Mining Human Mobility to Quantify Performance Status

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***Abstract*—Human mobility has been studied extensively in various biomedical contexts with applications in clinical rehabilitation, disease diagnosis, health risk prognosis, and general performance assessments. In this paper, we present ATOM-HP (Analytical Technologies to Objectively Measure Human Performance) Kinect: a system to objectively quantify human performance using the Microsoft Kinect as a single camera sensor to capture human mobility. We explore the viability of this non-invasive performance assessment system by studying a cohort of cancer patients undergoing various therapy regimens who are assigned a performance score based on a qualitative clinical test. The ATOM-HP Kinect is a clinically usable system which consists of tools for Kinect, clinical data collection, data quality validation, and mobility feature extraction, which can be used for downstream analysis of performance. Preliminary results based on the clinical case study indicate that ATOM-HP Kinect can quantify changes in kinematic parameters, and that these features are correlated with clinically measured risk factors which could be used for early prediction of diseases, or making decision on treatment modification.**

***Index Terms*—Human mobililty, feature extraction, human performance, motion capture, Microsoft Kinect, healthcare, cancer**

I. Introduction

Assessment of human mobility performance is necessary in many real-world contexts, such as sports analytics, physical therapy, early diagnosis of disease, and military preparedness. Observing human locomotion can provide various important insights about: the process of aging [1], [2], evolution in musculo-skeletal disorders [3], personal lifestyle [4], sports performance [5], [6], rehabilitation [7], prediction and correlation with diseases risk [2], [8], [9], and treatment decisions [3], [10].

In practice, human mobility is usually assessed based on observation of experts (e.g. physicians, coaches, etc.) directly, or specialized equipment providing kinematic or kinetic measurements. However, these methods may be limited in some cases due to human bias, or high cost. For instance, in the practice of oncology, cancer patients' performance is assessed by physicians, using standardized scoring systems. Limitations of these scoring scales have been discussed in [11]–[13], and include lack of reproducibility, difficulty to audit and biases, and can lead to increased risks of death as reported by [14].

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In this paper, we present ATOM-HP (Analytical Technologies to Objectively Measure Human Performance) Kinect - a system to objectively quantify human performance. The ATOM-HP Kinect is a clinically viable system which uses a Microsoft Kinect camera sensor to: i. capture a person's mobility, ii. visualize the human skeletal movement, iii. automatically extract kinematic features from mobility data. The data extracted and pre-processed by ATOM-HP Kinect is suitable for downstream analysis of human performance. Microsoft Kinect's usability has been evaluated in various motion capture (MoCap) systems for different computer vision applications, such as object detection [15], human pose, and motion analysis to perform action recognition [16]. Although the limitations of Kinect based biomechanical assessments have been well documented in gait analysis [17], the cost-benefit ratio of the non-invasive, albeit less accurate, Kinect motion data is still promising. Here, we demonstrate ATOM-HP Kinect in a clinical case study where the system has been setup in four medical centers to analyze the effect of therapy (e.g. chemotherapy, radiotherapy, imunotherapy) on cancer patients' fitness.

The remainder of this paper is organized as follows: in Section II, we present the ATOM-HP Kinect system design, and description of the system components' functionality, Section III provides details of how ATOM-HP Kinect is employed, and used in a clinical setting case study with preliminary analysis results.

II. ATOM-HP Kinect Overview

The ATOM-HP Kinect system (Figure. 1) includes 4 components: (1) the Microsoft (MS) Kinect camera sensor and Skeleton verification tool, (2) Klog tool connected to a secured server with secured File Transfer Protocol (FTP) connection, (3) data export, and (4) feature extraction and visualization.

