Predicting If Older Adults Perform Cognitive Tasks Using Body Joint Movements From RGB-D Videos

Jenna Ryan*, Sarah Inzerillo*, Jordan Helmick†, Ali Boolani‡, Natasha Kholgade Banerjee* and Sean Banerjee*
*Department of Computer Science, Clarkson University, Potsdam, NY, USA
†MedExpress, Morgantown, WV, USA
‡Department of Physical Therapy, Clarkson University, Potsdam, NY, USA
Email: {ryanjc, inzeris, aboolani, nbanerje, sbanerje}@clarkson.edu, jordan.helmick@medexpress.com

***Abstract*—We present an approach that performs automated detection of whether an older adult has performed cognitive tasks such as form filling or problem solving using RGB-D video data of older adults collected using the Microsoft Kinect v2 sensor. Our approach uses the variances of 25 joint points on the 3D skeleton obtained from the Kinect for training random forest classifiers to detect if cognitive tasks are performed, based on deviations in postural sway induced by cognitive tasks. We validate our approach using a dataset of 10 subjects performing the test on standing with eyes closed in the Berg Balance Scale (BBS) series of diagnostic tests before and after cognitive tasks. Using leave-one-subject-out cross-validation, we obtain an average detection accuracy of 69.5%, with accuracies of 60% and 79% at detecting that the test on standing with eyes closed was performed prior to and after cognitive tasks respectively. Our approach can be incorporated into intelligent health care systems to detect whether older adults have performed cognitively demanding activities that may induce stress or fatigue, and allow early intervention well before the occurrence of adverse events such as falls.**

***Keywords*–RGB-D; Kinect; cognitive; fatigue; random forest**

I. Introduction

The spread of low-cost sensors and computing in the consumer space has enabled the rise of approaches to perform automated health assessment in older adults. RGB-D sensors such as the Microsoft Kinect have been used for detection of falls [1], [2] and frailty [3], and encouragement of exercise [4]. Adverse events such as falls in older adults place high financial pressure on the health care system. The cost of fatal and non-fatal falls in the US was $19.2 billion in 2000 [5] and $23.3 billion in 2008 [6]. Instead of detecting adverse events after they have occurred, financial burden on the health care system can be significantly reduced by monitoring older adult health for signs of fatigue, which has been found to be correlated with fall risk in older adults [7]. In this work, we use random forests on RGB-D data from the Microsoft Kinect v2 sensor to perform automated detection of whether an older adult has performed cognitive tasks using variation in sway of standing posture before and after cognitive tasks have been performed. We define cognitive tasks in this work as activities involving reasoning and decision making, that involve the use of working memory [8]. The cognitive tasks used in our work include problem solving and questionnaire filling. Cognitive tasks have been found to be correlated to increase in postural sway [9], [10] due to weakening of sensory systems related to balance in older adults [11]. Increased sway has been found to be related to rise in fatigue [12]. Using off-the-shelf sensors such as the Kinect to detect the influence of cognitive tasks on balance in older adults can enable intervention in the event of stress induced by cognitive activities in daily living.

The primary challenge of our work is that cognitive tasks show a subtle change in postural sway. Traditionally, physical therapists detect deviation in postural sway by having subjects perform balance tests such as tests under the Berg Balance Scale (BBS) [13]. The BBS consists of 13 tests performed in various postures with eyes open and one test performed standing with eyes closed. The physical therapist provides a numerical score between 0 and 56 on assessing all 14 tests, with a lower value indicating lesser balance ability. However, due to variations between scores of multiple physical therapists, several studies [14], [15] have been conducted to determine the reliability of the BBS score in detecting a change in postural sway. The minimum detectable changes at an absolute reliability of 95% has been cited as 4 for scores between 45 and 56 by Donoghue et al. [14] and between 2.8 to 6.6 for eleven studies reviewed by Downs et al. [15] with BBS scores above 20. In the dataset used in our work where 10 subjects were evaluated doing BBS tests prior to and after cognitive tasks, the BBS score after cognitive tasks was found to be reduced by 1.6 points on average with scores ranging from 49 to 56. Since the reduction is lower than the thresholds discussed in Donoghue et al. [14] and Downs et al. [15], the BBS score alone cannot be used to detect movement changes induced by cognitive tasks.

