REAL TIME TRANSFER TECHNIQUE ASSESSMENT USING THE KINECT2 SENSOR

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INTRODUCTION

Approximately 3.3 million Americans over the age of 15 use wheelchairs daily (Census, 2010). Wheelchair users rely heavily on their upper extremities to complete common but essential activities of daily living such as getting in and out of bed, transferring to a toilet or a shower, and transferring in and out of a car. Manual wheelchair users will perform on average 14 to 18 transfers a day, which are extremely physically demanding and can lead to upper extremity pain and injury (Hogaboom, Worobey, & Boninger, 2016; Tsai, Hogaboom, Boninger, & Koontz, 2014). Research shows that the prevalence of upper extremity pain, specifically shoulder pain, in wheelchair users ranges between 31 and 73 percent (Cooper R, 1998). Unfortunately, shoulder pain leads to decreased quality of life and participation in physical activity (Gutierrez et al., 2007). The use of good transfer mechanics to avoid pain and injury is important for wheelchair users when performing transfers.

The Transfer Assessment Instrument (TAI) is a tool used by clinicians and therapists to assess transfer quality and identify problems in wheelchair transfers which can cause increased forces on upper extremity joints (Tsai, Rice, Hoelmer, Boninger, & Koontz, 2013) (Tsai et al., 2014). The TAI is a 2 part assessment, with the first part consisting of specific transfer issues rated on a “yes”, “no”, or “not applicable” scale. Part 2 consists of global performance of transfer quality, techniques and indication of assistance, which is scored from 0 to 4. The final TAI score is the average of both part 1 and part 2 from 0 to 10 (Koontz, Tsai, Hogaboom, & Boninger, 2016), where a 10 is perfect transfer technique and a 0 is very poor transfer technique. Some items of the TAI, particularly those related to the body mechanics can be subjective, and are open to different interpertations.

The Microsoft Kinect is a motion sensing device originally designed for use with video game systems. The Kinect sensor has been shown to be accurate at sensing joint centers and has found applications in various clinical and research settings (Xu, McGorry, Chou, Lin, & Chang, 2015). In preliminary work, we developed algorithms that combined selected biomechanical variables meaured by the Kinect and manual measurements of the body’s segments lengths to discern proper from improper technique (Lin Wei, 2017). The approach used Kinect’s developers software module, a separate post-processing module (Matlab and Mathmatica), and a statistical analysis module (SPSS). The requirement of having to take physical measurements of the person’s dimensions and the use of multiple applications to obtain results makes it an impractical solution to implement in a clinical setting.

The aim of this study was to 1) create an integrated software program that can automate the TAI scoring using the Kinect in real-time, 2) evaluate the performance of the program in predicting the TAI items scores correctly with manually-measured body measurements, and 3) evalute the performance of the program to predict TAI scores when Kinect-measured body measurements are used.

METHODS

For this study we focused our initial efforts on creating a program that could autoscore TAI part 1 items 1,2,3,6, and 7 (Tsai et al., 2013). These items address appropriate body/wheelchair setup for the transfer. Software code was written using C#, a general purpose object-oriented programming language. The Kinect 2 sensor collects position data of 25 joint centers in X, Y, and Z dimensions in 30 ms interval frames. This raw data is automatically saved as a .csv (comma seperated value) file, with 75 columns of position data, in rows indexed by time in milliseconds, also refered to as frames. Two additional columns of data include time stamps and elapsed time in milliseconds. These data are read into a module that calculates the information important to the transfer and subject. The information can be broken down into 3 categories, joint movements, body segment measurements, and TAI scoring. The joint movement variables of interest, which included linear and angular displacements of the trunk, hip, knees, ankles, and feet, were calculated from the raw Kinect data during both the setup and lifting phases of the transfer. The phases of transfer (e.g. the frames that defined their start and end times) were determined manually and input from a separate text file.

