NETWORK-CENTRIC WARFARE COMMUNICATIONS WITH WIRELESS SENSOR NETWORKS AND DATA FUSION

by

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ABSTRACT

NETWORK-CENTRIC WARFARE COMMUNICATIONS WITH WIRELESS SENSOR NETWORKS AND DATA FUSION

In this thesis we aim to design efficient algorithms for wireless ad hoc sensor networks that are supporting network-centric warfare operations. These algorithms should conform to the hard end to end QoS requirements. They should be energy efficient. They should fuse and aggregate data to reduce the network traffic and obtain more accurate assessment of the environment. A particular challenge in the wireless sensor network setting is the need for distributed estimation algorithms which balance the limited energy resource at a node with the cost of communication and sensing. Distributed processing strategies that use a subset of sensor measurements directly mitigate the volume of inter-node communication thereby conserving power. The challenge is to decide in an intelligent manner which sensor measurements to use. In other words, to select a sensor that is likely to provide the greatest improvement to the estimation at the lowest cost.

For target tracking applications, wireless sensor nodes provide accurate information since they can be deployed and operated near the phenomenon. These sensing devices have the opportunity of collaboration among themselves to improve the target localization and tracking accuracies. An energy-efficient collaborative target tracking paradigm is developed for wireless sensor networks (WSNs). A mutual information-based sensor selection (MISS) algorithm is adopted for participation in the fusion process. MISS allows the sensor nodes with the highest mutual information about the target state to transmit data so that the energy consumption is reduced while the desired target position estimation accuracy is met. In addition, a novel approach to energy savings in WSNs is devised in the information-controlled transmission power

adjustment (ICTP), where nodes with more information use higher transmission powers than those that are less informative to share their target state information with the neighboring nodes. Simulations demonstrate the performance gains offered by MISS and ICTP in terms of power consumption and target localization accuracy.

A fully-distributed collaborative multi-target tracking framework that eliminates the need for a central data associator or a central coordinating node for wireless sensor networks is defined. Details of the distributed data association architecture, which is more feasible than the ones relying on a coordinating entity, is described. It is shown that for target tracking applications, the collaboration improves the target localization performance of the distributed data collecting devices. In order to reduce the communication energy exhausted for collaboration, the performance of the collaboration logic manager is examined. Simulation results show that collaborating about a single target information is a rational decision. The problem of deciding which target information to collaborate among the detected targets arises. A mutual information based metric is shown to be a good candidate for deciding on the target which the sensor will collaborate about with the network.

A fuzzy network association algorithm (FUNA) for associating the target report from the neighboring sensor node with a track in the track list is described. The rule base of FUNA is created by consulting to the result of a voting mechanism among the fuzzy variables to support the association decision. Euclid distance, direction difference, and speed difference between the track report from the neighboring sensor node and the track in the track list are the fuzzy variables that support FUNA. It is shown by simulation that FUNA reduces the number of false network associations for the meandering targets. Moreover, better target localization accuracies achieved by FUNA when compared to the Euclid, likelihood, and Mahalanobis distance based network association metrics.

ÖZET

AĞ DESTEKLİ HARP İÇİN TELSİZ DUYARGA DESTEĞİ VE TAKTİK VERİ BİRLESTİRME

Hedef tespit ve izleme uygulamalarında, telsiz muhabere yeteneğine sahip küçük algılayıcılar harekat sahasına çok yakın olarak yerleştirilebildikleri için doğru bilgi sağlarlar. Bu küçük algılayıcılar hedef tespit ve izleme hassasiyetlerini arttırmak için birbirleri ile ortak çalışma yeteneğine sahiptirler. Telsiz muhabere yeteneğine sahip küçük algılayıcılar için enerjilerini verimli olarak kullanabildikleri dağıtık bir hedef izleme algoritması geliştirilmiştir. Bu algoritma ile hedefi tespit eden algılayıcılar arasında en fazla bilgiye sahip ve mükerrer bilgi taşımayan algılayıcıların bu bilgilerini komşu algılayıcılar ile paylaşması ile hedef takip doğruluğundan çok fazla kaybetmeden algılayıcı ağın yaşam süresi uzatılmıştır. Dağıtık veri birleştirme mimarisi, algılayıcıların ortak çalışabilmeleri için gerekli altyapıyı sunar. Bu küçük algılayıcıların enerji tahditleri nedeni ile genel bir eğilim, bazı algılayıcıları geçici olarak pasif duruma getirmektir. Enerji tasarrufunu arttırmak amacı ile, karşılıklı en fazla bilgi içeriğine dayalı seçici bir algılayıcı etkinleştirme algoritmasına ek olarak, bilgi içeriği ile kontrol edilen sinyal gönderme gücü ayar düzeni geliştirilmiştir. Müşterek hedef izleme için geliştirilen güç ayar düzeni algoritmasının özü, hedef hakkında daha fazla bilgiye sahip olan algılayıcıların daha az bilgiye sahip olan algılayıcılara göre daha fazla çıkış gücü kullanarak bilgilerini etraflarındaki algılayıcılarla paylaşmaları esasına dayanır. Tek bir hedefin izlenmesi için yapılan çalışmalar birden fazla hedefin izlenmesi için geliştirilmiş ve dağıtık çoklu hedef izleme mimarisi önerilmiştir. Önerilen mimariye ait performans testlerinde birden fazla hedefi tespit eden algılayıcıların sadece hakkında en fazla bilgiye sahip olduğu hedef bilgisini komşu algılayıcılarla paylaşmasının enerji tüketimi ve hedef izleme doğruluğu performansları için en doğru karar olduğu sonucuna ulaşılmıştır.

Komşu algılayıcılar tarafından rapor edilen temas bilgilerinin, algılayıcıya ait iz

listesinde mevcut temaslar ile ilişkilendirme probleminin çözümüne yönelik olarak bulanık mantık kullanan bir ağ iz ilişkilendirme algoritması önerilmiştir. Önerilen algoritmada bulanık kurallar, temas ilişkilendirme kararı için kullanılan bulanık değişkenler arasında bir oylama mekanizması kullanılarak oluşturulmuştur. İz listesindeki temas ile komşu algılayıcı tarafından rapor edilen temas arasındaki Euclid mesafesi, olabilirlik ve Mahalanobis mesafesi ilişkilendirme kararını destekleyen bulanık değişkenler olarak kullanılmışlardır. Önerilen algoritmanın, zikzaklı yolalan hedefler için temas ilişkilendirme performansını Euclid, olabilirlik ve Mahalanobis metrikleri kullanılarak yapılan ilişkilendirmelere göre arttırdığı, bunun sonucu olarak hedef takip doğruluğunu arttırdığı benzetim ile gösterilmiştir.

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LIST OF SYMBOLS/ABBREVIATIONS

b	Number of bits
cpu	Central processing unit
$d_{i,j}$	Distance between the sensor nodes i and j
D_M	Mahalanobis distance
E_T	Total number of targets in the surveillance area
$\mathbf{F}$	Target state transition matrix
$\mathbf{H}_m$	Observation matrix of an arbitrary sensor node
$\mathbf{i}_m$	Information state denomination(contribution) related with the observation of an arbitrary sensor node
$\mathbf{I}_m$	Information matrix denomination(contribution) related with the observation of an arbitrary sensor node
$\mathbf{I}_{m,n}$	Estimate of sensor S_m about the information matrix denomination of sensor S_n
J_m	The mutual information gained with the observation of an arbitrary sensor node
$J_{m,n}$	Estimate the sensor S_m about the mutual information value of all its neighboring sensor S_n
$\mathcal{J}_m(k)$	Ordered set of mutual information values as predicted by the sensor node S_m at time instant k
$\mathcal{J}'_m(k)$	Ordered set of $N_{\max}$ mutual information values as predicted by the sensor node S_m at time instant k
k	Time instant index
$\mathbf{L}_S$	Position of an arbitrary sensor
m	Sensor index
$N_{\max}$	Maximum number of sensors that can communicate
N_T	Total number of sensors in the surveillance area
O_n	An arbitrary observation of an arbitrary sensor node
P_ℓ	Communication transmission power level of an arbitrary sensor node
$\mathbf{P}_m$	Posterior target state estimation error covariance of an arbitrary sensor node

$\mathbf{P}_s$	Posterior target state estimation error covariance related with the target T_s
$\mathbf{Q}$	Covariance of the target movement noise
r_m	Ground truth range of the target from an arbitrary sensor node
$r_{m,d}$	Range of the target measured from an arbitrary sensor node
$\mathbf{R}_m$	Covariance matrix of the observation errors in the observed mean target state after the unbiased polar-to-Cartesian conversion
$\mathbf{R}_{m,n}$	Estimate of sensor S_m about the covariance matrix of the observation errors by sensor S_n
$\tilde{r}_m$	Measurement error of the range of the target
RX_i	Energy consumed by a sensor i in receiving a b-bit data packet
s	Time slot
S_m	An arbitrary sensor node
$\mathcal{S}_m(k)$	Set of neighboring sensors of sensor S_m at time instant k
$\mathcal{S}'_m(k)$	Set of neighboring sensors of sensor S_m that can communicate at time instant k
T_s	An arbitrary target
$TX_{i,j}$	Energy consumed by a sensor i in transmitting a b-bit data packet to sensor j
$\mathbf{v}$	Target movement noise
$\mathbf{x}$	Real target state
$\hat{\mathbf{x}}_m$	Target state estimate of an arbitrary sensor node
$\hat{\mathbf{y}}_m$	Information state related with the target state estimate of an arbitrary sensor node
$\mathbf{Y}_m$	Information matrix related with the target state estimate of an arbitrary sensor node
$\mathbf{Y}_{m,n}$	S_m's estimate of S_n's information matrix
ε_{amp}	Energy consumed for the transmitter amplifier
ε_{elec}	Energy consumed to run the transmitter or receiver circuitry
ζ	Target maneuvering index
η	Vertical position of the target

$\eta^c_{m,d}$	Vertical position of the target after the unbiased polar-to-Cartesian conversion
$\dot{\eta}$	Vertical speed of the target
θ_m	Ground truth bearing of the target from an arbitrary sensor node
$\theta_{m,d}$	Bearing of the target measured from an arbitrary sensor node
$\tilde{\theta}_m$	Measurement error of the bearing of the target
$\boldsymbol{\mu}_m$	Average true bias in the unbiased polar-to-Cartesian conversion
ξ	Horizontal position of the target
$\xi^c_{m,d}$	Horizontal position of the target after the unbiased polar-to-Cartesian conversion
$\dot{\xi}$	Horizontal speed of the target
σ_{θ_m}	Standard deviation of the observation errors of a sensor node in bearing
σ_{r_m}	Standard deviation of the observation errors of a sensor node in range
$\boldsymbol{\varphi}_m$	Observed mean target state after the unbiased polar-to-Cartesian conversion

APTEEN	Adaptive threshold sensitive energy efficient sensor network protocol
C4ISR	Command, control, communications, computer, intelligence, surveillance and reconnaissance
CEC	Cooperative engagement capability
CSIP	Collaborative signal and information processing
DDF	Distributed data fusion architecture
DHCP	Dynamic host configuration protocol
GEAR	Geographic and energy aware routing
FOA	Focus of attention
FUNA	Fuzzy network association
GCCS	Global command and control system
HAM	Hybrid association model
ICTP	Information controlled transmission power

IDSQ	Information driven sensor querying
IP	Internet Protocol
JPDA	Joint probabilistic data association
LEACH	Low energy adaptive clustering hierarchy
MC	Monte carlo
MECN	Minimum energy communication network
MHT	Multiple hypothesis testing
MIR	Micropower impulse radar
MISN	Most informative sensor node
MISS	Mutual information-based sensor selection
ML	maximum likelihood
NCW	Network-centric warfare
NN	Nearest neighbor
PEGASIS	Power efficient gathering in sensor information systems
QoS	Quality of service
SMECN	Small minimum energy communication network
SPIN	Sensor protocols for information via negotiation
TEEN	Threshold sensitive energy efficient sensor network protocol
TEWASA	Thread evaluation weapon allocation sensor assignment
UAV	Unmanned aerial vehicle
WSN	Wireless sensor network

1. INTRODUCTION

Network-Centric Warfare(NCW) is an attempt to effectively link all the elements of the warfighting enterprise to achieve the improved situation awareness, rapidity, and accuracy. NCW provides broader vision of the vicinity for the warfighting platforms than the one Platform Centric Warfare provides. Even a missile, contributes to the situation observations of the enterprise, until the time of its explosion at the target. Today's missiles have their own sensors on board to cruise towards the target and to improve the probability of hit. In NCW, the data that the missile observes during its travel towards the target is conveyed to the command and control center and fused with the existing information about the vicinity. Improved situation information is sent back to the missile and other related entities in the enterprise. Main difficulty in achieving the NCW is the problem of interoperability. Most modules aiming Network-Centric Warfare exists. However, a Network-Centric Warfare enterprise is envisioned in 2010 and beyond [1].

Advances in wireless communication, digital electronics, and embedded systems have led to the development of new generation ad hoc networks, namely wireless sensor networks (WSNs). Emerging WSNs with hundreds to several thousands of small sized, low cost, low power micro-sensor nodes deployed into an area of interest, enables us to sample the parameters of interest throughout the sensor field in a distributed manner. Micro-sensor nodes in a WSN are capable of collecting, processing, and storing the ambient information and communicating with the neighboring nodes in the wireless medium. A micro-sensor node is mainly comprised of a sensing unit, a processing unit, a transceiver unit, and a power unit. A typical micro-sensor processor board has a processor at 4 megahertz, 8 bit microcontroller, 128K on board flash memory, and 512K nonvolatile flash memory [4]. A sample micro-sensor processor board as compared in size with a coin is shown in Fig. 1.1. Wireless micro-sensor devices, with the duty of tracking a target, have two main functionalities. The first one is the distributed detection of the presence of a target and the estimation of the parameters of interest related with the target state. The second task involves wireless networking to organize and

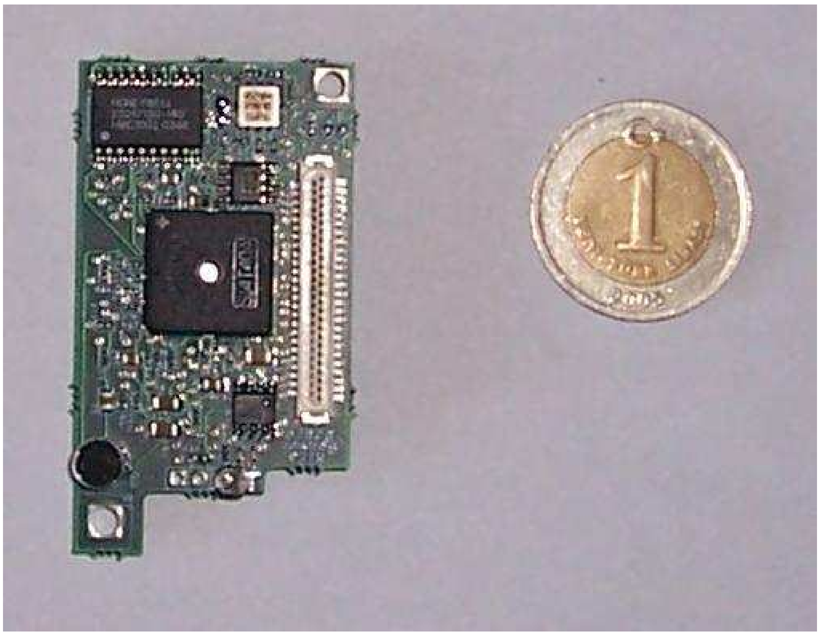

Figure 1.1. A micro-sensor processor board as compared in size with a coin.

carry information. Distributed detection and estimation have long been studied in the literature. Problems related to the wireless networking issues are also addressed extensively. However, there are not much work done on how wireless networking constraints affect the distributed detection and estimation duty of the wireless smart sensor networking devices. We aim to address this issue and to derive a formal understanding of how wireless networking constraints affect the distributed detection and estimation task and derive algorithms remedy the deficiencies.

Wireless sensors observing the diverse properties of the environment form an ad hoc network to convey their observations towards an evaluator entity. Diverse observations from the phenomenon provide better accuracies. For example, a radar sensor provides accurate range but poor angle data while infrared provides accurate angle but poor range data. Moreover, altitude information of the target can best be obtained from an optic sensor. Fusing these range, bearing, and elevation information from diverse sensors provides more accurate positioning of a track. Even for the similar sensor types, the different viewing angles of the physically distributed sensors can provide better target localization data. Furthermore, multiple sensors provide more robust performance due to their inherent redundancy.

It is crucial for the real time decision support systems, especially for a tactical defense system, to make fast decisions with limited resources. Though the evidences may be collected from many possibly allocated sensors with varying capabilities, it is important to avoid unnecessary or unproductive sensor actions and computations [5]. The more informative evidence is the one that decreases the uncertainty of the hypothesis more. Access to the information requires costs such as the cost of information retrieval, time delay and extra computation time.

Selecting a sensor that is likely to provide the greatest improvement to the estimation at the lowest cost is named as the sensor selection problem or the sensor scheduling problem in the literature. Reducing sensing interference for active sensors, reducing communication interference, improving sensor lifetime are the motivations for the sensor selection or scheduling algorithms. Sensor scheduling problem was cast as a non-linear deterministic control problem and shown to be solvable by a tree-search in general [6]. Also dynamic programming and gradient method for obtaining a solution were proposed. To deal with the complexity of tree-search, greedy algorithms have been proposed [7, 8, 9].

Compared to the centralized fusion, distributed fusion is a much less mature area of research. It is well known that in standard non-cooperative distributed detection problems correlation in the input statistics can both help and hurt the detection performance [10]. The goal of this work was to characterize general methods which exploit helpful statistical dependencies with the overall aim of further developing the understanding of distributed cooperative detection, classification, and tracking systems.

In [11], the information graph is introduced as a way of modeling information flow in distributed fusion systems. One of the central issues for Collaborative Signal and Information Processing (CSIP) to address is the energy constrained dynamic sensor collaboration.

Given the current belief state, we wish to incrementally update the belief by incorporating measurements of other nearby sensors. However, among all available sensors in the network, not all provide useful information that improves the estimate. Furthermore, some information might be useful, but redundant. The task is to select an optimal subset and decide on an optimal order of how to incorporate these measurements into our belief update. Due to the distributed nature of the sensor networks, this selection has to be done without the explicit knowledge of the measurement residing at each individual sensor. The decision has to be made based on the sensor characteristics such as the sensor position or sensing modality, and the predicted contributions of these sensors.

Example sensor selection strategies from the literature are minimizing the Euclid distance (nearest-neighbor), blind, minimizing the Mahalanobis distance, minimizing the entropy, maximizing the Kullback-Leibner distance (relative entropy) between predicted belief and expected belief [12]. In [13, 14], authors propose a sensor selection methodology based on fuzzifying the sensor characteristics and sensor reliability. They show that by choosing more reliable sensors, less error in the mobile robot localization problem is achieved when compared to using all the sensor contributions.

Previous work on data aggregation for wireless sensor networks focuses on the networking aspect like minimizing the total network flow. Aggregation trees are formed to remedy the problem. We examine the approaches to the data fusion/aggregation problem in Section 1.5. We also discuss in the same section, how emerging wireless sensor devices benefit from data fusion.

Without insight into questions like,"What should the detectors transmit and to whom?" the design of sensor networks will likely remain ad-hoc. This work ultimately aims to provide insight into these types of problems.

Target tracking, or processing of the measurements obtained from a target in order to maintain estimates of its current and future states, has major importance in Command, Control, Communications, Computer, Intelligence, Surveillance and Reconnaissance (C4ISR) applications [15, 16]. Due to environmental perturbations, data collected near the phenomenon are more reliable than those obtained far from it. Emerging wireless sensor technologies facilitate the tracking of targets just within the phenomenon. In Fig. 1.2, small-sized, battery-operated, wireless communicating sensor devices are deployed very close to the hostile environment, and they are used for distributed sampling of signals from the target of interest in a C4ISR application. An unmanned aerial vehicle (UAV) patrolling above the area of surveillance relays the target position that is obtained from the sensor network towards the command and control center, where the Threat Evaluation, Weapon Assignment and Sensor Allocation (TEWASA) function takes place [17, 18]. If the reported target is evaluated as a threat, then the most appropriate weapon is assigned to that target. At that moment, a firing channel between the wireless sensor network (WSN), UAV, command and control center, and the weapon is formed. The target position, where the weapon is to be directed, is fed continuously to the weapon via the firing channel. Command and control center monitors the communication delay in the firing channel in order to maintain the appropriate extrapolation about the target position. In the area of operation, units such as the soldier in Fig. 1.2 may need rapid and roughly accurate target position information. The soldier near the sensor field has limited communication capability when compared to the rocket launcher truck. Hence, the best the soldier can do is to ask a sensor node nearby him about the target position. The sensor node, with its current knowledge of the target state, immediately responds to the soldier's query. In this scenario, the rocket launcher truck obtains the target state information from the communication link composed of a sink node, UAV, and the command and control center. The target state information obtained by the rocket launcher truck is more accurate than that collected by the soldier. However, the soldier has the target state information more rapidly than the rocket launcher truck. With a distributed data fusion (DDF) architecture, benefiting from the far-reaching communication range of the sensor node compared to its detection range, we aim to have an acceptable target position information to be available at every sensor node. The reason is that the soldier may query any one of the sensor nodes that is close to him for an immediate and acceptably accurate target position information. The wireless communication characteristics of the emerging wireless sensor nodes provide an excellent distributed coordination mechanism to improve the global target localization accuracies in the WSN. Sensor nodes in the surveillance area, collaboratively monitor the tracks in the vicinity using

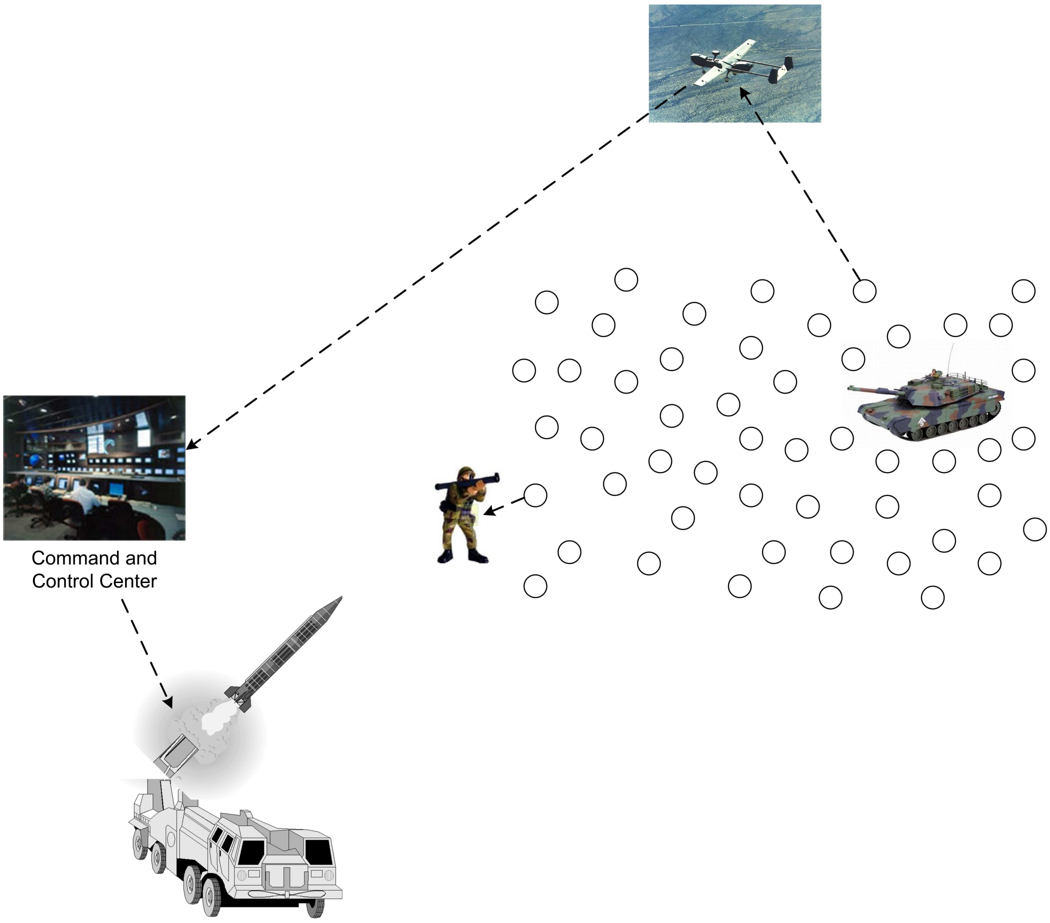

Figure 1.2. C4ISR scenario with wireless sensor devices.

distributed target tracking algorithms. Moreover, collaborated target position information is sent continuously to the command and control center for further investigation, analysis, and integration with other information sources. Collaborated target position information at each sensor node is also available for an interested querying unit.

Collaborative target tracking brings along questions such as how to dynamically determine who should sense, what needs to be sensed, and whom the information must be passed on to [19]. Sensor collaboration improves

1. Detection quality: Detection resolution, sensitivity, dynamic range, missed and false alarms, response latency.
2. Track quality: Tracking errors, track length, robustness against sensing gaps.
3. Scalability: Size of network, number of events, number of active queries.
4. Survivability: Robustness against node/link failures.

5. Resource usage: Power/bandwidth consumption.

As an example, collaborative beamforming is used in [20] to localize acoustical sources. A Bayesian approach to detecting and tracking multiple targets using acoustic data from multiple passive arrays is presented in [21]. In [22], a circular detection region is obtained by equipping each sensor node with several ultrasonic sensors. Sensor nodes in WSNs are battery-operated, which puts an energy constraint on their operation lifetimes. Reducing the energy exhausted by the nodes improves the duration of the time over which the sensor network's surveillance duty is carried out. In order to conserve the valuable battery power of the wireless devices, a common trend is to put some of the sensor nodes into a dormant state, which is controlled by a sleep schedule [23, 24]. Moreover, only a subset of the sensor nodes are active at any instant of time to also avoid redundant data flow in the network. Sensor activation strategies can be listed as *naive activation* in which all the sensor nodes are active, *randomized activation* in which a random subset of the sensor nodes are active, *selective activation* in which a subset of the sensor nodes are chosen according to some performance measure, and *duty-cycled activation* in which the sensor nodes are active for some duty cycle and in dormant state thereafter. There is an inevitable trade-off between the energy expenditure and the tracking quality in sensor networks [25].

Distance of the sensor node to the target is used in the activation decision in [26]. In information driven sensor querying (IDSQ) [19, 27], the so-called clusterheads decide on the sensor nodes that are to participate actively in the tracking task. In [28], a dual-space paradigm is presented in which the subset of nodes towards whom the target is approaching are selected to be active. Clusters are formed dynamically around the high-capability sensor nodes in [29]. In the location-centric approach to collaborative sensing and tracking, addressing and communication is performed among geographic regions within the network rather than individual nodes [30,31]. This makes localized selective-activation strategies simpler to implement. In [32], a selective sensor activation scheme is proposed in which the activation decision is based on the adaptive activation radius around the predicted position of the target. The proposed activation radius in [32] is inversely proportional to the tracking quality. Prediction-based target tracking techniques such as the Pheromones, Bayesian, and Extended Kalman Filter are presented in [33, 34], and a real implementation can be found in [35]. Multiple target tracking is examined in [36, 37, 38, 39].

Censoring sensors [40, 41, 42, 43, 44] is one approach to control the network traffic load. Sensor nodes that are deemed as non-informative do not send their decisions or observations if their local likelihood ratio falls in a certain single interval. A special case of this phenomenon occurs when the lower bound of the no-send interval is zero. In this particular case, the problem reduces to sending the local decision/observation if the local likelihood ratio is above some threshold. A deficiency with this approach occurs for tracking applications if all the sensor node local likelihood ratios fall in the no-send region, and no belief about the target state is shared among the nodes.

We concentrate on the WSN part of the C4ISR application depicted in Fig. 1.2. Sensor nodes try to collaboratively maintain accurate target position and speed estimates to report to the UAV or to an interrogator in an energy efficient manner. We first consider the problem of tracking a single target using immobile sensor nodes that collaborate with each other through a broadcast communication mechanism. With collaboration among the sensor nodes, we aim to improve the target localization accuracy achieved by each sensor node. Moreover, we try to retrieve the target location from the network with low delay by querying any one of the nodes in the network. Collaborative target tracking makes it possible for each sensor node in the network to have an acceptable localization accuracy. As an extreme case, if there were no communication constraints, in other words, if every sensor node could communicate with every other node in the network, then the posterior target position information after the collaboration would be the same value for all nodes. The above-mentioned capability of the collaborative target tracking framework eliminates the need for a sink node inside the sensor network to collect the target position estimates of the neighboring sensor nodes. Any node that can be communicated within a single hop is a neighbor.

Previous research [45, 46, 47] has focused on how to provide full or partial sensing coverage in the context of energy conservation. Nodes stay in a dormant state as long as their neighbors can provide sensing coverage for them. These solutions regard the sensing coverage of a certain geographic area as binary, i.e., coverage is either provided, or not [23]. They consider the sensor selection problem only in terms of coverage and energy-saving aspects, without paying attention to detection and tracking quality. In tracking applications, when selecting the subset of sensor nodes to contribute to the global decision, we have to consider how informative the sensor nodes are about the state of the target.

In [27, 48], the sensor node which will result in the smallest expected posterior uncertainty of the target state is chosen as the next node to contribute to the decision. Specifically, minimizing the expected posterior uncertainty is equivalent to maximizing the mutual information between the sensor node output and the target state [48]. An entropy-based sensor selection heuristic is proposed for target localization in [49] where a sensor node is chosen in each step and the observation of that node is incorporated into the target location distribution using sequential Bayesian filtering. An information utility description for bearing-only sensors is proposed in [50,51]. The proposed method does not require the estimation of the posteriori distribution of the target state and thus reduces the computational overhead.

The information state is a function of the real target state and the information matrix is a function of the target state uncertainty, i.e., target state covariance. The contribution of the sensor node to the information state is called its information state denomination. Similarly, the contribution of a sensor node to the information matrix is called its information matrix denomination.

Multiple sensor nodes usually perceive similar observations about the target state, which results in an inherent redundancy of sensory data. We develop an energy-efficient collaborative target tracking paradigm for wireless sensor networks (WSNs). To that end, the network lifetime is prolonged and the desired tracking accuracy is maintained by selecting a subset of sensor nodes that are the most informative in the mutual information sense. In addition to the selective sensor activation strategy based on the maximum mutual information, with a novel approach to energy savings in WSNs, we devise a transmission power adjustment scheme whose essence lies behind the idea that the sensor nodes with more information should use higher transmission powers in order to share their information about the target state with their neighbors than those that are less informative.

Sensor nodes share with the other nodes in the WSN their information state and the information matrix denomination values, which are obtained from the collected target location data. With this mechanism, a collaboration among the sensor nodes is maintained in order to improve the target location estimate. Another possibility is to share the location of the target with the WSN after local information filtering. The latter paradigm in the sensor collaboration requires more complicated fusion operations as described in [52, 53], whereas the former provides a simple additive fusion framework within the distributed architecture.

The multi-target tracking problem differs from the standard state estimation problem by the fact that the measurement origin is also uncertain. Problems related with the multi-target tracking phenomenon mainly focus on the association problem. There are several types of associations to deal with. The sensor-to-track association is studied in [54] as the *Focus of Attention* (FOA) problem, plot-to-plot association is named as the track initiation, plot-to-track association is named as track update/track continuation, and finally track-to-track association is named as track fusion [55]. Track-to-track association deals with how to decide whether two tracks coming from different sensors represent the same target, and if so the next problem is how to combine (fuse) the two track estimates together.