While there exist approaches to detect changes in gait and posture due to physical fatigue [16]–[18], these approaches use body-mounted sensors that hinder natural motion and may introduce noise that overpowers the subtle influence of cognitive tasks. Additionally, these approaches use sensors placed on a narrow range of locations, e.g., on the foot [16], [17] or on the lower back [18], which may prove insufficient to detect the influence of cognitive tasks on full body postural sway. Our work addresses the subtle influence of cognitive tasks over sway in the head, shoulders, arms, hands, spine, legs, and feet by using variances in the positions of 25 3D joints from the Kinect, which being a non-contact sensor allows natural unweighted motion. We use the 25 body joint variances as input to the random forest classifier, which provides a binary output on whether the person performed cognitive tasks. We enhance the contribution of sense of body joint location, i.e., proprioception, toward balance by using the BBS test on standing with eyes closed to eliminate the influence of visual cues, which have been found to have the largest contribution toward balance amongst the visual, proprioceptive, and vestibular balance mechanisms [19].

We use a linear mixed model with joint variances from the 10 subjects analyzed in this work to demonstrate that the 25 joint variances have a statistically significant effect in distinguishing the data prior to and after cognitive tasks.

We use a similar linear mixed model to demonstrate that in a control dataset where the same 10 subjects perform two rounds of the BBS tests on a different day with a break, i.e., without cognitive tasks between the rounds, the 25 joint variances do not have a statistically significant contribution in distinguishing between the pre- and post-break conditions. Using a leave-one-out cross-validation approach for training each random forest using 9 subjects and testing with the left out subject, we obtain an overall average accuracy of 69.5%, with average accuracies of 60% and 79.0% in detecting that the test on standing with eyes closed was performed prior to or after performing cognitive tasks respectively. We also obtain an average accuracy of 44.5% on the control dataset in distinguishing between pre- and post-break condition, which being close to random chance indicates that postural sway remains consistent in the absence of cognitive tasks.

The remainder of the paper is organized as follows. In Section II, we discuss contact based approaches for detecting fatigue, non-contact based approaches for detecting older adult health, and fatigue detection in driving using non-contact based sensors. In Section III, we describe the data collection procedure during the experimental and control days for our study. In Section IV, we describe our approach for detecting deviations in balance using joint variance analysis. In Section V, we describe the linear mixture model that we designed to determine that joint variances are appropriate predictors of whether older adults have performed cognitive tasks. In Section VI, we provide details of the random forest classifier we trained to determine if an older adult had performed cognitive tasks. In Section VII, we discuss the performance of our classifier and provide insights on where misclassifications occur. We conclude the paper in Section VIII and provide potential areas of future work.

II. Related Work

To the best of our knowledge, there exists no work on detecting whether a subject performs cognitive tasks from routine motions such as walking or standing. As cognitive tasks are known to impact postural sway [9], [10] which is related to fatigue [11], we discuss approaches to detect physical fatigue using contact-based and non-contact sensors, and fatigue during the cognitive task of driving.

Contact-Based Sensors for Detection of Fatigue. Traditional physiological approaches for automated fatigue detection have focused on the use of surface electromyography (sEMG) to measure muscle fatigue during physical exertion; a review of these approaches may be found in Al-Mulla et al. [20]. While sEMG electrodes do not puncture the skin, they require skin contact and use a significant amount of hardware, thereby being cumbersome for fatigue detection in everyday environments. There also exist approaches to use body-mounted sensors, such as pressure sensors at six points on the foot to estimate fatigue during walking [17] or running [16] gait as a function of maximum pressure. These gait-based approaches have multiple cues from asymmetries and variations in rotation or translation of the upper body, hips, legs, and feet during walking or running gait. Our work on detecting changes in standing body posture handles the challenge of working with a smaller set of cues restricted to body sway.

