Classification of Daily Activities Based on the Amount of Social and Physical Activity for Behavioral Change Toward Wellbeing

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ABSTRACT

In this study, we classify daily activities by focusing on the relationship between social and physical activities. By self-reflection through lifelogging, we aim to discover ways of spending and indicators that lead to physical and mental health, such as increased satisfaction and reduced fatigue. We classify daily activities based on the amount of physical activity obtained from a smartwatch and the amount of social activity obtained from a neck-worn face-counting device, and obtain insights into the relationship between social and physical activities. First, we conduct a hierarchical clustering of daily activities (8 types, 37 scenes, 10 minutes each) of an individual, which are then are classified into four groups. Then, the amount of physical activity and social activity are plotted on a two-dimensional plane to analyze the tendency. In addition, we plot the activities of a group of three participants on the same space and analyzed the tendency of each activity. Although there are differences in the amount of physical activity and social activity among the individuals, they tend to fall into the groups. Moreover, we visualize the transition of the amount of physical activity and social activity of one participant throughout a half-day. We are interested in the time-series rhythm and balance of the person's activities. We believe that our visualization will suggest activities for individuals based on their state of physical and social (mental) health.

CCS CONCEPTS

• **Human-centered computing** → *Visualization*; *Ubiquitous and mobile computing*.

KEYWORDS

visualization, lifelog, social and physical activity, wellbeing

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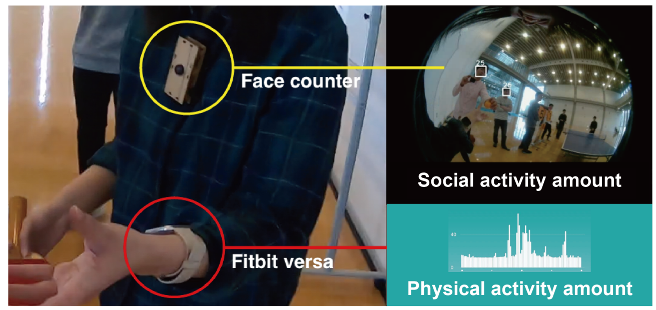

Figure 1: Aiming for wellbeing, we classify daily activities by focusing on the relationship between social and physical activity

1 INTRODUCTION

In this paper, we classify daily activities from lifelogs, focusing on the relationship between the amount of social activity and the amount of physical activity. It has been studied that physical activity has a positive impact on mental health [5, 19]. On the other hand, the quantity and quality of social relationships with people are thought to affect not only mental health but also physical health [9]. In addition, social connections with others are thought to be related to the maintenance of psychological and mental wellbeing [10]. We would like to focus not only on physical activity but also on the quantity and quality of social activities in which the way we interact with others is one of the factors that affect mental health. Therefore, by measuring both social and physical activities, we aim to classify daily activities and gain insights for behavioral change.

In our previous work, we studied the measurement of social activity from the simple idea of a "face-counting meter", which counts the number of faces in a face-to-face interaction [13]. Social activity, here, refers to any activity that involves face-to-face interaction with other people in a physical space. We assume standing conversations, meetings, collaborative work, and shared meals formed by two to ten people as examples of social activity. A face-counting system can distinguish between social activities such as people simply passing by each other and face-to-face interaction, and quantify the amount of social activity by considering the quality of the interaction. It has been found that the face of the other person tends to turn continuously when the person speaks, and that the impression can be reproduced by considering the proximity and temporal continuity of the face-to-face interaction in the calculation. On the other hand, research and commercialization of methods for measuring physical activity have progressed, and these methods are widely used in smartwatches and other devices. In this study, we measure physical activity based on calorie expenditure through the use of a Fitbit Versa [7], a commercial fitness smartwatch. We decided use calorie expenditure instead of the number of steps in order to include standing and sedentary activities.

We propose to classify daily activities based on the amount of physical activity obtained from a fitness smartwatch and the amount of social activity obtained from a neck-worn face-counting device, and to visualize them by mapping them on a two-dimensional plane. There are days when there is a lot of physical activity, days when there is a lot of social activity, and days when there is a lot and a little of both.

We believe that there is an appropriate amount of activity for each individual, and that the way people spend their days differs depending on factors including occupation, gender, and age. In addition to increasing the amount of activity, this study aims to encourage users to act with the goal of achieving a good balance between social and physical activity.

