Detection of Floor Level Obstacles and Their Influence on Gait

A Further Step to an Automated Housing Enabling Assessment

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***Abstract* - The demographic change in the industrial countries is a great social challenge. To ensure constant or better (health) care in the next decades, new care concepts for older people are needed. An approach is the use of Information and Communication Technology based solutions. Especially the preservation of personal mobility should be in focus because it is a key role to sustain autonomy and social interaction of senior citizens. In addition to the age-based declining mobility, there are secondary events, which reduce the mobility of senior citizens, e.g. diseases or fall events. Prevention of fall events is a goal for the Housing Enabling Assessments by adaption of room, e.g., by detecting and removing tripping hazards. Former work proves that an automated Housing Enabling Assessment executed by an autonomous service robot could achieve better quality and higher acceptance than a manually controlled Housing Enabling Assessment. In this article, two different methods for detecting relevant unevenness of floor in home environments and resulting challenges are presented. An adapted autonomous service robot is used as well as a Microsoft® Kinect for gait analysis and, regarding the detection of the floor's unevenness, a Prime Sense ® Carmine 1.08 depth sensor and a self- designed triangulation laser scanner were compared. First results indicate that floor characteristics have a relevant influence on gait parameters, such as gait speed, step / stride length and their variation. Also, results show that floor characteristics should become a mandatory factor for in-home gait analysis.**

Keywords-mobile robot; gait analysis; floor level; RGB-D camera; triangulation laser scanner.

I. INTRODUCTION

This article is based on the AMBIENT 2014 conference paper [1] and provides an extended approach to detect floor level obstacles and further results to their influence on gait.

Industrial countries face different challenges caused by the demographic change [2]. A possible way to cope with these upcoming problems is the use of Information and Communication Technology (ICT) in the area of Ambient Assisted Living (AAL). There are two main approaches to bring technology to the homes of senior citizens. The first approach is Smart Homes [3], which means that the entire technology is integrated into the apartment. The second solution would be autonomous service robots. In this case, sensors, actuators and computational units are attached to a mobile base. An example for "simple" household robots are autonomous vacuum cleaners. Because of a great sales volume of autonomous vacuum cleaners in the last years, they have a big impact on society. They have raised the acceptance for robots among users and show how the design influences it [4][5][6]. Advanced systems like service robots could support caregivers to help elderly maintain an independent lifestyle and preserve their indoor mobility up to a high age [7][8]. A potential advantage of service robots compared to Smart Homes is their low costs since they need fewer sensors to generate a good coverage based on their mobility. In order to cover areas, they can bring them in the area of interest [9]. In this approach, the mobility of these platforms is used to realize an automated Housing Enabling (HE) assessment [10]. A first step is the evaluation of the apartment, especially the examination of the floor in order to detect stumbling risks. This article is organized as follows; Section II motivates the topic and is followed by the State of the Art and current limitations (Section III). In Section IV, two approaches are presented to measure the unevenness of floors and the measurement of different gait parameters followed by the results in Section V. The conclusions and further steps complete the article (Section VI).

II. MEDICAL MOTIVATION

Prevention of fall events is an important research area. A fall event could have great impact on mobility, especially for senior citizens. An obvious fact is the reduction of mobility in case of a fracture of the neck of femur. But also the fear of, e.g., a second fall limits the mobility of older people [11] and a reduced mobility increases the risk of falling, which is the starting point of a vicious circle. Also, fall-related costs are a major factor for our health care system [12].

An important factor is that mobility problems reduce the personal radius of movement. Renteln-Kruse et al. show that this influences social participation; above the age of 55 years, the radius of movement is reduced to approximately 3 km around the home [13]. Also, 55% of fall injuries occurred inside the house [14], which raises the importance of in-home assessments. From a clinical perspective, long-term monitoring of changes in mobility has a high potential for early diagnosis of various diseases and for the assessment of fall risk [8]. As important as the age and potential diseases / disabilities of the patient [15][16] is the condition of the floor for the self-selected gait velocity and, in general, the risk of stumbling or slipping [17]. Especially in an unsupervised environment, the additional information about the quality of the floor could increase the precision of the gait analysis [18][19], which could be very helpful for the HE Assessment in order to estimate the personal factor. This approach, tries to realize both, i.e., a good data base for the HE Assessment and also gain additional information for a gait analysis to increase their precision.

III. State of the Art

This section gives an overview of the four most interrelated research areas of HE Assessment. First, the trend analysis of mobility in domestic environments is outlined, followed by mobility assessments using mobile robots. Afterwards, possible environmental hazards and housing modification are shown. Fourth point is the influence of the unevenness of the floor on gait parameters. Finally, the section is closed by the current limitations of the State of the Art.

A. *Trend Analysis of Mobility in Domestic Environments*

Various approaches for gait analysis in domestic environments are presented. Scanaill et al. present the possibility of upgrading a home with various sensors, especially from the home automation or security domain to a (health) Smart Home [20]. Most systems are used for trend analyses [21][22][23] and only some approaches use ambient sensors for detailed gait analyses [24]. Various groups use Home Automation Technologies like motion sensors, light barriers or reed contacts placed in door frames or on the ceiling. Cameron et al. use optical and ultrasonic sensors [21], which were placed on both sides above the door frames to determine the walking speed and direction of a person passing. Kaye et al. presented an intelligent system for assessing aging changes [22]. For the study, they installed several sensors in 265 homes for an average of 33 months and used, among others, wireless passive infrared motion sensors, which were covering different rooms of an apartment. A line of these sensors was modified and attached to the celling of some rooms within the apartment to estimate the resident's walking speed. Also, laser range scanners are used for different assessments. Frenken et al. presented an automated Time Up and Go (TUG) Assessment. Therefore, the laser range scanner is mounted underneath a chair and is used to recognize the legs of the test person [24]. Pallejà et al. have a similar approach but conducted a detailed gait analysis with a laser range scanner, which was mounted at 100 mm above the floor [25]. This low position of the laser has the disadvantage that it is possible that a foot could hide the corresponding leg. In this case, a laser scanner would only detect the tip of the foot and not the leg, which is important for a correct assessment. Poland et al. used a camera attached to the ceiling, recording a marked floor evenly divided into rectangles to estimate the gait speed [23]. Each of these rectangles is defined as a virtual sensor. For persons within these, the approach 'activates' the virtual sensor in, which they are currently located in. Stone and Skubic used the Kinect to analyze the gait in a home environment [26]. Especially the variation of gait parameters like step length and self-selected speed over time were measured and identified as independent factors for the personal stumbling risk. Also, Gabel et al. used the MS Kinect for a full body gait analysis, which is capable of a precise in home gait analysis [27]. A similar approach for a long-term in-house gait analysis by using the Kinect was published by Stone and Skubic [28]. But in addition, a monthly fall risk assessment protocol was conducted for each resident by a clinician, which included traditional tools such as the Timed Up and Go and habitual gait speed tests. Afterwards they compared the results of the clinician with their approach.

