Research article

Inertial sensors for motion detection of human upper limbs

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Abstract

Purpose – This paper seeks to present an inertial motion tracking system for monitoring movements of human upper limbs in order to support a home-based rehabilitation scheme in which the recovery of stroke patients' motor function through repetitive exercises needs to be continuously monitored and appropriately evaluated.

Design/methodology/approach – Two inertial sensors are placed on the upper and lower arms in order to obtain acceleration and turning rates. Then the position of the upper limbs can be deduced by using the kinematical model of the upper limbs that was designed in the previous paper. The tracking system starts from inertial data acquisition and pre-filtering, followed by a number of processes such as transformation of coordinate systems of sensor data, and kinematical modelling and optimization of position estimation.

Findings – The motion detector using the proposed kinematic model only has drifts in the measurements. Fusion of acceleration and orientation data can effectively solve the drift problem without the involvement of a Kalman filter.

Research limitations/implications – The image rendering is not undertaken when the data sampling is performed. This non-synchronization is applied in order to avoid the breaks in the continuous sampling.

Originality/value – This new motion detector can work in different environments without significant drifts. Also, this system only deploys two inertial sensors but is able to estimate the position of the wrist, elbow and shoulder joints.

Keywords Inertia, Sensors, Limbs, Motion, Rehabilitation

Paper type Research paper

1. Introduction

Johansson (1973) conducted his famous moving light display psychological experiment to perceive biological motion. In this experiment, he attached small reflective markers to the joints of human subjects, and then tracked these moving markers in order to render the articulated movements. Johansson's work helped the research community to establish a solid theory of human motion detection, which has been encoded in modern optical motion tracking systems. These intelligent systems, based on Johansson's theory, can be used to reliably and accurately measure fast human movements if sufficient markers have been applied and observed by the distributed cameras (Aggarwal and Cai, 1999; Welch and Foxlin, 2002). However, these optical systems can easily suffer from the occlusion problem because the human body is opaque to light. Therefore, alternative means must be explored in order to effectively handle this occlusion problem.

One of the methods that could cope with the occlusion problem is the use of inertial sensor-based systems (Welch and Foxlin, 2002). An inertial sensor does not need to emit/receive light and is light in weight while producing reasonably accurate linear acceleration (via accelerometers) and rates of turn (via gyros) (Braggins, 2004). In many circumstances, inertial sensor-based systems are preferred against other non-optical systems, e.g. mechanical, acoustic, radio or microwave systems, as it gains more robust performance and higher adaptation in the presence of occlusion. Although inertial sensors have promising applications in human motion detection, they have some limitations, i.e. most existing inertial sensors cannot effectively deal with the drift problem in non-laboratory environments (Welch and Foxlin, 2002). They only hold accurate results in a short period (e.g. a few seconds) because of measurement noise and fluctuating offsets if no external reference system is available for error correction.

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27/2 (2007) 151–158

[DOI 10.1108/02602280710731713]

This project was funded by the UK EPSRC under Grant GR/S29089/01. The authors acknowledge Dr Jackie Hammerton for generating Figure 1 and Mr Richard Davis for providing the animation package to show the rendered images. They are also grateful to Xsens Motion Technology and Charnwood Dynamic for considerable support. Valuable comments from anonymous reviewers are also acknowledged.

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This has seriously hampered the real-world application of inertial sensing systems.

Recent research has revealed that a sensor fusion technique is an effective way to reduce drifts in the motion measurements effectively. For example, accelerometers and/or magnetic sensors have been used to correct the drifts in orientation estimated from the gyroscopes (Foxlin, 1996; Luinge and Veltink, 2004; Zhu and Zhou, 2004). Meanwhile, visual cameras can be used to provide a calibration criterion for the inertial estimates. Applications of visual fusion techniques can be found in You and Neumann (2001), Chai *et al.* (2002) and Tao *et al.* (2007). Additionally, other sensor fusion strategies can be developed as a solution to some special problems. For example, fusion of acoustic and inertial sensors was able to provide fast orientation estimation in biology (Gilson *et al.*, 2006).

