Graphical Abstract

A Review of Terrain Detection Systems for Applications in Locomotion Assistance⋆

Ali H. A. Al-dabbagh, Renaud Ronsse

Highlights

A Review of Terrain Detection Systems for Applications in Locomotion Assistance

Ali H. A. Al-dabbagh, Renaud Ronsse

- Research highlight 1: This paper provides an extended review of terrain detection systems for disabled people assistance (lower limb amputees and visually impaired)

- Research highlight 2: It overviews the sensory systems and algorithms that were implemented to identify different locomotion terrains in indoor or urban environments (flat ground, stairs, slopes).

- Research highlight 3: Reviewed approaches are those that can be worn by a human user, and running in real-time.

A Review of Terrain Detection Systems for Applications in Locomotion Assistance

Ali H. A. Al-dabbagh, Renaud Ronsse

Institute of Mechanics, Materials, and Civil Engineering; Institute of Neuroscience; and Louvain Bionics; Université catholique de Louvain, Louvain-la-Neuve, Belgium

Abstract

Terrain detection systems have been developed for a large body of applications. For instance, a bionic leg prosthesis would have to adapt its behavior as a function of the terrain, in order to restore a sound lower-limb biomechanics to the amputee. Visually impaired people benefit from such systems in order to collect information about their locomotion environment and avoid obstacles. Finally, mobile robots use them for estimating terrain traversability, and adjusting control algorithms as a function of the surface type. This diversity of applications led to a large repertoire of systems, regarding both hardware (sensors, processing unit) and software used for classification. This paper provides an extended review of these systems, with a specific focus on the assistance of disabled walker. More precisely, it overviews the sensory systems and algorithms that were implemented to identify different locomotion terrains in indoor or urban environments (flat ground, stairs, slopes) in a way that they are or can be worn by a human user, and running in real-time. Contributions from mobile robotics are also included, pending that they could be adapted to a scenario of locomotion assistance. The systems are classified into two categories: these relying on proprioceptive sensors only and those further using exteroceptive sensors. Contributions from both categories are then compared according to their main specifications, such as accuracy and prediction time. The paper unambiguously shows that systems with exteroceptive sensors have higher prediction capability than systems with proprioceptive sensors only, and should thus be favored for assistive devices requiring predicting transitions between locomotion tasks.

Keywords: Terrain detection systems, human locomotion assistance, intent detection, stairs detection, ramp detection, Prostheses, locomotion modes prediction, environmental features recognition, vision, visually impaired, wearable sensors.

1. Introduction

Literature in legged robotics abounds of examples showing that legs are better than wheels regarding the capacity to handle a large variety of terrains. Similarly, human can navigate through complex terrains like stairs, ramps and rocks. However, humans often have to integrate sensory information from their environment in order to adapt their motions accordingly. Small obstacles like gravels are usually handled through force feedback and short-loop reflexes. In contrast, it is often necessary to visually observe larger terrain variations that would require major adaptations of the motor plan requiring the recruitment of cortical loops [1]. Without such adaptation, the occurrence of stumbling or falling is ubiquitous due to the large mechanical disturbance that is caused by interacting with an environment featuring a different ground geometry. These closed-loop mechanisms are driven by two types of sensory modalities, namely proprioceptive and exteroceptive sensors. Proprioceptive sensors measure the internal state of the body such

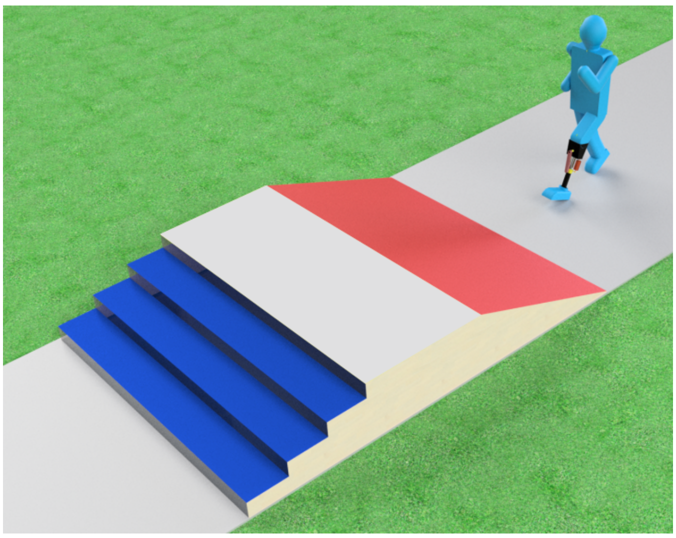

Figure 1: Terrain detection is necessary to adapt the controller of a walking assistive device (here, a bionic lower-limb prosthesis) as a function of the task being performed. In this example, the amputee is going to transition between overground walking (gray), slope climbing (red), and stairs descending (blue).

⋆This work was supported by the Conseil de l'action internationale of UCLouvain and the European Community's H2020 Research and Innovation Programme under grant number 731931 (the CYBERLEGsPlusPlus collaborative project)

Email addresses: ali.aldabbagh@uclouvain.be, ali.h.aldabbagh@gmail.com (Ali H. A. Al-dabbagh), renaud.ronsse@uclouvain.be (Renaud Ronsse)

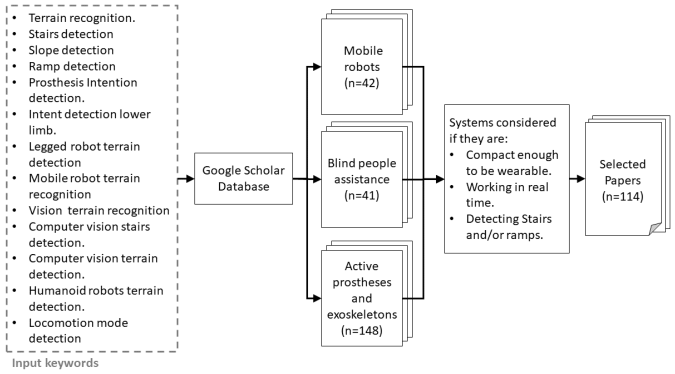

Figure 2: Overview of the selection process that was followed to construct the portfolio of this review. First, several keywords were entered in Google Scholar. The corresponding papers were sorted into three categories: those addressing mobile robotic applications (n=42), those providing assistance to blind people (n=41), and those addressing active prostheses and exoskeletons (n=148). For all categories, only developments satisfying further requirements were selected, reaching a total of 114 papers that are analyzed in this review.

as applied forces, joints orientation and limb position. Typical human proprioceptive sensors are the muscle spindles and Golgi tendon organs. In the scope of this work, we will also consider the vestibular system as being part of the proprioceptive pathway, since this sensory modality provides information about internal state of the body, i.e. rotational movements and linear accelerations of the head. Exteroceptive sensors provide information about the external environment such as distance to object and texture [2]. Typical human exteroceptive sensors are vision and touch. The same dichotomy exists in robotics, since robots can be equipped both with proprioceptive (e.g. join encoders) and exteroceptive sensors (e.g. camera).

The biomechanics of locomotion reveal that leg often produce mechanical energy in various locomotion tasks like walking or stair ascending/descending [3]. Moreover, each of these tasks corresponds to different kinetic and kinematic patterns, even in steady-state[4]. As consequence, active prostheses are necessary to provide lower-limb amputees with the capacity to display healthy gait patterns, and the control of such device should be adaptive to the task being executed (walking, taking stairs, etc.) [5]. In particular, the transition among these tasks should be timely detected in order to adapt the controller (see Fig.1).

Lower-limb amputees are not the only disabled who could benefit from terrain detection technologies for walking assistance. For instance, there are around 285 million visually impaired people worldwide relying on guide dog or cane for walking [6]. Using a guide cane provides only a short-range detection capacity to the user, such that safety might be compromised in a challenging environment. Consequently, there has been recent research efforts to develop augmented feedback technologies for visually impaired people, detecting the surrounding terrains in the local environment with a sufficiently short latency to let them adjust their gait accordingly [7].

Recent papers reviewed locomotion assistance approaches. For instance, control algorithms and assistive strategies used for lower limb prostheses and exoskeletons have been reviewed in [8, 9, 10]. More specific reviews focused on intention detection methodologies for lower- and upper-limb prostheses control [11, 12]. Smart walkers (i.e platforms used to assist people with locomotion disabilities) have been reviewed in [13]. Interestingly, all reviews cited above focused on sensors that can be classified as proprioceptive, i.e. providing information about the internal state of the (human) body. More recently, [14] also overviewed research efforts towards the integration of vision sensors in this picture, at least for lower-limb prostheses. Fusing these sensory pathways indeed holds promises for optimizing the detection latency and accuracy in locomotion assistance. Sensory fusion between different modalities is a transversal concept for locomotion intention detection in the context of such devices. Indeed, mechanical (e.g. inertial measurement units, IMUs), electromyographic (EMG), and/or electroencephalographic (EEG) sensors placed on the subject's body capture different aspects of the user's motion, thus reflecting different aspects of his/her locomotion intention. Interestingly, this holds both for the upper- and the lower-limb [15].

This paves the way towards terrain detection for locomotion assistance and, consequently, to the development of detection systems that would *predict* the future user intention rather than *reacting* to changes in behavior being captured by proprioceptive sensors like IMU or EMG. Said differently, perceiving and analyzing the environment around the user would offer to predict potential locomotion intentions several steps in advance. Intriguingly, comparable terrain detection systems have been widely developed for mobile robotic applications in various environments like urban [16], off-road [17], and planetary [18] explorations. Typically, these systems also combines several proprioceptive and exteroceptive sensory modalities such as cameras, IMUs, or 2D and 3D lasers [19]. Owing to the miniaturization of these components, voices raise claiming that similar wearable terrain detection systems will be integrated in the control loop of human locomotion assistance devices [20]. Therefore, terrain detection systems providing information about the surrounding environment with exteroceptive sensors are of high interest to guide the device controller as a function of the intended task [4, 21].

The objective of the present paper is to provide an exhaustive review of terrain detection systems for locomotion assistance in the widest perspective. This means that we will also include terrain detection approaches developed for mobile robots pending that they could be applied to assist visually impaired people and disabled walkers (see Fig.2). In sum, three types of terrain detection systems have been pooled in this review:

- Systems implemented for exoskeletons and active prostheses.

- Systems based on vision and ranging sensors to assist visually impaired people.

- Systems developed for terrain detection with mobile robots pending that they are compact enough to be worn by a human and that they can run in real time.

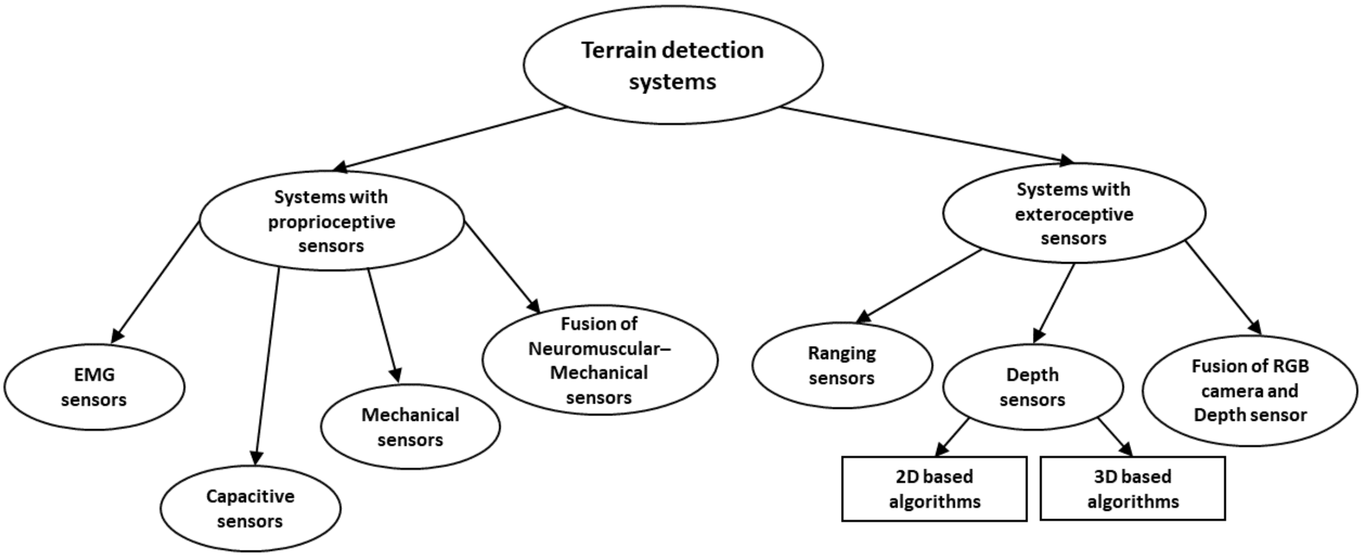

Figure 3: This figure shows a classification of typical sensors that are used in terrain detection systems as a function of whether they use proprioceptive sensors only, or also exteroceptive sensors

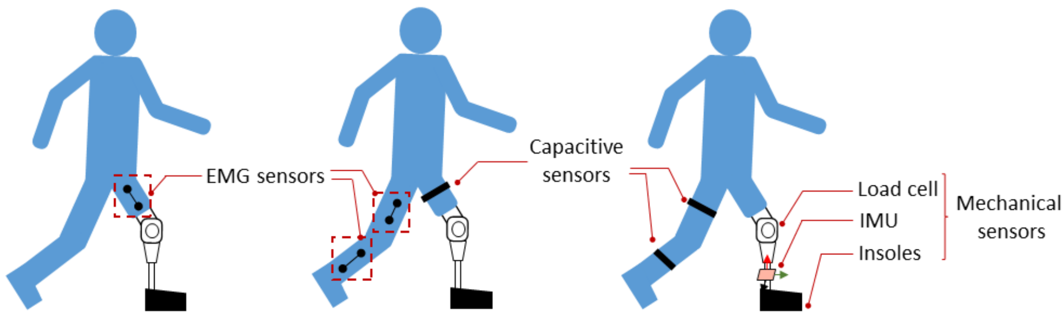

Figure 4: Representative configurations of sensors for terrain and locomotion intention detection with a lower-limb amputee wearing a prosthesis. It shows the possible distribution of proprioceptive sensors measuring muscular activity (EMG), muscle contraction (capacitive), or the leg kinematics (Mechanical).