B. *Mobility Assessments Using Service Robotics*

Service robots combine ideas of different fields of robotic research into one system in order to target a specific application. Most available platforms are still in (advanced) research states. There are different fields of interest, e.g., acting autonomously in home environments. For most mobile robot platforms it is difficult to interact with the human friendly environment. A closed door could be a problem for a robot. Petrovskaya and Ng present a probabilistic approach on how a mobile robot could detect and open doors [29]. Also, the interaction with humans is very important; Breazeal published a first approach on how to design a sociable robot and how it can learn from environmental factors and user behavior [30], this approach is similar to Ray et al. [31], who asked "What do people expect from robots?". To be able to interact with humans, it is very important for the robot to be able to recognize humans. Udsatid et al. present an approach of a mobile robot platform, which tracks humans and is able to drive side-by-side with a human by using a down facing Microsoft Kinect sensor to track the feet, to find out the heading and direction of the human [32]. Brell et al. presented a first approach of a mobility assessment with a mobile robot platform [33]. For this, a laser range scanner to detect the residents 'legs and to estimate the walking speed within different areas of the apartment was used. Within our own work, a new approach on how to enhance mobile robot navigation in domestic environments by use of mobility assessment data was recently presented [34]. The advantage of a mobile robot is that it can bring the needed sensor technology to the Optimal Observation sLots (OOL) for monitoring as introduced in [33]. In the observation phase, the robot stands at a safe place in the initial room of the apartment and observes the human behavior and environment. These data are used to compute new OOL, which fulfill different safety and quality criteria. After that phase, the robot will travel to the respective OOL and measure different gait parameters by using the laser range scanner and the Kinect, which can be used in HE Assessment.

C. *Environmental Hazards and Housing Modification*

T. M. Gill et al. presented a study, which sought to estimate the population-based prevalence of environmental hazards in the home of older persons [35]. Therefore, one thousand homes of senior citizens above 72 years were assessed. The most potential hazards are slip and trip hazards by rugs, carpets, etc. In second place are blocked pathways by e.g., small objects or cords and in third position insufficient lightning conditions (shadows or glare), curled carpet edges or other tripping hazards. T. M. Gill et al. pointed out that safety awareness at home may relate to one's personal capabilities. On the other side, M. E. Northridge presented a study on home hazards and the role of health and functional status of senior citizens [36]. It was pointed out that the presence of home hazards influence vigorous elderly persons twice in aspect of falling but it was not associated with the increased likelihood of falls among frail older persons. A quite popular assessment in the Scandinavian countries is the HE Assessment. It reduces the risk of fall in home environments and the near surrounding. The apartments are assessed depending on the personal health status of the residents and the structure of the apartment itself [37]. This rating gives advice on how to change the apartment with its furniture etc. so that it is suitable for the resident. The HE Assessment is split into three parts. The first part is the descriptive part for collecting general information on the apartment and the resident's condition. The second part is the evaluation of functional limitations and dependence on mobility aids. Also, detailed information about the medical condition of the user is collected, e.g., severe loss of sight or limitation of physical fitness. The last part is based on different questionnaires, which relate to the apartment and the vicinity. After completion of all questions, a score of the apartment in relation to the actual health status of the resident [38] is computed [39]. A customization of the apartment to reduce the risk of falling is also possible. This adaption is related to the rating [40] but is not an explicit part of an HE Assessment. Another survey to investigate the prevalence of environmental hazards in the homes of older people was presented by S. E. Carter [41]. This survey shows that 80% of the 425 inspected homes had at least one, and nearly 39% had more than 5 tripping hazards, while 62% showed "flooring" hazards. R. Cham and M. S. Redfern measured the change in gait when people anticipated slippery floors [42]. Therefore, three different floorings were used with the participants having to walk over each surface three times. In the first trial, the test person knew the floor was dry, next the test person was uncertain about the floor's condition (dry, wet, oily, soapy) and in the last try the condition was also known as dry. They found significant changes in the normal stride length and stance duration. It was also pointed out that the floor type had some influence on most gait variables.

D. Evenness of the Floor and its Influence

Also, the unevenness of the floor influences on gait parameters. S. B. Thies et al. reported on the effects of surface irregularity and lighting on step variability during gait [18]. Different gait parameters from 12 healthy young women and 12 healthy older women were measured. Each person had to walk over a 10m walkway in a personal comfortable speed with four different settings being tested: plain surface with regular lighting; plain surface with low lighting; irregular surface with regular lighting; and irregular surface with low lighting. As a final result, the lighting did not have a significant effect on any of the gait parameters, while the surface type had significant effects on the step time variability, step width variability, which was observed especially with the older women. Marigold and Patla also presented results on age-related changes in gait on multi-surface terrain [19] using a more outdoor-based scenario so that the multi-surface terrain consisted of solid, flexible, rocky, irregular, slippery, and uneven surfaces. Ten younger and ten older adults were tested and it was found that the step length, trunk pitch and roll, and head acceleration variability were increased on the multi-surface terrain compared to solid ground trails for both young and older adults. Older adults obtain a larger medial-lateral trunk center of mass acceleration Root-Mean-Square (RMS) and trunk roll RMS when walking on the multi-surface terrain. But they found no age-related differences in the step variability. The influence of an irregular surface and low light on the step variability of patients with peripheral neuropathy was researched by Thies et al. [43]. Also, the change in gait parameters by stepping over an obstacle was presented by different research groups using obstacles with a height between 0 mm and 152 mm [44][45]. McFadyen and Prince used an 11.75 cm height obstacle [46]. All studies measured differences in the gait patterns in general but they do not have a common result. The influence of surface slope on human gait characteristics was presented by Sun et al. [47]; for this study an outdoor set-up was used, so that the results are not exactly comparable to indoor set-ups. Nevertheless, all studies have shown that the surface does have an influence on gait. In order to estimate a maximum permissible value of the unevenness in homes, several building regulations are inquired [48][49][50][51]. They identified different levels of unevenness, which should not be exceeded. In general, all building regulations pointed out that office floors do not have uneven areas, no slots, stumbling areas or dangerous slopes. The maximum height difference between two even rooms are defined as 4 mm within the "Professional association rules for safety and health at work" [48] and the "Technical Regulations for Workplaces" [50]. The unevenness of the floor is only named as an environmental risk but has not exactly been defined. Also, the "Slip, Trip, and Fall Prevention" Guide from the University of Stanford [49] named some trip and fall hazards, e.g., uneven walking surfaces, holes, changes in level, broken or loose floor tiles, defective or wrinkled carpet or uneven steps/thresholds but it also has no exact dimensions for the different points. The DIN 18202 gives precise dimensions for evenness of the

TABLE I. LIMITS FOR FLATNESS TOLERANCES

Description	Limit of unevenness in mm among measurement distance in m				
	0.1	*1*	*4*	*10*	*14*
Screeds to receive e.g., floor coverings, flooring, tiling	2	4	10	12	15
Finished grounds with increased requirements	1	3	9	12	15

a. Excerpt from the DIN 18202:2013-4

floor (see Table I) [51]. If you measured a distance of 1m, a level difference of about 4 mm is tolerable for normal screed. These values are used as a reference point for the accuracy of our approaches. As shown before, it is important to have detailed information on the surface (floor) to raise the validity of domestic gait analysis. Udsatid et al. used a mobile robot and a Kinect sensor to measure the ground and calculate a virtual ground plane [32]. But, only for a background subtraction for a foot tracking algorithm, which was used for a side-by-side navigation algorithm. Currently, there are no mobile service robots to determine the unevenness of the floor.

