Joint Angle Measurements Using Magnetic Sensing: A Feasibility Study

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***Abstract*—Inertial measurement units (IMUs) are extensively used for body motion tracking applications. Despite their ubiquity, they often suffer from sensor drift over time, and environmental disturbances. Additionally, their use cases are mostly limited to applications with slowly varying accelerations and low-dynamic motions. Sensor fusion algorithms are used for scenarios where more dynamic, faster motions are encountered. However, such algorithms often come with high computational costs. In this work, we present a low-drift, computationally-efficient motion tracking system that suppresses ambient magnetic noise and is applicable to various motion dynamics. We augmented inertial sensors with localized magnets, and implemented a localization algorithm that takes in the magnetic measurements and outputs the sensor positions as the sensors move in the vicinity of the magnets. For applications with movements around a central joint, we extended our position tracking to a joint angle measurement platform. We conducted two preliminary studies to evaluate our system performance, and validated our system against a computer vision system. Our first study uses a goniometric setup to evaluate drift-reductions in angle estimates. Our method is compared against a commonly-used IMU-based method. We collected 60 minutes of data from 4 study sessions, with both static conditions and various dynamic motions. The motions had angular velocities ranging from 0 to 47 (°/sec). Results show the average root mean square error (RMSE) of 1° for static and 2.7° for dynamic motions. In the second study, an on-body setup monitors the knee flexions and extensions performed by a pilot user. We collected 30 minutes of data from 4 study sessions. Our system reports the average RMSE of 3.7° for dynamic motions with an average angular velocity of 17 (°/sec). Based on these promising results, in future work we will extend our user studies to a greater number of users to evaluate the generalizability.**

***Index Terms*—body motion tracking, joint angle measurement, magnetic sensing, drift reduction.**

I. Introduction

Body motion tracking is essential for various applications such as sports, medicine, and rehabilitation. While the gold standard tracking method leverages optical motion capture systems, such systems are costly and not well suited for out-of-lab use-cases. Accordingly, body-worn Inertial Measurement Units (IMUs), with minimal cost and ubiquitous availability, have gained popularity for many applications.

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Despite their ubiquity, IMUs suffer from major limitations. Accelerometers and magnetometers are often contaminated by dynamic accelerations, and geomagnetic fields and local magnetic anomalies [1]. Gyroscopes, which only estimate relative orientation changes, are subject to sensor drift over time. The longer the data collection duration, the more drift and accumulated errors in pose estimations [1]. Sensor fusion algorithms (e.g. Kalman filters) are proposed to address these limitations [2]. However, they often require high power consumption and computational costs, since tuning the filter parameters requires extensive optimization processes [3]. Moreover, such model-based approaches require prior knowledge of parameters such as *sensor-to-joint-center position*, and the *sensor-to-segment orientation*, both of which are difficult to compute accurately [2]. Most fusion algorithms are effective under specified biomechanical constraints with invariant accelerations and low dynamic movements that limit their application domains [2].

Among different approaches, pairing IMUs with magnets (e.g. permanent ones or electromagnets) that generate a local magnetic field, can provide a new avenue for drift-reduced pose estimations [4], [5]. In this work, we adopt a similar approach to propose a low-drift, computationally-efficient position tracking method that incorporates a robust background magnetic field (BMF) reduction technique. Our choice of using permanent magnets allows the system to passively generate magnetic fields, resulting in a low-power, cost-effective system using only off-the-shelf magnets and magnetometers.

Our main objective is to present a precise, millimeter-level position tracking system. We implemented a localization algorithm that inputs the magnetic measurements and outputs the sensor positions as it moves in the vicinity of the magnets. To train this algorithm, we used large-scale synthetic data collected from a robotic arm. This approach provides advantages such as maximizing system performance through the use of precise, high-resolution data, and removing the need for exhaustive participant data collection sessions.

