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Effect of walking variations on complementary filter based inertial data fusion for ankle angle measurement

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***Abstract*—A key problem on the measurement of lower-limb joint angles using inertial sensors is drift resulted in error accumulation after time integration. Several types of methods have been proposed to eliminate the drift. Among these methods, complementary filter-based sensor fusion algorithms are widely used in real-time applications due to its efficiency. Results from existing studies have shown that the performance of methods is relevant to walking speed. However, factors of walking variation have not been explored. This study first systematically investigated the walking variation factors and their effects on the accuracy of a proposed sensor fusion method during treadmill walking. Ten able-bodied participants participated in the experiment and walked on a treadmill with three different speeds (0.5, 1.0 and 1.5 m/s). A 12 camera Vicon motion capture system was used as the reference. The accuracy of the proposed method was evaluated in terms of the root-mean-square errors (RMSE), offsets and Pearson's correlation coefficients (PCC) in phases of a normalised gait cycle. A general linear model of analysis of variance (ANOVA) was used to analyze the factors including treadmill speed and gait phases. Results showed both factors had a significant influence on the RMSE, and only the treadmill speed had a significant influence on the offset. It provides an insight to improve the complementary filter-based method in future work.**

***Index Terms*—Gait analysis, data fusion, complimentary filter, ankle angle measurement, treadmill speed, gait phases**

I. Introduction

An ankle foot assist device is usually a wearable medical device that is attached to the wearer's ankle and foot, aiming to provide a certain amount actuation for the correction of drop foot. It would help individuals with a drop foot who suffer from a limited ability to lift the foot during early swing phase and enhance their independence to perform activities of daily living. To maximise the efficiency of gait interventions, real-time information presenting the movement need to be explored. The real-time gait feedback that highly correlated to the use of the system would augment proprioceptive inputs synchronised with the gait cycle [1], [2]. Kinematics is of importance for advanced control of wearable robotics.

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A key problem on the measurement of joint angles using inertial sensors is drift resulted in error accumulation after time integration. Several methods have been proposed to eliminate the drift: strap-down method [3], [4], high-pass filtering [5]. Morris et al. [3] set the signal equal at the begin and end of every gait cycle. Sabatini et al. [4] proposed a method that calculates body segment orientation from the angular velocity data and compensates the drift with the cycle properties. Tong et al. [5] derived the knee angle from segment angular velocities and applied a low-cut high-pass filter to remove the low-frequency component. Sensor fusion method seems a promising solution for the drift problem. The methods, such as Kalman filter [6] and complimentary filter [7], [8], could correct offset drift at each time online. Sensor orientation can be presented as a quaternion calculated from 9D IMU data and the joint angle is derived from the relative orientation of two adjacent segments [9], [10]. The use of magnetometer measurement where magnetometer disturbances occur may limit the algorithm accuracy and its indoor application. Favre et al. [11] proposed to use acceleration data to compensate the drift from the angular velocity angle. The complementary filter is relatively simple and easy to be applied in real-time applications. The sensor fusion of gyroscope-based and accelerometer-based angles has shown its good performance in gait analysis [7], [8].

Studies have demonstrated the IMU-based methods provide acceptable accuracy for lower limb angle measurement and high correlation coefficients with the measurements obtained from optical gait analysis system or goniometer. A higher Pearson's correlation coefficients (PCC) and a lower root-mean-square error (RMSE) between the reference and the angles obtained from the proposed methods for the knee angle are shown compared to the ankle [12]. Compared to the knee angle, the ankle angle measurement was also more affected by treadmill speed variation. It might be caused by the foot in the contact with the ground during walking resulting in external disturbances and noises for the ankle angle measurement. Variations during treadmill walking, such as walking speed and gait phases, might have a significant effect on the performance of the proposed method. However, to the authors' knowledge, no studies have explored the factors systematically.

We hypothesise that the treadmill speed and gait phase variation are significant factors for the performance of a complementary filter based data fusion algorithm for the ankle angle measurement. The study firstly aimed to explore the factors systematically. The paper is organised as follows: the data fusion method based on a complementary filter is presented in Section II. The experiments and results are described in Section III. The discussion and conclusions are given in Section IV.