E. Limitation of the State of the Art

As shown in Section III-A, most of the systems used ambient sensors and did not observe the user continuously but only measured the test person's presence at specific points. The problem herein is that it can only be used for trend analysis rather than for a detailed assessment to determine various mobility parameters of a person. For precise assessments of mobility, laboratory equipment and well-known vicinities are needed. On the one hand, the installation efforts and costs are too high to install such in domestic homes, on the other hand homes are dynamic, this means that, e.g., furnishing changes over time. All of the automated gait analyses do not respect the influence of the floor cover. Within the domain of health care and rehabilitation service robotics, there are quite few systems commercially available. Moreover, there is no robotic system, which is capable of performing HE Assessments and giving advice on how to reduce the risk of falling. The current HE tests suffer from some drawbacks, e.g., the estimation of personal disorders, the investigation and also the following customization of the apartment, which highly depends on the skill of the person executing the test. Little knowledge could lead to different or insufficient results. Furthermore, these assessments are mostly not done as a continuous assessment but rather as an event-triggered assessment after accident. In summary, there is currently no system or approach available, which is capable of conducting precise and continuous HE Assessments in domestic environments and using this additional information to raise the precision of gait assessment results.

IV. APPROACH

We are going to present two different approaches to detect relevant unevenness of the floor with a mobile robot platform. This is followed by a short description of how to estimate balance parameter under different environment conditions.

A. Detection of Unevenness with RGB-D Camera

Our first approach provided an automated and continuous detection of relevant unevenness of the floor assembly, which will be used to rate the apartment during the HE Assessment and to increase the quality of the gait analysis. In order to implement a stable algorithm in an unsupervised environment, an initial self-calibration was included.

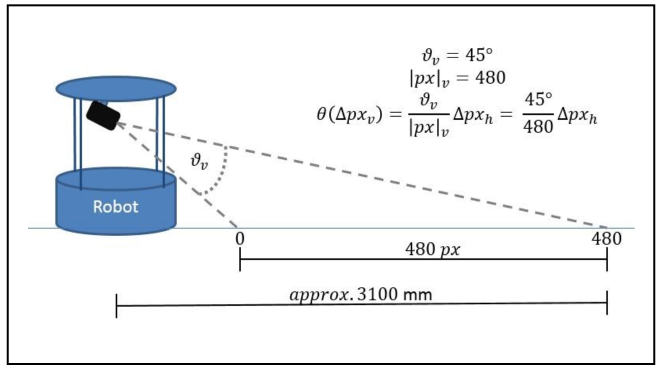

Figure 1. Schematic drawing of the mobile service robot with the Primesense Sensor and the calculation of the vertical aperture angle between two points (Δpx_h).

Therefore, the ground level and the sensor orientation for a better error correction were calculated in the beginning. This step was necessary to prevent the sensor from "losing" orientation between runs or the sensor underlying a drift over time. In this case, a pre-calculated ground plane would lead to a wrong detection of relevant unevenness of the floor.

In a first step, the quality of the current depth image of the sensor is estimated by calculating the RMS deviation of each pixel. For calculating the virtual ground, two points of the middle row and two of the middle column of the depth frame are selected, which satisfy three criteria. The first is that both points have the lowest possible RMS (minimum below the quality factor otherwise use other column or row), the second is a maximized distance between these points and the third criterion is that they do not belong to a known obstacle like walls. This information is taken from the navigation map of the mobile robot platform. In the following section, only the estimation of a vertical ground line is considered because the calculation of the horizontal ground line and also the ground plane is done equally. After the selection of two vertical points, it is possible to calculate the first ground line and the vertical orientation of the sensor. Only five parameters are known: the two distance values of the two selected points, the pixel distance between both points, the vertical aperture angle of the Prime Sense Sensor [52] and the resolution of the current depth frame. Figure 1 shows the aperture angle calculation of each pixel. Together with the pixel distance between the selected points, it is possible to calculate the angle between them. For all examples, a resolution of 640 x 480 pixel is used, which is the highest possible depth resolution of the Prime Sense Carmine Sensor. Using the law of cosines, it is possible to estimate the missing parameters, e.g. the height of the sensor or the vertical angle. After the complete calculation, all relevant values are known in order to be able to estimate the vertical ground line. The next step is similar to the background subtraction. The ground line is a kind of background used for calculating the difference to the current depth image. Figure 2 shows the normal depth image and a binary picture, which is generated by a root-mean-square deviation approach. If the difference is higher than the RMS, the pixel is set to 1, otherwise to 0. Now, it is easier to cluster this picture and find relevant tripping hazards. For clustering,

Figure 2. Left side: Depth values from the Sensor in grayscale (White near, dark grey far away) with a 10 mm tread in a distance of 80 cm, right side: Visualization after ground subtraction and converted to a binary image of depth values with the RMS as threshold.

various approaches are published, e.g., edge detection and many more. After found interesting blobs (e.g., size or shape), the height of these obstacles is calculated from the depth picture. This information is saved to the navigation map of the robot. After that, it can be used for scoring the apartment and for increasing precision of gait and balance analysis in the different areas.

Our second approach is similar in respect to the idea that a virtual ground is calculated to use it for a background subtraction and for estimating relevant obstacles on the ground. But instead of calculating the RMS for each pixel, finding the best two pixels near the middle row and column to calculate the virtual ground plane and so on, we used another approach; in respect to the limited calculation power of the mobile robot platform and the gained knowledge of the Prime Sense sensor, only a cut out from the depth image is used. For this approach, the depth picture was taken with the same resolution of 640 x 480 pixel, but only an area of approx. 30 cm vertical and 80 cm horizontal is used, which is located in front of the mobile robot platform. The advantages of this step are:

- four times less pixels in respect to the computational power
- less problems with distant objects, related to a higher sensor noise at greater distances
- higher linearity of the depth image in the area of interest

All these points influence the precision of the ground plane calculation. The disadvantage of a smaller field of view is negligible because of the mobility of the robot platform.

As mentioned in the previous section, only the estimation of a vertical ground line is presented here since the calculation of the horizontal ground line and the ground plane is straight forward. In a first step, a mean depth image of the current location is calculated from over 20 frames, followed by the estimation of median depth values from five columns for each row. The five columns are the middle column and their two left and right neighbors. This new calculated middle median column is used to estimate the horizontal virtual ground line. The first two steps represent a simple filter to reduce the noise of the Prime Sense Sensor due to the limitation of processor capacity. The third step is to calculate a regression line for the middle median column (see (1)). Then the regression line is used as virtual ground line for vertical direction. The following steps are similar to our first approach; the virtual ground is subtracted from the current depth image.

$$RSS = SS_{Res} = \sum_{i=1}^{n} e_i^2 = \sum_{i=1}^{n} \left(y_i - (a + bx_i)\right)^2 \rightarrow min! \quad (1)$$

If the difference is higher than the median value of the subtraction from the regression line and the middle median column, the pixel is set to 1, otherwise to 0. After finding interesting areas (e.g., size or shape), the height of these areas is calculated from the depth picture. This information is added to the navigation map of the robot. As mentioned in the first approach, these data are used to increase the quality of automated home gait analysis and also for the home score calculation of the HE Assessment.

