Stride Reconstruction Through Frequent Location Updates and Step Detection

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***Abstract*—Indoor positioning plays an increasingly important role in industrial spaces. Self-localizing autonomous machines are already well established and indoor positioning for pedestrians increases safety and productivity when interacting with (semi) autonomous machines. Positioning methods for pedestrians commonly use wearable or handheld sensors that rely on extensive calibration to tune gait detection heuristics. We present a method to automatically derive the target variables of these heuristics, stride length and stride orientation, for each individual user stride by using parallel location measurements during normal operation. We show that our method fits real world measurements of stride length. Additionally, we conduct simulations to verify the variance and bias of the derived stride length and orientation at varying accuracies of the reference position measurements. Our method provides a means for online annotation of raw data for pedestrian positioning, enabling both the online calibration of gait detection heuristics as well as data annotation for machine learning applications.**

***Index Terms*—Ultra-Wideband, Pedestrian Dead Reckoning, Stride Length, Virtual Sensor, Data Annotation**

I. Introduction

Indoor positioning for pedestrians is increasingly relevant for applications in modern industrial and public spaces, as it enables a wide range of location aware digital services: Reliable location updates allow workers to collaborate safely and efficiently with machinery and visitors are guided to their destination in places like hospitals, shopping centers or conventions. Additionally, indoor localization in living spaces is explored as a means of smart assistance for the elderly [1].

Two key technologies enable indoor localization: Infrastructure based systems with fixed base stations and mobile transceivers, and systems based on wearable Inertial Measurement Units (IMU). Among the Infrastructure based approaches, Ultra-Wideband (UWB) is becoming increasingly popular as it can provide high-frequency centimeter-level accuracy at reasonable cost [2]. Wearable IMUs, on the other hand, enable tracking of a user's path by detecting steps and their orientation. This approach is called Pedestrian Dead Reckoning (PDR) [3].

The two approaches complement each other. While UWB provides location updates in the world reference frame, PDR tracks location change more closely. In addition, PDR works independently of infrastructure and can be used to bridge areas without UWB coverage, such as factory floors divided by a corridor [4]. However, because PDR measures only the change of location, it is dependent on sporadic updates by absolute references, e.g. by an UWB-System. In addition, many PDR approaches rely on regression-based models that convert the raw inertial data into the user's step length and orientation. Such models need a reference (dependend variable) to tune their parameters, i.e. the current length and orientation of a users step.

Therefore, it is necessary to convert UWB data into a virtual measurement of the step that allows online calibration of the PDR method to limit its drift and serve as a reference for tuning the regression-based PDR.

In this work, we develop a model of consecutive UWB measurements and their distribution during a user's stride[1]. Based on this model, we derive an approach to derive length and orientation of individual strides by statistically analyzing a set of noisy UWB measurements. We call the resulting set of length and orientation the virtual stride vector. The method is validated by comparison with reference measurements and by simulations.

This paper is structured as follows: Section II describes related work regarding previous methods of stride or step estimation. The construction of the virtual stride vector is presented in Section III. The evaluation approach is described in Section IV and the results of the evaluation are presented in Section V. Section VI provides an analysis of the sources of stride length bias in the results. Final conclusions are drawn in Section VII.

II. Related Work

The Zero Velocity Update (ZUPT) method produces comparatively accurate estimates of the stride length and direction. It is based on double integration of inertial measurements of the users' foot, resulting in an estimate of the stride length and direction change. The method is exploiting the short moments of stand-still during contact of the foot with the ground. During this stance phase, the velocity estimate of the integrated inertial measurements is reset to zero. Consequently, the long term

[1]There is a distinction between step and stride: A stride refers to the movement of one foot from ground contact (stance) via swing to ground contact. A step on the other hand refers to the ground contact of either foot. The length of one stride is therefore twice the step length.

accumulation of errors is mitigated with each stride of the user [5]. In order to use ZUPT, the IMU has to be attached to the foot of the user, which may hinder widespread adaptation of this method [6].

Methods for estimating stride length using sensors that are not attached to the foot but are held in the hand or worn on other parts of the body are more common. These methods depend on heuristics with either tunable parameters, knowledge of the users height or leg length, or both [7]–[9]. However, because of the parameter tuning required, none of these methods are guaranteed to work well on new users without repeated adjustment of these parameters.