This research is an exploratory study to investigate how daily activities can be classified and visualized based on the amount of physical activity and social activity before implementing a system that provides visual feedback to users for behavioral change. Previously, we used a subjective classification method [14], but in this paper, we show the results obtained in detail after processing a more objective classification. We believe that by measuring both social activity, which is related to the mental side of a person, and physical activity , which is related to the physical side of a person, and by classifying daily activities, we can provide suggestions to obtain a good balance of both types of activity.

In this paper, the following contributions are two-fold:

(1) A method for recording both physical and social activity in lifelogs by using two wearable devices, a pendant-type face counter and FitBit Versa smartwatch, simultaneously.
(2) A method for classifying daily activities based on the amount of physical activity with respect to calorie expenditure and social activity with respect to face count in face-to-face interactions.

Furthermore, the following three considerations are made:

(1) We conducted a hierarchical clustering of the daily activities (8 types, 37 scenes, 10 minutes each) of an author. The daily activities were classified into four groups: one that provides both physical activity and social activity in a balanced amount at once, one that provides physical activity, one that provides social activity, and one that provides neither. Then, the amount of physical activity and social activity were plotted on a two-dimensional plane to analyze the tendency for each activity. We visualized the result that the amount of activity obtained depending on the behavior level even for the same activity. On the contrary, the result was found that the activities seemed to be different, and in fact, the same amount of activity was obtained.
(2) In the same space, the activities of three people were plotted on a two-dimensional plane, and the tendencies of each activity were analyzed. Although there were differences in the amount of physical activity and social activity between individuals, they tended to fall into the following groups.
(3) We visualized the transition of the amount of physical activity and social activity of a student during a half-day. By visualizing the transitions in both physical and social activity, we believe that we can understand the rhythm and balance of the person's activities.

2 RELATED WORK

There have been many studies on methods for classifying daily activities from lifelogs. The method proposed by Guo et al. [8] classifies daily activities based on acceleration changes, making it possible to determine whether the user is walking or running. The method of Ortis et al. [16] indexes activities such as watching TV, cooking, and reading books using image recognition.

Methods for quantifying daily activity levels have also been studied. The method proposed by Pal et al. [18] measures the degree of busyness of daily activities using the movement of the person captured by an environmental camera. The method proposed by Nakamura et al. [12] estimates energy expenditure in terms of multimodal data and egocentric videos. Also, by combining the exercise with an acceleration sensor, a voice with a speaker, and distance with a Bluetooth link, the method of Choudhury et al. [6] detects face-to-face interaction with an IR sensor. In their work, various aspects of social context are measured. Olguin et al. [15] shows results that include predictions about productivity and job satisfaction. Furthermore, the BeWell application by Lane et al. [11] visualizes daily activities by combining sleep, physical activity, and social interaction data and is developed aiming for wellbeing. In their work, physical activity is measured by smartphone sensors, and social interaction is measured by voice.

Metabolic equivalents (METs) have made it possible to propose various daily activities for wellbeing based on the amount of exercise [1, 2]. For example, it shows that playing exergames (e.g., Wii Fit) and cleaning a room in the house have the same amount of activity. METs are measures of activity intensity that indicate how many times more energy is expended by various activities compared to sedentary activities, which is one MET. In addition, a model to measure METs with a triaxial accelerometer has been developed, which can be easily acquired [17].

In this study, we measure the engagement level in social and physical activities using two wearable devices. Our idea is visualizing the personal quality of daily activities in terms of both mental and physical health. This is intended to focus on not only physical health but also on social health that affects other types of health including mental health [9, 10]. Thus, sleep is not included in this study.

We use the model that evaluates not only group social interaction but also one-on-one social interaction as having a high level of engagement to social activities [13]. The model also calculates momentary face-to-face interaction and continuous interaction separately. Physical activity is measured using calorie expenditure estimated from heart rate during exercise [7]. We use calorie expenditure using a smart watch to measure activities including sedentary and standing. We visualize the engagement level to the social and physical activity. The daily activities are measured and mapped to the two-dimensional planes of social and physical activities level.

Also, we show the trajectory of the data in order to visualize the changes.

3 MEASUREMENT OF PHYSICAL ACTIVITY AND SOCIAL ACTIVITY

Two wearable devices are used to measure the amount of social activity and physical activity. The amount of physical activity was measured by a Fitbit Versa [7]. The amount of social activity was measured by a neck-worn device that counts faces [13]. The details of measuring each type of activity are shown below.

3.1 Measurement of physical activity

We interpret physical activity as sedentary activities, standing, walking, running, and playing sports. We measured the amount of physical activity using the calorie expenditure estimated from the heart rate during exercise (Figure 1).

