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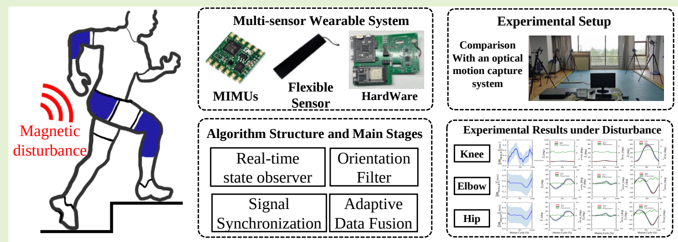
A Flexible Sensor and MIMUs Based Multi-sensor Wearable System for Human Motion Analysis

Yu Gu, Yi Han, Xiangzhi Liu, Ning Zhang, Xiufeng Zhang, Min Pan, Shuoyu Wang, Wei Dong, *Senior Member, IEEE*, Tao Liu, *Senior Member, IEEE*

***Abstract*— *Motivation*: Magnetic-Inertial Measurement Units (MIMUs) and flexible sensors are widely used in the wearable measurement system for human motion monitoring, clinical gait detection, and robotics motion control. However, MIMUs demonstrate measurement error due to magnetic disturbance in the indoor environment, and flexible sensors usually have low performance on linearity and accuracy. *Objective*: This paper is intended to eliminate the low-accuracy problem caused by magnetic disturbances and improve the measurement accuracy of MIMUs- flexible sensor based wearable systems. *Approach*: (1) a three-stage real-time data fusion (RT-ADF) algorithm is proposed, which contains an anti-disturbance filter based on a double Mathony filter along with a state observer, a signal holder for sensors' data transmit synchronously, and a data fusion based on an adaptive Kalman filter. (2) The proposed algorithm is utilized and validated its performance on a designed MIMUs- flexible sensor wearable system. (3) 10 groups of knee motions (flexion/extension), 10 groups of hip motions (adduction/abduction), and 10 groups of elbow motions(flexion/extension) have been done by 7 subjects in the experiments. *Main Results*: The designed multi-sensor wearable system based on the presented data fusion algorithm demonstrates a high-accuracy performance under the magnetic disturbance environment, and the maximum root mean square error (RMSE) of the measured continuous three-dimensional motion angle of the knee, hip, and elbow cross all the experiments were 1.23°, 1.15°, 3.67° for each axis.**



***Index Terms*— multi-sensor systems, magnetic disturbance, adaptive data fusion, wearable sensors**

I. INTRODUCTION

JOINT angle measurement systems are widely applied in human motion monitoring, clinical gait detection, and robotics motion control [1]–[3]. Compared with other joint angle measurement systems, such as the optical motion capture system, cameras, and joint angle encoders, the wearable measurement system is more flexible, portable, and easy to use in human daily life, therefore it becomes a promising candidate for human motion monitoring and analysis [4]–[6].

Due to the advantages above, several researchers have successfully designed various types of wearable systems which consist of microsensors or flexible sensors for daily behavior monitoring [7], [8] and medical rehabilitation assessment [9], [10]. Among all the sensors, Magnetic-Inertial Measurement Units (MIMUs) and flexible sensors are widely used and irreplaceable [8], [9], [11], [12]. However, imperfections from both MIMUs and flexible sensors in wearable systems for human daily life are supposed to be addressed. for example, MIMUs are easily affected by a magnetic field [13], especially in the indoor environment with ferromagnetic objects or electrical appliances. The disturbances of the local magnetic field will result in systematic errors when identifying the global north [14], which will thereby disturb the heading (yaw angle) of MIMUs. Flexible sensors usually have low performance on linearity and accuracy. Therefore, research on exploiting the potentialities of microsensors/flexible sensors, as well as improving the measurement accuracy and spatial dimension of these wearable joint angle systems have attracted the interest of many researchers.

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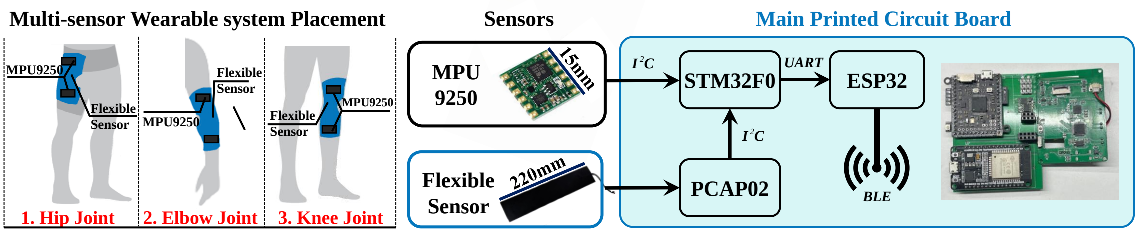

Fig. 1. Construction diagram of the proposed wearable system.

Some researchers employed treble flexible sensors to set up a coupling measurement system, aiming at getting three-dimensional angles of should joints [15]. This system is potable to use, however, its accuracy (average about $10°$ for each axis) is quite low [7], [15], [16] due to decoupling methods and the low accuracy of the flexible sensor itself; Some researchers have developed fusion algorithms based on the noise model [14], [17], [18] in the presence of magnetic disturbances. These methods compensating the attitude data according to the established noise model could improve the measurement accuracy of MIMUs and make orientation data reliable shortly [13], [19]–[21] under random magnetic disturbances, for instance, the complementary Filter has been utilized to improve the accuracy of knee/ hip/ ankle motion detection and its accuracy of x/y/z reaches to $2.7°$, $3.3°$ and $7.8°$ respectively [22], but the noise could not match up with the random disturbances and the cumulative error could cause the gyro drift problem [23], [24]; Multi-sensor systems [25], [26] have also been designed in recent research, for example, the Kalman Filter was used to realize data fusion of IMUs and FSRs in a wearable system for knee motion detection and its accuracy was improved to $11.9°$ [27]. Salvatore et al. [28]. developed an embedded fusion method to predict the angle of knee motion in the IMUs and EMG based wearable system. The RMSE of the predicted knee angle was between $5.5°$ and $10.4°$. Both attitude data from MIMUs and position data from cameras have been used to predict the orientation of an object. These data fusion algorithms based on the vision-MIMUs system have been widely used in obstacle-free environments [29] and have achieved good results with a relative error of less than 7% in the 3-DOF rotation and 8% in the 1-DOF translation.

