Adaptive Kalman Filter for Indoor Navigation

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Abstract—Indoor navigation for mobile devices enables new and exciting possibilities for interaction with venues. A critical aspect of this service is the positioning system. In this paper we present a solution for on-terminal deployment, that relies an Adaptive Kalman Filter (AKF) to fuse Pedestrian Dead Reckoning (PDR) and radio based position estimates. The filters adaptive algorithm minimizes the influence of outliers in position estimates, as well as reduce recovery time from poorly determined states. Experimental results show a 10% increase in obtained median positioning accuracy when enabling the adaptive algorithm.

I. INTRODUCTION

A multitude of approaches for obtaining reliable positioning without the availability of satellite signals have previously been explored. Most commonly used approaches are based on combinations of received radio signals, magnetic field strengths and motion sensor data [1]. Due to their low computational efficiency and limited resources on mobile devices, many solutions rely on Kalman Filter (KF) rather than other approaches such as particle filters [2], [3], [4], [5], [6]. In order to reach this level of efficiency, the KF reduces the state and all observation to Gaussian distributions [7]. As a consequence, it is sensitive to incorrect noise estimates or bias from both state and observations, which must be handled either by design in advance or by real-time adaption.

The Adaptive Kalman Filter (AKF) presented in this article is used by the indoo.rs Navigation System (iNS). The iNS provides the AKF with radio-based positions and step updates. Radio-based positions are obtained from radio signals by WiFi access points or Bluetooth beacons, while step updates are produced from motion sensor data by the Pedestrian Dead Reckoning (PDR) component of iNS. With these inputs, an adaptive algorithm is applied to make high quality noise estimates.

The remainder of this paper is organized as follows: in Section II an overview of the iNS is given, in Section III the AKF design is described, finally in Section IV test results are shown and the paper is concluded.

II. SYSTEM OVERVIEW

The iNS is comprised by a mobile positioning application, a radio infrastructure, and a cloud support system. The application runs the indoo.rs Mobile Locator (iML), which produces positions for navigation using a reference radio map retrieved from the cloud. Aiming at rapid and easy deployment, the radio maps are constructed in the

Fig. 1. indoo.rs Mobile Locator. The indoo.rs Mobile Locator combines motion and radio data measured by the mobile device into positions for navigation as well as quality controlled trajectory data for map updates and analytics.

In Fig. 1 the iML is presented. The iML runs in real time on the mobile device, and can be used offline with a downloaded radio map. In the PDR system, motion sensor data is processed to provide device orientation independent step events with headings for relative motion control. Live radio scans are compared to the radio map in order to select reference points likely to be near the true location. The selected references are rated using a scale independent dissimilarity measure. Using the rated points the radio po-

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sitioning estimates a position hypothesis with a weighted mean and covariance. The online trainer analyses recent trajectory history to assist the AKF with estimating low frequency state and input covariance. It also controls the data collection decision. Avoiding spurious uploads significantly reduces mobile energy usage, as well as the load on the cloud services. The AKF provides immediate positions for navigation by fusing PDR and radio positioning outputs.

III. ADAPTIVE KALMAN FILTER

The KF is one of the most common and efficient methods used in Markov chain state estimation. The KF utilizes both preceding information and succeeding information to estimate the targeting states [7]. Preceding information is handled by filtering, and succeeding information by smoothing. However, the KF in iML only focuses on the immediate estimation of the current state, there will only be the information from preceding states available for the KF. As a result, the only filtering part is relevant to the KF in this work:

\[
X_{k|k-1} = A_K (X_{k-1} + w_{k-1}) + w'_{k-1} + \frac{1}{2} \Sigma_{Xk|k-1} \]

\[
\Sigma_{Xk|k-1} = A_K (\Sigma_{Xk-1} + \Sigma_{Wk-1}) A'_K + \Sigma_{W'k-1} \]

The (1) and (2) form the prediction phase of the KF. It estimates the current state of the KF from previous states. In this equation, the \(X_{k-1}\) and \(\Sigma_{Xk-1}\) are the mean and covariance of previous states \(k - 1\); \(X_{k|k-1}\) and \(\Sigma_{Xk|k-1}\) are the predicted mean and covariance of current state \(k\) from previous states \(k - 1\); \(A_K\) is the design matrix of the states, which transfers the previous state to current state; \(w_{k-1}\) models the unmeasured states inconstancy that the states of the Kalman will change from time to time; \(w'_{k-1}\) is the addition noise caused by the observation noise. \(A\) and \(C\) are the mean and covariance of current state and observation, respectively. The states inconstancy that the states of the Kalman will change from time to time; \(w'_{k-1}\) is the addition noise caused by the observation noise. \(A\) and \(C\) are the mean and covariance of current state and observation, respectively.

The updating phase is written in (3)- (6). It couples the current observations \(L_k\) (of current state \(X_k\)) into the estimation. In the equations, \(C_K\) is the observations transform matrix; \(\Sigma_{L_k}\) is the covariance of the observation, \(\Sigma\) is the total covariance of the prediction and observation; and \(K_k\) is the kalman gain.

