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Preliminary Design of a Terrain Recognition System

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***Abstract*—This paper aims to design a wearable terrain recognition system, which might assist the control of powered artificial prosthetic legs. A laser distance sensor and inertial measurement unit (IMU) sensors were mounted on human body. These sensors were used to identify the movement state of the user, reconstruct the geometry of the terrain in front of the user while walking, and recognize the type of terrain before the user stepped on it. Different sensor configurations were investigated and compared. The designed system was evaluated on one healthy human subject when walking on an obstacle course in the laboratory environment. The results showed that the reconstructed terrain height demonstrated clearer pattern difference among studied terrains when the laser was placed on the waist than that when the laser was mounted on the shank. The designed system with the laser on the waist accurately recognized 157 out of 160 tested terrain transitions, 300ms-2870ms before the user switched the negotiated terrains. These promising results demonstrated the potential application of the designed terrain recognition system to further improve the control of powered artificial legs.**

I. Introduction

LOWER extremity amputation is a major impairment that affects the basic activities of the leg amputee's daily life. Recent developments in microprocessor-controlled, powered artificial legs have enabled the design of multi-functional prosthetic legs possible [1-3]. With the powered device, the patients with leg amputations are able to easily perform the activities that are difficult or even impossible when wearing the passive devices. The control of the powered artificial legs is mode-based [2-3] because the control strategies depend on the user's locomotion mode such as level walking and stair ascent/descent. To allow the prosthetic leg to switch among different modes, users have to "tell" the prosthesis the movement intent and the type of negotiating terrains.

Various approaches have been developed to interpret the user's intent. A recent study uses the mechanical measurements from the powered prosthetic legs to identify user intent [4]. Our previous study [5] employed surface electromyographic (EMG) signals to identify the user's locomotion modes. About 90% accuracy was reported for recognizing seven locomotion modes. Besides, the accuracy for user intent recognition was further improved by fusing EMG signals measured from the residual thigh muscles and the ground reaction forces/moments collected from the prosthetic pylon [6].

Although the previous studies have showed promising results, further improvement in accuracy and time response for user intent recognition is warranted to ensure safe and robust prosthesis operation. Previous study on human vision in locomotion [7] has reported that the pre-acquisition of environmental information and self-motion could guide the movements of the lower limbs to adapt to the walking terrains. Inspired by this biological mechanism, the information of the walking terrain in front of the prosthesis user and the user's movement status might provide a prior knowledge to the intelligent intent recognition system to further enhance the system accuracy and response time. Many techniques have been used to detect/recognize the external terrains, such as stereo camera [8], infra red rangefinder [9], and 3D laser scanner [10]. Applications of these techniques for prosthetic leg are, however, challenging because (1) the equipment is too heavy for wearable and portable design, or (2) the real-time 3D image processing is computational complex for terrain recognition.

In order to make the application of terrain recognition on powered artificial legs possible and practical, a terrain recognition system based on a portable laser distance sensor and wearable inertial measurement unit (IMU) sensors was designed. Two tasks were conducted in this study. (1) We compared the two sensor configurations for walking terrain reconstruction. (2) The sensor configuration that provided clearer geometry pattern for terrain recognition was selected to design a terrain recognition system. The system was preliminarily evaluated on one healthy human subject. The results of this study may aid to improve the control of powered prosthetic legs and also hope to benefit the optimization of the passive or semi-active prostheses.

II. Methods and Results for Task 1

A. Sensor Configurations

This study was conducted under Institutional Review Board (IRB) approval and consent of the tested subject. One male, healthy subject was recruited.

Two sensor configurations were investigated in this study as shown in Fig. 1. For the first configuration, a portable optical laser distance sensors (Leuze Electronic, US) was instrumented on the right waist. The laser distance sensor can measure a distance ranging from 300-10000 mm, with a high degree of independence from the terrain's reflectivity

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properties. The resolution of the signal was 1-3mm. Four inertial measurement units (IMU) (Xsens Technologies B.V., Enschede, The Netherlands) were used to measure the position and orientation of the distance sensor and the subject (Fig. 1A). One of the IMU sensors was placed on the laser sensor with one axis aligned with the direction of the laser beam; the rest three were put on the lateral side of the right thigh, the lateral side of the right shank, and the top of the right foot, respectively. For the second configuration (Fig. 1B), the laser sensor was placed on the lateral side of the right shank. Only two IMU sensors were used: one fixed on the laser sensor to track the orientation of the laser beam, and the other placed on the top of the right foot to measure the user's movement state.