In the area of detection of posture balance, Wall et al. [21] provide a balance prosthesis that measures head tilt using inertial sensors mounted on the shoulders and trunk, and displays the tilt to the user for user-driven balance re-adjustment. Their approach does not perform detection of differences in sway. Shahzad et al. [18] estimate balance impairment for fall risk by predicting the score of the BBS for older adults using acceleration data obtained from a triaxial accelerometer positioned at the lower back. Their approach shows a separation between the mean BBS scores of non-fallers at 53.3 ± 2.9 and fallers at 45.5 ± 7.2. The mean separation is greater than the thresholds discussed in Donoghue et al. [14] and Downs et al. [15]. This enables Shahzad et al. to use linear least squares and LASSO for regression of the BBS score. In our work, the average separation of 1.6 between BBS scores before and after cognitive tasks is much smaller than the Donoghue et al. or Downs et al. thresholds for change detection, preventing the use of the BBS score as a predictor of cognitive tasks. Our approach overcomes this issue by using the skeleton obtained with the Kinect sensor to detect whether cognitive tasks are performed from the effect they have in the increasing the sway of 25 body joints.

Physical fatigue or aging handled by the above approaches show gross changes in movement which can be picked up by body-mounted sensors. However, body-mounted sensors hinder natural user motions, and due to their added weight may prevent separation of data prior to and after cognitive tasks that have a subtle influence on motion. Our approach of using non-contact sensors retains natural motions, enabling us to detect the weak influence of cognitive tasks.

Non-contact RGB-D Sensors to Assess Older Adult Health. Despite the popularity of cameras and RGB-D sensors such as the Kinect in the consumer space, approaches to perform automated detection of anomalous health patterns in older adults using non-contact at-a-distance sensors have been limited. There exist approaches to perform detection of falls by tracking the vertical state of a subject [1] or the acceleration and distance of the center of mass [2]. However, these approaches enable intervention only after a fall has occurred. In contrast, our work evaluates postural instabilities to enable early intervention well before a high-risk incident such as a fall arises. Gianara et al. [3] use the Kinect to perform frailty assessment on subjects performing the Timed Up and Go (TUG) [22] test. They determine that gait parameters such as walking time and speed, distance covered, and swing correlate well with the Tillburg Frailty Indicator (TFI) score, while postural parameters such as torso inclination do not show a strong correlation with the TFI score. Unlike our work, they do not perform prediction of frailty in a novel individual.

Fatigue Detection During Driving. The body of work that resembles ours in using non-contact sensors to detect fatigue due to cognitive tasks is work on driving fatigue detection, surveyed extensively in Wang et al. [23]. Here, the cognitive tasks involved include paying attention to roads, signs, lanes, pedestrians, intersections, and other drivers. These approaches use a camera to analyze the user's face, whereas our work analyzes the body and assumes that the face may not be visible, an issue that can occur when the user looks away from the sensor, has their back toward the sensor, or is at a distance where the resolution is insufficient for face analysis.

Additionally, these approaches detect gross observable changes such as eyelid open versus closed [24]–[30], head tilt due to nodding versus upright head [24], [28], eye-gaze narrowed versus wide [24], and yawning versus not yawning [24], [28], [30], [31]. Our work detects the presence of subtle changes in body sway when cognitive tasks such as questionnaire filling and problem solving are performed by elderly individuals in whom body posture prior to induced fatigue shows low stability due to age [32].

III. Data Collection Procedure

Our dataset consists of 10 older adults with 6 female and 4 male subjects. The subjects in our dataset range in age from 57 to 68 years with a mean age of 63.50 $\pm$ 4.28 years. To reduce the effect of confounding factors, we ensure that all subjects have not been diagnosed with any neurological conditions, have no pre-existing balance disorders or recent orthopedic surgery, have visual acuity, and do not require assistive devices to stand or walk. We collect data from the subjects on two separate days—an experimental day when the subjects perform cognitive tasks and a control day when the subjects do not perform cognitive tasks and instead have a rest break. The time in between the two collection days ranges from 1 to 9 days, with an average of 2.4 $\pm$ 2.5 days, and with the order of experimental and control day randomized across subjects.

