Object Tracking in Random Access Sensor Networks: Extended Kalman Filtering With State Overlapping

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***Abstract*—In this paper, we address the problem of object tracking using sensor networks where the sensor nodes measure the strength of the field generated by a number of objects, and transmit their measurements to a fusion center in a random access manner for final reconstruction of the trajectories. Our focus is on underwater systems that use acoustic communication. Extended Kalman filtering is employed for detection and tracking of the objects inside the observation area. We propose a method for object tracking called state overlapping, which is based on exchanging and overwriting the estimated state vector between a number of independent Kalman filters. The method improves the scalability of the system, relieves the requirement for a time-varying state vector, and reduces the probability of divergence. Moreover, we propose an adaptive rate control scheme and refine an existing one to improve the estimation accuracy and the energy efficiency of the system. The performance of these methods is evaluated through simulation, showing the effectiveness of the approaches proposed.**

***Index Terms*—Kalman filter, object tracking, wireless sensor network, adaptive rate control, random access.**

I. Introduction

Wireless Sensor Networks (WSNs) with their wide range of potential applications have attracted increased research interest over the last few decades [1]. Recently, underwater WSNs have drawn research attention with increased human activities in the ocean. These networks rely on acoustic transmission for spanning longer ranges, and are consequently constrained by limited bandwidth, long propagation delays and pronounced Doppler effects [2], [3]. Random access relieves synchronization issues in such conditions, but introduces the risk of data packet collision at the fusion center (FC) of a network. To manage the scarce bandwidth and power resources, efficient control schemes are often necessary in acoustic WSNs [4].

One of the important applications of WSNs is object tracking, which has been studied extensively for several decades and numerous tracking algorithms have been proposed [5], [6]. However, it still remains a very challenging problem. In [7], a decentralized, dynamic clustering algorithm was introduced for acoustic object tracking. The authors in [8] considered the joint problem of packet scheduling and self-localization in underwater acoustic sensor networks and proposed a Gauss-Newton based localization algorithm for these schemes. In order to manage the resource scarcity of underwater WSNs, [9] introduced an adaptive object tracking approach where sensor nodes transmit to FC using random access in a centralized topology.

Kalman filter is by far the most popular method for object tracking. In [10], the authors considered the case where the packets may be lost due to collisions and communication noise, which is known in literature as Kalman filtering with intermittent observations. The authors in [11] studied the stability of standard Kalman filtering with intermittent observations. They showed the existence of a critical arrival rate below which the estimation error may diverge.

The tracking methods designated in the aforementioned references are derived based on the assumption that the number of objects in the area is known a-priori, so that one can easily define the state variables and employ Kalman filtering for location estimation. This is not a realistic assumption in localization and tracking applications where nodes can freely enter or depart the area at any time.

In this paper, we address the problem of object tracking in underwater acoustic WSN. We consider the case where the objects can freely enter or depart the area. In standard Kalman filtering this would require changing the state vector each time an object departs or enters the area. By employing a technique called state overlapping we relax this requirement. Similarly to [12], we assume that the sensor nodes access the channel in a random manner. As a result, the packets may be lost due to collisions or communication noise. Moreover, we introduce new adaptive rate control schemes to instruct the sensor nodes to adjust their transmission rate efficiently to enhance the accuracy of estimation. Simulation results show the benefits

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of the proposed method and the rate control schemes.

The rest of the paper is organized as follows. Sec. II presents the system model. Sec. III introduces the state overlapping method for object discovery in random access networks. Sec. IV presents the proposed adaptive rate control schemes. Simulation results are presented in Sec. V. Finally, we provide concluding remarks in Sec. VI.

II. System Model

We consider a two-dimensional observation area in which N sensors are placed at predefined locations. Each sensor knows its own location $[a(n),\ b(n)]^T, n = 1, ..., N$. Objects are moving in the area, and the location of the m-th object at collection interval k are denoted by $[x_k(m), y_k(m)]^T$. The duration of one collection interval, T, is short enough that the objects' locations can be considered fixed. Each object emits a signal of certain amplitude. The signal decays with distance d based on a signature function $f(d)$.

