.g., Space to bump into things if spreading hands Public (PUB), e.g., Office, Private (PRI), e.g., User's home	Performable exercise and interruptibility to current task

B. Recommendation Method

1) Contextual Information: Table I summarizes the categorization of contextual information and the elements in the subcategories. The types of information inferred from these subcategories are also presented. Contextual information from the user side is further divided into *basic behavior* and *main working part* as subcategories. *Basic behavior* consists of four elements: sitting, standing, walking, and lying down, which are common in various daily activities. This information can be used to infer performable exercises. For example, knee lift abdominal exercises are easier to perform while a person is seated and not walking. The body part mainly used during a specific task represents the availability (or unavailability) of a certain exercise, specified as upper and lower body parts. Standing push-ups are difficult to perform when a user is using a smartphone, regardless of their behavior, because the exercise mainly involves the arms. We refer to this subcategory as the *main working part*. We assume that information on the basic behavior and the main working part is obtained by analyzing signals from wearable sensors, such as those in smartwatches and smartphones.

Contextual information from the environment is also categorized into two subcategories: *object in use* and *characteristics of place*. The state of use and information of the objects represent the current task of the user, such that a person sitting on an office chair is involved in a task related to desk work, as well as representing the social context, identity, and place [13]. Thus, information regarding the object in use can be used to infer performable exercises and interruptibility in a current exercise recommendation task. Two elements exist in this subcategory: fixed and portable. We assume that the information is obtained by sensors embedded in the object to determine if the object is being used as intended [14] and that a dedicated "object-use detector (OUD)" is provided. For example, more than two fixed objects can exist in a system with a one-to-one relationship between the objects and OUDs. Moreover, the location of a user contains meaningful information, as indicated by the fact that location information has been used for the longest period among the contextual information [15]. For example, a person in front of a microwave appears to wait for the heated food, which indicates an appropriate timing for recommending heel lift-up exercises. As another example, a person standing in front of a wall is recommended to perform push-ups. On the other hand, standing push-ups may be inappropriate when climbing stairs in the office but is acceptable at home. These examples suggest that information regarding the location of a user can be used as a cue to infer the performable exercise and interruptibility of the user. We divided the characteristics of a place into six elements: places for staying/traveling, wide/narrow areas, and public/private areas. Location Information can be obtained in various manners, such as motion sensors, distance sensors, and cameras, which are placed in a specific location and tagged. A Global Positioning System (GPS) can also be used for outdoor localization, where the label is obtained from the original geographic coordinates using a reverse geocoding service. Similar to OUDs, we assume that a dedicated "presence detector (PD)" is available and that more than two PDs in the same place characteristic may exist. The left section of Figure 2 depicts the relationship between the context sources, detectors, and contextual information. This information is used to determine the recommended items by referring to the rules stored in the database, as described in Section III-B2.



*BBC: basic behavior classifier, MWPD$_U$: main working part detector (MWPD) for upper body, MWPD$_L$: MWPD for lower body, OUD: object in use detector, PD: presence detector

Figure 2. The scheme of recommendation.

2) Recommendation algorithm: An exercise is recommended based on the similarity of context between the user and candidate exercises in the rule database. A rule for a specific exercise is represented by a tuple with binary values indicating the suitability of the element of context for the exercise, that is, 0 and 1 for unsuitable and suitable, respectively. Table II shows a rule for the knee-lift abdominal exercise with

14 elements, indicating that the exercise is suitable for people who are sitting, with the lower body available for exercise, and using a fixed object, for example, a chair; conversely, it is unsuitable for people who are standing, walking, lying, or performing upper-body work.

The context similarity was measured using the cosine similarity. Cosine similarity is a measure of the similarity between vectorized items. Let $\boldsymbol{r_i}$ be a rule vector as presented above, containing the suitability and unsuitability of each contextual element for exercise $i \in [1, N]$, and let $\boldsymbol{c}$ be a vector that represents the user's context. The method of obtaining the value of each element of the vector depends on the implementation of the system. Section IVdescribes the proposed implementation. The posterior probability for each class can be applied to the values in a classification-based method such as those in basic behavior identification, whereas a binary value, that is, 0 or 1, can be used for threshold-based detection, such as for main working part detection, object usage detection, and place detection. The similarity (sim_i) between these rules for exercise i and the user's context are expressed in (1), where $\langle \boldsymbol{a}, \boldsymbol{b} \rangle$ indicates the inner product of vectors $\boldsymbol{a}$ and $\boldsymbol{b}$, and $\|\boldsymbol{a}\|$ is the length of vector $\boldsymbol{a}$.

