Lifelog Visualization Based on Social and Physical Activities

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ABSTRACT

This paper presents the visualization of lifelog based on the amount of social and physical activities for well-being. The motivation is that enables users to aware their social, physical, and moderate activities for behavioral change aiming a comfortable how to spend life for individuals. In this paper, three experiments were conducted to examine the feasibility of measuring and visualizing daily activities. We classified the one student's various daily activities to see the tendency of activity levels and classes. Also, we examined individual differences of three people in the same spatiotemporal space. Finally, we examined how the one student's activity changes of half-day can be visualized.

CCS CONCEPTS

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

KEYWORDS

Visualization; Lifelog; Social and Physical Activity; Well-Being.

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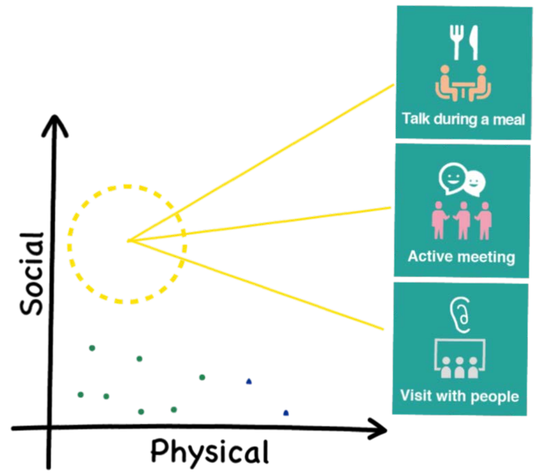

Figure 1: Our idea is to enable users to aware the amount of their social, physical, and moderate daily activities, for example, users who did not have social activity well will aware their behavior by looking at the amount of activity plotted on the two-dimensional plane.

1 INTRODUCTION

This paper presents the visualization of lifelog based on the amount of social and physical activities for well-being. The quantity and quality of social relationships are thought to affect health, not just mental [5]. Also, social ties are thought to be associated with maintaining psychological and mental well-being [6]. As one of the factors that affect mental health, we focus on the quantity and quality of social activity and visualize it in combination with physical activity. We are interested in visualizing the quality of daily activities in terms of mental and physical health. Therefore, we visualized daily activities based on the amount of social and physical activity.

To visualize the quality of daily activities, we measured social and physical activity amounts using wearable devices. We have examined ever how to measure the amount of social activity with a wearable "face counter" that calculates the level of engagement with people [7]. The social activity here refers to activities that have face-to-face interaction with people, for instance, conversations, meetings, collaborative works, meals with people, and so forth. The amount of physical activity was measured using calorie consumption estimated from heart rate during exercise wearing a smart watch of Fitbit [3]. The results of feasibility study showed that the measurement method was almost successful, however challenges remained in about measuring sports, and meals drinking alcohol. We discussed the scope of daily activities to visualize.

Our object is visualizing the quality of daily activities in terms of both mental and physical health. The motivation is that enables users to aware their social, physical, and moderate activities (Figure 1). We expect behavioral change aiming a comfortable how to spend life for individuals. In this paper, three experiments were conducted to examine the feasibility of measuring and visualizing daily activities (Figure 2). We classified the one student's various daily activities to see a tendency of activity levels and classes. Also, we examined individual differences in activities of three people in the same spatiotemporal space. Finally, we examined how the one student's activity changes of half-day can be visualized.

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Figure 2: Daily activities

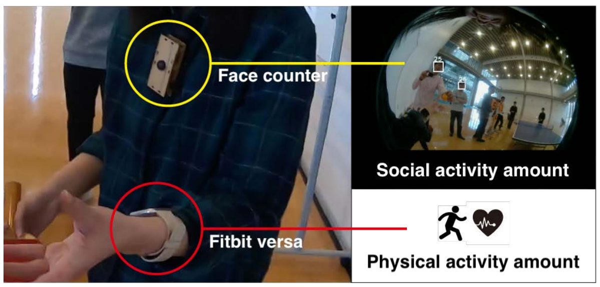

Figure 3: Measure the amount of social and physical activity

2 RELATED WORK

There have been many studies on methods for classifying daily activities from lifelog. In the method of classifying daily activities based on acceleration changes, it is possible to measure whether the user is walking or running [4]. The activities such as watching TV, cooking at kitchen, and reading books can be automatically indexed with image recognition [9]. The degree of busyness of daily activities is measured using the movement of the person captured in the environmental camera[10]. Also, by combining exercise with an acceleration sensor, a voice with a speaker, distance with a Bluetooth link, and face-to-face detection with an IR sensor [2], various aspects of social context have been measured. The results include predictions about productivity and job satisfaction [8].

