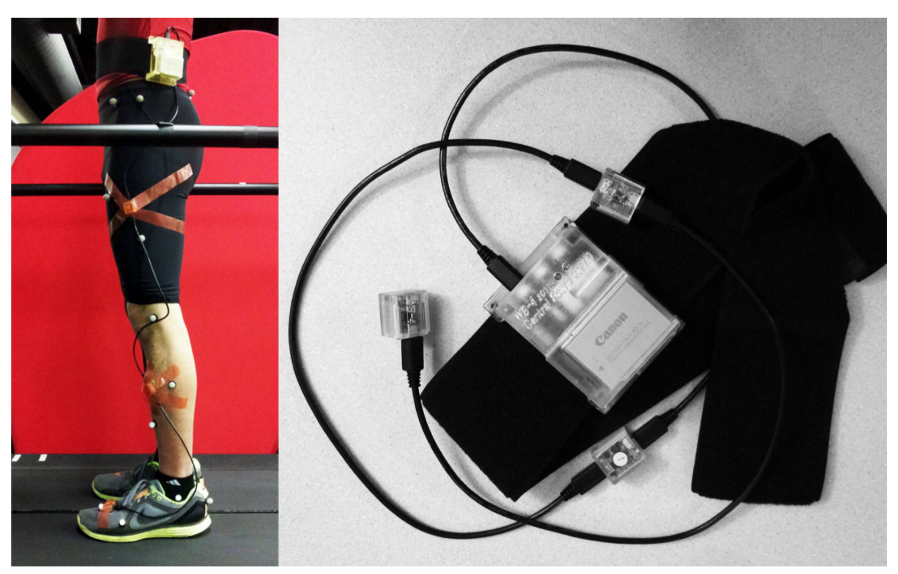
Improving Accuracy of Inertial Measurement Units using Support Vector Regression

CS 229

In this project, we attempt to improve the accuracy of inertial measurement units (IMUs) using supervised machine learning. We simultaneously capture the subject's motion with both the marker-based system and the IMUs. We use data from marker-based system to train the IMUs to more accurately estimate the clinical knee angles of the subject.

Data

The data is collected at the Stanford's Human Performance Lab. A subject is attached with 3 IMUs at each leg segment (foot, shank, thigh) and standard lower-extremity 17-marker set. The subject performs 42 trials of 10-stride walk on a treadmill.



From the IMUs' acceleration data, the knee joint angles are estimated using quaternion-based strap-down integration method. This data will be used as our input features. The marker-based system readily yields positional data, which can be used to compute an accurate clinical knee angles. This will serve as our target variable.

Learning Method

We apply support vector regression to the training set. The detail of the procedure is the following:

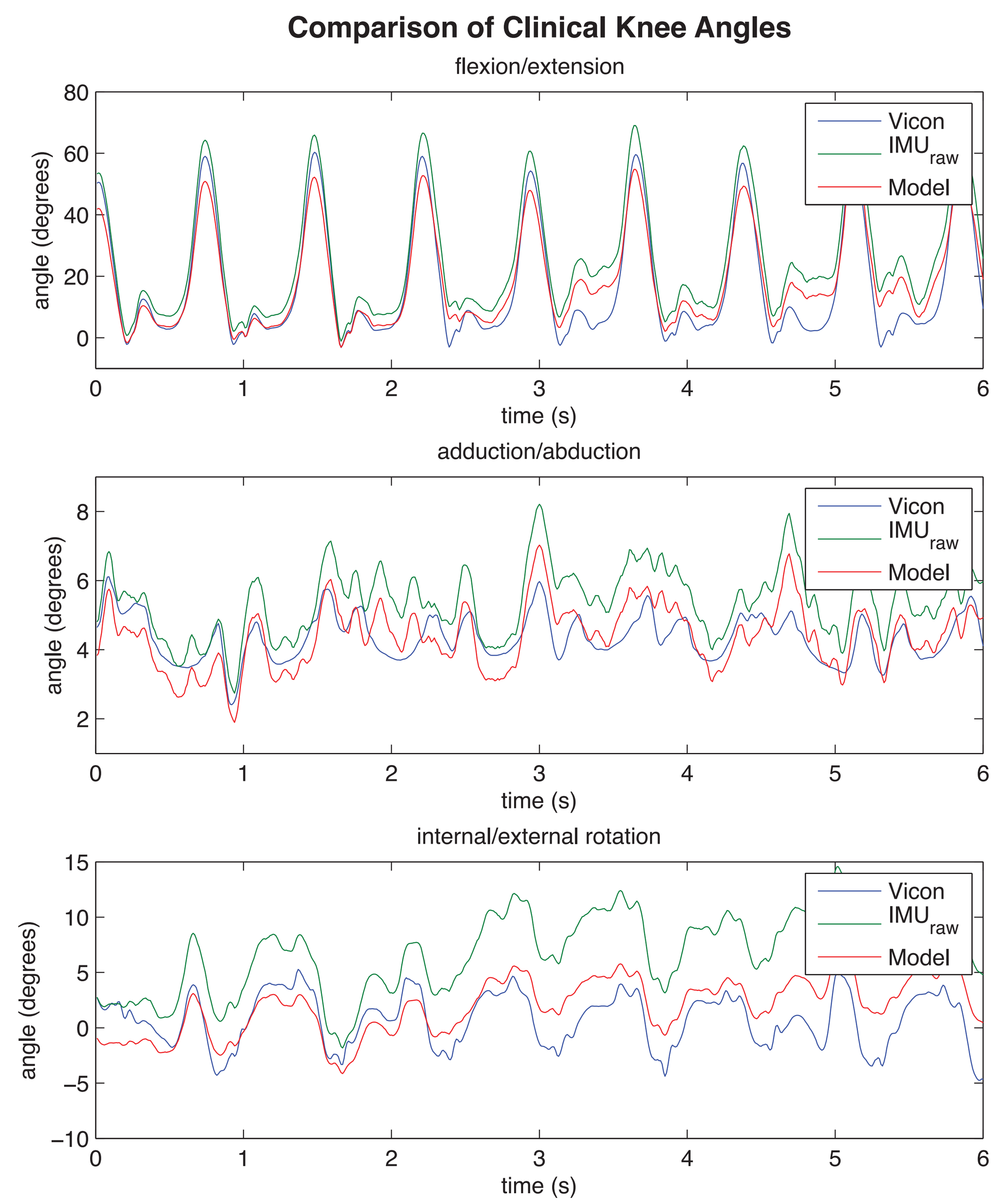
- Normalize the training sample to have range [0, 1].
- Apply v-SVR with parameter C = 1.
- Use leave-five-out cross validation as a criteria to select the kernel from: linear, polynomial, and RBF.
- Analyze in-sample performance using RMS error.