Moreover, the paper systematically focuses on the detection of simple terrain geometries, mainly corresponding to indoor or urban environments: grounds, slopes, and stairs. Such terrains are indeed faced in everyday life of (disabled) walkers, and illustrate the most critical need for adaptive assistance. Accordingly, the following sections review many sensory systems that were developed for terrain detection. These systems have been classified into two families as illustrated in Fig.3, namely those embedding only proprioceptive sensors (Section 2), and those further embedding exteroceptive sensors (Section 3). The main features of these systems are then pooled in two comparative tables, whose contents and other aspects are discussed in Section 4. Finally, the paper ends with a conclusion.

2. Systems with proprioceptive sensors only

These systems use no exteroceptive sensors like vision or ranging sensors. They rather detect terrains indirectly, through a detection of the user's locomotion intention via proprioceptive sensors like EMG, capacitive or mechanical sensors. The first measures the electrical muscle activity, the second determines muscles contraction, and the third measures body kinematics. Typical configurations for placing such sensors on the body are displayed in Fig.4.

A typical processes applied to identify the terrain type with such sensors is shown in Fig.5. Sensory signals are first filtered to remove measurement noise. Then, specific features are extracted from a time window of the filtered signals, such as mean absolute value, standard deviation, minimum and maximum, rate of change, amount of zero crossings, amount of slope sign changes, waveform length, etc. [22, 23, 24]. Finally, a classification methodology is applied to identify the terrain type as a function of these features.

Such systems are not suitable to be used for visually impaired people because they typically rely on the user's intact exteroceptive vision for anticipating changes in locomotion mode. Therefore, the literature covering them mostly addresses automatic control adjustment of active prostheses, thus for lower-limb amputees. Accordingly, this section reviews various terrain detection systems utilized for lower-limb prostheses based on EMG, capacitive and mechanical sensors. Note that such terrain detection systems have been already reviewed in

[8, 9, 10, 11, 12, 13, 15], and consequently, do not represent the main contribution of this paper. In the following sections, we thus survey and update the main contributions reported in these previous reviews.

2.1. EMG sensors

EMG signals generated by leg muscles can be used to identify the terrain type which the subject is moving on. EMGs are electrical signals that are sent to muscles to trigger their contraction [25], and they can be measured through sensors placed on the skin above the muscle. If the person is moving on different types of terrain (slopes, stairs and level ground), different EMG patterns will be observed [26]. Data processing techniques are applied to extract features from these signals in order to identify the terrain category, and enable the prosthetic controller to select the corresponding control mode [27, 28, 29]. Electrical signal from the muscle is typically detectable 100ms prior to the actual movement [25]. However, terrain identification requires filtering, feature extraction and classification, and thus causes computational delay [15].

Various methodologies have been developed to incorporate locomotion intention and/or terrain detection from EMG signals in the closed-loop controller of active prostheses. For instance, a finite state controller can be used to modulate the impedance and output power of the prosthesis as a function of the EMG-based classification [28, 30, 31]. More precisely, [31] implemented two finite state controllers to induce biomimetic movement patterns for level-ground and stair-descent gaits. In that contribution, the subject locomotion intent was inferred through classifying the EMG features with a neural network, and supervise the transition between finite state controllers.

Another approach consists in classifying the set of measured EMG features with classifiers such as Support Vector Machine (SVM) or Linear Discriminant Analysis (LDA) [32, 33]. In particular, a recent study tested applying SVM, LDA and Neural Network (NN) classifiers on single channel EMG for locomotion mode recognition [34]. The study also incorporated a feature selection algorithm which improved the performance of all the classifiers tested. The classifiers reached above 96% accuracy with slight differences from one to another [34]. Globally, there is a trend to promote LDA as the most appropriate classifier for EMG pattern recognition since it has similar accuracy as more complex classifiers, but it is computationally more efficient [33, 35, 36, 37].

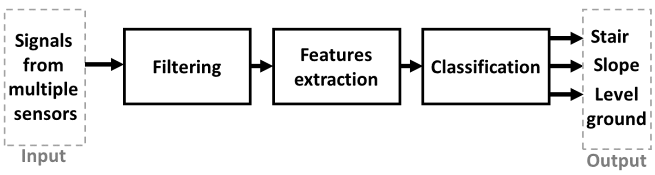

Figure 5: Processes applied to detect various terrains based on EMG, mechanical or capacitive sensors.

2.2. Capacitive sensors

Capacitive sensing relies on measuring the natural electrical capacitance of the human body. It has many applications, including human machine interfaces [38]. This technology has also been used to detect different locomotion modes by measuring changes in the leg configuration during locomotive movements. More precisely, this requires measuring the impedance between transmitter and receiver arrays of electrodes placed on the leg so that the leg dielectric capacitance captures morphological changes in soft tissues like muscles. This produces different output impedance profiles for different locomotion modes [39].

Similarly to EMG sensors, various classifiers can be used to identify locomotion modes from several capacitive sensors placed over the leg. Due to its low computational load and good performance, LDA has been used for human gait identification based on wearable capacitive sensors placed in direct contact with leg skin [40]. Moreover, LDA, QDA (Quadratic Discriminant Analysis) and LR (logistic regression) classifiers have been tested in [39] with the same hardware. LDA displayed similar performance as LR, and smaller classification error than QDA.

Non-contact capacitive sensing is an alternative approach of capacitive sensing. In such systems, copper wire mesh pieces are fixed on the outer surface of the prosthetic socket. Accordingly, the human body and the meshes form the capacitor electrodes, while the plastic material between them form the dielectric. During human movements, the physical distance between two electrodes changes, and this will results in different output voltage patterns across various locomotion modes [24].

In a non-contact capacitive sensing system, the QDA classifier outperformed both LDA and GMM in average locomotion mode identification accuracy by a small margin [24]. In contrast, SVM showed slightly higher accuracy than QDA regarding terrain recognition with a non-contact capacitive sensing based system [41].

2.3. Mechanical sensors

Mechanical sensors directly measure the human body kinematics (e.g. with IMUs) and interaction forces between the body and its environment (such as with instrumented insoles or load cells). Interaction force sensors lie therefore at the boundary between proprioception and exteroception since they measure a signal at the interface between the user and its environment. Such sensors reflect the current state of the user's segment, and/or of the prosthesis [42]. Various approaches have been developed to achieve terrain identification with this series of sensors.

Similarly to EMG signal classification, LDA has been widely used to classify features extracted from mechanical sensors data. For instance, merged signals from three IMUs and two foot pressure insoles have been used to achieve locomotion (transition) detection with a two-level LDA [43]. In another contributions, [44, 45] developed two LDA classifiers mixing several mechanical sensors. One classifier focused on data collected at heel contact and the other at toe-off, in order to detect transitions between different locomotion modes at least twice per locomotion cycle. LDA is sometimes further combined with other classifiers. For instance, combined LDA with a decision tree analysis (DTA) classifier are used to identify locomotion mode using only wireless foot insoles [46]. In [47], LDA has been used as a first stage classifier (followed by SVM) for feature extraction of IMU data mounted above the ankle to identify human gait kinematics. Interestingly, it displayed higher accuracy than using SVM alone. In contrast, a Phase Variable classifier (PV) presented in [48] showed higher accuracy than LDA when it is trained with nonsubject-specific data, while LDA outperformed PV with subject-specific training data. Another type of Gaussian distribution-based classifier (QDA), has been used in a cascaded classification algorithm [49]. More precisely, it was developed for intent recognition based on data from IMUs and load cell on the prosthesis. A first level classifier discriminates between standing and walking, a second level identifies the main gait phases (namely swing and stance), while the third level recognizes steady-state locomotion modes such as level ground walking, stair ascending, descending, ramp ascending and descending and the transitions between those modes.

Other families of classifier have been further tested for intention detection and terrain identification. For instance, [42, 50] used Gaussian mixture models (GMMs) to achieve real-time gait mode intent recognition. More complex classification approaches such as neural networks have been used to identify different gaits based on force sensors in the prosthesis socket, or IMU data [51, 52, 53]. Recently, a study compared a LDA classifier versus heuristic prediction algorithm using thresholds on estimated prosthetic ankle joint translations and ground slope [54]. Internal prosthesis sensory data (with mechanical sensors only) were fed to be classified by each method. The study showed that the heuristic prediction algorithm has slightly lower prediction error than the LDA classifier (2.8% vs. 3.4%). Interestingly, the heuristic prediction took only five features while the LDA required 45 features to reach such a low prediction error.

In order to enhance intent recognition performance, and make a more accurate prediction, many researchers added prior information using e.g. dynamic Bayesian networks (DBN) or hidden Markov models (HMM) [55, 56, 57]. For instance, [58] introduced a user independent intent recognition system based on classifying the data from 13 mechanical sensors (encoders, potentiometers, load cells and IMUs) directly integrated into a powered knee and ankle prosthesis. They tested various classification approaches and the history information included prior beliefs about locomotion history through DBN. Finally, it is suggested that fusion between capacitive and mechanical sensors could provide a good alternative to systems relying on the fusion between EMG and mechanical sensors[41], although further research is needed to support this claim.

Finally, recent studies paved the way towards combining IMU sensors only and advanced classification approaches. For instance, an approach presented by [59] converts the IMUs data into graysacle images that can then be classified into different modes of locomotion by a Convolutional Neural Network (CNN). The system uses 3- IMUs mounted on the thigh, shank, and ankle of the sound leg and achieved about 89% accuracy. Another contribution reached higher accuracy (about 98%) by using a single 9-axes IMU sensor placed on the sound foot [60]. The system tracks the sensor trajectory which reflects foot trajectory, and it is used to derive the inclination grade of the ground and locomotion mode recognition. The calculated trajectories are then analyzed for predicting the mode of locomotion.

2.4. Fusion of Neuromuscular and Mechanical sensors

Sensor fusion is combining data from multiple sensors in order to get higher accuracy for detection or classification. Human and animal brains routinely accomplish sensory fusion in order to optimally exploit information provided from their multiple senses such as audition and vision [61, 62]. Sensory fusion has also been applied in many technological fields such as medical and mobile robots [61, 63, 64]. For instance, data fusion has been applied in [65] to identify human daily activities based on multiple IMU sensors. In this section, we will specifically review the methods and results related to the fusion between EMG and mechanical sensors, i.e. the most used modalities for locomotion intention detection and terrain identification.

Locomotion features from mechanical sensors data and EMG signals have been extracted and concatenated in a single feature vector to be classified with various approaches [66]. One relies on using non-linear or linear classifiers such as SVM or LDA [21]. In general, SVM showed better classification accuracy and prediction as compared to LDA. More precisely, SVM predicted transitions between locomotion task modes before the critical event, and earlier than linear classifiers [21]. However, integrating prior information to LDA classifier resulted in improved accuracy and prediction time than using LDA without integrating this prior knowledge. This information was integrated through prior probabilities adjustment of discriminant functions of LDA [67].

Researchers in the field of neuromechanical sensors fusion considered alternative approaches focusing on hardware enhancement. For instance, using a FPGA as the computational engine with LDA classier for fast decoding and recognition resulted in better prediction time with the same accuracy [68]. Another hardware breakthrough consisted in using a Graphics Processing Unit (GPU) instead of Central Processing Unit (CPU). This provided faster response time for transitions with a SVM classifier. The system was evaluated using virtual reality with an avatar emulating intended movements [69]. Alternatively, a mobile CPU based system was presented in [70] targeting minimization of power consumption with a real-time SVM classifier.

