Detecting the Hazards of Lifting and Carrying in Construction through a Coupled 3D Sensing and IMUs Sensing System

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ABSTRACT

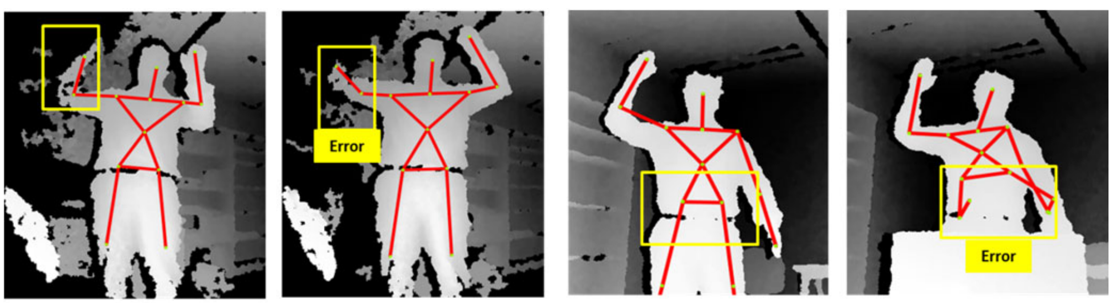
Construction companies in Hong Kong suffer huge losses due to labor fatalities and injuries. More than 25% of all of the injuries and fatalities in all industries in Hong Kong are caused by the construction industry. Different from the U.S., whose top injury cause is fall to lower level for fatal injuries (34%) and nonfatal injuries (23%); the most frequent type of injuries in Hong Kong is lifting and carrying (19.2%). Recently, automated 3D sensing systems (Kinect) have been employed to identify motion related hazards to improve construction safety condition. However, limitations (such as extreme light conditions, occlusions and misrepresentations) of 3D sensing systems hinder its application in engineering practices. To resolve those limitations, this research proposed a coupled system, which integrates and synchronizes the Kinect with Inertial Measurement Unit (IMUs). With the help of the coupled system, IMUs could uninterruptedly collect motion data (accelerations and angular rates) even under extreme light conditions or under occlusions; while Kinect could provide a reference system for IMUs to construct postures. The whole sensor network will be able to capture complete and reliable data, even if Kinect fail to work properly. Moreover, the proposed coupled system will also promote other human related research, such as productivities and labor tracking.

INTRODUCTION

The construction industry has one of the poorest safety records of all of the industries in Hong Kong. There are more than 275,000 employees in the construction industry in Hong Kong, and more than 69,000 employees do onsite manual labor (HKCSD 2012). In 2012, there were 3,160 injuries and 24 fatalities in the construction industry; this accounts for 25.2% of all accidents in all industries in Hong Kong (HKOSH 2013). Furthermore, more than 70% of the accidents were related to labor activities (HKOSH 2013). It has been demonstrated that workplace safety can be significantly improved if workers are provided with warnings and feedback (McSween 2003). However, due to the dynamic and unpredictable nature of construction environment and labor (Levitt and Samelson 1993), it is extremely hard to identify onsite hazards and provide feedback. The traditional approach is onsite observation, but it is a time-consuming and inefficient process that heavily relies on human observation and summarization (Laitinen et al. 1999). Self-reported exposure to construction hazards may be considerably biased, and observations are less accurate than technical measurements, which, in general, are highly accurate and precise (Buchholz et al. 2008; Hansson et al. 2001; Van Eerd et al. 2009). Starting from 2012, many researchers begin to adopt 3D sensors or depth cameras (Han et al. 2012; Rafibakhsh et al. 2012; Weerasinghe et al. 2012) as technical measurement tools to automatically detect construction jobsite hazards. Although this solution could dramatically improve detecting efficiency, it has its own limitations, which have hindered their implementation in real engineering practice, such as constraints on light conditions, occlusion, and misrepresentation (Meng et al. 2012). However, because of the inefficiency and inaccuracy of traditional manual hazard detection approaches, automated 3D sensors remain a promising substitutive solution, despite their own limitations. Therefore, a sophisticated system, which can overcome the limitations of existing 3D motion sensing technologies and is able to automatically detect site hazard and unsafe activities, is necessary. This research aims at developing such a system that will provide robust and reliable data for efficiently detecting site hazards and protecting laborers.