$$sim_i = \frac{\langle \boldsymbol{r_i}, \boldsymbol{c} \rangle}{\|\boldsymbol{r_i}\| \|\boldsymbol{c}\|} \tag{1}$$

We assumed that at least one wearable sensor was mandatory in the system, whereas sensors for the environmental context were optional. For example, if there is no sensor-augmented fixed object, the value is ignored in the calculation of proximity. Exercise k with the highest similarity for all exercises was recommended and selected by (2).

$$k = \underset{i \in [1,N]}{\arg\max}\, sim_i \tag{2}$$

The recommended items determined in this manner are passed to the information presentation (Figure 1 F), where a message is created with information such as the exercise method and the number of sets required. Figure 2 illustrates the recommendation scheme.

IV. Contextual information from the user

As shown in Section III-B1, contextual information from the user and the environment is used to recommend exercises. The information obtained from the user's movement or posture using wearable sensors is generic compared to that obtained from the environment, such as the object in use and the user location. This section presents methods for obtaining user contextual information.

A. Basic behavior classification method

The behavioral context assumes three values: sitting, standing, and walking. Thus, various daily activities must be classified as one such behavior. One approach may be to recognize each activity first, for example, brushing teeth and vacuum cleaning, and then categorize them into one of three behaviors based on predefined rules, for example, "brushing teeth is usually performed while standing." However, this approach must handle an unlimited number of daily activities in its recognition task, which is computationally infeasible. Instead, we assumed a different approach wherein the input signal obtained during various activities is forcibly classified into one of three classes.

Two accelerometers were attached to the left wrist and right thigh, assuming a smart watch and a smartphone stored in a trouser pocket, respectively. A machine learning-based classification approach was used, featuring a random forest classifier. In total, 66 features were calculated from a window of 256 samples (50 Hz) with four axes, that is, x, y, z, and magnitude ($= \sqrt{x^2 + y^2 + z^2}$), with 50 % overlap, as summarized in Table III.

The information from the two sensor nodes is integrated to obtain the final result, as follows: First, each classifier independently classifies the input feature vector into one of the three classes with posterior probabilities. Subsequently, the result of the classifier with the highest posterior probability is chosen as the final answer. An advantage of classifier-level fusion over data-level fusion, which uses a feature vector consisting of features from sensor nodes, is that our approach does not always require users to wear both sensors. If the sensor on the thigh (wrist) is missing, the result from the sensor on the wrist (thigh) is selected. From the perspective of classification performance, we validated the superiority of the proposed approach over data-level fusion.

B. Main working part detection method

Various daily activities need to be supported in the system. Unlike basic behavior classification, it is not feasible to judge the main working parts via individual daily activity recognition using a predefined list. Instead, we assumed an approach based on the information that "the moving body part is currently in use." Thus, if the acceleration signal exceeds a certain threshold, the body part is considered in use for an activity; otherwise, it is not in use.

The threshold was specified as follows: First, a moving variance calculation was performed on the entire dataset of daily activities described in Section V-A [16], using a window of 256 samples (50 Hz) with a 50 % overlap. The median of the variance values was specified as the threshold value. The threshold is determined for each axis of the acceleration signal. A threshold judgment was formulated for each axis, given the time-series data during an activity. If the mean of the variance of four consecutive windows exceeded the threshold on all three axes, the body part was judged as unavailable for exercise because it was in use; otherwise, it was considered available. Detection was performed for each sensor node on the left wrist and right thigh. The value in the context vector (c) is represented as binary, that is, 0 and 1, for unavailable and available, respectively.

V. Offline experiment

A. Daily activity dataset

We utilized a dataset previously collected by the authors' laboratory [16]. Data were collected from a Bluetooth-

TABLE II: A RULE FOR KNEE-LIFT ABS EXERCISE.

Basic behavior				Main working part		Object in use		Characteristics of place					
SIT	STD	WLK	LYN	UB	LB	FIX	POT	STY	TRV	WID	NRW	PUB	PRI
1	0	0	0	0	1	1	0	0	0	0	0	0	0

TABLE III: CLASSIFICATION FEATURES FOR BASIC BEHAVIOR CLASSIFICATION.