Calorie expenditure is estimated based on the person's BMR (basal metabolic rate) and other factors including height, weight, age, and gender; it also includes calories burned while at rest. This means that even when you are asleep or not moving, your body burns calories, so when you wake up, the device displays the calories burned, and this number increases throughout the day. In other words, the minimum amount of calories burned is not zero.

We downloaded the raw data of calorie expenditure recorded at one-minute intervals from the Fitbit account page and used it to calculate the amount of calories burned. In order to measure physical activity during non-walking activities such as sitting and standing, calorie expenditure was used instead of the number of steps.

3.2 Measurement of social activity

We interpret face-to-face social interaction and momentary contact with people as social activities in this study. Social activity was measured by calculating the number, proximity, and continuity of faces [13]. As shown in Fig. 1, we detect and count the number of faces in a face-to-face interaction. We evaluate the quality of social activity based on the proximity and temporal continuity of face-to-face interactions.

Specifically, the amount of social activity S at a certain time t is calculated by Equations (1) and (2). The size of a face in Equation (2), D_i, is the ratio of the area of that face to the entire image. The newly detected face is assigned a new identification number i. When a face corresponding to the same identification number is detected consecutively, its T_i is counted up, and the duration of the detection is defined as the detection time. The total amount of social activity S is the sum of the above for the time to be measured (i.e., $t : 1 \sim m$).

Using the extracted first-person lifelog videos of daily activities, we obtained the degree of participation in social activities every 5 seconds. A camera with a 200-degree angle of view was used to capture oblique and adjoining dialogues.

$$S = \sum_{t=1}^{m} \sum_{i=1}^{n} T_i(t) \cdot D_i(t) \tag{1}$$

$$\left(\begin{array}{l} i : \text{The identification number of the detected face,} \\ T_i(t) : \text{Continuity (same face-detection frame),} \\ D_i(t) : \text{Proximity (the area of the face occupying the} \\ \text{whole),} \\ m : \text{The number of measurement frames (elapsed ti-} \\ \text{me) up to time } t, \\ n : \text{The cumulative number of people (number of fa-} \\ \text{ces) up to time } t. \end{array} \right)$$

$$D_i = \frac{w_i \cdot h_i}{R} \cdot 100 \tag{2}$$

$$\left(\begin{array}{l} w_i : \text{The width of the detected face,} \\ h_i : \text{The height of the detected face,} \\ R : \text{Screen resolution.} \\ \text{The units are pixels.} \end{array} \right)$$

3.3 Mapping to a two-dimensional plane

The amount of physical activity and social activity were plotted on a two-dimensional plane for each 10-minute daily activity (Figure 1). The total amount of calories burned displayed on the Fitbit Versa during 10 minutes was calculated and used as the amount of physical activity. The horizontal and vertical axes of the two-dimensional plane are the physical and social activity levels, respectively, where the physical and social activity amounts are transformed to a range from 1 to 10. The conversion was done using the following map function [3].

return (value - fromLow) * (toHigh - toLow) / (fromHigh - fromLow) + toLow;

$$\left(\begin{array}{l} \text{value: Value to convert,} \\ \text{fromLow: The lower limit of the current range,} \\ \text{fromHigh: Upper limit of the current range,} \\ \text{toLow: Lower limit of the range after conversion,} \\ \text{toHigh: Upper limit of the range after conversion} \end{array} \right)$$

When visualizing the various daily activities on the two-dimensional plane, we used the activities with the highest and lowest amount of each type as the upper and lower limits of the plot, respectively.

When visualizing various daily activities of an individual, we used the upper and lower limits of the amount of physical and social activity in 37 scenes of the person's daily activities (Chapter 4). To visualize the activities of multiple people in the same space, we used the upper and lower limits of the physical and social activity of three people in six scenes of their daily activities (Chapter 5). To visualize the activity transitions of an individual over a half-day period, we used the upper and lower limits of the amount of physical and social activity in the person's seven scenes of daily activity (Chapter 6).