We visualize daily activities based on the lifelog aiming well-being. The amount of social and physical activity is measured with two body-worn devices (Figure 3). Combining these two types of activity can measure the quality of daily activities such as meeting and work. This is intended to focus on not only physical health but also social health that affects health including mental [5, 6].

3 MEASUREMENT OF SOCIAL AND PHYSICAL ACTIVITY

The amount of physical activity was measured by the fitbit versa [3], and the amount of social activity was measured by the face counter [7] (Figure 2). Details are as follows.

3.1 Data Collection

From the first-person view video, daily activities (Figure 3) were extracted for 10 minutes each. Data was prepared considering the diversity of daily activities, for example, the activities of meetings included attendance as well as presentations. There were also one-on-one meetings as well as groups. In addition, there were casual meetings.

3.2 Physical Activity Amount

Physical activity was measured using calorie consumption estimated from heart rate during exercise (Figure 2). Fitbit versa [3] was used. This calorie consumption is estimated according to the BMR (basal metabolic rate) calculated using height, weight, age, and gender information, and includes calories consumed at rest. We used calorie consumption per minute. The total amount of calories consumed for 10 minutes was calculated and defined as the amount of physical activity. The reason for using calorie consumption is that it was difficult to measure activities including squatting and standing when we used steps.

3.3 Social Activity Amount

Social activity was measured by calculating the number, proximity, and continuity of faces [7]. The social activity can be measured by detecting the face of the partner when the camera wearer performs an active behavior, without measuring the utterance or the gesture itself. From viewpoints of design simplicity and privacy, only face detection results were used without identifying individual faces. The level of engagement with people every 5 seconds was measured, and the total amount for 10 minutes was calculated as the amount of social activity. We used the 200 ° view camera to measure not only frontal social interactions but also adjacent social interactions.

4 FEASIBILITY STUDIES

Three experiments were conducted to examine the feasibility of measuring and visualizing daily activities.

4.1 Classification of Daily Activities

We classified the one student's various daily activities to see a tendency of activity levels and classes. Figure 4 shows the results of plotting the amount of social and physical activity on a two-dimensional plane for each 10 minutes. The horizontal and the vertical axis are the values obtained by converting the numerical values of each activity amount to values of 1 to 10 maintaining the ratio. Figure 5 shows the results of classifying the values into three groups by the k-means method. The group A is daily activities that has weight of social activity tends to be large. The group B is daily activities that has balanced weight of social and physical activity or tend to be small. The group C is daily activities that has weight of physical activity tends to be large.

4.2 Individual Differences in Daily Activities

To examine individual differences, we visualized the activities when three people spend the same time in the same space (Figure 6). The person 1 and person 3 are students, and person 2 is a professor. The activities with lab member are meal (First half and second half), visit the poster session, visit the exhibition at the museum, and move from campus to outside. The duration of each extracted activity is 10 minutes. The values on the axes were calculated using data from all three people. The large individual differences were at mealtimes only. The values with pictures of meal were measured in the latter half of the dinner with alcoholic drinks. The person 3 did not actively interact with people at the mealtimes, but the person 1 and the person 2 actively. The physical activity amounts of the person1 and the person 2 were large.

4.3 Change of University Student's Daily Activities

We examined how the one student's activity changes of half-day can be visualized (Figure 7). The data was obtained from the student belonging to the laboratory. Social and physical activity for each 10 minutes from 11:00 am to 17:00 pm were plotted. The peak social activity peaked at 13:00 at lunch with people. At 16:00 when both activities were high, the student was working with multiple people and moving alone.

5 DISCUSSION

5.1 Visualizing the Amount of Social and Physical Activity

The daily activities could be classified into three groups according to the amount of social and physical activities (Figure 4, 5). If the student wants to take care of the balance, it will be better to work with people. The meals and meetings had different groups depending on the level of engagement in activities. From these facts, we think not only the type of activity but also its level is important to aware.