In summary, state of art of wearable joint angle measurement systems, especially those based on MIMUs or flexible sensors, can be concluded as below: many researchers have designed types of multi-sensor wearable systems and proposed various data fusion algorithms, however, orientation error caused by magnetic disturbance [13] and the sampling synchronization problem has not been taken into consideration deeply.

To deal with these mentioned issues, (1) this paper proposes a three-stage data fusion algorithm for joint angle measurement, which reduces the cumulative measurement error and improves the accuracy under magnetic disturbances. The first stage employs a double Mathony Orientation Filter [19] and a designed real-time observer to describe the measurable disturbance of the magnetic field. The second stage uses a signal holder to make the flexible sensor and MIMUs of different sample rates to generate angle data synchronously. The third stage establishes a data fusion model based on a designed joint motion model and Kalman Filter, where joint data arrives from the second stage; (2) A FS-MIMUs(flexible sensor and MIMUs) based wearable system, which is embedded with the proposed three-stage data fusion algorithm, have been designed and validate to various human motions by 7 subjects, including the knee motion (flexion/extension), hip motion (adduction/abduction), and elbow motion (flexion/extension)

The paper is organized as follows. Section II introduces the FS-MIMUs Based wearable system. Section III describes a self-adaptive anti-magnetic disturbance algorithm in detail and then an online data fusion algorithm is proposed as well. Experimental procedures are listed in Section IV. In Section V, experimental results are discussed. Finally, Section VI concludes this paper.

II. Flexible Sensor and MIMUs Based Multi-sensor Wearable System

A. The Hardware of FS-MIMUs Based Wearable System

To realize higher accuracy, multi-axis measurement, and anti-disturbance performance for joint angle measurement, A wearable multi-sensor system (see Fig. 1) was designed and developed. The system consists of sensors of two types (see Table I), one type is the nine-axis attitude sensor MPU9250 (WITMOTION Corporation, China), which consists of triaxial gyroscopes ($\pm 2000°/s$), triaxial accelerometers (± 16 g), and triaxial magnetometers (± 200 μT), another is the flexible sensor ESSB (ELASTECH Corporation, China), which is a type of capacitive strain sensor chosen by us, and its measurement range and sensitivity has been listed in Table I.

TABLE I
The Specifications of Comprised Sensors in the Proposed Multisensor System

Sensor	Linear Range	Accuracy/Sensitivity	Limits
two MIMUs	gyroscopes: $\pm 2000°/s$ accelerometers: $\pm 16g$ magnetometers: $\pm 200uT$	gyroscopes: $\leq 0.1(\%F \cdot S)$ accelerometers: $\leq 0.1(\%F \cdot S)$ magnetometers: $\leq 0.1(\%F \cdot S)$	high accuracy but poor performance under disturbance
one flexible sensor	$0° - 120°$	$1.1pF/°$	low accuracy but good performance under disturbance

The entire data acquisition flow was described as below: The flexible sensor was connected to a commercial capacitance measurement module PCAP02 (ACAM Corporation, Germany), and the measurement value of the flexible sensor was transmitted to the master chip STM32F0 (STMicroelectronics Group, Switzerland) by I^2C protocol digitally, meanwhile,

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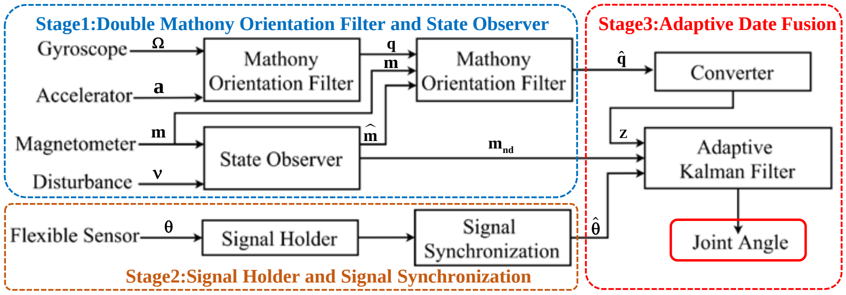

Fig. 2. The proposed algorithm architecture of the multi-sensor wearable system

orientation data from two MPU9250 modules were sent to the master chip STM32F0 by the same I^2C protocol. After the data processing and computing, the collected data, which was transmitted from the master chip STM32F0, will be uploaded to a laptop by the Bluetooth chip ESP32 (ESPRESSIF SYSTEMS Corporation, China).

B. Preparations and Calibration

In the subsection above, we introduced the design block diagram and basic hardware composition of the wearable system. Before this system comes into use, we first need to test the flexible sensor repeatedly and calibrate it. This part of the work has been described in detail in another article of our team [30], [31]. Work flow can be described as calibrating the flexible sensor by using high-precision MIMU (MTw Awinda-MTW2-3A7G6, XSENS b.V. Technologies, Enschede, Netherlands) to obtain the function relationship between the joint angles and the collected analog signals. The calibration process will not be described in detail here. According to calibration results, the functional relationship between changble capacitance ΔC and joint angle θ can be expressed as: $\Delta C/C_0 = f(\theta)$.

It is noting that MIMU generally has a better response rate and sampling frequency, and its sampling frequency is set as 100Hz generally, which is due to the advantages brought by MEMS manufacturing characteristics. the flexible sensor has better interactive performance, whereas its sampling frequency is common about 50Hz commonly. We select MIMU data of 100Hz in real-time and use a signal holder to synchronize the data of 50Hz flexible sensors. The detailed description and equation derivation could be seen in section II.

III. Algorithm

To eliminate the low-performance problem caused by the magnetic disturbance [13], we propose this three-stage algorithm for the flexible and MIMUs based multi-sensor wearable system. Compared with previous research, we design a real-time state observer according to the triaxial magnetic data from magnetometers, whose flow diagram is shown in Fig. 2. The first stage improves the anti-magnetic performance in a short time by using a double Mathony Orientation Filter [19]. The second stage uses a signal holder to make the flexible sensor and MIMUs of different sample rates to generate angle data synchronously. The third stage establishes a joint model with noise to describe the human joint motion, data generated from both flexible sensor and MIMUs are put into data fusion based on an adaptive Kalman filter to improve the system's measurement accuracy and anti-magnetic performance.

