Kansei Map
— Development and validation of a tool for analyzing behavioral information using geographic information system —

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September 2022

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When we describe our moods, we often use "light steps" and "heavy steps". The relationship between footsteps and human emotional states has been studied in emotion recognition today.

Using Kansei Design's methodology, this study created "My Footprint," a wearable information system that automatically records the wearer's real-time location and plantar pressure. The researcher used this device to aggregate and analyze user behavior through a geographic information system. This study began with a detailed literature study. The roles played by gait and location information in the recording and research were investigated separately.

Concerning many prior studies and various methodologies, this study proposes a design of a recording device (including physical structure, electronic design, and procedures).

Using this equipment, a pilot experiment was conducted to record walking routes in a defined environment. The researcher collected 30 path data in this experiment and plotted them on a map.

The researchers proposed a Dual-task walking experiment with prescribed walking motives based on the Pilon experiment results. And the subjective workload data of 7 study collaborators were measured by the NASA-TLX method. Based on the combined analysis with the measurement data of plantar pressure and path, it is possible to verify the specific performance of this study's measurement data in reflecting the subjects' subjective perception changes.

From the results of the two experiments, the researchers concluded that the data recorded by "My Footprint" can be linked to changes in the subjective perception of the wearer under certain conditions. By rendering the data in a map layer, further location-based research on visualizing Kansei can be facilitated.

The above is a summary of the research content included in this thesis.

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Chapter 1

Introduction

1.1 About this study

When we describe our moods, we often use "light steps" and "heavy steps". There are many studies about the relationship between footsteps and human emotional states in emotion recognition today. Because scholars Kale et al., 2004 proposed that each person's gait is a unique physiological indicator like fingerprints. Especially in recent years, machine learning techniques have been applied in the field of human recognition based on gait, for example, self-esteem prediction has been accomplished by gait analysis in recent years Sun et al., 2017. And the study of Bhattacharya et al., 2020 has built a very well established neural network for emotional judgment by recognizing the gait of walkers in animations.

Gait-related studies occupy a considerable place in both clinicopathology and behavior-related research. However, much of the gait data obtained in these studies are obtained actively in laboratory settings. People's walking characteristics are also altered under the influence of the Hawthorne effect Adair, 1984. The need for wearable and environmental devices to collect data when avoiding the Hawthorne effect was mentioned in the study of Muñoz et al., 2020.

Environmental devices have strong limitations when it comes to taking gait information. It becomes very difficult and costly to arrange environmental devices (e.g., depth cameras) that can readily capture time-series gait information over a large site area. And similarly, when data collection is performed in a daily life scenario, it is inevitable to deal with many people mixed in the scene. Although cameras and other devices can rely on face recognition and other ways to determine identity information, it is still difficult to efficiently track experiment participants in the crowd. With the help of wearable devices, it is possible to obtain specific time series information more accurately and completely.

On the other hand, behavioral analysis is also a popular direction based on location information. The study of Yuan, Zheng, and Xie, 2012 then proposed that location information can effectively distinguish the functional areas of cities. Not only cities, but also the location movement of people can be an important basis for behavioral profiling. As stated by Kisilevich, Mansmann, and Keim, 2010, such data are being readily generated in large quantities with the rapid spread of location-based devices. Based on the spatial data captured and stored by GIS (Fotheringham, Rogerson, and National Center for Geographic Information & Analysis (U.S.), 2014), we can link location information and people's behavior more precisely.

In summary, this study aims to develop a scheme that can collect data and perform behavioral and effective state correlation analysis with the help of a wearable device. This scheme consists of an original device that can continuously record gait data and GIS-based location trajectory information as behavioral trait data for long periods in a non-laboratory environment, and a method for analyzing the data taken by the device.

1.1.1 Research Questions

The following research questions can be formulated for this study based on the above research.

- *"Is it possible to accomplish long-term recording of accurate gait data and location information under synchronized time series by a lightweight wearable device ?"*
- *"Whether location information traces within a specific area (e.g., campus) will reflect the behavioral characteristics of the recorded person ?"*
- *"Whether the data recorded by the device can reflect changes in the wearer's gait and how such changes relate to behavioral characteristics ?"*

1.2 Research Features

In this study, an original design for a data logging device was developed and experiments were conducted to test the device. During the device design process, the authors were guided by the KANSEI DESIGN methodology and theory, which is described in detail in the literature study section.

Specifically the device design of this study is characterized by high accuracy, long duration of operation, unmanned monitoring, and no dependence on the Internet. The wearable nature of the device is utilized to minimize the effect of the Hawthorne effect and thereby collect data on the wearer's activity in its natural state.

1.3 Thesis Structure

Including this chapter, there are five chapters in the body of this paper. Each chapter begins with a brief description of what is contained in that chapter and a flowchart showing the location of that chapter in the text. The contents of each chapter beginning with Chapter 2 are as follows.

- CHAPTER 2: consists of three subsections: research background, research methodology, and KANSEI DESIGN. This section describes the background of the study development and the current state of research in the field. The research background section summarizes prior research and related studies; the research methodology section presents the relevant design methods and experimental measurement methods used in this study. The last section introduces the KANSEI DESIGN method as the guiding idea of this study.

- CHAPTER 3: consists of two subsections: device design and experimental design. This section details the specific technical details of the design of the measurement device completed in this study. It describes how the experiments were carried out to validate the research problem with the help of the technical parameters of the device. The device design section provides a complete overview of the development of the device from 0 to 1 in terms of both hardware and software. The experimental design section proposes more specific research hypotheses by considering the content of the study and designs experimental protocols to verify the corresponding hypotheses.

- CHAPTER 4: consists of four subsections: experimental preparation, experimental content, experimental results, and discussion. This section details the specific implementation details of the experiments conducted in this study. The Experimental Preparation section describes the ethical considerations of the experiment and the preparations made for the experiment. The experimental content section details the participants, the period of conduct, and the specific details of the implementation process. The results section presents the data obtained from the experiment in both qualitative and quantitative terms. The final discussion section explains the implications of the experimental results and whether the experimental hypothesis was successfully tested.

- CHAPTER 5: consists of five subsections: device, experiments, limitations, constructive conclusions, and future work. This section gives the final discussion of the overall study. The device and experimental sections summarize the main points about these two sections reflected in the conclusion. The limitations section explores the shortcomings of this study. The constructive conclusion section reviews the entire research history and explains the significance of the study conducted. Finally, the future work section illustrates what this study can bring to future researchers in the same field and suggests directions for improvement in the content of this study.

- APPENDIX: This section lists all the associated materials used in the study. This includes and is not limited to questionnaires, etc.

Chapter 2

Literature Research

2.1 Research Background

2.1.1 Emotional recognition of gait

In order to study human beings, human behavioral traits are often the object of research attention by researchers. And among the many behavioral characteristics, footsteps are valuable items to study (Nixon, Tan, and Chellappa, 2006). Intuitively, footsteps seem to be a simple and mechanical behavioral process. However, footsteps are an action that contains a lot of information generated and controlled by a complex human motor system (Paas and Sweller, 2012). Similar to behaviors such as heartbeat, upper limb movements, and gaze (Fabes, Eisenberg, and Eisenbud, 1993), they can be simply perceived because they are mechanically and repeatedly produced and are an indicator for studying human behavioral characteristics (Lord et al., 2013). Because of the very significant body movement changes, vision can observe footsteps simply and precisely (Harbourne and Stergiou, 2009). Also the mechanical feedback from walking gives various emotional impressions about the footsteps, such as the description of the lightness of the footsteps (Tajadura-Jiménez et al., 2015) at the beginning of the article. In order to characterize the behavior of footsteps correctly, researchers also data them in the form of stride length (Danion et al., 2003), stride frequency (Cavagna and Franzetti, 1986), and left-right offset of footsteps (Tariq, Trivailo, and Simic, 2020). In a specific scenario, the change in human footsteps state can be obtained by observing footsteps or foot movements (Patla and Vickers, 2003) as a reference item to determine the state change. However, at the same time, it is also difficult to restore (**hau)** human gait characteristics by measurement. Although researchers (Zijlstra and Hof, 2003,Sabatini et al., 2005) have given standard movements of footstep changes during walking, our usual walking is accompanied by the influence of a large number of environmental factors (Hartig et al., 2003). Also, as a large movement involving the whole body, walking involves various changes in body information. It is increasingly difficult to meet the needs of people when studying footsteps by simple means such as visual observation alone.

Machine learning, machine vision and gait research

As a remarkable action that is easy to quantify, walking has taken the lead as a door knocker on the way to research with the help of artificial intelligence. In recent years, research on mechanical learning methods (Horst et al., 2019) combined with machine vision to classify people's gait (Urtasun and Fua, 2004) has remained very popular. From the initial substitution of the human eye for walking observation, gait research has penetrated many areas that would otherwise be difficult to reach by visual observation alone. With the power of artificial intelligence (Connor and Ross, 2018), gait is an important reference in various studies (Roether et al., 2009,Venture et al., 2014) that analyze human behavior and emotions. It has also been mentioned that the human footsteps contain data on the characteristics of each individual

(Sanderson et al., 2002), which is sufficient to enable individual human recognition. Many studies have supported the idea that emotion recognition can be performed through gait analysis. Also, as a common human action, gait has been shown in many studies like the study done by Prakash, Kumar, and Mittal, 2018 to play at least a reference data role in detecting and predicting human emotions. The field remains a treasure of data worthy of deeper exploration.

On the other hand, while great advances in computation and analysis have advanced our interpretation of the information hidden in gait, there has been little research to discuss how to obtain the data (Kinoshita, 1985). Although we can "see" more accurately the changes in body posture during walking with the help of machine vision, we still lack better measures of walking behavior (Leslie et al., 2007). In fact, as walking is a highly temporally correlated behavior (actions can be decomposed and analyzed in a time-series, which is what many AI learners are doing or have done), a systematic measurement scheme with temporal correlation (Fritz and Lusardi, 2009) may be of great help in recovering human behavioral characteristics.

Gait research in clinical medicine

Gait has an important role in the behavioral sciences and the perception of disease and health (Hausdorff, 2007). Instead, more emphasis was placed on measuring and analyzing gait characteristics considered in terms of physical structure (Punt et al., 2017). In recent years attempts are being made to reduce walking by a broader range of means (Davis et al., 1991). Among the various human postures, including and not limited to walking, plantar pressure characteristics are a silent characteristic quantity (Woollacott and Shumway-Cook, 2002) that has provided important support for disease classification (Li et al., 2018) and body structure perception. Among them, with the help of contact measurement devices, we have resolved plantar pressure with a high degree of accuracy (Godi et al., 2014). Also there are obvious mechanical reasons for human standing and stable walking with the help of the foot arch (Jones, 1941). Numerous clinicopathological studies (Still and Fowler, 1998) have also been active in using the reaction force between the foot and the ground (i.e., plantar pressure) as an important reference data. Numerous studies in this field have demonstrated the important role of this ever-present physical quantity in the cognition of human behavior.

Gait and emotion

The roots of the gait produced by walking posture are the attempts of the human body to control itself and perform stable and agile movements. And in this process of control, the human motor system plays both an active and passive expressive role (Cullen and Roy, 2004). Since our feet tend to be outside our field of vision, the subconscious mind (Coutts, 1999) seems to take a higher percentage of expression in its movements compared to the upper body's motor system. Also there have been studies (Elias, Bryden, and Bulman-Fleming, 1998) verifying that changes in the feet can completely replace the hands in providing a basis for judgment in some specific brain and behavioral science evaluations. In some studies like the one by Smith and Lazarus, 1990, emotions have been defined as a combination of physical impairment, action tendencies and subjective feelings, which also coincides with the related ideas of KANSEI DESIGN that will be mentioned later. Human emotions arise for various reasons, but they affect human attention, memory, and perception (Rolls, 2005). These effects are reflected in human behavior. Compared to facial recognition studies like the work of Leeland, 2008, which often involve the expression of emotions, gait, because it is more likely to be in a state that is not subjectively noticed, has been proposed by many studies to reflect many unconscious emotional states (Sacco et al., 2006). It has been verified in several studies similar to the work of Franěk et al., 2018 that movement speed can significantly reflect the emotions of the exerciser.

2.1.2 Geographic-International-System-based behavior study

Location intelligence-based trajectory analysis ("Location prediction on trajectory data" 2018) and hot-spot map clustering (Lawson, 2010) have been important research methods for classifying or identifying people's behavior. The study of hot-pot in cities is a very mature and relevant area (Louail et al., 2015). In this field, researchers have established many clustering methods to uncover points of interest in cities using location information and other information based on time series. These points of interest can provide a reference to the population's behavioral characteristics in a macro perspective (Liu, Chen, and Liu, 2020).

For these studies, location information is an essential information reference item. This project is often composed by time series of positioning data and basic geographic information kept by GIS. It is possible to dynamically analyze the state of people's activities in various city functional areas with the help of time series characteristics. Currently there are two directions to obtain collocation information of specific objects, active and passive, one is to passively mark the emergence of recorded objects using action recording systems with known locations such as fixed cameras, and the other is to obtain a series of data including location and timing information in real time utilizing GNSS positioning systems (Hofmann-Wellenhof, Lichtenegger, and Wasle, 2008) that can be carried. The GNSS positioning system will be described in detail in the later section. With the increasing popularity of portable smart terminals, such records containing location information are now of considerable importance in environmental and spatial studies of specific regions. At the same time, in areas where different functional areas are well defined, a certain degree of back-propagation and behavior prediction can be made based on the known regional functions and the positioning trajectories of the users (Karatzoglou, Schnell, and Beigl, 2018).

2.1.3 Wearable device based data collection

Compared to laboratory environments, more emphasis is placed on recording devices' portability to obtain real-life user data (Vuorela et al., 2010). The device design should also be considered systematically from a human factors engineering perspective. The human loco-motor system is complex and fragile (Schaal, Ijspeert, and Billard, 2003), and one or two disturbing factors may cause a wide range of shifts and errors in the measured data. Meanwhile, in the medical laboratory environment, many high-precision devices can be applied with little interference. On the other hand, Wearable carrying devices face a more complex scenario, where reasonable performance intervals and lower power consumption can provide a higher role for research records than the mere pursuit of high accuracy (Starner, 2001). Among the many studies related to the analysis of behavioral patterns, many researchers, represented by Williams, Davids, and Williams, 2005, have mentioned that the reconstruction of behavioral research for human action is currently more dependent on fundamental advances in motor behavior monitoring systems.

Large-volume, high-quality data sets also play a critical role in analysis for research in machine learning and artificial intelligence. Considering many wearable system applications, smart carrying devices in the market today already carry many portable sensors to record user behavior data. And at the same time, portable devices demonstrate advantages in blind testing (Krafka et al., 2016). Subjects with low-interference measurements performed by silent experimental devices may provide more realistic information than those observed (Fotheringham, Rogerson, and National Center for Geographic Information & Analysis (U.S.), 2014). This significant gap between gait studies, especially tests of basic characteristic quantities such as gait speed in a laboratory setting and real life has been supported by many studies such as the work of Loo et al., 2004. There is a more pronounced Hawthorne effect in human gait. Therefore, considering the reliability and applicability value of data collection, research in this area should strive for methods closer to real-life environments.

In fact, in many studies, to simulate the daily life environment, methods such as suggestive dual tasks are often used to reduce the subjects' attention to their gait during the experiment to obtain more accurate results. And this consideration can be supported to the maximum extent by well-designed experimental equipment. This has been attempted so far by Xu et al., 2021, for example, by building an anthropomorphic environment assuming a good depth camera. And for wearable portable devices, this aspect and the contradiction in experimental cost should be most substantially alleviated.

2.2 Research Methodology

This study concludes that a more evolved human motion monitoring system based on non-invasive devices and wearable technology should be developed based on the above background. For this system to be useful in the fields of gait analysis, urban hot-spot analysis, etc., this study was conducted based on the following research methodology.

2.2.1 Global Navigation Satellite Systems

One of the main means of obtaining positioning information in outdoor conditions mentioned in the previous section is often referred to as the GPS positioning system. Currently, GNSS systems have evolved into maturity, where all major economies of the world have self developed and operated GNSS systems (Hofmann-Wellenhof, Lichtenegger, and Wasle, 2008). These systems are developed for civilian use and can provide higher accuracy positioning measurements in normal surface environments. there are currently three main categories of GNSS: global systems, regional systems, and augmentation systems. Among them, the well-known navigation satellite systems GPS (USA), GLONASS (Russia), GALILEO (EU) and BEIDOU (China) are global systems that provide positioning information signals on a global scale through a network of positioning satellites; regional systems represented by QZSS (Japan) use satellites to provide positioning services to parts of the Earth; and MSAS (Japan), the GNSS is a highly complex multi-system combination system (Hofmann-Wellenhof, Lichtenegger, and Wasle, 2008. However, it is designed with a unified communication specification and open service provision rules, which can open high precision positioning services for ground users. Meanwhile, the widely popular multi-mode combined positioning system can reduce the limitations and errors of a single system by calling information from several different positioning systems for integrated processing. Smartphone is its most typical application. Current smartphones can provide high accuracy positioning at 1 meter level under good signal condition.

