Sensor-enabled Functional-Mobility Assessment: An Exploratory Investigation

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***Abstract*—The population of adults aged 65 years and older is expected to double by 2050. Healthcare systems must adapt to in order to manage the care of this increasing population. Older adults with complex care needs require a significant amount of additional support from caregivers. To maintain, and possibly improve, their quality of life, it is ideal that they receive this support while continuing to live in their own homes. Recent advances in sensing technologies offer the ability to recognize and collect multiple different types of data around a person's movement and physical ability. This data can subsequently be analyzed in order to inform a person's functional-mobility assessment. In this paper, we present an exploratory feasibility study around the use of Microsoft Kinect™ and KINVENT's K-FORCE plates for the purpose of assessing balance skills. Our results indicate that the analysis of data streams from these two sensors can effectively lead us towards a portable and adaptable gesture-evaluation system.**

***Index Terms*—IoT, Kinematic Analysis, Gesture Recognition, Pressure Analysis, Microsoft Kinect™, K-FORCE Plates**

I. Introduction and Background

The population of older adults is rising at an unprecedented rate. By 2050, the world's total population is expected to grow by 34%, while the population of adults aged 65 and over is expected to double [1]. Long-term care for the elderly is essential for management, treatment and rehabilitation of chronic conditions typically associated with age. Such care is typically provided by family members, which implies that it may not be consistent with state-of-practice guidelines [2], [3], and it may not include standard rehabilitation and assessment techniques [4], [5].

The integration of Internet of Things (IoT) in healthcare has enabled caregivers to better observe patients and more systematically analyze the progression of their conditions [6]. IoT technologies enable the instrumentation and the collection of data around activities, previously impossible to systematically observe and measure, which presents a real opportunity for healthcare applications [7]. Moreover, IoT can potentially support telecare, which can be a cost-effective means for remote monitoring, rehabilitation, and assessment of patients in long-term situations [8]. As an example, Dasios et al. [9] presented a prototype, in which off-the-shelf and inexpensive ambient sensors where used in order to infer daily activities of older adults. The system is capable of issuing alerts to caregivers in case of unusual patterns of behavior, like falling, for example.

There is a rich and growing body of work that proposes the use of IoT systems for the assessment and rehabilitation of people with complex needs [10]–[12]. These systems vary in terms of the sensors they employ (e.g., smartphone, camera, RFID, BLE devices, etc) [13] but share many common characteristics, such as availability, ease-of-use, high accuracy, and objectivity [4]. Less attention has been dedicated to the assessment of functional mobility, and specifically balance skills, using IoT. Studies show that difficulty in balancing is common among the elderly. Difficulties in balancing can have one or more causes, including inner ear problems, eye problems, numbness, heart diseases, long-term diseases such as Parkinson's and Alzheimer's, or side effects of medications [14].

Several studies have focused on using technological devices for the kinematic analysis of patients [15]–[18]. In one study [19], researchers used the Kinect™ and the Wii balance board to estimate the center of mass, which is closely related to most movements. Due to the limited sensing area of the Wii balance board, their experiments were limited to participants' range of motion. The work described in this paper is similarly motivated but uses a special-purpose device, the K-Force plates, instead of the Wii. In our own work with VirtualGym [20], we demonstrated how the Kinect™ can be used to observe the postures and movements of a person so that they can be compared and evaluated against a prescribed exercise. VirtualGym focuses on analyses of large postures and movements for the purpose of guiding exercise; in this paper, we extend on this work, focusing on small movements of the lower limbs in the context of simple sitting down, standing up, and walking postures. Zhang et al. [21] proposed a method for full-body motion capture using three Kinect™ sensors and a pair of pressure-sensing shoes. This study showed that depth data alone is insufficient for accurately reconstructing movements of both feet. However, since different types of activities (e.g., walking, running, hammer throwing) produced different patterns of pressure forces, pressure measurements obtained from the customized sensor-enabled shoes helped to distinguish among particular activities. This setup is quite

