Upper limb motion estimation from inertial measurements

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Abstract

In this paper we introduce a real-time human arm motion detector that has been developed to aid the home-based rehabilitation of stroke patients. Two tri-axial inertial sensors are adopted to measure the orientation of the arm. Kinematics models then allow us to recover the coordinates of the wrist and elbow joints, given a still shoulder joint. One of the significant contributions of this paper is the use of a total variation based optimization in smoothing the erroneous measurements due to rapid or unstable movements. Comprehensive experiments demonstrate favorable performance of the proposed inertial tracking system in different sensor positions and motion speeds, compared to the outcomes of a marker-based optical motion tracker that is commercially available.
Keyword: Rehabilitation, motion tracking, inertial sensor, total variation.

I. Introduction

Evidence shows that over 100,000 people in the UK experienced stroke and 30% of these people required admission to hospital between 2001 and 2002 [1]. These stroke patients needed locally based multi-disciplinary assessments and appropriate rehabilitative treatments after they were dismissed from hospital [2]. Hospital-based rehabilitation can provide the stroke patients with accurate diagnosis and immediate treatments and nursing care. However, it raises a huge demand on the healthcare services, including human resources and equipments, etc., if the rehabilitation becomes a long-term commitment.

Since the recent advancement of sensor and Internet technologies, researchers have worked on the development of intelligent devices and systems equipments home-based post stroke rehabilitation instead of in hospital [3]. Rehabilitative progresses are immediately reported to health professionals who can review and comment on the outcomes. Further instructions on the future exercises will be sent back to the patients. On the one hand, these home-based systems may minimize the requirement of face-to-face therapy with healthcare professionals, and also reduce the total amount of costs. On the other hand, home-based rehabilitation is more focused toward actual therapy outcomes and can support patients to challenge the states of depression through active and organized exercises [4]. Therefore, developing home-based rehabilitation systems is valuable and becomes more and more overwhelming.

The goal of rehabilitation is to enable a person who has experienced a stroke to regain the highest possible level of independence and be as productive as before. Although a majority of functional abilities may be restored soon after a stroke, recovery is an ongoing process.

Rehabilitation is a dynamic process of using the available facilities to correct any undesired motion behavior in order to reach its expectation (e.g. reach mouth). To achieve this target, trajectories during the rehabilitation course have to be quantified, and hence appropriate instruments for quantitative measurements are desirable to capture motion trajectories and specific details of task execution. In this paper, we address on designing a motion detector to track the movements of human upper limbs. This is a critical component of the home-based rehabilitation system to be designed. However, the application of this motion detector in real home-based rehabilitation is beyond the scope of this paper and will be reported in due course.

II. Related work

There exists a number of motion tracking systems that can be used nowadays, which to our knowledge can be classified as non-vision based, marker based vision, markerless based vision, and robot-guided systems. Despite their favorable performance, significant weaknesses also have been found when these systems are deployed. In this section, these systems will be briefly summarized.

- **Non-vision based systems**: These systems recruit sensors, e.g. inertial, mechanical and magnetic ones, to continuously collect motion data. These sensors are of modality-specific, measurement-specific and circumstance-specific behaviors. For example, inertial sensors MTx [5] and magnometers Polhemus [6] have been successfully applied to detection of static and dynamic activities in daily life, etc. The systems of using these sensors may be used in most circumstances without specific limitations (e.g. illumination, temperature, or space, etc.). Unfortunately, accumulating errors (or drifts) can deteriorate the system performance after a long time execution.
- **Marker based vision systems**: In 1973 Johansson explored his famous Moving Light Display (MLD) psychological experiment to perceive biological motion [7]. He attached small reflective markers to the joints of human subjects, which allow these markers to be monitored during trajectories. Although Johansson's work established a solid theory for human movement tracking, it still faces the challenges such as space constraints, mutual occlusion and pre-calibration. CODA [6] and Qualisys [8] are two examples, where the former uses “active” markers and the latter exploits “passive” markers that can be observed by the surrounding cameras. These systems cannot ideally solve the problems as mentioned previously.
- **Markerless based vision systems**: As a less restrictive motion capture technique, a markerless based sensing system is capable of overcoming the mutual occlusion problem as it can detect boundaries or features on human bodies, which are normally invariant to rotation and scale. The main problem remaining as a challenge is the computational cost during the rendering. To solve this problem, people are exploring possible solutions by compromising robust performance and computational efficiency. For example, Fua *et al*. [9] proposed to fuse stereo and silhouette data for improvement of 3-D modeling, incorporating least squares tracking techniques. Comport *et al*. [10] presented a virtual visual servoing approach in order to address the problem of efficient tracking. They derived point-to-curves interaction matrices for different 3-D geometrical primitives and then used a local moving edges tracker to provide real-time tracking of points normal to the object contours. A vast number of similar systems/algorithms have been reported in literature. Regardless their partial successes, these markerless vision systems are still lack of sufficient efficiency and robust performance in practice.
- **Robot-guided systems**: Exercise therapy very likely influences plasticity and recovery of the brain following a stroke. Furthermore, abnormally low or high muscle tone may misguide the therapy expert to apply wrong forces to achieve the desired motion of limb segments. To

quantify these issues, an automatic system, named MIT-MANUS, was designed to move, guide, or perturb the movement of a patient's upper limb, whilst recording motion-related quantities, e.g. position, velocity, or forces applied [11]. This is a milestone work in biomechanics as it well combines the state of the art of engineering and biomechanics. The main constraint of this system is that the patient's arm must be fixated on the robot arm. This indicates that the system reluctantly supports free and flexible rehabilitation exercises.