NMEA-0183

This is a standard format developed by the National Marine Electronics Association for maritime electronics. It has become a standard protocol of RTCM (Radio Technical Commission for Maritime services) for GNSS equipment unification (Hong, Yang, and Lee, 2014). This format specifies the order in which GNSS devices return data and what each piece of data contains. By establishing a method for parsing the data under this protocol. The format specifies that data is passed in the form of `"$aaaccc,ddd,ddd,...,ddd*hh"` per frame, where `"$aaaccc"` indicates the start and data header, ddd is the data, and hh is the checksum used to verify that the data in that frame is correct. This format makes it possible to obtain latitude and longitude data in ddmm.mmmm (degree minutes) format, altitude and accuracy data, and to obtain timing from satellites in several formats. This study mainly uses the latitude, longitude and time information obtained with the help of this format.

2.2.2 Plantar pressure and Nyquist's sampling theorem

Plantar pressure is a proxy for the reaction force applied to the foot surface when it comes in contact with the ground. This force is mainly derived from the effect of gravity. In order to test the change in force on a specific fixed area (for a foot in motion, the shoe or the corresponding wearable device can also be considered as relatively stationary), the most widespread practical method is currently used to calculate the force by measuring the change in the resistance value of a variable resistance corresponding to the change in the magnitude of the pressure (which is generally considered as correlated within a certain interval), using the principle of the change in the resistance value of some materials under pressure (Pan et al., 2014). magnitude. This method was also used to measure the data in this study. The resistance value is generally measured by the following schematic diagram, where the resistance value is calculated by reading the change in the voltage value across one of the resistors when the size of another fixed resistance and the input voltage are known. The reading of this measurement is generally an analog signal, which can be converted into an electronic signal that can be processed by electronic devices using, for example, comparison with a reference voltage. This process is known as analog-to-digital conversion (Walden, 2008).

Since the processes of GPS data acquisition and analog-to-digital conversion mentioned above require a certain amount of computation time, data acquisition is usually performed at intervals, which leads to the existence of a corresponding frequency of data acquisition, called the sampling rate. The higher the sampling rate, the closer the acquired data is to the original characteristics of the model. However, it is meaningless to exceed the high sampling rate needed to restore data features, and for wearable carrying devices, the sampling rate control can significantly optimize power consumption, etc. In this study, the gait information desired to be restored is characterized by periodic changes during walking, and the optimization of the sampling rate for periodic data can be based on the Nyquist Shannon sampling theorem (Farrow et al., 2011). The theorem can be explained figuratively, we now need to take a picture of a rotating wheel, if our photo interval is exactly an integer multiple of the rotation time of one week, then we will record the photo at the same position every time we take a photo, and the photo taken at this time is a stationary wheel. If we lower the sampling rate and take pictures at half the rotation time, we can already know that the wheel is turning, but we cannot determine the direction of its rotation. Putting this in the context of sampling trigonometric functions, it can be understood that when sampling at exactly half the frequency of the function, the results obtained by sampling will be more severely distorted. In other cases, because the sampling rate and the frequency of the original cycle "staggered" can restore the function's true characteristics.

A simple summary is that the periodic variation of the characteristic quantity to be measured should be fully considered in the design phase of the device, avoiding integer multiples and halves of the sampling rate of that variation frequency. For the present study, it can be assumed that plantar pressure characteristics vary with step frequency. The average human stride rate has been given in relevant studies as generally 120 steps/min (2 Hz) without significant gender bias. A sampling rate greater than 4 Hz should be used as much as possible in the study.

2.2.3 Diary Study

In addition to the basic data analysis for the device, the research method in this study mainly refers to the diary study method in user behavior research (Janssens et al., 2018). A diary study is a qualitative data research method used to collect behavioral activities and experiences of subjects. The results of a log study consist of several logs reported by users according to a time series.

The logging method is a mimicry of the observation method performed in the field: it does not provide accurate data from field observations, but can be used as a reference data to provide results that approximate the observation method. It is a common method used in product usage research and development testing. The method is used in this study mainly to supplement the qualitative data that are not easily available in device measurements. Also because the log method is also based on a time series (albeit an approximation), the researcher considered the method to be a good fit for this study during the experimental design. On the other hand, the logbook method is more suitable for behavioral inquiry over long periods than the time-sensitive questionnaire method. Also, because this study wanted to avoid the effects of gait changes due to the Hopper effect, the researcher would not make other observations of the collaborators during the logging phase. The logbook study required the following phases: planning, preparation, recording, data collection and analysis. This process is also in line with the experimental design idea.

2.3 KANSEI DESIGN

The core device design and experimental design of this study and the core idea of the study itself are based on the methods and theories related to KANSEI DESIGN (Lee, Harada, and Stappers, 2002). This is a combination of a difficult-to-translate Japanese word and "design". It is sometimes referred to as affective design in the relevant research field. As mentioned in the definition of emotion in the previous section. I believe that the meaning that the definer intended to express is the very core of emotionality. The concept is not just a proximate term for subjective emotion. The field often expects to invoke the inclusion of sensitivity, subjectivity, feeling, and emotional expression as a collection for studying human behavior (Lee, Harada, and Stappers, 2002). Subjective emotion is only one dimension of this complex concept.

KANSEI DESIGN also plays an essential role in the growing opportunities for humans to learn more about themselves through sensing and wearable technologies that are currently evolving.

Human sensibility is not a simple concept that a single physical quantity can quantify but requires the creation of complex multidimensional models that invoke a variety of physical means to assess it. This idea coincides with today's academic field conducting in-depth studies of behavior with methods such as machine learning. Moreover, the gentle KANSEI DESIGN approach guided the researchers through this study.

Chapter 3

Research Methodology

This study experiments and explores the hypothesis of the study by developing a wearable device in the form of a record of the daily actions of the experimental subjects. The research device consists of several electronic modules and a housing that can be fixed to a shoe, and this section will be divided into two sections to introduce the research device used in this study and the experimental design of the experiment conducted through the device.

3.1 Device Design

The device developed in this research, named "MY FOOTPRINT", comprises several circuit modules connected to an MCU and partially built into a 3D printed housing. The research expects MY FOOTPRINT to track the wearer's path while walking and collect data on walking characteristics. The required features are automated GPS logging, guaranteed plantar pressure variation measurement accuracy, and calibration of the above two data during long time measurements. This section will present the device's design from both hardware and software perspectives. Also,MY FOOTPRINT underwent several iterations during the development process, and a brief description of the iterations in the device design will be presented at the end of this section.

3.1.1 Hardware Design

An exploded component diagram containing all the constituent components of My Footprint is shown in the figure 3.1. These components include: (1) MCU; (2)-a/(2)-b GNSS module; (3) pressure sensing module; (4) data storage module; (5)-a/(5)-b/(5)-c power management module; (6)-a/(6)-b/(6)-c switch and indicator module; and (7)-a/(7)-b/(7)-c housing. The next section describes each component in detail.

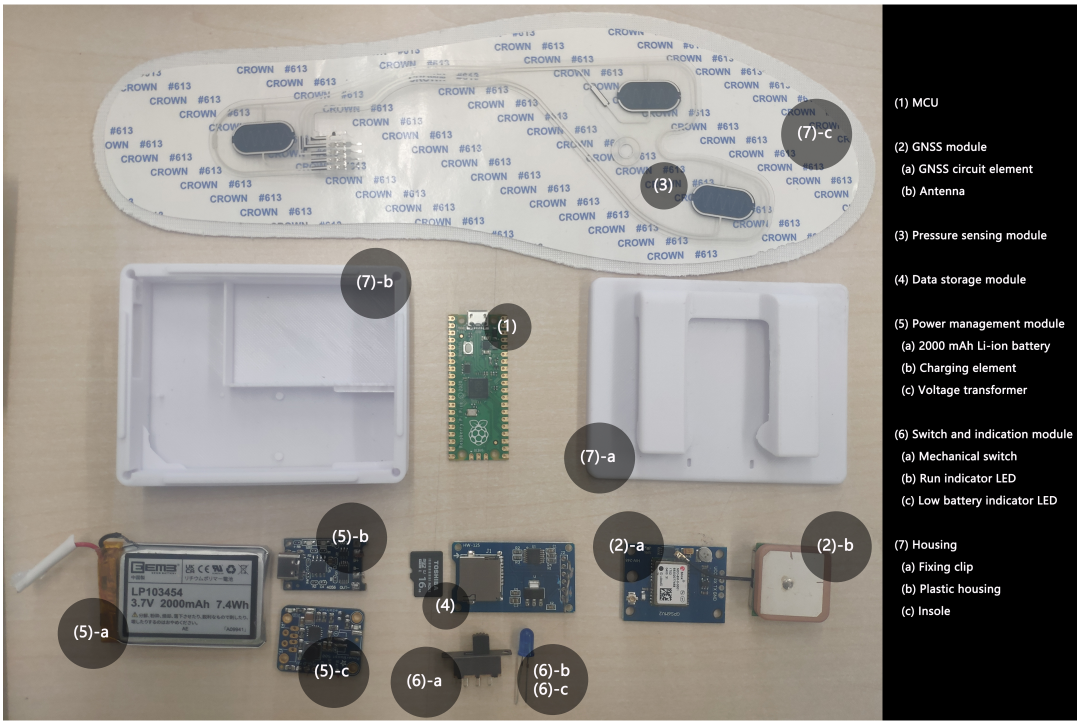


FIGURE 3.1: Picture of all device components

- (1) MCU. The final solution for the study device uses the Raspberry Pico as the main control unit. This MCU is characterized by its analog-to-digital converter, low power consumption, and high performance (high frequency sampling). By connecting the corresponding pins and components on the MCU and connecting the circuit, the device will automatically run and record the program written by the implementation.

- (2) GNSS module. The GNSS module consists of a a-circuit element and an b-antenna, which receives a series of positioning-related data and sends them to the MCU through the communication between the antenna and the satellite. In this study, the input in this format is processed by the MCU, and the three values of longitude, latitude and time are returned after parsing the statements. The module has a maximum data refresh rate of 4Hz. Inside buildings, the GPS loses signal due to the blockage of buildings. After the first power-up in the open air, the module takes about 27 seconds to connect to the satellite (cold start). It takes about 1 second to re-establish the connection to the satellite (hot start) while remaining powered on.
- (3) Pressure sensing module. This module consists of a custom thin film pressure sensor, a pressure sensing array consisting of three sensing regions. The sensing zones of the thin-film sensor are essentially variable resistors that change with pressure. In the device's hardware design, a fixed resistor is connected in series with each sensing zone and connected separately to the analog-to-digital converter built into the MCU. The surface pressure of the sensor is derived by measuring the change in resistance and fitting it to the standard curve of this sensor. The sampling rate of the module depends on the performance of the analog-to-digital converter, and in My Footprint more than 5hz can be achieved. The module is secured in the wearer's shoe by an insole with an adhesive surface and is connected to the device body by a cable.
- (4) Data storage module. This module consists of a MicroSD card reader module and an encrypted 16GB MicroSD memory card, where the MCU reads and integrates the data measured by the GPS module and the pressure sensing module and writes it to the memory card as a .log file.

The data can be retrieved by reading the memory card after the unit is recovered. Each time the unit is switched on and off a new data file is created and named with a time stamp.

- (5) Power management module. My Footprint's power management module consists of a a-2000 mAh Li-ion battery, a b-charging element and a c-voltage transformer. The charging element comes with a USB-TypeC port to access 5V power and manage the charging and discharging of the Li-ion battery. The voltage converter stabilizes the 3.7v-4.2v voltage provided by the discharged Li-ion battery to power all device components. This voltage is also used as a reference voltage for the analog-to-digital converter. After actual testing, the output voltage of the variable voltage element is stabilized at 3.99V when the device is operating.
- (6) Switch and indication module. This module consists of a-mechanical switch, b-run indicator LED, and c-low battery indicator LED. The mechanical switch directly controls the opening and closing of the output circuit of the variable voltage element in the power management module. When the switch is disconnected, the voltage transformer stops supplying power to the device components, leaving the device in a shutdown state, and when My Footprint starts running, the run indicator LED is lit and blinks at a certain frequency controlled by the MCU. When the built-in lithium battery is in low battery condition, the low battery indicator LED will be lit.
- (7)My Footprint's housing consists of the 3D-printed a-fixing clip, b-plastic housing and c-insole. The clip and the plastic shell can be connected by plugging together to form a box-like structure in which most of the electronic components of the device are contained. The clips hold

the box to the outer side of the shoe. The insole has a glued bottom surface, which allows the membrane pressure sensor to be fixed to the bottom surface of the shoe.

The device is connected for the electronic components, as shown in the component diagram 3.2 and the circuit diagram 3.3. The antenna of the GNSS module is directly connected to the part, and the GNSS component is connected to the output of the variable voltage component for power supply and the GPIO12 and GPIO13 (two UART0 communication IOs) interfaces of the MCU for serial communication data exchange. The pressure sensing module is connected to the varactor output for power supply and connected to the MCU's three analog-to-digital converter interfaces GPIO26, GPIO27 and GPIO28 in series with a 4.7kΩ resistor respectively. SPI data exchange. The three components of the power management module are connected, and the output of the variable voltage component supplies power to the other components and the MCU, while the low battery signal interface of the charging module is connected to GPIO4 of the MCU to provide signal input in case of low battery. The run indicator and low battery indicator LED are connected to GPIO1 and GPIO2 of MCU for control respectively.

After assembling the above components, the total weight of the device is about 150g. The box-shaped part of the shell measures about 70mm x 45mm x 25mm, and the longest part of the pressure sensor is about 195mm and the widest part is about 70mm, which can correspond to different sizes of insoles (Japanese standard 21cm for women and 30.5cm for men) depending on the size of the wearer′s shoes. In a fully charged state, My Footprint's 2000 mAh battery can keep the device running for over 6 hours of continuous power-on operation (fluctuating depending on how many times the GPS module is reconnected, but usually over 360 minutes). A few key components are

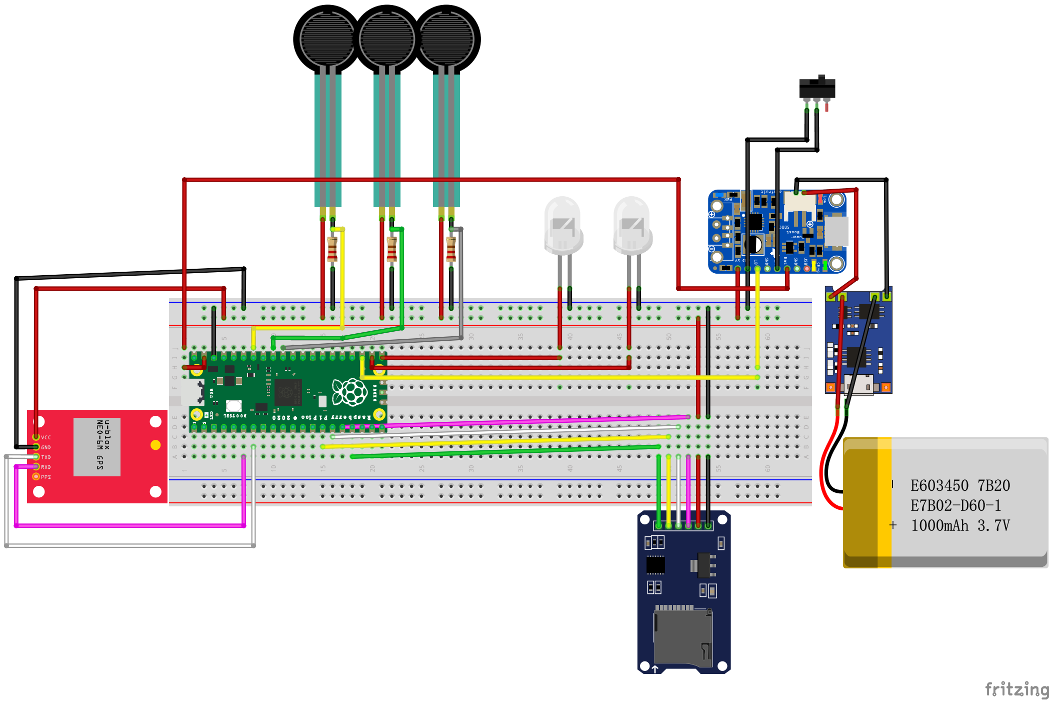


FIGURE 3.2: Figure of connection of all components

explained in detail here.

