A Feasibility Study of Using a Single Kinect Sensor for Rehabilitation Exercises Monitoring: A Rule Based Approach

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Abstract*—In this paper, we present a feasibility study for using a single Microsoft Kinect sensor to assess the quality of rehabilitation exercises. Unlike competing studies that have focused on the validation of the accuracy of Kinect motion sensing data at the level of joint positions, joint angles, and displacement of joints, we take a rule based approach. The advantage of our approach is that it provides a concrete context for judging the feasibility of using a single Kinect sensor for rehabilitation exercise monitoring. Our study aims to answer the following question: if it is found that Kinect's measurement on a metric deviates from the ground truth by some amount, is this an acceptable error? By defining a set of correctness rules for each exercise, the question will be answered definitively with no ambiguity. Defining appropriate context in a validation study is especially important because (1) the deviation of Kinect measurement from the ground truth varies significantly for different exercises, even for the same joint, and (2) different exercises have different tolerance levels for the movement restrictions of body segments. In this study, we also show that large but systematic deviations of the Kinect measurement from the ground truth are not as harmful as it seems because the problem can be overcome by adjusting parameters in the correctness rules.

***Keywords*—Therapeutic Systems and Technologies, Rehabilitation Exercises, Physical Therapy, Kinect, Motion Assessment**

I. INTRODUCTION

In rehabilitative health care, a patient is often required to perform extensive supplemental home exercises, in the range of thousands of practice repetitions, to attain faster and full recovery [1]. Exercise programs are prescribed individually for each patient to address his or her specific problems and therapeutic goals. The exercises must be individually tailored by a clinician to address and account for the patient's specific pathology and limitations, as well as the presence of comorbidities and additional impairments. Correct adherence to supplemental home exercises entails both performing the individual exercises precisely as prescribed, and performing them in the numbers and durations prescribed. Both are absolutely essential for safe, effective, and efficient care [2], [3].

The current state-of-the-practice for exercise instruction and monitoring is usually limited to written instructions, exercise recording logs, and simple repetition counting devices. Unfortunately, this practice is not conducive to patients' correct adherence because:

- The written instructions are typically hard to follow.
- Patients do not receive any feedback on the quality of the exercises that they are doing.

As a result, not only might patients do the exercises incorrectly, they might be frustrated and discouraged to continue carrying out the prescribed exercises due to the lack of interest, guidance and feedback. Furthermore, there is no accountability on the patient's side because the clinician has no way of knowing whether or not a patient has carried out the prescribed exercises correctly and with the required number of repetitions.

The lack of monitoring and feedback during home exercises is therefore a serious concern. The use of a simple counting device helps verify the exercise repetitions. However, such simple, commercially available devices can not capture all the required movements beyond the most basic, such as counting steps or recording overall durations of activity [4], [5], and are, therefore, not useful for most prescribed home exercises.

The release of the Microsoft Kinect sensor, which is equipped with a depth camera capable of measuring three dimensional positions of the objects in its view, has triggered tremendous interest in its use to monitor in-home rehabilitation exercises due to its low cost and relatively good motion sensing accuracy. Hence, a Kinect sensor based system could potentially provide sufficient feedback and guidance to patients performing clinician prescribed in-home exercises. This would facilitate proper performance of rehabilitation exercises, increase patient accountability, allow the clinician to identify and correct any errors in exercise performance, and enable program modifications or advancements as needed, thereby significantly minimizing costly and inconvenient trips to outpatient centers, and improving the effectiveness and outcomes of courses of treatment.

Several commercial rehabilitation systems based on Kinect have been developed, including Jintronix [6], Reflexion [7], VirtualRehabit [8], and SeeMe [9]. However, these systems typically only provide qualitative feedback to the users and we are not aware of any comprehensive validation study for such systems.

Unlike competing studies, which have focused on the validation of the accuracy of Kinect motion sensing data at the level of joint positions, joint angles, and displacement of joints, and will be reviewed in the next section, we take a rule based approach. The advantage of our approach is that it provides a concrete context for judging the feasibility of using a single Kinect sensor for rehabilitation exercise monitoring.

Our study aims to answer the following question: if it is found that Kinect's measurement of a metric such as a joint angle deviates from the ground truth by some amount, is this an acceptable error? By defining a set of correctness rules for each exercise, such questions will be answered definitively with no ambiguity. Defining appropriate context in a validation study is especially important because:

- The deviation of Kinect measurements from the ground truth varies significantly for different exercises, even for the same joint.
- Different exercises have different error tolerance levels for the movement restrictions of body segments.

We also show that large but systematic deviations of the Kinect measurements from the ground truth are not as harmful as it seems because the problem can be overcome by adjusting parameters within the correctness rules.

In this paper, we demonstrate our results using five common rehabilitation exercises: hip abduction, bowling, sit to stand, can turn, and toe touch. Some of these involve the movement of few body segments, while others involve full body movements. We show that even in the absence of occlusions, large deviations of the Kinect measurements may occur compared with kinematics obtained from an eight-camera motion capture system (Motion Analysis Corp, Santa Rosa, CA). However, such deviation is typically systematic in that it is caused by the particular skeletonization algorithm used in the Kinect software development kit, and it does not prevent one from using Kinect to assess the quality of exercises, provided that the parameters for the corresponding correctness rules are adjusted. Not surprisingly, Kinect is incapable of judging some correctness rules that involve severe occlusions, *e.g.,* in toe touch and can turn.