Two models for TAI scoring were developed for each TAI item using data (n=60+ wheelchair users) collected from previous work. One version of model used the body segment measurements gathered with a tape measure (Model 1), and the other one used the Kinect measured body segments (Model 2). Kinect measured joint movement variables (e.g. displacements, ranges of motion, etc.) were included in both models along with the segment lengths to predict the TAI result. Separate models were tested because the manual distance measurements and Kinect-calculated distances are expected to vary slightly. The Kinect measures a point to point distance from the center of each joint, while the manual measurements are from bone landmark to bone landmark. Discriminant function equations used to predict the TAI scores were modeled in SPSS 25 (SPSS Inc., Chicago, IL). The resulting model equations were implemented into the code. The model equations multiply calculated coefficients by each body segment and movement variable, and are added together. Using a threshold value defined in the previous work, the model result for a TAI item was classified by the code as either ‘proper’ or ‘improper’ and assigned a 1 or 0 respectively.

$$logist = a_{x1} + b_{x2} + c_{x3} + \cdots + constant \qquad (1)$$

, where a, b, c are coefficients defined by the previous modeling process; X1, X2, X3 are predicted variables (displacement of the joint centers, joint angles, etc.) calculated from the Kinect position data.

$$Predicted\ Value = \frac{e^{(logist)}}{1 + e^{(logist)}}$$

, where *e* is Euler's number, *e* = 2.71828 (2)

For example, for TAI item two the cut value is 0.5. If the predicted value is greater than 0.5, the trial would be assigned into the proper (1) group. If the predicted value is lower than 0.5, the trial would be assigned into the improper (0) group.

One test subject voluntarily participated in the study (male, age 33, height = 177cm; weight = 90.72kg). First, anthropometric data was manually collected from the subject, i.e. height, weight, upper arm, lower arm and leg lengths. Then a static hold trial was performed by the subject for 5 seconds, with arms extended perpendicular to the trunk. The static hold trial was used to calculate body segment measurents from Kinect automatically within the program. Manual measurements were uploaded into the program from a .csv file.

Next, the subject conducted 1 proper transfer, followed by 5 improper transfers for each item of the TAI part 1 items 1,2,3,6, and 7. For item 1, the wheelchair was positioned farther than 3 inches from the transfer bench. For item 2, the wheelchair was positioned parallel to the bench, and not within the 20-45 degree range of a correct transfer. For item 3, the subject transferred directly over the rear wheel of the wheelchair. For item 6, the subject did not place his feet on the ground before transferring, and for item 7, the subject did not move forward in the seat, and transferred directly from the back of the wheelchair seat. Each type of transfer was performed three times for a total of 18 transfer trials that were available for testing the new software.

<u>Data Analysis</u>

The 18 transfer files containing the raw Kinect position data were randomized and analyzed by a researcher who was blinded to the type of transfer performed (e.g. proper or improper). Descriptive statistics (means and standard deviations) were computed for the body segment variables measured manually and with the Kinect. Autoscoring performance for each model was evaluated using standard binary classification statistics (e.g. accuracy, specification, specificity, etc.)

RESULTS

The output of the program was .csv files: predicted TAI scores (Figure 1), calculated body segment distances, and calculated joint movements (Figure 2). The outputs were compared to manually measured joint distances, manually calculated joint movements, and TAI items scores for the actual type of transfer performed (e.g. proper (‘1’) or improper (‘0’)). Each transfer assessment with the new program took on average 500 ms to calculate, which is a huge improvement over performing manual measurements and running several separate software programs (5-10 minutes).