Raspberry Pi Pico

As the controller used in My Footprint, this component is an MCU product developed by the Raspberry Pi Foundation. It is equipped with an RP2040 microcontroller, which contains a dual-core Arm Cortex M0+ that can run at 133MHz. This provides it with strong computing performance. My Footprint uses these pins for UART communication, SPI communication, PWM control, and data input and output. Also, Pico comes with four 12-bit analog-to-digital converters (one for the on-board temperature detector and three for reading analog signal sources via IO connections), and it is through these high-precision, fast-response analog-to-digital converters that the device achieves higher accuracy measurements of plantar pressure characteristics. In addition, the Pico contains a high precision built-in timer. Although it cannot

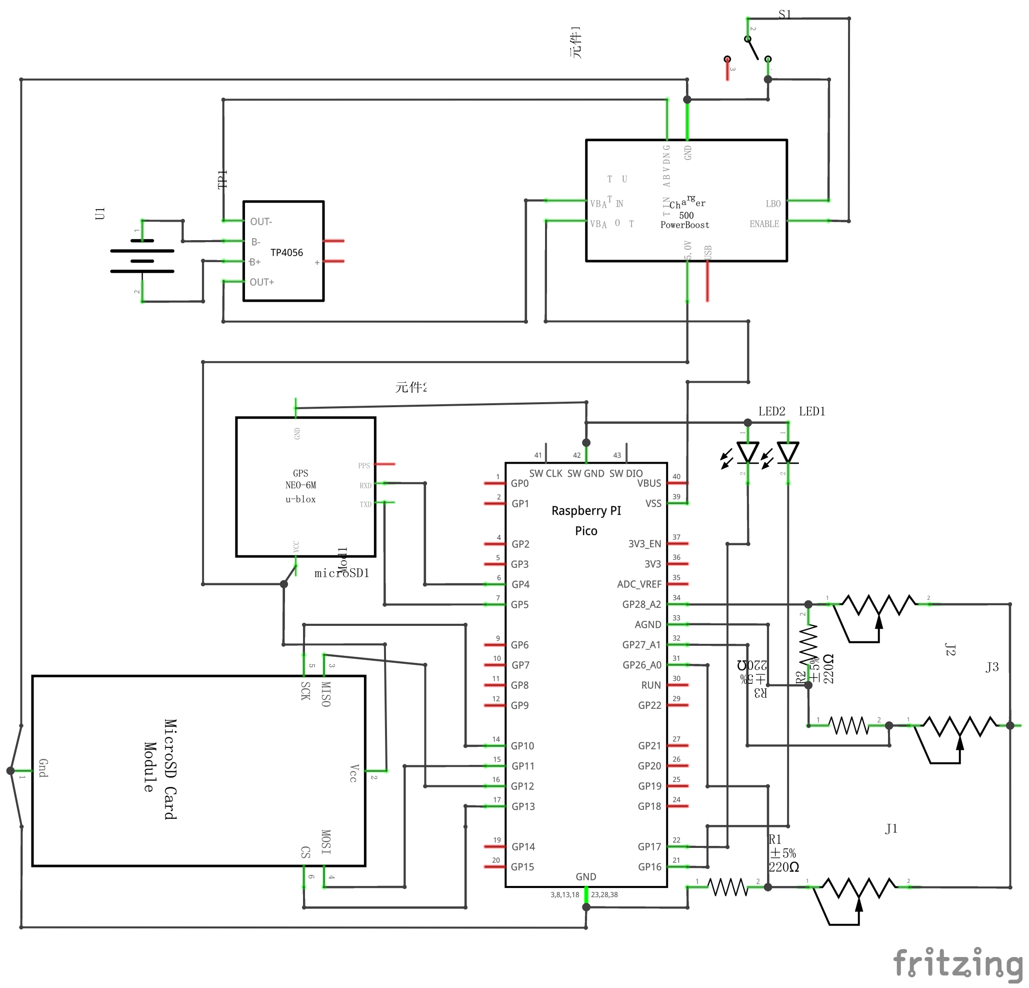


FIGURE 3.3: Figure of circuit schematic

save time data after a power failure, it can measure the time elapsed since the device was turned on with nanosecond accuracy. Using this feature only requires an initial time to be provided to function as a real-time clock.

GNSS Module (GY-GPSV3-M8T)

My Footprint's original design was tested with a GNSS module that only received GPS signals (KKHMF NEO6M MV2), but the accuracy of the data was difficult to achieve with a single satellite system. The average accuracy data provided by the official 24-hour test in the dual-system calibration mode is 2.0 meters. Also high precision timing data (outdoor clear error less than or equal to 20 nanoseconds, indoor less than or equal to 500 nanoseconds) can be received by the satellite. This device uses this data to time the MCU to obtain high-precision synchronized time data.

Membrane Pressure Sensor (FS-INS-3Z-V2)

The sensor is a three-sensing area thin-film sensor customized to the sensor manufacturer. The sensor consists of a circuit composed of pressure-sensitive material and a flexible conductive material printed between mylar films. When pressure is applied, the circuit is turned on and the sensing zone formed by the pressure-sensitive material is equivalent to a variable resistance that is turned on. The size of the resistance decreases as the force increases. The resistance value varies from approximately 1kΩ to 10kΩ in the on condition of the circuit. After physical testing in the early stages of the device design and fabrication, the variation curve resembles a hyperbolic function, and the resistance magnitude Ro and the force magnitude F can be roughly fitted to the equation

$$R_o = \frac{11672714}{(F + 1773)}, (F \neq -1773, R^2 > 0.99) \tag{3.1}$$

The sensor can respond to the force change with less than 1ms, and the force feedback within 0.1-30kg is tested to be more accurate. Also, the mylar film is waterproof and dustproof to protect the sensor and adapt it to the environment in shoes.

3.1.2 Software Design

This section describes the software development in this study based on the hardware in the previous section. The software is divided into two parts:

data collection and data processing. Where the data collection software runs on the device. The main purpose is to obtain the measurement data of each component and record it in a data file. The data processing software visualizes the data by reading the saved data files and organizing and analyzing them.

One of the data collection programs is written through MicroPython. The figure shows that the program consists of a-main program; b-GNSS driver; c-SD storage driver above three modules. Among them, the main program contains several data processing and control related modules. The GNSS driver uses the open source NMEA format interpreter MicropyGPS, which can parse the data statements obtained from the GNSS module by the MCU through UART communication and extract the data values from them. The SD storage driver defines how the MCU connects to the storage module via SPI communication and reads and writes data to the SD card. The source code for all programs in this section is available in the Appendix section. Next, the main program is explained in some detail.

- Since MicroPython inherits the modular programming feature of Python, the main program consists of several sub-modules. It consists of a-GNSS data formatting module, b-pressure sensor driver module, c-timing module, d-data logging module, and e-main loop. The a GNSS data formatting module parses the data and retains the latitude, longitude and time data by calling methods from the GNSS driver, and generates format-specific timestamps and timing data. And b The pressure sensor driver module is divided into two functions. The first function defines how the MCU reads readings from a specified analog-to-digital converter and converts them into pressure readings. The second function improves the accuracy of the measurement by calling the above method to take three measurements within 30ms and averaging them to output the final pressure reading. The third module, the timing module, calls the time data obtained by formatting the GNSS data and assigns it to the memory of the MCU as the initial time. This can be used to calibrate the MCU's timer and achieve the effect of a real-time clock. The module that calls the above method to get the data, format it and write it to the data file (*.log) is the d data logging module. (Data format: sequence number, time since last data (ms), time stamp, pressure 1, pressure 2, pressure 3, longitude, latitude, sequence number + E)

- As for the e-main program cycle, here is a simple explanation combined with the flow chart: light up the LED and check the battery level after power on; define the basic IO attributes and initialization parameters required by each module; initialize the main variables for saving data; execute self-test, self-test by checking the GNSS data, when the data is empty, it means the GNSS component has not been started yet, continue the cycle of self-test and flashing LED prompt; end the self-test after normal output of latitude, longitude and time data, write the time data into memory by calling the timing method to set the initial time, start the timer; get the time stamp from the real-time clock, load the SD card as the main working directory, create the log file, write the first line containing the start time of the log in the log file; enter the logging loop, call the data logging module every 60ms to write A record (because the three pressure sensors take 90ms to read, so the ideal interval for each record should be about 150ms), and call the PWM incremental (decremental) control LED brightness, while each cycle detects a low battery signal input. The operation indicator LED should show a gradual brightening and dimming breathing effect as the cycle progresses.

Also if low battery, the low battery indicator LED will light up.

- About running and stopping the program. For the Raspberry Pi pico, when the main program is saved as "main.py" in the onboard Flash storage, it will run automatically when the power is turned on. Each program module is stored in the Pico's onboard Flash memory (2MB) in this device. Toggling the mechanical switch connects the Pico to the voltage transformer and turns on the power. The Pico will boot up and automatically begin executing the main program from scratch. Since the data file will be opened and closed each time the data is recorded, the data file will not be affected by either an unexpected power failure or a shutdown. And after reboot will start recording from a new data file.

- Data processing. The log data file saved can be obtained by reading the SD memory card mounted on the device. The file is a simple text file that can be read line by line by the program to obtain the data. For the pressure sensing data, it should constitute a series of three data divided roughly by 150ms (in practice, the actual measurement is done at intervals of about 160ms, up to 200ms, according to the item "time since last data (ms)"). The device's sampling rate is greater than 5 Hz for each detection zone, and this sampling rate can satisfy the Nyquist's sampling theorem mentioned above concerning the normal human walking frequency (about 2 Hz), i.e., it can restore the mechanical characteristics of walking more completely. In the final experimental machine of My Footprint (two machines), the three data are named "L" (left front), "R" (right front) and "D" (back). They correspond to the sensing area of the specified location. The data are two floating-point numbers accurate to the sixth decimal place for latitude and longitude, corresponding to a realistic accuracy of about 1 meter. The time stamp defines the exact time to the second of each data for pressure sensing and location. The time to milliseconds can be obtained by adding the "time from previous data (ms)" term. By parsing the time and latitude and longitude data, it can be converted into a common GPS data format called "GPS eXchange Format" and used to plot the recorded trajectory. By assigning pressure-sensitive data values to the position points at the corresponding time points (since My Footprint's GPS position refresh is designed to be 1Hz, each position data corresponds to 5-6 pressure-sensitive data with the same time stamp), the pressure-sensitive and position data can be synchronized using the time stamp as a reference.

3.1.3 Design Iterations

My Footprint underwent several iterations during the design process, and the larger parameter changes and their corresponding justifications are listed here.

- The original design of this device used a thin-film sensor with multiple sensing zones. It was replaced with three separate sensors for power consumption and simplification reasons. The resolution of the plantar pressure data is therefore reduced. However, the three independent sensors are difficult to fix and can change position depending on the wearer. For the sake of stability and comparability of experimental data, a customized solution of three detection zones combined into one sensor was adopted. The experimental design was also adapted for data acquisition and analysis based on three detection zones.

- This is because GNSS elements do not work indoors. The device's original design considered the use of wireless positioning elements to maintain the positioning performance indoors. Due to power consumption and privacy and security concerns. In the data processing, the GNSS element returns "no signal" data when entering a building, which is used to determine the "break point" of the data, and the location point of the background map to determine which building the wearer has entered.

- The Pico can automatically convert a wider range of inputs to 3.3V outputs. The original design used the Pico's own 3.3 volt output port as a direct reference voltage for the three analog-to-digital converters to power the pressure sensing module. In the actual test, it was found that the voltage of this output port dropped significantly with the increase of access to appliances, and became more unstable with the change of temperature and other environmental factors, which greatly affected the accuracy of the pressure sensor. In addition, the load on the output also affected the performance of the MCU calculation. Therefore, a variable voltage element was added to stabilize the output voltage in the final design.

3.2 Experimental design

In order to answer the research questions mentioned in the research objectives, this study hopes to conduct wearing experiments with My Footprint. The device automatically collects plantar pressure and position data based on a time series after wearing. Based on these data, gait characteristics data can be calculated and analyzed. At the same time, the sequence of position information changes can constitute the movement trajectory of the wearer. This study expects to experimentally verify the correlation between action trajectory and gait characteristic data. This section will start with the experimental hypothesis obtained from the research question and prior studies, explain the expected data for the experimental verification of the hypothesis, and introduce the corresponding methods. Finally, the complete experimental procedure will be summarized.

3.2.1 Experimental hypothesis and expectations

The following experimental hypotheses can be formulated based on the three experimental questions posed in the experimental content and the relevant interpretation of literature studies and device design.

- H1: My Footprint can correctly and consistently acquire plantar pressure characteristic data and location information while walking in outdoor conditions.
- H2: When H1 holds, the data collected by My Footprint can be relevant to reflect changes in behavior.
  - H2.1: Changes in location information can be correlated to reflect changes in behavior.

- H3: When H1 holds, the data collected by My Footprint can reflect the relationship between gait feature information and location data.
  - H3.1: The position data can reflect the change in plantar pressure characteristics during walking.
  - H3.2: The step length/step frequency characteristics calculated from the time series data of plantar pressure can reflect the relationship with the position data.
- H4: When H2 and H3 hold, the data collected by My Footprint can reflect the relationship between characteristic gait information and behavioral characteristics.

For H1, it is easy to know a certain physical pattern of human position movement and plantar pressure changes during walking. The recorded results should be consistent with the prescribed route when walking a prescribed route with My Footprint. For the plantar pressure data, since the pressure sensors have been calibrated during the design and production of the device, and the human walking process regularly applies pressure to the three measurement points, the measurement data should also reflect this regularity. The measurement data in the standing stationary state should not show the data fluctuation of walking state.

For H2, the data collected by My Footprint should be classifiable and analyzable in the time series if it reflects behavioral changes. Specifically, for H2.1, the location data should be linked to form a time-series-based trajectory, and the different trajectory intervals should reflect significant differences in the classification of the wearer's behavior.

For H3, there should be at least one feature quantity associated with the classification of location information or trajectory information if the relationship can be reflected. Specifically for H3.1, the change in plantar pressure values (at least one of the three measurement points) should be associated with location information; and for H3.2, the calculated stride length/step frequency feature should be associated with location information. If there is more than one correlation term, a three-dimensional evaluation criterion based on all correlation terms should be established.

For H4, a judgment indicator reflecting behavioral change (associated with measurement data) can be established according to H2, and a judgment indicator of gait characteristic information can be established according to H3. The two indicators are tested for the correlation between behavioral change and gait characteristic information.

3.2.2 Experimental method

- For the inspection of H1 . To verify the correct data acquisition by the device, a task can be set to follow a prescribed route and check whether the output data matches the characteristics in the prescribed route. The prescribed route should contain straight-line walking, turning, and stopping items that can check the accuracy of the positioning data. The walk-stop-walk transition should also check the sensing condition of the pressure sensor. Since the device has been quantitatively calibrated during the assembly and commissioning phase, the output data visualization (trajectory map and pressure waveform graph) here is a qualitative check that the device is acquiring the required data correctly.

- For the test of H2 . In order to check the correlation, it is first necessary to obtain the relevant benchmarks of behavioral change. Because the data collected by My Footprint are time-series, the behavioral logs of the experimental collaborators can be collected separately. The relationship between the relevant data and behavioral change can be determined qualitatively by cross-referencing in the log study method. Since the source data are discrete quantitative data and behaviors are often continuous, they can be transformed into category data by intercepting a time segment and classifying it for easy comparison. Specifically for testing H2.1, by intercepting the location trajectory and converting it into qualitative data according to the "start-end", and then comparing it with the behavior log according to the time series, if the qualitative data of the trajectory can be classified and it is proved that the two are not unrelated, then H2.1 holds.

- For the test of H3. In order to test the correlation, the corresponding judgment index should be established from the data acquired by My Footprint. It is known that the data of pressure changes over time in three sensing areas (left front, right front and back) are collected, from which the number of steps in the specified time interval can be obtained (the number of peaks in the three sensing areas is averaged), and this data can be further processed to obtain the step frequency. At the same time, according to the position data recorded under the synchronized time series, the total distance moved can be calculated, and using this distance, the step length in the specified time interval can be calculated. Also, for plantar pressure data, the average of the eligible peaks in a time interval can be used as an evaluation criterion for the "force level" of walking during the interval. If a standard segment of data is collected that reflects the characteristics of a normal walking gait, and other records are compared to it, other records can be classified. Assuming that the criteria of "exertion" and "speed" are used, the records with walking speed exceeding the standard data obtained from the position data and time series can be classified as "fast" and vice versa as "slow". As for the "degree of exertion", if the average peak in the record is greater than the standard data, we can classify it as "heavy", and vice versa, we can classify it as "light", so that we can get four different gait categories (fast-heavy, fast-light, slow-heavy, slow-light). On this basis, we can continue to create "high frequency", "low frequency", "large step" and "small step" classification indicators Further refinement of the classification. H3 can be verified by performing correlation tests with the same classified location data records after establishing the judgment indicators.

- For the test of H4. After testing H2 and H3 by the above method and holding, H4 naturally holds because there is a correlation between two of the three.

3.2.3 Experimental procedure

After selecting the experimental method based on the above experimental hypothesis and related expectations, a set of experiments with three stages was designed in this study. The collaborators of the experiment were required to complete the corresponding experimental phases according to the researcher's instructions. Thirty collaborators were recruited for this experiment.

Preparation Stage

In the preparation phase, the main components were the description of the experiment, the selection of participants, the dressing exercise, and Task 1: prescribed route walking.

- The researcher will explain the experiment to the research collaborator based on the experimental instructions in the experimental description section. The explanation includes the entire procedure of the experiment and how to operate the device. After listening to and understanding the instructions, the investigator will sign a consent form indicating his or her willingness to participate in the experiment.

- Participants were screened after completing the experimental description using a screening questionnaire, a pre-designed evaluation scale consisting of three single-choice questions. Collaborators completed the questionnaire using a tablet prepared by the researcher. The five answer options for each of these questions were ranked in order of degree, and respondents were asked to select the one they felt best fit their situation. The purpose of this scale was to screen out participants who were unfit to wear My Footprint and to terminate the experiment in time to avoid any safety hazards or invalid participation. The experiment should be terminated immediately when the answer to any question was received [5]. In other cases, the researcher will decide to continue the experiment in the field. After completing the participant screening, the next step was taken.