BACKGROUND

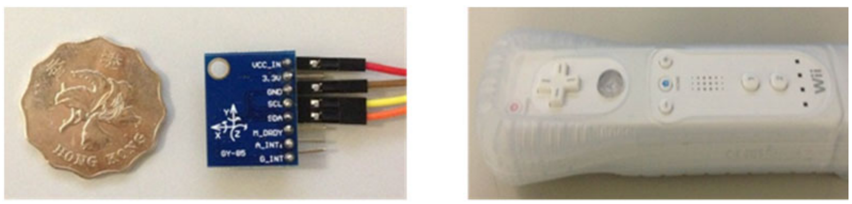
3D Sensors and their limitations. Recent research on construction safety place more attention on automatically collecting worker's motion data through 3D sensors, such as Kinect (Ray and Teizer 2012) and VICON (Han and Lee 2013). Kinect is more popular than VICON academic research, because VICON are expensive and inconvenient to wear during real construction work. Launched by Microsoft in 2010, Kinect is the most widely used 3D in-depth camera in the world. A Kinect consists of one RGB camera, one Infrared camera, one Infrared project, two sound sensors and two motors. Supported by middleware and software packages (i.e., OpenNI, NITE) developed by PrimeSense (Primesense), Kinect is not only able to capture human motions, but also to extract human skeletons. Compared to other motion sensing techniques, Kinect has some advantages for practical applications. First, Kinect is light-weight and portable. It is smaller, lighter, and more user-friendly than other motion-monitoring systems such as RFID, laser scanner or VICON. Second, Kinect is a low cost solution for 3D sensing. Kinect is normally priced at less than USD200 (dramatically cheaper than RFID, laser scanner or VICON), which makes Kinect feasible for commercial practice. Third, Kinect is easy to install and operate. Users can plug Kinect into any computer and only need to run a small piece of code to enable automatic data streaming. For these reasons, Kinect is becoming widely used by researchers. Weerasinghe et al. (Weerasinghe et al. 2012) proposed a tracking framework to locate and analyze workers using Kinect. Using both color and depth data from Kinect, Escorcia et al. were able to recognize and classify workers' activities (Escorcia et al. 2012). Based on ergonomic rules, Ray and Teizer used Kinect to classify awkward postures (Ray and Teizer 2012). Later, Han et al. proposed a stereo vision camera approach and Kinect to detect workers' unsafe movements when ladder climbing (Han and Lee 2013; Han et al. 2012). However, Kinect also has limitations as other 3D sensors, which greatly reduce its suitability for real engineering practices (Meng et al. 2012). The most important limitations are as follows: *(1) Constrained light condition.* When exposed to strong natural lights or indoor lights, the Kinect records inaccurate and incomplete outputs due to the sensitivity of Kinects' IR sensor (see Figure 1a). *(2) Occlusion.* One of most significant weakness of vision based sensors is occlusion. Occlusion happens when the subject that vision sensors are tracking is blocked by other subjects in the environment (see Figure 1b). *(3) Misrepresentation.* Another potential problem is that the videos and pictures captured by Kinect may misrepresent real motion conditions. Videos or images from different environments may look similar under direct observation, when, in fact, the motion dynamics and balance conditions are different. For example, when people are working to keep their balance, their muscle and bone will be slightly adjusted, but the cameras may not be able to observe these adjustments and miss the chance of detecting these potential hazards due to their visual resolutions. Therefore, even if the same object looks the same in two videos or pictures, the motion dynamics and balance conditions could be different. To resolve these limitations, this paper will use Inertial Measurement Units (IMUs) as a calibration and supplementary tool.



(a) Extreme light condition (b) Occlusion

Figure 1. Limitations of Kinect

Application of IMUs in Construction Industry. An IMU is an electronic device that measures and reports motion information in term of accelerations, tilts, and magnetic field directions through its built-in accelerometers, gyroscopes, and magnetometers. Compared to other motion sensors, IMUs have many merits. First, IMUs are portable and wearable. An IMU chip is normally as small and light as a coin (see Figure 2a). This makes an IMU extremely easy to attach to construction vests, clothes, helmets, gloves, or boots. Second, IMUs are economically competitive compared to other sensors. Third, IMUs can be wirelessly connected to computers with a Bluetooth or Wi-Fi shield. By adding a Bluetooth/ZigBee receiver, IMUs are readily connected to many other types of electronic devices. Although whole IMUs have not yet been adopted in the construction industry, the components of IMUs (accelerometers and gyroscopes) have been widely used in various areas. For example, in studies of construction processes, Chae et al. used accelerometers to monitor the health condition of suspension bridges (Chae et al. 2012); Lee et al. used accelerometers to evaluate pavement skid (Lee et al. 2009); and Rinehart and Mooney applied gyroscopes to the study of earthwork compaction. Other researchers have focused on construction vehicle tracking (Lu et al. 2007), activity identification (Cheng et al. 2013; Joshua and Varghese 2010), or equipment management (Ahn et al. 2013). However, IMUs also have the following limitations. *(1) Lack of reference.* As each IMU focuses on the motion variation of a single point, its integration into a reference system is commonly unnecessary and neglected. *(2) Negligence of environment information.* Due to their limited functionality, IMUs omit information about the surrounding environment (such as other objects), which is an important source of hazards. *Given the capacities and limitations of both Kinect and IMUs, a coupled system could create a valuable synergy and overcome the weaknesses of both sensing systems.*