On both the control and experimental day we measure the subject's vitals, i.e. height, weight, body composition, and radial pulse heart rate/blood pressure, and administer three questionnaires on current feelings of fatigue, mood and motivation. We then administer three standard diagnostic tests to measure static and dynamic balance. The tests include 14 assessments under the BBS [13], the Timed Up and Go (TUG) [22] test, and the 30 Second Chair Stand test [33]. On the control day, we give the subject a 1 hour break. On the experimental day, we have the subject perform cognitive tasks by asking them to fill out questionnaires on demographics, medical history, physical activity, sleep, grit, hope, satisfaction with life, interest, self management, and food frequency, and to perform problem solving activities such as Serial Subtract 3, Serial Subtract 7, Continuous Performance Test, Rapid Visual Information Processing Test, Trails B Test, and 8 minute Tapping Test [34]–[36]. The subject performs cognitive tasks on a tablet. After the break on the control day or cognitive tasks on the experimental day, we ask the subject to repeat the 30 Second Chair Stand, TUG, and BBS tests. We record the subject's vitals, and ask the subject to re-fill the three questionnaires on current feelings of fatigue, mood and motivation. The control day activities range from 64.7 to 71.6 minutes, with an average of 68.5 $\pm$ 2.0 minutes. The experimental day activities range from 93.6 and 120.4 minutes, with an average of 107.5 $\pm$ 8.5 minutes.

We developed a custom C# based application using the Kinect SDK to collect RGB-D video, face, and joint data for each subject. The RGB-D video data consists of both color and depth frames captured at 30 frames per second. The face data consists of 1347 3D face points for each frame of the video. The joint data consists of 25 3D joint points along with corresponding x and y coordinate points in color and depth space for each frame of the video. In Figure 1, we show color images and corresponding 3D skeletons for 4 different

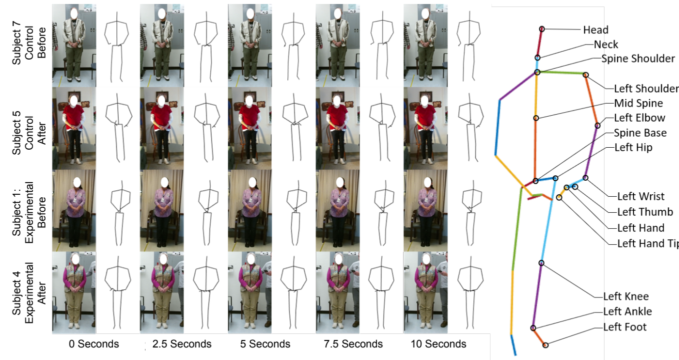

Figure 1. Left: Color and skeleton data from four subjects for various captures. Right: Kinect skeleton labeled with medial axis and left side joints.

subjects. The right side of Figure 1 shows the 3D Kinect skeleton from a frontal view with labels for joints along the medial axis and on the left side of the subject.

IV. Representing Balance Deviation using Joint Variances

To eliminate the influence of visual stimuli which show the largest contribution to balance [19], we use RGB-D videos representing the 'Standing with Eyes Closed' test from the BBS assessments for each subject. The 'Standing with Eyes Closed' test involves a subject standing upright with eyes closed for 10 seconds. Due to the short period of the test, it provides the added advantage of avoiding noise in the data due to motions such as straightening clothes, speaking to the experimenter for clarification, or accidental gesturing. The longer duration eyes open tests contain such motions, which while natural in everyday settings, overpower changes in motion due to the subtle impact of cognitive tasks. Our recognition of deviation in balance is based on the premise that increased movement in the balance tests is related to an increase in fatigue [12]. To evaluate amount of movement, we provide an algorithm in MATLAB that estimates the net variance in each body joint by computing the sum of the variances in the X, Y, and Z dimensions from the 3D joint data collected by the Kinect. The variances in the spread of 3D joint points represents the deviation of the subject from a mean standing position.