The remainder of this paper is organized as follows. Section II provides a comprehensive overview of related work. Section III describes our feasibility study results for the five exercises. We conclude our paper in Section IV.

II. Related Work

In [10], the accuracy of the Kinect sensor for motion sensing was partially compared with a passive marker based reference system (iotracker) in the context of two games for chronic pain rehabilitation. Only two metrics were compared, the vertical distance between the right hand and the right shoulder during a reaching movement, and the foot position. The former was obtained from the Kinect skeleton data, while the latter was calculated directly from the depth frames due to occlusion of the foot in the game setup. The differences between Kinect and iotracker measurements were rather small (in the order of a few centimeters) and were attributed to the difference in joint definitions in the two systems.

In [11], Kinect motion sensing accuracy was validated against a reflective marker based system (OptiTrack) in the context of several exercises, namely, shoulder external rotation, scapular retraction, and shoulder abduction. The 3D positions of the hand, elbow, and shoulder from the Kinect sensor were compared with those obtained from OptiTrack. It was found that, although the positions for hand and elbow measured by Kinect were highly consistent with those from OptiTrack, the positions for the shoulder deviated from those from OptiTrack significantly. No analysis was carried out regarding the impact on the exercise monitoring of the inaccuracy of the shoulder measurement however.

In [12], [13], two studies on the validation of Kinect's motion sensing accuracy were reported by the same group in the context of postural control and gait retraining. It was found that the measurement result for a sequence of joint displacements and angle ranges from Kinect was in close agreement with that of the marker based system (Vicon). This is not surprising because all of the movements were within the frontal plane, facing the Kinect sensor.

In [14], the accuracy of the Kinect measurement of several joint angles was studied by comparing the Kinect data with a marker-based multicamera system (Vicon). The exercises used in the study involved the movement of knee, hip, and shoulder separately within anatomical planes. It was found that the mean error in the joint angles as measured by Kinect ranged between 5 to 13 degrees.

In [15], the accuracy of the measurement of upper body joints was assessed with a rather simple model fabricated using plywood. The distance traveled for each upper body joint along each axis was measured when the subject was standing perpendicular to the Kinect camera's Z axis. The error of Kinect data was obtained using the calculated model data as ground truth. One benefit of characterizing the distance traveled instead of the joint position directly is that the systematic error in estimating the joint center in Kinect skeleton data can be offset. It was concluded that the maximum error is below 4 cm under the specific configuration.

In [16], several joint angles, including shoulder, elbow, hip, and knee angles, calculated from Kinect joint data were compared with a marker-based system (Vicon) in the context of a set of exercises involving movement within the frontal and saggital anatomical planes. At the maximum range of motion (i.e., maximum joint angle during each exercise), the differences of the joint angles as measured by Kinect and Vicon were within 11 degrees. These discrepancies were likely caused by inaccurate estimation of joint centers by Kinect, as evidenced by the variation of bone lengths from frame to frame. The study also showed that Kinect has good reproducibility.

In [17], the accuracy of Kinect data was validated against a marker based system (Vicon) in the context of a set of movements designed for people with Parkinson's disease, including standing still, reaching forward and sideways, stepping forward and sideways, and walking on the spot. The measured variables include the displacement and the maximum angle of several joints in the exercises, such as head displacement, vertical knee displacement, hip angle, and shoulder angle. It was observed that there were significant discrepancies between the measured quantities from Kinect and those from Vicon (for example, the difference in trunk flexion was as large as 41 degrees, 98.48 from Vicon vs. 57.34 from Kinect). As will be shown in the current paper, many such large deviations are due to systematic errors in Kinect skeletonization. With the proposed rule-based assessment of the quality of rehabilitation exercises, we will demonstrate in this paper that Kinect is a viable low cost motion sensing tool in most cases as long as the parameters for the rules are adjusted according to the systematic errors.

The most insightful work on the validation of Kinect motion sensing accuracy is described in [18]. Kinect skeleton data were compared against the data obtained from a marker based system (PhaseSpace) in the context of 6 exercises. The Kinect skeletonization accuracy was validated both at an individual joint level and at the body geometry (*i.e.,* bone lengths) level. It was observed that, while in a more controlled pose such as standing, Kinect provided highly accurate joint measurement, comparable to the much more expensive PhaseSpace system, in other types of poses, Kinect measurement error for non-occluded joints could be as large as 10 cm. Two other important results included: (1) Kinect skeletonization was obtained using a non-anthropometric kinematic model with bone lengths varying from frame to frame; and (2) the hip joints calculated by Kinect were significantly higher (by about 20cm) than those by the reference motion sensing system. As such, [18] concluded that Kinect may only be appropriate to be used to assess general trends in movement.