4 CLASSIFICATION AND VISUALIZATION OF VARIOUS DAILY ACTIVITIES OF AN INDIVIDUAL

We gathered data on 8 types of daily activities from an individual: sharing meals, cooking, attending meetings, observing, working,

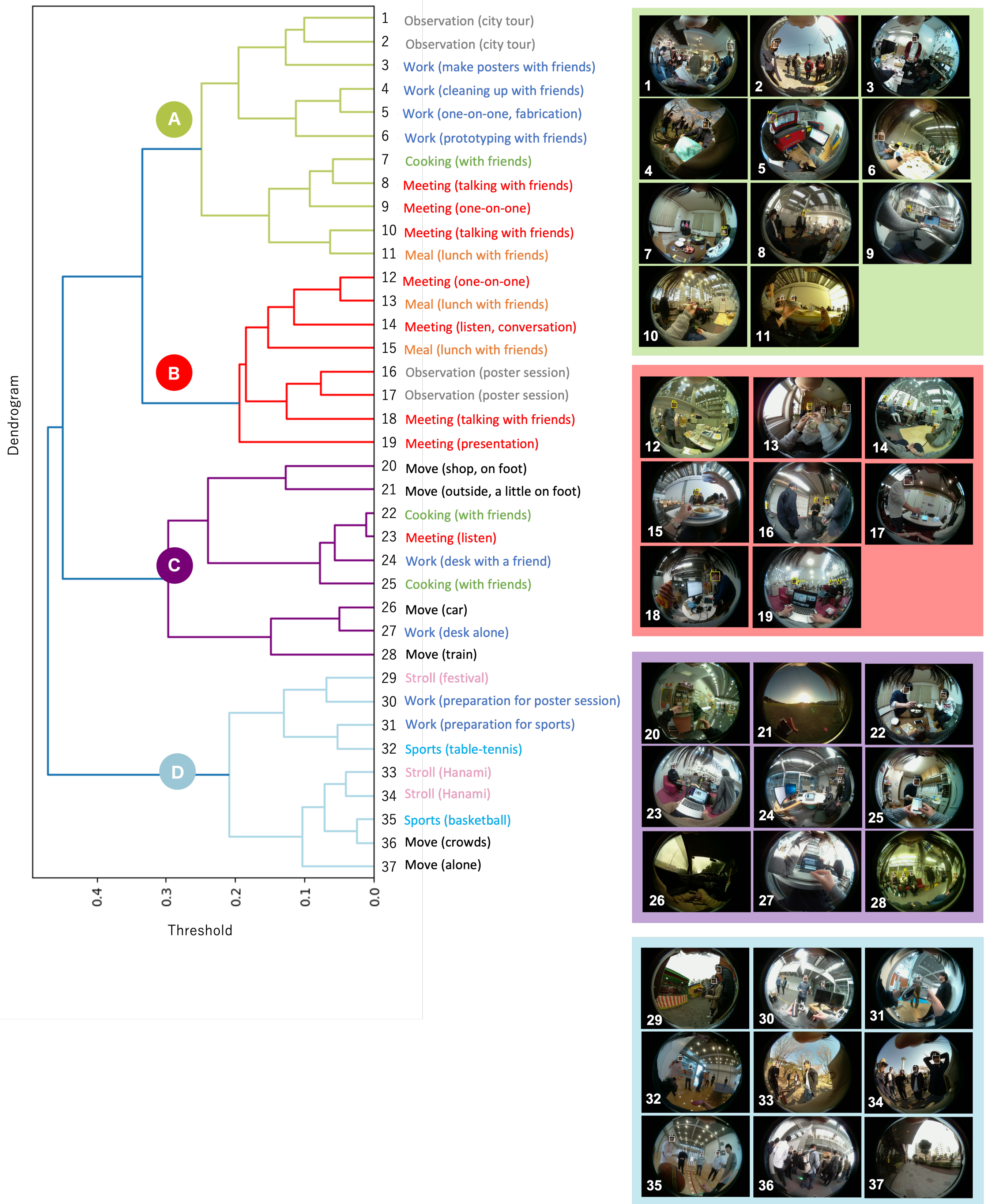

Figure 2: The result of clustering of various daily activities (8 types, 37 scenes, 10 minutes each) of an individual

