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An Investigation into the Accuracy of Calculating Upper Body Joint Angles using MARG Sensors

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Abstract

We investigate magnetic, angular rate, and gravity (MARG) sensor modules for deriving shoulder, elbow and lumbar joint angles of the human body. We use three tri-axial MARG sensors, placed proximal to the wrist and elbow and centrally on the chest, and employ a quaternion-based Unscented Kalman Filter technique to estimate orientations from the sensor data, from which joint angles are calculated based on a simple model of the arm. Tests reveal that the method has the potential to accurately derive specific angles. When compared with a camera-based system, a root mean square difference error between 5° - 15° was observed.

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Keywords: accelerometer; gyroscope; inertao sensor; Kalman filter; kinematics; magnetometer; MARG

1. Introduction

The automated kinematic analysis of upper-limb motor activity is a key component in a number of application domains including stroke rehabilitation, motor neuron diseases management and sports industry. Traditional methods for tracking the kinematic activity of the upper-limb involve the use of optical or camera systems. Advances in the area of Micro-Electro Mechanical Systems (MEMS) have, however, facilitated the development of miniature accelerometers, magnetometers and angular rate gyroscopes that can be grouped together in unobtrusive, wearable devices (MARG) that transmit data wirelessly; offering a great alternative to traditional systems.

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2. Kinematic model

We represent the upper-limb by a simple 2-link model, as shown in Fig. 1, with MARG sensors placed in positions 2 (elbow) and 3 (wrist), while the global point of origin is considered in position 1 (shoulder). A third MARG sensor is positioned on the chest for calculating lumbar flexion/extension angle which is of key importance in rehabilitation evaluation. The quaternion-based Unscented Kalman Filter algorithm (qUKF) inspired by [1, 2] operates on the MARG data and provides the 3-D orientation of each sensor and therefore the link upon which it is attached. Following this, two position vectors for the upper-arm and forearm are defined. By considering an initial position, the 3-D coordinates and orientation of the two position vectors in the global coordinate frame can be estimated during dynamic movements, with the use of rotation matrixes obtained from the sensors orientation. Additionally, a third position vector is defined from the neck pointing downwards toward the torso. Ultimately the desired angles of motion are calculated from the orientation angles of the three sensors attached to the body and the three position vectors as defined here. The initial starting coordinates of the position vectors is considered to be known and aligned to the X-axis of the illustrated 2-link model.

3. The qUKF data fusion algorithm

The proposed qUKF orientation algorithm fuses data from tri-axial MARG sensors in order to obtain the 3-D orientation of the sensor module, and thus of the body segment to which it is attached. To achieve this, the problem of orientation estimation is formulated as a non-linear dynamical estimation problem. Orientation information is expressed in quaternions which offer the advantage of being singularity-free. To obtain drift-free orientation information, the dynamic changes in orientation measured by the gyroscope are referenced to the vector of gravity (as expressed by the accelerometer output) in order to obtain the orientation against the horizontal plane, and referenced to the vector of the local magnetic field (as expressed by the magnetometer), in order to obtain the orientation against the vertical plane. A block diagram of the qUKF algorithm is illustrated in Fig. 2.

The dynamical model includes the state vector (x_n) which contains the orientation quaternion and the angular velocity as [q_n, w_n]. The state process model is formulated by considering constant angular velocity, corrupted with noise (e_n). By knowing the gyroscope output (w_x, w_y, w_z) and the duration of each time step, the differential rotation (change in orientation) is estimated and corrected by being referenced to the accelerometer (a_x, a_y, a_z) and magnetometer outputs (m_x, m_y, m_z) after they are transformed from the global coordinate system to the sensor's coordinate system using the vectors of gravity (g) and local magnetic north (b). This is achieved through the definition of the measurement model which provides the mathematical association between the measurement vector [a_n, m_n] to the state vector. This proposed model is heavily non-linear due to the quaternion multiplications that take place. Subsequently, we employed the Unscented Kalman Filter in order to iteratively estimate the value of the state vector x_n.

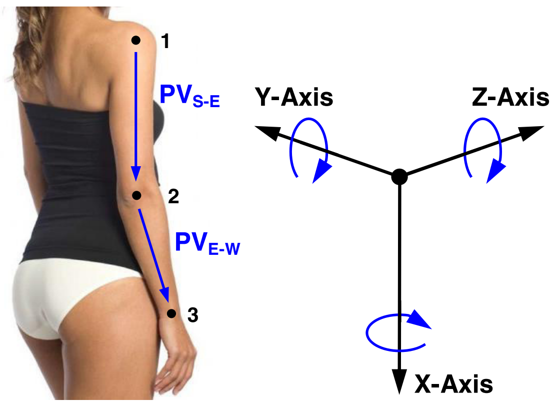

Fig. 1: Representation of 2-link model for the human upper limb.