- During the proper exercise, the researcher showed the collaborator how to use the device and how to stop it and informed the collaborator of the meaning of the LED signal. The participant selects an appropriate size adhesive insole. After confirming that the participant's shoe will hold the My Footprint properly, the researcher helps the participant attach the pressure sensor to the adhesive insole at the designated location. The My Footprint clip was used to secure the box-like structure to the outside of the shoe. After the researcher visually determined that the device was stable, he instructed the collaborator to wear the shoe. The collaborator then turned on the power and performed walking, standing, running, and jumping exercises as required by the researcher, taking a 30-second break after completing more than one set of activities before repeating the next set, for a total of three groups. The collaborators were asked to check whether the device interfered with their normal movement during the exercise and to adjust the position of the box-like structure of the device appropriately. The researcher also needed to check any unexpected power disconnections or restarts during the training. The experiment terminated if the collaborator felt that the average movement was hindered at the end of the activity or if the investigator felt that the device was acting abnormally. Once the exercise was completed, the participant left the initial location and proceeded to the next step outside.

- When performing Task 1: Prescribed Route Walking, the collaborator is considered to have adapted to the actions of the wearing device through the practice phase. After arriving at the designated outdoor location, the power restarts My Footprint and waits for the signal indicating that the GNSS is working properly to come on. After the signal appeared, the researcher explained the prescribed route to the collaborator. The prescribed route: In this experiment, it was designed to go from the entrance of the building where the experiment started to the main entrance of the supermarket Kasumi, about 100 meters away, and wait for 10 seconds (silent count to 10) before returning to the same location as the entrance of the starting point. After the collaborators indicated that they understood the route instructions, they were asked to take a deep breath, count silently to 50 (to calm their emotions and post-exercise signs), and then walk. The researcher was required to record the completion time of the prescribed route using a stopwatch and mark the 10-second interval in which to stop in the stopwatch record. After returning to the initial location to finish the route, the researcher stopped the stopwatch and instructed the collaborator to power off the device and remove the SD memory card. The researcher reads the data from the memory card and obtains the data record for Task 1. The SD card is then placed back into My Footprint, and the researcher checks the data from Task 1 and continues the experiment if there are no abnormalities.

After completing all the above steps, the preparation phase is considered over. This phase takes about 20 minutes.

Experimentation Stage

The main task included was Task 2: Record the experiment during the Experiment Phase.

- After the preparation phase, the collaborator can turn My Footprint on again and leave the initial location. my Footprint is considered the start of the experiment phase when it is turned on again. The collaborator needs to complete Task 2: Record the Experiment during this phase. The specific part of the task is to wear My Footprint for daily activities. The recording phase lasts for more than 5 hours and can be ended or postponed at any time if the collaborator wishes. However, only experimental phases lasting 60 minutes or more are considered valid. The duration of the experiment is calculated based on the total time My Footprint is on, and data within 300 minutes is considered valid. Data longer than 300 minutes cannot be used because of the drop in output voltage caused by the long working hours of the battery. No definite time is specified for the end of the phase, but data that crosses a natural day (until 24:00 pm) is also considered invalid. In order to obtain natural data, the first and last 30 minutes of the valid data (the time band that "leaving the initial location" and "returning to the initial location" may contain) are also not used in the data analysis. The return of the collaborator to the initial location and the unloading and return of the My Footprint with its power off was considered the end of Task 2 and the experimental phase.

There are no restrictions on how and what the collaborators can do during this phase. This phase took more than 60 minutes if the data were valid, ideally 300 minutes.

Closing Stage

When collaborators return My Footprint, the experiment is considered to have entered the closing phase. This phase consists of four steps: data recovery, collaborator grouping, presentation of results, and log recall.

- The researcher took out the device's memory card after getting the recycled My Footprint and put the device in the recycling place to wait for processing. After reading the recorded data stored in the memory card, the number of data files can be used to determine whether the device was turned off or restarted during the recording process. All data files are processed to obtain the total length of recording, and if the total length is greater than 60 minutes, it is saved as valid data. If the total length exceeds 300 minutes, the 300 minutes of records starting from the initial record is cropped and saved as valid records.

- In this experiment, all participating collaborators were divided into three groups, A, B, and C, for a controlled experiment (10 from each group based on a planned population of 30). Group A was used as the reference group and skipped the presentation step after data collection was completed; Group B was the map presentation group and Group C was the location data presentation group, and collaborators in these two groups proceeded to the next step.

- In the display of results step, a map of the data recording area is displayed for collaborators classified as group B. Collaborators classified as group C are displayed with their valid data portion of the location data constituting the action track on the map of the recording area. The next log recall step is performed simultaneously with the presentation.

- Collaborators were required to complete a log recall survey. This survey was a pre-designed questionnaire consisting of three main questions and three supporting questions. The collaborators completed the questionnaire using a tablet prepared by the researcher. The first main question asked the collaborators to recall and write a log of their activities during the recording experiment in the form of "time-place-action-mood" as much as possible. The second and third questions were two simplified five-item Likert scales that asked the collaborators to rate the ease of recalling the activity log and the supporting role of the presented results in the recall process. Answers were given on a scale from 1 to 5. To calculate the score, the answers were scored on a scale of -2 to 2 and the scores of the two outcomes were summed to obtain a scale value for evaluating the strength of the supporting role. For group A collaborators, the score is fixed at 0. For groups B and C collaborators, the score is a quantitative figure ranging from -4 to 4.

After completing the above three phases, a complete experimental cycle is considered to be completed. The investigator should archive the recovered data of the cycle according to the collaborator number and keep it for data analysis. At the same time, the My Footprint is disinfected and cleaned, and then the sensor is re-tested and calibrated for the next use.

3.2.4 Ethical Considerations

The Ethics Review Committee of the Faculty of Arts, University of Tsukuba on October 13, 2021, reviewed this experiment, and the specific results can be found in the document. All collaborators of the experiment received a complete description of the experiment and signed a collaborative consent form at the beginning of the experiment. In addition, the collaborators were allowed to stop the experiment at any time on their own during the long recording time. The experimental set-up was designed with full privacy in mind and was recognized by the ethical review.

Chapter 4

Experiment

4.1 Experiment preparation

Before the experiment, the investigators continued to The final design of the My Footprint device was completed in October 2021. The researcher built two experimental machines according to the final plan in the same month. To test the form of the data collected by the device and its reliability under prolonged operation, the researchers conducted a Pilot experiment consisting of two tasks. This experiment examined the accuracy of the device's positioning data through task 1: prescribed route walking, and task 2: recording experiment, which ran the machine for an extended period to examine the changes in recorded data over time. The different forms of the two tasks in this Pilot experiment were also used to determine the overall effect of "motivation" on the wearer's data feedback during walking.

4.1.1 Dual-task walking experiment

After the pilot experiment, an experiment with prescribed walking routes was designed to determine further the role of "motivation" in the overall walking behavior and the correlation between the data collected by the device and subjective Kansei performance. In this experiment, participants wore the device and completed four walking route tasks prescribed by the researcher. A NASA-TLX scale was administered after each task to obtain the facilitator's subjective assessment of the task load. Based on a comparison of the scale data with the recorded data, an attempt was made to find items in the recorded information associated with this subjective rating and their specific correlations. The experimental task consisted of four walking routes of approximate length, two of which were pure walking routes that did not include the execution of the task (the facilitator was asked to wait 10 seconds when reaching the turnaround point) and two of which had different kinds of motivational designs for the task. Other task execution sequences were used to avoid bias in the experimental results caused by the series of tasks. The specific tasks are shown in the figure. After the research collaborators completed each task, the collaborators were asked to complete the NASA-TLX scale for the route they had just taken and to rest. After one experimental cycle, each collaborator provided four sets of data results. The first set (fixed as a simple route task without a task) was used as the practice set, leaving the remaining three sets available for analysis and comparison. To further uncover possible associations with Kansei in the experimental results, the experimental design used a logical task (memorizing the names of books), which primarily invokes intellectual memory capacity, and a Kansei task (picking a favorite drink), which mainly relies on subjective judgments and habits, in a controlled manner.

4.2 Experiment implementation

The specific experimental arrangements considered the weather factors and avoided the periods when rain caused changes in pavement characteristics. Also, no sudden rainfall occurred during the experiment. It can be assumed that each collaborator experimented with approximate pavement conditions. The experimental data collection was restricted to the central and southern sections of the University of Tsukuba campus. The specific areas can be found on the campus map provided by the university.

There were some unexpected circumstances in the actual recording experiment. In the original design, the GNSS system would stop working immediately when the signal was lost indoors, and the "breakpoint" where the signal was lost could be used to identify and mark the building where the wearer was located during the data analysis. However, in the experiment, the collaborator received a weak GNSS signal near the window and the entrance/exit of the building, and even occasionally inside the building, and triggered the data recording of the device. In this case, the recorded data points deviated significantly from the actual location (similar to the "drift" phenomenon of smartphone GPS positioning when the signal is poor). Since the device algorithm does not filter for such cases, these deviations are also recorded as accurate data. This had a significant impact on the overall experimental recording results. The school also has areas where there are several buildings connected in a complex, and students often choose to move around inside the buildings instead of from outdoors daily. This further increased the amount of complex data. Since the problem arose from the underlying mechanism of the GNSS module, it could not be improved in a short period. After all, experiments were completed, the researchers screened the resulting data several times, removing the vast majority of the unanalyzable data through manual program and trajectory visualization methods. The problem also resulted in data from inside the building not being available for analysis.

In the dual-task walking experiment, the route was designed to avoid going through areas with many buildings. The collaborators were also allowed to carry a smartphone with a GPS location record during the experiment.

The recording results of the smartphone were compared with those of the device and corrected for the data around the buildings (in the case of this experiment: after entering the target library and supermarket).

FIGURE 4.1: Calibration is performed by comparing the smartphone's level measurement results with the device's data.

For the collected data, a point-to-point comparison was performed (since the nominal accuracy of the device is greater than that of the smartphone, the average value per second was used for the calculation). For the in-building scenario, a correction was made when the device's data showed a significant offset. An example of the calibration is shown in the table4.1, where the error between all measured data points and the results recorded by the smartphone was less than 0.5 m (the nominal accuracy of the smartphone is 1 m).

TABLE 4.1: Example of GPS calibration

Descriptive Analysis						
Items	**N of samples**	**Min**	**Max**	**Mean**	**Std. Deviation**	**Median**
Diff.longitude (measurement - smartphone)	5970	-2.060	2.630	0.423	0.594	0.140
Diff.latitude (measurement - smartphone)	5970	-3.350	1.830	-0.538	0.680	-0.140

4.3 Experiment results

4.3.1 Overall results

First, for the overall recording results. None of the experimental procedures of the Pilot experiment required stopping the recording and interrupting the experiment. The overall evaluation device run time for the experiment was approximately 288 minutes, closer to the five hours in the design. From the beginning to the end of the experiment, the investigator received no feedback or comments about the device interfering with daily movement, causing fatigue, injury, or discomfort.

Eight collaborators were called to participate in the prescribed route walk experiment and completed the defined task. One of the collaborators misunderstood the route during the practice route, but the rest of the data were recorded typically.

4.3.2 Task 1: prescribed route walking

This project measured walking data of a fixed route by wearing a device. A total of 30 valid experimental data were obtained. The project's experimental design required approximately 300 meters of walking, which was expected to be completed in 3 to 5 minutes. In the actual experiment, the average walking distance of the 30 experimental records was 287.798 (in meters, where the maximum value = 315.09 and the minimum value = 269.14). The median distance traveled was 286.690, with a standard deviation of 10.999. As for the overall time spent on the route, the average time spent for the 30 samples was 231.101 (in seconds, where the maximum value = 280.036, the minimum value = 171.456, and the median value = 232.582). The standard deviation of the time spent was relatively large, reaching 32.498. affected by this data, the calculated walking speed (mean = 1.322 meters per second, standard deviation = 0.186, median = 1.309) of the average number of pressure records in the sensing area (mean = 1091.47, standard deviation = 155.713, median = 1090) also produced a large standard deviation . In addition to the fixed route, the collaborators were asked to stand at a designated location for 10 seconds. The mental math of the collaborators determined these ten seconds, and the final stopping time averaged 9.278 seconds (maximum = 12.231, minimum = 6.799, standard deviation = 1.504).

In addition to the conventional results above, this experiment also provided 30 path records. These 30 records were a sequence of quantitative data based on a time series consisting of longitude, latitude, and three plantar pressure zone readings. The recording was performed in the researcher's line of sight throughout. The Hopper effect could be examined by sampling the walking portion of that segment of the data and the equivalent length of the recording experiment (which required being on foot), respectively, and then analyzing the entire sequence of recordings or other segments of the data. Here 4.2, a partial data sample of the path data trajectory visualization and pressure data left by the 30 paths.

4.3.3 Task 2: Recording experiments

A total of 30 recorded data were intercepted in this project by continuous recording by the device and following the rules designed by the research methodology. The standard data length in the design was 300 minutes, and

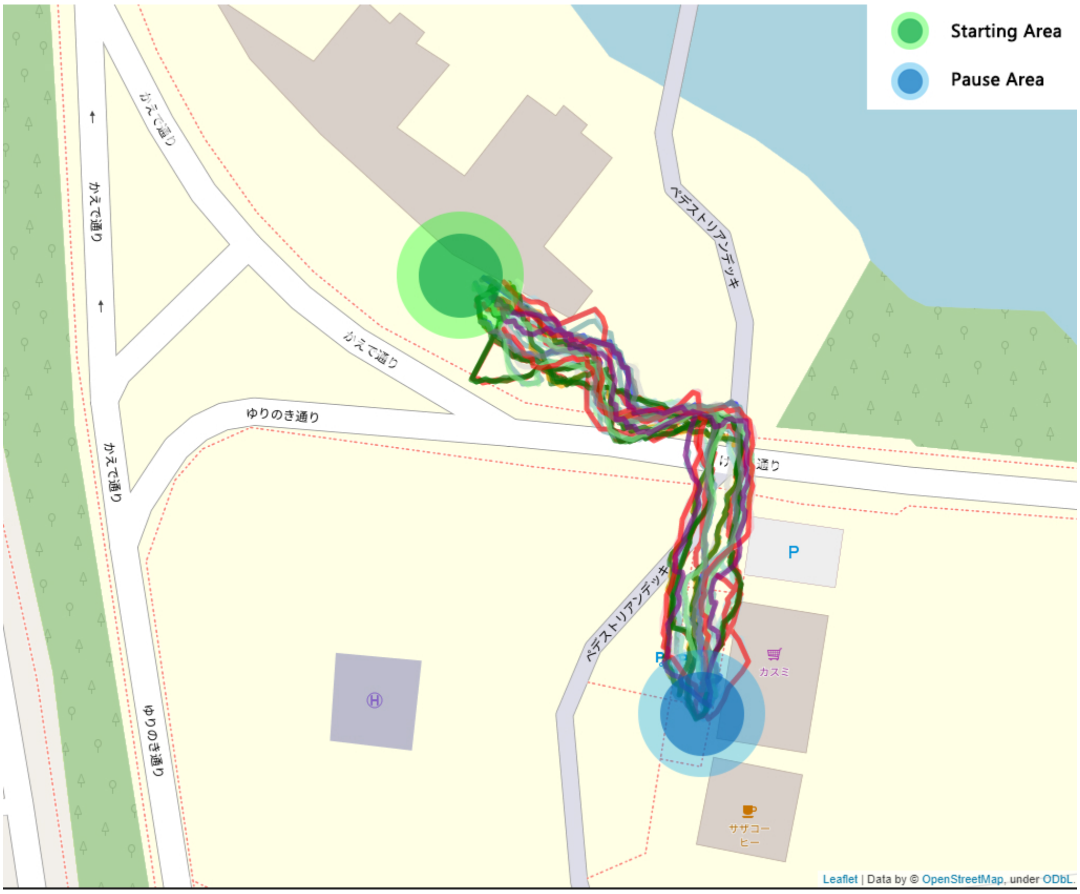


FIGURE 4.2: Plotting of all route tracing results in Task 1

the data content included data from the localization point and the three pressure zones. Because of the abnormal data caused by the abnormal operation of the indoor positioning device during the experiment, the data for this project were collated at the time of use, as described in the Data Processing subsection.

4.3.4 Dual-task walking experiment

For the task design, four task routes of approximately 150 m were designed for this project, and there were no areas requiring extensive walking at the task site. A total of 32 paths4.3 and their corresponding plantar pressure data were collected as experimental results and 32 responses to the NASA-TLX scale4.2. The experimental results corresponding to each subject are detailed in the Appendix.

FIGURE 4.3: Plotting of all route tracing results in Dual-task walking experiment

4.3.5 Data processing - Pilot experiment

Data organization is required for the collected positioning information and pressure sensing data. First, the positioning information can be qualitatively

TABLE 4.2: Statistical results of TLX scale

Items	**Subtotal**							**Total**
	Collaborator No.							
	01	02	03	04	05	06	07	
MD	38.750	2.500	16.250	25.000	45.000	42.500	40.000	30.000
PD	12.500	3.750	10.000	18.750	55.000	46.250	53.750	28.571
TD	10.000	3.750	51.250	42.500	52.500	50.000	55.000	37.857
Perf.	2.500	2.500	0.000	10.000	62.500	25.000	65.000	23.929
Effort	31.250	5.000	21.250	8.750	48.750	46.250	50.000	30.179
Frus.	28.750	1.250	10.000	0.000	23.750	32.500	30.000	18.036

visualized in the map with the time stamp to visualize the positioning information trajectory. Among them, the positioning information of item 2 needs to be processed in segments because of the very long duration it contains. In the original design, the data can be classified based on the device's loss of GNSS signal when the wearer enters or leaves the building. However, in the actual experiment, this determination point is very unreliable because of the GNSS hardware problem mentioned earlier. Therefore, the data from Task 2 were sorted manually, and a total of 52 pieces of valid data that could determine the starting and ending points were screened and truncated. The results of the trajectory visualization of the 52 path data are shown here 4.4.

