An engineer's perspective on the mechanisms and applications of wearable inertial sensors

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Introduction

Wearable inertial sensors provide a promising tool for capturing the movement of patients in their natural environment over a long duration of time (e.g., 24/7). This potential is further supported by the continual technological advances towards the miniaturization and reduction in cost of wearable inertial sensors. However, the said technology is no silver bullet. Although measured movement in the "wild" using wearable inertial sensors still faces a few challenges (e.g., measurement noise, soft tissue artifacts), some clinicians have started adopting the use of wearable sensors (1-3). Thus, it is important to understand the tools used for motion capture to help objectively determine the tool's clinical utility and build confidence in its use (e.g., in which situation can they trust the tool and what factors must they be wary of).

The technology for capturing movement has come a long way. Traditionally, bulky goniometers or strain gauges were used to measure body joint angles (4,5). However, these devices were cumbersome, restrictive, and requires a lot of manual processing. Eventually, this technology was replaced by optical systems (e.g., stereo cameras) which utilises multiple cameras within a confined space where the subjects are attached with multiple markers all over the body. It is the current industry standard and can estimate position up to millimetre accuracy if well-configured and calibrated. Then recently came wearable inertial sensors, capable of capturing movement 24/7 (e.g., spatio-temporal parameters), albeit with less detail compared to optical systems, with batteries capable of lasting weeks on a single charge. The portability of wearable inertial sensors has enabled larger number of samples and more types of movements to be studied (6). Indeed, up to the time of writing this paper, technology continues to evolve towards making motion capture as comfortable as possible [e.g., use of smart textiles (7,8), as few sensors as possible (9,10), and body mounted cameras (11)].

Wearable inertial sensors have opened the door of possibilities for health monitoring. Optical motion capture systems, though accurate, are costly (12), and may capture movements not representative of the patient's gait due to unfamiliarity of the capture environment (13). Wearable inertial sensors provide a more economical alternative and a means to tracking the patient's movement in their natural environment, which improves the likelihood of obtaining representative measurement of their gait, while also facilitating long-term monitoring, such that the progression of a disorder or effect of an intervention can be tracked over time-scales spanning days to years. When enough information is collected, such frequent remote gait monitoring has the potential to identify movement disorders in its early stages, which gives clinicians opportunity to intervene and possibly prevent the disorder from becoming worse [e.g., remotely track a patient's fall risk, and when the fall risk is increasing, execute exercise interventions to reduce fall risk (14)].

Given the potential and adoption of wearable inertial

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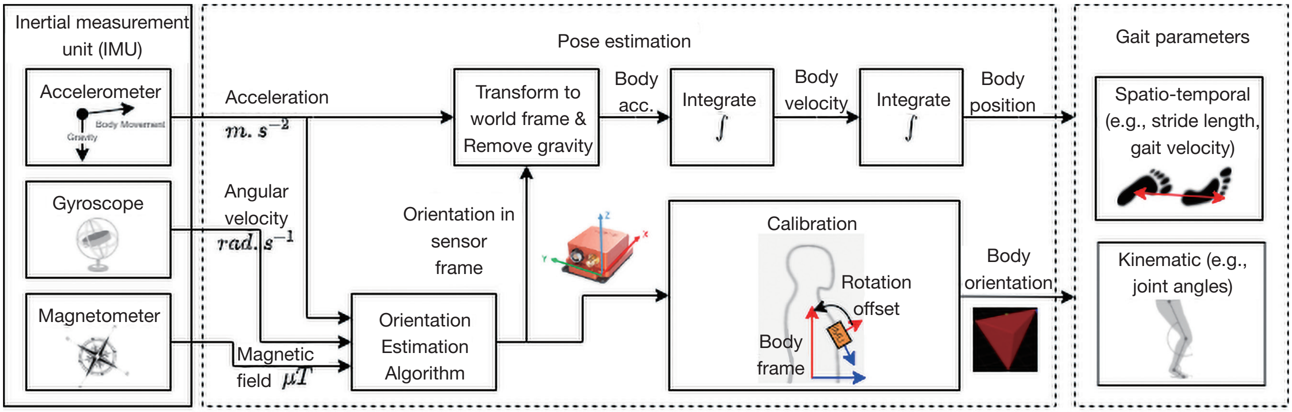

Figure 1 Overview of measurement outputs from inertial measurement unit.

sensors in clinical settings, this paper aims to provide clinicians insight into on how such sensors work. I will first describe the different measurements obtained from wearable inertial sensors, and I will then provide insight to how wearable inertial sensors are currently used in practice.

Measurements from wearable inertial sensors

Wearable inertial sensors, more commonly known as Inertial Measurement Units (IMUs), typically consist of accelerometer, gyroscope, and magnetometer, each measuring acceleration ($m.s^{-2}$), angular velocity ($rad.s^{-1}$), net magnetic field (μT), respectively. From these raw sensor measurements, an estimate of 3D position (i.e., where the tracked person is located) and orientation (i.e., posture of tracked person) may be obtained. For example, position tells you where a person is inside a hospital building, while orientation tells you how a person is lying in bed (e.g., facing up or sideways facing right).