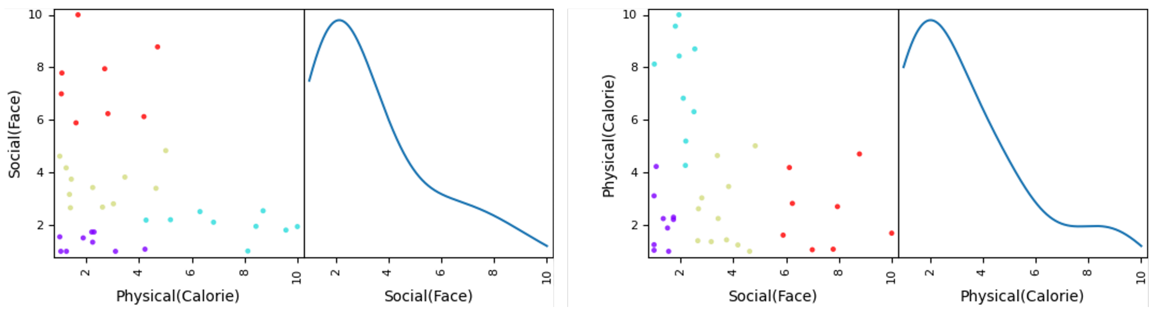

Figure 3: The results of clustering plotted on a two-dimensional plane

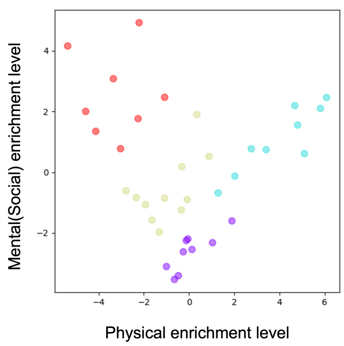

Figure 4: The result of mapping the clustering results onto the plot of the principal component analysis

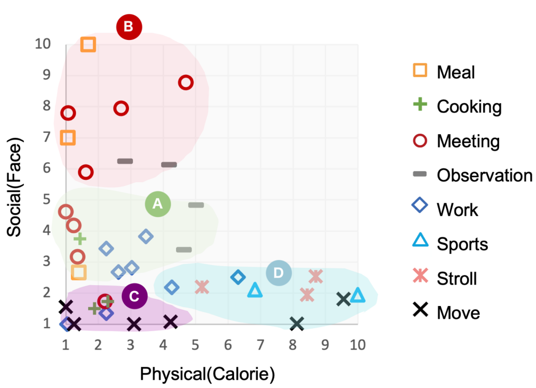

Figure 5: The result of clustering plotted on a two-dimensional plane with labels

playing sports, strolling, and moving. The activities were conducted over multiple days by one of the authors who is a student. Each activity was done and measured for 10 minutes. A total of 37 scenes were collected. After hierarchical clustering of the daily activities of the author, we plotted the data onto the two-dimensional planes based on the amount of physical activity and social activity measured and analyzed the tendency of each activity (Figure 2, Figure 3, Figure 4, and Figure 5).

Figure 2 shows the result of the hierarchical clustering of various daily activities of the author. It shows that the daily activities can be classified into four major categories based on the amount of social and physical activity. We used the UPGMA (unweighted pair group method with arithmetic mean) for hierarchical clustering [20], where the inter-cluster distance is the average of the inter-sample distances for all combinations between each cluster. This method is often used because it does not cause chain effects or diffusion phenomena. The threshold is the distance between clusters. We named the four categories groups A, B, C, and D, and color-coded them as yellow-green (A), red (B), purple (C), and light blue (D). The colors in Figures 3, 4, and 5 are consistent with Figure 2.

Figure 3 shows the results of clustering plotted on a two-dimensional plane. The horizontal and vertical axes are the physical and social activity amounts, respectively, where the values are transformed to a range from 1 to 10 (Chapter 3.3). As shown in the figure, there are no activities with high levels of both social and physical activity.

In Figure 4, we performed principal component analysis (PCA) on the clustered activities and plotted the results. We would like to name the vertical axis and horizontal axis as the mental and physical enrichment levels of the activities, respectively.

Figure 5 shows the same result of clustering plotted on a two-dimensional plane but with labels. The label for each activity in Figure 5 indicates the type of daily activity that was measured. The daily activities were classified into four groups: Group A that provides a balanced amount of both physical activity and social activity, Group B that provides high amounts of social activity, Group C that provides neither, and Group D that provides physical activity. Also, the results show that for the participant in this study, there is no group with high levels of both social and physical activity.

Since all the measurements were taken by a single person, the tendencies are considered to be those of that person only. The following is a detailed description of each type of activity measured.

Meal We measured a scene in which multiple people were having lunch. The amount of social activity obtained depends on the sitting position and the degree of participation in the dialogue during lunch.

Cooking We measured a scene where multiple people were cooking. They were in the kitchen checking the procedures and putting things in place. While they were cooking on a hot plate, they spent time watching TV or talking with their friends. Although the activity was conducted in a small space, it provided a small amount of physical and social activity.

Meeting We measured scenes in which multiple people and one-on-one conversations took place. The amount of social activity obtained depends on the degree of participation in the dialogue. In the case of sitting, standing, and moving during the dialogue, the amount of physical activity was also obtained.

Observation We measured the scenes of participation in poster sessions and city tours. It is an activity in which the amount of social activity obtained changes depending on the degree of participation in the dialogue. The amount of physical activity also was measured because the participants had to move during and after the dialogue.