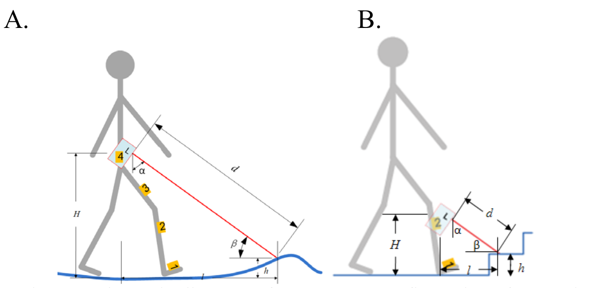

Fig. 1. Schematic diagram of two sensor configurations for terrain

B. Experimental Protocol

The distance senor and IMU sensors were secured to the human subject with a flexible strap. During the sensor calibration, the subject was instructed to stand still. The angle α between the laser beam and vertical direction was fixed at 45 degree for both configurations (Fig. 1). This angle varied when the subject started to move. The laser signal and the signals recorded from IMUs were sampled at 100 Hz. Experiments were videotaped. All the data recordings in this study were synchronized.

Six types of commonly encountered terrains were investigated in this study; they were level ground, up stair, down stair, up ramp, down ramp, and obstacle. An obstacle course was built in the laboratory, consisting of a level-ground walk way, 5-step stairs, 10-feet ramp, and obstacle block and flat platforms. During the experiment, the subject was instructed to walk at a comfortable speed with a predefined route. The subject started each trial from level-ground walking, transited to stair ascent, walked on a platform with a 90 degrees turn, descended a ramp, walked on another platform, descended a one-step stair, walked on the level-ground, stepped over an obstacle, and continued level-ground walking. Then, we asked the subject to stop and walk on the same path with a reversed direction. The trial was ended after the subject returned to the starting location. Totally 20 trials were conducted for each sensor configuration. Rest periods were allowed between trials.

C. Terrain Reconstruction Algorithm

The geometry of the terrain in front of the subject was reconstructed in the sagittal plane. Two geometrical parameters were used: the height of the terrain (h) and the horizontal distance from the subject to the terrain (l) as shown in Fig. 1. These two parameters at the moment t were calculated by

$$h(t) = H(t) - d(t)\sin\beta(t) \quad (1)$$

$$l(t) = d(t)\cos\beta(t) \quad (2)$$

where $H(t)$ denotes the vertical distance from the laser sensor to the ground, which can be obtained from the measurements of the IMU sensors. $d(t)$ denotes the distance measured from the laser sensor. $\beta(t)$ represents the tilt angle of the laser sensor in the sagittal plane, which can be obtained from the IMU sensor attached on the laser sensor.

D. Results and Discussion for Task 1

Two sensor configurations as shown in Fig. 1 were investigated and compared in this study. The terrain height, as the primary feature for designing the terrain recognition system, was used to evaluate two sensor configurations. The calculated terrain heights (h) in one representative trial derived from two sensor configurations were shown in Fig. 2A and 2B, respectively. The reconstructed terrain height demonstrated clearly distinguishable pattern among studied types of terrains when placing the laser sensor on the waist of the subject (Fig. 2A). When fixing the laser sensor on the subject's shank, however, the reconstructed terrain height was quite noisy and did not present obvious differences in pattern among tested terrains (Fig. 2B). The signal spikes presented in Fig. 2B were produced by the large motion of the shank during swing of each gait cycle. Therefore, the first sensor configuration with the laser sensor on the waist was employed in this study to recognize the terrains.

In addition, some noises were observed in both sensor configurations as indicated by the red circle shown in Fig. 2. These noises were caused by the objects in the ambient environment (e.g. the laser beam hit the railing of the staircase). Since these noises may affect the performance of the terrain recognition system, the interference from other objects in the environment must be separated from the studied terrains during the system design as discussed in the following sections.

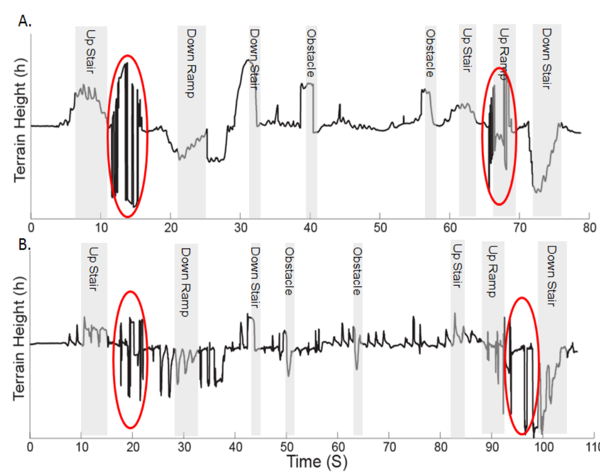

Fig. 2. The calculated terrain height ($h(t)$) in one representative trial with (A) laser sensor on the waist, and (B) laser sensor on the shank. The white area means the subject was walking on the level-ground; the gray area represents the subject was negotiating uneven terrains.