(a) IMU **(b) Wii Remote Plus**

Figure 2. IMUs

METHODOLOGY

Preliminary Experiment Design. To achieve the final objective, we plan to conduct the experiments in two stages. In the first stage, the motion capture mainly relies on the IMUs to test how accurately and sufficiently the IMU alone can provide data for motion analysis. Kinect will be used to register the initial position of each IMU and integrate that into the body skeleton later for the performance evaluation. In the second stage, both IMUs and Kinect will collect data at the same time and later the data accuracy will be improved through a data fusion process. The preliminary experiment in this paper aims at testing the validity of the coupled system at the first experiment stage.

Instead of IMU chips, Wii Remote Plus (Wiimote) (see Figure 2b) was adopted in the preliminary experiment. As a motion game controller launched in 2010 by Nintendo, Wiimote is a 6 degree IMU (3 degrees for accelerometers, 3 degrees for gyroscopes, and a Bluetooth receiver) and a cheap substitution (35 USD) of regular 9 degree IMUs. Before the experiment, we attached one Wiimote on the subject's left hand. During the experiment, the subject was requested to move a paper box from one side (location A) to the other side (location B) of a room and then move the box back to its original location (location A) for three times. Both Wiimote and Kinect were operated at the same time. The sensory data from Kinect was used as a counterpart to see if IMUs could resolve the Kinect's limitations and provide more accurate results.

The Coupled System. The coupled system in the preliminary mainly relies on IMUs to detect the motion of subjects. Kinect is used to automatically register the initial position of each sensing point (skeleton joints), create a reference system for IMUs, and benchmark the data collected from IMUs. The subjects in experiment or real practice could have different physical features, such as height, body shapes and initial posture. It is extremely inefficient to measure the location of each sensing point for every subject. However, Kinect could scan these information and setup coordination systems for IMUs instantaneously. Both Kinect and IMU collect data at the same time, then through the integration of both systems, the movement of body points could be calculated based upon accelerations, titling angles.

In the future experiment, the coupled system will conduct a data fusion process to exploit Kinect sensory data for not only comparison but also higher accuracy. Moreover, the Kinect will be used to detect environmental information (such as moving equipment or obstacles) as well. The coupled system has a great potential for both activities-related hazards detection and human and environment interactions identification in future.

RESULTS AND FINDINGS

Following figure (see Figure 3) shows the captured motion in the preliminary experiment. Although each type of sensors independently collected motion data through its own software platform, the collected data was synchronized through unified computer time. In case of any latency exists in both platforms, the subject was requested to shake his hand quickly (before moving the box) as a signal of initiation of the experiment. At the end of the preliminary experiment, the subject was requested to put down the Wiimote on the ground.

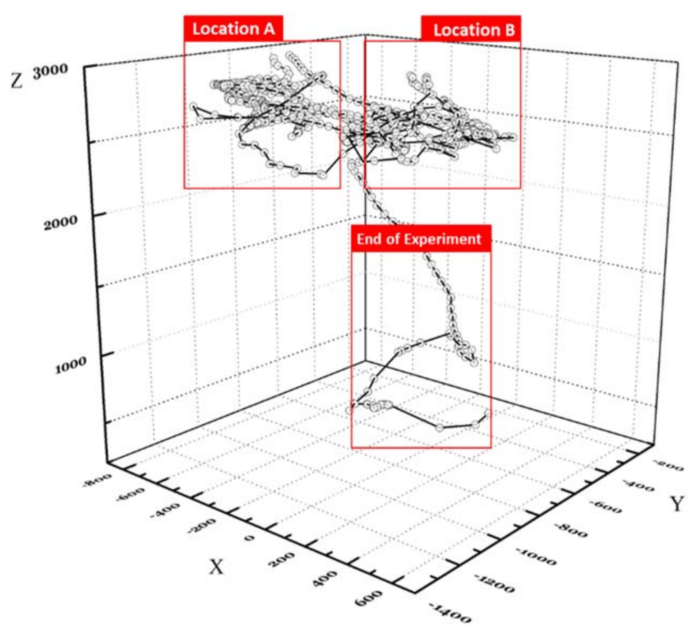


Figure 3. The positions of the subject's left hand captured by Kinect in the preliminary experiment