The calibration of stride length or orientation with simultaneous reference measurements has been explored in other works: Orientation and postion calibration of PDR is presented in [10]. However, step length calibration is left as future work. The combination of low-frequency position updates by a global navigation system to calibrate PDR is presented in [11]. The authors of [12] present a scheme of combined PDR and UWB positioning with orientation drift compensation and online step length estimation. It is unclear however, how the reference for the step length is derived from UWB and if certain requirements of the users gait, such as walking in a straight line, must be met. The challenge of deriving an absolute reference for the orientation (not the orientation change) is left open.

Recently, machine learning methods are used for PDR [13]. One work employs unsupervised training on neural networks to mitigate the problem of scarce labled data at the cost of reduced accuracy [14].

The aforementioned methods depend on reference data to tune step length heuristics or try to cope with limited annotated data at the cost of accuracy. The methods that do employ online calibration offer no complete solution for a reference of both step length as well as orientation from high-frequency location updates.

To solve this problem, we present a method that provides a ground truth for stride length estimation as well as the stride orientation from UWB measurements at runtime. This data may be used to calibrate a PDR system in real time, or to annotate raw data with an estimate of the stride length and orientation.

III. Construction of Virtual Stride Vector from UWB Measurements

The virtual stride vector V is constructed from two polar components: the stride orientation $\tilde{\varphi}$ and the stride length $\tilde{\varrho}$. This vector maps the relative motion of a person's foot from stance phase to stance phase.

$$V = \begin{pmatrix} \tilde{\varrho} \cdot cos(\tilde{\varphi}) \\ \tilde{\varrho} \cdot sin(\tilde{\varphi}) \end{pmatrix} \tag{1}$$

The polar coordinates are obtained by statistical analysis of a set $\boldsymbol{P}$ of n consecutive UWB position measurements, which are modeled as realizations of the random vector $P = (X, Y)$. A sample P_i at time i is thus composed of realizations on the x- and y-axes of the coordinate system within which the positioning by UWB occurs. The samples are collected in the sets $\boldsymbol{X} = \{X_0, X_1, \ldots, X_{n-1}\}$ and $\boldsymbol{Y} = \{Y_0, Y_1, \ldots, Y_{n-1}\}$:

$$\begin{pmatrix} X_i \\ Y_i \end{pmatrix} = P_i \in \boldsymbol{P} \subset \mathbb{R}^2 \quad \text{with} \quad 0 \leq i < n \tag{2}$$

The set $\boldsymbol{P}$ is sampled during one whole stride of the user, which is detected by separate step detection scheme.

In the following chapters III-A and III-B the stride orientation $\tilde{\varphi}$ and stride length $\tilde{\varrho}$ are derived, respectively.

A. Principal Component Analysis and Stride Orientation

The basis of the following calculations is a principal component analysis of the (sample) covariance matrix Σ of $\boldsymbol{P}$:

$$\Sigma = \begin{pmatrix} Var(\boldsymbol{X}) & Cov(\boldsymbol{X}, \boldsymbol{Y}) \\ Cov(\boldsymbol{Y}, \boldsymbol{X}) & Var(\boldsymbol{Y}) \end{pmatrix} \tag{3}$$

The first principal component maps the orientation and magnitude of the dominant dispersion in $\boldsymbol{P}$. The dispersion along this component is mainly generated by the locomotion of the user.

For the principal component analysis, it is necessary to first find the eigenvalues $\boldsymbol{\lambda} = (\lambda_1, \lambda_2)$ and the corresponding eigenvectors $\boldsymbol{v} = (v_1, v_2)$ by solving the eigenvalue problem

$$0 = (\Sigma - \lambda I_2)v \tag{4}$$

Without further proof, the solution of this problem results in the following eigenvalues and eigenvectors with $a = Var(\boldsymbol{X})$, $b = Cov(\boldsymbol{X}, \boldsymbol{Y}) = Cov(\boldsymbol{Y}, \boldsymbol{X})$ and $c = Var(\boldsymbol{Y})$:

$$\lambda_{1/2} = \frac{1}{2}\left(\pm\sqrt{(a-c)^2 + 4b^2} + a + c\right) \tag{5}$$

$$v(\lambda) = \begin{pmatrix} b \\ \lambda - a \end{pmatrix} = \begin{pmatrix} \lambda - c \\ b \end{pmatrix} \tag{6}$$

