A Wearable Motion Tracking System to Reduce Direct Care Worker Injuries: An Exploratory Study

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ABSTRACT

Patients with functional disabilities often require assistance to perform basic everyday activities, such as bathing, dressing, and getting into/out of bed. These activities typically require the direct care worker (DCW) to transfer (lift & move) the patient from one location to another. These patient transfers are a common cause of injury to health care workers. In fact, depending on the job site, on average a staggering 4% of DCWs are injured every year. Following proper lifting and transfer procedures can dramatically reduce the risk of injury. This research demonstrates that data collected from motion tracking systems, combined with computational analysis can detect risky patient transfer behavior. Testing of the system occurred as part of an exploratory study in an assisted living facility. Two common types of transfers were tested: transfers from bed to shower chair, and transfers from shower chair to wheelchair. These scenarios were tested on two types of patients, one that was completely disabled, and one that was partially disabled. Two major results were determined from this study: (1) risky patient transfer behavior is common in the assisted living facility, and (2) this behavior can be adequately detected via wearable motion tracking sensors. The longer term research goal is to extend these preliminary results to construct a fully wearable motion tracking system that can be used as a tool to reinforce proper lifting and transfer protocols to reduce work-related injuries among DCWs.

KEYWORDS

Motion tracking; wearable computing; injury prevention; patient transfers

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1 INTRODUCTION

In 2014, DCWs employed by nursing and residential care facilities owned by state governments experienced the second highest incidence rate (7.9%) of nonfatal occupational injury and illness. Most commonly (61%) from injuries related to the lifting, repositioning or transfer of care residents [5]. Only workers in rendering and meat byproduct processing owned by private industry had a higher rate (8.3%) of injury [6].

In addition to the obvious detrimental impact to the DCW and patient, the collateral damage of work-related injuries affects home care organizations, the health care system and the financial community. For the worker and the home care organizations, injuries induce worker shortages and high turnover, in turn introducing recruitment and retention problems. Although workers' compensation provides medical care, rehabilitation, and cash benefits for workers who are injured on the job or who contract work-related illnesses, studies have consistently concluded that various systems-including the US Bureau of Labor Statistics and state workers' compensation programs undercount workplace injuries and illnesses up to about 61% [3, 7], suggesting that work-related injuries are vastly under-recognized.

The costs associated with work-related injuries are high. For example, data published by the National Academy of Social Insurance indicate that in 2010, state and federal workers' compensation programs paid $57.5 billion in benefits. Workers' compensation costs to employers were $71.3 billion in 2010; these costs include premium costs and deductibles for insured employers plus benefits paid and administrative costs for self-insured employers.

Previous research suggests that proper training and reinforcement of lifting techniques and body mechanics are the most important factors to reduce injuries. For example, work by Nelson and Baptiste [4] states that, "the chasm between current practice and scientific evidence is huge, when assessing interventions to prevent or minimize the risks associated with patient handling." In other words, it is known that certain interventions and procedures can be effective in injury reduction, but current real-world practice does not match what is known to be effective procedure. Therefore, it is highly likely that proper training, monitoring and reinforcement are the critical elements needed to substantially reduce injury. To be effective, frequent and timely feedback to the DCW is critical in correcting improper behavior [11, 12].

Motion tracking has also been applied in medical settings ranging from automated fall detection [8] to gait analysis [10]. Motion tracking has also been commonly used for medical rehabilitation by providing frequent monitoring of patient movement and identifying appropiate corrections [11, 12]. However, to the best of the authors' knowledge, there has not been any significant published work that leverages full body motion tracking data to automatically assess injury risk for lifting and patient transfers. This provides an opportunity to fill some important gaps in the research, most notably by building a system that identifies and tracks the most important risk metrics, and testing the effectiveness of the system in a real-world environment.

To summarize, the research contributions include:

- Identification of the important motions and behaviors that increases the risk of injury during a patient transfer
- Description of motion tracking system for detecting risky behavior. To allow others to more easily extend and replicate this research, the source code and testing data is released on GitHub under an open-source creative commons license.
- Prototype system was tested with different workers (low vs. high experience levels), patients (partially assisted vs. totally dependent) and transfer settings (bed-to-chair and chair-to-chair).
- Preliminary results that indicate that improper transfer techniques and body mechanics are commonplace, based on initial results from small exploratory study.

Since this work focuses on the feasibility of a wearable motion capture system to assess injury risk, background on motion tracking technology is provided in the next section.

