# Improving Accuracy of Inertial Measurement Units using Support Vector Regression

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*Abstract*— **Inertial measurement unit (IMU) is a sensor that measures acceleration and angular velocity rate. It has become increasingly popular due to its small size and low cost comparing to typical marker-based motion capture system. Nonetheless, IMUs face considerable challenges, in particular noticeable inaccuracy from accumulated integration errors. In this project, we attempted to improve accuracy of IMUs in measuring clinical knee angles using supervised machine learning, specifically support vector regression. By employing high-accuracy data from marker-based motion capture system as training samples, we were able to see improvement in the performance of the IMUs estimation of clinical knee angles in walking motion. This result is promising and encourages further works that might extend the model to include a more general set of movements.**

## I. Introduction

Since its introduction in 1990, motion capture is used not only in the entertainment business such as films and games, but it is also used extensively in sports, medicine, and military. Traditionally, motion capture is done using images captured from cameras to triangulate positions of each reflective marker in the 3-dimensional space. While this marker-based system performs extremely well in terms of positional accuracy and continue to hold its status as the industrial standard, there is a number of undesirable features, including high cost, setup complexity, and space limitation.

Recently, an alternative method has gained popularity. Inertial motion capture uses sensors—inertial measurement units, IMUs—attached to different parts of the body, much like reflective markers used in the optical system, to measure acceleration and angular velocity. This raw data may then be used to calculate parameters of interest, such as joint angles and other positional data. Due to its small form factor, minimal setup requirements, and low cost, inertial motion capture has come to be an appealing alternative to the marker-based system. In addition, since inertial motion capture does not require camera setup, it is a viable solution for capturing outdoor motions like skiing or mountain biking that otherwise may never be achieved through traditional marker-based motion capture.

As good as it may sound, inertial motion capture has one big disadvantage. Unlike the marker-based system, inertial motion capture lacks absolute positional data and relies heavily on integrating acceleration as well as angular velocity vectors in order to compute its absolute position. Taking into account sensor errors and motion approximation, the errors from this integration procedure quickly add up, and the result becomes more inaccurate as time passes.

In this project, we attempted to improve the accuracy of inertial motion capture using supervised machine learning. Using both systems to simultaneously capture a subject's motion, we trained the inertial motion capture model to more accurately estimate the valuable clinical knee angles of the subject during a walking motion.

## II. System & Data Processing

### A. Inertial Measurement Unit (IMU)

In this project, we used a system of low cost wireless inertial measurement units. The system is shown in Fig. 1. The system consisted of two IMUs with the capability of expanding up to 128 units. Each IMU has a 3-axis accelerometer with $\pm$8g range, a 3-axis gyroscope with 1600 deg/s range, and a 3-axis magnetometer with $\pm$4 Gauss range, all in 16-bit resolution. The data was sampled at 100 Hz and transferred to mobile phone for processing and data storage via Bluetooth connection.

### B. Marker-based Motion Capture System

The marker-based motion capture system is widely accepted as the industry's 'gold standard.' In our experiment, the reference system was the Vicon motion capture system with 8 cameras setup, running at 60 frames per second with sub-mm accuracy.

### C. Experimental Protocol

We collected two standard static trials in order to estimate the rotation matrices from each IMU's body

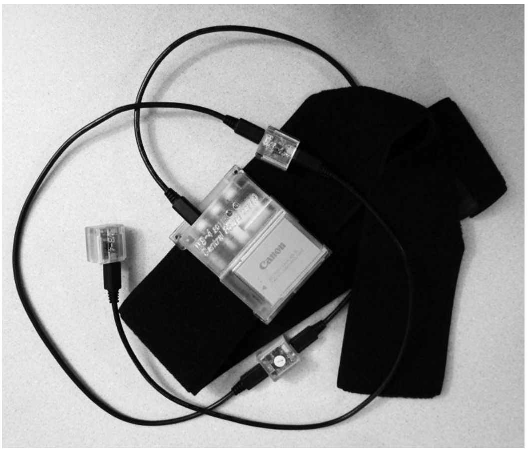

Fig. 1. Inertial measurement unit (IMU) system with Bluetooth capability.

frame to the reference frame. After the initial setup, we collected data of 42 normal walking trials on a treadmill at 1.00 m/s. For each trial, we collected the data using both IMUs and Vicon systems simultaneously. At the beginning of each trial, the subject jumped and stood still for a few seconds in order for us to be able to synchronize the timing of both systems. Of the 42 trials, three trials were dropped due to the corrupted data from the IMUs, leaving us with 39 trials.

### D. Clinical Knee Angle Estimation

Some of the key of parameters of a walking motion are the clinical knee angles. These parameters are very helpful for a physician to analyze knee-related injuries in patients. The clinical knee angle measurements consist of three parameters: flexion/extension, adduction/abduction, and internal/external rotation angles.

