Step Length Estimation Using Foot Mounted IMU Sensors

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ABSTRACT

Indoor localisation can be done effectively by use of a Pedestrian Dead Reckoning (PDR) system. This involves tracking the position of a person by utilising an inertial measurement unit (IMU). In a PDR system, the length and direction of each step taken by the user are estimated. Additionally, analysing the steps of a person, along with their respective step lengths, can help identify irregularities in gait, such as those caused by a gait disorder. Other applications of step length estimation include tracking progress in gait rehabilitation programs and motion tracking in Virtual Reality and Augmented Reality applications. In this project, we build a Step Length Estimation system, which calculates the length for every step of the walk. With the help of XSens Sensors, we measure the inertial data of people during a walk, extract the walk into step segments, and label the step length manually using a custom-built labelling tool. Later, these labelled steps are used to train Machine Learning based models, which are ultimately tested on unseen data.

KEYWORDS

Step Length, IMU Sensor, MAE, RMSE, Support Vector Regression, Random Forest Regression, Machine Learning

1 INTRODUCTION

During the past few years, a lot of research has been done around Indoor Localisation. Various technologies, such as ultrawideband (UWB), Wi-Fi, and Bluetooth low energy (BLE), are commonly employed for indoor positioning. These technologies calculate user positions based on distances to specific reference points in the environment, yielding reasonably precise location predictions. However, they rely on specialized infrastructure, leading to higher deployment costs as the tracking zone expands. The frequency of updates decreases with more users, impacting accuracy when obstacles obstruct the line of sight to reference points.

Pedestrian Dead Reckoning Systems (PDRs) offer a solution to the limitations of traditional indoor positioning methods. These self-contained navigation systems for pedestrians use sensors and algorithms to estimate user movements, without relying on additional infrastructure. Unlike GPS, which depends on satellite signals, PDR tracks the user's position by detecting steps, estimating step length, and determining walking direction. The key component of PDR is the Inertial Measurement Unit (IMU), an electronic device measuring user acceleration and angular rate. While IMUs provide relative positions, they may lead to estimation errors and drift from the true position.

Step length estimation holds diverse applications. Primarily, it is vital in Human Gait Analysis, aiding in understanding walking patterns, biomechanics, and intervention design. Secondly, it assesses rehabilitation progress, especially for those recovering from gait-affecting injuries or surgeries. Additionally, step length contributes to realistic motion tracking in Virtual and Augmented Reality, enhancing the immersive experience. Notably, step length plays a key role in indoor navigation systems, addressing challenges when GPS signals are weak or unavailable.

In this project, we approach 'Step Length Estimation' with Machine Learning based models, and estimate the step length using inertial data, for straight line walks on a plain surface. In our initial analysis, a single handheld sensor struggled to recognize acceleration peaks, leading us to opt for two sensors mounted on the back of the foot. The project unfolds in two phases. In Phase 1, we collect and pre-process data from walks by four individuals, using MT XSens sensors and a Labelling Tool for labeling step length. We also detect step start and end, removing pauses and erroneous steps. In Phase 2, we employ Machine Learning-based Support Vector Regressor and Random Forest Regressor for step length estimation. Spatio-Temporal Gait Parameters are configured in the Random Forest Regressor, incorporating height and shoe type. The system is trained with manually labeled steps and tested on unseen data from three individuals, achieving a finest Mean Absolute Error (MAE) of 4.17 cm.

2 DATA PRE-PROCESSING

In this phase, we collect the inertial data of people, pre-process the walks, extract the steps and label them. The output of this phase a well-labelled clean training dataset. Additionally, we perform a short analysis of the various positioning possibilities of sensors, compare the results, and conclude the positioning which give the highest efficiency.

2.1 Initial Sensor Analysis

We review various step length estimation systems who use IMU sensors. A handheld sensor was used for the calculation of step length by [7]. Additionally, V Renaudin et al. [6], A Wahdan et al. [8] and M Omr et al. [5] use handheld or wrist-bound sensors as well. Li et al. [1] and Yang and Li [9] proposed mounting a 2-axis accelerometer and a 1-axis gyroscope on the lateral side of the mid-shank. In some studies the IMUs were mounted in the pocket of the person. They were mounted in the front pocket in the studies by EM Diaz et al.[4] and S Miyazaki et al. [3], back pocket in the studies by S Yang et al. [10] and A Mikov et al. [2].