A. Architecture of the Proposed Algorithm

We first developed a three-dimensional orientation filter utilizing double Mathony orientation filters. This filter has shown a good anti-magnetic effect in a short time orientation estimation with a minimum 0.47° error and has been widely used in lots of similar research on MIMU [19], [20], [32], but it works less effective in a long-term magnetic environment [13], [32]. As a result, the accuracy of orientation data will be reduced, which is due to its three-axis data coupling with each other and the magnetometer failure; Therefore, in preference of a long-term magnetic environment, we designed an observer based on three-dimensional magnetic field data to get the real-time condition of the local magnetic field. The output of this observer is utilized for parameters adjusting both in double Mathony orientation filters and an adaptive Kalman filter (see Fig. 2), which reduces the variables by using a single parameter $\| \mathrm{m}_{\mathrm{mess,k}}\|_2$ to improve computing efficiency of this algorithm.

Considering that the goal of our algorithm is to take different types of sensors of a multi-sensor measurement system into account, proposed flexible sensors have low accuracy, but they have stable performance and interactive performance [31] in a magnetic environment because of their materials characterizations. To improve the accuracy of the whole measurement system, we establish an adaptive Kalman filter as a data fusion to improve the system measurement performance under a long-time magnetic disturbance. Till now, the algorithm's architecture has been explained, three stages of this algorithm will be described in detail.

B. A Preliminary Anti-disturbance Algorithm for MIMUs

Taking noise or environment disturbance into account, the ideal MIMU model (see Equation (1)) could be set as by adding bias $\boldsymbol{b}$ and noise parameter $\boldsymbol{\mu}$. The Mathony orientation filter is a common method [19], [20], [32] to deal with a short-time disturbance situation, so only key equation would be described here.

$$\begin{bmatrix} \widehat{\Omega} \\ \widehat{a} \\ \widehat{m} \end{bmatrix} = \begin{bmatrix} \Omega + b_\Omega + \mu_\Omega \\ R^T(a - g_0) + b_a + \mu_a \\ R^T h + b_m + \mu_m \end{bmatrix} \tag{1}$$

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In Equation (1), the instantaneous algebraic rotation R was built in equation (2) .

$$R = \arg\min \sum_{i=1}^{2} \lambda_i |v_x^* - Rv_x|^2 \tag{2}$$

wehere $R \in SO(3)$, when $i = 1, v_x = a \cdot |a|^{-1}$; when $i = 2, v_x = m \cdot |m|^{-1}$. v_x^* is the referential direction. the orientation quaternion reprensentation in $SO(3)$ was:

$$\dot{q} = \frac{1}{2} q P(\Omega) \tag{3}$$

where $q = \begin{pmatrix} q_w & \boldsymbol{q_v} \end{pmatrix} = \begin{bmatrix} q_w & q_x & q_y & q_z \end{bmatrix}$, q represents unit quaternion, $P(\Omega) = \begin{pmatrix} 0 & \Omega_x & \Omega_y & \Omega_z \end{pmatrix}$

Take (1) into (3) and we could get the equation below:

$$\dot{\hat{q}} = \frac{1}{2} \hat{q} P(\Omega - \hat{\boldsymbol{b}} + k_p w_{mes}) \tag{4}$$

Where $\hat{\boldsymbol{b}} = -k_I w_{mes}$, $w_{mes} = \sum_{i=1}^{2} k_i v_i \otimes \hat{v}_i$, w_{mes} is the sum of the results of two cross products, which are measurement value v_i and the prediction value $\hat{v}_i$. k_p and k_I are common parameters to be set in designed system. w_{mes} shows the differences between prediction value and measurement value, $\dot{\hat{q}}$ now represents a prediction quaternion. As a result, the discrete quaternion could be represented as:

$$\hat{q}_t = \hat{q}_{t-1} + \dot{\hat{q}}_t \Delta t \tag{5}$$

Equation (5) could be utilized as an iterator, $\dot{\hat{q}}_t$ is computed by Equation (4) as the present cumulative items and Δt is the sample time and in our system its value is set as $0.1s$.

C. A Real-time State Observer Based on Triaxial Magnetometers

This part describes the flow of real-time state observing. $\hat{v}_i$ (in Equation (4)) could be computed as a prediction value, and v_i is the real measurement value. In order to get the differences between prediction value and measurement value , the observer was designed and normalized as below:

$$m_{mess,k} = e_i \otimes \hat{e}_{ref} \tag{6}$$

Where $e_i = m \cdot |m|^{-1}$, $\hat{e_{ref}} = \hat{m_{ref}} \cdot |\hat{m_{ref}}|^{-1}$. If the prediction vector of a magnetic field is similar to the measurement vector, $e_{m,k}$ comes into a zero vector, or the result $(m_{mess,k})$ of cross products will be a unit vector. In order to simplify the result of state observer, we choose $\| \mathrm{m_{mess,k}} \|_2$ as the final the result of state observer.

D. Signal Holding and Synchronizing for Flexible Sensor

In the proposed multi-sensor measurement system, there are two types of sensors, MIMUs and flexible sensor, whose sampling periods are represented as τ and T respectively. Their relationship could be listed as $\tau \cdot T^{-1} = N$. If the last update timing of MIMU to the target state is $(k-1)\tau$, the next update timing is due to $k = (k-1)\tau + NT$; On the other hand, the last update timing of flexible sensor is $(k-1)T$, and the next update time of it is due to kT, which means that flexible sensor has N times measurements between two consecutive updates of the target state.

