The Lower Limbs Kinematics Analysis by Wearable Sensor Shoes

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Abstract—Inertial sensors designed for wearable devices in lower limbs need to be calibrated with complicated steps before measurements, and the attachments of body also influence the normal motion and bring measurement errors caused by relative movements. This paper proposes a method using ground reaction forces (GRFs) and moments measured by a pair of wearable sensor shoes to estimate the joint angles of lower limbs for gait analysis. The wearable sensor shoes are combined with motion sensors to construct a wearable gait analysis system in our previous research. Based on the reliable measurements of the wearable system, neural networks are trained with GRFs or GRFs and moments as an input, and the joint angles as the output. The joint angles obtained from the trained models and the measurements of the motion capture system show good agreements. The correlation coefficients (R) are more than 0.7, 0.9, and 0.9 for the joint angle of ankle, knee, and hip, respectively, and the normalized root mean square errors are less than 8°, 9°, and 5° for the three joints, respectively. The comparison results show low performance of rectification of biases and distortion of waveforms. As a major advantage, the method to acquire kinematics using the wearable sensor shoes is relative simple and reliable compared with multi-inertial sensors on body segments.

Index Terms—Extended Kalman filter, gait analysis, ground reaction force, joint angle, neural network, wearable sensor shoes.

I. INTRODUCTION

THE OPTICAL motion capture system, combined with several stationary force plates, has been implemented for gait measurement in the past years [1], [2]. This combined system has been commercialized for many years, and the accuracy of the measurement is guaranteed by the high quality of expensive high-speed cameras and elaborate stationary force plates. The limitation of measurement space and high cost of this system can no longer satisfy the increasing demand of gait analysis in health care and rehabilitation in daily life. In order to overcome the disadvantages of the conventional system, the inertial sensors and instrumented shoes [3] or insoles [4]–[6] mounted with force sensors become an alternative. Inertial sensors including gyroscope [7], [8], accelerometer [9]–[11] and magnetometer [12] have been used for measurement of segments’ attitude and the commercialized wearable sensor system for kinematics analysis are available in the market. Capacitive sensor [13] and bend sensor [14] are also available in motion detection such as gait measurement. Instrumented soles [3] or instrumented insoles [4], [5] are used to measure the ground reaction force, but both of them can only measure the vertical pressure instead of three axial force or moment. In our previous research, several kind of wearable sensor shoes have been developed with two mobile force plates in the insole or under each shoe [15], [16]. And lately, we developed a pair of wearable sensor shoes mounted with three mobile force plates in each insole [17]. The motion sensors integrated with inertial sensors are combined with the wearable sensor shoes by WIFI communication. Like the other body sensor networks [18], this wearable gait analysis system is more convenient than the former one [12].

In this article, based on the measurements of the wearable gait analysis system, we propose a new method for kinematics analysis of lower limbs without inertial sensors. The attachment and connection of inertial sensors [19] are complex and time consuming, and the calibration for the alignment of multi-inertial sensors and segments [20], [21] is a complicated process. Some researchers have focused on this problem and proposed methods with simple operation of multi-sensor system for long-term measurement of gait [22], [23]. However, no method used only the foot’s GRFs and moments for the assessment of gait parameters. But as we know, the human can sense the body attitude through the muscular forces, visual sense and organs in the internal ear for balance. In the last few years, inertial sensors are used to measure the orientation and motion of upper-limbs [24], [25] and lower-limbs [26], [27] with various kinds of algorithms. In this paper, neural networks are used to establish relationships between the joint angles and GRFs, moments. The force sensors mounted under the shoes can barely influence the...
normal gait. We intend to improve the performance of these models to control the prosthetic leg or exoskeleton leg in the future. Previously, position sensors [28], dynamic oxygen-uptake controller [29], force-field controller [30] and specific mechanical device [31] were used before in the control of robot-assist gait training system. These sensors are not convenient in daily life for patients compared with the wearable sensor shoes.

Extended Kalman filter (EKF) [32], [33] is widely used in the application of inertial sensors to deal with the noises in the measurements of gyroscope. But the updates of acceleration and magnetic field intensity in gait analysis are not reliable enough to acquire high accurate measurements. Because both gravitational acceleration and segment’s motion acceleration are measured by the accelerometers. So the acceleration could be influenced when the heel-strike happened or walking with high speed. In addition, the measurements of magnetometer can also be disturbed by the surrounding soft magnet or devices. The work in [34] provided a rider-bicycle dynamic model which explained the underlying relationship between the force and the inertial measurements. In this article, we proposed a modified EKF updated with ground reaction forces (GRFs) and moments from the wearable sensor shoes to reduce the biases of joint angle estimation. The neural networks used for estimating joint angles with GRFs and moments are acted as a linkage between GRFs, moments and quaternions. However, the performance of this method is not reliable and accurate as the neural network which demonstrates the advantages of the latter method.