At time k sensor n senses the field generated by the objects. The received signal is a combination of all the objects' signals,

$$v_k(n) = \sum_m f(d_k(m,n)) + w_k(n) \tag{1}$$

where $d_k(m,n) = \sqrt{(x_k(m) - a(n))^2 + (y_k(m) - b(n))^2}$ is the distance between the m-th object and the n-th sensor at time k, $f(d)$ models the propagation loss, and $w_k(n)$ is the sensing noise, modeled as zero-mean Gaussian of variance σ_w^2.

After sensing the field, each node encodes its measurement $v_k(n)$ into a digital data packet and transmits the packet to the FC. The transmissions happen at random instants in time, which we model here as a Poisson process with rate λ_n per sensor. The Poisson model was used as a general case, but other modes can be used as well.

The FC collects all the packets transmitted in one interval of duration T. Some packets will be dropped because of collision and noise. The FC may also receive multiple packets from one sensor. After discarding all the erroneous and redundant packets, the FC is left with useful packets, which arrive at an aggregate rate λ_{FC}. During each collection interval, the FC receives a random number of data packets. We define $\mathcal{R}_k$ as the set of nodes whose packets are received successfully during the k-th collection interval. These intermittent observations are used as an input to the tracking algorithm to estimate the location of the objects.

A. Modified Lossy Extended Kalman Filter

The modified lossy extended Kalman filter (MLEKF) was proposed in [10] as a method to incorporate intermittent observations into the extended Kalman filter. Since this method is the underlying approach for our rate-adaptation methods, we briefly discuss it here.

Suppose that the state of the system at time k is defined as

$$\mathbf{x}_k = [\mathbf{x}_k(1), \mathbf{x}_k(2), \ldots, \mathbf{x}_k(M_{max})]^T \tag{2}$$

where M_{max} is the maximum number of objects inside the observation area and $\mathbf{x}_k(m) = [x_k(m), y_k(m), \dot{x}_k(m), \dot{y}_k(m)]$ contains the location and velocity of object m. The state vector evolves as

$$\mathbf{x}_k = \mathbf{A}\mathbf{x}_{k-1} + \mathbf{q}_k \tag{3}$$

where $\mathbf{A}$ is the state transition matrix, and $\mathbf{q}_k$ is the process noise, which is modeled as zero-mean Gaussian with covariance matrix $\mathbf{Q}$. Considering AR-1 model with one-step correlation ρ and only one object moving in the area, $\mathbf{A}$ and $\mathbf{Q}$ matrices become

$$\mathbf{A} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & \rho & 0 \\ 0 & 0 & 0 & \rho \end{bmatrix}, \quad \mathbf{Q} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} . \sigma_v^2(1-\rho^2)$$

where T is the time interval between successive observations and σ_v^2 controls the variance of the process noise. The methods proposed in this paper are not limited to the AR-1 model, and can be applied to other models as well.

Some of the packets will be dropped due to collisions and communication noise, yielding the actual received observations $\tilde{\mathbf{v}}_k = \mathbf{G}_k\mathbf{v}_k$ where the matrix $\mathbf{G_k}$ is obtained from an $N \times N$ identity matrix by removing the rows corresponding to non-contributing sensors, i.e. those sensors that do not belong to $\mathcal{R}_k$. The matrix $\mathbf{G_k}$ is thus random, and it models the intermittent observations and lossy communications. The signal presented to the FC in the k-th collection interval is thus given by

$$\tilde{\mathbf{v}}_k = \mathbf{G}_k\mathbf{v}_k = \mathbf{G}_k[\mathbf{f}(\mathbf{x}_k) + \mathbf{w}_k] = \tilde{\mathbf{f}}_k(\mathbf{x}_k) + \tilde{\mathbf{w}}_k \tag{4}$$

where $\mathbf{f}(\cdot)$ is the nonlinear measurement function defined by (1) and $\mathbf{w}_k$ is the sensing noise with covariance $\boldsymbol{W} = \sigma_w^2\mathbf{I}$. Algorithm 1 shows the different steps involved in MLEKF, where

$$\mathbf{F}(\hat{\mathbf{x}}) = \frac{\partial \mathbf{f}(\mathbf{x})}{\partial \mathbf{x}}|_{\mathbf{x}=\hat{\mathbf{x}}} \tag{5}$$

is the Jacobian matrix.

III. Object Tracking Using State Overlapping

In conventional Kalman filtering it is assumed that the number of objects in the area, and hence the number of states, is known a-priori. Needless to say that such an assumption is not realistic in many practical situations where the objects can freely enter or depart the area at any time. A modification is thus required to address the entrance-departure identification issue. In addition to providing flexibility, such a modification also yields a scalable algorithm that can be applied to large coverage areas without undue increase in complexity.