A. Kalman Filter design in iML

The KF is to fuse relative motion from PDR and absolute locations from the radio positioning. The PDR must deal with mobile devices with cheap low quality motion sensor, differences between devices, as well as difference between navigating users (gait, weight, height, etc.); and hence, a lot of unpredictable noise is introduced. At the same time radio positioning depends on the mobile device radio scans, which commonly have larger than 4 dBm errors. This error can be partially overcome in a rich radio environment by least-square combination of several reference points by the radio similarities. However, this estimation is unreliable as the radio propagation is complex and environment dependant, the radio map may have poor quality (poorly generated, or outdated), or the signal density is not enough in some region. Hence, the iML has too much false or inadequate information to have a good location mean and covariance estimation. To make the matter worse, in our experience, the position outputs can have correlated clustering effects where many locations are squeezed into a single place; which causes the KF to track wrong states.

Although the noise can be bad and unpredictable, mostly it has zeros means and has gaussian like distribution (obtained by comparing the radio location, pdr data with SLAMed trajectory), thus there is no fundamental problem in using a KF. However, deviations in heading estimation due to magnetic disturbance have significant non zero bias and must be modeled separately from normal heading angles. The state vector of the KF is given:

\[
[x \ y \ v \ \theta \ \delta] \]

where \(x, y\) are the horizontal position components, \(v\) the speed, \(\theta\) the heading direction, and \(\delta\) the heading offset. The introduction of \(\delta\) compensates the bias between the real and observation headings. The transaction between different instant \(k - 1\) and \(k\) is straightforward:

\[
\begin{align*}
X_{k|k-1} &= x_{k-1} + v_{k-1} \cos(\theta_{k-1} + \theta_{\Delta k-1}) \\
Y_{k|k-1} &= y_{k-1} + v_{k-1} \sin(\theta_{k-1} + \theta_{\Delta k-1}) \\
v_{k|k-1} &= v_{k-1} \\
\theta_{\Delta k|k-1} &= \theta_{\Delta k-1}
\end{align*}
\]

\[
A_K = \begin{bmatrix} 1 & 0 & \cos(\hat{\theta}) & -v_{k-1} \sin(\hat{\theta}) & -v_{k-1} \sin(\hat{\theta}) \\ 0 & 1 & \sin(\hat{\theta}) & v_{k-1} \cos(\hat{\theta}) & v_{k-1} \cos(\hat{\theta}) \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}
\]

where \(\hat{\theta} = \theta_{k-1} + \theta_{\Delta k-1}\)

The two observations in the iML, relative motion and radio position, both are unreliable references: The radio location could be missing when there is too little radio data in the scan, or the use is out of the coverage of the radio map. And the PDRs could also fail due to the imperfect of the PDR algorithm. Thus, the observation matrix has three cases:

\[
C_K = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{all available}
\]

Or

\[
C_K = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \quad \text{xy available}
\]

Or

\[
C_K = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad \text{v, \theta available}
\]
B. Adaptive Design

A key aspect in KF design is getting realistic covariance estimation, which includes the state drifting covariance $\Sigma_w$, model intrinsic error $\Sigma_v$ and the observation $\Sigma_L$. However, all of them are hard to estimate in the smart phone based indoors navigation environment, because of the input noise, the complexities of the model, the dependence on both users and environments, as well as the possible errors in the radio map. As a result, the $\Sigma_w$, $\Sigma_v$ and $\Sigma_L$ are impossible to designed in advance. The AKF fading memory algorithm introduced in [11], [12], [13] uses statistics of the innovations between observations to generate a fading parameter which is used to degrade the precision estimation of Kalman state. The method in [14], [15] directly manipulate the $\Sigma_m$, $\Sigma_v$ and $\Sigma_L$ to degrade the precision, instead of using a fading parameter. Similarly in [16], [17], [18], methods work well with reliable observations, such as in the INS/GPS based navigation case. However, when the observation is also not stable, such as in the INS/GPS based navigation case.

In covariance estimation, the online trainer will run a very coarse path optimization (simplified graph SLAM like in [21]) on the last several cycles of the Kalman states. And then use Laplace method [22] to evaluate the averaging value of $\Sigma_w$, $\Sigma_v$, $\Sigma_L$. However, the method 1 is still in development and is out of scope of this paper. This additional variance accelerates recovery of the AKF from poorly determined states.

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The resulting residual errors trajectories are in Fig. 2. Residuals were calculated for the raw radio positioning, a non-adaptive Extended Kalman Filter (EKF), and the AKF. The resulting residual errors are shown in Fig. 3, showing spikes up to 25m errors. The cumulant residual error statistics are shown in Fig. 4, here it is evident that the AKF stays above the EKF which stays above the raw radio positioning – especially at large residual errors. The average as well as the 25%, 50%, 75% percentile of the residual error is shown in Table IV. The AKF outperforms the less advanced techniques, especially in suppressing large residuals where it shows more than 10% suppress large residuals where it shows more than 10%
improvement over the EKF, and 20% over the raw radio locations.

This property of reducing the large outliers enables iML to provide input good enough to provide crowd sourced data for radio map updates. In few cases when outliers are clustered together, the AKF may produce lower accuracy than the other methods. A priority in future work is to identify and alleviate such position residual error amplifications.

### REFERENCES


### TABLE I
Residual position error statistics.

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<th>Percentile</th>
<th>Raw</th>
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<th>AKF</th>
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