II. METHODS AND MATERIALS

A. Wearable Gait Analysis System

As shown in Fig. 1, a wearable gait analysis system was designed to replace the conventional combined system which composed of the optical motion capture system and stationary force plates. Similar to the working principle of the conventional system, the wearable gait analysis system consists of a pair of wearable sensor shoes which mounted with mobile force plates and motion sensors which measures body attitude.

![Fig. 1. The wearable gait analysis system.](image)

The circuit used in the motion sensor is integrated with a gyroscope, an accelerometer and a magnetometer (MPU-6050, InvenSense, USA), and an extended Kalman filter (EKF) method was used to calculate the orientation of the motion sensors with the measurements of the sensors mentioned above. As for the structure of the wearable sensor shoes, three mobile force plates connected with WIFI communication and power supply modules were mounted in the hollowed upside of the sole of each shoe and covered with an insole. In our previous research, two mobile force plates are available for each shoe [12], [16]. But later we found that the pressure under arch is significant for the detection of mid-stance, and the existence of the mobile force plate under the arch can improve the measurement precision without changing the comfort level for subjects. These mobile force plates encapsulate six-axial force sensors separately (M3552D: arch, M3553D: heel, M3554D: fore-foot, Sunrise Instruments, USA) with thin aluminous shells, and the specification of these force sensors is shown in TABLE I. As shown in Fig.2, the mobile force plates under the heel and the forefoot are mounted with inertial sensors respectively to acquire orientations and attitudes of the force plates. And the mobile force plate under the arch is considered as an extension part of the mobile force plate under the heel. So the resultant GRF and resultant moment can be calculated as described in (1) (2).

\[
F_{GRF} = R_{\text{heel}} \cdot (F_{\text{heel}} + F_{\text{arch}}) + R_{\text{forefoot}} \cdot F_{\text{forefoot}}
\]

\[
M_{\text{foot}} = R_{\text{heel}} \cdot (M_{\text{heel}} + M_{\text{arch}}) + R_{\text{forefoot}} \cdot M_{\text{forefoot}}
\]
where $F_{GRF}, M_{foot}$ denote the resultant GRF and the resultant moment. $F_{heel}, F_{arch}$ and $F_{forefoot}$ denote the GRF measured by the mobile force plate under the heel, arch and forefoot respectively. $M_{heel}, M_{arch}$ and $M_{forefoot}$ denote the moment measured by the mobile force plate under the heel, arch and forefoot respectively. And $R_{heel}, R_{forefoot}$ denote the transformation matrix of the mobile force plate under the heel and the forefoot respectively.

B. Neural Network Models Trained by GRFs and Moments

Intending to find the relation between the variation of foot pressure and joint angle, we used the measurement results of the wearable sensor system to train the artificial neural networks. As shown in Fig. 3, the variation of GRFs measured by the three force plates separately can give us more information compared to the final resultant GRF. As for the left leg, all the force plates are suspended in the swing phase and sensor data are close to zero if considering the additional pressure while wearing the shoes tightly. Then, the force plate under the heel begins to contact the ground when the heel-strike event happened, and the GRF of the heel increases firstly, the GRFs of arch and forefoot will increase subsequently. Only in the stance phase does the force plate under the arch have attached the ground. And the toe-off event happens next, the force plates under the heel and arch are already suspended while the GRF of forefoot reaches its maximum.

The x-axial and y-axial GRF also can imply the state of gait. The y-axial GRF is negative to slow down the body after heel-strike and positive to accelerate the body before toe-off. As for the left leg, the x-axial GRF is negative to pull the body to the left in the stance phase. According to the analysis above, we suppose that the state of contralateral limb can also be estimated to a certain extent because of the alternative motion regulation of lower limbs. So we take the triaxial GRFs of six force plates in the wearable shoes as the inputs of neural network and the joint angles of lower limbs as the outputs. In addition, the center of pressures (CoPs) changed in the gait as a result of motion. The triaxial moments measured by the force plates include the information of CoPs, so the triaxial moments of six force plates can be the inputs of neural network too.

