Pals: High-Accuracy Pedestrian Localization with Fusion of Smartphone Acoustics and PDR *

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Abstract. The indoor localization technology is bringing great convenience in location-based service (LBS) recent years. Most high-accuracy localization system is expensive and highly dependent on custom device instead of smartphone. In this paper, we propose a high-accuracy indoor localization system with fusion of smartphone acoustics and Pedestrian Dead Reckon (PDR) for pedestrians. Acoustic signals are designed with high frequencies chirp which is above the threshold of human auditory. Time Difference of Arrival (TDOA) is adopted to eliminate the synchronization with the broadcasting infrastructure. For more convenience of pedestrians, inertial sensor is introduced to analyze human gesture and gait. We revise Extended Kalman Filter (EKF) to adapt coarse-grained combination and different performance of acoustic and inertial sensors. The experiments show that Pals system can achieve localization error of 0.28 meter within 95% confidence.

Keywords: Acoustics · Extended Kalman Filter · TDOA · Pedestrian.

1 Introduction

On current trends, the most popular and valuable LBS applications are on the smartphone [1–3]. Humans in modern society prefer carrying an almighty phone to wearing one more piece of facility for positioning, which drives smartphone indoor positioning as a kind of invisible rigid demand [4]. Various kinds of smartphone applications which the secondary development of LBS pose an urgent need for high-precision indoor positioning [5, 6]. From opinions of Microsoft Indoor Localization Competition and Indoor Positioning and Indoor Navigation (IPIN) competition, acoustics and PDR are the best choices of indoor positioning in smartphone. For the former competition, AID from Zhejiang University won the first place with pure acoustics of 3D group [20], which was also the prototype

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system of this paper. For IPIN Track 3 and Track 4, Team WHU from Wuhan University won the first place with PDR.

We propose Pals, High-Accuracy Pedestrian Localization with Fusion of Smartphone Acoustics and PDR. Acoustics is outstanding for smartphone localization [7–9]. All of smartphones on the market are equipped with sound devices. So long as the speakers and microphones are suitably deployed, the demand of acoustic signal positioning can be met. Inertial Measurement Unit (IMU) is already integrated into smartphones for several years. Rough self-contained positioning can be achieved based only on them. IMU has little dependence on the environment, except for the magnetometer. PDR positioning principle is derived from the IMU reading integral, obtaining the displacement and orientation angle, estimating the stride size, and then reckoning the coordinates [10].

Things do not always go as well as we thought. Even if acoustics and IMU fusion simulation algorithm design is perfect, we still find oceans of obstacles in practical application. So this paper focuses on practical problems. In general, the main contributions of Pals are listed in the following three aspects:

Pals proposes a hybrid structure incorporating acoustic positioning coordinates and PDR stride length. The structure is fast and suitable for most mobile navigation scenarios.

Pals creates a empirical Extended Kalman Filter algorithm for fusion. We update coordinate by modified observation estimation matrix rather than status prediction matrix.

Pals improves PDR algorithm. We add speed-constraint to the pace event judgment, and adjusting stride length estimation by fusion coordinate.

2 Related Works of Smartphone Indoor Positioning

Recent commercial trends in high-accuracy indoor localization have led to a proliferation of studies. Chen [11] built a large number of fingerprint databases using the strength of WiFi signal, realizing the commercialization of indoor positioning in shopping malls and airports. [12] presented a smartphone inertial sensor-based PDR approach for indoor localization and tracking with occasional iBeacon calibration. Google Tango [13] estimated positioning with cameras. But camera casually may make troubles with others in an age which privacy is significant.

Acoustic localization enjoys a wide range of applications. BeepBeep [14] emitted the double Beep sounds during a ranging session by Round-Trip Time (RTT). In bi-directional communication mode of [14], user capacity is a major limitation. BatTracker proposed for the superiority of the high precision and infrastructure-free moblie device tracking system in 3D space [15]. They continuously emitted acoustic signals that bounced off surfaces of nearby object. It limited positioning range near the smooth wall. ALPS [16] in Carnegie Mellon University (CMU) was very considerate in non-Line-of-Sight (NLOS) recognition, Doppler effect and floor plan. [17] proposes an acoustic steering tracking system on smartphone.

Inertial localization system is also a hot topic of infrastructure positioning in academia. Considering the cost and Commercial Off-The-Shelf (COTS), the smartphone inertial sensor is lightweight, so IMU localization only cannot maintain high-accuracy for long-term caused by accumulative errors. The accumulative errors can also be efficiently removed by using Zero Velocity Update (ZUP-T) [18], but IMU are required to be mounted on the foot in ZUPT. In practical smartphone localization, all above methods are not suitable since the moblie is supposed to be held in hand or in pocket rather than to be mounted on waist or foot. Rui Z. [19] proposed a novel localization system fused the position information estimated by acoustic and inertial sensors. They are the closest to our structure design. We optimaize PDR of Pals with stride length feedback, fusion algorithm is also improved with experiment.

