Low-cost, Automated Assessment of Sit-To-Stand Movement in "Natural" Environments

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Abstract— **The ability to rise from a chair is a prerequisite for upright mobility and independent living. We are developing an inexpensive stereo based system capable of cheaply and automatically assessing the quality of "sit-to-stand" movements in environments outside of clinics. Automated assessments have been designed to translate perceived kinematics onto assessment scores that are consistent with expert opinion on the Berg Balance Scale (BBS). In addition, automated assessments reveal movement strategies associated with age and disability, like the use of the arms while rising or excess extension at the knees. In this paper, we present preliminary work to translate perceived movement kinematics from community dwelling balance impaired elders onto expert assessments of sit-to-stand health. Our ultimate goal is to create automated tools to identify falls risk, quantify real-world movement changes that result from therapeutic interventions, and perform ergonomic analyses of elders' seating arrangements in the home.**

Keywords— **Balance Assessment, Assistive Technology, Computer Vision, Rehabilitation Science**

I. Introduction

The ability to rise from a chair is vital to functional mobility. Difficulty rising from a chair, however, affects more than two million non-institutionalized Canadians over the age of 65 [1]. This difficulty is important for clinicians to monitor as it correlates with an increased likelihood of sustaining a fall [2].

We are currently working to develop affordable, home appropriate technologies to measure kinematic changes in elders' motion that impact their ability to rise from a chair. Our primary purpose is to enable early detection of mobility patterns associated with instability. In addition, we seek to enable automatic assessment of rehabilitation outcomes as they relate to activity at home, as well as interventions that more accurately target real world behavior.

Kinematic analyses of sit to stands have effectively been used to quantify postural abnormalities [3], the impact of seating on mobility [4], and the impact of therapeutic interventions. Some kinematics found to distinguish between the sit to stands of young and elderly individuals include the angular velocity of the torso during transitions as well as the position of the base of support relative to the center of mass [5]. Biomechanical researchers have used kinematics to constrain models of momentum transfer during sit to stand [6] and to better understand sit to stands that are likely to result in a fall [7].

Kinematic analyses, however, are typically made in laboratory settings and with commercial motion capture devices [5-7]; such devices often cost as much as \$100,000CAN. Although these devices are clinically common, consistent and precise, they are expensive and not readily portable to homes. In this paper, we explore the clinically utility of affordable and home appropriate motion capture alternatives that use multiple USB web cameras, each of which retails at about \$100CAN.

Our work is related to [12], wherein a single camera was used to explore kinematic differences in sit to stands of young and older adults. Our work builds upon this research in several ways. First, we explore the use of multiple cameras as opposed to a single camera. This provides access to diagnostic kinematics irrespective of the subject's position relative to the camera, and allows for tracking that is reasonably robust to occlusions. Second, we explore the ability of cameras to capture diagnostic kinematics based on movement that takes place in a community setting, not a laboratory. In this setting, backgrounds are complicated, people turn away from the cameras, therapists occasionally intervene to make movement corrections, etcetera.

In the sections which follow, we first describe the kinematic tracking system we have engineered. We then conduct a preliminary test of its ability to capture kinematic data that discriminates between the assessments of balance impaired elders. We currently use expert opinions as our "gold standard" for measurement of balance, as there is no motion capture device available in our target environment.

II. Sytsem Description

Video based motion capture has received a great deal of recent attention from the computer vision and biomechanics community [8, 9] and, in some cases, has proven to operate as accurately as motion capture even without markers [10]. Clinical applications, however, are only just beginning to be explored; examples include posture identification for ergonomic workplace analysis [11], automated stroke assessment [19] and as input to assistive Functional

Electrical Stimulation devices [13].

Vision algorithms used to track the body are as varied as the applications in which they are embedded. For dense and multi-camera stereo applications, iteratively deriving the three dimensional volume of the body from sets of human silhouettes or contours is popular [9]. Reconstructions produced this way may yield more surface detail than is possible with traditional motion capture devices [9]. Volumetric methods, however, are also time consuming, computationally intensive and generally run off-line.

