Context-aware Adaptive Extended Kalman Filtering Using Wi-Fi Signals for GPS Navigation

Mahsa Shafiee, Kyle O’Keefe and Gérard Lachapelle
Position, Location And Navigation (PLAN) Group
http://plan.geomatics.ucalgary.ca
Department of Geomatics Engineering
University of Calgary Schulich School of Engineering

BIOGRAPHY

Mahsa Shafiee is a PhD candidate in the PLAN Group of the Dept of Geomatics Engineering. She has a BSc and an MSc degree in electrical engineering (telecom) from Tehran Polytechnic University. Her research interests are mainly in the field of GNSS signal processing, integrated positioning systems and GPS acquisition/tracking algorithms.

Professor Kyle O’Keefe is an Associate Professor of Geomatics Engineering at the University of Calgary. He has worked in positioning and navigation research since 1996. His major research interests are GNSS system simulation and assessment, space applications of GNSS, carrier phase positioning, and local and indoor positioning with ground based ranging systems.

Professor Gérard Lachapelle holds a Canada Research Chair in Wireless Location in the Department of Geomatics Engineering where he has been since 1988. He has been involved in a multitude of Global Navigation Satellite Systems (GNSS) R&D projects since 1980, ranging from RTK positioning to indoor location and GNSS signal processing enhancements.

ABSTRACT

Due to the ever-growing coverage of WLAN networks, integrating Wi-Fi and GPS can be a promising approach to solving problems encountered by precise indoor GPS positioning such as severe multipath. In this paper, the question of indirect use of WLAN signals and exploiting the external information provided by Wi-Fi signals is addressed. One possible way to exploit knowledge of changes in user context is with adaptive positioning methods where the Wi-Fi information can be used to adjust uncertain parameters in the GPS positioning algorithm. The use of external information in a context-aware programming framework to improve GPS positioning performance within the navigation solution is investigated. A new two-layer adaptive extended Kalman filter positioning algorithm is proposed based on multiple model adaptive estimation.

An algorithm based on the Dempster-Shafer theory is proposed to fuse decision sequences of several identifiers to increase the probability of correct context identification. The algorithm is then modified to deal with high conflict situations and correlative decisions. Furthermore, to improve the robustness of the proposed context-aware algorithm a control block based on the type 2 finite state Markov Decision Process (MDP) is implemented with regard to the reward history in which a reward is realized based on the one-step transition between identified contexts in two consecutive epochs.

INTRODUCTION

Recently, Wi-Fi localization methods have been investigated as an approach to indoor positioning purposes and can be categorized into RSS (Received Signal Strength)-based or model-based methods. RSS-based methods are based on collecting a database of observed RSS from available Wi-Fi access points and then applying pattern recognition algorithms to define an unknown position with regard to AP positions. Therefore, these methods require fingerprinting the network coverage and collecting the database, which implies additional time and financial cost. Also, since the accuracy of the Wi-Fi access points database decreases over time these systems should frequently update the database, which is an expensive process (Pahlavan et al 2010). On the other hand, model-based methods suffer from lack of knowledge for modeling signal propagation especially in indoor environments and under multipath conditions (Leo & Chen 2007, Xiang et al 2004).
In this research, instead of using Wi-Fi data directly for localization, the information obtained by observing Wi-Fi signals (Wi-Fi features) are used as side information so that GPS can modify its behavior according to changes in environment (static/kinematic and indoors/outdoors). We propose and investigate the use of external information in a context-aware programming framework to improve GPS positioning performance within the navigation solution.

First, the existence of similar patterns in WiFi signal features under similar environmental and/or dynamic conditions is investigated. Results repeatability and consistency using WiFi features as context identifiers and pattern utilization to make assumptions or predictions about the current mode are demonstrated. Some simple effective identification algorithms are proposed based on features such as the number of available APs or the number of APs with RSS exceeding a certain threshold, the mean and the variance of the total RSS from available APs, etc. The performance of these algorithms has been tested through field tests under different conditions.

