

A Kinematics-based Approach To Future Joint Angle Prediction

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Abstract

Machine learning models and neural networks are powerful algorithms that can be used for predicting future joint angles in biomechanical applications. However, their high computational demand makes near-future prediction difficult or even impossible. As such, the purpose of this study was to establish a non-machine-learning baseline to future joint angle prediction for more complex model performance comparison. It was hypothesized that the use of simplistic, kinematics-based models would be beneficial for predicting joint angles in a near-future application due to lower computational demand, as long as their prediction accuracies could rival that of machine learning models. Six kinematically-informed prediction algorithms were developed to understand this tradeoff between runtime and prediction error. The prediction models were tested on the ankle flexion angle kinematic curves of nine individual subjects who each performed three distinct stair ascent trials (27 total trials). Each model's runtime and prediction error was recorded and compared with each other and to a baseline Random Forest machine learning model that was trained and tested solely on ankle flexion angles. The results of the study indicated that kinematically-informed models had runtimes ~50x faster than commonly used machine learning models (runtimes: Damped Angular Acc. model = 0.30 ms; Linear Extrapolation model = 0.31) while simultaneously rivaling the prediction error of the Random Forest model (prediction errors, reported in ° RMSE: Damped Angular Acc. model = 7.49; Linear Extrapolation model = 8.45; Random Forest model = 5.00). Such results provide the basis for inclusion of kinematically-informed algorithms in near-future joint angle prediction applications.

Key Words: kinematics; prediction; runtime; joint angles

Introduction

Predicted joint angle control methodology has been used in a wide range of biomechanical applications, including prosthetic (Antfolk et al., 2010), robotic (Bingul and Ertunc, 2005), and exoskeleton control (Coker et al., 2021). In an exoskeleton application, such a control scheme allows for actuation of a wearable robotic along a predicted curve that seeks to track the user's desired kinematics in order to increase machine-man agreement and reduce metabolic cost (Agarwal and Deshpande, 2018). As such, machine learning and neural networks are powerful algorithms that have been commonly used in this attempt to map data recorded from the body (e.g., accelerations, EMG-activity, pressure gradients) to a desired output kinematic curve (Tack, 2019). While previous studies have reported minimal prediction errors for machine-learning-based models used in future joint angle prediction (Chen et al., 2017; Huang et al., 2019; and Gautam et al., 2020), many fail to report the necessary runtime required to make such a prediction. For studies that do report computational demand, the runtimes are elevated such that real-time, near-future (~100ms) joint angle prediction becomes difficult or impossible with such machine learning algorithms (Luo et al., 2018; Xiao et al., 2018; Hua et al., 2019).

As such, alternative prediction methods and algorithms need to be considered for this application. Several studies have successfully predicted joint kinematic profiles using non-machine learning methods. Moissenet et al. (2019) developed a multiple-regression model for predicting lower-limb joint kinematics as a function of walking speed, BMI, gender and age. Rabani et al.

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(2022) used an empirical mathematical model and Fourier series expansions to predict lower-limb joint kinematics on varying surface gradients. While these models are beneficial for clinical or offline use, they are not designed to make real-time predictions for exoskeleton control. For near-future kinematic prediction, it may be beneficial to prioritize the current kinematic quantities of a joint over its kinetic and neuromuscular quantities. To our knowledge, a near-future joint angle prediction algorithm that is solely a function of current joint kinematics has not yet been developed for the sake of real-time exoskeleton control. Such kinematically informed models would seek to use simple kinematic equations of motion and historical trendline extrapolation to predict future joint kinematics. Due to their simplicity, these kinematic models would likely have a decreased computational demand when compared to machine learning performance on similar data.

However, decreased computational demand cannot often be achieved without an increase in prediction error (Yao et al., 2018; Hua et al., 2019). Therefore, the purpose of this study is to characterize the performance (prediction error and runtime) of various kinematically-informed algorithms in a near-future joint angle prediction application. Such an analysis will allow for the characterization of the trade-off between prediction error and runtime for such models. Additionally, the kinematically-informed models will be able to function as a baseline to which machine learning and neural network models will be compared to justify their use in time-restricted applications. The primary hypothesis of this study is that the kinematically-informed models will rival the prediction accuracy of the machine learning models while simultaneously having significantly lower computational demand for a near-future prediction application.