Alternate and comparatively computationally light algorithms employ "blob like" representations of body parts. Three dimensional reconstructions are then based on triangulation of "blob" features, like centroids [14]. While "blob" tracking tools do not recover surface detail well, they allow tracking to take place quickly. In our application, we employ similar "blob-like" body representations. We do this because we ultimately want to facilitate relatively fast analysis of large volumes of movement data from the home.

Our current system includes three Logitech web cameras that record at a rate of 30 frames per second and are synchronized by means of a DirectShow filter. Video is encoded in MPEG4 format, at a resolution of 340 x 280 pixels, and is transferred to a laptop via USB. To make it easier to see parts of the body in small images, we are currently asking subjects to wear a colorful shirt and colorful swatches of fabric on their legs. We expect ultimately to integrate automatic appearance acquisition algorithms [20] into the system, so as to avoid the need for this outfit.

To build three dimensional reconstructions of people, a three step process is employed. In the first step, potential "blobs", or ellipsoids, corresponding to the head, torso and feet are detected. Pixels are defined as members of "blobs" based on their color. More specifically, at each frame a pre-trained quadratic logistic regression is used to separate colors corresponding to limb segments from colors of the background; collections of pixels identified as the appropriate color are then grouped into ellipsoidal "blobs". Color separation functions are trained before tracking begins by a human who manually subjects' torsos, heads and feet in one example image from each Logitech camera.

In the second step, groups of "blobs" are assembled into two dimensional "bodies" in each two dimensional image. To group detected blobs into "body" arrangements, simple heuristics are used. The feet, for example, are constrained to be below the torso while the head is constrained to be above it. All parts of the body, moreover, are constrained to lie within a fixed radius of the prior position estimates for the same parts.

Finally, to create complete three dimensional reconstructions of the body, we triangulate centroids of "blobs" across the three camera views. This generates a set of three dimensional points that correspond to the positions of the head, torso and feet. The complete reconstruction process is illustrated in Figure 1.

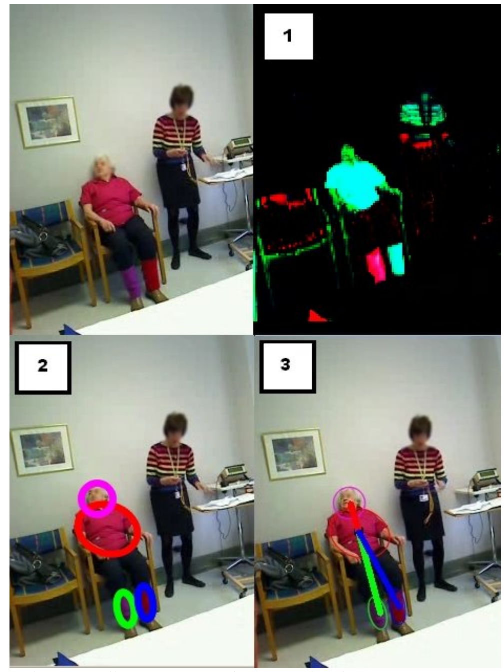

Figure 1. The recording system. Three Logitech USB cameras are used to record subjects as they perform functional activities on balance assessments. At the top left of the figure is an input image from one of the cameras. In the first stage of image processing, likely parts of the body (i.e. head, torso, feet) are detected based on their color. In the second stage of processing, collections of blobs are parameterized as ellipses and grouped to form a two dimensional "body". Two dimensional "bodies" are then triangulated to create three dimensional reconstructions. In the subfigure labeled '3', a 3D reconstruction generated from all camera data has been back projected onto the input image. Faces have been blurred in these images to protect subjects' identities.

III. Methods

A. Experimental Paradigm

Table 1: Subject demographics. The total BBS is the summed score achieved across all "items" on the Berg Balance Scale (range is 0 to 56). The STS BBS score is the score on the Berg item where subjects rise from sitting to standing without use of the arms (range is 0 to 4).

