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Stumbling Prediction Method Using an Inertial Sensor to Prevent Falls During Walking

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Abstract— **In modern society, where the population is aging, fall prevention is an extremely important issue for extending healthy life expectancy, preventing nursing care, and reducing the economic burden on families. However, while numerous studies have been conducted on fall risk estimation, fall motion detection, and fall occurrence detection, studies on fall prediction remain limited. This is because it requires multiple sensors and wearable devices, which lacks practicality. In this study, we investigated the possibility of predicting stumbling during the initial swing phase for the purpose of preventing falls during walking in elderly people. First, using Simscape Multibody, one of the toolboxes of MATLAB/Simulink, we developed a total of 36 models by combining six leg models and six walking models. Next, we attached one inertial sensor to the toe in the simulation and analyzed and compared the data. As a result, it was confirmed that stumbling can be predicted based on the positive or negative slope of angular acceleration in the first half of the initial swing phase just prior to stumbling.**

I. INTRODUCTION

In modern society, the global population is aging rapidly. The aging rate, which was 5.1% in 1950, rose to 9.4% in 2020, and is projected to reach 18.7% by 2060 [1]. In particular, Japan has the highest aging rate in the world, and this high rate is expected to continue in the future [1]. Moreover, there is a gap of about 9 years for males and 12 years for females between the healthy life expectancy—the period during which people can live without limitations in daily activities—and the average life expectancy, making the extension of healthy life expectancy an issue [1]. One of the reasons for this gap is the increasing number of elderly people certified as needing nursing care or support [1]. The main cause for needing nursing care is dementia at 16.6%, followed by cerebrovascular disease at 16.1%, fracture/fall at 13.9%, weakness due to aging at 13.2%, and joint disease at 10.2% [2]. Dementia, in particular, has been reported to increase the risk of falls by about 8 times, while other diseases and weakness due to aging also increase the risk of falls through the decline in physical function [3]. In addition, trauma and psychological changes caused by falls have a significant impact on physical function. In particular, proximal femoral fractures and post-fall syndrome significantly reduce activities of daily living (ADL) and quality of life (QOL) [4]. Therefore, falls are a main cause of needing nursing care or support. For these reasons, fall prevention is an extremely important issue for extending healthy life expectancy, preventing nursing care, and reducing the financial burden on families.

Previous studies on falls can be broadly divided into four categories: fall risk estimation, fall prediction, fall motion detection, and fall occurrence detection. Agrawal et al. developed insoles using embedded five wireless pressure sensors and machine learning to estimate fall risk [5]. Tarbert et al. developed a smart belt using embedded inertial sensor, airbag, and machine learning to detect fall motion and reduce impact on the hip [6]. Nho et al. proposed a method using an accelerometer and a heart rate sensor attached to the finger and wrist, along with machine learning, to detect fall occurrence [7]. These studies represent only a small part, but studies on fall risk estimation, fall motion detection, and fall occurrence detection have been extensively conducted.

On the other hand, studies on fall prediction are not widely conducted. In this study, "fall prediction" is defined as detecting the risk of a fall before it occurs and identifying abnormal walking patterns to prevent the fall. The most common fall prediction methods are those that use multiple sensors or wearable devices. For example, Majumder et al. proposed a method using four pressure sensors attached to shoes and a smartphone [8]. Ohashi et al. developed a wearable device using upper body muscles as a power source to promote ankle dorsiflexion [9]. However, these methods have practical issues such as poor wearing comfort and high cost.

In this study, we focused on the ankle joint angle during the initial swing phase of walking in elderly people and investigated the possibility of predicting stumbling by attaching only one inertial sensor to the toe. There are two methods for walking analysis: attaching sensors to the subject's bodies and developing walking models using simulation software. Since this study included stumbling motion, it was necessary to consider the risk of injury during the experiment. Therefore, we adopted the latter method and used Simscape Multibody, one of the toolboxes of MATLAB/Simulink. First, we designed three leg models for elderly males and elderly females, respectively. Next, we developed one normal walking model that reproduced the leg motion during the initial swing phase of walking. Furthermore, we developed five walking models with reduced ankle dorsiflexion angles compared to the normal walking model. Subsequently, we attached one inertial sensor to the toe in the simulation, and analyzed and compared the angle, angular velocity, and angular acceleration.

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II. STUMBLING

Stumbling is a phenomenon where the toe comes into contact with the ground or obstacles on the ground, and it is the most common cause of falls [10]. Stumbling during walking mainly occurs in the initial swing phase. The distance between the toe and the ground during the swing phase (toe clearance: TC) is considered to influence stumbling. In particular, minimum toe clearance (MTC) observed in the initial swing phase is closely related to stumbling [11].