Data association algorithms in the literature can be classified as follows: nearest neighbor (NN) hypothesis testing, multiple hypothesis testing (MHT) [56] [57], and joint probabilistic data association (JPDA) [58, 59]. NN hypothesis testing assumes that the measurement closest to the center of the validation gate represents the target. MHT exhaustively enumerates all the possible hypotheses over a number of most recent frames and chooses the most likely one. JPDA makes the assumption that the nearest detection from the extrapolated target estimate may not always originate from the target and that other detections which are farther away may be the real measurement. To account for this, the JPDA algorithm assigns certain probabilities to the latest set of measurements within a gate. The distributed versions of the JPDA algorithm for a hierarchical architecture and that of MHT are given in [60] and [61, 62], respectively. Monte Carlo (MC) implementation of JPDA algorithm is presented in [63] as a simplified version of JPDA for WSNs.

The optimal track-to-track fusion formula derived in [64] to combine the local estimates is a maximum likelihood (ML) estimator [65], and it has larger error than the optimal method with centralized configuration [66]. It was shown in [66] that as the number of sensors increases, the performance of distributed tracking keeps degrading in comparison to the centralized one. In this context, distributed tracking describes the local sensors' data processing capability. In centralized configuration, sensors send their observation to a data collecting center. Association, based on the received sensor measurements, is carried out at the center. In the distributed configuration, local sensors process their observations to form their local tracks and local associations. The sensor-level processor outputs are sent to the data collecting center, which further processes these preprocessed data.

Track initiation problem and associating the sensor measurements with the target tracks are the main difficulties in the multi-target tracking phenomena. The problem is even more challenging in the context of sensor networks, since association is coupled across the network. Chen et al. [39] propose a solution to the distributed data association based on the graphical models by means of the message passing algorithm in which iterative, parallel exchange of information among the neighboring nodes is required. Zhu et al. [67] applied this graphical model for the solution of the track to track association problem. In [61], the problem of jointly tracking and classifying several targets within a sensor network is examined. The solution requires only one sensor to be active and focused on a target. However, possible existence of other targets is ignored.

In existing research, the distributed data association takes place in a center to which the distributed units send their collected and processed data. We envision a fully distributed data association architecture in which every single node collaborates with its neighbors and does data association. In other words, sensor nodes share the data association task. This approach is more feasible than the ones that rely on a coordinating entity for the sensor network applications.

In Section 1.1, we briefly discuss the Network-Centric Warfare, in Section 1.2, we examine the problem of physical deployment of the sensing entities, in Section 1.3 unique identity assignment problem is examined, in Section 1.4, routing for sensor networks is examined, Section 1.5, describes the data fusion/aggregation problem, in Section 1.6, we describe the sensing options and the sensor model, in Chapter 2, we describe the DDF architecture. Then, in Chapter 3, mutual information-based sensor selection algorithm (MISS) for participation in the fusion process is defined. Information-controlled transmission power (ICTP) scheme is introduced in Chapter 4. In Chapter 5, we describe the multi-sensor multi-target tracking system architectures. In Chapter 6, we describe our multitarget tracking framework for WSNs. Performance of the collaboration logic in the proposed framework is examined in Section 6.1, in Section 6.2, we discuss the association problems of the multi-target tracking architectures, in Section 6.3, we describe a fuzzy network association algorithm (FUNA), in Section 6.4, we evaluate the performance of FUNA. In Chapter 7, we conclude our work, and give some directions towards future research.

1.1. Network-Centric Warfare

The Network-Centric Warfare (NCW) concept calls for an autonomous rather than hierarchic, decision making process, based on ubiquitous access to information by distributed entities [1]. NCW is an approach to the conduct of warfare that derives its power from the effectively linking or networking of the warfighting enterprise. NCW provides shared battlespace awareness and shared commander intend.

Command and control consists of six main phases these are; sensing, fusing, understanding, deciding, conveying the decisions, and acting (execution). Battlespace entities to serve these phases of the command control are the sensing entities, deciding entities, and acting entities. Sensing entities consist of every kind of diverse sensors from high capacity, high performance phase array radars to disposable, low power, low cost mote sensors. Deciding entities have the common situation information. Using this situation information, deciding entity is responsible for the threat evaluation weapon assignment and sensor a allocation (TEWASA) [17, 18]. Also, fire control problem is solved at the deciding entities. Physical positioning of the deciding entities is another design problem. The weapons are the acting entities. Today's platform centric warfare, tightly couples the sensing entities to the acting entities. In other words certain sensors are related to the certain actuators. Sensors on one platform provide the situation awareness to its own platform. Actuators on the platform can develop engagement to the targets obtained from the own platform sensors. In contrast, network-centric warfare decouples the sensors and the actuators. Any actuator on any platform can develop engagement to any target obtained from any sensor. Network-centric warfare obviously increases the engagement capability of any platform. The actuators on the platform can now engage any target even if it is not obtained from the own platform sensors. Actuator can receive the track information from the remote platform sensors. Network-centric warfare also provides enhanced situation awareness to all the platforms and remote command and control center namely headquarter. The information source is now diverse and shared among the warfighting entities. Dimensions of the information are the relevance, accuracy, and timeliness. Hence, timely, relevant, and accurate information is too valuable to the warfighting entities.

In [68] a hierarchical communication architecture to convey the battlefield awareness information towards headquarters is proposed. This architecture also conveys the headquarters intention and commands to the actuators in the battlefield. Sensors and actuators at the battlefield form the mobile subsystem of the communication architecture. Above the mobile subsystem, maneuver network in which the special nodes to form the ad hoc infrastructure. Above the maneuver network tier is the airborne network as an umbrella tier, where the manned or unmanned aerial vehicle exists. Finally, the satellite network provides ubiquitous coverage for the sensors and the actors.

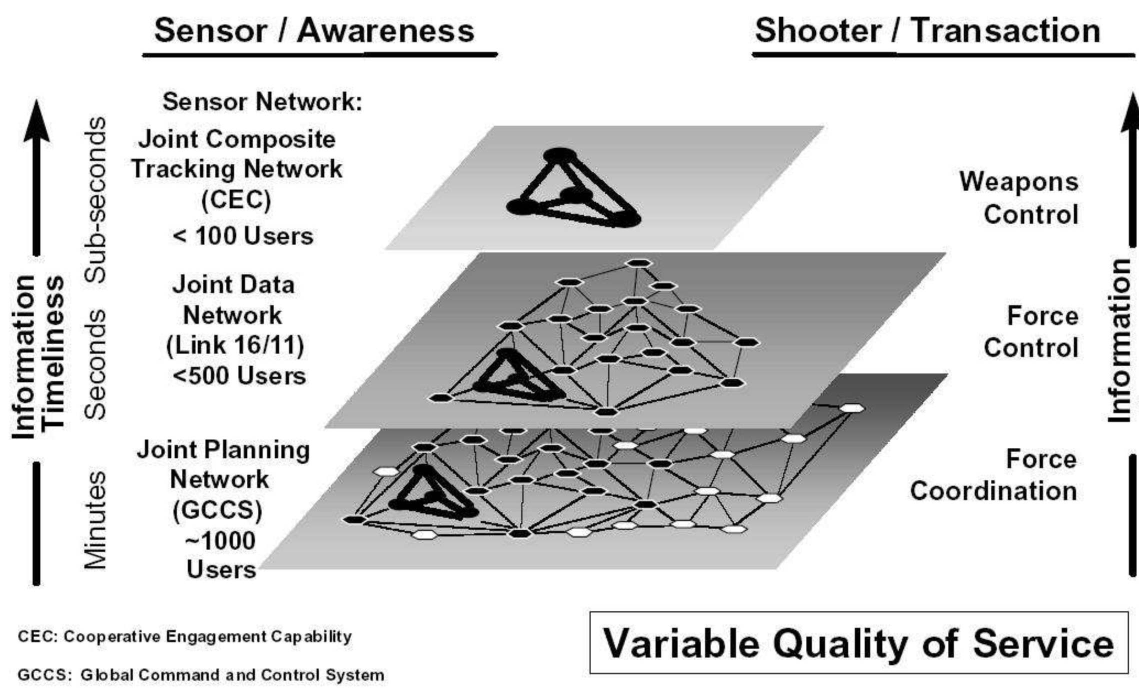

Figure 1.3. Information grids for the network-centric warfare operations [1].

Networked sensing offers unique advantages over traditional centralized approaches [69]. Dense networks of distributed networked sensors can provide improved Signal to Noise Ratio because of decreased average distance from the target, increased energy efficiency by multihop topology, in network processing, improved robustness and scalability.

The fog of battle is about the uncertainty associated with what is going on while the friction of war is about the difficulty in translating the commander's intend into actions. The changing character of modern conflicts leads to the need for a network-centric approach to warfare, in which information, including a timely picture of the situation, is made available to multiple distributed entities using multiple grids of differing quality of service.

Fig. 1.3 depicts the multiple information grids envisioned for the network-centric warfare operations; the engagement grid, awareness grid, and the planning grid [1]. The engagement grid is the most sensitive grid in terms of Quality of Service (QoS). This grid forms the joint composite tracking network and it is for weapon direction. Delay constraint for engagement grid is in sub-seconds. The middle layer is the awareness grid. This grid forms the joint data network and it is for common tactical picture. Delay constraint for awareness grid is in seconds. Finally the least delay sensitive grid in terms of QoS is the planning grid. This grid forms the joint planning network and it is for common operational picture. Delay constraint for planning grid is in minutes.

We partition the task of network-centric warfare into subtasks. These subtasks are; the physical deployment of the sensing entities, unique identity assignment to the involving entities, routing of situation information from the sensing entities to the deciding entities, data fusion and aggregation on the way to the deciding entity, and data fusion and aggregation at the deciding entity, deciding to an action according to the current observed situation, routing of decision from the deciding entities to the acting entities. There are also some integral tasks like, temporal and spatial synchronization of the involving entities.

1.2. Physical Deployment of the Sensing Entities

The physical positioning of the sensors effects coverage, communication cost, and resource management. The easiest technique to deploy sensors is the random deployment. However, more intelligent techniques for the initial deployment of sensors and the deployment tuning are required. In [70, 71, 72], the authors propose a tuning algorithm on the random initial sensor deployment based on the virtual attractive and repulsive forces. In this algorithm, sensors exert a repulsive force to each other if they are located closer than a threshold distance and an attractive force if they are located far from a distance threshold. The sensor deployment and sensor planning scheme proposed in [73] is suitable for the cases where we have priori knowledge about possible targets to be monitored. In the scheme proposed in [74], sensors are deployed in an incremental manner. That is they are deployed one by one in an adaptive fashion. In [75], an optimal polynomial time algorithm that uses graph theory and computational geometry constructs is used to determine the best case and the worst case coverage. Sensor placement on two and three dimensional grids has been formulated as a combinatorial optimization problem and solved using integer linear programming in [76, 77]. The authors in [78] propose a method for optimally locating the radars to achieve satisfactory surveillance with limited resources. A probabilistic optimization framework for minimizing the number of sensors for a two dimensional grid has been proposed in [79].

1.3. Unique Identity Assignment Problem

We should have a way to uniquely address the entities in the network-centric warfare enterprise. Traditional networks rely on centralized servers like Dynamic Host Configuration Protocol (DHCP) server. However, in a mobile ad hoc network, the DHCP functionality should be distributed among the participating units. This framework should support the joining of a node to the network and the departure of a node from the network. We can classify the approaches to the unique identity assignment problem in mobile ad hoc networks into three groups; IPV6 stateless auto configuration mechanism [80], flooding the entire network [81, 82], and distributing the IP addresses to be assigned among the nodes [83, 84, 85].

Flooding the entire network is a reactive approach. Distributing the IP addresses to be assigned, among the nodes is a proactive approach. Both approaches have pros and cons. The former approach suffers from the efficiency and the scalability due to the extensive flooding in the network. The later approach is vulnerable to the fraudulent nodes. In the later approach, each participating node in the network has a pool of identities to assign to a new coming node.

In the flooding approach, again two alternative strategies exists. First, the new coming node chooses its identification randomly and agrees with the network that it can use that identification. The second strategy is that the network converges on an identification to assign to the new coming node.

In the vertical traffic flow, traffic flows towards a sink instead of two peer nodes, and from sink to downwards. In wireless sensor networks that are in duty of sensing the close phenomena, we mostly do not need to address sensors uniquely. The sensor networks mostly involve in an attribute or location based addressing scheme with a vertical traffic flow.

1.4. Routing for Sensor Networks

Since, wireless sensing equipments contain limited power capacity, routing algorithms for the wireless sensor networks should be energy aware. Data delivery to the sink node can be continuous, event driven, query driven, or some combinations of these. Proposed routing algorithms for the wireless sensor networks can mainly be classified into three groups; data centric routing, hierarchical routing, and location based routing.

Data centric routing protocols are query based and they depend on the naming of the desired data. Data centric routing protocols help in eliminating many redundant transmissions. Hierarchical protocols aim at clustering the nodes so that the cluster heads can do some aggregation and reduction of data in order to save energy. Location based protocols utilize the position information to relay the data to the desired regions rather than the whole network.

We do not need to give a unique identity to each sensor for the data centric routing protocols. Routing is done by the attribute based naming. Two approaches to the data centric routing exist. First, the sensing entities advertise their data and the sink nodes concerning the advertised data create queries. Second, the sink nodes generate queries on demand and sensing entities having the queried data send their data towards the sink node. Former approach is called the Sensor Protocols for Information via Negotiation (SPIN) [86]. The later approach is called directed diffusion [87]. Many variants of the directed diffusion approach exist in the literature [27,88,89,90,91,92,93].

The aim of the hierarchical routing is to efficiently maintain the energy consumption of sensor nodes by involving them in multi-hop communication within a particular cluster and by performing data aggregation and fusion in order to decrease the number of transmitted messages to the sink. Cluster formation is typically based on the energy reserve of sensors and sensor's proximity to the cluster head [94] [95]. Hierarchical routing protocols proposed in the literature are; Low Energy Adaptive Clustering Hierarchy (LEACH) [96], Power Efficient GAthering in Sensor Information Systems (PEGASIS) [97], Hierarchical PEGASIS [98], Threshold sensitive Energy Efficient sensor Network protocol (TEEN) [90], Adaptive Threshold sensitive Energy Efficient sensor Network protocol (APTEEN) [99], Energy aware routing for cluster based sensor networks [100], self organizing protocol [101].

Location based protocols exploit the advantage of location awareness of the sensing and the querying nodes. Using the location information, these protocols reduce the number of messages transmitted. Examples of the location based protocols in the literature are, Minimum Energy Communication Network (MECN) [102], Small Minimum Energy Communication Network (SMECN) [103], Geographic Adaptive Fidelity [104], Geographic and Energy Aware Routing (GEAR) [105].

There are some routing protocols proposed for wireless sensor networks that the route setup is modeled and solved as a network flow problem [27, 106, 107]. Finally, another group of protocols exist in the literature that consider QoS requirements for the wireless sensor networks [108, 109, 110].

1.5. Data Fusion/Aggregation

Data fusion is usually defined as the seamless integration of data from disparate sources. Data aggregation can be interpreted as a set of automated methods of combining the data coming from many sensors into meaningful information [96]. An example of a data fusion system is the human and animal brain. The brain integrates the sensory information namely taste, smell, touch, sound, and sight to have a better assessment of the environment and evaluation of threats to increase the chance of survivability. Sensor fusion approach [111] is used in many engineering problems like, guidance, navigation, and control of vehicles that require large number of information from different sources [112]. There are also vehicle and target tracking applications employing fused data for better estimation of the vehicle and target position [113].

Data fusion techniques combine data from multiple sensors to achieve improved accuracies and more specific inferences than could be achieved by use of a single sensor alone [111]. Different sensors measuring the same physical phenomena reduce the uncertainty with the aid of the redundant data [114]. Different sensors measuring different aspects of the sensed environment reduce the uncertainty by means of the data diversity. An example of the data diversity is seen in an optical sensor and a radar sensor measuring the distance of an obstacle from a robot on which they are mounted. Another advantage of data fusion is that different sensors may observe a different subset of the environment space. Fusing this sensory information provides a broader environmental vision. In this way, we achieve data complementarity.

The most common data fusion/aggregation functions can be considered as the suppression (eliminating duplicates), minimum, maximum, average, count and sum. In a network-centric warfare environment, we need the tracking information about the threats. A track involves the history information about a reported contact. With the knowledge of the state history about a track, we can infer the estimates of the future states of the track. This future estimation has the crucial importance for the solutions of the fire control problems and for reducing the state observation noise. Hence, the sensors of the network-centric warfare should report not only the existence of a threat but also the exact position of the thread. New threat detection has three possibilities concerning the data association. First, the new observation can be the new state of an existing track. Second, the new observation can be a totally new thread; finally, the new observation can be false/fake detection.

Data fusion is performed based on one of the following approaches [112]; the probabilistic models like Bayesian reasoning, evidence theory, robust statistics, or recursive operators, the least-squares techniques like Kalman filtering, optimal theory, regularization, or uncertainty ellipsoids, and the intelligent fusion using fuzzy logic [115], neural networks [116], or genetic algorithms [117].

There are two main approaches in triggering the data gathering process. In the first approach, the sink node disseminates its interest to the sensing nodes. This is also known as querying [118]. The sensing nodes in reply, send their data to the sink node [87]. In the second approach, sensing nodes advertise their information and any sink node interested in that information requests the data [86]. The place of the aggregation provides another classification of the data aggregation techniques [119]. Aggregating the data in the interior router sensors on the way to its destination sink node is called as in-network aggregation. Aggregating the data from different sensors only at the sink node and forwarding the information received from other sensors towards the sink node without any processing is called out-of-network aggregation. Former reduces the network traffic, however requires some processing capability at the sensor nodes and introduces some processing delay at the sensor nodes. The node, which will perform an aggregation, should wait for the information from the other sensors. This also introduces a data collection delay at the aggregation node. In the later approach, simpler sensor nodes may be employed and the sensor routing delay decreases. However, the network traffic increases due to the redundant data. The sink node that will perform the out-of-network aggregation should have more processing capability to aggregate massive amount of data. The in-network data aggregation in which every intermediate node performs an aggregation on its received data has better performance in terms of the network communication cost than the out-of-network aggregation in which only the sink node performs the aggregation on the received data. This phenomenon has been shown theoretically in [120] and experimentally in [121]. The power consumption of each sensor node tends to be dominated by the cost of transmitting and receiving messages. In terms of power consumption, transmitting a single bit of data is equivalent to processing 800 instructions [122]. In the out-of-network aggregation approach, nodes close to the root send more data than the leaf nodes so that the power of the nodes closer to the sink node are drained off much earlier than the leaf nodes in the hierarchy. In-network aggregation provides fixed length transmission regardless of the depth of the sensor nodes in the aggregation tree.

In [87], authors introduce directed diffusion, where the sink node sends its interest to the network. Sensor nodes in response send their data to the sink node along the optimum path produced during the interest dissemination phase. The approach followed in digest diffusion is as follows; sensors do not send the data directly to the sink node; instead network converges on the aggregate value by exchanging data and current aggregate with one-hop neighbor sensors [123].

Another approach for collecting the desired data at any sink node is; sensor nodes only send their measurement data to the sink node throughout the network. In this approach, no local processing of the sensed data takes place. Upon receipt of the sensor measurements, the sink node aggregates all the data it receives. This approach requires high capacity sink nodes due to the large amount of sensory information to be aggregated. Another approach is that sensor nodes perform a fusion on their observations. The former approach is called centralized fusion where the later approach is called decentralized fusion. For some applications, a mixture of the centralized and decentralized fusion is employed. The place of the fusion affects the level of fusion. In the centralized fusion approach, the sink node performs signal level fusion. Sink node aggregates only raw signal data it received from the sensors. In the decentralized approach, each sensor performs a signal level fusion on its measurements. This fusion may be on the time series measurement of the environmental phenomena. The sink node in the decentralized approach performs a feature level or symbol level fusion. In the feature level fusion, sensors aggregate diverse data; where as in the symbol level fusion sensors aggregate complementary data. Another fusion level is the fusion of probabilities in which the detection reports are related with their accuracy probabilities in the fusion center [124]. Fusion of likelihood ratios related to the detection is another class of fusion level [125] [126]. Deciding the level of fusion is a design criterion between the accuracy of fusion and the communication bandwidth exhausted. If the signal level fusion is performed, detecting entities should communicate all the volume of their detection signals. Hence, high amount of communication bandwidth is exhausted, however accuracy of the fusion is high. If the decision is fused, communicated data is only the decisions of the sensing entities. This phenomena results in low bandwidth consumption in the expense of decision units participated in the sensing entities. Also, due to the information loss in the decision process at the local sensing entities accuracy of the global decision decreases.

The factors affecting sensor network performance are; the performance of component sensors, the locations of the sensors with respect to each other, the velocity of information, fusion capabilities, tasking capabilities.

1.6. Sensing Options and the Sensor Model

This section reviews a subset of sensors that are well suited for wireless sensor networks in general. Passive sensors detect and measure various analogues of a target including its magnetic, thermal, or acoustic signature. Active sensors, such as ultrasonic and radar, can measure a target's presence, range, velocity, or direction of travel by how the target modifies, reflects, or scatters a signal transmitted by the sensor. In Table 1.1, we list the strengths and the weaknesses of some sensors [127] [128].

Table 1.1. Strengths and weaknesses of the sensor types.

Sensor type	Strengths	Weaknesses
Magnetic sensor	-Well defined far-field target phenomenologies. -Discrimination of ferrous objects. -No line-of-sight requirement. -Passive nature.	-Poorly defined near-field target phenomenologies. -Limited sensing range.
Radar sensor	-No line-of-sight requirement. -Ability to operate through obstacles. -Estimate velocity. -Resist jamming.	-Active nature. -Interference.
Thermal sensor	-Excellent sensitivity. -Excellent selectivity. -Passive nature.	-Fresnel lens requirement. -Line-of-sight requirement.
Acoustic sensor	-Long sensing range. -High-fidelity. -No line-of-sight requirement. -Passive nature.	-Poorly defined target phenomenologies. -Moderately high sampling rates. -high time and space complexity for signal processing.
Chemical sensor	-No line-of-sight requirement. -Unique ability to detect gaseous compounds. -Passive nature.	-Lack of availability for most chemicals.
Electric sensor	-No line-of-sight requirement. -non-contact sensing of non-ferrous, fast or slow-moving, cool, quiet, odorless, steady, camouflaged objects.	-Electrode placement. -Nuisance parameters. -Active nature. -Interference.
Seismic sensor	-Long sensing range. -No line-of-sight requirement. -Passive nature.	-Signal propagation variations due to ground composition. -Moderately high sampling rates. -high time and space complexity for frequency domain analysis.
Optical sensor	-Long sensing range. -High-fidelity. -Passive nature.	-Poorly defined target phenomenologies. -Line-of-sight requirement. -High pixel sampling rates. -high time and space complexity for signal processing.
Ultrasonic sensor	-Multi-echo processing that allows sight beyond small obstacles.	-Signal propagation variations due to temperature and humidity. -Line-of-sight requirement. -Active nature. -Interference.

The sensor observation model is described by $O(z|x)$, where, x is the actual phenomena, z is the observation. The observation model incorporates observation uncertainty from all sources, including the noise corruption to the signal, the signal modeling error of the sensor estimation algorithm, and the inaccuracy of the sensor hardware [49]. The reason for explicitly representing sensor characteristics is due to the distributed and heterogeneous nature of the sensor processing tasks.

2. DATA PROCESSING ARCHITECTURE

In this section, we first define the process model for the target motion. The next state of the target is calculated with the knowledge of its current state and the target state transition matrix. The observation model is defined next to simulate the sensor behavior when the target's existence is known. It determines the observable state of the target by the sensor given the target's real state. The foundations of the DDF architecture are presented in Section 2.3.

The following assumptions are in effect regarding the system model:

- Due to the high energy consumption and the cost of the mobile sensor nodes [129], we assume that immobile sensor nodes are deployed in the surveillance area. Hostile and hard to access environments may make it necessary to deploy sensors uniformly randomly from an airplane [130].
- Sensors nodes are deployed and operated in a two-dimensional operation area in which the effect of the topographical obstructions are omitted. The effects of the obstructions in the three-dimensional topographical operation areas are investigated in MS. study of Arslan [131].
- In order to concentrate on the target localization and the energy consumption performances of the proposed algorithms, we assume that a single target is present in the environment for the performance evaluation of the MISS and the ICTP algorithms.
- Sensor nodes communicate with each other using a broadcast communication mechanism. They receive the broadcasted target location information from every neighboring node, and update their target state information with a simple additive fusion framework. The communicating sensor nodes for collaboration do not address their information denomination values to any specific sensor node. Instead, sensor nodes just broadcast their denomination values related with the information state and the information matrix they have. As a consequence, each sensor node receiving the denomination values from the neighbors just updates

its target state information. Broadcasting eliminates the need for a routing algorithm among the sensor nodes. It also helps achieve the aim of having as many sensor nodes as possible to update their beliefs about the target state.

- Sink nodes are not mandatory. Collaborative tracking makes it possible for any sensor node in the sensor field to respond to the target location queries from the command and control center. Moreover, the target position may be queried by the units that cannot reach or that do not have sufficient time to reach the sink node or to the command and control center. The soldier in Fig. 1.2 is an example of such a unit. Hence, any node in the sensor field must have an acceptable target position information available immediately to the querying unit. Producing the target position information at the sink node by collecting the information denominations of the detecting sensor nodes introduces a certain delay due to the data propagation towards the sink node and processing at the sink. In addition, the sink node is a single point of failure in the network and consensus is required for its selection. Instead, we distribute the data processing throughout the network.
- Sensor node coordinates are known. Sensor position estimation is a problem of its own (see e.g. [132, 133] for sensor localization), and it is beyond the scope of this thesis.
- Sampling is synchronized among the sensor nodes. Moreover, sampling periods are long enough to carry out the necessary communication needed for collaboration in the previous sampling period. While the detection signals are sampled at period s, the information obtained from the target at $s-1$ is broadcasted, as shown in Fig. 2.1. An optimization for the sampling interval is presented in [134]. Moreover, a particle filter based distributed target tracking methodology for asynchronous sensor networks that do not require time synchronization protocol is proposed in [135]. Efficient sensor network time synchronization protocols, in which one or more GPS synchronized sensor nodes synchronize the whole network, are proposed in the literature [136, 137].

The collaborative target tracking paradigm implemented by each sensor node is explained in Chapter 3. In the sequel, we describe the associated components of the

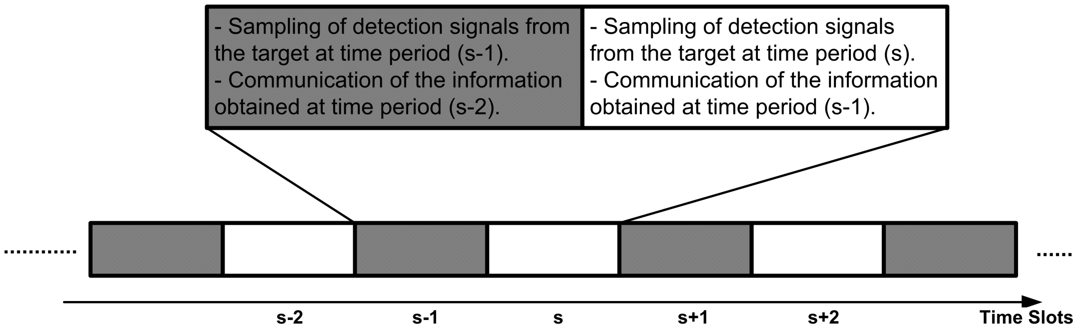

Figure 2.1. Time synchronization of sampling and communication periods of the sensor nodes.

system including the fusion procedure, the sensor selection strategy and the transmission power adjustment scheme, which collectively deliver good performance while simultaneously keeping the energy expenditure low. We consider a field that is put under surveillance with a total of N_T sensors. The reference will be some arbitrary sensor node S_m.

2.1. Process Model

The process model describes the target motion. The process model finds the state of the target at time instant $k+1$ given the state of the target at time instant k. The model contains a noise term to account for possible randomness in the target motion. The target state is a four-dimensional vector that consists of the two-dimensional position of the target, (ξ, η), and the velocity of the target at each of these dimensions, $(\dot{\xi}, \dot{\eta})$. The target state vector is defined by

$$\mathbf{x} = [\xi \ \eta \ \dot{\xi} \ \dot{\eta}]^T, \tag{2.1}$$

and it evolves in time according to

$$\mathbf{x}(k+1) = \mathbf{F}\mathbf{x}(k) + \mathbf{v}(k)$$

where $\mathbf{x}(k)$ is the real target state vector at time k as given in (2.1), $\mathbf{F}$ is the transition matrix and $\mathbf{v}$ is the independent, Gaussian distributed process noise with zero mean

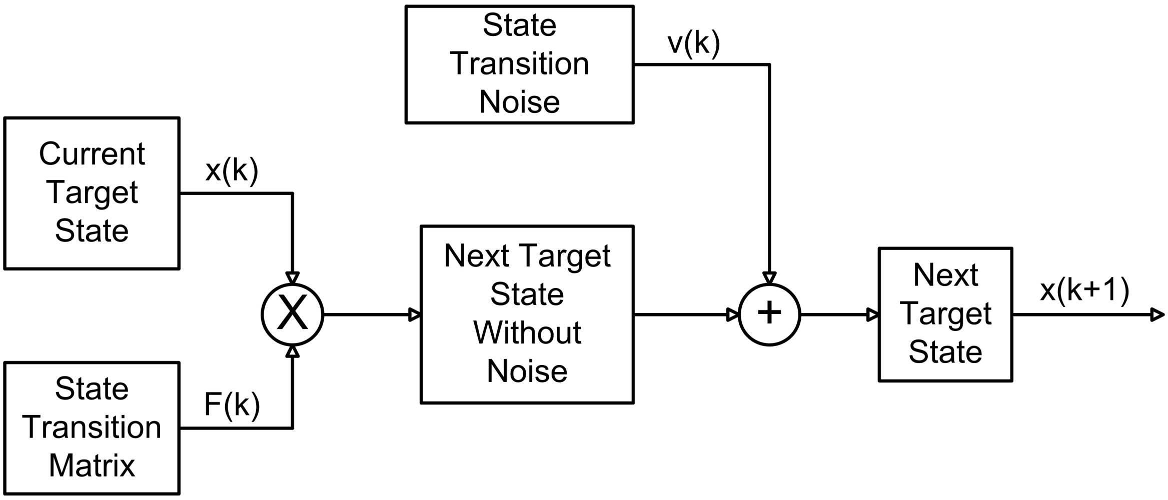

Figure 2.2. Target motion model.

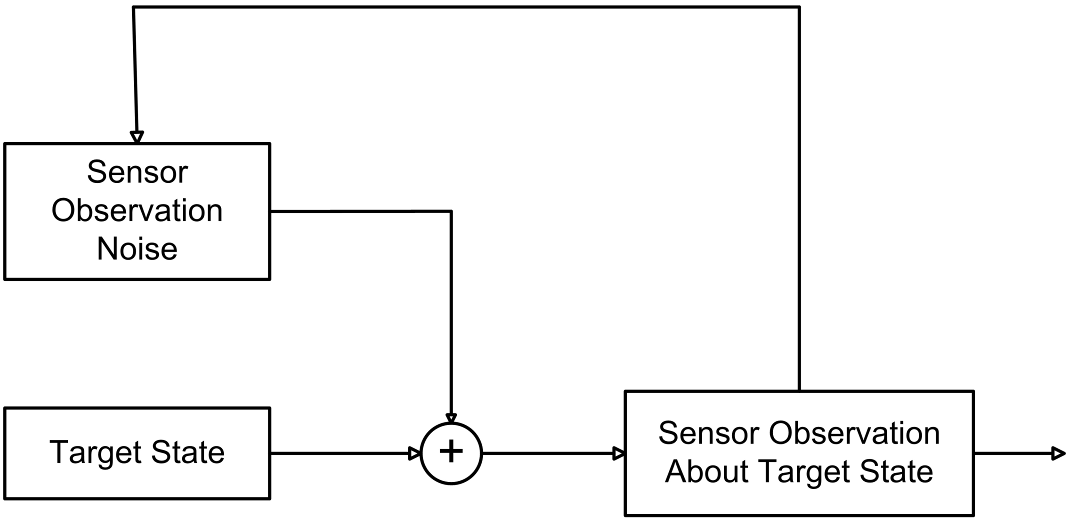

Figure 2.3. Sensor observation model.

and covariance matrix **Q**. Target motion is modeled as in Fig. 2.2.