The desired first principal component is defined by the largest eigenvalue $\lambda_{max} = max(\lambda_1, \lambda_2)$ and the corresponding eigenvector $v(\lambda_{max})$. This eigenvector can now be used as an estimate of the direction of motion. A check of cosine similarity with the history of UWB measurements determines the mirroring of the motion vector:

$$\vec{r} = \begin{pmatrix} r_x \\ r_y \end{pmatrix} = v(\lambda_{max}) \cdot sgn((P_{n-1} - P_0) \cdot v(\lambda_{max})) \tag{7}$$

with $sgn()$ as the signum function. The translation of the direction vector into the desired orientation angle $\tilde{\varphi}$ of the virtual stride vector is trivial:

$$\tilde{\varphi} = atan2(r_y, r_x) \tag{8}$$

B. Stride Length through Variance Decomposition

The length of the virtual stride vector $\tilde{\varrho}$ is determined by an analysis of the composite sample variance along the direction vector. This composite variance is composed of an equidistributed and a normally distributed component.

First, a model that describes the realization of the sample $\boldsymbol{P}$ is developed. Then, the composite variance is dissected and a formula for calculating the stride length from the two principal components of the sample covariance matrix of $\boldsymbol{P}$ is derived.

The UWB samples $P_i \in \boldsymbol{P}$ with $0 \leq i < n$ and sample size n are equidistributed over the actual stride length ϱ along the stride direction $\vec{r}$:

$$P_i = P_0 + i \cdot \frac{\varrho}{n} \cdot \frac{\vec{r}}{\|\vec{r}\|} + \varepsilon_i \tag{9}$$

The normally distributed noise component ε_i of the individual UWB measurements is assumed to be isotropically distributed and thus estimated by the smallest principal component λ_{min}:

$$\varepsilon_i \sim \mathcal{N}(0, \sigma_r^2 I_2) \quad \text{with} \quad \sigma_r^2 \approx \lambda_{min} = min(\lambda_1, \lambda_2) \tag{10}$$

The following calculations relate to the magnitude of the sample variance $S_P = \lambda_{max}$ component. Thus, for clarity, the following calculations omit vector space notation and are performed in scalar space along the direction vector of the first principal component $\vec{r}$.

It can be shown that S_P is itself a random variable composed of a constant, normally distributed and chi-squared distributed random variables.

$$\begin{aligned} S_P &= \frac{1}{n-1} \sum_{i=0}^{n-1} (P_i - E[P])^2 = \lambda_{max} \\ &= \frac{1}{n-1} \left[\frac{\varrho^2}{12} \frac{n^2-1}{n} + A_1 + A_2 + \sigma_r^2 B \right] \end{aligned} \tag{11}$$

The random variables A_1, A_2 and $\sigma_r^2 B$ have the following distributions:

$$\begin{aligned} A_1 &\sim \mathcal{N}\left(0, \frac{\varrho^2 (n-1)^2}{n} \sigma_r^2\right) \\ A_2 &\sim \mathcal{N}\left(0, \frac{2\varrho^2 (n-1)(2n-1)}{3n} \sigma_r^2\right) \\ \sigma_r^2 B &\sim \sigma_r^2 \chi_{n-1}^2 \end{aligned} \tag{12}$$

We will continue to work with the expected value $E[S_P]$, in order to extract the underlying stride length.

$$E[S_P] = \frac{\varrho^2}{12} \left(1 + \frac{1}{n}\right) + \sigma_r^2 \tag{13}$$