Work We measured scenes where a single person worked or multiple people worked together. No sustained face-to-face interaction occurred, but there was instantaneous communication, and the activity provided a small amount of social activity. In addition, when making or taking things away with someone, sitting, standing, and moving were involved, so the activity provided a small amount of physical activity at the same time.

Sports We measured scenes of multiple people playing table tennis and basketball. There was no sustained face-to-face interaction, but there was instantaneous communication, which resulted in a small amount of social activity. The amount of physical activity increased as the people walked and ran more.

Stroll We measured scenes of strolling through a park with friends to view cherry blossoms and strolling through festival stalls. There was no sustained face-to-face interaction, but there was instantaneous communication; hence, this activity provided a small amount of social activity. The amount of physical activity increased as the people spent more time walking.

Move We measured a scene in which one participant moved alone or with people. When there were people around during the movement, it provided a small amount of social activity. The amount of physical activity increased the more they traveled without riding a vehicle.

The groups belonging to the meal, meeting, observation, work, stroll, and move activities differ according to the level of activity. In other words, the amount of activity in sharing a meal and meeting, where the participant does not actively interact with others, is similar to that in cooking and desk work with friends. In addition, working with multiple people with a lot of movement yielded a similar amount of activity to strolling with multiple people with little movement. Furthermore, in current results, moving in a crowded place, playing basketball with a friend, and strolling to see cherry blossoms with friends showed similar activity levels.

The results obtained in this study are all from an author. The insights gained are described below.

- *Working with people is a good idea to increase both activities at once in a well-balanced manner.*
- *Having a meal and meeting with people can increase the amount of social activity easily if I interact with them.*
- *Cooking with friends is a good idea when I would like to play even when I am physically and mentally tired.*
- *It would be a fulfilling day if I had a meal with multiple people after playing sports.*
- *It's a surprising discovery for me that the time to observe something with people is more fulfilling than the time to work with people.*
- *Since playing sports and strolling are similar activities, I would like to increase the time for strolling. This is because I'm not good at sports and I prefer strolling more.*

By combining various activities such as these in a day or a week, we aim to improve our physical and mental wellbeing. We believe that our visualization will help suggest activities for individuals based on their state of physical and social (mental) health.

5 CLASSIFICATION AND VISUALIZATION OF DAILY ACTIVITIES OF A GROUP

Similarly, we measured the daily activities of a group of people. Three people participated, where they conducted and measured 4 types of activities together for 10 minutes per activity. A total of 6 scenes were collected. We plotted the activities of the three participants, A, B, and C, on a two-dimensional plane and analyzed the tendency of each activity (Figure 6).

Participant A is an author and professor, and Participant B and C are university students. Participant B is the author who gathered the data in Chapter 4. Participant A and C are male. Participant B is a woman. The following is a detailed description of each activity.

Work All three participants were able to gain both physical and social activity simultaneously. Before starting the poster session, several people set up equipment such as cameras and posters. They communicated instantaneously and moved on foot when procuring things.

Observation(poster session) All three participants were able to gain physical activity and a lot of social activity at the same time. They were participating in the poster session. Only Participant C was a presenter for the first half of the session. All three participants moved from one place to another in the first and second half of the session.

Observation(exhibition) All three participants were able to gain both physical activity and social activity at the same time. Participant B gained a very low amount of social activity because she was not engaged in a sustained dialogue with anyone. Participant A and C interacted with nearby people and the presenter when looking at the exhibits. all three participants went to several locations to look at the exhibits.

Move No social activity was gained, but physical activity was gained in this type of activity; all three participants walked, got into the car, and continued moving. Participant A and C communicated slightly in the moment.