For those applications with movements around a central joint e.g., knee flexions and extensions, the position tracking is extended to a joint angle measurement platform. [6] and [7] have proposed accurate knee tracking methods. Our work has an add-on benefit of precisely identifying the joint position. We implemented a *detector-optimizer* algorithm that continuously

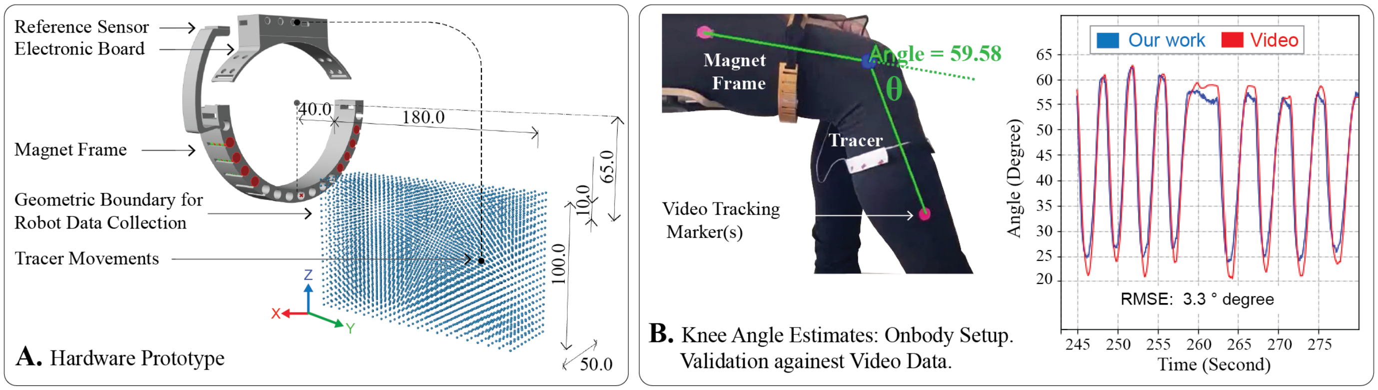


Figure 1. A. Our sensing prototype and the geometric volume in which the position tracking algorithm is trained. B. Knee angle estimates and their validation against a computer vision angle tracking method. Figure shows an illustrative example of angle estimates from one study session.

computes and updates the center of rotation and outputs the angles between two segments intersecting at the central joint. Our approach has a key advantage over most IMU-based solutions that require a prior knowledge of joint position [2].

We conducted two preliminary studies to evaluate our system performance. The first is a goniometric setup that evaluates drift-reductions in angle estimates (Fig. 3). The second is an on-body setup that monitors the knee flexion and extensions performed by a pilot user (Fig. 1). We evaluated our system for both static conditions and dynamic motions, and compared it against the commonly-used Madgwick filter (with 6 DoF using a gyroscope and accelerometer) and a computer vision angle tracking platform as ground truth.

II. Method

A. Prototype Setup

As Fig. 1 shows the hardware setup consists of two IMUs [8] as tracer and reference sensors, an electronic board for data acquisition and communication (similar to [5]), and a 3D-printed frame containing 24 magnets [9] that are symmetrically positioned around the center of the frame. We empirically chose the dimension and arrangement of the magnets as their resulting generated magnetic field properly covers a geometric boundary in which we estimate the tracer positions.