Signal domain	Feature
Time	mean, standard deviation, skewness, kurtosis, minimum first quartile, median, third quartile, maximum, inter-quartile range, correlation coefficient of two axes
Frequency	energy, entropy, average frequency, maximum amplitude frequency component at the maximum amplitude

based Inertial Measurement Unit (IMU) (ATR-Promotions Inc. TSND151 [17]), comprising three-axes acceleration data and three-axes angular velocity data of 23 daily life activities from seven positions on the bodies of 14 volunteers (five females and nine males in their 20s). Six of the seven sensor nodes were attached symmetrically to the upper arms, wrists, and thighs, whereas one node was placed on the chest.

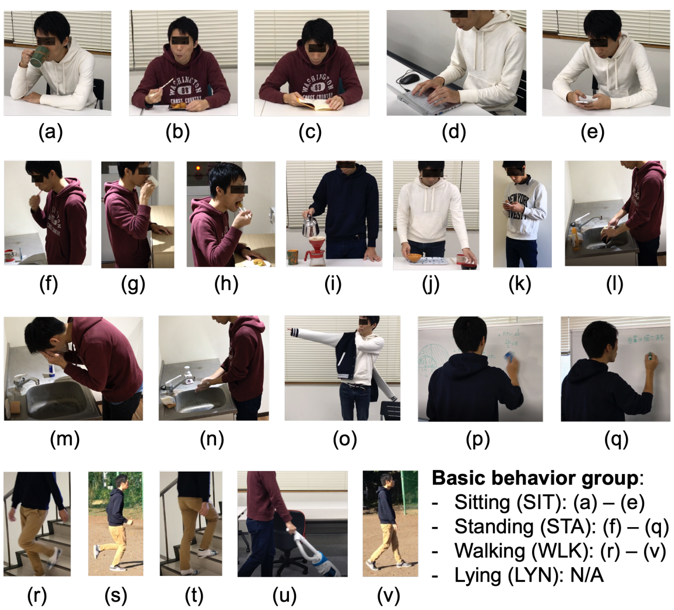


Figure 3. 22 daily activities and grouping into basic behaviors used in the evaluation: (a) having a drink while sitting down (DK_SIT), (b) eating food while sitting down (ET_SIT), (c) reading a book (RB), (d) using a computer while sitting down (UC), (e) using a smartphone while sitting down (SP_SIT), (f) brushing teeth (BT), (g) having a drink while standing (DK_STD), (h) eating food while standing (ET_STD), (i) making coffee (MC), (j) setting table (ST), (k) using a smartphone while standing (SP_STD), (l) washing dishes (WD), (m) washing face (WF), (n) washing hands (WH), (o) wearing and taking off the jacket (WJ), (p) erasing figures on a whiteboard (EW), (q) writing figures on a whiteboard (WW), (r) going down stairs (DS), (s) running (RN), (t) going up stairs (US), (u) vacuum cleaning (VC), and (v) walking (WK).

In the present study, we only used data from the sensors on the left wrist (LW) and right thigh (RT), assuming a smart watch on the wrist and a smartphone in the trouser pocket. Additionally, we removed the bicycle riding activity because it did not fit any basic behavior, and only signals from the three-axis accelerometer were used. The scenes of the activities are depicted in Figure 3, which also shows the grouping of basic behaviors as the ground truth for the basic behavior classification experiment described in the next section. Grouping (relabeling) was performed by judging the photographs shown in Figure 3.

B. Evaluation on basic behavior classification

1) Method: The performance of the basic behavior classification was evaluated. The basic behavior classifier was trained using data collected from 10 university students who were instructed to perform four basic behaviors. They were right-handed and attached to the same sensor nodes as those used in Section V-A on their LWs and RTs. The dataset described in Section V-A was used to test the classifier after we relabeled the original 22 activities with one of the four basic behaviors, as shown in the lower right of Figure 3. New labels were treated as the ground truth. Notably, no activity related to LYN exists in the dataset, and the results represent general classification performance because the participants in the training and test data collection were different.

2) Result and analysis: Figure 4 (a) presents the confusion matrix of basic behavior classification. For example, the numbers in the row of DK_SIT indicate that the instances of DK_SIT were judged 2718 times as "Sitting", 300 times as "Standing", 12 times as "Walking", and 903 times as "Lying".

