FUZZY INFERENCE SYSTEM AS A COLLABORATION LOGIC AND A NEW *M/N*-BASED TRACK INITIATION LOGIC FOR WIRELESS SENSOR NETWORKS

by

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FUZZY INFERENCE SYSTEM AS A COLLABORATION LOGIC AND A NEW *M/N*-BASED TRACK INITIATION LOGIC FOR WIRELESS SENSOR NETWORKS

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ABSTRACT

FUZZY INFERENCE SYSTEM AS A COLLABORATION LOGIC AND A NEW *M/N*-BASED TRACK INITIATION LOGIC FOR WIRELESS SENSOR NETWORKS

According to the advances in digital electronics, micro-electro-mechanical systems and wireless communication technologies, it is viable to integrate a device with sensing, computing and wireless communication capabilities within tiny dimensions. In this thesis, we focus on the target tracking issues on wireless sensor networks. First, we try to generate a new collaboration logic via a fuzzy inference system. We utilize Euclidean distance and mutual information metrics as the fuzzy membership functions to achieve a better sensor collaboration measure in order to lead most informative sensor node to broadcast its information. Our second aim is to improve the performance of the track initiation process of a target tracking system in cluttered environments via a new *M/N*-based track initiation logic. In generic *M/N* logic, the consecutive detections inside the gate are considered with identical weights and the initiation counter is increased by one. However, if the newly detected observations in the gate are away from the center of the predicted target position, the observations may not be a real target, the origin of the measurement may be the clutter. Thus, we should adjust the initiation counter weight of the observation according to the distance measure while utilizing *M/N* logic for the track initiation decision. For this purpose, we envisage different weighting schemes to determine the initiation counter weighting value. Consequently, elliptical weighting scheme for the *M/N* track initiation logic shows promising results for cluttered environments in terms of decreasing the false track initiations while sustaining an admissible level of true track initiations.

ÖZET

KABLOSUZ ALGILAYICI AĞLARDA YARDIMLAŞMACI MANTIK OLARAK BULANIK ÇIKARSAMA SİSTEMİ VE YENİ BİR *M/N*-TABANLI HEDEF İLKLENDİRME MANTIĞI

Sayısal elektronik, mini-elektro-mekanik sistemler ve kablosuz haberleşme teknolojilerindeki ilerlemeler neticesinde; algılayıcı, işlemci ve kablosuz haberleşme yeteneklerinin küçük boyutlardaki bir cihazda bütünleştirilmesi mümkün hale geldi. Bu tezde, kablosuz algılayıcı ağlarda hedef takibi meselesine odaklandık. İlk etapta, bulanık çıkarsama yöntemi kullanarak yeni bir yardımlaşmacı mantık üretmeye calıştık. En çok bilgi ihtiva eden algılayıcının bilgisini yayması amacıyla daha iyi bir algılayıcı yardımlaşma ölçütü elde etmek için Öklid mesafesi ve karşılıklı bilgi miktarı ölçütlerini bulanık üyelik fonksiyonları olarak kullandık. İkinci hedefimiz, *M/N*-tabanlı yeni bir ilklendirme mantığı kullanarak parazit yankının (saçıntı) olduğu ortamlarda, bir hedef takip sisteminin hedef ilklendirme süreç başarımını iyileştirmektir. Genel *M/N* ilklendirme mantığında, geçit içindeki ardışık sezimler eş ağırlıklarla değerlendirilir ve ilklendirme sayacı bir artırılır. Ancak, eğer geçitteki yeni sezimlenen gözlemler öngörülen hedef konum merkezinden uzaksa, gözlemler gerçek bir hedef olmayabilir, ölçümün kaynağı parazit yankı olabilir. Bu nedenle, hedef ilklendirme kararı için *M/N* mantığı kullanırken gözlemin ilklendirme sayaç ağırlığını mesafe miktarına göre ayarlamalıyız. Bu amaçla, ilklendirme sayacı ağırlık değerini belirlemek için çeşitli ağırlıklandırma tasarımları planladık. Sonuç olarak, parazit yankının olduğu ortamlarda, *M/N* hedef ilklendirme mantığı için oval ağırlıklandırma tasarımı kullanmak; yanlış hedef ilklendirmelerini azaltıp, doğru hedef ilklendirmelerinin kabul edilebilir bir seviyede idamesini sağlayarak umut verici sonuçlar vermektedir.

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LIST OF SYMBOLS/ABBREVIATIONS

E	Moments
$\mathbf{F}$	State transition matrix
g	Observation noise
$\mathbf{H}$	State observation matrix
I	Mutual information value
K	Kalman gain
M/N	M out of N logic
P	Prediction covariance
P_d	Probability of detection
P_{fa}	Probability of false alarm
$\mathbf{Q}$	State transition covariance matrix
$\mathbf{R}$	State observation covariance matrix
V	Unit volume of the observation area
v	Process transition noise
w	Additive Gaussian noise
$\mathbf{x}$	Target process state vector
$\hat{x}$	Observation state estimate
y	Information state
Y	Information matrix
z	Innovation
α	Spatial density in a Poisson model
$(\dot{\xi}, \dot{\eta})$	Two dimensional velocity of the target
λ	Expected number of Poisson distributed clutters in a snapshot
μ	Average true bias of target observation
μ_d	Average value of observation distances
(ξ, η)	Two dimensional position of the target
σ_d	Standard deviation of the average observation distances
φ	Target mean state observed

χ	Random variable
ψ	Random variable
Δ	Observation measurement
Φ	State transition matrix

CFAR	Constant-False-Alarm Rate
DCTC	Dynamic Convoy Tree-based Collaboration
EKF	Extended Kalman Filter
FDA	Fuzzy Data Association
IDSQ	Information-driven Sensor Querying
IPDA	Integrated Probabilistic Data Association
JPDA	Joint Probabilistic Data Association
JVC	Jonker-Volgenant-Castanon
LEACH	Low-energy Adaptive Clustering Hierarchy
MCMCDA	Markov Chain Monte Carlo Data Association
MCU	Micro-controller Unit
MEMS	Micro-Electro-Mechanical Systems
MHT	Multiple Hypothesis Tracking
MIR	Micro-power Impulse Radar
MMSE	Minimum Mean Squared Error
NBC	Nuclear Biological Chemical
NN	Nearest Neighbor
PDA	Personal Digital Assistant
PMHT	Probabilistic Multiple Hypothesis Tracking
ROC	Receiver Operating Characteristics
SMC	Sequential Monte Carlo
SNR	Signal-to-Noise Ratio
STUN	Scalable Tracking Using Networked Sensors
VDA	Viterbi Data Association
WSN	Wireless Sensor Networks

1. INTRODUCTION

As the technology evolves continuously, significant progress in digital electronics, micro-electro-mechanical systems (MEMS) and wireless communication technologies are achieved. We can see the ubiquitous effects of the technological improvements in our everyday life. For example, we are now arranging our schedules or look for the latest news or control our automated home security and even send commands for initiating a washing machine or an air conditioner with our personal digital assistant's (PDA) or handy cell phones. Our life is going to resemble the science fiction movies that have been released several decades ago.

As we have faced these huge changes, also new mechanisms became possible with the integration of the new tiny digital circuitry gadgets. One of the most interesting is the wireless sensor devices. These devices are also called as nodes or motes and we prefer to call them as nodes throughout the thesis. These wireless communicating nodes are constructed to execute some embedded services and capable of sensing, computing and transmitting the processed information. A generic hardware schema of a wireless sensor node is illustrated in [1]. Some other functionalities can be added to the nodes like location finder, power generator and mobilizer units. Sensor nodes can be deployed uniformly or randomly to the intended environment. In most outdoor scenarios, sensor nodes are scattered to the environment because of the hard terrain conditions or time constraint issues. As the nodes are scattered to the environment, a location determination utility is needed. Also, for rearranging the location of the sensor nodes, a mobilization feature can be added. While these extra capabilities consume more energy, joining a power generator equipment to the sensor nodes is plausible to enhance the lifetime period of the nodes and the network as well. All these functionalities are application dependent and can be utilized to obtain optimal performance from the sensor network system.

A sensor node can be structured to sense various events or situations according to its mission. Intended objectives can be sensing the environmental phenomena like

humidity, pressure, temperature, light, electromagnetic noise, acoustics, seismic, magnetic differentiations or dynamic phenomena like speed, acceleration, direction and size of the object. Nonetheless, sensor nodes can be designed for military purposes like sensing nuclear, biological and chemical (NBC) warfare attacks. Thus, various sensing features enable the sensor nodes to be utilized in diverse applications. Some of the main application areas are military, environmental monitoring, health, logistics, robotics, industrial monitoring and tracking issues like human, habitat or vehicle as surveyed in [2, 3].

Smart-dust concept is a radically different way of understanding the generic sensor node. Kahn *et al.* [4] introduces this new concept of sensors which deserves the meaning of the word *tiny*. The proposed sensors are designed to be in one to two millimeters wide. According to the application, millions of smart-dust sensor nodes would be scattered to the environment. It is an essential research area that the tiny size and the wide range of sensor nodes will enable very robust, fault-tolerant and concealed sensor network systems to be viable. Smart-dust phenomena promises to open new perspectives to the topic.

1.1. Motivation

In all application areas, the main characteristics of the sensor nodes drive the sensor network implementations, protocols and algorithms. While the wireless sensor network applications are going to be executed by tens to hundreds of sensor nodes, the unit cost of a node must be as low as possible in order to have a feasible application. Thus, to lower the prices, sensor nodes are made up of tiny and low-cost micro-electro equipments.

Designing the applications with the limited capabilities of the sensor nodes, appears to be the most challenging issue of the wireless sensor network phenomena. According to the above constraints, these tiny devices have limited power, processing capability and storage [5]. These are the typical characteristics and the constraints of a sensor node that must be handled via smart algorithms and protocols. The most

important constraint the sensor nodes have is their limited energies. In most scenarios, it is not convenient to replenish or to replace the batteries of a sensor node. Therefore, a better sensor node utilization policy must be developed throughout the network.

Most of the energy is consumed during the transmission phase of the communication process [6]. Executing more computation in order to transmit the filtered information becomes very crucial for conserving precious energy. Extensive research is being carried out on routing, data fusion and association, collaboration and sensor management issues to obtain an optimal sensor network system that is robust and consistent for the intended applications.

1.2. Thesis Organization

In this thesis, we deal with the target tracking issues in wireless sensor networks in two different aspects. Our first concern is the development of a better collaboration logic in sensor communication policy. We aim to enhance the energy-savings of sensor nodes. The second subject is to design a new track initiation scheme that can alleviate the false track initiation while not deteriorating the true track initiations in the cluttered environments.

In Chapter 2, we focus on the literature about the target tracking issues in wireless sensor networks (WSN). Also, a brief introduction to the information utility measure in the concept of collaboration among sensor nodes and the track initiation concept in WSNs is discussed. In Chapter 3, data processing architecture of the proposed WSN is explained and related work about the collaboration and track initiation issues is presented. In Chapter 4, we explain our proposed solution for the collaboration logic and the target track initiation scheme in WSNs. In Chapter 5, we present simulation results and achievements of the proposed algorithms. Consequently, we finalize the thesis with the analysis of the work done and the future research directions.

2. TARGET TRACKING IN WIRELESS SENSOR NETWORKS

2.1. Wireless Sensor Nodes

According to the advances in digital electronics, we get used to have hand-held devices and smart gadgets in our everyday life which usually accomplish very complicated jobs and have capable processors. This phenomena motivated to generate a wireless sensing network which consists hundreds of integrated tiny devices that can do sensing, computing and transmitting for a common purpose. There are several issues that effect the utilization policy of the sensor nodes like production cost, hardware constraints, transmission media and power consumption characteristics as stated in [1]. An optimized, application specific model has to be designed in order to get the best performance from the network system. In Figure 2.1, the schema of the basic components of a wireless sensor node is illustrated.

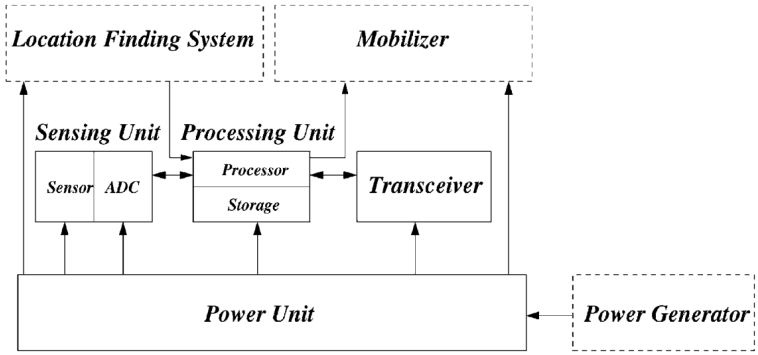


Figure 2.1. Components of a sensor node, courtesy of [1]

Sensing unit, processing unit, transceiver and power unit are the essential components of a wireless sensor node. Components like power generator, mobilizer and location finding system can be attached to the device in accordance with the application. As it is usually possible to use these devices in numbers of hundreds, an affordable system cost must be provided. Hence, attaching new equipments to the sensor device will totally increase the burden on the budget. Attaching more equipments will also

increase the size of the device where it can be a disadvantage for some applications like surveillance. Nonetheless, it is a new research area, various kinds of sensor nodes are viable and available on the market [5, 7]. A typical sensor node is as in Figure 2.2.

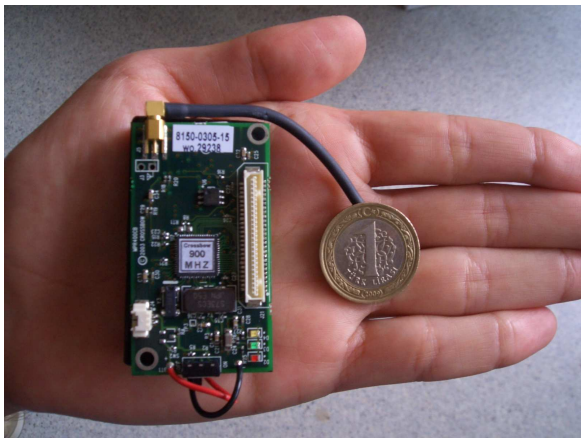


Figure 2.2. A typical sensor node

Sensing phenomena can be the tracking or monitoring of an object/environment. Sensing unit would be specialized according to the phenomena with different kinds of sensing equipments. These sensing equipments can have features that collect temperature, pressure, humidity, range, bearing, noise, acoustic, seismic, infrared etc. information from the observed incident. Also, some new types of sensors are being developed like quantum-based nano-sensors and carbon nanotube-based sensors [8].

The computing part of the sensor nodes are comprised of a microprocessor or a micro-controller unit (MCU) [6]. MCU governs computation power of the sensor node and responsible for all kinds of processing duties like gathering data, fusion, collaboration, control of communication protocols. Besides, MCU is one of the most energy consuming component of the sensor node. The other one is the transceiver component. While the processing and communication consumes most of the power resources, energy-aware computing is vital in wireless sensor network applications [6]. There are various kinds of protocols for transport, network and data link layers in order to enhance energy-aware capabilities of the sensor nodes [2]. As the research continues and the technology evolves, wireless sensor network phenomena promises to uncover new dimensions and opportunities to various kinds of applications.

2.2. Why the Wireless Sensor Network Phenomena is Important?

Spectacular evolutions in MEMS technology and wireless communication techniques bring a new era which led to producing low-priced devices that can do computation, communication and sensing operations all in one integrated equipment. While the early motivations are to generate information gathering networks of these tiny devices, various applications areas and new opportunities emerged like health or inventory monitoring as well as surveillance and tracking issues. Some of the applications like a fabric of a building security detection, are designed to be implemented within structured environments and certain numbers of sensors are utilized in designated locations. However, the most significant influence of the wireless sensor network concept is actually on the randomly scattered scenarios. Autonomous sensor nodes are scattered to the environment to collect information in a distributed manner and the processed data will be routed to a base station or to a management unit. With the help of the distributed infrastructure, we can easily change the number of sensors or the topology of the network without having any difficulty, just by adding new nodes to the environment. Also, having redundant nodes in the environment assures to provide consistent data, where all adjacent sensors to the incident will have the relevant information. Distributed architecture of the sensor network which also results heterogeneous processing, is the reliability basis of the system [9].