2 MOTION TRACKING PRIOR ART

This section provides a high level overview of the different options available for motion tracking. We will review the three most common approaches for collecting full body motion tracking data: (1) visual markers, (2) high resolutions cameras, and (3) wearable sensors. Additional details and approaches for collecting motion tracking data can be found in work by Zhou and Hu [11].

Visual Markers: There are a few different types of visual system with different limitations. One approach is to put visual markers on the individual being tracked. These visual markers make it easier to detect certain key parts of the body. Since the position of the markers is derived from video analysis, this approach has an advantage over active sensors, in that it does not require any wireless data transmission. However, visual marker methods have a major limitation, since they are unable to detect rotated joints or overlapped body parts [9]. This limitation makes these methods unusable in an environment where the line-of-sight between the camera and the markers is obstructed. For these reasons, a visual marker data collection approach lacks the necessary accuracy and reliability to be a suitable solution for this study.

High Resolution Cameras: Visual motion capture does not specifically require the use of wearable markers. It can also be collected using multiple high resolution cameras and computer algorithms that analyze the video and render a 3D model. Advantages of this approach is that it does not require anything to be worn, which thereby reduces the time and burden for the trackee. However, the two primary disadvantages of this approach are (1) having placement of video feeds in multiple prespectives and (2) intensive computation for rendering the model and reducing error [2]. The infrastructure requirements associated with this approach (significant computing power and camera placement) makes it an undesirable approach for this study.

Wearable Sensors: The advantages of accuracy and reliability of data acquisition outweighs the disadvantages of extra expense and burden of requiring active sensors. Therefore, for this study, we choose to use a non-visual system using wearable sensors. These wearable on-body sensors require strategic placement on major joints (e.g. elbows and knees) and body parts (e.g. head, hands and feet). Although, a variety of approaches exist in the literature, most sensors track relative position and orientation. More specifically, the easiest to use and most cost efficient sensors for full-body motion detection are inertial sensors such as accelerometers and gyroscopes [11]. Wireless data transmission allows for motion capture in near real time to a receiver. The receiver can be located nearby, potentially integrated into the same wearable system worn by the individual being tracked. Additional details on how the data was collected for this study are provided in the next section.

3 DATA COLLECTION

In this study, we collected data both using the wearable sensors and 3D video. Both forms of data collection are shown in Figure 1. The video feed was not used for automated motion tracking, but instead used to manually check the accuracy of the motion tracking data. Instead of using a simple video feed with time referencing, we used depth mapping which provides a coarse 3D model using Microsoft Kinect System. The Kinect system built a rough reference video feed that only shows gross details, while making subjects in the video unidentifiable.

In total, 17 wearable sensors on each participant in order to track the major body movements. Sensors were placed on the forehead(1), pelvis(1), shoulders(2), upper arms(2), forearms(2), hands(2), upper legs(2), lower legs(2), feet(2) and one sensor on the back (1) near the T8 vertebrate. All sensors were Xsens sensors, which uses a wireless system so that study subjects can move freely in the real world while movements are captured in a 3D virtual world. The resulting motion tracking data represented in an avatar using 21 points, as some of the points are interpolated based on the 17 sensor readings. The data was collected over a period of five days in an assisted living facility located near Albany, New York. The amount of time spent on each transfer (including putting on and taking off sensors) was approximately twenty to thirty minutes. The results in this study are exploratory due to the small sample size (seven DCWs, one gold standard for a total of 32 transfers). This is a major avenue for future work identified in Section 6.1.

Data was collected from 7 home health aids that are employed at the assisted living facility (n=7). One individual was used to represent the gold standard on proper transfer techniques. This individual is a licensed physical therapist who has a Doctorate in physical therapy and more than 15 years of experience in the field. Each participant completed a total of 4 transfers. Each participant completed a minimum of 2 transfers per patient. Each transfer was performed with two patients with different levels of functional disability. Two different types of patients were used in this study: partially dependent and completely dependent. The partially dependent individual could somewhat assist in the transfer tasks. The total dependent patient could not assist in the transfer,

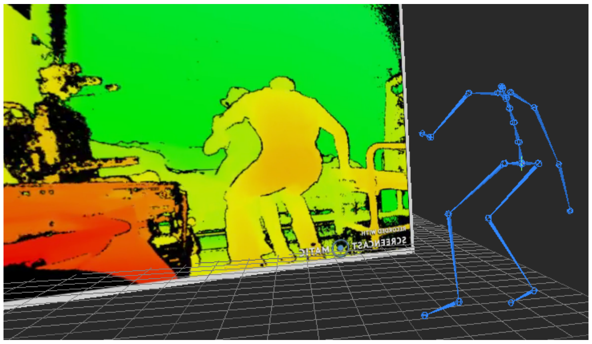

Figure 1: Data collection showing data from 3D video and wearable sensors.

in this case a mannequin was used to represent a total dependent patient. For each patient, 2 transfers were tracked: bed-to-chair and chair-to-chair.

