Wireless Sensor Network, 2012, 4, 264-272
http://dx.doi.org/10.4236/wsn.2012.411038 Published Online November 2012 (http://www.SciRP.org/journal/wsn)

A Practical Target Tracking Technique in Sensor Network Using Clustering Algorithm

Luke K. Wang, Chien-Chang Wu
Department of Electrical Engineering, National Kaohsiung University of Applied Sciences, Kaohsiung, Chinese Taipei
Email: lwang@mail.ee.kuas.edu.tw, baseball160404@yahoo.com.tw

Received August 15, 2012; revised September 16, 2012; accepted September 27, 2012

ABSTRACT

Sensor network basically has many intrinsic limitations such as energy consumption, sensor coverage and connectivity, and sensor processing capability. Tracking a moving target in clusters of sensor network online with less complexity algorithm and computational burden is our ultimate goal. Particle filtering (PF) technique, augmenting handoff and K-means classification of measurement data, is proposed to tackle the tracking mission in a sensor network. The handoff decision, an alternative to multi-hop transmission, is implemented for switching between clusters of sensor nodes through received signal strength indication (RSSI) measurements. The measurements being used in particle filter processing are RSSI and time of arrival (TOA). While non-line-of-sight (NLOS) is the dominant bias in tracking estimation/accuracy, it can be easily resolved simply by incorporating K-means classification method in PF processing without any priori identification of LOS/NLOS. Simulation using clusters of sensor nodes in a sensor network is conducted. The dependency of tracking performance with computational cost versus number of particles used in PF processing is also investigated.

Keywords: Sensor Network; Handoff Scheme; Particle Filter; K-means Clustering; NLOS

1. Introduction

Sensor networks can be applied in a variety of areas such as target tracking, environment monitoring, military surveillance, medical applications, etc. [1,2]. However, the majority of sensor node platforms are operated using the low power 802.15.4 wireless technology, and its transmission range is extremely limited especially in an indoor environment [3]. The measurements used in the estimate of mobile locations in sensor network may include received signal strength, time difference of arrival (TDOA), time of arrival (TOA), and angle of arrival (AOA) [4]. Eventually, the above propagation measurement scenarios are divided into two categories, line-of-sight (LOS) and non-line-of-sight (NLOS). In multi-path propagation environments, particularly indoors or urban areas, the LOS path between nodes may be obstructed [5]. However, the NLOS propagation usually leads to a positive bias and causes a serious error in the results of tracking estimation [6].

Lots of attentions have been focused on the identification of LOS/NLOS condition and the mitigation of NLOS bias. A simple hypothesis test has been conducted to tell whether it's LOS or NLOS by the fact that the standard deviation of the range measurement of NLOS is presumably larger than the LOS' [6]. Using the individual measurement detection (IMD), basically a hypothesis test to identify whether an incoming measurement is LOS or NLOS and those NLOS ones being discarded, to do target tracking is proposed [7]; extended Kalman filter (EKF) algorithm is applied accordingly to do the target tracking job. The noise modeling of LOS/NLOS is formulated by a two-state Markov process, and the degree of contamination by NLOS errors is correlated with the transition probability of the Markov process. A disadvantageous effect has been indicated, the number of selected LOS measurements by IMD is different at each step, resulting in dimension validation of the reconstructed LOS measurement vector being dynamic; slow convergence rate is also appearing in the tracking results when using EKF. A modified Kalman filtering technique, adopting the modification at the measurement update stage, is introduced to tackle the NLOS identification/mitigation problem [8]. The NLOS positive bias is estimated directly throughout the constrained optimization method; no prior distribution knowledge of the NLOS error is needed, as claimed by the authors.

Our proposed tracking algorithm utilizes clusters of sensor network with handoff scheme in a heterogeneous wireless environment. A handoff scheme specified in IEEE 802.11 network is the process whereby a mobile station shifts its association from one access point (AP) to another [9]. When a mobile station moves out of the

range of an AP and into another's, the handoff occurs during which there is an exchange of management frames [10].

On the other hand, clustering analysis is the method of unsupervised learning. It may include two parts, namely, partitional clustering and hierarchical clustering. Partitional clustering is a set of objects classified into K clusters without hierarchical structure [11]. The clustering method with PF can reduce the degradation of NLOS propagation efficacy in tracking estimation results. Meanwhile, handoff scheme is applied in the clusters of sensor network. In clusters of sensor network, each cluster has numbers of sensor nodes, including TOA and RSSI sensors. **Figure 1** shows the proposed architecture that illustrates an event of target tracking in clusters of sensor network.

The general approach to processing the LOS/NLOS signals in cellular communication network is to determine whether it's a LOS or NLOS condition. Even the fuzzy inference scheme is introduced to tell whether it is LOS or NLOS before any processing jobs can be done [10]. It is combined with adaptive Kalman filter to establish mobile location estimator; undoubtedly, system and computational complexities are increasing so tremendously, hindering the potentials in real-time applications.

