CRAMER-RAO BOUND-BASED ADAPTIVE QUANTIZATION FOR TARGET TRACKING IN WIRELESS SENSOR NETWORKS

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ABSTRACT

This work deals with the problem of target tracking in wireless sensor networks where the observed system is assumed to evolve according to a probabilistic state space model. We propose to improve the use of the variational filtering (VF) by quantizing the data collected by the sensors to higher levels respecting the trade-off between the information relevance of sensor measurements and the energy costs. In fact, VF has been shown to be suitable to the communication constraints of sensor networks. Its efficiency relies on the fact that the online update of the filtering distribution and its compression are simultaneously performed. But till now, it has been used only for binary sensor networks. In this paper, we propose an adaptive quantization algorithm taking benefit from the VF properties. At each sampling instant, by minimizing the Cramér-Rao bound, the adaptive quantization technique provides the optimal number of quantization bits per observation. The computation of this criteria is based on the target position predictive distribution provided by the VF algorithm. The simulation results show that the adaptive quantization algorithm, for the same sensor transmitting power, outperforms both the VF algorithm using a fixed optimal quantization level (minimizing the MSE) and the VF algorithm based on binary sensors.

1. INTRODUCTION

The problem of target tracking using wireless sensor networks has attracted considerable attention in both literature and application domains. Wireless nodes are highly resource constrained; i.e. they operate on limited battery power that needs to be sustained so as to prolong the operational lifetime of the network. Due to these factors, the observations are quantized before transmission. The problem is how to adapt the quantization level in order to minimize the error of the target trajectory estimate.

Generally, the problem of quantizing observations to estimate a parameter, either the target position or any other physical field (temperature, humidity, ...), is different from the problem of quantizing a signal for later reconstruction [1]. Instead of reconstructing a signal, our objective is rather finding an optimal estimator using quantized observations.

Target tracking using quantized observations is a nonlinear estimation problem that can be solved using e.g., unscented Kalman filter (KF) [2], particle filters [3] or variational filtering (VF) algorithm. In this paper, we consider the variational approach algorithm for solving the target tracking problem since: (i) it respects the communication constraints of sensor, (ii) the online update of the filtering distribution and its compression are simultaneously performed, and (iii) it has the nice property to be model-free, ensuring the robustness of data processing. The VF approach was only extended to Binary Sensor Network (BSN) considering a cluster-based scheme [4]. The BSN is based on the binary proximity observation model which consists of making a binary decision according to the strength of the perceived signal. Then, only on bit is transmitted for further processing if a target is detected. This work was done considering a cluster-based scheme, where sensors are divided into clusters. At each sampling instant, only one cluster of sensors is activated according to the prediction made by the variational filtering algorithm. Resource consumption is thus restricted to the activated cluster, where intra-cluster communications are dramatically reduced. For its power efficiency, the cluster-based scheme is also considered in this paper.

As only a part of information is exploited, tracking in binary sensor networks suffers from poor estimation performances. Assuming a fixed sensor transmitting power, we propose an online filtering algorithm that simultaneously provides the optimal quantization level and the Bayesian filtering distribution of the target position at each sampling instant. The Cramér-Rao bound (CRB) provides a consistent theoretic criteria in order to optimize the quantization level by maximizing the sensor data content relevance. As the target position $\boldsymbol{x}_t$ is unknown, the CRB is averaged according to the target position predictive distribution provided online by the VF algorithm.

The remainder of this paper is organized as follows. Section 2 presents the quantized observation model, the general state evolution model, the overview of the VF algorithm and the prediction-based cluster activation using VF algorithm. Then, the adaptive quantization algorithm is presented in section 3 after deriving the CRB expression based on the predicted target position. Section 4 gives some numerical results. Finally, section 5 concludes the paper.

