Gait Pattern-aware Displacement Estimation in Micro-Sensor Motion Capture

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***Abstract*-Micro-sensor motion capture (MMocap) systems do not have external references. It is challenging to estimate the displacement of human CoM (Center of Mass). This is especially true when gait pattern changes. This paper presents a novel gait pattern-aware algorithm that aims to estimate the displacement of human CoM during walking and jumping for MMocap systems. Firstly, we fuse the acceleration of sensors and hierarchical information of the body to detect the gait patterns. Secondly, according to the detected patterns, the displacement is adaptively calculated. 1) During walking the displacement is calculated by the extension and flexion angles of the lower body joints. 2) During jumping the displacement is calculated by integrating the acceleration of the root joint. The experimental results have demonstrated that our algorithm estimates the displacements accurately during both walking and jumping.**

I. Introduction

Motion capture has been applied in kinds of applications, such as sports training, animation and rehabilitation [1-4]. One of the most popular traditional methods is optical motion capture system, using multiple structured high-resolution cameras. Optical system works in global coordination system and obtains displacement with reasonable accuracy. However, it is usually expensive and not suitable for outdoor applications.

The advances of micro-electro-mechanical-systems (MEMS) sensors make motion capture available in a ubiquitous way. Micro-sensor motion capture system becomes attractive due to its low-cost and ubiquitousness [5]. MMocap system obtains motion signals from Inertial Measurement Units (IMUs), which can measure angular velocity, acceleration and magnetic field strength in 3 dimension degree. By fusing these signals, the motion parameters of body segments could be estimated.

MMocap has no reference in global coordinate system, which makes the global displacement estimation be a big challenge. One approach is double integral of acceleration. Schepers [6] proposed a method to estimate the center of mass (CoM) displacement during walking by double integrating high-pass filtered CoM acceleration. Usually double integration could produce considerable drift, so a method called zero velocity update (ZVU) was applied to compensate for the drift. Bebek [7] used ground reaction sensors to measure zero velocity duration to reset the accumulated integration error from accelerometer and gyroscope in displacement estimation. Ruiz [8] also used the ZVU method to reduce drift where a tight Kalman filter-based INS/radio frequency identification integration algorithm is used for pedestrian localization. Using the ZVU method, the ground contact detection is necessary. Besides the use of extra sensors such as pressure transducer, Yun [9], Gafurov [10] and Feliz [11] used the acceleration and angular rate of feet to detect the ground contact. Another approach to calculate the displacement is using the hierarchical model of human body. In our previous work, a novel hierarchical fusion method was proposed by Meng [12] , which first defines the bottom of the sacrum of human body as the reference point and then use geometrical relationship of human lower body segments to calculate CoM displacement. However, these methods work well for normal walking, not suitable for jumping and running because there is time period without a reference on ground.

In this study, we propose a novel algorithm to estimate the global displacement for both jumping and walking. At first, a reliable ground contact detection method is proposed, in which gait patterns are detected and distinguished between walking and jumping. Then different displacement estimation methods are applied adaptively. During walking, the displacement is calculated by the extension and flexion angles of the lower body joints. During jumping, the displacement is calculated by integrating the acceleration of the root joint. The experiment result shows that our algorithm estimate the CoM displacement accurately.

II. Methods

In our method, we first use 7 IMUs placed on the lower body segment to capture motion data, including acceleration, angular velocity and magnetic field. These data is filtered to get the orientation of segments and precise acceleration by a complementary kalman filter (CKF) which is used in one of our previous work [12]. Then the acceleration is used to detect the gait patterns. According to these patterns, jumping or walking, acceleration double integral and the hierarchical information are used to estimate the displacement respectively. Fig.1 shows the schematic of our method.

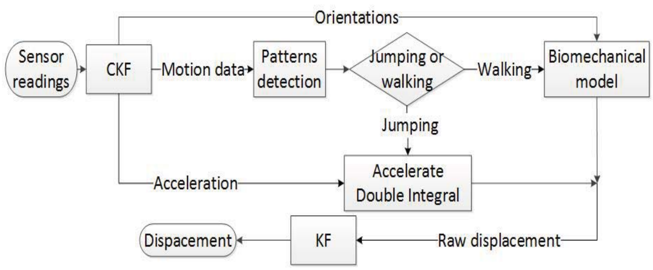

Figure 1. The algorithm schematic.