The workflow of ATOM-HP Kinect is described as follows. A single MS Kinect camera sensor is setup to capture the locomotion of a target subject's entire body. The camera sensor is connected to a laptop that runs the skeleton verification tool. The skeleton verification tool checks whether the captured movement follows the prescribed task standards. For instance, for the timed Get-up-and-go test [18] which is widely used in clinical settings to quantify functional mobility over time, the tool is able to validate if a patient starts the task sitting, then

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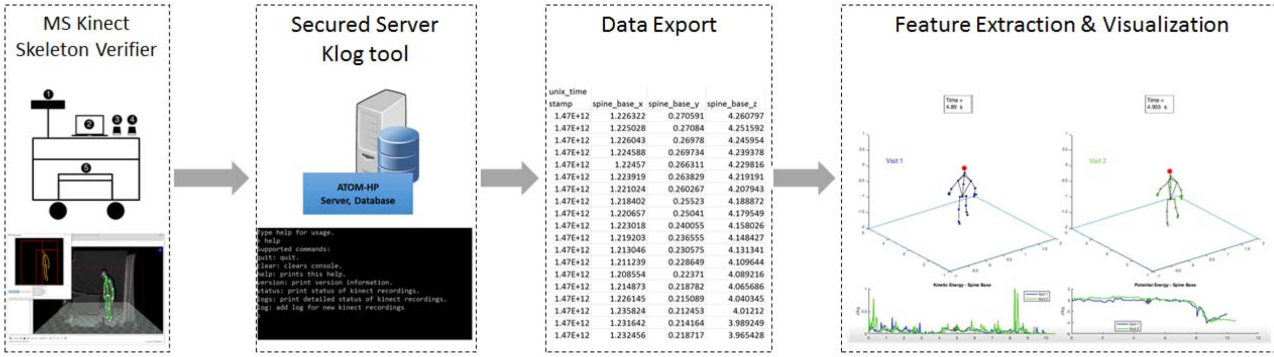

Fig. 1: The ATOM-HP Kinect System consists of four main components: (1) MS Kinect camera sensor and skeleton verification tool, (2) Kinect data log (Klog) tool, and a secured server with secured FTP connection, (3) data extraction, and (4) analysis: feature extraction, and visualization components.

gets up, moves forward towards the camera, and returns to the sitting position. After verification, the recorded movement is saved as a binary file which is uploaded to the ATOM-HP server using a secured FTP connection. ATOM-HP Kinect also includes a Klog tool that allows users to add descriptive information of the recorded movement, such as: subject's information, date and time, notes on the recording files, etc. The Klog information is stored in a secured database on the ATOM-HP server. Additionally, the recorded binary file is then exported into a comma-separate values (CSV) format that contains the time series of 25 human joints' movement data. For the data exploitation, we perform feature extraction, and also, visualize the skeleton data. The details of each ATOM-HP Kinect component are provided in the following sections.

A. *System Setup & Deployment*

The MS Kinect is a motion sensing device primarily used for gaming, and is adapted for clinical use here by a hardware solution which secures the Kinect to a tripod which in turn is mounted on a wheeled cart. The cart is further used to support the laptop, and external hard drives (HDs) which are required to operate the Kinect Studio, and other software used. To maintain reliability of experiments, clinical coordinators performing the experiments are given a tape measure and painter's tape to verify the distance between the patient's starting position and the camera. Furthermore, instructions are documented in a manual which is also provided to the clinical coordinators and other ATOM-HP Kinect operators.

B. *Data Quality Verification & Storage*

Raw Kinect files are large binary proprietary format files containing Kinect raw sensor data. We provide external HD for backup, and set up a secure File Transfer Protocol (FTP) to allow study coordinators to upload the files at the end of day as the files are too large for immediate upload during, or immediately after acquisition. Two tools are provided for data acquisition and monitoring. The first tool, "Kinect Verifier" (Figure 2a), allows the study coordinator or operator to visually monitor the quality of the recording, and generates a summary of the recording quality (e.g., whether the subject is at the correct start/end location). The second tool "Klog" (Figure 2b), is used to manage metadata (e.g., subject id, raw Kinect filename, size, checksum, document recording issues) that is written on the data collection server and made available on a dashboard to monitor data acquisition.