As we have an autonomous and distributed network system, the gathered information will be delivered independently by the selected nodes. Even if a failure or an energy exhaustion takes place in a node, the intended data is still delivered to the network and that feature yields the wireless sensor networks to be a robust, recoverable and a promising system.

2.3. Target Tracking with Wireless Sensor Nodes

Wireless sensor nodes have modest computation capabilities and resources. However, the autonomous nature of the nodes and the distributed architecture of the applications render these devices into effective instruments. The utilization of these devices

in target tracking applications exhibits that feature. The basic purpose in target tracking is to acquire position information of the objects around the intended area. As the sensor nodes can be uniformly or randomly scattered to the area, all nodes are dedicated to achieve the tracking process. Tracking quality is directly dependent on the sensor features, physical environment and the target dynamics. While the intended object flows inside the sensing range of a sensor node, it detects and initiates the track. After initiating a track, target's consecutive locations are predicted by the sensor via its tracking algorithm. As seen in Figure 2.3, a target moves around a sensor node and a tracking process takes place. The real positions of the roaming target is shown by the **x**, while the predicted target position at a time is illustrated as p.

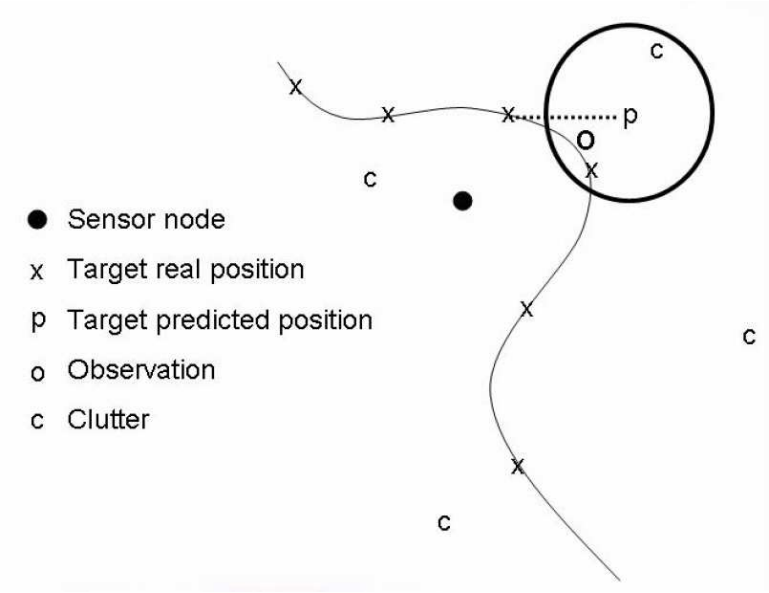


Figure 2.3. A target tracking trajectory for the wireless sensor nodes

The tracking algorithms like Kalman filter are utilized to enhance the position information of the targets. While these tracking algorithms cannot be precisely accurate, an area is defined around the predicted position to facilitate the tracking process. That area is called *validation gate*. As we know that the prediction is done due to the movement direction and speed of the target, the size of the validation gate can be determined according to the residual covariance matrix with n-dimensional *g-sigma* ellipsoid or an adjusted circular gate. This region provides to ignore unrelated detections in consequent snapshots for the intended track. Thus, tracks can be sustained consistently while their new detections are searched on the most probable detection

area.

As we look for the consequent detection inside the gate, observations from other target's or clutters can be detected. That issue complicates the association process of the targets. Especially, clutters can deteriorate the tracking accuracy and deceive the sensor nodes. To alleviate that false alarm issue, we try to enhance the track initiation performance of the sensor nodes via assigning different weighting values to the observation distances inside the gate in generic M/N track initiation logic. Thus, the clutter phenomena which is uniformly distributed over the sensing range of the sensor can significantly defused.

2.4. Classification of The Target Tracking Protocols

In target tracking issues, selecting the most informative sensor node is a fundamental part of the problem to enhance the tracking quality of the network. A pioneering work has done in [10] for exhibiting a data relaying protocol, directed diffusion, and a method for selecting the most informative node for tracking issues in wireless sensor networks. Moreover, several studies followed for sensor network node selection and collaboration paradigm in [11–13], as well as new tracking algorithms presented in [14, 15]. As many new target tracking approaches appeared in time, a classification of these algorithms can be made to recognize the differences among them. As in [16], target tracking techniques are classified into four different parts according to their perspectives in tracking issues. The classification of target tracking schemes are as follows:

- Hierarchical.
- Topological.
- Organizational.
- Sensor Management.

Hierarchical-based algorithms for target tracking are divided into three categories. These categories are tree-structured, cluster-structured and prediction-based

object tracking sensor networks. Tree-structured hierarchical approach is first proposed in [17]. The proposed scheme, STUN (Scalable Tracking Using Networked Sensors), utilizes a hierarchical tree-structure to be efficient when the number of tracked objects is high. In this concept, a leaf node senses the environment and transmits its detection information to the intermediate nodes. While that process continues similarly in consequent snapshots (sensing periods), intermediate nodes only accepts new detections to their detection lists. Thus, redundant reporting of the tracked objects by intermediate nodes towards the root is prevented. That message-pruning strategy provides reducing the communication cost throughout the network. Another tree-structured hierarchical model is presented in [18] which proposes to realize the logical tree by directly regarding to the sensors. Thus, their approach states that the transmission cost will be better evaluated with the new logical tree-structure. Dynamic Convoy Tree-based Collaboration (DCTC) is proposed in [19, 20]. It consists of a dynamic tree structure which is constructed by adding and pruning sensor nodes as the target moves. The dynamically evolving structure which is called the convoy tree needs to be constructed in an energy efficient way to alleviate the sensor node's energy constraints. The solution for that optimization problem is responded by two tree expansion and pruning schemes, namely the conservative and the prediction-based. Simulations show that the prediction-based scheme outperformed conservative scheme and presented similar performance as the optimal solution.

The other type of the hierarchical-based algorithms is classified as the cluster-structured object tracking sensor networks. While the cluster-based routing protocol LEACH (Low-energy Adaptive Clustering Hierarchy) [21] had great respect in energy optimization problem for sensor communication, the cluster-structured tracking schemes emerged in recent years. In [22], triangulation (sound source locating) technique is utilized for tracking objects with acoustic sensors. Also in [23], selecting the nearest sensor to the target as the cluster head based on Voronoi diagram distances reduces the estimation error remarkably according to the proposed dynamic clustering algorithm. Another dynamic cluster structure is used in [24] to reduce the energy consumption in information fusion process via using boundary sensors concept. It is shown that transmitting the sensor information according to the condition change be-

tween boundary and non-boundary sensors can lead to energy saving by reducing the communication cost.

Prediction-based object tracking algorithms specifically tries to anticipate the moving trajectory of the target by using some patterns. In [25], three prediction patterns are submitted: namely instant, average and exponential average. Instant pattern supposes that the target sustains its movement with the same direction and speed as in the last observation. Average pattern decides the new state of the target by averaging the previous movement archive. Exponential average pattern gives more weight on recent movement data, thus prediction can be more related to the future movements. In [26], a dual-prediction-based algorithm is proposed in which both base station and the detecting nodes predict the future movements of the target and transmit the data to the sink (base station) if the predictions are inconsistent with the target movements. A new version of dual-prediction-based algorithm is proposed in [27] which aims to monitor environmental events such as agriculture and ecology in an energy-efficient way via data gathering. While the environmental events need to be monitored for long periods, proposed algorithm provides sensor nodes to transmit information only if the prediction quality is high enough.

If we look from the topology perspective, we can classify the target tracking schemes according to their sensor location information designated to every node in the network. While the tree-structured schemes are globally informed about the sensor locations, we can call them as the globally informed tracking schemes as well. Besides, cluster-structured tracking schemes keep informed with local location information and thus, they can be classified as the locally informed tracking schemes.

In an organizational perspective, we can classify the target tracking schemes as centralized or distributed approaches. Cluster-structured schemes are managed locally by a cluster head and these cluster heads are selected autonomously among the sensors. Some of the examples for distributed target tracking schemes are like in [11], [28] and [29]. Contrarily, tree-structured target tracking schemes can usually be classified as centralized tracking approaches.

While considering the target tracking scheme in terms of a sensor management aspect, the classification can be done according to the collaboration tendency of the sensor network, namely the information-driven and the information-based. The first representatives for the information-driven sensor management scheme for target tracking issues are in [11] and [30] which introduce the IDSQ (Information-driven Sensor Querying) concept. IDSQ, briefly selects the most informative node by utilizing utility functions. Utility functions can be varied according to the application and sensor node characteristics. For example, Mahalanobis distance information utility shows better performance on range sensors than the bearing sensors, while the bearing sensors can only alleviate the uncertainty of the target bearing in perpendicular directions. In information-based approaches, the intuition is to select the sensor node whose information will decrease the entropy of the target location distribution. Information-based management of sensor nodes are structured in [31–33] where bearings-only sensors are used. Another sensor management logic utilized in bearings-only sensors for target tracking in WSNs is presented in [34]. In that study, only one sensor node is activated at each snapshot as a leader node to acquire and handoff the tracking information. The proposed method takes into account the angular diversity of the sensors as well as the predicted target belief state.

2.5. Collaboration Issues in Distributed Multi-Target Tracking

As we are struggling with tiny devices to engage complex signal processing algorithms in target tracking applications, energy efficiency appears to be the cardinal issue to handle. Sensor node is a multi-operational device that can sense its environment, do computation and transmit the observed data. While a sensor node is performing its duty, all three main components of the node consume various amounts of energy. As stated in [6], the energy consumption fashion of a node's components (MCU, sensing unit and radio unit) differentiates according to the execution modes. It is seen that all three components must be taken into inactive mode if it is not going to be used for some interval. Moreover, in radio unit, even in idle mode, sensor node continues to consume significant amount of energy. Thus, it is crucial to turn off the radio totally when it is not going to receive or transmit any data.

While we provide energy-aware execution modes for sensor node components, it is also essential to sustain energy-aware protocols in every layer of the wireless sensor network system. Thus, nodes can dynamically handle the tradeoff between the energy consumption and operational performance throughout the system. In order to pursue the energy optimization goals, collaboration among the sensor nodes is a major concern. An early work is done in [30] which represented the usage of information utility measures for informative sensor selection decision. Authors called this approach as IDSQ and various information utility measures can be utilized to select more informative sensors without having redundant transmission. Information content of a node is proportional to the size of the uncertainty region of the observed target. If the gained information in the consequent snapshot reduces the size and bearing interval of the uncertainty region, the information content becomes more reliable. Thus, in every information utility metric, reducing the uncertainty region's size is the symptom to better localize the intended target. In [11, 12], several information utility measures are used such as the nearest neighbor (NN), Mahalanobis distance, mutual information and entropy for the sensor node selection purposes in continuing snapshots. A closer look to these algorithms will be presented in the consequent chapters.

The important benefits of collaboration among the sensors is emphasized in [11] and itemized as follows:

- Detection quality.
- Track quality.
- Scalability.
- Survivability.
- Resource usage.

As far as the sensor nodes are collaborating through the network system, they can assist each other towards the possible information leakages. Besides, collaboration will lead the enhancement of the track location information throughout the network and consequently tracking quality will be increased. That's because the transmission range of the sensor nodes are much more bigger than the detection range. Thus, it became

possible to inform much more sensor nodes near the event. Furthermore, via informing redundant number of nodes, the system becomes more robust to node or broadcasting failures. Also, collaboration prevents all nodes to do the same computations and reduces the energy consumption.

Also, target detection and classification issues are investigated in [14]. Main emphasis of the paper is on developing collaborative signal processing schemes in distributed sensor networks. While providing collaboration among the sensors, classification algorithms are compared to reach a better solution for accurate classification. According to the simulations, support vector machine classifier showed promising results. In [35], a graphical model for data association in multi-target tracking issues have been developed as an inference problem and specifically various message passing algorithms are studied.

2.6. Introduction to Kalman Filter

The most known and the earlier one of the tracking algorithms is the Kalman filter [36]. Kalman filter is designed to achieve the tracking goal via utilizing the observation and target state prediction information as the arguments to its filtering. Kalman filter assumes to know some prior knowledge about the observation phenomena to achieve an optimal solution. While the coordinates of the measurements are in Cartesian form, the errors are expected to be independent and normally distributed since the target moving manner is formerly known by the filter. Thus, the Kalman filter can estimate the position and velocity of the target in a minimum mean squared error (MMSE). Otherwise, the position and velocity estimates may not be the optimum MMSE.

A simple Kalman filter is for estimating the position information of linearly moving targets. Velocity of a target may not be the same all the time. Thus, a Gaussian noise is added to the motion model. The motion and the measurement model of the Kalman filter is as in Equations 2.1 and 2.2, respectively. In every scan period, the previous state estimate is multiplied with the state transition matrix and a Gaussian

noise is added to it. Observation process is similar, but the sensor only detects the coordinates, not the velocity values.

$$\mathbf{x}(t+T) = \Phi(T)\mathbf{x}(t) + w(t) \tag{2.1}$$

$$\Delta(t) = \mathbf{H}\mathbf{x}(t) + g(t) \tag{2.2}$$

In Equation 2.1, $\mathbf{x}$(t) denotes the target state vector which comprises of position and velocity values. Φ(T) is the state transition matrix for the time interval T and the w(t) is for the state Gaussian noise. In Equation 2.2, Δ(t) denotes the observation measurement which is calculated through the observation matrix, $\mathbf{H}$. Also, observation noise g(t) is added and it is assumed to be independent from the state Gaussian noise. Actually, the estimation is done via an innovation value which indicates the difference between the actual measurement and the sensor's prediction which is based on the previous measurements of the sensor as illustrated in Equation 2.3.

$$z = \Delta - \mathbf{H}\hat{\mathbf{x}} \tag{2.3}$$

Where, $\mathbf{z}$ denotes the innovation value. The Kalman filter has two distinct phases named as *Prediction* and *Update*, the innovation is the crucial part of the prediction phase for a better estimation of the target position. Eventually, the innovation value is multiplied with the Kalman gain which is calculated from prediction covariance, observation covariance and the observation matrix as shown in Equation 2.4 and a new target state estimate is reached as in Equation 2.5.

$$K = P\mathbf{H}^T[\mathbf{H}P\mathbf{H}^T + R]^{-1} \tag{2.4}$$

$$\mathbf{x}(t) = \tilde{\mathbf{x}} + Kz \tag{2.5}$$

K denotes the Kalman gain and P is for the prediction covariance. In Equation 2.5, $\tilde{\mathbf{x}}$ denotes the previously best target state estimate. A brief information on Kalman filtering can be found in [37, 38].

2.7. Target Track Initiation

The surveillance concept has become a comprehensive research area as the advancements in electronics make it possible to run complicated algorithms for tracking the movements of the objects. In all target tracking algorithms, it is tried to enhance the knowledge about the precise position information, velocity and subsequent behaviors of the target via detecting and filtering previous accumulated information.

Several tracking and association algorithms like Multiple Hypothesis Tracking (MHT) [39], Joint Probabilistic Data Association (JPDA) [40], Fuzzy Data Association (FDA) [41], Viterbi Data Association (VDA) [42], Jonker-Volgenant-Castanon algorithm (JVC) [43] and non-Bayesian approaches like Nearest Neighbor (NN), Joint Likelihood function method has been proposed. There are also derivatives of these algorithms likewise Interacting Multiple Model Probabilistic Data Association (IMM-PDA) [44], Probabilistic Multiple Hypothesis Tracking (PMHT) [45] , multi-dimensional assignment algorithm [46] and etc. While these algorithms are developed for radar surveillance systems of ground bases, ships or aircrafts, significant computation power and memory resources are needed to achieve the proposed tracking goals. As our intention is to perform target tracking phenomena with the wireless sensor nodes, more simple and optimized algorithms are needed.