In general, systems relying on fused neuromuscular and mechanical sensors outperformed other approaches based on one kind of information source only [21, 67, 69]. However, in order to minimize the computational time and complexity, it is interesting to know which sources of information are the most valuable for achieving the highest accuracy among all mechanical and EMG sensors that could be used to instrument the human (lower-)body. In [71], a source selection algorithm called minimum-redundancy-maximum-relevance (mRMR) was used

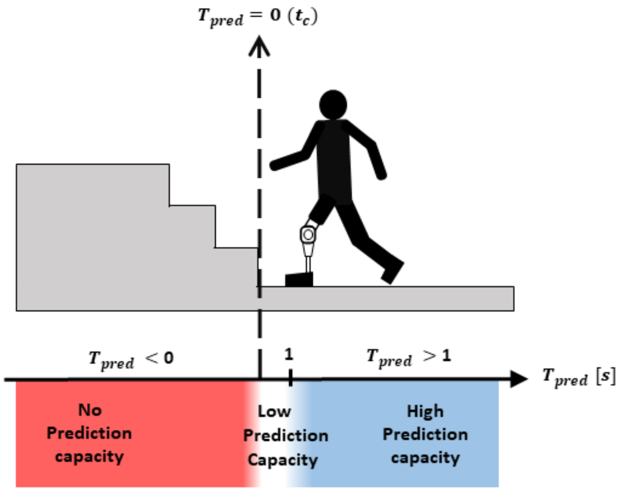

Figure 6: this figure highlights that prediction time (T_{pred}) is a critical metric for assessing the performance of a terrain identification system. Systems with high prediction capacity (T_{pred} > 1s) have a detection time t_d that occurs more than one second before the critical time t_c where a locomotion event is taking place (here, a transition between walking and stairs ascending). Systems with low prediction capacity (0s> T_{Pred} > 1s) have a prediction time of the same order than one footstep. Finally, systems with no prediction capacity detect the transition after the critical event took place, i.e. the prediction time is negative (T_{pred} < 0s).

for this purpose. Interestingly, the system was able to recognize the subject's locomotion intent with an accuracy of more than 95% when data sources were reduced from 26 to 10, despite a decrease in computational cost by a factor of about 1.9. Finally, it is suggested that accurate terrain detection requires the prosthesis to be equipped with at least four surface EMG sensors, a 6-DOF load cell mounted and one IMU [71].

2.5. Summary

In summary, representative systems using only proprioceptive sensors are listed in Table 1. It reports the terrains that can be detected by each approach, the corresponding sensors, and the developed classification algorithms. Note that all these methods have been tested both in indoor and outdoor environments. More quantitatively, the table also reports the detection accuracy and prediction time, when available. This prediction time T_{pred} is a metric assessing performance. We defined it as the difference between the critical time t_c, i.e. the time when the locomotion mode changes or should change due to terrain variation, and the time when this change is actually detected, i.e. the detection time t_d [72]:

$$T_{pred} = t_c - t_d \tag{1}$$

If $T_{pred} > 0$, the corresponding detection system can thus *anticipate* (or predict) the change of locomotion mode; while if $T_{pred} < 0$, the corresponding system would only *react* to a change of locomotion mode with some latency. According to Fig.6, we further used this prediction time as a metric for classifying the identified systems into two categories: those having no to low prediction capacities, i.e. with T_{pred} < 1s, vs. those having prediction capacities larger than 1s. This threshold of one second — thus approximately corresponding to one step — was considered to be the minimum detection time being necessary for incorporating an anticipation of locomotion change within the device high-level controller. Note that several papers report different levels of accuracy and prediction time, as a function of the task transition (i.e. ground to stairs, stairs to ground, etc.). For the sake of making fair comparisons, only data corresponding to a transition from level ground to stairs ascending are reported, since this is likely the most frequent and most representative transition requiring a high level adaptation of the device controller [58]. Therefore, all systems reported in Table 1 can thus be classified as having no to low prediction capacity, since T_{pred} is systematically lower than 1s.

3. Systems with at least one exteroceptive sensor

Next to the systems reported in the previous section, several contributions further focused on equipping locomotion assistive devices with large prediction capacities, typically corresponding to a few steps ahead of time. These systems rely on exteroceptive sensors, i.e. sensors receiving stimuli originating from the environment, outside of the body. They typically deploy various kinds of ranging or vision sensors observing the terrain in front of the subject. Their large prediction capability relies on detecting the terrain type before the subject steps into it. One traversal challenge with these sensors is that they move with the wearer's body. Therefore, an accurate and dynamic estimation of the sensor orientation is necessary to transform the obtained data [73]. Consequently, many implementations of these systems integrate IMUs. Importantly, a vast literature of terrain detection systems with vision or ranging sensors has been developed for mobile robots, towards autonomous navigation and obstacle avoidance. Interestingly, these approaches could be transposed to locomotion assistance with similar hardware and algorithms. In the following sections, we will pool several terrain detection strategies that were developed either directly for human locomotion assistance (including visually impaired people and amputees) or for mobile robot navigation, pending that adaptation to locomotion assistance would be feasible.

3.1. Ranging Sensors

These sensors can be classified as a function of whether they emit a single or multiple beams. Actually, many approaches introduced for terrain detection used single beam sensors. For instance, [74] developed a system to identify level ground, up and down stairs with a single ultrasonic sensor. Data collected from this sensor over time —while the subject was moving— has been classified with SVM. However, the system did not achieve an average classification accuracy higher than 70% [74]. Another development consisted in mounting a single beam laser sensor and an IMU on one side of the subject's waist (see Fig.7(a) for illustration). Authors showed that it is possible to detect various terrain types with classification or decision tree [75, 76, 77]. In particular, the classification tree used the terrain height as primary feature for recognition [78]. Although authors reported a classification accuracy as high as 98%, this system achieved prediction time of about 700ms. In such system,

Table 1: Overview of representative systems with proprioceptive sensors only. The last two columns report the average prediction time and detection accuracy — when available — for the representative task of transitioning from overground walking to stair climbing. $0s < T_{pred} < 1s$ captures that all these methods detected the transition before it actually happened, but in a time window that is smaller than 1s.

References	Targeted Terrains	Sensor	Algorithm	T_{pred}[ms]	detection accuracy[%]
[33]	Stairs, ramps	EMG electrodes	LDA classifier	\	97
[21]	Stairs, ramps	EMG electrodes	SVM classifier	254±132	\
[43]	Stairs, ramps	Mechanical sensors	Two level LDA classifier	222±14	99.71
[49]	Stairs, ramps	Mechanical sensors	Cascade classification (QDA based)	64±133	93.21
[60]	Stairs, ramps	Single IMU sensor	IMU trajectory tracking	202	98
[67, 21]	Stairs, ramps	Neuro-mechanical fusion	LDA classifier	340±136	96
			SVM classifier	420±175	99
[67]	Stairs, ramps	Neuro-mechanical fusion	LDA with prior knowledge	415±138	98
[68]	Stairs	Neuro-mechanical fusion	LDA based classifiers with FPGA as computing engine	549.83 ±139.2	99.31
[71]	Stairs, ramps	Neuro-mechanical fusion	All sources with SVM classifier	120	98
			Source selection algorithm with SVM	119.3	95
[39]	Stairs	Capacitive sensing (C-Sens)	LDA classifier	\	93
[24]	Stairs	Contactless C-Sens	QDA classifier	\	94.8
[41]	Stairs	Contactless C-Sens	SVM classifier	\	95.8

the user should keep his/her hands away from the waist to avoid covering the sensor and preventing detection [79]. A possible solution is to fix the laser sensor on the subject shank (or on the prosthesis), but this configuration produces noisy measurements, and did not show obvious differences in pattern among terrains that were tested [76]. However, using a wearable Frequency Modulated Continuous-Wave (FMCW) radar attached to a lower limb prosthesis succeeded in stairs detection [4]. The radar position is pictured in Fig.7(a). It scans the objects in front of the prosthesis in the sagittal plane during the rotational movement of the tibia. Distances to the detected objects are further measured during the stance phase. This resulted in multiple distances that must then be transformed to the global frame. To get rid of clutter noise, the Cell-Averaging CA-CFAR algorithm presented in [80] was applied. 2D radar scans were converted into a binary image, and the reflections of each scan on objects were casted as ellipse shaped regions [81]. It is important to point that single range sensor do not allow to detect some important features of the environment, like stairs width and height. Also, when the subject is standing or turning, the recognition process is disabled because it requires the subject to move forward in order to scan the terrain [79]. A recent new method used multiple ranging sensors placed on the shank of the user's leg. When it becomes perpendicular to the ground during the stance phase, ranging sensors are triggered to observe the terrain type in front of the user. The system reached 99% of classification accuracy [82].

With multi-beam ranging sensor, it is possible to robustly detect a richer repertoire of terrain features. A first approach presented a step detection system for the visually impaired in [83]. It used LIDAR sensor mounted on the subject's chest, and provides distance estimates in the vertical plane. Neighboring points are connected to form multiple segments, further classified into vertical and horizontal. Stairs detection is done by comparing each segment length with a threshold [83].

Another stairs and steps detection system introduced by [84] also used a single LIDAR. The sensor beam is divided into three beams (two vertical and one horizontal) through reflective mirrors to ease steps detection. This system is mounted on a wheelchair for disabled people; and would likely be too bulky to be used as a wearable sensor.

Estimating the 3D structure of the environment leads to more robust terrain detection [85]. This can be achieved with 2D-LIDAR, 3D-LIDAR, or Depth sensors. There are many techniques used to obtain a 3D estimation of the environment with 2D-LIDAR sensors through adding another LIDAR or using an arm to scan the environment. However, such adaptions are mostly applied with wheel chairs or mobile robots [86, 87, 88, 89], and adapting this to a wearable system would again be infringed owing to the large size of hardware components and delay of scanning, while using 3D-LIDAR such as in [90, 91] is also costly and bulky. An alternative solution is to use a depth sensor as discussed in the next section.

3.2. Depth Sensors

Depth sensors have been widely used as wearable terrain detection systems for locomotion assistance mounted on mobile robot for navigation purposes. This is because they are low-cost, compact, and robust to various textures and lightning con-

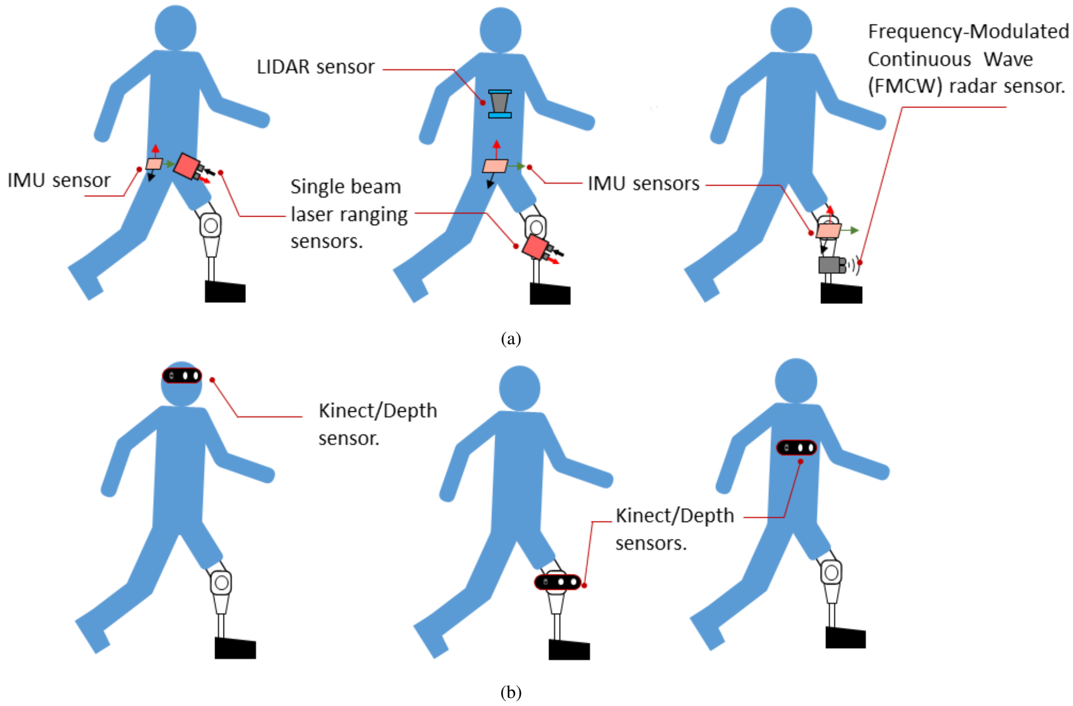

Figure 7: Representative configurations of exteroceptive sensors for terrain and locomotion intention detection with a lower-limb amputee wearing a prosthesis. Panel (a) highlights exteroceptive ranging sensors, that can be either laser-based or FMCW, and that can be placed on several body parts. Similarly, panel (b) highlights possible placements of exteroceptive vision sensors (depth). This also represents possible sensor configurations to assist visually impaired people

ditions. Moreover, they provide accurate mapping of the environment leading to robust terrain type recognition [85].