Before processing any data, we synchronized the data from both IMU and Vicon together using the jumping event at the beginning of the trial. We then only used the data after jumping for training and reporting results.

From the IMUs data, we performed a quaternion-based strap-down integration method [1], [2], [3] in order to estimate the rotation matrices. Our raw data consisted of gyroscopic rates, denoted by $\omega(t)$, and acceleration with respect to the body frame $\mathcal{B}$. We need to find a rotational matrix that transformed an IMU body frame into the world reference frame $\mathcal{W}$. We will denote this rotation matrix by $R(t)$. A convenient way to keep track of $R(t)$ is to use the quaternion representation $\tilde{\mathbf{q}} = [q_0, \tilde{\lambda}\tilde{\lambda}^T]$, where $q_0$ is a scalar and $\tilde{\lambda}$ is a $3 \times 1$ vector. Given the quaternion representation, the rotation matrix can be computed as follow:

$$R(\tilde{\mathbf{q}}) = (q_0^2 - \tilde{\lambda}^T\tilde{\lambda})I + 2\tilde{\lambda}\tilde{\lambda}^T - 2q_0[\tilde{\lambda}\times], \tag{1}$$

where $I$ is the identity matrix and $[\tilde{\lambda}\times]$ is standard vector cross product. Then the following differential motion describes the dynamic of body angular motion:

$$\frac{d\tilde{\mathbf{q}}(t)}{dt} = A_\omega(t)\tilde{\mathbf{q}}, \tag{2}$$

where

$$A_\omega(t) = \frac{1}{2}\begin{bmatrix} 0 & -\omega_z & \omega_y & \omega_x \\ \omega_z & 0 & -\omega_x & \omega_y \\ -\omega_y & \omega_x & 0 & \omega_z \\ -\omega_x & -\omega_y & \omega_z & 0 \end{bmatrix}$$

and $\omega(t) = [\omega_x, \omega_y, \omega_z]$, the angular velocity of $\mathcal{B}$. Let $\Delta t$ denote the system's sampling interval and assume that $\tilde{\mathbf{q}}(t)$ is constant for $t \in [k\Delta t, (k+1)\Delta t]$. Then we can solve equation (2) explicitly and get a discrete-time quaternion

$$\tilde{\mathbf{q}}_{k+1} = e^{A_k \Delta t}\tilde{\mathbf{q}}_k,$$

where $\tilde{\mathbf{q}}_k$ is the quaternion at time $k\Delta t$ and $A_k = A_\omega(k\Delta t)$. $\tilde{\mathbf{q}}_0$ is computed so that the rotation matrix is consistent with our initial static position. Once the discrete system above is solved, the rotation matrix is updated using equation (1).

After we found the rotation matrix representing the rotation from IMUs' body frame to the world frame, we used a joint coordinate system (JCS) as recommended by ISB and defined by Grood and Suntay [4], [5] to calculate the clinical knee angles.

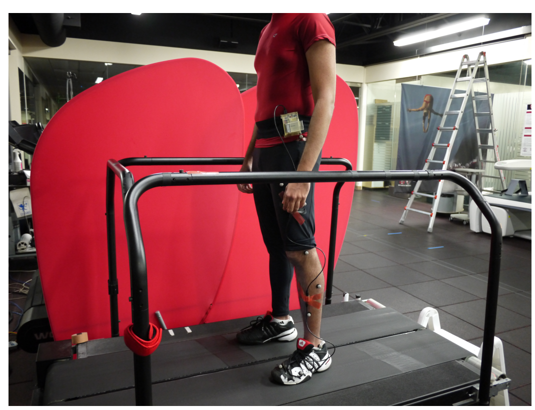

Fig. 2. Experimental Setup: A subject is wearing both IMUs and reflective markers.

## III. Methodology

As mentioned earlier, inertial motion capture suffers from buildup of errors. In this section, we describe the use of supervised machine learning procedure, in particular support vector regression, to improve the estimation from measurement of IMUs.

After processing the data as described in the previous section, the clinical knee angles estimation $\theta^{\text{IMU}}(t)$ are computed. Using relatively accurate position data from marker-based system, we were able to compute these angles with great accuracy. This set of data served as the target value. We then train the model using $\nu$-SVR with the pairs $(\theta^{\text{IMU}}(t), \theta^{\text{Marker}}(t))$.