2.2. Observation Model

Sensor observation model is shown in Fig. 2.3. Noise is added to the real target state in order to model the sensor observation uncertainties. Sensor nodes can only observe the first two dimensions of the target state. The velocity of the target is not observable. Furthermore, nodes collect range and bearing data, but they do not have the coordinates of the target directly. Because the target state is observed in polar coordinates, linear filtering formulations do not help. There are two implementation alternatives to remedy this problem: (1) by using the inverse transformation, obtain directly a converted measurement of the target position; (2) leave the measurement in its original form. The former yields a purely linear problem, allowing for linear filtering. The latter leads to a mixed coordinate filter [138]. In [139], the mean and covariance of the errors of Cartesian measurements, which are obtained by converting polar measurements, are derived. This conversion provides better estimation accuracy than the Extended Kalman Filter, in which the nonlinear target state measurements are utilized without conversion [139].

The range $r_{m,d}$ and bearing $\theta_{m,d}$ measured by S_m are defined with respect to the true range r_m and bearing θ_m as

$$\begin{aligned} r_{m,d} &= r_m + \tilde{r}_m, \\ \theta_{m,d} &= \theta_m + \tilde{\theta}_m, \end{aligned} \tag{2.2}$$

where the errors in range $\tilde{r}_m$ and bearing $\tilde{\theta}_m$ are assumed to be independent and Gaussian distributed with moments

$$E[\tilde{r}_m] = 0, \quad E[\tilde{\theta}_m] = 0, \quad E[\tilde{r}_m^2] = \sigma_{r_m}^2, \quad E[\tilde{\theta}_m^2] = \sigma_{\theta_m}^2,$$

where the time-dependence is implicit. The mean target state observed after the unbiased polar-to-Cartesian conversion is given by [139]

$$\boldsymbol{\varphi}_m = \begin{bmatrix} \xi_{m,d}^c \\ \eta_{m,d}^c \end{bmatrix} = \begin{bmatrix} r_{m,d} \cos\theta_{m,d} \\ r_{m,d} \sin\theta_{m,d} \end{bmatrix} - \boldsymbol{\mu}_m \tag{2.3}$$

where $\boldsymbol{\mu}_m$ is the average true bias

$$\boldsymbol{\mu}_m = \begin{bmatrix} r_{m,d} \cos\theta_{m,d}(e^{-\sigma_{\theta_m}^2} - e^{-\sigma_{\theta_m}^2/2}) \\ r_{m,d} \sin\theta_{m,d}(e^{-\sigma_{\theta_m}^2} - e^{-\sigma_{\theta_m}^2/2}) \end{bmatrix}.$$

The covariance matrix $\mathbf{R}_m$ of the observation errors in $\boldsymbol{\varphi}_m$ is [138, 139]

$$\mathbf{R}_m = \begin{bmatrix} R_{m_{11}} & R_{m_{12}} \\ R_{m_{21}} & R_{m_{22}} \end{bmatrix} \tag{2.4}$$

where

$$\begin{aligned} R_{m_{11}} &= r_{m,d}^2 e^{-2\sigma_{\theta_m}^2}[\cos^2\theta_{m,d}(\cosh 2\sigma_{\theta_m}^2 - \cosh\sigma_{\theta_m}^2) \\ &\quad + \sin^2\theta_{m,d}(\sinh 2\sigma_{\theta_m}^2 - \sinh\sigma_{\theta_m}^2)] \\ &\quad + \sigma_{r_m}^2 e^{-2\sigma_{\theta_m}^2}[\cos^2\theta_{m,d}(2\cosh 2\sigma_{\theta_m}^2 - \cosh\sigma_{\theta_m}^2) \\ &\quad + \sin^2\theta_d(2\sinh 2\sigma_{\theta_m}^2 - \sinh\sigma_{\theta_m}^2)], \end{aligned}$$

$$\begin{aligned} R_{m_{22}} &= r_{m,d}^2 e^{-2\sigma_{\theta_m}^2}[\sin^2\theta_d(\cosh 2\sigma_{\theta_m}^2 - \cosh\sigma_{\theta_m}^2) \\ &\quad + \cos^2\theta_{m,d}(\sinh 2\sigma_{\theta_m}^2 - \sinh\sigma_{\theta_m}^2)] \\ &\quad + \sigma_{r_m}^2 e^{-2\sigma_{\theta_m}^2}[\sin^2\theta_{m,d}(2\cosh 2\sigma_{\theta_m}^2 - \cosh\sigma_{\theta_m}^2) \\ &\quad + \cos^2\theta_{m,d}(2\sinh 2\sigma_{\theta_m}^2 - \sinh\sigma_{\theta_m}^2)], \end{aligned}$$

$$R_{m_{12}} = R_{m_{21}} = \sin\theta_{m,d}\cos\theta_{m,d} e^{-4\sigma_{\theta_m}^2}\left[\sigma_{r_m}^2 + (r_{m,d}^2 + \sigma_{r_m}^2)(1 - e^{\sigma_{\theta_m}^2})\right].$$

2.3. Distributed Data Fusion Architecture

In the information filter formulation, the information state $\hat{\mathbf{y}}_m$ and the information matrix $\mathbf{Y}_m$ associated with the state estimate $\hat{\mathbf{x}}_m$ and the posterior estimation error covariance $\mathbf{P}_m$ of sensor node S_m, $m = 1, 2, \ldots, N_T$, at time instant k are given by

$$\begin{aligned} \hat{\mathbf{y}}_m(k) &= \mathbf{P}_m^{-1}(k)\hat{\mathbf{x}}_m(k), \\ \mathbf{Y}_m(k) &= \mathbf{P}_m^{-1}(k). \end{aligned}$$

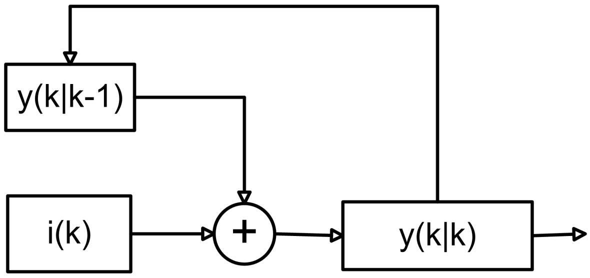

Figure 2.4. Information state calculation.

In [140], it is shown that by means of sufficient statistics, the observation $\boldsymbol{\varphi}_m$ contributes $\mathbf{i}_m(k)$ to the information state $\hat{\mathbf{y}}_m$, and $\mathbf{I}_m(k)$ to the information matrix $\mathbf{Y}_m$ where the denomination values are computed as

$$\begin{aligned} \mathbf{i}_m(k) &= \mathbf{H}_m^T \mathbf{R}_m^{-1}(k) \boldsymbol{\varphi}_m(k), \\ \mathbf{I}_m(k) &= \mathbf{H}_m^T \mathbf{R}_m^{-1}(k) \mathbf{H}_m \end{aligned} \tag{2.5}$$

with $\mathbf{H}_m$ being the observation matrix of S_m that relates the target state estimate $\hat{\mathbf{x}}_m$ to the sensor measurement $\boldsymbol{\varphi}_m(k)$. The node updates its own belief upon receiving its own sensory observation according to

$$\begin{aligned} \hat{\mathbf{y}}_m(k|k) &= \hat{\mathbf{y}}_m(k|k-1) + \mathbf{i}_m(k), \\ \mathbf{Y}_m(k|k) &= \mathbf{Y}_m(k|k-1) + \mathbf{I}_m(k) \end{aligned} \tag{2.6}$$

where $\hat{\mathbf{y}}_m(k|k-1)$ represents the information state estimate at time k given the observations up to and including time $k-1$.

Instead of sending the measurements related to the target state to the collaborating sensor nodes, sharing the information form of the observations results in a simple additive fusion framework that can be run on each of the tiny sensing devices. The distributed data fusion process for the information state is given in Fig. 2.4 and for the information matrix is given in Fig. 2.5. Locally extracted or network received information state and the information matrix denomination values are added to the current information state and the information matrix respectively as they arrive.

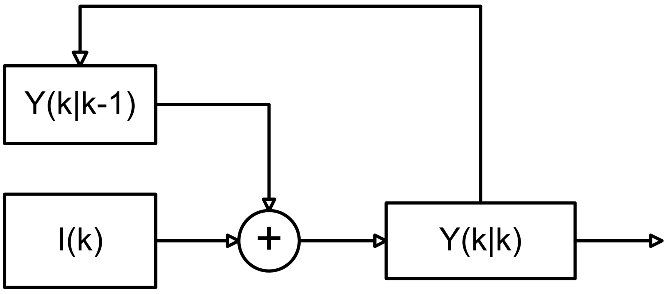

Figure 2.5. Information matrix calculation.

Other advantages of the information form of filtering over the canonical form are [138]:

- Saving the limited energy resources of sensor nodes by reducing the computational load of the processors.
- In the canonical form of filtering, updates in the state covariance matrix may cause loss of symmetry and positive definiteness as a result of rounding errors. Information filtering improves the numerical accuracy by preserving the symmetry and positive definiteness property of the state covariance matrix.
- Information filtering provides a means for the start-up of the estimation without an initial estimate.

Note that the fusion of posterior information requires the extraction of the information denomination values. This procedure, which should be done for every received posterior information, leads to a drastic growth in the amount of processing, especially with increasing number of sensor nodes in the network. Define $\mathcal{S}_m(k)$ to be the set of nodes that are neighbors with S_m at time k. Letting $\mathbf{i}_n(k)$ and $\mathbf{I}_n(k)$ denote the nth neighboring node's contribution to $\hat{\mathbf{y}}_m$ and $\mathbf{Y}_m$, respectively, the DDF equations are

$$\hat{\mathbf{y}}_m(k|k) = \hat{\mathbf{y}}_m(k|k-1) + \sum_{n:S_n \in \mathcal{S}_m(k)} \mathbf{i}_n(k), \tag{2.7}$$

$$\mathbf{Y}_m(k|k) = \mathbf{Y}_m(k|k-1) + \sum_{n:S_n \in \mathcal{S}_m(k)} \mathbf{I}_n(k).$$

Just before the data at time k are collected, if we are given the observations up to $k-1$, the predicted information state and the information matrix at time k can be calculated as

$$\begin{aligned} \hat{\mathbf{y}}_m(k|k-1) &= \mathbf{Y}_m(k|k-1)\mathbf{F}_m\mathbf{Y}_m^{-1}(k-1|k-1)\hat{\mathbf{y}}_m(k-1|k-1), \\ \mathbf{Y}_m(k|k-1) &= [\mathbf{F}_m\mathbf{Y}_m^{-1}(k-1|k-1)\mathbf{F}_m^T + \mathbf{Q}_m]^{-1} \end{aligned} \quad (2.8)$$

where $\mathbf{Q}_m$ is the noise covariance matrix for node $S_m, m = 1, 2, \ldots, N_T$.

The state estimate of the target given the observations up to and including the time k can be found from

$$\hat{\mathbf{x}}_m(k|k) = \mathbf{Y}_m^{-1}(k|k)\hat{\mathbf{y}}_m(k|k). \quad (2.9)$$

The information state and information matrix denominations in (2.6) are functions of $\boldsymbol{\varphi}_m$ as in (2.5). However, in the DDF paradigm described by (2.7), these are obtained from the neighboring sensor nodes by means of wireless communication. A sensor's own observation and the information received from the neighboring nodes have similar means for updating the belief about the target state. The ease of the belief update in the target position estimation is another reason for utilizing the information filtering while distributing the target tracking process throughout the network.

2.4. Energy Model

Our energy model for the sensor nodes is based on the first order radio model described in [96, 106, 141]. A sensor node consumes $\varepsilon_{elec} = 50nJ/bit$ to run the transmitter or receiver circuitry and $\varepsilon_{amp} = 100pJ/bit/m^2$ for the transmitter amplifier. Thus the energy consumed by a sensor node i in receiving a b-bit data packet is given by

$$RX_i = \varepsilon_{elec} b$$

While the energy consumed in transmitting a b-bit data packet to sensor j is given by

$$TX_{i,j} = \varepsilon_{elec} b + \varepsilon_{amp} d_{i,j}^2 b$$

where, $d_{i,j}$ is the distance between the sensor nodes i and j and b is the number of transmitted bits.

3. MAXIMUM MUTUAL INFORMATION-BASED SENSOR SELECTION ALGORITHM

Mutual information measures how much uncertainty is removed by one random variable about another one. By computing the mutual information between the target state and the measurement, one can gain insight as to how much the current observation tells about the current target state. The unit of the mutual information measure is in bits [142].

The mutual information gained with the last observation of the mth sensor can be formulated as

$$J_m(k, \boldsymbol{\varphi}_m(k)) = J_m(k) = \frac{1}{2} \log \left[\frac{|\mathbf{Y}_m(k|k)|}{|\mathbf{Y}_m(k|k-1)|} \right], \tag{3.1}$$

where $\mathbf{Y}_m(k|k)$ is the information matrix at time instant k after the target state is observed, $m = 1, 2, \ldots, N_T$ [140].

In the data fusion paradigm described by (2.7), the number of neighboring nodes, which is counted by the cardinality $|\mathcal{S}_m(k)| \leq N_T$, is usually too large, causing excessive data communication in the network and a strain on the energy resources. To alleviate this problem, we introduce the Maximum Mutual Information-Based Sensor Selection (MISS) algorithm, where node S_m shares its own information about the target state with all its neighbors at time k only if the mutual information gain $J_m(k)$ is high enough to participate in the current cycle. Otherwise, S_m withholds transmission. To that end, all neighboring nodes of S_m are ranked in decreasing mutual information order. Let $\mathcal{J}_m(k) = \{J_{m,1}(k), J_{m,2}(k), \ldots, J_{m,|\mathcal{S}_m(k)|}\}$ be the ordered set of mutual information values as predicted by S_m at time instant k. Thus, $J_{m,n}(k)$ is S_m's estimate of $J_n(k)$, and $J_{m,1} \geq J_{m,2} \geq \ldots \geq J_{m,|\mathcal{S}_m(k)|}$. Define $\mathcal{J}'_m(k) = \{J_{m,1}(k), J_{m,2}(k), \ldots, J_{m,N_{\max}}(k)\} \subset \mathcal{J}_m(k)$, where $N_{\max} < |\mathcal{S}_m(k)|$, as the ordered subset that keeps the first $N_{\max}$ elements of $\mathcal{J}_m(k)$. Let $\mathcal{S}'_m(k) \subset \mathcal{S}_m(k)$ denote the set of nodes that are sufficiently informative[1] to contribute to data fusion at S_m in the kth cycle.

For $N_{\max} < |\mathcal{S}_m(k)|$, the MISS algorithm can be formulated as follows.

1. If S_m detects the target, and $J_m(k) > \min \mathcal{J}'_m(k)$, then S_m broadcasts its information state and the information matrix denominations, $\mathbf{i}_m(k), \mathbf{I}_m(k)$, to the network, and

$$\mathcal{S}'_m(k) = \{S_n \in \mathcal{S}_m(k), n = 1, 2, \ldots, |\mathcal{S}_m(k)| : J_{m,n} \in \mathcal{J}'_m(k)\} - S_{N_{\max}}.$$

2. If S_m detects the target, and $J_m(k) \leq \min \mathcal{J}'_m(k)$, or if S_m does not detect, then S_m withholds, and

$$\mathcal{S}'_m(k) = \{S_n \in \mathcal{S}_m(k), n = 1, 2, \ldots, |\mathcal{S}_m(k)| : J_{m,n} \in \mathcal{J}'_m(k)\}.$$

The algorithm tries to limit the maximum number of sensors that communicate in the neighborhood (in the sense defined by Assumption A3) of each node to $N_{\max}$. Revisiting (2.7), the current belief is updated with the received information from the nodes in $\mathcal{S}'_m(k)$ according to

$$\hat{\mathbf{y}}_m(k|k) = \hat{\mathbf{y}}_m(k|k-1) + \sum_{n:S_n \in \mathcal{S}'_m(k)} \mathbf{i}_n(k), \tag{3.2}$$

$$\mathbf{Y}_m(k|k) = \mathbf{Y}_m(k|k-1) + \sum_{n:S_n \in \mathcal{S}'_m(k)} \mathbf{I}_n(k).$$

In the event that $N_{\max} \geq |\mathcal{S}_m(k)|$, all nodes in $\mathcal{S}_m(k)$ simply transmit their data. The MISS algorithm, implemented by each sensor node, is presented in an algorithmic fashion in Fig. 3.1.

[1] The informativeness of a sensor node will be associated with a quantitative measure in (3.3).

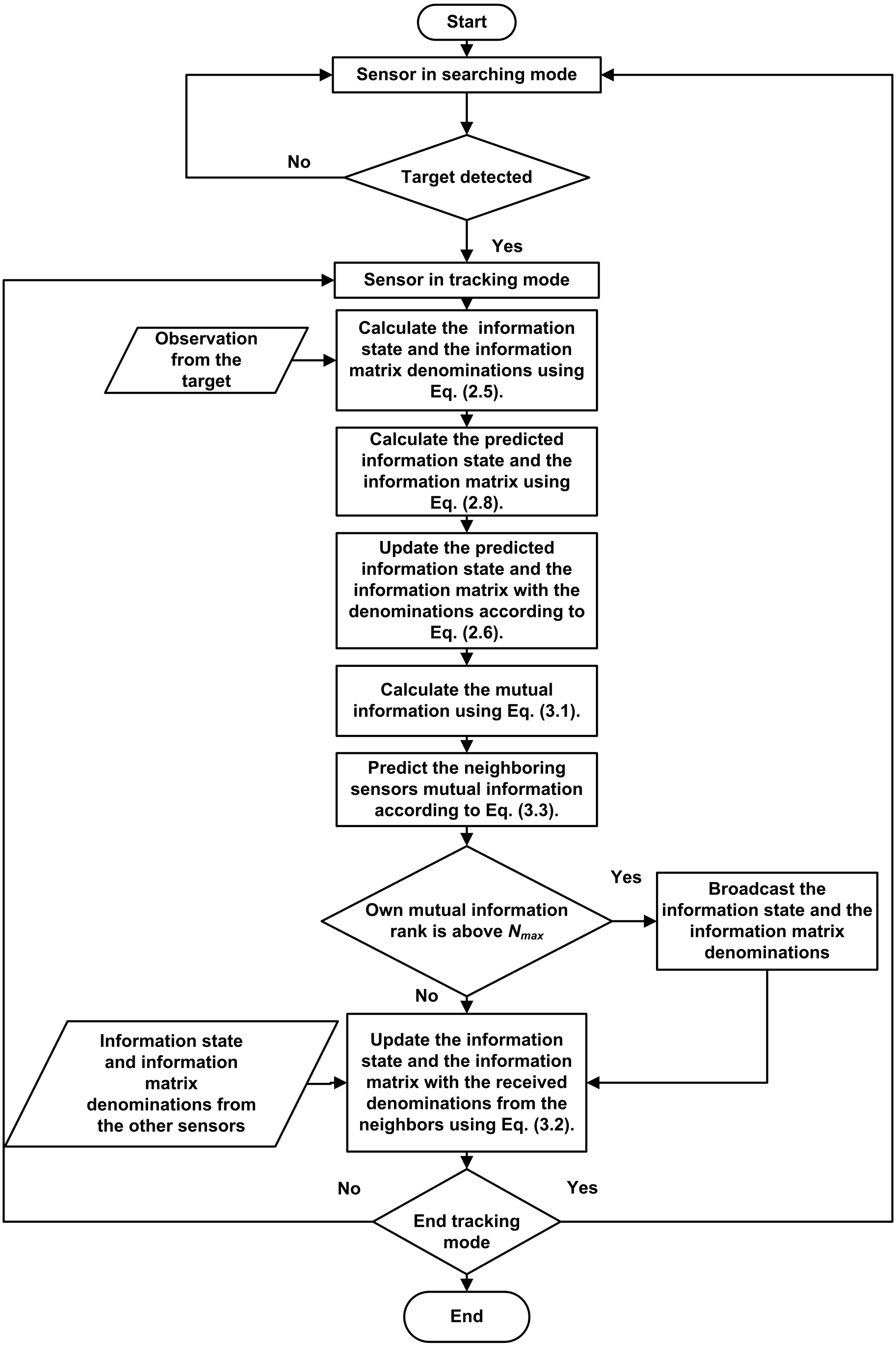

Figure 3.1. Target tracking algorithm employed by a detecting sensor node.

For some sensor node S_m to implement the MISS algorithm in the kth cycle, S_m has to locally create $\mathcal{J}_m(k)$. That is, every node needs to estimate the mutual information values of all its neighbors. Assuming that $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1), \forall S_n \in \mathcal{S}_m(k)$, due to the past collaboration among the neighboring nodes, and $\mathbf{H}_n = \mathbf{H}_m, \forall S_n \in \mathcal{S}_m(k)$, because neighboring sensor nodes observe the same properties of the target, we define

$$J_{m,n}(k) = \frac{1}{2} \log \left[\frac{|\mathbf{Y}_{m,n}(k|k)|}{|\mathbf{Y}_m(k|k-1)|} \right] \tag{3.3}$$

where

$$\mathbf{Y}_{m,n}(k|k) = \mathbf{Y}_m(k|k-1) + \mathbf{I}_{m,n}(k)$$

with

$$\mathbf{I}_{m,n}(k) = \mathbf{H}_m^T \mathbf{R}_{m,n}^{-1}(k) \mathbf{H}_m. \tag{3.4}$$

being the information matrix denomination estimate of S_n by S_m. The *informativeness* of a node is measured by (3.3), which assesses the reduction in the target state uncertainty with the incoming new data. The higher the value obtained from (3.3), the more informative the sensor about the target state. $\mathbf{R}_{m,n}$ is the estimate of S_m about the covariance matrix of the observation errors by S_n. Consequently, $\mathbf{Y}_{m,n}$ is the information matrix estimate of S_n by S_m. Therefore by (2.4), to have the estimate $\mathbf{R}_{m,n}$ in (3.4) (and hence the estimate $\mathbf{Y}_{m,n}(k|k)$ in (3.3)), it is required that each sensor node holds a list whose elements are the standard deviations of the target range observations, σ_{r_n}, and the standard deviations of the target bearing observations, σ_{θ_n}, for all $S_n \in \mathcal{S}_m(k)$. Moreover, S_m needs to find $r_{n,d}, \theta_{n,d}$, which can be determined from $r_{m,d}, \theta_{m,d}$ and S_n's position information, which is assumed to be known. Note that before the observation at time instant k arrives, node S_m already has the prediction $\mathbf{Y}_m(k|k-1)$ about the target state information at k.

The list $\mathcal{J}_m(k)$ is formed using the estimated mutual information values of its neighbors. During the simulation studies, which are reported in Section 3.1, we also examine the number of times the actual mutual information list differs from the estimated list.

Collaboration among the sensor nodes in the network results in $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1), \forall S_n \in \mathcal{S}_m(k)$, which follows from (3.2). If every node in the network was able to communicate with the others (i.e., fully connected network topology), the equality $\mathbf{Y}_n(k|k-1) = \mathbf{Y}_m(k|k-1)$ would hold. The reason for having $\mathbf{Y}_n(k|k-1) \approx \mathbf{Y}_m(k|k-1))$ lies behind the fact that the communication range is much larger than the detection range of the sensor node, S_m. With its own observation from the target, S_m can find $\mathbf{Y}_m(k|k)$. The decision as to whether S_m should collaborate with S_n or not depends on the utility of the information that comes from S_n, and it should be made before S_n transmits. To remedy this, we assume that S_m and S_n detect the target at the same location. With the aid of this assumption, S_m can predict $\mathbf{Y}_{m,n}(k|k)$ and use it instead of $\mathbf{Y}_n(k|k)$. Moreover, S_m neglects the discrepancy between $\mathbf{Y}_{m,n}(k|k)$ and $\mathbf{Y}_n(k|k)$ that is caused by the observation noises of S_m and S_n. A better approach in terms of precision would be S_m to predict the target position and the uncertainty estimation of S_n using the mean of L predictions. However, this would incur a delay and an increase in the processing power requirements.

3.1. Performance Evaluation of the MISS Algorithm

We run Monte Carlo simulations to examine the performance of the proposed MISS algorithm in terms of power consumption and target localization accuracy. We examine two scenarios: the first is the sparser one, which consists of 300 sensor nodes randomly deployed in a 200 m $\times$ 200 m area. The second is a denser scenario in which 800 sensor nodes are placed in the same area. All data points in the graphs represent the means of twenty runs. A target moves in the area according to the process model described in Section 2.1. We use the parameters of the TWR-ISM-002-I micro-power impulse radar (MIR) with pseudo-random signaling whose lifetime is up to several years on AA batteries [143]. The integrated sensor processor board, MIR board, MIR

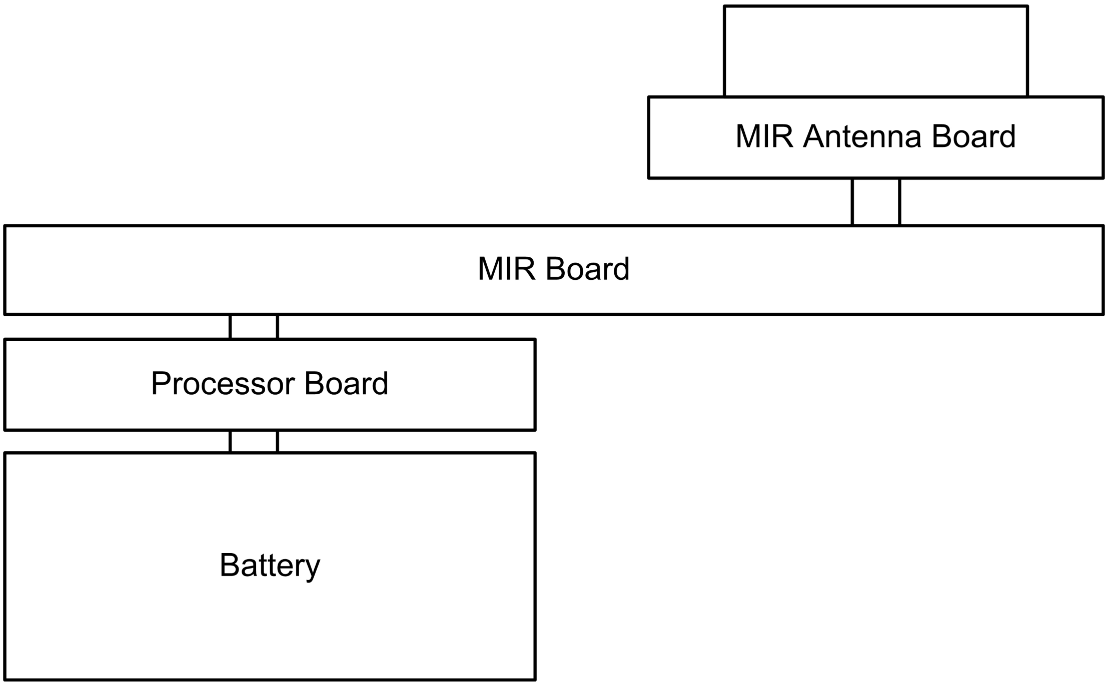

Figure 3.2. Integrated processor board, MIR board, MIR antenna board, and battery [2].

antenna board, and the battery is redrawn from [2] in Fig. 3.2. Fig. 3.3 shows the picture of this integration and Fig. 3.4 shows the packed MIR. Typical detection range of a TWR-ISM-002-I is 18 meters [3]. As in [139], we assume constant range and bearing standard deviation of $\sigma_{r_m} = 0.1$ m and $\sigma_{\theta_m} = 1^o$, respectively, for all sensory observations.

The sensor node tracks the target locally using the information form of the Kalman filter [144] as described in Section 2.3. If the sensor does not detect a target, it updates its belief about the target state according to the track history.

In collaborative information fusion, if a sensor node is eligible to share its belief about the target state with other sensor nodes, it broadcasts its information state and the information matrix denominations. Sensor nodes update their belief about the target state with these received denominations as described in Section 2.3.

The simulations are run for a flat, rural setting where the radio signal propagation is characterized by the shadow-fading model with parameters given in Table 3.1 [145].

Figure 3.3. Integrated circuit boards of the MIR [2].

Figure 3.4. Packed MIR [3].

Table 3.1. Shadow fading communication model parameters.

Carrier frequency	1.8 GHz
Path loss exponent	2
TX & RX antenna height	0.1 m
Shadow-fading standard deviation	4
Sensor node transmission power	-30 dB

As the target state transition matrix and the target state transition covariance, we respectively use

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}, \quad \mathbf{Q} = \zeta \cdot \begin{bmatrix} 0.1 & 0 & 0 & 0 \\ 0 & 0.1 & 0 & 0 \\ 0 & 0 & 0.1 & 0 \\ 0 & 0 & 0 & 0.1 \end{bmatrix}.$$

for all sensors where ζ is the target maneuvering index. A lower ζ value means that the target maneuvers slowly, and vice versa. In the simulations, ζ is set to unity. A sensor node can only observe the position related with the target. The velocity information is not directly observable. We therefore use

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

as the observation matrix of each sensor node.

Even for the sparse scenario, the mean number of sensor nodes detecting the target is 14 so that at most 14 sensor nodes can actively participate in the collaboration. Hence, it is assumed that the sampling period of the signals from the target is sufficiently long to allow for the collaboration of 14 nodes.

On average, 12 per cent of the sensor nodes are located in positions different than the true mutual information list. Moreover, an inaccurately formed list contains on the average just two sensor nodes that are ranked in wrong positions in the mutual information list. This deviation from the correct list is acceptable from a practical standpoint as evidenced by the performance graphs. The reason behind the successful mutual information score list formation lies in the fact that communication ranges are more far-reaching compared to the detection ranges of the sensor devices. This results in consistent posterior target information state and information matrix estimates with collaboration, which in turn help generate consistent mutual information scores throughout the sensor network. Inconsistencies in the target information state and information matrix estimates are caused by sensor nodes which cannot hear each other primarily due to radio propagation characteristics, including path loss.

Tests show that average target localization errors are on the order of 0.5 meters based on 20 simulations, each one run for 100 seconds and with a distinct random seed. The sensor with the worst target position estimation has a localization error of 3.7 meters. Target localization errors are measured from the weight center of the target, which results in point target tracking errors. Using the region centroid for the tracking system is investigated in [146].