(a) Kinect Verifier tool

(b) Klog tool

Fig. 2: Software developed for clinics in ATOM-HP KINECT

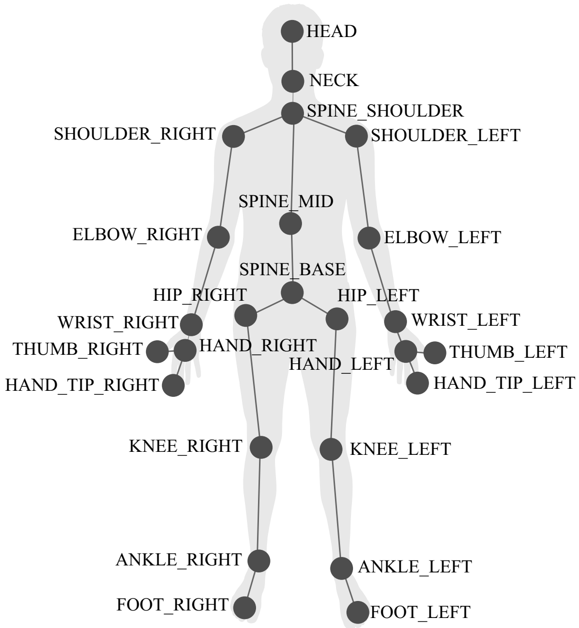

Fig. 3: 25 joints of MS Kinect human skeleton. The left, and right side of skeleton are swapped as the same with how MS Kinect proceeds with human bodies.

C. Data Export

In order to employ downstream machine learning algorithms and data analysis,the raw data has to be extracted and converted to a usable format. The MS Kinect raw files are large binary format files containing a variety of sensors streaming data (depth, RGB, Infrared). We use the MS Kinect software development kit (SDK) to extract skeletal movement data for further analysis. The extracted data is a set of 25 three-dimensional time series corresponding to the displacements of 25 body joints shown in Figure 3. We build the Kinect Skeleton Extractor tools, and use it in conjunction with the metadata from Klog to automatically generate comma-separated values (CSV) format files of exported data containing human skeletal movement of patients, and corresponding filenames following a standard naming convention. Note that this is needed to avoid clerical naming errors between MS Kinect recordings, and Klog metadata. Additionally, tools to visualize these data are also developed to facilitate post-processing, and analysis.

D. Feature Extraction & Visualization

Biomechanical characterization of motion is imperative for understanding health and performance status, and the Kinect system has been used to perform gait analysis using rotational displacements [17], joint movement analysis for rehabilitation applications [19], and upper extremity analysis using joint positions and angles [20]. Consequently, we focus on extracting a comprehensive list of kinematic features to obtain a complete signal of the biomechanical performance, and to allow unbiased downstream mining. After three-dimensional displacement time series of 25 skeletal joints are extracted from the MS recordings, these raw displacements $(\vec{x}_i, \vec{y}_i, \vec{z}_i)$ are used to extract further dynamical features.

TABLE I: Extracted Features

Feature	Formula
Displacement	$(\vec{x}_i, \vec{y}_i, \vec{z}_i), i \in [1, 25]$
Translational velocity	$\left(\dot{\vec{x}}_i, \dot{\vec{y}}_i, \dot{\vec{z}}_i\right), i \in [1, 25]$
Translational acceleration	$\left(\ddot{\vec{x}}_i, \ddot{\vec{y}}_i, \ddot{\vec{z}}_i\right), i \in [1, 25]$
Rotational displacement	$\vec{\theta}_{ij} = \tan^{-1}(\Vert\vec{a}_i \times \vec{b}_j\Vert / \vec{a}_i \cdot \vec{b}_j)$
Rotational velocity	$\dot{\vec{\theta}}_{ij}$
Rotational acceleration	$\ddot{\vec{\theta}}_{ij}$
Specific potential energy	$g\Delta\vec{z}_i, \Delta\vec{z}_i = \vec{z}_i - \vec{z}_i(t = t_1)$ $, i \in [1, 25]$
Specific kinetic energy	$\frac{1}{2}\vec{v}_i \cdot \vec{v}_i, \vec{v}_i = \sqrt{\vec{x}_i^T\vec{x}_i + \vec{y}_i^T\vec{y}_i + \vec{z}_i^T\vec{z}_i}$ $, i \in [1, 25]$