As an experiment for the surveillance problem in WSNs, "A Line in the Sand" [47] exhibits the challenges and constraints that can be confronted in the real life applications. Recently, several target tracking algorithms are proposed for WSNs applications [48–51]. Brooks *et al.* [48], presented a new collaborative signal processing logic for target classification and tracking issues in WSNs. Location-aware data routing is the key to decrease energy and bandwidth usage in terms of allowing only a subset of the nearest sensor nodes to the phenomena to collaborate their data. In [49], target

tracking and classifying problem is discussed with the probable presence of false alarm detections. A sequential Monte Carlo (SMC) based filtering is proposed for tracking the state of the objects. Also, the maximum mutual information metric is utilized for the leader sensor selection in a leader based tracking scheme. Two particle filtering approaches are presented in [51] and [50]. Both of them are using JPDA algorithm for track association purposes. Another multiple-target tracking algorithm for WSNs is proposed in [15] which deals with the false alarm detections and the low sensor detection probability issues while trying to initiate and terminate tracks in the aim of having robust, energy conserving, less memory using and scalable tracking algorithm. The proposed algorithm, Markov chain Monte Carlo data association (MCMCDA), presents better performance than the MHT data association algorithm under extreme conditions like low detection probabilities and high false alarm rates. Also, MCMCDA needs less memory while it only stores the latest hypothesis and the nearest posterior one. Distributed target tracking is also covered in [52] that a group management of sensor nodes via selecting a leader node can reduce the redundant communication and computation processes.

Although the MHT algorithm shows better performance than most of the data association algorithms, it requires much more computational power and memory resources to execute the association process [53]. While the JPDA needs less computational resources than the MHT, it still needs overwhelming computation and memory resources than the naive nearest neighbor (NN) data association method. While the energy resources of the sensor nodes are limited, we utilize less computation and memory demanding algorithms.

Sensor devices are not only dealing with the real objects, they are also detecting some unwanted measurements named clutters (or false alarms) which emerges because of diverse occasions like terrain, thermal noise, precipitation, or obstacles inside the detection range. Detection features of a radar sensor is presented in the receiver operating characteristics (ROC) graph of the sensor. The ROC is actually a plot of P_d (Probability of detection) versus P_{fa} (Probability of False Alarm). The probability of false alarm (P_{fa}) gradually gets higher as the probability of detection (P_d) approaches

to one (as an absolute detection capability) [54]. It seems plausible to increase the probability of detection level of the sensor, but if the track initiation logic is not adequate for a smart discrimination of the false track initiations, the system will overflow with spurious tracks. To handle this issue, target tracking and association algorithms such as MHT, Integrated Probabilistic Data Association (IPDA) and IMM-PDA uses a track quality measure as stated in [55]. If the track quality measure of a track is above the determined *threshold* value, the track will be declared as a *true* track, otherwise the track will be designated as a *false* track and deleted from the track list.

In some applications, constant-false-alarm rate (CFAR) and detection parameters or a clutter map can be used to discover the clutter density. However, a resource addict algorithm is needed to compute the track and association processes among the new hypothesis and the continuing tracks in each snapshot. On the other hand, track initiation is usually performed by a detection in two consecutive scans or an M out of N (M/N) initiation logic [56]. Utilizing the generic track association algorithms like MHT, JPDA, IMM-PDA are not eligible for WSN applications. To alleviate the need for computation power and memory resources, we determined to use the nearest neighbor (NN) data association logic in our WSN target tracking architecture. The NN data association logic is naive in dense cluttered environments. False track initiations caused by the false alarms, must be eliminated. Therefore, we propose a modified (M/N) initiation logic to initiate tracks for WSNs. In Chapter 3, we try to analyze the principal properties of the track initiation and association concept in terms of algorithms and examine the behavior of a generic track formation logic.

3. COLLABORATIVE TARGET TRACKING AND TRACK INITIATION IN WIRELESS SENSOR NETWORKS

There are two aims of this thesis. First one is to develop a better information utility measure for collaborative target tracking issues in wireless sensor networks. For this purpose, we designed a fuzzy inference system which is formed by two membership functions. We have utilized two information utility measures as the fuzzy logic membership functions: Euclidean distance and the maximum mutual information. Second aim of the thesis is to build a smart track initiation logic that can eliminate the false initiated, clutter caused, tracks while not deteriorating the number of true target initiations.

This thesis is a successor of the studies accomplished by Onel *et al.* [13]. All analytical works, simulator environment and also models for information processing, observation and distributed data fusion is inherited from the studies of Onel *et al.*.

3.1. Data Processing Architecture

In this section, we will try to explain the target motion model and the distributed data fusion as stated in [13].

3.1.1. Process Model

The purpose of the process model is to find the position of the target in consequent scan periods. If we know the position of a target at time t, we can predict the position of the target at time t+1. In the process model, the target information is retained as a four dimensional vector. Initial two parameters of the vector exhibits the two dimensional position information of the target, (ξ, η). Subsequent two parameters are the velocity information of the first two dimensional position information respectively,

$(\dot{\xi}, \dot{\eta})$. Thus, the target process state vector is as follows:

$$\mathbf{x} = [\xi \, \eta \, \dot{\xi} \, \dot{\eta}]^T \tag{3.1}$$

When we will advance the position of the target in time, we are multiplying the real target state $\mathbf{x}$(t) with $\mathbf{F}$, the transition matrix, and add v, the Gaussian distributed process noise with zero mean and covariance matrix $\mathbf{Q}$.

$$\mathbf{x}(t+1) = \mathbf{F}\mathbf{x}(t) + v(t) \tag{3.2}$$

$$\mathbf{F} = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \tag{3.3}$$

3.1.2. Observation Model

In our applications, we utilized TWR-ISM-002-I micro-power impulse radar (MIR) sensors that can only sense the relative range and the bearing data of the detected object. Therefore, a conversion must be done from polar coordinates to cartesian coordinates in order to have convenient type for the filtering of the target. Thus, conversion technique in [57] is utilized where it shows better estimation accuracy due to less errors in position and velocity, according to the Extended Kalman Filter (EKF) which uses nonlinear target state measurements without conversion.

The range, r, and the bearing, θ values are added with an assumed range error, $\tilde{r}$, and bearing error, $\tilde{\theta}$, as in Equation 3.4 which is independent and Gaussian distributed

with moments in Equation 3.5.

$$\begin{aligned} r_m &= r + \tilde{r} \\ \theta_m &= \theta + \tilde{\theta} \end{aligned} \tag{3.4}$$

$$E[\tilde{r}] = 0, \quad E[\tilde{\theta}] = 0, \quad E[\tilde{r}^2] = \sigma_r^2, \quad E[\tilde{\theta}^2] = \sigma_\theta^2. \tag{3.5}$$

After the conversion from polar to Cartesian coordinates, the target mean state is calculated as in Equation 3.6, while the average true bias is in Equation 3.7.

$$\varphi = \begin{bmatrix} \xi_m^c \\ \eta_m^c \end{bmatrix} = \begin{bmatrix} r_m \cos\theta_m \\ r_m \sin\theta_m \end{bmatrix} - \mu \tag{3.6}$$

$$\mu = \begin{bmatrix} r_m \cos\theta_m (e^{-\sigma_\theta^2} - e^{-\sigma_\theta^2/2}) \\ r_m \sin\theta_m (e^{-\sigma_\theta^2} - e^{-\sigma_\theta^2/2}) \end{bmatrix} \tag{3.7}$$

In [57], the covariance values of the observation errors of φ is given as in Equation 3.8. Besides, the observation covariance is utilized as in Equation 3.9 matrix form for

the filtering processes.

$$\begin{aligned}
R_{11} = r_m^2 e^{-2\sigma_\theta^2}[&\cos^2\theta_m(\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\
&+ \sin^2\theta_m(\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)] \\
+\sigma_r^2 e^{-2\sigma_\theta^2}[&\cos^2\theta_m(2\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\
&+ \sin^2\theta_m(2\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)], \\
R_{22} = r_m^2 e^{-2\sigma_\theta^2}[&\sin^2\theta_m(\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\
&+ \cos^2\theta_m(\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)] \\
+\sigma_r^2 e^{-2\sigma_\theta^2}[&\sin^2\theta_m(2\cosh 2\sigma_\theta^2 - \cosh\sigma_\theta^2) \\
&+ \cos^2\theta_m(2\sinh 2\sigma_\theta^2 - \sinh\sigma_\theta^2)], \\
R_{12} = R_{21} = \sin\theta_m\cos\theta_m e^{-4\sigma_\theta^2}&[\sigma_r^2 + (r_m^2 + \sigma_r^2)(1 - e^{\sigma_\theta^2})].
\end{aligned} \tag{3.8}$$

$$\mathbf{R} = \begin{bmatrix} R_{11} & R_{12} \\ R_{21} & R_{22} \end{bmatrix} \tag{3.9}$$

3.1.3. Distributed Data Fusion Architecture

Information filtering process formulations are given in [58] that the information state, $\hat{y}$, and the information matrix, Y, is associated with the observation state estimate, $\hat{\mathbf{x}}$, and the error covariance of the observation state estimate, P for time t as in 3.10.

$$\begin{aligned}
\hat{y}(t) &= P^{-1}(t)\hat{\mathbf{x}}(t) \\
Y(t) &= P^{-1}(t)
\end{aligned} \tag{3.10}$$

Also, it is stated in [58] that the φ is contributing to the information state, $\hat{y}$, via the information state denomination value, i(k), and the information matrix, Y, via the

information matrix denomination value, I(k).

$$\begin{aligned} i(t) &= \mathbf{H}^T\mathbf{R}^{-1}(t)\varphi(t) \\ I(t) &= \mathbf{H}^T\mathbf{R}^{-1}(t)\mathbf{H} \end{aligned} \tag{3.11}$$

While the velocity information is not directly observed by the sensors, the observation matrix, $\mathbf{H}$, is utilized for each sensor node.

$$\mathbf{H} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{3.12}$$

Collaboration among the sensor nodes is the key issue in energy saving. As it is important to avoid redundant communications, the type of the data transmitted to the network is essential in the energy consumption aspect as well. It is better to broadcast only the information state (i(k)) and information matrix denomination values (I(k)), instead of raw observation information. Thus, all the receiving sensors will not need to do the same computation for information fusion process. The information fusion is done due to the distributed architecture of WSN as follows:

$$\hat{y}(t \mid t) = \hat{y}(t \mid t-1) + \sum_{i=1}^{N} i_i(t) \tag{3.13}$$

$$Y(t \mid t) = Y(t \mid t-1) + \sum_{i=1}^{N} I_i(t) \tag{3.14}$$

In Equation 3.13, $\hat{y}(t \mid t-1)$ illustrates the information state estimate which inherits all the observations up to time t (excluding time t) and new information state denomination values from N number of sensors participated in the fusion process is added to supply a new updated information state. Equation 3.14 represents the same process for the information matrix estimate to have its updated form.

The calculation of the predicted information state and matrix at time t is done as in Equation 3.15.

$$\hat{y}(t \mid t-1) = Y(t \mid t-1)\mathbf{F}Y^{-1}(t-1 \mid t-1)\hat{y}(t-1 \mid t-1)$$
$$Y(t \mid t-1) = [\mathbf{F}Y^{-1}(t-1 \mid t-1)\mathbf{F}^T + \mathbf{Q}]^{-1} \tag{3.15}$$

Eventually, the estimated state of a target can be found from Equation 3.16 at any t time of the tracking process.

$$\hat{\mathbf{x}}(t \mid t) = Y^{-1}(t \mid t)\hat{y}(t \mid t) \tag{3.16}$$

3.2. A Collaborative Distributed Multi-Target Tracking Framework

Collaborative distributed multi-target tracking framework consists of two basic parts. These parts are illustrated in Figure 3.1. The upper part is the network track manager and the lower is the local track manager part. Both parts are being executed by all sensors autonomously.

The local track manager starts with sensing the bearing and distance information from the detected object. Next, the information extractor converts the raw sensing data into information denomination values as in Equation 3.11. The local plot list manager accepts the information state and the information matrix denomination values of the tracks. However, as the local plot list manager does not know the origins of the plots, it cannot determine which plot belongs to which track in the track list of the sensor node. The association of the information denomination values flowing from the local plot list manager with the tracks in the track list is performed in the local track associator. Consequently, the information state and the information matrix values are predicted according to Equation 3.15 and a detection list is formed. Each plot in the detection list can only be attached to a unique target whose track state and the information denomination values are passed to the information update filter to implement the track state updates. Also, the collaboration logic manager decides whether to broadcast the

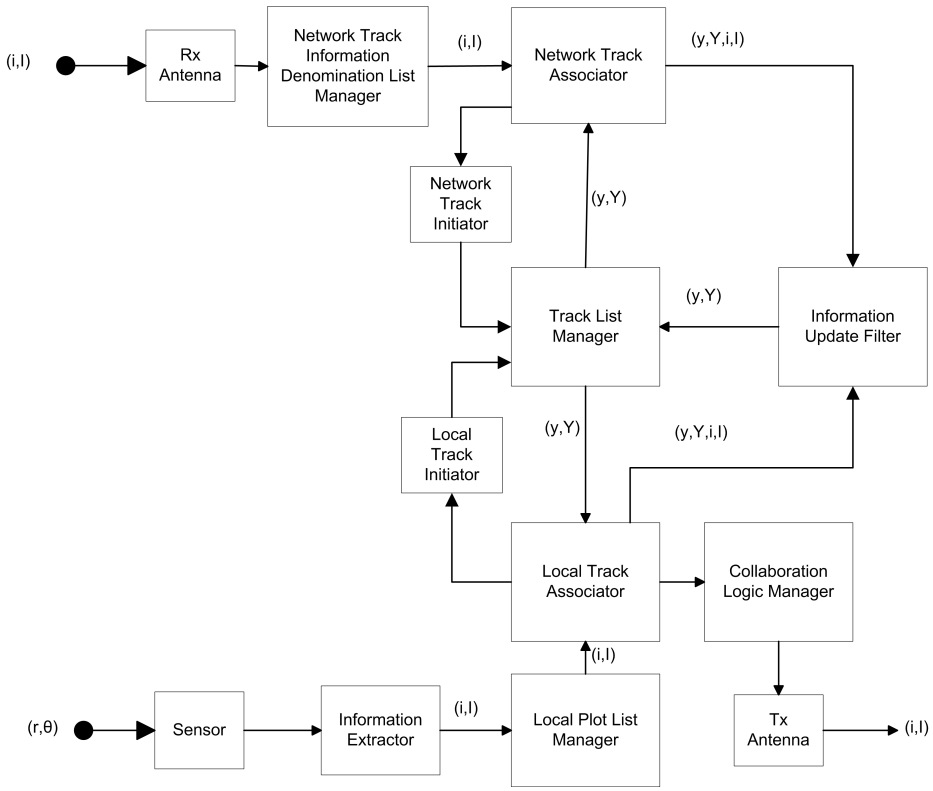


Figure 3.1. Distributed multi-target tracking framework [13]

information denomination values of selected tracks in according to the information utility measures. If the information denominations cannot be associated with any of the tracks in the track list, a new track will be initiated by the local track initiator in accordance with the track initiation constraints. (e.g., if it has been received two consequent detections from the same target)

Since our target tracking system is a distributed one, all detecting sensors will contribute their assured detections to the network in accordance with the collaboration constraints. Thus, broadcasted denomination values will be received and stored in the network track information denomination list manager. However, several sensors may have transmitted denomination values related to the same track. The duty of the network track associator is to correlate the received information denomination values with the tracks in the track list manager. When an information denomination value is associated with a track, the associated pair is sent to the information update filter and afterwards passed to the track list manager to update the state of the track. If

an information denomination value does not associate with a track, then the network track initiator starts a new track and passes that new track to the track list manager. If a track in the track list manager cannot be detected or reported by any of the neighboring sensors according to the constraints, track will be deleted from the track list manager.

In [59], the utilized pseudo-code of the mutual information-based sensor selection algorithm has given as illustrated in Figure 3.2. One of the key feature of that algorithm is in statements 9, 10 and 11. The interesting ability in here is to predict the neighboring nodes mutual information values. As the sensor estimates its mutual information value from the current local target estimate and the previously collaborated target state estimate, it also predicts the other sensor's mutual information. With this capability, the sensor nodes can predict which sensor has the most valuable information and decide if its information is eligible to collaborate or not. While the most informative sensor broadcasts its information to the network, a significant energy saving is achieved in terms of less communication and computation.

