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An Efficient Real-Time Human Posture Tracking Algorithm Using Low-Cost Inertial and Magnetic Sensors

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Abstract—**Real-time accurate human posture tracking in unconstrained environments will provide an enabling technology for physicians and other care providers to monitor the movements of their patients in real-life situations. Constructing a posture tracking system with the form factor suitable for human wear requires the development of miniature units that can be attached to the limb segments of interest in an unobtrusive way. Simultaneously, fast algorithms that can produce real-time posture estimates at sufficient rates are needed. In this paper, we focus on the development of efficient and accurate algorithms that compute the human posture information from low-cost miniature inertial and magnetic sensors. We present a new technique that computes posture estimates from the sensor data 23.8 times faster than the most efficient previously proposed technique, and simultaneously increases the accuracy of the estimates.**

Keywords-posture, motion tracking, inertial, magnetic, accelerometer, magnetometer, complementary filter.

I. INTRODUCTION

The real-time tracking of human postures in an unconstrained environment will provide an enabling technology for physicians and other health care professionals. It will allow physicians to perform long-term monitoring of patients, care providers to supervise the activities of elderly subjects, or biomechanic researchers to carry out studies of human movements during everyday activities. Tracking postures, however, presents many challenges due to the large number of degrees of freedom of the human body, and the number of environments to which an average human is exposed to during daily activities.

Current systems do not lend themselves well for tracking postures during everyday activities. Camera-based systems restrict the user to the laboratory or a constrained environment where the cameras are installed. Systems based on magnetic field emitters restrict the user to the area around the magnetic source, and are generally tethered.

A posture tracking system that works in an unconstrained environment needs to be sourceless, wireless, small, light, and unobtrusive. Constructing such a system requires the development of miniature sensor units that can be attached to the user's limbs and body in an unobtrusive manner. Given the size, weight and ergonomic restrictions, these sensor units can only include limited processing power. The sensor data can either be processed locally by including an embedded program with the unit, or sent to a central server for processing. In the first case, only the limited computing power of an embedded processor is available for the algorithm. In the latter case, the central server needs to process concurrently the data from each of the units on the user (and possibly multiple users.) For either scenario, efficient posture tracking algorithms that can make the most advantageous use of the computing resources available are needed.

The recent miniaturization of inertial and magnetic sensors has enabled the development of systems that fulfill the needed requirements for real-time human posture tracking in unconstrained environments. Inertial (accelerometers and rate gyroscopes) and magnetic (magnetometers) sensors are completely sourceless: they are self-contained, not requiring the use of any external apparatus such as cameras or magnetic emitters. However, the inertial and magnetic sensors available with the size and weight factors applicable for wearable applications tend to be very noisy. Theoretically it is possible to recover complete posture information either by using only three-dimensional accelerometers and magnetometers (in the static case), or by using only three-dimensional rate gyroscopes. Unfortunately, the quality of the signals of miniature sensors does not permit this in practice. Posture tracking systems that use only accelerometers and magnetometers produce posture estimates that are only reasonably accurate during static or quasistatic situations in environments containing only small magnetic sources: These systems make a strong assumption that the accelerometer's readings are measuring the earth's gravity and that the magnetometer's readings are measuring the earth's magnetic field. In dynamic situations that introduce motion accelerations, or environments containing magnetic sources, the assumptions are invalid, and the performance of the systems degrades. A posture tracker that only relies on miniature rate gyroscope signals is not feasible due to accumulation of integration error. The drift of the sensor will render the approximation invalid within a few seconds. Fortunately, signals coming from the accelerometer-magnetometer pair and the signal from the rate gyroscope have complementary natures and a system that combines these three types of sensors is able to overcome many of the drawbacks described and produce better posture estimates.

Despite the difficulties that arise when using only a subset of accelerometers, magnetometers and rate gyroscopes, many researchers have attempted to develop such type of systems by