### A. Model

Accepted as the 'gold standard' for position capturing, $\theta^{\text{Marker}}(t)$ is treated as 'actual' knee joint angle and we have the following model:

$$\theta_t^{\text{IMU}} = \theta_t^{\text{Marker}} + \varepsilon_t,$$

where $\varepsilon_t$ is the error from the measurement (sensor noise) and integration. Since our main application is to measure knee joint angle related to a specific body movement (walking, running, etc.), one might expect the error to be correlated with the angle $\theta^{\text{Marker}}(t)$. Let

$$\varepsilon_t = \phi(\theta_t^{\text{Marker}}) + \tilde{\varepsilon}_t,$$

so that

$$\theta_t^{\text{IMU}} = \theta_t^{\text{Marker}} + \phi(\theta_t^{\text{Marker}}) + \tilde{\varepsilon}_t = \tilde{\phi}(\theta_t^{\text{Marker}}) + \tilde{\varepsilon}_t.$$

Inverting this relationship, we have

$$\theta_t^{\text{Marker}} = \psi(\theta_t^{\text{IMU}}) + \tilde{\varepsilon}_t,$$

which gives a setting where the support vector regression can be applied. This derivation is not meant to be rigorous, but rather to motivate our use of support vector regression.

### B. Learning Method

From each trials, we collected and processed our data to get a sample path of angles measurement from both IMUs and marker-based motion capture as a function of time. The processed data consisted of triplets $(t, \theta_{t,i}^{\text{IMU}}, \theta_{t,i}^{\text{Marker}})$, where $t = 1, 2, \ldots, T$, and $i = 1, 2, \ldots, N$. $T$ is the number of time steps and $N$ is the number of trials (39 in our experiment). Our training size is $N \cdot T$ where $(t, \theta_{t,i}^{\text{IMU}})$ gives us input samples to be trained with target $\theta_{t,i}^{\text{Marker}}$.

We applied $\nu$-SVR with various kernels to the training set and compared the performance among different kernels. To evaluate the generalization capability of the model, we used leave-five-out cross validation method with root mean square error as a criteria. More concretely, we performed 8 trainings and trained the model using 34 walks and cross validated with 5 walks (except for the last training in which we used 35 walks to train and 4 walks to cross validate). The learning procedure can be summarized as follows:

- Normalize the training sample to have range [0,1]. Let $\theta_m, \theta_M$ be the minimum and maximum of our sample angles, then

$$x_{t,i} = \left( \frac{t}{T}, \frac{\theta_{t,i}^{\text{IMU}} - \theta_m}{\theta_M - \theta_m} \right), \qquad y_{t,i} = \frac{\theta_{t,i}^{\text{Marker}} - \theta_m}{\theta_M - \theta_m}.$$

- Apply $\nu-$SVR with regularization parameter $C = 1$ to the normalized training set $\{(x_{t,i}, y_{t,i})\}, i = 1, 2, \ldots, N, t = 1, 2, \ldots, T\}$. We use `libsvm` toolbox [6] which provides all necessary Matlab functions.
- Compute leave-five-out cross validation error using root mean square error as a metric.

TABLE I

Root mean square error

| Clinical Knee Angle | Linear | Polynomial | RBF |
|---|---|---|---|
| Flexion/Extension | 6.1215 | 6.1169 | 6.1278 |
| Abduction/Adduction | 0.6324 | 0.6328 | 0.6329 |
| Internal/External Rotation | 2.3546 | 2.3555 | 2.3545 |

## IV. Results

For kernel selection in our support vector regression method, we tried linear, polynomial, and radio-basis function (RBF) kernels. The results showed no significant advantage of one kernel over others across all three angle measurements, as can be seen in Table I. For knee flexion/extension angle, we found the RMS error to be approximately 6.12 degrees. Knee adduction/abduction angle had an RMS error around 0.63 degrees, and for the knee internal/external rotation angle, the RMS error was 2.35 degrees.

By using our model from SVR, we found a significant improvement in all three knee angles estimation from IMUs. As seen in a sample walking trial in Fig. 3, the IMU$_{model}$ (i.e. IMU data processed with SVR) was closer to the Vicon reference system, on average of more than 50%. In addition, our estimated model reduced the RMS errors over time across all trials at least in half, as seen in Fig. 4.