In this paper, we show that Kinect can be used to provide much more meaningful assessment than general trends in movement. Rehabilitation exercises are typically quite tolerant, in that there is often a generous allowable deviation of the movement of the designated body segments. By clearly defining a set of correctness rules for each exercise with appropriate error bounds, one could judge the quality of an exercise performed using Kinect as long as the measurement error does not exceed the tolerated limit. Furthermore, systematic deviation in Kinect measurement can be masked by adjusting the corresponding rule parameters.

III. Validation Study

To validate the motion sensing accuracy of the Kinect sensor for rehabilitation exercises, we compared the measurement results from Kinect with those obtained concurrently from an eight-camera motion capture system (Cortex, Motion Analysis Corp, Santa Rosa, CA). The results from Cortex were used to establish the ground truth. The data acquisition software for Kinect is written in C++ programming language using Microsoft Kinect Software Developement Kit version 1.5.

We experimented with a total of five common physical therapy exercises: hip abduction, bowling, sit to stand, can turn, and toe touch. In the following, we first provide an overview of the correctness rule design, and then we describe our results and analysis for each of the five exercises. During all exercises, the Kinect sensor is placed about 2 meters away in front of the subject.

We show that Kinect is useful in assessing the correctness rules for the first three exercises. It is useful to enforce only some rules for can turn due to Kinect's inability to detect the rotation of the arms. Kinect does not produce accurate enough motion sensing data to assess the rules for toe touch due to a severe occlusion problem when the arms are forward and the fingers approach the toes.

A. Correctness Rules for Rehabilitation Exercises

The rules for rehabilitation exercises in general can be divided into three types: (1) dynamic rules, (2) static rules, and (3) invariance rules, as further explained below.

1) Rules for dynamic movement: Each rule defines a sequence of monotonic segments [19] of a key body segment. A monotonic segment is defined as a segment of movement in which the key metrics for the movement are either non-increasing or non-decreasing. For example, if a joint angle is the key metric for some movement, during a monotonic segment, the angle may reduce continuously from some maximum value to some minimum value. Hence, there are two requirements in each dynamic rule: (1) the values of the metrics at the boundary of monotonic segments, and (2) in between two consecutive boundary values, the values of the metrics must change accordingly (non-decreasing or non-increasing).

2) Rules for static poses: Some exercises only involve stationary poses. In some other exercises, it is also possible for some body segments to remain stationary at their desirable positions while other parts are moving . In these cases, static rules are needed. In general, a rule for a static pose can be expressed in terms of the desired angle for a particular joint, or the position of a body segment with respect to the frontal, sagittal, or horizontal plane. It is also possible to describe a static pose in terms of the distance between different joints or relative positions of different joints.

3) Rules for movement invariance: An invariance rule dictates the requirement for a moving body segment that must be satisfied during each iteration of the exercise. The rule is typically defined in terms of the relative angle between the moving body segment and the frontal plane, sagittal plane, or horizontal plane.

B. Assessment for Hip Abduction

For the hip abduction exercise, the primary quantifiable rules include the following:

- Dynamic rule: the abducting leg (in this case the right leg) moves from 0 degree with respect to the stationary leg (in this case the left leg) to beyond 45 degrees, and then back to 0, *i.e.,* the hip angle changes from 0 to beyond 45 and back to 0 degrees for each iteration. Hence, there are two monotonic segments with each segment having boundary values of 0 and a value 45 degrees or larger.
- Invariance rules: (1) The abducting leg must remain straight at the knee joint; (2) The abducting leg must move within the frontal plane; and (3) The non-abducting leg must also remain straight.

The hip angle was calculated by taking a dot product of two vectors: (1) left hip to left knee, and (2) right hip to right

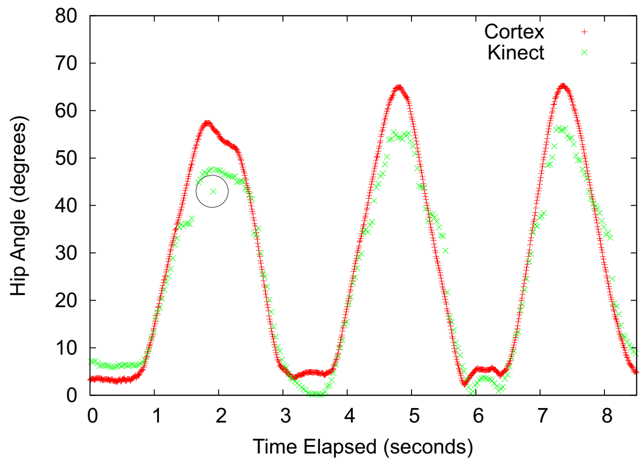

Fig. 1. Hip angle for 3 correct iterations of hip abduction.