In general, visual tracking systems hold very good accuracy. However, these systems cannot properly deal with the occlusion problem and lack efficiency because of the requirements of the calibration process and intensive computation. Also, these visual systems are of relatively large size. Magnetic sensing systems can produce significant errors in the vicinity of ferromagnetic materials. This consequence becomes more serious if the magnetometer systems are used in a home environment, where large amounts of ferromagnetic materials are most likely to exist (e.g. metal chairs and computer cases). Kalman filters have been successfully used to fuse gyroscopes, accelerometers, and/or magnetometer signals for measuring relatively slow movements, e.g. head and trunk. Nevertheless, the performance of these filters may be deteriorated if they were applied to detecting much faster movements of lower or upper limbs (Dejnabadi *et al.*, 2006).

In a preliminary study, we designed an inertial sensing-based motion detector for tracking human upper limbs (Zhou *et al.*, 2006c). This motion detector was developed so as to support a home-based rehabilitation scheme funded by the UK Engineering and Physical Sciences Research Council (EPSRC), in which the recovery of stroke patients' motor function through repetitive exercises needs to be continuously monitored and appropriately evaluated. The main challenge in the system design was that this new detector had to work in a less constrained environment (i.e. a home), with the patient permitted to manipulate the system him/her-self. Our system appeared to be compact, portable, and user friendly. Although the clinical evaluation work has not been completed yet, evidence has shown that this motion tracker achieved fast computation and the measurements were stable during the testing period. The most significant technical novelty is that our system only applied two tri-axial inertial sensors but was able to provide position estimates of three joints of the upper limb at the same time (Zhou *et al.*, 2006c). This feature is extremely useful when one has to envisage an economic way to build up a motion tracker.

In this paper, a novel motion tracking prototype will be developed on the basis of the previously designed motion detector, followed by an evaluation against a commercially available optical motion tracker. Healthy subjects were recruited to perform a number of task-related motion tests. These tests, including reach, drink, etc. have been used to aid mobility recovery after stroke in a clinical environment (Tsang and Mak, 2004). An optimal match between the outcomes of these two systems will suggest that the system proposed herein has sufficient supports to work in the domain of home-based rehabilitation, given the modelling constraints as described in later sections. Starting from the next section, we briefly outline the new motion tracking system and then describe the strategy to integrate tri-axial accelerometers, gyroscopes and magnetometers embedded in the used inertial sensors to measure the position of wrist, elbow and shoulder joints. The upper limb is modelled as a skeleton structure consisting of two segments linked by a revolute joint, whereas rigid motion of each segment dominates during the arm motion. This assumption allows us to simplify the modelling work and reduce intensive computation.

2. Inertial sensing-based motion detector

Our motion detector is based on the kinematics of the human upper limb. Therefore, a kinematical model of the arm is generated. To use this model, two inertial sensors placed on the upper and lower arms are used to obtain acceleration and turning rates. The kinematical model then yields the position of the arm. The tracking system comprises the following components: inertial data acquisition and pre-filtering, transformation of coordinate systems of sensor data, and kinematical modelling and optimization of position estimation.

2.1 System configuration

Two commercially available inertial MTx (Xsens Motion Technology, Netherlands) sensors are adopted. Each MTx sensor consists of three orthogonally placed piezo-resistive accelerometers (ADXL202E, Analog Devices), three vibrating beam gyroscopes (ENC03J, Murata), and three magneto-resistive sensors (KMZ51, Philips). In addition, a thermometer is used for thermal data correction when the environmental temperature changes. One of the MTx sensors is placed on the lower arm at a distance of 2 cm away from the wrist joint. The other is fixated on the upper arm at around 5 cm away from the elbow joint. The positions of the sensors are away from the joints in order to avoid poor rotation estimation. These sensors are placed in such a way that the top of the sensors faces away from the trunks when the whole arms are naturally down. Figure 1 shows the system configuration and sensor attachments.

The proposed motion tracking system is implemented in Visual C++ and embedded in a Media PC with a VIA Nehemiah/1.2 GHz CPU. The data link between the computer and MTx sensors is wireless (using Bluetooth devices) via a digital data box called "XBus" where the transmission rate is set to be 115 kbps. The XBus box is placed on the subject's waist and the sensors attached to the arm are battery-powered. This wireless feature enables the subject to carry out comfortable motion exercises. The acquisition rate of the inertial sensors is 25 Hz (the maximum acquisition rate of the system is 100 Hz). Although this rate does not cover all motion speeds of a healthy subject, it is sufficiently fast to capture a stroke patient's motion activities because of the degraded motor function. The determination of this rate was based on a compromise between computational capability and human motion velocity, as a real time process was required. Three-dimensional rendering of the samples is off-line, which allows the patient to replay his/her arm motion without interfering with the on-line sampling and degenerating the quality of the sampled data.