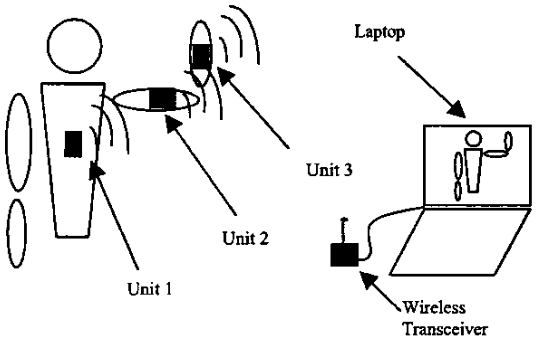

Figure 1. System schematic

using domain specific knowledge or computationally intensive optimization algorithms. Luinge [1] and Myagoitia et al. [2] designed systems based on accelerometers and gyroscopes to track human movements. Systems based solely on inertial sensors can only provide accurate posture estimates in two dimensions and have a well-known drift problem around the vertical axis. The motion tracking system in [1] uses knowledge of the joint limits as well as still periods to partially correct for the drift. The tracking application in [2] does not deal with rotations around the vertical. Neither of these techniques is suitable for accurate complete posture tracking. Geber-Egziabher et al. [3] and McGhee et al. [4] proposed methods to compute complete posture estimates in quaternion format using systems based on accelerometers and magnetometers by Newton-Gaussian iteration. While overcoming the drift problem, both these methods are computationally intensive, and their performance degrades substantially during periods of high acceleration or the presence of an external magnetic field.

Systems that use accelerometers, rate gyroscopes and magnetometers to track posture have also been previously studied. Ang et al. [5] proposed a technique to detect the jitter of a surgeon's scalpel and correct for it. While this approach works very well in its domain of application, the expected range of movements is small (hand motion during surgery,) and does not generalize to the more dynamic situations expected in full body posture tracking. Bachmann et al. [6] developed a complementary filter that tracks posture in the quaternion representation. Roetenberg et al. [7] used a complementary Kalman filter to compute posture in the rotation matrix representation. Marins et al. [8] proposed an extended Kalman filter to calculate posture using the quaternion representation. Techniques that employ the Kalman filter require a computationally intensive matrix inversion operation at each estimate calculation to maintain optimality, and creating a good process model requires the use of many states, increasing the dimensionality of the matrices involved in the calculations. Further, most of these techniques perform optimization in the quaternion space [3, 4, 6, 8]. While mathematically sound, the reduction of the sensor data to the quaternion space tends to couple the errors of the different sensor signals leading to less accurate posture estimates.

In addition to the research community, commercially available sensors using miniature inertial and magnetic sensors

Figure 2. System Display during a Posture Estimation Session

have also begun to appear. Examples of these systems are Microstrain's 3DM-G, Intersense's InertiaCube2, and Xsens Sport Technologies' MT9. These systems compute the posture of the units using proprietary algorithms running on an embedded processor on the unit and send the data to a PC through the serial or USB port. A subject using these systems is restricted to the length of the wires connecting the units to the PC, and the onboard embedded processor of the units increases their size and power requirements, which may make these systems unviable in scenarios where small size and long battery life are of essence.

In this paper, we develop a very efficient, real-time and accurate algorithm to compute posture using the rotation matrix representation. We first review how posture can be computed using only an accelerometer-magnetometer pair or a rate gyroscope. We show that the estimates from these two sources have complementary frequency spectra, and propose a new complementary filter technique that obtains accurate posture estimates from the sensor signals. Finally, we compare our results against two recently proposed techniques, and discuss future directions of research.

II. SYSTEM DESCRIPTION

Our prototype system consists of three body-mounted units (wrist, upper-arm, and chest) that are completely wireless, sending data to a laptop equipped with a wireless transceiver. A schematic of the system is shown in Figure 1.

Each unit consists of a sensing unit, a wireless transceiver and batteries, measures 10.75×5.40×3.80 cm. and weighs 142 grams. For this prototype system, the Microstrain 3DM-G was chosen as the sensing unit since it contains all the sensors of interest. The 3DM-G contains accelerometers with a range of ±2g and a sensitivity of 312 mV/g, magnetometers with a range of ±2gauss and a sensitivity of 3mV/gauss, and rate gyroscopes with a ±300deg/s range and a sensitivity of 0.67 mV/(deg/s). The wireless transceiver consists of a Free2Move Serial Plug that uses the Bluetooth protocol to send and receive data using the serial port profile. The Bluetooth transceivers have a range of 100 meters and can send data to any other Bluetooth-enabled device. The data is collected by the laptop through a custom made Java application and the posture of the body is displayed on the computer screen using a VRML humanoid model. The application is fully multithreaded and can read the data from each sensor concurrently. The system and computer display are shown in Figure 2.