2. MODELING AND PROBLEM STATEMENT

2.1. Quantized observation model

Consider a wireless sensor network, in which the sensor locations are known $\boldsymbol{s}^i = (s_1^i, s_2^i)$, $i = 1, 2, ..., N_s$. We are interested in tracking a target position $\boldsymbol{x}_t = (x_{1,t}, x_{2,t})^T$ at each instant t ($t = 1, ..., N$, where N denotes the number of observations). Consider the activated sensor i (the activation procedure is explained in section 2.4), its observation γ_t^i is modeled by:

$$\gamma_t^i = K\|\boldsymbol{x}_t - \boldsymbol{s}_t^i\|^\eta + \epsilon_t \tag{1}$$

where ϵ_t is a Gaussian noise with zero mean and a variance σ_ϵ^2. η and K are known constants. The sensor transmits its observation if and only if $R_{min} \leq \|\boldsymbol{x}_t - \boldsymbol{s}_t^i\| \leq R_{max}$ where R_{max} denotes the maximum distance at which the sensor can detect the target, and R_{min} is the minimum distance from which the sensor can detect the target. Before being transmitted the observation is quantized by partitioning the observation space into N_t intervals $\mathcal{R}_j = [\tau_j(t), \tau_{j+1}(t)]$, where $j \in \{1, ..., N_t\}$. N_t presents the quantization level ($N_t = 2^{n_b}$ where n_b denotes the number of quantization bits per observation) which is to be determined. The quantization level N_t is sub-indexed by the sampling instant t since it will be optimized online jointly with the target position online estimation. The quantizer, assumed uniform, is specified through: (i) the thresholds $\{\tau_j(t)\}_{j=1}^{j=N_t+1}$, where (if $\eta \geq 0$): $\tau_1(t) = KR_{min}^{\eta}$, $\tau_j(t) \leq \tau_{j+1}(t)$ and $\tau_{N_t+1}(t) = KR_{max}^{\eta}$; and (ii) the quantization rule:

$$y_t^i = d_j \;\text{ if }\; \gamma_t^i \in [\tau_j(t), \tau_{j+1}(t)] \tag{2}$$

where $d_j = \frac{\tau_j(t) + \frac{j-1}{2}\delta}{\tau_{N_t+1}(t) - \tau_1(t)}$ and $\delta = \frac{\tau_{N_t+1}(t) - \tau_1(t)}{N_t}$.
Then, the signal received by the cluster head is written as,

$$z_t^i = \beta^i * y_t^i + n_t, \tag{3}$$

where β^i is the i^{th} sensor channel attenuation coefficient (in this work β^i is assumed the same for all sensors) and n_t is a random Gaussian noise with a zero mean and a variance σ_n^2.

2.2. General state evolution model

In this paper, we employ a General State Evolution Model (GSEM) [5] instead of the kinematic parameter model [6] usually used in tracking problems. In fact, the GSEM model, introduced in [5] for visual tracking, is more practical to non-linear and non-gaussian situations where no a priori information on the target velocity or its acceleration is available. Considering a planar geometry, the target position $\boldsymbol{x}_t$ at instant t is assumed to follow a Gaussian model, where the expectation $\boldsymbol{\mu}_t$ and the precision matrix $\boldsymbol{\lambda}_t$ are both random. Gaussian distribution for the expectation and whishart distribution for the precision matrix form a practical choice for these distributions. The hidden state $\boldsymbol{x}_t$ is extended to an augmented state $\boldsymbol{\alpha}_t = (\boldsymbol{x}_t, \boldsymbol{\mu}_t, \boldsymbol{\lambda}_t)$, yielding an hierarchical model as follows,

$$\begin{cases} \boldsymbol{\mu}_t & \sim & \mathcal{N}(\boldsymbol{\mu}_t \mid \boldsymbol{\mu}_{t-1}, \bar{\boldsymbol{\lambda}}) \\ \boldsymbol{\lambda}_t & \sim & \mathcal{W}_{\bar{n}}(\boldsymbol{\lambda}_t \mid \bar{\boldsymbol{S}}) \\ \boldsymbol{x}_t & \sim & \mathcal{N}(\boldsymbol{\mu}_t, \boldsymbol{\lambda}_t) \end{cases} \tag{4}$$

where the fixed hyperparameters $\bar{\boldsymbol{\lambda}}$, $\bar{n}$ and $\bar{\boldsymbol{S}}$ are respectively the random walk precision matrix, the degrees of freedom and the precision of the Wishart distribution. Note that assuming random mean and covariance for the state $\boldsymbol{x}_t$ leads to a prior probability distribution covering a wide range of tail behaviors allowing discrete jumps in the target trajectory.