Methodology

Participants. Nine healthy subjects (5 male, 4 female, age = 21.1 ± 1.6 years, height = 172.2 ± 8.3 cm, weight = 72.3 ± 11.1 kg) participated in the study. Each participant was a nonpathological ambulator who reported no lower extremity pain or surgery in the six months prior to the study. The study protocol was approved by the Auburn University Institutional Review Board (IRB), and each participant provided informed consent prior to the study.

Experimental setup and procedure. A ten camera Vicon motion-capture system was used to record lower-limb kinematics. Retroreflective markers were placed on each of the subjects according to the in vivo point-cluster method developed by Andriacchi et al. (1998). Subjects were asked to perform three stair climb trials, consisting of the ascent of two consecutive seven-inch steps, and three level-walking trials. Musculoskeletal models for each trial were developed within Visual 3D from marker positional data filtered with a 15Hz low-pass Butterworth filter. From this model, joint angles in the sagittal, frontal, and transverse planes at the ankle, knee, and hip were calculated. However, only ankle angles in the sagittal plane (the ankle flexion angles) were used through the remainder of this study.

Model Architecture

Six kinematically-informed algorithms and one machine learning algorithm were developed as joint angle prediction models. Each of the models were developed from trendline extrapolation, kinematic forecasting techniques, or from an existing Python (v3.9.12, Python Software Foundation; <https://www.python.org/>) library, as follows.

Naïve forecasting. Naïve forecasting is the simplest of the extrapolation methods. This method uses the current joint angle, $\hat{\theta}(t + t_{pred})$, at a given time, t_{pred} , in the future. Therefore, the naïve approach is a function of only one recorded joint angle. The naïve approach is governed by Eq. (1) below:

$$\hat{\theta}(t + t_{pred}) = \theta_i \quad (1)$$

Although a naïve prediction is merely a responsive replication of a previous data point, and therefore may not be supremely beneficial in a predictive exoskeleton control scheme, such a model was included in the analysis to serve as a baseline comparison for the other kinematically-informed models.

Linear extrapolation. The linear extrapolation method is a function of two consecutive joint angle data points, seeking to define a linear curve through the historical data. Future joint angles are computed by evaluating this linear curve at a desired future time as defined by Eq. (2).

$$\hat{\theta}(t + t_{pred}) = \theta_i + \left(\frac{\theta_i - \theta_{i-1}}{t_i - t_{i-1}} \right) * t_{pred} \quad (2)$$

Deriving the slope of the linear curve effectively yields an angular velocity, $\omega_{i,avg}$, of the joint. As such, the linear extrapolation method is identical to a kinematic approach assuming an average angular velocity and constant angular acceleration, as is outlined by Eq. (3) and (4).

$$\hat{\theta}(t + t_{pred}) = \theta_i + \omega_{i,avg} * t_{pred} \quad (3)$$

...where:

$$\omega_{i,avg} = \left(\frac{\theta_i - \theta_{i-1}}{t_i - t_{i-1}} \right) \quad (4)$$

Quadratic extrapolation. The quadratic extrapolation method seeks to fit a quadratic curve, $f_{quad}(x)$ (governed by coefficients a , b , and c), to the previous three recorded angular data points by. Predicted joint angles are computed by evaluating this quadratic-fit curve at the desired future time, as demonstrated by Eq. (5) below.

$$\hat{\theta}(t + t_{pred}) = a(t + t_{pred})^2 + b(t + t_{pred}) + c \quad (5)$$

Cubic extrapolation. The cubic extrapolation method is the final extrapolation method deployed in this study. The cubic extrapolation method uses the four previously recorded joint angle data points to develop a polynomial cubic curve, $f_{cubic}(x)$ (governed by coefficients a , b , c , and d). By evaluating this resulting cubic-fit curve at a future time, a joint angle prediction can be reported, as is indicated by Eq. (6).

$$\hat{\theta}(t + t_{pred}) = a(t + t_{pred})^3 + b(t + t_{pred})^2 + c(t + t_{pred}) + d \quad (6)$$