The WSN has two modes of operations, namely the searching and the tracking modes. Any sensor that detects a target or receives a tracking mode alert from a neighboring sensor node goes into tracking mode and warns the neighboring nodes to do the same. In the tracking mode, the communication transmitter circuit is activated according to the selective activation strategy with the maximum mutual information metric whereas the receiver circuit and the sensor circuit are active all the time. However, in the searching mode, we utilize a duty-cycled activation in which the sensor node receiver and sensing circuit is active for some duty cycle and inactive thereafter. In the simulations, we compare the mean error about the target localization for the collaborative tracking framework described in Section 2.3. We achieve the maximum tracking accuracy when all sensor nodes detecting the target participate in the DDF task. As the number of sensor nodes allowed to participate in the fusion task is reduced, the tracking quality deteriorates. This yields higher localization errors about the distributed target position estimates. However, when fewer sensor nodes take part in the collaboration, fewer communication packets travel in the network. A reduction

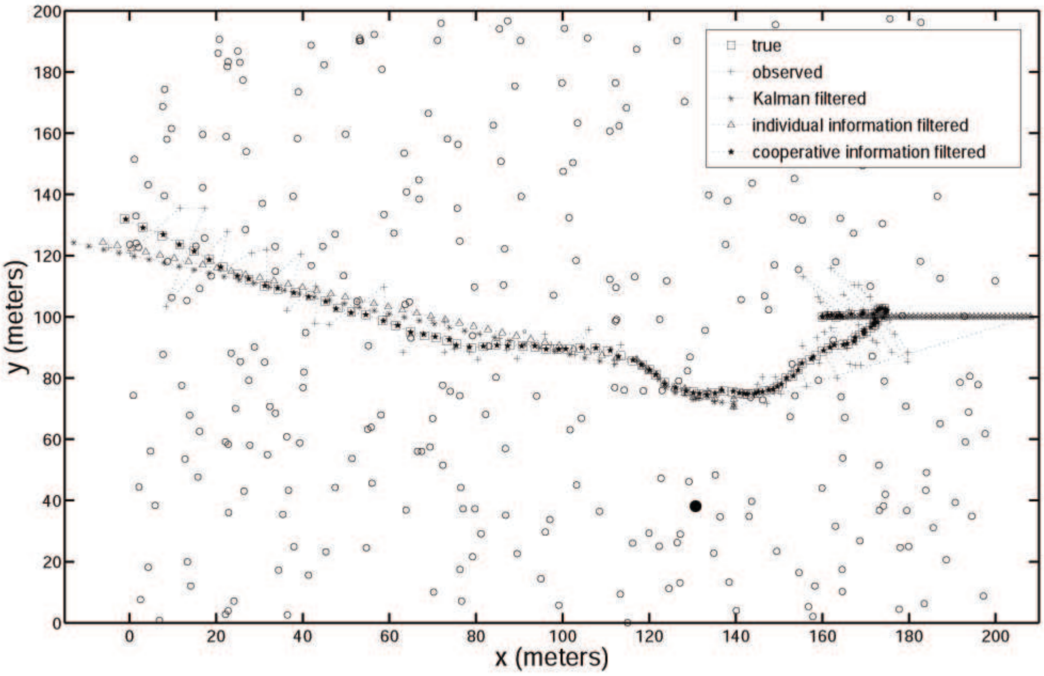

Figure 3.5. Target trajectory as seen by the sensor node represented with a solid dot (•) in the 300-sensor scenario.

in the number of sent packets affects the energy expenditure of the wireless sensor devices directly. Selecting the sensor nodes to actively participate in the fusion task in an intelligent manner improves tracking quality while allowing the same number of sensor nodes to communicate. Fig. 3.5 depicts the 300-sensor scenario, target location observation errors, Kalman and information-filtered target localization errors, and cooperative information-filtered target localization errors from the viewpoint of the sensor node that is marked as a solid dot at the grid point (132,40). As the target moves away from the sensor node, observation errors increase. Kalman or information-filtering reduces the observation errors. However, at some target maneuver points, if the sensor cannot detect the target, the node tracks the target position by resorting to the target history only. In other words, the Kalman gain is set to zero if the sensor cannot detect the target. This results in the erroneous linear tracking of the target until a positive detection is achieved. Poor detection performance results if target maneuvers are missed by the sensor. With the aid of collaboration amongst the sensor nodes, these target maneuver misses are avoided. We track the target for 100 seconds in the simulations.

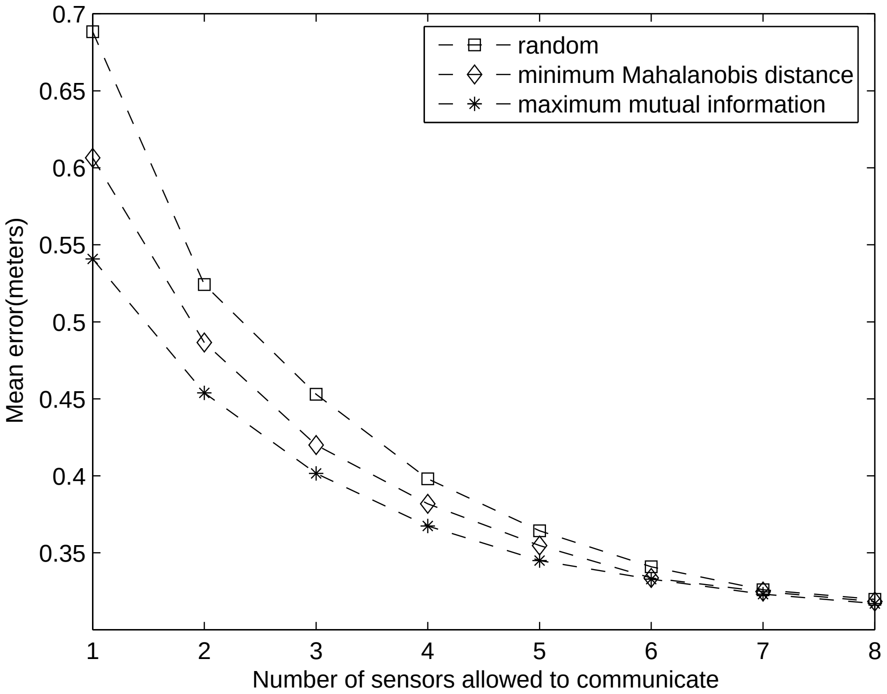

Figure 3.6. Mean error comparison for the sparse scenario.

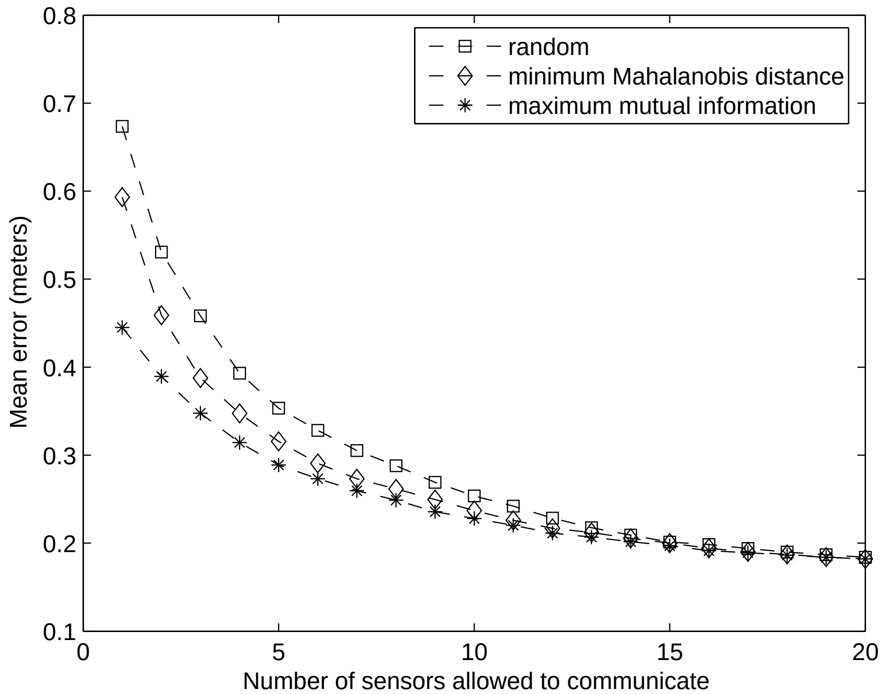

Figure 3.7. Mean error comparison for the dense scenario.

In collaborative target tracking, selecting the participating active sensor nodes randomly means that a node detecting the target broadcasts its information immediately if the maximum number of sensor nodes to participate, $N_{\max}$, has not yet been reached. This can be decided by counting the number of target position announcements received from the neighboring sensor nodes. The competing approach considered in the simulations selects the closest sensor nodes to the target location in terms of the Mahalanobis distance, which differs from the Euclidian distance in a way that it takes into account the correlation in the uncertainty over the target position. Mahalanobis distance between the two random vectors, the observed target position $\boldsymbol{\varphi}_m(k)$ and the sensor position $\mathbf{L}_S(k)$, is defined as

$$D_M\Big(\boldsymbol{\varphi}_m(k), \mathbf{L}_S(k)\Big) = \sqrt{\Big(\boldsymbol{\varphi}_m(k) - \mathbf{L}_S(k)\Big)^T \mathbf{P}_m(k)^{-1} \Big(\boldsymbol{\varphi}_m(k) - \mathbf{L}_S(k)\Big)}$$

where $\mathbf{P}_m(k)$ is the covariance matrix of the sensor observations at time k. If $\mathbf{P}_m(k)$ equals the identity matrix, then the Euclid and Mahalanobis distance measures are the same [147]. Figures 3.6 and 3.7 show, for the sparse and dense scenarios respectively, that as the maximum number of sensor nodes allowed to communicate increases, the mean error occurring throughout a 100-second scenario decreases for all three sensor selection algorithms. Target localization errors are calculated each second. For the cases studied with the sparse scenario, selecting sensor nodes which improve the global belief about the target position according to the mutual information measure results in average tracking quality improvements of 4.7 per cent and 10.8 per cent over the minimum Mahalanobis distance-based sensor selection and random selection, respectively.

For the dense scenario of 800 sensors, these improvements with MISS respectively become 8.9 per cent and 19.4 per cent for the two selection strategies.

Fig. 3.8 depicts the total exhausted energy in the network for all three sensor selection algorithms for the sparse scenario. The consumed energy grows as the maximum number of sensor nodes that are allowed to communicate increases. This is a natural result of the increasing number of communication packets in the network. However, the sensor selection algorithm does not have any effect on the exhausted energy of the network. The same arguments are also valid for the dense scenario, However, due to the broadcast-based communication mechanism among the sensor nodes, incre-

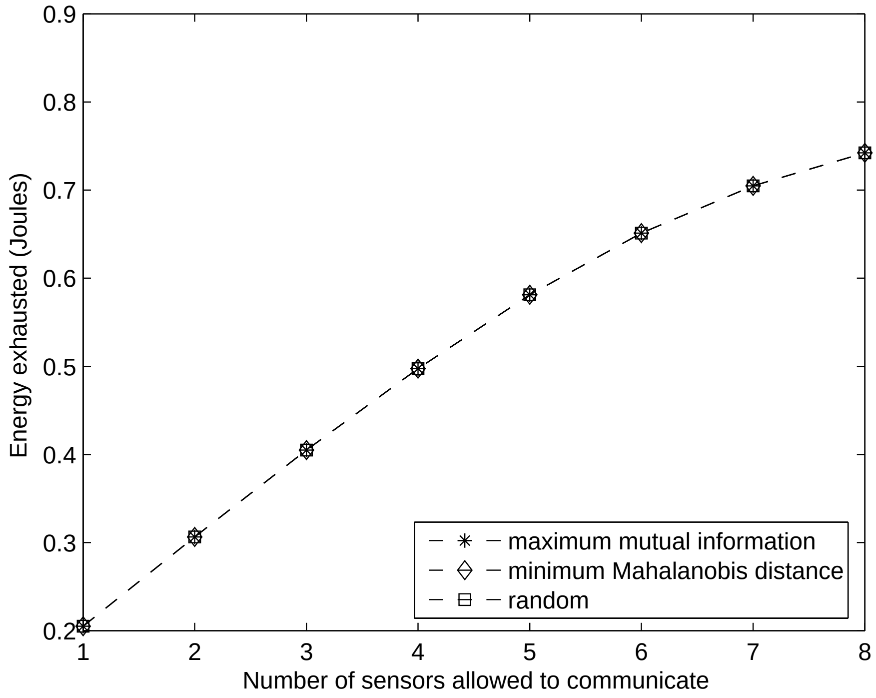

Figure 3.8. Comparison of the consumed energy for the sparse scenario.

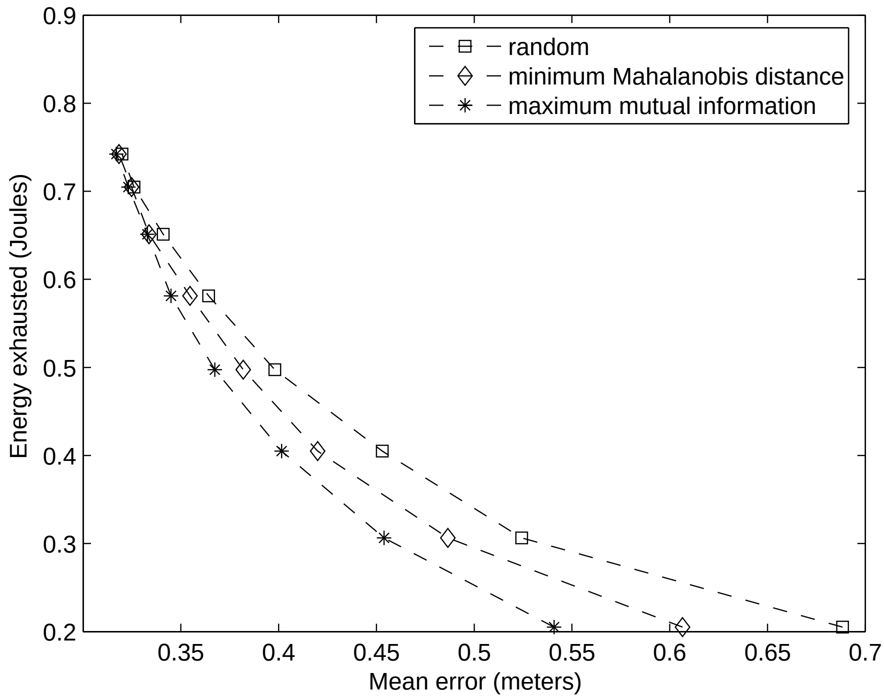

Figure 3.9. Comparison of the consumed energy for the desired target localization accuracies for the sparse scenario.

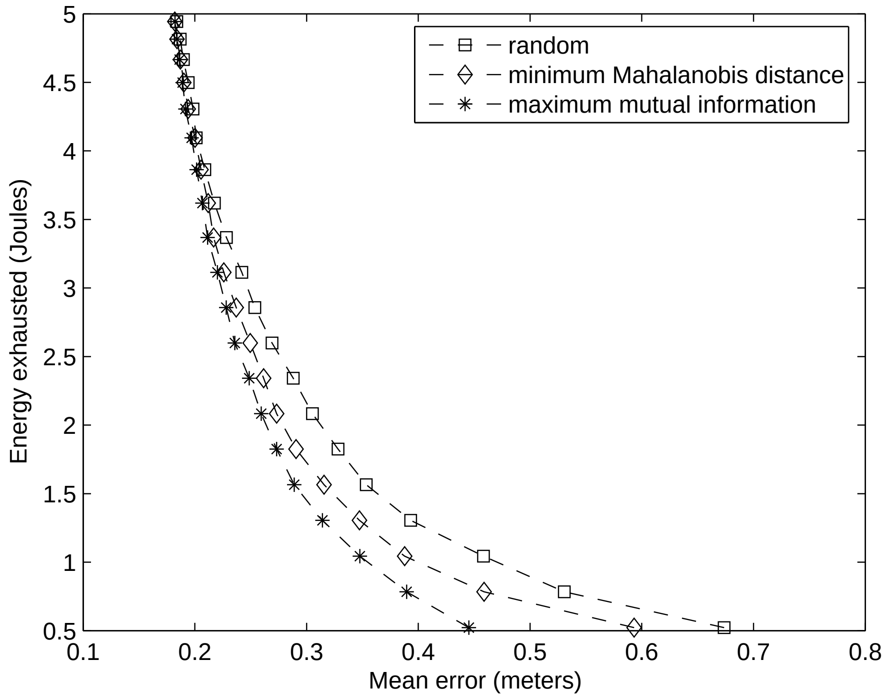

Figure 3.10. Comparison of the consumed energy for the desired target localization accuracies for the dense scenario.

menting the number of deployed sensor nodes results in a rise in the total consumed communication energy. The increase in the mean exhausted energy with the increment in the number of deployed sensor nodes is caused by the receivers of the sensor nodes. Broadcast messages are received by more sensor nodes in the dense scenario than in the sparse one.

For a given target tracking accuracy level, we examine the amount of conserved energy by selecting the sensor nodes to participate in the collaboration in an intelligent manner. If we select 0.4 meters as the target tracking accuracy level operating point, the energy savings attained can go up to 30 per cent for the sparse scenario and 75 per cent for the dense scenario. Figures 3.9 and 3.10 depict the energy savings for the given target tracking accuracies for the sparse and dense scenarios, respectively.

4. AN INFORMATION-CONTROLLED TRANSMISSION POWER ADJUSTMENT SCHEME

In this section, we introduce the Information-Controlled Transmission Power adjustment (ICTP) scheme as the energy saving strategy, in addition to the MISS algorithm. The block diagram representation of the sensor node whose task is distributed target tracking with MISS and ICTP is shown in Fig. 4.1. Sensory observation is transferred to the information extractor module to retrieve the information state and the information matrix denomination values from the received observation using (2.5), which are then passed to the local information filter module where local target tracking takes place according to the operations in (2.6). The target state belief obtained from the local information filter is handed over to the collaboration logic and the network information filter modules. Using the mutual information measure in (3.3), the collaboration logic decides if the sensor node is going to share the current target observation with the network or not. The collaboration logic works as described in Chapter 3. The network information filter is the place where the information state and the information matrix denominations received from the neighboring sensor nodes are incorporated to the current target state estimate of the sensor node according to (3.2). The resulting collaborated target state estimate is passed to the target next state predictor module which functions as described by (2.8).

The ICTP scheme is embodied in the power adjustment logic module in which a node consults the mutual information list index of the sensor node and the preset power adjustment pattern, and subsequently decides on the transmission power for communicating its information state and information matrix denominations to the network. Sample power adjustment patterns are shown in Fig. 4.2. In general, each pattern consists of an ordered set of transmission power levels, $\mathcal{P} = \{P_1, P_2, \ldots, P_{N_{\max}}\}$ where $P_1 \geq P_2 \geq \ldots \geq P_{N_{\max}}$. If the node S_m is such that $J_m(k) > \min \mathcal{J}'_m(k)$ and if $J_m(k)$ is ranked ℓth in the ordered set $\mathcal{J}''_m(k)$ that lists $\mathcal{J}'_m(k)$ and $J_m(k)$ together, then S_m broadcasts with power P_ℓ at k. If S_m is ranked first in $\mathcal{J}''_m(k)$, then it has the

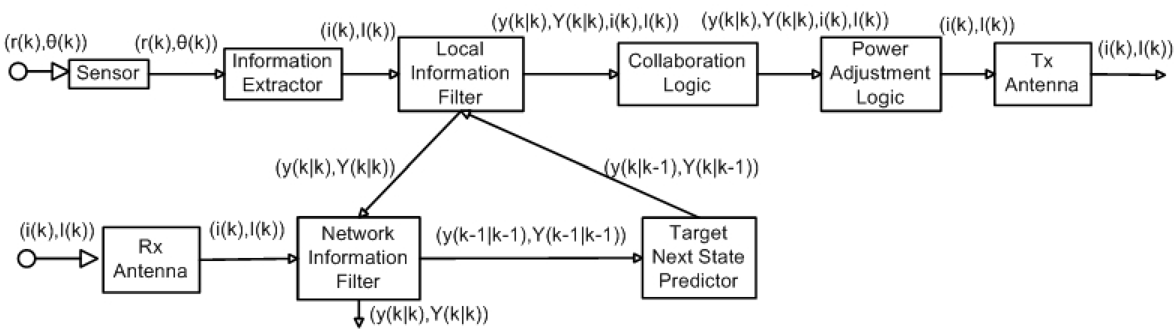

Figure 4.1. Block diagram of the sensor node employing the MISS and ICTP algorithms.

privilege of broadcasting with the maximum power, P_1.

Transmitting with a lower power shortens a detecting node's communication range, which results in a reduced degree of collaboration for the DDF architecture. With the ICTP scheme, we aim to decrease the energy expenditure of each sensor node by regulating its communication transmission power according to its information content. The higher the mutual information a sensor node has about the target state, the more the communication transmission power it uses. Low-power transmission of a sensor node having low information assists the non-detecting sensors to update their belief about the target state.

The performance of ICTP varies depending on the way the network is queried about the target location information. In sensor network applications, the data collected by the network are carried to a processing (data collection) center on a periodic basis or upon a query [148]. The DDF paradigm makes it possible to query any one of the nodes in the WSN to get an immediate response owing to the communication ranges that are far-reaching in comparison to the sensing ranges. Alternatively, the processing center can be informed by the most informative sensor node (MISN), which is the one with the maximum mutual information J_1. There is a delay-accuracy trade-off in the above-mentioned two query-response mechanisms. Routing the query packets to MISN increases the query-response time of the WSN. Responding to a query immediately without consulting the MISN, on the other hand, reduces the query-response time with the cost of reduced target localization accuracy.

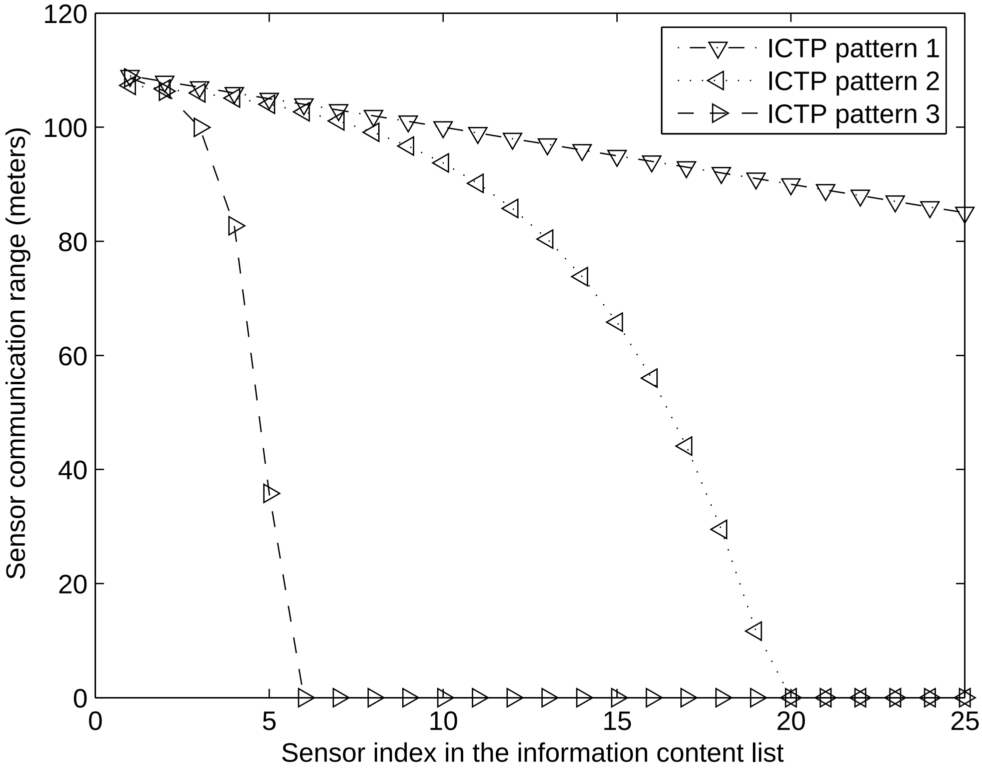

Figure 4.2. Power adjustment patterns.

The experiments in Section 4.1 show that if a sensor network queries any one of its sensor nodes, then reducing the transmission power deteriorates the overall tracking quality due to the reduced degree of collaboration. However, if the MISN is queried, then adjusting the communication transmission powers of the sensing nodes according to their information content lowers the energy consumption while maintaining the tracking accuracy.

The MISS algorithm requires that every sensor node be aware of the expected mutual information content of their neighboring nodes. This facilitates each sensor node to locate the MISN in its vicinity. The main cost incurred in querying the MISN is in routing the query packets to that node, and routing the target state information packets back to the querying node. The pseudo-code of the algorithm of a sensor node running the ICTP scheme in the DDF architecture is given in Fig. 4.3. Sensor nodes obtain the target state observations in Statement 1 of the algorithm in Fig 4.3. Information state and the information matrix denominations are calculated in Statements 2 and 3. The next information state and the information matrix are predicted in Statements 4 and 5. In Statements 6 and 7, the local information filter runs for the predicted information state and the information matrix together with the information denominations obtained from the local sensory observations about the target state. The sensor's own mutual information value is calculated in Statement 8 with the last observation. In Statements 9, 10, and 11, the neighboring sensor nodes' mutual information values are estimated using the current local target state estimate and the previous collaborated target state estimate. The neighboring sensor nodes and the sensor node itself are sorted according to the decreasing mutual information scores in Statement 12. In Statement 13, the index of the sensor node itself in the sorted mutual information score list is found. In Statements 14, 15, 16, and 17, using the mutual information score index, the sensor node decides to actively participate or not to participate in the collaboration cycle. If the index value is smaller than the maximum number of sensor nodes allowed to communicate, then the sensor node calculates the transmission power to broadcast the information state and the information matrix denominations to the WSN using the mutual information score index value and the transmission power reduction pattern used. In Statements 18, and 19, the sensor node updates the information state and the information matrix related with the target location using the received information state and the information matrix denomination values from the neighboring sensor nodes. The estimated target position is calculated in Statement 20 of the algorithm in Fig. 4.3 using the collaborated information state and the information matrix values.

The time complexity of the algorithm in Fig. 4.3 is bounded with the cardinality of the set of neighboring sensors in lines 9-11 and 18-19. Hence, the time complexity of the algorithm in Fig. 4.3 is $O(|S_m(k)|)$. Assuming 50 cpu cycles for each floating point operation [149], 156750+8450$|S_m(k)|$ cpu cycles are required for the algorithm in Fig. 4.3. Moreover, typical 15 neighboring sensor nodes utilize 2.18 per cent cpu of an xbow sensor node with an Intel PXA271 xscale processor [4] working with 13 MHz in low frequency mode. The processor frequency can be scaled up to 416 MHz. PXA271 processor exhausts 10.73 nJ per cpu cycle [4]. Using 2 $\times$ AA batteries each of which has 11050 J energy can operate the sensor node running algorithm in Fig. 4.3 with a typical of 15 neighbor sensors in tracking mode for 1701 days.

4.1. Performance Evaluation of the ICTP algorithm

We run Monte Carlo simulations to examine the performance of the proposed ICTP scheme in a 200 m $\times$ 200 m area in which 500 sensors are deployed randomly. All data points in the graphs represent the means of ten runs in which not only the detection and communication uncertainties but also the random sensor deployment change. A target moves in the area according to the process model described in Section 2.1. We utilize TWR-ISM-002-I radar with pseudorandom signaling, whose typical range is 18 meters. The sensor tracks the target locally using the information form of the Kalman filter as described in Section 2.3. In our simulations, we use the shadow-fading radio propagation model for the communication signals.

We test the performance of the proposed ICTP scheme according to three power adjustment patterns depicted in Fig. 4.2. Pattern 3 exhibits the steepest power reduction, while Pattern 1 has the softest slope. In Fig. 4.4, we observe that the energy savings increase proportionally to the steepness in power reduction. On the other hand, Fig. 4.5 points out that the mean error increases as well with the steepness of the power adjustment pattern. Lines representing the maximum mutual information present the case in which no power adjustment is made. If we adjust the transmission powers of the sensor nodes according to Pattern 3, on average, we achieve 2.14 times less energy usage with respect to the case in which no transmission power adjustment is made (Fig. 4.4). However, power adjustment, on average, doubles the target localization errors as observed from Fig. 4.5. We conclude from Fig. 4.6 that the gain in terms of the exhausted communication energy does not compensate the increase in the target localization error. Hence, reducing the communication transmission power is not desirable. In Figures 4.4, 4.5, and 4.6, we measure the expected target localization error when the WSN responds to queries from any sensor node in the network. Another possibility is to query the MISN in the network, which is the one with the highest mutual information about the target state. This querying scheme has the cost of locating the MISN and routing the target location information query and response packets to and from it. The cost of locating the most informative sensor node is negligible as described at the end of Chapter 4.

When the MISN is queried, as the power reduction pattern becomes steeper, the exhausted energy drops as shown in Fig. 4.7, and the target localization error decreases as shown in Fig. 4.8. The reason for this is that the less informative sensor nodes begin to harm the target localization performance of the more informative nodes with their marginal information. In Fig. 4.9, we see that the power reduction Pattern 3 consumes the least amount of energy with ICTP. We observe the ceiling effect in the exhausted energy when the number of sensor nodes allowed to communicate reaches 14 (Fig. 4.7). The reason of this ceiling effect lies behind the number of detecting sensor nodes. For the cases studied in the simulated scenario, the mean number of detecting sensor nodes is about 14. Even if we allow more than 14 nodes to communicate, the rest will not have detection information to share with the others. For the cases studied, the mean distance of the most informative sensor node to the target is 2.17 meters. This results in very accurate target localization if the MISN is queried. If the most informative sensor node will be queried, operating at the minimum energy operation point is a rational decision. The minimum energy operation point is achieved only if the MISN shares its information with the neighboring nodes as shown in Fig. 4.7. Transmission power adjustment according to Pattern 3 results in 2.11 times the energy savings on the average compared to having no power adjustment (Fig. 4.7). On average, 23.7 per cent improvement is achieved in the target localization as deduced from Fig. 4.8. This happens due to the filtering of the information coming from the less informative sensor nodes that corrupt the information of the more informative sensor nodes.

A 2.34-fold energy conservation is possible for a desired target tracking accuracy over the no power adjustment scheme as deduced from Fig. 4.9.

We also examine the case where only the MISN broadcasts its data. Thus, other detecting sensor nodes do not transmit, and they consume energy just to process the incoming information signal from the most informative sensor node. The line with stars in Fig. 4.7 depicts the low energy exhausted by the sensor nodes if only the

MISN broadcasts. However, the error of MISN is high as demonstrated with a line with stars in Fig. 4.8, because the MISN changes in time as the target moves. Low level of collaboration results in the new most informative sensor node having low prior information about the target. The prior information obtained by means of collaboration causes the information-filtering performance of the most informative sensor node to improve.

Given: Observations $r_m(k)$, $\theta_m(k)$ from the target at time instant k, information state $\mathbf{i}_i(k)$ and information matrix $\mathbf{I}_i(k)$ at time k from the neighboring sensor nodes i, system variables $\mathbf{F}$, $\mathbf{Q}$, $\mathbf{H}$, $\mathbf{R}$.

Find: Target position estimate $\hat{\mathbf{x}}(k|k)$ at time k.

Obtain the observation from the target.

$\varphi_m(k) \Leftarrow f(r_m, \theta_m)$

Calculate the information denominations.

$\mathbf{i}(k) \Leftarrow \mathbf{H}^T\mathbf{R}^{-1}(k)\varphi_m(k)$

$\mathbf{I}(k) \Leftarrow \mathbf{H}^T\mathbf{R}^{-1}(k)\mathbf{H}$

Predict the target's next information state.

$\hat{\mathbf{y}}(k|k-1) \Leftarrow \mathbf{Y}(k|k-1)\mathbf{F}\mathbf{Y}^{-1}(k-1|k-1)\hat{\mathbf{y}}(k-1|k-1)$

$\mathbf{Y}(k|k-1) \Leftarrow [\mathbf{F}\mathbf{Y}^{-1}(k-1|k-1)\mathbf{F}^T + \mathbf{Q}]^{-1}$

Local information filter.

$\hat{\mathbf{y}}(k|k) \Leftarrow \hat{\mathbf{y}}(k|k-1) + \mathbf{i}(k)$

$\mathbf{Y}(k|k) \Leftarrow \mathbf{Y}(k|k-1) + \mathbf{I}(k)$

Find own mutual information value.

$J(k, \varphi_m(k)) \Leftarrow \frac{1}{2}\log\left[\frac{|\mathbf{Y}(k|k)|}{|\mathbf{Y}(k|k-1)|}\right]$

Estimate other sensor nodes' mutual information values.

for all $sensor$ such that $sensor$ is a neighbor **do**

$\quad J_{array}(k, \varphi_m(k))[sensor] \Leftarrow \frac{1}{2}\log\left[\frac{|\mathbf{Y}_{sensor}(k|k)|}{|\mathbf{Y}_{sensor}(k|k-1)|}\right]$

end for

Produce the mutual information content list.

sort $J_{array}(k, \varphi_m(k))[sensor]$

Find own sensor node's index value in the mutual information content list.

$index \Leftarrow$ index of $J(k, \varphi_m(k))$ in $J_{array}(k, \varphi_m(k))$

Decide to collaborate or not to collaborate. If decision is to collaborate then calculate the transmission power and broadcast the denomination values.

if index $\leq$ maximum number of sensor nodes allowed to communicate **then**

$\quad$ Transmission Power $\Leftarrow f(index)$

$\quad$ Broadcast $\mathbf{i}(k)$ and $\mathbf{I}(k)$

end if

Network information filter.