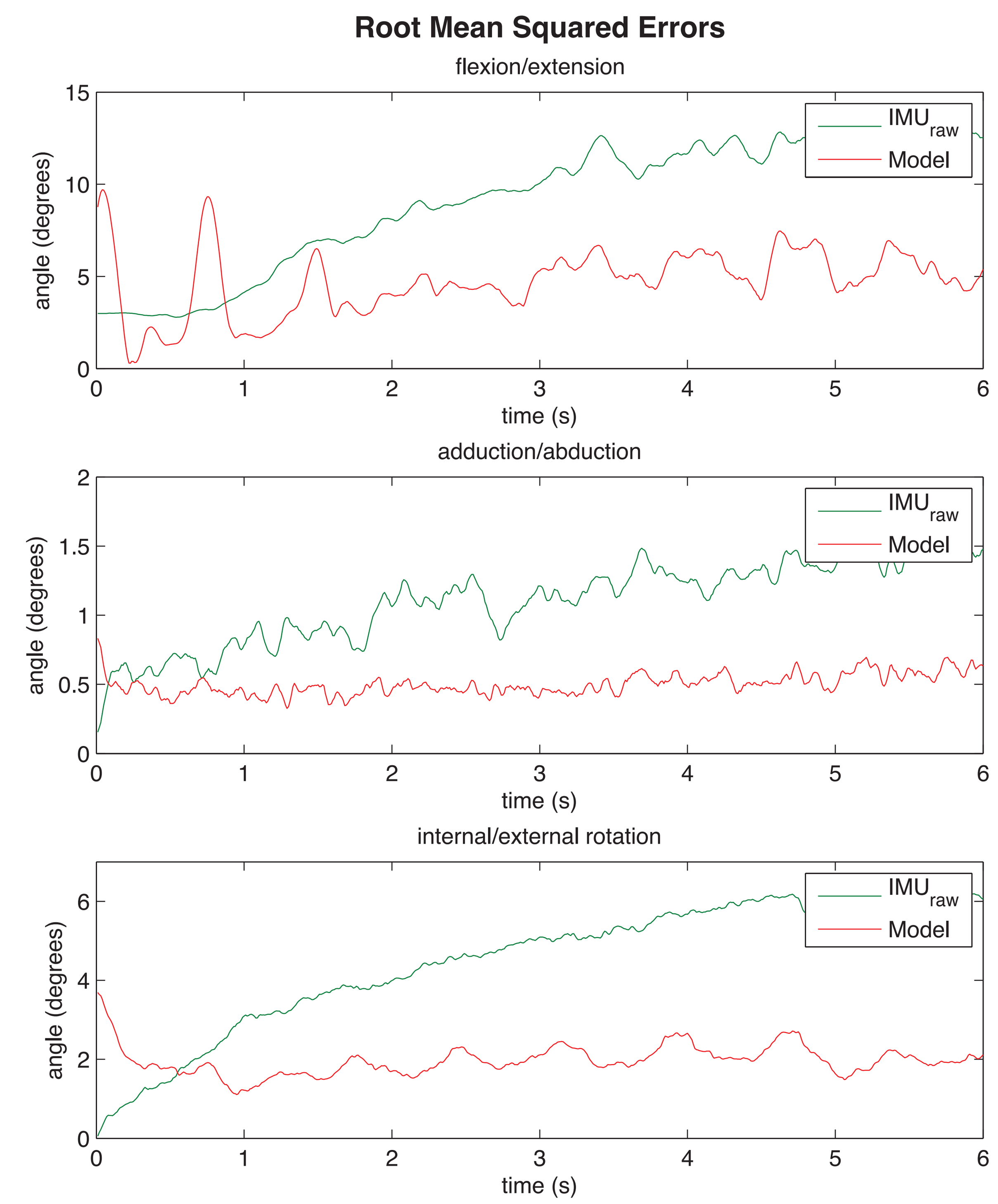
Result

The RMS error of each kernel and clinical angle is presented in the table. We found a significant improvement in all three knee angles estimation from IMUs. Each kernel (linear, polynomial, RBF) shows the comparable performance across all three type of knee angles. This is possibly due to the structure of the error that is not specific to any kind of kernel.

We also found the RMS error from the raw data to be increasing over time. By adding time since last static position variable, we are able to reduce errors due to accumulation significantly. Overall, our model estimation reduced the errors at least in half and reduced the time-dependent effect significantly. However, SVR is unable to completely remove nonsystematic errors such as sensor noises.

In addition, SVR allows us to fit the actual angle measurement without overfitting the data as shown by relatively low cross validation 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

Conclusion

In this paper, we explore SVR method to help improve knee angle estimation from multiple IMUs. We train our model using data from a gold standard marker-based motion capture system using cross-validation method in our kernel selection.

One possible explanation for a considerably good result is that our experiment is limited to walking motion. Further works could generalize our model to include various motions.

Project Members

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