International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

Wireless Ranging Performance Improvement Technique

Neethu Verjisen[1], Ajily Rachel Varghese[2]

[1, 2]Mount Zion College of Engineering, Kadamanitta, Pathanathitta (Dst:),Kerala, India

Abstract: ***In the last few years many research efforts have been focused on various wireless measurement techniques for indoor object positioning. In this paper we focuses on the performance improvement of the classical wireless ranging techniques such as RSS approach and ToF approach. The novelty of the proposed method is a data fusion algorithm which combines the data obtained through the RSS approach and ToF approach with the aid of a kalman filter. The advantage of this proposed algorithm is that it provides great improvement in wireless ranging. The algorithm has been implemented and simulated to check the performance of the proposed system. The result obtained shows that there is typical improvement in the ranging accuracy and the combination of these two classical approach can significantly reduce the measurement uncertainity***

Keywords: ranging measurement ,kalmanfiltering, ToF and RSS approach, timestamping

1. Introduction

In the last few years many research efforts have been focused on various wireless measurement techniques for indoor object positioning. The dynamic and unpredictable characteristics of wireless channels in harsh environments have resulted in a poor performance of localization systems. unfortunately most of the existing solution are restricted by line of sight, since they work only in a specified direction. There are various methods relying on different sensing technologies for indoor object positioning have been proposed such as laser range finders, ultrasonic devices, infrared devices, inertial platforms etc. But most of these systems are subjected to directional constraints, high power consumption and computational burden. In order to achieve a good trade-off between accuracy, range and omnidirectionality, various radio techniques have been used for distance measurements. The two most common approaches are based on received signal strength (RSS) and on packet time of flight (ToF) measurements. The RSS based method relies on the relationship between received signal strength and transmitter .The received signal strength is easier to measure because most of the integrated wireless chips are equipped with RSS indicator. The main drawback of RSS approach is they are sensitive to multipath and shadowing phenomenon. Multipath propagation disturbs the ideal relationship between RSS values and distance. Thus the uncertainty in the measurement increases with distance. The ToF method measure the propagation time of a packet. There are two types of ToF approach, they are time of arrival (ToA) and round trip time (RTT) approach. The TOA approach requires synchronization because of the propagation time of the packet is measured at different device. When we are considering the case of RTT the propagation time of the packet is measured at same device hence synchronization is not required. The main drawback of RTT based approach is that they are subjected to latency constraints. So if we are considering the each approach alone they have some performance limitation that is RSS based ranging is more preferable around reference distance and RTT based ranging approach is more promising over a longer range. Therefore combining both approaches is a good strategy to improve wireless ranging. This can be achieved with a data fusion algorithm. The fusion of data is achieved with the aid of two kalman filters. The performance of this system is evaluated and found that this method provides a greater performance improvement.

2. Wireless Ranging Technique

2.1 RSS Approach

In the RSS based approach the distance between transmitter and receiver are can be estimated using the following equation

$$d_R(t) = d_0 . 10^{\frac{s_0 - s(t)}{10.\alpha}} \quad (1)$$

where **s**(t) is a random variable describing the power (typically expressed in dBm) associated with a packet received by a given node at time t, s_0 is the random variable modeling the RSS at a reference distance, and **α** is the path loss coefficient for the considered environment. But when we are using (1) for calculating the distance measurement there are various uncertainty contributions and this may result in variations from the actual measurement. The worst case uncertainty is given by

$$u(d_R(t)) = \frac{d_0 10^{\left(\frac{|\hat{s}_0 - \hat{s}(t)|}{10.\hat{\alpha}}\right)}}{\hat{\alpha}} . [u(s_0) + u(s(t)) + \frac{|\hat{s}_0 - \hat{s}(t)|}{\hat{\alpha}} u(\alpha)] \quad (2)$$

where u(s(t)), u(s0), and u(α) are the standard uncertainties associated with the individual input quantities, whereas $\hat{s}_0$, $\hat{s}(t)$, and $\hat{\alpha}$ are the corresponding values measured at time t. But, an uncertainty stochastic model for the RSS is difficult to obtain, and many researches are going on in this area.