B. *Detection of Unevenness with Triangulation Laser Scanner*

As mentioned in Section III.D, it is mandatory to detect an unevenness down to 4 mm, which is near the limit of the most consumer RGB-D Cameras with a detection range from up to 2.5 meters. In order to detect small tripping hazards from 2mm to 20 mm, a triangulation line laser scanner was developed, which consists of two IR line laser modules and a Raspberry Pi B single board computer with associated "NoIR" Camera module, which is able to record visible and infrared light. Both line laser modules are attached to the opposite edges (a distance of 24.5 cm) of the first level of the

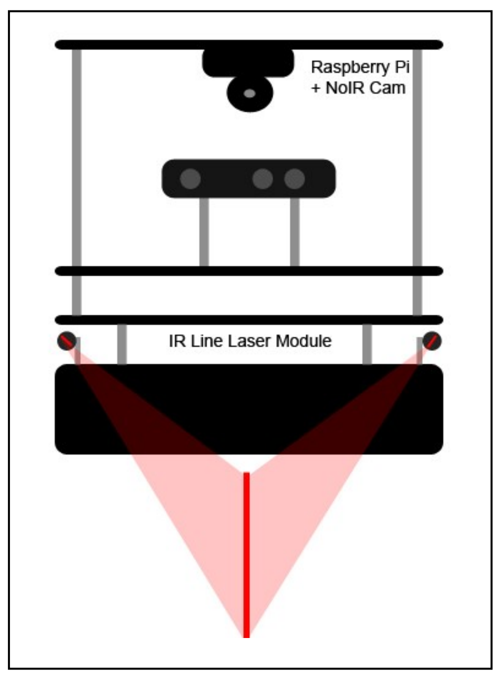

Figure 3. Schematic draw of the set-up of the new triangulation ground laser scanners.

mobile robot platform (at a height of 11.8 cm). The Raspberry Pi with the camera module was mounted upside down to the highest level, approx. 35 cm above the floor (see Figure 3). The camera module can be tilted between 0° to approx. 180°. An angle of approx. 30° was used for the measurements, which provided a horizontal field of view of approx. 36 cm at the beginning and approx. 54 cm at the end and approx. 100 cm in vertical in front of the mobile robot platform. Because of the intensity of the IR laser modules, the entire 100 cm of the vertical field of view were used, which guarantees a good contrast between the IR line and the environment. Both line laser modules were aligned with each other so that they projected a common line onto an even floor in the vertical middle of the camera image, which means that both laser modules have an angle of approx. 46°. The "NoIR" Camera has a single picture resolution of up to 2592 x 1944 pixel [53]. The latest stable OpenCV version 2.4.10 is used for capturing the "NoIR" Camera pictures and the whole computation on each picture.

In a first step, the picture is trimmed to the needed dimensions. As mentioned before, the entire 100 cm of the vertical field of view of the camera were used and have sufficient contrast for the most indoor environments in respect to lighting conditions and floorings. The first step of the image processing is the conversion to a binary image. To find the best possible threshold for this step, two factors are taken into account. The first factor is the current illumination of the room and the second aspect is the current back scatter of the IR line laser on this surface. For the current illumination of a room, the TSL2561 sensor is used.

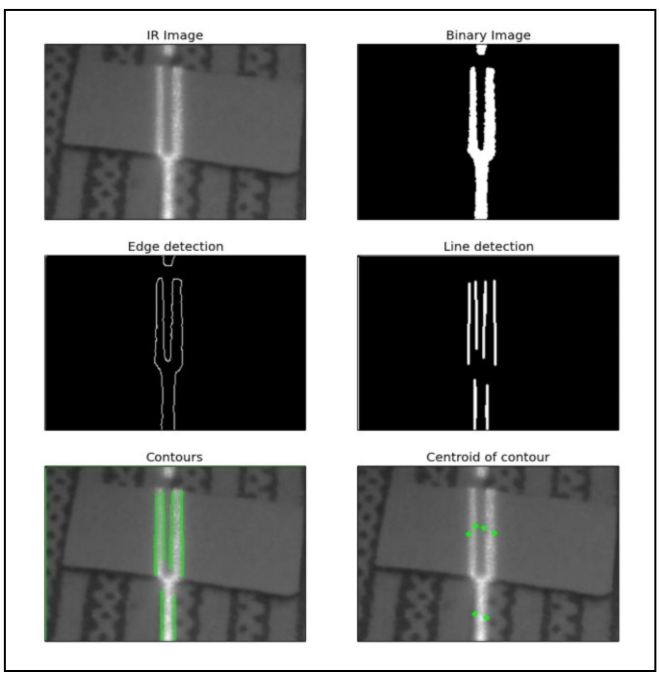

Figure 4. Upper left: part of the raw image from the NoIR Cam with an obstacle (2 mm height), upper right: binary image with calculated threshold, middle left: image after canny edge algorithm, middle right: image after probabilistic Hough line algorithm, lower left: Contours of the Hough lines, lower right: Centroids of the corresponding contours.

A great advantage of this sensor is that it detects both, IR and visible light. So it is possible to estimate the average brightness of the current image without time consuming computation. To improve the estimation, the current reflection of the surface is also taken into account. Therefore, the previous knowledge about the approximate position of the IR laser line within the image is used. In this area, the algorithm searches for the brightest pixel. These two values are used to estimate a threshold value to generate a binary image, in which only the laser line is still visible as a white line. This approach has a high reliability in finding a good threshold to detect only the laser line without having to cut away too much of the edge region of the line. Especially in the upper region of the image, which had - in most cases - the lowest contrast. In the case of the threshold being too high, too much of the edge region has been cut off. This would lead to an inaccurate result during the height estimation of an obstacle. In the case of the threshold being too low, it is possible that there are a lot of artefacts in the binary picture, which make the following computations much more complicated or time consuming.