4 INJURY RISK METRICS

Proper lifting and transfers (carrying) techniques have been extensively studied in the literature. Common in the bio-mechanical evaluation of different lifting and carrying techniques are four main features (shown below). Adoption of these guidelines appears, in general, to minimize the stresses on the disc, vertebra, muscles and ligaments of the low back and thus reduce the risk of injury [1]. The list below defines the four metrics that are used in this study to define lower risk vs. higher risk transfers (Figure 2). This list does not include other important individual metrics that are important for accessing injury risk (such as age, weight and height). These metrics will be reviewed and incorporated in our model of injury risk in subsequent work. Results of data collected from these metrics are described in more detail in Section 5.

Figure 2A - Detecting Wide Support Base: Sensors placed on each foot allow computing the support base. This support base is the distance the feet are positioned from each other when lifting or lowering the patient. As shown in Figure 2A the individual with a lower injury risk has legs spread wide and is preparing to lower himself into a squatting position. The high injury risk individual has a narrow support base, which is less stable and is likely to cause the worker to lean forward causing unnecessary large forces to be applied to the back when lifting.

Figure 2B - Detecting Squat: Squatting was fairly easily measured by computing the distance of the pelvis to the floor. In Figure 2B, shows two individuals that are in a squatting position. A proper squat reduces injury risk, since the lifting force is applied using legs and not the back.

Figure 2C - Detecting Good Posture (Upright Stance): Measuring good posture has two metrics: maintaining an upright stance and avoiding twisting the spine. Detecting the upright stance was defined in this study by the amount of lower back bending from a perfect upright position (Calculation shown in Figure 3). In Figure 2C, you can see two examples, a low injury risk where the individual keeps the back mostly upright, and a higher injury risk where the individual bends forward. We measure the amount of bending compared to a perfect upright position of the L5 and T8

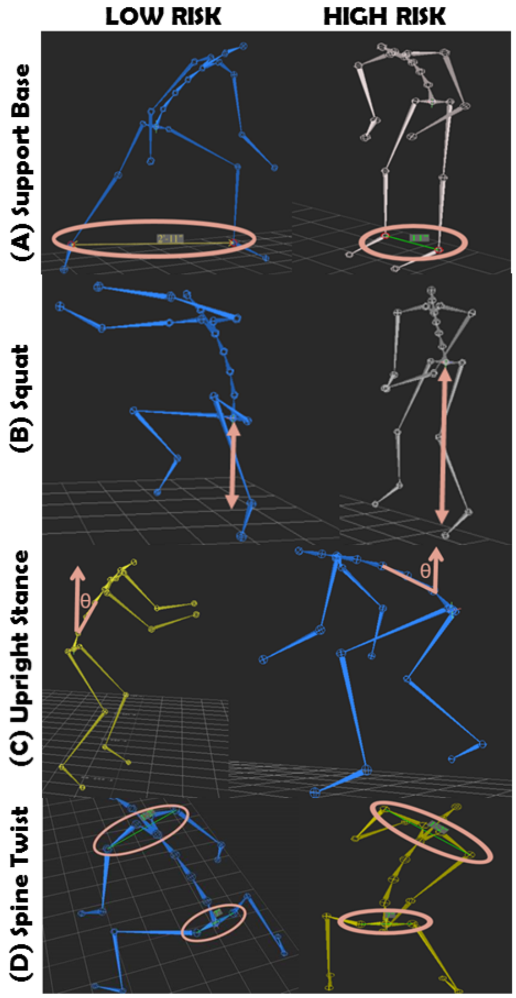

Figure 2: Low vs. high risk motions for each metric.

vertebrate. The L5 and T8 vertebrate were chosen, since lower back injuries are the most common type of DCW injury.