We present an architecture which utilizes clustering analysis method with particle filter (PF) to track a moving target. Particle filter implements sequential Monte Carlo simulation based on a set of particles to construct prior density with associated weights for the approximation of posterior density.

The beneficial features of the proposed scenario are listed as bellows,

- Intuitive but feasible for real-time applications due to its low system and computational complexity attributes

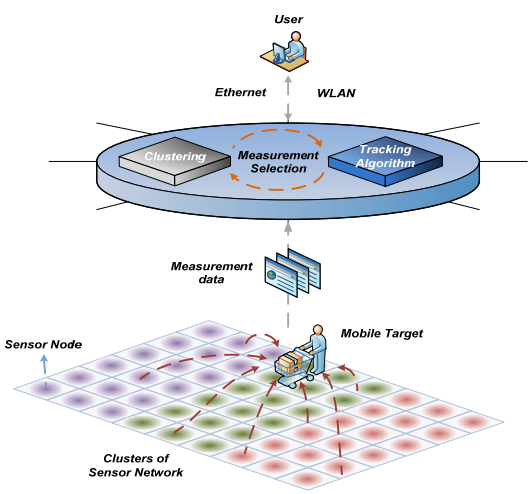


Figure 1. The proposed architecture in clusters of sensor network.

- No need to identify whether it is under LOS or NLOS condition prior to any processing of the target location estimation
- Only RSSI and TOA sensor measurements are required, practical and low-cost; fingerprinting scheme, the build-up of a "radio map" database [6], and extra hardware (sophisticated measurement devices) are not employed, always leading to a low complexity, cost-effective scenario.
- Both K-means clustering and hand-off schemes are incorporated into the particle filter, minimizing the system complexity to the most.

This analysis is set up as follows. The target's motion model and the associated measurement equation and NLOS propagation are described in Section 2. Particle filter is described in Section 3. Section 4 discusses the proposed tracking algorithm which includes the handoff scheme. The proposed tracking algorithm with clustering method is derived in Section 5. The simulation and performance analysis are presented in Section 6. Section 7 includes the conclusion.

2. Motion Models

We assume a mobile target's movement is on a two-dimensional (2-D) plane. Besides, the measurement of signal propagation with LOS/NLOS conditions may be modeled as a two-state Markov process if the performance at transient stage is under investigation.

2.1. Target Model

The moving target's state vector is defined as $\mathbf{x}_{1,k} = \left[x_k \ \dot{x}_k \ y_k \ \dot{y}_k\right]^{\mathrm{T}}$, consisting of position and velocity at a time instant k, where $()^T$ stands for transpose operation of matrix. The target's motion is modeled as

$$\mathbf{x}_{1,k} = A_1 \mathbf{x}_{1,k-1} + w_{1,k-1} \tag{1}$$

where

$$A_1 = I_2 \otimes A_s$$

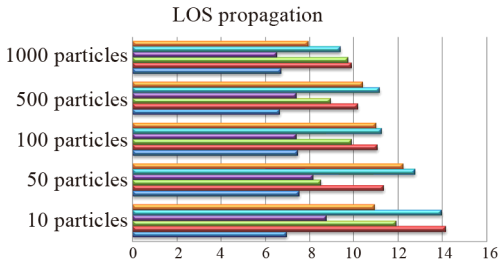
$$A_s = \begin{bmatrix} 1 & T_s \\ 0 & 1 \end{bmatrix}$$

and I_2 is the 2 × 2 identity matrix; ⊗ is the Kronecker product operator; A_1 is the state transition matrix; T_s is the sampling time; and $w_{1,k-1}$ is a zero mean white Gaussian noise process with covariance matrix Q_1, *i.e.*, $w_{1,k-1} \sim N\left(0, Q_1\right)$. The covariance matrix Q_1 is

$$Q_1 = E\left[w_{1,k} w_{1,k}^{\mathrm{T}}\right] = q_1 I_2 \otimes Q_s$$

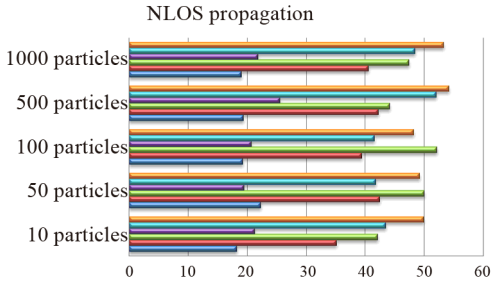
$$Q_s = \begin{bmatrix} T_s^3/3 & T_s^2/2 \\ T_s^2/2 & T_s \end{bmatrix}$$