After characterizing different receiver contexts, this additional information should be used as the next step to enhance the performance of GPS positioning algorithms. One possible way to take these changes into account is to implement adaptive positioning algorithms. More specifically, Wi-Fi information can be used to adjust the uncertain parameters of an adaptive Kalman filter. This can include both the variance/covariance matrices and the system model. Specifically, the model can be adapted based on the user being static or in motion while the observation covariance can be adapted based on whether the receiver is indoors or outdoors.

In this paper, a new two-layer adaptive extended Kalman filter positioning algorithm is proposed based on multiple model adaptive estimation in which each individual Kalman filter, matched to a different dynamic model, has an IAE (Innovation-based Adaptive Estimation) structure and external information obtained from Wi-Fi signals, is used to adjust the adaptive parameters based on the different situations.

The remainder of the paper is organized as follows: First the concept of adaptive filtering and existing methods for navigation are introduced. Then the structure proposed algorithm is described and the performance of the proposed algorithm is analyzed using real data. The problem of context identification based on WiFi signals is then discussed and the structure of the DST-based decision fusion block and MDP control block are explained. Finally, the performance of the proposed algorithm replacing the bank of Kalman filters with a single constraint-based Kalman filter is analyzed and conclusions and suggestions for further development are proposed.

**ADAPTIVE KALMAN FILTERING FOR NAVIGATION**

Different adaptive Kalman filtering algorithms have been investigated in the literature. The performance of positioning algorithms and the optimality of the Kalman filter are closely related to the a priori knowledge of the model, the process noise and the measurement noise.

An Innovation-based Adaptive Estimation (IAE) algorithm is based on adapting the covariance matrix of measurements or the process noise (Mohammed 1970, Mohammed & Schwarz 1999). A second approach is based on introducing fading factors to the covariance matrix of the states (Geng & Wang 2008, Moreno & Pigazo 2009). The fading factor and IAE models are actually following the same procedure of controlling the amount of noise introduced in the dynamic model (or covariance matrix of the observations) to control the performance and assure the convergence of the Kalman filter.

The other approach is to use Multiple Model Adaptive Estimation (MMAE) methods in which the state estimation is achieved by using a weighted sum of the estimates from a series of parallel filters matched to different system models. Recent improvements in processor speed have made the MMAE algorithms one of the major groups of adapting algorithms used in navigation applications such as in integrating INS/GPS data (Mohammed & Schwarz 1999, Moreno & Pigazo 2009). The optimal state estimation is then computed using the weighted combination of the states from all individual Kalman filters. The weighting scheme is based on the a posteriori probabilities for each of the hypothesis.

Most adaptive filters use the information in the innovation sequence or residuals to adapt the covariance matrix of measurements or the process noise covariance matrix and are categorized as IAE adaptive Kalman filtering algorithms. A Maximum Likelihood (ML) Innovation-based Adaptive Estimation Kalman filtering can be formulated as follows:

The probability density function of the measurements conditioned on the adaptive parameter \(\alpha\) at a specific epoch can be considered as a Gaussian distribution and be written as (Mohammed & Schwarz 1999)

\[
    f(z|\alpha) = \frac{1}{\sqrt{(2\pi)^n |C_\alpha|}} e^{-\frac{1}{2} (z - C_\alpha)^T C_\alpha^{-1} (z - C_\alpha)}.
\]

By applying the formula

\[
    \frac{\partial f}{\partial \alpha} = 0
\]

\[
(2)
\]
the ML estimation for the adaptive Kalman filter can be obtained as in (Mohammed & Schwarz 1999):
\[
\sum_{j=0}^{\infty} \text{tr}[(C_{11}^{-1} - C_{01}^{-1} v_j C_{01}^{-1}) \frac{\partial R_j}{\partial a_k} + H_j \frac{\partial Q_{j1}}{\partial a_k} H_j^T] = 0.
\]