The risk factors for falls in elderly people, other than disease, are functional weakness due to aging and lifestyle habits. The main cause of stumbling during walking in elderly people is the weakness of the tibialis anterior muscle, which is responsible for ankle dorsiflexion [12][13]. This weakness can lead to delayed ankle dorsiflexion or a reduced range of motion in ankle dorsiflexion, which contributes to a decrease in MTC.

Figure 1 shows the basic axes and definitions of motion for each joint. Each joint has a basic axis defined where the angle is 0deg [14]. The basic axis of the hip joint is generally a line parallel to the trunk, but in this study, it was defined as a line vertical to the ground. The basic axis of the knee joint was defined as the extension line of the thigh (Red area), and the basic axis of the ankle joint was defined as the point where the angle between the lower leg (Blue area) and the foot (Green area) is a right angle. In addition, each joint motion has a positive and negative direction relative to its basic axis. The hip joint is represented as flexion in the positive direction and extension in the negative direction. The knee joint is represented as extension in the positive direction and flexion in the negative direction. The ankle joint is represented as dorsiflexion in the positive direction and plantarflexion in the negative direction. Each joint motion varies with the walking cycle. For example, during the initial swing phase, the hip and knee joints are both in flexion motion, while the ankle joints are in dorsiflexion motion.

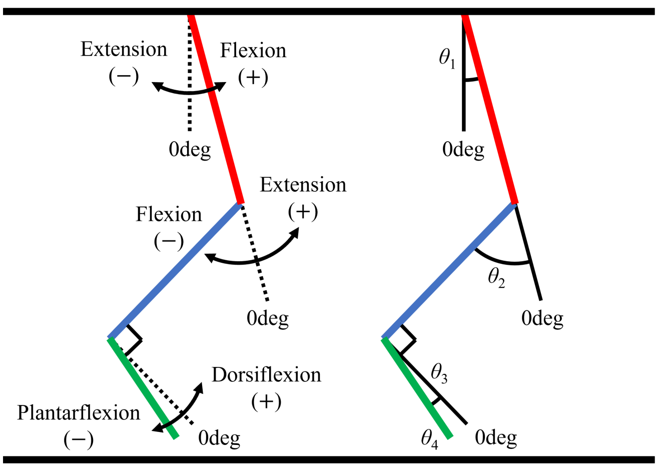


Fig. 1. The basic axes and definitions of motion for each joint (Red area: Thigh, Blue area: Lower leg, Green area: Foot)

Furthermore, θ_1, θ_2, and θ_3 shown in Fig. 1 are the hip joint angle, knee joint angle, and ankle joint angle, respectively. θ_4 is the angle obtained from the inertial sensor attached to the toe.

Based on the above, in this study, we decided to focus on the ankle dorsiflexion angle during the initial swing phase of walking, and to attach an inertial sensor to the toe in order to predict stumbling.

III. PROPOSED METHOD

In this study, we investigated the possibility of predicting stumbling during the initial swing phase for the purpose of preventing falls during walking in elderly people. Walking analysis was conducted using Simscape Multibody (MATLAB R2024a version), one of the toolboxes of MATLAB/Simulink.

A. *Definition of Human Body Parameters*

Table I and Table II show the dimensions and masses of the thigh, lower leg, and foot of the leg model designed in this study. The leftmost column of these tables lists the leg dimension and mass items used in the leg model design. The right columns list the dimension and mass values of the leg model (100% dimension model) cited and calculated from [15] and [16], as well as the dimension and mass values of the leg models (95% and 105% dimension models) where only the dimensions were varied by ±5% based on the 100% dimension model.

TABLE I
LEG DIMENSIONS AND MASSES OF ELDERLY MALE MODEL [15][16]

Item name	95% dimension	100% dimension	105% dimension
Thigh length [mm]	362.1	381.2	400.3
Lower leg length [mm]	341.7	359.7	377.7
Sphyrion height [mm]	60.3	63.5	66.7
Foot length [mm]	230.3	242.4	254.5
Thigh mass [kg]		5.90	
Lower leg mass [kg]		2.81	
Foot mass [kg]		0.843	

TABLE II
LEG DIMENSIONS AND MASSES OF ELDERLY FEMALE MODEL [15][16]