Considering flexible sensor as a low-accuracy measurement, it would be less effective to use interpolation approches [33] to make data redundant. Use a signal holder is a easy and fast method to keep signal of flexible sensor as real as possible, let $\theta_k = \begin{cases} \theta_k & t_k = t_{update} \\ \theta_{k-1} & t_k \neq t_{update} \end{cases}$, and $H = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix}^T$, so $z_{flexible,k}$ is represented as below.

$$z_{flexible,k} = H\theta_k \tag{7}$$

E. Joint Angle Predict Model

A real-time data fusion based on adaptive Kalman filter [32] was been established, so the state-space representation to describe the joint angle is modeled as below:

$$\begin{cases} x_k = Ax_{k-1} + Bu_k + w_{k-1} \\ z_k = Cx_k + v_k \end{cases} \tag{8}$$

In Equation (7), w_{k-1} is the process noise, v_{k-1} is the measurement noise. $x_k = \begin{bmatrix} x_{pitch,k} & x_{roll,k} & x_{yaw,k} \end{bmatrix}^T$, $A = I_3$, $B = I_3(\Delta t)$, $C = I_3$, $w_{k-1} = \begin{bmatrix} w_{pitch,k} & w_{roll,k} & w_{yaw,k} \end{bmatrix}^T$, $v_{k-1} = \begin{bmatrix} v_{pitch,k} & v_{roll,k} & v_{yaw,k} \end{bmatrix}^T$. The measurement noise w_{k-1} represents the original measurement accuracy of sensors, and the process noise v_{k-1} could be used to show the disturbance of the environment. The measurement noise w_{k-1} could be set as a constant vector , whereas the process noise v_{k-1} is supposed to be changeable with the different disturbance.

Result of state observer could be applied for this part, a function was designed to relate $\|m_{mess,k}\|_2$ with the process noise v_{k-1} as below.

$$v_{k-1} = g(\|m_{mess,k}\|_2) = 20(1 + e^{-10(2\|m_{mess,k}\|_2 - 1)})^{-1} \tag{9}$$

Data fusion based on adaptive Kalman filter is applied here to make use of different sensors' values. Some variables including $\hat{x}_{k-1}$, P_k^-, k_k, $\hat{x}_k$, p_k are very common parameters in Kalman filter and will be described in the next subsection. Other variables, such as R and Q, are both covariance matrix, and could be represented as $Q = E[\begin{array}{cc} w_{k-1} & w_{k-1}^T \end{array}]$, $R = E[\begin{array}{cc} v_{k-1} & v_{k-1}^T \end{array}]$. Combing with Equation 9, R is represented as:

$$R = E[\begin{array}{cc} g(\|m_{mess,k}\|_2) & g^T(\|m_{mess,k}\|_2) \end{array}] \tag{10}$$

F. Adaptive Data Fusion and Algorithm Flow Design

After resolving the results $(\hat{q}_t)$ of the Mathony filter from the nine-axis attitude sensor and the angel $z_{flexible,k}$, a data fusion was designed here based on the real-time state observer proposed before.

$$\hat{z}_k = \hat{x}_k + \|m_{mess,k}\|_2 \cdot (\hat{z}_{flexible,k} - \hat{x}_k) \tag{11}$$

The whole process of the proposed iterative algorithm, which is decribed as a real-time adaptive anti-disturbance data fusion (RT-ADF), is shown in Table 1. In the first step, 8 model

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parameters are supposed to be initialized. In the second step, all the variables, including joint angle $\hat{q}_t$ from MIMUs, the prior probability P_k^-, the prior coefficient k_k, the posterior probability p_k, joint angle $z_{flexible,k}$ in z-axis from the flexible sensor, and the joint angle $\hat{z}_k$ from proposed system, need to be computed according to mentioned formulas. In the third step, particular variables are updated here. The output of state observer $m_{mess,k}$ is updated to gain the real-time magnetic disturbance, and so is the noise matrix R. In the end, this iterative algorithm will end with the stop command.

Algorithm 1 RT-ADF

Initialization:$A, B, C, Q, R, \hat{x}_{k-1}, P_{k-1}, \theta_k$
repeat
  $\hat{q}_t = \hat{q}_{t-1} + \dot{\hat{q}}_t \Delta t$
  $P_k^- = AP_{k-1}A^T + Q$
  $k_k = P_k^- \, C^T \cdot (C \, P_k^- \, C^T + R)^{-1}$
  $\hat{x}_k = \hat{x}_k^- + k_k(z_k - C \, \hat{x}_k^-)$
  $p_k = (I - k_k C) \, P_k^-$
  $z_{flexible,k} = H\theta_k$
  $\hat{z}_k = \hat{x}_k + \|m_{mess,k}\|_2 \cdot (\hat{z}_{flexible,k} - \hat{x}_k)$
  Update $m_{mess,k}$ based on Equation (6)
  Update R based on Equation (10)
until Shut down the system
Output: Real-time joint angles $\hat{z}_k$

IV. EXPERIMENTAL PREPARATIONS AND PROCEDURES

After designing the algorithm flow design, it is necessary to evaluate the performance of the proposed algorithm based on the multisensor system. Traditional data fusion methods towards multisensor systems [34]–[37] do not fully take disturbance into account, which means their model could have low accuracy under disturbance situation. We have conducted experimental verification of the proposed algorithm in this section, and given an intuitive demonstration of real-time angle measurement.

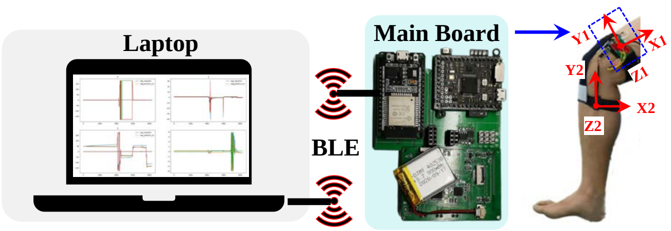

Fig. 3. The experimental set-up for data collection .

