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A novel data glove for fingers motion capture using inertial and magnetic measurement units

Bin Fang, Fuchun Sun, Huaping Liu, Di Guo

***Abstract*—A novel data glove embedded low cost MEMS inertial and magnetic measurement units, is proposed for fingers motion capture. Each unit consists of a tri-axial gyroscope, a tri-axial accelerometer and a tri-axial magnetometer. The sensor board and processor board are compactly designed, which are small enough to fit the size of our fingers. The data glove is equipped with fifteen units to measure each joint angle of the fingers. Then the calibration approach is put up to improve the accuracy of measurements by both offline and online procedures, and a fast estimation method is used to determine the three orientations of fifteen units simultaneously. The proposed algorithm is easy to be implemented, and more precise and efficient measurements can be obtained as compared with existing methods. The fingers motion capture experiments are implemented to acquire the characteristics of the fingers and teleoperate the robotic hands, which prove the effectiveness of the data glove.**

I. INTRODUCTION

The ability to capture kinematic motion of human limb or other objects is emerging as an invaluable tool in several application areas, such as rehabilitation, sports, animation industry and robotic control. Hands are considered as the most dexterous part of humans and play an important role in many daily life activities such as grasping, reaching, lifting, sensing, hand writing and other fine operation tasks. Therefore, the hand capturing systems are of great concern recently. The state of art in hand capturing systems can be divided in two categories, namely camera-based system and data gloves [1-2].

Camera-based systems can easily capture the contours of the bare hand, but the captured images cannot provide information enough for tracking hands in three-dimensional space because the derivation of the spatial position information can lead to multiple 2D-3D mapping solutions. The well-developed RGBD sensors have been widely used nowadays. The Kinect sensor consisting of a laser projector and a CMOS sensor, provides the ability to monitor 3D motions [3] under any illumination condition. However, camera based systems are subjected to the volume space in which the cameras are placed. Furthermore, the occlusion of fingers results in a non-observable problem, leading to a poor estimation of the hand pose [4].

Data gloves worn on the hand have equipped with various kinds of sensors, such as resistive flex sensors, optical fiber sensors and hall-effect sensors [5-6]. Resistive flex sensors with low cost and good sensitivity are used to determine the flexion of fingers, and the optical fiber sensor with smaller size are used, being more comfortable when wearing. The data glove has the highest accuracy, but it is more expensive and requires an accurate alignment of sensors with the particular joint, and often recalibration is necessary during utilization. Recent years, the inertial sensors are gradually used for the data glove. The availability of MEMS technology enables the inertial sensors to be integrated into single chips. It has made inertial sensors so small and low-power that they have already become a common practice in ambulatory motion analysis [7-8]. Meanwhile, the magnetic sensors are used together with inertial sensors for accurate and drift free orientation estimation [9]. Inertial and magnetic measurement system using inertial and magnetic sensors has proven to be an accurate approach in estimating body segment orientations without the external cameras [10]. It demonstrates higher correlation and lower error compared with a visual motion capture system when the same motions are recorded [11]. The low-cost, small wearable inertial sensors are becoming increasingly popular for data glove. A glove system using inertial sensors was presented in [12], where six dual axis accelerometers are placed on the back of the hand and fingers, and was able to detect only different static postures of the hand. The data glove containing sixteen inertial sensors for hand habilitation was presented in [13], however heading observation was not examined. The inertial and magnetic sensors were used in [14], which allowed the data glove to be more flexible and smaller. But this kind of 9-axis IMU data glove cannot calculate the precise angle of every joint angle because there were only four 9-axis IMU modules on the data glove.

A novel data glove that uses inertial sensors combined with magnetic ones is presented, which was few presented before to our knowledge. The sensors are placed on various finger segments to accurately assess full 3D finger orientations. The online and offline calibration are implemented to improve the accuracy of the measurements. Besides, a novel algorithm is proposed to estimate the optimal orientation of the fingers. Finally, some experiments are designed to recognize the fingers motion with the proposed data glove.