Afterwards, the OpenCV 2 implementation of the Canny edge detection algorithm with a 5 x 5 kernel is used to find the edges of the laser line. Followed by a probabilistic Hough-Line algorithm, which estimates lines on the base of the canny edge picture (see Figure 4). The result of the probabilistic Hough Line algorithm are different lines, which represent the edges of the canny algorithm. After that, the contours of these lines and their centroids are estimated. Finally, these centroids are used for the calculation of distance and, therefore, for the approximation of the height or depth of obstacles or the unevenness of the floor. To get this final information, some additional steps are needed:

- Finding corresponding centroids
- Calculating distance of corresponding centroids
- Estimate orientation of obstacle
- Calculate level of obstacle

The next step is to find lines that belong to the same segment of a laser line. Therefore, the centroids are sorted depending on the x and y coordinates of each centroid. Together with the pre - knowledge of, e.g., width of a laser line, it is possible to estimate relationships between two centroids. If two pairs of corresponding centroids are found, which are near the same horizontal segment and out of the vertical center, the pixel distance between the both inner centroids of these pairs are calculated. This distance is proportional to the height or depth of an obstacle. To find out if it is a positive or negative elevation of the floor, the left line laser module is switched off and a new image is taken and it is calculated, which lines or centroids are missing. With the knowledge that the even floor is the sectional plane of both line lasers, a left missing line means the obstacle has a positive elevation, a right missing line means the obstacle has a negative elevation. Now there is enough information to calculate the height (positive or negative) and also the length of the obstacle at this point. This information will be added to the corresponding point in the 2D map of the mobile platform. In future developments, it is planned to generate a complete 3D model of this obstacle. Therefore, the fact that the triangulation line laser scanner is mounted to a mobile robot platform is utilized, and we are able to move the robot along or around an obstacle to estimate the missing parameters, e.g., shape and length. With the additional motion information of the mobile robot platform, it will be possible to generate a complete 3D model of the obstacle.

C. Calculate Balance Parameter

In our first approach, the Microsoft Kinect is used to track the person because of the low price and the existing openNI skeleton tracking algorithm from ROS [54]. The mobile platform does not move during the measurements because of the specification from the openNI algorithm. During the observation phase the timestamp and the x-, y- and z- coordinates of the following skeleton joint point from the openNI tracker node will be saved:

- Foot and hip (each: left, right)
- Torso and Neck

In respect to the low processor capacity of the Turtlebot 2 netbook, an offline approach is used. After the observation phase, different balance and gait analysis parameters are calculated. In a first validation, the distances of the joint points are checked, whether they are between ranges of 0.80 – 3.00m, which is the effective distance of the Kinect sensor. After that, the gait speed, step and stride length and, related to those values, the stance and swing phase of each foot are calculated. First, the different phases for each foot during a measurement are estimated by using (2).

$$\lfloor x_i - x_{i+1} \rfloor_{i=0}^{n} = \begin{cases} \leq 0.02\ m, stance\ phase \\ > 0.02\ m, swing\ phase \end{cases} \quad (2)$$

This means that a foot needs a minimum acceleration of approx. 0.6 m/s to be marked as moving. This value reflects a compromise of literature values and a kind of error correction of the drift from skeleton tracking. After that, the middle index of each phase for each foot is calculated, this is used to estimate stride and step length. Also, the calculation of the gait speed uses these indexes by choosing the first and the last stand phase of each measurement and then calculates the distance between these points. Now, the corresponding timestamps are used to determine the elapsed time. By dividing the distance by time, the gait speed for each measurement is calculated. Two factors are used to get a better reliability between measurements; the first is that the mobile robot stands on a defined OOL, so the global coordinates and the direction are nearly equal between the measurements; the second helpful point is that humans used more or less the same path between two points in the home environment. These points help to get a bigger and comparable data base from the same OOL’s

V. Results

In this paragraph the results of our approaches are presented, which were tested and verified in the OFFIS IDEAAL Lab. It provides a complete demo apartment for first measurements in a realistic environment. As a mobile platform, a Turtlebot 2 (Kobuki) was used.

A. Detection of Unevenness with RGB-D Camera

To test and verify our first approach, a Primesense Carmine 1.08 sensor was used, which is mounted upside down underneath the third level of the robot platform and looks down to the ground with an angle of approx. 35 degrees at a height of approx. 34 cm. The resolution of the depth sensor is set to 640 x 480 pixel and a frame rate of 30 Hz. The platform, the sensors and the mounting of both have not been changed during the measurements. To get comprehensive measuring results, the IDEAAL Lab and a normal office space were used to test our approach on different floor types. This configuration gave results from two different carpets, a laminate and a PVC- coating. The measurements in between two floors represent the change between coatings (laminate / carpet). To measure normalized height differences, five wooden tread layers were used. Each piece had a height of 5 mm, so that it was possible to measure between (un-)even doorways (0 mm) up to 25 mm.

For our first approach, we saved 30 single frames for each test set-up, calculated and saved the mean values and the standard deviation for each pixel in order to verify the precision of the sensor. According to different building regulations [48][49][50][51], the requirement is to detect differences of a minimum of 4 mm between two surfaces or an area of 1 square meter. The measured minimal standard deviation is approx. 3.94 mm and the median value is 6.29 mm. This means that the precision of the Prime Sense Carmine 1.08 sensor is near to the required precision of 4 mm. After this result, further tests to verify our first results were performed. Therefore, different measurements in the IDEAAL Lab and within the office with wooden treads were made. The proceeding for each measurement was the same; first, 30 frames of the even surface were taken, then 30 frames with a 5 mm tread in a distance of 80 cm followed by 30 frames with 10 mm tread and so on until the maximum of 25 mm was reached. After that, the distance was reduced to 40 cm and started over without any obstacles and then raised the treads in 5 mm steps.

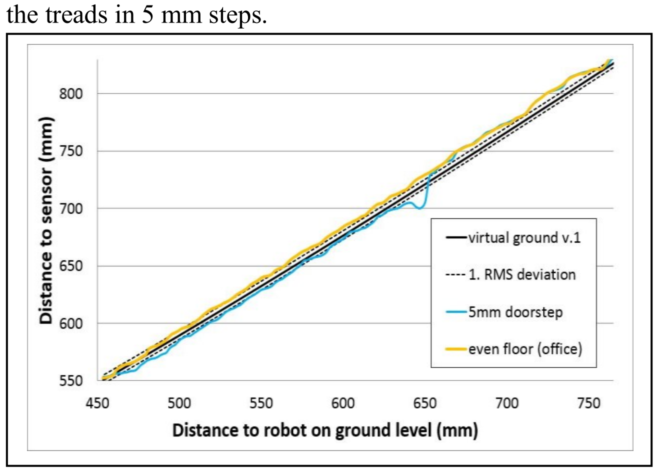

Figure 5. Visualization of the calculated virtual ground v.1 (black), the first RMS deviation (dotted lines) and the measurement from the ground (orange) and a 5 mm tread (blue).

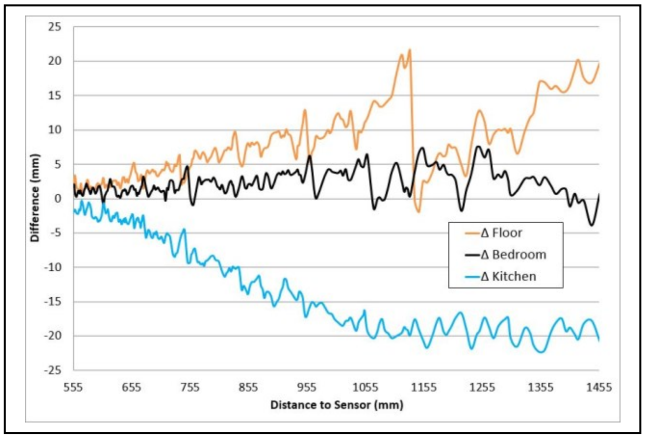

Figure 6. Visualization of dependency of different floorings in comparison to the general mean ground value.

