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Adaptive Walker: User Intention and Terrain Aware Intelligent Walker with High-resolution Tactile and IMU Sensor

Yunho Choi[1], Seokhyun Hwang[2], JaeYoung Moon[1], Hosu Lee[3], Dohyeon Yeo[1], Minwoo Seong[1], Yiyue Luo[4], SeungJun Kim[1], Wojciech Matusik[5], Daniela Rus[5] and Kyung-Joong Kim[1]

***Abstract*— In this paper, we present an adaptive walker system designed to address limitations in current intelligent walker technologies. While recent advancements have been made in this field, existing systems often struggle to seamlessly interpret user intent for speed control and lack adaptability across diverse scenarios and terrain. Our proposed solution incorporates high-resolution tactile sensors, deep learning algorithms, IMU sensors, and linear motors to dynamically adjust to the user's intentions and terrain changes. The system is capable of predicting the user's desired speed with an error margin of only 20.99%, relying solely on tactile input from hand and arm contact points. Additionally, it maintains the walker's horizontal stability with an error of less than 1 degree by adjusting leg lengths in response to variations in ground angle. This adaptive walker enhances user safety and comfort, particularly for individuals with reduced strength or cognitive abilities, and offers reliable assistance on uneven terrain such as uphill and downhill paths.**

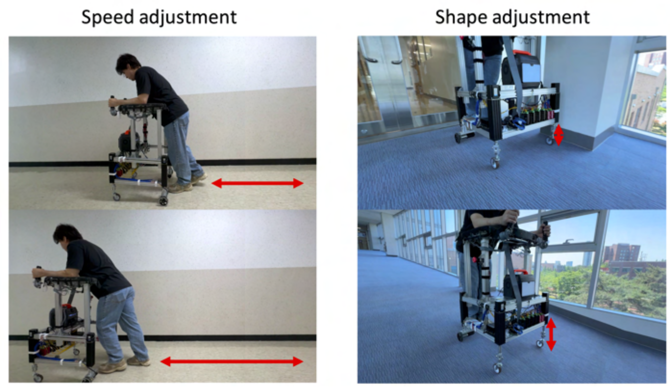

Fig. 1. The actual operation of the adaptive walker. The adaptive walker automatically adjusts its speed according to the user's intended speed. Additionally, based on the slope of the ground, the walker alters its form to maintain a stable posture, ensuring safety and support for the user as they move.

I. INTRODUCTION

The global elderly population is increasing rapidly. As people age, they experience physiological changes that affect various body systems and sensory functions [1]. These changes can significantly raise the risk of falls, leading to greater dependency on others for daily activities, a need for long-term care, and an increased risk of premature mortality [1]. To mitigate these risks, assistive walking devices such as canes and walkers are widely used to improve balance, prevent falls, and enhance mobility among older adults [2].

Traditional walkers have long been used to assist the mobility of the elderly. These devices, typically equipped with 3-4 legs to support the user's weight, can be categorized into two main types: no-wheeled walkers (rigid or folding) and wheeled walkers (with two, three, or four wheels) [3]. While these walkers provide support, they can also cause discomfort depending on the design. For example, no-wheeled walkers require users to lift and move them forward, which can be challenging for elderly individuals, particularly those with reduced muscle strength or mobility in one arm [3], [4]. Wheeled walkers are generally more convenient since they don't need to be lifted; however, users may struggle to apply enough force to engage the brakes, especially on uneven terrain [5], [6]. This can be particularly problematic on uphill or downhill slopes, where maintaining control of the walker in unstable situations can lead to hazardous outcomes [5], [7].

Researchers have recognized these issues and have made efforts to develop more advanced types of walkers. The most basic approach has been to maintain the convenient four-wheel structure of existing walkers while making brakes easier and safer to use by sensitive brake buttons or servo brakes [6], [8]. This method can prevent falls because it enables the use of brakes with less force. A more advanced approach involves devices that control the walker's actions through buttons [9]. These types of walkers are designed to minimize physical effort by allowing users to operate various controls with buttons such as acceleration, break, and turn. However, as many elderly individuals experience cognitive decline, some users may find it difficult to operate the walker according to specific instructions [10], [11].