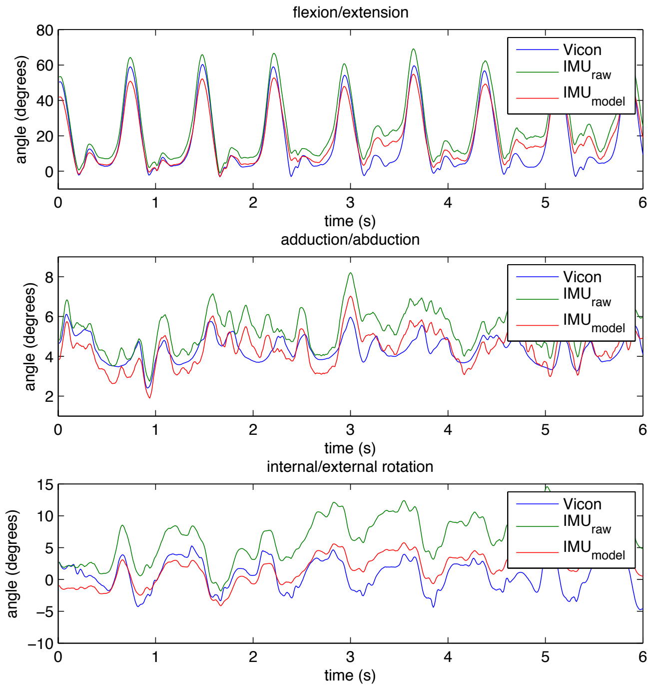


Fig. 3. Estimations of three clinical knee angles using data from IMUs improve by more than 50% using SVR, as we can see IMU$_{model}$ is close to the reference system (Vicon).

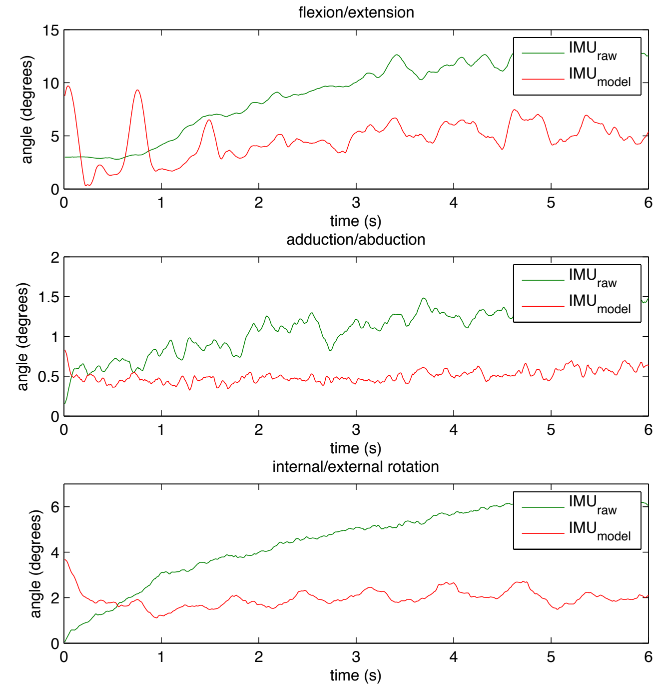


Fig. 4. Root-mean-squared errors due to time effect from IMUs are reduced by more than 40% on average.

## V. Discussion

Each kernel (linear, polynomial, and RBF) showed comparable performance across all three types of knee angles, as seen in Table I. This is possibly due to the structure of the error that was not specific to any kind of kernel. These relatively low cross validation errors allowed the model to fit the actual angle nicely without over fitting the data. Also note that the magnitudes of these errors are relatively good comparing to what have been found in a few other similar studies [7], [8], [9], [10]. Our model estimation has an advantage of very little computation time requirement (around 15 seconds for a sample of 34 trials, polynomial kernel). However, our model only considered a specific normal walking condition on a treadmill. Thus further experiments involving various motions and speed will be required to improve the generalization of the model.

Support vector regression was able to reduce the error in the knee angle estimation significantly, as seen in Fig. 3. One observation from the data is that the error increased in time due to accumulation of error from each time step discretization. By adding time since last static position parameter into our model, we were able to reduce accumulating errors significantly. Nevertheless, SVR is still unable to completely remove non-systematic errors such as hardware sensor noises.

With regards to the nature of the subject's movement, we notice that when the subject's foot hit the ground, the IMU registered significant noise in acceleration. This would suggest that we might observe periodic spikes in errors from the IMU. However, Fig. 4 showed that the root-mean-squared error from the IMUs does not appear to be periodic as expected. This was due in part by the not completely synchronized step cycles from our pre-processed data. Therefore these spikes were averaged out over 39 trials. The residuals, on the other hand, exhibits higher degree of periodicity. This might be due to SVR, which takes into account of the time parameter, was able to notice the cyclical trend.

## VI. Conclusion

In this paper, we explored support vector regression method to help improve knee angle estimation from multiple inertial measurement units. We used a gold standard marker-based motion capture system as our learning examples. We then utilized cross validation method to find an appropriate kernel to train the model. The results demonstrated a vast improvement of clinical knee angles estimation over the typical IMUs measurement. This would allow us to capture the essence of knee motion in a near-real-time calculation, suitable for activities that require outdoor setting and instant feedback. Future work would require testing and learning of multiple motions and joint angles in order to improve the generalization of the model.

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