Improved wireless tracking for indoor sports

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Received 16 March 2011; revised 29 April 2011; accepted 30 April 2011

Abstract

Wireless tracking technology is being used in a wide range of applications including performance analysis of athletes. While GPS is commonly used in outdoor environments, there are no widely deployed solutions for indoor environments to date. Indoor sports venues are often fabricated using metal structures and cladding which create difficult radio propagation environments for localization. In this paper we present a new algorithm based on measurement of time of arrival with greatly reduced susceptibility to multipath interference. Data has been collected in an indoor netball court using the WASP localization system that we developed. Using this data we show that our algorithm is able to reliably and accurately track multiple players under conditions in which conventional localization algorithms fail.

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Selection and peer-review under responsibility of RMIT University

Keywords: Wireless tracking; netball; Kalman filter; localisation

1. Introduction

Wireless tracking has seen substantial advancement in technology in recent years, particularly with the global positioning system (GPS), leading to widespread use. There are a number of GPS based products that are used, for example, to determine total distance travelled and to estimate the work load and athlete fitness. The accuracy of these units is not generally sufficient for more detailed analysis of performance and strategy, and they do not operate at all in covered and indoor venues. There are a few products for indoor tracking, but none has yet achieved significant market penetration due to issues with performance and cost. In this paper we present a new algorithm that substantially improves the accuracy and performance of indoor tracking and present experimental results for trials conducted in a netball court.

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Wireless tracking in indoor venues is particularly challenging due to the complex radio propagation environment. Radio signals are used to measure the distance between tags, typically worn by athletes, and fixed nodes (called anchor nodes). Refraction and reflection of radio signals by objects in the environment, including the athletes and the building itself, result in multipath interference where nodes receive not one but many closely separated signals. In addition, the desired radio signal travelling directly between each tag and anchor is not always present in the received data due to interference and blockage. These propagation effects can lead to large errors in the computed location of mobile nodes. In this paper, we will present results that demonstrate extensive errors due to such propagation effects when using standard localization algorithms in a netball court, and present results from our new algorithm that almost completely eliminate these errors. The data was collected using our localization system, called WASP (Wireless Ad-hoc System for Positioning) which is described in the next section.

2. WASP System Overview

The WASP platform was developed for accurate localization and high-rate data communications using low-cost hardware in difficult radio propagation environments (e.g., strong multipath interference), and to be suitable for rapid deployment in unknown environments. These challenging requirements make the system well suited to applications including tracking first responders in indoor environments, improving safety and production monitoring in underground mines, and tracking athletes in indoor venues. Designing algorithms and low-cost hardware for accurate tracking have been the key challenge in implementing the WASP system. The hardware has been previously described in [1] and the algorithms for super-resolution measurement of the time of arrival (TOA) and measurement of range were presented in [2] and [3] respectively. This section provides a brief overview.

WASP deployments consist of a number of WASP nodes forming a network, the topology of which depends upon the application. In general, the nodes form a wireless sensor network. Geo-location of mobile nodes requires that several nodes in the network, called anchor nodes, are at known locations. Only relative coordinates are required, and how these are determined is application-dependent and may include conventional survey techniques and use of building plans.

Accurate tracking in unknown environments requires that TOA-based localization is used [1]. To maximize tracking accuracy, we have used the entire 125 MHz bandwidth available in the 5.8 GHz frequency band allocated for industrial, scientific, and medical (ISM) purposes. The accuracy that we have achieved depends upon the venue, varying from a quarter of a metre in indoor sporting venues to a couple of metres when operating through multiple walls of solid construction materials. The network stack was custom designed to support our system requirements. The physical layer uses orthogonal frequency division multiplexing (OFDM), similar to the 802.11a/g wireless network standards, with data rates of 4 Mbps and 8 Mbps (binary and quadrature phase shift keying respectively). The wireless medium access controller (MAC) uses a time division multiple access (TDMA) protocol with distributed allocation of slots for beacons and data. The stack supports multiple network layers, with flooding being used for mission critical data.

There are several processing stages used by the system. Each node transmits a periodic beacon, and all nodes receiving the beacon use a super-resolution algorithm to determine the TOA with high accuracy (better than one nanosecond in indoor sporting environments). Through the exchange of transmit and receive time between nodes, the range between nodes is determined, correcting for time and frequency offsets, node motion and variable signal propagation delay in the electronics. The location of the mobile nodes is computed using multi-lateration and a tracking filter reduces noise and provides velocity estimates. The system provides a tradeoff between the maximum number of tags simultaneously tracked and the update rate of each tag. The maximum update rate is 200 Hz.
Two versions of the WASP hardware have been built, and are shown in Figure 1. Both have the same radio and signal processing electronics, however the larger node ($115 \times 90 \times 55$ mm excluding external antenna) has a larger 6.5 Ahr battery for longer life and greater connectivity options, while the small node ($90 \times 50 \times 25$ mm) has a 1.9 Ahr battery and a compact internal patch antenna. The radio operates in the 5.8 GHz ISM band with a transmit power of up to 100 mW and the receiver has a noise figure of 5 dB. Digital processing is performed using both an FPGA for low level processing and a DSP for high level processing.

3. Conventional Localization Algorithm

This section outlines a conventional iterative localization algorithm to provide the basis for the presentation of the improved algorithm described in the next section. The localization algorithm uses a linear least-squares approximation to initialize a non-linear least-squares method based on a Taylor expansion [4,5,6].