As for the mechanical sensing information, there is no complete mechanism for classifying specific movements in this study, which makes it impossible to distinguish the different movements of the wearer in the measured data, although the data of Task 1 can clearly distinguish between "walking" and "standing" data. Here, the pressure sensing data corresponding to the 52 path trajectories were analyzed as the pressure change pattern during "walking."

At the same time, the total amount of pressure sensing data is vast, and each data needs to be pre-processed during the analysis to be analyzed effectively. In general, the valid primary data that can be calculated from this

FIGURE 4.4: Plotting of organized route tracing results in Task2

data include "number of steps" and "plantar pressure intensity."

The number of steps is calculated by first standardizing a sensing data series, i.e., the pressure data above the threshold is recorded as 1. Otherwise, it is recorded as 0. After standardization, we can solve the number of times the corresponding sensing point touches the ground according to this data series. Because of the location characteristics of the sensing area, here we average the calculation results obtained from the front two areas, which can be considered as the number of times the front of the foot touches the ground.

This value is then averaged with the corresponding results of the rear sensing zone to obtain the number of sensing times within a time series, i.e., the measured value of the number of steps.

As for the plantar pressure strength, after repeated tests, the accurate range of the pressure sensor used in this experiment is about 0-20 kg. At this time, the data will be normalized, the results above 20 kg are normalized to 20 kg, the threshold value in the step count calculation is taken, and the data below the threshold value is recorded as 0. At this time, the corresponding average plantar pressure data can be calculated for each of the three sensing points within a time series.

The data of task 1 is taken as an example, and the step count, forefoot pressure, and heel pressure of 30 samples can be obtained after processing. The average number of steps was 195.8, with a standard deviation of 20.054. The average forefoot pressure was 6.54 kg with a standard deviation of 0.706. The average heel pressure was 3.70 kg with a standard deviation of 0.508.

4.3.6 Data processing - Dual-task walking experiment

The data collected for each collaborator contains four large data series (data pairs containing both the collected data and the questionnaire scale data). To make these sequences analyzable, the researcher must extract the corresponding characteristic quantities. In the case of the NASA-TLX scale, the researcher performed no weight calculation in the data processing because the experimental purpose was not to evaluate workload according to weights. Still, the scores of the corresponding items were extracted directly from the scale for simple analysis. For the recorded data, the plantar pressure data series can be removed from the data according to the previously described method. After processing, the "number of steps," "average plantar pressure" (left, right, and back), "walking speed," "completion time," etc., can be obtained for each task route. Time to completion" and other evaluation indicators. Using the location data, these indicators can be further subdivided, and the task route includes three nodes: "departure," "execution," and "return." The departure and return can be grouped using the location data, and the grouping can be compared to analyze the collaborators' status changes before and after the task is performed.

Chapter 5

Conclusion

5.1 Discussion

5.1.1 Pilot experiment

The results obtained in this experiment have been presented in the experimental section with qualitative data and their visualization. Based on the experimental results, the parameters "number of steps" and "plantar pressure" were calculated to evaluate the relevant characteristics of walking. For Task 1, due to the similar length of the route, the researcher summarized the following table of statistical data.

TABLE 5.1: Descriptive Analysis Result of Task 1

Descriptive Analysis						
Items	**N of samples**	**Min**	**Max**	**Mean**	**Std. Deviation**	**Median**
Walking Distance	30	269.140	315.090	287.798	10.999	286.690
Total Time	30	182.278	291.717	231.101	32.498	232.582
Walking Time	30	171.456	280.036	221.823	31.873	222.298
Waiting Time	30	6.799	12.231	9.278	1.504	9.425
Number of Records (Pressure)	30	860.000	1394.000	1091.467	155.713	1090.000

At the same time, for some of the extracted routes in Task 2, the researcher visualized them using heat maps5.1.

After visualization, the researcher noticed that the heat map distribution of pressure showed different characteristics in different paths. After reading

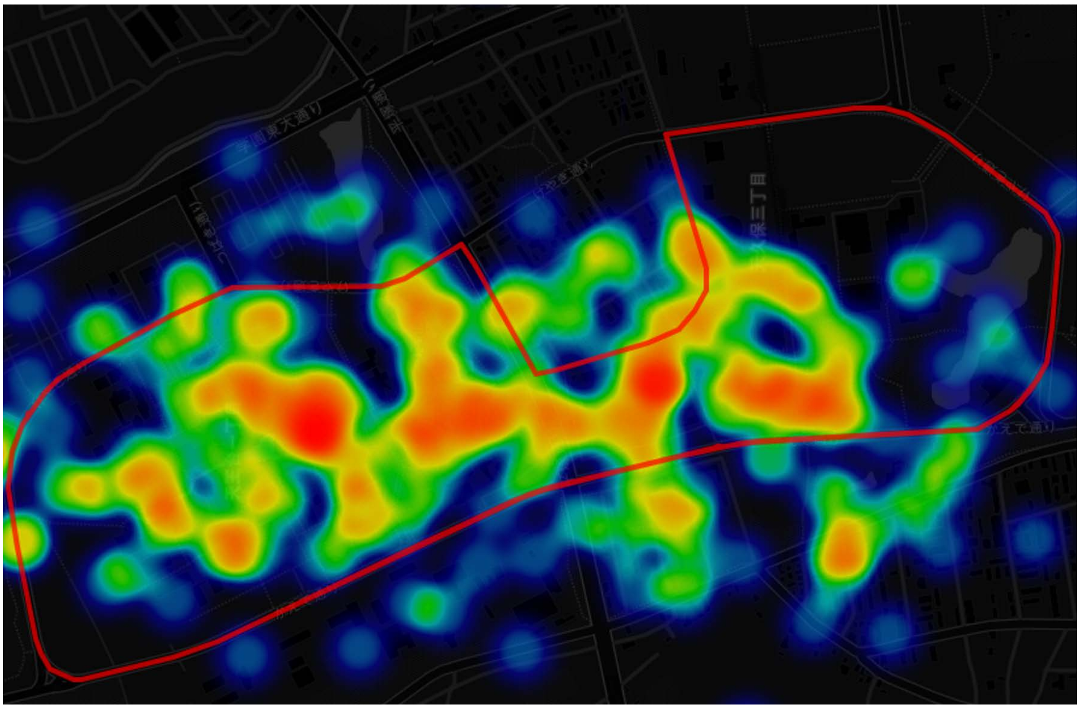


FIGURE 5.1: Heat map plotting of results in Task2

the data, it was found that the distribution could be significantly different under the influence of significantly different motives such as "going to the cafeteria" and "going to the library" 5.2.

Therefore, the researcher proposed the hypothesis:

H5. The recorded data of My Footprint can reflect the walking characteristics driven by different motives.

For the pre-existing experimental hypothesis, the investigators concluded that for H1, the experimental results from Task 1 showed that the recording results were consistent with the prescribed route when walking the prescribed route wearing My Footprint. As for the plantar pressure data, the variation of the data in the three pressure zones showed a regularity of fluctuation in each step. The measurement data in the standing still condition showed flat and straight data characteristics. It can be assumed that the My Footprint recordings can reflect the natural movement state.

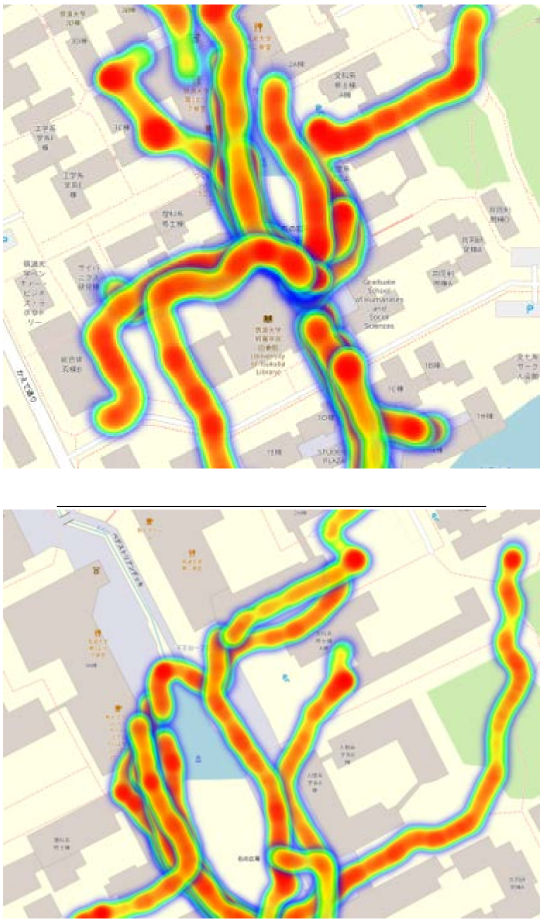


FIGURE 5.2: Heat map plotting of "go to library" and "go to cafeteria" results in Task2

For H2, according to the experimental results of task 2 and task 1, we can draw different trajectory images and obtain the pressure sensing data of the time series. Each trajectory record has its corresponding pressure change information. Specifically for H2.1, we can obtain 52 different path trajectories by task 2, and these path trajectories reflect the differences in the wearer's actions.

For H3 and H4, specifically for H3.1, we tried to establish an evaluation criterion of "number of steps" and "average plantar pressure" through the results of task 1. Each trajectory could calculate its corresponding value and reflect the association between the average value of plantar pressure and The relationship between the average plantar pressure value and the trajectory. However, further analysis and more experimental data are needed to verify the relationship.

Therefore, the researcher believes that, through the experiment, H1 and H2 are more fully validated, which is sufficient to show that the design device of this experiment can meet the data recording needs related to gait and position information recording. H3 and H4 are partially validated. Qualitative data can evaluate the correlation between trajectory data and plantar pressure, but the specific correlation characteristics need further experimental verification.

The study requires further motivation-specific driven experiments to further validate H3, H4, and H5.

5.1.2 Dual-task walking experiment

Through the data mentioned above processing method, the researcher analyzed the data of each collaborator in terms of "collected data" and "scale data." The data can be grouped in several different ways. First, do the "subjective scores" and "recorded data" change depending on the "different tasks"? Since the experiment was conducted in a broken order, it is possible to ignore the effect of the order of conduct to consider whether there is an intuitive difference in the results between task 1 (library) and task 2 (supermarket). To visualize the data, we can create a heat map of the task in progress by combining the position data with evaluation benchmarks such as "plantar pressure" and "speed." One of the heat maps based on the change of plantar pressure is shown in Fig5.3.

Second, is there a link between "recorded data" and "subjective scores"? By comparing the scores on each TLX scale with each recorded data indicator,

TABLE 5.2: Table of subjective scale scores and plantar pressure results obtained according to task grouping

Items	Subtotal				
	Task				Total
	1	2	3	4	
TLX-MD	35.714	48.571	15.714	20.000	30.000
TLX-PD	20.714	30.714	33.571	29.286	28.571
TLX-TD	30.714	40.714	40.000	40.000	37.857
Pressure-R	11964.985	12497.596	14125.592	14215.154	13200.831
Pressure-L	12462.517	12911.825	14683.312	14607.460	13666.279
Pressure-D	12917.961	13364.268	15137.022	15131.972	14137.805
Pressure-Avg	12448.488	12924.563	14648.642	14651.529	13668.305

it was possible to consider whether any recorded data reflected changes in the subjective perceptions of the collaborators.

By correlating the "subjective scores" and "plantar pressure data" as quantitative data, we can obtain the following results5.4.

It can be seen that the correlation coefficients between MD (mental demand score) and R (right side pressure), L (left side pressure), D (bottom pressure), and Pre-Avg (mean pressure) are not significant. The correlation coefficient values are -0.064, -0.106, -0.096, and -0.089, all of which are close to 0. The p-values are all more significant than The correlation coefficients were -0.064, -0.106, -0.096, -0.089, all close to 0, and all p-values were more significant than 0.05, implying no correlation between MD and R, L, D, Pre-Avg. The correlation coefficients were 0.649, 0.640, 0.675, and 0.661, and all of them were greater than 0, implying a positive correlation between PD (physical demand score) and R, L, D, and Pre-Avg. TD (temporary demand score) and R, L, D, and Pre-Avg all showed significant correlation with coefficient values of 0.544, 0.504, 0.468, 0.511, and all correlation coefficient values were greater than 0, implying a positive correlation between TD and R, L, D, Pre-Avg.

It is easy to see that the plantar pressure in the measured data changed with the task. And at the same time, the subjective workload perception of the collaborators through the TLX feedback also varied depending on the task. By comparing the physical and temporary load scores with the plantar pressure measurements in the TLX results, it can be concluded that the changes in the measured plantar pressure data under the conditions of this experiment may be correlated with the subjective perception of physical load (corresponding to the perception of "fatigue").

5.2 Discussion of the results combined with Kansei

5.2.1 Interpretation of subjective perception scores

During data analysis, the researcher noticed a strong correlation between some of the scores on the TLX scale and the collected data. At the same time, there were regular variations depending on the task. The first is Physical Demand (PD), which intuitively represents the perceived physical load of the task on the collaborator. (In other words, "fatigue") In the design of the four tasks, the round-trip distances were intentionally designed to be approximately equal in length. It means that the objective physical loads of the four tasks should be similar. The differences in subjective ratings can be considered as feedback from the "fatigue" of the collaborators. Since the experiment was conducted consecutively, the problem that the later tasks were more likely to produce fatigue inevitably arose, so the tasks were released in a disordered manner.

Next is Temporal Demand (TD). Similar to the interpretation of PD, TD can be interpreted as a "sense of urgency," which in this experiment is the degree of urgency to complete the task felt in the process of moving.

TABLE 5.3: ANOVA analysis of TLX results according to task classification

ANOVA						
	Task (Mean±Std. Deviation)				*F*	*p*
	1 (n=7)	2 (n=7)	3 (n=7)	4 (n=7)		
PD	20.71±12.72	30.71±23.88	33.57±28.97	29.29±26.84	0.374	0.772
TD	30.71±21.30	40.71±26.68	40.00±24.66	40.00±28.28	0.248	0.862
MD	35.71±23.70	48.57±27.65	15.71±9.76	20.00±22.55	3.297	0.038*
Perf.	27.86±33.77	25.00±29.86	21.43±26.57	21.43±27.19	0.078	0.971
Effort	27.86±16.55	45.71±25.24	18.57±19.30	28.57±30.37	1.625	0.210
Frus.	12.14±11.85	31.43±31.05	11.43±9.45	17.14±22.89	1.405	0.266

*** p<0.05 ** p<0.01**

From the above discussion, we found that if there is a correlation between the collected data (in the previous case, mean plantar pressure) and the above subjective scores, it may be possible to describe the "fatigue" and "urgency" of the collaborators through the data.

So do these scores vary by the task? The researchers conducted an ANOVA analysis of TLX results according to task classification. The results were as follows5.3.

It can be found that using ANOVA analysis to investigate the differences of Task for PD, TD, MD, Perf., Effort, Frus. for a total of 6 items, it can be seen from the above table that the different Task samples do not show significant (p>0.05) for PD, TD, Perf. All of them show consistency and no difference. In addition, 1 item of the Task sample showed significance for MD (p<0.05), meaning there is a difference between Task samples for MD.

5.2.2 Discussion of the correlation between recorded data and subjective scores

The above discussion has led us to two interpretations of the experimental results: 1. there is a significant association between mean plantar pressure and the results of PD and TD scores; 2. there is no significant difference in

TABLE 5.4: Linear regression analysis of PD score and mean plantar pressure

Parameter Estimates (n=28)									
	Unstandardized Coefficients		Standardized Coefficients	t	p	VIF	R^2	Adj R^2	F
	B	Std. Error	$Beta$						
Constant	-119.773	33.154	-	-3.613	0.001**	-	0.438	0.416	$F(1,26)=20.225, p=0.000$
Pre-Avg	0.011	0.002	0.661	4.497	0.000**	1.000			

Dependent Variable: PD
D-W: 1.533
* p<0.05 ** p<0.01

TABLE 5.5: Linear regression analysis of TD score and mean plantar pressure

Parameter Estimates (n=28)									
	Unstandardized Coefficients		Standardized Coefficients	t	p	VIF	R^2	Adj R^2	F
	B	Std. Error	$Beta$						
Constant	-82.644	39.969	-	-2.068	0.049*	-	0.261	0.233	$F(1,26)=9.182, p=0.005$
Pre-Avg	0.009	0.003	0.511	3.030	0.005**	1.000			

Dependent Variable: TD
D-W: 1.570
* p<0.05 ** p<0.01

the results of PD and TD scores with task change. In order to further understand the association between the measured data and subjective scores, the researcher needed to analyze the specific type of association that existed between them. The investigators performed a linear regression analysis of the mean plantar pressure and PD and TD scores for each task, with the following results 5.4 and 5.5.

It can be seen that linear regression analysis was performed with Pre-Avg (mean plantar pressure) as the independent variable and PD as the dependent variable. From the table above, the model equation is PD = -119.773 + 0.011*Pre-Avg, and the model R-squared value is 0.438, which means that Pre-Avg can explain 43.8% of the variation in PD. The F-test of the model found that the model passed the F-test (F=20.225, p=0.000<0.05), which means that Pre-Avg must have an effective relationship with PD, and the final specific analysis shows that.