$\hat{\mathbf{y}}(k|k) = \hat{\mathbf{y}}(k|k-1) + \sum_n \mathbf{i}_n(k)$

$\mathbf{Y}(k|k) = \mathbf{Y}(k|k-1) + \sum_n \mathbf{I}_n(k)$

Find the target state estimate.

$\hat{\mathbf{x}}(k|k) = \mathbf{Y}^{-1}(k|k)\hat{\mathbf{y}}(k|k)$

Figure 4.3. Pseudo-code of the MISS/ICTP algorithm running on a sensor node described in Fig. 4.1

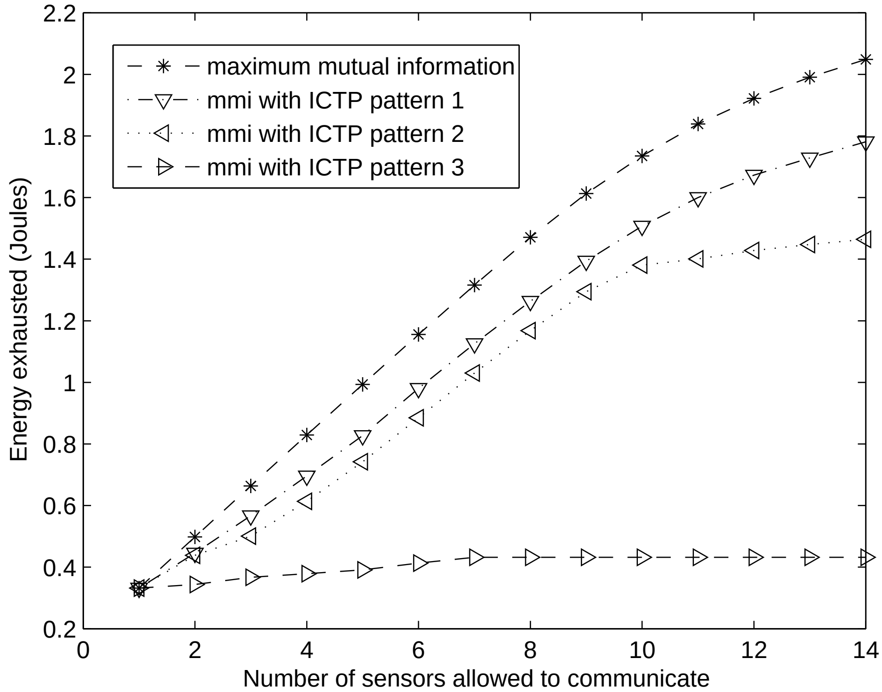

Figure 4.4. Mean consumed communication energy if any sensor node in the network can be queried.

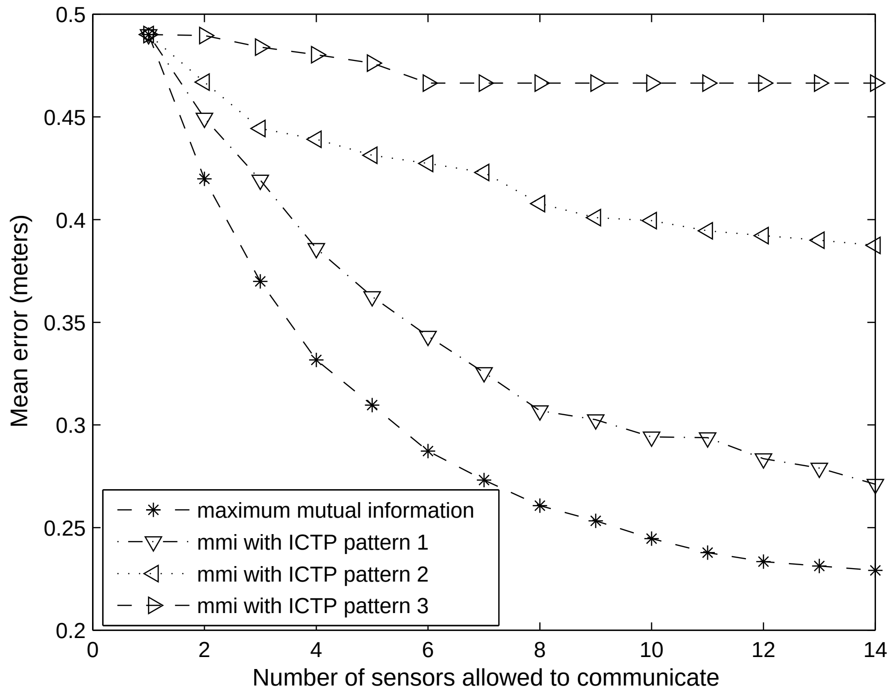

Figure 4.5. Mean target localization error for different power adjustment patterns if any sensor node in the network can be queried.

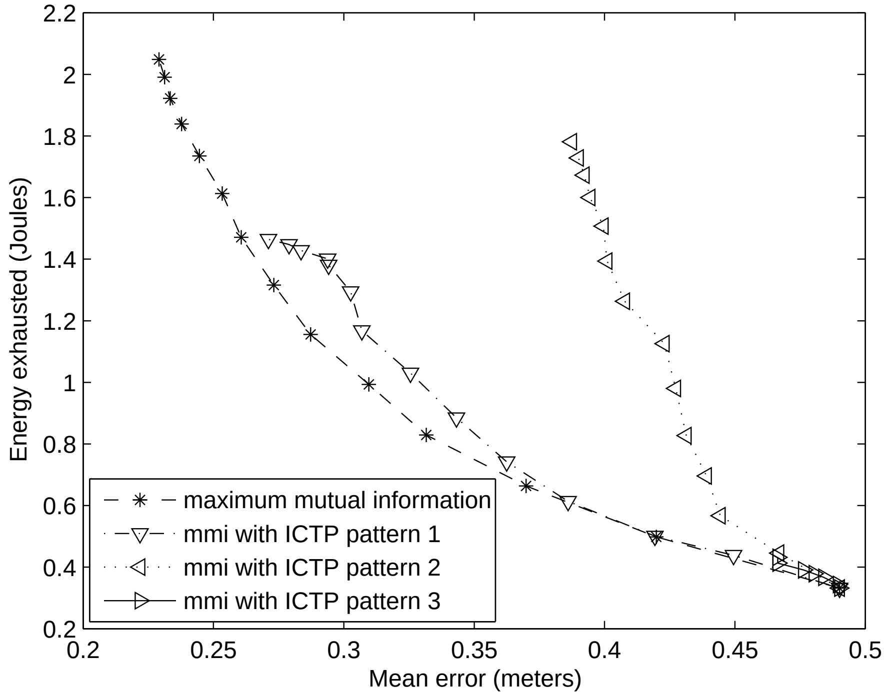

Figure 4.6. Effect of power adjustment on the consumed energy for the desired target localization accuracies if any sensor node in the network can be queried.

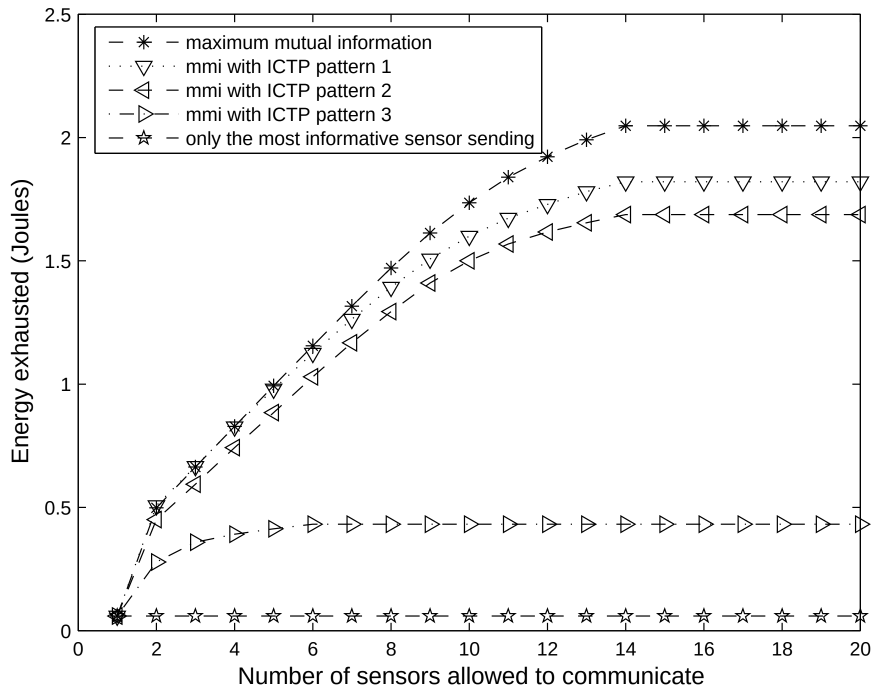

Figure 4.7. Mean consumed communication energy if the most informative sensor node is queried.

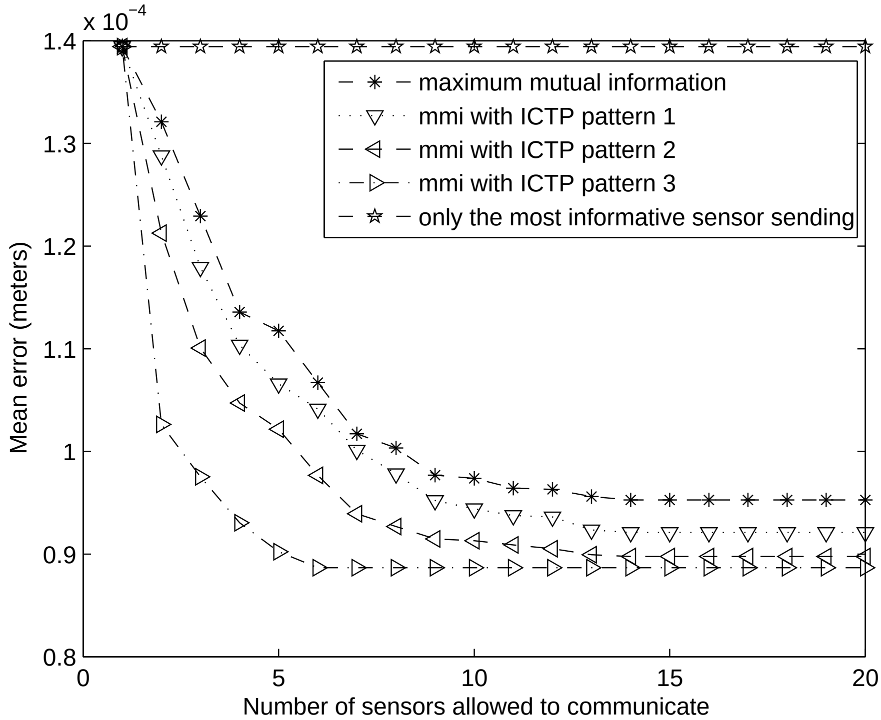

Figure 4.8. Target localization error for different power adjustment patterns if the most informative sensor node is queried.

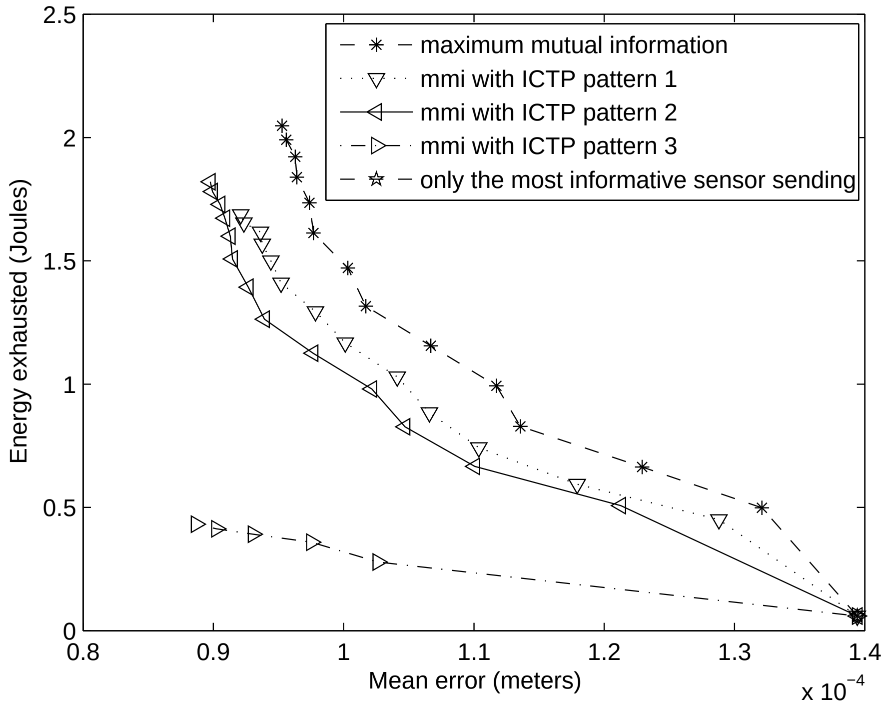

Figure 4.9. Effect of power adjustment on the consumed energy for the desired target localization accuracies if the most informative sensor node is queried.

5. MULTIPLE SENSOR MULTI-TARGET TRACKING SYSTEM ARCHITECTURES

In this section, architectures for tracking multiple targets using multiple sensors are examined according to their communications cost. The local sensor tracks and the local measurements are the two possible information units to be shared with the sensor network. Also the place of the track fusion for the former and the composite tracker for the later is another classification criteria for the multi-sensor multi-target tracking architectures. In the centralized tracking, local measurements and the local sensor tracks are send to a central track fusion or composite tracking entity. In network-centric tracking, there is no need for a central entity for track fusion or composite tracking. Multiple-sensor multiple-target tracking system architectures are given in Fig. 5.1.

- Centralized track fusion with reporting responsibility: Local sensor tracker caries on tracking related with its detections, however only the information related with the assigned track are send to a central track database. Optionally, local track database may send the track information in the central track database back to the sensors. Each track is reported by just one sensor, hence, central database only appends the track reports from the responsible sensors.
- Centralized track fusion: Differs from the centralized track fusion with reporting responsibility in the sense that all the local sensor tracks are sent to the central

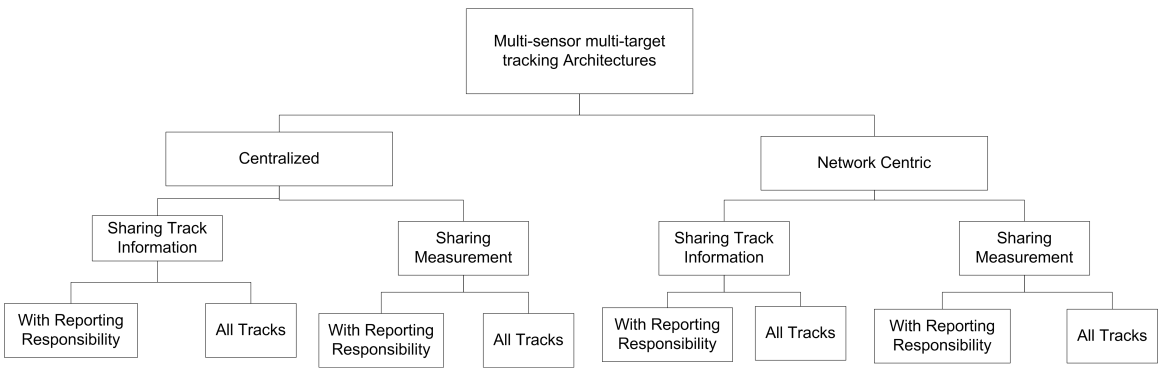

Figure 5.1. Multi-sensor multi-target tracking architectures.

track fusion center, where the track-to-track association from different sensors takes place.

- Centralized tracking with reporting responsibility: The sensor sends the local sensor measurements related with the target it is responsible for monitoring. The centralized tracker performs the tracking operations. With the knowledge of sensor target assignment, the central tracker knows with which target in the central track database the received sensor measurements are related. Hence, an associator is not needed in this architecture.
- Centralized tracking: Local Sensor measurements are sent to a central composite tracker which performs the association and the tracking of the targets. Optionally, tracks in the central track database may send back to the sensors.
- Network-centric track fusion with reporting responsibility: In this architecture, each sensor updates all of its tracks with own measurements, however only one sensor is responsible for reporting about the track state. The responsible sensor is chosen according to the accuracy of the target state estimate. This architecture, as with the other reporting responsibility architectures, has the problem of deciding and assigning the responsible sensor for the track.
- Network-centric track fusion: Track information related with all the local tracks are shared with the network. Track-to-track fusion takes place in all sensors.
- Network-centric tracking with reporting responsibility: Sensor measurements related with the target that the sensor is responsible for monitoring are shared with the sensor network. Measurements related with the targets that the sensor is not responsible for monitoring are used to track the targets locally. The locally tracked targets are also updated with the measurements received from the other sensors.
- Network-centric tracking: Local sensor measurement reports related with all the detected targets are shared with the network. Composite tracking takes place in every sensor using the remote sensor measurement reports.

We compare the multi-sensor multi-target tracking architectures in terms of their exhausted energies and mean target localization accuracies. For the composite tracking architectures, measurement reports are shared with the network. Information state vector size is four. We reserve 32 bits for each element of the information state. 128 bits are required to share the information state with the network. 10 elements of the 4x4 information matrix are enough to share the information matrix with the network whose each element is represented by 32 bits. A total of 448 bits are needed for a data packet carrying one track measurement report. We reserve 64 bits for auxiliary usage in the data packet. 512 bits long data packets are used for composite tracking architectures. Track fusion architectures require exchange of track position in two dimensions and 3 elements of the 2x2 covariance matrix each is represented by 32 bits. With 64 auxiliary reserved bits 224 bit packets are used for track fusion architectures. We do not need to exchange the information matrix and the covariance matrix for the reporting responsibility architectures. Each track is maintained with their responsible sensors. Hence, the required packet sizes are reduced to 192 and 128 for the composite tracking and the track fusion architectures respectively. We run Monte Carlo simulations that consists of 900 sensors which are randomly deployed in a 20 m $\times$ 200 m area. Five targets move in the area as in Fig. 6.3. The comparison of the exhausted energies and the mean target localization errors for the multi-sensor multi-target tracking system architectures are presented in Fig. 5.2 and Fig. 5.3 respectively. Network-centric tracking exhaust most energy among the other architectures. Reporting responsibility architectures have higher target localization errors. The reason lies behind the lack of collaboration. Centralized tracking architectures require a center node to exists in the system. For the sake of simplicity, we assume one center node in the middle of the surveillance area throughout the scenario, whose energy assumed to be unlimited. 110 meters approximate communication range of a sensor node makes each node in a 20 m $\times$ 200 m area to communicate with the center node. For the practical cases, the center node may be outside the area or the center node may change over time. For the communication energy in the centralized architectures, we assume the sensor nodes transmit with a power sufficient for them to communicate with the center node. Although the centralized track fusion appears to be a good compromise among the multi-sensor multi-target tracking system architectures, the problem with the centralized track fusion architectures arises when the local trackers use different target motion models or operate on different target state spaces [150,151]. Moreover, the center node is the single point of failure and a consensus among the sensor nodes is required for the

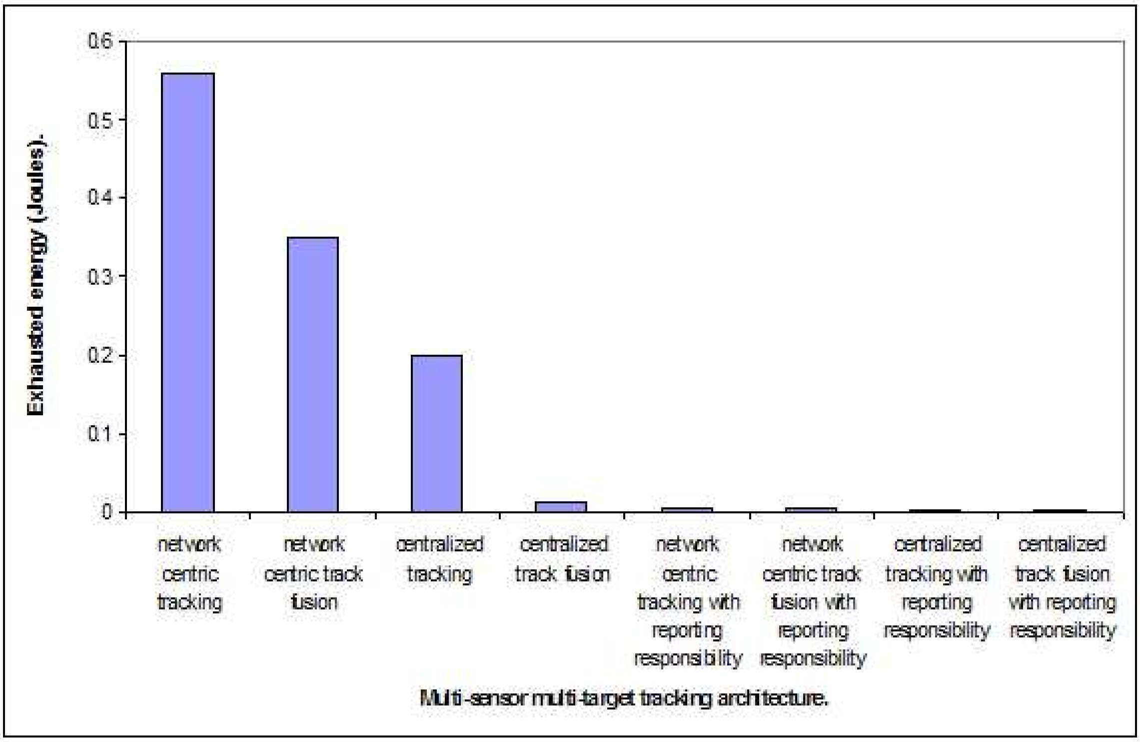

Figure 5.2. Exhausted energy comparison of the multi-sensor multi-target tracking architectures.

election of the center node. Due to the robustness, reliability, expansibility, modularity, and the distributed operation properties, in Chapter 6, we define a network-centric tracking framework for the WSN nodes and try to achieve the performance improvements in the network-centric tracking architecture.

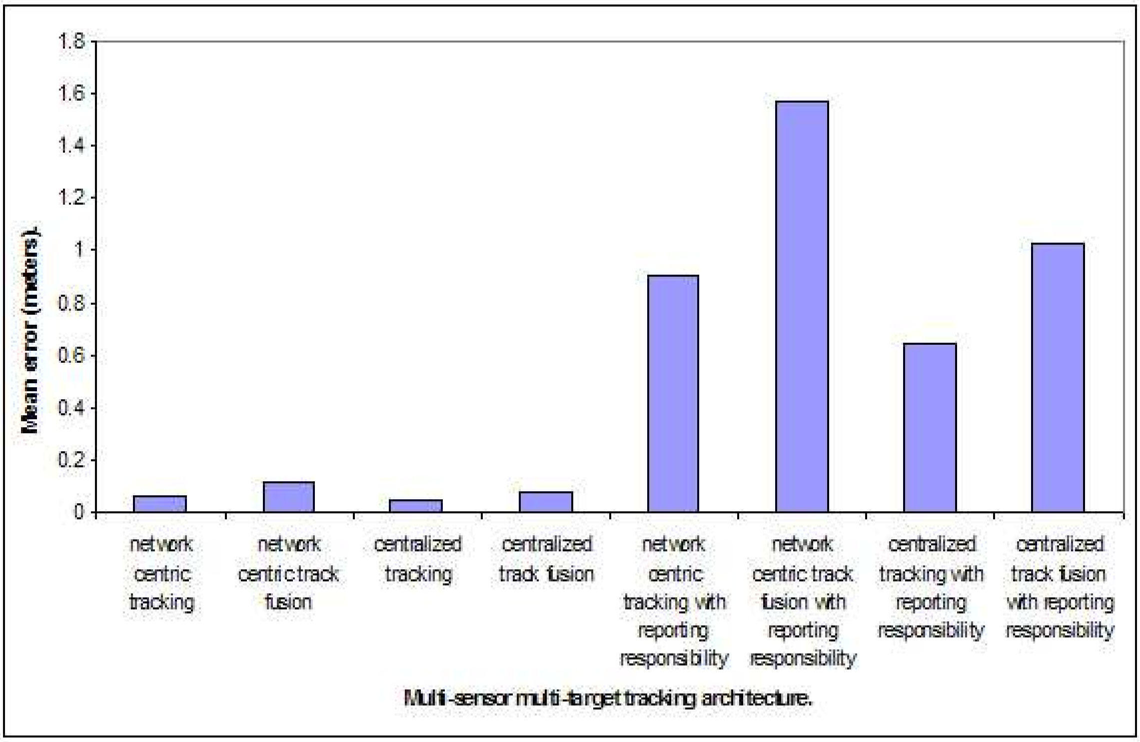

Figure 5.3. Mean error comparison of the multi-sensor multi-target tracking architectures.

6. COLLABORATIVE DISTRIBUTED MULTI-TARGET TRACKING FRAMEWORK

The distributed multi-target tracking framework is presented in Fig. 6.1. Modules shown at the upper part of the track list manager module belong to the network track manager part. Modules shown at the lower part of the track list manager module belong to the local track manager part.

On the local track manager part, the sensor receives the targets range and bearing data with the aid of its sensory circuit. Information extractor converts the range and bearing data related to the targets within the sensors detection range into the information denomination form according to (2.5). These information denominations are passed to the local plot list manager. Elements of an entry in the local plot list manager are the information state and the information matrix denomination values. The local plot list manager can have only one plot related with a track. In other words, we assume each target can generate at most one plot for the sensor. Since the origins of the plots in the plot list manager are unknown, we cannot know with which target the received plot is related. Local track associator takes the current track list from the track list manager whose elements are the information state and the information matrix related with the currently tracked targets, and associates the denominations in the plot list manager with them. In order to carry out the distributed data association, using (2.8) each sensor calculates the predicted states and the covariances of the targets in their track-lists using their predicted information state and the information matrix. Afterwards, a list whose elements are the states of the detections from the targets in the vicinity is formed. Likelihood of each plot in the plot list to the targets in the track list is calculated according to the Gaussian distributions whose means are the predicted states and the covariances as the inverse of the information matrix predicted in the prediction phase. Each target in the track list can be assigned only one plot from the plot list. Associated information denomination and track pairs are passed to the information update filter to update the current track state. Detailed investigations

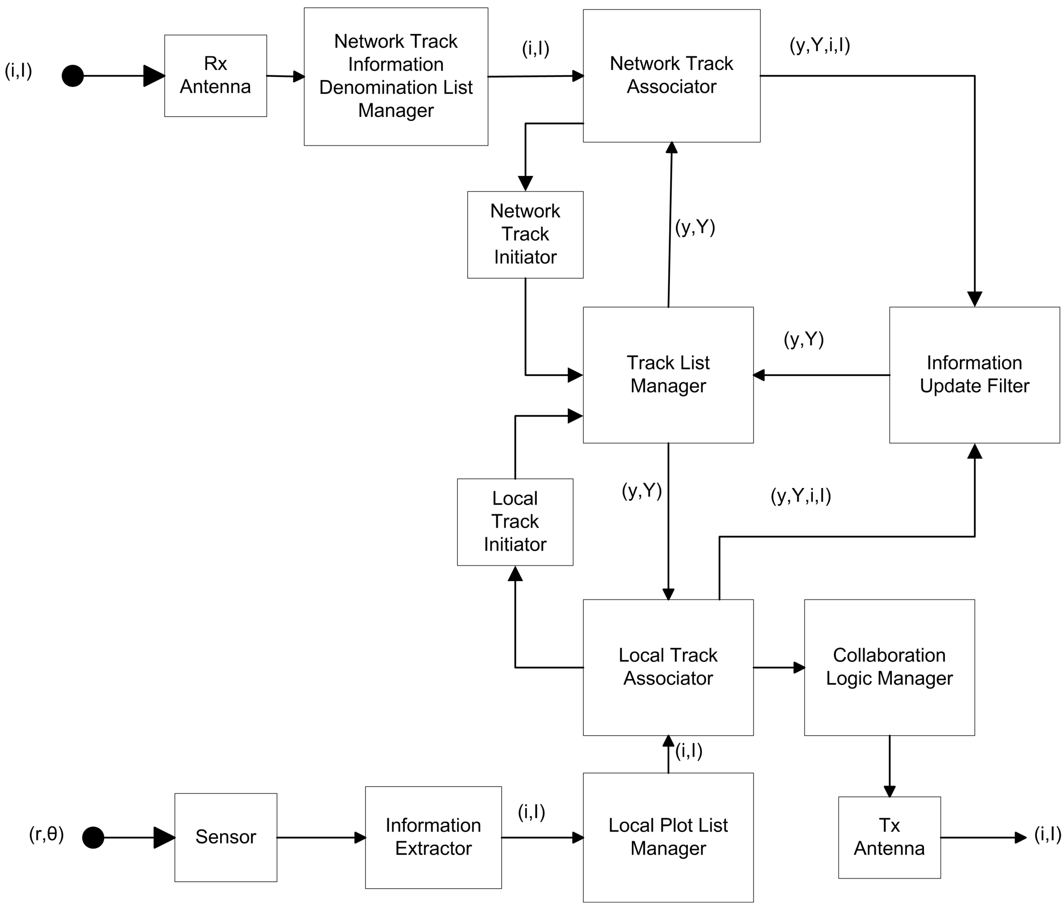

Figure 6.1. Distributed multi-target tracking framework.

related with the track update filter algorithms can be found in MS. thesis by Tolgay [152]. Information denominations are passed to the collaboration logic manager to be sent to the neighboring sensors. Collaboration logic manager decides to share or not to share the denomination values with the neighboring sensors. Denominations that cannot be associated with the current tracks in the track list are sent to the local track initiator. New track initiation takes place right after several continuous detections received from the target. Each information denomination value is assigned to the track to whom it has the maximum likelihood with the constraint that only one information denomination can be associated with one track and with one track at most one information denomination can be associated. In order to satisfy these constraints, the association of the information denominations in the local plot list to the tracks in the track list is achieved by evaluating the association likelihoods in a joint manner. The local track initiator initiates a track and sends the track information to the track list manager in order to be added to the track list only if the track initiation criterion is satisfied. e.g., eight continuous detections from the same target have been received. Detailed investigations of the local track initiation logic by Akduran in his MS. study [153] show a good compromise with a modified M out of N local track initiation logic in the cluttered environments.

On the network track manager part; communication circuit of the sensor receives the information state and the information matrix denominations from the neighboring sensor which have been decided to be shared with the sensor network by the sensors that are detecting the target. Different than the local plot list manager, the network track information denomination list manager may have many plots received from different sensors related with one track. The network track associator, associates the information denominations in the network track information denomination list manager with the tracks in the track list manager. Shared information between sensors are the denominations related with the observations, not the target state estimations. The associator needs target state estimations in order to associate denominations with them. One solution is to put the burden on the communication and sharing target state estimates together with the denominations. Instead, by putting the burden on computation, we update the the local target state estimates with the received denominations and afterwards perform the most likely association in a joint manner. The constraint in the network track associator is that each plot can be assigned at most one target. A sensor receiving an information matrix and the information state, calculates the target state information related with the received information from the neighboring sensors. For each received information, likelihood values according to the local track states are calculated. As the mean and the covariance values of the local track states, we use the predicted states and the covariances of them. Associated denomination-track pairs are sent to the information update filter which updates track states and send them to the track list manager. Denominations that cannot be associated with the tracks in the track list manager are sent to the network track initiator to initiate a track immediately and to send them to the track list manager. Tracks that have not been detected or reported from the neighbors for the last several cycles (e.g., eight) have been deleted from the track database in the track list manager.

For both local and the network track manager parts of the distributed multi-target tracking framework, we use the same validation region definition from [56] given as;

$$(\boldsymbol{\varphi} - \mathbf{H}\overline{\mathbf{x}})^T \mathbf{B}^{-1} (\boldsymbol{\varphi} - \mathbf{H}\overline{\mathbf{x}}) < 1$$

where;

$$\mathbf{B} = \mathbf{H}\overline{\mathbf{P}}\mathbf{H}^T + \mathbf{R}.$$

Target-plot pairs are deemed as related if they satisfy the above criterion, and not related otherwise. Both local and network track associations are done only among related pairs.