Figure 1 Illustration of system configuration and sensor attachments

2.2 Pre-filtering and calibration

After the raw sensor data have been collected, we applied pre-filtering and necessary calibration to the data. Pre-filtering can remove high frequency noise and low frequency drifts in the turning rates and acceleration (these drifts result from the fluctuating offsets and noise). Calibration is performed at this stage to ensure that orthogonal measurements are validated. For each three-dimensional measurement (acceleration, turning rate or magnetic reading) three one-dimensional sensors are used, and therefore we need to align these sensors to a common orthogonal coordinate system. This alignment/calibration is accomplished using the method reported in Ferraris *et al.* (1995).

In our implementation, an anti-aliasing filter of 50 Hz is applied to the raw data from the accelerometers and gyroscopes so that high frequency components (>10 Hz) in the raw data from the magnetometers are removed, as are low frequency components (<0.05 Hz) in the gyroscopic readings.

3. Estimation of the arm position

In this section, we will calculate the position of three joints of the arm. The rendering flowchart is shown in Figure 2. In order to estimate the position of a human arm in space, we start from the transformation of coordinate systems of the inertial measurements. We adopted the world coordinate system so that the estimated three-dimensional coordinates can be correctly posed. Data fusion of the accelerometers and gyroscopes allows us to provide consistent orientation estimates while diminishing the fluctuating gyroscope offset and measurement noise. Assuming the length of each arm segment has been obtained, we then compute the position of the three joints using a kinematical model combined with the inclination of the upper-arm, based on the estimated orientation from the data fusion. Further technical details appear as follows.

3.1 Localization of the wrist and elbow joints

Inertial sensors can only produce readings related to a sensor body frame. Transforming the measurements from the sensor body frame to the world frame helps us compare the three-dimensional estimation of the proposed system to that of the standard motion detector. In addition, the coordinate transformation works as a low pass filter and further gets rid of spikes or noise from the data produced in the pre-filtering and calibration stage (Figure 2). The detail of coordinate transformation can be found in Zhou *et al.* (2006c).

Once the coordinate transformation has been performed, we introduce the kinematic model for calculating the joint position. The main concern of our motion detection analysis is the orientation estimate that can be fed into the proposed kinematic model (Zhou *et al.*, 2006c). To obtain the rotation of the segments, a strapdown integration algorithm can be adopted (Bortz, 1971); however, noise or small offsets in the measurements of angular velocity will lead to large integration errors. Many available multi-sensor fusion techniques (Foxlin, 1996), have produced promising orientation estimation. Unfortunately, they failed to achieve fast computation due to the frequent use of nonlinear models, i.e. quaternions.

In our approach, we utilized a fast and simple technique to reduce the measurement drift instead of a Kalman filter. If a gyroscope detects a rotation, the linear accelerometers placed on the plane normal to this gyroscope must have corresponding readings. For example, if the three-dimensional gyroscope has valid readings of angular velocity around x-axis, then linear acceleration along y- or z-axis should be changed. From a reverse engineering point of view, the variation of y- or z-acceleration indicates whether or not the angular change detected by the gyroscope is due to the real movements. Hence, if the variation of acceleration in two adjacent time-stamps is larger than $0.3\,\mathrm{m/s^2}$ (empirically), the turning rates are considered valid. The threshold $0.3\,\mathrm{m/s^2}$ is the compromise between the noise removal and signal validation.

It must be pointed out that quaternions need to be used to determine the orientation and to avoid singularity (for a Euler angle set) when the pitch reaches $\pm 90°$. One of the solutions reported in Malis and Chaumette (2002) can be used to solve the singularity problem. Using the estimated orientation without drifts, we can accurately compute the position of the wrist and elbow joints based on the kinematical model