The extracted features (Table I) include: translational kinematics, rotational kinematics, potential energies, kinetic energies, flexion-extension angles, and anatomical plane angles (e.g. angle between torso, and sagittal axis). Velocities, and accelerations are calculated using the mean-value theorem, and angles are computed using directional vectors, and the inverse tangent formula ($\theta = \tan^{-1}(\Vert\vec{a} \times \vec{b}\Vert / \vec{a} \cdot \vec{b})$). For example, to compute sagittal angle, the directional vector $\vec{a}$ points from spine base to the forward horizontal direction, and the directional vector $\vec{b}$ originates at the spine base and points to the spine shoulder joint. While the features in Table I are time series features, general statistical properties of each time series (e.g. min, max, standard deviation, etc.), and task completion times can also be extracted. The ATOM-HP Kinect supplements displacement features with additional biomechanical variables which can then be studied using machine learning and statistical methods. We hypothesize that these biomechanical features can explain qualitative performance assessments, and explore the ability of the ATOM-HP Kinect system to test this assumption in a preliminary clinical case study.

III. Demonstration

A. Case Study

The ATOM-HP initiative consists of two experimental arms: a clinical cohort comprised of 60 prospective patients from four medical centers (Los Angeles County + University of Southern California Medical Center, USC Norris Comprehensive Cancer Center, and Hoag Hospital Newport Beach), and a prospective military cohort of 60 war-fighters. The ATOM-HP Kinect has been developed to analyze the effect of therapy (e.g. chemotherapy, radiotherapy, immunotherapy) on cancer patient fitness in the clinical setting, and to detect performance changes of war-fighters over the course of physically demanding tasks.

We focus our demonstration on the preliminary results from the clinical application of ATOM-HP Kinect where oncologists assign treatment regimens based, in part, on their qualitative assessment of a patient's fitness during supervised tasks performed at the clinic. Each patient is assigned an

Eastern Cooperative Oncology Group (ECOG) score([21], [22]), which categorizes patients into 6 fitness groups (0: fully active, 1: ambulatory, 2: no work activities, 3: partially confined to bed, 4: totally confined to bed, 5: deceased). Due to the qualitative nature of ECOG score assignment (Table II) in current medical practice, the ATOM-HP Kinect has been designed to quantify the performance of the clinically supervised tasks, with the ultimate goal of linking task performance to quantitative measures of fatigue, and fitness. Here, we demonstrate ATOM-HP Kinect being employed in the clinical setting to track the performance of patients performing a walking task. Specifically, the video demonstration [1] shows a patient performing a task which consists of the patient walking towards a target approximately 8 ft from the starting point before returning back to the original position. Two examples of extracted features are plotted alongside the animated patient skeletal data.

TABLE II: ECOG scale [22]

Grade	Performance Status
0	Fully active, able to carry on all predisease activities without restriction
1	Restricted in physically strenuous activity but ambulatory and able to carry out work of a light or sedentary nature. For example, light housework, office work.
2	Ambulatory and capable of all self care but unable to carry out any work activities. Up and about more than 50% of waking hours.
3	Capable of only limited self-care, confined to bed or chair 50% or more of waking hours.
4	Completely disabled. Cannot carry on any self-care. Totally confined to bed or chair.
5	Dead

B. Post-processing

The system is able to capture the movement of 25 anatomical joints over the course of the task, and the corresponding 3-dimensional (x,y,z) time series are de-identified, and stored in the database for downstream analysis. The mean frame-rate of the Kinect motion captures is 24.1 fps ($\sigma = 5.99$), calculated from 56 motion recordings of 28 patients performing the walking task. Task recordings are segmented manually to capture only the active walking portion of the task, and alterations in the Kinect camera orientation due to human error are overcome by performing a coordinate transformation such that each repetition is performed on a level plane.

C. System Reliability

To test the reliability of the ATOM-HP Kinect system, we compare repetitions of the task performed on the same clinical visit (before therapy), and repetitions performed across visits (visit 1: before therapy, visit 2: after therapy). Similarities between time series extracted from a pair of repetitions is calculated using the Dynamic Time Warping (DTW) distance [23]. Figure 4 shows the DTW distances for five types of features between repetitions performed on the same visit (green), and between repetitions performed across visits (red) for a subset of $n = 10$ patients. Only the spine base acceleration (Figure 4A), kinetic energy (Figure 4B), and potential energy (Figure 4C) have been shown because the spine base time series are comparatively less noisy due to the stable nature of this anatomical joint. The standard deviation in the DTW distances between same day repetitions are less than those between across visit repetitions, particularly for the average of all 3D displacements for the 25 anatomical sites (Figure 4E). This is a validation of the reliability of the ATOM-HP Kinect because the same day repetitions represent a patient with a fixed fitness and fatigue level; therefore, the DTW distance should be lower for repetitions performed during the same clinical visit.