The composite variance S_P can also be described by variance decomposition:

$$Var(P) = E[Var(P|d)] + Var(E[P|d]) \tag{14}$$

Where P is the UWB measurement and d is the distance traveled along the current stride ($0 \leq d \leq \varrho$). Here, $Var(P)$ is estimated by S_P:

$$Var(P) = E[S_P] \approx S_P = \lambda_{max} \tag{15}$$

An estimate is also available for $E[Var(P|d)]$ by the magnitude of the second principal component λ_{min}:

$$E[Var(P|d)] = Var(\varepsilon) = \sigma_r^2 \approx \lambda_{min} \tag{16}$$

This now allows us to estimate the last unknown term of (14). The variance component of the UWB measurement induced by locomotion alone results in:

$$\begin{aligned} Var(E[P|d]) &= E[S_P - \sigma_r^2] \approx \lambda_{max} - \lambda_{min} \\ &= \frac{\varrho^2}{12} \left(1 + \frac{1}{n}\right) \end{aligned} \tag{17}$$

Finally, rearranging to ϱ and using the estimated variances from the principal component analysis, the length of the virtual stride vector $\tilde{\varrho}$ is:

$$\tilde{\varrho} = \sqrt{\frac{12n}{n+1} (\lambda_{max} - \lambda_{min})} \approx \varrho \tag{18}$$

IV. Experimental setup

Our method is verified using simulations of the model described in (9) and with comparisons to actual measurements using a ZUPT system. All simulations assume an actual stride length of 1.4 m and 8 samples per stride, which is the average stride length and sample count in our real world comparison.

In the real world test, a Hillcrest FSM-9 IMU is attached to the top of the users foot and is sampling at a rate of 125 Hz. The corresponding ZUPT algorithm is described in [15]. The algorithm detects swing and stance phases of the users gait and produces estimates of the stride length at the beginning of a each stance phase. The ZUPT thesholds were adapted to each user individually.

The UWB system by COMNOVO is producing location measurements at a frequency of 7.15 Hz. The tests are carried out in the Demag Research Factory hall, shown in Figure 1, in an area of about 8 m by 22 m with 8 UWB base stations evenly distributed above the factory floor. Here, three users were instructed to walk along fixed paths around the hall with a handheld UWB-Transceiver. UWB data was segmented at the beginning of each stance phase. The paths that the users walked and the placement of the UWB base stations is shown in Figure 2. Each path was walked five times from start to end by each user.

Both the IMU and the UWB transceiver were connected via USB to a Raspberry Pi 3, which recorded the data.

Fig. 1: The environment of the experiment at the Demag Research Factory

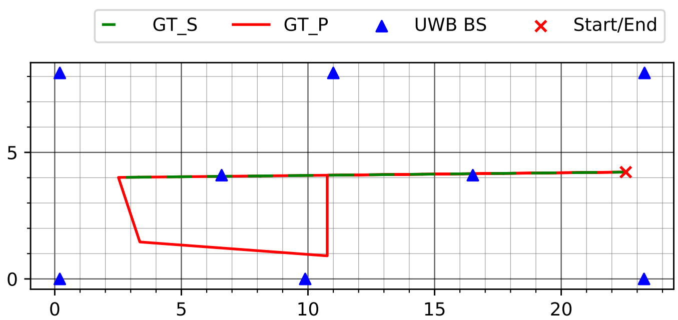


Fig. 2: The two paths, GT_S and GT_P, walked in the experiment and the placement of the UWB base stations (BS). All units in meters.

V. Experimental results

In the previous chapters, the estimates of stride orientation $\tilde{\varphi}$ (8) and stride length $\tilde{\varrho}$ (18) were derived. This chapter now evaluates how random errors influence these estimates and how well the stride length estimate compares to real measurements of a ZUPT system. This is done through boxplots to visualize and compare the respective error distributions. It should be noted, that the whiskers of all plots are chosen to enclose 90 % of the samples.

First, the distribution of stride length estimation error is simulated for a range of typical UWB noise variances. Figure 3 shows the results of the simulation.

It is apparent that the error of the estimated length increases with the noise of the UWB system. There is also a slight increase in the median error, indicating a small systematic bias in the step length estimate that increases with UWB noise.

The distribution of the measured stride length error in the real-world experiment is shown in Figure 4. The real distribution fits the simulated ones at noise standard deviations between 0.12 m and 0.14 m. Like the simulation, it also exhibits a slight positive bias, here at an average of 0.0248 m.

