PART 11 Walking Speed Estimation with Gaussian Process Regression on Inertial Sensors

PART 11.1 Overview

Nearly half the United States population (45%) is expected to be obese by 2020, decreasing life expectancy and quality of life significantly. It is believed that weight gain could be prevented by achieving small changes in behavior, such as 15 minutes per day of walking. Walking is the most common type of activity among people who are physically active. Walking speed is a critical component in energy expenditure and monitoring energy metabolism. In the face of the current obesity epidemic, findings suggest that encouraging walking habits in the general population could be effective in preventing and reducing obesity. Accurate detection of walking speed could be a valuable tool in enhancing public health efforts. Over the past decade, there has been considerable research directed towards the detection and classification of physical activity patterns from body mounted inertial sensors. Typical inertial sensors contain an accelerometer with two or more gyroscopes to provide kinematic information. The emergence of MEMs based inertial sensors has the potential to be able tov revolutionize physical activity tracking by providing ubiquitous tracking capabilities.

PART 11.2 Approach

Periodicity in Walking

Steady state walking is cyclic. Our approach involves capturing this inherent periodicity from a single inertial sensor worn above the illiac crest on the right hip. Fig. 1 shows a typical plot of the signals received while walking at a constant speed of 2.5 mph. Movement data are captured in the form of six time series using a tri-axial accelerometer and tri-axial rate gyroscope. These signals correspond directly to the accelerations and rotational rates of the hip as felt by the sensor in its local frame of reference.

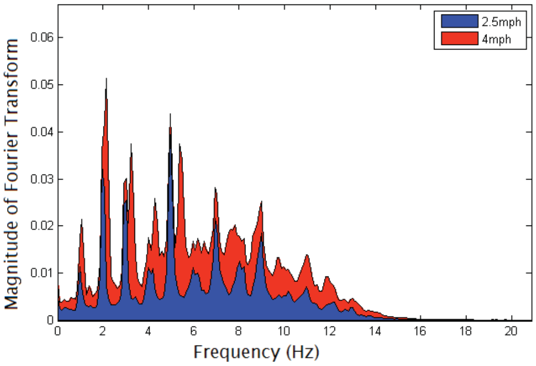


Figure 1

We use Gaussian Process based Regression (GPR) to find the correspondence between feature vectors and the speed of walking. GPR was chosen because it represents a data driven regression method. The utility of GPR stems from its ability to define a probabilistic model over data, mitigating the effects of overfitting and avoiding cross-validation. GPR is described in terms of kernels, avoiding the explicit introduction of a feature space allowing us to use feature spaces of infinite dimensionality thus allowing non-linear mapping. We compare our approach to Least Squares Regression (LSR) and Linear Regression (BLR). LSR offers a baseline performance comparison with GPR. BLR allows comparison of GPR to a probabilistic parametric model. BLR was chosen to avoid the issues of cross validation and over fitting (BLR also incorporates a probabilistic framework). We restrict our experiments to straight line walking to isolate the effect of speed on inertial sensor data.

PART 11.3 System(s) Description and/or Experiments

Hardware and Data collection

A modified version of the Sparkfun 6DoF Inertial Measurement Unit (IMU) [21] was used to collect motion information. Data were sampled at 100 Hz. The unit uses Bluetooth to transmit data to either a nearby PC or mobile phone. The use of sensors in all three axes allows us to capture periodicity in all three planes – sagittal, frontal and transverse. Eight healthy adults (four men, four women) of varying heights, weights and ages (subjects 1-8) walked at 7 predetermined speeds (2.5 mph, 2.8 mph, 3.0 mph, 3.3 mph, 3.5 mph, 3.8 mph, 4.0 mph), or until breaking into a run. The duration of walking at each speed was 5 minutes. All subjects wore a single inertial sensor above the illiac crest on the right hip. The treadmill used for the experiments was the research quality NordicTrack A2550 PRO. Subjects were deliberately chosen to represent a cross-section of heights, ages, Body Mass Indices (BMI) and both genders to demonstrate the utility of GPR across a diverse population. Ground truth for treadmill walking was the displayed treadmill speed.