To obtain an explicit expression for $R$, the $Q$ matrix is assumed to be completely known and independent from the adaptation parameter $a$. By considering the adaptation parameters to be the diagonal elements of the $R$ matrix, the expression for adapting the covariance matrix of the observations can be obtained as
\[
R_k = \hat{C}_n - H_k P_k (-)H_k^T
\]
where one has
\[
\hat{C}_n = \frac{1}{N} \sum_{j=0}^{\infty} y_j y_j^T.
\]

By the same strategy, assuming the $R$ matrix to be known, an approximation for the process noise covariance can be achieved as
\[
\hat{Q}_k = \frac{1}{N} \sum_{j=0}^{\infty} \Delta x_k \Delta x_k^T + P_k (+) \cdot \Phi P_{k-1} (+) \Phi^T
\]
where the state correction sequence can be computed as
\[
\Delta x_k = \hat{x}_k (+) - \hat{x}_k (-).
\]
Assuming a steady state condition and using the relation
\[
\Delta x_k = K_k v_k
\]
the expression for process noise can be simplified to
\[
\hat{Q}_k = K_k \hat{C}_n K_k^T
\]

**SYSTEM MODEL OF THE PROPOSED WiFi-BASED MMAE ALGORITHM**

In the proposed method motion contexts are used to weigh multiple models while indoor/outdoor contexts are used to adapt the statistical information through the measurement covariance matrix or the process noise. The weighted sum of all individual estimates is used as the adaptive optimal estimate of the states. The decision procedure to identify contexts can be a soft process instead of a hard decision process, so that the decision sequence takes the values between $[0, 1]$ instead of the binary values of 0 or 1.

As the measurements evolve with time, the proposed adaptive algorithm will converge to the correct hypothesis by learning the correct filter and making its weight factors approach 1 (if the state remains unchanged for a considerable amount of time) or adapting the system model to the most recent state. The proposed algorithm has a closed loop structure and the weighted sum is exploited to provide feedback information for both Kalman filters in a recursive scheme.

An important parameter, which affects the performance of the proposed algorithm, is the probability of correct context identification (PCCI). Combining multiple identifiers can be a promising approach to improve PCCI. An algorithm based on the Dempster-Shafer Theory (DST) (Richards & Jia 2007) is proposed to fuse decision sequences of several identifiers, which may or may not use the same source of external information. The algorithm is then modified to deal with high conflict situations and correlated decisions as DST theory fails in high conflict situations and does not deal with the correlation between decision sequences (Murphy 2000, Richards & Jia 2007).

To improve the robustness of the proposed context-aware algorithm a control block based on a type 2 finite state Markov Decision Process (MDP) is implemented with regard to the reward history in which a reward is realized based on the one-step transition between identified contexts in two consecutive epochs. Here the reward is a function of adaptation rates in different modes and an optimum decision strategy (policy) is estimated so that the expected reward (performance measure) is maximized. Exploiting the reward function to determine the optimal policy is a considerable contribution, which does not appear to have been addressed in the literature for this particular problem. The transitions are controlled by both transition probabilities and reward history and a policy iteration method is used to find the optimum policy via two procedures of value-determination and policy-improvement.

It should be noted that the control block is optional and one can decide to activate or deactivate it based on the required robustness of the system and at the cost of increasing the complexity of the algorithm.

In the proposed MMAE WiFi-based algorithm a bank of Kalman filters is used to estimate the final states. Each of the Kalman filters is matched to a specific model and the final state estimation is obtained from the weighted sum based on the model probabilities and the decision sequence. The DST-based decision block effectively combines N decision sequences coming from N context identifiers using the reliability factors and the correlation coefficients. These parameters can be fed to the system as a priori known information or can be computed adaptively in an online manner. Each individual Kalman filter has an IAE structure and the external information is used as a context to adjust the adaptive parameters based on the different situations. Weighted sum of all individual estimates is used as the adaptive optimal estimate of the states. The weighting scheme is based on the posteriori probabilities for each of the hypothesis.
In the WiFi-based MMAE algorithm, the KFs other than the KF that best matches the current mode perform adaptive Q filtering so that the transitions between contexts are smoother and the algorithm can track the changes. In the soft combination the weighting block is developed to deal with abrupt changes in the decision sequences and make the weight of the best-matching KF converge to 1. In the hard combination the weights are simply binary sequence of (0,1). A block diagram of the proposed algorithm is indicated in Figure 1.