Depth sensors are said to be either passive or active. For the first kind, two aligned RGB cameras are used, and range is computed by triangulation between matching pixels in both images [92]. In contrast, an active depth sensor measures the range either by detecting the light wave phase shift between the emitted and received light (the so-called time of flight camera, TOF)[93], or by determining the disparity between a projected infrared light pattern and the measured one [94]. This is the working principle of the famous Microsoft Kinect. In comparison, active depth sensors can work in low illumination or even dark places, while stereo matching may fail in low contrast environments [95]. Some active sensors are affected by the sunlight [96].

Targeting locomotion assistance, such a depth sensor can be typically placed on three different parts of the human body, as illustrated in Fig.7(b):

- On the head: mounting the depth camera on the head is typically used for assisting people with visual impairment. Two configurations are found in the literature. The first consists in mounting two cameras on specific glasses, and through stereo matching, depth data can be reconstructed [97]. The second requires to fix an active depth sensor or stereo cameras on a helmet worn by the user [98, 99, 100].

- On the leg: this configuration is mainly used with lower limb amputees. The depth camera can be mounted on either the sound or the prosthetic leg, and either above or below the knee [79, 101, 102].

- On the chest: this approach is appealing both for visually impaired individuals and lower limb amputees. Moreover, it tends to provide more stable images than concurrent configurations [85, 103].

Both passive and active depth sensors provide range information as a gray scale depth image or point cloud data. In a depth image, each pixel corresponds to the same image pixel, and the gray level corresponds to the distance between this point and the sensor [104]. With the point cloud approach, the environment is represented by a set of 3D points in space and the coordinates of each point corresponds its 3D location in the real world, centered on the camera. An example of depth image and point cloud for the same scene is shown in Fig.8. There are two types of methodologies to process information acquired from depth sensors. The first method consists in applying 2D image processing approaches on depth image, while the second method consists in applying 3D vision algorithms on point cloud or depth data. In the next subsections, we will explore both of these approaches for terrain detection.

3.2.1. 2D-based algorithms

These approaches are applied on depth image in order to detect terrains having a sharp variations in height such as stairs, steps, and holes. This process of terrain detection from a depth image is sketched in Fig.9.

Firstly, edges are detected with a corresponding algorithm such as Sobel or Canny. Details retention is reported to be better with the later than the former [105]. However, since stairs or step edges are easy to detect in depth images,

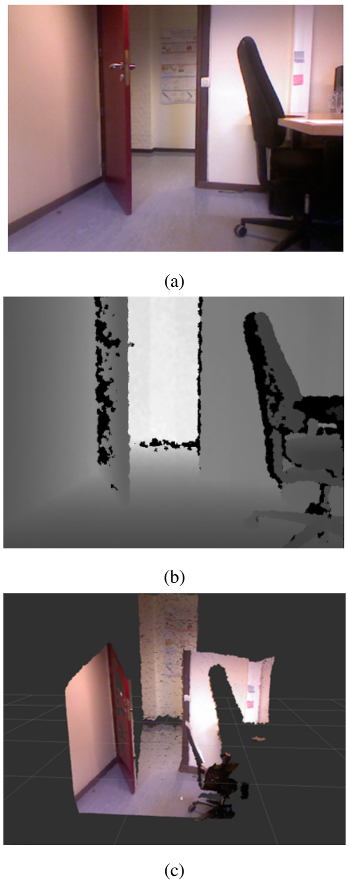

Figure 8: (a) original RGB image, (b) depth image, and (c) corresponding point cloud

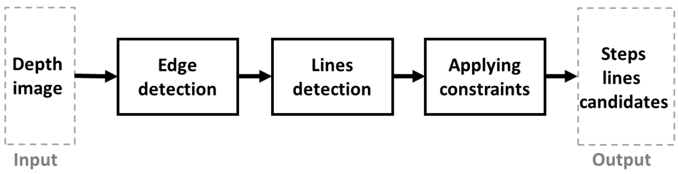

Figure 9: Stair and step detection process with depth image

Sobel is often preferred for its cheapest computational cost [106, 107, 108, 109, 110] and less contributions reported the use of Canny [111, 112]. The second step consists in extracting the horizontal lines in the image, for instance by using the Hough transform [113, 114]. Finally, the detected lines are filtered in order to discriminate convex and concave edges corresponding to steps as shown in Fig.10. This filtering is done through applying various constrains. Such as:

- A threshold on the tilting angle of the detected lines, in order to filter out the vertical and non-horizontal edges [106, 107, 109]. It is, however, possible to omit this step, and directly isolating the horizontal lines with a Hough transform [108].
- Lines whose length is below a certain threshold are removed, in order to keep only those that can be part of steps. [106, 107, 109, 108]

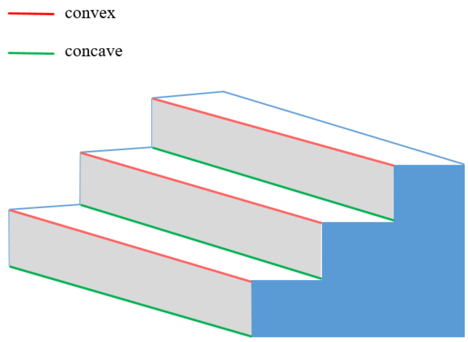

Figure 10: convex(red) and concave(green) edges of a typical staircase

- The vertical distance between two consecutive lines should be within a certain range, in order to remove the detected lines being either very close to each other (multiple detection of the same edge) or far away and thus do not belonging to the same object [109].
- If the horizontal distance between two lines is smaller than a specified threshold, then these lines are assumed to belong to the same edge that could be e.g. obstructed by an obstacle [106, 107].
- The depth difference between two adjacent convex lines is typically used to compute the size of footstools. If it is smaller than a specific value, then the detected line is assumed to be not belonging to a staircase [109].
- Finally, the number of parallel lines is sometimes used to reject stair case candidates if it is not composed of enough edges [112]. Also, this number can be used to distinguish between single steps (or curbs) and stairs.

After detecting the stair line candidates, an extra verification can be applied. For instance, a plane is fitted through the parallel lines, and if its slope is out of a specific range, the staircase candidate is rejected [112]. An alternative approach is to fit a line through all the candidates, and obtain a single dimensional feature which contains the depth information as a function of the coordinate along the forward axis of the depth image. Then, the feature is classified using SVM or other classifiers [106, 109].

Other researchers developed an algorithm to identify human gaits based on the difference between two depth images. This differential image is generated by subtracting multiple consecutive depth frames from each other. The resulted image is classified using SVM in order to identify the human gait during different activities such as stair climbing, descending, and level-ground walking [101, 102].

3.2.2. 3D-based algorithms

These methods are applied on point cloud or depth data. It is possible to detect various terrain types such as slopes, steps, holes, and uneven ground based on such scheme, and there are several techniques achieving this classification. The overall process of terrain detection based on point cloud data is shown in Fig.11. First of all, the point cloud is passed to multiple processes before feeding it to the main algorithm for terrains recognition. These filters are typically applying low-pass filtering, down sampling, transformation, normal estimation and plane detection. After that, the computed planes are fed to a detection algorithm identifying the terrains in front of the sensor. Furthermore, other computations can be performed in parallel to plane detection, as illustrated in Fig.11. In the following sections, we will review these commonly used filters and algorithms.

Pre-processing: this step aims at improving the signal to noise ratio and reducing the computational load. This is achieved by using various filters such as outlier removal and averaging [115, 116], although this comes with the cost of decreasing the frame rate [117]. Computational savings are obtained by down-sampling. Indeed, the high density of point cloud data causes processing delay, and not all the points bring a significant part of new information. The point cloud resolution is down sized by using algorithms such as 3D voxel grid filter [118], Narrow Down Filtering (NDF) [119], or by averaging with a sliding 2 x 2 block [120]. To further reduce the computational cost, a region of interest (ROI) can be specified in order to eliminate data lying out of this region. For instance, [121] specified a 150 cm wide ROI in front of the user, so that the points lying out of this range were not treated.

Transformation: point cloud data acquired from depth sensor are provided in a coordinate frame being centered on the camera, and this causes issues for proper terrain detection. For instance, if the camera points downwards, level ground will be detected as a ramp [79]. A solution is to transform the reference coordinate system to the ground or world coordinates [103, 122]. In general, the depth sensor orientation is acquired either from an IMU embedded within the camera (such as with the Kinect [122]), or from an external IMU attached nearby [79]. This transformation can also be applied on the depth data [122].

Normal estimation: for each point, a normal vector is estimated from its neighboring points [123]. Various approaches were developed for this computation, balancing the classical trade-off between the accuracy and computational cost [124]. One simple approach consists in computing the cross product of two vectors being tangent to the surface, giving thus the vector being normal to it at a specific point [99, 123, 125]. Another methodology consists in estimating the normals based on Principal Component Analysis (PCA) [85, 103, 117]. This approach is efficient and has been used by many researchers [115, 126, 127]. It computes the eigenvalue and eigenvector of a covariance matrix created from direct neighboring points. The normal direction is estimated as the eigenvector having the smallest eigenvalue [103]. After this normal estimation, points cloud data can be segmented into multiple groups based on their orientation. This brings the identification of relevant features like ground plane, ceiling, walls or slopes [117]. Also, it is possible to filter some irrelevant groups of points away [98, 120, 121].

Plane detection: this step consists in fitting a 3D plane model on a set of point cloud data, and again this can be performed using various methodologies. A common approach relies on the RANdom SAmple Consensus (RANSAC) algorithm presented by Fischer and Bolles [128]. Basically, it repeats two iterative steps on a given point cloud. First, a hypothesis is made and then it is verified [129]. This algorithm has been frequently applied for human locomotion assistance [98, 121, 130, 131] or mobile robot navigation [119]. The output of this algorithm is the set of detected planes and their normals. A concurrent methodology for plane estimation is regional growing. It starts from a point with minimum curvature called *seed*, and expands the region to include neighboring points having quasi-parallel normals and similar curvature [85]. When the region cannot be expanded anymore, a new seed is chosen, and the process is repeated until a pre-specified threshold is reached. This algorithm outputs a set of points (clusters) belonging to the same smooth surface [118]. Some people argued that the regional growing algorithm has a better physical relevance since the planes are detected from a closed region depending on single element (seed) rather than from set of uncorrelated points distributed in the scene [85, 103].

Terrain detection algorithms: various methods can applied after plane detection to recognize different types of terrains. For example, a ramp lying in front of the subject and its tilting angle can be identified from the detected plane normal. This can be implemented with regional growing and RANSAC to capture an inclined plane over the cluster having a normal tilted with respect to the ground plane [132]. Also relying on normal filtering, a more complicated framework has been developed for humanoid robots, based on the detection of the geometric primitives in the environment. What each primitive can offer to the individuals (called "affordances" by the authors) is obtained based on its normal vector and area. For example, the object affords support if it is in the same orientation as the ground and its area is larger than a pre-defined threshold. A similar approach can be used for stairs, slope, and ground detection [133].

Alternatively, a common approach consists in identifying the step candidates from their height and orientation [98, 120, 121]. For instance, the tread of each step has the same orientation as the ground, although it is located at a different height. Each candidate (starting from the lowest) can thus be examined to be either classified as a step or an obstacle (a table for instance) [85]. On the other hand, if the height is negative, the terrain in front of the user is likely either a descending stair or a hole, which can be again tentatively discriminated by using predefined thresholds. In another approach, the stairs convex edges are identified from the detected planes, by applying a Concave Hull algorithm followed by normal based filtering. This methodology is applied to detect single or multiple steps in both ascending and descending stairs [119].

After that, a molding algorithm can be applied to compute the amount of steps and their features such as tread width and length and height of the riser [103]. Again, different approaches have been tested, such as PCA or Preemptive RANSAC [98, 103].