III. METHODS AND RESULTS FOR TASK 2

A. Architecture of Terrain Recognition System

The block diagram of the designed terrain recognition system is demonstrated in Fig. 3. This system consists of three parts: terrain reconstruction module, stand still/turn detection module, and terrain recognition module. The distance signals measured from the laser sensor and the measurements collected from the IMU sensors were simultaneously fed into the terrain reconstruction module. Based on these inputs, the terrain reconstruction module can calculate the parameters that represent the geometrical characteristics of the terrain in front of the subject. These parameters were then sent into the terrain recognition module to identify the front terrain type. In addition, the measurements from the IMU sensors were also streamed into the designed stand still/turn detection module, which was used to detect the subject's movement status. If no movement or turning is detected, the terrain recognition module is disabled; otherwise, this module outputs the final prediction of the terrain types.

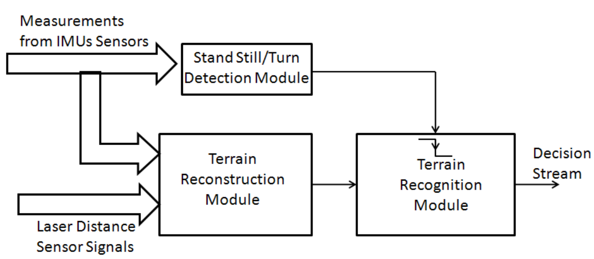

Fig. 3. Block diagram of the terrain recognition system.

B. Terrain Recognition Algorithm

A terrain recognition algorithm was designed based on decision tree. The decision tree, one of most used classification approaches, has been used in many fields such as data mining, machine learning, and pattern recognition [11]. The structure of the terrain recognition algorithm is demonstrated in Fig. 4.

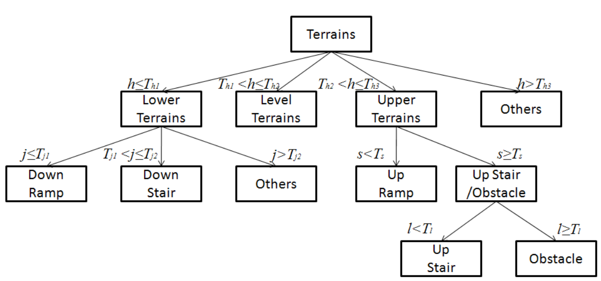

Fig. 4. Structure of the terrain recognition algorithm.

Besides the height of the terrain (h) and horizontal distance from the subject to the terrain (l) estimated by equations (1) and (2), another two features were used for the terrain recognition: the slope of the terrain (s) and the rate of terrain height change (j). They were calculated by

$$s(t) = h(t) / l(t) \tag{3}$$

$$j(t) = h(t) - h(t-1) \tag{4}$$

where t means the current time and t-1 represents the previous sample time. The included classes included level ground, up stair, down stair, up ramp, down ramp, obstacle, and others. The class of "others" includes the objects other than studied terrains in the laboratory (e.g. tables, walls, etc.), which cause noises in laser reading and reconstructed terrain geometry as shown in *Part II. D*. In the first node of the decision tree, the terrain height (h) was used as the key feature to classify the terrains that are above current negotiated terrains (upper terrain), terrains that are below the current terrain (lower terrain), terrain with the same height as the current terrain (level terrain), or others. In the second level of the decision tree, the lower terrain was further separated into down ramp, down stair, and others based on the rate of terrain height change feature ($j(t)$). The upper terrain was classified as up ramp and up stair/obstacle, according to the terrain slope. In the third level, up stair and obstacle were recognized by comparing the distance ($l(t)$) to the defined threshold. The classification thresholds were obtained based on the collected training data as well as the known dimension of staircases and obstacles and incline angles.

The terrain recognition accuracy was affected by the user's movement status. Therefore, a standstill/turn detection module was designed to enable/disable the terrain recognition module. No movement was detected based on the current velocity of the subject, measured by IMUs. The turning detection was achieved by monitoring the angle displacement in horizontal plane. The detection thresholds were selected based on the collected training data.