For simplicity assume that there is a single mobile node

$$\mathbf{x}_m = [x_m, y_m, z_m]$$

and that there are $N$ anchor nodes ($i = 1$ to $N$)

$$\mathbf{x}_i = [x_i, y_i, z_i]$$

Denote the true range between the mobile node and anchor node $i$ by $r_i$ and the measured range by $\tilde{r}_i$ which is degraded by noise. Denote the vectors of all such values by $\mathbf{r}$ and $\tilde{\mathbf{r}}$ respectively. Define the following function

$$f_i(\mathbf{x}) = \sqrt{(x-x_i)^2 + (y-y_i)^2 + (z-z_i)^2}$$

and $\mathbf{f}(\mathbf{x})$ is the vector of all $f_i(\mathbf{x})$. The estimated location of the mobile node is determined as

$$\hat{\mathbf{x}}_m = \arg \min_{\mathbf{x}} \|\mathbf{f}(\mathbf{x}) - \tilde{\mathbf{r}}\|^2.$$
This optimization is non-linear, and the usual approach is based on a Taylor expansion of the equation [4]. This non-linear optimization requires an initial estimate of location which is the previous or predicted location when available. If this is not available then a linear algorithm provides a non-optimal initial solution. The non-linear algorithm is detailed in [6] and the key equations are repeated below.

To calculate a sub-optimal linear solution we start with the true range given by \( r_i = (x_m - x_i)^2 + (y_m - y_i)^2 + (z_m - z_i)^2 \), and subtract a reference equation from the other equations. The result is a (usually overdetermined) set of linear equations than can be solved using the Moore-Penrose inverse for the mobile location. This is used to initialize the non-linear algorithm.

The non-linear algorithm takes an initial estimate \( x_0 \) and computes an updated estimate of location according to

\[
\hat{x}_m = (H^T H)^{-1} H^T (\vec{r} - f(x_0)) + x_0
\]

\[
h_i = \begin{bmatrix}
\frac{\partial f_i}{\partial x} & \frac{\partial f_i}{\partial y} & \frac{\partial f_i}{\partial z}
\end{bmatrix} = \begin{bmatrix}
x - x_i & y - y_i & z - z_i
\end{bmatrix}
\]

where \( H \) is the matrix with rows \( h_i \). This updated value for the location of the mobile node becomes the initial estimate for the next iteration. Generally less than five iterations are required for the algorithm to converge to within a millimeter of the final solution.

4. Problem with Conventional Localization

The image in Figure 2 shows the computed location of mobile WASP nodes in a netball court. The true motion was an approximately square walk, but serious errors are evident in the figure. A problem in indoor environments is that blockage of radio signals, particularly by players, can cause the radio signal that would travel directly between a mobile node and anchor to be blocked, while a reflected signal that is not blocked is received with an incorrect and larger range being recorded. When this happens for many nodes even the robust localization algorithm [6] that attempts to find outliers fails, resulting in the localization errors seen in the figure. In the next section an improved algorithm is presented that can successfully track the players under these conditions.
5. Improved Algorithm

The basis of the improved algorithm is to implement a tracking algorithm which takes into account temporal as well as spatial information, and based on this form a prediction of the location of the mobile nodes. The range measurements from the anchor nodes to each mobile node are gated, if they are not consistent with the predicted location of the mobile to within a threshold they are discarded as non line of sight (NLoS) measurements. Once these are discarded the location of the node is computed using the remaining range values, and the computed location forms an input to the tracking filter to calculate a filtered location and prediction for the next location. This is now described in more detail.

The algorithm uses a Kalman filter with a nearly constant velocity motion model. The state vector \( \mathbf{x}_k \) contains the estimated location and velocity of a mobile at each discrete time (corresponding to a sampling interval for the system). The state transition equation is

\[
\mathbf{x}_k = F_k \mathbf{x}_{k-1} + \mathbf{v}_k
\]

where \( F_k \) is the state transition matrix and \( \mathbf{v}_k \) is the model dependent process noise, \( T_k \) is the time between successive sampling intervals \( k-1 \) and \( k \), and \( I_D \) is a \( D \)-dimensional identity matrix, and \( D \) is the dimension of the space where tracking is performed, i.e., \( D \) is either two or three. The process noise \( \mathbf{v}_k \) is assumed to be a zero mean white Gaussian sequence, with covariance matrix \( Q_k \) given by

\[
Q_k = q_k^2 \begin{pmatrix} T_k^3 / 3 & T_k^2 / 2 \\ T_k^2 / 2 & T_k \end{pmatrix} \otimes I_D
\]

where \( q_k \) is the process noise intensity. The measurement model is given by

\[
\mathbf{z}_k = H \mathbf{x}_k + \mathbf{\omega}_k
\]

where \( \mathbf{z}_k \) is the vector of range measurements obtained at all the anchors and \( H \) is the measurement function which is simply extracts the location from the state vector. The covariance of the measurement noise \( \mathbf{\omega}_k \) can be determined experimentally.

There is a Kalman filter for each mobile node, and for each new position measurement the Kalman filter is updated. The predicted location for the next measurement is given by Eq. (7). The range from this predicted location to each anchor node is computed, and range measurements that differ by this by more than a fixed threshold are rejected. If the location cannot be computed (due to insufficient range measurements) prediction is only applied for a few intervals, after which the track is reinitialized.

6. Results and Conclusion

Processing the same data as used to produce Figure 2 with the new algorithm results in the plots in Figure 3. It is seen that the algorithm has successfully removed the artifacts, and the number of samples at which location could not be computed has reduced from 40% to 2.5%. Figure 4 shows the tracks of the players from a few seconds of a netball game. The improvement in quality using the proposed algorithm is evident.

These results demonstrate a significant improvement in our ability to track players in environments with severe multipath reflections, particularly from the use of metal cladding in the venue.
Figure 3: Computed location of walk around netball court using gated localisation without (left) and with (right) filtering.

Figure 4: Computed location of players for a few seconds in a netball game with ungated (left) and gated (right) algorithms.

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