SubjectNum	Test numbe	TAI1_1	TAI1_2	TAI1_3	TAI1_6	TAI1_7
1	1	0	1	0	0	1
1	2	1	1	0	0	1
1	3	1	1	0	0	1
1	4	1	1	0	1	1
1	5	1	1	0	1	1
1	6	1	1	0	0	1
1	7	1	1	0	0	1
1	8	1	1	0	0	1
1	9	1	1	0	1	1
1	10	0	1	0	0	1
1	11	1	1	0	0	1
1	12	1	1	0	0	1
1	13	1	1	0	0	1

Figure 1: Screen shot of the TAI scoring output

SubjectNum	TestNum	spineBaseX	hipleftX	hipRightX	SpineBaseY_trail	HipLeftY_trail	HipRightY_trail
1	1	660.5682	612.9423	696.9642	187.38527	187.20019	208.93252
1	2	774.8121	733.8148	793.3093	238.17159	260.443435	211.9722
1	3	605.9973	595.7959	602.818	209.43174	206.87614	211.03454
1	4	645.8958	633.5309	646.1121	202.94596	227.26905	204.0474
1	5	612.5668	598.7169	620.4164	185.68951	180.08272	201.66166

Figure 2: A screen shot of the joint movement output: displacement of the joint centers calculated by the Kinect (units: mm).

As expected, the Kinect measured body segment lengths differed from the manual measured lengths (Table 1). While differences in magnitudes were found the variance within both methods was low.

Table 1: Manual segment lengths compared to Kinect measured segment lengths (units: cm)

Segment	Manually measured segment lengths Mean(std)	Kinect measured segment lengths Mean(std)
Right Upper Arm Length	35.5 (3.3)	24.0 (2.1)
Left Upper Arm Length	35.9 (3.1)	24.3 (2.1)
Right Forearm Length	26.4 (2.6)	24.7 (2.3)
Left Forearm Length	26.6 (1.8)	24.3 (2.6)
Right Thigh Length	45.6 (4.3)	39.3 (5.5)
Left Thigh Length	45.9 (4.9)	40.3 (5.7)
Right Leg Length	41.1 (6.3)	38.4 (5.5)
Left Leg Length	42.3 (4.8)	39.4 (6.0)
Right Foot Length	20.7 (2.1)	13.0 (1.9)
Left Foot Length	20.6 (1.9)	12.9 (1.9)
Trunk Length	54.7 (7.9)	45.9 (6.2)

Model 2 using the Kinect measured segment lengths was slightly more accurate overall than Model 1 (Tables 2 and 3). We found both models to have high specificity (≥81%) for all items except Item 6 for Model 2. Item 6 had the lowest specificity (29%) (Table 3), this is most likely due to the Kinect having difficulty sensing the lower extremities while seated in a wheelchair. Both models also had higher positive predictive values (PPV) than negative predictive values (NPV) (Table 2).

Table 2: Model 1 Using Manually Measured Segment Lengths; PPV and NPV: Positive and Negative predictive values

Item	Accuracy	Sensitivity	Specificity	PPV	NPV
1	.70	.64	0.92	0.96	0.44
2	.95	0.97	0.88	0.96	0.89
3	.65	0.58	0.88	0.94	0.39
6	.62	0.46	0.88	0.87	0.49
7	.73	0.72	0.81	0.87	0.36

Table 3: Model 2 Using Kinect Measured Segment Lengths

Item	Accuracy	Sensitivity	Specificity	PPV	NPV

1	0.84	0.81	0.93	0.97	0.64
2	0.75	0.66	1.00	1.00	0.51
3	0.87	0.88	0.82	0.94	0.67
6	0.72	0.93	0.29	0.73	0.67
7	0.86	0.86	0.86	0.98	0.49

DISCUSSION

The results show that it is possible to automate several steps in determining a TAI score with one program. The application combines the analysis normally completed by post-processing modules (Matlab and Mathmatica) and a statistical analysis module (SPSS) into a one-step program making it a more practical solution to implement in a clinical setting. The classification results were promising for replacing manually measured body lengths with Kinect measured ones which would further speed up performance and reduce burden on the operators and end users. The code currently requires knowledge of when the setup phase of the transfer ends and the lift part of the transfer begins. This is determined off-line using manually methods and read into the code as a separate file which would not be feasible for clinical use. We are currently developing an algorithm to automatically differentiate the phases of a transfer using only the Kinect data which would make the runtime of the program even faster and practical for the clinic.