The paper is organized as follows. Section 2 presents the design of the data glove. Section 3 describes the methods of calibration. Section 4 reports the sensors fusion algorithm. Section 5 gives the results of proposed method through simulations and shows the performance of our data glove by several fingers motions. Conclusions are drawn in section 6.

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II. PROPOSED DATA GLOVE

A. Design of the data glove

The proposed data glove is designed according to human hand model which has 20 kinematic DOFs. The left in Fig. 1 shows the hand joints and the degrees of freedom typically used to describe hand motions [15]. The distal interphalangeal (DIP) and proximal interphalangeal (PIP) joints of each finger have 1 DOF while the metatarsophalangeal (MCP) joints have 2 DOFs (flexion/extension and abduction/adduction). The third DOF of the trapeziometacarpal (TMCP) joint allows the thumb to rotate longitudinally as it is opposite to the fingers. According to the above descriptions, 15 sensor modules can be used for estimating the orientations of the fingers. Meanwhile, the characteristics of the hand should be considered. When the hand posture is like shown the right in Fig.2, the bending angle cannot be estimated only by inertial sensors. Hence, the inertial and magnetic sensors are used to determine the complete orientations of each finger.

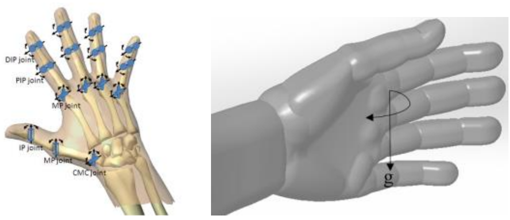


Figure 1. Human hand model

The data glove is developed using the ultra-small, low-power MEMS sensors named MPU-9250, where a 3-axis gyroscope, a 3-axis accelerometer, a 3-axis magneto -meter are integrated into a small 3×3×1mm package. The sensors are used to estimate the orientations of each finger, hence the size of the sensors must be considered to ensure that they are small enough to be equipped on the knuckles. Each MEMS sensor is mounted on a solid PCB with dimensions of 10×15×2.6mm and a weight of about 6g. The STM32F4 microcontroller is used as processing module in the system. The processing module offers a low power consumption with small dimension and standard interfaces such as USB and I^2C, and demonstrates the ability to achieve complete orientation sensing with limited processing capability. The connections between the sensors and the MCU are realized using flexible cables. A series of sensors that consists of three sensor boards deploy each joint of the finger and is connect to the MCU board. The MCU processes the raw data and estimates results, encapsulates them into a packet, and then sends the packet to the PC. The baud rate for transmitting data is 115200 bps. By using this design, the finger motion recognition can be demonstrated on the PC immediately. The system architecture is shown as Fig.2.

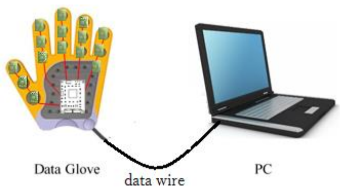


Figure 2. System architecture

The proposed data glove is designed based on the nine-axis inertial sensor, which can capture the more information of fingers than the traditional sensors. It is more compact, more durable and more robust. Meanwhile, the modularized design is easy to setup and use.

B. calibration

Calibration is a vital step to improve the accuracy of sensors. Normally equipment is needed to implement the calibration [16]. Here a simplified calibration is used, which only consider the main calibration parameters including the bias and scale of accelerometers and magnetometers, and the bias of gyroscopes. The calibration is divided into offline procedure and online procedure.

The offline calibration uses the six-position method [17], which requires sensors to be mounted on a leveled surface with each sensitivity axis of each sensor pointing alternately up and down. All sensor boards are placed on the surface of the square body, and accomplish the global calibration, as shown in Fig.3. The accelerometers and magnetometers are calibrated offline, and their parameters are determined by the following equations,

$$bias = \left(m_{up} + m_{down}\right)/2 \tag{1}$$

$$scale = \left(m_{up} - m_{down}\right)/2s_{local} \tag{2}$$

where m_{up} is the sensors' measurement when staying up, m_{down} is the sensors' measurement when staying down, and s_{local} is the value of magnetic intensity or gravity acceleration in local.