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A. Human Biomechanical Model

The human biomechanical model is assumed to be comprised of body segments which are linked by joints [13]. In this paper, we only describe the lower body model because displacement estimation is closely related to the lower body. The lower body model is composed of 7 segments and 8 joints. These segments include pelvis, femur, tibia and feet and the joints include hips, knees, ankles and toes. They are structured as a topological tree with the joints obeying a parent-child relationship. The length of segment and offset from sensor to segment are measured manually at the initialization phase. The root of the tree is defined as pelvis and every joint is the child node of the parent joint. 7 IMUs are placed on every segment of the lower body to capture the motion data of the corresponding body segments. The orientations of segments are estimated by CKF [12], represented by unit quaternions. Quaternion offers a singularity-free description which is more computationally efficient compared to Euler angles and rotation matrices.

B. Gait Pattern and Support Leg Detection

1) Gait Pattern detection

To apply the CoM displacement estimation method to human motion, a novel method to detect the gait patterns is proposed. In this method, foot and root joints are used to detect the patterns. Jumping is simplified to a projectile motion. After jump into the air, no feet are in contact with the floor and the motion relies on the inertia. According to the operational principle of the accelerometer, the acceleration measurement should decline from gravity (g) to 0 when taking off and rise from 0 to g when landing. When in the air, the measurement should be 0. Root joint is the relatively stable joint compared with other joints which is the reason why we choose the data of root joint to detect the gait pattern.

Fig.2 shows the vertical acceleration of root drops rapidly during jumping and keep 0 before rising to gravity (g) again. When the acceleration rises to 15 m2/s the negative edge is searched. If Acc_{t3} - Acc_{t2} < -5 and Acc_{t2} - Acc_{t1} < -5, t_1 is considered as the beginning of falling edge and t_2 is selected as the beginning of jumping (BoJ), where Acc_{ti} denotes the acceleration at time ti and ti is time sequence. After BoJ, the positive edge is selected if Acc_{t6} – Acc_{t5} > 7 and Acc_{t5} – Acc_{t4} >10. Then t5 is considered as the end of jumping (EoJ). Here, to eliminate the interference of the rapid squat, we use the accelerations of feet as a constraint.

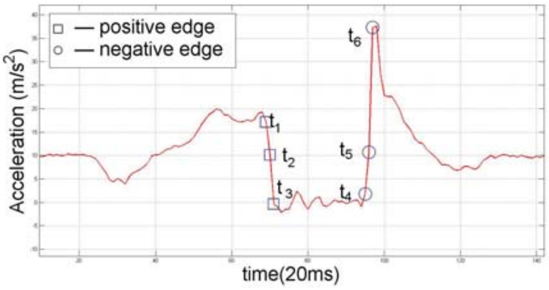

Figure 2. Vertical acceleration of root during jumping

If only the acceleration measurement is between [g-e, g+e], the former detection is invalid and the patterns is walking, where g is the gravity and e is a threshold. Then patterns, jumping or walking could be detected precisely and quickly by this method.

2) Support leg detection

For walking, human gait is a cyclical motion. Each cycle is divided into two phases, stance phase (ST) and swing phase (SW). The stance phase begins with a heel-strike (HS) which means the foot will be in contact with the ground. The swing phase begins with a toe-off which means the foot will not be in contact with the ground. During walking, the support leg should be in the stance phase. During walking, the support foot's acceleration should contain the gravity (g) only and the angular velocity should be small. At the same time, supposing that the root joint is the reference joint and then, we can calculate the positions of two feet. The support foot should be lower than the other one. These are applicable for different kinds of walking including walking forwards, backwards and sideways. The Euclidean norm of the acceleration and angular velocity, is denoted as a_t and w_t respectively. When the foot is stationary on the floor, a_t should be equal to g and w_t should be small. At the swing phase, at will be significantly different from g and w_t is much bigger.