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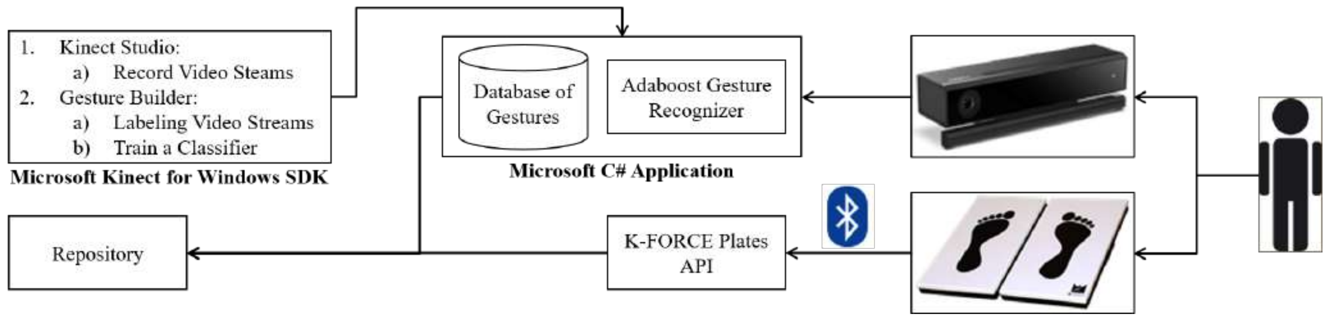

Fig. 1. Overall Hardware/Software Architecture.

complex and expensive, which makes it unrealistic for at-home deployment. According to Ejupi et al. [21] using Kinect™ is promising in assessing "choice stepping reaction time", a metric for measuring risk of falling, thus enabling the classification of individuals in "faller" and "non-faller" categories. The above research studies demonstrate that the Kinect™ , typically in combination with other wearable sensors, can potentially provide a more informative assessment of kinematic movements in individuals, thus enabling a more systematic assessment of the functional mobility of seniors at home.

In this paper, we present an assessment tool, composed of a Microsoft Kinect™ (a 3D motion sensor [22]) and a pair of K-FORCE plates (a pair of portable pressure sensors [23]), to recognize, using machine-learning techniques, and evaluate essential therapeutic gestures, mainly used to measure balance skills. In this exploratory feasibility study, we trained our assessment tool with samples of each gesture of interest. We describe situations where Kinect™ fails to recognize correct gestures and K-FORCE Plate data stream assists in distinguishing them. We also discuss how such an assessment system could potentially be used by older adults at home, and receive feedback as to their balance skills and how to improve them. In addition, the system analysis is communicated through a simple visualization so that seniors and their caregivers can gain a better intuition about this information. Our results indicate that the analysis of data streams from both the Kinect™ and the plates can lead us towards a portable and adaptable gesture-evaluation system.

The remainder of this paper is organized as follows. Section II describes the architecture of our proposed system and the overall process it implements. Section III reviews some traditional functional-mobility assessment procedures, currently performed by therapists observing the subject. Section IV reports on our findings when we used this system with one of the authors as the subject. Section V discusses the implications of this pilot study for the overall feasibility of our method. Finally, Section VI concludes with a summary of our work and our plans for the future.

II. Methodology

Fig.1 shows the overall architecture of our system. The user is monitored by the Kinect™ (as they move) and the K-FORCE Plates (as they step on and off them), and through the corresponding APIs, the raw data is sent to a repository for further analysis. We use pushing and pulling data-collection techniques for the Kinect™ and the K-FORCE Plates, respectively. The Kinect™ sensor streams data only when necessary; as long as it does not recognize a body, there is no reason to collect and process data and the sensor goes into a stand-by mode. In contrast, it is necessary to continuously monitor the plates data, in order to recognize how fast the user performs a task: for example, if a task involves stepping on (and off) the plates, the interval between each step could be an indication of how difficult the task is for the subject.

A. *The Microsoft Kinect™ Pipeline*

In this work, we use Microsoft Kinect™ Version 2 and Kinect™ for Windows SDK 2 [24]. As shown in Fig. 1, we use Kinect™ Studio and Visual Gesture Builder toolboxes from the SDK, in order to design a classifier for recognizing gestures. The first toolbox is responsible for capturing RGBD video streams that are required to train the classifier. The latter toolbox provides an interface for easily labeling the video streams, frame by frame. Every frame can be labeled with positive or negative tags according to a specific gesture. For instance, if the gesture of interest is "sitting", every frame in which the subject is seated should be tagged as positive, and all other frames as negative, thus resulting in a set of positive and negative frames for each gesture. The result of the labeling process is a database of gestures, which is used to train a classifier (Visual Gesture Builder only provides AdaBoost as a gesture classifier). The database and the classifier can be utilized in any Microsoft C# application.