Therefore, studies are being conducted to recognize the user's acceleration intent from their natural movements and

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[1]School of Integrated Technology, Gwangju Institute of Science and Technology, 123 chem-dan-gwa-gi-ro, Gwangju, Republic of Korea kjkim@gist.ac.kr

[2] Information School, University of Washington, Mary Gates Hall, Ste. 370, Seattle, Washington, USA seokhyun@uw.edu

[3] Department of Control and Robot Engineering & School of Aerospace Engineering, Gyeongsang National University, Jinju-daero, Jinju-si, 52828, Republic of Korea lakelee77@gnu.ac.kr

[4] Electrical and Computer Engineering, University of Washington, 1410 NE Campus Pkwy, Seattle, Washington, USA yiyueluo@uw.edu

[5]Computer Science Artificial Intelligence Laboratory, Massachusetts Institute of Technology , USA

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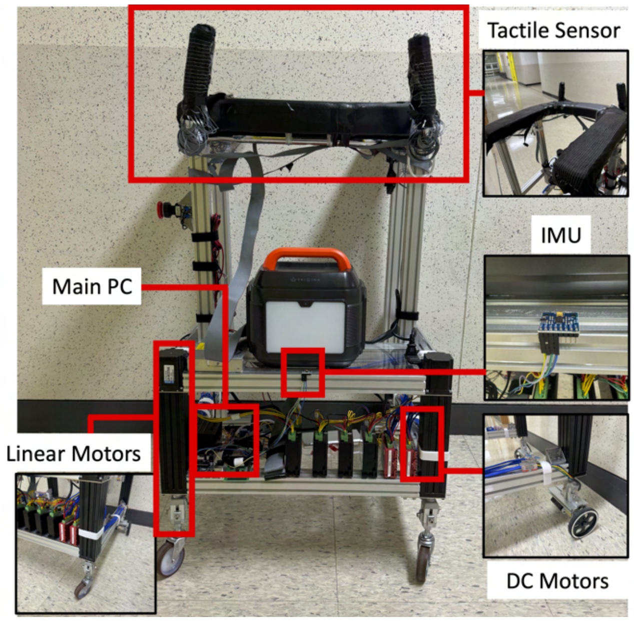

Fig. 2. Adaptive walker system hardware overview. The overall system structure and each part of the system (tactile sensor, DC motors, IMU sensor, linear motors). The walker captures human and terrain changes through the tactile sensor and IMU sensor, changing its speed and shape to adapt to the user and terrain.

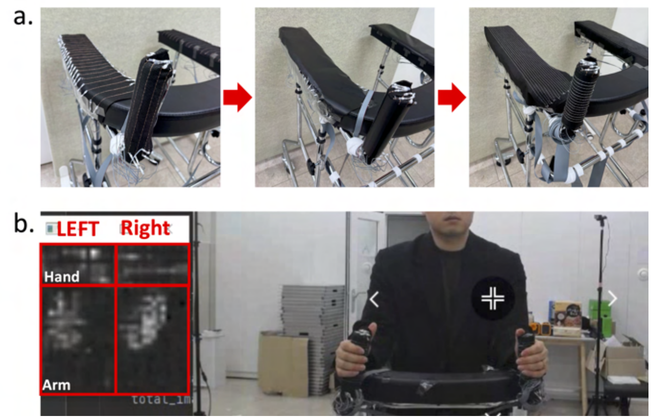

Fig. 3. Tactile sensor structure and response. (a) shows the structure of the tactile sensor and its manufacturing sequence. Additionally, (b) shows how the sensor detects the pressure from both hands and arms.

TABLE I

SPECIFICATIONS OF THE ADAPTIVE WALKER

Item	Specification
PC	Jetson AGX Xavier (8-core ARM v8.2 64-bit CPU)
Tactile sensor	Hand made (1024 sensing points, 12 FPS)
IMU sensor	MPU-6050
DC motor	PH42-BL4259E DC24V (460kgf.cm)
DC motor driver	BDD-240 240W BLDC moter digital diver
Linear motor	LM-NK237540 Linear actuator (50∼500mm, 500N)
Linear motor drive	4.5A MSD-2C45 Step mother driver