After the measurement, the virtual ground plan was calculated and subtracted from different test images. The result was unexpected; in the first approach, only two small areas had good results. These areas were around the selected points for the calculation of the ground plane. Even for a floor without any unevenness. After a small modification (also considered in the description of the approach) of the algorithm, which selects the point for estimate the ground plane, a vertical ground line was calculated, which only matched the lower third of the depth picture. Figure 5 shows that the difference between the calculated ground and the real ground in the upper two thirds of the picture was too big to detect any relevant barriers.

After these results, the first step was to verify the measurement, by subtracting the mean value of the even ground from the mean values of the modified ground. These values showed acceptable results for the detection of barriers from 5 mm up to 25 mm. The next step was the linearity of the sensor over distance. If it had a linear characteristic for the depth sensor, then our approach should work in general. The result in Figure 6 shows that the sensor does not have a perfect linear characteristic with objects more than 1.4 m away from the sensor. This means that our approach to calculate a virtual ground, which is represented by a plane or line and use it for a simple background subtraction, is not applicable to the complete range of the Prime Sense sensor. After that, our second approach was developed and tested with the same data set, which we generated during the test for our first approach. This guaranteed a high comparability of these two approaches. As mentioned in Section IV.A, only a cut out of the original depth images was used for the second approach. The final depth image for the second approach has a size of 320 x 240 pixel, which represented the lower half of the original picture, it belongs to an area of approx. 30 cm (vertical) x 80 cm (horizontal) in front of the mobile robot platform. Based on this extracted data set, the new virtual ground was calculated with (1). The virtual ground was subtracted from depth images of all 12 set-ups. The results for our second approach were much better than for the first approach. As you can see in Figure 7, the new virtual ground fits nearly perfectly to the depth image of the even floor. Also, the difference to the depth image with the 5 mm tread seems to be good enough to be able to guarantee a detection of obstacles of at least 5 mm. Now, the second approach was tested if the main goal of being able to recognize obstacles in an easy way without having a complete 3D map of the even floor in an apartment could be achieved. Therefore, the measurement was repeated in different rooms of the IDEAAL apartment with different floor types and subtracted the new depth images from the generated virtual ground v.2. These results were surprising again. In some rooms, the virtual ground v.2 fits quite well to the depth image of the even floor and the differences are in the first order of the RMS deviation. But in some cases, huge areas were found, which were marked as potential obstacles on an even floor. A good example was the depth image from the kitchen (see Figure 8). In the lower area, both lines fit quite well but the in the upper area the depth image and the virtual ground v.2 have a great gap. The difference between the calculated and the real ground is bigger than the first RMS deviation, which means that false positive barriers were detected. The difference between the virtual ground v.2 and a 5 mm tread in the kitchen is only few mm above the first standard deviation. Also the difference between the even ground and the virtual ground v.2 are quite better than the difference between the even ground and virtual ground v.1 (see Figure 9). It seems to be possible to detect obstacles with a height of approx. 10 mm but as mentioned in Section III.D for the HE Assessment, obstacles needed to be detected with a height of 4 mm. Therefore, a sensor resolution up to 1.5 – 2 mm is needed.

B. *Detection of Unevenness with Triangulation Laser Scanner*

Because of the insufficient results from our two approaches with the RGB-D-Camera, an own triangulation laser scanner was developed as described in Section IV.B. In order to evaluate this new scanner, it was tested under comparable conditions to the approaches with the Prime Sense Carmine sensor. In a first test, the office floor with different obstacles was used. These had a height of 2 mm, 5 mm, 10 mm, 15 mm, 20 mm and 25 mm and were placed in front of the mobile robot platform in a distance of approx. 80 cm and 40 cm, which is similar to the set-up of our first two approaches. For each set-up, 10 pictures were taken with the Raspberry Pi NoIR Camera for estimating the height of each obstacle with the approach of Section IV.B. As you can see in Figure 4, both laser lines are clearly separated, also for obstacles of a height of down to 2 mm. This depends on a relative low position over ground and great distance between both laser modules, which resulted in a shallow angle and guaranteed a good separation for low obstacles. Because of the relatively high position of the Raspberry Pi and its camera module, we have a great field of view and so it is also possible to detect obstacles up to 25 mm. The upper right picture in Figure 4 shows only a cut out from the whole image of the NoIR Camera module. The obstacle that is shown was placed in front of the mobile robot platform with a distance of approx. 80 cm and the picture still shows a good resolution and contrast. Therefore, it is possible to estimate the height with an accuracy of approx. 1.5 mm over the complete range of 100 cm.

C. Dependence of the Surface

The dependence of the Prime Sense sensor on the flooring was tested by measuring four different floor types, two different kinds of carpet, PVC- coating and laminate. Also, the transition from laminate to carpet was tested. For each surface, 30 single measurements were made and the mean value over all 30 single frames on pixel base was computed. Then, these mean values were used to calculate the overall mean value of the ground. The mean value of the middle column was selected from each measurement and subtracted from the corresponding value of the overall mean depth picture. The results are shown in Figure 6 and lead us to the fact that different floorings have an influence on the distance values and the reliability of the sensor. As you can see in Figure 6, the deviations in the first 50 pixel, which are equivalent to a distance of approx. 20 cm in front of the mobile robot platform, represent a difference within the first RMS deviation of about 3.94 mm. The total measurement represents a distance between approx. 10 cm to 84 cm from the mobile robot platform. This result points out that it is advisable to calibrate the sensor daily and for each subsurface in order to reduce errors during the measurement, or use a different model of this sensor type, e.g., the Prime Sense Carmine 1.09 with higher depth resolution or a complete other type of sensor to detect the unevenness of the floor. We also conducted first tests on different floorings with our triangulation laser scanner. Right now only two different set-ups have been tested; on the office carpet and the PVC in the IDEAAL apartment kitchen. The line laser modules obtain an energy output of approx. 5mW, which should guarantee a good contrast over a wild field of different variables (i.e., sunlight, floor type). The first test was to estimate a threshold for the office carpet, which was relatively easy because of the good optical properties. This means, the back scatter of the IR light was very high and the picture had a good contrast. So, it was not a challenging test for our threshold estimation because the range for a good threshold was relatively great. As a second test flooring, a PVC-coating was used, which laid in the IDEAAL apartment kitchen. It has a shiny finish, which means that the back scatter is lower, which makes it challenging to our approach of finding the right threshold. Under some circumstances, e.g., sunny days, it was possible that the estimated threshold was too low in order to be able to separate the laser line from the rest. The result was that the binary picture had some sprinkles. Most of these artefacts were too small / short, so that the canny edge algorithm or the probabilistic Hough line algorithm ignored them. But in few cases they lead to false positive centroids. During the correspondence check, it was possible to separate these points. For final results, more tests have to be performed to be sure that our new triangulation line laser scanner works reliably under most conditions in an apartment and that it is not possible that sprinkles lead to wrong results under special circumstances.