2.2ToF approach

Among the two alternatives in ToF approach we consider the case of RTT since it has the advantage that synchronization between the transmitter and the receiver is not required. In principle the distance between transmitter and receiver is obtained using the following expression

$$d_T(t) = \frac{c}{2}[\tau(t) - o_\tau(t)] \quad (3)$$

Where τ (t) is a random variable modeling the total RTT, is the speed of light, and $o_\tau(t)$ is the random temporal overhead. The equation (3) provides good only if the node the node distance variation during the whole RTT is negligible $o_\tau(t)$ is approximately constant. The random fluctuations associated with τ (t) and $o_\tau(t)$ results in uncertainty and the worst case uncertainty is given by

$$u(d_T(t)) = \frac{c}{2}[u(\tau(t)) + u(o_\tau(t))] \quad (4)$$

where u(τ (t)) and u((t)) are the standard uncertainty and they are assumed to be stationary and perfectly correlated. The uncertainty mainly depends on timestamping jitter at the transmitter and the receiver. If we are considering the case that the packet is collected as soon as the first symbol is correctly detected the impact of ToF uncertainty on ranging uncertainty tends to decrease as the distance between the transmitter and the receiver increases.

3. Data Combining Algorithm

On analyzing the RSS and ToF approach the RSS approach is more preferable over short range and ToF method is promising over longer range.So by fusing the data obtained through these classical approach provides a significant improvement in performance and reduces uncertainty in the distance estimation. The nodes must be continuously monitored to track object. The proposed system mainly consist of two steps such as signal processing and estimation process A visual interpretation is as shown in figure (1)

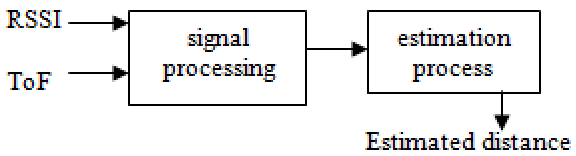

Figure 1: Visual interpretation of data combining algorithm

In the signal processing step, an essential preliminary step is data filtering which improve ranging accuracy. This process also helps to remove random fluctuations and the movement that are not compatible with real target. The raw measurement result denoted as $d_R(t)$ and $d_T(t)$ contains both wideband stationary and nonstationary noise. This problem can be addressed using a series of linear filter that have a noval nonlinear heruistic technique. Here we use a moving average (MA) filter which reduces random wideband noise and it is computationally simple. So, if M consecutive measurement of RSS and ToF technique are filtered by a moning average filter , the resulting distance value is given by

$$\bar{d}_R(n) = d_0 . 10^{\frac{\bar{s}_0 - \frac{1}{M}\sum_{i=0}^{M-1}\bar{s}(n-i)}{10.\bar{\alpha}}} \quad (5)$$

$$\bar{d}_T(n) = \frac{c}{2}\left[\frac{1}{M}\sum_{i=0}^{M-1}\bar{\tau}(n-i) - \bar{o}_\tau\right] \quad (6)$$

Another uncertainty associated with measurement result are position-dependent errors which alters the measurement results. In order to overcome this problem a criterion based on human-motion is considered. In an indoor environment , the human speed is smaller than v_{max} = 2 m/s. And this criterion leads nonlinear filters defined by:

$$\hat{d}_R(n) = \begin{cases} \hat{d}_R(n-1) + v_{max}T_c & \bar{d}_R(n) - \hat{d}_R(n-1) \geq v_{max}T_c \\ \hat{d}_R(n-1) - v_{max}T_c & \bar{d}_R(n) - \hat{d}_R(n-1) \leq -v_{max}T_c \\ \bar{d}_R(n) & otherwise \end{cases} \quad (7)$$

$$\hat{d}_T(n) = \begin{cases} \hat{d}_T(n-1) + v_{max}T_c & \bar{d}_T(n) - \hat{d}_T(n-1) \geq v_{max}T_c \\ \hat{d}_T(n-1) - v_{max}T_c & \bar{d}_T(n) - \hat{d}_T(n-1) \leq -v_{max}T_c \\ \bar{d}_T(n) & otherwise \end{cases} \quad (8)$$