Our results demonstrate that a refined method is needed for improving the specificity of Item 6. If this can be achieved, the Kinect model may be an effective tool for assessment of proper transfer setup. The item 6 checks that the subject places his feet in a stable position (on the floor if possible) before the transfer. The program used the displacement of the subject's toe, feet, and knee joint center before the transfer to evaluate this item. Ideally if the subject placed the feet on the floor, the displacement of the lower extremities joints should be larger than if the subject kept his feet on the wheelchair pedals. However, the seated position and the wheelchair itself may have introduced errors into the sensor readings (a common issue with infrared depth sensors). Using a more advanced depth sensor and/or using another type of sensor (e.g. pressure sensors on the footrests) may help resolve the issues with erroneous data.

For the other four items that were modeled, the model is unlikely to tell a patient they are doing the movement correctly when they are actually doing it incorrectly. This ability may be valuable to a clinician because incorrect behaviors are not reinforced as though they were correct (Lin Wei, 2017). In clinical practice, it is much more detrimental to diagnose a false-positive TAI score (e.g. saying that the patient is doing it right when they are actually doing it wrong) than to diagnose a false-negative TAI score (e.g. saying that the patient is wrong when they are doing it right). Thus, we aimed to achieve high specificity and PPV in this study, which will minimize the false-positive TAI scores.

To further improve TAI scoring accuracy, a machine learning algorithm is being developed to continually adjust and improve the TAI scoring equations. These new algorithms will replace the existing discriminant functions and allow for a more robust clinical tool.

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REFERENCES

Census, U. S. (2010). Facts for Features: 20th Anniversary of Americans with Disabilities Act: July 26 - Facts for Feature.pdf>.

Gutierrez, D. D., Thompson, L., Kemp, B., Mulroy, S. J., Physical Therapy Clinical Research, N., Rehabilitation, R., & Training Center on Aging-Related Changes in Impairment for Persons Living with Physical, D. (2007). The relationship of shoulder pain intensity to quality of life, physical activity, and community participation in persons with paraplegia. *J Spinal Cord Med, 30*(3), 251-255.

Hogaboom, N. S., Worobey, L. A., & Boninger, M. L. (2016). Transfer Technique Is Associated With Shoulder Pain and Pathology in People With Spinal Cord Injury: A Cross-Sectional Investigation. *Arch Phys Med Rehabil, 97*(10), 1770-1776. doi:10.1016/j.apmr.2016.03.026

Koontz, A. M., Tsai, C. Y., Hogaboom, N. S., & Boninger, M. L. (2016). Transfer component skill deficit rates among Veterans who use wheelchairs. *J Rehabil Res Dev, 53*(2), 279-294. doi:10.1682/JRRD.2015.02.0023

Lin Wei, H. W. K., PhD, Alicia Koontz, PhD. (2017). *Evaluating Wheelchair Transfer Technique by Microsoft Kinect.* Paper presented at the ISS 2017, Washington DC.

Lin Wei, Tsai, C. Y., PhD, H. W. K., PhD, Alicia Koontz, PhD. (2016). *Can the Kinect detect differences between proper and improper wheelchair transfer techniques*. Paper presented at the RESNA 2016, Pittsburgh.

Tsai, C. Y., Hogaboom, N. S., Boninger, M. L., & Koontz, A. M. (2014). The relationship between independent transfer skills and upper limb kinetics in wheelchair users. *Biomed Res Int, 2014*, 984526. doi:10.1155/2014/984526

Tsai, C. Y., Rice, L. A., Hoelmer, C., Boninger, M. L., & Koontz, A. M. (2013). Basic psychometric properties of the transfer assessment instrument (version 3.0). *Arch Phys Med Rehabil, 94*(12), 2456-2464. doi:10.1016/j.apmr.2013.05.001

Xu, X., McGorry, R. W., Chou, L. S., Lin, J. H., & Chang, C. C. (2015). Accuracy of the Microsoft Kinect for measuring gait parameters during treadmill walking. *Gait Posture, 42*(2), 145-151. doi:10.1016/j.gaitpost.2015.05.002