3.3. Information Utility Measures

Collaboration improves the target localization and tracking accuracies as well as assisting the energy saving policy via allowing only the most informative sensor nodes to communicate. While the sensors are collaborating in a distributed manner, less computation is needed to acquire the consistent view of the network. In [11], IDSQ is represented as the selection strategy of the appropriate sensor node for designating the following base station in according to information utility measures. The performance of the utility measures will be diverse and application specific. In Onel *et al.*'s collaboration logic in [13], three information utility measures are used for deciding which target information denomination values to be shared within the network. The utilized information utility measures were Mahalanobis distance, maximum mutual information and random sensor selection metrics. Mahalanobis distance and the mutual information utility measures are briefly studied in the subsequent subsections.

Require: 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 $\mathbf{F}$, $\mathbf{Q}$, $\mathbf{H}$, $\mathbf{R}$.

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

Obtain the observation from the target.

$\boldsymbol{\varphi}_m(k) \Leftarrow f(r_m, \theta_m)$

Calculate the information denominations.

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

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

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.

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

Estimate other sensor nodes' mutual information values.

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

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

end for

Produce the mutual information content list.

sort $J_{array}(k, \boldsymbol{\varphi}_m(k))[sensor]$

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

$index \Leftarrow$ index of $J(k, \boldsymbol{\varphi}_m(k))$ in $J_{array}(k, \boldsymbol{\varphi}_m(k))$

Decide to collaborate or not to collaborate. If decision is to collaborate then broadcast the denomination values.

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

    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 3.2. Pseudo-code of the mutual information-based sensor selection algorithm [59]

3.3.1. Mahalanobis Distance

Mahalanobis distance metric is based on correlating two variables and discovering the similarities between them. The measurement procedure of the Mahalanobis distance is shown in Figure 3.3. The blue colored ellipse shows the uncertainty of the predicted target position in the previous scan. Suppose two sensor nodes, one is perpendicular to the target's collaborated uncertainty ellipse as $S2$ and the other's position is nearly parallel to the axis of the uncertainty ellipse as $S1$.

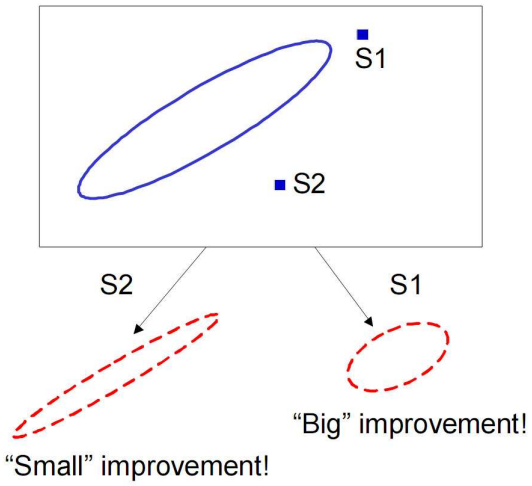


Figure 3.3. Illustration of information gain according to Mahalanobis distance [11]

When we use the Mahalanobis distance metric to evaluate the belief state update, the sensor on the longer axis will exhibit better improvement as seen in the dashed ellipsoids in Figure 3.3. The Mahalanobis distance-based utility measure works well with range sensors when the detecting sensor position lies far and parallel to the longer axis of the uncertainty ellipse. In the Mahalanobis distance metric, not only the Euclidean distance of the sensor to the target is important, but also the position of the sensor according to the longer axis of the uncertainty ellipse of the target plays a key role in the decision process.

3.3.2. Mutual Information

Entropy of a random variable tells about the uncertainty level of that random variable. If we want to discover the relation between two random variables, we can take the relative entropy of these random variables, which gives us the information distance between these variable distributions. As we are trying to find a better way in deciding which information denomination value to collaborate within the network, a special case of relative entropy named mutual information shows promising performance as stated in [13].

The mutual information is "a measure of the amount of information one random variable contains about another" as stated in [60]. If we name the probability mass functions of two random variables χ and ψ as p(χ) and p(ψ), and the joint distribution of these variables as p(χ,ψ), the mutual information is calculated as in Equation 3.17.

$$I(\chi;\psi) = \sum_{\chi,\psi} p(\chi,\psi) \log \frac{p(\chi,\psi)}{p(\chi)p(\psi)} \tag{3.17}$$

Thus, the mutual information metric allows us to perceive the quality of our prediction about the subsequent state information values of a sensor node for the intended object.

3.4. Track Initiation and Association

Target tracking is basically to trace the objects in the environment. We have been utilizing tracking systems in radars of air controllers, planes, ships, missiles and similar systems that need an exact position of the objective. It also started to take a huge part in our everyday life beyond our perception as well as it has critical usage in military applications. Target tracking is conceptually a combination of track state estimation and track association. However, the quality of tracking is a complex function of several parameters [11]; sensor placement density, sensing range, communication range, spatial extent of the physical phenomenon being observed, target dynamics, signal-to-noise

ratio. All of these issues are interconnected in the multi-target tracking framework. While estimating the states of the targets, we must validate and ensure that the tracks are associated to the real targets. Determining the authenticity of the tracks is the objective of the track initiation.

As a first phase of a target tracking phenomena, we denominate it as the track initiation phase. The track initiation must be managed carefully while there may become some unwanted echoes which is usually referred to as clutter. Clutters are actually radar returns from ground, sea, atmospheric turbulence, rain, birds, insects, trees or man-made structures. Clutters are random and confuses the target tracking systems with the eruption of those unreal echoes [61]. This situation disturbs the sensor system's tracking quality due to the generated false tracks. If we allow the system to generate false track initiations, the track database of the sensor unit will be full of unreal target tracks and eventually it will increase the burden on computation and increase the energy consumption on the tiny sensor devices. Furthermore, the sensors will transmit false tracks to the network which will render the system even more error prone and energy exhausting.

While the target tracking becomes more susceptible to faulty target generation in cluttered environments and maintaining the true tracks gets harder, fault tolerant track association algorithms are needed. There are several track association algorithms for multi-target tracking in the literature [62]. Most basic one is the NN association. There are also some Bayesian probabilistic approaches like MHT and JPDA algorithms. As there are some common parts in association algorithms, the decision of which measurement hypothesis to choose for integrating to the tracking system and how to process the hypothesis make the original difference.

Both the NN and JPDA filtering need a track initiation process before the association logic of the tracks can be specified. The initiation of the tracks can be done via M/N logic which basically determines a tentative track to be initiated as a true track if the sensor detects the target M times over N scans. This initiation rule naturally shows better performance as the time passes and the number of false track initiations

degrades to an admissible measure. However, the true track initiations are also affected in this initiation scheme. A good track initiation algorithm should keep the balance in the false track initiations and the true track misses.

In NN association, association logic is due to a single hypothesis. Only the nearest measurement to the predicted target state is considered to update the track estimate. If the environment gets denser in terms of targets, there can be several other track measurements in the validation gate. It means that the probability of closer moving targets will be higher and NN association can choose some other target's detection or a close clutter in the validation gate. This would cause the tracking quality to degrade while the tracks are updated with wrong detections or false alarms. Moreover, updating the tracks with wrong detections will carry the track data to erroneous positions and it will decline the recovery probabilities while the predictions will be from irrelevant areas where true track measurements cannot be found in the validation gate. As an optimistic view, subsequent association decisions would find the correct track and eventually the filter can converge to the true track position.

For dense target and cluttered environments, more sophisticated JPDA and MHT data association techniques are developed. In JPDA filtering [40], all of the measurements in the validation gate are joined to the association decision with a weighting value which is computed from conditional probabilities. Weight computation is based on the statistical distance of the measurement to the predicted track state and on each scan, only the latest set of measurements in the validation gate are taken into consideration. Also, JPDA needs an initiation and a track deletion procedure just like the NN association algorithm. However, MHT executes these issues in its own tracking algorithm.

In MHT [39], every measurement is simultaneously granted as a new track, a false alarm track and as an update track for all measurements in the validation gate. Each of these assumptions generates new hypothesis. These hypothesis may lead the tracking system to initiate a new track or the deletion of an inactive track. All hypothesis are associated with a probability value and those values are updated at each scan. While

MHT allows some delay and ambiguity in the track estimation process, subsequent scans will supply measurement information about the targets and probability values will be assigned to each hypothesis in accordance with likelihood of the hypothesis to a true track.

Eventually, the tracking system will eliminate the false alarm and inactive tracks as the higher probability values will be given to correct hypothesis. However, at each scan period the number of hypotheses would increase dramatically as the number of targets increases. This issue shows the major handicap of the MHT algorithm which obligates to have much more energy, computation and memory resources than a wireless sensor node have in today's technology. While the NN association method is the simplest and relatively a low cost solution in terms of computational complexity and data storage capacity, we decided to utilize NN algorithm in our track association process.

However, NN data association approach is error prone in dense target or clutter environments. In NN association method, only one of the many hypothesis is chosen and the others are discarded while there is no evidence if the association choice is correct. Especially in high cluttered environments, the decision can be probably wrong. But, the continuation of filtering with false measurement makes the predictions even worse. A faulty association decision will definitely lead the tracking filter to further errors on subsequent measurements and the result of the filtering process will continue to mislead the target localization decision. While there is no "backing out" mechanism in NN filtering approach, incorrect association decisions will progress through the flow of filtering. In a better scenario, subsequent correct decisions may improve the performance of the filter and help it to find a correct position estimate of the target. However, we know that in low probability of detection and high false alarm rate conditions, the performance of NN association will significantly degrade.

3.5. Validation Region (Gate)

In target tracking phenomena, the state estimation of the intended objects is a prior job before the track association and correlation decisions. While the accuracy and consistency of the association depends on the track state estimation process, various methods are developed for this purpose as stated in the previous section. However, there is a principal issue that directly effects the performance of the association algorithms. This feature is known as the *gating*. A validation/association region (gate) is utilized to eliminate unrelated observations from the track association process. The basic principle in the *gating* process is to provide a probable region around the predicted target position that the subsequent position of the target can coincide in this region. Thus, the filtering process is simplified via eliminating unrelated observations and the performance of the track localization is increased by dealing with only the most probable observations. Determining the size of the gate is the most critical decision while it directly effects the performance. The gate size depends on the target dynamics and and the elapsed time since the last predicted state of the target. The gate size can be calculated from the tracking filter covariance matrix and the shape of the gates can be formed as rectangular, ellipsoidal or circular. Besides, the size of the gates can grow or shrink depending on the missed detections. Also, there are various researches on adaptively detecting the size of the gate which is based on localization quality and the available resources [63].

In Figure 3.4, we tried to illustrate how the gating process is achieved as stated in [64]. There are two predicted target positions presented as P_1 and P_2. While only the observations inside the gates will be taken into account on the association process, observations O_1, O_2 and O_3 will be the candidates to attend the track updating process. All the track-observation pairing will be done by the selected association algorithm. The observations which are not related to any track will be assigned to form a new tentative track. Also, there would be common detections that can be coincided on the gates of the various target predictions as O_3. These incidents are handled according to the characteristics of the association algorithms as well. For example, the NN association algorithm dedicates O_3 as the updating observation of P_2, while

all-neighbor approach would determine the association according to the weighted sum of all observations.

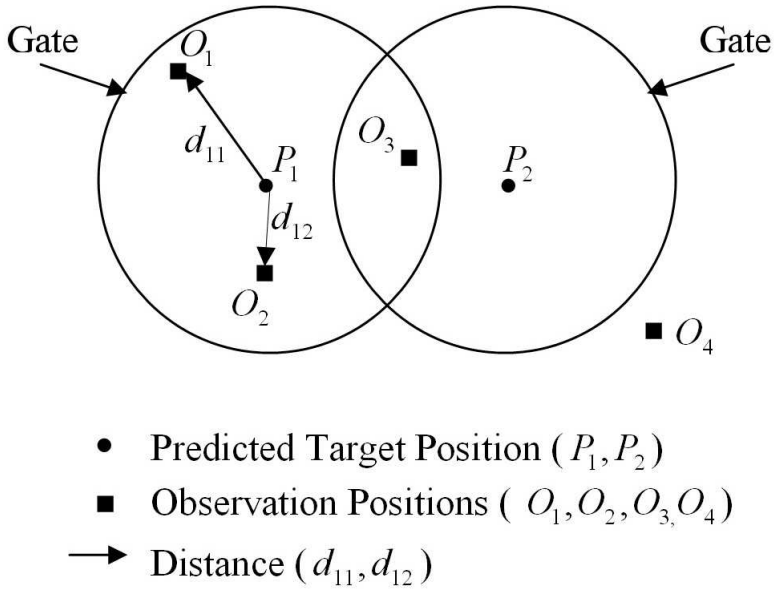


Figure 3.4. Illustration of gating for two closely spaced tracks [64]

3.6. Track Management

When we conceive an application of object tracking with the autonomous wireless sensor nodes, we have to constitute a consistent picture of the whole system on each participating unit of the network. It means that we have a distributed WSN tracking system and all the sensors must have a reliable and identical view of the scanned area. By means of reliability, the track that we have initiated must guarantee some constraints like gating area and initiation criteria. These constraints ensure that even in high cluttered environments, the false track initiations are avoided and the negative effects to the whole network is prevented. In order to build the identical view of the scanned area, we must enumerate the tracks and keep the enumeration of these tracks consistent over all of the tracking sensors. Moreover, there must be a mechanism to correlate the identical tracks in all sensors which also performs the necessary track associations.

As might be imagined, in order to accomplish a reliable sensor network tracking system, we must have a track management system which executes the functions described above [65]. If we separate these functions into phases, the first one will be the initiation of tracks. While initiating a track, some track validation constraints like gating and initiation criteria are needed to have a sustainable system against noise originated false alarm tracks. After the track initiation, we need a track numeration phase to keep the proper trace of the targets. Every track must be enumerated and consistent maintenance of the track numbers must be done in all sensors. The track number assignment and the consistent maintenance of track numbering are significant issues where it is the only way to have a correct tracing of the targets. Also, the same target track numbers must be utilized by all sensors for the identical targets around the network to keep the system consistent. The track number management process also includes the deletion of false initiated tracks and lost tracks. Thus, it can be seen that the track number management process is much more difficult in a distributed network than a centralized one. Because, all detecting sensors will try to enumerate and broadcast its detections while other sensors in the detection range are doing the same. It will cause a race condition and must be handled via a collaboration logic thorough the network.

The subsequent phase will be the track correlation and association. All detecting sensors are operating on the targets and information gathered must be distributed around the network for having an identical view. This process includes the correlation of splitting and diverging tracks as well as track swapping. In fact, the correlation and association phase is strongly interconnected with the previously explored phases. One without another, the track management system will not work properly.

Our work will intensify on the target track initiation phase of the track management system. While it is the first step in target localization process, the optimum initiation performance must be achieved as hindering the false track initiations.

3.7. *M* over *N* Track Initiation Criteria

As stated in the previous section, the target tracking starts with the track initiation phase which can be done in several ways. Most simply, it can be done via the two-point initialization process [66]. In this method, observations from the two consecutive snapshots are utilized to initialize a track state. However, tracking algorithms such as MHT does not need a track initiation phase while the tracking algorithm itself yields the suitable detections as newly initiated tracks. However, multiple hypothesis-based target tracking algorithms require significant computation and energy resources. Therefore, in WSN applications, we need a simplistic method that can initiate tracks in admissible time and accuracy. M out of N initiation logic (*M/N Logic*) can be used in this mission while it is not computationally expensive and relatively good in sparse cluttered environments.

The basic idea behind the M/N logic is to catch *M hits over N scans* in consecutive snapshots. In each snapshot, the tentative or initiated track is checked if it is still providing the initiation constraint or not. When the constraint is satisfied, it becomes eligible to nominate the track as a true track. If the track could not be detected up to the track deletion threshold, the track will be deleted from the track list. The track deletion threshold depends on the application and can be adjusted according to the environmental conditions. M/N logic can be designed as a n block composite logic. The implementation of a two block logic can be done as M_1/N_1 x M_2/N_2 which is the composition of $M_2(M_1/N_1)/N_2$. The two block logic supplies better distilled track initiations while increasing the computation demand. Actually, composite logics are suitable for high data rate sensor devices [67].

