Nonlinear Feature for Gait Speed Estimation Using Inertial Sensors

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ABSTRACT

Gait speed is an important feature in many health applications. To obtain this information, a machine-learning approach is often preferred to first principle modeling for its generality in dealing with systematic errors. In this approach, extracting predictive features is critical to the estimation accuracy. Therefore, identifying and extracting highly correlated features for gait speed estimation become the first important steps for the machine-learning framework.

This paper proposes a novel nonlinear feature for gait speed estimation using shank-mounted inertial sensors. Rooted in analytic mechanics, this nonlinear feature captures the dynamics of angular position and angular velocity – two interdependent variables for gait speed – simultaneously by examining the area of the phase portrait. Among all the features extracted, this nonlinear feature was ranked as the most important by an automatic feature selection algorithm given its highest correlation with gait speed among all features evaluated, and it improves the accuracy for gait speed estimation in intra-subject cross validation compared to using commonly extracted linear features alone.

General Terms

Algorithms, Measurement, Experimentation, Verification.

Keywords

Phase Portrait; Gait Speed; Feature Selection; Machine Learning.

1. INTRODUCTION

Gait speed information is a common product expected from inertial body sensors because of its vast applicability. In fitness and wellness tracking, gait speed is used to estimate energy expenditure during walking. In medical research, gait speed is usually tested to score the gait performance. In geriatrics, gait speed is identified as the number one predictor of mortality in adults over 65 years old, with differences of just a couple tenths of a meter per second predicting statistically significant outcome differences [1]. Moreover, the longitudinal, out-of-lab opportunities brought about by inertial sensors have further highlighted the significance of extracting gait speed information from the sensors.

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Seemingly a trivial problem, there is no direct mathematical mapping from inertial sensor data to gait speed, since the sensing nature is derivative of spatial information and the intrinsic senor noise [2]. Meanwhile, because of the individual difference and complexity of the human gait, individual parameters are usually required (e.g. leg length as in [2] and [3]) for first principle models. Such parameters not only cause burden for the users in real-world deployment, but also can bring in impactful measurement errors for the estimation system. In a framework based on first principle models, different calibration procedures are usually applied to minimize these measurement errors along with the systematical errors at each step of the workflow. Therefore, it is more appealing to adopt a framework that accounts for all such errors through a generalized calibration procedure than strictly applying first principle models for future real-world deployment.

Machine learning approaches, on the other hand, can account for parameter difference by learning from the training data without relying on complex gait models, and hence are implemented more in studies of gait speed estimation using inertial sensors [4]. The accuracy of the results depends on both feature extraction and regression algorithms. As for inertial sensors, temporal gait features such as cadence can be extracted more accurately from accelerometer and gyroscope data and are therefore widely used. Ready-made statistical features such as magnitude, range, and variance are also extracted from the raw acceleration or angular velocity within a time window. However, whether such features can provide a good correlation to gait speed with meaningful interpretation remains a question.

This paper explores and compares features that can be extracted from inertial sensors for gait speed estimation. Features that are intuitively related to gait speed are presented first. Then we propose a novel nonlinear feature that is rooted in analytical mechanics. Our results demonstrate that the nonlinear feature can be extracted from analytic mechanic models with better interpretation for the problem and enhance the accuracy of the machine learning framework with reduced complexity at the regression stage.

The rest of the paper is organized as follows. Section 2 describes the experiment setup for data collection using inertial body sensors, providing the data for exploration. Section 3 details the features for evaluation in this paper: besides commonly extracted linear features intuitively related to first principle models, the novel nonlinear feature is also extracted, presenting high correlation with gait speed. Section 4 details the analysis based on regression and classification techniques. Section 5 discusses the analytical insights of the nonlinear feature proposed in Section 2. Section 6 concludes the paper.