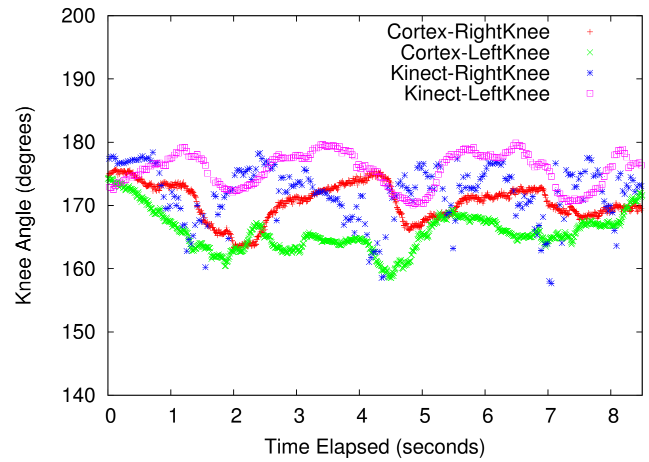

Fig. 2. Left and right knee angles for 3 correct iterations of hip abduction.

knee. Figure 1 shows the hip angle variations for 3 correct iterations, as measured by both Kinect and Cortex. As can be seen, the Kinect measurement results were highly consistent with those of the Cortex system except close to the boundary of each monotonic segment. At the beginning pose, the hip angle was at about 3 degrees as measured by Cortex, while the angle as measured by Kinect varied between 0 degrees and 8 degree. At the maximum range, the hip angle as measured by Kinect was significantly smaller than those by Cortex (48 vs. 57, 58 vs. 65, 57 and 65 degrees). Furthermore, there was one outlier from Kinect, as highlighted in the figure using a circle. The outlier deviates from the expected value by about 4 degrees.

The experimental results imply that Kinect can be used to assess the dynamic rule provided that:

- The error bound for the minimum angle is set at 8 degrees or larger.
- The error bound for the maximum angle is set at 9 degrees or larger.
- An appropriate low pass filter is used to filter out the outlier.

Figure 2 summarizes the results for the right and left knee angles with the right leg being the abducting leg using both Kinect and Cortex. As can be seen, for both legs and for both motion analysis systems, the angle varied significantly between 180 degrees (*i.e.,* straight leg) and 160 degrees. This observation implies that the error bound for the knee angles must be set at 20 degrees or larger to avoid false positives. Hence, a Kinect based system would perform as well as the Cortex based system in enforcing these two invariance rules.

To assess the last invariance rule, we calculated the angle between the abducting leg (*i.e.,* right leg) and the frontal plane using 3D vector math. The frontal plane was determined using two vectors, one from the hip center to the left shoulder, and the other from the hip center to the right shoulder. Figure 3 shows the comparison of the off-frontal-plane angle as measured by Kinect and Cortex of the abducting leg. As can be seen, the angle varied between 0.6 to about 6 degrees as measured by the Cortex system, while the angle appeared to vary more significantly between 0 and about 15 degrees.

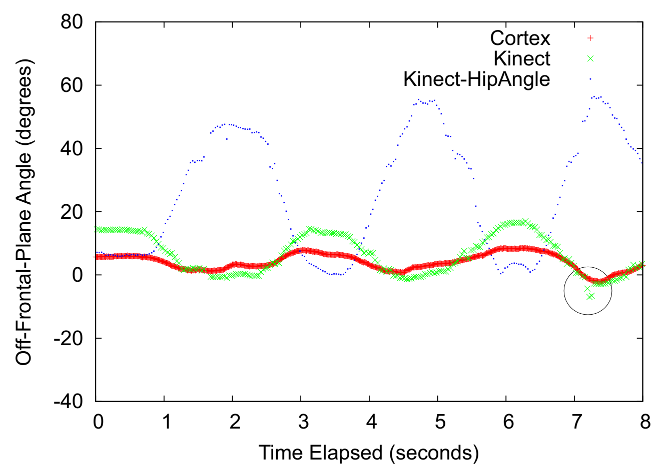

Fig. 3. Off-frontal-plane angle for 3 correct iterations of hip abduction.

It is interesting to note that the discrepancy between the two systems was in fact quite small (ı..,e less than 5 degrees) when the abducting leg extended to the side when the hip angle was greater than 10 degrees as shown by the superimposed hip angle curve in Figure 3. Because it is unlikely that one would abduct the leg outside the frontal plane for small hip angles, there is no harm in enforcing the last invariance rule only when the hip angle is larger than 10 degrees while using a tight 5 degrees error bound.

C. Bowling

The bowling exercise is designed for a patient to practice straight plane shoulder flexion. It can be used in individuals post stroke who need to learn to isolate shoulder flexion from elbow flexion, as this exercise requires shoulder flexion with elbow extension. It can also be used to work on progressively greater amounts of anti-gravity shoulder flexion. The following correctness rules are used for a typical patient:

- Dynamic rule: Except at the beginning of the exercise, in which the bowling arm (in this case the right arm) moves from the side of the trunk back to about 40 degrees with respect to a reference vector pointing