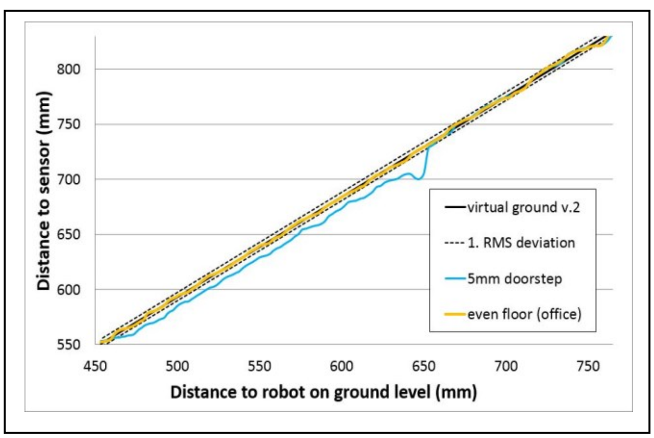

Figure 7. Visualization of the calculated virtual ground v.2 (black), the first RMS deviation (dotted lines) and the measurement from the ground (orange) and the 5 mm tread (blue).

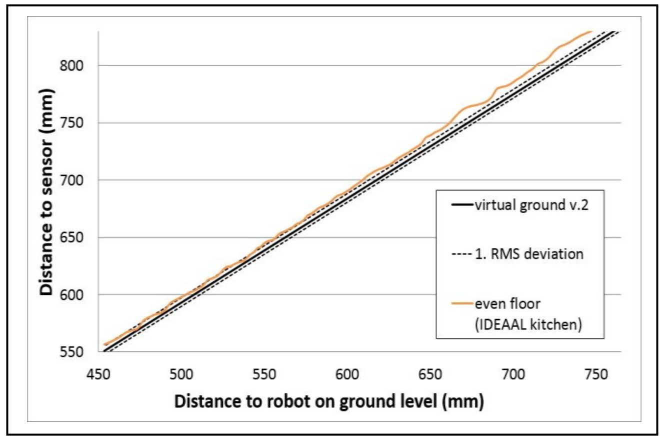

Figure 8. Visualization of the calculated virtual ground v.2 (black), the first RMS deviation (dotted lines) and the measured ground of the kitchen (orange).

D. Gait Parameters vs. Floorings

Parallel to the tests for detection of unevenness of the ground, first measurements in a domestic environment with five users (two females/ three males) between 42 – 76 years were made. These results are used as a first validation of our approach for calculating gait speed, stride and step length and, when possible, to see differences between different floorings by using the Microsoft Kinect and openNI tracker. For all measurements, the Turtlebot 2 stands at a predefined position, similar to the final setup when the mobile robot drives to various OOL's for measurement. Each subject had to walk towards the mobile robot five times under the same conditions. Each test person had to fulfill this test with 10 different conditions. In general, they had to walk over two different coatings (carpet / parquet). On each coating, three treads of different height (5 mm, 10 mm and 25 mm height) were placed in the middle of the walking distance. The test person also had to manage all these set-ups under dark and normal lighted conditions. This lead to a data base of 250 measurements including all conditions and subjects. The first results for the step-, stride length and self-selected gait speed (SGS) on parquet, high pile carpet and different treads are presented. As depicted in Figure 10 and Figure 11, a difference between stride length and SGS could not be detected for elderly persons only but also for mid-aged persons, depending on the floorings. Also, it seems as if the variation of step- and stride length depends on the coatings. But further tests with more measurements, longer walking distances and time periods must be conducted to verify our first results. Nevertheless, evidence that the floorings have an impact on the gait analysis in the domestic environment was shown. Without the knowledge of the characteristics of the flooring, like the most classical automated approaches, it could lead to false decisions related to the decreasing of the SGS on some coatings. This gives first evidence that the quality of balance and gait analysis depends also on the floorings. Further tests must be conducted in order to get reliable data on what kind of obstacles have an influence and how big the impact is.

VI. Conclusion and Future Works

A new approach for the detection of fall relevant unevenness of floorings and a first idea of an advanced gait analysis, which uses this information for enhanced results in the context of an automated HE Assessment was presented. For this, a mobile robot platform, i.e., the Turtelbot 2 was used. As a depth sensor, a Prime Sense Carmine 1.08 with the original OpenNI driver v.2.1.0 and a self-constructed triangulation line laser scanner was used for the detection of unevenness; and a Microsoft Kinect with the ROS openNI tracker Node was used for the balance and gait analysis. The Carmine sensor was mounted up-side down underneath the third level of the Turtelbot platform in a height of approx. 34 cm. For the triangulation line laser scanner approach, the Prime Sense sensor was replaced by the Raspberry Pi with the NoIR camera module. The Kinect was mounted to the highest level (height approx. 55 cm). Our approach with the RGB-D camera aimed at a calculated virtual ground, which is the reference for barriers because in a normal scenario it is unrealistic to have the chance to make a clean depth picture from each part of the room without any carpets on the subsurface or other stumbling blocks. It was possible to determine the position and orientation of the sensor only from a small knowledgebase. Still, our measurements have shown that the combination of our approach with this sensor, the mounting and the needed resolution does not work in a proper way.

This depends on three factors:

- First: the depth resolution of the sensor. The noise of the sensor is near the values that we want to detect.
- Second: the dependence of the sensor. As shown, the floorings and the gloss of it have a big influence on the depth values. The difference is sometimes even more than the third standard deviation.
- Third: the quality of our first algorithm to select the points for the calculation of the virtual ground.

Our second approach shows better results for the estimation of the virtual ground (see Figure 9) but the first two points are still valid. There are different possibilities to cope with these problems; it is possible to try better filter algorithms over more frames to reduce the noise and get better results or try to generate different virtual grounds for each room to handle the dependence on different floorings. But this step would lead us away from our original idea of having a general virtual ground. Finally, we could say that the Prime Sense Carmine 1.08 sensor has some advantages, like the price, the relatively good resolution and low noise in relation to the price and range. But the quality is not high enough for this application in the frame of HE Assessment or to determine relevant unevenness of the ground. Our triangulation line laser scanner shows better results in respect to accuracy for the estimation of the height of obstacles.

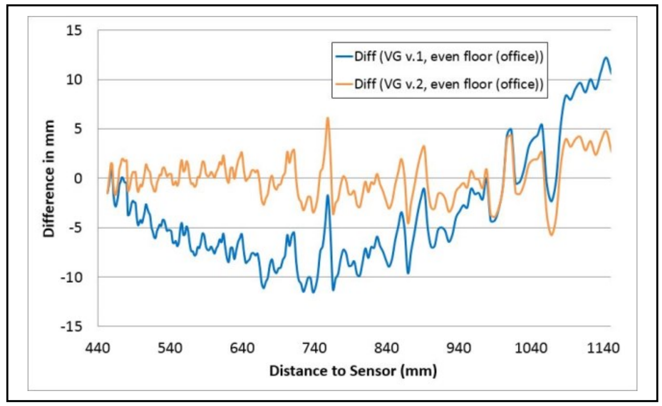

Figure 9. Shows a comparison between our first (VG v.1, blue) and second (VG v.2, orange) approach of estimate a virtual ground. The difference between the calculated virtual grounds and the measured ground of the office is shown.