4. FUZZY INFERENCE SYSTEM AS A COLLABORATION LOGIC AND A NEW *M/N*-BASED TRACK INITIATION LOGIC FOR WIRELESS SENSOR NETWORKS

4.1. A New Information Utility Measure Via Fuzzy Inference System

With an effective collaboration logic, increasing the tracking accuracy and alleviating the effect of the missed detections becomes easier as well as reducing the false alarm initiation rate. Moreover, distributed collaboration provides the system to be immune to node failures and prevents futile power consumptions. While most of the sensors around the event will have nearly similar observation information, avoiding the transmission of every sensor in the area is crucial for energy saving. Effective collaboration logic will supply the more informative sensors to transmit their data according to the information utility measure.

In Chapter 3, we explain the foundations of the work done in [13]. In that study, Onel *et al.* propose information collaboration schemes to reduce the energy consumption of the sensor nodes exhausted for collaboration without much sacrificing from the target tracking accuracies. They use three sensor selection metrics to decide which sensors to collaborate in the network. These metrics were maximum mutual information, minimum Mahalanobis distance and random selection. The performance of these metrics is compared in terms of mean target detection error and total consumed energy while increasing the number of targets to be reported by a sensor [13]. Also, consumed energy for the desired target localization accuracies is investigated with these metrics. Eventually, simulation results show that the maximum mutual information metric is a reasonable choice to utilize while deciding which sensor information to broadcast to the network.

In this respect, we decide to build a new collaboration decision metric to lower the detection error as well as contributing more consistent information to the network. We utilize a fuzzy inference system which includes two membership functions. Since it shows better performance than the other information utility measures, we decided to use the mutual information metric as one of our membership functions. The other membership function is the Euclidean distance metric. While the signal-to-noise ratio (SNR) and quality of observations deteriorates as the distance to the phenomena increases, we aim to investigate the performance gains by using the combination of the maximum mutual information and Euclidean distance metrics in terms of fuzzy logic.

4.1.1. Proposed Fuzzy Logic Model

To solve the real world problems, we need the ability to perceive the events in their actual vague situations just like a human being do. Fuzzy logic is the instrument to achieve this goal. All in all, fuzzy logic tries to combine evaluation techniques, that's how it pretends to be human-being via computer talent. Details of the fuzzy logic systems can be found in [68].

We utilize Mamdani's fuzzy inference method to generate a fuzzy decision process [69]. In order to apply fuzzy logic to our system, we have to implement four steps as seen in the Figure 4.1.

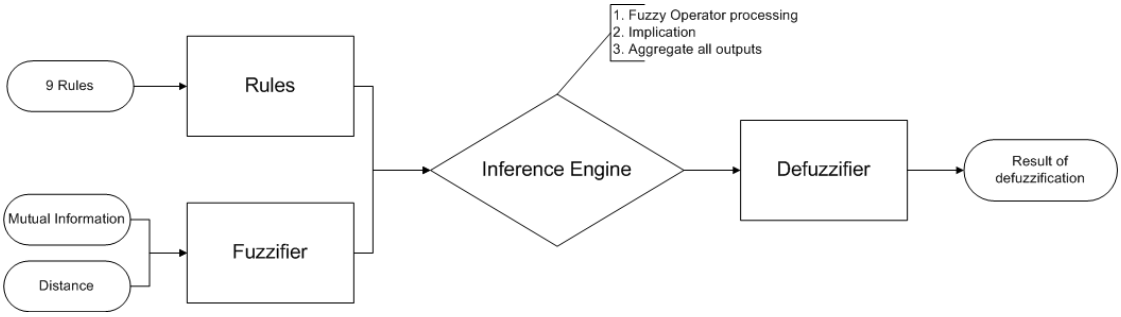


Figure 4.1. Fuzzy inference system

The first step is to *fuzzify* the inputs. Fuzzifying means mapping each input value to a degree between 0 and 1 via the membership function. This process is called as the

fuzzification. One of the key subjects of fuzzy logic inference system is the membership function. The membership function determines the appropriate membership value of an input fuzzy variable. Therefore, it is very crucial to set the membership function in proper values to have a realistic model of the system. In our model, we have two fuzzy variables named as the maximum mutual information and Euclidean distance. Both of these fuzzy variables have three fuzzy sets named as Bad, Medium, Good and Close, Moderate-Close, Far, respectively. The membership functions of these fuzzy sets are shown in Figures 4.2 and 4.3. The membership functions display the evaluation policy of the fuzzy sets. Thus, a sufficient number of trials must be done to adjust the mapping value ranges and types of the membership functions.

Mapping value ranges of the membership functions must be a set according to the system model. In Figure 4.3, the values of the fuzzy sets are arranged in harmony with the TWR-ISM-002-I radar whose typical detection range is 18 meters. As we utilized a Gaussian noise distribution, distance observations would be oscillating which can differentiate range border lines. Thus, there are soft transitions between the values of fuzzy sets. That's the strength of the fuzzy logic.

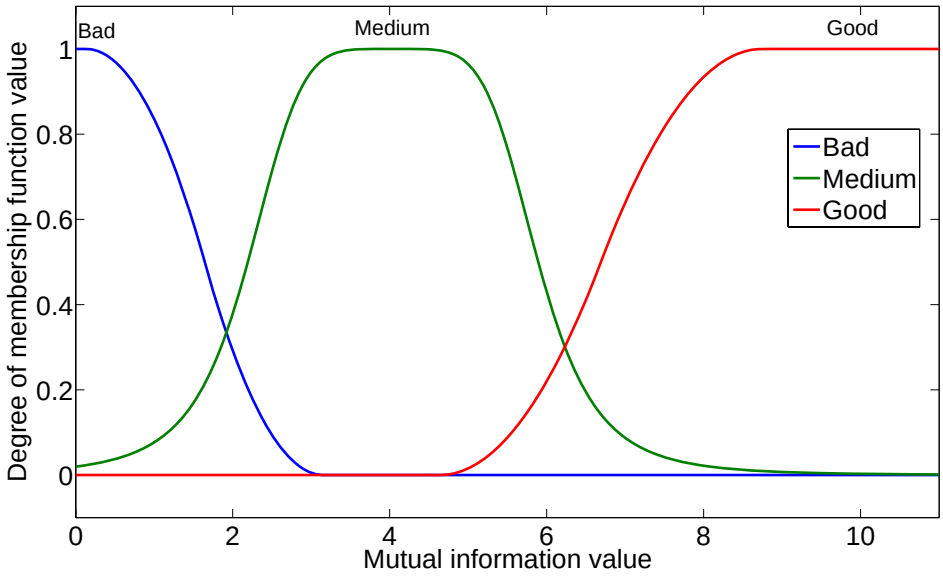


Figure 4.2. Membership functions of mutual information fuzzy sets

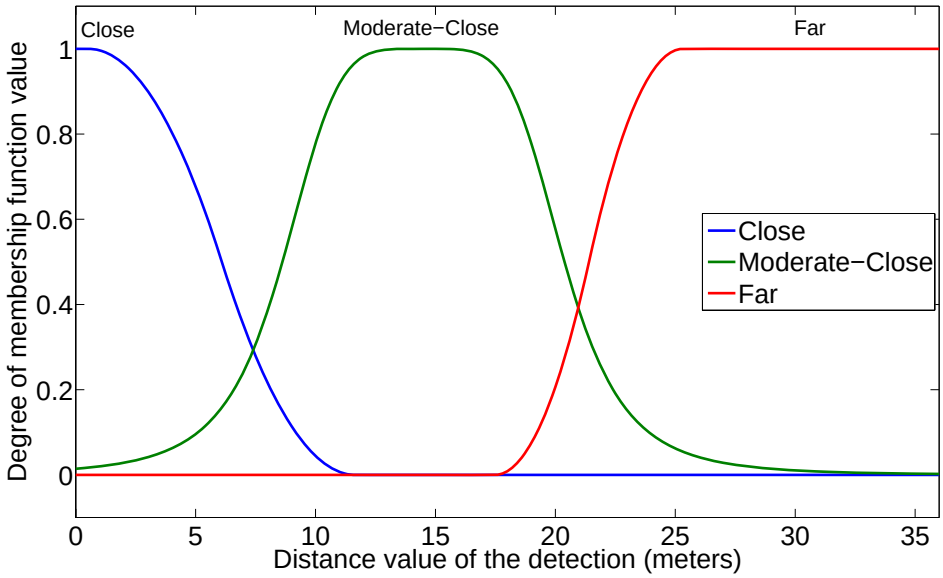


Figure 4.3. Membership functions of Euclidian distance fuzzy sets

The second step is to specify the rules of the fuzzy system. Fuzzy rules are comprised of *if-then* statements and provide the conditional decision map of the fuzzy logic system. If-part of the rule is called as antecedent and then-part is called as consequent. While we have two fuzzy variables and three fuzzy sets, there will be $3^2 = 9$ rules in order to map every possibility in the fuzzy logic ruler of the inference system. We designated the rules into 5 different rule classes. The names of the rule classes and the relation between membership degrees are as in Figure 4.4. Matching the fuzzy rules into classes is another key point of the fuzzy inference system. Each rule must be consistent with the remaining part of the ruler logic in order to avoid unwanted results. Also, we can assign different weights to the rules between 0 and 1. Weighting effects the impact of rules in the implication process.

As in Figure 4.4, names of the mapping classes are Bad, Less, Middle, Better and Excellent. The system maps to the appropriate class based on the fuzzy rules in according to the input values of the mutual information and Euclidean distance fuzzy sets. The mapping of the weight values calculated from the input membership function results are designated according to the fuzzification operation as illustrated in Figure 4.5. If we need to change the effect of fuzzy sets, it can be achieved by altering the

1. (*Mutual Information* is *Bad*) and (*Distance* is *Close*) then (*Weight* is *Middle*)
2. (*Mutual Information* is *Bad*) and (*Distance* is *Moderate Close*) then (*Weight* is *Less*)
3. (*Mutual Information* is *Bad*) and (*Distance* is *Far*) then (*Weight* is *Bad*)
4. (*Mutual Information* is *Medium*) and (*Distance* is *Close*) then (*Weight* is *Better*)
5. (*Mutual Information* is *Medium*) and (*Distance* is *Moderate Close*) then (*Weight* is *Middle*)
6. (*Mutual Information* is *Medium*) and (*Distance* is *Far*) then (*Weight* is *Less*)
7. (*Mutual Information* is *Good*) and (*Distance* is *Close*) then (*Weight* is *Excellent*)
8. (*Mutual Information* is Good) and (*Distance* is *Moderate Close*) then (*Weight* is *Better*)
9. (*Mutual Information* is Good) and (*Distance* is *Far*) then (*Weight* is *Middle*)

Figure 4.4. Rules of the fuzzy inference system

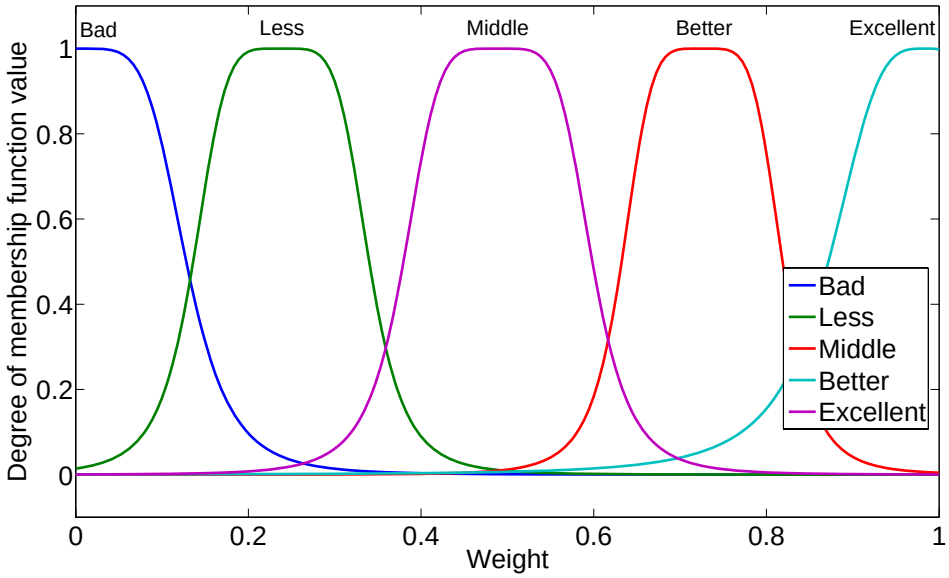


Figure 4.5. Membership functions of output fuzzy sets

mapping class of the intended rule.

After fuzzifying and defining the rules, the inference engine will begin to operate. Inference engine does three main jobs. The first one is to apply Boolean logic operators like AND, OR and NOT to execute the rules if there are more than one statement in the antecedent part of the rule. Secondly, we apply *implication* method to the consequent part of each rule. Implication method basically truncates the membership function according to the input fuzzy set. Eventually, all outputs of the implication process are

aggregated into a single fuzzy set as seen in Figure 4.6. There are three aggregation types named as *maximum*, *probabilistic OR* and *sum* which means the summing of each rule's output set. We utilized the *sum* method in the aggregation process.

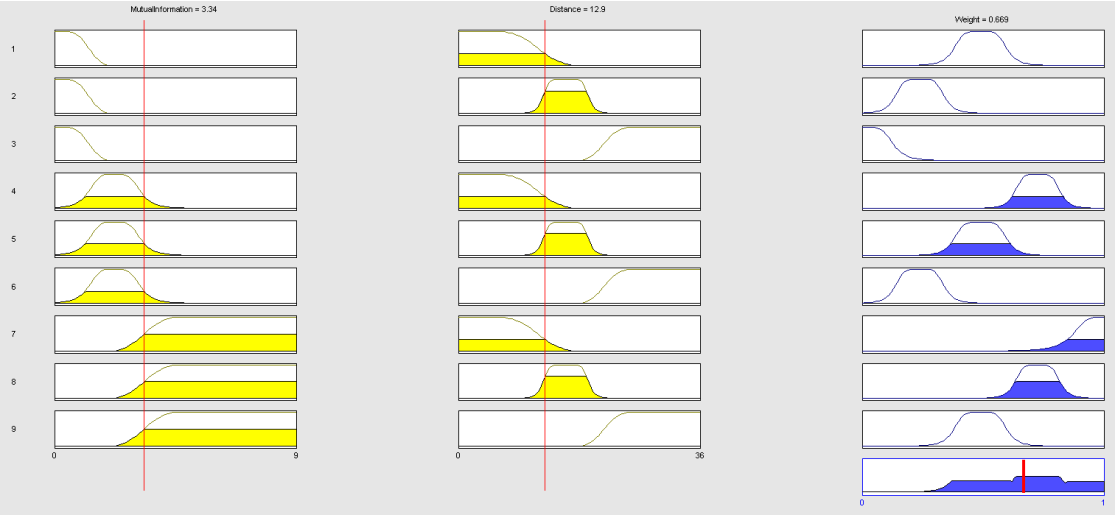


Figure 4.6. Activation states of the rules in the fuzzy inference engine for the values of the input fuzzy variables mutual information 3.34 and Euclidean distance 12.9.

After having an aggregated single fuzzy set, we execute the defuzzifcation process to map the fuzzified parameters into a precise outcome of the system. Finally output is a single number representing the decision of the fuzzy inference system. There are also various defuzzification types. We utilized the *centroid* defuzzification type which calculates the center of the area formed after the aggregation process. Thus, we can see that the fuzzy inference is a method that interprets the values of the input fuzzy sets based on user-defined rules and assigns values in according to the rule weights. Then, it yields an output value due to the aggregated areas filtered from the membership functions.

4.2. A New *M/N* Logic-based Track Initiation for Cluttered Environments

The second purpose of this thesis is to present a new M/N track initiation logic in cluttered environments for WSNs. In order to approach to our aim, we have to analyze the effects of clutters and their creation nature. The clutters are unwanted radar echo's and can be caused by the wind, precipitation, temperature variations, terrain

etc. The clutter formation phenomena is canonical, the number of clutter points are Poisson distributed in time while their locations are uniformly distributed over the sensing area of an individual sensor as stated in [70–73]. Also, the clutter formation concept is admitted identically for the wireless sensor nodes as well [74, 75]. As the emerging position of the clutters, or can be named as the false alarm's (echo's), are uniformly distributed over the sensing region, we can designate diverse weights to the present observations in the gate in accordance with the distance to the track's predicted position.