Item name	95% dimension	100% dimension	105% dimension
Thigh length [mm]	338.3	356.1	373.9
Lower leg length [mm]	317.7	334.4	351.1
Sphyrion height [mm]	60.6	63.8	67.0
Foot length [mm]	214.9	226.2	237.5
Thigh mass[kg]		5.32	
Lower leg mass [kg]		2.54	
Foot mass [kg]		0.761	

First, using Simscape Multibody of MATLAB/Simulink, we designed three leg models for elderly males and females, each with different leg dimensions and masses, as shown in Table I and Table II. Next, for each leg model, we developed one normal walking model (Model−1) that reproduced the leg motion during the initial swing phase of walking. Furthermore, we developed five walking models (Model−2 to Model−6) with different ankle dorsiflexion angles and smaller ankle dorsiflexion angles than Model−1. After designing the leg models and developing the walking models, we attached one inertial sensor to the toe in the simulation, as shown in Fig. 2, and analyzed and compared the angle, angular velocity, and angular acceleration.

In this study, the start time of the initial swing phase was defined as the moment when the hip joint reached 10deg extended position, and the end time was defined as the moment when the knee joint reached its most flexed position [17][18]. Based on this definition, we calculated the “Initial swing phase time”. Additionally, MTC in Model−1 was set to 12.7mm [19]. Furthermore, we defined the ankle joint angles at the start and end times of the initial swing phase of Model−1 to Model−6 as follows. First, the start time of the initial swing phase was defined as about 15deg plantarflexion position for all walking models. The end time was defined as about 5deg plantarflexion position for Model−1, about 8deg plantarflexion position for Model−2, about 9deg plantarflexion position for Model−3, about 10deg plantarflexion position for Model−4, about 11deg plantarflexion position for Model−5, and about 12deg plantarflexion position for Model−6 [17].

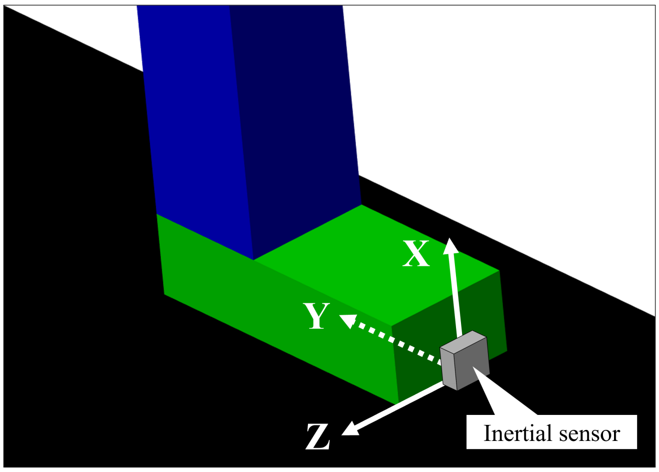
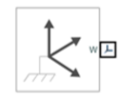
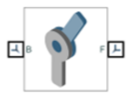


Fig. 2. Attachment position and 3-axis direction of an inertial sensor

B. Overview of Model and Simulation

Table III shows the blocks used in this study and the role of each block within this model. Additionally, Fig. 3 shows a block diagram of the developed walking model. Furthermore, Fig. 4 shows an example simulation of the developed walking model. Table III lists, from left to right, the images and names of the blocks and their roles in this model. Simscape Multibody, one of the toolboxes of MATLAB/Simulink, is software that creates a block diagram by connecting blocks with roles as shown in Table III and Fig. 3 and conducts simulation on a time axis.

TABLE III
THE BLOCKS USED IN THIS STUDY AND THE ROLE OF EACH BLOCK WITHIN THIS MODEL

Block	Block name	Role in this model
f(x) = 0	Solver Configuration	Definition of the configuration values for the simulation
	World Frame	Definition of the origin of the coordinate system
	Mechanism Configuration	Definition of gravity and direction of gravity
	Rigid Transform	Setting the distance between the hip joint and the ground and the position of the axis of rotation of each joint
	Revolute Joint	Definition of hip joint, knee joint, and ankle joint
	Brick Solid	Definition of thigh, lower leg, foot and ground
	Transform Sensor	Measurement of angle, angular velocity, angular acceleration, and y-axis translation at the toe
	PS-Simulink Converter	Setting the output signal unit for each data
simout	To Workspace	Logging of the output signal for each data

