Poster Abstract: Improving the Error Drift of Inertial Navigation based Indoor Location Tracking

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ABSTRACT

Inertial sensing based indoor localization currently requires fairly precise layout maps, to help provide constraints and landmarks that bound the error drift. In this paper, we seek to improve the accuracy of one component of inertial-based tracking, namely the estimation of an individual's stride-length, so as to reduce the cumulative drift. We show that an individual's stride-length is affected by both his/her movement speed and heading-changes in the trajectory, and present an adaptive, online stride-length estimation algorithm that learns appropriate stride-length distributions for different (speed, heading) combinations. Initial experiments conducted using our proposed approach in combination with state-of-the-art step counting and heading estimation techniques, reduce the 95th percentile of average localization error by $\approx$ 30%. We thus envisage that inertial tracking may become practical even with coarse-grained map information.

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Algorithms, Performance

Keywords

Indoor Localization, Inertial Navigation, Mobile Sensing

1. MOTIVATION

Inertial sensing based indoor localization has received significant attention in recent years, largely due to the availability of smartphone embedded sensors such as accelerometers and gyroscopes. Most of these methods require precise map-layouts to provide appropriate constraints and landmarks that acts as *resetpoints* for reducing the problem of error drift. The accumulative nature of such errors occur due to inaccurate estimation in one or more of the following: step-counting [1, 3], stride-length [2] and heading. We propose a novel method for adaptive stride-length estimation that takes into account an individual's short-term movement speed and orientation. Experimental results show, the error drift progressively reduces with time, thereby suggesting our method to be a reasonable alternative to prior data-intensive methods such as linear regression [2]. Our hope is that such lower errors in location tracking improve the robustness of the approach, by allowing the use of layout maps which are less precise and lack fine-grained, potentially time-varying constraints (e.g., cubicle walls).

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2. PROPOSED APPROACH

The key components of our approach are as follows.

2.1 Step Counting & Heading Estimation

Given our focus on improving the stride-length estimation accuracy, we utilize prior approaches for accurate estimation of (i) step counts and (ii) heading/orientation information. The AcTrak system [1], known to be robust to accelerometer noise and on-body location of the smartphone, is used to detect steps. Similarly, we utilized Fan *et.al.*'s method [2] to obtain the user's heading estimate. Based on this information, we classify the user's heading into two bins: θ_{turn} denotes the instances where the user's mean orientation (over a window size that varies between 1-2 secs) registers a significant change-i.e., $\theta(t) - \theta(t-1) \geq \delta$ ($\delta \approx 70°$) whereas θ_{str} denotes the instances where the user moves in either a straight line or with relatively low orientation changes.

2.2 Stride-Length Estimation

In the proposed approach (see Algorithm 1) we use a particle filter for adaptively estimating the stride-lengths of users. During the phase of online learning, we initially sample from a uniform distribution of stride lengths (5 distinct values in the range (0.35,..., 0.75) meters) to generate new particles. However, this uniform distribution is rapidly updated, independently for each combination of 3 different movement speeds ($\mathcal{S}$=*slow, normal, fast*) and 2 heading values ($\mathcal{H}= \theta_{turn}, \theta_{str}$), based on the infeasibility of each corresponding stride. In other words, if a particle of stride length k generated corresponding to a context of $\mathcal{S}$ and $\mathcal{H} = (s, h)$ turns out to violate a map-based constraint, then its probability mass $p_{s,h}(k)$ is reduced accordingly. In practice, a counter $CTR_{s,h}[k]$ is maintained for each value of k for each (s, h) combination, and the normalized inverse of these dynamically updated CTR vector is used to generate subsequent

Algorithm 1 Online Stride-length Estimation

Input: Accelerometer(Acc), heading(θ), window-size W, Array of stride-lengths $Str = \{0.35, 0.45, 0.55, 0.65, 0.75\}$, Initial distribution of N particles
Initialize Infeasible stride counter $CTR_{s,h}[k]$=1 $\forall s, h, k$
for $t \leftarrow 1$ to length(Acc): step W

1. $[StepTime, StepFreq]$=AcTrak($Acc_{t:t+W-1}$)
2. $s = index(StepFreq \in \{slow, normal, fast\})$
3. $h = index(\theta_{StepTime} \in \{\theta_{str}, \theta_{turn}\})$
4. $p_{s,h}[k] = \text{Normalize}(CTR_{s,h}[k]^{-1})\ \forall k$
5. $Str\_index = \text{Sample}(p_{s,h}, N)$
6. $Strides = Str[Str\_index]$
7. $CTR_{s,h}[Str\_index[k]]$=$CTR_{s,h}[Str\_index[k]]$+ $\text{I}(RejectParticle(Strides[k], \theta_{StepTime}))\ \forall k$

end for
Output: $p_{s,h}\ \forall s, h$

particles. Eventually, at the end of the training phase, we obtain the distinct stride-length distributions for each combination of (movement speed, heading) context.