In order to obtain the independent speed and position data required to implement data combining via kalman filter differentiation process is done at the signal processing step. In the signal estimation process the main component is the two kalman filters. The kalman filter consist of two stages such as prediction step and estimation step. The prediction equation is given by

$$\begin{aligned} \hat{r}^*(n+1) &= \hat{r}(n) + T_c\hat{v}(n) \\ \hat{d}^*(n+1) &= \hat{r}^*(n+1) \\ \sigma_r^{*2}(n+1) &= \sigma_r^2(n) + T_c^2\sigma_v^2(n) \end{aligned} \quad (9)$$

The update step is given by

$$\begin{aligned} \hat{r}(n+1) &= \hat{r}^*(n+1) + K(n+1)[\hat{d}(n+1) - \hat{d}^*(n+1)] \\ \sigma_r^2(n+1) &= [1 - \sigma_r^{*2}(n+1)]K(n+1) \end{aligned} \quad (10)$$

where K(n+1) is the kalman gain.

The measurement result is applied to the kalman filter .In principle one of the two kalman filers should be used. However, both of them are suboptimal since the distribution of the uncertainty contributions is unknown and nonstationary both in time and in space. As a consequence, the most sensible approach is to run both KFs in parallel and then to weigh $\hat{r}_A(n)$ and $\hat{r}_B(n)$ using the reciprocal values of the respective variances. As a result, the measured distance is finally given by

$$\hat{r}(n) = \frac{\sigma_{r_B}^2(n)\hat{r}_A(n) + \sigma_{r_A}^2(n)\hat{r}_B(n)}{\sigma_{r_B}^2(n) + \sigma_{r_A}^2(n)} \quad (11)$$

A kalman smoother is utilized to further improve the output from the kalman filter. Entire process is illustrated as shown in fig.2.

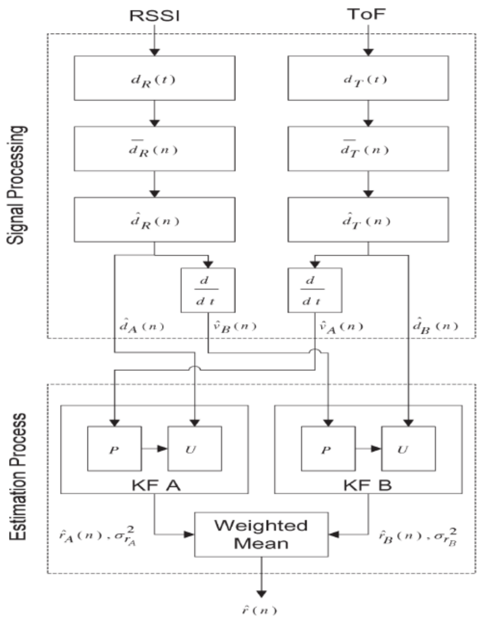

Figure 2: Block diagram of the distance estimation algorithm based on RSS and ToF data fusion.

Experimental Result

Here the simulation is done using matlab software. The simulation is done by taking the reference distance approximately equal to one. The stability and the effect of uncertainty on measurement result were analyzed on the basis of different fixed distance between the nodes. The analysis of the proposed system by considering each kalman filter alone and running them in parallel is analyzed. It is found that the usage of two kalman filter provides better performance. From the simulation it is found that the uncertainty associated with the distance estimation is found to be 1m. But, it may sometimes measure 2 m. Thus, we can say that the worst case uncertainty increases with distance , but it is smaller in the shorter distance, which is as shown in fig.3.

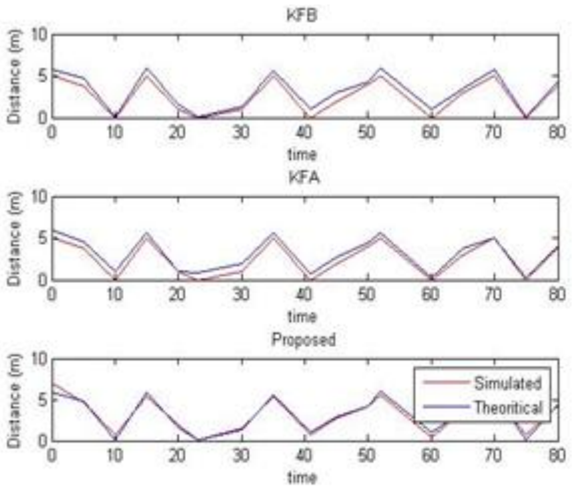

Figure 3: Measurement results obtained with the (a) KF B only, with the (b) KF A only, and with the (c) both KF A and KFB