The algorithm of a sensor node that implements the described multi-sensor multi-target tracking architecture is given in Fig. 6.2.

The time complexity of the multi-target tracking algorithm is $O(|S_m(k)|E_T)$.

Where, $|S_m(k)|$ is the cardinality of the set of neighboring sensor nodes and E_T is the number of targets in the vicinity. Assuming every target in the vicinity is detected, multi-target tracking algorithm requires $479200E_T + 18450|S_m(k)| + 50$ cpu cycles with the assumption that each floating point operation can be performed in 50 cpu cycles [149]. Moreover, typical 15 neighboring sensor nodes and five targets utilize 20.56 per cent cpu of an xbow sensor node with an Intel PXA271 xscale processor [4] working with 13 MHz in low frequency mode. The processor frequency can be scaled up to 416 MHz. PXA271 processor exhausts 10.73 nJ per cpu cycle [4]. Using 2 $\times$ AA batteries each of which has 11050 J energy can operate the sensor node that runs the multi-target tracking algorithm depicted in Fig. 6.2 with a typical of 15 neighbor sensors and five targets in tracking mode for 180.43 days.

6.1. On the Performance of the Collaboration Logic Manager Part of the Collaborative Distributed Multi-Target Tracking Framework

We run Monte Carlo simulations that consist of 900 sensors which are randomly deployed in a 20 m $\times$ 200 m valley bottom type strip area. Five targets move according to the process model described in Section 2.1. Fig. 6.3 shows the scenario. We use the parameters for the TWR-ISM-002-I radar [3], whose typical detection range is 18 meters. In our simulations, we use the shadow-fading radio propagation model for the communication signals whose parameters are given in Table 3.1. All data points in the result graphs represent the means of fifteen runs.

The mean target localization error decreases as the number of targets that a sensor is allowed to report to the network increases. This phenomena is shown in Fig. 6.4 which depicts the target localization performance of the three different target selection strategies. In the random target selection strategy, collaboration logic manager selects a random subset of the detected targets about whose information denomination values will be shared with the network. Targets that have the lower Mahalanobis distance between the estimated target position and the updated target position with the latest measurement are selected in minimum Mahalanobis distance based target selection. This selection is done according to the volume of the improvement achieved

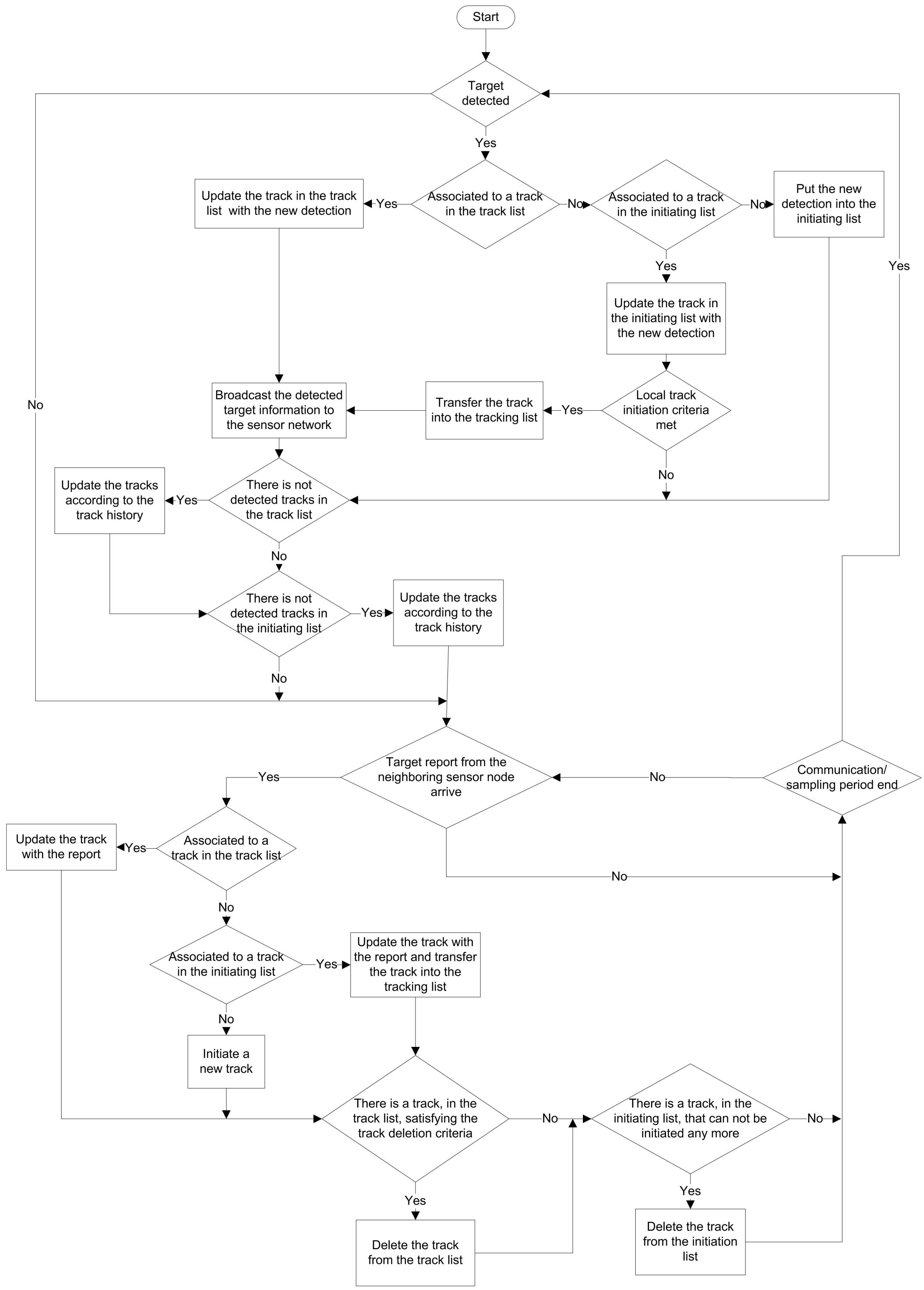

Figure 6.2. The algorithm of a sensor node to implement the distributed multi-target tracking framework.

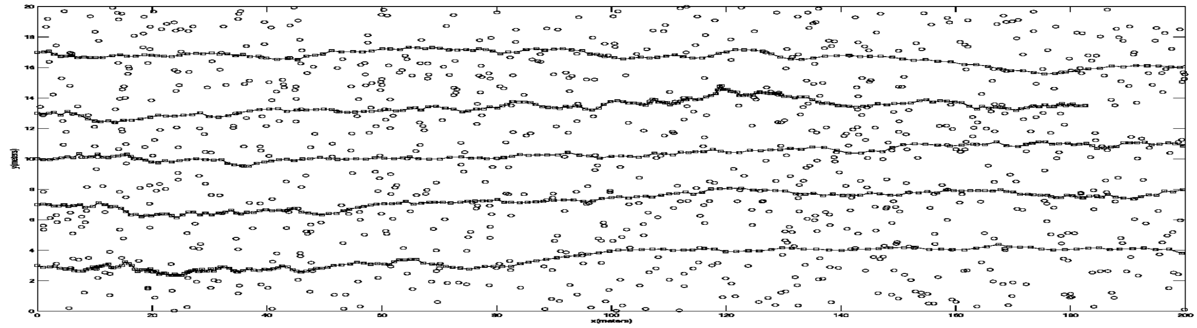

Figure 6.3. Illustration of the valley bottom type strip simulation scenario.

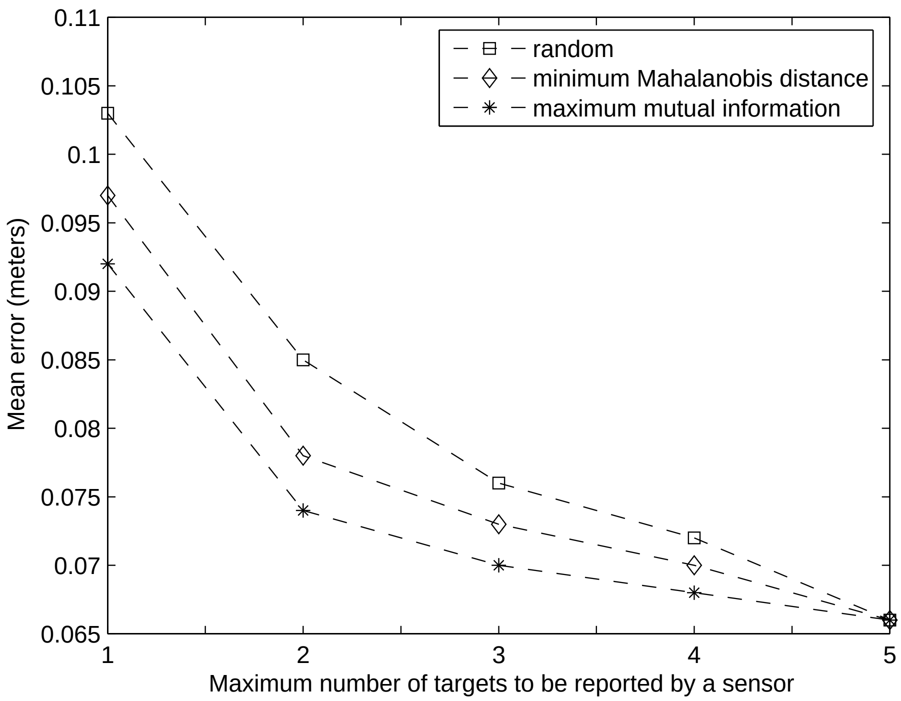

Figure 6.4. Mean target localization error of a sensor node.

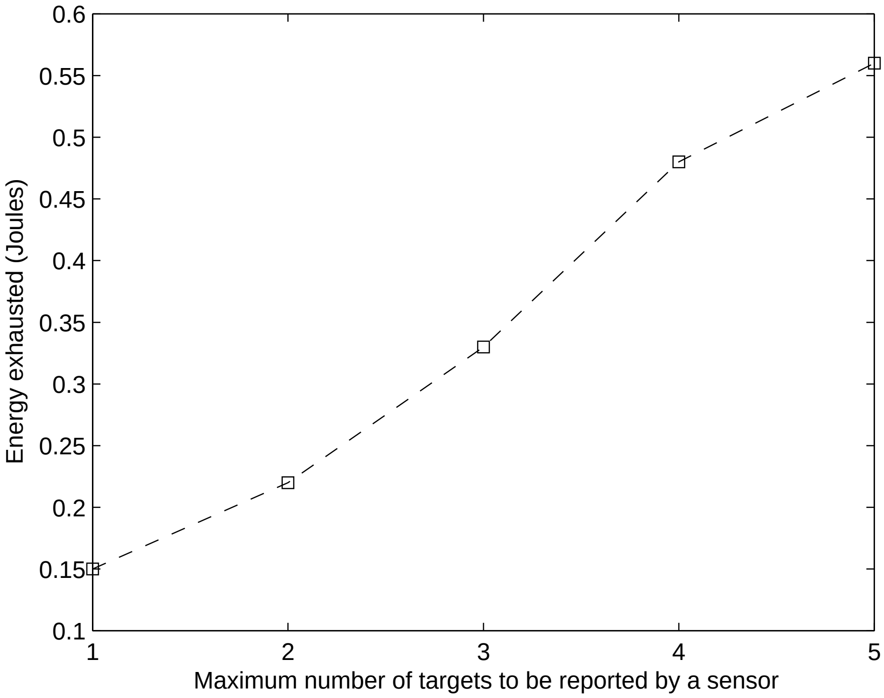

Figure 6.5. Mean exhausted energy of a sensor node.

in the target state information obtained with the latest observation. Higher the above-mentioned improvement, higher the mutual information sensor has about the target state. Information denominations of the targets about whom the sensor has more mutual information are selected to be transmitted to the network. Fig. 6.4 shows that the best target localization performance is achieved by selecting the targets according to the mutual information metric. Mutual information equation is given by

$$J(k, \boldsymbol{\varphi}(k)) = \frac{1}{2} \log \left[\frac{|\mathbf{Y}(k \mid k)|}{|\mathbf{Y}(k \mid k-1)|} \right],$$

where $\mathbf{Y}(k \mid k)$ is the information matrix at the time instant k after the target state is observed. The mean exhausted energy by each sensor is depicted in Fig. 6.5. 19 per cent more accurate target localization is possible by exhausting 36 per cent more energy by allowing two targets to be reported to the neighboring sensors instead of one. Six per cent more accurate target localization can be performed by allowing three target information to be shared with the neighboring sensors instead of two with the expense of 33 per cent more energy exhausting. We can localize targets four per cent more accurate by allowing four targets information to be shared instead of three. The penalty of

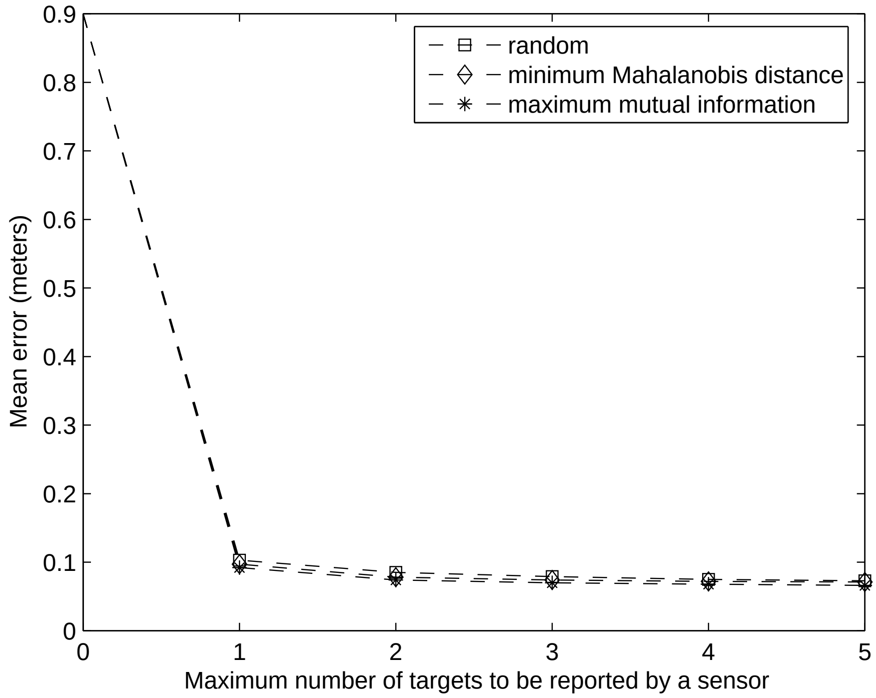

Figure 6.6. Mean target localization error of a sensor node compared to the non-collaborative tracking error.

allowing four targets information to be shared instead of three was 24 per cent. Finally, three per cent more accurate target localization is possible by allowing information related to five targets to be shared with the neighboring sensors by exhausting 19 per cent more energy. We have a decreasing pattern of target localization error gain as the maximum number of targets about whom the information denominations will be broadcast by a sensor to the network increases. However, the penalty of exhausted energy paid to transmit more targets' information denomination values to the network keeps almost constant for every additional target to report.

Comparison with only the local tracking mode is shown in Figures 6.6 and 6.7. The zero value of the maximum number of targets to be reported by a sensor in the x-axis of these graphs corresponds to the case in which the sensors tracking the target with their local observations without collaborating with the neighboring sensors.

Simulation results showed that the collaboration improves the tracking performance. However, improvements achieved by sharing more than one target information

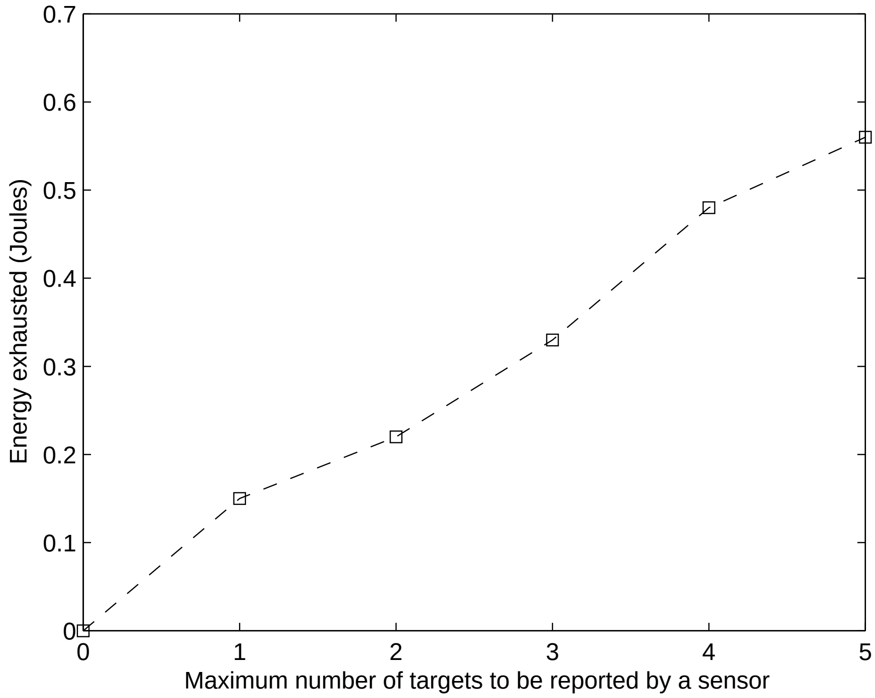

Figure 6.7. Mean exhausted energy of a sensor node compared to the non-collaborative exhausted energy.

with the neighboring sensors result in the increased exhausted energy. Hence, sharing only one target information with the neighboring sensors is a rational decision for the studied cases. Now, the problem is to decide which target information to share among the detected targets. For a single target, in Chapter 3 it was shown that the mutual information is a good measure to select the subset of the sensors to collaborate. Our simulations show that sharing the information denominations of the targets whose mutual information index among the detected targets is higher, results with the better target localization accuracy among the random and the minimum Mahalanobis distance based target selection strategies.

Although the focus of our simulations were on the collaboration logic manager part of the collaborative distributed multi-target tracking framework described in Fig. 6.1, keeping the number of shared tracks low, reduces the computational complexity of the network track associator modules of the sensors.

We compare the target localization performances of the single-target tracking algorithm without sensor selection and power adjustment with the multi-target tracking algorithm with one target and perfect association in a 100 m $\times$ 100 m area for 100 seconds with 50 sensor nodes and 10 sensor nodes. for 50 sensor nodes the mean target localization error is 0.5723 m for the single-target tracking algorithm and 0.5548 m for the multi-target tracking algorithm with 50 sensor nodes. With 10 sensor nodes in the surveillance area, the mean target localization error is 1.9714 m for the multi-target tracking algorithm and 1.9856 m for the single-target tracking algorithm. Hence, single-target and the multi-target tracking algorithms perform similar while five times less sensor node usage results in 3.5 times increase in the target localization error.

6.2. Association Problems for Multi-Target Tracking

In order a sensor node to follow the states of the multiple targets, the major problem is to associate the sensory observation with the previous targets in the sensor node's track list. False associations result in the updating of the track states in the sensor node's track list with the wrong observations. As will be shown in the performance evaluation of the association algorithms in Section 6.4, false associations consequently reduces the target localization accuracies of the sensor nodes drastically. If sensor nodes collaborate with each other, aiming to increase the target localization accuracies, the more challenging problem, for associating the neighboring sensor node's target kinematics reports to the tracks in the sensor nodes track list, arises. We call the former as the *local association* and the later as the *network association*. The local association constitutes the relations between the sensory measurement and the tracks in the sensor nodes track list, hence it is the measurement-to-track association, whereas the network association relates the received track reports of the neighboring sensor nodes to the tracks in the track list of the sensor node, hence it is the track-to-track association. In [56], hypothesis testing is proposed to solve the local association problem. If sensor node S_m has two targets in the track list and observes three targets at time k, the hypotheses can be formed by;

1. The probability that all the three new observations are related with the three new targets, maximizes the number of targets in the sensor node's target list.

In this case, the sensor node will have five targets in the target list. The sensor node is not detecting the two targets in the target list and detecting the three new targets. We can number to the old targets in the sensor node's track list as 1 and 2, and plausible new targets as 3, 4, and 5.

2. Local association hypotheses for the three new observations with the two existing tracks in the track list of a sensor node are as in Table 6.1. The sensor node has 13 hypotheses to test. The hypothesis with the highest probability will be the valid association. The hypothesis in the first line (1,2,5) of Table 6.1 states that the observation 1 is related with the track 1, the observation 2 is related with the track 2, and the observation 3 is the new track with number 5. The following hypothesis in Table 6.1 can be interpreted similarly.
3. While calculating the possibility of the hypothesis 1, the sensor node needs three possibilities. Namely, the possibility of the observation 1 is related with the track 1, the possibility of the observation 2 is related with the track 2, and the possibility of the observation 3 is the new track.
4. Summing these three possibilities yields with the possibility of the hypothesis 1.
5. Calculation of the probability that an observation O_n is related with a track T_s in the track list can be carried on by estimating the T_s's state at time k with the aid of T_s's state at time $k-1$ in the sensor node's track list. This operation is called the *time update* phase of the track. Similarly the covariance $\mathbf{P}_s$, measuring the reliability of the T_s's state at time k can be estimated with the track filtering operations. Finally, the position of the new observation O_n in the Gaussian distribution whose mean is the estimated track state and the covariance is the estimated track covariance is interpreted as the possibility that the observation is related with the track.

Each track in the track list of the sensor node is updated using the observation obtained from the association hypothesis with the highest probability. This update of the track list is called the *measurement update* phase. In hypothesis of Table 6.1, false alarms and clutters are not considered.

Table 6.1. Hypothesis matrix for the association of the three new observations with the two existing tracks.

observation 1	observation 2	observation 3
1	2	5
1	4	2
1	4	5
2	1	5
2	4	1
2	4	5
3	1	2
3	1	5
3	2	1
3	2	5
3	4	1
3	4	2
3	4	5

network association problem differs from the local association problem in the sense that the former is related with the target reports received from the communication circuitry of the sensor node, while the later is related with the sensor node's own sensory observation.

The main difference among the local and the network association problems lies in the fact that one target can be observed at most once with the sensor node's on board sensor, where as one target can be reported as many times as the number of detecting sensors in the communication range of the sensor node. Hence, the constraint of one target can be associated with at most one observation, is applicable for the local association, whereas for the network association this constraint is not applicable.

6.3. Fuzzy Network Association

Sensor node maintains a validation region for each track in the track list. Every observation report from the neighboring sensor node within this validation region is a candidate for updating the related track. Observation reports of the neighboring sensor nodes, that fall outside of the validation regions of all the track's in the track list, are deemed as the new track and added immediately to the track list of the sensor node. Size of the validation region directly affects to the number of false initiated network tracks.

If the observation report from the neighboring sensor node, lies within the validation region of just one track in the track list, then the target report is associated immediately with that track. The problem arises if the observation report from the neighboring sensor node lies within the validation region of more than one tracks in the track list of the sensor node. One possible solution to break the tie is to associate the report from the neighboring sensor with the track, which has the minimum distance according to a metric, in the track list. Candidate metrics for this association are the Euclid distance, the Mahalanobis distance, and the likelihood measure of the report to the track.

Instead of relying on just one metric for the network association decision, we aim to rely on more than one metrics. With this aim, we take the advantage of fuzzy logic in mapping different metrics into a single crisp value to be used in the network association decision. Fuzzy logic also has the advantage of modeling the complex real world with the expertise that can be expressed easily using the rule set defined by a model similar to the human reasoning.

Fuzzy association of measurements to existing target tracks was investigated in [154, 155, 156, 157, 158, 159]. Due to the large number of rules in the fuzzy knowledge base, the fuzzy logic approach in [154] is computationally infeasible for more than three or four targets. A fuzzy measurement to track association that can handle the cases, where the measurements are not well described as Gaussian random variables is proposed in [115]. In [160] an adaptive neuro-fuzzy inference system with fuzzy clustering means algorithm is used for measurement-to-track association. A fuzzy clustering means algorithm is proposed in [161] for track to track association and track fusion that requires all the sensor track information to be collected in a fusion center for processing. A voting based fuzzy rule base is proposed in [162] and [163] to support the handoff decision of the mobile terminals in an environment with the mobile access points.

A sensor node S_m uses three fuzzy variables in order to associate the target observation report T_r of a neighboring sensor node S_n with a track T_l in the track list. These three fuzzy variables are;

1. Euclid distance between T_r and T_l.
2. Direction difference between T_r and T_l.
3. Speed difference between T_r and T_l.

Each of the three fuzzy variables has three fuzzy sets named *LOW*, *MEDIUM*, and *HIGH*. Membership functions of the three fuzzy variables are depicted in Figures 6.8, 6.9, and 6.10 for the Euclid distance, direction difference, and the speed difference respectively.

We design a fuzzy system with the product inference rule and the centroid defuzzifier. A rule base to mimic the real world behavior is designed by consulting to the voting results among the defined fuzzy variables. Each fuzzy variable votes one of the *high*, *medium*, or *low* decision in order to express the degree of belief regarding that T_r is associated with T_l. Three fuzzy variables can reach to the consensus in seven different ways as shown in Table 6.2. Three good votes, i.e. low Euclid distance, low speed difference, and low velocity difference, of the fuzzy variables result with the seventh rule class. Likewise three bad votes result with the first rule class. Consensus on three *good*, means that it is most likely that T_r reported by the neighboring sensor is representing the same physical object with T_l in the track list. Similarly, consensus on three *bad* means, it is most likely that T_r and T_l are representing different physical ob-

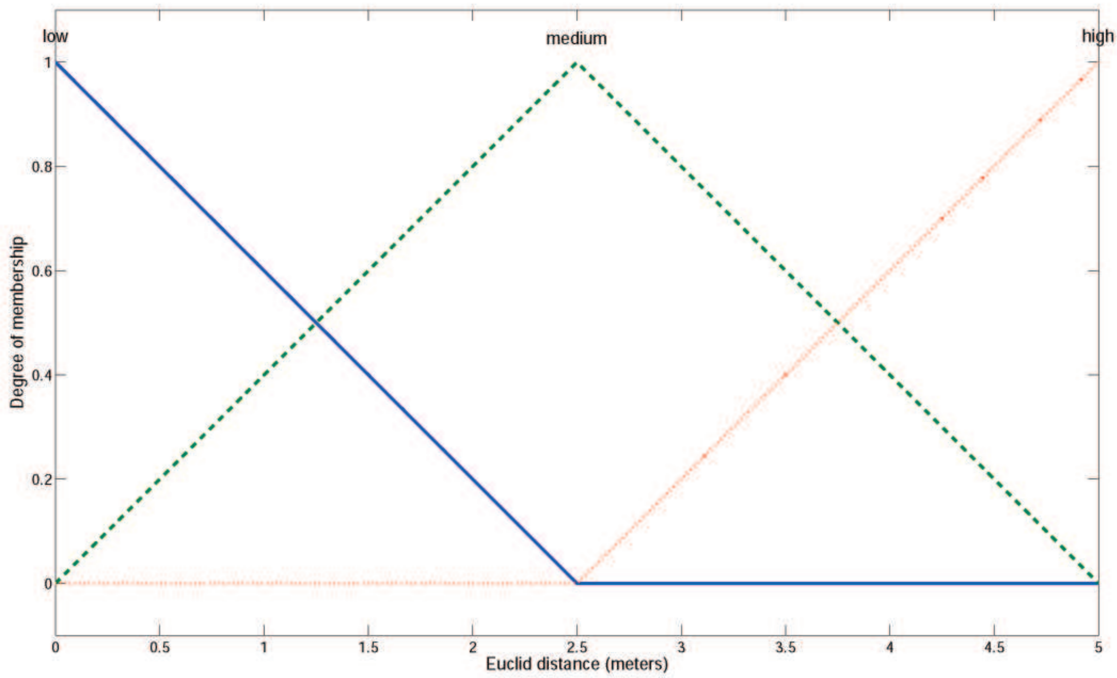

Figure 6.8. Membership functions of the Euclid distance.

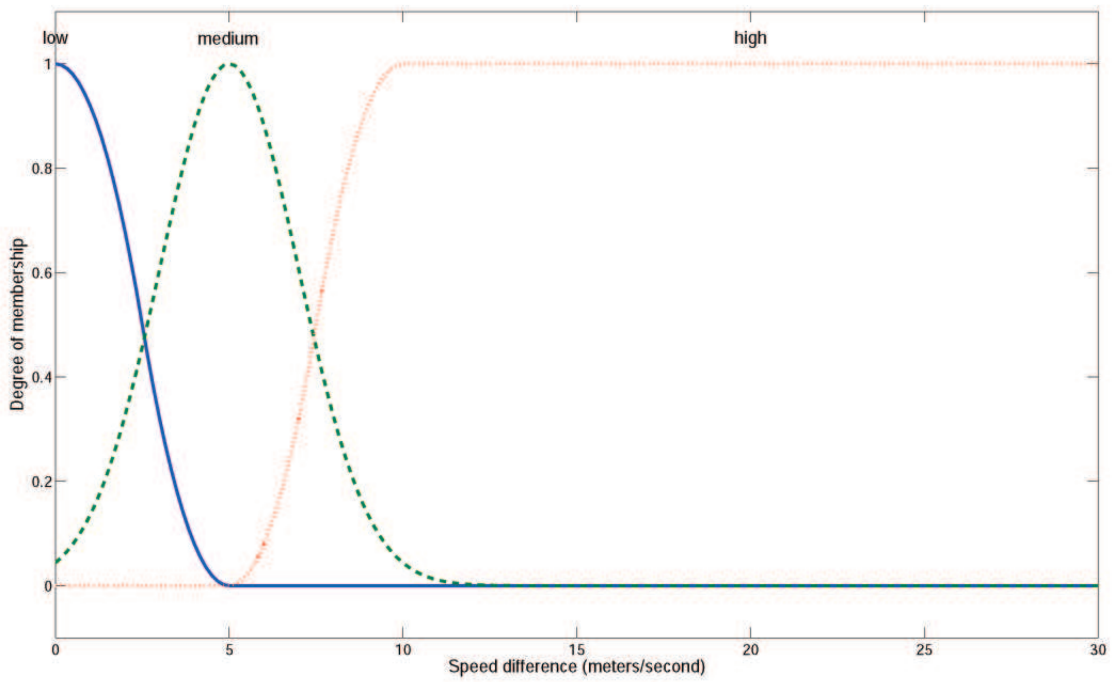

Figure 6.9. Membership functions of the velocity difference.

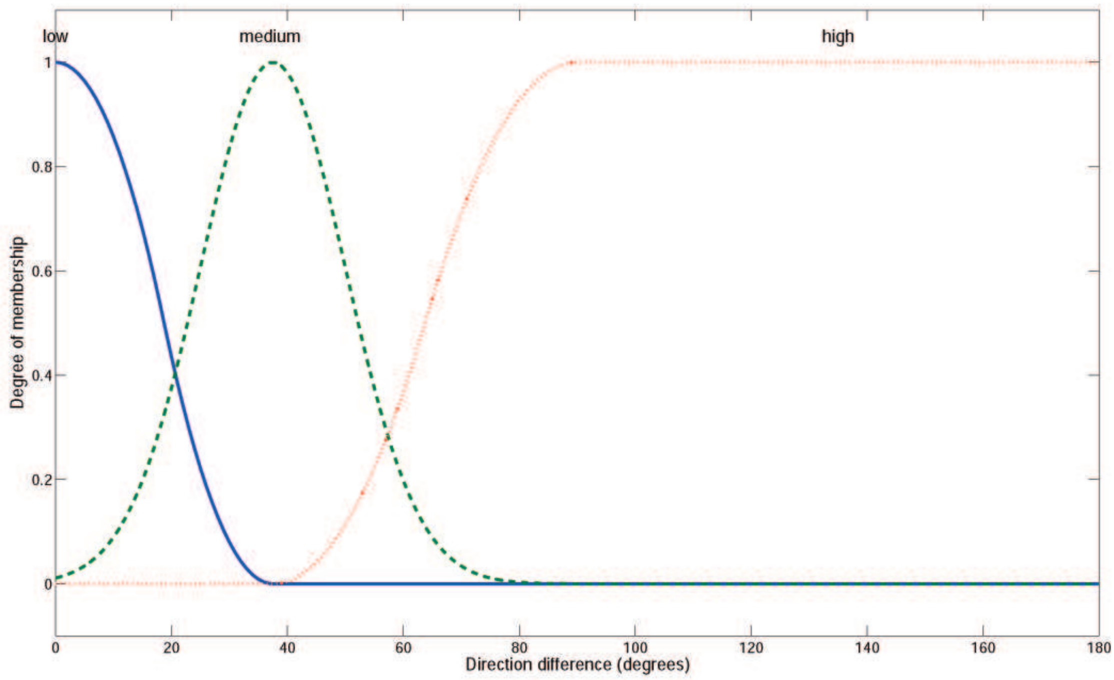

Figure 6.10. Membership functions of the direction difference.