2.3. Overview of the VF algorithm

According to the model (4), the augmented hidden state is now $\boldsymbol{\alpha}_t = (\boldsymbol{x}_t, \boldsymbol{\mu}_t, \boldsymbol{\lambda}_t)$. The distribution of interest for target tracking takes the form of marginal posterior distribution $p(\boldsymbol{\alpha}_t \mid \boldsymbol{z}_{1:t})$, where $\boldsymbol{z}_{1:t} = \{z_1, z_2, \ldots, z_t\}$ denotes the collection of observations gathered until time t. The variational approach consists in approximating $p(\boldsymbol{\alpha}_t \mid \boldsymbol{z}_{1:t})$ by a separable distribution $q(\boldsymbol{\alpha}_t) = \Pi_i q(\boldsymbol{\alpha}_t^i)$ that minimizes the Kullback-Leibler (KL) divergence between the true filtering distribution and the approximate distribution,

$$D_{\mathrm{KL}}(q||p) = \int q(\boldsymbol{\alpha}_t) \log \frac{q(\boldsymbol{\alpha}_t)}{p(\boldsymbol{\alpha}_t \mid \boldsymbol{z}_t)} d\boldsymbol{\alpha}_t \tag{5}$$

To minimize the KL divergence subject to constraint $\int q(\boldsymbol{\alpha}_t) d\boldsymbol{\alpha}_t = \Pi_i \int q(\boldsymbol{\alpha}_t^i) d\boldsymbol{\alpha}_t^i = 1$, the Lagrange multiplier method is used, yielding the following approximate distribution [5]

$$q(\boldsymbol{\alpha}_t^i) \propto \exp \langle \log p(\boldsymbol{z}_t, \boldsymbol{\alpha}_t) \rangle_{\Pi_{j \neq i} q(\boldsymbol{\alpha}_t^j)} \tag{6}$$

where $\langle . \rangle_{q(\boldsymbol{\alpha}_t^j)}$ denotes the expectation operator relative to the distribution $q(\boldsymbol{\alpha}_t^j)$.
Skipping all the details of the VF for space limitation, the updated separable distribution $q(\boldsymbol{\alpha}_t)$ has the following form:

$$\begin{array}{lcl} q(\boldsymbol{x}_t) & \propto & p(\boldsymbol{z}_t \mid \boldsymbol{x}_t) \mathcal{N}(\boldsymbol{x}_t \mid \langle \boldsymbol{\mu}_t \rangle, \langle \boldsymbol{\lambda}_t \rangle) \\ q(\boldsymbol{\mu}_t) & \propto & \mathcal{N}(\boldsymbol{\mu}_t \mid \boldsymbol{\mu}_t^*, \boldsymbol{\lambda}_t^*) \\ q(\boldsymbol{\lambda}_t) & \propto & \mathcal{W}_{n^*}(\boldsymbol{\lambda}_t \mid \boldsymbol{S}_t^*) \end{array}$$

where the parameters are iteratively updated according to the following scheme:

$$\begin{array}{l} \boldsymbol{\mu}_t^* = \boldsymbol{\lambda}_t^{*-1}(\langle \boldsymbol{\lambda}_t \rangle \langle \boldsymbol{x}_t \rangle + \boldsymbol{\lambda}_t^p \boldsymbol{\mu}_t^p) \\ \boldsymbol{\lambda}_t^* = \langle \boldsymbol{\lambda}_t \rangle + \boldsymbol{\lambda}_t^p \\ n^* = \bar{n} + 1 \\ \boldsymbol{S}_t^* = (\langle \boldsymbol{x}_t \boldsymbol{x}_t^T \rangle - \langle \boldsymbol{x}_t \rangle \langle \boldsymbol{\mu}_t \rangle^T - \langle \boldsymbol{\mu}_t \rangle \langle \boldsymbol{x}_t \rangle^T + \langle \boldsymbol{\mu}_t \boldsymbol{\mu}_t^T \rangle + \bar{\boldsymbol{S}}^{-1})^{-1} \\ \boldsymbol{\mu}_t^p = \boldsymbol{\mu}_{t-1}^* \\ \boldsymbol{\lambda}_t^p = (\boldsymbol{\lambda}_{t-1}^{*-1} + \bar{\boldsymbol{\lambda}}^{-1})^{-1} \end{array} \tag{7}$$