A. Experimental Preparations

The wearable multi-sensor system was arranged and fixed on the subjet's leg, waist, and hand respectively to detect knee motion, hip motion, and elbow motion. Meanwhile, The body motions motioned above were recorded with an optical motion capture system (VICON, UK), with markers attached to the posterior arm (PA), forearm, waist, thigh, shank, elbow joint, hip joint, and knee joints (see Fig. 4). Electromagnetic signals were released to disturb the MIMUs by activating electronic equipment at a particular time which was held in the subjet's hands. Measured data from the multi-sensor system and VICON system were synchronized by a laptop. All the experiments data were collected on a laptop through the Bluetooth communication (see Fig. 3)

Seven subjects (6 males and 1 female, age: 25.14 ± 3.33years, body height: 1.73 ± 0.05 m, body mass: 65 ± 9.33 Kg) were recruited to participate in this study. The experimental procedure was approved by the Medical Ethics Committee of the School of Medicine, Zhejiang University (No.2018-005). Anthropometric data included length of upper leg and lower leg.

B. Experimental Procedures and Data Collection

The first experiment was conducted to get an initial insight into the proposed algorithm based on the multi-sensor system and verify the performance of system's measurement stability under different types of magnetic disturbance in our study. In the first 10 s, no disturbance was released. From 10 s to about 20 s, random dynamic disturbance signals were released. In the last 10 s, static disturbance signals were released around the system.

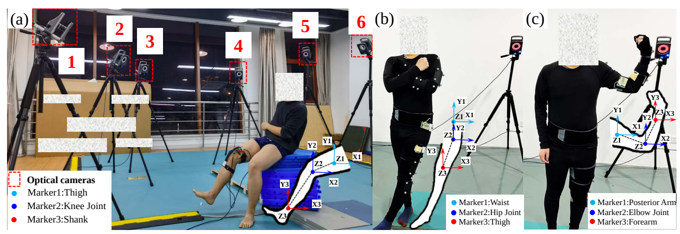

Fig. 4. Introduction of experiment equipment. (a): Experiment setup and knee motion experiments. (b): hip motion experiments. (c): elbow motion experiments

The second experiment was conducted to get results on the accuracy and performance of the proposed multi-sensor system with/without magnetic disturbance. In this experiment, 10 groups of tests were carried out to verify the algorithm based on the FS-MIMUs system, and each experiment, which contained several joint movements, was about 30s. To test the system within a wide range of angles, the subject was ordered to sit on a seat and to wiggle their legs as large as possible. Due to the limited number of cameras, the subject was required to seat with hands across their chests to avoid covering the markers on the leg. All data, which included results of the state observer $\| \mathrm{m_{mess,k}} \|_2$, joint angle z_k from the proposed system, the data from MIMUs, and the data from the flexible sensor, were collected thoroughly.

The third experiment was carried on to further validate the response of the system to other human motions, including the knee motion (flexion/extension), hip motion (adduction/abduction), and elbow motion (flexion/extension). In this experiment, subjects were asked to wear tight clothes for fewer distractions. 10 groups of knee motions, 10 groups of hip motions, and 10 groups of elbow motions had been done by 7 subjects. Data $\| \mathrm{m_{mess,k}} \|_2$ from the state observer and joint angle data z_k from the multi-sensor system were gotten.

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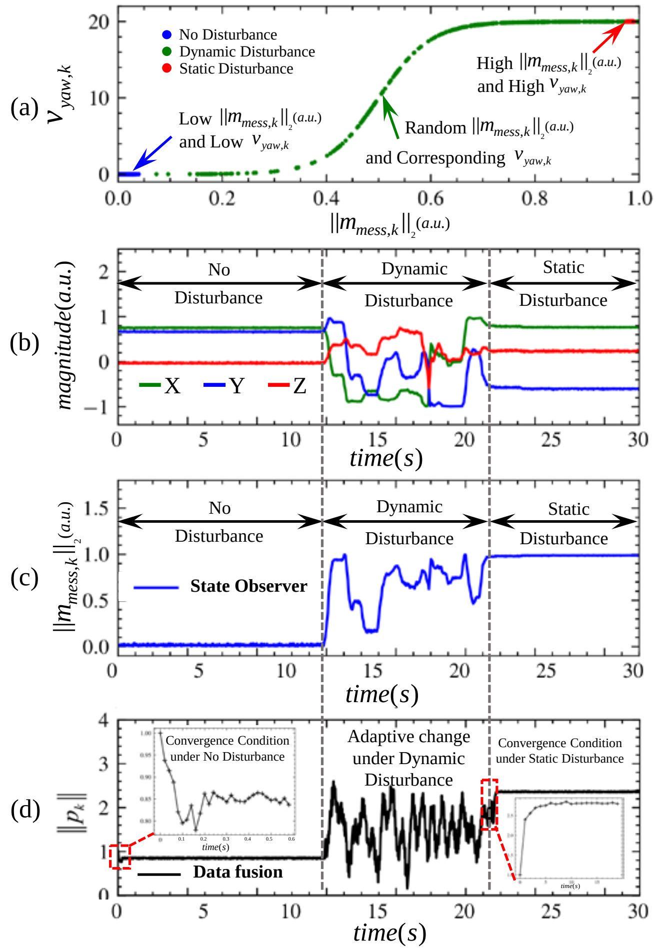

Fig. 5. Measured values of triaxial magnetometers and results of designed state observer. (a): Correlation function about results of the state observer and the process noise. (b): Values of triaxial magnetometers under different types of disturbances. (c): Results of designed state observer under various disturbances. (d): The posterior probability p_k under different types of disturbances.

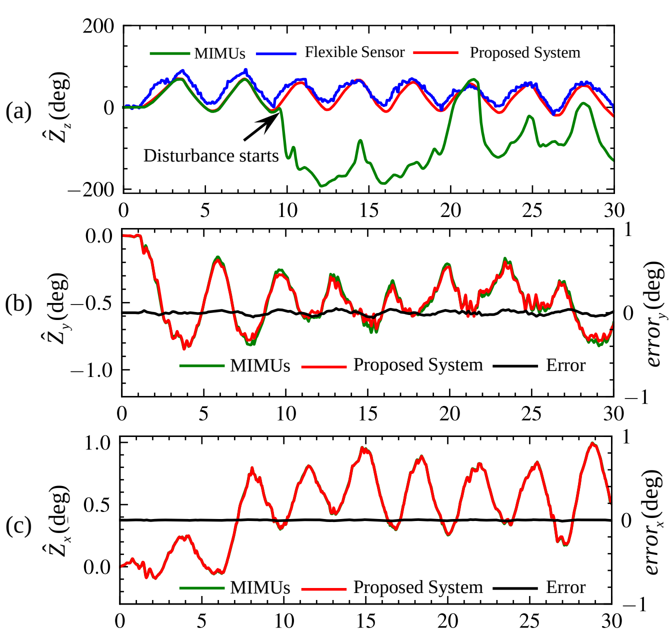

Fig. 6. Triaxial angle data when facing with disturbance. (a): Data of z-axis. (b): Data of y-axis. (c): Data of x-axis.