Figure 2D - Detecting Good Posture (Avoid Spine Twist): To detect spine twist, we observe the position of two line segments based on the left & right hip, and the left and right shoulders. As shown in Figure 2D, we can use the control points that define the shoulders and the hips to generate two line segments. Twisting of the shoulders relative to the hips is associated with a higher injury risk. Figure 4 shows how to compute the degree of spine twisting. The shoulder line segment is defined by two points, the left shoulder S_L and the right shoulder S_R. Similarly, the hip line segment is defined by two points the left hip H_L and the right hip H_R. For each line segment, the midpoint is calculated (S_{mid} and H_{mid}). The midpoints are used to correct the positions of the shoulder and hip, in order to calculate the degree of spine twist. In particular, a translation occurs to move the shoulder line segment midpoint to be equal to the position of the hip midpoint. At this point, it's a simple calculation to measure the spine twist angle.

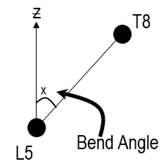

Figure 3: Upright stance metric is the angle of the lower back (L5-T8 vertebrate) compared a perfect upright position.

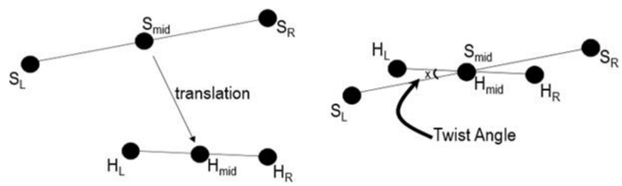

Figure 4: Spine twist metric is the angle between the hips and the shoulders.

5 RESULTS

This section documents the results from our exploratory study that took place over the course of 5 days in an assisted living facility. These results provide useful insights and opportunities for future work which are described in Section 6.1. Of particular interest in this section is the comparison of the results of the DCWs to the gold standard. Please recall that the gold standard is the highly experienced physical therapist with a Doctorate in physical therapy and over 15 years experience. The DCWs and the gold standard are compared based on different types of patients (partially able to assist in the transfer / totally dependent) and two different types of transfers (bed-to-chair / chair-to-chair). The units are in meters for the support base and squat metrics, and in degrees for the upright stance and spine twist metrics. A lower value indicates a lower injury risk, except for the wide support base metrics.

It's important to understand how the values in this section are calculated. As an example one of the metrics (spine twist) over a complete transfer is shown in Figure 5. Note that the transfer is broken out into 5 discrete steps. Injury is most likely to occur during the stages where weight is being lifted or carried (i.e. the stages: lift, transfer, stand-sit). Therefore, we are specifically focused on those three stages, since that defines the time period where increased forces are being placed on the workers' spine and lower back. The graph shows a particularly large and risky spine twist as the worker lowers the patient from a standing position to a sitting position. In other words, the work violated the "good posture" requirement for a safe lift and is therefore at a higher risk for injury. Quantitatively, this metric is assigned a very high value of 73 degrees, since that is the maximum degree of spine twisting during the lift, transfer and stand-sit stages.

In the overview table (Table 1), the gold standard is shown to have consistently better metrics, which indicate patient transfers that have a lower injury risk. This overview table aggregates results from both types of patients (totally & partially dependent). The numbers are averages, using 28 DCW transfers and 4 gold standard transfers. Recall from the previous section that a lower number indicates reduced risk behavior for all metrics, except for support base. The most striking different between the DCWs and the gold standard are the wide support base and spine twist metrics (highlighted in Table 1). The least difference was in the maintaining an upright stance where there was little difference between the two groups. A sizable difference is noted in the "squat" metrics, showing that the gold standard was more likely to lift with legs rather then his back.

Tables 2 & 3 break out the results based on the type of patient. Table 2 depicts the results of a partially dependent patient, while table 3 shows the results of a totally dependent patient. For almost all the metrics across both tables, the gold standard demonstrated a significantly reduced injury risk compared to the DCWs. These results indicate that unsafe patient lifting and transfer behavior is common in the assisted living facility.