In order to discuss the influence of CoPs in gait assessment, we make a comparison between the neural networks trained by GRFs and both GRFs and moments. The moments’ unit is transformed into Ncm to keep a same order of magnitude with GRFs, and all the GRFs and moments were normalized to body mass (N/kg, Ncm/kg). Each model is divided into two parts, one part is to discuss the accuracy of estimation for a specific person, and another part is to discuss the general applicability of the model method. In the first model, we used the GRFs of all the mobile force plates to train the neural networks. In part 1, we used half of subject A-D’s measurements to train a neural networks which had 15 hidden nodes (as shown in Fig. 4) respectively, and we used another half of results to validate the neural networks respectively. In part 2, we used half measurement results of each subject from subject A-F(known subjects) to train a neural network and another half to validate the neural network separately. Besides, we used subject G, H’s(unknown subjects) measurement results to validate the neural network to test the general applicability.

In the second model, all the model process and validation process were the same as the first one, but the neural networks were trained by both GRFs and moments. Only the sagittal plane joint angle was considered in this article.

Our developed wearable gait analysis system was designed to be an alternative system of the optical capture system and stationary force plates. The latter is a combined system of high cost and relative accurate measurement. But the wearable system can be easier to carry and implement some outdoor successive measurement in daily life without indoor settings.

C. EKF Used in the Wearable System

This section here is to demonstrate the previous method of EKF for the comparison of the modified EKF described
in the next section. The extended Kalman filter used in the wearable gait analysis system consists of the prediction and the update of the state vector (see Fig. 5). We chose the quaternion \( q = [q_0, q_1, q_2, q_3] \) as the state vector, and the differential equation of the quaternion is shown in (3). The state equation can be described in (4). So, the state transition matrix \( \Phi_{k, k-1} \) at \( t = k \cdot \Delta t \) can be calculated in (5). The x-axial, y-axial and z-axial angular velocities measured by the gyroscope are denoted as \( \omega_x, \omega_y, \omega_z \) respectively. The sampling period is denoted as \( T \) and \( w(k-1) \) is the white noise of the state vector. This method has been used before in our previous research [16], the usual way to implement this EFK is described in the form of the following equations for a comparison of the modified EKF below.

\[
\begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix} = \frac{1}{2} \begin{bmatrix}
0 & -\omega_x & -\omega_y & -\omega_z \\
\omega_x & 0 & -\omega_z & \omega_y \\
\omega_y & \omega_z & 0 & -\omega_x \\
\omega_z & -\omega_y & \omega_x & 0
\end{bmatrix} \begin{bmatrix}
q_0 \\
q_1 \\
q_2 \\
q_3
\end{bmatrix} + w(k-1)
\]

\[
\Phi_{k, k-1} = \begin{bmatrix}
1 & -\frac{1}{2} \omega_x T & -\frac{1}{2} \omega_y T & -\frac{1}{2} \omega_z T \\
\frac{1}{2} \omega_x T & 1 & -\frac{1}{2} \omega_y T & -\frac{1}{2} \omega_z T \\
\frac{1}{2} \omega_y T & -\frac{1}{2} \omega_x T & 1 & -\frac{1}{2} \omega_z T \\
\frac{1}{2} \omega_z T & -\frac{1}{2} \omega_x T & -\frac{1}{2} \omega_y T & 1
\end{bmatrix}
\]

The measurement results of the MEMS gyroscope always mix with severe zero drift and random errors. In order to solve this problem, the measurement results of accelerometer and magnetic sensor are used to update the predicted state vector. The observation function \( h(k) \) around the predicted state vector \( q(k)' \) can be acquired by transforming the reference vector \( v \) to the local coordinate system of the motion sensor. The transformation matrix is denoted as \( R \).

\[
h(k) = R \cdot v
\]

\[
R = \begin{bmatrix}
q_0^2 + q_1^2 - q_2^2 - q_3^2 & 2(q_1q_2 - q_0q_3) & 2(q_1q_3 + q_0q_2) \\
2(q_0q_3 + q_1q_2) & q_0^2 - q_1^2 + q_2^2 - q_3^2 & 2(q_2q_3 - q_0q_1) \\
2(q_1q_3 - q_0q_2) & 2(q_0q_1 + q_2q_3) & q_0^2 - q_1^2 - q_2^2 + q_3^2
\end{bmatrix}
\]