Figure 2 shows 3D plots for the Kinect joints data obtained for a sample subject performing the 'Standing with Eyes Closed' test on the control day prior to and after the break, and on the experimental day prior to and after the performance of cognitive tasks. Each plot shows the 3D skeleton from the first frame of the data, together with clusters of 3D points at each joint representing the locations of the joints throughout the capture. As each cluster indicates, deviations in balance inherent to the human body introduce variations in the locations of the joints. The cluster of points from the left shoulder is magnified at the bottom of each plot. Note that on the experimental day after cognitive tasks, the shoulder points trace a more spread out trajectory in comparison to the experimental day prior to cognitive tasks and the control day after the break. The joint variance captures this spread. Also, while there is a high spread of points on the control day prior to the break, the bulk of the points are concentrated

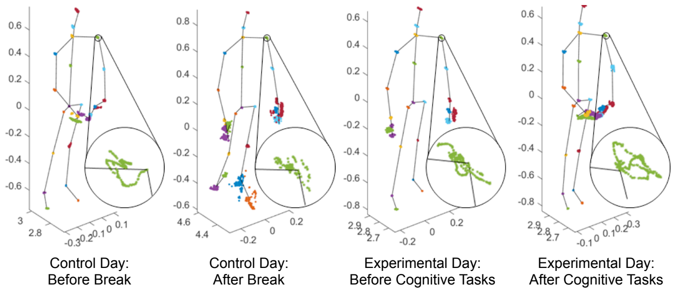

Figure 2. Positions of 3D joints for control and experimental day before and after. Each inset shows the left shoulder points zoomed in.

around the shoulder, and the trailing points are largely outliers. The joint variance in this case is weighted toward the higher concentration of points near the mean.

V. Hypothesis Testing on Diagnostic Tests and Joint Variances

The three diagnostic tests—30 Second Chair Stand, TUG and BBS—provide a holistic understanding of changes in static and dynamic balance. To determine if cognitive tasks have an observable impact on the diagnostic test scores, we perform a two-sided paired Wilcoxon Sign Rank Test to test the following sets of hypotheses on both the control and experimental day:

Null: Difference between [diagnostic test] scores before and after is 0.
Alt.: Difference between [diagnostic test] scores before and after is not 0.

Here [diagnostic test] refers to the 30 Second Chair Stand test, the TUG test, and the BBS tests. Since the three diagnostic tests are performed sequentially, and a subject's performance may be impacted by a prior test we apply a Bonferroni correction and reject the null hypothesis if $p < 0.05/3$, i.e., if $p < 0.016$. On both the control and experimental day we fail to reject the null hypothesis for all three balance tests, indicating that cognitive tasks do not create a statistically significant difference in the diagnostic test scores. For the 30 Second Chair Stand test, we obtain a p-value of 0.76 for the control day, and 0.34 for the experimental day. For the TUG test we obtain a p-value of 0.68 for the control day, and 0.37 for the experimental day. For the BBS, we obtain a p-value of 0.11 for the control day, and 0.06 for the experimental day. By failing to reject all three null hypotheses on the diagnostic tests, we show that cognitive tasks do not show a gross change in static and dynamic balance tests, indicating that the test scores are poor predictors of whether cognitive tasks are performed.

The 25 joint variances computed in Section IV provide a fine-grained understanding of how cognitive tasks affect movement. We construct a linear mixed model on both the experimental and control days to determine whether cognitive tasks impact the joint variances in the 'Standing with Eyes Closed' test before and after cognitive tasks are performed. Using a log-linear transformation, in the experimental day we obtain a confidence interval bound of $[30.80\%, 98.59\%]$ for the percent difference between the joint variances before and after cognitive tasks. The percentages indicate a statistically significant increase of 30.80% to 98.59% in joint variance after cognitive tasks. On the control day, we obtain a confidence interval bound of $[-34.31\%, 3.76\%]$ for the difference between the joint variances before and after the rest break. In this case, since 0 lies within the confidence interval, we show no statistically significant difference in joint variance before and after the rest break. The statistically significant percent increase in joint variances after cognitive tasks on the experimental day substantiates the need for fine-grained joint-based analysis.