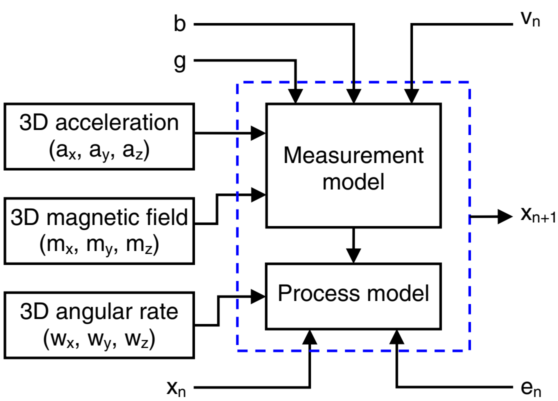

Fig. 2: Process diagram of data fusion algorithm.

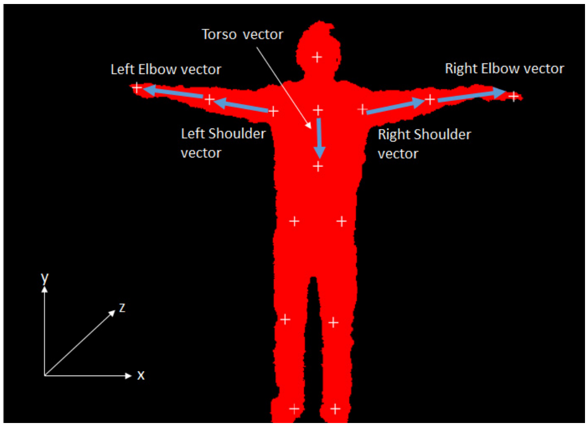

Fig. 3: Human body skeleton model obtained from Asus Xtion Pro.

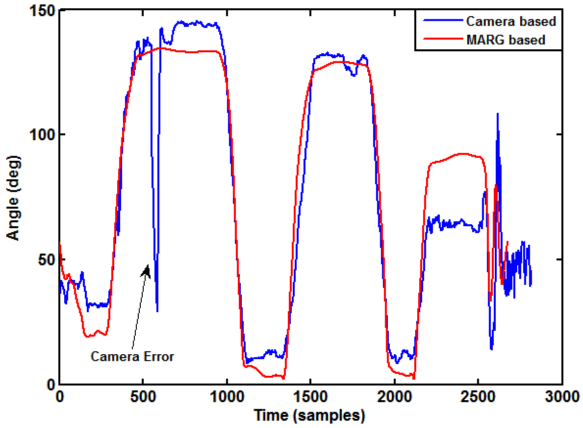

Fig. 4: Comparison of elbow flexion – extension angles.

4. Evaluation

To evaluate the proposed qUKF orientation determination algorithm, we conducted a series of arm motion experiments while collecting data from wireless MARG sensors attached to the wrist, elbow and chest, using the Xsens MTw module. We compared specific limb angles calculated by qUKF with those obtained from an Asus Xtion Pro camera sensor. The latter tracks body motion in real time, providing 3D coordinates of a 15 point skeleton-model, as depicted in Fig. 3. In our experiments one degree of freedom of the upper limb was investigated in each trial. We capture the entire normal motion range of each movement in steps of approximately 90° with a brief rest between them, starting from a neutral position with the arm lying motionless at the side of the body.

5. Discussion

Representative examples from our experiments are illustrated in Fig. 4 to Fig. 8, while Table 1 lists the achieved level of performance in terms of the root mean square difference error (RMSD) between the two systems. Note that elbow pronation-supination cannot be calculated from the camera sensor, hence the RMSD is not reported for this case. Some errors (cf. Fig. 4) are attributed to the camera sensor losing its ability to track the notional 'markers' of the skeleton model. This is a common case for camera sensors since they require un-hindered line-of-sight.