Most of the approaches for terrain detection with depth sensors are usually derived from one of the processes described

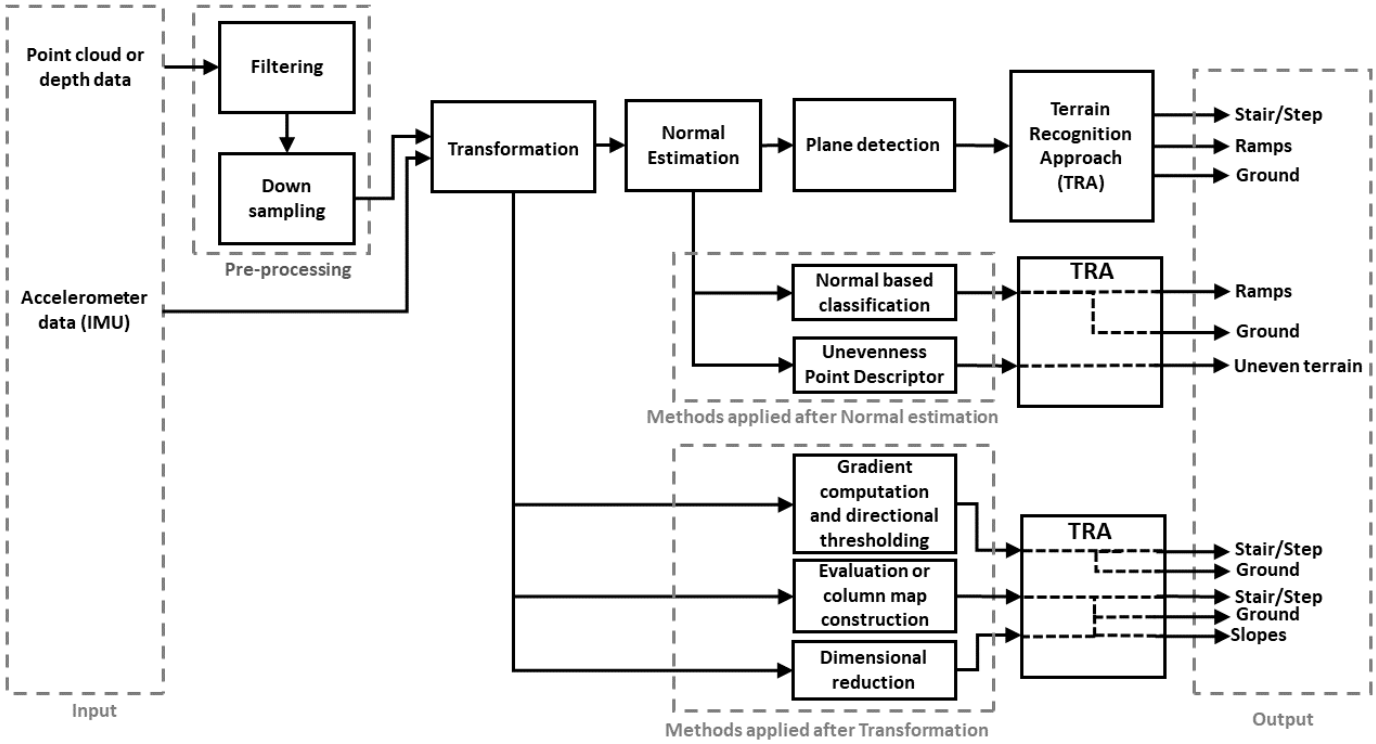

Figure 11: Overall process of terrain detection systems based on point cloud and accelerometer/IMU data. Typical process starts with point cloud filtering and down sampling. Then in the transformation step, the point cloud is mapped to the world coordinates. After that, the point cloud normals are estimated, and a plane detection algorithm is applied. Finally the terrains are detected and modeled. However, there are various other methodologies that can be applied after transformation or normal estimation processes which lead to terrains detection and modeling

previously. The following sections review some of the most common among them. According to Fig.11, there are two types of methodologies: methods used after the transformation step, and those being applied after the normal estimation process.

Methods applied after transformation: based on depth data, An algorithm consists in computing the normal gradient and applying directional thresholding on the depth data in the three main spacial directions [122]. This algorithm extracts 3D information from 2D depth image. It is usually followed by a stair detection and modeling algorithm for estimating the amount of steps [123]. This approach has already been applied to assist visually impaired people [99]. However, based on point cloud, identifying steps and slopes can be done by applying point cloud dimensional reduction after the transformation process [134]. Then, the resulting single dimensional feature is classified with a neural network algorithm, and stairs can be modeled using 2D RANSAC [79, 135]. An alternative algorithm for steps and slopes detection relies on the so-called column map estimation [136, 137]. These maps are constructed through 2D-grid located on the ground plane. Then, the 3D points are mapped to individual cubes located on the grid. Points lying outside the cubes are ignored. The evaluation histogram map is then computed through a voting scheme. This approach can be used to detect steps, slopes and holes [137, 138]. It has been developed for legged mobile robots [138, 139], although nothing precludes its adaptation for human locomotion assistance.

Methods applied after normal estimation: many approaches can also be applied right after the normal estimation process. A simple algorithm detects ground and slopes by classifying point cloud data according to their normal [117]. Then, the remaining point cloud data are used to detect and model stair-cases with a histogram based method [117].

Finally, non-traversable or uneven grounds can be detected using Unevenness Point Descriptor (UPD), again using the normal vectors estimation [115]. UPD can also detect terrain inclinations [126]. This algorithm has been developed mainly for mobile robots to avoid highly irregular grounds [127]. Again, nothing would prevent the adaptation of this framework for human locomotion assistance. Indeed, detecting uneven ground can be used to warn the visually impaired walking towards an hazardous zone. Similarly, it could be applied to adjust the control parameters of a lower limb prosthesis to provide assistance adapted to uneven surfaces, and thus mitigate the risk of falling [140].

3.3. Fusion of RGB and Depth Sensors

A RGB camera is a cheap sensor, compact in size, and covers wide angle and long range. Literature showed that it was possible to detect various terrain types such as stairs [141], slopes [142] or ground with a single RGB camera [143]. Indeed, the process of stair detection in a RGB image is similar to the one used for depth images, pending that the image is converted to gray scale and denoised with appropriate filters [144]. Another methodology is to train a deep neural network with RGB images for human locomotion mode classification. Such systems achieved high accuracy in identifying stairs ascending, stairs descending and level ground locomotion modes [145, 146]. However, more advanced features like dimensions, or distances can hardly be estimated from such an image. Also, such sensor is useless in dark environments [147].

Consequently, fusion of depth with RGB images has been proposed to get better detection results. The depth sensor being affected by the sunlight, thus the RGB camera is used for stairs detection in outdoor scenarios [108]. Another approach used the RGB camera for stair edges detection, and the depth image for identification of the slopes (ascending or descending) [109]. Similarly, a stair detection system for visually impaired people assistance combined a RGB camera for stair candidate detection, and the depth information acquired from stereo images to exclude false positive candidates based on ground plane detection [97]. This fusion is also useful for distinguishing between pedestrian cross walks and stairs to assist visually impaired people. Indeed, both generate consecutive horizontal lines in the RGB image but can be discriminated by using depth information [106].

3.4. Summary

Similarly to what we did for systems with proprioceptive sensors only, a list of representative systems embedding exteroceptive sensors is provided in Table 2. Moreover, the table reports the ability of the systems to work in indoor or outdoor environments based on the sensor limitation or on the tested environments mentioned in the referenced paper. The table further reports the maximum detection distance.

To have a consistent comparison between systems with proprioceptive and exteroceptive sensors, the prediction time T_{pred} is also reported in Table 2. However, T_{pred} is not reported in most of the papers developing systems with vision or ranging sensors. They rather tend to report the maximum distance from which the system can detect the terrains. Consequently, we computed an approximation of T_{pred} based on the ratio between the maximum detection distance, and a typical human walking speed.

According to [148, 149], the comfortable walking speed of transfemoral amputees is 3.6km/h, and it is 4.53km/h for transtibial amputees [148]. Therefore, we took 4km/h as an average between both values. In some papers, the authors did not mention the maximum detection range of their systems; therefore, we considered a typical active range of the sensor that was used, as reported in its datasheet.

4. Discussion

In the previous sections, we classified terrain detection systems for human locomotion assistance into two categories depending on whether they rely on proprioceptive sensors only or on exteroceptive sensors as well. The following paragraphs review the most important trends that are emerging from this extensive reporting, regarding both hardware and software. We will start with discussing the main trends appearing within each category. After that, a comparison between both categories is reported, leveraging several important features.

For systems with proprioceptive sensors only, Table 1 showed that the LDA classifier is the most popular for different sensory systems, either in its original form or pending some improvements. This is due to the fact that it combines a low computational cost and classification accuracy being similar to the one obtained with more greedy non-linear classifiers [150]. Lowering the computational cost has a direct impact on the achievable prediction time and sampling rate. The highest prediction time has been achieved by combining a LDA classifier with a dedicated computing engine, namely a FPGA. However, SVM holds promise to outperform LDA in accuracy [21, 67], pending a more greedy computational load. We did not find papers reporting SVM development on dedicated engine like FPGA. Capacitive sensing have been developed by a small community. Therefore, there is still some work to be done to estimate their exact prediction capacities, the most appropriate classifiers, and the potential development in a dedicated engine.

For systems using exteroceptive sensors, terrain detection with a single beam ranging sensor did not achieve high prediction time in comparison to systems which use wider range sensors such as LIDAR or depth camera. However, high prediction time was recorded with single beam ranging sensor when these sensors are mounted on moving parts of the human body in such way that they can scan the environment [4]. Terrain detection by computing the difference between depth images did not lead to high prediction time. However, depth camera achieved higher prediction time using point cloud or depth data based algorithms. The following paragraphs review the main features of terrain identification systems across both categories and highlight their respective pros and cons.

Prediction time: prediction time results provided in Tables 1 and 2 clearly show that systems with exteroceptive sensors outperforms those using proprioceptive sensors. Prediction time of systems using proprioceptive sensors is strongly influenced by several user-related and gait-related factors such as the leading leg and transition type. For instance, previous research showed that the prediction time of the transition from level ground to stair ascending is negative when the sound leg is leading and positive when the prosthesis is leading [49]. Moreover, such systems typically displayed different prediction times for different transitions when tested with the same user, such as for the same transition with different users. These differences can reach up to 500ms [43, 49]. Systems using exteroceptive sensors, i.e. with high prediction capacity, are typically less or not affected by such factors.

Detection accuracy: the vast majority of systems reviewed in this paper, and in particular in Tables 1 and 2, achieved high accuracy. However, this statement has to be mitigated since accuracy might also be sensitive to the user, transition type, and even gait phase. For instance, [21] reported 99% accuracy for terrain detection conducted during the stance phase and 95% during the swing phase of walking. Again, this sensitivity to user- and locomotion-related features is more prominent in systems using proprioceptive sensors, i.e. displaying low prediction capacity.

Reliability: proprioceptive and exteroceptive sensors are respectively sensitive to variations in body and environmental conditions. Exteroceptive sensors like depth sensors are affected by sunlight while stereo cameras cannot work in low contrast or dark environment. As a result, some of them can work only in either indoor or outdoor environments. Proprioceptive sensors are robust against lighting and weather conditions, so they can be used in a larger spectrum of environmental conditions than those relying on vision. Reliability is also depending on the capacity of the different systems to work whatever the user's dress code. Indeed, systems having no vision sensor, i.e. with low predictability, can be hidden or worn under the clothes, while this is typically more challenging for systems using exteroceptive sensors. The body condition itself might have an impact on reliability. For instance, lower limb amputees do not display the same muscle activity as intact people. Consequently, EMG sensors would convey different patterns as a function of the level of amputation, skin condition and socket loading [56]. Similarly, signals recorded by contact capacitive sensors will tend to drift because of slip of the sensory bands due to sweat and movements. This will eventually cause wrong terrain estimation if the system is not periodically re-calibrated. These body-related factors have thus a stronger influence on in systems using proprioceptive sensors. Finally, the learning curve that is typically displayed by people using an assistive device such as a powered artificial leg might also have an impact on reliability. Again, a gait recognition algorithm based on proprioceptive sensors would have to be periodically re-calibrated following the user's learning curve [67]. However, it is likely that systems based on vision sensors, i.e. with high prediction capacity, would be less sensitive to changes in locomotion patterns. Hence, such periodic re-calibration training may not be necessary.

Usability: systems with exteroceptive sensors can provide an accurate modeling of the terrains in front of the subject. Therefore, they provide a surrogate of vision to visually impaired people in order to help them achieving their path planning, i.e. planning of their locomotion trajectory. Indeed, vision-based sensing can be translated into a signal that is perceived by an intact sensory modality of the user. For instance, an audio tone can be delivered to convey several features such as terrain type or distance to obstacle. Interestingly, these vision-based strategies can be swiftly applied to assist not only visually impaired people, but also lower limb amputees and people with gait disorders. In particular, terrain modeling turns to be critical for adapting the control strategy of an assistive locomotion device at the right time, i.e. just when the terrain transition is faced. In contrast, proprioceptive sensors can be deployed only for people having both an intact exteroceptive system – and thus managing their own path planning – and capable of producing voluntary muscle contractions and/or movements; this is why they have been developed mostly to assist people with lower limb amputation. In contrast, people with lower limb amputation may not prefer using exteroceptive sensors which are mounted on their body (above the clothes) since they may not like their assistive system to be visible.

Computational load: systems using exteroceptive sensors need higher computational power than systems which use proprioceptive sensors only. In particular, vision based systems with depth camera provide a large amount of data about the environment, and this data has to pass through multiple processes for detecting the corresponding terrains. This has a negative impact on the size of the hardware and battery that the user has to carry when using such assistive systems. In contrast, simpler data are obtained from proprioceptive sensors, and these data can be classified with single layer classifiers (e.g., LDA and SVM) with smaller and lighter hardware. Moreover, systems with proprioceptive sensors using these classifiers achieve comparable classification performance as more complex classifiers such as artificial neural networks (ANN) which need more computational resources [21, 36].