3 Pals in Fusion

Pals fusion algorithm belongs to heterogeneous fusion. In practice, the data size of PDR obtained is much larger than the acoustics, so Pals coordinates are mostly given by PDR. Fusion occurs when mobile cache receives the acoustic coordinates, or when mobile sensor detects that the pedestrian has stopped.

3.1 Hybrid structure incorporating acoustics and PDR

According to Extend Kalman Filter (EKF), we define the PDR algorithm as the state transition of EKF as

$$\mathbf{X}_{k+1} = f(\mathbf{X}_k) + \mathbf{w}_{k+1},\ f(\mathbf{X}_k) = \mathbf{X}_k + S_k\mathbf{u}_k\mathbf{T}, \tag{1}$$

where $\mathbf{X}_k = [x_k\ y_k]$ is denoted horizontal and vertical coordinate when $t = k$ at indoor coordinate axis. Generally, there is a stationary deflexion in the horizontal direction between the indoor coordinate system and the geodetic coordinate system. The building is of course fixed, so the interior coordinate system is also constant. In dealing with the coordinate deflexion of ϕ fixedly, we only need to multiply by a constant rotation matrix $\mathbf{T} = \begin{bmatrix} \cos\phi & -\sin\phi \\ \sin\phi & \cos\phi \end{bmatrix}$, and S_k is denoted stride length in k. $\mathbf{u}_k = [\sin\theta\ \ \cos\theta]^{\mathrm{T}}$ is controller vector where θ is azimuth angle. $\mathbf{w}_k$ follows a normal distribution with zero mean and variance $\mathbf{Q}_k$.

Then $\mathbf{X}^A$ is obtained from acoustics, we take it out of mobile cache. Then observation model can be defined as

$$\mathbf{z}_{k+1} = h(\mathbf{X}_{k+1}) + \mathbf{v}_{k+1},\ h(\mathbf{X}_{k+1}) = \bar{J}_{k+1}\mathbf{X}_{k+1} + (1 - \bar{J}_{k+1})\mathbf{X}^A_{k+1}, \tag{2}$$

where $\bar{J}_{k+1}$ is normalization of cost function $J(\bullet)$ in MLE of TDOA in acoustic. $\mathbf{v}_{k+1}$ follows a normal distribution with zero mean and variance $\mathbf{R}_{k+1}$. In other words, the observation model is weighted mean with noise.

Pals employs the time update equation of EKF are given as

$$\mathbf{X}_{k+1|k} = f(\mathbf{X}_k), \mathbf{P}_{k+1|k} = \mathbf{P}_k + \mathbf{Q}_k, \tag{3}$$

where $\mathbf{P}_{k+1|k}$ and $\mathbf{P}_k$ are a priori and a posteriori covariances. The update of EKF are given as

$$\mathbf{K}_{k+1} = \mathbf{P}_{k+1|k}\mathbf{H}_{k+1}^{\mathrm{T}}(\mathbf{H}_{k+1}\mathbf{P}_{k+1|k}\mathbf{H}_{k+1}^{\mathrm{T}} + \mathbf{R}_{k+1})^{-1}, \tag{4}$$

$$\mathbf{X}_{k+1} = \mathbf{z}_{k+1|k} + \mathbf{K}_{k+1}(\mathbf{z}_{k+1|k} - \mathbf{H}_{k+1}\mathbf{X}_{k+1|k}), \tag{5}$$

$$\mathbf{P}_{k+1} = (\mathbf{I} - \mathbf{K}_{k+1}\mathbf{H}_{k+1})\mathbf{P}_{k+1|k}, \tag{6}$$

where $\mathbf{K}$ is the Kalman gain, $\mathbf{I}$ is 2-order identity matrix. In conventional EKF, (6) can be competent the update of variance.

At the end, the fusion position trace is displayed by 2-order Gaussian s-moothing. Notice that (5) exerts the predicted $\mathbf{z}_{k+1|k}$ of the measured values, while formal EKF exerts the estimation of the state $\mathbf{X}_{k+1|k}$ values. This is the third of originality in Pals system and is based on empirical inference. Smart-phone sensors are consumer-level, not industrial-level. Our acoustic system is more excellent by contrast. Thus Pals infers measurements matrix have a higher probability of reliability over the state predictions.