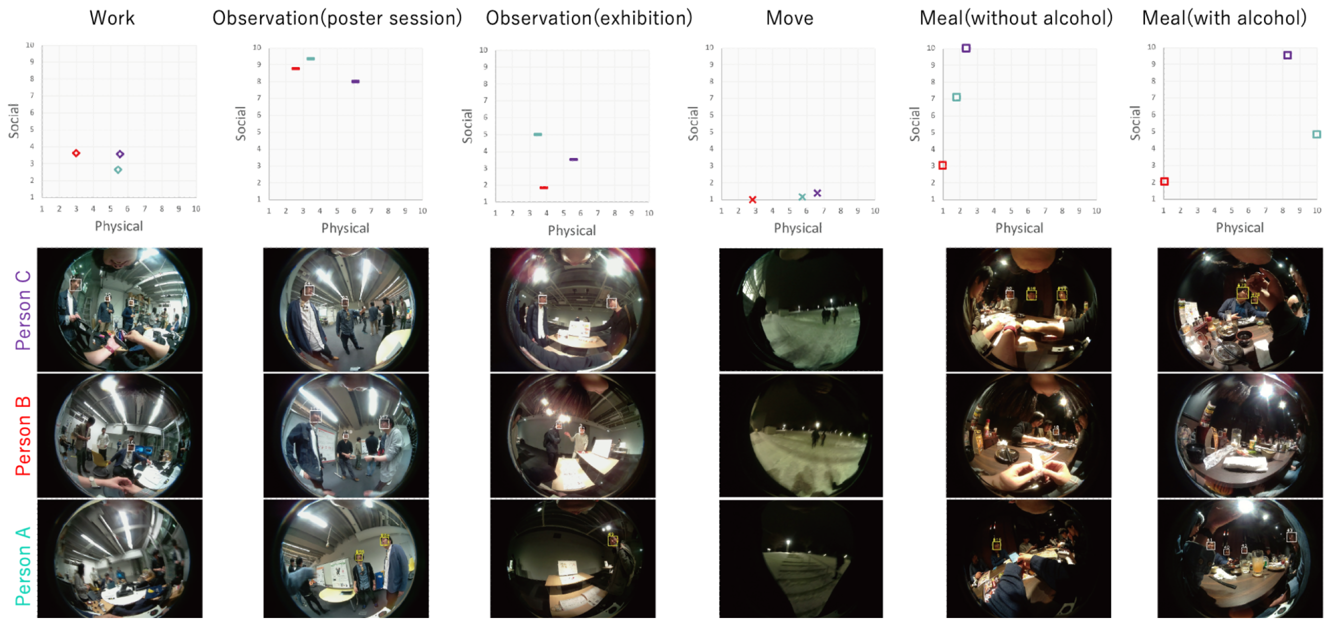

Figure 6: The daily activities of multiple people in the same space

- **Meal(without alcohol)** All three participants obtained an amount of social activity, but the amount was different for each person. Participant A and C picked up a menu tablet or a smartphone to order, and became the center of the conversation when ordering food. Participant B, on the other hand, sat on the edge of the seat and was the listener.
- **Meal(with alcohol)** Participant A and C gained a large amount of both social and physical activity. Participant B did not gain much activity. Participant A and C participated in the conversation and were excited, while Participant B was on the edge of seat listening to the conversation group next to her. Participants A and C drank alcohol and had high levels of physical activity.

Although there were differences in the size of the values, or in other words, individuality, the mapped positions of the activities of the three individuals in the plot tended to fall into the following groups: activities that provide a good balance of both physical and social activities, activities that provide a high amount of physical activity, that provides neither, and activities that provide a high amount of social activity.

On the other hand, the amount of calories consumed also changed depending on the activity in the body due to drinking, and the amount of calories consumed increased for both Participant A and C. This was an unexpected result, as they were able to obtain both a large amount of social activity and physical activity. We believe that many people drink alcohol throughout the course of their daily activities. It is necessary to examine how users feel about treating the amount of physical activity obtained by drinking and the amount of physical activity obtained by exercise in the same way.

Note that the BMR (basal metabolic rate estimated, which includes calories burned at rest) is calculated based on the amount of calories burned by participants A, B, and C, heart rate during exercise, and information on their height, weight, age, and gender [7]. Note that the amount of physical activity of Participant B is therefore lower than that of the other two participants. When actually presenting users with a comparison of their activity levels with others, it is necessary to handle the comparison so that the physical activity levels are compared equally.

6 VISUALIZATION OF ACTIVITY TRANSITION OF AN INDIVIDUAL THROUGHOUT A HALF-DAY

We measured both physical and social activities to visualize the transition of daily activities of a student throughout a half-day (Figure 7). The student is same person as Participant C from the previous experiment (Chapter 5) belonging to the same laboratory as the authors. The amount of physical activity and social activity were measured hourly from 11am to 5pm. We plotted the amount of physical activity and social activity on a two-dimensional plane. The following is a detailed description of each activity.

- **11:00 - Meeting** Both physical activity and social activity are low. He was participating in a lab meeting. He was sitting, looking at the PC and the projector screen, and listening to the discussion.
- **12:00 - Meeting** He gained a low amount of both physical and social activity. He was sitting in a chair and interacting, then standing and interacting with a friend and starting to move around.
- **13:00 - Lunch** He gained a high amount of social activity. He was sitting on a chair, interacting with his friend, and having lunch. He sat down and talked with his friend while having lunch.