Subject	Age	Total BBS	Sit to Stand BBS	Medical Conditions
1	84	54	4	arthritis
2	79	53	4	none
3	73	54	4	none
4	76	50	3	neuropathy
5	86	42	4	neuropathy

To determine the clinical utility of kinematic measurements made with web cameras, we performed a pilot experiment in which the sit to stand motions of five elderly and balance impaired subjects were recorded. Kinematics were then extracted from recorded video and related to balance assessments from therapists. The goal of the experiment was to determine measurable statistics that significantly correlated with expert opinions of functional health during "sit-to-stands" and which revealed movement strategies (like the use of the arms while rising) that are known to reflect disability [1].

Each of the five subjects were referred by a healthcare professional to participate in an outpatient Falls Prevention Program at a local Toronto hospital. The mean age of the group was 79 years (5.4 years standard deviation) and all provided informed consent. Basic demographics of the group are in Table 1.

All sit-to-stand movements were recorded during intake assessment to the Falls Program. The intake assessment used was the Berg Balance Scale (BBS); this consists of 14 functional movement items that require some balance. Scores are assigned to the "sit-to-stand" item in particular based on use of the arms to rise from the seat, the degree of assistance required, and the perceived overall quality of the motion. The BBS is the standard assessment for the Falls Prevention Program; the only alterations to the program's intake procedure required for this study involved attaching colored fabric to subjects' clothes.

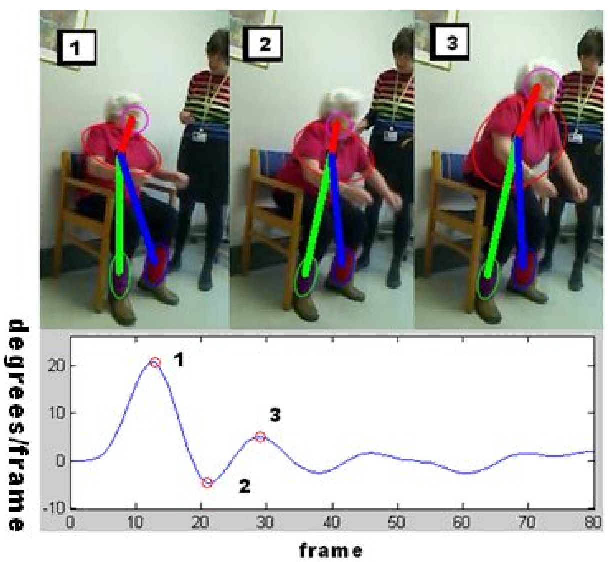

Figure 2. The angular velocity of the torso for one subject during a sit to stand motion. At frame 1, angular velocity is at a peak; the subject is building the momentum required to transfer weight from the chair onto her legs. This velocity slows at frame 2; here, the subject is completing her weight transfer horizontally. Velocity increases again at frame 3, as the subject moves her center of mass vertically to complete the stand.

Video corresponding to each subject's performance of the "sit-to-stand" BBS item was manually extracted. The beginning of each segment was located at the first frame in which movement to rise was visible, and the end of each segment was at the first frame in which subjects were seen to stably stand on two feet. Kinematic data were reconstructed only for extracted video segments. After reconstructing kinematics, all 3d point trajectories were smoothed with a fourth order low pass Butterworth filter. Example kinematic reconstructions from one subjects' "sit-to-stand" movement are illustrated in Figure 2.