Table 1: Overall

Metric	To / From	DCWs	Gold	Diff
Support Base	Bed-to-Chair	0.40m	0.83m	-0.43m
Support Base	Chair-to-Chair	0.37m	0.65m	-0.28m
Squat	Bed-to-Chair	0.80m	0.53m	-0.27m
Squat	Chair-to-Chair	0.84m	0.73m	-0.11m
Upright Stance	Bed-to-Chair	55.95°	55.79°	-0.20°
Upright Stance	Chair-to-Chair	50.83°	45.19°	-5.64°
Spine Twist	Bed-to-Chair	40.84°	29.53°	-11.31°
Spine Twist	Chair-to-Chair	40.67°	21.22°	-19.45°

Table 2: Partially Dependent

Metric	To / From	DCWs	Gold	Diff
Support Base	Bed-to-Chair	0.42m	1.00m	-0.58m
Support Base	Chair-to-Chair	0.38m	0.55m	-0.22m
Squat	Bed-to-Chair	0.75m	0.37m	-0.38m
Squat	Chair-to-Chair	0.83m	0.69m	-0.14m
Upright Stance	Bed-to-Chair	55.17°	67.87°	+12.70°
Upright Stance	Chair-to-Chair	52.68°	40.45°	-12.23°
Spine Twist	Bed-to-Chair	41.01°	42.65°	+1.64°
Spine Twist	Chair-to-Chair	49.67°	18.29°	-31.38°

Table 3: Totally Dependent

Metric	To / From	DCWs	Gold	Diff
Support Base	Bed-to-Chair	0.38m	0.66m	-0.27m
Support Base	Chair-to-Chair	0.36m	0.76m	-0.40m
Squat	Bed-to-Chair	0.85m	0.69m	-0.16m
Squat	Chair-to-Chair	0.85m	0.76m	-0.09m
Upright Stance	Bed-to-Chair	56.7°	43.70°	-13.03°
Upright Stance	Chair-to-Chair	49.28°	49.92°	+0.63°
Spine Twist	Bed-to-Chair	40.67°	16.51°	-24.16°
Spine Twist	Chair-to-Chair	33.17°	24.16°	-9.01°

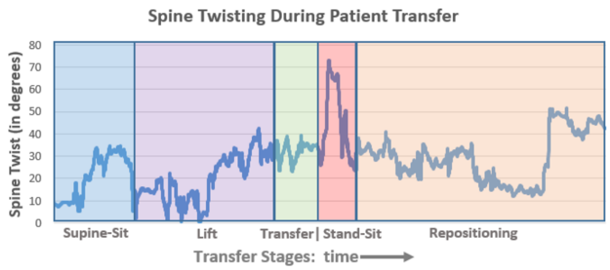

Figure 5: The amount of spine twist during all stages of patient transfer. The worker in this scenario significantly twisted their spine while lowering the patient into a chair.

6 DISCUSSION

6.1 Limitations & Future Work

The study was developed to determine the feasibility of detecting risky lifting and transfer behaviors and to determine requirements for building a wearable system. Based on our initial results, several exciting and important areas of future work have been identified (shown below).

- **Sample Size:** Results in this study are exploratory and have a small sample size (seven DCWs, one gold standard worker and a total of 32 transfers). A larger sample will make more conclusive claims.
- **Completely Automated System:** Development of an algorithm that takes the risk metrics identified in this study, along with patient information (e.g. age, sex, height, and weight) and computes a single estimate of the injury risk.
- **Generalizable Solution:** The approach described in this study was built and tested for the specific purpose of detecting injury risk during patient transfers. However, it is the authors' belief that the approach is generalizable and can be applied in almost any situation in which a person is lifting objects.
- **Detection of Lifting/Transfer Stages:** Automatic detection of lifting and transfer stages, which might require integration with weight (load sensors) to identify when a worker is carrying significant weight.

Our future work seeks to address the challenges above, as we strive towards development and testing of a wearable system for detecting injury risk alongside development of injury prevention procedures.

6.2 Open Source Code

Python source code, sample test data and additional technical documentation are available under GitHub. Other researchers are encouraged to extend this work, suggest enhancements and/or contribute to the source code with additional features and software fixes. To encourage maximum use of this work, this source code is released under the Creative Commons license.

7 CONCLUSIONS

Direct care workers are injured at astonishingly high rates. The majority of these injuries are back injuries that result during patient lifting or transfers. These injuries result in higher worker turnover, increase healthcare costs, and jeopardize the health and safety of both the workers and patients. Wearable technology has matured to the point where it is feasible to mount sensors to automatically detect improper lifting and patient transfer techniques. This study gathered initial results on the feasibility and usefulness of a wearable motion tracking system for alerting workers and supervisors when workers are risking injury based on lifting and transfer movements. Initial results of this exploratory study indicate that workers are often engaging in unsafe practices, which were captured by motion tracking sensors. The preliminary evidence is encouraging and indicates that a wearable motion tracking system could be an effective new tool in injury prevention.

8 COMPETING INTERESTS

The authors have declared that no competing interests exist.

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