II. Data fusion based on a complementary filter

Fig. 1 shows the diagram of the angle calculation where gyroscope and accelerometer data are combined to remove the angle drift using a complementary filter. A sensor-to-segment calibration was taken prior to obtaining joint axes so that there is no requirement in precision placements of sensors in our algorithm.

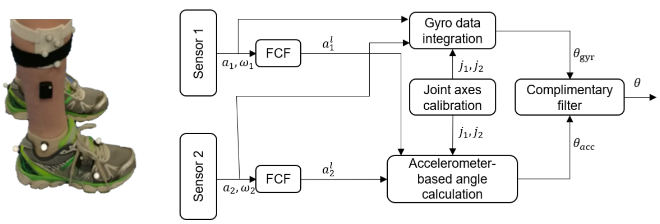

Fig. 1. The diagram demonstrates the algorithm for calculating the ankle angle. Two sensors were attached to the shank and foot respectively whilst acceleration (a_i) and angular velocity (ω_i) were collected. A fast complimentary filter (FCF) algorithm was firstly used to obtain the local acceleration (a_i^l). As there is no requirement in precision placements of sensors, a sensor-to-segment calibration was taken in prior to obtaining joint axes j_1 and j_2. The functional joint axes were applied to calculate gyroscope-based and accelerometer-based ankle angle. The ankle angle drift was removed by using a complementary filter algorithm.

A. Identification of the joint Axes

In our study, inertial sensors are attached to the hip, shank and foot segments as shown in Fig. 2. It is assumed that the local sensor axes do not coincide with the joint axes. The flexion axes of the shank and foot are determined respectively during the knee flexion/extension and ankle dorsi-/plantarflexion movement. The joint axes j_1 and j_2 can be identified using a least square cost function, Eq 1.

$$C(j_1, j_2) = \sum_{t=1}^{N} (\|\omega_1(t) \times j_1\| - \|\omega_2(t) \times j_2\|)^2 \tag{1}$$

where ω_i is angular velocity, N is the total sample number during the movement, $\| \cdot \|$ is the Euclidean norm.

The j_1 and j_2 are written in spherical coordinates:

$$j_i = (cos(\phi_i)cos(\theta_i), cos(\phi_i)sin(\theta_i), sin(\phi_i))^T$$

where $-\pi/2 \leq \phi_i \leq \pi/2, -2\pi \leq \theta_i \leq 2\pi$.

MATLAB function *fmincon* (MATLAB 2017b, MathWorks, Natick, USA) is used to solve the cost function C. It needs to be noted that the flexion axes should point in the same direction and the thigh sensor is only used for the calibration procedure. Details of joint axes identification can be found in [7].

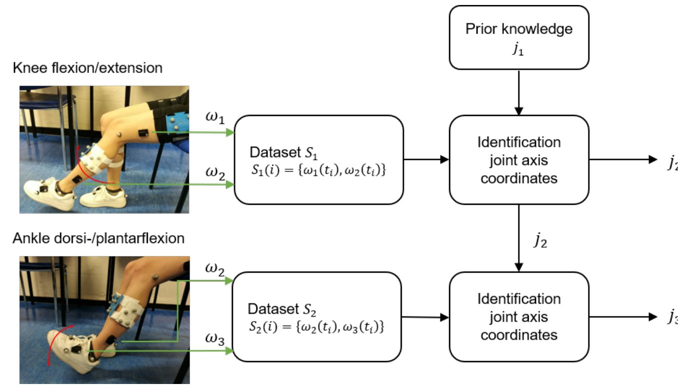

Fig. 2. The procedure of sensor-to-segment calibration. Sensors were attached to the thigh, shank and foot. The subject performed knee flexion/extension and ankle dorsi-/plantarflexion when angular velocity data were recorded. The joint axis of the thigh sensor (j_1) was set based on prior knowledge and the flexion axis of the shank (j_2) was estimated during the knee sagittal movement. The ankle axis (j_3) was calculated with the obtained j_2 during the ankle dorsi-/plantarflexion movement.