The performance metrics are calculated and summarized in Table IV, where the recall, precision, and F-measure are defined by (3), (4), and (5), respectively. Suffix i indicates the basic behavior classes, and $N_{correct_i}$, N_{tested_i}, and N_{judged_i} represent the number of instances correctly classified as class i, the total number of instances in class i, and the number of instances judged as class i, respectively.

$$recall_i = N_{correct_i}/N_{tested_i} \tag{3}$$

$$precision_i = N_{correct_i}/N_{judged_i} \tag{4}$$

$$F-measure_i = \frac{2}{1/recall_i + 1/precision_i} \tag{5}$$

Table IV and Figure 4 (a) imply that the daily activities were mostly classified into the appropriate basic behaviors that the authors labeled, with some exceptions. Presumably, the sitting-related activities, i.e., DK_SIT, ET_SIT, RB, UC, and SP_IT, were judged as "Lying" because they involved minimal movement and the postures of the sensors were similar,

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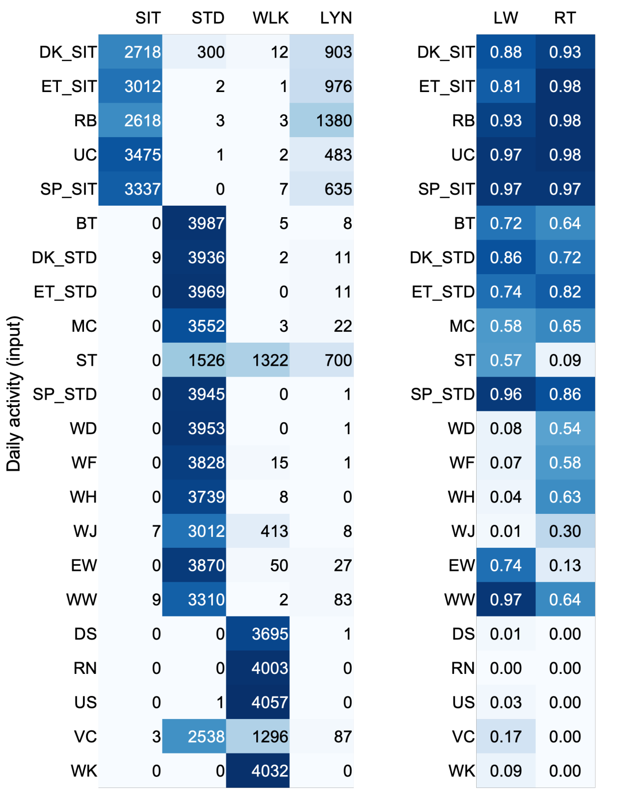
TABLE IV: SUMMARY OF BASIC BEHAVIOR CLASSIFICATION.

Basic behavior	Recall	Precision	F-measure
SIT	0.763	0.998	0.865
STD	0.940	0.937	0.939
WLK	0.867	0.902	0.884
LYN	N/A	N/A	N/A
Macro average	0.857	0.946	0.896



(a) Number of classified basic behavior (b) Availability of basic body parts

Figure 4. Offline experimental results.

particularly when the participants were lying on their backs. Vertical positioning must be considered to reduce misclassifications. Furthermore, the classification of ST (setting table) into "Walking" occurs because the activity includes occasional walking around the table during serving meals. Similarly, we consider that the judgment on VC (vacuum cleaning) was dichotomized into "Standing" and "Walking" because the vacuuming behavior is a mixture of standing and walking. Because we expect to use posterior probabilities rather than classification results (i.e., labels) for the elements of context vector (c), we do not consider these trends problematic for the recommendation in which multiple behaviors exist in a single activity.

C. Evaluation on main working part detection

1) Method: The appropriateness of the main working part detection was evaluated by counting the number of instances judged as "being used." The same dataset used to calculate the thresholds was used for testing.

2) Result and analysis: Figure 4 (b) shows the availability of each part by the ratios of "being not used" to the total number of instances per activity. The closer the value is to 0.0, the more cases are judged as "the body part is being used," while the closer it is to 1.0, the more cases are judged as "the body part is not being used." Note that the sum of the ratios of "Upper body part" and "Lower body part" is not equal to 1.0 because the judgment was performed independently.

From Figure 4 (b), it was judged that the availability of the wrist was lower than that of the thigh for hand-dominated movements such as washing dishes (WD) and washing faces (WF), and the value of the thigh was lower than that of the wrist for activities involving movement but minimal hand movement such as setting a table (ST), both of which were judged to be low when the arms and legs were moved together, such as walking (WK), climbing down stairs (WD), and vacuuming (VC). In these cases, the proposed method using threshold values functioned appropriately.