operate walkers in a more user-friendly manner. This kind of research usually uses force sensors or load cells to move the walker by detecting the force of grips or pushing [10], [12], [13]. This method is more intuitive than manipulating buttons. Additionally, it also allows motor-assisted movement through DC motors, making it easier for users with weak strength to operate. However, since these systems still require the user to grip and apply force at the handle it might be challenge for arm-disabled elders or those who need body weight support to walk. Especially on up/downhill elderly people need to support their body weight in the direction of gravity, therefore, it may be difficult to handle the system accurately. More advanced research also exists that fully supports the user's body, providing fall detection and intent recognition [14]. However, speed control still relies on button operations, and aside from properly engaging brakes on slopes, these systems do not offer features to stabilize the user's posture. To the best of our knowledge, no walker currently offers a stabilizing function that adjusts the user's posture by recognizing changes in the terrain, such as on a slope.

We propose an adaptive walker system that utilizes high-resolution tactile sensors and IMU sensors to adaptively respond to the user's intent and terrain changes. Our proposed system has two main contributions. First, as Fig. 1, our adaptive walker system leverages high-resolution tactile sensors and deep learning technology to interact with users, recognizing user intent and allowing for movement at desired speeds more naturally. Second, it detects and reacts to the inclines of the surrounding terrain, adjusting its form to enable stable walker use on both uphill and downhill paths.

To evaluate the proposed system, we conducted intended acceleration prediction test with individual test data and we also conducted slope applying test. The test results showed that the walker was able to predict the walking speed with an error margin of 20.99% and maintain balance with an error margin of less than 1 degree. These features may helps to allow elderly users to use walkers more comfortably and safely who may have diminished cognitive abilities and slower reaction times. In addition, adjusting the walker's shape on slopes can help users stabilize their posture, allowing for safer movement. Thus, our adaptive walker system offers user-friendly functionality by responding adaptively to both the user and their terrain.

II. Walker System Overview

The adaptive walker system is configured as shown in Fig 2. This device is designed to naturally detect interaction with the user and change its form to adapt to changes in the external terrain. Tactile sensors attached to the handle and armrests, which are in direct contact with the human body, detect the interaction between human and walker. The IMU sensor mounted on the front of the walker detects its tilt. The main PC, which operates on batteries, uses signals from these sensors to implement the desired speed through DC motors and adjusts the walker's form to maintain a stable posture using linear motors. Specifications of the adaptive walker demonstrated in Table 1.

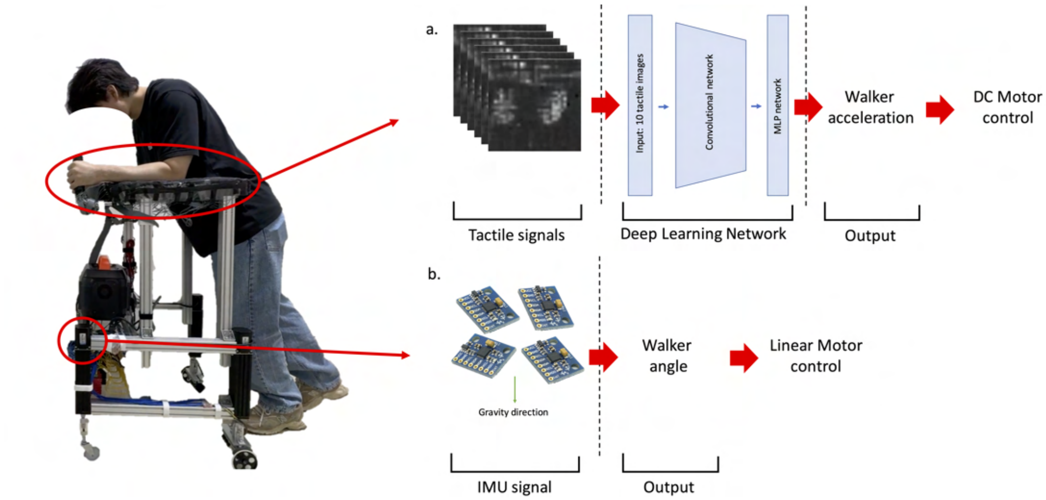

Fig. 4. Adaptive walker software structure. The adaptive walker includes two control software systems. The software that utilizes the tactile sensor (a) uses a trained deep learning network to infer the desired walker acceleration from the user's tactile inputs. The inferred acceleration is transmitted to the motor, adjusting its speed for acceleration or deceleration. The software using the IMU sensor (b) measures how much the walker is tilted relative to the ground and calculates the necessary adjustments for the walker's angle. It then controls the linear motor to adjust the walker's form to make the walker stable.