V. Experimental Results and Discussion

A. Data Processing

Data from the VICON system were processed offline with customized PYTHON programs. Collected Joint angles were filtered with a low pass Butterworth filter with a cut-off frequency of 10 Hz. Parameter settings of the filter are demonstrated in Table IV, the order N of the filter is set as 2, and the normalized cut-off frequency w_n is computed by: $w_n = 2 \cdot (w_c/w_s)$. All motion data has been divided into segments by motion cycles for efficient analysis.

TABLE II
The Parameters of Low Pass Butterworth Filter

Mode	Cut-off frequency w_c	Sampling frequency w_s	Normalized cut-off frequency w_n	Order N
low pass	10 Hz	100 Hz	0.2	2

B. Verification of System's Measurement stability under different types of magnetic Disturbance

As is shown in Fig. 6, in the first 10s, the MIMUs, the flexible sensor, and the proposed system can measure the joint angles accurately. In this period of the experiment, the original data from magnetometers (see Fig. 5(a)) reflected the situation of the regular environmental magnetic field. Similarly, the value $\| \mathrm{m_{mess,k}} \|_2$ from the designed state observer represented a no disturbance moment (see Fig. 5(b)) and the environmental noise parameter v_k was set to zero in yaw orientation (see Fig. 5(c)). From 10s to 20s, when dynamic disturbance signals were detected, the data fusion algorithm set a bigger trust weight to the flexible sensor in the z-axis (see Equation (11)) and the proposed system could still get correct joint angles, whereas others failed. In the last 10s, when static disturbance signals occur, the state could still detect the static magnetic disturbances, and set a high noise parameter $v_{yaw,k}$ (see Fig. 5(c)).

Although MIMUs were inaccurate under magnetic disturbance [13], the results (see Fig. 6(b)(c)) showed that the Mathony filter was a good choice to decouple roll and pitch orientation with yaw orientation. In addition, the flexible sensor supplied low-accuracy but stable angle data during the entire experiment. From this perspective, a single-axis flexible sensor compensated for the errors and played a significant role in the data fusion part when it came to measurements of z-axis angle. The posterior probability [38], [39] was commonly utilized for stability analysis in the adaptive Kalman filter-based method.the convergence condition for the posterior probability under different types of disturbances was demonstrated in Fig. 6(d). On the no disturbance condition, the posterior probability decreased and converged to a stable value within about ten iterations; On the dynamically random disturbance condition, the posterior probability changed adaptively according to the magnitude of the external disturbance; On the static disturbance condition, increased and also converged to a stable value.

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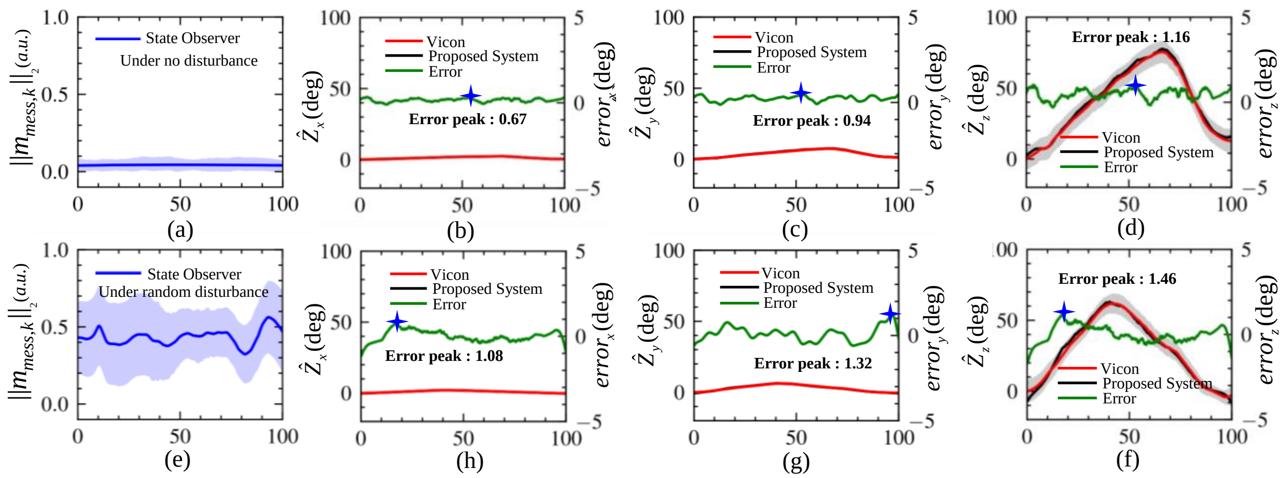

Fig. 7. Results of the second experiment. (a): Results of state observer with no disturbance. (b)-(d): Joint angles with no disturbance in the x-axis, y-axis, and z-axis. (e): Results of state observer with random disturbance. (f)-(h): Joint angles with random disturbance in the x-axis, y-axis, and z-axis.