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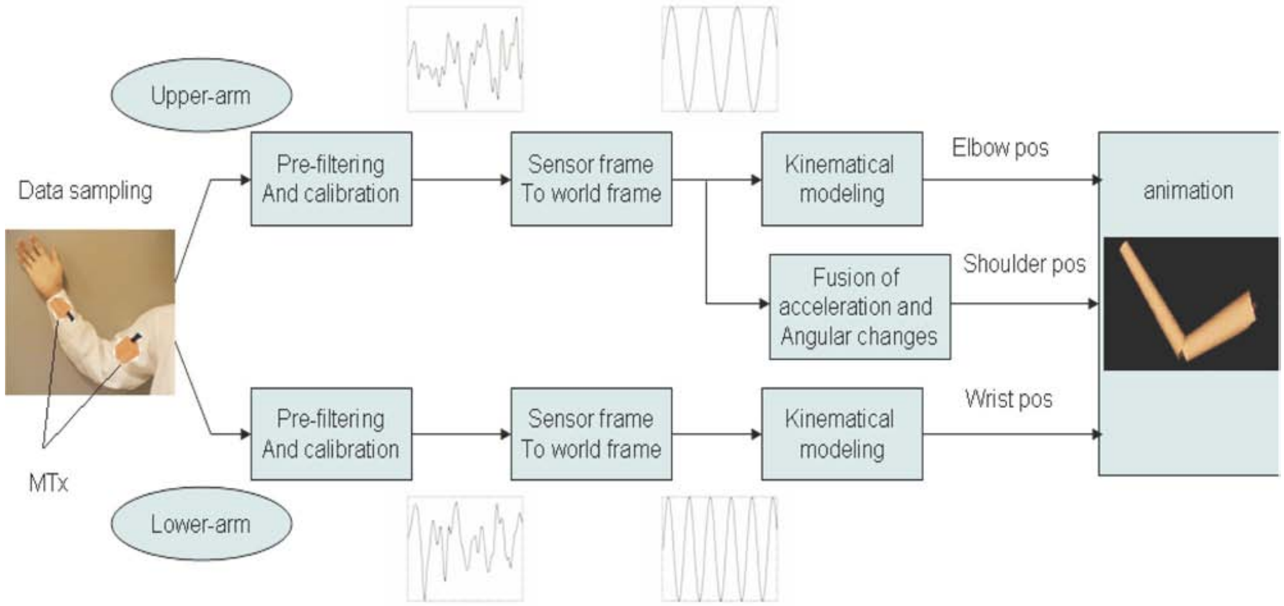
Figure 2 Illustration of the rendering flowchart



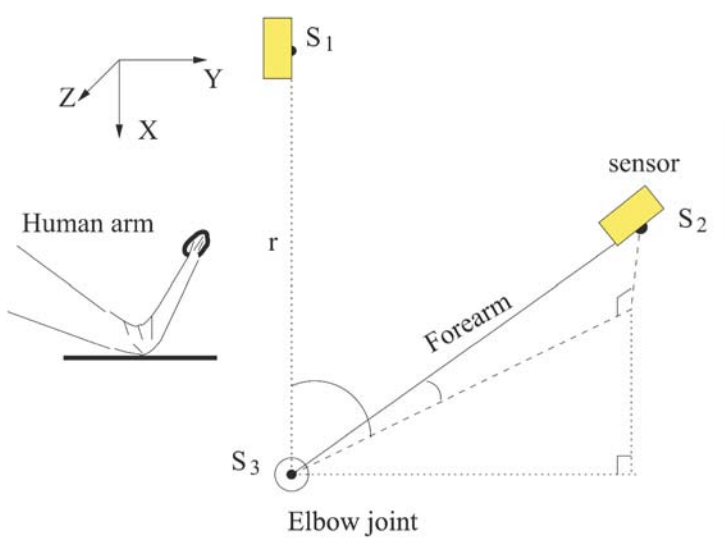
reported in Zhou *et al.* (2006c). For example, the position of the wrist joint is estimated using a geometric model as shown in Figure 3 (estimation of the elbow position is similar to that of the wrist position), whereas the projection of the arm onto different planes is generated using sin or cos functions of rotation angles around individual axes. This projection will lead to the tri-axial coordinates of the arm accordingly. In the presence of large noise or errors we can use a total-variation minimization to obtain better estimation (Zhou *et al.*, 2006a).

3.2 Localization of the shoulder joint

To estimate the position of the shoulder joint, a Lagrangian-based optimization method was reported in Zhou *et al.* (2006c). By solving a Lagrangian equation, the shoulder position can be well determined. Although this method has produced accurate estimates, in some cases (e.g. with large noise) it is not efficient, as the optimization strategy has to run a number of iterations in order to converge. A novel method is proposed here that works very fast and also achieves decent performance.