2.4. Prediction-based cluster activation using the VF algorithm

The main advantage of the variational approach is the compression of the statistics required for the update of the filtering distribution between two successive instants. This implicit compression makes the variational algorithm adapted to be distributively implemented through the network. In other words, it can be executed on a cluster-base which is considered in this paper. The cluster head is here determined based on the predicted target position given by the VF algorithm. Indeed, after updating the VF distribution, the role of the cluster head CH_t (at the sampling instant t) is to calculate the predictive distribution. The predictive distribution can be efficiently updated by the VF approach. In fact, taking into account the separable approximate distribution at time $t-1$, the predictive distribution is written,

$$p(\boldsymbol{\alpha}_t | \boldsymbol{z}_{1:t-1}) \propto p(\boldsymbol{x}_t, \boldsymbol{\lambda}_t | \boldsymbol{\mu}_t) \int p(\boldsymbol{\mu}_t \mid \boldsymbol{\mu}_{t-1}) q(\boldsymbol{\mu}_{t-1}) d\boldsymbol{\mu}_{t-1}$$

The exponential form solution, which minimizes the Kullback-Leibler divergence between the predictive distribution $p(\boldsymbol{\alpha}_t | \boldsymbol{z}_{1:t-1})$ and the separable approximate distribution $q_{t|t-1}(\boldsymbol{\alpha}_t)$, yields Gaussian distributions for the state and its mean and Wishart distribution for the precision matrix:

$$\begin{array}{lcl} q_{t|t-1}(\boldsymbol{x}_t) & \propto & \mathcal{N}(\boldsymbol{x}_t \mid \langle \boldsymbol{\mu}_t \rangle, \langle \boldsymbol{\lambda}_t \rangle) \\ q_{t|t-1}(\boldsymbol{\mu}_t) & \propto & \mathcal{N}(\boldsymbol{\mu}_t \mid \boldsymbol{\mu}_t^*, \boldsymbol{\lambda}_t^*) \\ q_{t|t-1}(\boldsymbol{\lambda}_t) & \propto & \mathcal{W}_{n^*}(\boldsymbol{\lambda}_t \mid \boldsymbol{S}_t^*) \end{array}$$

where the parameters are updated according to the same iterative scheme as (7) and the expectations are exactly computed as follows:

$$\begin{cases} \langle \boldsymbol{x}_t \rangle_{q_{t|t-1}} & = & \langle \boldsymbol{\mu}_t \rangle_{q_{t|t-1}}, \\ \langle \boldsymbol{x}_t \boldsymbol{x}_t^T \rangle_{q_{t|t-1}} & = & \langle \boldsymbol{\mu}_t \rangle_{q_{t|t-1}} + \langle \boldsymbol{\mu}_t \rangle_{q_{t|t-1}} \langle \boldsymbol{\mu}_t \rangle_{q_{t|t-1}}^T. \end{cases}$$

Based on the predicted target position $\langle \boldsymbol{x}_t \rangle_{q_{t|t-1}}$, the head cluster at sampling instant t, CH_t, is chosen to be the nearest sensor to $\langle \boldsymbol{x}_t \rangle_{q_{t|t-1}}$ i.e :

$$CH_t = argmin_{i=1,\ldots,|\mathcal{B}_t|}\{\|\langle \boldsymbol{x}_t \rangle_{q_{t|t-1}} - \boldsymbol{s}_t^m\| \;\; m \in \mathcal{B}_t\} \quad (8)$$

where $|.|$ denotes the cardinality, and $\mathcal{B}_t$ is the set of cluster heads.