In a home environment, there commonly exist cluttered scenes and occlusion (observation of the movements of upper limbs can be obstructed by the body parts). These limitations discourage the application of vision-based systems that easily suffer from them. Moreover, professional interaction in computation or program proceeding, e.g. pre-calibration, is desirable in using these systems. Therefore, a vision-based system is not an ideal solution to home-based rehabilitation. Robot-guided systems are costly. Moreover, if a wireless feature needs to be concerned, then these robot systems may become less applicable. Evidence shows that inertial/magnetic-sensing systems can be an optimal solution to this specific environment [12, 13]. In spite of the weaknesses, e.g. the drift problem, inertial/magnetic sensors have fewer costs, compact size, lightweight, and no motion constraint. Most importantly, these sensors do not suffer from the occlusion problem [6]. In this paper we report an inertial/magnetic sensor based system for monitoring human upper limbs. It has the advantages such as computation efficiency, reliability and wireless communication. In addition, a novel optimization strategy for minimizing the errors due to rapid or unstable movements is integrated.

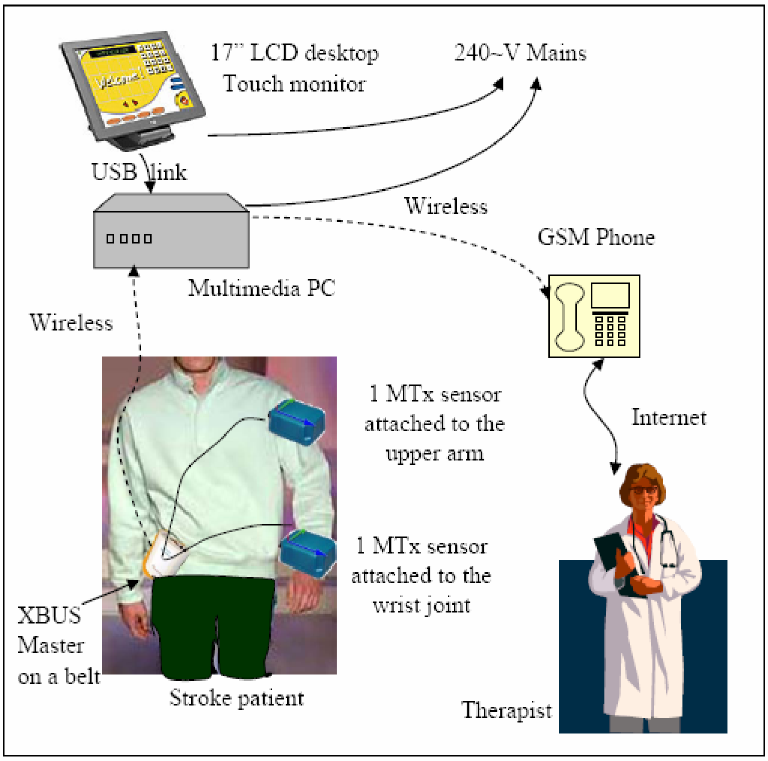


Fig. 1 Illustration of a home-based rehabilitation system including the proposed motion detector

III. Methodology

A. General

A human arm can be represented by a skeleton structure with two segments linked by a revolute joint. Assuming the shoulder is still, only the position of the wrist (in the middle between the radial and ulnar styloid processes) and elbow (lying anterior to the olecranon process) needs to be calculated (the application with a moving shoulder was described in [13]). The arm movements are sampled using two commercially available MTx inertial/magnetic sensors (Xsens, Netherlands), placed on the two segments respectively. The motion tracking system (attached with the stroke patient shown in Fig. 1) is implemented in the environment of Visual Studio C++, where the computer is a Media PC with a VIA Nehemiah/1.2 GHz CPU.