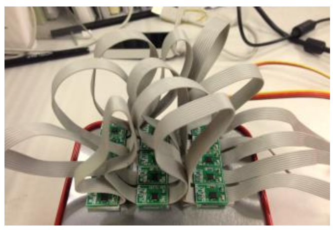


Figure 3. Global calibration-offline

The online calibration is implemented to remove the gyro bias. The data glove keeps stationary for a while before used and the bias is the mean value of the measurements.

III. ORIENTATION ESTIMATION METHODS

A. Related methods

There are two independent ways to determine the attitude and heading according to the characteristics of three kinds of sensors. One is obtained from open-loop gyros, which has high dynamic performance, however, the gyro errors would lead to wandering attitude angles and the gradual instability of the integration drifting. The other is determined by open-loop accelerometers and magnetometers. The orientations can be correctly obtained from accelerometers and magnetometers in the ideal environment. It is quite difficult for these two independent ways to achieve satisfactory performance. So sensor fusion is a proper approach to attain the stable and accurate orientations.

Generally, multisensory fusion algorithm is usually used to determine the sensor's change in 3D orientation over time by continuously integrating the angular velocity vector measured by gyroscopes. The algorithm then employs 3D accelerometer measurements to prevent integration drift with respect to the earth's gravity vector (attitude or inclination), and the 3D magnetometer measurements is used to prevent integration drift with respect to magnetic north (heading). Among the computation procedures, the Kalman filter is adopted to a useful tool for combine and process the measured data. The Extended Kalman filter [18] is a general method for determining orientation, and has been applied in the products of AHRS. However, the EKF suffers from the following drawback: it is not easy to choose numerous parameters and computation. And the complementary filter is proposed [19] to combine two independent noisy measurements of the same signal, in which each measurement is corrupted by different types of spectral noise. The filter provides an estimate of the true signal by fusing high-pass signals that provided by gyroscopes and the data from low-pass accelerometers and magnetometers which provide a relatively accurate measurement at low frequencies. Besides, the two-step optimal filter is designed under two different optimal criteria [20]. In our design, fifteen units are used, which means 3×45 measurements can be attained and so more information need to be processed by only one processor, therefore, a fast and effective estimation method should be proposed to determine the pose of the fingers.

Two assumptions about accelerometer and magnetometer measurements are made: (1) only inertial accelerations due to translational movements are considered; (2) The local static magnetic field is homogeneous throughout the whole hand.

4.2. The Proposed Method

The sensor boards on the hand are commonly in static or rotation status since rotational joints are used for fingers. When the sensors are in static, the pose can be estimated by accelerometers and magnetometers instead of gyros. While the sensors are in rotation, the gyros will be in good place, since estimated pose by accelerometers and magnetometers has lower dynamic characteristics. As a result, a combined measurement method is proposed as below.

Considering a rigid body rotating in inertial space, the kinematics of the rigid body can be described as,

$$\dot{\boldsymbol{R}}_r = \boldsymbol{S}(\omega)\boldsymbol{R}_r \tag{3}$$

where $\boldsymbol{S}(\omega)=\begin{pmatrix} 0 & \omega^z & -\omega^y \\ -\omega^z & 0 & \omega^x \\ \omega^y & \omega^x & 0 \end{pmatrix}$, ω^x, ω^y, ω^z are the measurements of the angular velocity presented in the body frame.

The linear structure can be used when designing the pose estimator, as it will turn out a linear kalman filter. Clearly, the estimator will be implemented in discrete time. Hence equation (3) should be discretized and linearized, and we assume the sample frequency is high, then,

$$\begin{pmatrix} \theta_{k+1} \\ \gamma_{k+1} \\ \psi_{k+1} \end{pmatrix} = \begin{pmatrix} \theta_k \\ \gamma_k \\ \psi_k \end{pmatrix} + T \begin{pmatrix} \omega_k^x \\ \omega_k^y \\ \omega_k^z \end{pmatrix} \tag{4}$$

where, γ_k is roll, θ_k is pitch, ψ_k is yaw, T is the sampling period.

It is easy to design the linear kalman filter for pose estimation with the system structure described in equation (4). The two states of the sensors will be discussed respectively.