3. CRAMER-RAO BOUND AND ADAPTIVE QUANTIZATION ALGORITHM

3.1. Cramér-Rao Bound

The Cramér-Rao expresses a lower bound on the variance of estimators of a parameter. In its simplest form, the bound states that the covariance of any estimator is at least higher as the inverse of the Fisher Information (FI) matrix. The FI matrix is a quantity measuring the amount of information that the observable variable $\boldsymbol{z}$ carries about the unknown parameter $\boldsymbol{x}$. The FI matrix elements at the sampling instant t are given by:

$$[FI(\boldsymbol{x}_t)]_{l,k} = E_{\boldsymbol{z}_t|\boldsymbol{x}_t}[\frac{\partial \log(p(\boldsymbol{z}_t|\boldsymbol{x}_t))}{\partial \boldsymbol{x}_{(l,t)}} \frac{\partial \log(p(\boldsymbol{z}_t|\boldsymbol{x}_t))}{\partial \boldsymbol{x}_{(k,t)}}], \quad (9)$$

$$(l,k) \in \{1,2\} \times \{1,2\} \quad (10)$$

where z_t denotes the observation at the sampling instant t, $\boldsymbol{x}_t = [x_1, x_2]^T$ is the unknown 2×1 vector to be estimated, and $E_{\boldsymbol{z}_t|\boldsymbol{x}_t}[.]$ denotes the expectation with respect the likelihood function $p(\boldsymbol{z}_t|\boldsymbol{x}_t)$, which is given by

$$p(z_t|\boldsymbol{x}_t) = \sum_{j=0}^{N_t-1} p(\tau_j(t) < \gamma < \tau_{j+1}(t))\mathcal{N}(\beta d_j, \sigma_\epsilon^2) \quad (11)$$

where

$$p(\tau_j(t) < \gamma_t < \tau_{j+1}(t)) = \int_{\tau_j(t)}^{\tau_{j+1}(t)} \mathcal{N}(\rho_{\gamma_t}(\boldsymbol{x}_t)d_j, \sigma_n^2)d\gamma_t \quad (12)$$

is computed according to the quantization rule defined in (2), in which

$$\rho_{\gamma_t}(\boldsymbol{x}_t) = K\|\boldsymbol{x}_t - \boldsymbol{s}_t^m\|^\eta, m = 1, \ldots, N_s \quad (13)$$

Then, the derivative of the log-likelihood function can be expressed as,

$$\frac{\partial \log(p(z_t|\boldsymbol{x}_t))}{\partial \boldsymbol{x}_{l,t}} = \frac{2\eta K}{\sqrt{2\pi\sigma_n^2}}(x_{l,t} - s_{l,m})\|x_{l,t} - s_{l,m}\|^{\eta-2} \times \sum_{k=0}^{N_t-1}[erfc(\frac{\tau_k - \rho_{\gamma_t}(\boldsymbol{x}_t)}{\sqrt{2}\sigma_n}) - erfc(\frac{\tau_{k+1} - \rho_{\gamma_t}(\boldsymbol{x}_t)}{\sqrt{2}\sigma_n})] \times \exp(-\frac{1}{2}\frac{(z_t(k) - \beta d_k)^2}{\sigma_\epsilon^2}) \quad (14)$$

Substituting expression (14) in (9), the FI matrix is easily computed by integrating over the likelihood function $p(\boldsymbol{z}_t|\boldsymbol{x}_t)$.
It is worth noting that the expression of the FI given in (9) depends on the target position $\boldsymbol{x}_t$ at the sampling instant t and on the quantization level N_t. However, as the target position is unknown, the FI is replaced by its expectation according to the predictive distribution $p(\boldsymbol{x}_t|\boldsymbol{z}_{1:t-1})$ of the target position:

$$< FI(\boldsymbol{x}_t) >= E_{p(\boldsymbol{x}_t|\boldsymbol{z}_{1:t-1})}[FI(\boldsymbol{x}_t)] \quad (15)$$

Computing the above expectation is analytically untractable. However, as the VF algorithm yields a Gaussian predictive distribution $\mathcal{N}(\boldsymbol{x}_t; \boldsymbol{x}_{t/t-1}, \lambda_{t/t-1})$, expectation (15) can be efficiency approximated by a Monte Carlo scheme:

$$< FI(\boldsymbol{x}_t) >\simeq \frac{1}{L}\sum_{l=1}^{L} FI(\tilde{\boldsymbol{x}}_t^l), \quad \tilde{\boldsymbol{x}}_t^l \sim \mathcal{N}(\boldsymbol{x}_p(t); \boldsymbol{x}_{t/t-1}, \boldsymbol{\lambda}_{t/t-1}) \quad (16)$$

where $\tilde{\boldsymbol{x}}_t^l$ is the $l-th$ drawn observation at the sampling instant t, and L is the total number of drawn vectors $\tilde{\boldsymbol{x}}_t$.