We developed a simple C# component to visually communicate the output of the classifier (Fig. 2). The Kinect™ is able to recognize up to six body skeletons at the same time, thus there exist six tiles in the left side of the application's user interface. As soon as the sensor recognizes a new skeleton, it assigns to it a gesture classifier that only works with that body skeleton. Hence, the application supports the recognition of gestures of up to six people standing in front of the Kinect™. The classifier's confidence at each time interval for the first person has been plotted in the bottom right corner of the application. In this figure, the subject is performing a "Left foot up" gesture in an unstable way.

B. The K-FORCE Plate Pipeline

K-FORCE is the KINVENT product line for rehabilitation and assessment of human balance using precise dynamometry instruments. We use K-FORCE Plates for assessment of lower limb strength, as well as balance. The K-FORCE Plates device consists of two platforms, each with two embedded dynamometers. Each plate has a surface of 320 x 160 mm and can record forces up to 150 kg (300 kg for the pair). A Bluetooth Low Energy (BLE) device attached to the plates communicates the collected data; we used the Bluetooth Generic Attributes (GATT) SDK for Python, and BlueZ [25] in order to develop a client for this device to read and store the data they emit.

III. Metrics for Measuring Balance Skills

In principle, rehabilitation experts use any of the following assessments to measure an individual's balance skills [24]. Today, these tests are performed with the subject being observed by a trained therapist with a stop-watch, pen and paper. This process is resource intensive, since it requires the time of a specially-trained person, and also subjective. Sensor-embedded smart devices can potentially mitigate both these shortcomings.

a) Six Minute Walk Test: This test is used to evaluate the aerobic capacity and the endurance of the subject. In this simple test, the distance that a subject can cover is used to assess the performance of the subject.

b) Timed Up and Go Test (TUG): This metric helps therapists determine fall risk and assess the balance of a subject while performing "sit to stand" and "walking" activities.

c) Functional Reach Test: In this test, the subject holds their balance while standing, holding one hand horizontally, and trying to reach to a specific point using their hand. The distance that the subject can reach is the measurement of interest.

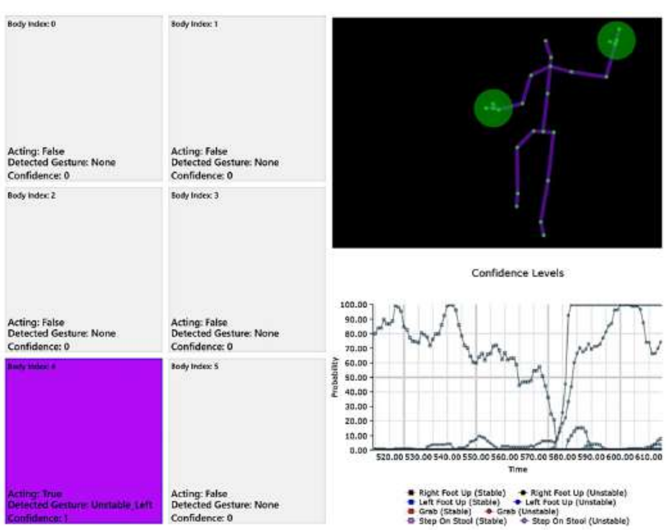

Fig. 2. Visual Analysis Software.

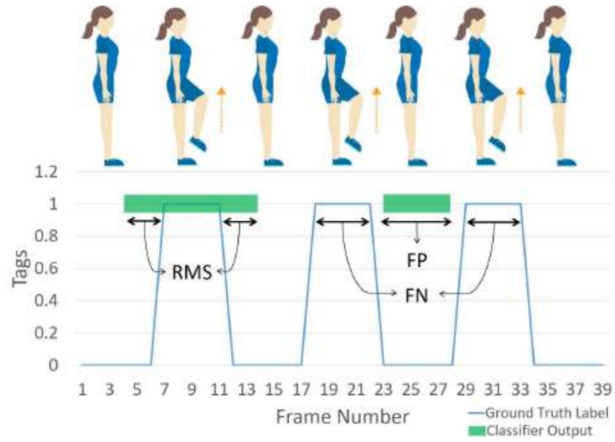

Fig. 3. The illustration of RMS, FP, and FN metrics in our application.

d) Tinetti Balance Test: This test is designed to assess the gait and the balance of a subject, who sits on a hard, armless chair and stands up, without any help of the hands. The subject should then turn 360 degrees and sit down again.

e) Sit to Stand Test: Similar to the previous test, this test measures the ability of a subject to maintain balance while standing up from a seated position.

f) Dynamic Gait Index: This test evaluates how well subjects can perform a steady-state walking activity. Therapists can also measure the same metrics during more challenging tasks, such as holding a box (e.g., shoe box).

g) Berg Balance Scale: This comprehensive set of tests is designed to measure balance during various tasks. It consists of 14 tasks, each one scored on a five-point ordinal scale between zero and four.