In this paper, we introduce a method for addressing a variable number of objects in a system. The method is called state overlapping, and is based on exchanging and overwriting the estimated state vector between a number of independent Kalman filters.

Suppose that we are interested in finding the location and velocities of objects inside a specific area called the primary zone as illustrated in Fig. 1. To do so, we consider a larger area called the observation area in which the primary zone resides.

Algorithm 1 MLEKF Algorithm

Input: $\hat{\mathbf{x}}_0$, $\boldsymbol{P_0}, \boldsymbol{A}, \boldsymbol{Q}, \boldsymbol{G_k}, \boldsymbol{W}$

Output: $\hat{\mathbf{x}}_k$

1: Find the predicted mean $\hat{\mathbf{x}}_k^-$ and predicted covariance $\boldsymbol{P_k^-}$

$$\hat{\mathbf{x}}_k^- = \boldsymbol{A}\ \hat{\mathbf{x}}_{k-1}$$

$$\boldsymbol{P_k^-} = \boldsymbol{A P_{k-1} A^T} + \boldsymbol{Q}$$

2: Form

$$\tilde{\mathbf{F}}_k = \boldsymbol{G_k}\mathbf{F}(\hat{\mathbf{x}}_k^-)$$

3: Find measurement prediction covariance

$$\boldsymbol{S_k} = \tilde{\mathbf{F}}_k \boldsymbol{P_k^-} \tilde{\mathbf{F}}_k^T + \boldsymbol{G_k W G_k^T}$$

4: Find filter gain matrix

$$\boldsymbol{K_k} = \boldsymbol{P_k^-} \tilde{\mathbf{F}}_k^T \boldsymbol{S_k^{-1}}$$

5: Update $\hat{\mathbf{x}}_k$

$$\hat{\mathbf{x}}_k = \hat{\mathbf{x}}_k^- + \boldsymbol{K_k}(\tilde{\mathbf{v}}_k - \tilde{\mathbf{f}}_k(\hat{\mathbf{x}}_k^-))$$

6: Update $\boldsymbol{P_k}$

$$\boldsymbol{P_k} = \boldsymbol{P_k^-} - \boldsymbol{K_k} \tilde{\mathbf{F}}_k \boldsymbol{P_k^-}$$

The observation area is divided to N_z zones out of which one is the primary zone and the rest are secondary zones.

Objects can freely enter or depart the primary zone at any time. Corresponding to each of the zones there is one Kalman filter running at the FC. At each time instant the FC thus runs N_z Kalman filters in parallel. All Kalman filters work at state vector dimension M_{max}, corresponding to the maximum number of objects that can be present in the observation area. This number can be established from historical data and the expected density of objects.

At the end of each updating interval the estimated locations of objects are checked. If the estimated location of one object resides inside the i-th zone, the corresponding state in all other Kalman filters will be overwritten by the estimated value of the i-th filter. Such an approach is justified by the fact that whenever an object is inside the i-th zone, the value obtained by the i-th Kalman filter is expected to be more reliable than the ones obtained by other filters. Consequently, we simply discard the less reliable values and continue with the more reliable one. In cases where more than one zone claims a specific object, we simply choose one of the zones randomly. Later, we will see that by employing this simple method we not only solve the entrance-departure issue, but also reduce the probability of divergence. In practice, we only need to update the Kalman filter for the zones in which an object is found at time k. Hence, at each point in time, we update at most $min[N_z, M_{max}]$ filters. Moreover, since each of the filters is running only on the measurements received from the sensors within one zone ($\frac{N}{N_z}$ at most), the complexity will be proportionately reduced. This is an appealing feature of the state overlapping method.

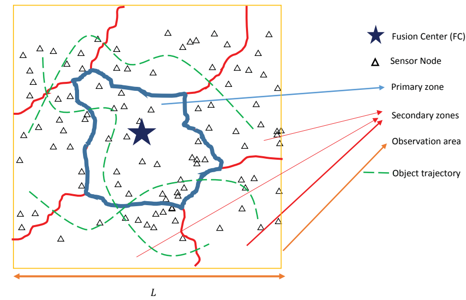

Fig. 1. The observation area, primary and secondary zones.