III. Posture Estimation From Sensor Data

Accurate posture estimates can be obtained from a unit containing accelerometers, magnetometers and rate gyroscopes by fusing the posture estimates from the accelerometer-magnetometer pair and from the rate gyroscope. We show that the posture can be obtained from the accelerometer-magnetometer pair in three simple vector algebra steps in the static case by a simplified version of the Triad algorithm [9]. Similarly, the posture from the rate gyroscope can be obtained in only three steps. Fusion of these two independent posture estimates provides an improved estimate that retains accuracy over a broad range of situations.

A. Obtaining Posture Estimates from an Accelerometer-Magnetometer Pair

An ideal accelerometer undergoing no forced accelerations (static case) produces a gravity reading that points towards the center of the earth. Similarly, an ideal magnetometer undergoing no external magnetic fields produces a reading pointing to the magnetic north pole. The accelerometer-magnetometer combination then gives us readings for the orientation of two fixed vectors with known direction (down and north.) Obtaining a posture from these two readings is then a simple application of the Triad algorithm, and we can compute a posture estimate by simply tracking the direction of these two vectors. For the sake of efficiency, we assume that one of our sensor readings is ideal (the gravity reading.) Under this assumption, the posture can be estimated in three simple vector steps.

We denote a fixed world frame as Frame 0 (with axes x^0, y^0 and z^0,) and a sensor frame attached to the sensors as Frame 1 (with axes x^1, y^1 and z^1.) We label the gravity vector and the magnetic field vector given in Frame 1 as g^1 and e^1 respectively. By choosing the fixed world frame, so that z^0 is points towards the center of the earth and x^0 points to the north, g^1 is collinear with z^0 and e^1 is restricted to the XZ plane of Frame 0. Figure 3 shows the relationship between these vectors. Computing the cross product of g^1 and e^1 will automatically produce a vector aligned with the y-axis of Frame 0.

Since the magnetometer vector e^1 has a positive x component on any latitude south of the magnetic north pole, we can find the three axes of Frame 1 in these three steps:

$$z^1 = g^1 \tag{1}$$

$$y^1 = g^1 \times e^1 \tag{2}$$

$$x^1 = y^1 \times z^1 \tag{3}$$

If we assume that x^1, y^1 and z^1 are column vectors, the rotation matrix R that computes the posture of the sensors in the fixed world Frame 0 is simply:

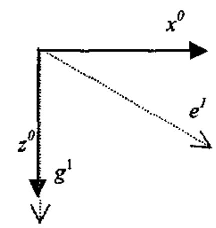

Figure 3. Gravity and magnetic vectors on a z-down, x-north coordinate frame

$$R = \begin{bmatrix} (x^1)^T \\ (y^1)^T \\ (z^1)^T \end{bmatrix} \tag{4}$$

Besides its efficiency, this algorithm has other advantages. It does not require an initial estimate of the magnetic field vector like other proposed methods [3, 4, 6, 8]. Obtaining this initial estimate imposes an additional recalibration step whenever there is a change in location.

B. Obtaining Posture Estimates from Rate Gyroscope

An ideal rate gyroscope produces readings of the angular velocity it is exposed to. Assuming an initial posture estimate is given, obtaining posture estimates from the rate gyroscope involves only simple integration steps. If an initial estimate is given in Euler angles, simply integrating the angular velocity obtained from the three axes of the rate gyroscope and adding the integration results to the initial posture produce all consequent postures.

C. Obtaining Combined Posture Estimatess

In the previous sections, we obtained posture estimates from the accelerometer-magnetometer pair and the rate gyroscope assuming that the sensors provide noise-free ideal signals. In reality, however, all sensor readings contain noise.

i. Sensor Signal Analysis

A real accelerometer or magnetometer under external stimuli will produce readings that can be decomposed into four parts:

$$s_t = d + s_f + b + n \tag{5}$$

where s_t is the total sensor reading, d is the vector we are tracking (gravity or the earth's magnetic field), s_f is the external stimuli (forced acceleration or magnetic field), b is a sensor bias component, and n is a wide-band noise component. The sensor bias can be mostly calibrated away, and the magnitude of n is usually small with respect to the desired component d and can be attenuated using standard frequency signal processing. Decoupling d and s_f is much more complex. The relationship between these two components is dependent on the movement (in the case of the accelerometer) or the external magnetic field the sensor is measuring (in the case of the magnetometer), and the relative magnitudes of these components can vary greatly. However, frequency analysis of the sensor signals shows that d tends to lie towards the low end of the frequency spectrum, while s_f has more high frequencies components.