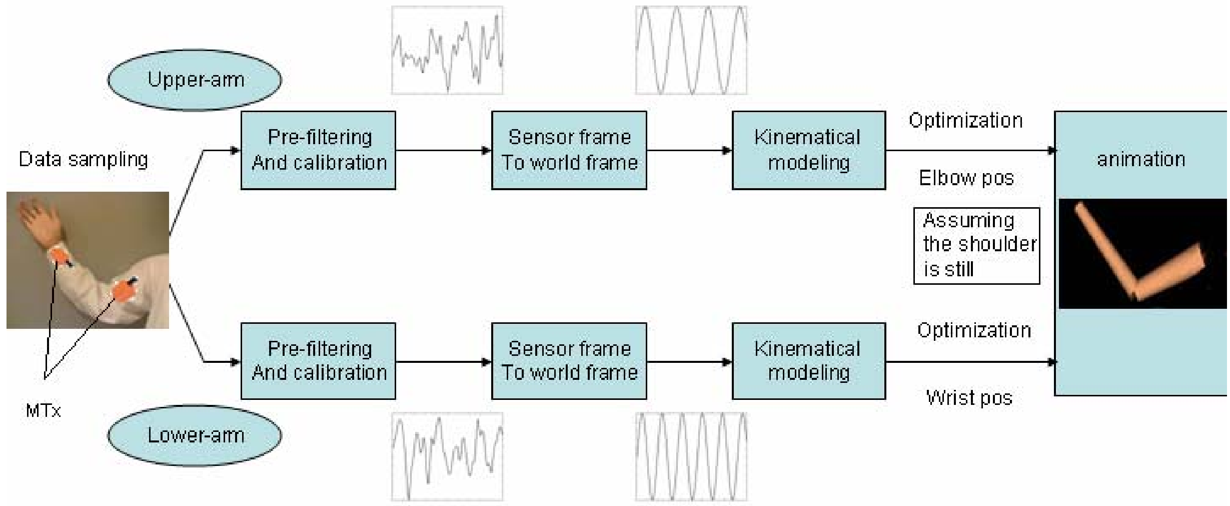


Fig. 2 Flowchart of the estimation of the arm position by our method

Measurements from the proposed tracking system are compared to the ground-truthed data from an optical motion tracker, Qualysis (Qualysis Motion Capture Systems, Gothenburg, Sweden), which as a reference provides absolute position of the moving arm. For system comparison, the coordinate system of the proposed tracker can be aligned with that of the reference data using a direct 3-D coordinate transformation. To relate the movements of the sensor to those of the segments, a sensor calibration needs to be conducted [14]. Errors in motion estimation can be presented using the mean, standard deviation, and root of the mean of the squared errors (RMS). The numerical statistics are tabulated for individual motion excercises, and based on the repeated trials as required. Additionally, correlation coefficients and non-parametric tests (Wilcoxon sign rank tests or p-values) are used for evaluating the similarity between the outcomes of our system and the Qualysis system.

B. Estimation of the joint position

The flowchart of the dynamic estimation is illustrated in Fig. 2. The raw acceleration signals are low-passed filtered (cut-off frequency: 10 Hz) to remove high-frequency noise, while the raw gyroscopic signals are high-pass filtered (cut-off frequency: 0.05 Hz) to reduce the internal drift. To determine the position of an arm in a world (global) coordinate system, we need to transform the inertial measurements from the sensor coordinate system to the world (global) coordinate system. Then, kinematic models will be used to locate the wrist and elbow joints.

Consider a rigid body moving in the earth frame. The world frame is w, and the sensor body frame is b. $\mathbf{R}_b^w$, a 3-by-3 rotation matrix, indicates the orientation transformation from the b-frame to the w-frame: $\mathbf{v}^w = \mathbf{R}_b^w \mathbf{v}^b$, where $\mathbf{v}^w$ and $\mathbf{v}^b$ represent the linear velocity vector of the sensor in the w- and b-frames, respectively. The state of $\mathbf{R}_b^w$ at the next instant, $\mathbf{R}_b^{w-}$, can be updated as follows: _$\mathbf{R}_b^w = \mathbf{R}_b^w S(\omega^b)$, where $S(\omega^b) = [\omega^b \times]$ is the skew-symmetric matrix that is formed using the cross-product operation of the angular velocity estimates ω^b. In fact, the new rotation matrix $\mathbf{R}_b^{w-}$ will be equivalent to the previous $\mathbf{R}_b^w$ plus _$\mathbf{R}_b^w$ multiplied by a time interval (0.04 seconds herein). Once the rotation matrix has been obtained, then the acceleration readings in the w-frame will be deduced as $\mathbf{a}^w = \mathbf{R}_b^w \mathbf{a}^b + \mathbf{G}^w$, where $\mathbf{G}^w = [0, 0, 9.81]^T$ m/s^2 is the local gravity vector whose effect on the acceleration needs to be eliminated. Euler angles can be estimated using a Kalman filter based strapdown integration scheme, based on the method reported in [15], where signals from the tri-axial magnometers, gyroscopes and accelerometers in the MTx sensors are fused to provide stable and driftless orientation. To improve the performance, we have used the estimated accelerations as a proper threshold to evaluate whether or not the estimated Euler angles are valid. In this study, we used Euler angles rather than quaternion to represent the angular changes, as the latter demands a non-linear and intensive computation.

Once having the representation of accelerations and Euler angles in the world frame, we can locate the position of the wrist and elbow joints in the world frame using the estimated Euler angles. This will be done using kinematic models. Before this computation starts, let us assume that the length of the upper arm (olecranon process to acromian process) is L_1, and the length of the lower arm (ulna styloid to olecranon process) is L_2. In the static state, the *x*-axis of these two inertial sensors was collinear with the direction of the upper and lower arm. During dynamic movements, the elbow tri-axial position $\mathbf{P}_e$ (x, y, z) in the shoulder-originated coordinate system was calculated as $\mathbf{P}_e = \mathbf{R}_{es}\mathbf{P}_{e0}$, where $\mathbf{R}_{es}$ is the rotation matrix of the upper arm and can be computed using three Euler angles of the upper arm that are estimated above, and $\mathbf{P}_{e0} = [L_1, 0, 0]^T$. Based on the estimation of the elbow position, the wrist position $\mathbf{P}_w$ in the shoulder-originated coordinate system was deduced as $\mathbf{P}_w = \mathbf{R}_{we}\mathbf{P}_{w0} + \mathbf{P}_e$, where $\mathbf{R}_{we}$ is the rotation matrix of the lower arm (the origin is the elbow joint) and can be computed using three Euler angles of the lower arm, and $\mathbf{P}_{w0} = [L_2, 0, 0]^T$. Up to now, the position of the human arm can be fully determined. The entire algorithm for arm positioning has been outlined in Fig. 3.