The regression coefficient of Pre-Avg is 0.011 (t=4.497, p=0.000<0.01), which means that Pre-Avg will have a significant positive effect relationship on PD. Summarizing the analysis, it is clear that the mean plantar pressure will have a significant positive effect relationship on PD.

Similarly, a linear regression analysis with Pre-Avg as the independent variable and TD as the dependent variable showed that the model equation was TD = -82.644 + 0.009*Pre-Avg with a model R-squared value of 0.261, implying that Pre-Avg explained 26.1% of the variation in TD. The F-test of the model found that the model passed the F-test ($F=9.182$, $p=0.005<0.05$), which means that Pre-Avg must have an impact relationship on TD, and the final specific analysis shows that.

The value of the regression coefficient of Pre-Avg is 0.009 ($t=3.030$, $p=0.005<0.01$), which means that Pre-Avg will have a significant positive effect relationship on TD. To summarize the analysis, it is clear that mean plantar pressure will have a significant positive effect relationship on TD.

By summarizing the results of these two analyses, it can be concluded that the mean plantar pressure measurements reflect a significant relationship between PD and TD and a positive linear relationship. Further, in conjunction with the interpretation of the meaning of the scores in the previous section, we can conclude that the mean plantar pressure measurements can reflect the collaborators' perception of "fatigue" and "urgency." The higher the mean plantar pressure over a distance, the more intense the physical fatigue and urgency felt by the collaborator.

5.2.3 Visualization of analysis results and their application

From the above analysis, we found that the average plantar pressure, as a characteristic quantity extracted from gait characteristics, can reflect the "fatigue" and "urgency" during a certain period of movement. This means that if plantar pressure is used as a reference item in a heat map, we can create a map that allows us to understand and quantify human feelings changes without using subjective evaluation tools. This seems to be a triumphant return to the concept of the "Kansei map" expected by the researcher. As an example, a new interpretation of the previously obtained heat map5.3 using mean plantar pressure as an indicator is possible: the closer the path to red (high heat), the higher the mean plantar pressure, which means that the collaborator is experiencing a stronger sense of fatigue and urgency, while the path closer to green (low heat) indicates a more relaxed mental state of the collaborator.

With this analysis, researchers see the potential for more behavioral traits to reflect Kansei in humans. Although it is not possible at this time to show that mean plantar pressure data can be correlated with more emotional expressions. However, as in the example completed in this study with the TLX scale and gait characteristics, it is likely achievable to continuously portray subjective affective shifts in humans by creating a subjective scale for controlled analysis, ultimately drawing out a characteristic amount of behavioral traits as an indicator. With similar recording and visualization tools, researchers can more intuitively determine and understand at which point in time and at which location such changes occur.

5.3 Performance of the device

In the present experiment, the device operated stably for all 30 collaborators. The recording conditions set by the experimental design were satisfied. Due to the limitations of the GNSS part of the design, the device still needs further improvement in recording the position trajectory in the natural environment. In addition, the acquired raw data need to go through a more complicated pre-processing before they can be used. Future design improvements should enhance the automatic processing performance of the device in terms of data output.

5.4 Limitations

The design and experiments of this study reflect several limitations, which also impact the experimental results, and are described here under the following headings.

- The design of the experimental device is still relatively bulky, reaching 150 grams. Although no feedback was received from the collaborators in the actual experiment about the negative feeling of the device being bulky, it is believed that the design could be further optimized to reduce weight and volume.
- Problems with the GNSS module in operation were encountered during the experiments, and the researchers believe that such problems stem from inadequate module testing during the design process.
- The data analysis and processing of the experiments did not create a more specific mathematical model to give more accurate results. Since the initial concept of this study was to complete a complete evaluation of the relationship between changes in position information and gait, however, due to time and various condition constraints, only the design and evaluation of the device was completed in this study.

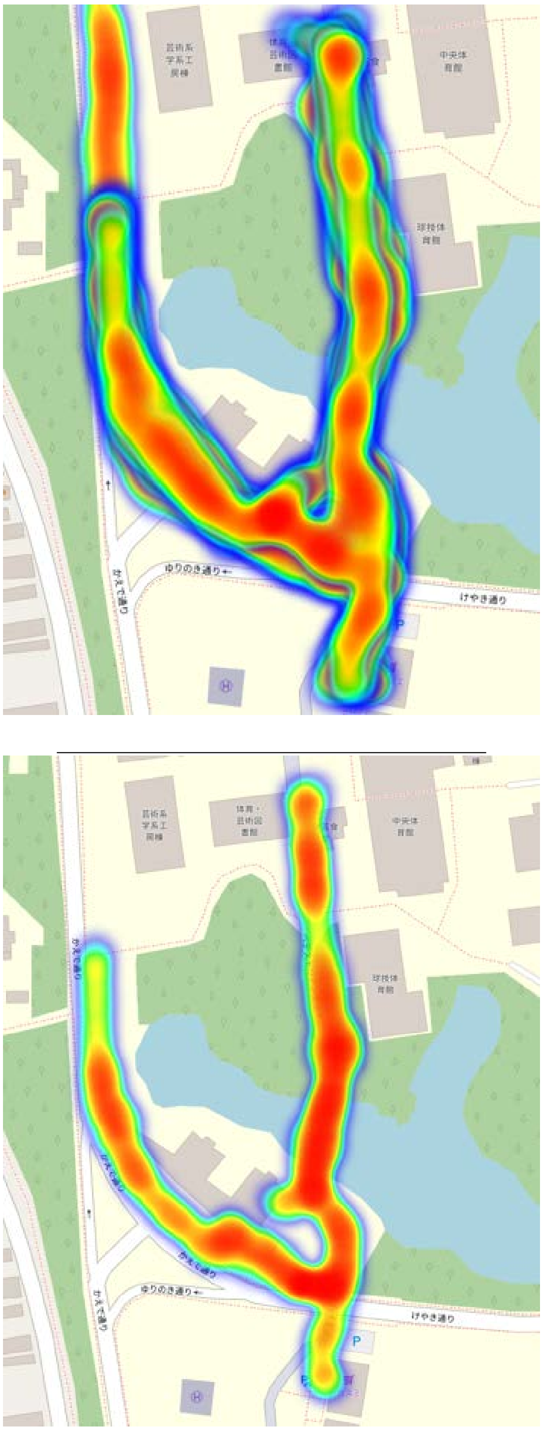


FIGURE 5.3: Heat map of the change in "plantar pressure" characteristics during mission execution

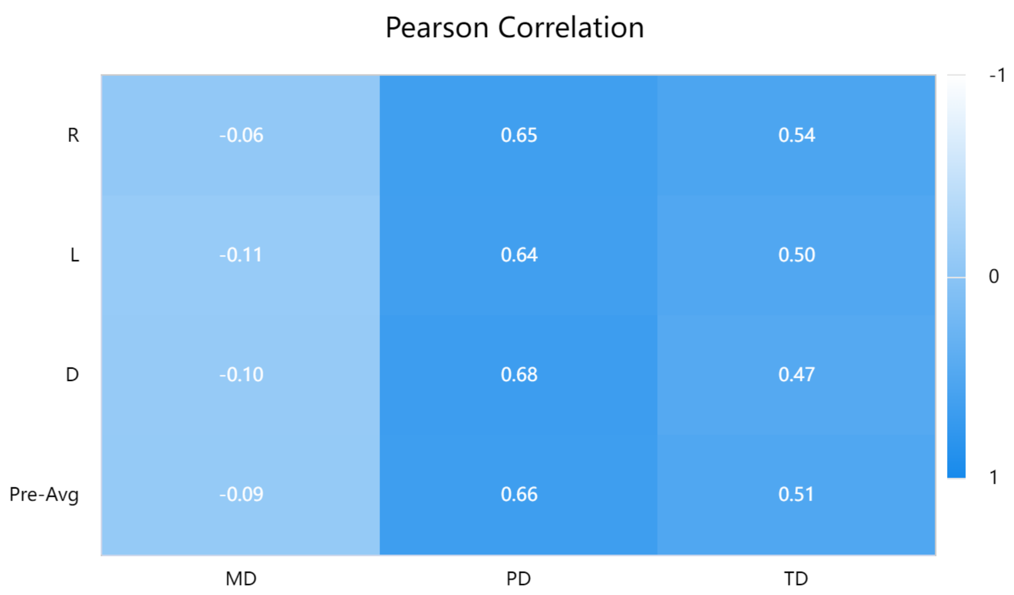


FIGURE 5.4: Results of the correlation analysis between plantar pressure data and TLX scores

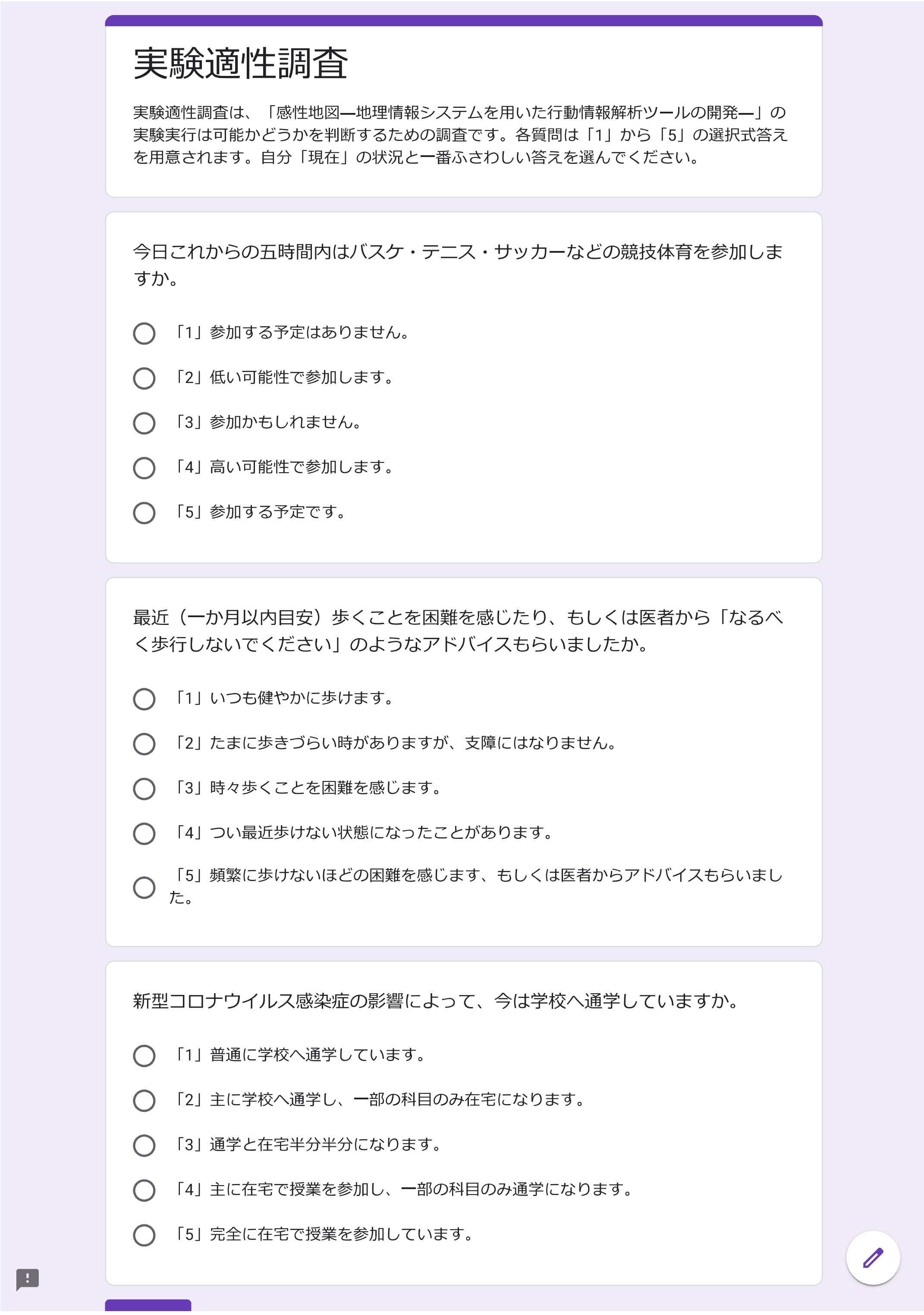
5.5 Constructive conclusions

This study verified the feasibility of a set of device designs experimentally. The constructive conclusions of the study include the following.

- The device provides a means to obtain data for experiments related to gait analysis in natural environments by recording information in real-time and continuously.
- In the experiment, the researcher tried to establish a "step count"-"plantar pressure" evaluation criterion corresponding to the action trajectory through the collected experimental results. This evaluation criterion can be used to reference other studies in the same field.
- The study reaffirms the insights of KANSEI DESIGN regarding the definition of Kansei by combining the appropriate methods of KANSEI DESIGN for the analysis of human behavior data, which reflects the significance of obtaining behavior data by various means in action research.

Appendix A

Diary recall questionnaire



実験適性調査

実験適性調査は、「感性地図—地理情報システムを用いた行動情報解析ツールの開発—」の実験実行は可能かどうかを判断するための調査です。各質問は「1」から「5」の選択式答えを用意されます。自分「現在」の状況と一番ふさわしい答えを選んでください。

今日これからの五時間内はバスケ・テニス・サッカーなどの競技体育を参加しますか。

- 「1」参加する予定はありません。
- 「2」低い可能性で参加します。
- 「3」参加かもしれません。
- 「4」高い可能性で参加します。
- 「5」参加する予定です。

最近（一か月以内目安）歩くことを困難を感じたり、もしくは医者から「なるべく歩行しないでください」のようなアドバイスもらいましたか。

- 「1」いつも健やかに歩けます。
- 「2」たまに歩きづらい時がありますが、支障にはなりません。
- 「3」時々歩くことを困難を感じます。
- 「4」つい最近歩けない状態になったことがあります。
- 「5」頻繁に歩けないほどの困難を感じます、もしくは医者からアドバイスもらいました。

新型コロナウイルス感染症の影響によって、今は学校へ通学していますか。

- 「1」普通に学校へ通学しています。
- 「2」主に学校へ通学し、一部の科目のみ在宅になります。
- 「3」通学と在宅半分半分になります。
- 「4」主に在宅で授業を参加し、一部の科目のみ通学になります。
- 「5」完全に在宅で授業を参加しています。

FIGURE A.1: Collaborator screening questionnaire

Appendix B

Diary recall questionnaire

記憶喚起調査

記憶喚起調査は、「感性地図—地理情報システムを用いた行動情報解析ツールの開発—」の記録実験を参加した後、記録期間中に起こった出来事を想起することで、記録の行動軌跡をまとめる調査です。記憶喚起を完成したら、そのプロセスの思い出しやすさを5段階で評価してください。アンケートの最後に、研究協力者様の基本情報を収集させていただきます。これらの情報は、実験データの解析の補助としてのみ使用され、個人を特定できるような目的には一切使用されません。

*必須

今日の記録実験中の行った活動を思い出してみてください。答えにはできる限り「時間」「場所」「活動」「気持ち」の四つの要素を含めてください。時間分けは制限しません。(例:　9:30　図書館　読書　嬉しい)特別な提示条件のあるグループでは、研究分担者が提示した条件を参照して答えてください。もし提示した条件は記憶と相違した場合も、相違のところを示してください。 *