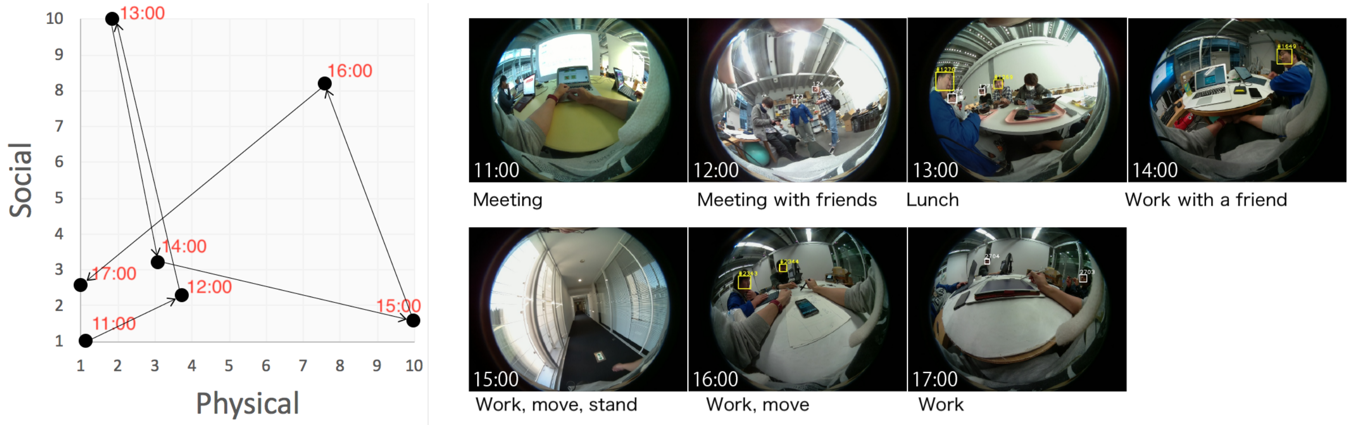

Figure 7: Transition of daily activities of an individual

14:00 - Work He gained a low amount of both physical and social activity. He was seated and working on his PC while interacting with his friend. He was working with a PC while talking with his friend after being seated.

15:00 - Work, move, stand He gained a high amount of physical activity. After working, he moved alone and then stood talking with his friend for a while. After working, he moved alone and had a short talk with his friend.

16:00 - Work, move Both physical and social activities were high. He worked with his friend and then moved alone.

17:00 - Work He gained a low amount of social activity. He was working with his friend.

As plotted in Figure 7, we visualized that the half-day activity of the university students did not always stay at the same coordinates, but changed. We believe that there is an appropriate amount of activity and activity rhythm for each individual, and that the way we spend our days differs depending on our occupation, gender, and age. In addition to the goal of increasing the amount of activity, we would like to enable users to act with the goal of achieving a good balance between mental and physical activity. We would like to suggest the next activity that is good for the user's mental and physical health based on the user's transition and current state throughout the day, and lead to behavioral changes that improve satisfaction and fatigue.

7 CONCLUSION

In this paper, we measured both social activity (mental aspect) and physical activity (body aspect) to classify and visualize daily activities and to clarify what kind of activities a person does to obtain a good balance of both. By self-reflection through lifelogging, we aim to discover ways of spending and indicators that lead to physical and mental health, such as increased satisfaction and reduced fatigue. We believe our proposal may provide suggestions for increasing options for the person in what combination of activities can balance the amount of mental and physical activity.

In this study, as a first step, we mapped the amount of physical activity obtained from an existing smartwatch device and the amount of social activity obtained from a neck-worn face-counting device onto a two-dimensional plane to investigate how daily activities can be visualized based on the amount of physical and social activity. The participants in the experiment were the authors themselves and a student. We plan to present multiple people with an easy to understand fulfillment in day visualization method like a pie chart using clustered groups to investigate behavior change of the person and colleague.

The data used in this study were obtained before the outbreak of the new coronavirus in 2020. On the other hand, as of 2022, meetings are increasingly being held online, and activities that require a high level of social activity while seated have become commonplace. It has been reported that in online meetings, people may feel fatigued due to the fact that the other person's eyes are always looking in their direction [4]. Currently, we would like to investigate what kind of activities should be combined in order to obtain a good balance of both physical and social activities safely. We are interested in visualizing the rhythms of activity and the appropriate amount of activity for each individual, which are thought to vary depending on age, gender, personality, and occupation.

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