The reference vector \( v = [v_x, v_y, v_z] \) can be the gravitational acceleration or the intensity of geomagnetic field when the observation of acceleration or magnetic field intensity is used in update. And the observation matrix \( H(k) \) which described in (8) is the Jacobian matrix of partial derivative for \( q(k)' \).

\[
H(k) = \frac{dh(k)}{dq(k)}
\]

D. Modified EKF Algorithm With GRFs and Moments

We have built the neural networks which can estimate the joint angle by inputting the GRFs and moments of the mobile force plates. Now we can use the neural network as an observation model to rectify the predicted state vector. We attempt to use the fusion of GRFs and moments in EKF to decrease the drift in measurements. Unlike the work in [34], the neural networks were used instead because physical model is not suitable for human segments. According to the training result of the neural network, we can consider that (9) is approximately equal. \( A^{ANN} \) denotes the joint angle estimated by the neural network, \( A^{M} \) denotes the joint angle measured by the wearable gait analysis system, and \( k, c \) are proportional constant and constant vector respectively.

\[
A^{ANN} = k \times A^{M} + c
\]

The angle of each joint can be acquired by transform the lower segment’s attitude angle into its upper segment’s coordinate system, so the transformation matrix of the joint can be described as:

\[
R_j = R^{upper} \cdot R^{lower}
\]

where \( R_j, R^a \) and \( R^l \) are the transformation matrices of the joint, the upper segment and lower segment respectively. Then, the triaxial joint angle can be calculated using the following equations:

\[
\text{Angle}_x = \tan^{-1}(R_{j32}/R_{j33})
\]

\[
\text{Angle}_y = -\sin^{-1}R_{j31}
\]

\[
\text{Angle}_z = \tan^{-1}(R_{j21}/R_{j11})
\]

where \( \text{Angle}_x, \text{Angle}_y \) and \( \text{Angle}_z \) represent the x-axial, y-axial and z-axial joint angle respectively.
In order to avoid the complex calculation of inverse trigonometric functions, we chose the observation vector in the form of (14).

\[
Z = \begin{bmatrix}
\tan(A_x^{ANN} - c)/k & \sin(-A_y^{ANN} + c)/k \\
\sin(A_y^{ANN} - c)/k & \tan(A_z^{ANN} - c)/k
\end{bmatrix}\begin{bmatrix}
R_{j32}/R_{j33} & R_{j31} & R_{j21}/R_{j11}
\end{bmatrix}
\]

(14)

The modified EKF algorithm is based on the prediction and update of quaternion. In this situation, the trigonometric values of triaxial joint angle are related to the quaternion of both upper segment and lower segment. So, it’s necessary to extend the state vector to contain them all. The quaternion of the upper segment and lower segment are denoted as \( q^u \) and \( q^l \) respectively. The extended state vector and the corresponding state equation can be described in (15) (16).

\[
X = \begin{bmatrix}
q^u \\ q^l
\end{bmatrix}^T
\]

\[
X(k)' = \begin{bmatrix}
\Phi_{k,k-1}^u & 0 \\
0 & \Phi_{k,k-1}^l
\end{bmatrix} \cdot X(k-1) + \begin{bmatrix}
w^u(k-1) \\ w^l(k-1)
\end{bmatrix}
\]

(16)

where \( \Phi_{k,k-1}^u \) and \( \Phi_{k,k-1}^l \) are the transition matrices of the upper segment and lower segment respectively, and \( w^u(k-1) \), \( w^l(k-1) \) are the corresponding white noises. So, the observation equation is determined by (17).

\[
Z(k) = H^A(k) \cdot X(k)'
\]

\[
H^A(k) = \frac{dZ(k)}{dX(k)'}
\]

(18)

If the reference vector such as gravitational acceleration or intensity of geomagnetic field is allowed to be used in this algorithm, the reference vector should be extended to fit the state vector. The extended reference vector \( v' \) and extended observation function \( h(k)' \) are described in (19) (20).

\[
v' = \begin{bmatrix}v \\ v\end{bmatrix}^T
\]

\[
h(k)' = \begin{bmatrix}R^u & 0 \\ 0 & R^l\end{bmatrix} \cdot v'
\]

(19)

(20)

In this article, limited by the measurement accuracy of wearable gait analysis system, we only used the x-axial joint angle to validate the modified EKF algorithm. In this part, the measurements updated with only acceleration, acceleration and GRFs, acceleration and both GRFs and moments were compared with the measurements of the reference system.