2. EXPERIMENT SETUP

To collect data and explore possible solutions, a set of experiments was undertaken as follows. Four subjects were recruited for the experiment. Each subject had inertial sensors mounted on both shanks and was asked to walk on the treadmill or ground. First, three subjects of varying height and weight were asked to walk on treadmill at 11 speeds varying from 1 mile per hour (MPH) to 3 MPH at a 0.2 MPH interval. Second, three subjects including two from the treadmill experiment group were asked to walk on the ground at various cadence and step lengths controlled by metronome and a tape measured grid to obtain a variety of the gait data. The data from the shank mounted sensors were recorded on a laptop, and the time series of shank angular velocity and shank angle were post processed in Matlab®.

3. FEATURE EXTRACTION METHODS

In this section, linear features for gait speed estimation using inertial sensors are studied. Moreover, we propose a novel approach to extract nonlinear feature, and will further test it against other linear features. All the features are extracted and computed on a per gait cycle basis. In other words, each data point contains features extracted from only one gait cycle's data.

3.1 Linear Features

Linear features can be identified based on intuition of the variables related to gait speed. For example, cadence is selected for gait speed estimation because of either its accessibility (i.e. accelerometer-only sensor platform) or its apparent link to gait speed (i.e. it is self-evident that faster pace results in higher gait speed). This information will be included in our linear feature set.

Linear features can also be extracted by generalizing the variables from first principle models. For example, in [2], the variables involved in the gait speed algorithm include the leg length (L_{Leg}), shank length (L_{Shank}), and maximum shank angle during the forward swing (θ_{min}) and backward swing phase (θ_{max}), as shown in Figure 1. For a particular individual, the variable will be θ_{min} and θ_{max} since body parameter does not vary. We also include two of the statistical measures in our study: range of angular velocity and range of angular position per gait cycle for testing the algorithm of gait speed estimation. Thus in total, there are five linear features evaluated in machine learning algorithm: sine of θ_{max}, sine of θ_{min}, time span of a gait cycle, range of angular velocity and range of angular position per gait cycle.

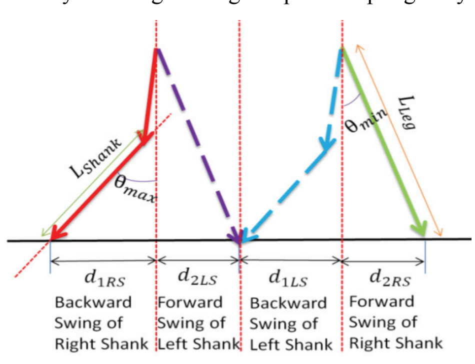

Figure 1. Pendulum model of human gait from [2].

3.2 Nonlinear Feature

Nonlinear features are features capturing characteristics of a dynamic system. Unlike linear features, these features do not possess superposition properties, i.e. linearity. As human gait is such a dynamic system that is not determined well by linear rules, it is intuitive to characterize such a system with chaos theory. In nonlinear analysis, one type of analysis important for repetitive motion patterns is the phase portrait, which captures the trajectory of a particular motion in phase space. In a phase portrait, position information is plotted against its first time derivative. It has been used as a visualization tool in mechanics because of the unique geometric pattern it represents for a certain dynamic system.

3.2.1 Phase Portrait

To discover the relationship between the phase portrait and gait motion at different speeds, phase portrait of a female's shank angular velocity data on the treadmill varying from 1 MPH to 3 MPH is extracted for each gait speed. This set of phase portrait from all gait speeds are plotted together in Figure 3.