Besides it is obvious that the position of the support foot is lower than the other one. Let L_{thigh} and L_{shank} denote the length of thigh and shank segments respectively. The initial position of human body is perpendicular to the ground and regarding the root joint as reference joint, the initial thigh and shank vector will be $V_{thigh,0} = [0\ 0\ -L_{thigh}]$ and $V_{shank,0} = [0\ 0\ -L_{shank}]$. Using the segments' quaternion, filtered by CKF [12], we can get the position as follows,

$$V_{thigh,t} = (q_{thign,t})^{-1} * V_{thigh,0} * q_{thigh,t} \tag{1}$$

$$V_{shank,t} = (q_{shank,t})^{-1} * V_{shank,0} * q_{shank,t} \tag{2}$$

$$P_{foot,t} = V_{shank,t} + V_{thigh,t} \tag{3}$$

where $P_{foot,t}$ is the position of foot at time slice t and the $q_{shank,t}$ and $q_{thigh,t}$ are the orientation quaternion of shank and thigh at time t respectively. $*$ represents quaternion multiplication. By comparing the positions of two feet, the lower one should be the support leg.

Finally, we fuse the results detected by the above two methods as follows,

$$\vartheta = (|acc - g| \div g) \wedge 0.5 \tag{4}$$

$$\alpha = (1 + \vartheta - |1 - \vartheta |) \div 2 \tag{5}$$

$$\beta = 1 - \alpha \tag{6}$$

$$Sup_{all} = \alpha \cdot Sup_b + \beta \cdot Sup_i \tag{7}$$

where, Sup_b denotes the result detected by hierarchical information and Sup_i is by the data of inertial sensors while *acc* denotes the acceleration of support foot. Sup_i, Sup_b equals 0 or 1 only, representing the left and right leg respectively. Using (7), if $Sup_{all} > 0.5$ the left leg is selected as the support let and if $Sup_{all} < 0.5$ the right leg is the support leg. If $Sup_{all} = 0.5$, the support leg is selected randomly.

C. Global Displacement Estimation

Our method is gait pattern-aware which will use different algorithms to estimate the global displacement according to the patterns. During jumping, displacement is estimated by double integral of root acceleration as follows,

$$S_{CoM,t} = S_{CoM,t-1} + (v_{t-1} + 0.5 \cdot a_{t-1} \cdot \Delta t) \cdot \Delta t \tag{8}$$

where $S_{CoM,t}$, v_{t-1}, a_t denote the global displacement, velocity, acceleration of CoM at time t. All of them have been transformed into global coordinate, where X points forward, Y points right and Z points down.

During walking, we use the hierarchical information to estimate the displacement as follows,

$$V_{hip,t} = V_{Supthigh,t} + V_{Supshank,t} \tag{9}$$

$$P_{CoM,t} = P_{CoM,t-1} + V_{hip,t} - V_{hip,t-1} \tag{10}$$

where $V_{hip,t}$, $V_{Supthigh,t}$ and $V_{Supshank,t}$ are vectors of hip, thigh and shank of the support leg at time t respectively. $P_{CoM,t}$ is the global displacement of CoM at time t.

III. EXPERIMENT AND RESULTS

A. Experimental Setup

To evaluate the performance of the proposed algorithm, detailed experiments were conducted. In our experiments, 7 IMUs were placed on the human lower body segments.

Fig.3 shows the IMUs attached on body segments. The sensors are produced by MicroSens company [14]. These sensors were connected to a base station by SPI serial data buses, and the sensor measurements were sent to a PC via Bluetooth in the base station. Owl System (from Motion Analysis Corp., USA) is chosen as the reference system for indoor experiments, in which reflective ball markers can be identified by 8 high-speed infrared cameras. One marker was placed on the root joint to get the displacement as the truth. For outdoor experiments, we will measure the truth manually instead.

B. Experiment and Discussion

To investigate the accuracy and reproducibility of the algorithm for the global displacement estimation, three different experiments were conducted to test the two patterns: walking, jumping and compound movements, in which the walking experiment was conducted outdoor and others was indoor.