III. EXPERIMENT METHODS

A. Validation of the Wearable Gait Analysis System

In order to verify the performance and accuracy of the developed system, we established a reference system (as shown in Fig. 6) which composed of 8 high-speed cameras and three stationary force plates (NAC Image Tech., Japan) to validate the measurement results of the developed system. Eight health experiment subjects without lower extremities diseases or injuries were consented to participate in this research. The subjects’ segments of lower extremities were labelled with optical markers for the reference system to capture the motion in gait. And a synchronization trigger was used in the experiments to keep all the sensor modules in the wearable system and the reference system working simultaneously. Before the trial, calibration of joint angles was implemented in a simplified way. The subjects were asked to stand still for aligning the inertial sensors to the corresponding segments as well as possible, then the calibration quaternions were obtained to make the initial joint angles equal to zero. Some better calibration procedures have been mentioned in the work of [35] and [36] for knee joint. However, we chose the simplest method this time because only the flexion/extension angle was considered in this article. After that, the subjects wearing the wearable gait analysis system were asked to walk from the beginning position to the data acquisition area of the reference system. Every trial was repeated 15 times to ensure the repeatability of the measurement. Subjects will have a 5 minutes’ interval before the next trial to exclude the abnormal gait caused by fatigue. The global coordinate system is defined as below: the x-axial positive direction is the right of the body; the y-axial positive direction is anterior; and the z-axial positive direction is upright. Based on the measurements of the wearable system acquired in the dynamic verification described above, the neural networks and calculation method of modified EKF with GRFs and moments were
accomplished using the MATLAB software (The Mathworks, Natick, MA, USA) off-line.

B. Outdoor Experiment of the Wearable System

In this experiment, eight healthy subjects are recruited and two kind of common walking situations (lawn and sidewalk) are chosen to verify the feasibility of the wearable system in outdoor conditions. As shown in Fig. 7, each subject wears the whole wearable system including the wearable sensor shoes and motion sensors to walk normally on the lawn and the sidewalk. Each walking condition was repeated 20 times and the subject has a 5-minute rest between trials to avoid fatigue. All the measurements were transmitted from the modules of the wearable system through WLAN to a PC. The software installed on the PC extracted the resultant GRF and joint angles of ankle, knee and hip. The neural networks were trained using the GRFs and moments of force sensors as inputs and joint angles of the ankle, knee, hip as outputs. In the outdoor experiment, only the second model was used to train the neural networks. Each subject’s measurements were divided into two parts. Half of the measurements were used to train the neural network and the other half were used to validate the performance of the neural network model. The performance of the proposed system during outdoor experiment was evaluated.
by calculating the correlation coefficients (R Value) and RMSE between the estimated joint angles from the neural networks and the respective measured joint angles from the wearable system.

IV. RESULTS
A. Dynamic Verification of the Wearable Gait Analysis System

TABLE II shows the comparison results of the measurements between the wearable gait analysis system and the reference system. GRF\textsubscript{z} denotes the z-axial GRF. A\textsubscript{ankle}\textsubscript{x}, A\textsubscript{knee}\textsubscript{x}, A\textsubscript{hip}\textsubscript{x} denote the x-axial joint angle of ankle, knee and hip respectively. The comparison results are expressed as both root mean square error (RMSE) and correlation coefficient (R). The joint force (N/kg) and joint moment (Nm/kg) were normalized to the body mass.

B. Validation of the Neural Network Model

TABLE III shows the comparison results of joint angles of ankle, knee and hip between the estimations of the neural networks and the measurements of the reference system. In this table, the first modeling represents the modeling method that used the GRFs to train the neural networks. And the second modeling represents the modeling method that used the GRFs and moments to train the neural networks. Both them were divided into two parts. Part 1 represents the model trained by the measurements of subject A-D separately and validated by the remaining measurements of subject A-D respectively. Part 2 represents the model trained by the measurements of subject A-F and validated by the remaining measurements of subject A-F and the measurements of subject G, H separately. The comparison results were expressed as RMSE and R. Both the training results and validation results were shown in TABLE III.

C. Verification of Outdoor Experiment

TABLE IV shows the outdoor experiment results expressed as R and RMSE between the measurements of the wearable system and the estimations of the neural networks.