TABLE I. Accuracy of predicting whether cognitive tasks have been performed on the experimental day and on the control day (Pred. = Predicted).

	Experimental Day		Control Day	
	Pred. Before	Pred. After	Pred. Before	Pred. After
Before	**60.0%**	40.0%	**42.0%**	58.0%
After	21.0%	**79.0%**	53.0%	**47.0%**

VI. Predicting If Cognitive Tasks Are Performed Using Random Forests

As determined by the linear mixed model, joint variances on the experimental day have strong discriminative power to distinguish whether the 'Standing with Eyes Closed' test was performed before or after cognitive tasks. We use the joint variances as input features in a random forest classifier, with the output being 0 prior to cognitive tasks and 1 after cognitive tasks. We use the `treebagger` function in MATLAB to train a random forest with 500 decision trees and $\sqrt{n}$ predictors for each decision split as recommended in Breiman [37], where n is the number of features, i.e., $n = 25$. We use a leave-one-out cross-validation approach for testing our model on data from the experimental day, where in each fold, 9 of the 10 subjects are used for training, while the left-out subject in that fold is used for testing. The joint variances from the data captured before and after cognitive tasks are removed from the training data for the left-out subject, enabling our approach to perform prediction of cognitively induced fatigue without prior knowledge of the subject. The randomness in formation of decision of trees induces slight differences in the classification at each run of the random forest algorithm. To account for the randomness, we aggregate the results of the random forest classification for each leave-one-out fold over 10 re-runs of the random forest algorithm. To determine if the random forest classifier substantiates the control hypothesis in Section V by detecting close to chance, we similarly use leave-one-out cross-validation to train and test the random forest classifier on data from the control day, where the joint variances are calculated prior to and after the rest break.

VII. Results

We show overall results of classification using random forests in Table I. Results of classifying whether the subject performed the 'Standing with Eyes Closed' test before and after cognitive tasks on the experimental day are shown on left. We obtain an overall classification accuracy of 69.5% on the experimental day, where the average and standard deviation are computed over 10 runs of the random forest classifier. We obtain a classification accuracy of 60.0% for the 'Standing with Eyes Closed' test being performed before cognitive tasks,

TABLE II. PER-SUBJECT EXPERIMENTAL DAY CLASSIFICATION BEFORE AND AFTER COGNITIVE TASKS.

Subject	1	2	3	4	5	6	7	8	9	10
Before	100%	0%	100%	100%	100%	0%	0%	0%	100%	100%
After	100%	80%	100%	100%	100%	100%	20%	100%	0%	90%

and an accuracy of 79.0% for the test being performed after cognitive tasks. The false positive rate is 40.0%, while the false negative rate is 21.0%. The lower false negative rate using the standard random forest algorithm with $\sqrt{n}$ split predictors proves advantageous to our work, as it is essential to accurately detect stress induced by cognitively demanding tasks for intervention. Higher false positives, while inconvenient, do not adversely affect the health of the monitored individual. The right side of Table I shows results of classifying whether the subject performed the test prior to or after the break on the control day. The overall classification accuracy is 44.5% which being close to chance at 50% substantiates the hypothesis test in Section V that in the absence of cognitive tasks, discernible changes in movement may not be produced. Table II shows per-subject classifications on the experimental day averaged over all classifier runs. The classifier correctly classifies subjects 1, 3, 4, and 5; 6 and 8 after cognitive tasks; and 10 before cognitive tasks. It generally shows correct classification for 2 and 10 after cognitive tasks.

Incorrect classifications for data prior to cognitive tasks occur due to clothing adjustment for subject 2 as seen in Figure 3(a), and influence of hand motions toward the center and experimenter hand support for subject 7 as seen at the top of Figure 3(b), all of which cause the joint points to show large deviations from the mean posture. Incorrect classification for data after cognitive tasks may occur due to directed motions corresponding to a downward shrug observed at the bottom of Figure 3(b), and due to a steady movement of the shoulders along the camera axis as observed for the skeleton of the upper body for subject 6 on the left of Figure 3(c) which is larger than the motion after cognitive tasks on the right. The motions in both subjects may resemble the hand motions of subject 2 adjusting clothing prior to cognitive tasks. These steady, largely uni-directional, movements may not be related to balance which tends to show movements with spread along multiple dimensions as in the shoulder points in Figure 2.