Misjudgment of the availability of activity that was assumed to use the dominant hand (i.e., the right hand without a sensor) was unavoidable, for example, DK_SIT (drinking while sitting). However, we found that even UC (using a computer while sitting) had high availability of the left wrist (0.97). In a UC, we can assume that the computer user uses both hands. Therefore, there is a possibility of misjudging the main working part of daily activities that use the fingertips, which does not occur in wrist movements. To solve this problem, a value corresponding to the confidence level of the judgment can be calculated instead of using a binary judgment of "being used" (unavailable). Furthermore, two types of exercises suitable for the upper and lower body can be recommended simultaneously such that the user can determine which exercise to perform if their confidence level is low. This may prevent mismatches between the recommended exercise and the user's situation, given that the final judgment is exercised by the user.

D. Evaluation on recommendation

1) Method: Similar to the previous evaluations, a simulation-based experiment was carried out using the dataset described in Section V-A in a situation where a user performs 22 daily activities, which determines one of the following six exercises based on context: knee pull-up abdominal exercise (KLA), leg-pushing exercise (LP), standing push-up (SPU), heel lift-up exercise (HL), breathing with a protruding belly (DI), and striding with a large belly and fast walking (FW). Table V lists the rule vectors ($\boldsymbol{r}$) for the six exercises. As described in Section III-B2, the values '0' and '1' indicate that the element is unsuitable and suitable for the exercise, respectively.

Regarding information on the use of objects and halts in certain locations, the dataset did not gather such information when it was collected. Thus, we specified the values '1' by assuming that a sensor-augmented chair, e.g., [6], was used in the five activities categorized into “Sitting” and that an area in front of a microwave was occupied by a person who was preparing coffee (MC); otherwise, the values were set to ‘0’. These assumptions also imply 100 % complete detection.

2) Result and analysis: Figure 5 shows the results of the exercise recommendations for daily activities. The columns in the matrix represent the recommended exercises, whereas the rows represent the assumed daily activities. Note that normalized values are shown because the amount of data for each daily activity was different; thus, the number of recommendations varied. KLA and LP, which are exercises performed while sitting, are recommended more frequently for daily activities performed while sitting such as sitting and eating (ET_SIT) and reading a book (RB). When a user is in a sitting position, the user often performs tasks that use the upper body; therefore, LP, an exercise that uses the lower body, is recommended more often. For daily activities that require standing, such as preparing coffee (MC) and washing the face (WF), SPU and HL, which are exercises performed in the standing position, were recommended more often. However, DI was most frequently recommended for ST (Setting Table). Catering involves walking around a table, similar to walking. Therefore, exercises that can be performed during walking are recommended. In addition, DI and FW, which can be performed while walking, such as going downstairs (DS) and going upstairs (US), are often recommended. As the lower body is used while walking, DI, an exercise that uses the upper body, has been recommended in many cases.

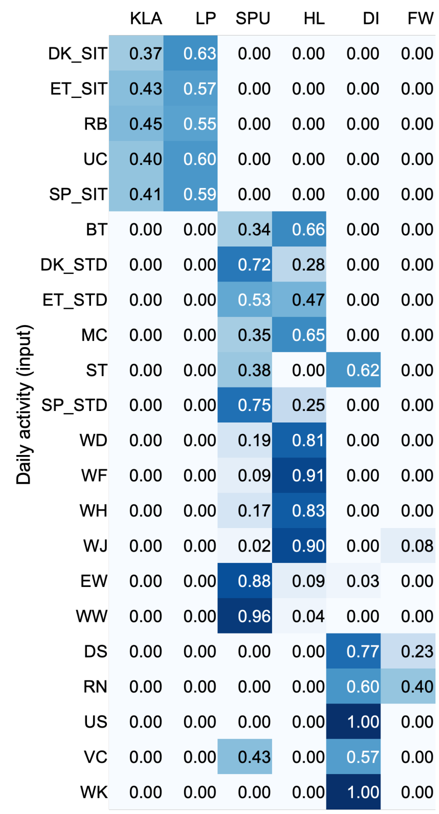


Figure 5. Recommendation results for exercise in daily activities.