Here the bank of Kalman filter consists of two Kalman filters with random walk position and random walk velocity dynamic models given by

\[ \dot{p} = w \]  
(10)

and

\[ \dot{v} = w \]  
(11)

respectively.

![Block diagram of the proposed algorithm](image)

In each Kalman filter the prediction step computes the state vector and its covariance matrix as

\[ x_k^{\text{p}} = \Phi x_{k-1}^{\text{p}} \]

\[ P_k^{\text{p}} = \Phi P_{k-1}^{\text{p}} \Phi^T + Q \]  
(12)

where \( x_{k-1} \) and \( P_{k-1} \) are estimated based on the final estimate of the algorithm which has been fed back to each individual Kalman filter. In the update step, the updated state vector and covariance matrix are given by

\[ x_k = x_k^{\text{p}} + K_k Z \]

\[ P_k = (I - K_k H) P_k^{\text{p}} \]  
(13)

where \( K_k \) is the Kalman gain for the \( i \)-th dynamic model as

\[ K_k^i = P_k^{i,+} H^T (H P_k^{i,+} H^T + R)^{-1} \]  
(14)

For the clock bias and clock drift, the following oscillator model is used:

\[ \begin{bmatrix} cdt \\ cdt \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} cdt \\ cdt \end{bmatrix} + \begin{bmatrix} w_b \\ w_d \end{bmatrix} \]  
(15)

where \( w_b \) and \( w_d \) are process noises for the clock bias and the clock drift respectively. The spectral densities of these process noises are also respectively given as

\[ a_b = \frac{h_b}{2} c^2 \]

\[ a_d = 2\pi^2 h_d c^2 \]  
(16)

where \( h_b \) and \( h_d \) are oscillator specific parameters assumed to be

\[ h_b = 10^{-21} \text{Hz}^{-1}, h_d = 10^{-20} \text{s}^{-2}\text{Hz}^{-1} \]  
(17)

It should be noted that since a specific model is defined for the clock, this model is not modified or affected by the adaptive Kalman filtering.

In comparison to the other adaptive Kalman filtering algorithms, the proposed algorithm has a two layer adaptive scheme, which means that each of the Kalman filters performs IAE adaptive filtering itself. The indoors/outdoors context sequence is used to choose between the adaptation parameter for IAE filtering, namely the adaptation parameters changes from the covariance matrix of the observations (R) to the process noise of the system (Q), when moving from indoors to outdoors.

In indoor environments the adaptation parameter is the R matrix to adapt the covariance matrix of observations based on the quality of measurements while in outdoor environments the better choice will be to adapt the process noise of the system to deal with the mismatches between the assumed and the actual dynamic models of the system. Results showing the advantage of using this method are discussed in the next section.

**PERFORMANCE ANALYSIS OF THE PROPOSED ALGORITHM IN THE POSITION DOMAIN**

To analyze the performance of the proposed algorithm, static and kinematic WiFi and GPS data were collected in pedestrian mode inside and outside the McEwan Student Center at the University of Calgary. The selected location is a four story shopping center-like building with a glass ceiling. Since this research is done in the navigation solution domain, this is to make sure that some GPS position solutions exist in the indoor environment (Figure
2). The equipment used is shown in Figure 4. A Netstumbler and a wireless D-Link card were used to collect WiFi RSS values. A UBlx receiver was used for GPS data collection. A NovAtel Span-LCI system was to collect IMU data and create GPS/INS reference trajectory shown in Figures 2 and 3 in blue.