B. Joint angle calculation

Gravity-based acceleration can be expressed by:

$$a^l = D(\hat{q}_{a\omega})G \tag{2}$$

Where $G = (0, 0, 1)^T$ at the global reference frame, D is the direction cosine matrix in the form of (D_1, D_2, D_3) with quaternion $\hat{q}_{a\omega}$ [13]. Eq. 2 can be decomposed as:

$$a^l = D_3(\hat{q}_{a\omega}) = \begin{pmatrix} -q_2 & q_3 & -q_0 & q_1 \\ q_1 & q_0 & q_3 & q_2 \\ q_0 & -q_1 & -q_2 & q_3 \end{pmatrix} \begin{pmatrix} q_0 \\ q_1 \\ q_2 \\ q_3 \end{pmatrix} \tag{3}$$

Its rotation can be represented by the normalised quaternion $\hat{q}_{a\omega}$ that is calculated through acceleration and angular rate data fusion at current time instant.

An accelerometer-based joint angle can be approximated by the angle between the projections of a_i^l into the joint plane, which is defined as following:

$$\theta_{acc} = \arctan(\frac{v_2 \times v_3}{v_2 \cdot v_3}) \tag{4}$$

Where $v_2 = (a_2^l \cdot x_2,\ a_2^l \cdot y_2,\ 0)^T$, $v_3 = (a_3^l \cdot x_3,\ a_3^l \cdot y_3,\ 0)^T$. The joint plane is defined by a pair of axes $x_i, y_i \in \mathbb{R}^3$:

$$\begin{aligned} x_2 &= j_2 \times c, y_2 = j_2 \times x_3 \\ x_3 &= j_3 \times c, y_3 = j_3 \times x_3 \\ c &\nparallel j_2 \nparallel j_3 \end{aligned} \tag{5}$$

c is an arbitrary normalised vector that is not parallel to the axes j_2 and j_3.

A gyroscope-based joint angle is calculated by the integration of the difference of the angular velocity around the joint axis:

$$\theta_{gyr}(t) = \int_0^t (\omega_2(\tau) \cdot j_2 - \omega_3(\tau) \cdot j_3) d\tau \tag{6}$$

The gyroscope-based angle is precise on the short time scales but exhibits slow drift over long time measurement. The accelerometer-based angle is not affected by drift, but it is sensitive to measurement noise and may not be reliable at moments when large acceleration change occurs. A complementary filter is used to combine two angles in order to remove the drift in the gyroscope-based angle. An implementation of the complementary filter is given as below:

$$\theta(t) = \lambda\alpha_{acc}(t) + (1-\lambda)(\alpha(t-\triangle t) + \alpha_{gyr}(t) - \alpha_{gyr}(t-\triangle t)) \tag{7}$$

III. Experiment and Results

A. Experiment set-up

The study was approved by the ethics committee of the Department of Biomedical Engineering at the University of Strathclyde. ten participants (six males and four females, age $= 26.5 \pm 6.2$ years) participated. Each participant wore Trigno™ IM sensors (Delsys Inc., USA) attached to the thigh, shank and foot of both legs. To validate our real-time gait measurement system, the participant also wore a marker set of Strathclyde functional cluster model [14], as shown in Fig 3. A 12 camera Vicon motion capture system (Vicon MX Giganet, Oxford Metrics Ltd., UK) was used as the reference. Marker trajectories were recorded at 100Hz. IMU and stereophotogrammetric data streams were synchronised via an audio signal of START button clicking.

Fig. 3. Placement of inertial measurement units and optical marker clusters on a subject. The Strathclyde functional cluster model was used to analyse gait phases and kinematics. The IMUs were attached to the thigh, shank and foot without restricting their positions.

Each participant was instructed to perform knee flexion/extension and ankle dorsi-/plantarflexion in the calibration trial. Each movement was repeated ten times. The joint axes were calculated using the method in Section II-A and saved as a *MAT* file. Subsequently, the participants walked on the treadmill at three different speeds (0.5, 1.0 and 1.5 m/s) for 1 minute. The sensor data and marker trajectories were gathered. Reference of kinematic outputs and gait phases were post-processed using MATLAB-Nexus interface model (MATLAB 2017b, MathWorks, Natick, USA) while the ankle angle was calculated through the model script described in Section II-B in which λ and $\triangle t$ were set to 0.05 by trial and error.