We have observed that the inclination of the sensor mounted on the upper-arm results from the rotation of the upper-arm around the shoulder joint and the trunk motion around the hip joint. Therefore, shoulder displacements can be extracted by subtracting the inclination using the gyroscopic readings from the one using the acceleration data (a proper calibration for axial alignment between different

Figure 3 Illustration of a geometric model for recovery of the wrist position



sensor measurements is necessary). Under this constraint, we finally have the following approximation for computing the shoulder displacements $\mathbf{D}$:

$$\mathbf{D} \approx L[\sin(\arctan(\mathbf{E}_x)), \sin(\arctan(\mathbf{E}_y)), \sin(\arctan(\mathbf{E}_z))]$$

where ($\mathbf{E}_x$, $\mathbf{E}_y$, $\mathbf{E}_z$) indicate the x, y and z components of the inclination estimate $\mathbf{E}$ that is $\mathbf{E}_A - \mathbf{E}_G$ ($\mathbf{E}_A$ and $\mathbf{E}_G$ stand for the estimated inclination using the acceleration and gyroscopic data, respectively); L is the length of the human trunk (from the shoulder joint to the pelvis). The equation shown above is validated when the human trunk conducts rigid (or pseudo-rigid) rotation around the hip joint. Figure 4 shows example measurements of the shoulder position in the forward leaning exercises. A 10th order low pass Butterworth filter with normalized cutoff frequency 0.1 was applied to the measurements of the proposed system. Clearly, the estimation of the shoulder displacements is close to the ground-truth from a Qualysis motion tracking system.

4. Results

Our new motion tracker has been evaluated by comparing its performance with that of a marker-based motion tracking system CODA (Charnwood Dynamic, UK). The first CODA marker was placed on the ulna of the wrist, the second one was on the brachialis of the elbow, and the third one was placed on the scapula of the shoulder. Immediately before the tests started, the upper limb was at its natural position (straight down).

Our new system has a sample rate of 25 Hz and the commercial system samples at 200 Hz. For direct comparison, an interpolation process was applied to down sample from 200 to 25 Hz. To register the estimates from these two systems we adopt the calibration method of Zhou *et al.* (2006b). Four healthy male subjects (27-40 years old) were invited to participate in the experiments. Their limb lengths were measured before the tests started and then used in the kinematical model.

The experimental work consisted of the following daily activities: reach, drink, flexion-extension and elevation. These ambulatory movements are frequently observed in a home-based environment. Statistical analysis based on the estimates from the subject group will be introduced afterwards.

First, we evaluate the proposed system by observing and comparing its outcomes to the real movements. One example is shown in Figure 5, where the reach test is conducted. The reach test has been commonly used by physiotherapists to improve a patient's coordination capability. Figure 5 shows the effectiveness of arm position estimation system by allowing the reader to make a visual comparison between the true arm positions and the arm positions in the rendered images created by our system.

Another example is the drink test, shown in Figure 6. In such a test, the lower-arm experiences flexion-extension movements so as to improve relevant motion function. Internal rotation to some extent exists in both segments. Figure 6 shows that the rendered images approximate the real motion pictures. Therefore, the new motion tracker enables us to correctly estimate the three-dimensional position of the human upper limb in this complicated motion style.

Second, we tabulate the experimental results of four tests in Table I (each test period lasts 40 s). This is about the differences between CODA's measurements and our system's estimation of arm position in different tests. The position estimation of the wrist, elbow and shoulder joints is taken into account. All the statistical values actually stand for the averaged estimation of the three joints. Mean and root-mean-squares values are calculated, and correlation coefficients between the measurements of CODA and estimation by our system are used to represent the similarity of the two measurements. It is revealed that the proposed motion detector has achieved accurate and stable estimation of the arm position in the overall tests. In addition, empirical evidence shows that the relocation of the sensors (e.g. 1-3 cm away from the original positions) does not lead to significant errors in rotation and position estimation of the upper limbs. This feature permits the system to properly work with different sensor placements.