回答を入力

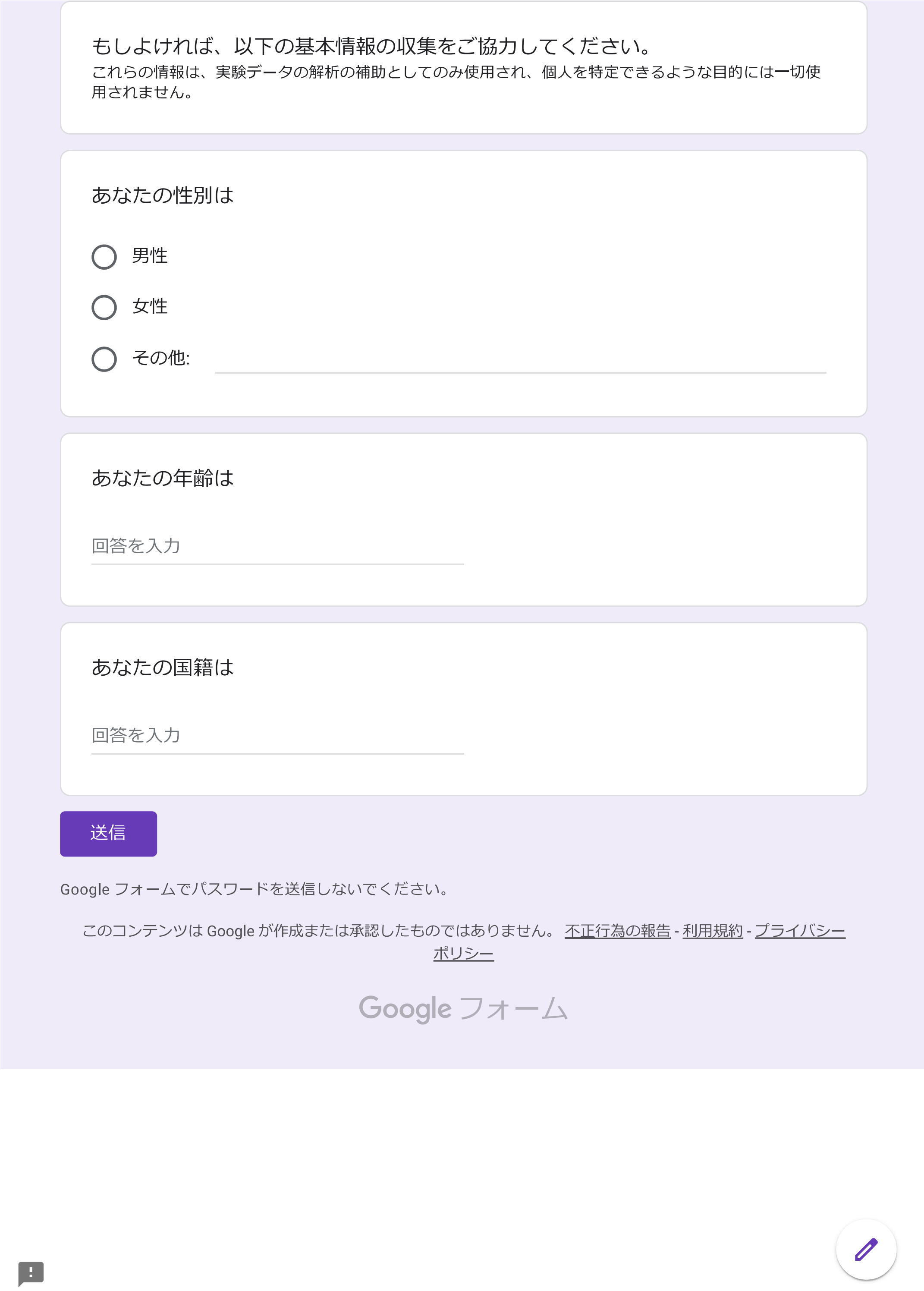
前問を答えたときの思い出しやすさを5段階で評価してください。 *

	1	2	3	4	5	
すごく困難でした	○	○	○	○	○	すごく簡単でした

研究分担者が提示した条件は思い出すときの参考になりましたか。（なにも提示されていない場合は 1 を選んでください。） *

	1	2	3	4	5	
全然参考になりません	○	○	○	○	○	すごく参考になりました

FIGURE B.1: Diary recall questionnaire -01



もしよければ、以下の基本情報の収集をご協力してください。

これらの情報は、実験データの解析の補助としてのみ使用され、個人を特定できるような目的には一切使用されません。

あなたの性別は

- 男性
- 女性
- その他:

あなたの年齢は

回答を入力

あなたの国籍は

回答を入力

送信

Google フォームでパスワードを送信しないでください。

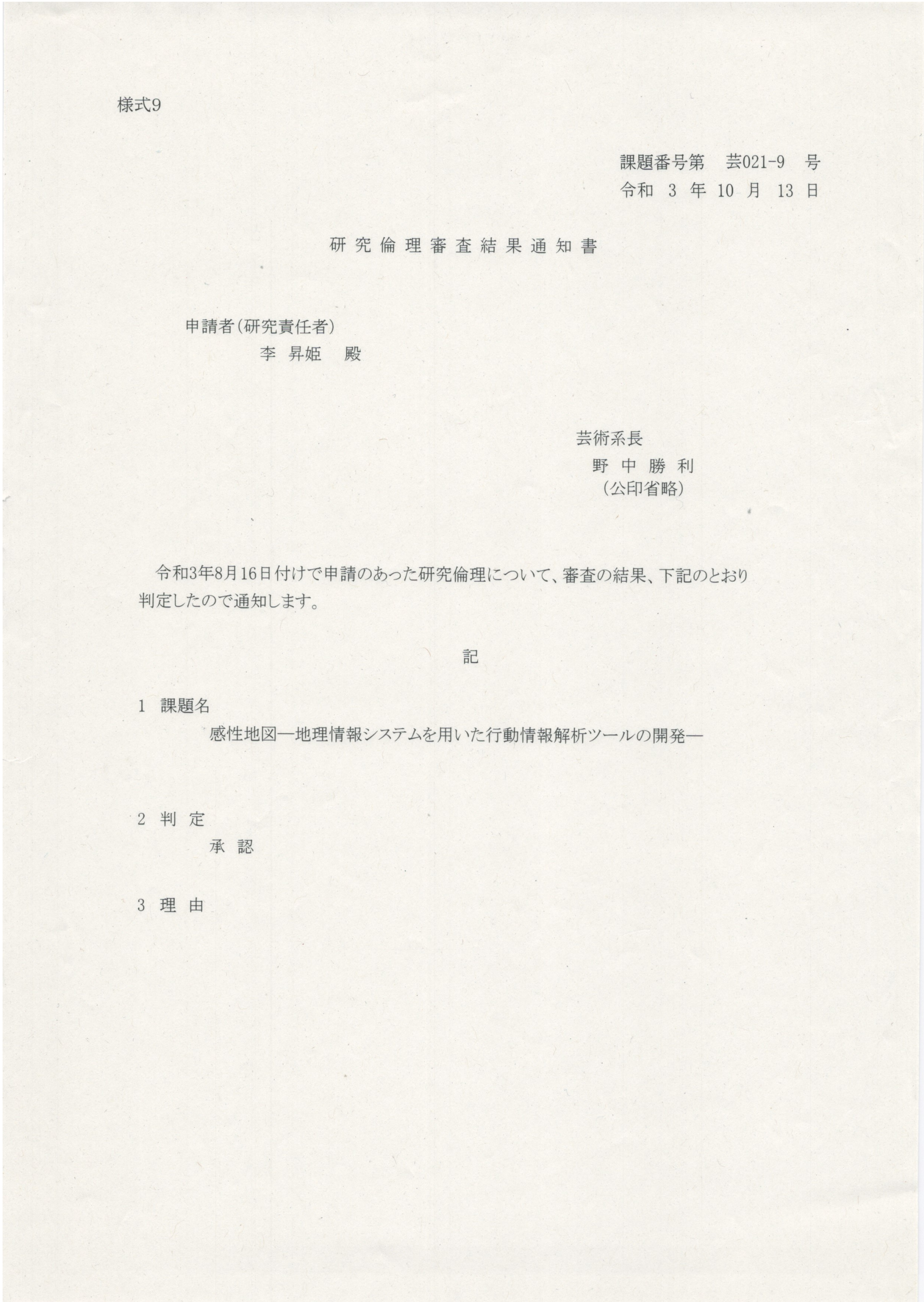
このコンテンツは Google が作成または承認したものではありません。 不正行為の報告 - 利用規約 - プライバシーポリシー

Google フォーム

FIGURE B.2: Diary recall questionnaire -02

Appendix C

Ethics Review Document



様式9

課題番号第　芸021-9　号
令和　3　年　10　月　13　日

研 究 倫 理 審 査 結 果 通 知 書

申請者（研究責任者）
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野 中 勝 利
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令和3年8月16日付けで申請のあった研究倫理について、審査の結果、下記のとおり判定したので通知します。

記

1 課題名
感性地図―地理情報システムを用いた行動情報解析ツールの開発―

2 判 定
承 認

3 理 由

FIGURE C.1: Ethics Review Document

Appendix D

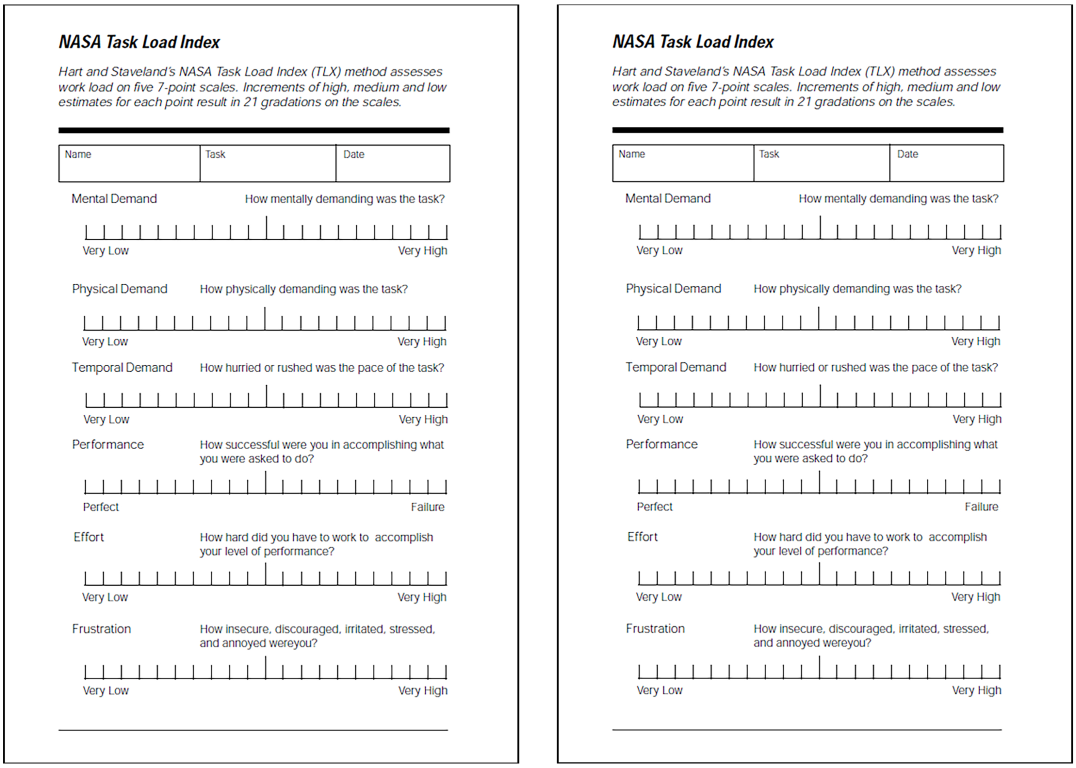
Dual-task walking experiment

FIGURE D.1: Dual-task walking experiment - Task1

FIGURE D.2: Dual-task walking experiment - Task2

Appendix E

NASA-TLX Scale



NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?
Very Low — Very High

Physical Demand — How physically demanding was the task?
Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?
Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?
Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?
Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?
Very Low — Very High

NASA Task Load Index

Hart and Staveland's NASA Task Load Index (TLX) method assesses work load on five 7-point scales. Increments of high, medium and low estimates for each point result in 21 gradations on the scales.

Name	Task	Date

Mental Demand — How mentally demanding was the task?
Very Low — Very High

Physical Demand — How physically demanding was the task?
Very Low — Very High

Temporal Demand — How hurried or rushed was the pace of the task?
Very Low — Very High

Performance — How successful were you in accomplishing what you were asked to do?
Perfect — Failure

Effort — How hard did you have to work to accomplish your level of performance?
Very Low — Very High

Frustration — How insecure, discouraged, irritated, stressed, and annoyed wereyou?
Very Low — Very High

FIGURE E.1: Dual-task walking experiment - NASA-TLX

Bibliography

Adair, John G. (1984). "The Hawthorne effect: A reconsideration of the methodological artifact." In: *Journal of Applied Psychology* 69.2, pp. 334–345. ISSN: 0021-9010. DOI: 10.1037/0021-9010.69.2.334. URL: http://content.apa.org/journals/apl/69/2/334.

Bhattacharya, Uttaran et al. (Apr. 3, 2020). "STEP: Spatial Temporal Graph Convolutional Networks for Emotion Perception from Gaits". In: *Proceedings of the AAAI Conference on Artificial Intelligence* 34.2, pp. 1342–1350. ISSN: 2374-3468, 2159-5399. DOI: 10.1609/aaai.v34i02.5490. URL: https://aaai.org/ojs/index.php/AAAI/article/view/5490.

Cavagna, G A and P Franzetti (Apr. 1, 1986). "The determinants of the step frequency in walking in humans." In: *The Journal of Physiology* 373.1, pp. 235–242. ISSN: 00223751. DOI: 10.1113/jphysiol.1986.sp016044. URL: https://onlinelibrary.wiley.com/doi/10.1113/jphysiol.1986.sp016044.

Connor, Patrick and Arun Ross (Feb. 2018). "Biometric recognition by gait: A survey of modalities and features". In: *Computer Vision and Image Understanding* 167, pp. 1–27. ISSN: 10773142. DOI: 10.1016/j.cviu.2018.01.007. URL: https://linkinghub.elsevier.com/retrieve/pii/S1077314218300079.

Coutts, Fiona (Feb. 1999). "Gait analysis in the therapeutic environment". In: *Manual Therapy* 4.1, pp. 2–10. ISSN: 1356689X. DOI: 10.1016/S1356-689X(99)80003-4. URL: https://linkinghub.elsevier.com/retrieve/pii/S1356689X99800034.

Cullen, Kathleen E. and Jefferson E. Roy (May 2004). "Signal Processing in the Vestibular System During Active Versus Passive Head Movements". In: *Journal of Neurophysiology* 91.5, pp. 1919–1933. ISSN: 0022-3077, 1522-1598. DOI: 10.1152/jn.00988.2003. URL: https://www.physiology.org/doi/10.1152/jn.00988.2003.

Danion, F. et al. (Aug. 2003). "Stride variability in human gait: the effect of stride frequency and stride length". In: *Gait & Posture* 18.1, pp. 69–77. ISSN: 09666362. DOI: 10.1016/S0966-6362(03)00030-4. URL: https://linkinghub.elsevier.com/retrieve/pii/S0966636203000304.

Davis, Roy B. et al. (Oct. 1991). "A gait analysis data collection and reduction technique". In: *Human Movement Science* 10.5, pp. 575–587. ISSN: 01679457. DOI: 10.1016/0167-9457(91)90046-Z. URL: https://linkinghub.elsevier.com/retrieve/pii/016794579190046Z.

Elias, Lorin J., M.P. Bryden, and M.B. Bulman-Fleming (Jan. 1998). "Footedness is a better predictor than is handedness of emotional lateralization". In: *Neuropsychologia* 36.1, pp. 37–43. ISSN: 00283932. DOI: 10.1016/S0028-3932(97)00107-3. URL: https://linkinghub.elsevier.com/retrieve/pii/S0028393297001073.

Fabes, Richard A., Nancy Eisenberg, and Lisa Eisenbud (1993). "Behavioral and physiological correlates of children's reactions to others in distress." In: *Developmental Psychology* 29.4, pp. 655–663. ISSN: 0012-1649. DOI: 10.1037/0012-1649.29.4.655. URL: http://doi.apa.org/getdoi.cfm?doi=10.1037/0012-1649.29.4.655.

Farrow, Christopher L. et al. (Oct. 18, 2011). "Nyquist-Shannon sampling theorem applied to refinements of the atomic pair distribution function". In: *Physical Review B* 84.13, p. 134105. ISSN: 1098-0121, 1550-235X. DOI: 10.1103/PhysRevB.84.134105. URL: https://link.aps.org/doi/10.1103/PhysRevB.84.134105.

Fotheringham, A. Stewart, Peter Rogerson, and National Center for Geographic Information & Analysis (U.S.) (2014). *Spatial analysis and GIS*. OCLC: 1064938364. ISBN: 978-1-4822-7246-8. URL: https://nls.ldls.org.uk/welcome.html?ark:/81055/vdc_100058364157.0x000001.

Franěk, Marek et al. (Apr. 14, 2018). "Effect of Traffic Noise and Relaxations Sounds on Pedestrian Walking Speed". In: *International Journal of Environmental Research and Public Health* 15.4, p. 752. ISSN: 1660-4601. DOI: 10.3390/ijerph15040752. URL: https://www.mdpi.com/1660-4601/15/4/752.

Fritz, Stacy and Michelle Lusardi (2009). "White Paper: "Walking Speed: the Sixth Vital Sign":" in: *Journal of Geriatric Physical Therapy* 32.2, pp. 2–5. ISSN: 1539-8412. DOI: 10.1519/00139143-200932020-00002. URL: http://journals.lww.com/00139143-200932020-00002.

Godi, Marco et al. (2014). "Test-retest reliability of an insole plantar pressure system to assess gait along linear and curved trajectories". In: *Journal of NeuroEngineering and Rehabilitation* 11.1, p. 95. ISSN: 1743-0003. DOI: 10.1186/1743-0003-11-95. URL: http://jneuroengrehab.biomedcentral.com/articles/10.1186/1743-0003-11-95.

Harbourne, Regina T and Nicholas Stergiou (Mar. 1, 2009). "Movement Variability and the Use of Nonlinear Tools: Principles to Guide Physical Therapist Practice". In: *Physical Therapy* 89.3, pp. 267–282. ISSN: 0031-9023, 1538-6724. DOI: 10.2522/ptj.20080130. URL: https://academic.oup.com/ptj/article/89/3/267/2737718.

Hartig, Terry et al. (June 2003). "Tracking restoration in natural and urban field settings". In: *Journal of Environmental Psychology* 23.2, pp. 109–123. ISSN: 02724944. DOI: 10.1016/S0272-4944(02)00109-3. URL: https://linkinghub.elsevier.com/retrieve/pii/S0272494402001093.

Hausdorff, Jeffrey M. (Aug. 2007). "Gait dynamics, fractals and falls: Finding meaning in the stride-to-stride fluctuations of human walking". In: *Human Movement Science* 26.4, pp. 555–589. ISSN: 01679457. DOI: 10.1016/j.humov.2007.05.003. URL: https://linkinghub.elsevier.com/retrieve/pii/S0167945707000322.