In generic (canonical) M/N logic, the consecutive detections inside the gate are considered with identical weights and the initiation counter is increased by one. However, if the newly detected observations in the gate are away from the center of the predicted target position, the sensor observation may not be a real target. Hence, we should adjust the initiation counter weights of the tentative tracks according to the distance measure while utilizing M/N logic for the track initiation decision. For this purpose, we envisaged different weighting schemes as illustrated in Figure 4.7.

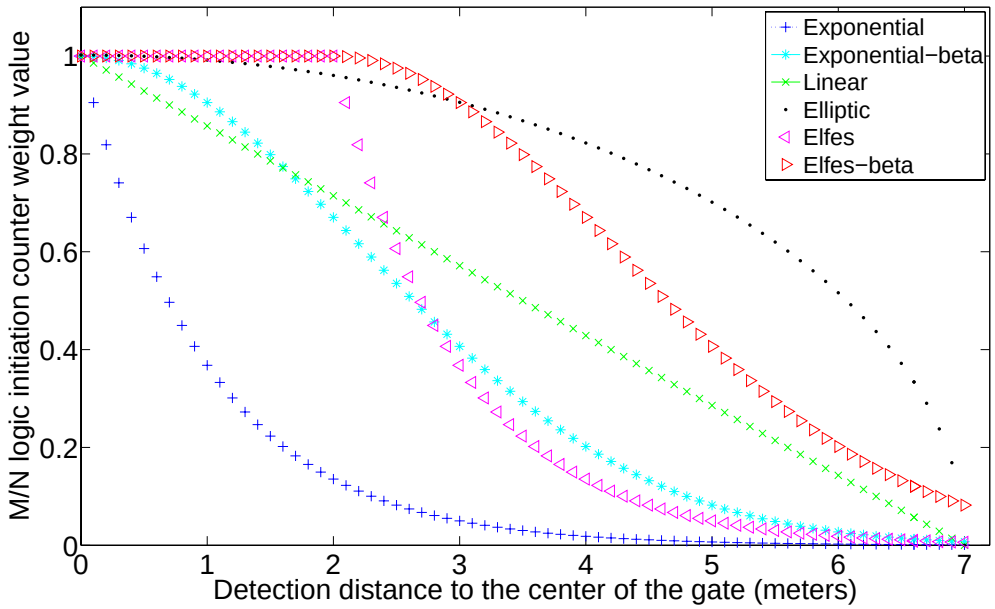


Figure 4.7. Schemes for calculating the M over N logic initiation counter weight

While we expect to find the majority of the true detections near the predicted target position and the false detections relatively distant from the center of the gate because of uniformly distributed clutter phenomena, it is plausible to give low weighting value to the far detections inside the gate, in order not to initiate false tracks. Hence, we conceived six different models for determining the weighting value of the track initiation counter. These models are exponential, linear, elliptic, Elfes and two versions of the exponential and Elfes models. The exponential, linear and elliptic models are just like the known generic figures in which our application dictates the trajectory of the curves by the radius of the gate.

Elfes model [76] is utilized for simulating the sensing capabilities of wireless sensor nodes in [77]. In our work, we tried Elfes model for determining the weighting value for the track initiation counter according to the distance of the observation to the gate center likewise the other five track initiation counter weighting models. Inherently, Elfes model starts with a constant value for an interval. The constant value of our Elfes model is assigned to one which is the same weighting value as a generic M/N logic. Moreover, we continued this constant value up to the mean (μ_d) plus one standard deviation (σ_d) of the distance values calculated from the detected observations. Hence, the constant value weighting will comprise nearly the 85 per cent of the real detections while lowering the initiation probability of the tracks which have usually distant observations to the gate center. The following part of the Elfes model resembles to an exponentially degrading profile. The beta versions of the generic exponential model and the Elfes model presents similar inclinations that both alleviate the decline of the exponential curve.

In Chapter 5, we explore the possible contributions of these track initiation counter weighting models and exhibit their tradeoffs.

4.3. Track Filtering and Track Initiation Architecture

The target tracking architecture is composed of several parts that are interconnected with each other. Detection, gating, association and filtering processes are exe-

cuted in harmony to achieve optimum localization and accuracy performance from the tracking operation. Tracking phenomena starts with the detection of the intended objects around the sensors as illustrated in Figure 4.8. As new observations are delivered by the sensing equipment, filtering of the previously detected tracks conveys to a gating area around the predicted track positions. If a suitable observation is found inside the gate for the intended track according to the association process, the track state estimation is updated by the new observation. NN association algorithm is the best choice in scarce target and clutter environments. However, as the situation starts to get denser in terms of the target number and clutter, NN association scheme generates increasingly overwhelming false tracks caused by the false alarms and in parallel to that phenomena, maintaining the true tracks becomes difficult. Moreover, JPDA and MHT association algorithms are better in cluttered and dense target environments. However, they require more computation power and memory resources. As we intend to commit target tracking with weak computation and energy powered tiny sensor devices, JPDA and MHT association algorithms appears to be extravagant for our wireless sensor network tracking system [15]. Though there are recent studies utilizing JPDA in multi-target tracking [78], we determined to utilize NN association algorithm in order not to exceed our energy and computation constraints and consequently have a better cost effective solution.

We utilize the Kalman filter for the state estimation process of the tracks. As the Kalman filter uses its prediction and observation information for the target state estimation, the association algorithm and the target's movement trajectory effects its performance. Actually, the Kalman filter with NN association algorithm is a good candidate for object tracking in sparse target and clutter environments while the possibility of an unrelated detection to coincide in the same gate is much lower.

While the NN association algorithm needs a track initiation procedure prior the association process, an initiation logic is required. In some applications, a simple *two-point differencing* initiation scheme can be adequate for this purpose [56]. However, in high cluttered and dense target environments, more sophisticated instruments to activate the initiation logic are needed. While there are algorithms like MHT that does

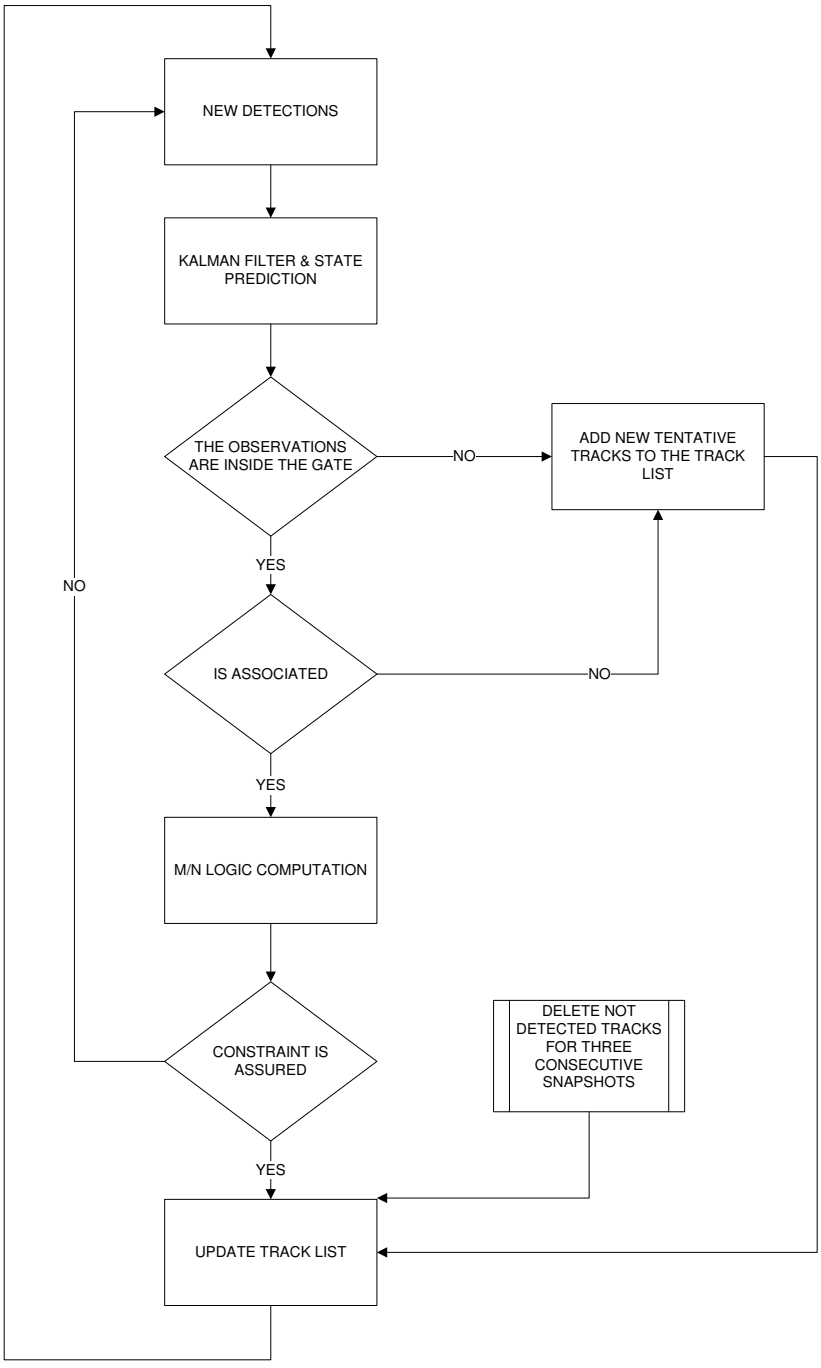


Figure 4.8. Track initiation flow diagram

not require a track initiation phase, M/N logic can achieve admissible performance and a better power saving policy for WSN applications. In Chapter 5, we try to scrutinize the effects and contributions of our proposed M/N logics that adjust their track initiation counter weights according to the distance of the observations.

Also, there may be some observations which coincide inside of a gate but have not been associated to any of the targets, or the observations can be totaly outside of any gate. In this situation, observations are send to the track list as a tentative track and will be tried to be associated with the consecutive detections. If any tentative track satisfies the constraints of the M/N initiation logic, a new target track is initiated.

This cycle continues for every new snapshot, and the track list is updated according to the track deletion and initiation constraints.

4.4. Clutter Generation Model

Clutters (false alarms) complicate the target tracking process while they effect the localization accuracy of the true tracks as well as confusing the sensors due to the initiated false tracks. Clutters can be formed from various factors like electromagnetic noise, heavy rainfall, habitat. Even the wind effects the sensor nodes via moving the sensor itself or the nearby leafs, bushes, trees [75].

According to the literature, it is assumed that the clutters are uniformly distributed over the sensing region and the number of these clutters follow a Poisson distribution [70, 74]. In [79], it is stated that "the number of clutters in area $10\,V$ yields the actual number of clutter points falling in area V" which is Poisson distributed with an expected number of clutter αV. α represents the spatial density in a Poisson model. The spatial density of the clutters in our model is the probability of false alarm, P_{fa}.

In [75], experiments are executed to acquire the detecting features of the TWR-ISM-002, Advantaca's radar sensor platform [80]. In the simulation, six walking passes

and four running passes are being done by a person in order to observe the radar signal trace. It is observed that two false alarms has detected in ten real detections. This gives a ratio of 0.2 false alarm probability. In another sensor network target detection application in [81], individual sensor's false alarm probability is set to $P_{fa} = 0.2$. Thus, it is plausible to use $P_{fa} = 0.2$ as the false alarm detection probability in our target tracking model as well.

A Poisson random number generator is presented in [82] and it is also utilized for a clutter generation application for target tracking issues in [74]. We utilized the same algorithm as our clutter generation scheme.

The input arguments of the generator are α, the probability of false alarm in our application, and V, the unit volume. The unit volume will be taken as the whole sensing volume of a sensor node. Since we assume that the number of clutters in $10\,V$ gives the actual number for the unit volume can generate, we will assume the unit volume as $10\,V$. As the assumed probability of false alarm is P_{fa}=0.2, we approach an average of the expected number of clutters for each snapshot of the sensor node as in Equation 4.1.

$$\lambda = P_{fa} \cdot V \tag{4.1}$$

Thus, for normal cluttered scenarios, we assume that we have on average λ=2 false alarm detections uniformly distributed inside the sensing region of each sensor. While we do not have the ROC curves of the Advantaca sensor nodes, we assume the detection probability as P_d=1. Also we assume that the false alarm and the detection probabilities are identical for all sensors.

5. RESULTS OF THE SIMULATIONS ON COLLABORATION DECISION WITH FUZZY INFERENCE SYSTEM AND THE NEW *M/N* BASED TRACK INITIATION LOGICS

5.1. Comparison of the Fuzzy Inference System with Other Information Utility Measures for Collaboration Decision

In order to build up a fuzzy inference system, we utilize the Fuzzy Logic Toolbox of the Matlab Simulator [83]. Our fuzzy system is based on two membership functions. These membership functions have the properties of mutual information and Euclidean distance metrics. We converged two metrics via the fuzzy inference logic of Mamdani's type [69, 84]. Our new collaboration logic decides whether to broadcast information or not according to the result of the fuzzy inference system. The three-dimensional view of the fuzzy inference mapping from input membership functions to output membership function in fuzzy inference system is in Figure 5.1.

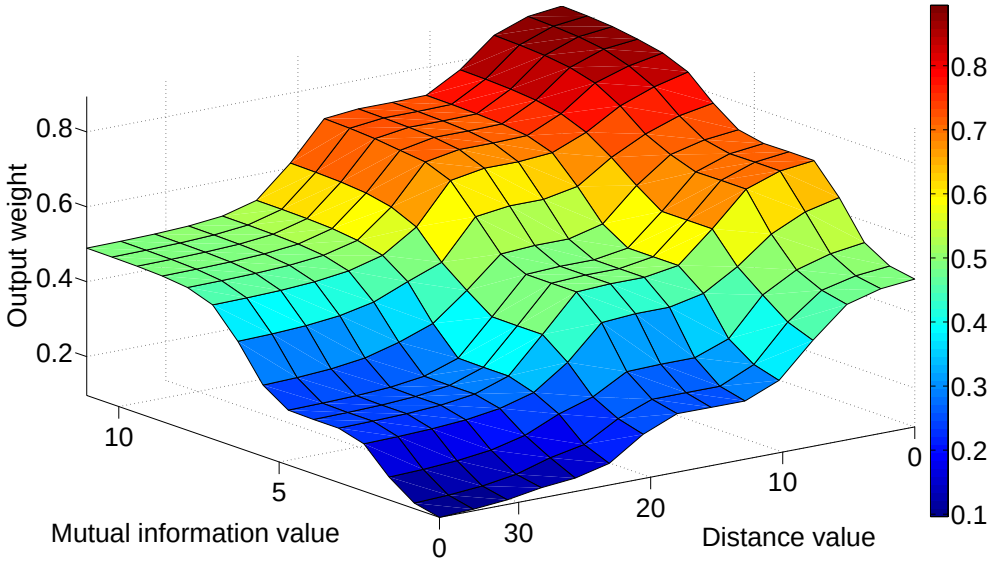


Figure 5.1. Fuzzy mapping of input variables to output variable

In the simulations, we use the parameters listed in Table 5.1. We run the simulations for 20 times with different seeds and in the result graphs, average of these 20 runs are presented. Sensors are randomly deployed to the area and one target is randomly roaming through the tracking area. The simulation area is a square with 200 meters side length. We utilize the TWR-ISM-002-I radar sensor [80] with approximately 18 meters detection range. While the communication range is much more than the sensing range, the collaboration of the more informative sensors provide an opportunity to a wide range of sensors to update their target belief states with a consistent view. Hence, we have nearly similar and accurate target localization among the sensors, due to the robustness and flexibility of the distributed wireless sensor network architecture.