In this paper, we use the Berg Balance Scale (BBS) [26], one of the most comprehensive scales, as the basis for developing a system that can objectively evaluate the balance skill of an individual. The scale allows for interpretation from different perspectives. BBS consists of 14 tests. The equipment needed to perform the tests are a ruler, two standard chairs (one armchair and one side-chair), a footstool or step, a stopwatch or wristwatch, and a 15 ft. walkway. Readers are encouraged to read [26] for more details about the tests. To consider all the tests included in the BBS suite, a large training data set would be required and a corresponding data-collection protocol, which is beyond the scope of the exploratory feasibility study. This paper reports how well our system can recognize and evaluate a subset of three BBS tests, as an initial proof of concept:

- Standing with the left foot up,
- Standing with the right foot up,
- Grabbing an object from the floor, and
- Stepping on a stool.

Each of these tests can be performed in either a stable or an unstable manner. Therefore, in total, we have to recognize eight classes of gestures.

IV. Results

We record a video stream and capture data from K-FORCE Plates while a person performs each of the above mentioned gestures. We train a classifier, using Adaboost method, in order to recognize gestures from Kinect™'s data stream. Each video is labelled accordingly using the Visual Gesture Builder toolbox.

The accuracy of the gesture classifier was measured using three metrics: Root Mean Square (RMS), False Negatives (FN), and False Positives (FP). Fig. 3 illustratively depicts these metrics. The figure shows a window of 39 frames while a subject is performing the Right foot up task. Each frame is tagged accordingly and shown as ground truth in the figure with a blue line; and the output of the classifier is shown with green bars. RMS is defined by the following equation:

$$RMS = \sqrt{1/n(f_1^2 + f_2^2 + ... + f_n^2)}, \tag{1}$$

where $f_i, i \in [1, n]$ are the frames that the classifier detected the true label either in advance or with delay in compare to ground truth labels. FP and FN metrics show the number of incorrect labeling events and the number of missed true events, respectively.

Two of the authors, P1 and P2, both young healthy male adults, performed each of the eight gestures twice and once respectively. We have labeled all the frames of the Kinect data stream accordingly and trained our classifier using 50% of the data collected from P1's demonstration. We tested the classifier using the rest of P1's data and all the data from P2.

Fig. 4 shows the RMS value for each person. P1's RMS is lower than P2's RMS, which is not surprising since the classifier was trained using P1's video streams. We calculated an unpaired t-test on the values; by conventional criteria, the difference between the RMS values for P1 and P2 was not statistically significant ($p_{value} = 0.0878$). The system did not have a high number of FP and FN errors.

Fig. 5 shows the data streams from both the Microsoft Kinect™ and the K-FORCE Plates over a time interval. In this interval, the subject was performing the "stable right foot up", "unstable right foot up", and "stable left foot up" tasks. The plates data clearly indicate the unstable state of the subject. For this reason, the plates can be used as a source of information to distinguish unstable gestures from stable ones.

The K-FORCE Plates can also be used to justify the classifier output, especially in cases where the output does not have a sufficiently high confidence level. This use of the Plates data is shown in Fig. 6, where the classifier has relatively high confidence for the "stable grab", "unstable grab", and "stable step on stool" tasks. Although the classifier's output is correct (e.g., "stable grab"), it is not necessarily always true. When the subjects bend and try to grab something on the floor, the skeleton data of the Kinect™ gets noisy; in this case, distinguishing between a stable grab and unstable grab is almost as accurate as choosing one by chance. This is where it becomes important to include the data from the K-FORCE Plates. From the plates data, we can see that the subject is performing a stable gesture as there is significant difference in both lower and upper forces in comparison between stable and unstable gestures ($p_{value} = 0.00001$) in both upper and lower parts of the plates).