5. Conclusion

In this paper, we reviewed many sensory systems that were developed to identify terrains during locomotion tasks, and in particular in order to identify the locomotion intention of a disabled user across different possible tasks (flat ground walking, stairs ascending/descending, etc.). We sorted these systems into two categories, i.e. these deploying proprioceptive sensors only, and those further relying on exteroceptive sensors like vision-based devices. This last category is only emerging in the field of locomotion assistance, but we further reviewed contributions from mobile robotics that could be adapted to assist human users. This review brought the conclusion that exteroceptive sensors are necessary if the assistive device requires to anticipate the locomotion transition by more than one step, i.e. what we denoted to correspond to high prediction capacity. Owing to the emergence of active assistive devices for locomotion like exoskeleton or bionic prostheses, it is likely that such proprioceptive sensors will become a key ingredient to promote synergetic behavior between the user and the device in different locomotion contexts. The paper ended with a discussion highlighting specific challenges related to these exteroceptive systems, such as usability, and reliability.

Table 2: Overview of systems with high prediction capacity. Columns 5 and 6 indicate whether these methods were tested for indoor and/or outdoor environments. The last three columns report the maximum distance for detecting a terrain change, the average prediction time, and detection accuracy — when available — for the representative task of transitioning from overground walking to stair climbing. $T_{pred} > 0$ captures that all these methods detected the transition before it actually happened

References	Targeted Terrains	Sensor	Algorithm	Indoor	Outdoor	Max distance [m]	T_{pred} [ms]	Accuracy [%]
[74]	Stairs	Ultrasonic sensor	SVM classifier	✓	✓	1	910*	72.41
[75, 76, 78]	Stairs and slopes	Laser ranging sensor	classification tree	✓	✓	\	692.68±74	98
[4]	Stairs	FMCW radar	Filtering and clustering	✓	✓	5	4500*	\
[83]	Stairs	LIDAR	Classifying the points into horizontal and vertical segments, and filtering based on segment length	✓	✓	4	3600*	95
[106, 107]	Stairs	RGB-D	Stairs lines detection in depth image with Hough transform, and SVM for up and downstairs recognition (2D-based algorithm)	✓		3.5**	3153*	97.2
[101, 102]	Stairs	TOF camera	Feature extraction of depth difference image with SVM classifier (2D-based algorithm)	✓	✓	1	910*	94.1
[98, 121, 120]	Stairs	RGB-D	RANSAC for plane fitting, stairs detection based on difference in highet between planes (3D-based algorithm)	✓		3.5**	3153*	97.33
[119]	Stairs	RGB-D	RANSAC for Plane detection, and concave hull algorithm for steps recognition (3D-based algorithm)	✓		3.5**	3153*	95.8
[79, 134]	Stairs and slopes	TOF camera	Dimensional reduction, and neural network for classification (3D-based algorithm)	✓	✓	\	3340	98.5
[138, 137]	Stairs and slopes	RGB-D	Evaluation/histogram map construction (3D-based algorithm)	✓		3	2700*	\
[122, 123]	Stairs	RGB-D	Gradient computation Directional thresholding (3D-based algorithm)	✓		1.5	1351*	98.8
[117]	Stairs and slopes	RGB-D	Points classification according to their normal (3D-based algorithm)	✓		3.5**	3153*	\
[115],[126],[127]	Uneven terrains	RGB-D	Unevenness Points Descriptor(3D-based algorithm)	✓		3.5	3153*	\
		Stereo camera		✓		22	19820*	\
[109]	Stairs	RGB and depth cameras	Edge detection , one dimensional feature extraction from depth image, and classification with SVM (Fusion of RGB and Depth)	✓		2	1800*	92.7

*Estimated from the maximum detection distance if the wearer would walk at 4 km/h.
**Estimated based on the effective depth range which is up to 3.5 meter as determined in [121].

References

[1] K. Hauser, Adaptive locomotion on uneven terrains, Humanoid Robotics: A Reference (2016) 1–20.

[2] B. Siciliano, O. Khatib, Springer handbook of robotics, Springer, 2016.

[3] R. Riener, M. Rabuffetti, C. Frigo, Stair ascent and descent at different inclinations, Gait & posture 15 (1) (2002) 32–44.

[4] B. Kleiner, N. Ziegenspeck, R. Stolyarov, H. Herr, U. Schneider, A. Verl, A Radar-Based Terrain Mapping Approach for Stair Detection Towards Enhanced Prosthetic Foot Control, in: Proceedings of the IEEE RAS and EMBS International Conference on Biomedical Robotics and Biomechatronics, 2018. doi:10.1109/BIOROB.2018.8487722.

[5] N. Ramstrand, K. A. Nilsson, A comparison of foot placement strategies of transtibial amputees and able-bodied subjects during stair ambulation, Prosthetics and Orthotics International 33 (4) (2009) 348–355. doi:10.3109/03093640903074891.

[6] IABA, Home.
URL `https://www.iapb.org/`

[7] Á. Csapó, G. Wersényi, H. Nagy, T. Stockman, A survey of assistive technologies and applications for blind users on mobile platforms: a review and foundation for research, Journal on Multimodal User Interfaces 9 (4) (2015) 275–286.

[8] C. Ferreira, L. P. Reis, C. P. Santos, Review of control strategies for lower limb prostheses, in: Robot 2015: Second Iberian Robotics Conference, Springer, 2016, pp. 209–220.

[9] H. Vallery, M. R. Tucker, O. Lambercy, R. Gassert, A. Pagel, M. Bouri, J. d. R. Millán, R. Riener, H. Bleuler, J. Olivier, Control strategies for active lower extremity prosthetics and orthotics: a review, Journal of NeuroEngineering and Rehabilitation 12 (1) (2015) 1. doi:10.1186/1743-0003-12-1.

[10] T. Yan, M. Cempini, C. M. Oddo, N. Vitiello, Review of assistive strategies in powered lower-limb orthoses and exoskeletons, Robotics and Autonomous Systems 64 (2015) 120–136.

[11] J. Lobo-Prat, P. N. Kooren, A. H. Stienen, J. L. Herder, B. F. Koopman, P. H. Veltink, Non-invasive control interfaces for intention detection in active movement-assistive devices, Journal of neuroengineering and rehabilitation 11 (1) (2014) 168.

[12] A. Parri, E. Martini, J. Geeroms, L. Flynn, G. Pasquini, S. Crea, R. Molino Lova, D. Lefeber, R. Kamnik, M. Munih, et al., Whole body awareness for controlling a robotic transfemoral prosthesis, Frontiers in neurorobotics 11 (2017) 25.

[13] M. M. Martins, C. P. Santos, A. Frizera-Neto, R. Ceres, Assistive mobility devices focusing on smart walkers: Classification and review, Robotics and Autonomous Systems 60 (4) (2012) 548–562.

[14] K. Zhang, C. W. de Silva, C. Fu, Sensor fusion for predictive control of human-prosthesis-environment dynamics in assistive walking: A survey, arXiv preprint arXiv:1903.07674 (2019).

[15] D. Novak, R. Riener, A survey of sensor fusion methods in wearable robotics, Robotics and Autonomous Systems 73 (2015) 155–170.

[16] G. Lidoris, F. Rohrmuller, D. Wollherr, M. Buss, The autonomous city explorer (ace) project—mobile robot navigation in highly populated urban environments, in: 2009 IEEE International Conference on Robotics and Automation, IEEE, 2009, pp. 1416–1422.

[17] R. Manduchi, A. Castano, A. Talukder, L. Matthies, Obstacle detection and terrain classification for autonomous off-road navigation, Autonomous robots 18 (1) (2005) 81–102.

[18] I. Halatci, C. A. Brooks, K. Iagnemma, Terrain classification and classifier fusion for planetary exploration rovers, IEEE Aerospace Conference Proceedings (2007). doi:10.1109/AERO.2007.352692.

[19] L. Iocchi, S. Pellegrini, Building 3d maps with semantic elements integrating 2d laser, stereo vision and imu on a mobile robot, in: 2nd ISPRS International Workshop 3D-ARCH, 2007.

[20] M. R. Tucker, J. Olivier, A. Pagel, H. Bleuler, M. Bouri, O. Lambercy, J. del R Millán, R. Riener, H. Vallery, R. Gassert, Control strategies for active lower extremity prosthetics and orthotics: a review, Journal of neuroengineering and rehabilitation 12 (1) (2015) 1.

[21] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, K. B. Englehart, Continuous locomotion-mode identification for prosthetic legs based on neuromuscular–mechanical fusion, IEEE Transactions on Biomedical Engineering 58 (10) (2011) 2867–2875.

[22] B. Hudgins, P. Parker, R. N. Scott, A new strategy for multifunction myoelectric control, IEEE Transactions on Biomedical Engineering 40 (1) (1993) 82–94.

[23] A. J. Young, A. Simon, L. J. Hargrove, An intent recognition strategy for transfemoral amputee ambulation across different locomotion modes, Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS (2013) 1587–1590doi:10.1109/EMBC.2013.6609818.

[24] E. Zheng, L. Wang, K. Wei, Q. Wang, A noncontact capacitive sensing system for recognizing locomotion modes of transtibial amputees, IEEE Transactions on Biomedical Engineering 61 (12) (2014) 2911–2920.

[25] C. Fleischer, G. Hommel, A human–exoskeleton interface utilizing electromyography, IEEE Transactions on Robotics 24 (4) (2008) 872–882.

[26] D. Jin, J. Yang, R. Zhang, R. Wang, J. Zhang, Terrain identification for prosthetic knees based on electromyographic signal features, Tsinghua Science and Technology 11 (1) (2006) 74–79. doi:10.1016/S1007-0214(06)70157-2.

[27] L. J. Hargrove, A. M. Simon, R. Lipschutz, S. B. Finucane, T. A. Kuiken, Non-weight-bearing neural control of a powered transfemoral prosthesis, Journal of NeuroEngineering and Rehabilitation 10 (1) (2013) 1–11. doi:10.1186/1743-0003-10-62.

[28] C. D. Hoover, G. D. Fulk, K. B. Fite, Stair ascent with a powered transfemoral prosthesis under direct myoelectric control, IEEE/ASME Transactions on Mechatronics 18 (3) (2013) 1191–1200. doi:10.1109/TMECH.2012.2200498.

[29] L. Ambrozic, M. Gorsic, J. Geeroms, L. Flynn, R. Molino Lova, R. Kamnik, M. Munih, N. Vitiello, CYBERLEGs: A user-oriented robotic transfemoral prosthesis with whole-body awareness control, IEEE Robotics and Automation Magazine 21 (4) (2014) 82–93. doi:10.1109/MRA.2014.2360278.

[30] B. Aeyels, W. Van Petegem, J. V. Sloten, G. Van der Perre, L. Peeraer, An emg-based finite state approach for a microcomputer-controlled above-knee prosthesis, in: Proceedings of 17th International Conference of the Engineering in Medicine and Biology Society, Vol. 2, IEEE, 1995, pp. 1315–1316.

[31] S. Au, M. Berniker, H. Herr, Powered ankle-foot prosthesis to assist level-ground and stair-descent gaits, Neural Networks 21 (4) (2008) 654–666.

[32] L. Chen, P. Yang, X. Xu, L. Zu, X. Guo, Above-knee prosthesis control based on posture recognition by support vector machine, in: 2008 IEEE Conference on Robotics, Automation and Mechatronics, IEEE, 2008, pp. 307–312.

[33] J. D. Miller, M. S. Beazer, M. E. Hahn, Myoelectric walking mode classification for transtibial amputees, IEEE Transactions on Biomedical engineering 60 (10) (2013) 2745–2750.

[34] R. Gupta, R. Agarwal, Single channel emg-based continuous terrain identification with simple classifier for lower limb prosthesis, Biocybernetics and Biomedical Engineering 39 (3) (2019) 775–788.

[35] K. Englehart, B. Hudgins, P. A. Parker, M. Stevenson, Classification of the myoelectric signal using time-frequency based representations, Medical engineering & physics 21 (6-7) (1999) 431–438.

[36] L. J. Hargrove, K. Englehart, B. Hudgins, A comparison of surface and intramuscular myoelectric signal classification, IEEE transactions on biomedical engineering 54 (5) (2007) 847–853.

[37] K. Englehart, B. Hudgins, et al., A robust, real-time control scheme for multifunction myoelectric control, IEEE transactions on biomedical engineering 50 (7) (2003) 848–854.

[38] T. Instruments, Fdc1004: Basics of capacitive sensing and applications (2014).

