Longitudinal High-Fidelity Gait Analysis with Wireless Inertial Body Sensors

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1. INTRODUCTION

Gait analysis has long been used for various medical and healthcare assessments [1]. In orthopedics and prosthetics, gait analysis is essential for identifying the pathology and assessing the efficacy of the orthopedic assistants or prosthetics prescribed. For example, the efficacy of ankle-foot orthoses (AFOs), usually prescribed to patients with muscle disorders, (e.g., cerebral palsy, spinal cord injury, muscular dystrophy, etc.) to prevent contractures [2], remains unclear. Studies on recovery and rehabilitation from knee surgery have shown that gait analysis focusing on knee joint angles is the key to evaluating the efficacy of treatment. In elderly healthcare, gait analysis has also played an important role in studies of fall risks and fall prevention [3]. Even in cognitive and neuropsychology studies, gait analysis becomes an important parameter because of the close relationship between human cognitive skills and motor function. For example, [4] and [5] have shown the research value of gait analysis in Parkinson's disease and early childhood autism diagnosis, respectively.

Most of these gait analysis applications would benefit from continuous, longitudinal observation. As important is the fidelity of the medical instrument, requiring accuracy and precision for a number of gait parameters (e.g., gait speed, joint angle, stride length, gait cycle, etc.) that is far beyond what is possible with modern pedometers or activity monitors. The current gold standard technology for such motion analysis is an optical motion capture system such as Vicon® [6]. However, although such systems can deliver highly accurate human movement analysis, these expensive systems require expert operation and are limited to in-lab monitoring. For gait analysis to be realized in the real world, measuring devices enabling continuous, high-fidelity motion tracking out-of-lab are necessary.

Ongoing work by the INERTIA Team at the University of Virginia, along with a number of medical collaborators, is exploring the use of inertial body sensor networks (BSNs) to provide this longitudinal, high-fidelity gait analysis capability. A demonstration is presented to prove the feasibility of such technology in gait analysis and possible challenges in its operation. In this demonstration, human motion is sensed by a body-worn wireless inertial BSN system, TEMPO 3.1 (as shown in Figure 1(a)), which provides six-degree-of-freedom motion capture at each node in the form factor of a wristwatch [7]. This sensed data is processed for reconstruction of an animated 3D model with detailed gait parameters that have been validated by extensive Vicon® testing. Key challenges of propelling this technology in medicine and healthcare are also discussed.

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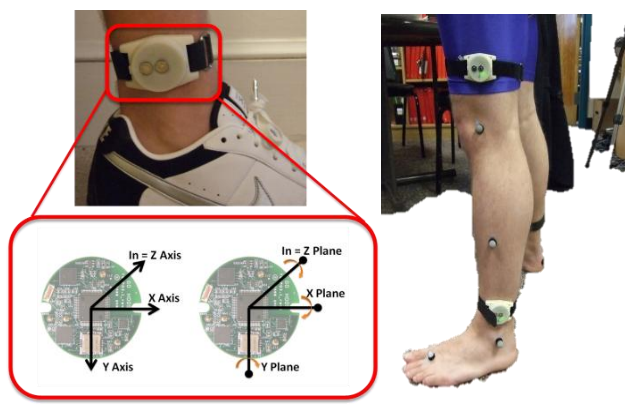

Figure 1. (a) The TEMPO 3.1 node with mounting position. (b) The TEMPO nodes mounted on-body, along with Vicon® markers for validation.

2. METHODOLOGY

2.1 Data Collection

In order to obtain accurate and precise information from the wireless inertial BSN, synchronization of the network and calibration of the sensors are indispensable before data collection [8]. As human motion is a synergy of different body segments, and the orientations of each locomotory segment are spatiotemporal signals, synchronization is necessary for multiple nodes mounted on different body segments. In our demonstration, a general synchronization method [9] is used, and an error of 1-2 samples at 120Hz is achieved. A post-processing method is used to calibrate the analog-to-digital (ADC) sensor data using the optimum calibration solution [8].