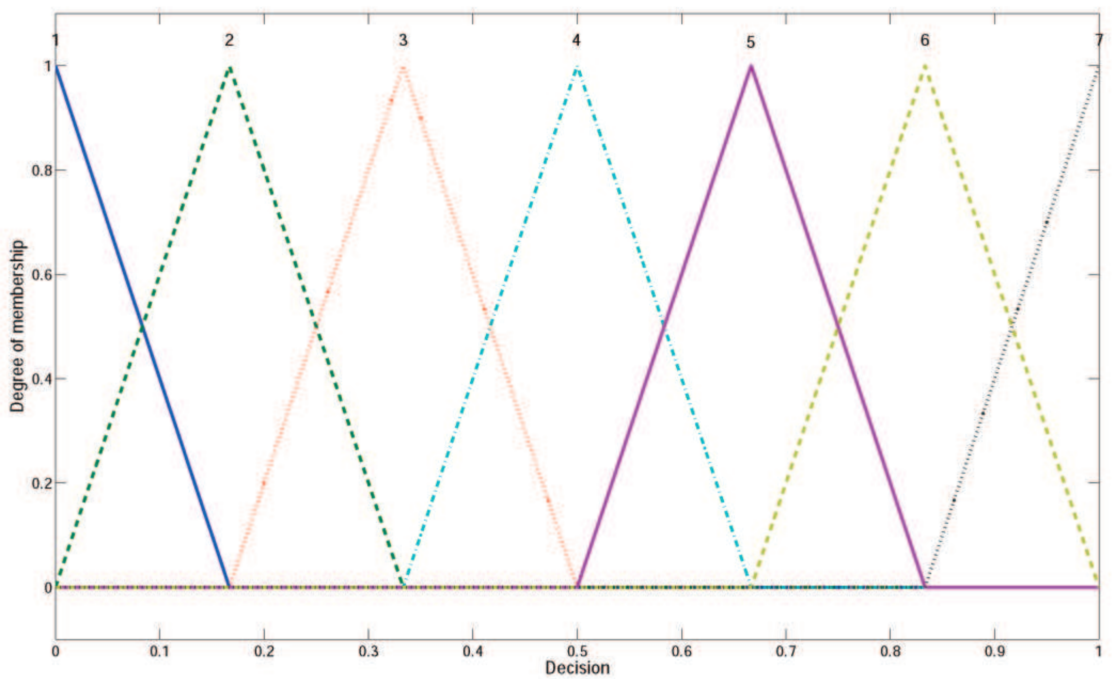

Figure 6.11. Output membership function.

Table 6.2. Rule classes corresponding to the voting results.

Voting result	Rule class
3 Bad	1
2 Bad	2
1 Bad	3
Draw	4
1 Good	5
2 Good	6
3 Good	7

jects. Three voters with three different vote types can result in $3^3 = 27$ different types of voting as in Table 6.3. Using Table 6.2, possible 27 different cases that can happen with three voters of three different vote types are classified into seven rule classes as in in Table 6.3. *High* Euclid distance, *high* speed difference, and *high* direction difference between T_r and T_l as in the first line of Table 6.3 means three bad votes and consensus on three bad is the first rule class in Table 6.2. 27 lines in Table 6.3 are the fuzzy rules of the fuzzy inference system.

Euclid distance, speed difference, and direction difference between T_r and T_l are the inputs of the fuzzy network association algorithm. 22.5 degree direction difference is interpreted as 40 per cent *low*, 40 per cent *medium* 0 per cent *high* as in Fig. 6.10. Together with other input fuzzy variables and using the rule base in Table 6.3, the input variables are mapped to the output fuzzy variable shown in Fig. 6.11. Finally the output of the FUNA is a real *crisp value* value between 1 and 7. Unrelated tracks generate lower crisp values, whereas the related tracks generate higher crisp values.

6.4. Performance Evaluation of FUNA

We investigate the FUNA performance in terms of the number of false network associations and the target localization error with the simulation scenario in Fig. 6.12. 30 sensors in a 50 m $\times$ 50 m area are tracking seven targets for 50 seconds. We compare FUNA performance with the maximum likelihood, the minimum Euclid distance,

Table 6.3. Fuzzy rules in the knowledge base.

Euclid distance	Speed difference	Direction difference	Rule class
H	H	H	1
H	H	M	2
H	H	L	3
H	M	H	2
H	M	M	3
H	M	L	4
H	L	H	3
H	L	M	4
H	L	L	5
M	H	H	2
M	H	M	3
M	H	L	4
M	M	H	3
M	M	M	4
M	M	L	5
M	L	H	4
M	L	M	5
M	L	L	6
L	H	H	3
L	H	M	4
L	H	L	5
L	M	H	4
L	M	M	5
L	M	L	6
L	L	H	5
L	L	M	6
L	L	L	7

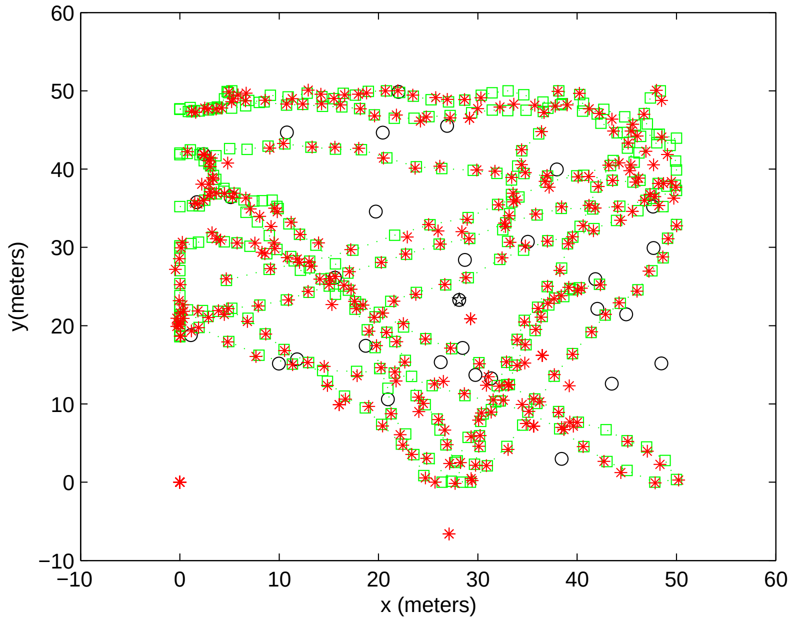

Figure 6.12. FUNA tracking scenario for seven targets.

and the minimum Mahalanobis distance based network association performances. The results are in Table 6.4, where the total number of true and false network associations, the mean target localization error, and the mean sensor track list length for all the sensors are presented. Each value in Table 6.4 represents the mean of the 50 simulation runs with different random seeds effecting the detection, communication, and deployment states of the sensor nodes. The total number of true network associations are presented in Fig. 6.13. The total number of false network associations are presented in Fig. 6.14. The mean target localization errors are presented in Fig. 6.15. The mean track list length for each sensor is presented in Fig. 6.16. FUNA performs 15 per cent less false network association when compered to the Euclid distance based network association. The Euclid distance based network association performance is better than the Mahalanobis and the likelihood distance based network association performances in terms of the total number of false network associations. FUNA 26 per cent reduces the target localization errors. In Tables 6.5 and 6.6, over 99.99 per cent significance for the false network association and the target localization error performance improvements gained with FUNA is shown respectively with the confidence tests.

With FUNA, sensor at position (28,16) which has a star in it tracks the seven

Table 6.4. Number of true and false network associations, mean target localization error, and mean sensor track list length for the scenario of tracking seven targets.

	Euclid	Mahalanobis	likelihood	FUNA	omniscient
total number of true network associations	59510	57184	55043	62686	80447
total number of false network associations	19998	22591	24694	16872	0
mean target localization error	3.84	4.33	4.39	2.84	0.3
mean sensor track list length	7.32	8.19	8.28	7.35	6.86

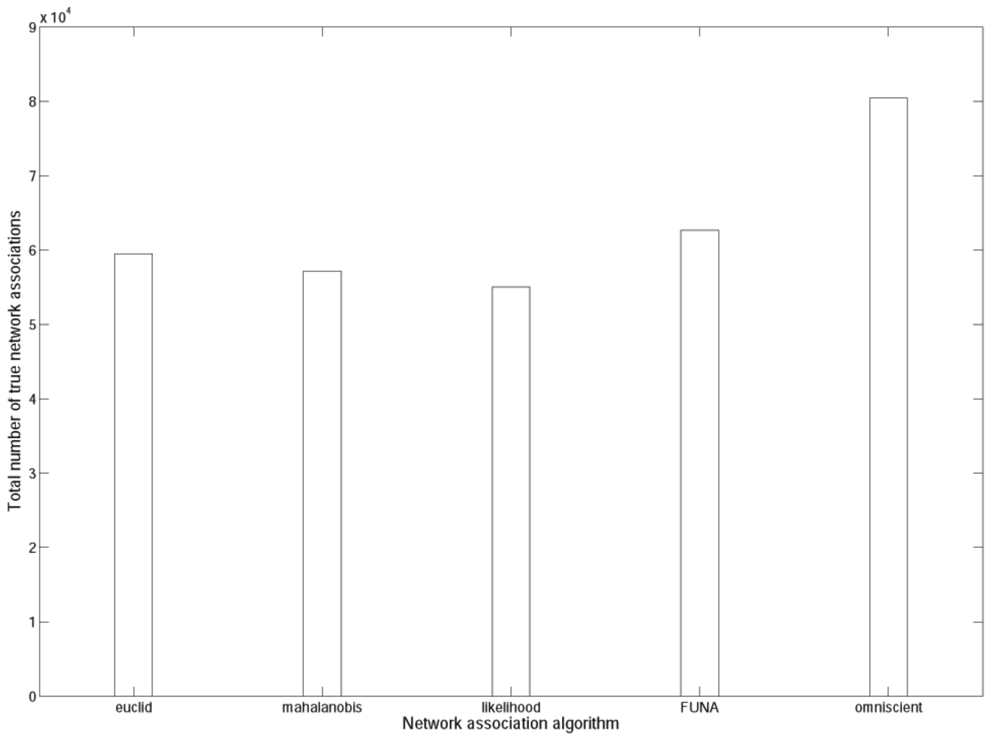

Figure 6.13. Total number of true network associations for the seven targets scenario.

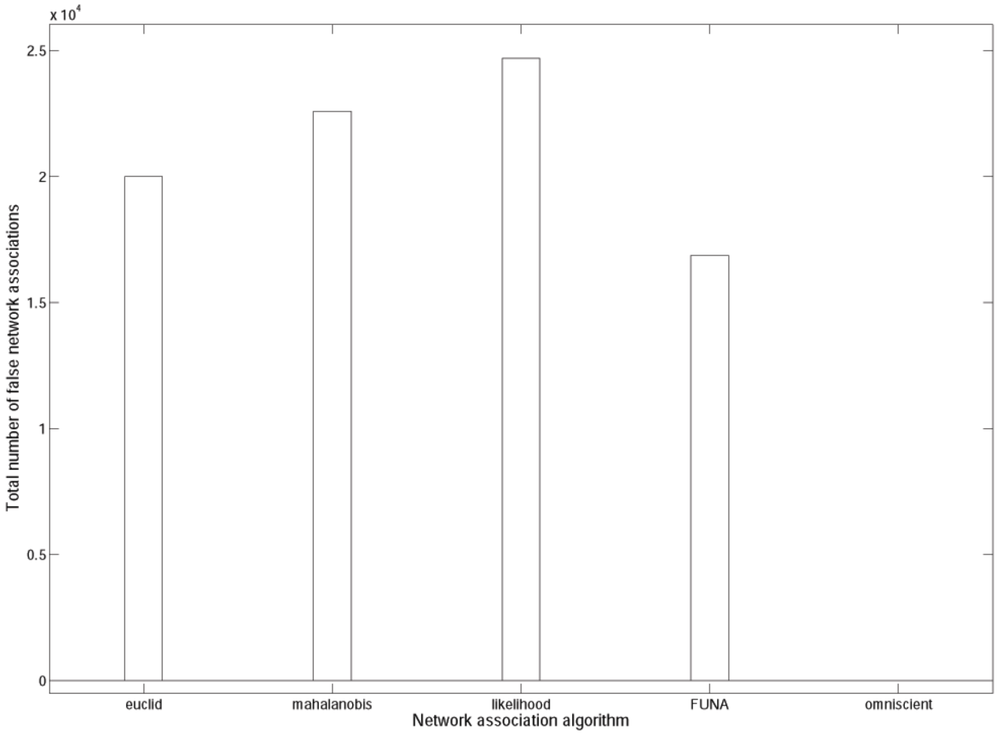

Figure 6.14. Total number of false network associations for the seven targets scenario.

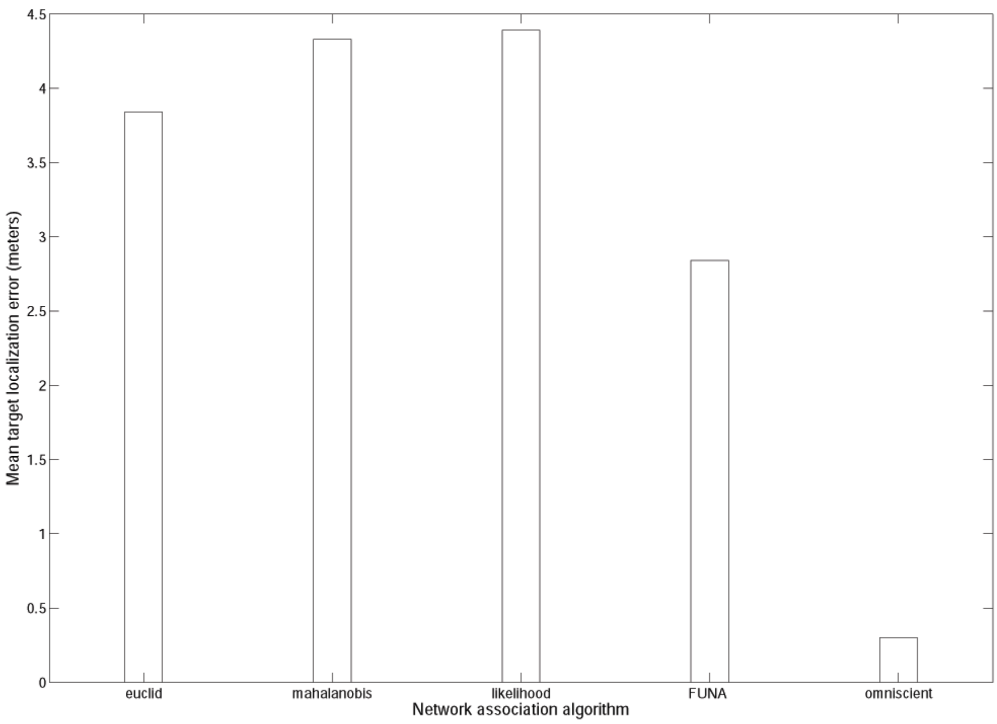

Figure 6.15. Mean target localization error for the seven targets scenario.

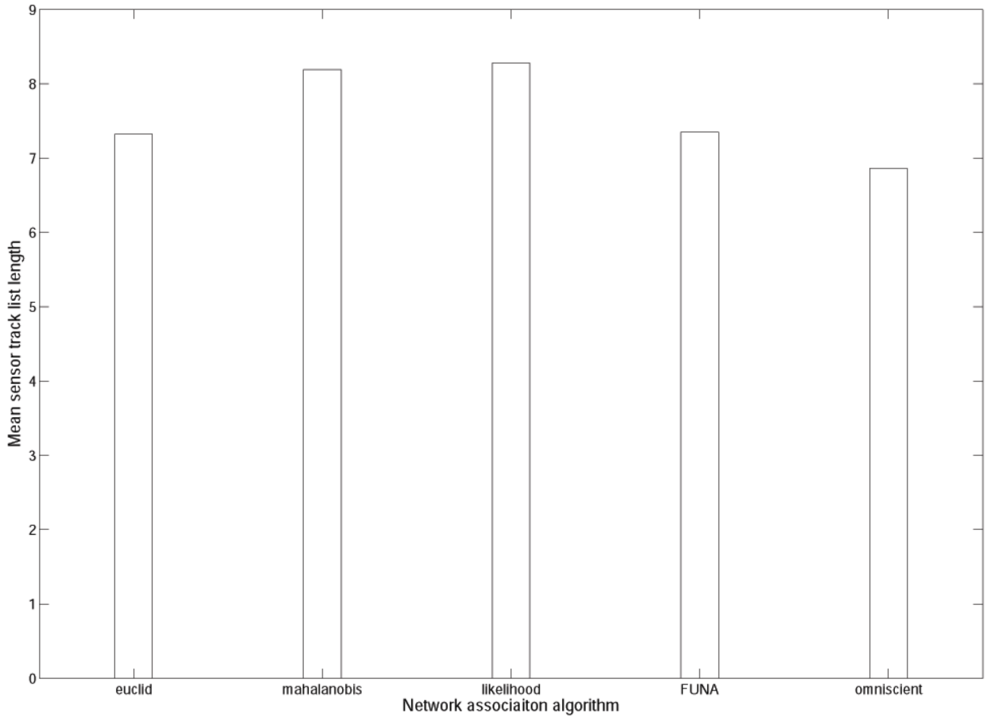

Figure 6.16. Mean track list length for the seven targets scenario.

Table 6.5. Significance for the number of false associations.

	Euclid	Mahalanobis	Likelihood	FUNA
Euclid	1	$1.07x10^{-4}$	$6.11x10^{-10}$	$2.39x10^{-6}$
Mahalanobis		1	$2.9x10^{-3}$	$5.69x10^{-15}$
Likelihood			1	$1.36x10^{-20}$
FUNA				1

Table 6.6. Significance for the mean target localization error.

	Euclid	Mahalanobis	Likelihood	FUNA
Euclid	1	$2x10^{-2}$	$8.6x10^{-3}$	$3.11x10^{-7}$
Mahalanobis		1	0.755	$8.53x10^{-14}$
Likelihood			1	$7.73x10^{-15}$
FUNA				1

targets as in Fig. 6.12. Squares show the true positions of the targets, * symbols show the estimated position of the target by the sensor with a star in it.

The last line of Table 6.4, shows the mean track list length of each sensor node throughout the scenario. If the sensor nodes would associate each network track report with the true track in the track list, each sensor node would follow on the average 6.86 tracks of the seven tracks in the 50 seconds scenario. As the false network track initiations caused by the false network associations begin, the average number of tracks followed by each sensor node increases up to 8.28 for the likelihood based network association. This situation arises when the association of the neighboring sensor node track report with an existing track in the track list cannot be established and a new track is initiated in the track list. These new network track initiations are not always true network track initiations. Some of them are false network track initiations. This is the reason behind having more than seven tracks in the track list of a sensor node. For the examined network association metrics, the number of false network associations throughout the 50 seconds scenario are shown in Fig. 6.17. In the first 20 seconds of the scenario, Euclid based network association performance is better, whereas after 20 seconds, FUNA performance is better when the total number of false network associations are considered. Revisiting the simulation scenario in Fig. 6.12 by considering the mobility patterns of the seven targets, relative movements seems similar for the first 20 seconds and starts to deviate from each other afterwards. Relative directions and speeds of the seven targets are similar in the first 20 seconds, dissimilar afterwards. We can say that FUNA performance is better when the relative directions and speeds of the tracks in the track list are dissimilar.

Omniscient method shows the case in which none of the network associations are false. The sensor node always associates the new track report with the correct track in the track list. Omniscient method is a hypothetical method for determining the upper limit of the target localization performance if we could have a perfect method for associating the network track reports from neighboring sensor nodes with the tracks in the track list.

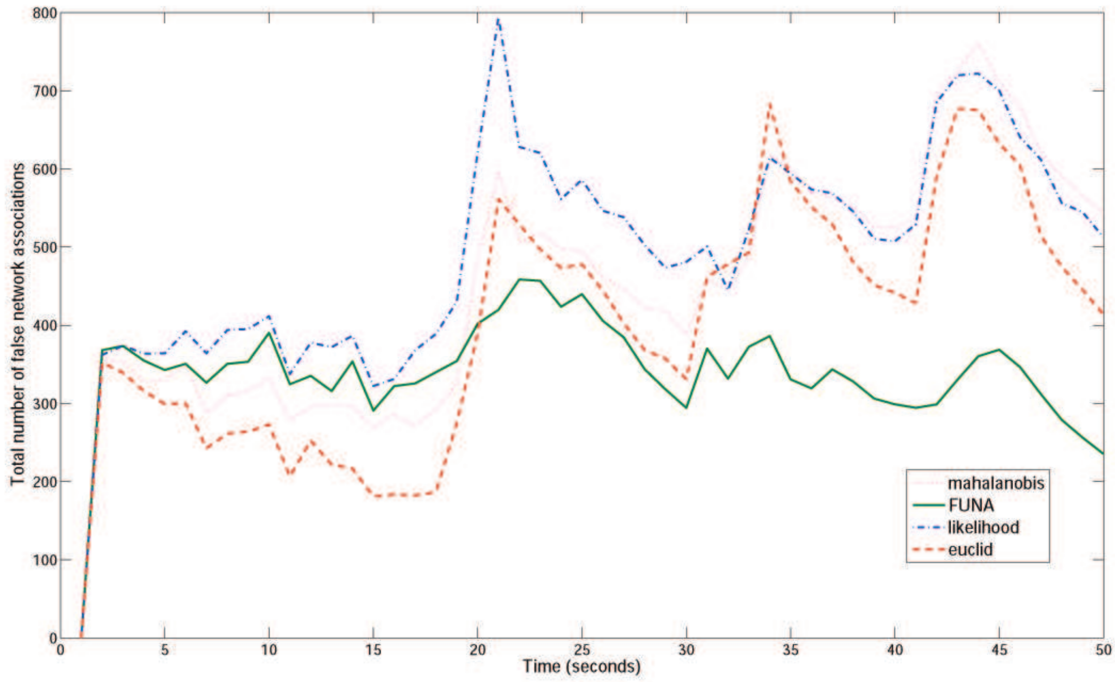

Figure 6.17. Total number of false network associations throughout the 50 seconds scenario.

According to the two-sample t-test [164], the confidences related with the significance that the total number of false network associations differ among the examined network association algorithms are as in Table 6.5. The value one in Table 6.5 means corresponding two algorithms performs the same. The closer the value in Table 6.5 to zero means that the corresponding network association algorithms differs more significantly in terms of the number of false associations. We have 0.0000239 significant difference between the FUNA and the Euclid network association metrics. We conclude that FUNA and Euclid based network association algorithms are differ from each other with 99.99 per cent confidence.

Similarly, significance values for the target localization errors are presented in Table 6.6.

The box and whisker plot [165] with the minimum, the maximum, and the median values of the number of false network associations obtained from the 50 runs with

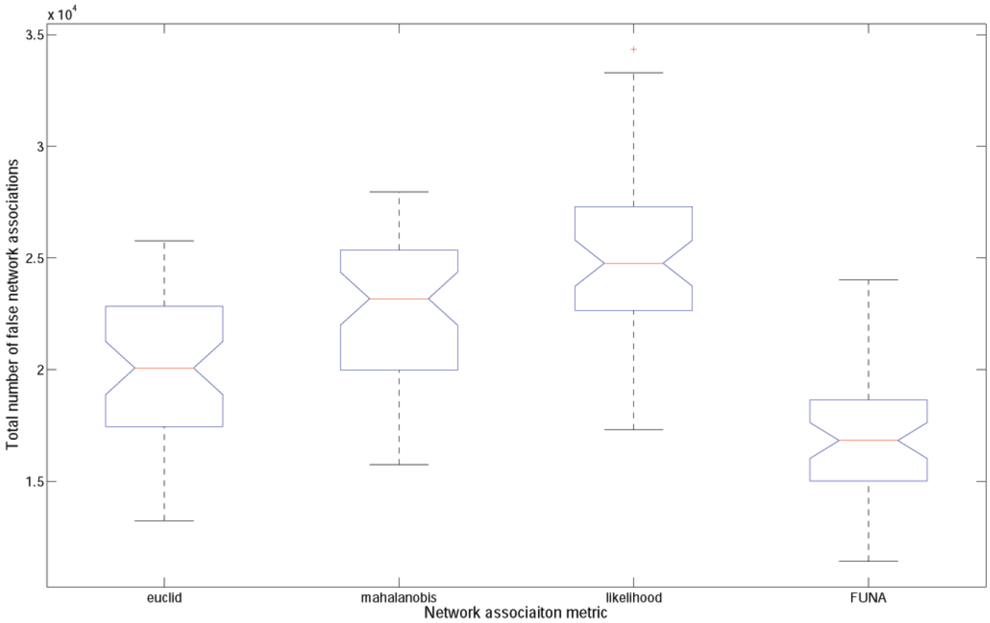

Figure 6.18. Minimum, maximum and median values for the total number of false network associations in the seven targets scenario.

different random seeds are presented in Fig. 6.18. Horizontal lines in the middle of the boxes represent the median value of the 50 runs. Upper and the lower boundaries of the boxes represent the median of the upper and the lower half of the data points respectively. Horizontal lines at the top and the bottom represent the minimum and the maximum values in 50 simulation runs. Plus signs below the minimum line and above the maximum line represent the values labeled as the outlier values. If the notches in the middle of the boxes do not overlap two data group differs from each other with 0.05 significance (95 per cent confidence).

Similarly, the box and whisker plot for the mean target localization errors are presented in Fig. 6.19.

We examine the scenario with 300 sensor nodes and 10 targets in a 50 m × 500 m area for 300 seconds. The mobility patterns of the 10 targets in the 300 seconds simulation scenario are presented in Fig. 6.20. The total number of true network associations, the total number of false network associations, the total number of mean target localization error, and the mean sensor track list lengths for the Euclid, Mahalanobis,

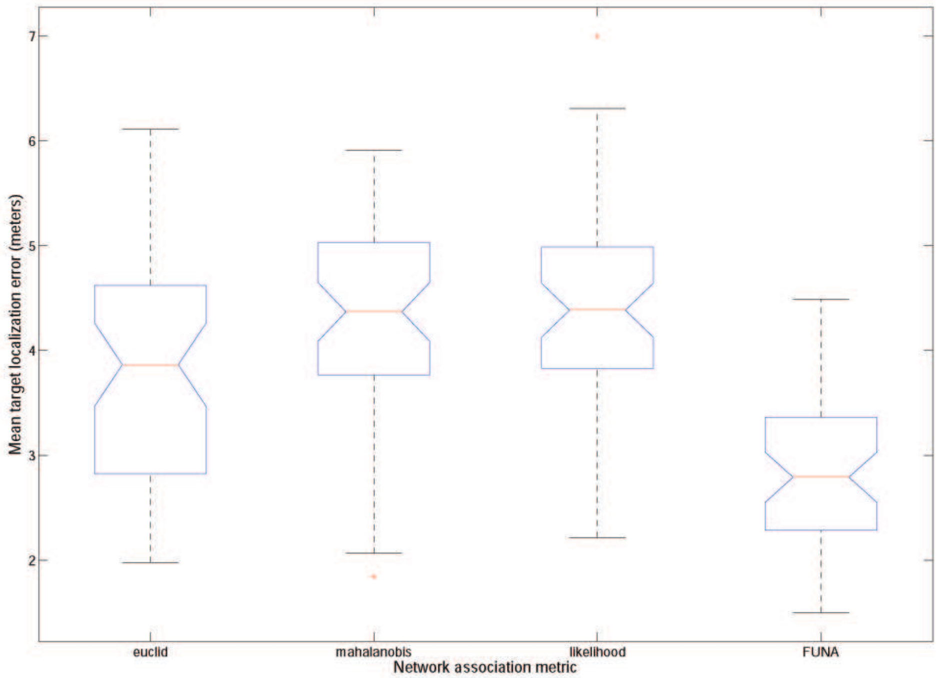

Figure 6.19. Minimum, maximum and median values for the mean target localization errors in the seven targets scenario.

likelihood, FUNA, and the omniscient methods are as in Table 6.7. The total number of false network associations for the examined network association metrics are shown in Fig. 6.21. The mean target localization errors for the examined network association metrics are shown in Fig. 6.22. Although FUNA performs 37.56 per cent better that the Mahalanobis, 36.8 per cent better than the likelihood based network association, Euclid based network association performs 1.29 per cent better than FUNA in terms of the number of false network associations. Performance difference in FUNA and the Euclid based network association in terms of the number of false network associations is not significant. Fig. 6.23 shows that in the first 160 seconds of the scenario, Euclid based network association outperforms FUNA, afterwards FUNA outperforms Euclid based network association. Examining the target mobility patterns in Fig. 6.20 drives us to the conclusion that, in the first half of the scenario, tracks were moving to the similar directions with similar speeds with respect to each other, whereas in the second half of the scenario, where FUNA performance was better, tracks were moving to the different directions with more speed differences with respect to each other.

Although FUNA performance was slightly worse that the Euclid based network association algorithm, the mean target localization error for FUNA was 7.42 per cent better than the Euclid based network association algorithm. FUNA target localization performance was also 37.69 per cent better than the Mahalanobis based network association algorithm, 33.89 per cent better than the likelihood based network association algorithm. Target localization error of the omniscient method shown in the last column of Table 6.7 is 88.82 per cent better than FUNA. If the sensor node could be able to associate all the neighboring sensor node's track reports with the correct tracks in the track list, 88.82 per cent better target localization accuracy would be possible. Track list lengths in the last row of Table 6.7 can give intuition about the number of false network track initiations. If no false network track initiation would happen 5.7867 tracks on the average would take place in the track list of a sensor node. This is the average track list length of the omniscient method. More the track list lengths means more the false network track initiations.

The total number of the true network associations throughout the 300 seconds scenario are as in Fig. 6.24. Omniscient method in Fig. 6.24 represents the upper limit for the number of true network associations. We conclude from the previous two simulation scenarios that for the targets which have direction and speed differences relative to each other, FUNA outperforms the Euclid based network association. In order to support our conclusion, we design a scenario with meandering targets.