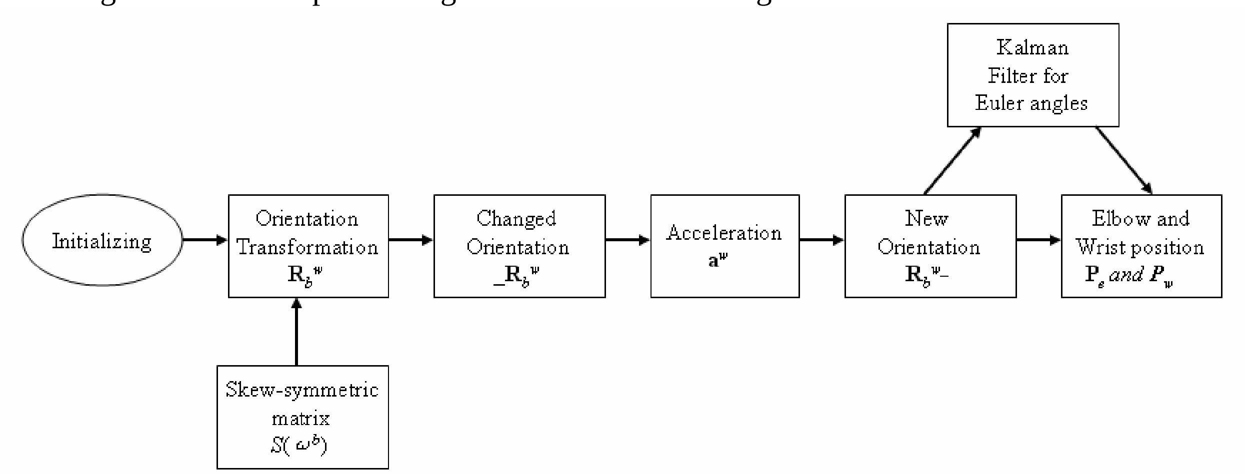


Fig. 3 Illustration of the proposed kinematic modeling method for arm positioning

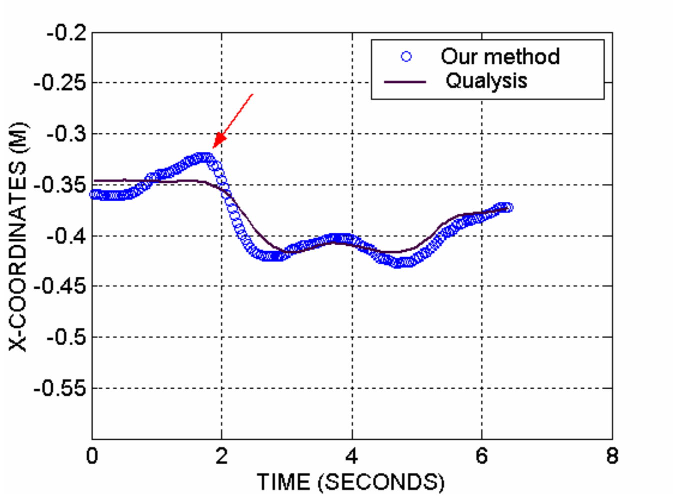


Fig. 4 Comparison of position estimates by the kinematic modeling method and the Qualysis system

C. Error reduction

It has been observed that significant errors, e.g. rapid variations, quite often appeared in the measurements. This mainly results from the soft tissue effects and inertial properties, where the relative movements between the sensors and the rigid structures (i.e. bones) are sampled. These erroneous measurements do not represent the real movements of the rigid body. Fig. 4 illustrates a comparison between the estimation of the wrist position (x-axis) by the proposed kinematic models and the absolute position by the Qualysis system. The Qualysis system consists of three infrared cameras allocated around the object at a distance of 2-5 meters. These cameras can allow the markers mounted on the object's segments to be identified and localized in space. In terms of Fig. 4, in the area with the arrow symbol our estimates present significant biases. It has been found that this "jump" was due to the fast orientation change leading to overshoots of the inertial recordings. This overshoot cannot be totally removed and will strongly affect the accuracy evaluation. However, it may be lessened to some extent. One of the potential methods is an attempt to "smooth" the areas that have abrupt amplitude changes. To "smooth" this jump, we utilize a total variable based minimization strategy that follows the kinematic modeling introduced above.