1) Walking

In our first experiment, the subject walked along the path outdoor as shown in Fig.4. The path is a circle with a 10 meters

Figure 3.Attachment of seven IMUs to the lower body. The sensors are marked by red circles.

radius and the subject walk along the circle. Here, because of the limitation of Owl System for outdoor application, the radius, which represented the true path of this experiment, was measured with a meter stick manually.

Fig.5 shows the displacement estimation results compared with the true path and the results acquired by double integration of acceleration. The path starts at (0, 0), goes ahead anticlockwise and back to (0, 0). In the figure, the dashed red line represents the displacement estimated by the proposed geometric information fusion, the solid black line is the true path and the dotted blue line is the one obtained by double integration of acceleration measured by the sensor attached on the pelvis. It is obvious that the integration can only estimate the displacement accurately for a short time. The drift increases as time goes on because any small error will accumulate during integration. On the other hand, the results estimated by our proposed method is quite similar to the true value. It is obvious

Figure 4. The path of walking experiment.

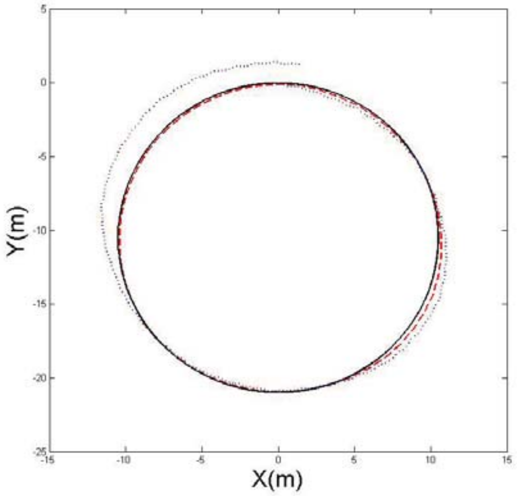

Figure 5. Global displacement of walking.
Solid black line: true path;
Dashed red line: displacement by our algorithm;
Dotted blue line: displacement by double integration.

that our algorithm could acquire CoM displacement accurately. To further compare the performance difference between the different methods, quantitative analysis was also conducted. Table I shows the displacement RMSE values for walking on X and Y axis, provided by our method and integration method. The experiments were performed 5 times. The RMSE errors between the estimated displacements and the truth were averaged over five trials on each axis. By our proposed algorithm, the RMSE errors for each component of the displacement are (0.11 ± 0.04) m (mean ± standard deviation) for the forward X-direction and (0.14 ± 0.05) m for the lateral Y-direction, which are only about one-tenth of the values obtained from integration. From the results, we can conclude that our proposed gait pattern-aware fusion method can estimate the displacement precisely.

2) Jumping

In this experiment, the subject jumped vertically and forward to evaluate our proposed method.

Fig.6 shows the displacement estimation results. In the figure, the solid black line represents the true value provided by the optical system, the red dotted line is the result estimated by our method and the blue dashed line is the estimation by integration. Our method performs better than the integration method again with the accurate displacement with regards to the truth provided by the optical system. In our method, the integration drift is eliminated by hierarchical information, which is the reason why our method performs better than integration. Table II shows the displacement RMSE values for

TABLE I
CoM RMSE+STD

Axes	Est(m)	INT(m)
X	0.11±0.04	2.12±0.73
Y	0.14±0.05	2.01±0.81

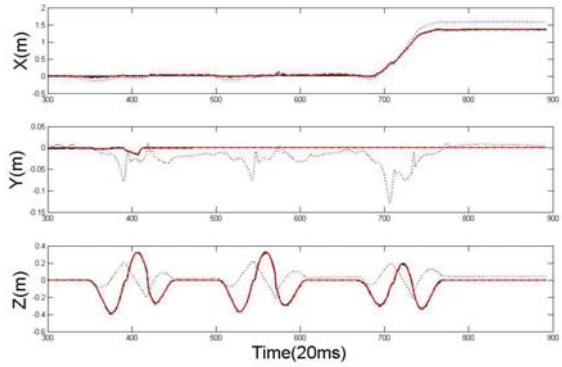

Figure 6. Global displacement of jumping.
Solid black line: truth;
Dashed red line: displacement by our method;
Dotted blue line: displacement by double integration.