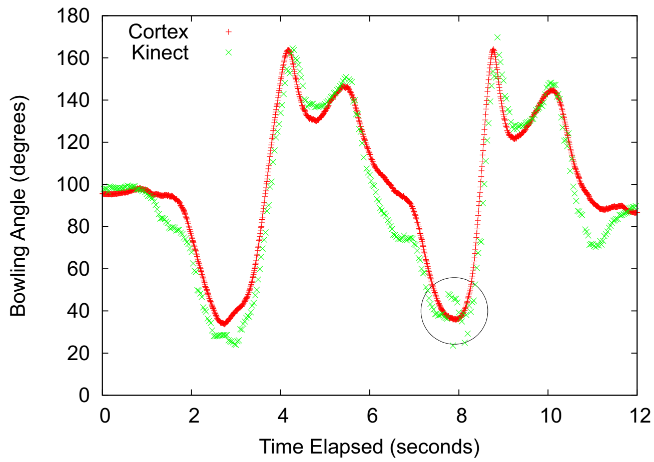

Fig. 4. Bowling angle for 2 iterations of the bowling exercise.

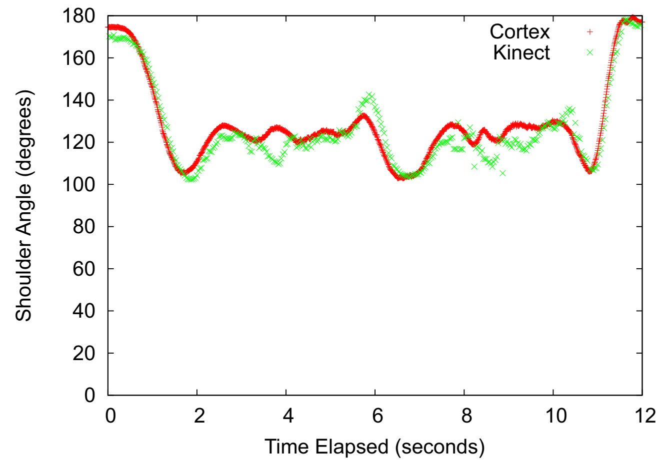

Fig. 5. Shoulder angle for 2 iterations of the bowling exercise.

to the back of the trunk (which is perpendicular to the frontal plane), each iteration starts when the arm is placed at the 40 degrees backwards position, then it moves forward until the arm is pointing straight forward (about 180 degrees with the reference vector). This is followed by a movement backward to the initial position. Hence, there are two monotonic segments for each iteration, with the boundary values of 40 degrees and 180 degrees (ideally) between the arm and the reference vector.

- Invariance rules: The bowling arm should move within the sagittal plane.

The reference vector needed by the dynamic rule is perpendicular to the frontal plane. Hence, we used the cross product of two vectors that represent the frontal plane: (1) hip center to the right shoulder, and (2) hip center to the left shoulder. Because during the bowling exercise, the shoulders would inevitably move, we used the vectors of the initial pose (i.e., at the beginning of the exercise). The arm was represented by a vector from the shoulder to the elbow of the bowling arm. The angle between the arm vector and the reference vector, which we refer to as bowling angle, was then calculated. Figure 4 shows the comparison of the measured bowling angles using Kinect and Cortex. As can be seen, the angle measured by Kinect followed closely to that by Cortex. The biggest discrepancy occured when the arm was at the side of the trunk. Fortunately, this does not have a negative impact on the assessment of the dynamic rule, in which only monotonic movement and the boundary values matter. We do notice that occasionally there were significant jitters in the Kinect data, as highlighted by the circle at the second iteration in Figure 4. A low pass filter is necessary to remove the outliers.

It is interesting to note that there was significant instability when the subject extended his arm to the forward-most position, as indicated by the double peaks at the forward positions as shown in Figure 4, even though the authors judged visually that the subject did the exercise correctly. To accommodate this instability (so that the computer based system produced consistent judgment as that of a clinician), a very large error bound needs to be used. Furthermore, the measured forward angle was not even close to 180 as expected in both motion sensing systems. This suggests a systematic bias in the way we calculated the bowling angle, also evidenced by the larger than expected angle at the initial position (90 degrees were expected when the measured angles were about 95 degrees). A practical solution to this problem is to use 160 degrees as the boundary value instead of 180 degrees. With this work-around in place, together with a large error bound and a low pass filter, a Kinect based system can be used to assess the dynamic rule with low false positives.

The invariance rule was evaluated by measuring the angle between the arm vector and a shoulder line vector from the bowling shoulder to the non-bowling shoulder, which we refer to as the shoulder angle. Again, to obtain more reliable data, the shoulder line vector is obtained using the joint data at the initial pose. If the arm moves within the sagittal plane, then the shoulder angle would remain at 90 degrees. Note that this is a necessary, but not sufficient requirement for the invariance rule.

Figure 5 shows the measurement result for the shoulder angle as defined above. At the beginning and the end of the exercise (only 2 iterations are performed), the angle was close to 180 degrees. This was due to the T-pose the subject used. When the arm was extended straight sideways, the shoulder angle was indeed expected to be 180 degrees. During the exercise, the shoulder angle fluctuated around 120 degrees instead of 90 degrees as measured by both Kinect and Cortex. Again, this may be due to the method we used to evaluate this invariance rule and the issue can be resolved by setting an expected value of 120 instead of 90 in the actual rule. To accommodate the large fluctuations exhibited by both systems, it is necessary to use a large error bound of 25 degrees or larger.