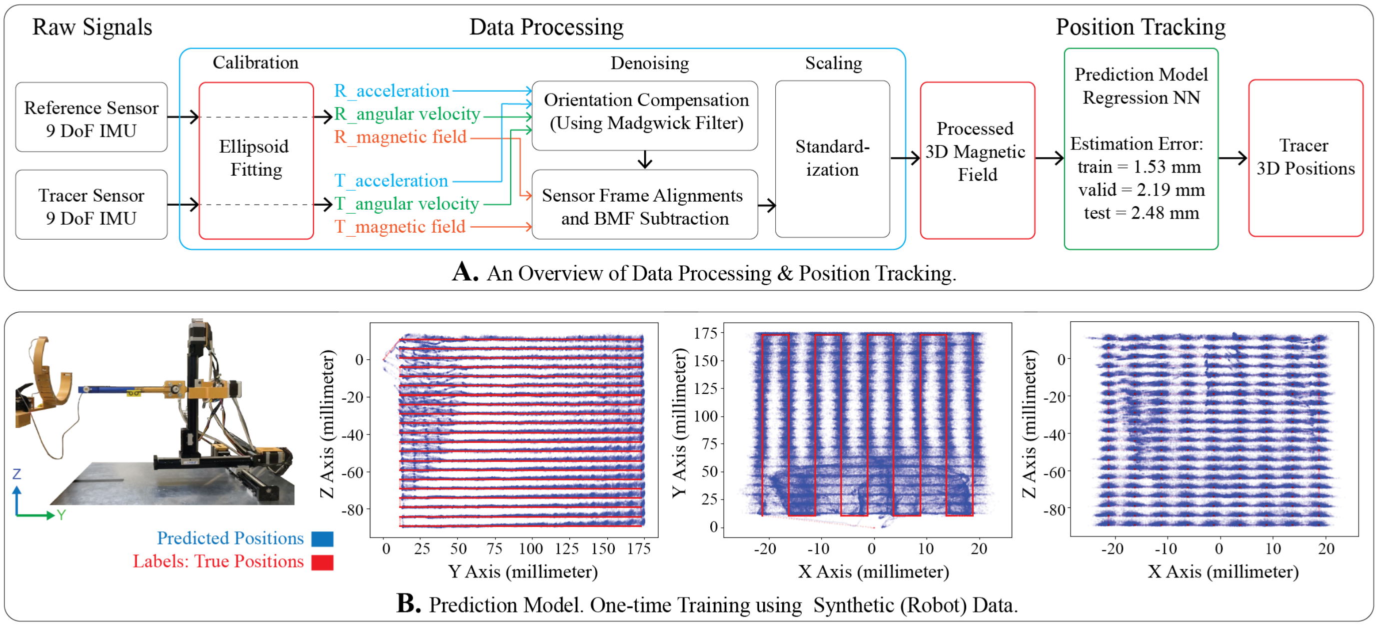
Fig. 2 shows the data processing pipeline. First, the tracer and reference sensors are calibrated using the *3D ellipsoid fitting* method [10]. Second, environmental disturbances are removed. To do so, it is necessary to determine if the changes in magnetometer readout are caused by tracer's (magnetometer) movements relative to the magnet frame, or because of the BMF. For such a determination knowing two parameters is essential; (1) tracer's orientation and (2) the magnitude and direction of the BMF. We implemented an *orientation compensation* method (similar to [5]) that estimates the tracer's orientations. We further used a reference sensor that contributes to BMF measurements and suppression. To elaborate, the tracer signal indicates the combination of sensor movements relative to the magnet frame, plus BMF. The signal from the reference sensor only indicates the BMF since the sensor is in a fixed position relative to the magnet frame. Hence the subtraction of the reference signal from the tracer signal removes the BMF noise from the tracer readout. Third, cleaned magnetic field data is scaled for further processing in the position tracking algorithm that outputs the tracer's 3D positions.

B. Position Tracking

As Fig. 2 shows, our pose estimation model intakes the processed 3 degree of freedom (DoF) magnetic data as the input features and predicts the tracer's positions that correspond to those magnetic data. Such a prediction requires prior knowledge of a mapping function that correlates the input features to the tracer's position at every time instance. We adopted a supervised approach to identify and tune this mapping function. We implemented a deep neural network (NN) prediction model that only requires one-time training in an off-line mode, and can be used in various test conditions.

In this implementation we used synthetic data collected from a 5DoF robotic arm (Fig. 2). This approach allows us to collect precise, large-scale datasets that are uniformly distributed over the entire test space. This also minimizes user burden, since there is no need for user data to train the model. Notably, it makes the prediction model applicable to many users with different body sizes, as collecting data from a relatively large geometric volume (larger than most typical body sizes) eliminates issues of over-fitting to a particular user's body or test session. Moreover, one-time training of the prediction model minimizes computational costs, leading to more efficient on-device computations. Here we will explain data collection processes, and the implementation and performance of our tracking algorithm.