A. *Tactile sensor*

High-resolution tactile sensors were used for tactile sensing. In this case, a high-resolution pressure mat, specifically designed to fit the shape of the walker's armrest and handle, was used for tactile sensing [15], [16]. The tactile sensor, covering a total area of $0.15m^2$ with 1024 pressure detection points, placed sensing points at intervals of 8 mm. The sensor was designed by fixing thin copper wires to non-woven fabric using an embroidery machine, placing a piezo-resistive film on top, and then positioning another set of copper wires perpendicularly over it, creating sensing points at the intersections of the wires. As shown in Fig. 3 (a) we can easily create a tactile sensor in a few steps.

Each sensing point can measure pressure up to 14kPa with the highest sensitivity of 0.3kPa [15], [16]. Since the materials required to make the sensor are only copper wire, non-woven fabric, and piezoresistive film, our sensor can be manufactured inexpensively ($\sim$ 20 USD). Additionally, since the resolution or form of the sensor can be freely changed according to needs, it is convenient to use in different types of walkers or other assistive devices. The sensor can collect data at a rate of about 12 FPS when processing 1024 sensing points information through a mini-computer (Jetson AGX Xavier). The actual response of the tactile sensor is shown in Fig. 3 (b) The pressure generated by both hands and arms is well collected from sensing points.

B. *IMU sensor*

IMU sensor was used for tilting sensing. The IMU sensor is fixed to the front of the walker, detecting the tilting degree of the walker. In this study, since the goal is to change the shape of the walker on uphill and downhill slopes, only the tilting angles front and back were detected and used. The IMU sensor used here is the MPU-6050, which cannot directly extract angle values, but estimates the degree of tilt of the walker through the direction of gravitational acceleration.

C. *Computing system*

We used Jetson AGX Xavier PC for the computing system, responsible for acting as the brain of the adaptive walker. This system provides the necessary computing power for our deep learning models, as well as managing the walker's various sensors and motors. Herein, the system drew 30W from a power bank of a 100Ah to ensure sufficient computing performance.

The Jetson AGX Xavier is equipped with an 8-core ARM v8.2 64-bit CPU, supported by 8 MB L2 cache and 4 MB L3 cache, as well as a 512-core Volta GPU with Tensor Cores, capable of performing up to 32 trillion operations per second (TOPS) for AI tasks. As the walker is designed for elderly users, ensuring high computational performance is crucial to avoid any hazards resulting from insufficient processing power.

D. *Actuation system*

The actuation system in this study is divided into two parts: 1) a dual BLDC motor acceleration system for speed control and 2) a four linear motor system for adjusting the shape of the walker.

First, we installed two BLDC motors, one on each rear wheel, to control the speed of the walker. The motor driver used is the BDD-240 240W BLDC Motor Digital Driver. The front wheels of the walker are equipped with passive wheels with 2 degrees of freedom (2DoF), allowing the user to change direction. The speeds of the two BLDC motors are dynamically adjusted by acceleration signal from computing system.

Next, we implemented a system to dynamically adjust the walker's slope by utilizing four linear motors that control

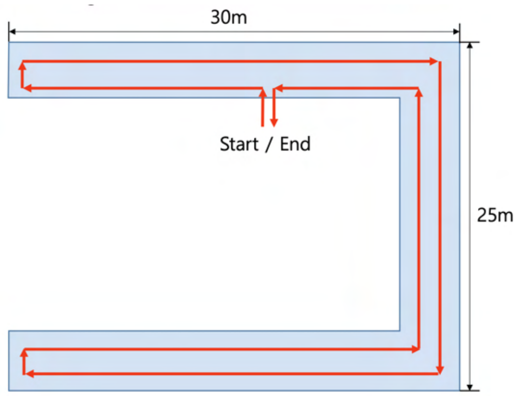

Fig. 5. Data collection method illustration. Five different individuals were tasked with walking a predetermined route using the walker, where they were instructed to repeatedly stop and go according to random signals. This allows we can collect acceleration and deceleration data from tactile and IMU sensors simultaneously.