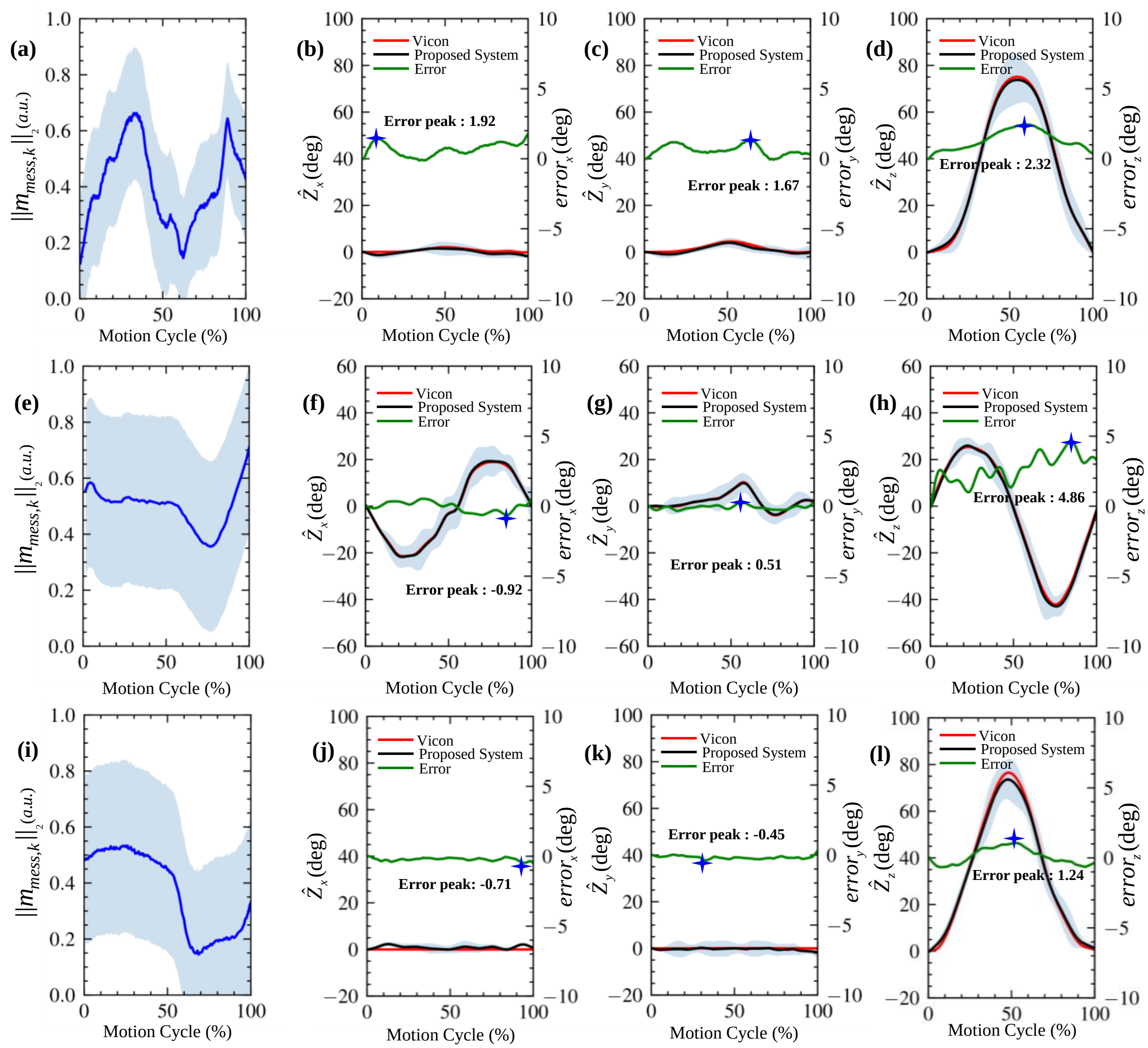

Fig. 8. Experimental results of the third experiment. (a): Results of state observer in knee motion experiment. (b)-(d): Knee motion angle from the x-axis, y-axis, and z-axis respectively. (e): Results of state observer in elbow motion experiment. (f)-(h): Hip motion angle from the x-axis, y-axis, and z-axis respectively. (i): Results of state observer in hip motion experiment. (j)-(l): Elbow motion angle from the x-axis, y-axis, and z-axis respectively.

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C. Verification of System's Measurement Accuracy with/without magnetic Disturbance

Fig. 7(a)-(d) showed the results of the proposed system under the regular environmental magnetic field. The response of the system under random magnetic disturbance was demonstrated in the rest part of Fig. 7. The state observer $\| \mathrm{m}_{\mathrm{mess,k}}\|_2$ reflected the field strength of surrounding magnetic disturbance signals.

Fig. 7(a)-(d) showed the results of the proposed system under the regular environmental magnetic field. The response of the system under random magnetic disturbance was demonstrated in the rest part of Fig. 7. The state observer $\| \mathrm{m}_{\mathrm{mess,k}}\|_2$ reflected the field strength of surrounding magnetic disturbance signals. The average three-dimensional joint motion data of the knee flexion/extension angle without disturbance were $1.08 \pm 0.27°$, $2.21 \pm 0.36°$ and $43.17 \pm 9.24°$, another knee motion test with disturbance demonstrated that the proposed algorithm could ensure the stable and precise measurement with random magnetic disturbance, and the average joint motion data was $1.03{\pm}0.38°$, $1.08{\pm}0.41°$ and $41.22{\pm}10.14°$. The maximum root mean square error (RMSE) between the Vicon system and the proposed system with/without disturbance were $0.76°/0.88°/1.26°$, respectively. Although double Mathony Orientation filters and a state observer have been utilized for better anti-disturbance performance, the maximum joint angle error across the task was still from the z-axis. Considering the huge impact of the magnetic disturbance (see Fig. 6(a)), measurement accuracy has been effectively improved .

In the second experiment, we verified the system measurement accuracy with/without magnetic disturbance and the proposed real-time adaptive anti-disturbance data fusion (RT-ADF) was verified to improve the accuracy of the multi-sensor system under a random disturbance environment.

D. Verification of System's Measurement Accuracy with magnetic Disturbance for multiple human motions

A real-time state observer based on triaxial magnetometers manifested that our multi-sensor system was in operation in a random magnetic disturbance. Fig. 8(b)-(d) showed one example of the knee motion for the multi-sensor system to detect. Our system could measure the entire process of knee motion accurately and the maximum error is $2.32°$ in the z-axis. Elbow motions detection's maximum error was $1.24°$ in the y-axis and showed a similar result (Fig. 8 (f)-(h)) with the knee motion experiment. Both elbow motion and knee motion were mainly about joint flexion/extension movements, so the maximum error came from the main motion axis. The maximum measurement error of hip motion is $4.86°$ (Fig. 8(i)-(k)) and the response of the wearable system to hip motion is slightly inferior. The hip joint was more complex than the knee and elbow joint, so if the wearable system was not fixed in the correct position, the bias between the human body's coordinates and the sensor's coordinates might reduce the accuracy slightly.