3.2. Adaptive quantization algorithm

The key idea behind the quantized optimization is that under constant transmitting power, a higher quantization level could affect the estimation performances. In fact, if the quantization level increases, the quantized values d_j are very close and the distance between the symbols decreases. A small noise could then decrease the information content relevance of measured data, thus the estimation error increases (see the Fig.**??**).
The adaptive quantization algorithm is summarized in Fig.1. At sampling time $t-1$, the selected cluster head CH_{t-1} executes the VF algorithm and provides the Gaussian predictive distribution $\mathcal{N}(\boldsymbol{x}_p(t); \boldsymbol{x}_{t/t-1}, \lambda_{t/t-1})$. The predicted position allows the selection of the cluster to be activated as described in section 2.4. Furthermore, this target position predictive distribution is used by the CH_{t-1} to give the optimal quantization level N_{opt}^t minimizing the predicted CRB. This optimal quantization level is then transmitted to the CH_t before being diffused to the activated cluster sensors so that they use it to quantize their observations. These quantized observations are then used by the CH_t to execute the VF algorithm at the sampling instant t.

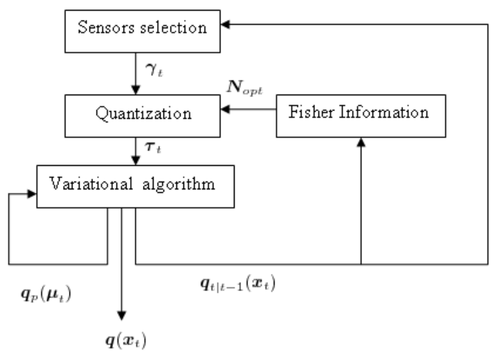

Fig. 1. Adaptive quantization algorithm diagram explaining how the optimal quantization is determined based on the predictive distribution.

4. NUMERICAL EXAMPLES

The performance of the tracking algorithm can be essentially quantified by the tracking accuracy, which is evaluated by the distance between the estimated trajectory and the true target trajectory. In the following, we compare the tracking accuracy of the VF algorithm using different quantizing strategies. All the simulations shown in this paper are implemented with Matlab version 7.1, using an Intel Pentium CPU 3.4 GHz, 1.0 G of RAM PC.

For the evaluation purpose, the target motion is simulated by a random walk mobility (RWM) model. The RWM model, referred to as Brownian Motion and described first by Einstein in 1926 [7], mimics the erratic movement of a target in extremely unpredictable ways.

In the region under surveillance, sensors were randomly deployed with a density $\lambda = 0.1$ sensor/m^2. The system parameters considered in the following simulations are: $\eta = 2$ for free space environment, the constant characterizing the sensor range is fixed for simplicity to $K = 1$, the cluster head noise power $\sigma_n^2 = 0.5$, the total number of sensors $N_s = 100$, the total sampling instants $N = 100$, the sensor noise power $\sigma_\epsilon^2 = 0.1$ and the channel fading coefficient $\beta = 1$.

To investigate the impact of the choice of a fixed (in time) quantization level on the VF algorithm performances, we run the VF algorithm for different number of bits per observation and compute the error estimation over all the target trajectory. Fig.2 plot the MSE versus the number of bits per observation varying in $\{1, 2, ..., 8\}$. We note that for $SNR = 3$, the MSE is minimum for $N_{opt} = 3bits$.

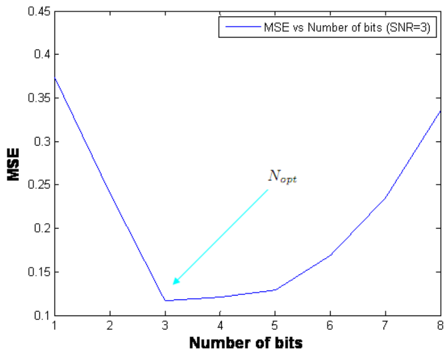

Fig. 2. MSE versus the number of quantization bits (fixed in time) varying in $\{1, 2, ..., 8\}$ for $SNR = 3$.