5.2 Individual Differences in the Amount of Activity

The proposed method measured different activity levels of people in the same space-time (Figure 6). It is expected that there will be comfortable ways and amounts of activity for each individual. We will also are interested in whether there is something in common for many people.

5.3 Concept of visualization of daily activity rhythm of individual

By visualizing the change between social and physical activities (Figure 7), there is a possibility that the daily activity rhythm can be easily aware. We are interested in visualizing from a large amount of data on the daily trajectory whether the person's mind, body, or environment have changed in a good or bad direction.

5.4 Scope of the Daily Activities to Visualize

The results of feasibility study showed that the measurement method was almost successful, however challenges remained in about measuring sports such as basketball, and meals drinking alcohol (Figure 4, 6). It would be preferable to apply the current idea to activities other than cooperative activities that require quick teamwork and activities that increase physical activity due to internal factors. We also expect that the accuracy will be improved if the head direction affinity is added to the social metrics [1, 11].

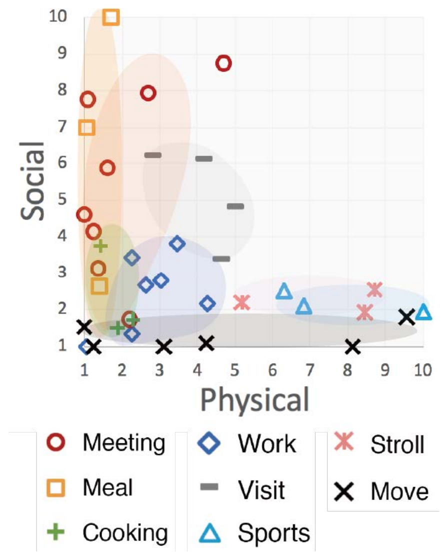

Figure 4: Relationship between social activity and physical activity of daily activities

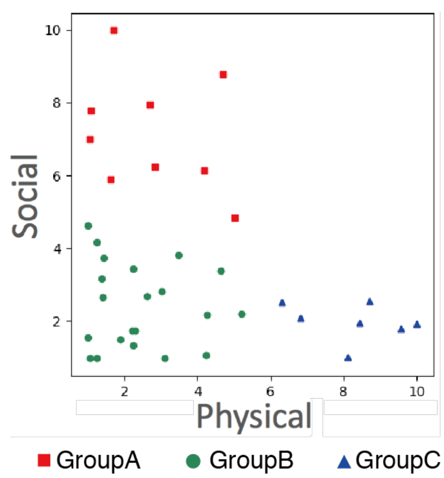

Figure 5: Results of classifying daily activities into three groups using the k-means method

6 CONCLUSION

In this paper, we presented a work-in-progress that visualizes daily activities of the social and physical for user's behavioral change aiming their mind and body health. We conducted three experiments to examine the feasibility of measuring and visualizing daily activities. In the future, we would like to examine how the type, quantity and quality of daily activities are related to daily satisfaction and fatigue.

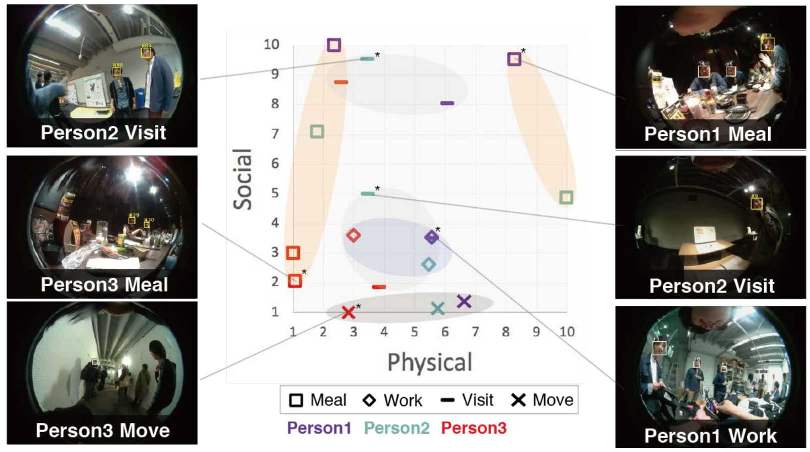

Figure 6: The activities measured when three people participated in the same activity at the same time

Figure 7: Change of university student's daily activities

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