Total variation exhibits the solution of recovery of corrupted data as a minimizer of an appropriately chosen function. The minimization technique of applying total variation involves the solution of nonlinear partial differential equations (PDFs) [16], subject to constraints from the statistics of the noise. The constraints are applied via Lagrange multiplier, which leads to a solution based on the gradient-projection method [16].

Let us start the algorithmic description by estimating the wrist position (the estimation of the elbow will be very similar). The goal is to reconstruct a true data point u from its observation $\tilde{u}$ (i.e. position vector): $\tilde{u} = u + \tau$, where τ is noise or an unknown error. This uncertainty can be solved using a minimization function of gradient as

$$\min_{u} F_{\varepsilon,p}(u)$$

subject to

$$F_{\varepsilon,p}(u) = \int_{\Omega} |\nabla^{\varepsilon} u|^{p}\ dx + \lambda \|\tilde{u} - u\|^{2}$$

where λ is a non-negative Lagrangian multiplier, and ε is a regularization coefficient:

$$|\nabla^{\varepsilon} u| = (u^{2} + \varepsilon^{2})^{1/2}$$

The *Euler-Lagrange* equation is used to solve the minimization problem:

$$u_1 = \nabla \bullet \left(\frac{\nabla u}{|\nabla^{\varepsilon} u|^{2-p}}\right) + \beta(\tilde{u} - u)$$

where β (= 2λ/p) is the constraint parameter for the descent direction, and λ is available if we take the derivative for the minimization function with respect to u and then set it to zero. In a simple case, $\varepsilon = 0$ and $p = 1$. Searching for an ideal solution u involves a number of iterations. The initial value of u is randomly chosen.

Let (x, y, z) be the estimated wrist coordinates, $(\omega_x, \omega_y, \omega_z)$ be the Euler angles of the forearm, and r be the segment length of the forearm (equal to L_1). Assume $a = (\cos\omega_x)^2$, $b = (\cos\omega_y)^2$, and $c = (\cos\omega_z)^2$. Since orientation is the main variable used here, we then have the required first order derivatives with respect to three Euler angles estimated individually [17]:

$$\frac{\partial x}{\partial w_x} = \frac{2rab^2c^2 \sin w_x}{(1+a^2b^2c^2)^2} - \frac{2rab^2c^2d \sin w_x}{(1+a^2b^2c^2)^2} + \frac{rab^2c^2 \sin w_x(-c^2+b^2c^2-2a^2b^2c^2)}{(1+a^2b^2c^2)d}$$

$$\frac{\partial x}{\partial w_y} = \frac{2ra^2bc^2 \sin w_y}{(1+a^2b^2c^2)^2} - \frac{2ra^2bc^2d \sin w_y}{(1+a^2b^2c^2)^2} + \frac{ra^2bc^2 \sin w_y(1-c^2+b^2c^2-a^2b^2c^2)}{(1+a^2b^2c^2)d} + \frac{r(-bc^2 \sin w_y + a^2bc^2 \sin w_y)}{d}$$

$$\frac{\partial x}{\partial w_z} = \frac{2ra^2b^2c \sin w_z}{(1+a^2b^2c^2)^2} - \frac{2ra^2b^2cd \sin w_z}{(1+a^2b^2c^2)^2} + \frac{ra^2b^2c \sin w_z(1-c^2+b^2c^2-a^2b^2c^2)}{(1+a^2b^2c)d} + \frac{r(c \sin w_z - b^2c \sin w_z + a^2b^2c \sin w_z)}{d}$$

$$\frac{\partial z}{\partial w_x} = -\frac{x\frac{\partial x}{\partial w_x} \sin w_x}{\sqrt{r^2-x^2}} + \sqrt{r^2-x^2}a$$

$$\frac{\partial z}{\partial w_y} = -\frac{x\frac{\partial x}{\partial w_y} \sin w_x}{\sqrt{r^2-x^2}}$$

$$\frac{\partial z}{\partial w_z} = -\frac{x\frac{\partial x}{\partial w_z} \sin w_x}{\sqrt{r^2-x^2}}$$

$$\frac{\partial y}{\partial w_x} = -\frac{z\frac{\partial z}{\partial w_x} \sin w_z}{\sqrt{r^2-z^2}}$$

$$\frac{\partial y}{\partial w_y} = -\frac{z\frac{\partial z}{\partial w_y} \sin w_z}{\sqrt{r^2-z^2}}$$

$$\frac{\partial y}{\partial w_z} = -\frac{z\frac{\partial z}{\partial w_z} \sin w_z}{\sqrt{r^2-z^2}} + \sqrt{r^2-z^2}c$$

where $d = \sqrt{1-(1+a^2b^2c^2)(1-c^2+b^2c^2-a^2b^2c)}$. The stopping criterion of the iteration is that the difference between two neighboring steps is smaller than 0.001. One example is illustrated in Fig. 5, where an elbow flexion test was performed and trajectories were hence recovered. Clearly, the optimization method has improved the estimates of the kinematics modeling by "smoothing" the estimates from the kinematics models.