As shown by Figure 3(d), subject 9 shows dense clusters of points both prior to and after cognitive tasks in the upper body, causing the data obtained after cognitive tasks to be classified as being prior to cognitive tasks. One reason for the misclassification may be that the subject had a higher amount of physical and mental energy in comparison to the average physical and mental energy across all subjects on the experimental day. According to the summarization of the physical and mental energy for each subject obtained from self-reported responses to the three questionnaires for fatigue, mood, and motivation discussed in Section III, the average physical and mental energy of all 10 subjects prior to cognitive tasks was 184.7 ± 55.0 and 193.8 ± 64.9 respectively, while the average physical and mental energy after cognitive tasks was 155.1 ± 71.1 and 150.2 ± 81.0 respectively. Subject 9 showed higher values of physical and mental fatigue prior to cognitive tasks at 266 and 263, and after cognitive tasks at 259 and 243.

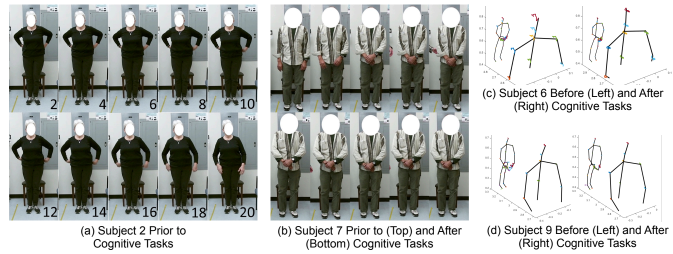

Figure 3. Frames demonstrating reasons for incorrect classification.

VIII. DISCUSSION

In this paper, we have presented an approach to predict if cognitive tasks have been performed by an older adult by analyzing deviations in the standing posture of subjects using the Kinect. Even though the Kinect has been discontinued, our approach for movement analysis can be performed using third party skeleton tracking [38] with other depth sensors such as the Asus Xtion Pro or Intel RealSense. Our approach provides an average accuracy of 69.5%, with 79% accuracy in detecting that cognitive tasks have been performed. By using low-cost non-contact sensors, our approach enables detection of the subtle effect of cognitive tasks on motion, and enables implementation of monitoring technologies in homes and health care facilities without body-mounted equipment. In this work, we focus our analysis on subjects performing the ‘Stand with Eyes Closed’ test on the BBS scale to eliminate the effect of visual cues. In future work, we will analyze eye gaze patterns from video data to account for the contribution of the visual system in re-adjusting for balance after cognitive tasks are performed in the open eyes tests. To account for potential subject-dependency on balance as indicated by subject 9 in Section VII, we will build subject-specific models for detection of the effect of cognitive tasks by using data on the control day to learn regular subject behavior. Such a system may be propagated to everyday environments for older adult health monitoring by using occasional input from health-care providers to update movement models. We will also analyze the performance of classifiers such as linear regression, logistic regression, and support vector machines to determine optimal classifiers prior to propagation in the field.

While our approach on joint variances enables detection of balance based on increase in deviation from upright posture, extraneous motions such as clothing adjustments, hand gestures, and body motions while speaking can overpower the subtle effect of cognitive tasks. However, such motions are natural in everyday interactions, and must be accounted for in a health monitoring system deployed in average user spaces. The signature of extraneous motions unrelated to balance may show a higher directional dependence, e.g., downward movement of a cluster of points belonging to the hand during clothing adjustment, whereas joint motions related to balance may have a higher degree of isotropy. In future work, we will perform principal components analysis to use the magnitude of movement along various directions at each joint in predicting the performance of cognitive tasks based on balance ability. We will also perform an extended data collection on movement patterns of subjects in everyday environments.

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