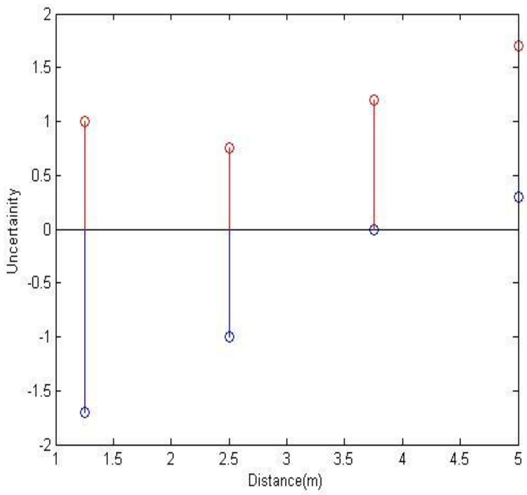

Figure 4: Plot of uncertainty as a function of distance.

One of the common issue RF wireless ranging technique is that the uncertainty may grow two to three times in real situations. One solution to this problem is to choose the position of the nodes in such a way to maximize the reciprocal visibility between nodes.

3. Conclusion

This paper deals with a data combining algorithm fusing RSS and ToF measurement results in order to improve the accuracy in measurement result and to reduce the measurement uncertainty. The proposed system is simulated using matlab and to provide a better result than the classical wireless ranging techniques. Also this method is computationally simple, thus it can be implemented in future transceiver chips. Further improvement can be achieved by improving the accuracy in timestamping This can be achieved by using an interpolator at the output of the moving average filter.

Acknowledgment

We would like to express profound gratitude to our Head of the Department, Prof.Rangit Varghese, for his encouragement and for providing all facilities for our work. Also, we express our highest regard and sincere thanks to our guide, Asst.Prof. Ann Susan Varghese, who provided the necessary guidance and serious advice for our work.

References

[1] L. Angrisani, A. Baccigalupi, and R. Schiano Lo Moriello, “Ultrasonictime-of-flight estimation through unscented Kalman filter,” *IEEE TransInstrum. Meas.*, vol. 55, no. 4, pp. 1077–1084, Aug. 2006.

[2] B. Andó and S. Graziani, “Multisensor strategies to assist blind people:A clear-path indicator,” *IEEE Trans. Instrum. Meas.*, vol. 58, no. 8,pp. 2488–2494, Aug. 2009.

[3] B. Krach and P. Robertson, “Integration of foot-mounted inertial sensorsinto a Bayesian location estimation framework,” in *Proc. 5th WPNC*,Hannover, Germany, Mar. 2008, pp. 55–61.