Figure 4 Measurements of the shoulder position in forward leaning exercises

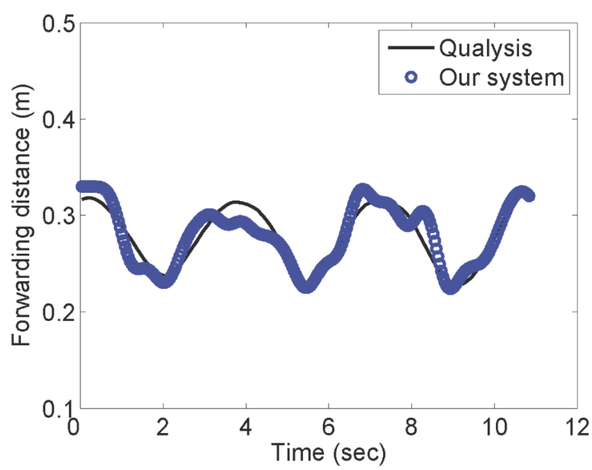
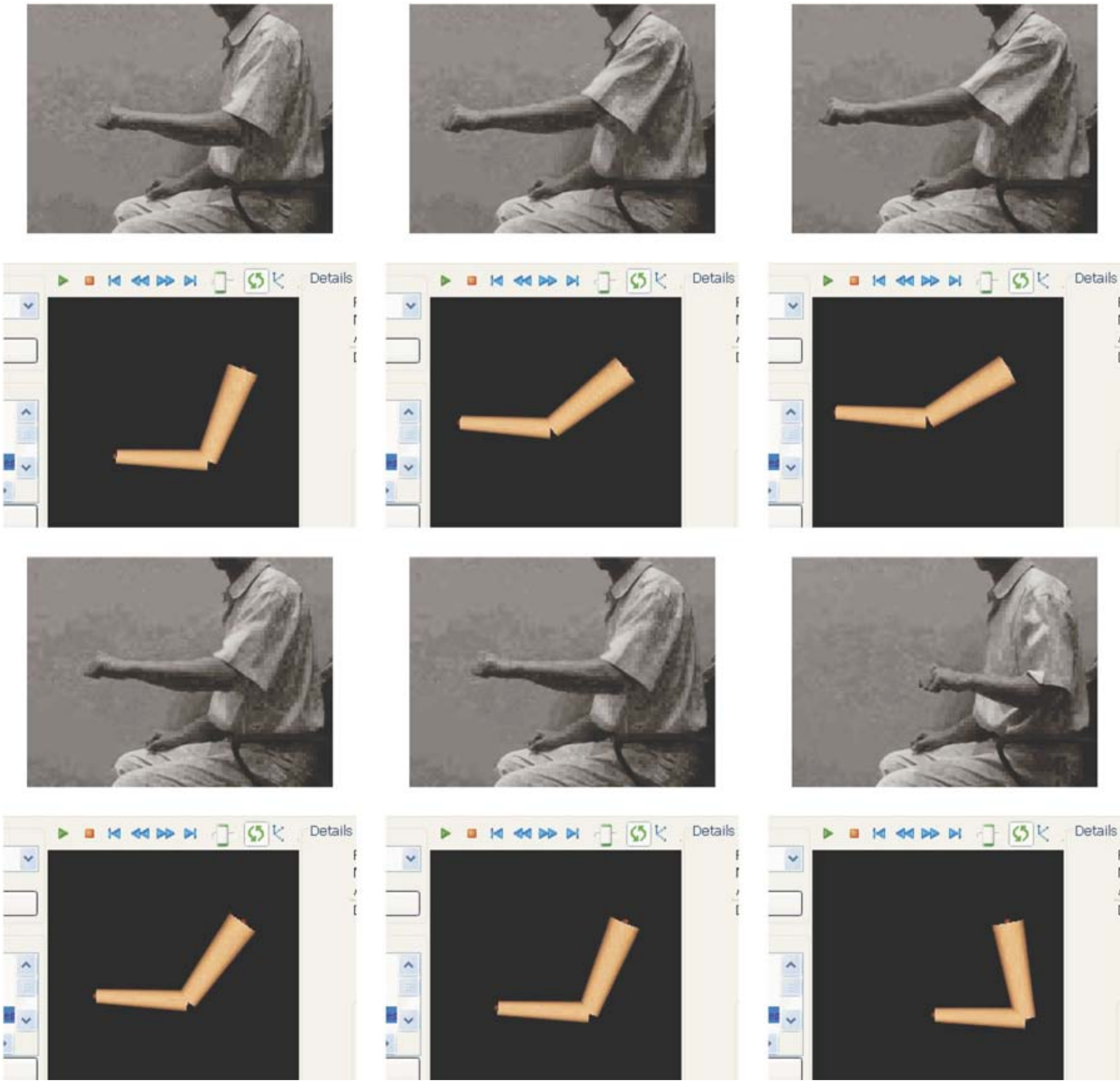