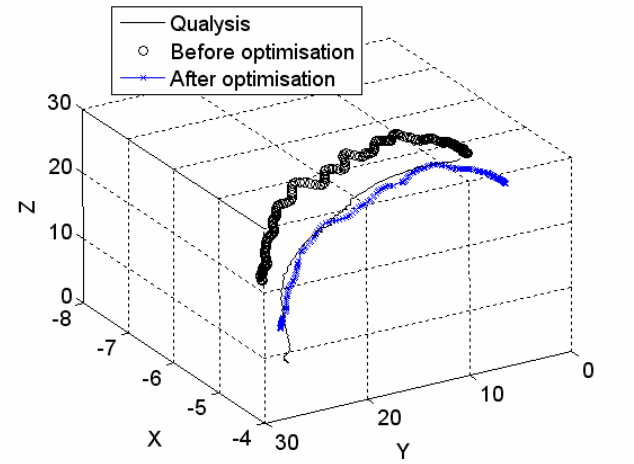


Fig. 5 Trajectories recovered by different methods in the elbow flexion test (units: cm)

IV. Experimental work

We here evaluate the performance of the proposed motion detector against that of the commercially available "Qualysis" motion tracking system. The Qualysis system uses retro-reflective ball marker that can be captured by three cameras surrounding the object (the distance between the subject and the cameras is 2-5 meters). These cameras are used to reduce the possibility of occlusion. The Qualysis system directly reconstructs 3-D position of the arm after a proper calibration has been achieved.

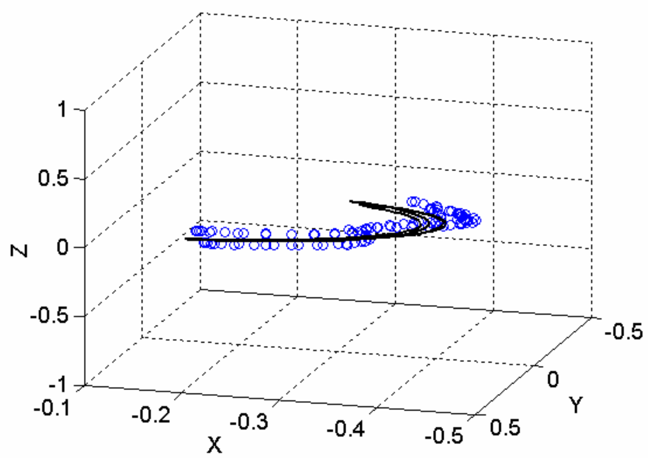
In our experiments, the first Qualysis marker is attached to an area next to the MTx sensor. Both the marker and sensor are very close and placed nearby the wrist joint (1 cm between the sensor/marker and the wrist joint). The second marker is placed on the upper arm and is next to the elbow joint (1 cm away). All sensors and markers face outwards away from the human body. Appropriate alignment between the coordinate system of the inertial sensors and that of the Qualysis system is conducted using the method reported in [18]. The Qualysis markers and MTx sensors are attached to the arm using double adhesive tapes.

Three healthy male subjects are recruited in the experiments. Before the experiments start, the length of each segment of upper limbs is measured and then encoded into the computer program to be executed. Each of the subjects is seated and performs the requested experiments individually. These experiments consist of reach-target, drink, elevation, and elbow flexion. Each of these tests lasts 20 seconds and is repeated three times. Between any two sessions of each test, subjects are allowed to take a rest of 30 seconds. To avoid the violation of the rigidness assumption in the mathematical modeling, we notify the subjects that regular and repeated movements are preferable, while they can use the motion speeds that they like. Any inter-rotation due to the bones under the skins will be avoided or minimized.

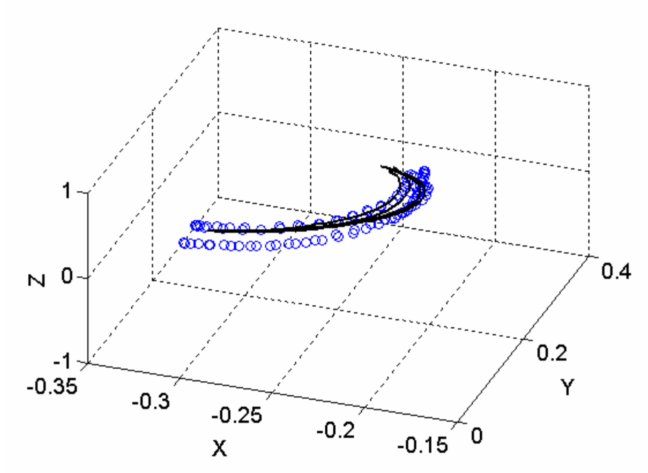
- *The reach test*: all the subjects are asked to reach two specific points in space. This is a periodic motion. It involves the displacement of both wrist and elbow joints. To demonstrate the system performance, we show the estimated trajectory by our method, in comparison to that by the Qualysis system. Fig. 6 illustrates two cycles of the recovered trajectory of the wrist and elbow joint, respectively. Clearly, the estimates by the new method are very similar to those by the Qualysis system. The maximum discrepancy in the wrist and elbow estimates between our method and the optical system is 0.014 m. The similarity of the two approaches is verified in Table 1, where the correlation coefficients of the measurements of the two approaches are 97% (wrist) and 98% (elbow), respectively. Results of the Wilcoxon sign rank tests aslo confirm this observation ($p > 0.05$).