Similarly, we can decompose the readings from real rate gyroscopes into four parts:

$$r_t = r_w + \omega + c + m \qquad (6)$$

where r_t is the total sensor reading, r_w is a slow-moving drift component, ω is the angular velocity of the gyroscope, c is the sensor bias, and m is a wide-band noise component. The drift, being a slow moving process, tends to reside towards the lower end of the spectrum, and our desired signal, the angular velocity, has more high frequency components.

ii. Filter Design

The desired signals coming from the accelerometer-magnetometer pair tend to lie towards the low-end of the frequency spectrum, while the desired signals coming from the rate gyroscope tend to have more high frequency components. Our signals have complementary frequency spectra, and we can use a simple first-order complementary filter to fuse the estimates. We take a complementary filter approach instead of the more standard Kalman filter because of two reasons: (1) A complementary filter structure is very efficient. A Kalman filter requires an expensive matrix inversion operation at every estimate. While it is possible to obtain reasonable results without performing this update at every step, the filter loses its optimality. (2) The nature of our signals lends itself very well to a complementary filter approach. Creating a Kalman filter with equivalent performance would require a process model with multiple states leading to a much larger computational overhead.

We designed a simple time-domain first-order complementary filter that performs low-pass filtering on the signals from the accelerometer-magnetometer pair, and high-pass filtering on the signals from the rate gyroscope. While some previous approaches to obtaining postures from the same sensors have also used complementary filter techniques, our approach differs in two key aspects: (1) Previous techniques compute the posture using the readings from the accelerometer-magnetometer pair, and fuse that posture estimate with the posture obtained from the readings of the gyroscope. Instead, our filter simply tracks the direction of the gravity and earth magnetic field vectors. We then use the accelerometer-magnetometer algorithm described in section III.A on the filter's output to solve for the posture. (2) Most previous techniques involve filtering in the quaternion space. The signal (and noises) from the accelerometer and magnetometer are coupled together, and given the different relative weights of each quaternion component in different parts of the quaternion space, it is difficult to know which component should be weighed more heavily. While the approach of weighing all components equally is very common, it may not produce the best results. Our technique resolves this issue by staying in a linear space. Figure 4 shows the filter structure, including the final step of transforming the filter outputs into posture estimates.

The kernel of the filter is the core section that performs the signal processing and fusion, producing estimates of the directions of the gravity and earth's magnetic field vector. Simple frequency analysis of the kernel can be used to analyze the filter's operations. The inputs to the filter's kernel are two 6×1 vectors: (g_o, e_o) is a 6×1 vector containing the readings from the accelerometer and the magnetometer, and $(\Delta g_1, \Delta e_1)$ are the step change to the filter's output (g_{es}, e_{es}) as computed from the rate gyroscope's readings. The Laplace domain equivalents of these three vectors will be denoted by (G_o, E_o), (sG_1, sE_1) and (G_{es}, E_{es}) respectively. Solving for the filter's output, we find that G_{es} is given by:

$$G_{es} = \left(\frac{k_1}{s+k_1}\right)G_0 + \left(\frac{s}{s+k_1}\right)G_1 \qquad (7)$$

and E_{es} is given by:

$$E_{es} = \left(\frac{k_2}{s+k_2}\right)E_0 + \left(\frac{s}{s+k_2}\right)E_1 \qquad (8)$$

where k_1 and k_2 are constant gains. Equations (7) and (8) show that the signals from the accelerometer-magnetometer pair (G_o, E_o) are filtered by a first-order low-pass filter, while the estimates obtained from the rate gyroscope (G_1, E_1) are filtered by a first-order high-pass filter. By filtering out the high frequency components of the signal from the accelerometer-magnetometer pair and the low-frequency components of the rate gyroscope's signal, the complementary filter produces an estimate of the desired components of the sensors' signals and combines these components to produce the filter output.

The gains k_1 and k_2 determine the crossover frequencies of the complementary filter, that is the frequencies at which the signals from both inputs are given equal weight. The crossover frequency f_c (in Hertz) of a first-order complementary given a gain k can be calculated by the formula:

$$f_c = \frac{k}{2\pi} \qquad (9)$$

An initial estimate of the crossover frequency can be obtained by analyzing the spectra of the sensor signals to find where the cutoff frequency of the low-pass and high-pass filters should be. Some manual fine-tuning is usually required.