TABLE II
CoM RMSE+STD

Axes	Est(m)	INT(m)
X	0.03±0.01	0.21±0.13
Y	0.04±0.02	0.19±0.11
Z	0.03±0.01	0.23±0.14

jumping on each axis. The values are provided by our method and integration method and The RMSE errors were averaged five trials on each axis. The RMSE errors provided by our method are (0.03 ± 0.01) m for the forward X-direction, (0.04 ± 0.02) m for the lateral Y-direction and (0.03 ± 0.01) m for the downward Z-direction. It is evident that the RMSE errors obtained by our method are much smaller than the errors obtained by integration. The quantitative analysis shows the good accuracy of our proposed algorithm.

3) Compound movement

In this experiment, the subject squatted and walked around at will, after which he jumped forward and backward.

Fig.7 and table III shows the experiment results.

Fig.7 shows that the integral error in X direction increase by time but the error in Y direction is in a muddle. In Z direction,

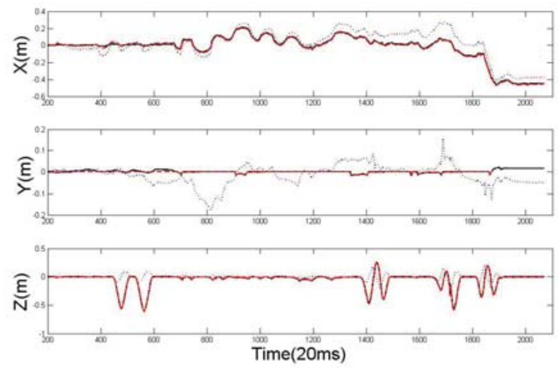

Figure 7. Global displacement of compound movement.
Solid black line: truth;
Dashed red line: displacement by our method;
Dotted blue line: displacement by double integration.

TABLE III
CoM RMSE+STD

Axes	Est(m)	INT(m)
X	0.03±0.01	0.21±0.13
Y	0.04±0.02	0.19±0.11
Z	0.03±0.01	0.23±0.14

when the subject squats, the integral error is as large as 0.5m, which means the integral method obtains a low precision when the movement is mild. On the other hand, the algorithm we proposed could obtain a high precision for various movements.

Table III shows that the significant reduction in RMSE error and error standard deviation once again which could illustrate the advantage of our method. We also noticed that the RMSE errors increased slightly over jumping patterns. This is mainly because the complex motion could produce more interference than only jumping.

IV. Discussion

In our proposed method, the gait patterns and the support let detection play a significant role in achieving the CoM displacement of human body. By using the motion data of root joint, the gait pattern, which is used to fuse the integration of acceleration and hierarchical information for drift elimination, is detected precisely and rapidly. The support leg, which is the key of the fusion of hierarchical information, is detected by a fusion of hierarchical information and motion data of feet accurately.

On the other hand, the body segment orientations are estimated first before applying the hierarchical information and acceleration integration to achieve the global displacement. So the accuracy of CoM displacement heavily depends on how precisely we can acquire the orientation of the segment. As we all know, the magnetic disturbance and the acceleration interference are big challenges of orientation estimation.

In our experiments, we need to measure the body segments' length manually. Therefore, the accuracy of the estimated CoM displacement could also be improved by measuring carefully. We also noticed that the joint constraint is helpful to improve the accuracy. In our experiments, the joints are assumed to have 3 degrees of freedom while some joints have less degree of freedom. For example, the knee joint could only conduct flexion and extension movements which means the knee joint only have two degrees of freedom. These constraints will be utilized to compensate for the drift of displacement.

V. Conclusion

In this paper, a new gait pattern-aware algorithm is proposed to acquire the CoM displacement of walking and jumping. The gait patterns is detected which is the key to fuse the hierarchical method and acceleration integration to estimate the displacement. To improve the accuracy of estimation, a new method which fuses the biomechanical information and motion data is proposed. The good experimental results have demonstrated that our algorithm could estimate the global human displacement of walking and jumping precisely.

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