C. System Performance Evaluation

The ultimate goal of this study is to apply the terrain recognition to artificial legs, which allows prosthesis users to smoothly transit among different walking modes. Hence, the designed terrain recognition system is required to identify the terrain type before the user step on it. In order to evaluate the time response of designed terrain recognition system, prediction time was defined as the elapsed time from the moment when the change of terrain in front of the user is correctly recognized to a critical timing when the user is actually switch the locomotion mode. For all the transitions from level ground to other terrains, the critical timing was defined as the moment that the subject started to lift the foot from level ground to another terrain; for all the transitions from other terrains to level ground, the critical timing was defined as the time that the subject started to place the foot from one terrain to level ground.

In addition, the number of missed terrain transitions was used to evaluate the system performance. If the targeted terrain cannot be correctly recognized before the defined critical timing, a missed terrain was counted. Ten trials data were used as the training data to build the terrain recognition system and find the thresholds. The rest ten trials data were used to evaluate the system performance.

D. Results for Task 2

There were 160 terrain transitions in the testing dataset. Three terrain transitions were misclassified as the transitions from level ground to up stair, when the subject actually walked from the level ground to the up ramp. The rest 157 terrain transitions were correctly recognized before the defined critical timing. The overall recognition accuracy was 98.12%. The terrain prediction time was shown in Table I.

The terrain recognition results in one representative testing trial were demonstrated in Fig. 5. The vertical boundaries of the blue area in this figure indicated the critical timing for each type of terrain transition. All the 16 terrain transitions were correctly identified before the critical timing. Two errors (I and II), as shown in Fig. 5, were observed when the subject switched from level ground to the obstacle. However, the terrain recognition decisions switched back to obstacle before the critical timing, which were, therefore, not considered as the missed terrain.

TABLE I

TERRAIN PREDICTION TIME

Terrain Transitions	LG-US	US-LG	LG-DR	DR-LG	LG-DS	DS-LG	LG-OB	OB-LG	LG-UR	UR-LG
Prediction Time (s)	2.34 ± 0.13	0.95 ± 0.07	2.54 ± 0.18	0.34 ± 0.09	1.86 ± 0.16	1.05 ± 0.11	1.22 ± 0.14	1.78 ± 0.21	2.87 ± 0.24	1.98 ± 0.20

Note: level ground (LG), up stair (US), down stair (DS), up ramp (UR), down ramp (DR), obstacle (OB).

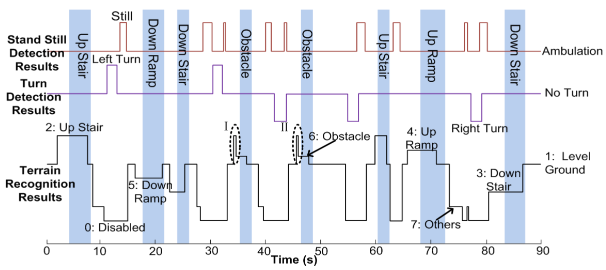

Fig.5. Terrain recognition results in one representative testing trial.

E. Discussion for Task 2

A terrain recognition system was designed and preliminarily tested on one healthy human subject. The results showed the promise of the designed system for accurate recognition of the terrains in front of the walking person. The output of the terrain recognition system may be used to provide the control system in the artificial legs with prior knowledge of walking environment. Therefore, the intelligent controller can modify the control strategy of prosthetic legs based on the known environment and allow the prosthesis user to switch walking terrains seamlessly. It is noteworthy that although the transition prediction time (e.g., 2.34±0.13s for LG-US) may be beyond the duration of one normal gait cycle, it will not cause the inappropriate reaction of the prosthesis (e.g., trigger the prosthetic leg to response too early), since the outputs from terrain recognition system only provide the prior knowledge while the mode switch of the prosthetic legs also depends on other control signals.

The presented study was preliminary, future investigations are needed. First, the system was only evaluated in the laboratory environment with a known terrain setup, which means both the training and testing data were collected in the same conditions. The performance of the system should be further quantified when the subject walks in unknown or unpredictable environment. Second, only limited walking status and constant walking speed were investigated in present study. More user status (such as sitting on a chair) and different walking speed should be considered in the future system design. In addition, further design is demanded for integration of terrain recognition system with artificial leg control system to achieve smooth locomotion mode transitions.

IV. CONCLUSION

In this study, a wearable terrain recognition system was designed, which may be used to assist the control of the powered artificial prosthetic legs. The preliminary testing results showed that the designed system can accurately recognize the terrain in front of the subject with a prediction time 300ms-2870ms. These results demonstrated the potential application of the designed terrain recognition system to further improve the control of powered artificial legs.

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