D. Performance Features

The ATOM-HP Kinect system can be used to extract a general list of features (Table I); however, the importance of these features depends on the application. For instance, in the clinical setting described above, patients undergoing therapy may experience a change in weight. The change in weight between visits can be correlated to the DTW distance between each feature extracted from repetitions performed on the first (before therapy), and second (after therapy) visit to identify a subset of most important features. For a set of $n = 26$ patients, the Pearson correlation coefficient between percent change in weight, and the five features shown in Figure 4 are $r = 0.250, 0.247, 0.1167, 0.365, 0.0513$ for spine base acceleration, spine base kinetic energy, spine base potential energy, sagittal angle, and average of all 3D displacements respectively. Therefore, ATOM-HP Kinect can be used to explain existing clinical measurements, and the system also provides an intuitive feature selection process in the clinical setting due to the biomechanical nature of the extracted features.

Furthermore, we correlate for $n = 25$ patients (Figure 5) the same set of sample features with changes in physician assigned ECOG scores assigned during visits before and after therapy. Patients whose ECOG score decreased in the visit after chemotherapy (ΔECOG $= -1$, green) have improved fitness, those whose ECOG scores stay the same across visits (ΔECOG $= 0$, gray) have no discernible change in performance, and those whose ECOG scores increase across visits (ΔECOG $= -1$, red) are considered to have deteriorating fitness. These three patient performance patterns may be learned from the extracted features as shown in Figure 5, as the preliminary results show a relation between change in performance status and change in biomechanical features before, and after therapy.

IV. Conclusion

We demonstrate ATOM-HP Kinect, an integrative tool based on a 3-D camera sensor for capturing, visualizing, and extracting kinematic features for the purpose of analyzing human motion in a clinical environment. A case study based on preliminary clinical data from the ATOM-HP initiative shows the ability of the system to extract features, and the potential

[1] https://www.dropbox.com/s/3dpg1rgyxj55itt/P9_V1_V2_T2.avi?dl=0

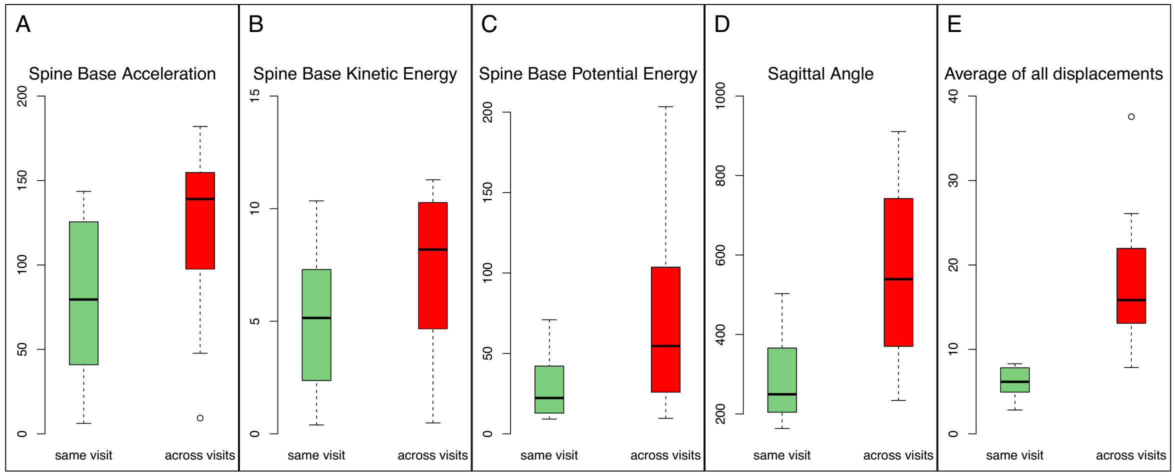

Fig. 4: DTW distances between repetitions performed on the same visit (green) and between repetitions performed across visits (red) for: A) spine base acceleration ($\sigma_{SAME} = 46.6$, $\sigma_{ACROSS} = 54.6$), B) spine base kinetic energy ($\sigma_{SAME} = 3.01$, $\sigma_{ACROSS} = 3.59$), C) spine base potential energy ($\sigma_{SAME} = 19.09$, $\sigma_{ACROSS} = 57.2$), D) sagittal angle ($\sigma_{SAME} = 111.5$, $\sigma_{ACROSS} = 216.7$) and E) average of all 3D displacements of the 25 anatomical sites captured ($\sigma_{SAME} = 1.880$, $\sigma_{ACROSS} = 8.61$).