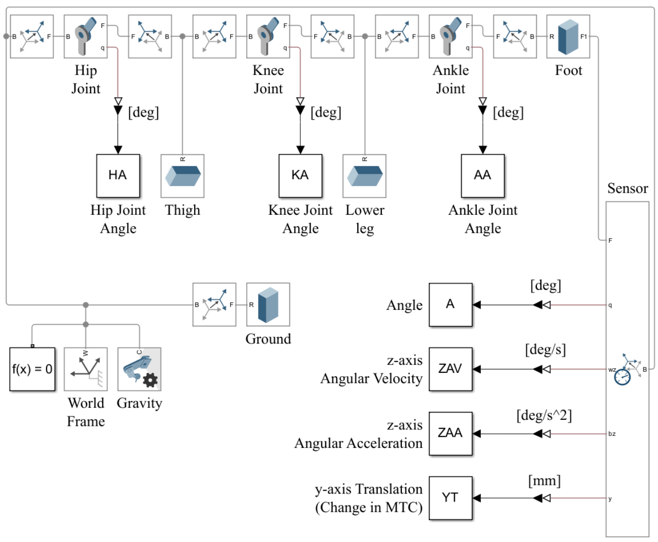


Fig. 3. Block diagram of the developed walking model

First, the model is described. Since the lower limb movement during the initial swing phase, which is the focus of this study, can be expressed as a double pendulum movement with two pivot points at the hip and knee joints. Therefore, we fixed the distance between the hip joint and the ground [20]. The coordinate system of this model was set as the world coordinate system, with the origin defined at the point where the ground and the hip joint axis intersect vertically. Next, Model−2 to Model−6 were developed based on Model−1. This study focuses on the ankle dorsiflexion angle. Therefore, in these models, the following two parameters of the block (Revolute Joint) that defines the ankle joint were adjusted to make the ankle dorsiflexion angles differ across the models. The first parameter is "[Internal Mechanics]-[Damping Coefficient]", which adjusts the damping amount of ankle dorsiflexion. By increasing this parameter, the ankle dorsiflexion angle is reduced, indirectly reflecting muscle weakness. The second parameter is "[State Targets]-[Specify Position Target]-[Value]", which adjusts the initial angle of the ankle joint at the start of the simulation. This parameter was adjusted to approximate the aforementioned ankle joint angles at the start and end times of the initial swing phase, while considering the first parameter. All other settings were identical to those of Model−1. Furthermore, although sudden changes are observed in the inertial sensor data at the moment of stumbling, to eliminate these changes and improve visual clarity, we did not define contact with the ground (Black area in Fig. 4) in this model.

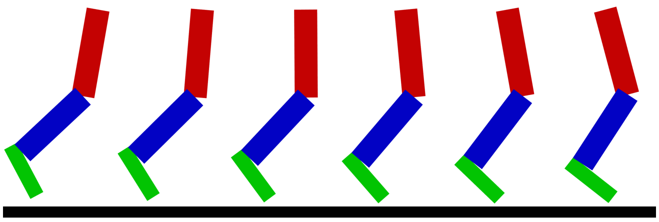


Fig. 4. Simulation example of the developed walking model (Model−1, 100% dimension model of elderly male model)

Next, the simulation is described. The sample time was set to 1msec. Additionally, for the model in which stumbling occurs, the "Pre-stumbling time" was considered. This is because, with a sample time of 1msec, it is difficult to accurately record the moment when the distance between the toe attached to the inertial sensor and the ground becomes 0mm. In this study, we defined "Pre-stumbling time" as the time with the smallest positive value closest to 0mm for the distance between the toe and the ground. Furthermore, since the coordinate system of this model is the world coordinate system, the angle θ_4 obtained from the inertial sensor shown in Fig. 1 is expressed as $\theta_4 = \theta_1 + \theta_2 + \theta_3$ using the hip joint angle θ_1, knee joint angle θ_2 and ankle joint angle θ_3. Similarly, angular velocity and angular acceleration are expressed as the sum of the data from each joint.

IV. RESULTS

A. Simulation Result

As a result of the walking model simulations, it was confirmed that stumbling did not occur in Model−1 to Model−4, whereas stumbling occurred in Model−5 and Model−6 for all leg models. Table IV shows the initial swing phase time for all models developed in this study. Additionally, Table V shows the pre-stumbling time for Model−5 and Model−6, where stumbling occurred. The leftmost columns of these tables list the model names of the leg and walking models. The right columns list the initial swing phase time and the pre-stumbling time for 95%, 100%, and 105% dimension models. From Table IV and Table V, it is evident that as the ankle dorsiflexion angle decreases, the initial swing phase time becomes shorter and the pre-stumbling time becomes earlier.