![Figure 2: Data trajectories (blue line indicates the reference trajectory, red line indicates UBlx trajectory, blue crosses show the static points)](image)

![Figure 4: Data collection equipment](image)

![Figure 3: Reference trajectory in local level coordinates](image)

The reference trajectory is plotted versus time in the north and east direction in Figure 5. The trajectory begins and ends with figure-eights to allow for INS calibration and fine alignment. There were several turns along the data collection trajectory that affect the performance of the algorithm in those epochs since the random walk acceleration and constant velocity model is used. The figure-eights and turns are highlighted in Figure 5. The correct contexts as a function of time are shown Figure 6.

![Figure 5: Data collection trajectory in north and east direction versus time; the turn is shown in the right hand upper picture](image)
To analyze the performance of the algorithm, first the algorithm is compared to conventional non-adaptive Kalman filtering with a kinematic dynamic model. Position errors for both are shown in Figure 7.

There are larger improvements with the right choice of the model in the static indoors case since the proposed method uses both the adaptation of covariance matrix of the observations and the right dynamic model. The figure-eight motion is better matched to the static model with a larger process noise as opposed to the kinematic model.

During turns, the proposed algorithm shows position improvements but these are not as large as for the rest of the test. This can be explained by the fact that the dynamic model used in the algorithm (constant velocity model) is not the best model fit for the turns.

In Figure 8, the proposed algorithm performance is compared to that of the innovation-based estimator kinematic Kalman filter with observation covariance matrix adaptation. Since in the proposed algorithm both the dynamic model and the adaptation parameter are sensitive to the context, the WiFi-based MMAE algorithm outperforms the conventional adaptive Kalman filtering. The results show that the WiFi-based MMAE algorithm improves the position errors by correctly switching between multiple models (as in static indoors). In kinematic outdoors the model is right for IAE KF but the adapting parameter (R) cannot improve the performance.

Also note that in kinematic indoors the performance of the two algorithms is very similar, since both methods use the same dynamic model and also the same adaptation parameter (observation covariance matrix).
To show how switching the adaptation parameters based on external information will improve the positioning performance of the adaptive Kalman filtering, the performance of the proposed algorithm is compared in Figure 9 to the performance of the multiple model adaptive-R Kalman filter where the dynamic model is switched (weighted) as in the proposed algorithm but the difference is that individual Kalman filters perform adaptive R IAE Kalman filtering. In this case multiple-model Kalman filtering is used and each individual Kalman filter adapts its R matrix. Comparison with adaptive-R multiple-model KF shows that performances are very similar for the kinematic motion in indoor environment. This is because both the algorithms use the same model and the same covariance matrix adaptation. However, the modification to the proposed algorithm which allows the non-matching IAE Kalman filters to adapt their Q-matrices shows considerable improvements in indoor environments, while both algorithms use correct dynamic model and the same adaptation parameter.

**CONTEXT IDENTIFICATION BASED ON WiFi DATA**

Now that it has been shown that knowing the context is useful, the next question is how accurately can the context be determined based on Wi-Fi RSSI measurements.

Simple tests have been implemented to identify contexts based on extracted features from Wi-Fi data. It is of great importance that the tests are designed to effectively distinguish between different modes (indoors/outdoors, static/kinematic) while at the same time they are kept fairly simple to implement.

**Identification of Static and Kinematic Context using Wi-Fi RSSI Observations**

It can be observed that the features (for instance mean and standard deviation of total SNR received) remain approximately constant during the times when the user is static. So in the case of identifying static/kinematic contexts one simple test can be implemented by comparing the feature changes within sliding windows. The window length should be chosen as the smallest value through which the changes are observable. The length of sliding window represents the time within which we can distinguish between switching contexts (static/kinematic). A simple WiFi static/kinematic identifier has been implemented based on the standard deviation of average SNRs within sliding windows of length N epochs as in

\[
\text{std} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2}
\]  

(18)

where \(x\) is the vector of observations within a window of length N. For static mode it can be assumed that

\[
\alpha = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (x_i - \bar{x})^2} = \text{Const.}
\]

(19)

So that one has

\[
\text{std} = \alpha \sqrt{\frac{1}{N}}.
\]