Table 5.1. Simulation parameters for the fuzzy inference system based collaboration logic metric

Parameter	**Value**
Area Size	200x200 m^2
Scan Period	100 times
# Sensors	300, 800
Sensor Max. Communication Range	110 meters
Sensor Max. Detection Range	18 meters
Communication Model	Shadow fading
Detection Model	Binary

We divide our scenarios into two parts as sparse and dense. The sparse scenario is build with 300 sensors while the dense one comprises 800 sensors. The simulation time consists of 100 scan periods (snapshots) for both scenarios.

We compare the information utility measures which stated by Onel *et al.* in [59] with the proposed fuzzy logic inference system metric. We consider the single target tracking case for the sake of concentrating on the performance of the proposed fuzzy logic inference system for collaboration decision. We compare five metrics in our

simulations. The maximum mutual information, the minimum Mahalanobis distance and the random target selection metrics are from Onel *et al.*'s work, and the other two is the Euclidean distance and fuzzy inference system metrics.

In Figure 5.2, the mean target localization error comparison of the five metrics are illustrated. The random and the minimum Mahalanobis distance sensor selection strategies show worse performances than the other three metrics. Euclidean distance, mutual information and the fuzzy inference system metrics show similar performance in the mean target localization error comparison case. Also, it is clear that the increase in the number of collaborating sensors improves the tracking performance all over the network. When the number of sensors allowed to communicate is one, Euclidean distance, mutual information and fuzzy inference system metrics achieve approximately 17 per cent and 11 per cent tracking quality improvement, in terms of the target localization accuracy, over the random and minimum Mahalanobis distance metrics, respectively. As the number of sensors allowed to communicate ascends, the mean error values decreases and converges. In the dense scenario, which is illustrated in Figure 5.3, similar performance for the compared metrics are observed. However, the mean error value convergence of the metrics occurs more slowly.

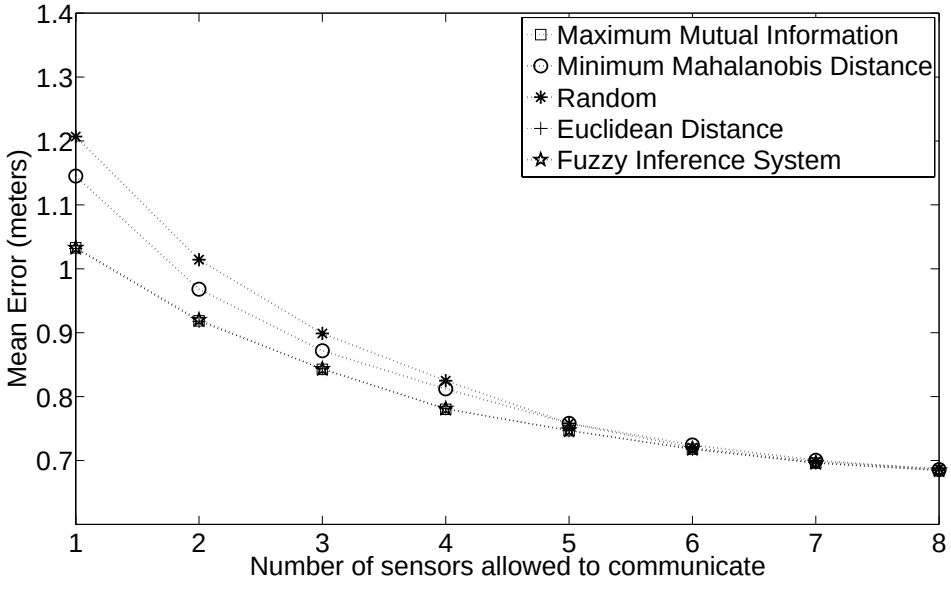


Figure 5.2. Mean error comparison for the sparse scenario

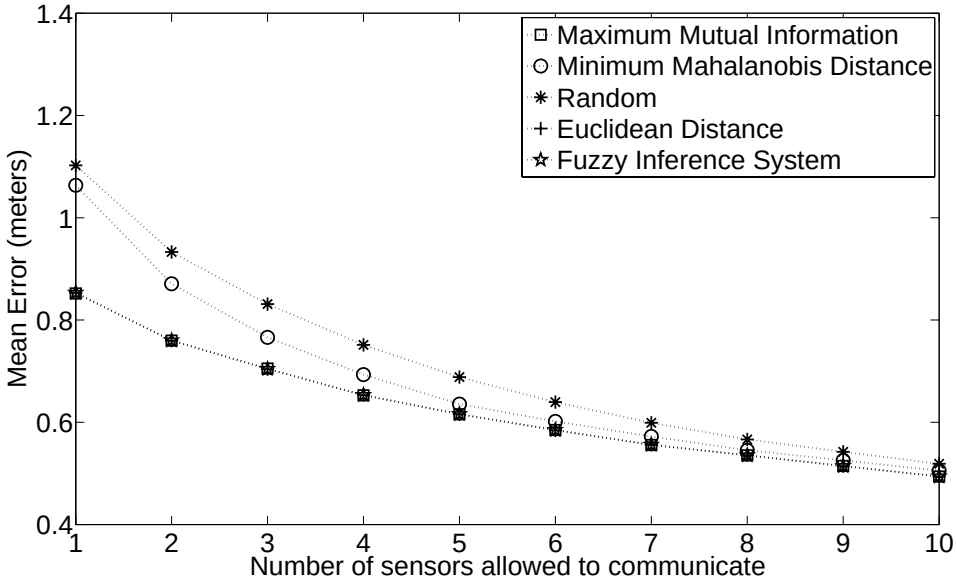


Figure 5.3. Mean error comparison for the dense scenario

In Figure 5.4, the total energy consumption volume is illustrated for all five sensor selection metrics in the sparse scenario. As the number of sensors that are allowed to communicate increases, the number of transmitting sensors increases and this leads the system to consume more energy. While the sensor selection metrics have no difference in terms of the energy consumption policy, all five metrics show similar performance for the energy usage.

When we compare the energy usage versus the average target localization error of the sensor selection metrics, the tracking error increases proportionally to the decline in energy consumption. Moreover, utilizing the maximum mutual information, Euclidean distance and the fuzzy inference system metric yields better localization performance even in low energy consuming scenarios as in Figure 5.5 and Figure 5.6 for sparse and dense networks, respectively. When we compare the sparse and dense scenarios in terms of the maximum energy consumption, the sparse scenario reach its peak value with 0.7 joules while the mean error was nearly 0.7 meters.

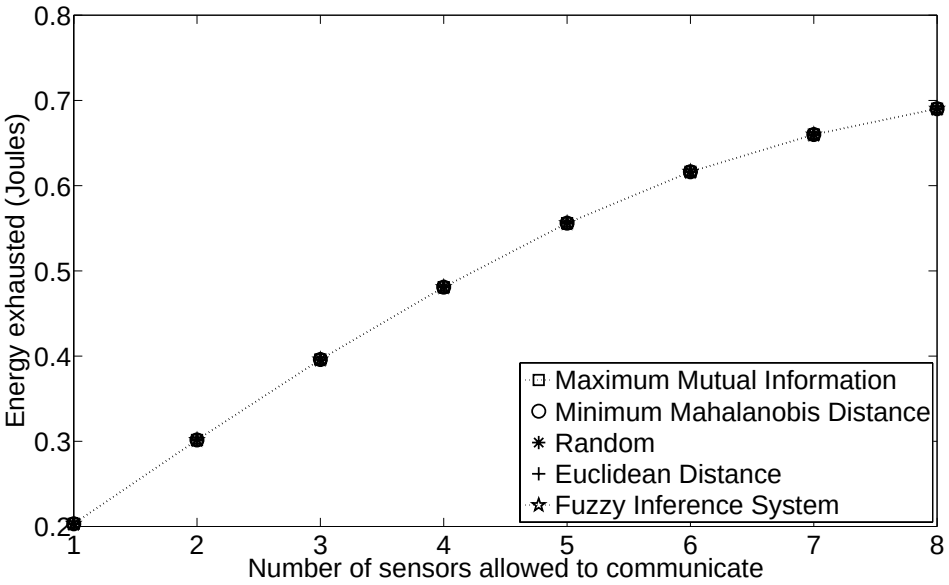


Figure 5.4. Comparison of the consumed energy for the sparse scenario

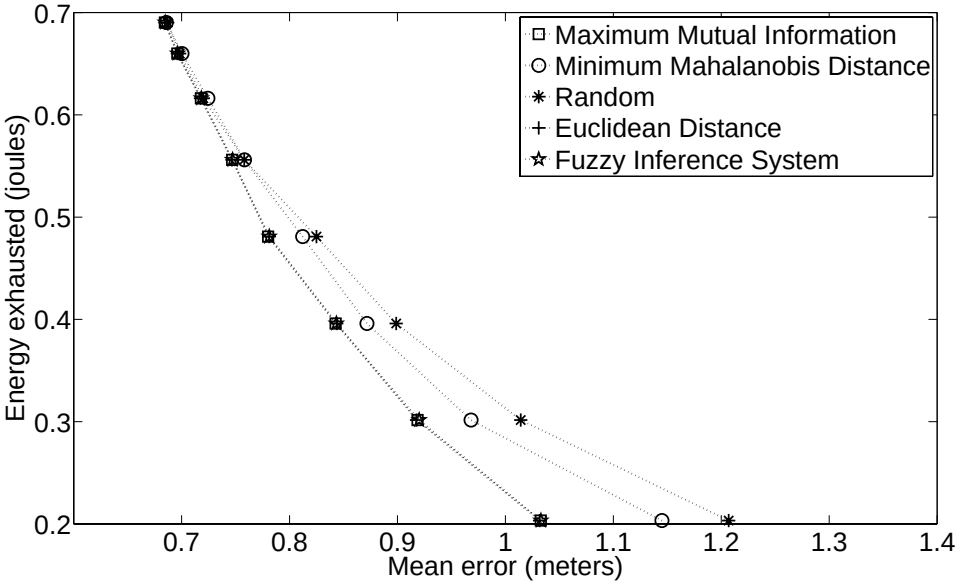


Figure 5.5. Comparison of the consumed energy for the desired target localization accuracies for the sparse scenario

However, in the dense scenario, the peak energy consumption value is approximately 2.8 joules while the mean localization error is nearly 0.5 meters. In this respect, increasing the number of sensors in the tracking area escalates the amount of energy

spent in the network. Nevertheless, mean localization error of the system improves significantly.

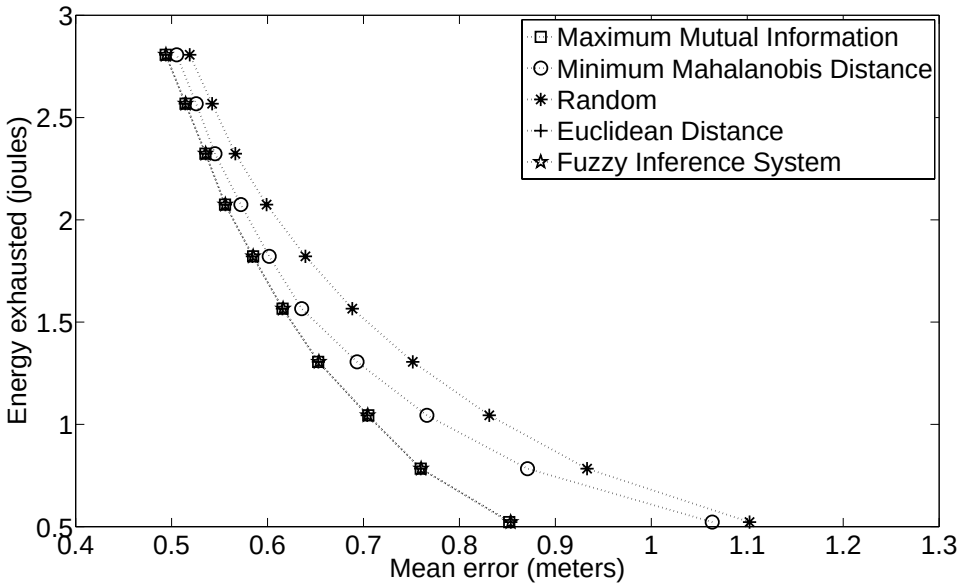


Figure 5.6. Comparison of the consumed energy for the desired target localization accuracies for the dense scenario

5.2. Comparison of The Track Initiation Methods with Linearly Moving Targets in Cluttered Environments

We also aim to improve the track initiation logic performance. We utilize prospective target movement patterns in our simulations in order to have realistic scenarios. Target's movement patterns can be in various types according to the application. In our scenarios, we propose the targets as the intruders to an area. It is expected that an intruder trespasses the region as soon as possible in order to avoid being detected. Hence, we try two different target movement patterns in our scenarios to simulate a realistic intruder.

In the first scenario, the target's movement pattern is regarded as a linearly trespassing intruder. The wireless sensor nodes are scattered randomly in to a 200x200 meters area. Three targets enter the area from eastern side and there are 60 meters

distance among them. The scenario layout is as in Figure 5.7, in which the observation and Kalman filtering processes of the sensor node located at (70,157) are also illustrated. A closer view of this tracking process is given in Figure 5.8.

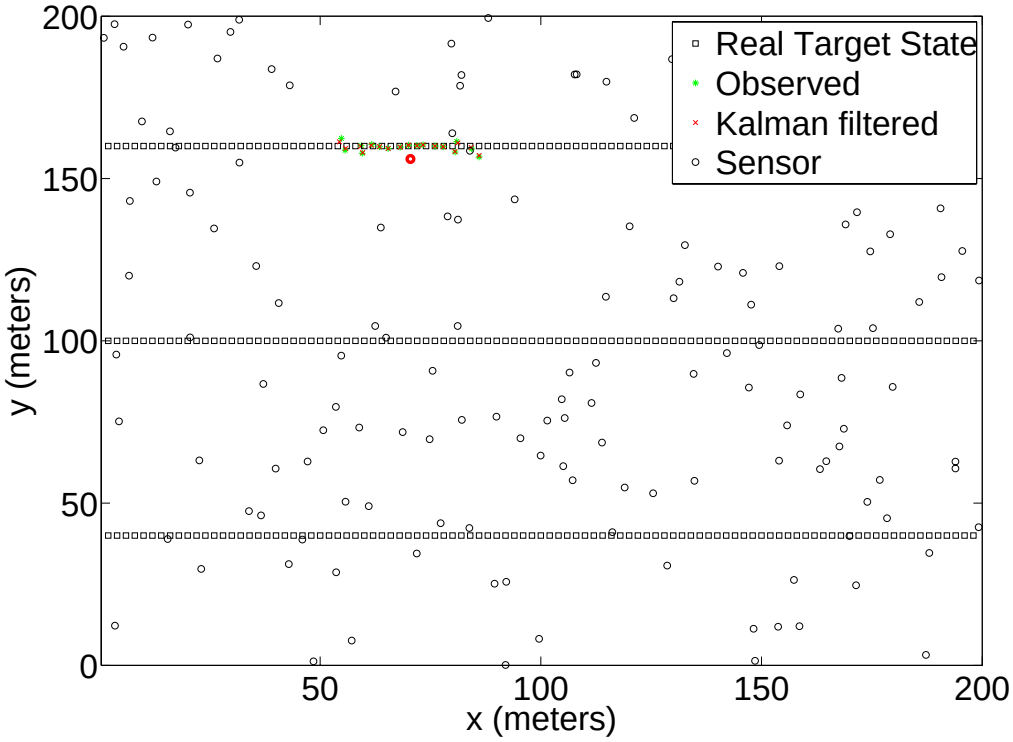


Figure 5.7. Linearly trespassing scenario layout

As seen from Figure 5.8, the tracking performance of the sensor (70,157) gets better as the distance of the target decreases. Also, the decline in the angular change of the target is crucial for the tracking performance treatment issue. In the first detections, sensor node's observations are not consistent due to the noise and distance, therefore the Kalman filter's location predictions are erroneous. As the target gets closer, observations become more consistent and the track localization error decreases significantly.