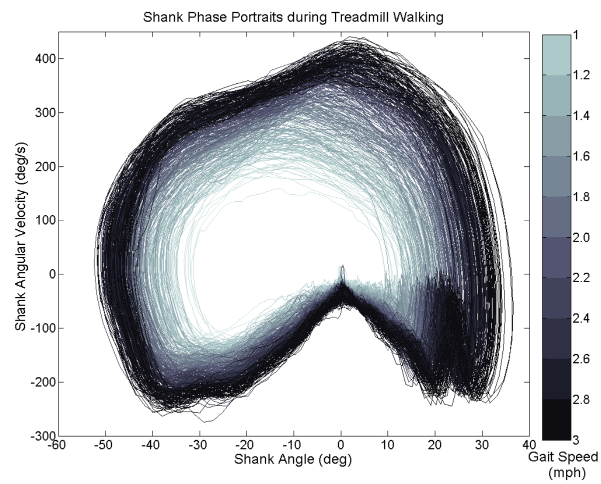

Figure 2. Phase portrait of healthy subject at different gait speeds.

Figure 2 reveals the relations between phase portrait of the shank segment and the gait speed. The darker colored phase portrait with a larger enclosed area indicates a faster walking speed on the treadmill and, consequently, with higher mechanical energy to maintain during each cycle. The metric of phase portrait area is profoundly rooted in physical models.

To analytically explain this, an equation is derived relating the shank angular velocity and shank angle by modeling the shank motion during swing phase as a pendulum, as shown in Figure 3. During the swing phase, the shank can be considered as a simplified pendulum model, roughly conserving the mechanical energy generated at the push-off phase. Thus, its mechanical energy can be written as:

$$E = T + V \tag{1}$$

$$T = \frac{1}{2}mv^2 + \frac{1}{2}I\dot{\theta}^2 \tag{2}$$

$$V = mg(l - l\,cos\theta) = mgl\,(1 - cos\theta) \tag{3}$$

where

$$v = l sin\theta \tag{4}$$

$$sin\theta \approx \theta \tag{5}$$

$$cos\theta \approx 1 - \frac{\theta^2}{2!} \tag{6}$$

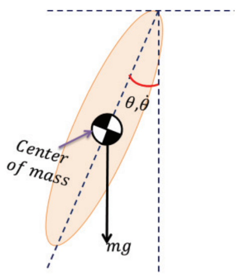

Figure 3. Pendulum model of shank motion.

when θ is small after applying Taylor expansion. E, T and V represent mechanical energy, kinetic energy and potential energy, respectively. m is the mass of the shank, l is the length of the shank, θ is the shank angle with respect to plumb line, and $\dot{\theta}$ is the shank angular velocity. By simplifying Equations (1) to (6), we can obtain:

$$E = \frac{\dot{\theta}^2}{A} + \frac{\theta^2}{B} \tag{7}$$

where A and B are coefficients given certain body parameters (i.e., m, l). Equation (7) is an ellipse function, in which the mechanical energy E is related to the radius of the ellipse and, resultantly, its area. Hereto we have shown that the area of the phase portrait during swing phase represents the mechanical energy level. This corroborates the proportional relations between the energy and phase portrait area.

3.2.2 Quantify Phase Portrait

Motivated by this discovery, a gait speed estimation method independent of body parameters (e.g., shank length and thigh length as in [2]) is designed and tested. First, to quantify the mechanical energy, the area of the phase portrait from Figure 2 is computed by numerical representation of Green's theorem [5]. Second, the area of the phase portrait computed is plotted against its corresponding treadmill speed shown in Figure 4 to investigate the linearity.

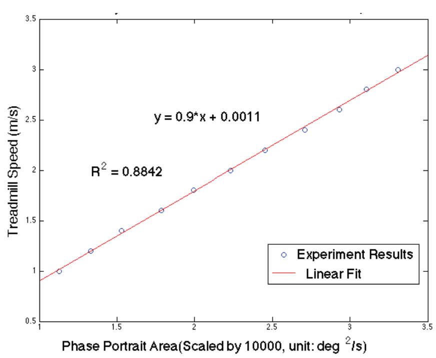

Figure 4. Regressed linear speed model by phase portrait area.