where q_1 is a scalar which determines the intensity of the



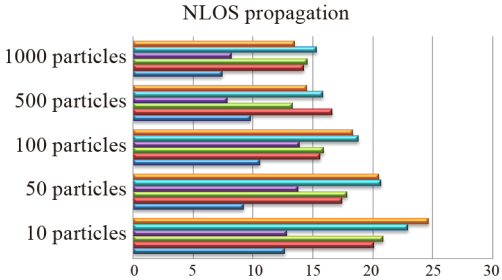
	10 particles	50 particles	100 particles	500 particles	1000 particles
x-axis position	10.9439	12.2317	11.0108	10.4087	7.9404
x-axis velocity	13.9616	12.7805	11.2445	11.1779	9.4037
x-axis acceleration	8.7646	8.1579	7.4238	7.4311	6.5316
y-axis position	11.9274	8.5246	9.9069	8.9654	9.7459
y-axis velocity	14.1546	11.3401	11.0665	10.1731	9.9087
y-axis acceleration	6.9858	7.5477	7.4651	6.6503	6.711

Figure 12. The results, estimation errors versus numbers of particles, using solely particle filtering in a surrounded LOS propagation environment.



	10 particles	50 particles	100 particles	500 particles	1000 particles
x-axis position	49.9661	49.2846	48.1913	54.1573	53.3286
x-axis velocity	43.4733	41.8349	41.5752	52.0958	48.4216
x-axis acceleration	21.3256	19.5778	20.7743	25.6271	21.9349
y-axis position	42.1214	50.0817	52.1323	44.2144	47.4691
y-axis velocity	35.2211	42.4538	39.4701	42.2123	40.5311
y-axis acceleration	18.3326	22.2981	19.3266	19.4063	19.1158

Figure 13. The results, estimation errors versus numbers of particles, using solely particle filtering in a surrounded NLOS propagation environment.



	10 particles	50 particles	100 particles	500 particles	1000 particles
x-axis position	24.6508	20.5456	18.3168	14.4855	13.4896
x-axis velocity	22.9567	20.6677	18.8074	15.8587	15.3321
x-axis acceleration	12.8406	13.8118	13.8985	7.8624	8.2434
y-axis position	20.8904	17.8349	15.9136	13.3067	14.5598
y-axis velocity	20 1223	17.4479	15.5954	16.6464	14.2717
y-axis acceleration	12.6818	9.2299	10.5755	9.823	7.4452

Figure 14. The results, estimation errors versus numbers of particles, using particle filtering with K-means clustering in a surrounded NLOS propagation environment.

As the simulation results shown from **Figure 12** to **Figure 14**, each figure is simulated with 1000 time instants, and we compute its associated estimation errors, position, velocity, and acceleration.

As position, velocity, and acceleration are estimated, not too much benefit can we expect in a LOS propagation environment when we vary the number of particles in PF processing. The number of particles we choose is 50, being attractive in real-time tracking applications. The estimation errors gradually reduce with the increaseing of particle numbers. On the contrary, situated in a NLOS environment, substantial improvement of estimation errors are illustrated in **Figure 14** with K-means clustering scenario; eventually, the trade-off among the increment of particle numbers, estimation errors, and computational load is accomplished via the use of moderate number of particle, *i.e.*, 50, and the augmentation of K-means clustering scheme in the particle filter processing job.

7. Conclusions

Sophisticated and high system/computational complexity algorithms are always proposed to mitigate the NLOS effect and estimate the mobile/target location. In this article, we propose a simple and feasible generic tracking algorithm to track the moving target in clusters of sensor network. The proposed tracking algorithm is the technique that adds handoff decision to the ordinary tracking algorithm, based on TOA and RSSI measurements; the handoff decision is implemented on clusters of sensor network.

Besides, K-means clustering is utilized, and it combines with particle filter to reduce the NLOS propagation effect. Finally, the proposed algorithm can accomplish higher accuracy in tracking estimation for sure.

Simulations illustrate that the estimation results of tracking trajectory is well predicted, even around the NLOS propagation environment. This analysis applies to any motion modes, even with varying acceleration. Moreover, we also compare the results of tracking algorithm with and without K-means clustering in statistics. Through the performance analysis, it demonstrates that the proposed tracking algorithm may find potentials in real-time tracking/localization applications as the particle numbers used are reducing to as low as 50.

8. Acknowledgements

This work was partially supported by the National Science Council of Taiwan, Republic of China under contract NSC 99-2221-E-151-022.