1) Data Collection Procedure: As shown in Fig. 2, the sensing hardware is placed in the vicinity of the robot arm, and the tracer sits in the robot end-effector. As the robot arm moves, the tracer traverses along known positions while our system synchronously records data from both sensors and the robot end-effector's corresponding position. The dimension of the geometric volume for data collection is 180 x 100 x 50 mm^3 with 5 mm resolution and offset 40 mm from the center of the frame. The dimensions and position of this boundary are empirically achieved, and is tuned for knee angle



A. An Overview of Data Processing & Position Tracking.

B. Prediction Model. One-time Training using Synthetic (Robot) Data.

Figure 2. A. An overview of the data processing pipeline and position tracking algorithm. B. Using a 5DoF robot arm to collect synthetic data and train the position tracking model. Comparing predicted positions against true labels indicates 2.48 mm error (third quartile) in test data.

measurements. We collected 3 datasets to train, validate, and test the model (1,557,814 samples). The validation and test data are shifted by 3 mm in all axes respectively in 3D space to ensure the model is evaluated using unseen data.

2) Neural Network Architecture and Performance: As Fig. 2 shows, the processed magnetic field values are fed into a feed-forward neural network responsible for estimating the tracer's 3D positions. We implemented the NN model similar to [5], and an architecture with the following parameters led to the lowest errors in our position estimates (training = 1.53 mm, validation = 2.19 mm, and testing=2.48 mm). The parameters are set as: hidden layers = 3, number of neurons per layer = 50, activation function = exponential linear unit (ELU), optimizer = stochastic gradient descent (SGD), batch size = 256, and learning rate = 0.01.

C. Angle Estimates from Predicted Positions

For applications with cyclic movements e.g. knee flexions and extensions, we propose a detector-optimizer algorithm that computes the center of rotation and converts the predicted positions into joint angles. In the presence of movements around a central joint, predicted positions are fitted into an arc. By selecting 4 random points on the arc circumference, the center and the radius of the arc are computable. Therefore, as shown in Fig. 3 we can compute the θ angle using predicted positions of the tracer at run-time. In real world applications like on-body setup with constant micro-movements of the prototype around the joint, such a parameter should continuously be updated. To do so, we can process the streamed data in two threads, one for position/angle estimation, and the other for constantly updating the position of the center point. The first thread takes in the most recent center point from the second thread as it predicts the position/angle at every sample.

III. Evaluation and Results

We evaluated the accuracy of angle estimates for two experimental studies. The first is a goniometric setup to evaluate drift reductions. Our approach is compared against a commonly-used IMU-based solution that relies on accelerometer and gyroscope measurements. The second one is an on-body setup in which we measure knee flexions and extensions for a pilot user. In both experiments we validated our measurements against a computer-vision approach as ground truth. This study was performed under a Georgia Tech Institutional Review Board (IRB) approved protocol with number H22061.

1) Goniometer Setup: As Fig. 3 shows, a goniometer is equipped with our sensing hardware. The tracer is mounted on the goniometer's moving arm and the other arm is fixed in the center of the magnet frame. We collected data in 4, 15-minute sessions. Study sessions include static conditions and dynamic motions. During static measurements, the average RMSE of our work is 1 °and that of the 6 DoF IMU is 2.3°. Part B in Fig. 3 is an illustrative example that compares sensor drift after about 8 minutes of recording data. During dynamic movements, with angular velocities ranging from 15 to 47°/sec, the average RMSE of our work varies from 1.7 to 4.4°while the 6 DoF IMU shows inferior performance with error ranging from 3.2 to 9.8°. Part B in Fig. 3 illustrates how error accumulates in IMU angles whereas our system shows minimal drift after 11 minutes of data recording. Although we are not claiming superior performance of our work over all existing IMU-based solutions, we believe this results indicate a robust, low-drift angle estimation method.