(20)

Setting the threshold requires values associated values with the expected observation standard deviation variations (\(\alpha\)) while static and also the length of the sliding window. For a constant value of \(\alpha\), the higher the window length, the lower the threshold since in this case smaller standard deviation values are expected. By computing the threshold assuming 1.5 dB variations in the standard deviation of the average SNRs within sliding windows of length 10 seconds for indoor environments, the decision threshold will be set to 0.5 dB as it can be seen in Figure 10. To avoid complexity, the threshold is set based on the available datasets collected for this research. The allowed variation is set based on the average value of standard deviations observed for the few datasets. The sequence of contexts achieved is plotted in Figure 11. Note that at the end of the data collection the Netstumbler and SPAN-LCI system were turned off while the UBlox was still collecting GPS data. So the data lengths are not exactly the same for all data types. The end epochs are considered Static/Outdoor mode for all data types. Using the appropriate threshold gives a decision sequence that is in high agreement with the sequence of correct contexts.
The two other criteria used in this paper are based on the moving average of the highest SNRs received within a window length of N and the standard deviation of the total SNR received. These were chosen since the average and standard deviation of the received SNR are expected to be of higher values in indoor environments.

In the first method an equal weight moving average with a specific window length is applied to the vector of 10 highest SNRs observed. So by appropriately setting the thresholds it is expected that we can distinguish between indoors/outdoors contexts using these criteria. Examples are shown in Figures 13 and 14.

One possible way to determine the threshold offline in a simple and reasonable way in this case is to set the decision threshold based on one set of training data or using a priori knowledge and modeling to obtain the expected values required:

$$\text{Decision threshold} = \frac{\text{Average Static SNR Indoors} + \text{Average Static SNR Outdoors}}{2}$$

Then the decision threshold can be applied to other datasets to identify context. Using this method the decision sequences obtained from Wi-Fi data are plotted in Figure 15.
The two first decision sequences appear to be correlated since the two identifiers both use received SNR. There are some disagreements in the decision sequences obtained from the different context identifiers.

Also note that as expected, the indoor/outdoor decision sequences have difficulty distinguishing between indoors and outdoors when the user is very close to a building as shown in Figure 16.

The position domain results presented earlier were assuming the correct sequence of contexts, so a very important factor which affects the performance of the algorithm is the probability of the correct identification and how well one can determine and distinguish different modes. The combination of the context identifiers can result in more reliable decisions under different situations. More reliable decisions result in the improvement of system performance.

To combine the different decision sequences in an effective and reasonable manner, the DST-based decision fusion is proposed. Dempster-Shafer theory is a generalization of the Bayesian theory in which instead of requiring probabilities for each decision, belief functions are used to combine the decision sequences.

A function \( bel : 2^\Omega \rightarrow [0,1] \) is a belief function iff with (Murphy 2000, Richards & Jia 2007)

\[
\begin{align*}
(B_1) & \quad bel(\emptyset) = 0 \\
(B_2) & \quad bel(\Omega) = 1 \\
(B_3) & \quad \text{for all } A_1, \ldots, A_n \subseteq \Omega,
\quad bel(A_1 \cup \ldots \cup A_n) \geq \sum_{I \subseteq \{1, \ldots, n\}} (-1)^{|I|+1} bel\left( \bigcap_{i \in I} A_i \right)
\end{align*}
\]

(21)
The idea is to obtain degrees of belief for one decision from subjective probabilities for a related question and then use Dempster's rule for combining these degrees of belief. This is a generalization of Baysian theory to deal with uncertainties.