I. Static mode

When the sensors are in static, orientation values are constant and measurements of gyros can be omitted. Therefore the filtering equations can be written as,

$$\begin{cases} \boldsymbol{x}_{k+1} = \boldsymbol{x}_k \\ \boldsymbol{y}_k = \boldsymbol{x}_k + \boldsymbol{w}_k \end{cases} \tag{5}$$

And the estimation algorithm is given by,

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + \boldsymbol{K}_k\left(\boldsymbol{y}_k - \boldsymbol{x}_k\right)$$

$$\boldsymbol{K}_k = \boldsymbol{P}_k\left(\boldsymbol{P}_k + \boldsymbol{R}\right)^{-1}$$

$$\boldsymbol{P}_{k+1} = \boldsymbol{P}_k - \boldsymbol{P}_k\left(\boldsymbol{P}_k + \boldsymbol{R}\right)^{-1}\boldsymbol{P}_k \tag{6}$$

where $\boldsymbol{R}$ is the noise covariance matrix of the accelerometers or magnetometers.

II. Rotation mode

When the sensors are in rotation, the orientations are changing with time and the dynamic characteristics of the gyros should be used. Therefore the filtering equations can be written as,

$$\begin{cases} \boldsymbol{x}_{k+1} = \boldsymbol{x}_k + T\cdot\boldsymbol{\omega}_k + \boldsymbol{v}_{k+1} \\ \boldsymbol{y}_k = \boldsymbol{x}_k + \boldsymbol{w}_k \end{cases} \tag{7}$$

And the estimation algorithm is given by,

$$\boldsymbol{x}_{k+1} = \boldsymbol{x}_k + T\cdot\boldsymbol{\omega}_k + \boldsymbol{K}_k\left(\boldsymbol{y}_k - \boldsymbol{x}_k - T\cdot\boldsymbol{\omega}_k\right)$$

$$\boldsymbol{K}_k = \boldsymbol{P}_k\left(\boldsymbol{P}_k + \boldsymbol{R}\right)^{-1}$$

$$\boldsymbol{P}_{k+1} = \boldsymbol{P}_k - \boldsymbol{P}_k\left(\boldsymbol{P}_k + \boldsymbol{R}\right)^{-1}\boldsymbol{P}_k + \boldsymbol{Q} \tag{8}$$

where $\boldsymbol{Q}$ is the noise covariance matrix of gyros.

I. Rotation detection

Since the combined measurement is between static mode and rotation mode of pose estimation, how to identify two cases would be the key point (valuable to be able to detect rotation state or rather, to detect non-rotation). Recall that the gyro model is $\omega_m = \omega + w_g$, so the necessary condition for non-rotation can be expressed as follows

$$\left|\left(\omega_k^x\right)^2+\left(\omega_k^y\right)^2+\left(\omega_k^z\right)^2-\delta\right|=0 \tag{9}$$

where the δ is the setting signal magnitude.

II. Hybrid estimation-switching

In this section, a switching rule will be presented to identify these two modes. The new parameter λ is introduced and defined by,

$$\lambda\left(t_k\right)=\begin{cases}0 & \left|\left(\omega_k^x\right)^2+\left(\omega_k^y\right)^2+\left(\omega_k^z\right)^2-\delta\right|=0\\ 1 & otherwise\end{cases} \tag{10}$$

Using equation (10), the combined filter can be conveniently written as,

$$\begin{cases}\boldsymbol{x}_{k+1}=\boldsymbol{x}_k+\lambda\left(t_k\right)\left(T\cdot\omega_k+\boldsymbol{v}_{k+1}\right)\\ \boldsymbol{y}_k=\boldsymbol{x}_k+\boldsymbol{w}_k\end{cases} \tag{11}$$

$$\boldsymbol{x}_{k+1}=\boldsymbol{x}_k+\lambda\left(t_k\right)\cdot T\cdot\boldsymbol{\omega}_k+\boldsymbol{K}_k\left(\boldsymbol{y}_k-\boldsymbol{x}_k-\lambda\left(t_k\right)\cdot T\cdot\boldsymbol{\omega}_k\right)$$

$$\boldsymbol{K}_k=\boldsymbol{P}_k\left(\boldsymbol{P}_k+\boldsymbol{R}\right)^{-1}$$

$$\boldsymbol{P}_{k+1}=\boldsymbol{P}_k-\boldsymbol{P}_k\left(\boldsymbol{P}_k+\boldsymbol{R}\right)^{-1}\boldsymbol{P}_k+\lambda\left(t_k\right)\cdot\boldsymbol{Q} \tag{12}$$

So the switching between the two modes indicted in Fig.4 is encoded with the λ function.