D. Sit to Stand

Sit to stand is used to help people to be more independent standing up after various types of surgeries and injuries, such as post total knee replacement, or after a stroke. It is also used with older adults having difficulty standing up. The correctness rules for sit to stand are defined below:

- Dynamic rule: An iteration of sit to stand consists of

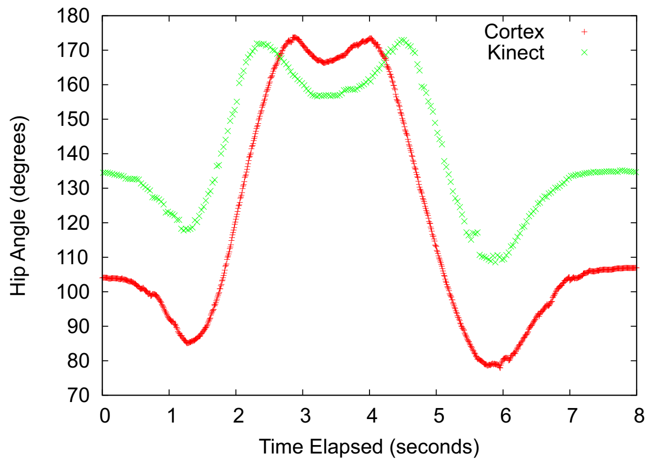

Fig. 6. Hip angle for a single iteration of sit to stand.

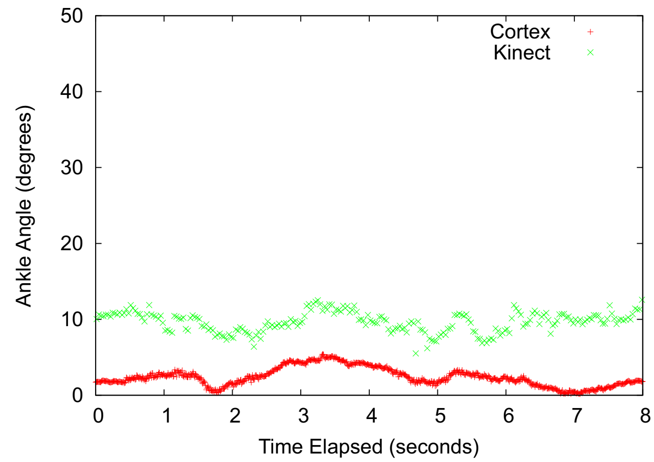

Fig. 7. Angle between the ankles and the frontal plane for a single iteration of sit to stand.

4 monotonic segments. The first two segments happen when a subject is standing up from the sitting pose, and the last two happen in the reverse process. We use the hip angle formed between the trunk and the leg as the metric. The hip angle would change from 90 degrees (in the sitting pose) to a minimum value, *e.g.,* , 60 degrees, and then increases to the maximum of 180 degrees (in the standing pose). This is followed by the reverse steps. The boundary values for the hip angle are 90, 60, 180, and 60 degrees (ideally).

- Static rule: The feet are evenly placed underneath the body.

In our experiment, the hip angle was calculated by using the dot product of two vectors, one from the hip center to the shoulder center (representing the trunk), and the other from the left hip to the left knee or the right hip to the right knee. In our experiments, we did not observe any significant differences in the hip angles obtained using the left leg vs. the right leg. Hence, we only show the results obtained using the left leg in Figure 6.

We can see in Figure 6 that the hip angle calculated from the Kinect skeleton data deviated significantly from that from the Cortex system. Except in the standing pose, in which the angle was fairly consistent with the results from Cortex, the hip angle as measured by Kinect was systematically larger than that by Cortex. We speculate that it was due to the wrong hip joints estimated by Kinect, as pointed out in [18]. Nevertheless, the systematic but large deviation does not prevent one from using a Kinect-based system to evaluate the dynamic rule, provided that the boundary conditions in the rule are adjusted accordingly with an appropriate error bound. For example, instead of using 90, 60, 180, and 60 degrees as the boundary values, one could use 135, 115, 170, and 115 degrees. It is interesting to note that the hip angle calculated from Cortex also systematically deviated from normal expectations. The observed boundary values were 105, 85, 170, and 85 degrees for Cortex. For a Kinect-based system to be viable in assessing this rule, an error bound of about 15 degrees would need to be used.

The static rule regarding the placement of the feet was evaluated by calculating the angle between the vector from the left to right ankle and the frontal plane. If the rule is strictly satisfied, we would expect the angle to remain 0 the entire time. As shown in Figure 7, the angle measured from Kinect skeleton data was noticeably larger (by about 7-8 degrees) than that from Cortex. However, the variation of the angle value tracked the results from Cortex fairly well. In practice, one could set the value at 10 degrees instead of 0 with a tight error bound of 5 degrees to ensure reliable assessment for the static rule in a kinect-based system with low false positives.