2) On-body Setup and Knee Angle Estimates: As Part B in Fig. 1 shows, our on-body setup monitors the knee flexions and extensions performed by a pilot user. We collected data from 4, 8-minute sessions. The user's knee moves from 20 to 65°,

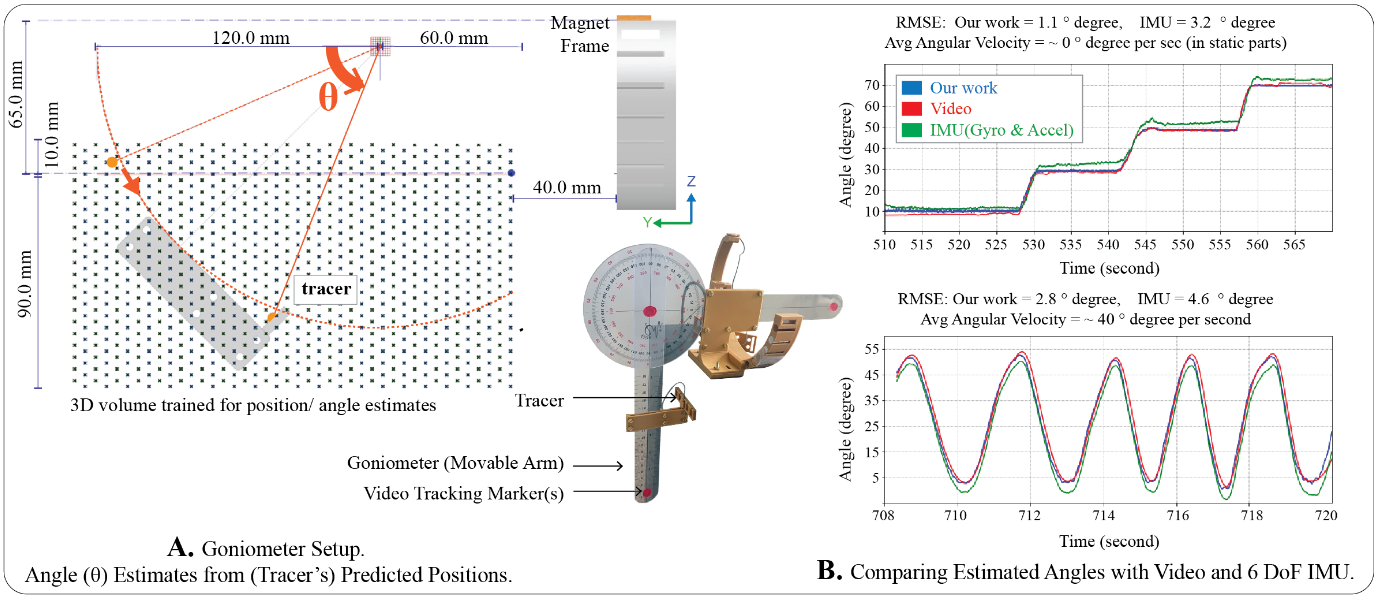


Figure 3. A. Goniometer setup shows the conversion of predicted (tracer's) positions into joint angles. B. Goniometer is equipped with the sensing hardware and tracer's static and dynamic motions are measured and compared against a commonly-used 6 DoF IMU and computer vision angle tracking method. Figure shows an illustrative example of angle estimates from two study sessions.

with accompanied rest periods. For dynamic movements with the average angular velocity of 17°/sec, the average RMSE is 3.7°. Overall, we did not observe an error increase over time or with faster motions. We believe the reported results are promising, as we will extend the experiment to more users for various activities in the future.

IV. Conclusion

A precise, millimeter-level position tracking method with practical applications for joint angle measurements is presented here. The method augments inertial sensing and incorporates localized magnets to estimate sensor positions using their magnetic measurements. The presented method mitigates common problems of sensor drift, sensitivity to dynamic accelerations, and ambient magnetic disturbances. The method offers a low-power, computationally-efficient tracking method that supports real-time predictions independent of varying motion dynamics. We believe this proof-of-concept work provides a new avenue for joint motion tracking applications that should be evaluated in the future in larger user studies.

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