TABLE II
DETAILED DEEP LEARNING NETWORK STRUCTURE

Name	Type	Size
Input	Multi layer tactile image	10 × 32 × 32
Conv 0	Convolution network (k=3) LeakyReLU BachNorm2d	32 × 32 × 32
Conv 1	Convolution network (k=3) LeakyReLU BachNorm2d MaxPool2D (k=2)	64 × 16 × 16
Conv 2	Convolution network (k=3) LeakyReLU BachNorm2d	32 × 16 × 16
Conv 3	Convolution network (k=3) LeakyReLU BachNorm2d MaxPool2D (k=2)	16 × 8 × 8
FC 1	Fully connected layer	128
FC 2	Fully connected layer	1
Output	Predicted acceleration	1

the length of the four legs. The linear motors employ step motors for position control, which are managed by the MSD-2C45 step motor driver. To prevent the walker legs from twisting, the front two linear motors and the rear two motors were grouped together, ensuring that each group's length is synchronized. This design allows the slope to be adjusted while maintaining contact with the ground for all four legs.

III. User Intention and Terrain Recognition

The walker's software system consists of two main components. First, intention recognition. this software uses tactile sensors to detect the user's intent and accordingly controls the speed of the walker. By interpreting slight pressure changes and movements detected by the sensors, the system adjusts the walker's speed to match the user's desired pace. Second, terrain recognition. this part of the system recognizes changes in the surrounding terrain and adapts the walker's shape accordingly. For example, if it detects an uphill or downhill slope, it can adjust the walker's legs to maintain stability and ease of use. In the following subsections, each of these software components is explained in more detail to provide a comprehensive understanding.

A. Intent recognition

The goal of the intent recognition algorithm is to use tactile interactions between the user and the walker to predict the desired acceleration, enabling the walker to move smoothly in response to the user's intent. Collected data on tactile interactions when a user accelerates or decelerates the walker. The data was collected with five participants asked to walk with a walker along a predetermined route of approximately 170 meters, as illustrated in Fig. 5. During the data collection, users were instructed to randomly stop and restart walking with the walker in response to random external stop/go signals. The wheels of the walker were left free to roll without motors, and both the tactile sensor and IMU sensor simultaneously collected data on tactile interactions and the corresponding walker acceleration. A total of 15,402 frames of data were collected, with the initial 80% of each user's data used for training and the remaining 20% used for testing.

The train data was used to train a deep learning network as shown in Fig. 4 (a) In this setup, the deep learning network needed to operate on a small PC with limited computational power, so a lightweight multi-layer CNN structure was utilized. The tactile signals capture interaction forces exerted by the user to move the walker, while the walker's acceleration data, collected simultaneously, represents the desired acceleration induced by the user's intent. To enable control of the walker based on user interaction forces, ten consecutive tactile information frames from the hands and arms are used as inputs to a deep learning network. This information is processed by a lightweight deep learning model optimized for onboard operation, enabling it to predict the acceleration (user's desired acceleration) of the walker.

B. Terrain recognition

The terrain recognizing function aims to stabilize the posture of both the walker and the user by recognizing the surrounding terrain. This utilizes algorithm that calculates the current angle of the walker relative to the ground using the IMU signal, as depicted in Fig. 4 (b), and sends appropriate signals to the linear motor based on these calculations. Here, the MPU-6050 accelerometer is used to calculate the angle, determining the tilt of the walker by analyzing the direction of gravitational acceleration.

Here, the angle calculation for the walker is performed individually with acceleration prediction. If any time the walker is tilted more than 1 degree from its initial orientation, motor control begins. Even after starting control, the walker's angle is continuously calculated and monitored to prevent excessive adjustments. Here, to prevent walker tilting, linear

Algorithm 1 adaptive walker algorithm to control hardware

Require:
Pressure signal from tactile sensor T
Tilted angle signal from IMU sensor I
Trained deep learning model M
procedure WALKER CONTROL(T, I, M)
  Pressure threshold T_{thresh}
  Safe angle range $R = [-1, 1]$
  Initialize T and I
  Set DC motor speed V
  Set Linear motor length L
  Set acceleration buffer B_{acc} ▷ max len = 5
  Set walker angle buffer B_{angle} ▷ max len = 5
  while run **do**
    Pressure strength T_s
    if $(T_s) > T_{thresh}$ **then**
      $Acc = M(T)$, $Angle = I$
      Put Acc in B_{acc}, $Angle$ in B_{angle}
      $V += \text{Mean}(B_{acc})$
      if Mean(B_{angle}) not in R **then**
        Change Ls **until** Mean(B_{angle}) in R
      end if
    else
      $V = 0$
    end if
  end while

motor lengths are modified. The velocity of the tilting adaption can be determined as the user's wish.