4. ANALYSIS AND RESULTS

In this section, both linear and nonlinear features mentioned in Section 2 are extracted for comparison. First, the correlation between features and gait speed are examined. A feature selection algorithm is also used to vote the most important feature. Second, to evaluate the performance of the features in regression, intra-subject cross-validation is used to compare accuracy and training size. The results are shown as follows.

4.1 Feature Importance

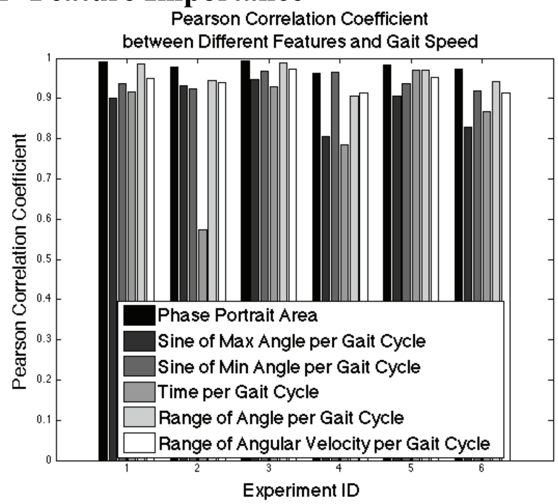

Figure 5. Pearson correlation coefficient between different features and gait speed.

Figure 5 shows that the phase portrait area has become the most correlated feature with gait speed in comparison to other linear features. Across all the experiments, phase portrait area provides an average correlation coefficient of 0.9799, which is 0.04 point higher than the linear feature with the second highest correlation among all features (range of angle per gait cycle). This highest correlation finding conforms to the feature importance ranking given by feature selection techniques such as ReliefF [6] and LASSO [7], which further confirms that the proposed nonlinear feature is the best feature to predict gait speed.

4.2 Comparison Based on Machine Learning

Knowing that the proposed nonlinear feature provides the highest correlation with gait speed, we feed the features into several machine-learning algorithm to test their performance in regression. Learning algorithms including Naïve Bayesian (Bayes), Random Forest (Bagged Tree), Multivariate Adaptive Spline Fitting (MARS), Multi-linear Regression (MLR), and K-Nearest Neighbors (KNN) are used to compare feature performance.

Intra-subject cross validation is applied to simulate the scenario where an individual user is required to conduct a pre-use data collection after system deployment. In the process of the cross-validation, a certain amount of data is left out for the training set (pre-use data collection stage after deployment), and the rest is used as testing set (system in use after deployment). To find out how much training data is required in order to produce accurate results, training set percentage is set ranging from 10%~90% of the entire data at 10% interval (equivalently around 1 minute). The results are shown in Figure 6 ~ Figure 8.

Comparing Figure 6 and Figure 7, both linear features and the nonlinear feature have provided good accuracy for intra-subject learning. We also find that using the nonlinear feature can achieve similar accuracy as using the combination of linear features. Plus, with less training data (~10%), the nonlinear feature alone can estimate the gait speed as accurately as the linear feature combinations. Moreover, for most of the regression and classification methods, the performance from using the nonlinear feature alone tends to rely on the regression methods less than using all linear features, showing the robustness of the nonlinear feature regardless of the regression method.

Figure 8 further evaluates the feature performance with linear regression (commonly used for its simplicity) as the learning method. The results show that the nonlinear feature alone achieves an RMSE of 0.189 m/s, surpassing using all linear features together (with an RMSE of 0.024 m/s). This feature alone also provides more interpretable results (rooted in fundamental mechanics) in comparison to combined linear features. Moreover, adding the nonlinear feature to the linear feature set will increase the accuracy to 25% higher than that using linear features alone.