Figure 5 Comparison of real movements and estimated arm position in the reach test (1st and 3rd rows are real movements; 2nd and 4th rows are rendered images based on the estimation)



5. Conclusions and future work

In this paper, we have presented a novel motion tracking system for monitoring human arm movements using two inertial sensors mounted on the arm. A novel sensor fusion technique was proposed to tackle the drift problem in orientation estimation. The experimental work has clearly demonstrated that the proposed scheme is able to achieve high accuracy in arm localization, based on the outcomes of the rendered images and numerical statistics. This suggests that this tracking system can be used to detect real movements in the scope of the home-based rehabilitation.

Although the experimental results are very promising, we should emphasize that the image rendering is not undertaken when the data sampling is performed. We deployed this non-synchronization scheme in order to avoid the disrupted sampling. In future work, we expect to achieve sampling and rendering in the same time. This strategy allows the sensor data to be continuously sampled, and the user can also immediately discover what the acquired data looks like. This helps the rehabilitation user modify his/her motion trajectory on line. Possibly, a multi-threading technique based on the current implementation will be considered to support this function. On the other hand, home-based trials using the proposed tracking system are imminent. Although our strategy has the capability to work in different environments, a real home situation may be dramatically different from what we predict. For example, there may be some materials around that may affect the inertial readings. Therefore, it is necessary to investigate this issue in the future work.

Figure 6 Comparison of real movements and estimated arm position in the drink test (1st row indicates real motion, and 2nd row shows rendered images based on the estimation)

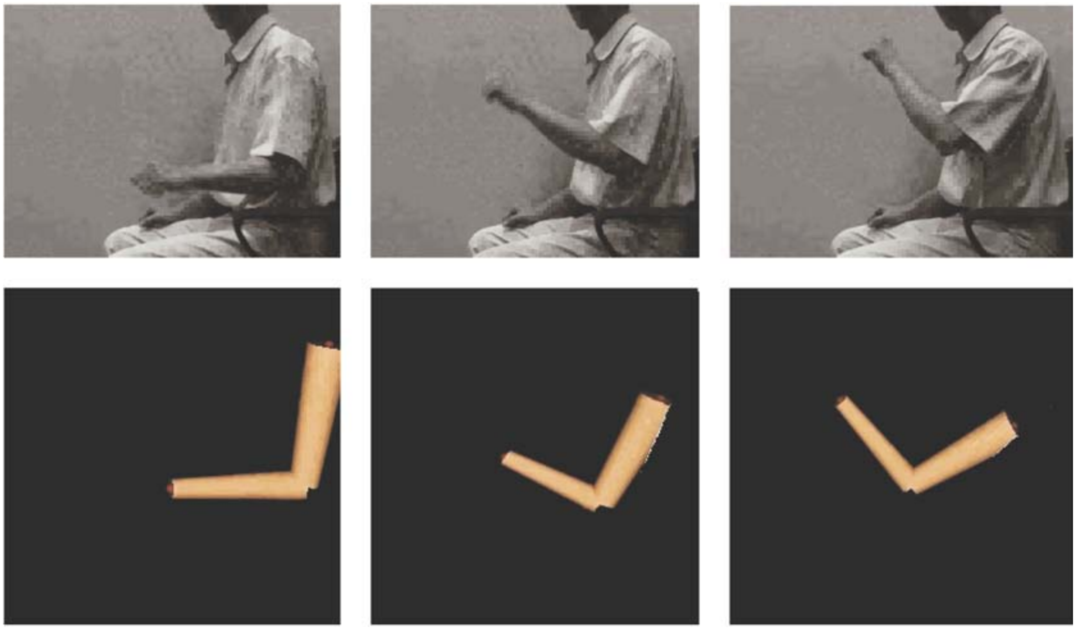


Table I Difference between CODA's measurements and our system's estimation of arm position in different tests

Tests	Mean	RMS	Correlation
Reach	0.002	0.006	0.98
Drink	0.004	0.008	0.95
Flexion-extension	0.001	0.004	0.97
Elevation	0.001	0.005	0.97

Note: Units of mean and RMS: meters

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