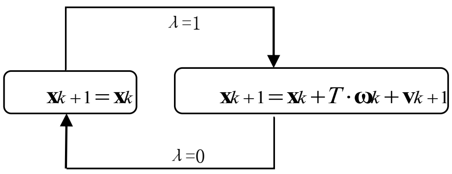


Figure 4. switching architecture

It turns out that the preceding filter equations can be simplified for an appropriate choice of the tuning parameters $\boldsymbol{Q}$ and $\boldsymbol{R}$, namely $\boldsymbol{Q}=q\boldsymbol{I}$ and $\boldsymbol{R}=r\boldsymbol{I}$ with $\boldsymbol{P}_0=p_0\boldsymbol{I}$ known. Furthermore assuming that $\boldsymbol{P}_k=p_k\boldsymbol{I}$, then the following equation can be deduced,

$$\begin{aligned}\boldsymbol{P}_{k+1}&=p_k\boldsymbol{I}+\lambda\left(t_k\right)\cdot q\boldsymbol{I}-p_k\boldsymbol{I}\left(p_k\boldsymbol{I}+r\boldsymbol{I}\right)^{-1}p_k\boldsymbol{I}\\ &=\left(p_k-\frac{p_k{}^2}{p_{k+r}}\right)\boldsymbol{I}+\lambda\left(t_k\right)\cdot q\boldsymbol{I}\\ &=\left(p_k-\frac{p_k{}^2}{p_{k+r}}+\lambda\left(t_k\right)\cdot q\right)\boldsymbol{I}\end{aligned} \tag{13}$$

$$\boldsymbol{x}_{k+1}=\boldsymbol{x}_k+\lambda\left(t_k\right)\cdot T\cdot\boldsymbol{\omega}_k+\frac{p_k}{p_k+r}\left(\boldsymbol{y}_k-\boldsymbol{x}_k-\lambda\left(t_k\right)\cdot T\cdot\boldsymbol{\omega}_k\right) \tag{14}$$

$$p_{k+1}=p_k-\frac{p_k{}^2}{p_{k+r}}+\lambda\left(t_k\right)\cdot q \tag{15}$$

It is shown in Eq. (13)-(14) that the algorithm is quite simple to be implemented.

III. Orientations determination

The orientations estimation is divided into two steps. The attitude is estimated in the first, and then the heading is estimated. The state equations and the measurement equations of the algorithm are described as,

Attitude:

$$\gamma_k=arctg\left(a_k^y/a_k^z\right) \tag{16}$$

$$\theta_k=-arctg\left(a_k^x\cdot\cos\gamma_k/a_k^z\right) \tag{17}$$

$$\begin{pmatrix}\gamma_{k+1}\\ \theta_{k+1}\end{pmatrix}=\begin{pmatrix}\gamma_k\\ \theta_k\end{pmatrix}+\lambda_k\cdot T\begin{pmatrix}\omega_k^x\\ \omega_k^y\end{pmatrix} \tag{18}$$

Heading:

$$\psi_k=arctg\left(\frac{h_k^z\cdot\sin\gamma_k-h_k^y\cdot\cos\gamma_k}{h_k^x\cdot\cos\theta_k+\left(h_k^y\cdot\sin\gamma_k+h_k^z\cdot\cos\gamma_k\right)\cdot\sin\theta_k}\right) \tag{19}$$

$$\psi_{k+1}=\psi_k+\lambda_k\cdot T\omega_{k+1}^z \tag{20}$$

IV. Finger orientations

Each finger has four DOFs, the mechanism of the fingers includes one u-hinge and two revolute joints. The orientations of the finger orientation can be divided into two situations, as is shown in Fig.5.