When comparing the reference and simulation data, it should be noted that the virtual stride length estimates are

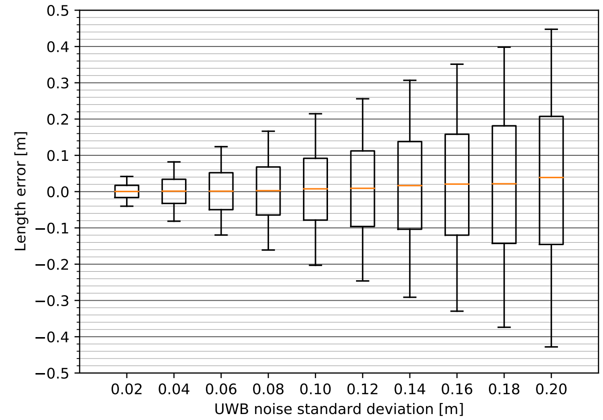


Fig. 3: The error distribution of the stride length estimate using 10 000 simulated strides with exactly 1.4 m length and 8 UWB samples per stride.

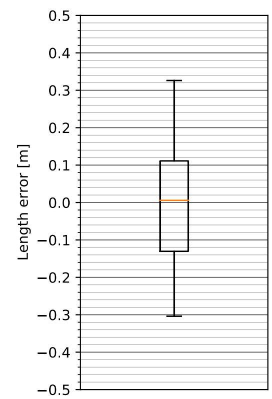


Fig. 4: The error distribution of stride length estimates from real UWB data compared to simultaneous measurements by ZUPT with 355 strides ranging between 1.2 m and 1.6 m length and an average of 8 UWB samples per stride.

compared to the inexact measurements by ZUPT. Thus, the actual error distribution of the presented method is expected to be smaller than the one shown in Figure 4.

Finally the error in the orientation estimate is simulated. The results are shown in Figure 5. It can be seen that the orientation error increases with increasing UWB noise. There is no apparent bias in the orientation estimate.

An example of the ZUPT measuremts, virtual stride vectors and the corresponding simulations is shown in Figure 6. Figure 6a shows the simulated realizations of noisy UWB measurements and their corresponding virtual stride vectors based on a single reference stride. Here, the varying orientation and length of the individual realizations is clearly visible. In Figure 6b, the variation of the stride vector length compared to the ZUPT measurements can be seen. The ZUPT measurements and the corresponding virtual stride vectors are shifted and rotated to a

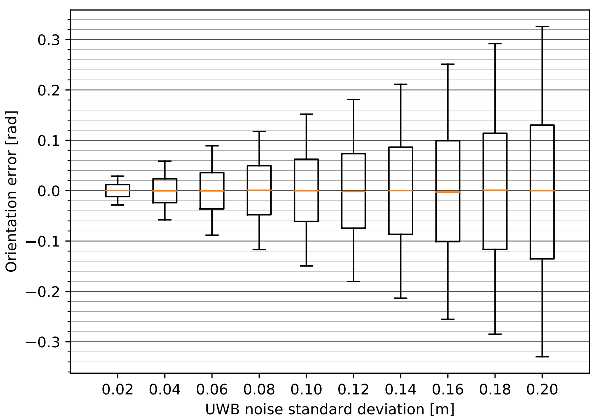
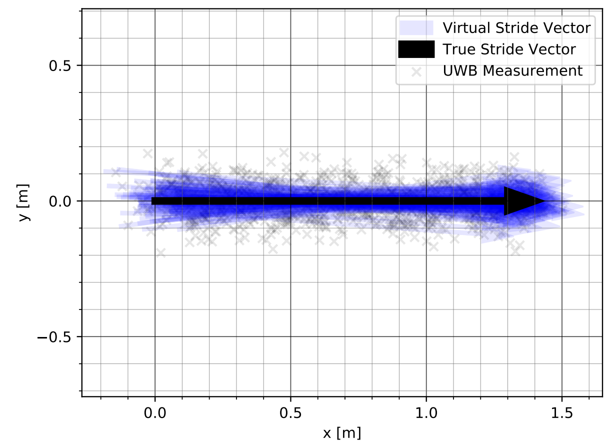
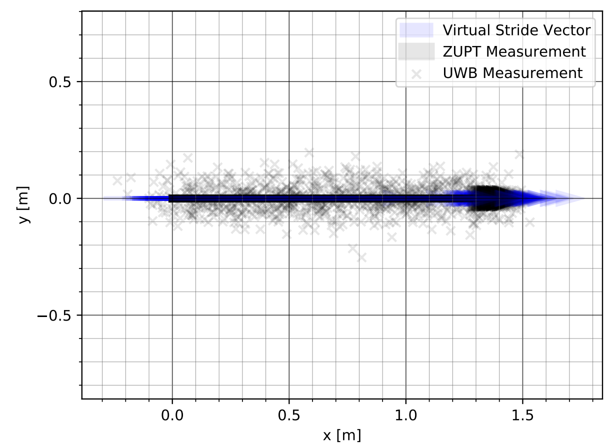