IV. ADAPTIVE WALKER SYSTEM INTEGRATION

The system runs on a custom Linux operating system, based on Ubuntu 18.04, distributed via NVIDIA's Jetpack. This terrain closely mirrors the environment of a standard Linux PC. It allows the use of popular native libraries, making development and maintenance straightforward.

The system provides 40-pin headers which can directly connect with general-purpose input ouput (GPIO) pin. The walker's two DC motors, four linear motors, and IMU were connected to this system through this pin connection. Since it is hard to supply 5V of power to the motors simultaneously, the motors drew power from the power bank via motor drivers and received pulse signals from the system to operate them.

In terms of control, the walker uses GPIOs with Pulse Width Modulation (PWM) signals, implemented via Python GPIO packages for Jetson. Since the direction of the walker is determined by varying the speed of the DC motors, and the linear motors adjust its tilt based on the slope of the road and the user's walking speed, each motor requires its own PWM signal (six in total). While the Jetson AGX Xavier provides only three analog PWM pins, we implemented the PWM signals in software.

Once our system completes sensing, model inferencing, and motor control setup, it controls the walker using the logic shown in Algorithm 1. This process involves continuously reading tactile and IMU data, performing inference with the trained model, and controlling motor movements based on these results.

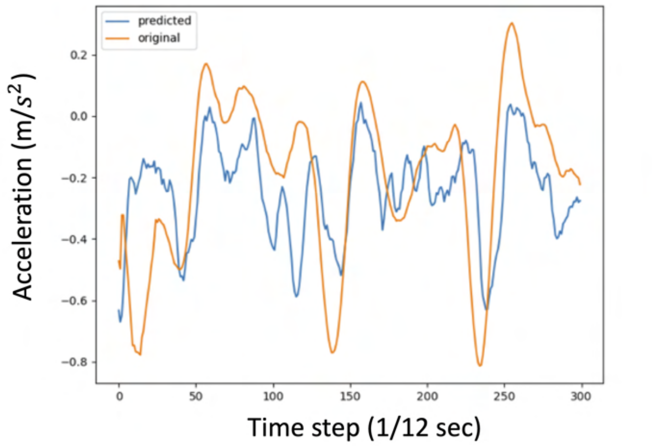

Fig. 6. The predicted acceleration result of the walker using a trained deep learning network. The orange line represents the actual acceleration generated by the person, and the blue line represents the desired acceleration predicted based on the user's tactile information.

V. SYSTEM EVALUATION

We evaluated to verify the proper functioning of the walker system. The evaluation focused on whether our model predicted the desired acceleration using the tactile signals. This evaluation used the latter 20% of the collected data from five participants that were not included in the training. The test data was inputted into the trained model to predict the user's desired acceleration, which was then compared to the actual acceleration recorded by the walker. The results obtained through this training are shown in Fig. 6. This figure displays the comparison graph of predicted walker acceleration inference by trained model and original acceleration data.

Despite not receiving any direct information about the walker's acceleration, the deep learning model effectively estimated the intended acceleration using tactile information. However, to make the walker evaluation more clearer, we integrated the acceleration to calculate the speed per second and checked how much difference occurred between the model's predictions and the actual acceleration every second. The error in the generated velocity by the model, when integrated per second, is approximately 0.293m/s ± 0.226. Considering that the average walking speed of the men in their 20s-30s who participated in the data collection is about 1.396m/s, the model can infer speed with an error of 20.99% of walking speed [17]. This error rate is a bit high, but considering that this paper focused on the system configuration and collected limited participant data, it can be improved with additional data collection.