(1) In the first situation, $\gamma_1\neq\pi/2$,the bend angles are,

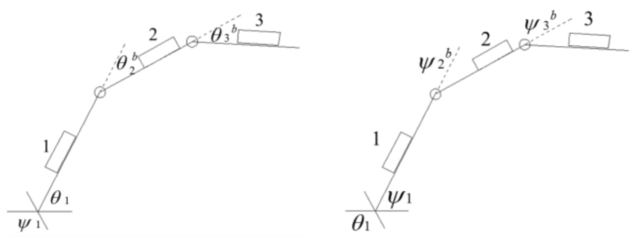
$$\theta_2^b=\theta_1-\theta_2 \tag{21}$$

$$\theta_3^b=\theta_2-\theta_3 \tag{22}$$

(2) In the second situation, $\gamma_1=\pi/2$, the bend angles are,

$$\psi_2^b=\psi_1-\psi_2 \tag{23}$$

$$\psi_3^b=\psi_2-\psi_3 \tag{24}$$



a. The first situation b. The second situation

Figure 5. Orientations of the fingers

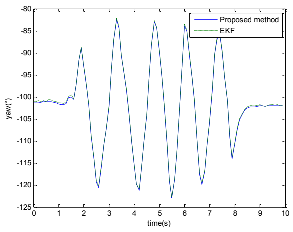
4.3. Remarks

The proposed method considers the computation accuracy in order to estimate the orientations of fifteen inertial and magnetic measurement units simultaneously. The traditional EKF filter commonly has a 9-D measurement vector, consisting of 3-D angular rate, 3-D acceleration, and 3-D local magnetic field. The first three components of the output equation (angular rate portion) are linearly related to the state vector. However, the other six components of the output equation are nonlinearly related to the state vector. It is a nonlinear system because of the nonlinear nature of the rotation matrix, and the EKF approach requires that a first-order Taylor-Mac Laurin expansion is carried out by computing the Jacobian matrix. The EKF designed with this output equation is computationally inefficient and may be divergence due to the linearization. However, the linear kalman filter is deduced. It is significantly simpler, owing to the fact that the measurement equations are linear. Moreover, the linearization of the EKF approach distorts the noise characteristics of the sensors, which would affect the precision of the estimation. Nevertheless, no linearization is performed in the proposed algorithm and the practical noise characteristics are considered. Furthermore, the switching mode is used to improve the accuracy and efficient. Fifteen filters are used to determine the three orientations of the units, so that the fingers orientations can be fully determined whatever the pose of hand is.

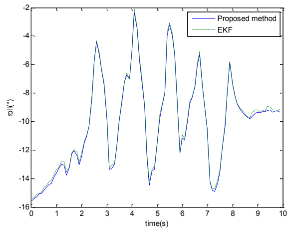
IV. EXPERIMENTS

A. simulation and results

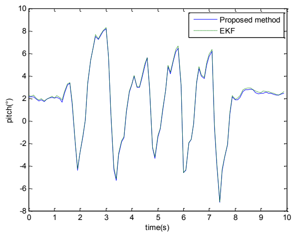
The simulation experiments are implemented to verify the accuracy and efficiency of the proposed algorithm. The real sensors data are used in the simulation. After deriving all the required parameters to initialize the filters, they were implemented using MATLAB to test the performance and accuracy of the orientation estimates. Fig.6 shows the performance of the proposed method and Extended Kalman filter using the real measurements. The solid lines denote the results of proposed method and the dashed lines denote estimated values of traditional EKF. The RMSE of the angles determined by the two methods are compared in the Table 2. The accuracy of the two algorithms are similar but the efficiency of proposed method is almost twice faster than that of the original EKF.



a. the estiamted yaw



b. the estiamtedroll



c. the estimated pitch

Figure 6. the results of the proposed method and the traditional EKF

TABLE I. PARAMETER VALUES USED IN THE SIMULATIONS

RMSE(°)	yaw(°)	roll(°)	pitch(°)
Proposed method	0.76	0.25	0.21
Traditional EKF	0.87	0.3	0.2

B. Motion capturing experiments

Several experiments are carried out to illustrate the superior performance of the data glove as shown in Fig.7-Fig.10. The orientations that computed by the MCU board are sent to the computer, meanwhile the fingers motion is performed using MATLAB.