iii. Filtering the Sensor Signals

The filter vectorizes the accelerometer and magnetometer readings (g_o, e_o) into a 6×1 vector. Simultaneously, it computes the rates of change to the current filter estimates of gravity and earth magnetic field vectors (g_{es}, e_{es}) by simply taking the cross product of the gyroscope readings (ω) with the current filter estimates:

$$(\Delta g_1, \Delta e_1) = (\omega \times g_{es}, \omega \times e_{es}) \qquad (10)$$

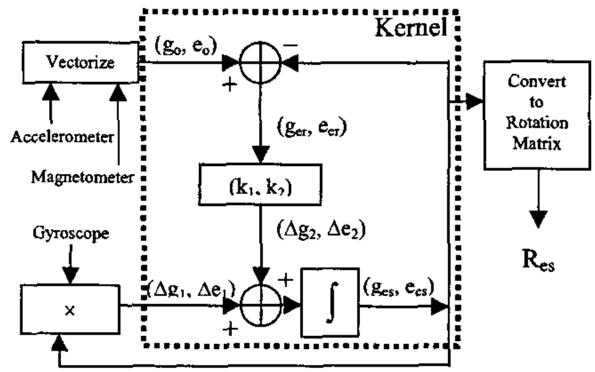

Figure 4. Complementary filter to obtain posture based on an accelerometer-magenetometer pair and a rate gyroscope

The difference signals (g_{er} , e_{er}) between the readings of the accelerometer-magnetometer pair and the filter estimates of gravity and magnetic north are given by a simple vector substraction:

$$\left(g_{er}, e_{er}\right)=\left(g_{o}, e_{o}\right)-\left(g_{es}, e_{es}\right) \tag{11}$$

and the gain-adjusted difference signals (Δg_2 , $\Delta e2$) are computed by simply multiplying this vector by the gains:

$$\left(\Delta g_2, \Delta e_2\right)=\left(k_1 \cdot g_{er}, k_2 \cdot e_{er}\right) \tag{12}$$

where using independent gains for the gravity and earth magnetic field estimates provides flexibility in dealing with interferences to either of these vectors. Finally, the filter estimates are updated by fusing the rate of change estimates from both sensor streams:

$$\left(g_{es}, e_{es}\right)=\left(g_{es}, e_{es}\right)+\left[\left(\Delta g_1, \Delta e_1\right)+\left(\Delta g_2, \Delta e_2\right)\right] \cdot T \tag{13}$$

where T is the sampling period. Using these estimates of the direction of gravity and the earth's magnetic field (g_{es} , e_{es}), the current posture estimate in rotation matrix format R_{es} is calculated using the accelerometer-magnetometer algorithm described in section III.A.

IV. Validation

We tested the accuracy of our algorithm by comparing the posture estimates obtained from our technique against the actual postures obtained using a robot manipulator. We collected data by attaching one of our wearable units simultaneously to the end effector of the manipulator, and the wrist of our subjects. Our subjects performed several movements we expect to encounter in every day life such as walking and running (in place), brushing teeth, and putting on clothes. We then compared the accuracy and speed of our algorithms to two other comparable techniques by implementing the algorithms described in [6] and [8]. The description of the algorithm in [7] does not provide enough details for implementation.

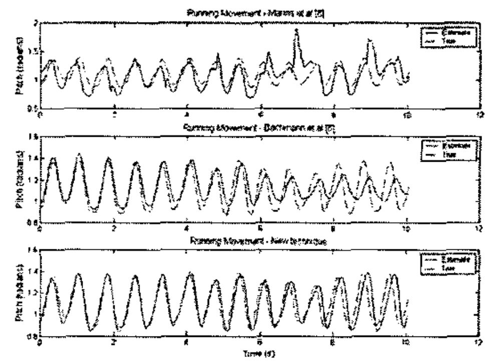

Figure 5. Posture estimates during a running movement

A. *Experimental Setup*

We used a PHANToM 1.5 robot made by Sensable Technology. The PHANToM has millimeter positional accuracy, but has a limited workspace. We extended the workspace of the robot by adding an 38.75 cm. extensor rod to the end effector of the PHANToM. This extensor rod served two purposes: It allowed us to stay away from the magnetic interference caused by the metallic parts of the robot and it provided us with a workspace large enough for realistic human movements. The effect was to more than triple the size of the last link of the robot kinematic chain.