B. Data analysis

Gait events including heel strike (HS), flat foot (FF), heel off (HO) and toe off (TO) were found, Fig.4. One gait cycle is defined as the time period between two adjacent HS events. All data were normalised to the gait cycle. The normalised gait cycle was further divided into four phases, namely loading response (LR), middle stance (MS), terminal stance (TS) and swing (SW). The accuracy of the algorithm was evaluated in terms of the RMSE, offset and Pearson correlation coefficient (PCC) between the ankle angles obtained from our proposed method and the optical reference, Eq 8. All results were analysed through a general linear model including analysis of variance (ANOVA) with the following factors: the treadmill walking speed and gait phases.

$$\begin{aligned} b &= \frac{1}{N}\sum_{t=1}^{N}(\theta(t) - \theta_{opt}(t)) \\ RMSE &= \sqrt{\frac{\sum_{N}^{t=1}(\theta(t) - \theta_{opt}(t) - b)^2}{N}} \end{aligned} \tag{8}$$

where b is offset, θ is the ankle angle obtained from our method, θ_{opt} is the angle measured from the optical reference system.

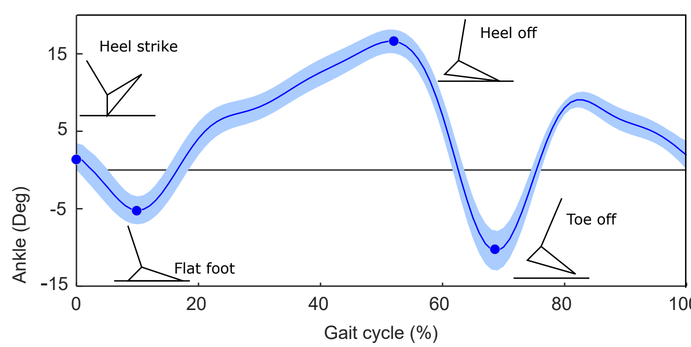

Fig. 4. The ankle angle measured from one participant walking on the treadmill was divided into normalised gait cycle. Four gait events, namely heel strike, flat foot, heel off and toe off, segments the gait cycle into four gait phases.

C. Results

Comparison of the ankle angles between the IMU-based algorithm and Vicon reference based on normalised gait cycles was shown in Table I. The results show that the estimated angle using the proposed method had a good agreement with the optical reference (PCC > 0.90) with an accuracy of RMSE below 3.25 degrees. The offset and RMSE values increased while the PCC values decreased with the treadmill speed incremented by a step of 0.5 m/s.

TABLE I
COMPARISON OF THE ANKLE ANGLES BETWEEN THE IMU-BASED ALGORITHM AND VICON REFERENCE BASED ON NORMALISED GAIT CYCLES.

Treadmill speed	Offset (deg)	RMSE (deg)	PCC	p
0.5m/s	0.32 $\pm$ 3.77	1.71 $\pm$ 1.17	0.94 $\pm$ 0.03	0
1.0m/s	4.86 $\pm$ 3.49	2.07 $\pm$ 1.01	0.92 $\pm$ 0.03	0
1.5m/s	5.88 $\pm$ 4.74	2.47 $\pm$ 1.41	0.90 $\pm$ 0.04	0

Results from the general linear model ANOVA (Table II) showed that the treadmill speed had a significant influence on the offset and RMSE of the ankle angle estimation. As shown in Fig 5, the offset and RMSE errors significantly increased with an increasing treadmill speed. The gait phase had no significant effect on the offset but was a significant factor that affected the RMSE. Larger RMSE were obtained during the TS and SW phases.