E. Can Turn

The can turn exercise is typically done to strengthen the supraspinatus muscle, especially after rotator cuff injury. In the can turn exercise, the patient is expected to move his or her arm straight forward such that it is in parallel to the transverse plane and remain in that pose while performing the can turn movement. Because the current version of Kinect could not track joint rotation (elbow and shoulder joints in particular), it is impossible to use Kinect to assess the rotation movement. What can be evaluated using Kinect is the arm position only. The correctness rules for can turn are defined below:

- Static rule: The can turn arm extends forward such that the arm is in parallel to the transverse plane. The angle between the arm and the sagittal plane can be flexible.
- Invariance rule: The can turn arm must remain straight, *i.e.,* the elbow angle should be at 180 degrees.

We evaluate the static rule by examining the angle formed by the can turn arm vector (in our experiment, the right arm is used) and a vector from the hip center to the shoulder center. We refer to this angle as the arm angle. If the rule is strictly observed, we would expect the angle to be 90 degrees. This is a necessary, but not sufficient condition that the arm is in parallel to the transverse plane. The arm vector is derived using the shoulder and wrist joints. Normally we would have determined the arm vector using the shoulder and elbow joints. As we will show that there is strong evidence that the elbow joint is

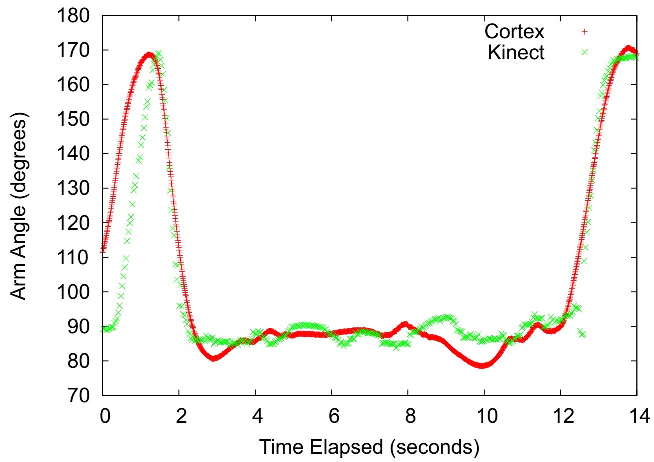

Fig. 8. Arm angle measured in the can turn exercise.

partially occluded in the Kinect based system, which causes large jitters in the measurement as seen in Figure 9.

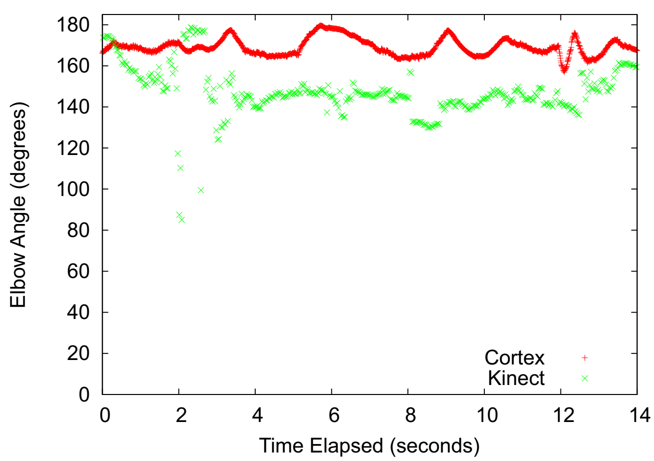

Fig. 9. Elbow angle for the can turn arm in the can turn exercise.

As can be seen in Figure 8, the arm angle as measured by both systems fluctuates closely around 90 degrees within 10 degrees as expected when the arm has moved to the can turn position. This clearly shows that the Kinect measurement is accurate enough to assess the static rule. To reach the correct arm position, the arm moves from a T-pose (with the arm angle being 90 degrees in the Kinect measurement) to the side of the trunk (results in a close-to-180 degree arm angle), and then extends forward (again results in a 90 degrees arm angle). At the end, the arm is moved back to the size of trunk.

The invariance rule regarding the elbow angle was determined using the angle between two vectors, one from the elbow to the shoulder, and the other from the elbow to the wrist. The measured elbow angle is shown in Figure 9. It is apparent that we cannot use Kinect to assess this rule (unless a large error bound) is used in the setup we used in which the subject is facing directly to the Kinect sensor as the elbow joint is partially occluded when the arm is extend straight forward. A workaround is to position the arm with an angle such as 45 degrees off the sagittal plane so that the elbow is not occluded.

F. Toe Touch

As the name suggests, this exercise involves the hands moving from the sides of the trunk to touching the toes. Toe touch is typically used as a stretching exercise for the hamstring muscles. The main correctness rules are defined below:

- Dynamic rule: An iteration for toe touch consists of two monotonic segments in which the hands move from the sizes of the trunk to close to the toes, and back to the initial position. In a fully and ideally completed iteration, the subject's hands would be flat on the floor in front of the feet, with the wrist joints at the same vertiacal position as the toes. Very few adults can achieve this fully flexed position however. The distances between the left/right hand and the left/right foot joints can be used as the metrics in quantifying this rule. To accommodate the size difference between different patients, the distance should be normalized to the maximum distance (which is at the initial position). Hence, the boundary values would be 1 and nearly 0 in an ideal iteration in which the wrists can approach the toes. However, the minimum boundary value must be customized for each patient's reaching capability.
- Invariance rule: The knee should remain straight, i.e., the knee angle should remain 180 degrees.