3.2 Stride length update based on Pals coordinates

As mentioned in Section IV, Weinberg's stride length estimation involves a specific parameter γ. Now in order to update γ, we push back stride length according to the fusion coordinates. Assuming consecutive two-step model is (7) on the basis of (1), the cost function of S_k is denoted as

$$\mathbf{X}_{k+1|k+1} = \mathbf{X}_{k|k} + S_k\mathbf{u}_k\mathbf{T} + \mathbf{w}_{k+1}, \tag{7}$$

$$J_s(S_k) = \|\mathbf{X}_{k+1|k+1} - \mathbf{X}_{k|k} - S_k\mathbf{u}_k\mathbf{T}\|_2^2. \tag{8}$$

To minimize the cost function $\hat{S}_k = \arg\min\limits_{S_k \in R} J_s(S_k)$, the stride length estimation $\hat{S}_k$ must satisfy

$$\hat{S}_k = [(\mathbf{u}_k\mathbf{T})^{\mathrm{T}}(\mathbf{u}_k\mathbf{T})]^{-1}(\mathbf{u}_k\mathbf{T})(\mathbf{X}_{k+1|k+1} - \mathbf{X}_{k|k}). \tag{9}$$

Then γ is calculated as (10)

$$\hat{\gamma} = \hat{S}_k/(|\hat{a}_k|_{max} - |\hat{a}_k|_{min})^{\frac{1}{4}} \tag{10}$$

Through the above process, Pals accomplishes the specific parameters of the Least Squares (LS) update γ. Generally speaking, γ is relatively stable for the same person with the same posture, maybe no change in short-term. Once the pedestrian posture has changed, such as from slow walking to fast walking or running, γ will be changed correspondingly. Based on above inference, we update γ value every five seconds.

4 Experiment and Analyze

Pals design pays more attention to user experience. In this section, we commit plenty of experiments, operating by different people, different smartphones and different experimental paths.

4.1 Experimental setup

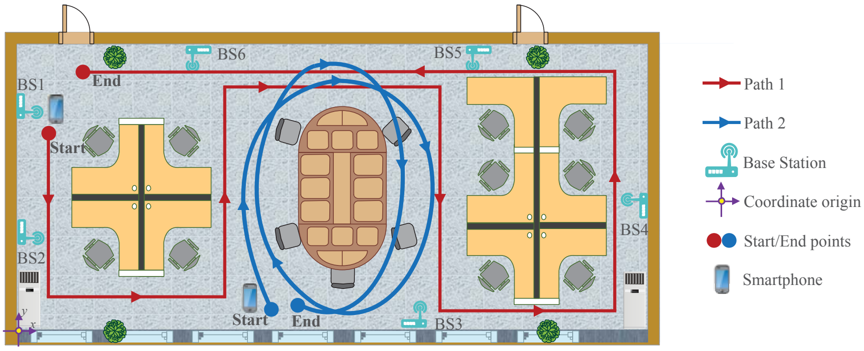

Fig. 1. Experimental environment. Path 1 in red is a straight line, while Path 2 in blue deliberately follows a curve and goes around twice to test Pals' extreme performance

Experiments are shown in the Fig. 1. We arrange the base station in the position shown in Fig. 1, and all the positions are temporarily determined. All of base stations can be synchronized via Bluetooth as they are developed by us manually. Set the coordinate origin in the left bottom, and follow the right-handed rule to establish indoor coordinate. Then measure $\phi = 161.5°$ between indoor coordinate system and the geodetic coordinate system. The rest of the details are shown in Fig. 1. The ground truth positioning (GTP) of the experiments were measured by WHU system. [21]

4.2 The implementation of experiment

Test phone is Huawei Mate 9. Tester is of medium height with standard body. During the experiment, tester holds the smartphone, walks along the path in ordinary posture and locates in real-time. The results of path are shown in Fig. 2. As can be seen, acoustic signals are of high accuracy. The reason is, acoustics always filters out jump points with overlarge MLE value J, and remaining points are relatively ideal. However, this implementation and slow update rate maybe lead to discontinuous trajectory. For experimental convenience, the initial coordinate of PDR is as well provided by the acoustic system. The short-term accuracy of PDR positioning is high precision, but even if the drift error of IMU is calibrated, the long-term PDR algorithm still has significant cumulative error.

It takes 43 seconds to walk through Path 1, and 27 seconds to Path 2. The PDR error in this paper is not constrained with other conditions, e.g. map, which is completely within the tolerance range. The cumulative error of PDR rotation estimation is more obviously reflected in Path 2, while the acoustic system is not affected but the current environment elements. The fusion algorithm in Path 2 still shows strong stability.