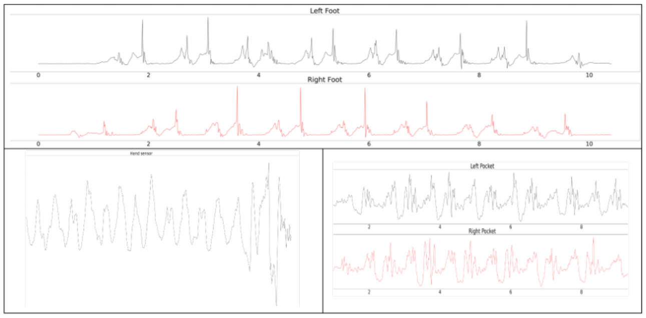

Figure 1: Sensor Data Peaks

As a part of the analysis, we measured the acceleration of a person walking, with different sensor mounting possibilities. As shown in Figure 1, peaks of distributions of acceleration measured using a single handheld sensor, and the sensors in back and front pockets; were not recognised as sharply as for the foot mounted sensors. The detection of peaks is highly significant, since we label the data manually, and detecting step start and step end is crucial while calculating the step length through the Labelling tool. As foot mounted IMUs provide a clear graph with accurate peaks, we decided to use two IMU sensors, mounted on the back of the foot of the person.

2.2 Data Collection and Labelling

Accurate step length estimation relies on high-quality and abundant data. In this project, we utilize MTi XSens technology, employing MTi sensors to measure person acceleration. The MT Software Manager captures sensor data, exporting it as CSV files. Simultaneously, we record a video of the person walking on a manually drawn 5-meter scale on the ground. This data, along with the video, is processed using a custom-built Labelling tool, as illustrated in Figure 2. The tool synchronizes the acceleration graph with the video, featuring pointers for identifying samples contributing to step start and end. Using the video, we manually calculate step lengths for each step and assign them to the selected samples.

2.3 The Dataset

We have gathered data from seven people, each having different heights, resulting in a total of 1754 annotated steps. After organizing these steps by Person, we extracted 1604 steps from four individuals for our training set. Regarding the test set, we curated a total of 150 steps, with each of the three remaining people contributing 50 steps, distinct from those included in the training set.

2.3.1 Preprocessing the Data: The collected accelerometer data includes raw acceleration measurements $a_L = [a_{Lx}, a_{Ly}, a_{Lz}]$ for the left foot and $a_R = [a_{Rx}, a_{Ry}, a_{Rz}]$ for the right foot, where IMU sampled at 100 Hz. To reduce the impact of accelerometer noise, we apply a third-order low-pass Butterworth filter with a cutoff frequency of 3 Hz, This results in the filtered acceleration sequences $\tilde{a_L} = [\tilde{a_{Lx}}, \tilde{a_{Ly}}, \tilde{a_{Lz}}]$ and $\tilde{a_R} = [\tilde{a_{Rx}}, \tilde{a_{Ry}}, \tilde{a_{Rz}}]$. Additionally, we calculate the magnitude of the filtered acceleration using $|\tilde{a}| = \sqrt{\tilde{a_x}^2 + \tilde{a_y}^2 + \tilde{a_z}^2}$ resulting in $|\tilde{a_L}|$ and $|\tilde{a_R}|$, for each sample of