A function $m : 2^\Omega \rightarrow [0,1]$ is a mass function iff (Murphy 2000, Richards & Jia 2007)

$$(M_1) \ m(\emptyset) = 0$$

$$(M_2) \sum_{A \subset \Omega} m(A) = 1$$

and can be written as

$$\text{bel}(A) = \sum_{B \supseteq A} m(B)$$

Dempster combination rule states that if $m_1$ and $m_2$ are mass functions their combination is denoted as $m_1 \oplus m_2(A)$ and one has

$$m_1 \oplus m_2 \oplus \ldots \oplus m_n(A) = c \sum_{Q_1 \cap Q_2 \cap \ldots \cap Q_n = 0} \prod_{i=1}^{N} m_i(Q_n)$$

where $c$ is a normalizing constant. The normalization constant is necessary to account for “leaks” as described below:

Sometimes $B \cap C = \emptyset$, but $m_1(B)m_2(C) > 0$, regarding the fact that (M1) should be satisfied so one has

$$c = (1 - \sum_{Q_i \cap Q_j = 0} \prod_{i=1}^{N} m_i(Q_n))^{-1}$$

It can be shown that this theory fails under high conflicts and does not take into account the correlations between the decisions. Hence a modified DST is used herein by introducing reliability factors and correlation coefficients to the algorithm. To deal with the correlative decisions, correlation coefficients $\rho$ are introduced to the basic formula as follows:

$$m_1 \oplus m_2 \oplus \ldots \oplus m_n(A) = c \sum_{Q_i \cap Q_j = 0} \prod_{i=1}^{N}(1 - \rho_{i,j})m_i(Q_n)$$

For simplicity the correlation coefficients are assumed to be known parameters in advance which is not an unrealistic assumption since the information of criteria used to design different identifiers are supposed to be available, which is the case in this research.

For combining two identifiers $m_1 \oplus m_2 \oplus \ldots \oplus m_n(A)$ simplifies to

$$m_i \oplus m_j(A) = \frac{1 - (1 - \alpha m_i(A))(1 - \alpha m_j(A))}{\beta}$$

where one has

$$\alpha = \text{mass factor} = \frac{1 - \rho_{i,j}}{1 - \rho_{i,j}/2}$$

and beta can be considered as a sample space contraction as in

$$\beta = \text{sample space contraction} = \frac{(1 - \rho_{i,j}/2)^2}{1 - \rho_{i,j}}$$

In addition, under conflict conditions, the DST theory fails. To deal with this problem it is proposed to introduce reliability factors to the combination algorithm and associate reliability factors $r_i$ to different context-identifiers. The reliability coefficients can be treated as a priori known information or can be determined adaptively in an online manner (as an example the MDP-based control block can be used to determine the reliability coefficient of the context identifiers based on the amount of correction implied in the decision sequences):
that in incorrectly identified contexts the effect of higher number of identifiers selecting the incorrect mode is reduced. In other words, the agreements between three sequences will be highlighted while in disagreements the weights are more fairly and reasonably distributed in comparison to the regular DST.

The correlation coefficient of the two correlated decision sequences is assumed to be 0.8 in this case. Using the achieved sequences from two decision blocks (regular and modified DST) as shown in Figure 17, the performances of the WiFi-based MMAE algorithm in the positioning domain using two methods for combining the decision sequences are compared in Figure 18. The use of the modified DST algorithm improves the performance of the proposed algorithm in terms of position error.

A Markov Decision Processes (MDP) consists of a state space $X$ and an action space $A$, at time epoch $t$, the state is denoted as $x_t$ and the action is $a_t$. The average reward function is explained as a function of the action sequence at specific states (Cao & Guo 2007). Here the reward function is defined for one-step transition between states as

$$
E[g(i, X_{n+1})|X_n=i] = \sum_{j \in g_i} g(i, j)p(i,j)
$$

where $g(i, j)$ is a one step transition gain and $p(i, j)$ a one-step transition probability. An optimum decision strategy (policy) is estimated so that the expected reward (performance measure) is maximized.

The transitions are controlled by both transition probabilities and reward history and a policy iteration method is used to find the optimum policy via two procedures of value-determination where a value is achieved for the vector of next period expected gains using the transition matrix. Then the policy is improved so that the maximum gain is achieved (Courcoubetis & Yannakakis 1998).