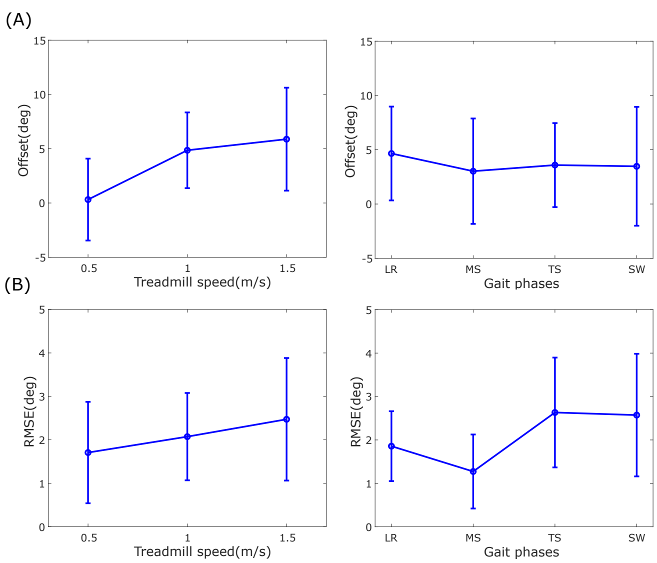

Fig. 5. The offset (A) and RMSE values under different treadmill speeds and gait phases.

TABLE II
RESULTS FROM THE GENERAL LINEAR MODEL ANOVA OF THE OFFSET AND RMSE.

	Factors	SumSq	DF	MeanSq	F	pValue
Offset	Gait phase	226.85	1	226.85	10.291	1.35e-03
(Deg)	Speed	12384	1	12384	729.61	1.60e-140
RMSE	Gait phase	394.3	1	394.3	284.09	2.50e-60
(Deg)	Speed	234.8	1	234.8	161.43	7.67e-36

IV. DISCUSSION AND CONCLUSION

The proposed IMU-based method provides good accuracy for ankle angles and high correlation coefficients with the Vicon reference in a treadmill walking experiment of ten able-bodied participants. This paper gives a good insight into variation during treadmill walking and their effect on the accuracy of the ankle angle estimation. It would help to improve the performance of IMU-based algorithms with adaptive parameters corresponding to environment variations. The results showed that the performance of the data fusion algorithm based on a complementary filter was sensitive to the treadmill speed and gait phases.

Three treadmill speeds were selected and submitted to comparative analysis. The slow speed (0.5 m/s) yielded the lowest offset of 0.32 $\pm$ 3.77 and the smallest RMSE of 1.71 $\pm$ 1.17 degrees and highest PCC of 0.94 $\pm$ 0.03 while the method obtained the worst performance with the fast speed (offset = 5.88 $\pm$ 4.74, RMSE = 2.47 $\pm$ 1.41, PCC = 0.90 $\pm$ 0.04). The findings are consistent with the previous study that the accuracy of angle measurement is influenced by varying the treadmill speed [12]. The results in [12] also showed that the ankle angle measurement was more affected compared to the knee.

The treadmill speed influences the angle measurement from the following two perspectives. Firstly, the increased offset value with an incrementation of treadmill speed might come from the linear displacement of the foot on the treadmill during the stance phase as the foot is the only segment interacting with the environment. Secondly, skin tissue artefacts (STAs) result in an addition of noise to the body-fixed sensors and the STA amplitude depends on the type, speed and range of movement [15]. The propagation of the STAs might be the cause of the increase of RMSE value while increasing the treadmill speed as well as during the TS and SW phases (Fig. 5). It should be noted that the gait phase does not have a significant effect on the offset as shown in Table II. The treadmill speed would be the main cause of the offset while the RMSE resulted from the STAs.

As the complementary filter combines the accelerometer-based angle to the gyroscope angle in order to remove the angle drift, the filter coefficient usually needs to be well tuned before the application. However, the fixed filter coefficient can not respond robustly to variations during human walking. This study showed that limitations of the sensor fusion algorithm by the complementary filter in practical applications. A novel adaptive algorithm based on the complementary filter will be more suitable for real-time implementations in conditions of fast motions [16]. Moreover, the effect of treadmill speed on the accuracy of the sensor fusion method should not be neglected. Further work is required to develop a machine learning algorithm for removing the treadmill effect.

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