In the third experiment, we validated the measurement performance of the system in the multi-axis joint motion, our system was tested for the knee, hip, as well as elbow motions, and shows high precision measurement characteristics under random magnetic disturbance. As is shown in Table III, the overall average measured joint motion data of the knee flexion/extension angle across the experiment were $41.17 \pm 9.24°$, $2.26 \pm 0.33°$ and $1.08 \pm 0.27°$, the average hip adduction/abduction angle across all tasks were $-5.24{\pm}7.13°$, $3.16 \pm 4.25°$ and $-12.18 \pm 11.31°$, and the average the elbow flexion/extension angle across all tasks were $0.94 \pm 0.26°$, $0.34 \pm 0.36°$ and $41.34 \pm 10.15°$. Besides, the root mean square error (RMSE) of the three-dimensional motion data was $0.98°/1.15°/1.67°$ for knee motion, $1.23°/0.47°/3.67°$ for hip motion, and $0.66°/0.31°/1.08°$ for elbow motion. The maximum error was from the knee motion and the hip motion, the complex hip joint as well as the bias between coordinates were supposed to cause this problem.

In addition, the computational results from the third experiment were compared with other previously reported data (see Table IV). Compared with other single-sensor systems, our multi-sensor system performs better. Angle data in the z-axis of MIUMs was affected by the magnetic disturbance, the MIMUs and flexible sensor based measurement system and data fusion strategy in our study could help improve the accuracy of the wearable joint angle measurement system.

VI. Conclusion and Future work

Accurate measurement is a significant performance factor in the wearable measurement system. To eliminate the magnetic disturbance and the signal synchronization problem [13], [28], this paper proposed a three-stage data fusion algorithm firstly, in which a real-time state observer was designed and two filters (Mathony filter and Kalman filter) were utilized respectively to set up a data fusion. Second, a MIMUs and flexible sensor based multi-sensor system was designed for joint angle measurement. Finally, experiments were carried on respectively to verify the algorithm with equipment fixed on the subject's knee/ elbow/ hip joint. As a result, the multi-sensor wearable system can accurately measure the knee/hip/elbow joint angle under random disturbance environments and the accuracy was improved to **1.23°** (x-axis), **1.15°** (y-axis) and **3.67°** (z-axis) respectively under the magnetic disturbance environment.

Moreover, the proposed data fusion algorithm makes it possible for a multi-sensor system to realize accurate measurement and friendly interaction. In our paper, we take advantage of two types of sensors, the designed state observer and the double Mathony filter play a crucial role to solve the magnetic disturbance problem, which is a common indoor environment issue for MIMUs. Though this work was developed with the joint angle measurement application for MIMUs and flexible based wearable systems in the original idea, a similar architecture can also be realized for MIMUs and other types of sensors to achieve a high-accuracy joint angle measurement.

In the immediate future, we anticipate this wearable system based on the proposed algorithm being applied in the areas of activity recognition, long-term monitoring of rehabilitation progress, and telemedicine (or mHealth), which is relevant to current needs in the joint health space [40]. The convenient

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TABLE III
THE MEAN, SD, AND RMSE(DEG) OF THE VERIFICATION EXPERIMENTS

Accuracy verification experiments		The three-dimensional angle	
		Mean $\pm$ SD	RMSE
Knee motion with/without disturbance	without disturbance	1.08 ± 0.27; 2.21 ± 0.36; 43.17 ± 9.24	0.76; 0.87; 1.02
	with disturbance	1.03 ± 0.38; 1.81 ± 0.41; 41.22 ± 10.14	0.71; 0.88; 1.26
Multiple human motions under disturbance	knee motion (flexion/extension)	41.17 ± 9.24; 2.26 ± 0.33; 1.08 ± 0.27	0.98; **1.15**; 1.67
	hip motion (adduction/abduction)	-5.24 ± 7.13; 3.16 ± 4.25; -12.18 ± 11.31	**1.23**; 0.47; **3.67**
	elbow motion (flexion/extension)	0.94 ± 0.26; 0.34 ± 0.36; 41.34 ± 10.15	0.66; 0.31; 1.08

[1] The column “Mean $\pm$ SD and RMSE” presents the mean $\pm$ standard deviation and root mean dquare error repectively of x/y/z angles for each experiment.

TABLE IV
COMPARISION OF THE PROPOSED SYSTEM TO MEASURE JOINT ANGLE WITH OTHER WEARABLE SYSTEMS

Studies	Sensors	Methods/Filters	Joint angle[1]	Human motion	Synchronism/ Anti-disturbance
Hyosany et al.2016 [15]	flexible sensors	Least Square Method	about10°/ about10°/ about10°	shoulder motion	–
Karinal et al.2017 [22]	MIMUs	Complementary Filter	2.7°/ 3.3°/ 7.8°	knee/ hip/ ankle motion	Anti-disturbance
Mohamed et al.2016 [27]	IMUs/FSRs	Kalman Filter	–/–/ about11.9°	knee motion	–
Salvatore et al.2019 [28]	IMUs/EMG	Embedded Fusion Method	–/–/ 10.4°	knee motion	Synchronism/ Anti-disturbance
The Proposed System	MIMUs/flexible sensor	**The Proposed Algorithm**	**1.23°**/ **1.15°**/ **3.67°**	knee/hip/elbow motion	Anti-disturbance

[1] The column “Joint angle” presents the maximum RMSEs of x/y/z angles between all the motions.

wearable system can be rapidly deployed by physiotherapists with access to large clinical users and their associated medical data. Such studies may improve an understanding of joint motions, as knowledge of human motion data and their properties are still developing [41], [42], largely due to a lack of high-accuracy measurement systems and cross-sectional databases. Ultimately, we envision this work will serve as the fundamental algorithm construction for future multi-sensor wearable systems, thus deepening the understanding of precise joint angle measurement and broadening its applications.

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