In each figure, the left is the operation scenario for data glove, and the right is motion recognition result shown in MATLAB. Figure 7 shows the fingers are flat on table. We find that when the hand naturally placed on the horizontal plane, the fingers are tend to be bent. Figure 8 shows the fingers hold a cup, it shows that the grasping mainly depends on the thumb and index finger. Moreover, the fingertip of thumb kneads the PIP joint of index. Figure 9 shows the fingers hold the spoon, it depends on the thumb and index finger, the motion is similar to the motion of holding a cup. Figure 10 shows the fingers playing the mobile, the fingertip of the index finger is mainly used, and the DIP joints are elastic and adaptive in motion. Based on these experiments, we can draw that the finger motion capture can be easily achieved by the proposed data glove.

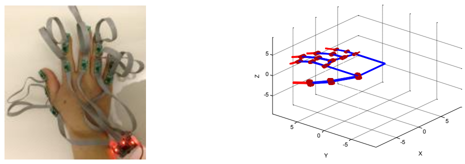


Figure 7. the fingers flat on table

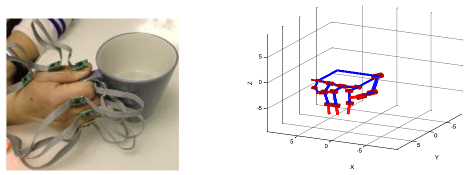


Figure 8. the fingers hold the cup

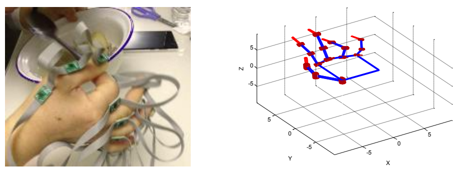


Figure 9. the fingers hold the spoon

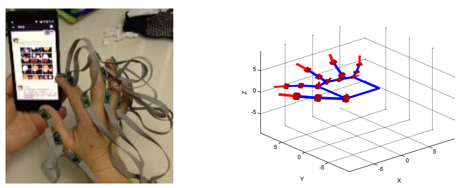


Figure 10. the fingers play the mobile

Furthermore, the experiments of teleoperation of robotic hand by the data glove are implemented. The robotic hand has three fingers, hence the bendings of PIP joints of forefinger, midfinger and thumb are used to teloperate the Barrett hand. The status of teloperation are shown in the Figure 11. The robotic fingers can bend fluently following the motions of human fingers, which also prove the effectiveness of the proposed data glove.

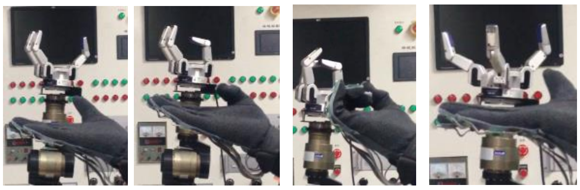


Figure 11. teleoperation of robotic hand by the data glove

V. CONCLUSION

This paper presents the design and implementation of finger motion capture using our novel proposed data glove. The data glove is based on inertial/magnetic sensor modules having triads of accelerometers, angular rate sensors, and magnetometers. It can capture the more information of fingers than the traditional sensors. Moreover, the used sensors are low-cost. The proposed design is organized in a distributed way that fifteen sensor-boards are deployed on separated sections of the fingers, and the orientations are computed by one processor-board. The calibration method is implemented to improve the accuracy of the sensors by both offline and online procedures. And the estimator based on the linear kalman is deduced, the switching mode can take fully advantage of the characteristics of the sensors. Moreover, the features of the hand mechanism are used to determine the pose of the fingers. The experiments demonstrated that it is easy to implement to capture the motion of fingers. The proposed data glove is more compact, more durable than the commercial data gloves. In the future, the design can be used not only for finger motion capture but also for the experience learning of robotic grasping.

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