Using N_z local filters instead of a single filter also helps to reduce the probability of divergence. Namely, when a single filter diverges, there is no mechanism for recovery. In contrast, when we have more than one filter, each will converge or diverge independently from the others. If one filter starts to diverge, the values from the other filters may help to stop divergence by overwriting. Also, since each filter only estimates the location of close objects, the probability of divergence is lower. Together, these facts help to improve the divergence rate. Hence, in addition to solving the entrance departure issue, state overlapping promotes convergence and helps with the general reduction in computational complexity. These benefits come at a slight sacrifice in performance, as measured by the mean squared error of location estimates.

State overlapping is scalable to any larger area. If a larger area needs to be covered, the process of assigning the primary and secondary zones will be repeated across that area. Tracking in a different primary zone remains the same in principle, i.e. it employs state overlapping between the new local primary area and its secondary areas. The Kalman filters still operate at the same state dimension M_{max}, which corresponds to the maximum number of objects expected in one observation area, not the total area covered. Thus, the algorithm retains the same computational complexity, while the total coverage area can grow without bounds.

IV. Rate Control

As we mentioned earlier, nodes transmit packets based on a Poisson process with rate λ_n , which can be different for each node $n = 1, \ldots, N$. The FC collects the measurements during an observation window T. Fig. 2 shows the diagram of the system. Following the treatment of [12], the rate of useful packets at the FC is modeled as a Poisson process with aggregate arrival rate

$$\lambda_{FC} = \frac{\sum_{n=1}^{N} (1 - e^{-p_s \lambda_n T})}{T} \tag{6}$$

where $p_s = (1 - p_e)e^{-2\sum_{n=1}^{N} \lambda_n T_p}$ is the probability of successful reception of the packet at the FC, p_e is the probability of a packet being lost to communication noise, and T_p is packet duration.

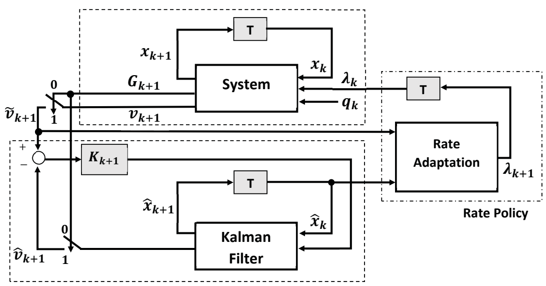

Fig. 2. Overview of the system. The observations are transmitted over an unreliable communication channel and can be lost.

Here, we consider three rate schemes. The first one is a fixed rate scheme. In this case, all sensors transmit at a fixed rate $\lambda_n = \lambda_f$ for all $n = 1, ..., N$. The aggregate rate (6) thus becomes

$$\lambda_{FC} = \frac{N}{T}(1 - e^{-p_s \lambda_f T}) \tag{7}$$

where $p_s = (1 - p_e)e^{-2N\lambda_f T_p}$. Assuming L_p as the length of each packet in bits and S_f as the spectral efficiency of the transmission method in bits/s/Hz, we can relate the value of T_p to bandwidth by

$$BW = \frac{L_p}{S_f T_p} \tag{8}$$

To find the optimal number of sensors to use within a given bandwidth, we take the derivative of λ_{FC} with respect to λ_f, set it equal to zero, and identify the optimum value as

$$\lambda_{f,opt} = \frac{1}{2NT_p} \tag{9}$$

Using this value in (7), we find the corresponding aggregate rate of useful packets at the FC as

$$\lambda_{max} = \frac{N}{T}(1 - e^{-\frac{(1-p_e)T}{2NT_p e}}) \tag{10}$$

This is the maximum achievable rate at which the FC can receive useful packets from sensor nodes. Note that as $N \to \infty$, the rate saturates at

$$\lambda_{lim} = \lim_{N \to +\infty} \lambda_{max} = \frac{(1 - p_e)}{2T_p e} \tag{11}$$

The fixed rate scheme is a simple, but inefficient approach for random access sensor networks. As the packets from different sensors are not of the same importance, an adaptive rate control scheme can improve the tracking accuracy and the energy efficiency of the system. Here, we first upgrade an existing rate control scheme, then we propose a new one.