From the kinematic trajectories, a variety of mobility

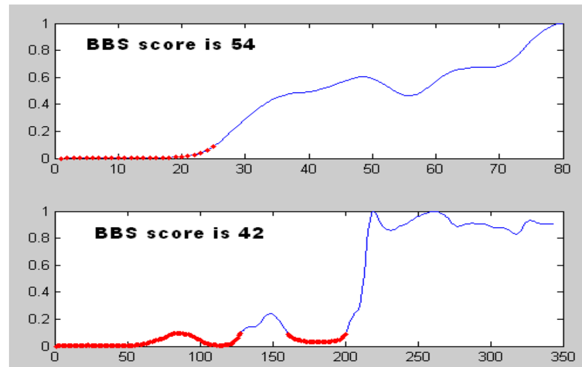

Figure 3. Recorded distance of the head from its start position for a high and low scoring subject. Periods of time where the subject was determined to be on the chair are indicated in red. The subject at the bottom failed to rise on his first effort to stand and fell backwards into the chair. His Berg score is relatively low.

statistics were computed to characterize "sit-to-stand" performance. Statistics were based on prior kinematic studies of sit to stand motions and included the angular velocity of the torso [4, 16], the smoothness of angular velocities, and the time required for to move the body off of the seat [4]. Smoothness has typically been characterized based on frequency dispersions [18] or the sum of squared jerk; we compute smoothness, however, based on the number of "peaks" in recorded velocity profiles. "Peaks" are detected by scanning velocity profiles, and locating spots where the values of profiles are elevated relative to neighbors in time.

To detect the time required to move off the seat, the distance of subjects' heads from their starting positions was computed at every frame. At the last point where the distance was over 10% of its maximum, the subject was said to have left his or her seat. This distance is illustrated for two subjects in Figure 3. To compare between subjects, the time of lift off was normalized with respect to the total time required for the subject to complete the movement.

Finally, statistics were related to expert assessments using Pearson correlations. "Significant" correlations were determined to be those with p-values below 0.05.

IV. Results

In Table 2 we report Pearson correlations between select computed statistics and BBS scores. We report correlations with overall BBS scores as well as with the "sit-to-stand" item in specific. We also report 95% confidence intervals surrounding correlations and p-values.

Table 2: Relationships between measured statistics and BBS scores. The correlations between BBS scores and measured statistics are reported with 95% CIs surrounding correlations. 'BBS Correlations' are correlations with overall BBS scores. 'STS Correlations' are correlations with scores on the "Sit to Stand" item. P-values below 0.05 are indicated in bold.

Statistic	BBS Correlation	P-value	STS Correlation	P-value
Time to rise from the seat	**-0.94 (-1,-0.35)**	**0.02**	-0.2 (-0.92,0.83)	0.75
Variance in torso flexion	0.61 (-0.59,0.97)	0.27	0.54 (-0.65,0.96)	0.34
Mean angular velocity	0.75 (-0.39,0.98)	0.14	0.59 (-0.61,0.97)	0.29
Peaks in angular velocity	-0.73 (-0.98,0.43)	0.16	-0.72 (-0.98,0.45)	0.17

The time required to leave the seat proved to be the statistic most strongly related to functional score; the p-value relating this statistic to overall BBS score was 0.02. Interestingly, this statistic was not strongly related to the score for the "sit-to-stand" item in specific. The range of scores for this particular item, however, was extremely limited in our preliminary subject pool. Mean angular velocities and the smoothness of angular velocities also proved to be strongly, but not significantly, related to overall functional scores. The p-values relating both these statistics to BBS scores were below 0.2.

V. Discussion

Elderly individuals have been found to rise from a chair slowly relative to young individuals, to have less variation in their torso motion and less speed [5, 17]. A decrease in smoothness of torso motion has also been documented among the elderly and balance impaired [18]. In [18], fractal analysis of data from an inertial sensor located on elders' torsos revealed less erratic sit to stand velocities after rehabilitation.

Our preliminary results are consistent with prior analyses and demonstrate the potential to measure well known and clinically meaningful kinematic statistics affordably and in community situations. Vision based tools may therefore be able to perform some quantitative balance assessment in real world settings both economically and effectively. In future work, we will be gathering data from more subjects so as to make more confident correlations. We will also relate our measurements to analyses of stability from standard clinical instruments, like commercial motion capture and force plates.

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