The reward function is defined herein based on the ratio of the amount of adaptation (trace of the process noise matrix) of two different models (kinematic Q adaptation to static Q adaptation ratio) as in Figure 21. In other words the information that is used from the individual Kalman filters is how well the dynamic models fit to the actual mode of the system. A lower amount of adaptation example could be in places where no or a very poor WiFi coverage is available). Also the control block can be used to determine the reliability coefficient of the context identifiers based on the amount of correction applied to the decision sequences.

**MDP CONTROL BLOCK**

The control block is an optional block and can be added when higher robustness is required. Until now, the decision sequence has only been a function of the external WiFi observations. The purpose of the control block is to allow the navigation KF estimates to influence the decision sequence.

Control block is based on the type 2 finite-state Markov Decision Process (MDP) and has been implemented with regard to the reward history in which a reward is realized based on the one-step transition between identified contexts in two consecutive epochs. The reward function can be determined based on the output of the individual Kalman Filters to modify the final decision sequence and the model probabilities. The use of the control block increases system robustness and reduces the sensitivity to false identifications in case of high uncertainties (an
in one dynamic model compared to the other dynamic model could be considered as a criterion to conclude that the model is better fitting to the actual mode.

The performance of the MDP control block can be demonstrated in terms of the amount of correction it implies for the incorrect sequence. Two cases are considered: one is how the MDP block corrects a totally incorrect sequence where all the states are identified to be kinematic. This can be the case where the WiFi context identified totally fails (e.g. there is no WiFi coverage) and the decision sequence is totally corrupted. The other case is the performance of the MDP control block with the collected real data, for this case the threshold of the WiFi identifier is chosen in a way that it shows a larger difference from the correct sequence. Considerable improvements are achieved in both cases as shown in Figures 22 and 24. The improved context identification also aids positioning performance as shown in Figures 23 and 25.

![Figure 20: MDP corrected decision sequence for a totally corrupted sequence; a 29% match sequence is corrected to a 86% match sequence which means having about 66% improvements.](image)

![Figure 21: Performance analysis of proposed algorithm using the MDP control block and with a totally corrupted sequence](image)

![Figure 22: MDP corrected decision sequence for a WiFi sequence based on inappropriate threshold; a 87% match sequence is corrected to a 94% match sequence which means having about 49.8% improvements.](image)
PROPOSED ALGORITHM WITH CONSTRAINED SINGLE MODEL KALMAN FILTER

It is also possible to replace the bank of Kalman filters in the proposed algorithm with a single kinematic Kalman filter and a velocity constraint that is activated by the static/kinematic decision sequence. The zero velocity constraint consists of additional velocity observations in each direction with variance of 0.001 (m/s)^2.

The performance of this approach is compared with the MMAE algorithm in Figure 26. The two methods perform similarly. However the multiple-model outperforms the constraint method, particularly in the vertical direction. This can be explained by the fact that turning on the constraint may result in locking the position error into the system, which could be moderated by improving the weight associated with the constraints. This requires further investigation.

CONCLUSIONS AND FUTURE WORK

This paper presented a method for exploiting WiFi signals indirectly as a source of external information in a context-aware framework to improve the GPS navigation solution. A WiFi-based multiple model adaptive algorithm was proposed. The algorithm was implemented and tested through field testing and results demonstrate considerable improvements in terms of positioning error. The proposed algorithm outperforms conventional Kalman filtering and IAE Kalman filtering. A decision fusion block was developed based on the modified Dempster-Shafer theory for effective combination of different context identifiers to improve the probability of correct context identification.

The modified method DST method permits effective combination of different context identifier to improve the reliability even under high correlation and high conflicts. A control block based on a Markov Decision Process was shown to improve the robustness of the algorithm under the condition of unreliable decision sequences.

In future, threshold setting algorithms should be added to the context identification system based on mathematical modeling of the WiFi signal features. Also the bank of Kalman filters could be modified to include a wider range of motions along the trajectory. Furthermore the identified contexts could be used to aid the GPS acquisition and tracking stages, in addition to the navigation solution.

REFERENCES