- *The drink test*: the subjects repeatedly simulate the drinking activity by lifting the hand to meet the mouth and then returning to the starting point. This test in physiotherapy will be used to train a stroke patient for improvement of motion coordination. Fig. 7 illustrates that the outcomes of our method approximate those of the optical system. Interestingly, we observe that the elbow estimates are of a significant discrepancy in Fig. 7 (b) but it is due to the visualizing effect. The maximum discrepancy in the elbow case is 0.017 m. Table 1 shows that the RMS error of the elbow is 0.013 m and the correlation coefficient is 94%. This suggests that the estimation by our method is still satisfactory.
- *The elevation test*: we ask the subjects to lift the whole arm from a lower position to a higher position. During trajectory, the wrist and elbow joints will experience similar rotation and displacements. In Fig. 8, it is observed that the estimates of the two joints by our method have small discrepancy to the Qualysis system. Table 1 reveals that the RMS errors of the two positions are less than 0.01 m. The correlation coefficients of the two methods are 98% and 97%, respectively. Wilcoxon sign rank tests show the results complying with the correlation coefficiencts ($p > 0.05$).
- *The flexion test*: the subjects are asked to flex the forearm while attempting to keep the upper arm still. This test is used to aid a stroke patient to regain the motor function of controlling different segments. Due to insignificantly small outcomes from the elbow joint we here only show the recovered trajectory of the wrist joint. Fig. 9 shows the wrist trajectories rendered from the outcomes of our method and the optical system, respectively. Both measurements are very close with a RMS error of 0.007 m. Table 1 shows a good similarity between the two data groups (correlation: 97%; $p > 0.05$).

To evaluate whether or not our method has robust performance in different sensor positions and motion speeds, we apply the same subjects and allow the two sensors to be re-located. In the new testing trials, the sensors are about 0.03 m from their original places but still on the same segments. Two test protocols are made up: in the first testing protocol the overall subjects carry out the same tests as introduced above. In the second testing protocol, when the subjects undertake the tests, they significantly change the motion speeds of the arm. The second protocol to our knowledge has never been reported in a similar work and may challenge the proposed motion detector. The corresponding results are tabulated in Table 2, where only a range of the statistic values is generated (the wrist and elbow estimates are not shown independently). These results verify the favorable performance of our method in these experiments.

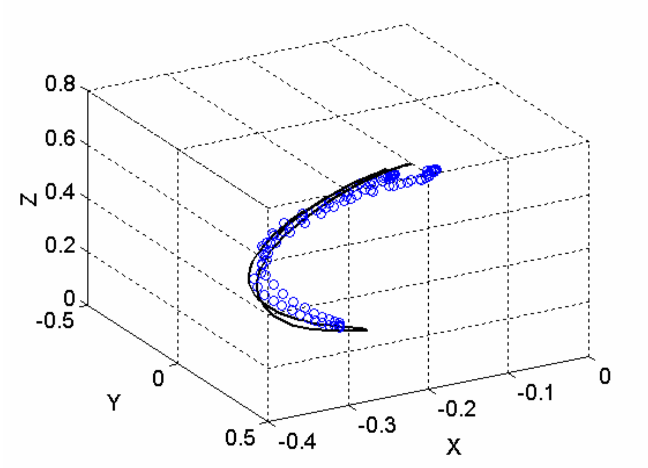


(a) Wrist trajectory

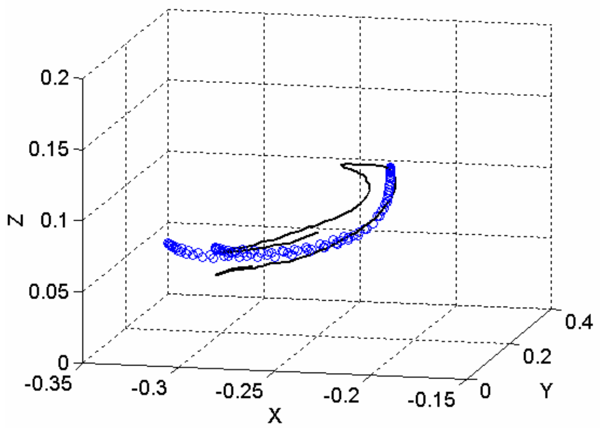


(b) Elbow trajectory

Fig. 6 Comparison of the wrist and elbow measurements in the reach test by our method ("o") and the Qualysis system ("-"). Units: m.