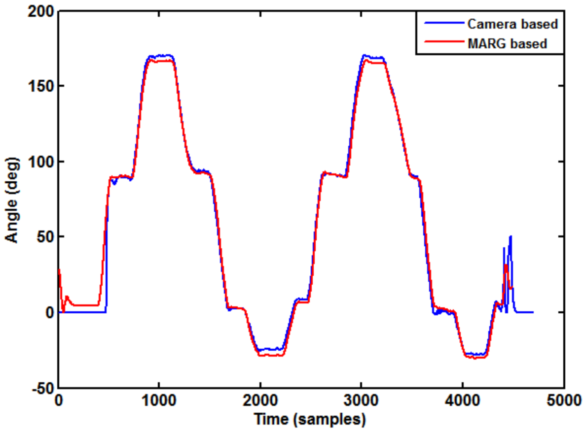

Fig. 5: Comparison of shoulder flexion – extension angles.

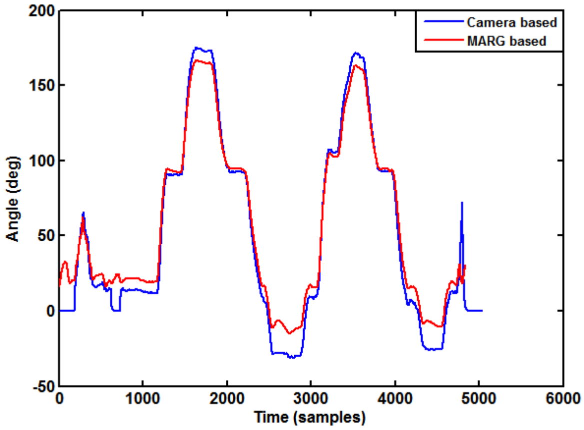

Fig. 6: Comparison of shoulder abduction – adduction angles.

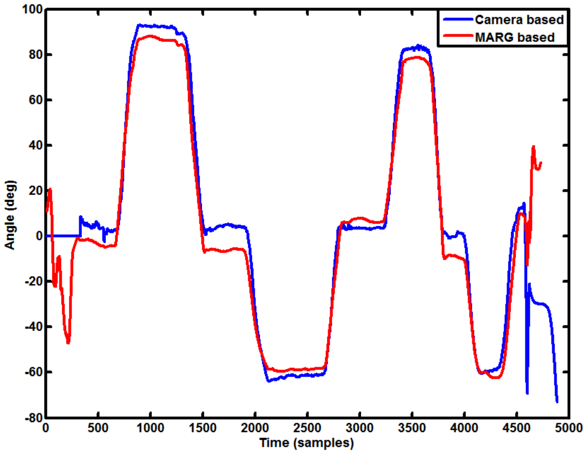

Fig. 7: Comparison of shoulder medial – lateral extension angles

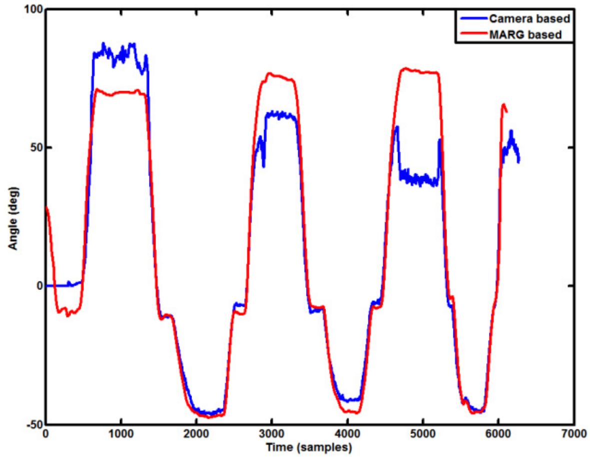

Fig. 8: Comparison of lumbar flexion– extension angles.

In general the obtained RMSD was in the range of 5° - 15° which reveals that the two systems are in accordance. This prompts us to deduce that a MARG sensor-based solution is capable of calculating the upper-limb joint angles with similar accuracy to camera sensor-based systems while maintaining significant advantages in terms of cost and coverage since line-of-sight is not a requirement. Nevertheless, considering the need for constant calibration and alignment of the body-attached MARG modules, a future direction could be focused on developing a hybrid system where a camera sensor is employed periodically to calibrate and realign the MARG modules, resulting in a more robust system combining the advantages of both approaches.

Table 1. Summary of measured errors between the two systems as a function of movement type.

Movement type	RMSD (°)	Movement type	RMSD (°)
Shoulder flexion –extension	5.3	Elbow flexion – extension	15.2
Shoulder abduction – adduction	9.3	Elbow pronation – supination	N/A
Shoulder medial – lateral extension	6.8	Lumbar flexion – extension	14.2

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