TABLE IV
INITIAL SWING PHASE TIME [SEC]

Model name		95% dimension	100% dimension	105% dimension
Elderly male	Model−1	0.123	0.127	0.130
	Model−2	0.118	0.121	0.125
	Model−3	0.116	0.120	0.123
	Model−4	0.115	0.118	0.121
	Model−5	0.113	0.116	0.120
	Model−6	0.111	0.115	0.119
Elderly female	Model−1	0.122	0.125	0.128
	Model−2	0.116	0.119	0.122
	Model−3	0.114	0.117	0.121
	Model−4	0.112	0.116	0.119
	Model−5	0.110	0.114	0.117
	Model−6	0.108	0.112	0.116

TABLE V
PRE-STUMBLING TIME [SEC]

Model name		95% dimension	100% dimension	105% dimension
Elderly male	Model−5	0.090	0.090	0.090
	Model−6	0.074	0.076	0.076
Elderly female	Model−5	0.094	0.095	0.095
	Model−6	0.074	0.076	0.077

B. Inertial Sensor Analysis Result

There were no differences in trends for angle and angular velocity regardless of whether stumbling occurred or not. Therefore, this result focuses only on the angular acceleration, which showed the largest differences. Figure 5 and Figure 6 show the changes in angular acceleration in the initial swing phase for 100% dimension models of the elderly male and female models. Figure 5 and Figure 6 have time on the horizontal axis and angular acceleration obtained from the sensor on the vertical axis, and the horizontal axis range is set to Model−6, which has the shortest initial swing phase time. Focusing on the 0sec to 0.03sec interval of these graphs, the lines within the blue frame represent Model−1 to Model−4, all showing negative slopes. On the other hand, the lines within the red frame represent Model−5 and Model−6, both showing positive slopes. This result was similar for 95% and 105% dimensional models. Table VI shows the slopes between 0sec and 0.03sec that can be regarded as straight lines in Fig. 5 and Fig. 6. The leftmost column of Table VI lists the model names of the leg model and walking models. The right columns list the slopes from 0sec to 0.03sec for the 95%, 100%, and 105% dimension models. From Table VI, it is also evident that the positive and negative slopes are reversed depending on whether or not stumbling occurs.

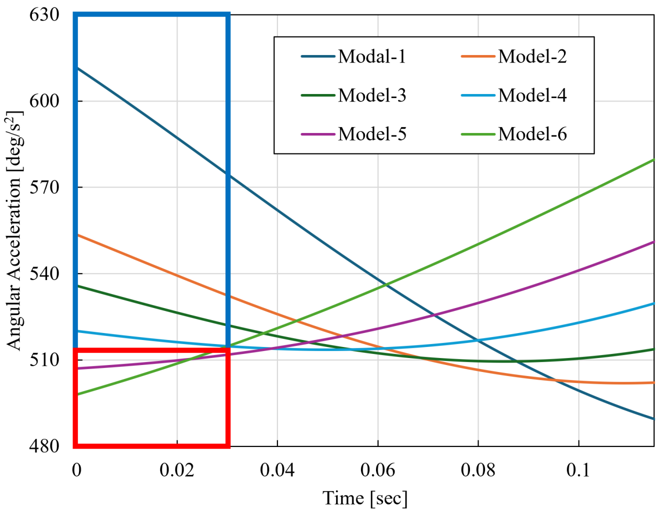


Fig. 5. Angular acceleration changes in the initial swing phase of 100% dimension model for elderly male model (Blue frame: Model with no stumbling, Red frame: Model with stumbling)

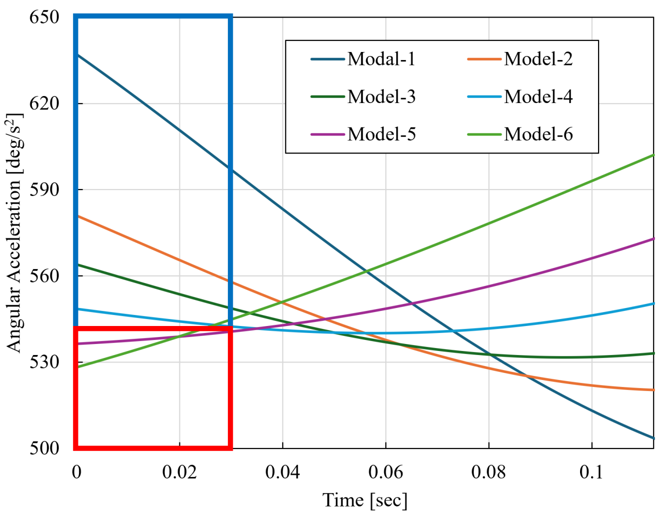


Fig. 6. Angular acceleration changes in the initial swing phase of 100% dimension model for elderly female model (Blue frame: Model with no stumbling, Red frame: Model with stumbling)