VI. Online User Evaluation

As elaborated in Section V, we validated the feasibility of the proposed exercise recommendations for daily activities through a simulation-based experiment. Subsequently, we conducted an online experiment with 15 participants to validate the recommendations based on the users’ actual work context. Two conditions were specified: specified and free conditions. In the “specified” condition, the participants were instructed to perform three tasks in a laboratory room that corresponded to three basic behaviors, i.e., watching videos on a computer as SIT, waiting for their snacks to warm up in front of microwave as STD, and entering and leaving the room as WLK. In contrast, in the “free” condition, the participants performed freely in the same room for 10 minutes. To understand the effectiveness of each of the main-category of contextual information, i.e., “User” and “Environment” shown in Table I, recommendation in the following three cases were performed.

1) User: Basic behavior and main work part obtained by two accelerometers on the user’s body.
2) Environment: The state of use of a chair from a sensor-augmented chair [6] and the presence of a microwave detected by a distance sensor placed on a shelf under the microwave.
3) All: All the contextual information and sensing devices above.

Under both conditions, the participants were provided with recommendations by the system while performing certain activities. A questionnaire survey was conducted for each recommendation to evaluate whether the recommended exercise was appropriate for the situation on five levels 5: appropriate, 4 = slightly appropriate; 3 = neither appropriate nor inappropriate; 2 = slightly inappropriate; and 1 = inappropriate.

Table VI summarizes the relative frequencies of the user evaluation scores for each experimental condition. Values in the row with a score of 5 indicate participants. As listed in the table, more than 80 % of participants in all conditions evaluated the recommended exercise as appropriate. The “All” conditions exhibited the highest ratios in both specified and free activity conditions. We assumed that the users always wore sensors on their bodies. The results show that the recommendation accuracy can be improved by combining information from the environment.

VII. Conclusion

In this study, we present an exercise recommendation method based on the contextual information of the user and the environment, which is a core part of an exercise facilitation system for performing other activities. Both offline and online experiments were conducted. An offline experiment was performed to simulate an already-collected dataset. The recommended items were deemed reasonable for each of the

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TABLE V: RULE VECTORS (r_i) REPRESENTING THE RULES OF EXERCISE RECOMMENDATION WITH THE NAMES OF EXERCISE.

Exercise[a]	Basic behavior				Main working part		Object in use		Characteristics of place					
	SIT	STD	WLK	LYN	UB	LB	FIX	POT	STY	TRV	WID	NRW	PUB	PRI
KLA	1	0	0	0	0	1	1	0	0	0	0	0	0	0
LP	1	0	0	0	1	0	1	0	0	0	0	0	0	0
SPU	0	1	0	0	0	1	0	0	1	0	0	0	0	0
HL	0	1	0	0	1	0	0	0	1	0	0	0	0	0
DI	0	0	1	0	0	1	0	0	0	0	0	0	0	0
FW	0	0	1	0	1	0	0	0	0	0	0	0	0	0

[a] KLA: knee lift abdominal exercise, LP: leg-pushing exercise, SPU: standing push-up exercise, HL: heel lift-up exercise, DI: drawing-in exercise, and FW: striding with a large belly and fast walking.

TABLE VI: RELATIVE FREQUENCIES OF THE USER EVALUATION SCORES ON THE RECOMMENDED EXERCISES.

Score	Specified			Free		
	User	Environment	All	User	Environment	All
1	0.014	0.000	0.005	0.014	0.012	0.014
2	0.032	0.022	0.014	0.041	0.012	0.010
3	0.045	0.034	0.032	0.041	0.043	0.024
4	0.104	0.134	0.127	0.092	0.092	0.077
5	0.805	0.810	0.824	0.812	0.840	0.876
N_{rec}[*]	221	179	221	218	163	209

[*] Total number of recommendation

main activities of sitting, standing, and walking, as well as for the availability of the working part. An online experiment was conducted using a real-time system to obtain user feedback in real-world situations. The result showed that more than 80 % of the participants judged the recommended exercise as appropriate ones in their current situations.

In the current implementation, the association of the elements in the object in use and the characteristics of the place with specific objects and places were performed by the authors; however, numerous objects and places exist in real-world conditions. Considering this aspect, we recommend that extensibility and scalability in various operating environments should be considered in practical systems. Regarding the recommendation rule, the set of rules used in the experiment was created by the authors and was thus not optimized for individual users or a large population. In the future, we shall report a method for user-driven recommendation rule creation using an Interactive Genetic Algorithm (IGA), where the rules listed in Table V are considered as gene sequences and the user's subjective evaluation is applied as a fitness function to perform evolutionary processes, such as crossover and mutation, to generate the user's preferred rules.

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