[4] E. Lobaton, R. Vasudevan, R. Bajcsy, and S. Sastry, "A distributed topologicalcamera network representation for tracking applications," *IEEETrans. Image Process.*, vol. 19, no. 10, pp. 2516–2529, Oct. 2010.
[5] F. Chavand, E. Colle, Y. Chekhar, and E. C. N'zi, "3-D measurementsusing a video camera and a range finder," *IEEE Trans. Instrum. Meas.*,vol. 46, no. 6, pp. 1229–1235, Dec. 1997.
[6] P. Vadakkepat and L. Jing, "Improved particle filter in sensor fusion fortracking randomly moving object," *IEEE Trans. Instrum. Meas.*, vol. 55,no. 5, pp. 1823–1832, Oct. 2006.
[7] A. Bonarini, P. Aliverti, and M. Lucioni, "An omnidirectional visionsensor for fast tracking for mobile robots," *IEEE Trans. Instrum. Meas.*,vol. 49, no. 3, pp. 509–512, Jun. 2000.
[8] A. Fod, A. Howard, and M. A. J. Mataric, "A laser-based people tracker,"in *Proc. IEEE Int. Conf. Robot. Autom.*,May 2002, vol. 3, pp. 3024–3029.
[9] T. Pavani, G. Costa, M. Mazzotti, A. Conti, and D. Dardari, "Experimentalresults on indoor localization techniques through wireless sensors network," in *Proc. IEEE 63rd Veh. Technol. Conf.*, Melbourne, Austrialia, May 2006, vol. 2, pp. 663–667.
[10] K. Benkic, M. Malajner, P. Planinsic, and Z. Cucej, "Using RSSI value for distance estimation in wireless sensor networks based on ZigBee," in *Proc. IEEE Int. Conf. Syst., Signals Image Process.*, Jun.2008, pp. 303–306.
[11] D. Lymberopoulos, Q. Lindsey, and A. Savvides, "An empirical characterization of radio signal strength variability in 3-D IEEE 802.15.4 networksusing monopole antennas," in *Wireless Sensor Networks*. Berlin, Germany: Springer, 2006, pp. 326–341.
[12] K. Whitehouse, C. Karlof, and D. Culler, "A practical evaluation of radio signal strength for ranging-based localization," *SIGMOBILE Mob. Comput. Commun. Rev.*, vol. 11, no. 1, pp. 41–52, Jan. 2007.
[13] P. Pivato, L. Palopoli, and D. Petri, "Accuracy of RSS-based centroid localization algorithms in an indoor environment," *IEEE Trans. Instrum. Meas.*, vol. 60, no. 10, pp. 3451–3460, Oct. 2011.
[14] E. Elnahrawy, L. Xiaoyan, and R. P. Martin, "The limits of localization using signal strength: A comparative study," in *Proc. IEEE SECON*, Santa Clara, CA, Oct. 2004, pp. 406–414.
[15] A. Savvides, H. Park, and M. B. Srivastava, "The bits and flops of the n-hop multilateration primitive for node localization problems," in*Proc. ACM Int. Workshop Wireless Sens. Netw. Appl.*, Atlanta, GA, 2002, pp. 112–121.
[16] I. Guvenc and C.-C. Chong, "A survey on TOA based wireless localization and NLOS mitigation techniques," *IEEE Commun. Surveys Tuts.*, vol. 11, no. 3, pp. 107–124, Third Quarter, 2009.
[17] J. X. Lee, Z. W. Lin, P. S. Chin, and K. P. Yar, "One-way ranging time drift compensation for both synchronized and non-synchronizedclocks," in *Proc. Int. Conf. Syst. Sci. Eng.*, Taipei, Taiwan, Jul. 2010, pp. 327–331.
[18] Y. Jiang and V. Leung, "An asymmetric double sided two-way ranging for crystal offset," in *Proc. Int. Symp. Signals, Syst. Electron.*, Montreal, QC, Canada, Aug. 2007, pp. 525–528.
[19] D. Wang, R. Kannan, L. Wei, and B. Tay, "Time of flight based two way ranging for real-time locating systems," in *Proc. IEEE Conf. Robot. Autom. Mechatron.*, Singapore, Jun. 2010, pp. 199–205.
[20] M. Kwak and J. Chong, "A new double two-way ranging algorithm for ranging system," in *Proc. 2nd IEEE Int. Conf. Netw. Infrastructure Digital Content*, Beijing, China, Sep. 2010, pp. 470–473.
[21] IEEE Standard for Information Technology—Telecommunications and Information Exchange Between Systems—Local and Metropolitan Area Networks—Specific Requirement Part 15.4: Wireless Medium Access Control (MAC) and Physical Layer (PHY) Specifications for Low-Rate Wireless Personal Area Networks (WPANs), IEEE Std., 2007.

Author Profile

Neethu Verjisen received BTech degree in Electronics and Communication Engineering from Kerala university, Kerala, India. Currently She is MTech student specialising in Communication Engineering in Mahatma Gandhi university, Kerala. Her topics of interest are Wireless Communication System and Wireless Networks.

Ajily Rachel Varghese received B.E Degree in Electronics and Communication Engineering from Anna university, Tamilnadu, India. Currently is a MTech student specialising in Communication Engineering in Mahatma Gandhi university, Kerala. The topics of interest are Wireless Communication System and Wireless Networks.