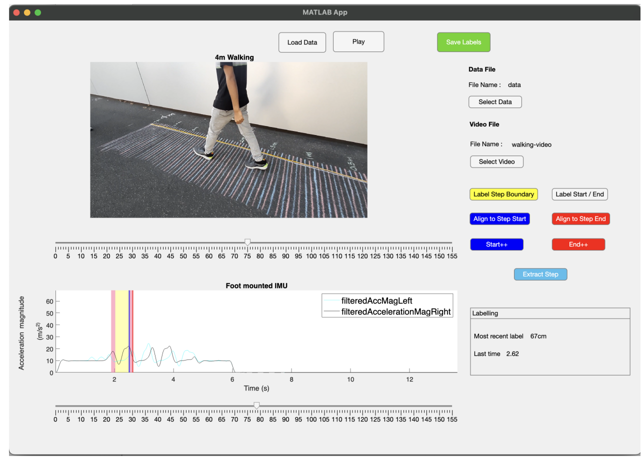

Figure 2: Labelling Tool

the accelerometer we now have a 8-D vector incorporating both left and right foot sensors $a_n = [\tilde{a_{Lx}}, \tilde{a_{Ly}}, \tilde{a_{Lz}}, |\tilde{a_L}|, \tilde{a_{Rx}}, \tilde{a_{Ry}}, \tilde{a_{Rz}}, |\tilde{a_R}|]$. Describing the dataset $\mathbf{X} \in \mathbb{R}^{n \times D}$, where n represents the total number of accelerometer samples within a single step, and $\mathbf{X}_i$ refers to the ith step. We shuffled the resulting steps, preserving sample order within each. Moreover, it is notable that the quantity of samples within each step exhibits variability. Table 1 outlines the characteristics of the steps recorded in the dataset.

In Figure 3, we present the distributions of step lengths observed in both the train and test sets. In the subsequent sections, we provide a brief overview of the feature sets utilized for training Machine Learning models.

2.3.2 Feature set for Support Vector Regression : After obtaining a 2-D matrix for $\mathbf{X}_i$ for each step i, we compute several statistical measures for each column of the step. Let $\mathbf{X}_{i,k,j}$ represents the value of the $j-$th dimension in the $k-$th accelerometer sample of the $i-$th step. The computations are as follows.

1. Mean :
   $\mu_j = \frac{1}{n} \sum_{k=1}^{n} \mathbf{X}_{i,k,j}$, where μ_j represents the mean of the $j-$th column, and n is the total number of accelermeter samples in the step.
2. Standard deviation:
   $\sigma_j = \sqrt{\frac{1}{n} \sum_{k=1}^{n} (\mathbf{X}_{i,k,j} - \mu_j)^2}$ where σ_j represents the standard deviation of the $j-$th column.
3. Maximum:
   $max_j = max_{k=1}^{n} \mathbf{X}_{i,k,j}$
4. minimum:
   $min_j = min_{k=1}^{n} \mathbf{X}_{i,k,j}$
5. Range:
   $range_j = max_j - min_j$

This results in feature vector $s \in \mathbb{R}^{40}$, where $s^{(i)}$ represents the i-th step.

2.3.3 RF features : In this model, we added features to evaluate their impact on step length estimation.

Table 1: Summary of Step Characteristics.

Person ID	Total Steps ↓	Min Step Length (cm)	Max Step Length (cm)	Average Step Length (cm)	Shoe Type	Height (cm)	Age Group
1	425	23.0	80.0	59.35	Sneaker	168	23-30
2	412	22.0	65.0	49.83	Heels	158	23-30
3	394	26.0	70.0	58.89	Sneaker	163	23-30
4	373	30.0	72.0	57.71	Sneaker	182	23-30
5	50	32.0	72.0	56.07	Sneaker	183	45-59
6	50	27.0	61.0	47.59	Sneaker	160	23-30
7	50	30.0	77.0	61.43	Heels	178	23-30

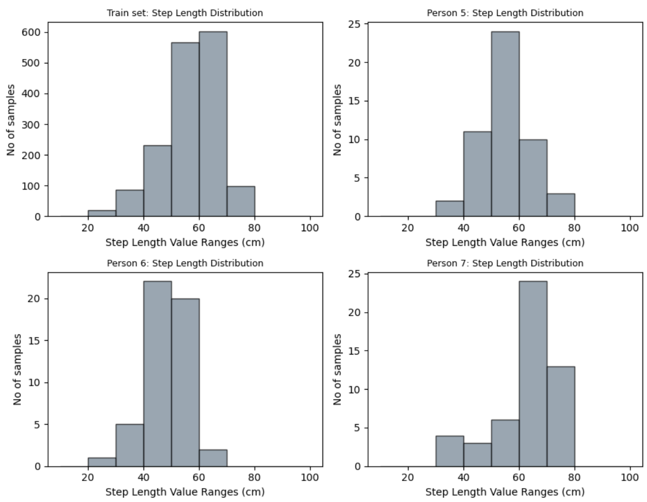

Figure 3: Distribution of step lengths

Alongside raw acceleration vectors indicating step start and end, we included step start and end times (in seconds) for each step, obtained from the labelling tool during labeling. Additionally, we manually introduced Height and Shoe Type as features in the dataset. Height is represented as an integer indicating height in centimeters, and the available configurations for Shoe Type are 'Heeled Shoes' and 'Sneaker'.