Following Figure 4 shows the three-axis accelerations collected both from Kinect and the IMU. Through the results we can derive three major observations: (1) Kinect is not as sensitive as IMUs. The hand shaking signals can be easily observed from IMU's outputs, but it is difficult to identify the same events through Kinect data. One explanation for this is the mechanism how both sensors collect data. Motion data collected by Kinect is derived from indirect videos estimation; while IMUs provide a direct monitoring. (2) Compare to Kinect, signals from IMU are more robust. According to the experiment design, between two hand shaking events, the subject moved the paper box from location A to location B and then moved the box back to its original location (location A). During the process of moving the box back, the hand in video was blocked by the box. During these periods, Kinect received unstable signals while the singles from IMU are still stable, especially for x and y axis accelerations. (3) IMU has higher sampling rate. The maximum frequency for Kinect is 30 Hz; while IMU can streaming data more than 50 Hz. Richness in data is extremely helpful to reduce the noise and conduct single processing.

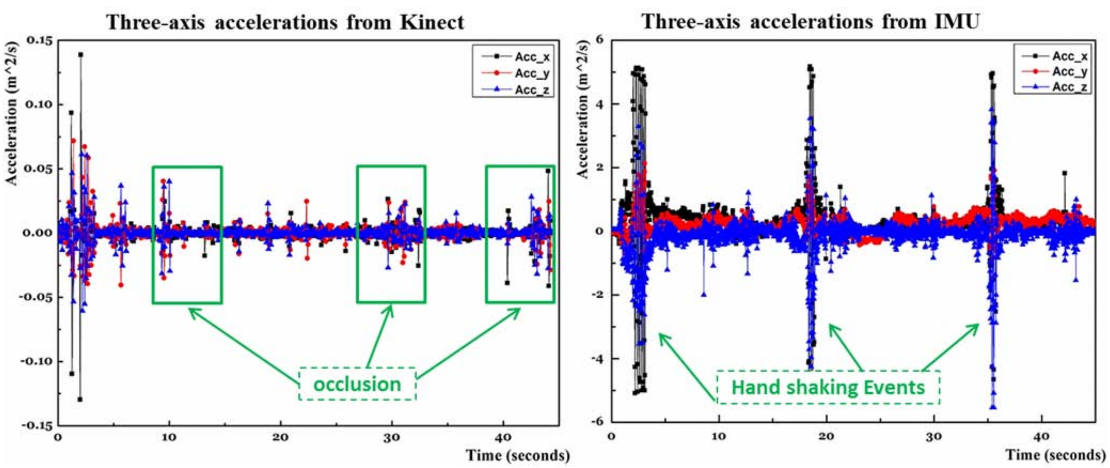


Figure 4. Three-axis accelerations captured in preliminary experiment

Based upon above observations, IMUs show a great potential in overcoming the limitations of Kinect and providing robust data with higher frequency. Therefore, IMUs could be a potential supplement for Kinect in motion detection. Through integrating IMU and Kinect sensors, the coupled system will significantly improve the motion detection accuracy.

DISCUSSION AND CONCLUSION

Conventional observation approaches are inaccurate and time-consuming in construction hazards detection. Although many researchers adopted Kinect as a tool to identify onsite hazards, the use of Kinect is still trapped in the theoretical stage because of its limitations (Meng et al. 2012). In order to resolve these limitations, the coupled system proposed in this research explores the potential of using IMUs. Comparing to Kinect, IMUs show higher accuracy and reliability in the preliminary experiment. Therefore, IMUs have been proved an effective supplement for Kinect or other 3D sensors.

Different from the workers in other industry, the majority of injuries in construction are due to the workers' continuous exposures to awkward postures (postures when the body parts are away from neutral position), which potentially cause injuries. Combined with ergonomics and posture assessment tools, the coupled system could end up with innovative approaches that can give a quick, systematic and quantitative assessment of the postural risks of onsite construction workers.

In future research, we could also utilize Kinect data to improve the accuracy of IMUs through data fusion and to encompass the site environment information. The ultimate system will be able to accurately detect the unsafe behavior and dangerous environment at the same time. The future coupled system will extensively improve the monitoring efficiency and accuracy and automation in construction industry; it could also benefit other human-activities related research, such as productivity management, labor training, and quality control.

In conclusion, this research bridges the research gap that hurdles the application of 3D sensors in construction industry. The coupled system created a synergy by utilizing Kinect to generate reference system and IMUs to detect human subjects' activities. Since there is no previous research on 3D sensor aided safety management in Hong Kong before, this research could have profound impact on Hong Kong's construction industry.

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