Angular acceleration informed. The angular acceleration approach seeks to expand upon the linear extrapolation method, additionally including the effects of angular acceleration on the prediction. Eq. (7) below indicates the development of an average angular acceleration value, $\alpha_{i,avg}$, of three joint angles, similar to how Eq. (4) outlines the calculation of an average angular velocity from current and past joint angles.

$$\alpha_{i,avg} = \left(\frac{\omega_{i,avg} - \omega_{i-1,avg}}{t_i - t_{i-1}} \right) \quad (7)$$

The calculation of this average angular acceleration allows for the use of a kinematic relationship to predict future joint angles, as is defined by Eq. (8).

$$\hat{\theta}(t + t_{pred}) = \theta_i + (\omega_{i,avg} * t_{pred}) + \dots + (\alpha_{i,avg} * t_{pred}^2) \quad (8)$$

Damped angular acceleration effect. The damped angu-

lar acceleration approach seeks to minimize the effect of potential noise in the system, as angular accelerations are not reported directly but are rather twice-derived from marker positional data. In the hope of still including some effect of the joint's angular acceleration on the predicted value, a scaling factor, β , was included on the acceleration term of the kinematic relationship. This scaling factor alters the effect of the acceleration in the equation and is constrained such that $0 < \beta < 1$. Therefore, this approach is a function of three historical kinematic data points and a variable damping coefficient. The damped angular acceleration approach is defined by Eq. (9) below.

$$\hat{\theta}(t + t_{pred}) = \theta_i + (\omega_i * t_{pred}) + \dots + \beta * (\alpha_i * t_{pred}^2) \quad (9)$$

Were $\beta=0$, the resulting equation would mirror that of the linear extrapolation method and Eq. (3). Were $\beta=1$, the resulting representation would be identical to the general angular acceleration approach outlined in Eq. (8). This damped approach allows for the exploration of effective β values that provide the benefit of including acceleration data for prediction during changes of direction while neglecting the effects of positional data noise. The effect of the scaling factor on model performance was explored by indexing β on the range $0 < \beta < 1$ at an interval of 0.001. Model performance was then compared to the varied values of β to understand the optimal sizing of the scaling factor for this dataset.

Random Forest. Finally, a Random Forest (RF) model was developed to serve as the baseline machine learning model for comparison. An RF algorithm is a supervised machine learning algorithm that consists of several branches of decision trees and can be used for both classification and regression applications. The RF regression model developed for this study was tested and trained on the ankle flexion angle curves for level-walking that were collected prior to this study. The RF model was developed using the *Scikit-learn* Python module, using the default hyperparameters (for example, $n_estimators = 100$, $max_depth = None$). Although the RF model used in this study was trained and tested on a different dataset than the kinematically-informed models, it is expected that the difference in performance of the RF model from level-walking to stair-ascent would be minimal for an initial comparison. Ensemble RF regression model source code and

documentation is accessible via <https://scikit-learn.org/>.

Model Performance Evaluation

Each of the six kinematically-informed models was used for joint angle prediction for each stair ascent trial. Model performance was evaluated on all three trials for each subject, a total of 27 stair ascent trials. For each trial, each model predicted the sagittal ankle angles for a single gait cycle of the leading limb at a $t_{pred}=100\text{ms}$ into the future. The leading limb was defined as the limb that was in stance phase on the initial step, and a single gait cycle was defined from heel strike of the leading limb on the initial step to heel strike of the leading limb on the top step. The models incorporated varying sliding window sizes, depending on the number of frames required by each model to make a prediction. Sliding window sizes are documented below in Table 1. Predictions were computed for every measured angle.

Table 1 Sliding window sizes for each kinematically-informed prediction model. Data collected at 120 Hz (8.33 ms per frame).

Model	t_{window} [ms]
Naïve forecasting	8.333
Linear extrapolation	16.667
Quadratic extrapolation	25
Cubic extrapolation	33.333
Angular acceleration informed	25
Damped angular acceleration effect	25

Each model was developed within the Python programming language on a Lenovo ThinkPad x270 (Lenovo Group Limited; Hong Kong) with an Intel Core i5-7200U CPU (Intel Corporation; Santa Clara, CA). Models were tested on each subject's stair climb ankle angle kinematics in an offline analysis. Model performance was evaluated by comparing the predicted joint angles to the ankle angles measured by the motion-capture system using a root-mean-square error (RMSE) metric. Additionally, the computational runtime for each of the models was recorded. RF prediction accuracies and runtimes discussed in this paper are indicative of testing performance only and not training time or training error. A repeated measures ANOVA followed

by post-hoc paired t-tests were performed to compare the differences between each of the models' prediction errors and runtimes.