In the following sections, more description will be provided about position (Sec. *Position estimation*) and orientation (Sec. *Orientation estimation*) estimates. Sec. *Calibration* will then describe the often not discussed step of calibration between the sensor reference frame and body frame. *Figure 1* shows an overview of a typical computational processing that occurs from raw IMU measurements to clinical gait parameters.

Position estimation

An accelerometer measures acceleration in $m.s^{-2}$ along one or multiple axes. Measured acceleration consists of acceleration due to body movement, gravity, and noise which represents every non-idealities. It can be expressed in the world frame using orientation estimate and after the gravity component is removed, can be integrated once to obtain velocity ($m.s^{-1}$), and twice to obtain position (m). However, along with the true acceleration, noise is double integrated resulting to a large drift in position estimate. There are many techniques to reduce this drift including zero velocity update (i.e., velocity is assumed to reset to zero every time the foot is flat on the ground). Spatio-temporal parameters such as stride length, gait velocity, step variability can then be estimated from position and velocity estimates. Note that there are also techniques to obtain spatio-temporal parameters directly from raw measurements, as well as performing gait cycle identification or activity classification from raw measurements.

Orientation estimation

Angular velocity can be integrated to obtain orientation estimates. Similar to position estimation, along with the true angular velocity, noise is integrated resulting to drift in orientation estimate. Nevertheless, this drift can be resolved by the orientation estimation algorithm through leveraging of global reference vectors from accelerometer measurements (i.e., when the sensor is not moving, measurement acceleration points along the gravity vector) and magnetometer measurements (i.e., net magnetic field points along the magnetic north). Note that orientation estimation algorithms typically output the orientation estimate of the inertial sensor with respect the world frame, whereas the parameter of interest is the orientation estimate of the body segments. Hence, an additional calibration step, typically a fixed rotational offset, is needed to align the orientation estimate of the sensor with the orientation estimate of the body segment. Finally, kinematic parameters such as knee and hip joint angles can then be estimated from orientation estimates of two or more linked body segments.

Calibration

Obtaining prior knowledge about the patient being tracked is critical for accurate body pose estimation. Obtaining height, body measurements, and mass may be easily obtained from manual measurements or through questionnaires. However, a special calibration procedure is typically needed to obtain the sensor-to-body-segment orientation offset, typically assumed as a fixed rotational offset between two rigid objects. Note that although inertial sensors are typically rigid, your body segment is not 100% rigid due to soft tissues, which can be a source of error specially prominent during dynamic movements. Sensor-to-body-segment orientation calibration can be done offline before or at the beginning of motion capture. For example, the clinician can carefully attach the sensor to the body such that the sensor frame aligns with the body frame, which can be found from palpation of anatomical landmarks. However, this approach is difficult, time consuming, and usually requires well trained personnel for accuracy and reliability. Another approach is to ask the subject to take a predefined posture or movement at the start of the motion capture session (15). The predefined posture could be as simple as standing upright, while the predefined movement can be fully flexing and extending your knee (16,17). However, such predefined posture or movement is individual and may not be repeatable. Other approaches also include exploitation of kinematic constraints (18), and the use of external calibration devices (19).

Inertial wearable sensors in practice

Ultimately, single or multiple inertial sensors, each providing position and orientation estimates or derivatives of it, can be used to compute gait parameters (20). Gait parameters provide quantitative measurements clinicians may use to objectively make clinical inference/decisions. Spatio-temporal parameters (e.g., speed and stride length) are typically obtained from a single inertial sensor, while kinematic parameters (e.g., joint angles) typically require two or more. Kinetic parameters (e.g., joint moments) are computed from kinematic parameters combined with force sensor (e.g., pressure insoles) measurements. On one hand, using fewer inertial sensors is more comfortable for everyday use and will more likely be used in everyday life, albeit only capturing less detailed gait parameters (i.e., the patient is modelled as a single point) (21). On the other hand, multiple inertial sensors can be quite cumbersome, with the additional challenges of synchronisation and cost, however, at the benefit of more detailed gait parameters (i.e., patient is modelled as a skeleton stick figure).

Many consumer electronics now a days (e.g., mobile phone, smart watch) have inertial sensors. For example, most smart watches have accelerometers and gyroscopes, as they consume less power capable of lasting a week on a single charge. Note, however, that due to the loss of magnetometers, such devices are more susceptible to yaw orientation drift. On the other hand, even when a magnetometer is present, care must be taken as the magnetic field in indoor environments is known to be inhomogeneous, typically with stronger disturbances closer to the floor (22). Indeed, this is an existing challenge for the engineering community to develop orientation estimation algorithms that do not depend on magnetometers or are robust against magnetic disturbance (23,24).

Technology will continue to evolve, producing cheaper, smaller, power efficient, and more accurate sensors. Software, both inside wearable devices and on mobile applications or the cloud, will also continue to improve. In addition to wearable inertial sensors, wearable devices will continue to increase in capability, measuring other health parameters such as heart rate and ECG. Indeed, one can claim that the future of ubiquitous 24/7 health monitoring is not so far away. Nevertheless, care must be given as new technologies are adopted to clinical practice. A better understanding of the technology enabling the innovation can not only remove the mysticism around the black box technology, but will also accelerate clinical adoption and effective use of innovation, ultimately leading to better clinical outcomes.

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