In [9] an adaptive rate control scheme was proposed for the special case of an exponentially decaying signature function. Assuming that d_n is the distance from sensor n to the closest object it sees, the transmission rate of the n-th sensor is

$$\lambda_n = \lambda_e e^{-\frac{d_n^2}{2\sigma_e^2}} \tag{12}$$

where λ_e and σ_e are model parameters. At time $k = 0$ each node transmits at rate $\lambda_{f,opt} = \frac{1}{2NT_p}$. No specific method is proposed to set the values of λ_e and σ_e in [9]. As we will see in Sec. V, it is very important to determine appropriate values for these parameters as the method may otherwise fail.

In general, the optimal values of λ_e and σ_e depend on N, T, T_p, the number of objects, etc. The value of σ_e should be determined based on the dimension of the area. For example, if we want to give more priorities to sensors which are located in a circle of radius R of each object, then we should choose $\sigma_e = R$. For the special case of exponential signature function $f(d) = e^{-\alpha d}$, an appropriate choice for σ_e is $1/\alpha$. This choice gives priorities to the nodes located in the $1/\alpha$ neighborhood of each object. In this neighborhood the received signal power is at least $e^{-1} \approx \%36$ of the transmitted signal.

In order to find an appropriate value for λ_e, we recall from the fixed rate scheme that if all sensors transmit at a fixed rate of $\lambda_{f,opt} = \frac{1}{2NT_p}$ the received rate at FC is maximized. Therefore, an appropriate choice for λ_e would be

$$\lambda_e = \frac{1}{2NT_p} \tag{13}$$

The exponential rate adjustment scheme thus becomes

$$\lambda_n = \frac{1}{2NT_p} e^{-\alpha^2 d_n^2} \tag{14}$$

In this way, a node that is very close to an object is given 64% more transmission opportunities compared to a node which is located at distance $1/\alpha$.

Now, we introduce a more general and more efficient adaptive rate control scheme which is based on the intuition that the sensors which receive a more powerful signal in a given collection interval should have higher transmission rate in that interval. The proposed method is called relative power rate control and provides better accuracy of tracking. Based on this method, at time k the n-th sensor transmits at rate

$$\lambda_n = \lambda_r \frac{v_k(n)}{\sum_{i=1}^{N} v_k(i)} \tag{15}$$

where λ_r is a fixed value, and $v_k(n)$ is the received signal at n-th sensor at time k, as defined in (1).

Intuitively, the sum of rates should be equal for an adaptive and a fixed rate scheme, i.e.

$$\sum_{n=1}^{N} \lambda_n = N \times \frac{1}{2NT_p} = \frac{1}{2T_p} \tag{16}$$

According to (15) we have $\sum_{n=1}^{N} \lambda_n = \lambda_r$ which implies that $\lambda_r = \frac{1}{2T_p}$. Substituting into (15) we find the rate adaptation scheme to be

$$\lambda_n = \frac{v_k(n)}{2T_p \sum_{i=1}^{N} v_k(i)} \tag{17}$$

In the next section we will see how various rate schemes perform compared to each other in terms of different metrics.

Although, we introduced three rate schemes in this paper, any method for deciding the per sensor transmission rate is

TABLE I
LIST OF THE PARAMETERS USED IN SIMULATION

Parameter	Description	Default value
L	length and width of the observation area	1 km
N_z	Total number of zones	9
N	# of sensors inside the observation area	36
M_{max}	Maximum number of objects	10
f_r	frequency of acoustic signal	10 kHz
k	spreading factor	1.5
SNR	signal to noise ratio (sensing)	10 dB
T	collection interval	1 s
T_p	packet duration	10 ms
ρ	AR-1 correlation factor	0.999
p_e	packet error rate	0.1

potentially a rate scheme and other factors such as time of arrival or time difference of arrival can be used instead of the received power.