Results

ANOVA results indicated strong statistically significant differences between each of the models' prediction errors. Prediction errors are plotted by model type in comparison with the RF model in Figure 1, while prediction errors are presented numerically in Table 2 below for each of the models. The top performing kinematically-informed models demonstrated comparable prediction errors to that of the RF model (Damped Angular Acceleration = 7.49° RMSE; Linear Extrapolation = 8.45° RMSE; RF model = 5.0° RMSE).

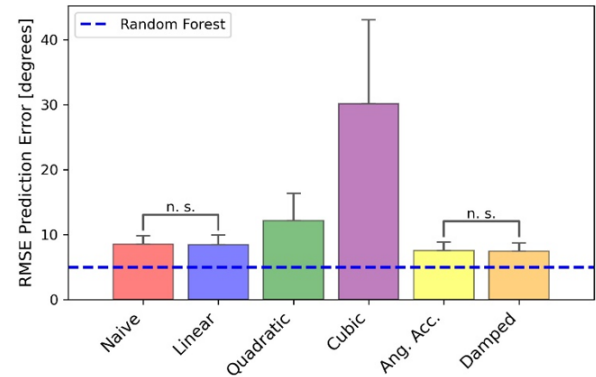


Figure 1 Average prediction errors (reported in $^\circ\text{RMSE}$) of individual models over all stair ascent trials. Error bars denote one standard deviation from the average. The dashed-horizontal line denotes RF model prediction error. Unless indicated with n.s. (no statistical difference), all models exhibited statistically significant differences in their prediction errors.

Table 2 Prediction errors and standard deviations for each kinematically-informed model.

Model	Average RMSE ($^\circ$)	Std. Deviation ($\pm 1\sigma$, $^\circ$)
Naïve forecasting	8.55	1.28
Linear extrapolation	8.45	1.48
Quadratic extrapolation	12.19	4.19
Cubic extrapolation	30.20	12.91
Angular acceleration informed	7.56	1.31
Damped angular acceleration effect	7.49	1.23

Additionally, the computational demand of each prediction model is presented in Figure 2.

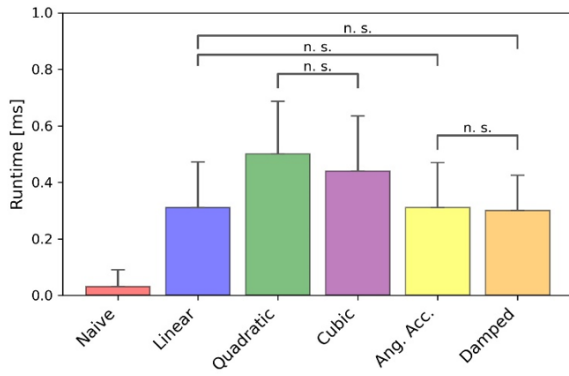


Figure 2 Average runtimes (reported in milliseconds) of each prediction model. Machine learning models trained and tested on similar datasets reported runtimes of ~30ms. Unless indicated with n.s. (no statistical difference), all models exhibited statistically significant differences in their computational demand.

Finally, the effect of scaling factor β on the prediction accuracy of the damped angular acceleration model is shown below in Fig. 3. For this analysis, a $\beta=0.802$ was determined to be the most effective value for minimizing prediction error – unless otherwise stated, this value for β has been used throughout this analysis to represent the maximum performance that the damped angular acceleration model (Eq. 9) could attain for this dataset.