Feature Computation

Each signal was passed through a bandpass filter with 3dB cutoff between 0.1 Hz and 20 Hz. These cut-off frequencies were chosen keeping in mind that everyday activities fall in the frequency range of 0-10 Hz. The feature vector is computed on sliding windows with 50% overlap by finding their N-point FFT. The optimum window size was

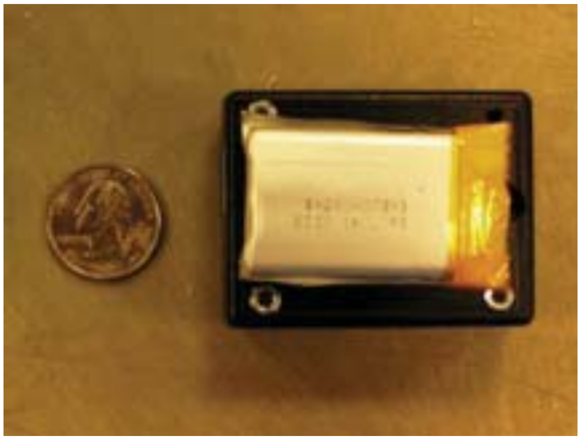
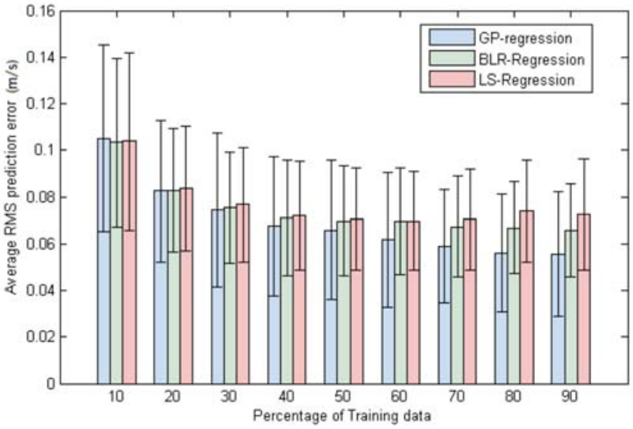


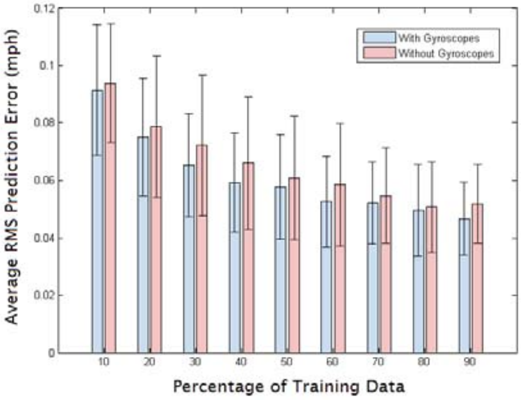
Figure 2

chosen in hindsight from experimental results as 1024 samples per window over 512 samples. The complete feature vector consists of the Fourier transforms of the respective window instants for each sensor stream.

PART 11.4 Accomplishments

Our results showed that GPR had a lower average RMS prediction error when compared to BLR and LSR across all subjects. Analysis on a single subject showed that GPR had significantly lower RMS prediction error than LSR with BLR showing comparable but higher errors). Increase in relative percentage of training data greatly improved estimation of accuracy of both GPR and BLR with LSR displaying effects of over-fitting. Using a window size of 1024 samples resulted in a lower error across users as compared to using a window size of 512 samples because of an increased resolution in frequency features. The addition of tri-axial gyroscopes reduced the RMS prediction error of walking speeds when compared to using only accelerometers. Prediction across all speeds was not uniform. Using GPR to estimate overground walking speeds from overground motion data alone resulted in reduced error with increase in relative percentage of training data. A strong linear correlation existed (rX,Y = .8861) between overground walking speeds predicted from treadmill data and ground truth walking speed measured. Combining treadmill data from multiple subjects with similar height characteristics improved the prediction capability of GPR for overground walking speeds.





PART 11.5 Future Directions

We plan to address inter-subject variance by performing an extensive study on the training and prediction of treadmill walking speeds for a much larger population by categorizing individual models in terms of physiological parameters such as age, height, gender and BMI. By doing so, we aim to explore whether each of these models can be organized as clusters, each of which is a function of these parameters. This would imply that to characterize subjects and to ensure accurate prediction for each subject, one would need to derive the corresponding parameters and map the subject to a cluster. The prediction model would be unique to that cluster. As more data are collected for new subjects, the accuracy of each cluster would gradually improve. Also, from a data collection perspective, it is easier to record small datasets from a large pool of subjects than a large dataset from a single subject. The use of clusters would facilitate data collection by grouping people with similar physiological parameters in the same equivalence class. Using clusters might also enable extrapolation to new subjects who do not fall in a particular category. Finally we plan to explore the use of our techniques to map feature vectors directly to a measurement of energy expenditure. If successful, this will involve learning a data driven functional mapping from the periodicity of walking to energy expended thus bypassing walking speed estimation.