Hofmann-Wellenhof, Bernhard, Herbert Lichtenegger, and Elmar Wasle (2008). *GNSS - Global Navigation Satellite Systems: GPS, GLONASS, Galileo and more*. Wien New York: Springer. 516 pp. ISBN: 978-3-211-73017-1 978-3-211-73012-6.

Hong, Sung-hwa, Seong-Ryul Yang, and Seong-Real Lee (2014). "The Efficient Multimedia Data Transmission Using NMEA-0183". In: *Journal of Advanced Navigation Technology* 18.2, pp. 121–127. DOI: 10.12673/JANT.2014.18.2.121. URL: https://doi.org/10.12673/JANT.2014.18.2.121.

Horst, Fabian et al. (Dec. 2019). "Explaining the unique nature of individual gait patterns with deep learning". In: *Scientific Reports* 9.1, p. 2391. ISSN: 2045-2322. DOI: 10.1038/s41598-019-38748-8. URL: https://www.nature.com/articles/s41598-019-38748-8.

Janssens, Karin A. M. et al. (Dec. 2018). "A qualitative approach to guide choices for designing a diary study". In: *BMC Medical Research Methodology* 18.1, p. 140. ISSN: 1471-2288. DOI: 10.1186/s12874-018-0579-6. URL: https://bmcmedresmethodol.biomedcentral.com/articles/10.1186/s12874-018-0579-6.

Jones, Russell L. (Jan. 1941). "The human foot. An experimental study of its mechanics, and the role of its muscles and ligaments in the support of the arch". In: *American Journal of Anatomy* 68.1, pp. 1–39. ISSN: 0002-9106, 1553-0795. DOI: 10.1002/aja.1000680102. URL: https://onlinelibrary.wiley.com/doi/10.1002/aja.1000680102.

Kale, A. et al. (Sept. 2004). "Identification of Humans Using Gait". In: *IEEE Transactions on Image Processing* 13.9, pp. 1163–1173. ISSN: 1057-7149. DOI: 10.1109/TIP.2004.832865. URL: http://ieeexplore.ieee.org/document/1323098/.

Karatzoglou, Antonios, Nikolai Schnell, and Michael Beigl (2018). "A Convolutional Neural Network Approach for Modeling Semantic Trajectories and Predicting Future Locations". In: *Artificial Neural Networks and Machine Learning – ICANN 2018*. Ed. by Věra Kůrková et al. Vol. 11139. Series Title: Lecture Notes in Computer Science. Cham: Springer International Publishing, pp. 61–72. ISBN: 978-3-030-01417-9 978-3-030-01418-6. DOI: 10.1007/978-3-030-01418-6_7. URL: http://link.springer.com/10.1007/978-3-030-01418-6_7.

Kinoshita, Hiroshi (Sept. 1985). "Effects of different loads and carrying systems on selected biomechanical parameters describing walking gait". In: *Ergonomics* 28.9, pp. 1347–1362. ISSN: 0014-0139, 1366-5847. DOI: 10.1080/00140138508963251. URL: https://www.tandfonline.com/doi/full/10.1080/00140138508963251.

Kisilevich, Slava, Florian Mansmann, and Daniel Keim (2010). "P-DBSCAN: a density based clustering algorithm for exploration and analysis of attractive areas using collections of geo-tagged photos". In: *Proceedings of the 1st International Conference and Exhibition on Computing for Geospatial Research & Application - COM.Geo '10*. the 1st International Conference and Exhibition. Washington, D.C.: ACM Press, p. 1. ISBN: 978-1-4503-0031-5. DOI: 10.1145/1823854.1823897. URL: http://portal.acm.org/citation.cfm?doid=1823854.1823897.

Krafka, Kyle et al. (2016). "Eye Tracking for Everyone". In: Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, pp. 2176–

2184. URL: https://www.cv-foundation.org/openaccess/content_cvpr_2016/html/Krafka_Eye_Tracking_for_CVPR_2016_paper.html.

Lawson, Andrew B. (June 2010). "Hotspot detection and clustering: ways and means". In: *Environmental and Ecological Statistics* 17.2, pp. 231–245. ISSN: 1352-8505, 1573-3009. DOI: 10.1007/s10651-010-0142-z. URL: http://link.springer.com/10.1007/s10651-010-0142-z.

Lee, S., Akira Harada, and Pieter Jan Stappers (2002). "Pleasure with products: Design based on Kansei". In: *Pleasure with products: Beyond usability* 219. Publisher: Taylor and Francis New York, p. 229.

Leeland, Katherine B., ed. (2008). *Face recognition: new research*. OCLC: ocn226984558. New York: Nova Science Publishers. 157 pp. ISBN: 978-1-60456-466-2.

Leslie, Eva et al. (Mar. 2007). "Walkability of local communities: Using geographic information systems to objectively assess relevant environmental attributes". In: *Health & Place* 13.1, pp. 111–122. ISSN: 13538292. DOI: 10.1016/j.healthplace.2005.11.001. URL: https://linkinghub.elsevier.com/retrieve/pii/S1353829205000845.

Li, Qiannan et al. (Feb. 2018). "Classification of gait anomalies from kinect". In: *The Visual Computer* 34.2, pp. 229–241. ISSN: 0178-2789, 1432-2315. DOI: 10.1007/s00371-016-1330-0. URL: http://link.springer.com/10.1007/s00371-016-1330-0.

Liu, Lina, Hong Chen, and Tao Liu (2020). "Study on Urban Spatial Function Mixture and Individual Activity Space From the Perspectives of Resident Activity". In: *IEEE Access* 8, pp. 184137–184150. ISSN: 2169-3536. DOI: 10.1109/ACCESS.2020.3029177. URL: https://ieeexplore.ieee.org/document/9214834/.

"Location prediction on trajectory data" (June 2018). "Location prediction on trajectory data: A review". In: *Big Data Mining and Analytics* 1.2, pp. 108–

127. ISSN: 2096-0654. DOI: 10.26599/BDMA.2018.9020010. URL: https://ieeexplore.ieee.org/document/8336847/.

Loo, M. A. van et al. (Oct. 2004). "Test–re-test reliability of walking speed, step length and step width measurement after traumatic brain injury: a pilot study". In: *Brain Injury* 18.10, pp. 1041–1048. ISSN: 0269-9052, 1362-301X. DOI: 10.1080/02699050410001672314. URL: http://www.tandfonline.com/doi/full/10.1080/02699050410001672314.

Lord, S. et al. (July 1, 2013). "Independent Domains of Gait in Older Adults and Associated Motor and Nonmotor Attributes: Validation of a Factor Analysis Approach". In: *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences* 68.7, pp. 820–827. ISSN: 1079-5006, 1758-535X. DOI: 10.1093/gerona/gls255. URL: https://academic.oup.com/biomedgerontology/article-lookup/doi/10.1093/gerona/gls255.

Louail, Thomas et al. (May 2015). "From mobile phone data to the spatial structure of cities". In: *Scientific Reports* 4.1, p. 5276. ISSN: 2045-2322. DOI: 10.1038/srep05276. URL: http://www.nature.com/articles/srep05276.

Muñoz, Beatriz et al. (Feb. 5, 2020). "Smart Tracking and Wearables: Techniques in Gait Analysis and Movement in Pathological Aging". In: *Smart Healthcare*. Ed. by Thomas F. Heston. IntechOpen. ISBN: 978-1-78984-351-4 978-1-78984-352-1. DOI: 10.5772/intechopen.85294. URL: https://www.intechopen.com/books/smart-healthcare/smart-tracking-and-wearables-techniques-in-gait-analysis-and-movement-in-pathological-aging.

Nixon, Mark S., Tieniu Tan, and Rama Chellappa (2006). *Human identification based on gait*. International series on biometrics 4. New York: Springer. ISBN: 978-0-387-29488-9.

Paas, Fred and John Sweller (Mar. 2012). "An Evolutionary Upgrade of Cognitive Load Theory: Using the Human Motor System and Collaboration to Support the Learning of Complex Cognitive Tasks”. In: *Educational Psychology Review* 24.1, pp. 27–45. ISSN: 1040-726X, 1573-336X. DOI: 10.1007/s10648-011-9179-2. URL: http://link.springer.com/10.1007/s10648-011-9179-2.

Pan, Lijia et al. (May 2014). “An ultra-sensitive resistive pressure sensor based on hollow-sphere microstructure induced elasticity in conducting polymer film”. In: *Nature Communications* 5.1, p. 3002. ISSN: 2041-1723. DOI: 10.1038/ncomms4002. URL: http://www.nature.com/articles/ncomms4002.

Patla, Aftab and Joan Vickers (Jan. 1, 2003). “How far ahead do we look when required to step on specific locations in the travel path during locomotion?” In: *Experimental Brain Research* 148.1, pp. 133–138. ISSN: 0014-4819, 1432-1106. DOI: 10.1007/s00221-002-1246-y. URL: http://link.springer.com/10.1007/s00221-002-1246-y.

Prakash, Chandra, Rajesh Kumar, and Namita Mittal (Jan. 2018). “Recent developments in human gait research: parameters, approaches, applications, machine learning techniques, datasets and challenges”. In: *Artificial Intelligence Review* 49.1, pp. 1–40. ISSN: 0269-2821, 1573-7462. DOI: 10.1007/s10462-016-9514-6. URL: http://link.springer.com/10.1007/s10462-016-9514-6.

Punt, M et al. (2017). “Do clinical assessments, steady-state or daily-life gait characteristics predict falls in ambulatory chronic stroke survivors?” In: *Journal of Rehabilitation Medicine* 49.5, pp. 402–409. ISSN: 1650-1977. DOI: 10.2340/16501977-2234. URL: http://www.medicaljournals.se/jrm/content/?doi=10.2340/16501977-2234.

Roether, C. L. et al. (June 1, 2009). “Critical features for the perception of emotion from gait”. In: *Journal of Vision* 9.6, pp. 15–15. ISSN: 1534-7362. DOI: 10.1167/9.6.15. URL: http://jov.arvojournals.org/Article.aspx?doi=10.1167/9.6.15.

Rolls, Edmund T. (2005). *Emotion explained*. Series in affective science. OCLC: ocm60837756. Oxford ; New York: Oxford University Press. 606 pp. ISBN: 978-0-19-857003-5.

Sabatini, A.M. et al. (Mar. 2005). "Assessment of Walking Features From Foot Inertial Sensing". In: *IEEE Transactions on Biomedical Engineering* 52.3, pp. 486–494. ISSN: 0018-9294. DOI: 10.1109/TBME.2004.840727. URL: http://ieeexplore.ieee.org/document/1396389/.

Sacco, K. et al. (Sept. 2006). "Motor imagery of walking following training in locomotor attention. The effect of 'the tango lesson'". In: *NeuroImage* 32.3, pp. 1441–1449. ISSN: 10538119. DOI: 10.1016/j.neuroimage.2006.05.018. URL: https://linkinghub.elsevier.com/retrieve/pii/S1053811906005489.

Sanderson, Eric W. et al. (2002). "The Human Footprint and the Last of the Wild". In: *BioScience* 52.10, p. 891. ISSN: 0006-3568. DOI: 10.1641/0006-3568(2002)052[0891:THFATL]2.0.CO;2. URL: https://academic.oup.com/bioscience/article/52/10/891-904/354831.

Schaal, Stefan, Auke Ijspeert, and Aude Billard (Mar. 29, 2003). "Computational approaches to motor learning by imitation". In: *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences* 358.1431. Ed. by C.D. Frith and D.M. Wolpert, pp. 537–547. ISSN: 0962-8436, 1471-2970. DOI: 10.1098/rstb.2002.1258. URL: https://royalsocietypublishing.org/doi/10.1098/rstb.2002.1258.

Smith, Craig A. and Richard S. Lazarus (1990). "Emotion and adaptation." In: *Handbook of personality: Theory and research.* New York, NY, US: The Guilford Press, pp. 609–637. ISBN: 0-89862-430-4 (Hardcover).

Starner, T. (Aug. 2001). "The challenges of wearable computing: Part 2". In: *IEEE Micro* 21.4, pp. 54–67. ISSN: 02721732. DOI: 10.1109/40.946683. URL: http://ieeexplore.ieee.org/document/946683/.

Still, Gregory P. and Morris B. Fowler (Nov. 1998). "Joplin's neuroma or compression neuropathy of the plantar proper digital nerve to the hallux: Clinicopathologic study of three cases". In: *The Journal of Foot and Ankle Surgery* 37.6, pp. 524–530. ISSN: 10672516. DOI: 10.1016/S1067-2516(98)80030-6. URL: https://linkinghub.elsevier.com/retrieve/pii/S1067251698800306.

Sun, Bingli et al. (Oct. 2017). "Self-esteem recognition based on gait pattern using Kinect". In: *Gait & Posture* 58, pp. 428–432. ISSN: 09666362. DOI: 10.1016/j.gaitpost.2017.09.001. URL: https://linkinghub.elsevier.com/retrieve/pii/S0966636217308974.

Tajadura-Jiménez, Ana et al. (Apr. 18, 2015). "As Light as your Footsteps: Altering Walking Sounds to Change Perceived Body Weight, Emotional State and Gait". In: *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*. CHI '15: CHI Conference on Human Factors in Computing Systems. Seoul Republic of Korea: ACM, pp. 2943–2952. ISBN: 978-1-4503-3145-6. DOI: 10.1145/2702123.2702374. URL: https://dl.acm.org/doi/10.1145/2702123.2702374.

Tariq, Madiha, Pavel M. Trivailo, and Milan Simic (Mar. 17, 2020). "Mu-Beta event-related (de)synchronization and EEG classification of left-right foot dorsiflexion kinaesthetic motor imagery for BCI". In: *PLOS ONE* 15.3. Ed. by Dhakshin Ramanathan, e0230184. ISSN: 1932-6203. DOI: 10.1371/journal.pone.0230184. URL: https://dx.plos.org/10.1371/journal.pone.0230184.

Urtasun, R. and P. Fua (2004). "3D tracking for gait characterization and recognition". In: *Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2004. Proceedings.* Sixth IEEE International Conference on Automatic Face and Gesture Recognition, 2004. Seoul, Korea: IEEE, pp. 17–22. ISBN: 978-0-7695-2122-0. DOI: 10.1109/AFGR.2004.1301503. URL: http://ieeexplore.ieee.org/document/1301503/.

Venture, Gentiane et al. (Nov. 2014). “Recognizing Emotions Conveyed by Human Gait”. In: *International Journal of Social Robotics* 6.4, pp. 621–632. ISSN: 1875-4791, 1875-4805. DOI: 10.1007/s12369-014-0243-1. URL: http://link.springer.com/10.1007/s12369-014-0243-1.

Vuorela, Timo et al. (May 2010). “Design and Implementation of a Portable Long-Term Physiological Signal Recorder”. In: *IEEE Transactions on Information Technology in Biomedicine* 14.3, pp. 718–725. ISSN: 1089-7771. DOI: 10.1109/TITB.2010.2042606. URL: http://ieeexplore.ieee.org/document/5415564/.

Walden, R. H. (Sept. 15, 2008). “Analog-to-Digital Conversion in the Early Twenty-First Century”. In: *Wiley Encyclopedia of Computer Science and Engineering*. Ed. by Benjamin W. Wah. Hoboken, NJ, USA: John Wiley & Sons, Inc., ecse014. ISBN: 978-0-470-05011-8. DOI: 10.1002/9780470050118.ecse014. URL: https://onlinelibrary.wiley.com/doi/10.1002/9780470050118.ecse014.

Williams, A. M, K Davids, and J. G Williams (2005). *Visual Perception and Action in Sport*. OCLC: 1027144712. Milton: Taylor & Francis. ISBN: 978-0-203-97995-2. URL: https://public.ebookcentral.proquest.com/choice/publicfullrecord.aspx?p=5292704.

Woollacott, Marjorie and Anne Shumway-Cook (Aug. 2002). “Attention and the control of posture and gait: a review of an emerging area of research”. In: *Gait & Posture* 16.1, pp. 1–14. ISSN: 09666362. DOI: 10.1016/S0966-6362(01)00156-4. URL: https://linkinghub.elsevier.com/retrieve/pii/S0966636201001564.

Xu, Yangfan et al. (Mar. 24, 2021). “A Depth Camera–Based, Task-Specific Virtual Reality Rehabilitation Game for Patients With Stroke: Pilot Usability Study”. In: *JMIR Serious Games* 9.1, e20916. ISSN: 2291-9279. DOI: 10.2196/20916. URL: https://games.jmir.org/2021/1/e20916.

Yuan, Jing, Yu Zheng, and Xing Xie (2012). “Discovering regions of different functions in a city using human mobility and POIs”. In: *Proceedings of the 18th ACM SIGKDD international conference on Knowledge discovery and data mining - KDD '12*. the 18th ACM SIGKDD international conference. Beijing, China: ACM Press, p. 186. ISBN: 978-1-4503-1462-6. DOI: 10.1145/2339530.2339561. URL: http://dl.acm.org/citation.cfm?doid=2339530.2339561.

Zijlstra, Wiebren and At L Hof (Oct. 2003). “Assessment of spatio-temporal gait parameters from trunk accelerations during human walking”. In: *Gait & Posture* 18.2, pp. 1–10. ISSN: 09666362. DOI: 10.1016/S0966-6362(02)00190-X. URL: https://linkinghub.elsevier.com/retrieve/pii/S096663620200190X.