[39] B. Chen, E. Zheng, X. Fan, T. Liang, Q. Wang, K. Wei, L. Wang, Locomotion mode classification using a wearable capacitive sensing system, IEEE transactions on neural systems and rehabilitation engineering 21 (5) (2013) 744–755.

[40] E. Zheng, B. Chen, K. Wei, Q. Wang, Lower limb wearable capacitive sensing and its applications to recognizing human gaits, Sensors 13 (10) (2013) 13334–13355.

[41] E. Zheng, Q. Wang, Noncontact capacitive sensing-based locomotion transition recognition for amputees with robotic transtibial prostheses, IEEE Transactions on Neural Systems and Rehabilitation Engineering 25 (2) (2016) 161–170.

[42] H. A. Varol, F. Sup, M. Goldfarb, Multiclass real-time intent recognition of a powered lower limb prosthesis, IEEE Transactions on Biomedical

Engineering 57 (3) (2009) 542–551.

[43] B. Chen, E. Zheng, Q. Wang, A locomotion intent prediction system based on multi-sensor fusion, Sensors 14 (7) (2014) 12349–12369.

[44] A. J. Young, A. M. Simon, N. P. Fey, L. J. Hargrove, Classifying the intent of novel users during human locomotion using powered lower limb prostheses, in: 2013 6th International IEEE/EMBS Conference on Neural Engineering (NER), IEEE, 2013, pp. 311–314.

[45] A. J. Young, A. M. Simon, L. J. Hargrove, A training method for locomotion mode prediction using powered lower limb prostheses, IEEE Transactions on Neural Systems and Rehabilitation Engineering 22 (3) (2013) 671–677.

[46] B. Chen, X. Wang, Y. Huang, K. Wei, Q. Wang, A foot-wearable interface for locomotion mode recognition based on discrete contact force distribution, Mechatronics 32 (2015) 12–21.

[47] S. Wen, F. Wang, C. Wu, Realtime gait kinematics classification using lda and svm, in: 2011 Chinese Control and Decision Conference (CCDC), IEEE, 2011, pp. 592–595.

[48] H. L. Bartlett, M. Goldfarb, A phase variable approach for imu-based locomotion activity recognition, IEEE Transactions on Biomedical Engineering 65 (6) (2017) 1330–1338.

[49] D. Xu, Y. Feng, J. Mai, Q. Wang, Real-Time On-Board Recognition of Continuous Locomotion Modes for Amputees with Robotic Transtibial Prostheses, IEEE Transactions on Neural Systems and Rehabilitation Engineering 26 (10) (2018) 2015–2025. doi:10.1109/TNSRE.2018.2870152.

[50] H. A. Varol, F. Sup, M. Goldfarb, Real-time gait mode intent recognition of a powered knee and ankle prosthesis for standing and walking, in: 2008 2nd IEEE RAS & EMBS International Conference on Biomedical Robotics and Biomechatronics, IEEE, 2008, pp. 66–72.

[51] A. Mai, S. Commuri, Intelligent control of a prosthetic ankle joint using gait recognition, Control Engineering Practice 49 (2016) 1–13.

[52] Mai, S. Commuri, Gait identification for an intelligent prosthetic foot, in: 2011 IEEE International Symposium on Intelligent Control, IEEE, 2011, pp. 1341–1346.

[53] M. Islam, E. T. Hsiao-Wecksler, Detection of gait modes using an artificial neural network during walking with a powered ankle-foot orthosis, Journal of Biophysics 2016 (2016).

[54] R. Stolyarov, M. Carney, H. Herr, Accurate heuristic terrain prediction in powered lower-limb prostheses using onboard sensors (2020).

[55] A. J. Young, A. M. Simon, N. P. Fey, L. J. Hargrove, Intent recognition in a powered lower limb prosthesis using time history information, Annals of biomedical engineering 42 (3) (2014) 631–641.

[56] Z. Liu, W. Lin, Y. Geng, P. Yang, Intent pattern recognition of lower-limb motion based on mechanical sensors, IEEE/CAA Journal of Automatica Sinica 4 (4) (2017) 651–660.

[57] A. J. Young, A. Simon, L. J. Hargrove, An intent recognition strategy for transfemoral amputee ambulation across different locomotion modes, in: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2013, pp. 1587–1590.

[58] A. J. Young, L. J. Hargrove, A classification method for user-independent intent recognition for transfemoral amputees using powered lower limb prostheses, IEEE Transactions on Neural Systems and Rehabilitation Engineering 24 (2) (2015) 217–225.

[59] B.-Y. Su, J. Wang, S.-Q. Liu, M. Sheng, J. Jiang, K. Xiang, A cnn-based method for intent recognition using inertial measurement units and intelligent lower limb prosthesis, IEEE Transactions on Neural Systems and Rehabilitation Engineering 27 (5) (2019) 1032–1042.

[60] F. Gao, G. Liu, F. Liang, W.-H. Liao, Imu-based locomotion mode identification for transtibial prostheses, orthoses, and exoskeletons, IEEE Transactions on Neural Systems and Rehabilitation Engineering (2020).

[61] D. L. Hall, J. Llinas, An introduction to multisensor data fusion, Proceedings of the IEEE 85 (1) (1997) 6–23.

[62] R. Ronsse, R. C. Miall, S. P. Swinnen, Multisensory integration in dynamical behaviors: maximum likelihood estimation across bimanual skill learning, Journal of Neuroscience 29 (26) (2009) 8419–8428.

[63] H. Huang, S. L. Wolf, J. He, Recent developments in biofeedback for neuromotor rehabilitation, Journal of neuroengineering and rehabilitation 3 (1) (2006) 11.

[64] R. C. Luo, C.-C. Yih, K. L. Su, Multisensor fusion and integration: approaches, applications, and future research directions, IEEE Sensors journal 2 (2) (2002) 107–119.

[65] C. Zhu, W. Sheng, Human daily activity recognition in robot-assisted living using multi-sensor fusion, in: 2009 IEEE International Conference on Robotics and Automation, IEEE, 2009, pp. 2154–2159.

[66] F. Zhang, H. Huang, Real-time recognition of user intent for neural control of artificial legs, in: Proceedings of the 2011 MyoElectric Controls/Powered Prosthetics Symposium Fredericton, Fredericton, NB, Canada, 2011, pp. 14–19.

[67] L. Du, F. Zhang, M. Liu, H. Huang, Toward design of an environment-aware adaptive locomotion-mode-recognition system, IEEE Transactions on Biomedical Engineering 59 (10) (2012) 2716–2725.

[68] X. Zhang, H. Huang, Q. Yang, Implementing an fpga system for real-time intent recognition for prosthetic legs, in: Proceedings of the 49th Annual Design Automation Conference, ACM, 2012, pp. 169–175.

[69] F. Zhang, W. DiSanto, J. Ren, Z. Dou, Q. Yang, H. Huang, A novel cps system for evaluating a neural-machine interface for artificial legs, in: 2011 IEEE/ACM Second International Conference on Cyber-Physical Systems, IEEE, 2011, pp. 67–76.

[70] R. Hernandez, Q. Yang, H. Huang, F. Zhang, X. Zhang, Design and implementation of a low power mobile cpu based embedded system for artificial leg control, in: 2013 35th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2013, pp. 5769–5772.

[71] F. Zhang, H. Huang, Source selection for real-time user intent recognition toward volitional control of artificial legs, IEEE journal of biomedical and health informatics 17 (5) (2012) 907–914.

[72] H. Huang, F. Zhang, L. J. Hargrove, Z. Dou, D. R. Rogers, K. B. Englehart, Continuous locomotion-mode identification for prosthetic legs based on neuromuscular - Mechanical fusion, IEEE Transactions on Biomedical Engineering 58 (10 PART 1) (2011) 2867–2875. doi:10.1109/TBME.2011.2161671.

[73] I.-K. Jung, S. Lacroix, High resolution terrain mapping using low altitude aerial stereo imagery., in: ICCV, Vol. 3, 2003, p. 946.

[74] S. A. Bouhamed, I. K. Kallel, D. S. Masmoudi, Stair case detection and recognition using ultrasonic signal, in: 2013 36th International Conference on Telecommunications and Signal Processing (TSP), IEEE, 2013, pp. 672–676.

[75] M. Liu, D. Wang, H. Helen Huang, Development of an Environment-Aware Locomotion Mode Recognition System for Powered Lower Limb Prostheses, IEEE Transactions on Neural Systems and Rehabilitation Engineering 24 (4) (2016) 434–443. doi:10.1109/TNSRE.2015.2420539.

[76] F. Zhang, Z. Fang, M. Liu, H. Huang, Preliminary design of a terrain recognition system, in: 2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2011, pp. 5452–5455.

[77] S. Carvalho, J. Figueiredo, C. P. Santos, Environment-aware locomotion mode transition prediction system, in: 2019 IEEE International Conference on Autonomous Robot Systems and Competitions (ICARSC), IEEE, 2019, pp. 1–6.

[78] X. Zhang, D. Wang, Q. Yang, H. Huang, An automatic and user-driven training method for locomotion mode recognition for artificial leg control, in: 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society, IEEE, 2012, pp. 6116–6119.

[79] K. Zhang, C. Xiong, W. Zhang, H. Liu, D. Lai, Y. Rong, C. Fu, Environmental Features Recognition for Lower Limb Prostheses Toward Predictive Walking, IEEE Transactions on Neural Systems and Rehabilitation Engineering 27 (3) (2019) 465–476. doi:10.1109/TNSRE.2019.2895221.

[80] M. A. Richards, Fundamentals of Radar Signal Processing, US: McGraw-Hill.

[81] C. Panagiotakis, A. Argyros, Parameter-free modelling of 2D shapes with ellipses, Pattern Recognition 53 (2016) 259–275. doi:10.1016/j.patcog.2015.11.004.
URL `http://dx.doi.org/10.1016/j.patcog.2015.11.004`

[82] S. Sahoo, M. Maheshwari, D. K. Pratihar, S. Mukhopadhyay, A geometry recognition-based strategy for locomotion transitions' early prediction of prosthetic devices, IEEE Transactions on Instrumentation and Measurement (2019).

[83] K. Ishiwata, M. Sekiguchi, M. Fuchida, A. Nakamura, Basic study on step detection system for the visually impaired, in: 2013 IEEE International Conference on Mechatronics and Automation, IEEE, 2013, pp.