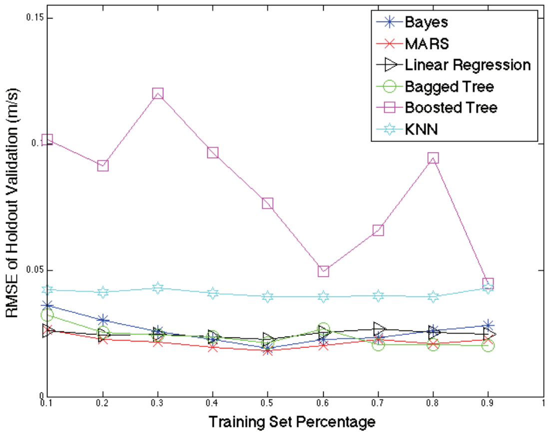

Figure 6. Intra-subject validation with linear features.

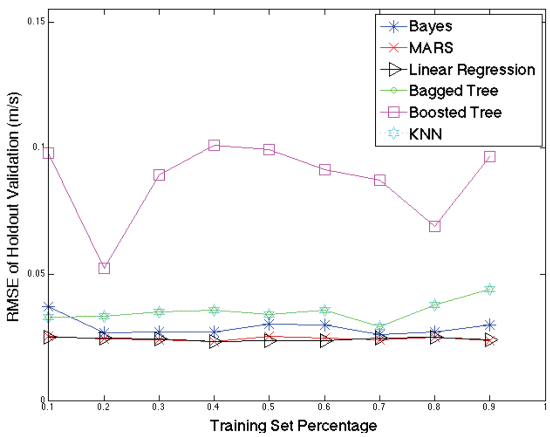

Figure 7. Intra-subject validation with one nonlinear feature.

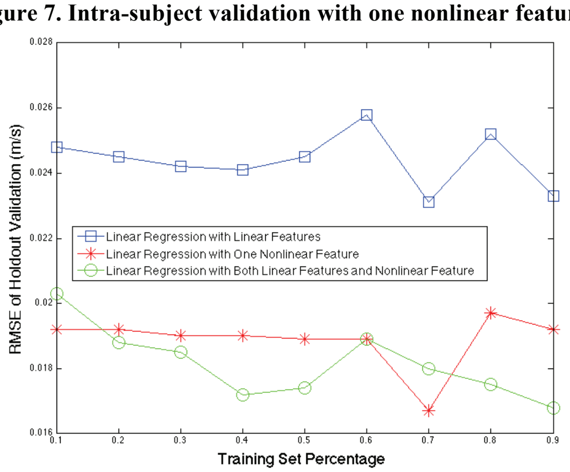

Figure 8. Feature comparison in intra-subject validation with linear regression.

5. DISCUSSION

The insight provided in Section 3 shows that the phase portrait area intuitively correlates with both angular position information and angular velocity information in a nonlinear mapping. In comparison, existing linear feature extraction observes the amplitude of angular position and angular velocity sequentially, providing only information of the extremes of amplitude per gait cycle instead of the whole picture of a gait cycle. Such methods do not reveal the mechanics behind the motion range, and rather assess the two interdependent variables -- angular velocity and angular position – in isolation. In contrast, the phase portrait area takes into account the sample-by-sample signal amplitude level that is bounded by mechanical fundamentals and is proven to be better correlated with gait speed. This correlation advantage of the proposed nonlinear feature, ultimately, boosts the estimation accuracy for the regression algorithm.

6. CONCLUSION

This paper explored the possibility of extracting a higher correlation feature from inertial body sensor data for gait speed estimation. With the discovery of the high correlation between phase portrait area and gait speed, a nonlinear feature for gait speed estimation is proposed and evaluated in comparison to linear features. Compared to the current features applied to gait speed estimation, this new nonlinear feature provides better interpretability and correlation for machine learning based gait speed estimation system. Evaluated on 6 groups' human gait data, this nonlinear feature can not only predict gait speed more accurately with an RMSE of 0.0189 m/s by itself with less training data; but, when combined with linear features, can also increase the accuracy by 25% over using linear features alone, showing its usefulness in enhancing machine learning based gait speed estimation using inertial sensors.

7. ACKNOLEDGEMENT

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