The dependency on different types of surfaces seems to be lower compared to the Prime Sense Carmine 1.08 sensor. For general valid answers, we have to conduct more tests with this new sensor. In general, this sensor type has the disadvantage of generating 2D information only, since it can only analyze a height profile along a single line. In a further step, the mobile robot platform will be used to generate 3D information by moving the sensor to different points but the computational demands are still higher compared to a RGB-D camera, which generates an entire 3D point cloud of the surrounding.

Our approach to use additional information on the floorings in order to raise the quality of gait analysis in the domestic environments seems to be essential to generate reliable data. As a first result, we were able to show that an influence of the flooring exists but for final statements we have to evaluate this approach with more users and with more flooring and other influence factors. The first results allow the statement that all automated gait analyses in unsupervised environments should consider the texture and unevenness of the flooring.

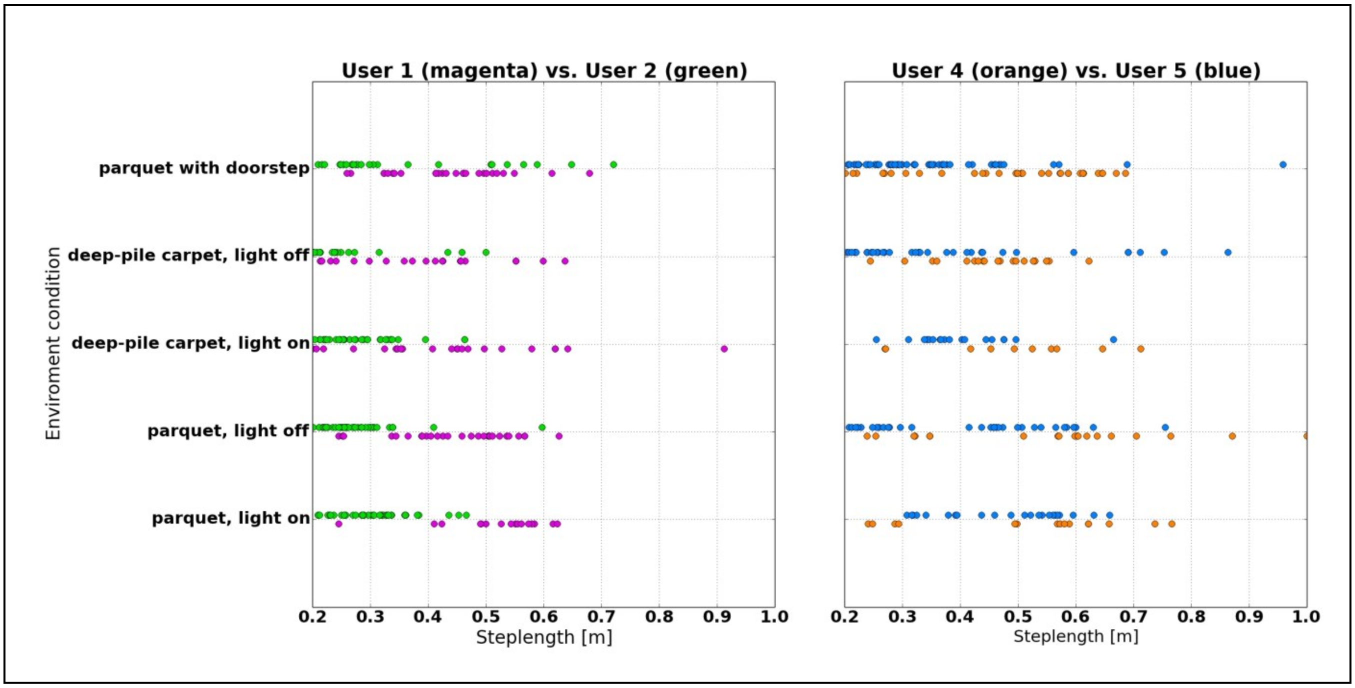

Figure 10. Influence of floor conditions to the step-length of different subjects (magenta/orange: mid-age, green/blue: elderly). Left side: two female subjects and on the right site two male subjects.

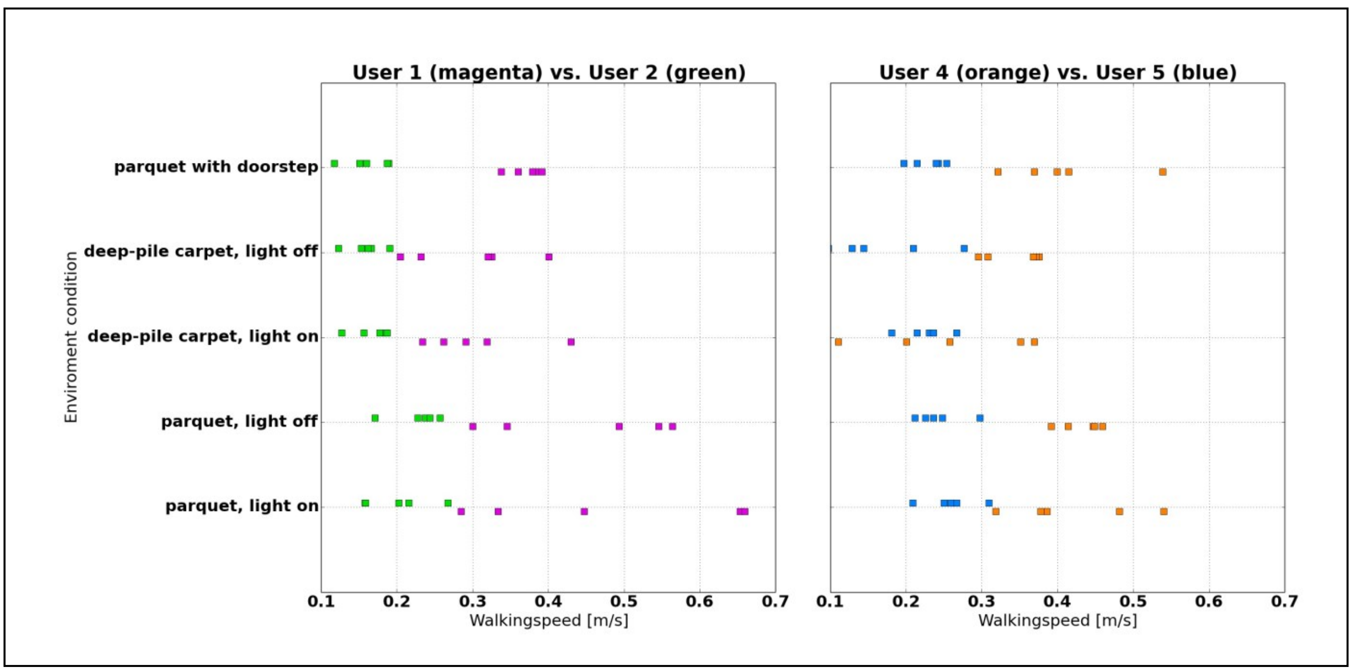

Figure 11. Influence of floor conditions to the gait speed of different subjects (magenta/orange: mid-age, green/blue: elderly). Left side: two female subjects; Right site: two male subjects.

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