1332–1337.
[84] S. Al Mamun, A. Lam, Y. Kobayashi, Y. Kuno, Single laser bidirectional sensing for robotic wheelchair step detection and measurement, in: International Conference on Intelligent Computing, Springer, 2017, pp. 37–47.
[85] A. Pérez-Yus, G. López-Nicolás, J. J. Guerrero, Detection and modelling of staircases using a wearable depth sensor, in: European Conference on Computer Vision, Springer, 2014, pp. 449–463.
[86] G. Capi, H. Toda, A new robotic system to assist visually impaired people, in: 2011 RO-MAN, IEEE, 2011, pp. 259–263.
[87] Z. Zheng, G. Zhong, H. Deng, A method to detect stairs with three-dimensional scanning for hexapod robot stair climbing, in: 2016 IEEE International Conference on Mechatronics and Automation, IEEE, 2016, pp. 2541–2546.
[88] S. Oßwald, J.-S. Gutmann, A. Hornung, M. Bennewitz, From 3d point clouds to climbing stairs: A comparison of plane segmentation approaches for humanoids, in: 2011 11th IEEE-RAS International Conference on Humanoid Robots, IEEE, 2011, pp. 93–98.
[89] T. Westfechtel, K. Ohno, B. Mertsching, D. Nickchen, S. Kojima, S. Tadokoro, 3d graph based stairway detection and localization for mobile robots, in: 2016 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2016, pp. 473–479.
[90] L. Nalpantidis, V. Krüger, J. O. Eklundh, A. Gasteratos, Object Detection and Terrain Classification in Agricultural Fields Using 3D Lidar Data, Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics) 9163 (2015) 188–197. doi:10.1007/978-3-319-20904-3.
[91] M. Bibuli, M. Caccia, L. Lapierre, Vision-aided Guidance and Navigation for Close Formation Flight, Journal of Field Robotics 7 (PART 1) (2015) 81–86. arXiv:10.1.1.91.5767, doi:10.1002/rob.
[92] M. Hebert, Active and passive range sensing for robotics, in: Proceedings 2000 ICRA. Millennium Conference. IEEE International Conference on Robotics and Automation. Symposia Proceedings (Cat. No. 00CH37065), Vol. 1, IEEE, 2000, pp. 102–110.
[93] B. Langmann, K. Hartmann, O. Loffeld, Depth camera technology comparison and performance evaluation., in: ICPRAM (2), Citeseer, 2012, pp. 438–444.
[94] J. Fu, S. Wang, Y. Lu, S. Li, W. Zeng, Kinect-like depth denoising, in: 2012 IEEE International Symposium on Circuits and Systems, IEEE, 2012, pp. 512–515.
[95] T. Braun, H. Bitsch, K. Berns, Visual terrain traversability estimation using a combined slope/elevation model, in: Annual Conference on Artificial Intelligence, Springer, 2008, pp. 177–184.
[96] À. Santamaria-Navarro, E. H. Teniente, M. Morta, J. Andrade-Cetto, Terrain classification in complex three-dimensional outdoor environments, Journal of Field Robotics 32 (1) (2015) 42–60.
[97] Y. H. Lee, T.-S. Leung, G. Medioni, Real-time staircase detection from a wearable stereo system, in: Proceedings of the 21st International Conference on Pattern Recognition (ICPR2012), IEEE, 2012, pp. 3770–3773.
[98] T. J. J. Tang, W. L. D. Lui, W. H. Li, Plane-based detection of staircases using inverse depth, in: Australasian conference on robotics and automation (ACRA), 2012.
[99] S. Caraiman, A. Morar, M. Owczarek, A. Burlacu, D. Rzeszotarski, N. Botezatu, P. Herghelegiu, F. Moldoveanu, P. Strumillo, A. Moldoveanu, Computer vision for the visually impaired: the sound of vision system, in: Proceedings of the IEEE International Conference on Computer Vision, 2017, pp. 1480–1489.
[100] H. Harms, E. Rehder, T. Schwarze, M. Lauer, Detection of ascending stairs using stereo vision, in: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2015, pp. 2496–2502.
[101] H. A. Varol, Y. Massalin, A feasibility study of depth image based intent recognition for lower limb prostheses, in: 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), IEEE, 2016, pp. 5055–5058.
[102] Y. Massalin, M. Abdrakhmanova, H. A. Varol, User-independent intent recognition for lower limb prostheses using depth sensing, IEEE Transactions on Biomedical Engineering 65 (8) (2017) 1759–1770.
[103] A. Perez-Yus, D. Gutiérrez-Gómez, G. Lopez-Nicolas, J. Guerrero, Stairs detection with odometry-aided traversal from a wearable rgb-d camera, Computer Vision and Image Understanding 154 (2017) 192–205.
[104] P. Costa, H. Fernandes, P. Martins, J. Barroso, L. J. Hadjileontiadis, Obstacle detection using stereo imaging to assist the navigation of visually impaired people, Procedia Computer Science 14 (2012) 83–93.
[105] M. Nixon, A. S. Aguado, Feature extraction and image processing for computer vision, Academic Press, 2012.
[106] S. Wang, H. Pan, C. Zhang, Y. Tian, Rgb-d image-based detection of stairs, pedestrian crosswalks and traffic signs, Journal of Visual Communication and Image Representation 25 (2) (2014) 263–272.
[107] S. Wang, Y. Tian, Detecting stairs and pedestrian crosswalks for the blind by rgbd camera, in: 2012 IEEE International Conference on Bioinformatics and Biomedicine Workshops, IEEE, 2012, pp. 732–739.
[108] S. Murakami, M. Shimakawa, K. Kivota, T. Kato, Study on stairs detection using rgb-depth images, in: 2014 Joint 7th International Conference on Soft Computing and Intelligent Systems (SCIS) and 15th International Symposium on Advanced Intelligent Systems (ISIS), IEEE, 2014, pp. 1186–1191.
[109] R. Munoz, X. Rong, Y. Tian, Depth-aware indoor staircase detection and recognition for the visually impaired, in: 2016 IEEE international conference on multimedia & expo workshops (ICMEW), IEEE, 2016, pp. 1–6.
[110] D. S. Chan, R. K. Silva, J. C. Monteiro, F. Lizarralde, Efficient stairway detection and modeling for autonomous robot climbing, in: 2017 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), IEEE, 2017, pp. 5916–5921.
[111] X. Lu, R. Manduchi, Detection and localization of curbs and stairways using stereo vision, in: Proceedings of the 2005 IEEE International Conference on Robotics and Automation, IEEE, 2005, pp. 4648–4654.
[112] J. A. Delmerico, D. Baran, P. David, J. Ryde, J. J. Corso, Ascending stairway modeling from dense depth imagery for traversability analysis, in: 2013 IEEE International Conference on Robotics and Automation, IEEE, 2013, pp. 2283–2290.
[113] P. V. Hough, Method and means for recognizing complex patterns, uS Patent 3,069,654 (Dec. 18 1962).
[114] T. Yan, Y. Sun, T. Liu, C.-H. Cheung, M. Q.-H. Meng, A locomotion recognition system using depth images, in: 2018 IEEE International Conference on Robotics and Automation (ICRA), IEEE, 2018, pp. 6766–6772.
[115] M. Bellone, G. Reina, N. I. Giannoccaro, L. Spedicato, Unevenness point descriptor for terrain analysis in mobile robot applications, International Journal of Advanced Robotic Systems 10 (7) (2013) 284.
[116] M. Bibuli, M. Caccia, L. Lapierre, Terrain Classification in Complex Three-dimensional Outdoor Environments, Journal of Field Robotics 7 (PART 1) (2015) 81–86. arXiv:10.1.1.91.5767, doi:10.1002/rob.
[117] K. Yang, K. Wang, R. Cheng, X. Zhu, A new approach of point cloud processing and scene segmentation for guiding the visually impaired (2015).
[118] R. B. Rusu, S. Cousins, Point cloud library (pcl), in: 2011 IEEE international conference on robotics and automation, 2011, pp. 1–4.
[119] L. Souto, A. Castro, L. Gonçalves, T. Nascimento, Stairs and doors recognition as natural landmarks based on clouds of 3d edge-points from rgb-d sensors for mobile robot localization, Sensors 17 (8) (2017) 1824.
[120] M. Vlaminck, L. Jovanov, P. Van Hese, B. Goossens, W. Philips, A. Pižurica, Obstacle detection for pedestrians with a visual impairment based on 3d imaging, in: 2013 International Conference on 3D Imaging, IEEE, 2013, pp. 1–7.
[121] H.-H. Pham, T.-L. Le, N. Vuillerme, Real-time obstacle detection system in indoor environment for the visually impaired using microsoft kinect sensor, Journal of Sensors 2016 (2016).
[122] N. E. Krausz, T. Lenzi, L. J. Hargrove, Depth sensing for improved control of lower limb prostheses, IEEE Transactions on Biomedical Engineering 62 (11) (2015) 2576–2587.
[123] A. Ciobanu, A. Morar, F. Moldoveanu, L. Petrescu, O. Ferche, A. Moldoveanu, Real-time indoor staircase detection on mobile devices, in: 2017 21st International Conference on Control Systems and Computer Science (CSCS), IEEE, 2017, pp. 287–293.
[124] A. Dargazany, K. Berns, Terrain traversability analysis using organized point cloud, superpixel surface normals-based segmentation and pca-based classification, in: Workshop on field and assistive robotics, Lahore, Pakistan, 2014, pp. 17–18.
[125] D. Holz, S. Holzer, R. B. Rusu, S. Behnke, Real-time plane segmentation using rgb-d cameras, in: Robot Soccer World Cup, Springer, 2011,

pp. 306–317.

[126] M. Bellone, A. Messina, G. Reina, A new approach for terrain analysis in mobile robot applications, in: 2013 IEEE International Conference on Mechatronics (ICM), IEEE, 2013, pp. 225–230.

[127] G. Reina, M. Bellone, L. Spedicato, N. I. Giannoccaro, 3d traversability awareness for rough terrain mobile robots, Sensor Review 34 (2) (2014) 220–232.

[128] R. S. Consensus, A paradigm for model fitting with applications to image analysis and automated cartography, MA Fischler, RC Bolles 6 (1981) 381–395.

[129] L. Li, F. Yang, H. Zhu, D. Li, Y. Li, L. Tang, An improved ransac for 3d point cloud plane segmentation based on normal distribution transformation cells, Remote Sensing 9 (5) (2017) 433.

[130] K. Yang, K. Wang, R. Cheng, W. Hu, X. Huang, J. Bai, Detecting traversable area and water hazards for the visually impaired with a prgb-d sensor, Sensors 17 (8) (2017) 1890.

[131] H.-C. Huang, C.-T. Hsieh, C.-H. Yeh, An indoor obstacle detection system using depth information and region growth, Sensors 15 (10) (2015) 27116–27141.

[132] M. Nejati, B. D. Argall, Automated incline detection for assistive powered wheelchairs, in: 2016 25th IEEE International Symposium on Robot and Human Interactive Communication (RO-MAN), IEEE, 2016, pp. 1007–1012.

[133] P. Kaiser, D. Gonzalez-Aguirre, F. Schültje, J. Borras, N. Vahrenkamp, T. Asfour, Extracting whole-body affordances from multimodal exploration, in: 2014 IEEE-RAS International Conference on Humanoid Robots, IEEE, 2014, pp. 1036–1043.

[134] K. Zhang, W. Zhang, W. Xiao, H. Liu, C. W. de Silva, C. Fu, Sequential decision fusion for environmental classification in assistive walking, arXiv preprint arXiv:1904.11152 (2019).

[135] K. Zhang, J. Luo, W. Xiao, W. Zhang, H. Liu, J. Zhu, Z. Lu, Y. Rong, C. W. de Silva, C. Fu, A subvision system for enhancing the environmental adaptability of the powered transfemoral prosthesis, IEEE Transactions on Cybernetics (2020).

[136] S. Kuthirummal, A. Das, S. Samarasekera, A graph traversal based algorithm for obstacle detection using lidar or stereo, in: 2011 IEEE/RSJ International Conference on Intelligent Robots and Systems, IEEE, 2011, pp. 3874–3880.

[137] A. Sinha, P. Papadakis, M. R. Elara, A staircase detection method for 3d point clouds, in: 2014 13th International Conference on Control Automation Robotics & Vision (ICARCV), IEEE, 2014, pp. 652–656.

[138] H. Yue, W. Chen, X. Wu, J. Zhang, Kinect based real time obstacle detection for legged robots in complex environments, in: 2013 IEEE 8th Conference on Industrial Electronics and Applications (ICIEA), IEEE, 2013, pp. 205–210.

[139] D. Belter, P. Łabecki, P. Fankhauser, R. Siegwart, Rgb–d terrain perception and dense mapping for legged robots, International Journal of Applied Mathematics and Computer Science 26 (1) (2016) 81–97.

[140] N. Ramstrand, K.-Å. Nilsson, A comparison of foot placement strategies of transtibial amputees and able-bodied subjects during stair ambulation, Prosthetics and orthotics international 33 (4) (2009) 348–355.

[141] N. E. Krausz, L. J. Hargrove, Recognition of ascending stairs from 2D images for control of powered lower limb prostheses, International IEEE/EMBS Conference on Neural Engineering, NER 2015-July (Figure 2) (2015) 615–618. doi:10.1109/NER.2015.7146698.

[142] K. Du, J. Xin, Y. Shi, D. Liu, Y. Zhang, A high-precision vision-based mobile robot slope detection method in unknown environment, in: 2018 Chinese Automation Congress (CAC), IEEE, pp. 3192–3197.

[143] A. Cherian, V. Morellas, N. Papanikolopoulos, Accurate 3D ground plane estimation from a single image, Proceedings - IEEE International Conference on Robotics and Automation (2009) 2243–2249doi:10.1109/ROBOT.2009.5152260.

[144] D. C. Hernandez, K.-H. Jo, Stairway segmentation using gabor filter and vanishing point, in: 2011 IEEE International Conference on Mechatronics and Automation, IEEE, 2011, pp. 1027–1032.

[145] B. Laschowski, W. McNally, A. Wong, J. McPhee, Preliminary design of an environment recognition system for controlling robotic lower-limb prostheses and exoskeletons, in: 2019 IEEE 16th International Conference on Rehabilitation Robotics (ICORR), IEEE, 2019, pp. 868–873.

[146] G. Khademi, D. Simon, Convolutional neural networks for environmentally aware locomotion mode recognition of lower-limb amputees, in: ASME 2019 Dynamic Systems and Control Conference, American Society of Mechanical Engineers Digital Collection, 2019.

[147] I. Bogoslavskyi, O. Vysotska, J. Serafin, G. Grisetti, C. Stachniss, Efficient traversability analysis for mobile robots using the kinect sensor, in: 2013 European Conference on Mobile Robots, IEEE, 2013, pp. 158–163.

[148] T. Vllasolli, B. Zafirova, N. Orovcanec, A. Poposka, A. Murtezani, B. Krasniqi, Energy expenditure and walking speed in lower limb amputees: a cross sectional study., Ortopedia, traumatologia, rehabilitacja 16 (4) (2014) 419–426.

[149] V. Ruiz Garate, A. Parri, T. Yan, M. Munih, R. Molino Lova, N. Vitiello, R. Ronsse, Experimental validation of motor primitive-based control for leg exoskeletons during continuous multi-locomotion tasks, Frontiers in neurorobotics 11 (2017) 15.

[150] U. Gregory, L. Ren, Intent prediction of multi-axial ankle motion using limited emg signals, Frontiers in Bioengineering and Biotechnology 7 (2019).