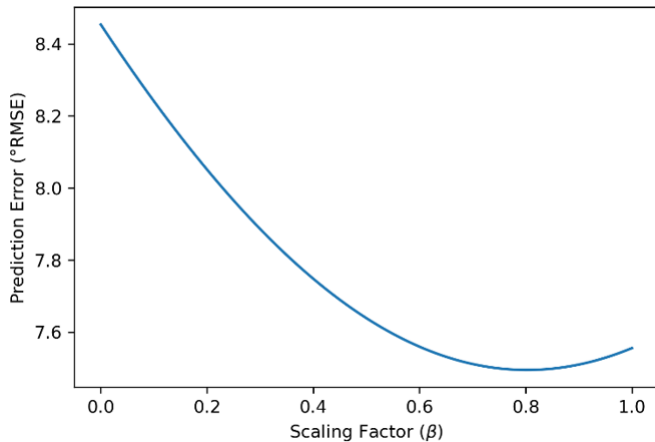


Fig. 3 Prediction error as a function of the scaling factor (β) for the damped angular acceleration prediction model. A $\beta=0$ yields the linear extrapolation model, while a $\beta=1$ yields the angular acceleration informed model.

Discussions and Conclusions

The primary hypothesis of this study was confirmed: the kinematically-informed models had significantly decreased computational demand with comparable prediction errors to a machine learning approach. The root-mean-squared errors (RMSEs) of the kinematic models ranged from 7.49° - 30.20° , depending on the model architecture. The RMSEs of the most accurate kinematic models (Damped Angular Acc. model = 7.49° ; Linear Extrapolation model = 8.45°) were comparable to the prediction error of 5.0° reported by the RF machine learning model. It is expected that the prediction error for this RF model (which was trained and tested on level-walking trials) would be comparable to a RF model trained and tested on stair ascent trials. Subsequent studies that seek to expand upon this work should ensure that the datasets being used by both the kinematically-informed models and RF model are identical. Additionally, the runtime of the slowest prediction model was reported as $<0.5\text{ms}$, which is ~50x faster than common machine learning models trained and tested on similar datasets.

Such results may provide the basis for inclusion of kinematically-informed prediction models in real-time ankle exoskeleton applications. Because of the decreased computational demand of these models, additional time can be allocated towards exoskeleton actuation to the desired joint angle without significantly compromising prediction accuracy. Additionally, because kinematically-informed models are not “trained” on specific datasets like machine learning models, they can be considered task agnostic. As such, kinematics-based models can be used in future joint angle prediction for varying actions without significant loss of accuracy, which may be beneficial for free-exploration exoskeleton applications that are not restricted to a single action in a laboratory setting.

The primary limitation of this study involves the noise associated with marker positional data. Developing a method that seeks to report acceleration more accurately is critical to mitigate the effects of noise in joint angle prediction. Potential solutions to such a problem may include expanding the sliding window size of models that rely on acceleration as an input, such as the Angular Acceleration Informed model. Expanding the sliding window would allow for the development of

an effective acceleration that incorporates a larger set of datapoints, thus reducing the effects of noise in between consecutive points. In practice, a potentiometric goniometer or an encoder would likely be used to measure joint angles rather than retroreflective markers. In addition to a goniometer, aligning IMUs with respect to a local joint axis, as outlined by Seel et al. (2014), would provide a more robust value of acceleration that does not rely on the derivation of angular position and velocity.

Additionally, studies that seek to expand upon this study and understand the performance of kinematically-informed models in a real-time application should be performed. While an offline analysis of near-future joint angle prediction provides a fundamental understanding of the relative performances of each model, the true performance and ability of each model will only come during an online test that requires each model to make joint angle predictions in real-time. Such a study will further provide justification for such kinematically-informed models in a near-future exoskeleton control application.

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Nomenclature

α = angular acceleration [deg/sec/sec]

β = acceleration scaling factor [dimensionless]

i = timestep

ω = angular velocity [deg/sec]

t = time [sec]

t_{pred} = prediction time [sec]

t_{window} = sliding window length [sec]

θ = measured angle [deg]

$\hat{\theta}$ = predicted angle [deg]

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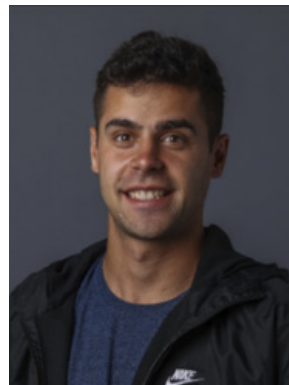
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