TABLE VI
ANGULAR ACCELERATION SLOPE IN THE FIRST HALF OF THE INITIAL SWING PHASE (0SEC TO 0.03SEC)

Model name		95% dimension	100% dimension	105% dimension
Elderly male	Model−1	-1362.4	-1234.9	-1143.7
	Model−2	-777.02	-706.47	-642.59
	Model−3	-513.81	-457.94	-415.35
	Model−4	-203.29	-177.10	-152.16
	Model−5	152.30	158.51	168.54
	Model−6	570.67	557.99	540.39
Elderly female	Model−1	-1479.0	-1340.3	-1222.8
	Model−2	-849.81	-771.82	-702.45
	Model−3	-572.30	-511.87	-455.13
	Model−4	-246.60	-205.32	-173.96
	Model−5	130.22	141.58	151.32
	Model−6	572.88	554.23	538.95

From these results, it was confirmed that Model−1 to Model−4, where stumbling did not occur, and Model−5 and Model−6, where stumbling occurred, can be distinguished by the positive and negative slope of the angular acceleration in the first half of the initial swing phase. Furthermore, since the pre-stumbling time was 0.074sec at the earliest and the time that could be discriminated by the positive/negative slope ranged from 0sec to 0.03sec, stumbling prediction is considered to be possible.

V. DISCUSSION

It was confirmed that stumbling could be predicted based on the positive or negative slope of the angular acceleration in the first half of the initial swing phase (0sec to 0.03sec).

In this study, we focused on the ankle joint angle and intentionally altered only the ankle joint parameters in the model development. Also, since the world coordinate system is used, the angular acceleration obtained from the inertial sensor attached to the toe is the sum of the angular accelerations at each joint. Therefore, the reason for the reversal of the positive and negative slope between Model−4 and Model−5 is considered to be influenced by the relationship between the sum of the changes in the angular acceleration at the hip and knee joints and the change in the angular acceleration at the ankle joint.

Furthermore, it was confirmed that the results of stumbling prediction showed consistent trends even when the leg dimensions and masses were varied. These results indicate that the effectiveness of the prediction method is maintained even with variations in leg dimensions and masses within a certain range. However, it remains unclear whether the same results can be obtained when these conditions differ significantly, and further verification considering various physical conditions is needed in the future.

The simulation results confirmed that as the ankle dorsiflexion angle decreased, the duration of the initial swing phase shortened, and the timing of stumbling occurred earlier. It is also known that in actual walking, a decrease in the ankle dorsiflexion angle leads to reduced stride length and walking speed, as well as a shorter walking cycle [21]. Therefore, the walking model developed in this study is a highly accurate simulation that relates to actual walking.

Future challenges include the development of an extended model that incorporates the effects of joints and muscle activity other than the ankle joint. Additionally, it is necessary to verify this model using actual data from elderly people to confirm its effectiveness in a real-world environment. Furthermore, to expand the scope of application of this study's model, further verification considering various physical conditions (e.g., leg dimensions and masses) is required.

VI. CONCLUSION

In this study, we investigated the possibility of predicting stumbling during the initial swing phase for the purpose of preventing falls during walking in elderly people. The verification method adopted was simulation using Simscape Multibody (MATLAB R2024a version), one of the toolboxes of MATLAB/Simulink. First, we designed two leg models based on leg dimensions and masses. In addition, we developed six walking models with different ankle dorsiflexion angles in the initial swing phase. Then, we analyzed and compared the angle, angular velocity, and angular acceleration obtained from the inertial sensor attached to the toe. As a result, it was confirmed that stumbling could be predicted based on the positive or negative slope of the angular acceleration in the first half of the initial swing phase (0sec to 0.03sec). Additionally, the same results were obtained even when the leg dimensions were varied by $\pm 5\%$, confirming a certain degree of versatility of the prediction method.

In the future, we plan to build on the results of this study and proceed with verification in a real-world environment. During this process, we will conduct an analysis considering the effects of noise and time delays present in the inertial sensor data. In addition, we aim to elucidate the mechanism by which the positive and negative slopes of the angular acceleration reverse, with the goal of improving the accuracy of stumbling prediction and establishing its practicality.

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