REFERENCES

[1] P. M. Djuric, M. Vemula and M. F. Bugallo, "Tracking

with Particle Filtering in Tertiary Wireless Sensor Networks," *IEEE International Conference on Acoustics, Speech and Signal Processing*, 18-23 March 2005, pp. 757-760. doi:10.1109/ICASSP.2005.1416119

[2] S. Maheswararajah and S. Halgamuge, "Mobile Sensor Management for Target Tracking," 2*nd International Symposium on Wireless Pervasive Computing*, San Juan, 5-7 February 2007, pp. 506-510. doi:10.1109/ISWPC.2007. 342656

[3] J. Wu, H. Xiong, J. Chen and W. Zhou, "A Generalization of Proximity Functions for K-means," 7*th IEEE International Conference on Data Mining*, Omaha, 28-31 October 2007, pp. 361-370.doi:10.1109/ICDM.2007.59

[4] J. F. Liao and B. S. Chen, "Robust Mobile Location Estimator with NLOS Mitigation Using Interacting Multiple Model Algorithm," *IEEE Transactions on Wireless Communications*, Vol. 5, No. 11, 2006, pp. 3002-3006. doi:10.1109/TWC.2006.04747

[5] S. S. Moghaddam, V. T. Vakilim and A. Falahati, "New Handoff Initiation Algorithm (Optimum Combination of Hysteresis & Threshold Based Methods)," 52*nd IEEE VTS-Fall VTC of Vehicular Technology Conference*, Vol. 4, 2000, pp. 1567-1574. doi:10.1109/AMS.2009.11

[6] C.-D. Wann, "Kalman Filtering for NLOS Mitigation and Target Tracking in Indoor Wireless Environment," In: V. Kordic, Ed., *Kalman Filter*, Intech Publication, 2010, pp. 16-33.

[7] L. Yi, S. G. Razul, Z. Lin and C.-M. See, "Target Tracking in Mixed LOS/NLOS Environments Based on Individual TOA Measurement Detection," *IEEE Sensor Array and Multichannel Signal Processing Workshop*, Jerusalem, 4-7 October 2010, pp.153-156. doi:10.1109/SAM.2010.5606720

[8] W. Kei and L. Wu, "Mobile Location with NLOS Identification and Mitigation Based on Modified Kalman Filtering," *Sensors*, Vol. 11, No. 2, 2011, pp. 1641-1656. doi:10.3390/s110201641

[9] S. Venkatesh and R. M. Buehrer, "NLOS Mitigation Using Linear Programming in Ultrawideband Location-Aware Networks," *IEEE Transactions on Vehicular Technology*, Vol. 56, No. 5, 2007, pp. 3182-3198. doi:10.1109/TVT.2007.900397

[10] J. F. Liao and B. S. Chen, "Adaptive Mobile Location Estimator with NLOS Mitigation Using Fuzzy Inference Scheme," 8*th International Symposium on Communications*, Kaohsiung, Taiwan, 2005.

[11] B. S. Gukhool and S. Cherkaoui, "Handoff in IEEE 802.11p-Based Vehicular Networks," *IFIP International Conference on Wireless and Optical Communications Networks*, Cairo, 28-30 April 2009, pp. 1-5.

[12] J. F. Liao and B. S. Chen, "Robust Mobile Location Estimator with NLOS Mitigation Using Interacting Multipke Model Algorithm," *IEEE Transactions on Wireless Communications*, Vol. 5, No. 11, 2006, pp. 3002-3006. doi:10.1109/TWC.2006.04747

[13] C. C. Tseng, K. H. Chi, M. D. Hsieh and H. H. Chang, "Location-Based Fast Handoff for 802.11 Networks," *IEEE Communications Letters*, Vol. 9, No. 4, 2005, pp. 304-306. doi:10.1109/LCOMM.2005.04010

[14] S. Arulampalam, S. Maskell, N. Gordon and T. Clapp, "A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking," *IEEE Transactions on Signal Processing*, Vol. 50, No. 2, 2002, pp. 174-188. doi:10.1109/78.978374

[15] Z. Yang and X. Wang, "Joint Mobility Tracking and Handoff in Cellular Networks via Sequential Monte Carlo Filtering," *IEEE Transactions on Signal Processing*, Vol. 51, No. 1, 2003, pp. 269-281. doi:10.1109/TSP.2002.806580

[16] R. Prakash and V. Veeravalli, "Adaptive Hard Handoff Algorithm," *IEEE Journal on Selected Areas in Communications*, Vol. 18, 2000, pp. 2456-2464. doi:10.1109/49. 895049

[17] G. Welch and G. Bishop, "An Introduction to the Kalman Filter," Technical Report, University of North Carolina, New Caledonia, 2002.

Nomenclature

$\boldsymbol{A}_i$, $i = 1, 2$	State transition matrix
b_k, $k = 1, 2$	Binary sequence (LOS or NLOS)
E_k^i, $i = 0, 1$	Handoff/non-Handoff event
NLOS_k	Measurement error at time instant k
$p(\bullet\|\bullet)$	Conditional probability distribution
$q(\bullet)$	Importance density
$\boldsymbol{X}_{i,k}$, $i = 1, 2$	Target state vector at time instant k
W_k^i	Weighting associated with ith particle at time instant k