We compare the target localization, the network association, and the network track initiation performances of FUNA with the Euclid and the likelihood based network association algorithms for the meandering targets whose mobility patterns are shown in Figures 6.25, 6.26, and 6.27 from the viewpoints of the sensors at location (10,16), (138,6), and (292,7) respectively. Circles represent the sensor node positions, squares represent the real target trajectories, * symbols represent the estimated position of the target by the sensor node. Total number of true and false network associations, mean target localization error and the mean track list length for the meandering targets scenario are compared for the FUNA, Euclid, and likelihood based network association metrics in Table 6.8. The total number of false network associations for the examined

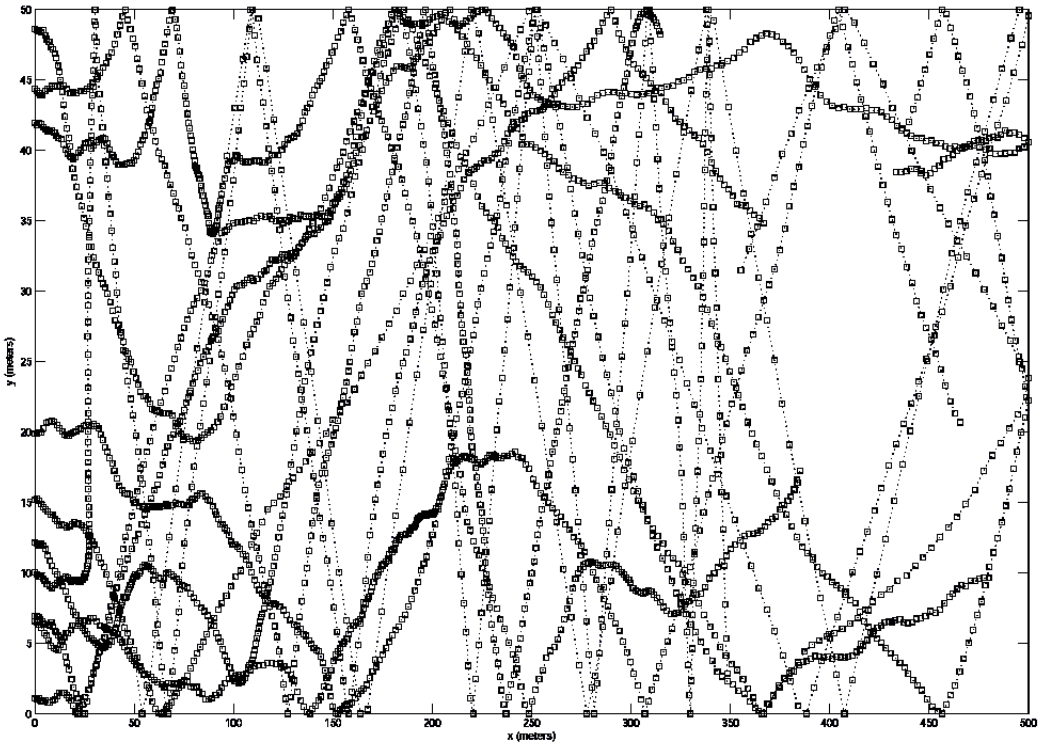

Figure 6.20. Scenario of 10 targets in the 50 m $\times$ 500 m simulation area.

Table 6.7. Total number of true and false network associations, mean target localization error, and the mean sensor track list length for the 300 seconds scenario.

	Euclid	Mahalanobis	likelihood	FUNA	omniscient
Total number of true network associations	2828400	2517100	2525900	2824400	3371600
Total number of false network associations	506980	822510	812540	513580	0
Mean target localization error	6.0698	9.0191	8.5009	5.6200	0.6288
Mean sensor track list length	6.5360	8.5379	8.4757	6.6918	5.7867

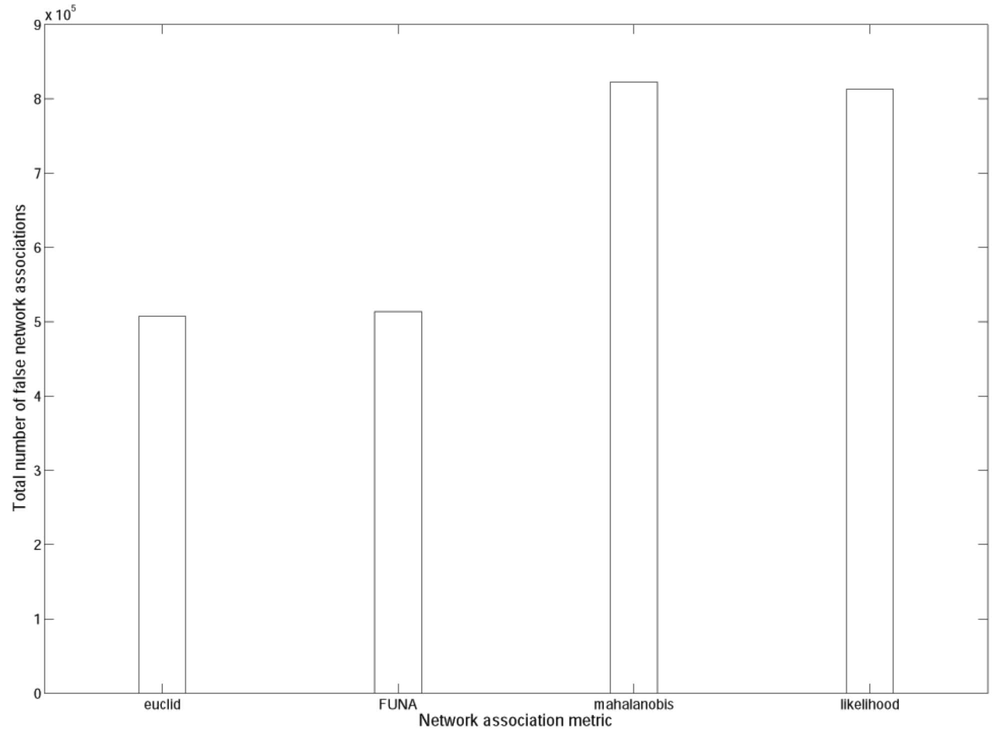

Figure 6.21. Total number of false network associations for 10 targets scenario.

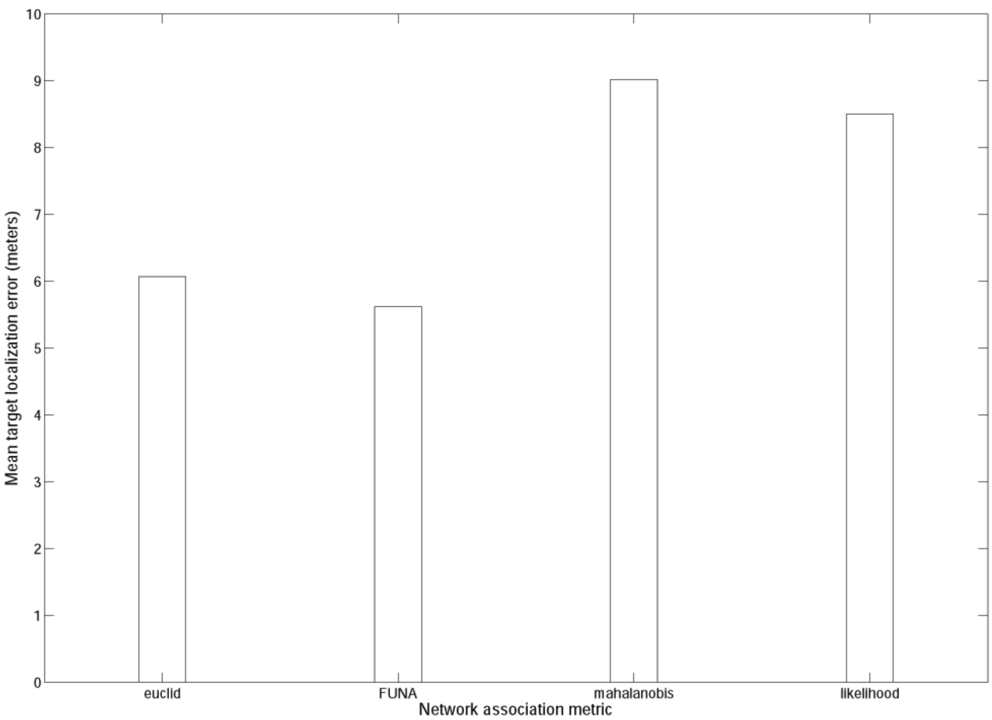

Figure 6.22. Mean target localization error for the 10 targets scenario.

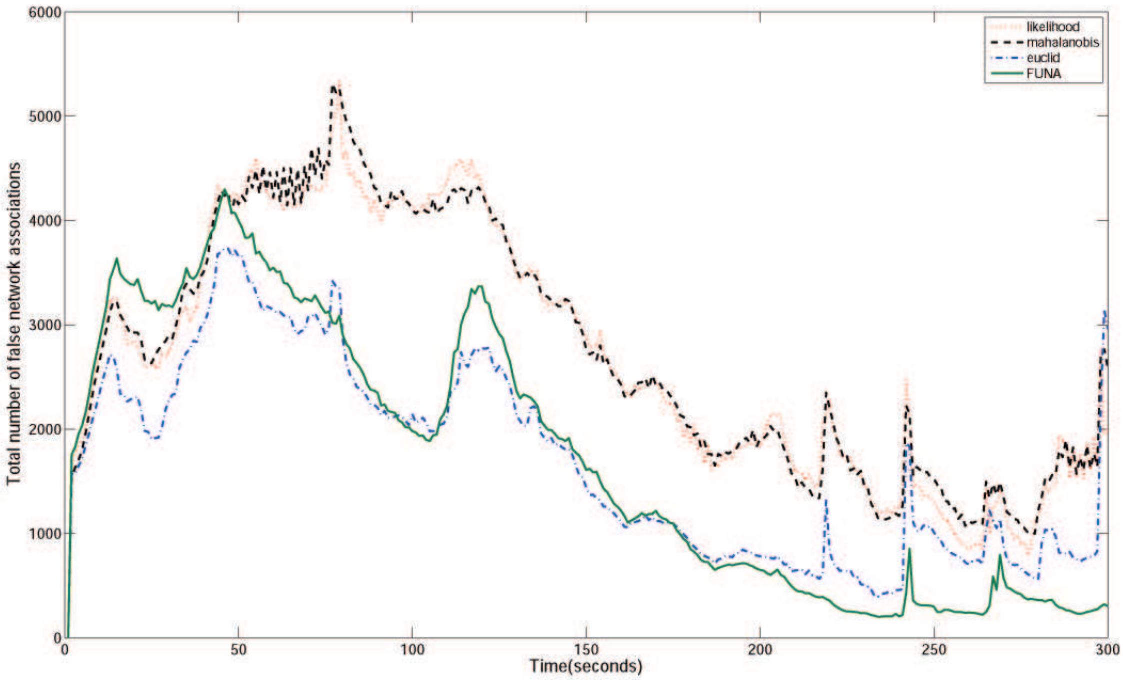

Figure 6.23. Total number of false network associations throughout 300 seconds for the 10 targets scenario.

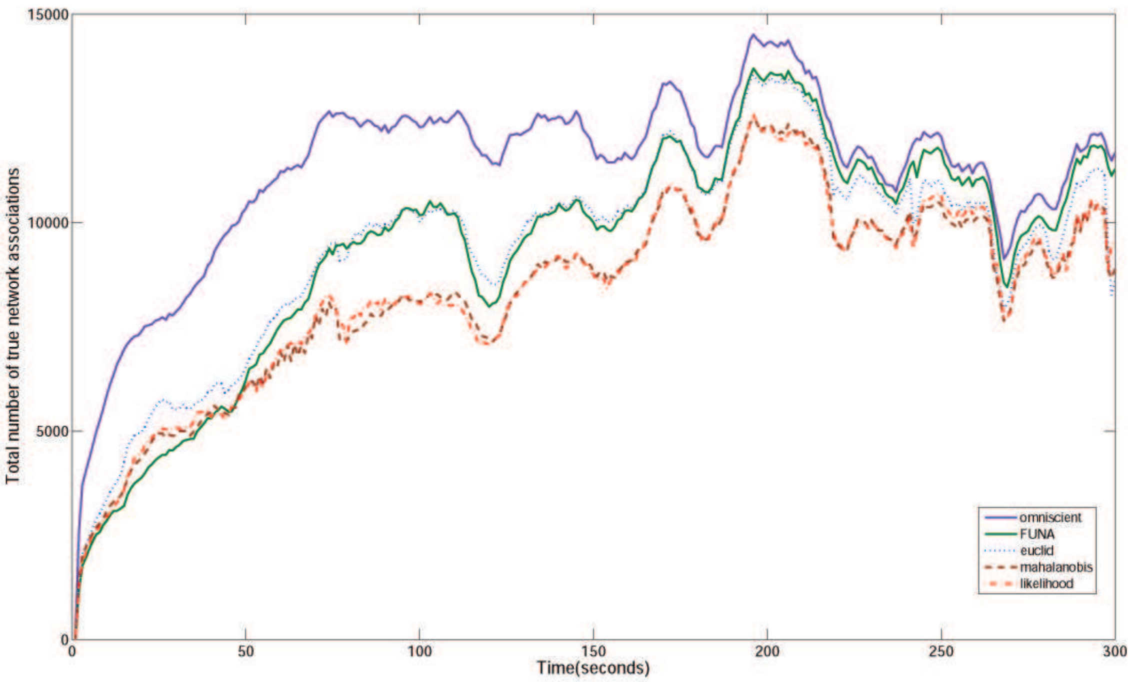

Figure 6.24. Total number of true network associations throughout 300 seconds for the 10 targets scenario.

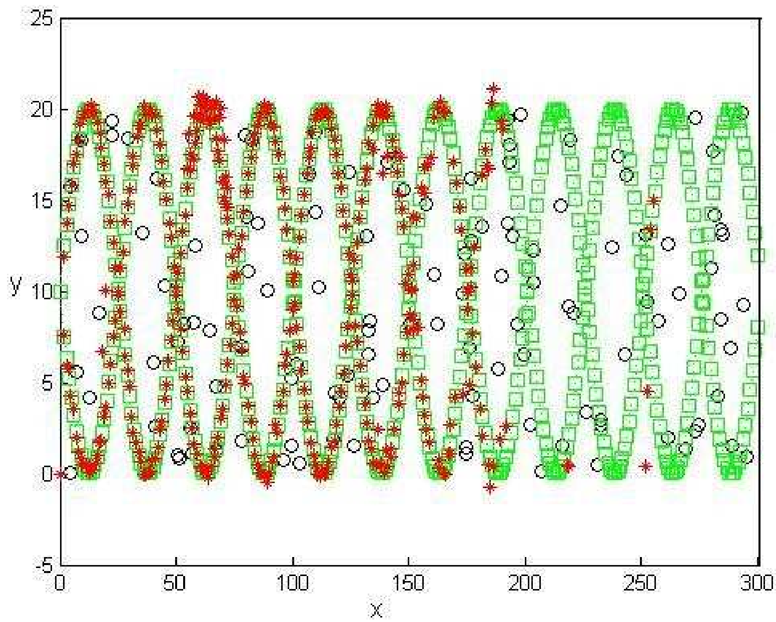

Figure 6.25. Viewpoint of the sensor at (10,16) for the meandering targets.

network association metrics are compared in Fig. 6.28. The mean target localization errors for the examined network association metrics are compared in Fig. 6.29. Total number of false and true network associations throughout the 300 seconds scenario for the meandering targets are as in Figures 6.30 and 6.31 respectively.

FUNA 83.563 per cent reduces the number of false network associations for the meandering targets. Reduction in the target localization error is 69.45 per cent with FUNA w.r.t. the Euclid based network association algorithm.

Simulation scenarios show that for the meandering targets, FUNA drastically outperforms Euclid based network association algorithm. However, for the targets moving relatively to the similar direction with similar speeds, Euclid based network association performance is better. As the future work, we envision a "Hybrid Association Model" (HAM) in which if the tracks in the track list of a sensor node moves relatively to a similar direction with similar speeds, the network association is done according to the Euclid metric. Just after the relative direction and the speed differences among the tracks in the track list of the sensor node exceeds a threshold, network association is done with FUNA.

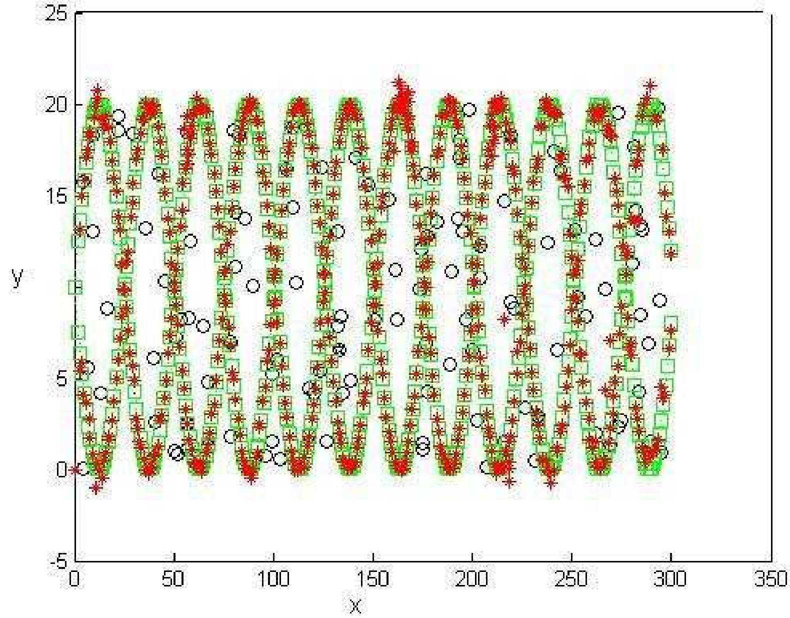

Figure 6.26. Viewpoint of the sensor at (138,6) for the meandering targets.

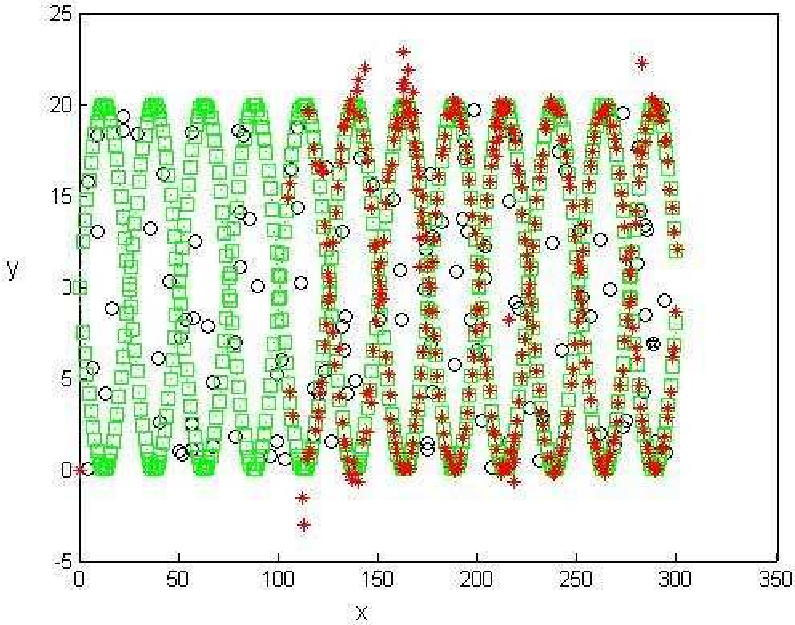

Figure 6.27. Viewpoint of the sensor at (292,7) for the meandering targets.

Table 6.8. Total number of true and false network associations, mean target localization error, and the mean sensor track list length for the meandering targets.

Associations	Likelihood	Euclid	FUNA
Total number of false network associations	203480	201020	33042
Total number of true network associations	300540	302620	471480
Mean target localization error	5.2190	5.3131	1.6234
Mean sensor track list length	2.8715	1.8843	1.8387

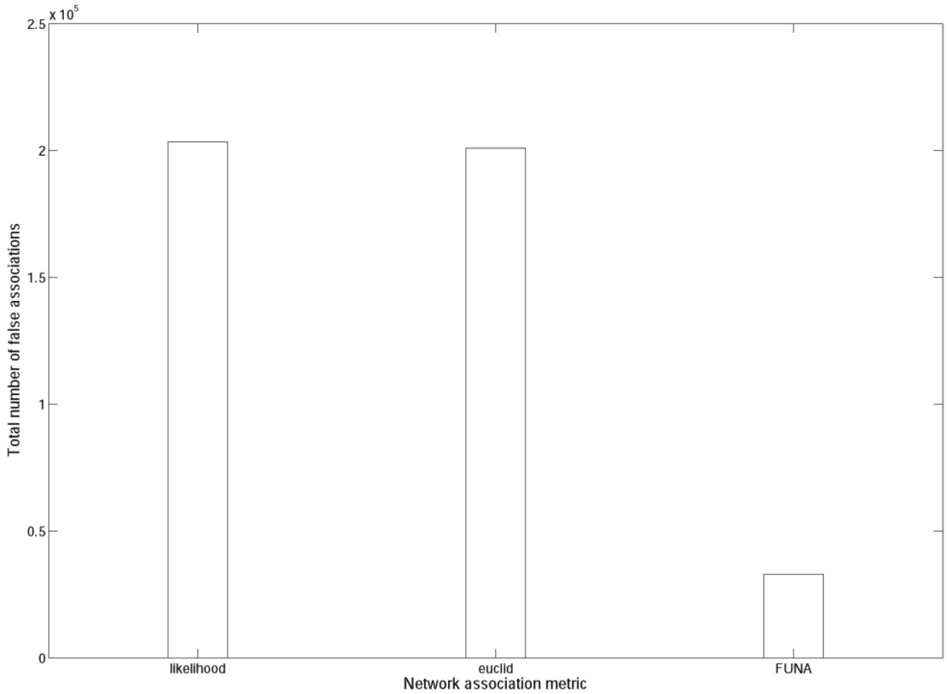

Figure 6.28. Total number of false network associations for the meandering targets scenario.

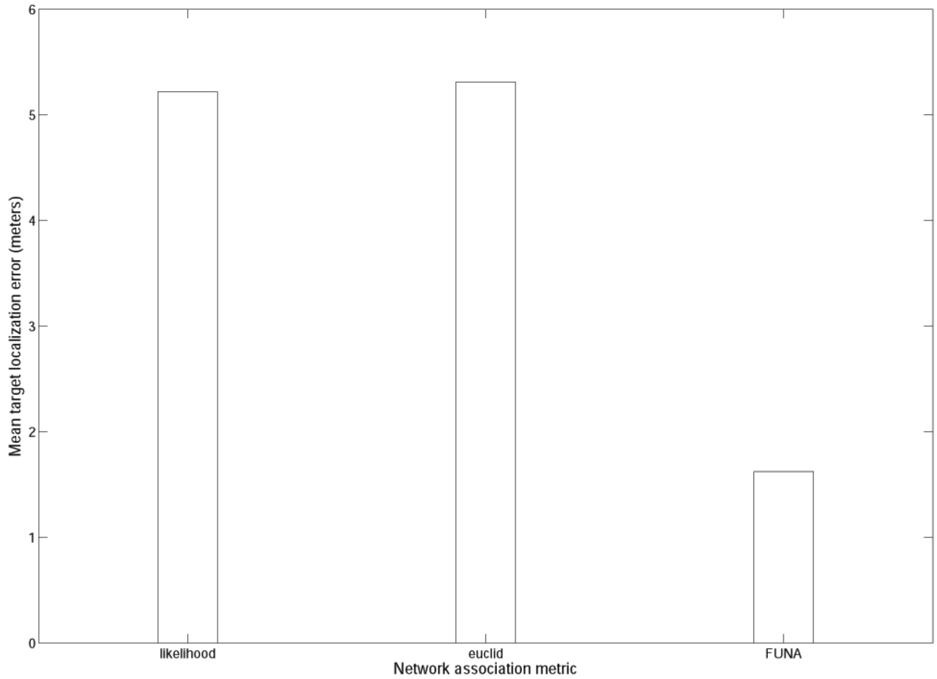

Figure 6.29. Total number of true network associations for the meandering targets scenario.

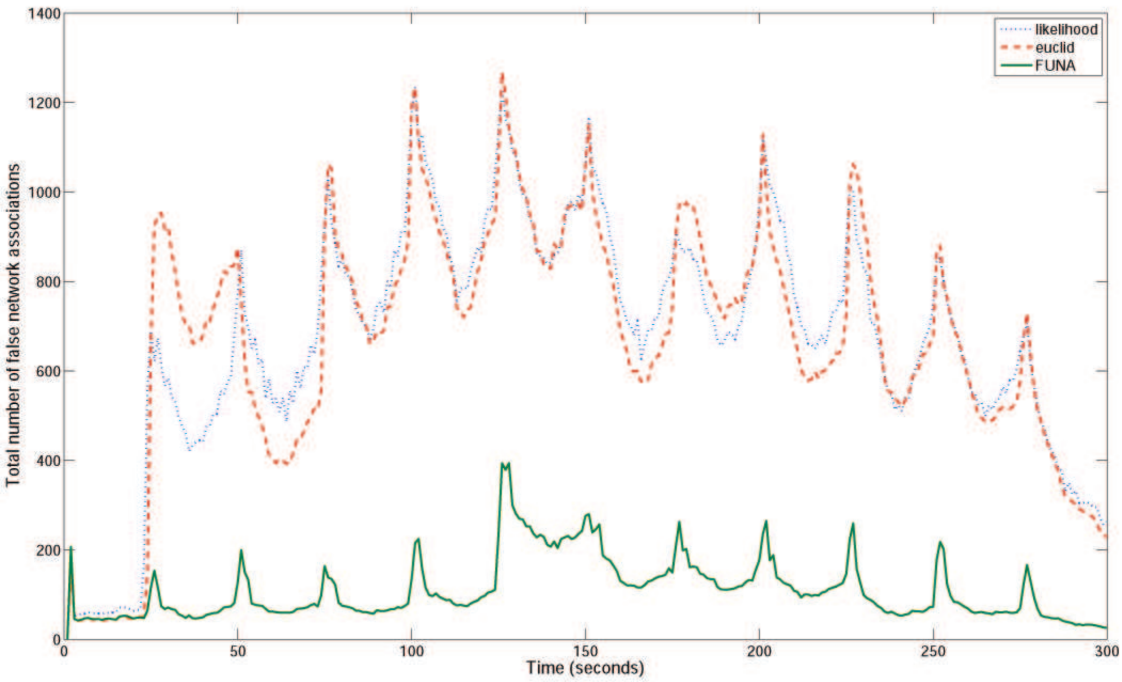

Figure 6.30. Total number of false network associations throughout the 300 seconds for the meandering targets scenario.

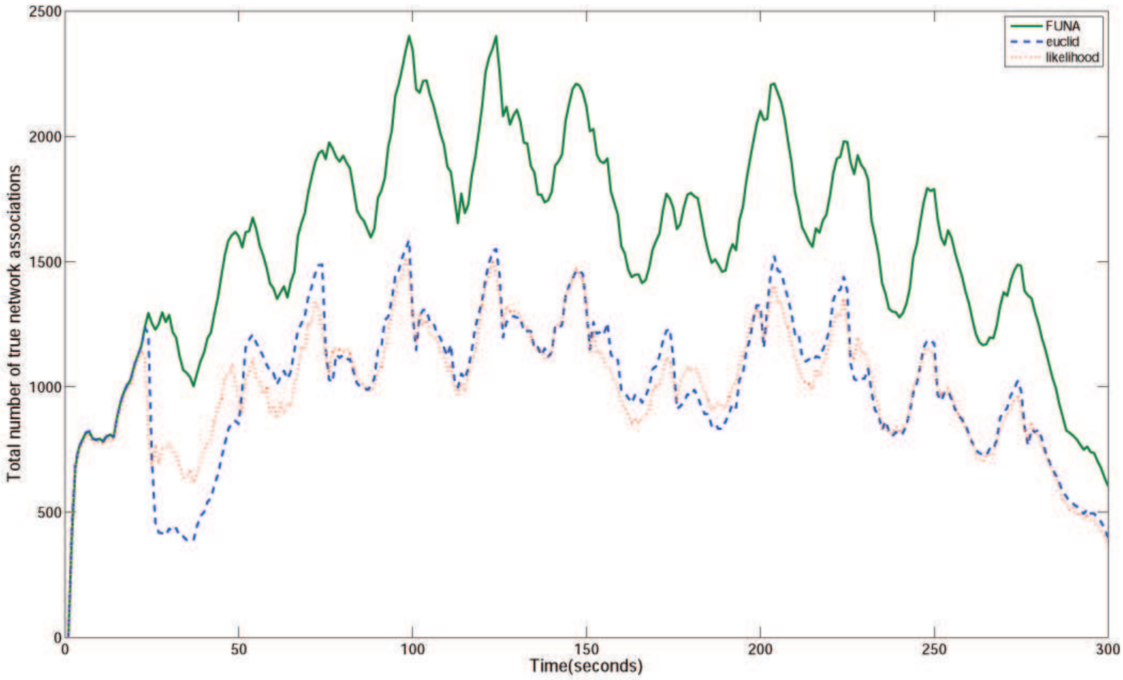

Figure 6.31. Total number of true network associations throughout the 300 seconds for the meandering targets scenario.

7. CONCLUSIONS

A mutual information based measure is adopted to select the most informative subset of the sensor nodes to actively participate in the distributed data fusion framework, where the duty of the WSN is to accurately localize and track the targets. The DDF architecture takes advantage of the long communication range of the wireless sensor devices, relative to their sensing range, and facilitates a sensor node to update its belief about the current state of the target. With the detection reports from its neighbors, a belief update takes place even if the sensor is not detecting the target. The information obtained from the neighboring nodes about an approaching target before it is sensed reduces the target localization error by improving the target state filtering performance.

A new communication transmission power adjustment scheme is proposed to further improve the energy savings while preserving the tracking quality constraints. Sensor nodes adjust their transmission powers in proportion to their knowledge: those that know more about the target state should use more power to share their information. Tests indicate that the performance of the proposed power adjustment scheme depends on the network querying technique. If the application is delay-sensitive and needs an immediate response from the network, any sensor node in the WSN can respond right away to the query with an acceptable target localization error. If the application can tolerate some delay and has strict target localization error constraints, querying just the MISN improves the target localization performance. The proposed Information-Controlled Transmission Power adjustment scheme improves the energy savings while preserving the desired target tracking accuracy when the most informative node is queried. However, querying any sensor node, while reducing the transmission powers of the less informative sensor nodes, ends up with drastically worse target tracking accuracies.

For the cases studied, simulation results show that 75 per cent energy savings can be achieved for a given tracking quality by selecting the sensor nodes to cooperate according to the mutual information measure. Moreover, if the sensor network queries are to be routed to the MISN within one hop distance of the query entry node, 2.34 times more energy savings compared to the no power adjustment scheme can be achievable by adjusting the communication transmission powers of the sensor nodes.

A fully distributed collaborative multi-target tracking framework is described for the distributed data fusion architecture. With the proposed architecture, the need for a central data associator node or a central coordinating node is eliminated. Every node in the network is capable of tracking all the targets in the network. The presence of multiple targets brings along challenges with measurement-to-measurement association, measurement-to-track association track-to-track association and track-to-sensor association. In the multiple target case, sensor nodes would report only about the target which they were associated to. Simulation results show that collaborating information denomination values of the target about whom the sensor has the maximum mutual information is a rational decision.

A fuzzy inference system is defined to support the network association. Network association relates the neighboring sensor reports with the tracks in the track list of the sensor node. A rule base for the fuzzy inference system is formed by consulting to the voting results among the fuzzy variables. Fuzzy network association (FUNA) reduces the false network associations 83.5 per cent, the mean target localization error by 69.45 per cent for the meandering targets.

It is generally assumed that all sensor nodes send reliable data to the network. In the future work, the detection of faulty and outlier sensor nodes in the network, and possible precautions that can be taken against them can be investigated. The scenarios which we simulate were not containing the clutter or false alarms on the sensory observations. Also our scenarios were with the fixed number of targets. Test with scenarios containing clutter, false alarm, dynamic target initiation and termination can be done. Sensors with different sensing modalities (i.e. bearing only acoustic sensor) can be examined. We initiate a target report from the neighboring sensor node as a track immediately. This increases the false network track initiations. More sophisticated algorithms for deciding the network track initiation are required. Outlier sensor detection can also reduce the false network track initiations. For the meandering targets FUNA performance is better than the Euclid metric based network association. However, for the targets moving in relatively similar directions and speeds, Euclid metric based network association algorithm is better. A Hybrid association model that monitors the direction and speed differences of the targets in the track list of the sensor node is envisioned for the network association decision. When the relative speeds and the directions of the tracks in the track list increase, network association is done with FUNA, otherwise Euclid metric is used for the network association. Monitored relative speed and direction differences of the tracks in the track list of a sensor node may help the adaptive fuzzy membership function usage. The type of the target information may also be used for the adaptive fuzzy membership value determination. Multi-target tracking architectures other than the network-centric tracking architecture defined in Chapter 5 can be examined in detail. Besides the effect of 3-D topographical surfaces, the effect of obstacles and jamming that may cause the tracking system can be examined. We assume synchronized sampling and communication among the sensor nodes. Asynchronous algorithms can be investigated in order to get rid of the synchronization cost among the sensor nodes.

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