For each data sample, we transformed the acceleration vector into histogram features. This histogram-based approach effectively captures the movement distribution, proving particularly valuable for tasks such as motion analysis and action recognition. To achieve this, we utilized 20 bins and assigned higher weights to 10 elements in the middle of the acceleration vector to mitigate potential human labeling errors. Finally, we computed the mean of all the obtained values.

3 STEP LENGTH ESTIMATION

3.1 Support Vector Regression

To apply Support Vector Regression (SVR), we utilize the features extracted for each step as outlined in 2.3.2. Furthermore, we apply the MinMaxScaler to scale both the feature vector $\boldsymbol{s}$ and the target variable y (Step Length), aiming to reduce training time and enhance performance. The MinMaxScaler is fitted to the entire feature vector $\boldsymbol{s}$, resulting in $\hat{\boldsymbol{s}} \in \mathbb{R}^{40}$. Similarly, the MinMaxScaler for y is fitted to the entire training target variable (Step Length) $\boldsymbol{y}$, resulting in $\hat{\boldsymbol{y}}$. Subsequently, we partition the training dataset using an 80/20 split, allocating 80% for training and 20% for validation.

Next, we proceeded to train the Support Vector Regression (SVR) model. Utilizing grid search with cross-validation (CV) of 20 folds, we explored various combinations of hyperparameters to fine-tune the SVR model. The hyperparameters included the regularation parameter C, the kernel coefficient γ and the kernel type. Table 2 outlines the parameters list. In our experiment we found that $C = 1$, $\gamma = 1$ and rbf kernel yielded the best results. Hence the trained model resulted in a total of 488 support vectors.

Table 2: SVR Hyperparameter Grid

Parameter	Values
C	0.1,1,10,100
γ	0.1,0.01,0.001,1
Kernel	rbf, sigmoid, poly

3.2 Random Forest Regression

After preprocessing the data as mentioned in 2.3.3 we employed the Random Forest Regressor, a powerful ensemble learning algorithm, for its ability to handle complex relationships and capture non-linear patterns within the data. 80% data was used to train and 20% to validate the model. To optimize the performance of the Random Forest Regressor, we used grid search over a range of hyperparameter values. The best-performing set of hyperparameters, determined through the grid search, is as follows:

Table 3: Best Parameters For Random Forest

Parameter	Value
bootstrap	True
max depth	80
max features	3
min samples leaf	5
min samples split	12
n estimators	500

4 RESULTS AND DISCUSSION

Here, we provide a comparative analysis of the results from the test set presented in Table 4. The table underscores the variability in model performance among different individuals. SVR excels with Person 5 and Person 6 but performs less optimally with Person 7, whereas RF outperforms with Person 7.

Table 4: Comparison of Model Performance Across Three Individuals

Model	Person 5		Person 6		Person 7	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVR	5.12	6.17	4.17	5.37	13.05	14.92
RF	6.15	7.90	6.04	8.25	10.82	11.84

Furthermore, our analysis of prediction distributions in Figure 4 reveals notable insights. Despite ample samples for step lengths between 60-70 cm in the training set, both models struggle to predict accurately on the test sets, especially for test Person 7 with an average step length of 61.43 cm. This discrepancy is evident in the MAE values: 13.05 for SVR and 10.82 for RF. These disparities highlight a bias towards step length ranges of 40-60 cm in both models, likely due to the imbalanced distribution of the target variable (step length) y.