Then, the tracking performances of the adaptive quantization VF algorithm are compared to both the VF algorithm based on BSN and the VF algorithm using the optimal fixed number of bits per observation $N_{opt} = 3$ (minimizing the MSE as shown in Fig.2. One can notice from Fig.3 and Fig. 4 that the best tracking quality is ensured by the adaptive quantization VF algorithm compared to the two other algorithms.

5. CONCLUSION

In this paper, the problem of target tracking in wireless sensor networks is investigated when using an adaptive quantization variational filtering algorithm. At each time instant, the algorithm provides the optimal quantization level which minimizes the predicted Cramér-Rao Bound. It has been shown that, for the same transmitting power per sensor, this adaptive scheme outperforms the VF algorithm using a fixed (optimally set) quantization level. Furthermore, the proposed algorithm has a low computation complexity since it is directly based on the Gaussian predictive distribution of target position.

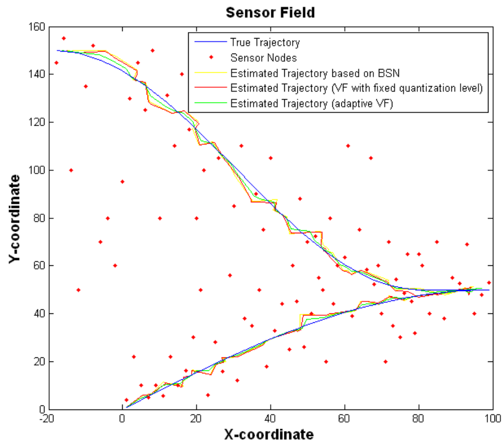

Fig. 3. True (blue) and estimated trajectories using the adaptive quantization algorithm (green), using VF algorithm (red) and using VF based on BSN (yellow).

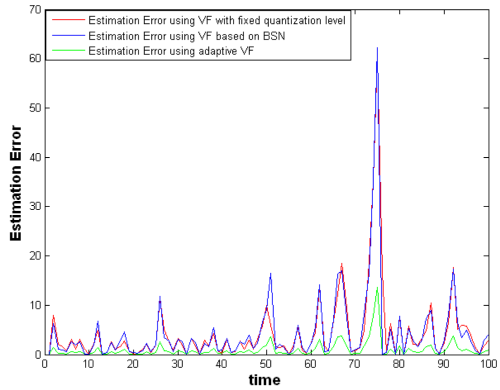

Fig. 4. Estimation error between the original and the estimated trajectories.

6. REFERENCES

[1] R. M. Gray, "Quantization in task-driven sensing and distributed processing," in *IEEE International Conference on Acoustics, Speech, and Signal Processing*, May 2006, vol. 5, pp. 1049–1052.

[2] S. Julier and J. Uhlmann, "Unscented filtering and non-linear estimation," in *Proceedings of the IEEE*, Mar. 2004, vol. 92, pp. 401–422.

[3] P. Djuric, J. Zhang J. Kotecha, Y. Huang, T. Ghirmai, M. Bugallo, and J. Miguez, "Particle filtering," *IEEE Signal Processing Magazine*, vol. 20, pp. 19–38, Sept. 2003.

[4] J. Teng, H. Snoussi, and C. Richard, "Binary Variational Filtering for target tracking in wireless sensor networks," in *IEEE Workshop on Statistical Signal Processing*, Aug. 2007, pp. 685–689.

[5] Hichem Snoussi and Cédric Richard, "Ensemble learning online filtering in wireless sensor networks," in *IEEE ICCS International Conference on Communications Systems*, 2006.

[6] Petar Djurić, Mahesh Vemula, and Mónica Bugallo, "Tracking with particle filtering in tertiary wireless sensor networks," in *ICASSP*, Philadelphia, PA, USA, March 18-23 2005.

[7] T. Camp, J. Boleng, and V. Davies, "A survey of mobility models for ad hoc network research," vol. 2, pp. 483–502, 2002.