V. SIMULATION RESULTS

We consider an observation area of size 1 km by 1 km which is divided to N_z squared zones. N sensors are distributed uniformly inside the observation area. Each object generates an acoustic signal of power P_t. The acoustic path loss model we used is

$$A(d, f_r) = (d/d_{ref})^k a(f_r)^{(d-d_{ref})} \tag{18}$$

where

$$10\ log\ a(f_r) = 0.11(\frac{f_r^2}{1+f_r^2}) + 44(\frac{f_r^2}{4100+f_r^2}) \\ +2.75\times 10^{-4} f_r^2 + 0.003 \tag{19}$$

is the absorption loss as a function of reference frequency f_r in kHz, k is the spreading factor and d_{ref} is the reference distance. Table I lists salient system parameters and their default values. The velocities of the objects change with time based on the AR-1 model with an average absolute value on the order of a few meters per second. The sensing SNR is defined as $SNR = P_t/\sigma_w^2$, where σ_w^2 is the variance of the sensing noise. (Note that the sensing SNR is defined with respect to transmit power, as the power received at each sensor may be different.) First, we consider the performance of state overlapping method in a perfect communication case. Fig. 3 shows the percentage of the times in which entrance/departure of objects is successfully detected. For example, assume that at time $k = k_0$ an object enters/departs the primary zone. A detection is called successful if the algorithm can detect the entrance/departure of the object at most at time $k = k_0 + k_{lag}$, where k_{lag} is a constant number of iterations. Fig. 3 quantifies the increase in successful detection rate with SNR and the number of sensors.

Fig. 4 shows the minimum rate of successful transmissions per collection interval required to ensure the MSE of -20 dB or less in the perfect communication scenario. We call this rate λ_{20dB}. For example, for $M_{max} = 5$ objects and $SNR = 15$ dB, we need at least 28 measurements in each collection interval. Using (11) we can find an upper bound on the range

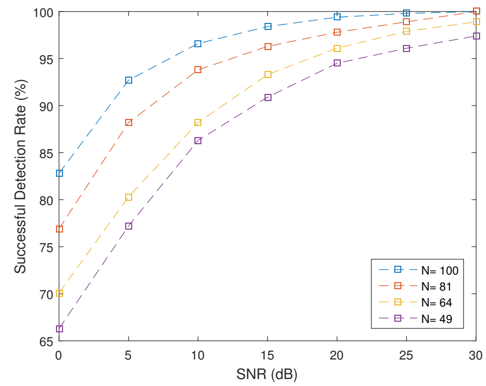

Fig. 3. Successful detection rate vs. SNR for different number of sensors N and $N_z = 9$. Three objects are moving in the area. $\rho = 0.999$, $\sigma_v = 10$ m/s, $T = 1$ s, $k_{lag} = 10$.

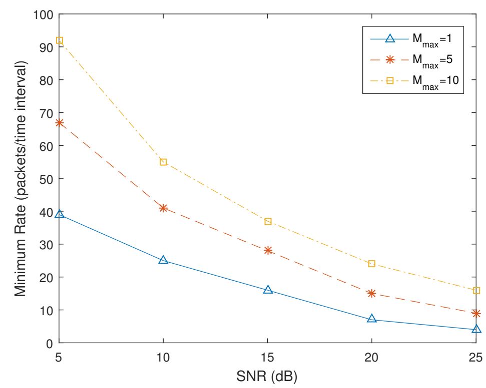

Fig. 4. Minimum rate (packets per collection interval) required to ensure MSE≤-20 dB in perfect communication scenario. $\rho = 0.999$, $\sigma_v = 10$ m/s, $T = 1$ s.

of T_p values for which the fixed rate scheme can lead to this MSE:

$$T_p \leq \frac{(1-p_e)}{2e\lambda_{20dB}} = T_{p,20dB} \tag{20}$$

For example, for $\lambda_{20dB} = 28$, the maximum acceptable value is $T_{p,20dB} = 5.9$ ms. In practical situations, the number of nodes is limited. Using Eqs. (8) and (10) we can find (N, BW) pairs for which the $MSE = -20$ dB is guaranteed. Fig. 5 shows such curves for $L_p = 32$ bits, $S_f = 1$ bit/s/Hz and a varying number of objects. As a rule of thumb, one can choose a pair in the knee part of the curves. Increasing the bandwidth beyond this point does not lead to a significant reduction in the number of sensors. For example, for $M_{max} = 5$ a reasonable choice would be $BW = 10$ kHz, and $N = 36$.

Now, we evaluate the performance of the rate control schemes. Fig. 6 shows the MSE vs. sensing SNR for different rate control methods. This result shows that the relative power method and the exponential rate method perform nearly identically and both outperform the fixed rate method.