Another error occurring in inertial BSNs that needs calibration is mounting error [8], as sensor nodes cannot be aligned ideally to match the bone-to-bone model and are at risk of shifting around during muscle contractures. A practical procedure recording the relative position of nodes to the body segments on which they are mounted is used to calibrate the data in post processing. This procedure finds orientation through the determination of the gravity vector and an axis of correction rotation and should be applied before the actual motion data taking session.

In our demonstration, a healthy subject is mounted with a TEMPO node on each leg segment – left thigh, left shank, right thigh and right shank, as shown in Figure 1(b). The subject is asked to walk at multiple speeds, and the TEMPO data is wirelessly transmitted to and stored in a handheld PC.

2.2 Data Processing

After the data collection, the signal processing and angular displacement computation are done offline in Matlab®. The relative angular displacement is obtained by integrating the gyroscope signals, and the orientation information in global coordinates is obtained from the accelerometers. Due to the sensor bias and noise residing in the gyroscopes, integration drift inevitably occurs. To eliminate this drift, a Kalman filter is used [10] to fuse the orientation information obtained from the gyroscopes with that of the accelerometers. This filter adjusts the original estimate based on the estimated error of each of the sensors. Mounting error is compensated for using the mounting calibration method as stated in Section 2.1. From the corrected signals, it is possible to determine an accurate estimate of knee joint angles over time as well as the position of the leg segments relative to each other.

To validate the accuracy of TEMPO 3.1 system, Vicon® has been used as a reference system [8]. Data was taken by the Vicon® system and the TEMPO system simultaneously in a pre-defined synchronization procedure, as illustrated in Figure 1(b). The verification shows that the final results have an error within Vicon®'s error range of an RMSE of 1.5 degrees [8].

2.3 Data Visualization

Once the angular displacement of each body segment has been calculated, a Java script transforms the position information into a visualized 3D animation model. First, the script constructs a 3D model of a human body, with the initial position defined as standing with both legs straight and perpendicular to the ground. Then it animates the 3D model by pivoting the thighs around the hip joints and the shanks around the knee joints by constructing a rotation matrix from the 3D angular displacement information obtained in previous steps. The angular displacement of a joint angle from an initial value of zero is also plotted in sync with the 3D animation to present the joint angle quantitatively. A screen capture to illustrate the model is shown in Figure 2.

3. CONCLUSION

This abstract reviews the potential of applying wireless inertial BSNs to gait analysis related healthcare and medical research. A demonstration to illustrate the feasibility of this methodology is presented. Gait parameters are tracked for a healthy human subject wearing a set of wireless inertial BSN nodes and are reconstructed in an animated 3D model. The accuracy of this demonstration was verified by optical motion analysis system Vicon®, and provides an RMSE of about 1.5 degrees [8].

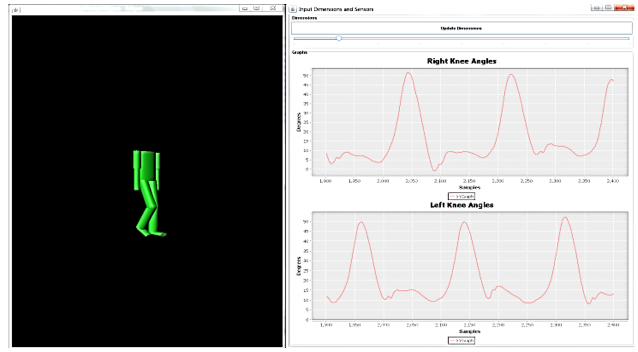

Figure 2. 3D animation and corresponding knee joint angles.

To further propel wireless inertial BSN technology into medical fields, challenges from system design to signal processing remain. The intrinsic sensor drift and noise and the unavoidable mounting error in BSNs need to be overcome for more accurate and precise information. While our model can achieve high accuracy for in-lab data collections on healthy subjects using signal processing techniques such as high-pass filtering and Kalman filtering, additional research is necessary for robust longitudinal data collection on gait-impaired individuals in the real world.

4. REFERENCES

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