D. Validation of the Modified EKF With GRFs and Moments

TABLE V shows the comparison results of joint angle calculated by different algorithms. Only the x-axial joint angle was discussed in this article, and the measurements of the reference motion capture system were considered as the standard measurements. The joint angle calculated by the EKF updated with acceleration, acceleration and GRFs, acceleration and both GRFs and moments were compared with the joint angle measured by the reference system respectively. Fig. 11 shows a random sample of the comparison results between different calculation algorithms. The measurements of the wearable gait analysis system are calculated using the EKF updated with acceleration and magnetic field intensity.

V. DISCUSSIONS

The wearable gait analysis system is capable of measurement in ambulatory and non-laboratory environments. As shown in TABLE II, the z-axial GRF, and x-axial joint angle of knee, hip showed good agreements with the reference system. As for the x-axial joint angle of ankle, the waggle of shoes in walking is the main reason of the low consistency of the two systems. The performance of the wearable gait analysis system has been discussed in detail in [17].

As shown in TABLE III, as for knee joint and hip joint, the estimation values of neural network in “Part 1” of the first model showed a good agreement with the measurement results of the reference system. The RMSE and R of joint angle of ankle, knee and hip were 6.70°, 8.32°, 4.66° and 0.71, 0.91, 0.91 respectively. The comparison results of joint angle of knee and hip in “Part 1” of the second model also showed a good agreement with average RMSE of 8.83°, 4.90° and correlation coefficient of 0.90, 0.91 respectively. But the ankle joint showed a relative low agreement with average RMSE of 7.47° and R of 0.74. From Fig. 8, we can see that the errors existed in the measurements of wearable system can cause the estimation errors of neural networks. But it's necessary to choose the measurements of wearable system instead of motion capture system as training data, because the motion capture system is extremely limited in narrow indoor environments. As for subject A-F in “Part 2” of the first model, the joint angles of knee and hip showed acceptable agreements with average RMSE of 7.93°, 5.69° and correlation coefficient of 0.88, 0.88 respectively. The ankle joint angle showed low agreement with average RMSE of 6.85° and R of 0.73.

In “Part 2” of the second model, the comparison results were similar to the first model again. The RMSE and R of joint angle of ankle, knee and hip were 8.65°, 8.65°, 6.58° and 0.76, 0.89, 0.88 respectively. No significant difference was found between the comparison results of the neural networks trained by GRFs and the other models which were trained by both GRFs and moments. Although the results in the first model
Fig. 8. A sample comparison results of subject A of x-axis joint angle between the estimations of neural networks and the measurements of wearable system and reference system. (a) first model (trained by GRFs), part 1, ankle; (b) first model (trained by GRFs), part 1, knee; (c) first model (trained by GRFs), part 1, hip; (d) second model (trained by GRFs and moments), part 1, ankle; (e) second model (trained by GRFs and moments), part 1, knee; and (f) second model (trained by GRFs and moments), part 1, hip. Solid line: estimations of the neural networks; dot line: measurements of the wearable system; dash line: measurements of the reference system.

Fig. 9. A sample comparison results of subject G of x-axis joint angle between the estimations of neural networks and the measurements of wearable system and reference system. (a) first model (trained by GRFs), part 2, ankle; (b) first model (trained by GRFs), part 2, knee; (c) first model (trained by GRFs), part 2, hip; (d) second model (trained by GRFs and moments), part 2, ankle; (e) second model (trained by GRFs and moments), part 2, knee; and (f) second model (trained by GRFs and moments), part 2, hip. Solid line: estimations of the neural networks; dot line: measurements of the wearable system; dash line: measurements of the reference system.

As for subject G, H in “Part 2” of the first model, the comparison results showed a low agreement between the estimation values of neural networks and the measurement were a little better than in the second model, the limitation of experiment data volume can cause this phenomenon rather than the difference of models.
Fig. 10. Sample experiment results from the outdoor environments: (a) ankle joint angle during sidewalk walking; (b) knee joint angle during sidewalk walking; (c) hip joint angle during sidewalk walking; (d) ankle joint angle during lawn walking; (e) knee joint angle during lawn walking; and (f) hip joint angle during lawn walking. Red solid line represents the measurements from the wearable system, blue dash line represents the estimated joint angle by the neural network model.

results of the reference system. The RMSE and R of the joint angle of ankle, knee and hip were 10.64°, 13.91°, 9.16° and 0.66, 0.70, 0.76 respectively. In “Part 2” of the second model, the RMSE and R of the joint angle of ankle, knee and hip were 13.21°, 15.03°, 9.30° and 0.62, 0.76, 0.74 respectively. In total, the validation results of subject G, H were not as good as expected. The amount of training data was still not sufficient to build a universal neural network for the estimation of joint angle of an unknown person. The position changes of CoPs may be a good indicator for gait assessment according to the similar performance of the second modeling in “Part 2”. But the change regulation of CoPs is variable due to different person. The usage of original moments may bring in disturbances which were caused by the diverse walking habits.