B. *Results*

We implemented all algorithms in C++ using the optimized Intel Math Kernel Library on a 1.7GHz Pentium IV computer. The parameters of all three algorithms were chosen for maximum posture estimate accuracy. Data from both the unit and the PHANToM robot was recorded at 50Hz, and each recorded activity lasted 10 seconds. To compare the accuracy of each technique, posture estimates were computed for each data sample and compared to the postures computed from the robot. To calculate the upper bound update frequency of the algorithms, the data was recorded and analyzed off-line. We timed the execution time of each algorithm and found the average frequency at which they can produce posture estimates by simply dividing the total execution time by the number of samples.

Typical results for two of the recorded movements are shown on figures 5 and 6. These figures show only the pitch angles of the posture estimates for visualization purposes. The figures plot the pitch estimates in radians against time in seconds for all techniques. The plot on the top corresponds to the Kalman filter approach proposed in [8], the plot in the middle to the complementary filter approach proposed in [6], and the bottom plot corresponds to our new technique. Figure 5 shows the posture estimates during a running movement, and Figure 6 shows the pitch estimates during a brushing teeth movement. The running movement had an average angular

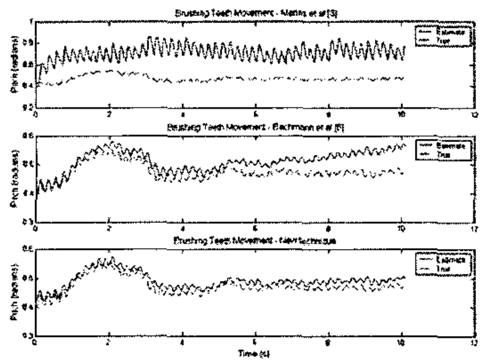

Figure 6. Posture estimates during a brushing teeth movement

velocity of 1.80 rad/s, and the brushing teeth movement had an average angular velocity of 0.79 rad/s.

A unit placed on the wrist during a running movement (such as that of Figure 5) undergoes oscillatory motion as the wrist swings back and forth. The sensor unit experiences high movement acceleration at the beginning and the end of each swing as the arm gathers or loses speed. During these moments, the acceleration due to the movement is of the same order as the acceleration due to gravity, and the accelerometer readings do not provide a good estimate of the direction of gravity. The simple process model proposed in [8] does not incorporate enough information to deal with cases of high movement acceleration and has special trouble handling acceleration peaks (R^2 = 0.197). The complementary filter approaches handle these peaks better: Since the filter performs a low-pass operation on the acceleration signal, peaks are smoothed out. However, the complementary filter proposed in [6] couples the accelerometer and magnetometer data and performs the smoothing in quaternion space. The non-linearity of the quaternion space and the necessary quaternion renormalizing step after every filter negatively affects the accuracy of the filter by introducing accumulating errors in the posture estimates (R^2 = 0.529). By performing the filtering in the linear acceleration and magnetic field space, our filter produces more accurate estimates (R^2 = 0.790).

Similarly, a unit placed on the wrist during a brushing-teeth motion (such as that of Figure 6) will undergo highly vibratory motion with consecutive acceleration peaks at every up and down motion. The Kalman filter approach in [8] is unable to recover fast enough from these peaks to produce reasonable results (R^2 = 0.0091). The complementary filter technique outlined in [6] produces estimates that drift away from the true posture as the quaternion update steps cause quaternion estimates that heavily deviate from unit magnitude and larger renormalizations are required (R^2 = 0.549). In contrast, our complementary filter again produced posture estimates that closely matched the true postures (R^2 = 0.873).

Our speed tests showed that both complementary filter techniques are faster the Kalman filter approach described in [8], due to computationally intensive mathematical operations required by the filter. Comparing the complementary filter

TABLE I. COMPARISON OF RESULTS

Movement	Running (R^2)	Brushing (R^2)	Frequency (KHz)
Marins [8]	0.197	0.0091	1.380
Bachmann [6]	0.529	0.549	5.284
Our technique	0.706	0.873	125.75

techniques, our technique produced posture estimated at an update frequency of 125.75 KHz, compared to the update rate of 5.284KHz of the approach in [6]. This represents a 23.8 factor increase. All results are summarized in Table 1.

V. CONCLUSION

We have presented a new technique that computes accurate posture estimates in real-time from sourceless, miniature inertial and magnetic sensors. We compared this technique to previous approaches and showed that it produced more accurate results 23.8 times faster than the next fastest algorithm. This technique is suitable for use in both units with embedded programs onboard, as well as servers handling multiple units concurrently.

Future work will include the development of more robust algorithms that can handle the presence of surrounding magnetic sources, and the creation of custom-made wearable units better suited for long-term wear.

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