In addition, the pressure is almost half in comparison to the situation when the subject is standing on one foot, and it not as low as if he or she steps up on the plates. Therefore,

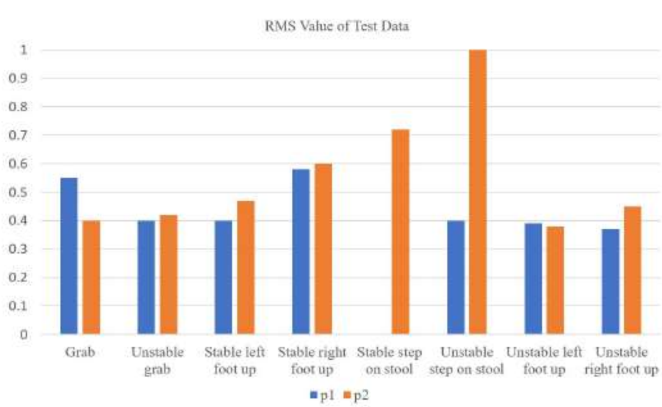

Fig. 4. The RMS value for person one (P1) and person two (P2) in each class.

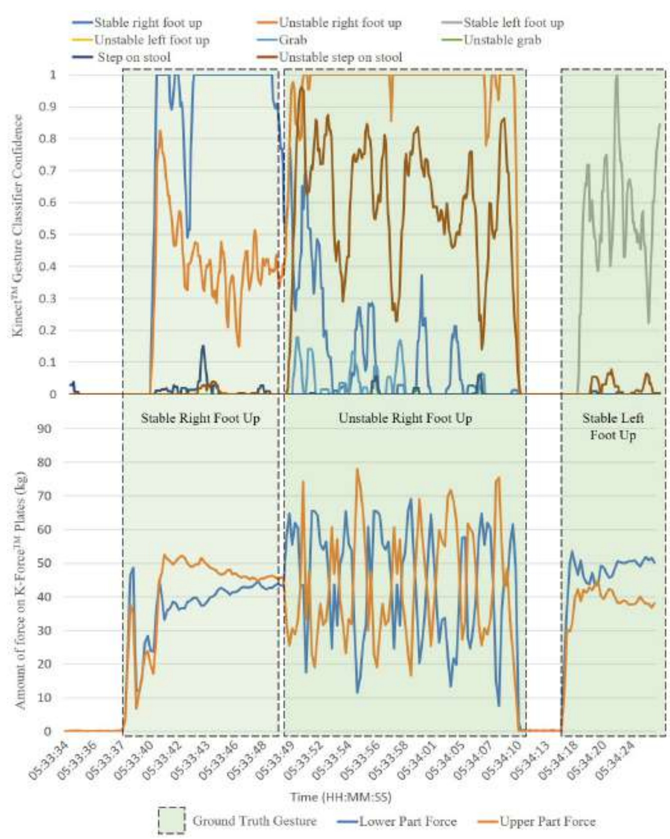

Fig. 5. The output of the gesture classifier and K-FORCE Plates while the subject is performing three tasks: stable right foot up, unstable right foot up, and stable left foot up.

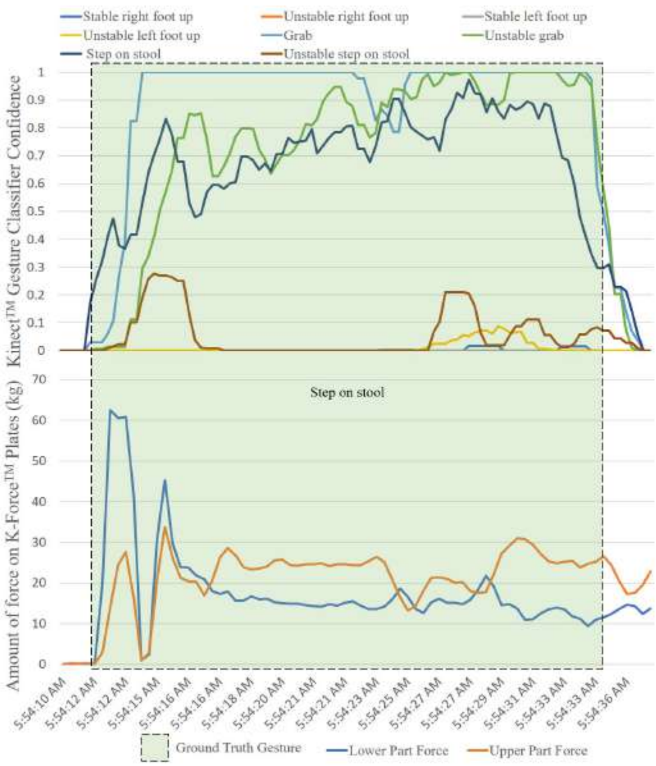

Fig. 6. The output of the gesture classifier and K-FORCE Plates while the confidence of classifier is relatively high for three gestures: "stable grab", "unstable grab", and "stable step on stool". This is an example where K-FORCE can be used to justify the output of the classifier.

by additionally using the K-FORCE Plates as a source of information, it can be confirmed that the subject is performing the "stable grab" gesture in this scenario.