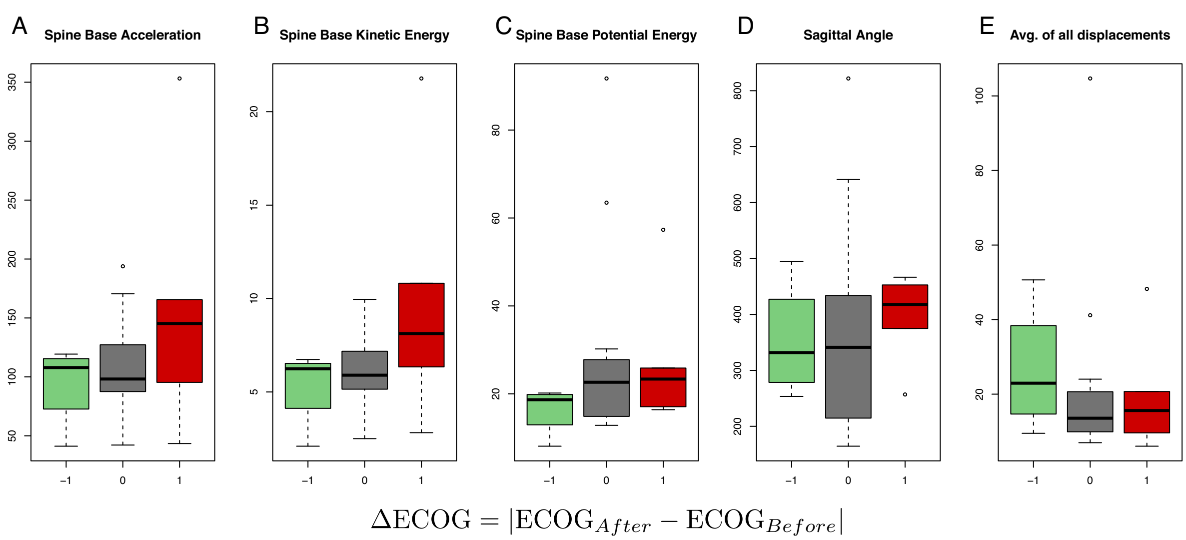

Fig. 5: DTW distances between repetitions performed across visits (before and after therapy) for: A) spine base acceleration, B) spine base kinetic energy, C) spine base potential energy, D) sagittal angle and E) average of all 3D displacements of the 25 anatomical sites captured. Time series for $n = 25$ patients are used here, and the three patient groups represent: i) improved performance (green), $\Delta\text{ECOG} = -1$, ii) no change in performance (gray), $\Delta\text{ECOG} = 0$, and iii) worsening performance (red), $\Delta\text{ECOG} = -1$.

of these features in describing other clinical measurements to quantify patients' performance under therapy. The ATOM-HP Kinect offers a non-invasive method to measure the kinematics required for the biomechanical description of motion and can reliably detect changes in biomechanical features, therefore it is suitable for a variety of applications. Particularly, the ATOM-HP Kinect system has been successfully used by clinical staff without the direct assistance and oversight of engineers or additional personnel, therefore the system offers a promising data collection pipeline for quantitative clinical assessments. Challenges in implementing ATOM-HP Kinect based clinical performance assessments include: the lower accuracy of displacements from the Microsoft Kinect [17], unavailability of appropriate clinical cohorts with labeled conditions to train models, network limitations in transferring large raw Kinect recordings from point of collection to storage databases, and lack of existing work correlating clinical tasks to existing measures of performance, e.g. ECOG scores. Future work will focus on further testing the system and analyzing clinical and military cohort data collected using the the ATOM-HP Kinect system.

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