From the results of the indoor experiment (TABLE III), we found that the universal model produces larger errors for the unknown subjects. Moreover, the first model and second model built for the specific person have similar performance, and therefore we simply chose the second model in outdoor experiments. As shown in TABLE IV and Fig. 10, the estimation errors in outdoor experiments are slightly larger than the indoor results. This is due to the fact that the subject movement area is much larger in the outdoor experiments when compared with the indoor environments. The signals of wireless modules are weaker when subjects walked away from the receiving router. This would have caused out of synchronization among measurements between sensors. The asynchronization of measurements affected the quality of the trained neural network model. In addition, the drifts in the inertial sensors caused accumulative biases in the estimated joint angles in long-duration outdoor experiments. The inaccuracy of joint angles, the output for training the neural network model, again affects performance of the model.

As shown in TABLE V, the performance of modified EKF with GRFs and moments currently is not acceptable in the application of gait analysis. The purpose of this section is to discuss a novel method to solve the accumulated drifts in long term measurement for the wearable system. As we know, the EKF usually used is updated with measurements of the accelerometer and magnetic sensor to rectify the noises of the measurements of gyroscope. But the measurements of gravitational acceleration are mixed with motion accelerations of human segments, the measurements of geomagnetic field intensity can be easily influenced by the surrounding soft magnet. In the work of [34], the fusion of force and inertial sensors was used to eliminate the drift caused by inertial sensors. The modified EKF method was proposed to apply the neural network models to the measurement to eliminate large deviations, but the noises and errors existed in the estimates of neural networks are also brought into the calculations. Another reason could be the complicate calculation of this method.
For the quaternions are decimals smaller than one, the calculation value could not be equal the real value after several steps of calculation using software. From Fig. 11, we can see the performance of this method is not stable.

In this article, the quality of the neural networks is limited, because the accuracy of the measurements of the wearable system is not perfect and the volume of the data is not sufficient enough. Random errors are also existed in the estimations of neural networks. The accuracy of the joint angle calculated by the EKF updated by GRFs or both GRFs and moments are not as good as the joint angles estimated by the neural networks, which demonstrates that the kinematics analysis with only measurements from wearable sensor shoes is an easier and more accurate option.

VI. CONCLUSION

Using the GRFs and moments measured by the wearable sensor shoes, two kinds of model methods were presented in this paper for gait assessment. The models have good performance in the estimation of knee and hip joint angles but not the ankle joint angle. According to the verification results of wearable system, the unstable joint angle measurements of ankle joint with low accuracy used in training should be the main reason. The change rules of GRFs on the heel, arch, and fore-foot are good indicators for gait assessment. The change rules of CoPs on the heel, arch, and fore-foot need to be further studied for better model performance. Similar results were obtained in the second modeling compared with the first modeling. The moments contain the information of CoPs,
but the positions of CoPs at heel, arch and forefoot change for different person. The extract of global CoP at the whole foot could be a better strategy in finding the regulation of gait.

For most prosthetic legs or exoskeleton legs, we expect that the mechanisms could work normally in daily life with only few force sensors under user’s feet. On the one hand, the neural networks trained by a certain person’s measurement data can be stable and accurate for the estimation of joint angle but can’t be used for other persons. On the other hand, the neural networks for universal estimation of joint angle showed a low performance, but there is still a possibility to reach this goal. Firstly, we need to build a comprehensive database of GRFs, Cops and the corresponding kinematic data including most kinds of physiques. Secondly, a new algorithm should be found for the preprocessing of data to eliminate the influences of the body mass, leg length, body height, etc. At last, we need to study the change rules of GRFs and CoPs on foot deeply to propose a better method for the partitioning and modeling of foot. The accuracy of the EKF updated with GRFs or both GRFs and moments is not acceptable in the current research. In our future work, we are going to focus on seeking for the appropriate modeling methods for the measurement of 3D gait or the control of human walking assistant robots.

REFERENCES

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