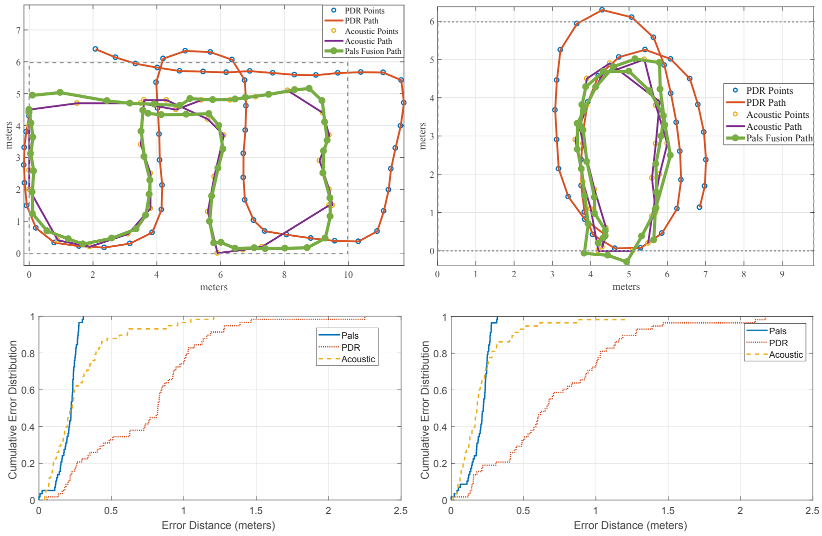

Fig. 2. Under different paths, separate acoustics, separate PDR and fusion algorithm are compared. Path 1 on top left and Path 2 on top right. Cumulative error distributions for paths. Path 1 on bottom left and Path 2 on bottom right.

From Fig. 2, it can also be seen that acoustic signal positioning error is not worse than fusion algorithm in some data, but Pals is stronger in terms of stability. The reason is that acoustics still remains some large error points, which are more likely to appear near the walls. The acoustic cumulative is slightly stronger than the Pals with a probability of about 50%, while about 75% in Path 2. In general, Pals algorithm can maintain within 95% of 0.28 meter error and within 90% of 0.27 meter error, which is more robust than acoustic and PDR positioning severally.

4.3 The analysis of Pals supplement approach

The experimental results shown in Fig. 3 include different approach. However, stride length feedback update approach is necessary. The green small dot line in Fig. 3 reflects the positioning performance without the approach. Compared with Pals standard system, the mean error is down by about 9.7 centimeters. The motion posture in our experiment is fortunately only normal walking steps. Pals method will have more advantages if the walk/run switch is added. Cumulative error distribution of the normal EKF with $\mathbf{X}_{k+1|k}$ are shown by carmine dash-dotted line. The accuracy is about 10 centimeters lower than Pals.

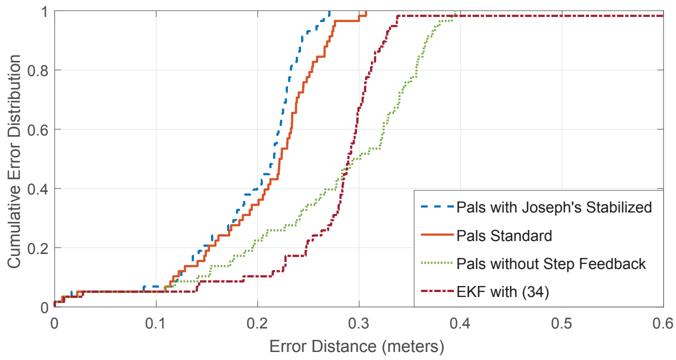

Fig. 3. Cumulative error distributions with different approach.

5 Conclusion and Prospects

Pals, High-Accuracy Pedestrian Localization with Fusion of Smartphone Acoustics and PDR, is proposed in this paper. To further enhance the smartphone indoor positioning accuracy, Pals compares (6) with routine improves EKF in which combined with the characteristics of smartphone sensor and selected the observation value as fusion update strategy. Pals also amends the stride length of the individual state parameter γ according to fusion coordinates. The experiments show that Pals system can achieve indoor error of 0.28 meter within 95% confidence. Pals has been signed in 2022 Hangzhou Asian Games, as a security personnel and tourists indoor positioning.

Of course, Pals has it drawbacks. In this paper, Pals only takes into account the discrimination of motion or stillness when holding smartphone, and without considering putting it in the pocket, which is applicable to the scenario of walking follow the phone screen. We will combine the methods of deep learning and edge computing [6] for next research.

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