In our experiment, we chose to use the wrist joint instead of the hand joint, and the ankle joint instead of the foot joint because the positions reported by Kinect are less accurate for hands and feet. Figure 10 shows the normalized wrist-to-ankle distance as measured by Kinect and Cortex. As can be seen, the minimum normalized value of the distance was about 0.4 (*i.e.,* 40% of the maximum distance). Even though the Kinect data tracked the Cortex data for the most part, the distance measurement for the 2nd iteration on the left side is apparently not reliable. Even if a low pass filter is applied, frequent false positives might occur in a Kinect-based system. We believe that the problem is caused by the occlusion of the hip and knee joints, which would result in wrong Kinect skeletonization of the lower body joints, including ankles.

Our speculation is further supported by the measurement of the knee angles, which were derived using the angle between two vectors, one from the knee to the hip, and the other from the knee to ankle. As shown in Figure 11, the knee angles as measured by Kinect were completely useless for assessing the invariance rule due to wrong Kinect skeletonization.

IV. CONCLUSION

In this paper, we presented a feasibility study of using a single Microsoft Kinect sensor to assess the quality of rehabilitation exercises via five common exercises, including hip abduction, bowling, sit to stand, can turn, and toe touch. A unique contribution of this research is the rule based approach for judging the feasibility of using Kinect for rehabilitation exercise monitoring with automated patient feedback. This would greatly facilitate in-home rehabilitation exercises with improved effectiveness using a low-cost Kinect based system. The definition and application of correctness rules provides

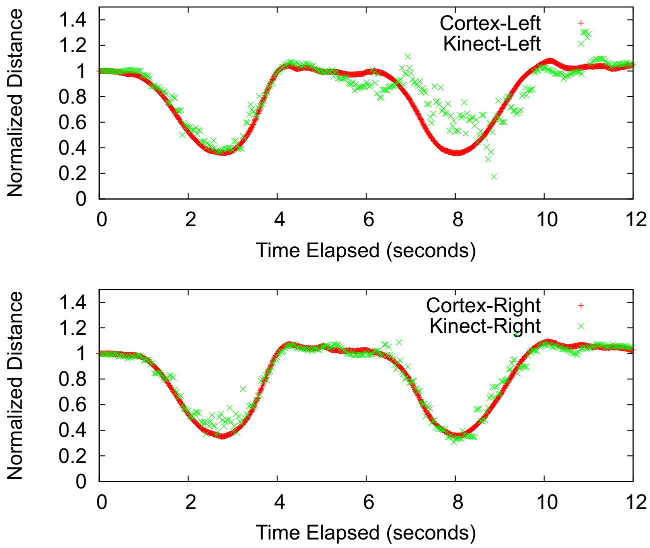

Fig. 10. Normalized wrist-to-ankle distance for 2 iterations in the toe touch exercise. The top figure is for the left side, and the bottom figure is for the right side

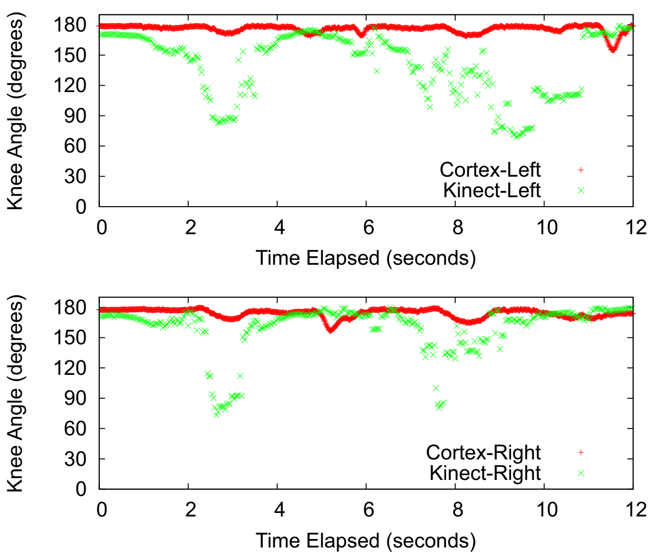

Fig. 11. Knee angle for 2 iterations in the toe touch exercise. The top figure is for the left knee, and the bottom figure is for the right knee.

a concrete context in determining whether or not the Kinect motion sensing data is accurate enough. We find that choosing the right rule parameters and error bound values are critical to using Kinect effectively in the absence of severe occlusions. Some rules that involve occluded joints cannot be reliably evaluated by Kinect based systems.

The development of correctness rules and the lessons learned in this study also paved the way for us to implement a Kinect based system that is capable of performing realtime assessment of motion quality and provide specific feedback to the patients. A sequence of human subject trials have been carried out using our system. The results are promising and will be published separately.

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