Fig. 5: The error distribution of the stride orientation estimate using 10 000 simulated strides with exactly 1.4 m length and 8 UWB samples per stride.



(a) Simulated strides of exactly 1.4 m length



(b) Real strides between 1.2 m and 1.6 m length. Shifted into the coordinate origin and rotated.

Fig. 6: The distribution of (on average) eight UWB measurements along 125 strides in the xy-plane and the derived virtual stride vectors

common origin and orientation, due to a missing ground truth for the true orientation of the individual strides.

The following chapter provides an analysis regarding the sources of bias in the step length estimate.

VI. Sources of Step Length Bias

We identify two systematic sources of bias that skew the accuracy of stride length estimation:

Bias 1: The first principal component of the scattered UWB measurements never corresponds exactly to the movement direction. This can be seen, for example, in the varying orientation of the simulated virtual stride vectors in Figure 6a. As such, the variance in the walking direction tends to be overestimated, while the variance orthogonal to it tends to be underestimated. Consequently, the estimate of the variance component $Var(E[P|d]) = E[S_P - \sigma_r^2] \approx \lambda_{max} - \lambda_{min}$ introduced in (17) has a positive bias.

Bias 2: The transformation of the variance estimate to the step length, on the other hand, is subject to a negative bias. Due to the nonlinear transformation between the variance estimate and the step length estimate $\tilde{\varrho}$, under- and overestimated variances have an unequal influence on $\tilde{\varrho}$.

According to Jensen's inequality for a concave function $f(x)$ such as (18):

$$f(E[x]) \geq E[f(x)] \tag{19}$$

With the expected value of the estimate of the uniformly distributed variance component

$$E[S_P - \sigma_r^2] \approx E[\lambda_{max} - \lambda_{min}] \tag{20}$$

this results in:

$$f(E[\lambda_{max} - \lambda_{min}]) \geq E[f(\lambda_{max} - \lambda_{min})] \tag{21}$$

Which expands to:

$$\sqrt{\frac{12n}{n+1} E\left[\lambda_{max} - \lambda_{min}\right]} \geq E\left[\sqrt{\frac{12n}{n+1}(\lambda_{max} - \lambda_{min})}\right] \tag{22}$$

Thus, the expected value of the individual step length estimates is smaller than the step length estimated from the expected value of the variance estimates. In other words, assuming that the expected value $E[S_P - \sigma_r^2] \approx E[\lambda_{max} - \lambda_{min}]$ has no bias (i.e. corresponds to the true variance $Var(E[P|d])$), the step length estimate turns out to be too small on average, even if the underlying variance is correct on average. However, it was established as *bias 1* that $E[S_P - \sigma_r^2] < E[\lambda_{max} - \lambda_{min}]$.

Accordingly, the two effects are expected to partially cancel each other out.

VII. Conclusion

We present a method to derive individual stride lengths and orientations from a series of position measurements. Because we analyze the trend of position measurements in the users' absolute reference frame, we can derive the absolute orientation of individual strides. This may be used to tune pedestrian localization with inertial sensors, i.e. to calibrate stride length and orientation heuristics, for arbitrary user paths. The derived virtual strides can also serve as annotations for machine learning based PDR. We verify the stride length estimate with reference measurements by a ZUPT system. Additionally, we provide simulations that show the evolution of bias and variance of the derived parameters at varying noise levels of the positioning reference data. Lastly, the sources of step length bias are analyzed, which provides a basis for further research to predict and compensate it.

A limitation of our method could be the slight positive bias in the stride length estimates (less than 3 cm in the real world test). The variance of the virtual estimates should be mitigated by simply collecting more data for use as a target variable in a regression task.

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