Fig. 7 shows the performance of different rate control methods as a function of N. Here, we also included the result from another method that we call semi-adaptive exponential scheme, in which $\sigma_e = 1/\alpha$ as before, but $\lambda_e = 0.6$ is fixed

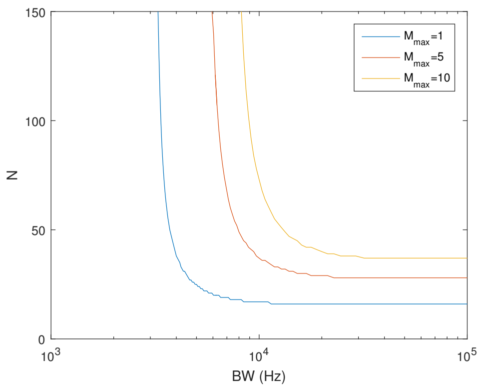

Fig. 5. (N, BW) pairs required to guarantee a MSE $= -20$ dB. $\rho = 0.999$, $\sigma_v = 10$ m/s, $T = 1$ s, sensing SNR $= 15$ dB, $p_e = 0.1$, $L_p = 32$ bits, $S_f = 1$ bit/s/Hz.

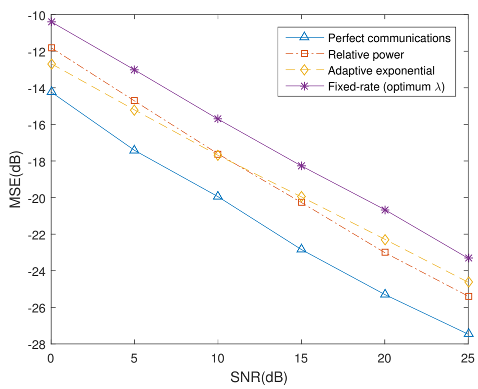

Fig. 6. MSE vs. sensing SNR for different methods. Five objects are moving in the area. $N = 36$, $\rho = 0.999$, $\sigma_v = 10$ m/s, $T = 1$ s, $T_p = 10$ ms, $p_e = 0.1$, $\sigma_e = 0.5$ km.

rather than changing with N as outlined in Eq. (13). The value of $\lambda_e = 0.6$ is the optimum value for $N = 81$. That is why the two exponential schemes perform the same at $N = 81$. Other than this, the adaptive exponential scheme always outperforms the semi-adaptive one. At the same time, the other methods are self-adaptive and their performance becomes better with increasing N.

VI. CONCLUSION

In this paper we proposed a new method for object discovery and tracking in sensor networks where sensor nodes transmit to the FC in a random access manner. The proposed state overlapping method relieves the need for time-varying size of the state vector in Kalman filtering. This makes the algorithm more scalable and easily applicable to any observation area. A group of Kalman filters is employed at the FC, each filter making use of one set of sensing values observed by the nodes. In this way, each Kalman filter benefits from the more reliable sensory values at each point in time. We also analyzed different control schemes for adjusting the transmission rate from sensor nodes to the FC. These schemes have model parameters that need to be adjusted carefully, and we proposed methods to set appropriate values for these parameters. By

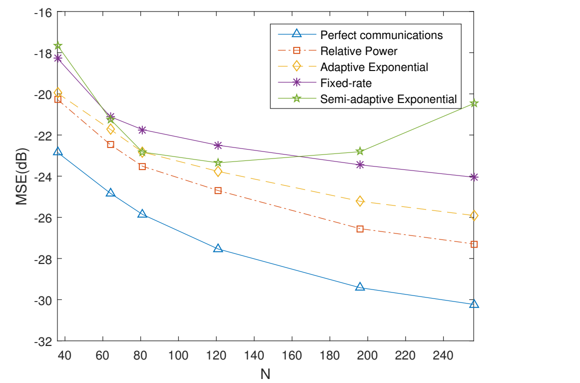

Fig. 7. MSE vs. N for different rate control methods. Five objects are moving in the area. Sensing SNR $= 15$ dB, $\rho = 0.999$, $\sigma_v = 10$ m/s, $T = 1$ s, $T_p = 10$ ms, $p_e = 0.1$, $\sigma_e = 0.5$ km.

adjusting the transmission rate adaptively, we make better use of the available bandwidth and improve the tracking capability and the energy efficiency of the system. Although we used acoustic path loss model for simulation, the method is not limited to this case and can be applied to other signature functions including radio communications. Future research should focus on finding additional rate adjustment policies, taking into account factors such as the speed of objects, as well as mobile systems, where the sensors' locations can be controlled.

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