3. RESULTS AND DISCUSSION

The proposed approach was used for learning walking characteristics of 2 individuals over 7 trajectories in an office floor. Three trajectories were arbitrarily chosen for learning the stride-length distributions while the remaining were used for testing. During testing, an imprecise map consisting partial information about only corners and straight paths was used. We compared our approach with the naive particle-filtering based method which uses a) Linear regression model of stride-length and b) samples from a Gaussian distribution of stride-length with added tolerance to accommodate errors.

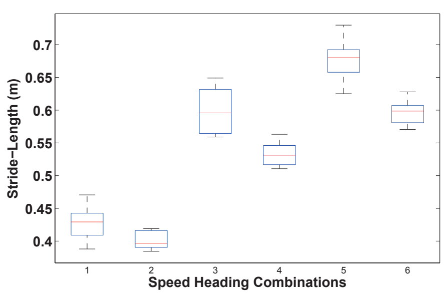

Figure 1: Block diagram showing the distribution of stride-lengths during test walks at (1) slow(str) (2) slow(turn) (3) normal(str) (4) normal(turn) (5) fast(str) and (6) fast(turn)

Distinct stride-length Distributions for (s, h) Values: Figure 1 shows the actual distribution of stride-lengths for 3×2=6 different combinations of (s, h). We can see that the 6 distributions are sufficiently distinct (with the possible exception of (normal, str) vs. (fast, turn)), indicating the importance of using distinct stride-lengths corresponding to different movement speed and heading values. Figure 2 plots the average error in the stride-length estimates, between the observed ground truth values vs. those generated

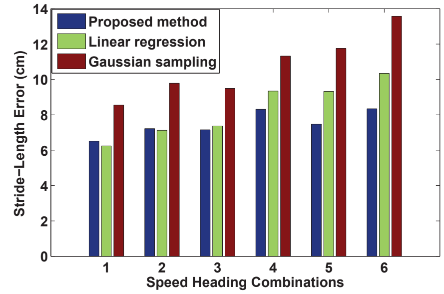

Figure 2: Bar plots of average stride-length estimation errors during test walks at (1) slow(str) (2) slow(turn) (3) normal(str) (4) normal(turn) (5) fast(str) and (6) fast(turn)

by our adaptive method and those generated by previously proposed Linear regression [2] and Gaussian sampling methods. We see that our adaptive method has a lower average error (7.51 cm) compared to the Gaussian method (10.74 cm) and Linear regression model (8.29 cm), across all (s, h) combinations.

Location Accuracy: Figure 3 shows the resulting impact (via a CDF plot) on the average localization error, across all the 7 trajectories. The new method results in an error of $\approx$ 4.5 m (at the 95^{th} percentile), corresponding to an error of $\approx$ 5.5 m and $\approx$ 6.5 m for Linear regression model and Gaussian sampling method, respectively. While additional results are clearly needed to establish conclusive claims, the existing results show that the proposed adaptive stride-length estimation algorithm can improve inertial motion tracking accuracy, and thus reduce the dependence on the availability of fine-grained layout maps.

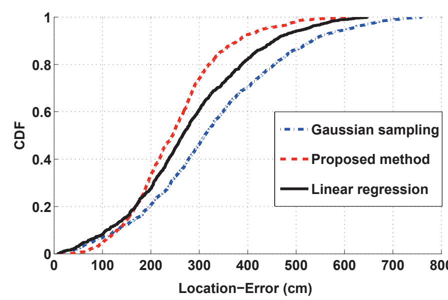

Figure 3: Block diagram showing CDF of average localization error using Gaussian Sampling (blue dots), Proposed method (red dots) and Linear Regression (solid black)

4. REFERENCES

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