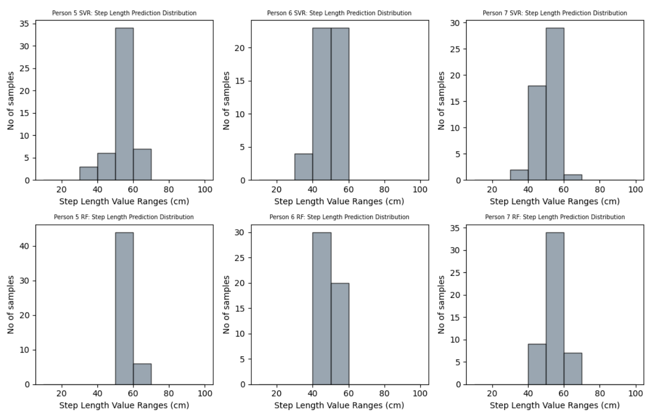

Figure 4: Step Length Predictions Distributions

We assessed the predictions of SVR and RF models by plotting scatter plots of predicted values against ground truth values (see Figure 5). Each point represents a step, with the x-axis denoting ground truth values and the y-axis representing predicted values. We identified instances where the absolute difference between predicted and ground truth values exceeded certain thresholds: 7.4 for SVR and 7.67 for RF, determined based on the mean of the Mean Absolute Error (MAE) across data from three test persons. Points exceeding these thresholds were highlighted in red, indicating potential areas of concern where predictions deviate notably from actual outcomes.

Based on Figure 5 its clear that the models exhibited substantial discrepancies between predicted and actual values, due to the imbalance within the target distribution in the trainset. We addressed this by applying a weighting factor for SVR: assigning a weight of 5.0 to samples whose (step length) y is below 30 and those exceeding 65, and 1.0 to the remaining samples. However, this failed to yield substantial improvements. Detailed results are presented in Table 5

Table 5: Model Performance Across Three Individuals after weighting

Model	Person 5		Person 6		Person 7	
	MAE	RMSE	MAE	RMSE	MAE	RMSE
SVR	4.79	5.86	4.26	5.46	14.93	16.82

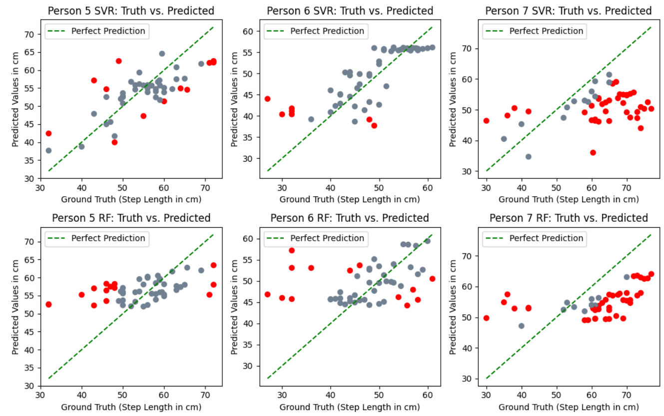

Figure 5: Ground Truth vs. Predicted: Regression Analysis

5 LIMITATIONS

5.1 Small Steps

During a natural walk from one point to another, the steps taken at the very start and at the end, are generally smaller than the middle steps. Since majority of the training data comprises of middle steps, the model is not able to predict accurate step lengths for the start and end steps.

5.2 Suitable only for straight-line walk

In this project, we focus on estimating the length of the steps taken only during a straight line walk on a plain surface. Our system does not account for the gyroscopic data resulting from directional changes during the walk. Since the step length may vary when person is taking a turn, the system might not give best results if tested on the data acquired in these cases.

6 CONCLUSIONS

In conclusion, our examination of prediction distributions and scatter plots provided valuable insights into the performance of Support Vector Regressor (SVR) and Random Forest (RF) models in step length estimation. Despite ample samples within the 60-70 cm range in the training set, both models encountered challenges in accurately predicting step lengths on the test sets, particularly evident for test Person 7 with an average step length of 61.43 cm. This discrepancy was quantified through Mean Absolute Error (MAE) values of 14.93 for SVR and 10.82 for RF, highlighting a bias towards step length ranges of 40-60 cm. However, attempts to address imbalances through weighting strategies did not yield substantial improvements in model performance.

7 CODE AND DATA

For access to the code and data used in this paper, please visit our GitHub repository: https://github.com/vishnu-prasad007/SLE-MAI.git

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