V. Discussion

The combined use of the Microsoft Kinect™ and the K-FORCE Plates in measuring an individual's balance skill is promising. The former can provide useful information about the body skeleton that is essential for recognizing full-body movements and detecting whether a gesture is stable or unstable. In some situations, the recognition task becomes more difficult because of noise in the input data; potential causes for such noise include changes in the environment, the lighting, and the position of the Kinect™ sensor relative to the subject and the gesture. The K-Force data shows that it can be used to distinguish between stable and unstable gestures, but it has the added capability of filtering out unlikely gestures based on the amount of pressure on each plate. Therefore, to effectively recognize balance-based gestures, it is useful to use the combined data from both of these sensors.

Statistical analysis is required to show that the amount of pressure for each gesture and the distribution of the data between stable or unstable is indeed significantly different. Because each K-FORCE Plate has its own Bluetooth Low Energy (BLE) device, we faced some implementation challenges regarding the frequency of collecting data. The plates work on the 25 (Hz) frequency. However, if we adjust the frequency to 75 (Hz), two problems arise: 1) one of the plates sends packages of data about three times faster than the other, and 2) the plates have delays in stopping the data stream. The first problem makes synchronization of the data streams between the Kinect™ and the K-FORCE Plates challenging. The second problem prevents us from running experiments for periods of time longer than two minutes; the plates stop sending packages of data after this period of time. We anticipate that this issue illbe resolved in the next version of the device.

Based on our observations in this paper, we describe, in Table I, different scenarios where information from either Kinect™or K-FORCE Plates or both provide more discriminative hints in order to recognize gestures.

Although we observe that the system performance in recognizing gestures is promising, the system works for a limited subset of the Berg Balance Scale tasks. To have a system that can recognize all 14 tasks in the BBS correctly, a larger volume of training data (with more than one subject performing each task within a variety of environments) is necessary. Recording other videos for a gesture from different angles would also help the classifier to be robust to environmental features such as light, other objects, etc.

Our initial results suggest that a comprehensive study is warranted. For a comprehensive study, two group of subjects (i.e., control and intervention) are required. The control group could consist of older adults with balance difficulties who receive traditional treatment; the intervention group could consist of the same population as the control group, with the added feature that they also use this system as exercises or activities while using system, the system gives them feedback that they can use to improve their balance, and an additional intervention in their home setting. Through this approach, we could determine if the system has a statistically significant effect on the intervention group. We envision that the system should be combined with a user interface, e.g., a video game, that gives real-time feedback to its users. This way, the subjects would be motivated to perform tasks more regularly.

TABLE I
A LIST OF SCENARIOS, IN WHICH EACH SENSOR WITH BETTER DISCRIMINATIVE INFORMATION IS SPECIFIED.

Scenarios	Kinect™	K-FORCE Plates
Clear sight on body skeleton	✓	✓
Unclear sight on body skeleton		✓
Discriminating unstable from stable gestures		✓
Discriminating upper body gestures	✓	
Measuring pace of a gesture	✓	✓

VI. Conclusion

Older adults often experience difficulties with their balance, and more generally their mobility. It is essential to assess these skills regularly, in order to recognize if they need any new supports and of what kind. Traditional assessment methods require older adults to visit therapists and perform standardized tests involving walking, sitting and standing up, and reaching. This process is costly, since many older adults may require assistance to visit their healthcare professionals. Furthermore, these tests are interpreted, to some degree, subjectively by the therapist observing the activity.

There are many studies that have examined various technological systems that this population can utilize in their home, in order to minimize the need to visit therapists in a clinical setting. In this paper, we examined the use of Microsoft Kinect™ and K-FORCE Plates in order to intervene and assess the therapy tasks needed to improve the balance skill in older adults. We extracted a subset of four tasks from the Berg Balance Scale (BBS), which includes 14 tasks that are widely used in rehabilitation assessment to evaluate balance.

Detection and evaluation of this BBS task subset are used as a proof of concept that our system works with a useful level of accuracy. Our preliminary results show that the combination of the data from the Kinect™ and the K-FORCE Plates can be used to detect tasks and assess the subject's balance skills. The system can add biomechanical information that the Berg Balance Scale does not provide, which generates a better feedback to the user. This information could be a good complement to current balance assessment procedures. This paper suggests that a more extensive study on this topic is warranted.

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