For the angle values, we successfully controlled the linear motors in all cases when tilting the walker at random angles,

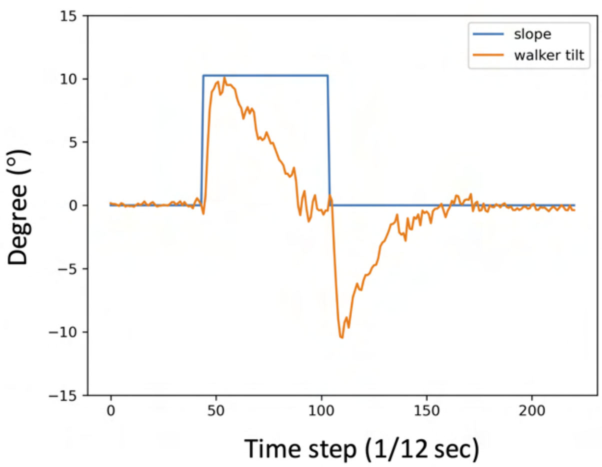

Fig. 7. The predicted acceleration result of the walker using a trained deep learning network. The orange line represents the actual acceleration generated by the person, and the blue line represents the desired acceleration predicted based on the user's tactile information.

ensuring the IMU values remained within the range of -1 to 1 degree. This result can be achieved because our angle control method continuously adjusts the motors while referencing IMU values until reach the desired angle.

Fig. 7 shows part of the experimental results in more detail. This experiment demonstrates the changes in the walker's tilt angle when a 10-degree tilt was applied to the walker and then removed. It can be observed that, even with sudden slope changes in the surrounding terrain, the walker adjusts its tilt degree to 0 degrees within a few seconds through shape modification.

VI. Limitations and Future Works

This study proposes a new method for walker mobility, but it includes several limitations. First, the speed prediction performance within 20% of normal walking still can be improved. In this study, data was collected from only five individuals; however, performance can be enhanced through additional data collection and model training or by using a more improved network structure. Secondly, there is a need to add more functions. Other walker studies already incorporate user convenience features such as autonomous driving modes and call functions. To make the adaptive Walker more widely used, it is necessary to integrate such convenience functions. Lastly, Human-Computer Interaction (HCI) studies need to be conducted. It is essential to research the actual impact of the walker on users, especially the elderly, to further analyze the practicality of the walker.

We will conduct further studies to improve these limitations. In particular, the short-term goal is to collect data from the elderly in addition to the general users and use it for model training. Here, we hope this additional training improves the performance of the model so that the elderly can operate the walkers more comfortably. We will also conduct further research to generate a more practical walker system by upgrading various convenience functions and upgrading usability through user study.

VII. Conclusion

This study addresses limitations found in previous walker-related research, where the systems hard to naturally detect users' acceleration or deceleration intentions. By incorporating deep learning and high-resolution tactile sensors, this research enables such detection. Furthermore, while traditional walker systems only offer braking and assist moving functions on slopes, this study utilizes IMU sensors and linear motors to alter the walker's form on the slope. This research shifts the focus towards more natural and comfortable interactions between the walker and its user, and between the walker and its terrain, proposing a new direction for creating smarter walker systems.

The results of this research show that the desired walker speed can be predicted by a deep learning network with high-resolution pressure sensor input within 20.99% error. This is a distinct approach from previous studies that controlled walker speed through physical handles or buttons. Here, users can rely entirely on the walker for support while walking, allowing the walker to adjust its speed automatically. This feature may provide particularly beneficial for elderly users who may find it challenging to exert force with their arms or those with cognitive declines, providing them with a comfortable and safe way to use the walker. Additionally, by using linear motors and IMU sensors to adjust the length of the walker's legs, the system ensures that the walker's body remains parallel to the ground with less than 1-degree of error. This stabilization through the walker's form may help users maintain a stable posture on both uphill and downhill paths, preventing them from tilting forwards or backwards and promoting safe mobility in inclines.

This research is particularly significant because it proposes a new approach to control walker movement in convenience. Additionally, this study has the potential to merge with previous studies to develop improved walker systems. For example, it could be combined with research that used low-resolution soft sensors to predict user falls [14]. Here, high-resolution sensors and a deep learning approach may enable more precise predictions and adjust walking speed in detail. Moreover, similar to prior studies that used high-resolution tactile sensors to predict a user's pose, this research could enable real-time pose prediction for walker users, facilitating posture diagnostics or status checks [15]. It is also expected that this research could be integrated with studies that assisted movements on inclines and declines, further enhancing research on movement and posture assistance [7].

Acknowledgment

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