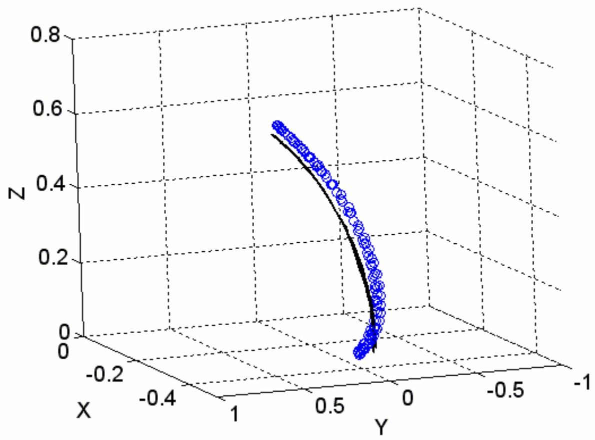


(a) Wrist trajectory

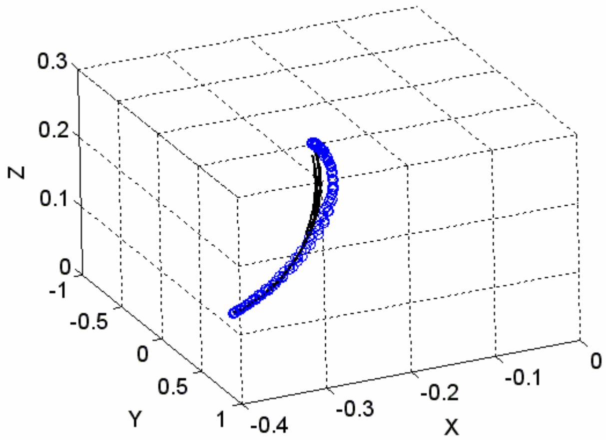


(b) Elbow trajectory

Fig. 7 Comparison of the wrist and elbow measurements in the drink test by our method ("o") and the Qualysis system ("-").Units: m.



(a) Wrist trajectory



(b) Elbow trajectory

Fig. 8 Comparison of the wrist and elbow measurements in the elevation test by our method (“o”) and the Qualysis system (“-“).Units: m.

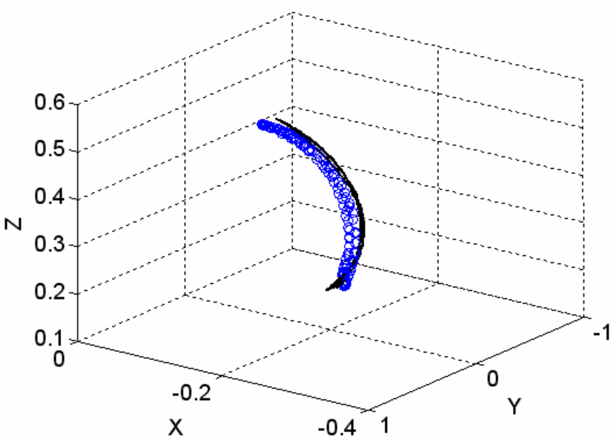


Fig. 9 Comparison of the wrist measurements in the flexion test by our method (“o”) and the Qualysis system (“-“).Units: m.

Table 1 Error statistics of the estimates by the proposed method in regular exercises (w – wrist; e – elbow; cc – correlation coefficient). Units of mean and RMS: m

	Mean (w/e)	**RMS (w/e)**	**CC %(w/e)**	**p-value (w/e)**
Reach	-0.002 / 0.003	0.013 / 0.011	97 / 98	0.18 / 0.26
Drink	-0.005 / -0.002	0.009 / 0.013	96 / 94	0.26 / 0.21
Elevation	0.004 / -0.006	0.008 / 0.009	96 / 96	0.31 / 0.3
Flexion	-0.001	0.007	97	0.22

Table 2 Error statistics of the estimates by the proposed method in different sensor locations and motion speeds (w – wrist; e – elbow; cc – correlation coefficient). Units of mean and RMS: m

	Mean (w/e)	**RMS (w/e)**	**CC % (w/e)**	**p-value (w/e)**
Reach	-0.007 – 0.006	0.011 - 0.018	91 - 97	0.14 - 0.23
Drink	-0.004 - 0.008	0.007 - 0.015	93 - 95	0.16 - 0.21
Elevation	-0.002 - 0.005	0.009 - 0.016	90 - 94	0.17 - 0.25
Flexion	-0.004 - 0.006	0.011 - 0.015	91 - 98	0.16 - 0.23

V. Conclusion and future work

We have presented an inertial sensing based tracking system that integrates kinematics of human arm movements and a total variation based optimization strategy. The coordinate system of an inertial sensor needs to be transformed from local to global, followed by position estimation via kinematic models. The 3-D reconstruction of the human arm is performed in real-time. Compared to the commercially available tracking system “Qualysis” that uses markers, our system has the advantage that it is easy to use and can recover the real human arm movements with a simple set-up. This is extremely useful when people look at the automatic synthesis of realistic human motion in computer graphics in addition to the rehabilitative applications.

The future work will be addressed to extend the ideas presented here in order to consider the improvement of accuracy. Due to high degrees of freedom of upper limbs, in this paper we have not addressed the issue where non-rigid movements appear. For example, elbow flexion may accompany forearm supinations or pronations, where the rotation of the muscles nearer to the wrist and elbow joints respectively is not identical. This situation literally violates the rigidness assumption in our model and may lead to erroneous measurements. One of the possible solutions is to add an extra MTx sensor, or integrate the current MTx sensors with other non-visual sensors, e.g. potentiometers or laser fibers, etc. In the latter solution, the MTx sensors provide an initial position for the arm and the other sensors work as a “verifier” or “corrector”. In due course, the whole tracking system may have more robust performance in a non-rigid circumstance while keeping high accuracy in measurements.

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