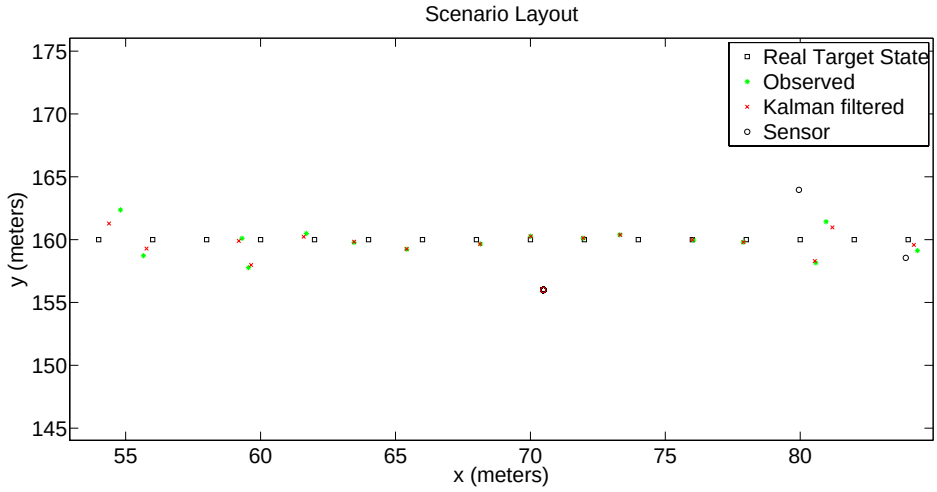


Figure 5.8. Closer view of the tracking process

The simulation parameters for the performance evaluation of the M/N logic track initiation counter weighting models are presented in Table 5.2. We utilize the same 200x200 meters square area for our simulations. The duration of the simulations are 100 scan periods. While we are aiming to develop a new track initiation logic that is robust in cluttered environments, we designed to scatter the wireless sensor nodes proportional to the area in plausible numbers. Thus, 150 sensor nodes are scattered randomly to the simulation area as it can cover nearly four times bigger than the simulation area if it were placed uniformly. Three targets are roaming in the simulation area. In our first scenario, the targets are moving linearly from one side to the other side.

The communication and the detection range parameters of the sensor nodes are according to the features of the TWR-ISM-002-I radar sensor [80]. The shadow fading model is applied our simulation environment to model the wireless communication media. While the actual detection range of the sensors are changing due to the observation covariance, we utilize a binary detection model considering the noise effect in the measurements. If the measured range of the target is inside the 18 meters range of the sensor, it is ratified as a detection.

The parameters explained above are valid for all track initiation models in the simulations. There are two parameters that we have altered to observe the effects in the

simulations. These are the false alarm probability and the M/N logic. We apply two different scenarios as normal and dense cluttered which supposed to be P_{fa}=0.2 and P_{fa}=0.25, respectively. While a typical initiation confirmation criteria can be three out of four or three out of five as stated in [85], we use the 3/5 M/N track initiation logic in our early simulations.

Table 5.2. Simulation parameters for track initiation

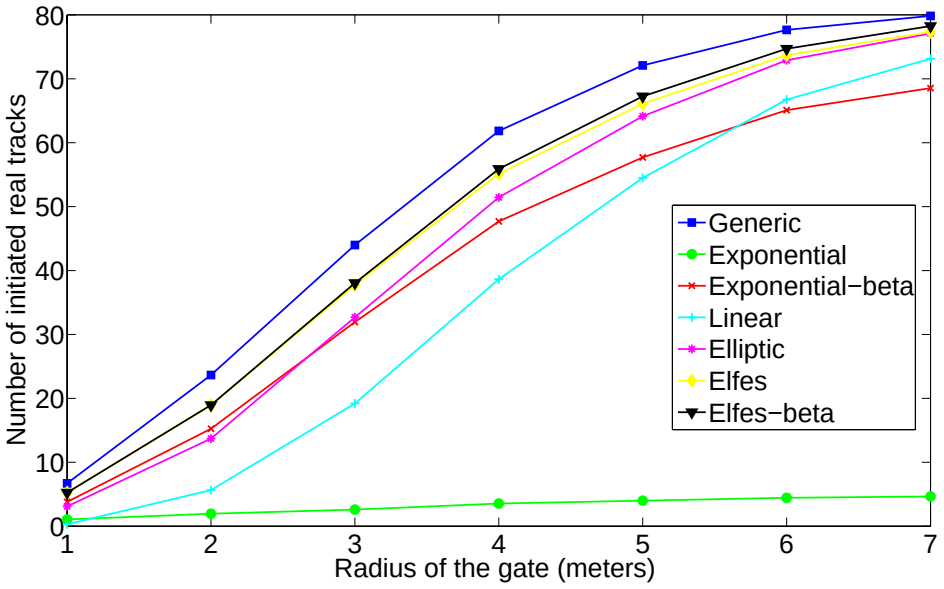
Parameter	**Value**
Area Size	200x200 m^2
Scan Period	100 times
Number of Sensors	150
Number of Targets	3
Sensor Max. Communication Range	110 meters
Sensor Max. Detection Range	18 meters
Probability of Detection	P_d=1
Probability of False Alarm in normal/dense cluttered scenario	P_{fa}=0.2, 0.25
Expected number of clutter in normal/dense cluttered scenario	λ=2, 2.5
Communication Model	Shadow fading
Detection Model	Binary
Initiation Logic	M/N=3/5

Our first interest is on the differentiations of the M/N logic track initiation methods in terms of the true and the false track generations. Gating has a significant impact on the number of track initiations. As the circular gate radius increases, the number of true track initiations increase radically. However, this situation also yields more false initiations as a tradeoff. Our proposed M/N logic-based methods are for alleviating the effect of that tradeoff in favor of true track initiations. As seen in Figure 5.9, generic M/N logic achieves the best performance in terms of the true track initiations. However, the number of false track initiations are also the highest with the generic M/N method.

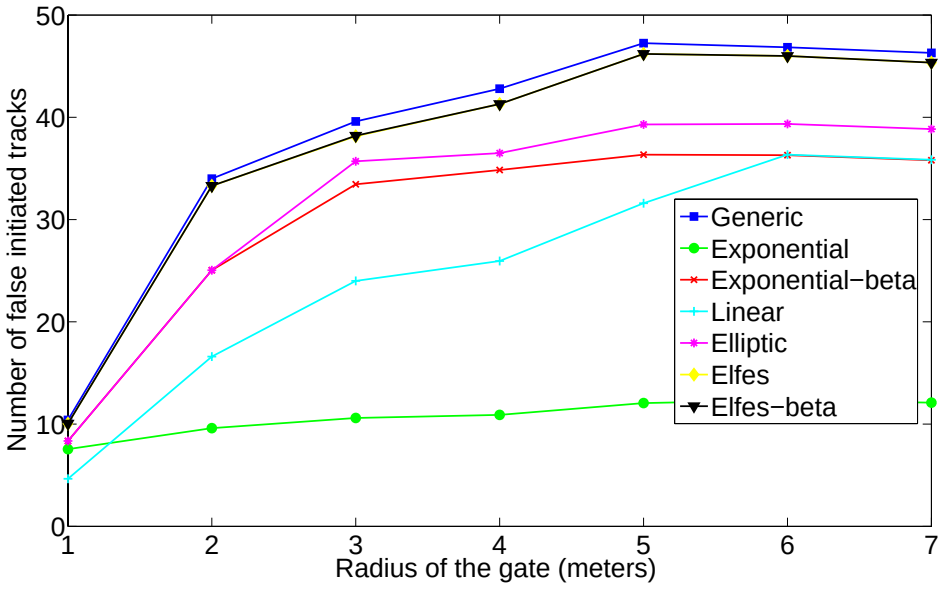
In Figure 5.9 (a), The Elfes and Elfes-beta methods exhibit the same performance and show a close trajectory to the generic track initiation method. The elliptic and exponential-beta methods show similar performances till the gate radius is 3 meters. Afterwards, the elliptic model converges to the Elfes models while the exponential-beta model could not continue to rise like the elliptic model. The linear track initiation counter weighting model has a slow start, but it achieves to approach the performance of the elliptic model when the gate radius is 7 meters. The exponential model has the worst performance on the true track initiation case.

In Figure 5.9 (b), the performance sequence of the track initiation counter weighting models is nearly the same, but in inverse order. The exponential model exhibits the best performance while not allowing too many false alarm initiations. The linear method shows a good performance while the gate radius is small. As the gate radius increases, the linear, exponential-beta and elliptic models exhibit similar false alarm generation performance. As the generic and Elfes models exhibit the best performance on true track generation case, they show the worst performance on false alarm track generation.

As seen in Figure 5.10, similar results are observed for the true track initiations while the false alarm probability is increased to P_{fa}=0.25. However, the number of false initiated tracks nearly doubles in comparison with the normal cluttered scenario. Moreover, the distinction among the methods diminish and their performance converges to each other except the exponential model.

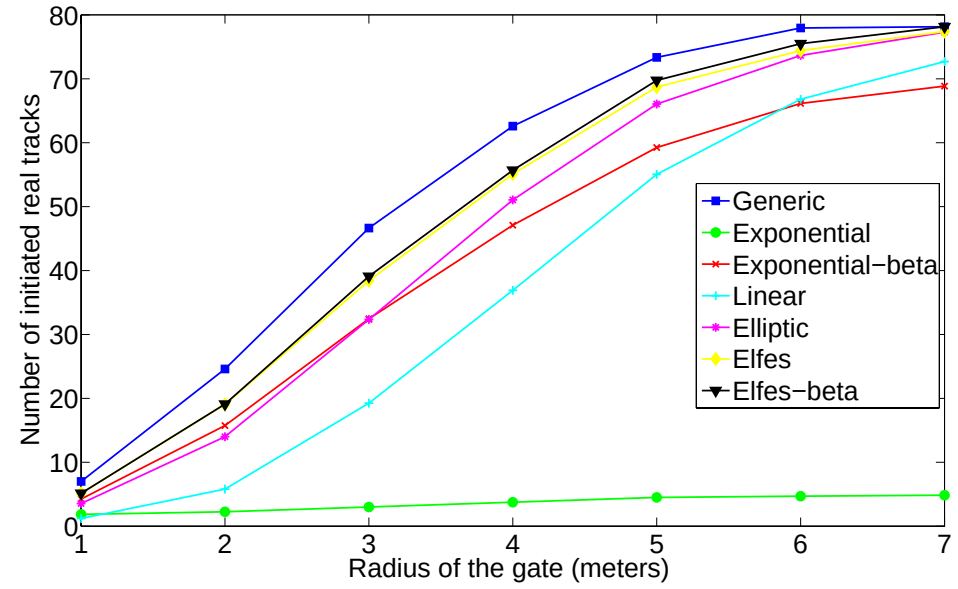


(a)

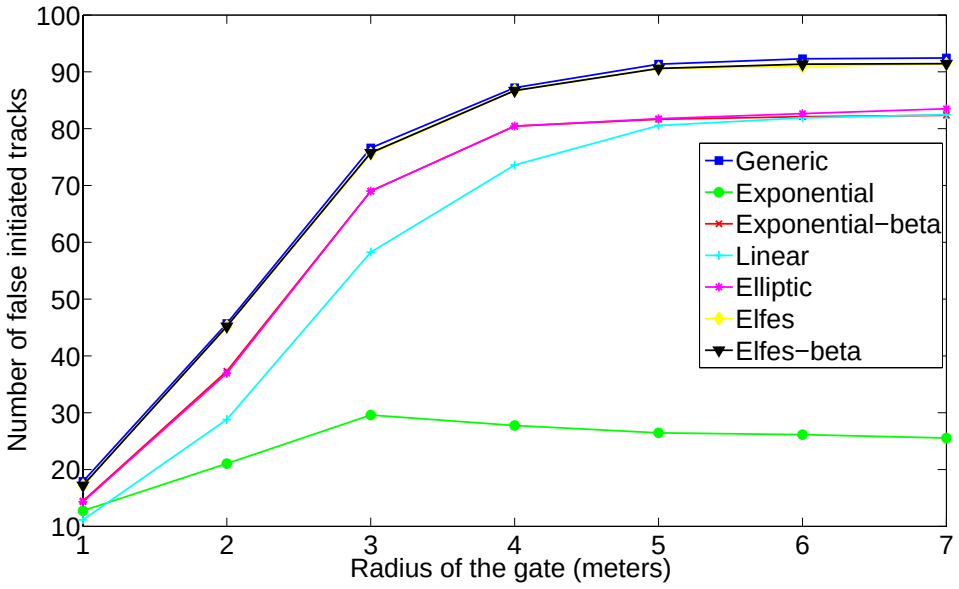


(b)

Figure 5.9. In normal cluttered environments with linear moving targets (a) True track initiations according to various gate radius and (b) False alarm track initiations according to various gate radius



(a)



(b)

Figure 5.10. In high cluttered environments with linear moving targets (a) True track initiations according to various gate radius and (b) False alarm track initiations according to various gate radius

As the number of true track initiations increases with the rise in the gate radius, the number of tracks generated by the generic *3/5* method approaches to the real number of true tracks that can be generated while the gate radius is seven meters. As the real number of true tracks that can be generated is reached when the gate radius

is seven meters, we will focus our research on that saturation point. The true and false track initiation comparison among the M/N track initiation counter weighting models in normal clutter environment while the gate size is seven meters is shown in Figure 5.11.

The generic M/N method yields 46.3 false initiated tracks on the average while all the true track generations are achieved. In that circumstance, exponential-beta, linear and elliptic methods succeed to reduce the false track initiations. Especially, the elliptic model achieves to reduce the number of false initiated tracks with 16 per cent while the true initiations only degrades 1.5 per cent. The linear and exponential-beta track initiation models also provide a decrease in the number of false track initiations but the true track initiations are reducing seven per cent and 14 per cent, respectively. While the false track initiations are decreasing 22 per cent for both the linear and exponential-beta model, the tradeoff must be envisaged. The exponential and the Elfes models achieve significant performance in terms of reducing false initiated tracks and increasing the number of true track initiations, respectively. However, all three models are not contributing any progress due to the decline in the true track initiations and gain in the false initiated tracks in an unacceptable level.

In Figure 5.12, it is seen that the effect of high cluttered environment increases the number of the false initiated tracks overwhelmingly. However, the elliptic model still achieves to reduce the number of false initiated tracks by 10 per cent while the true initiations decrease only one per cent. Besides, the linear and the exponential-beta models exhibit similar performances with the elliptic model for decreasing the false initiated tracks, but the elliptic model outperforms both of the models while it achieves to sustain more true initiated tracks.

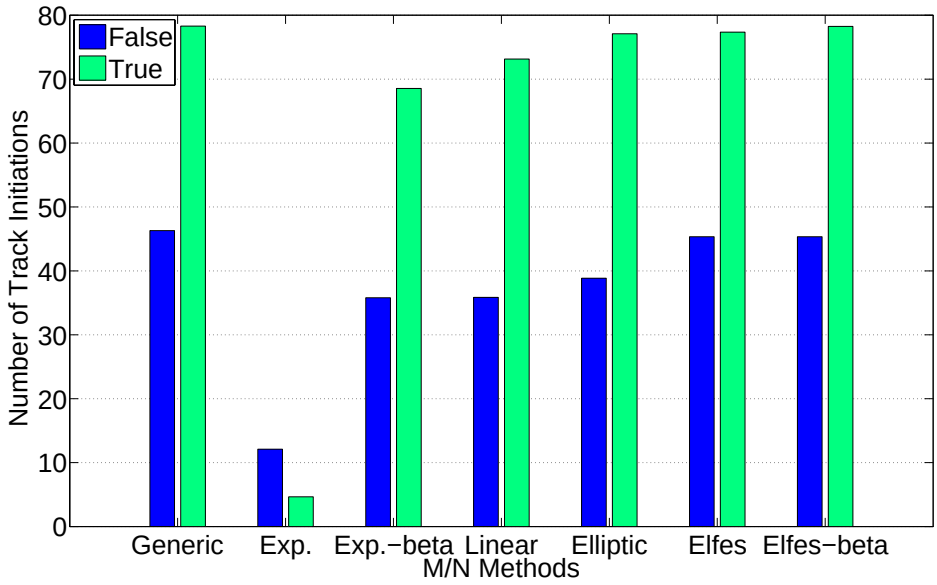


Figure 5.11. True and false track initiation comparison among the M/N methods in normal clutter while the gate size is seven meters

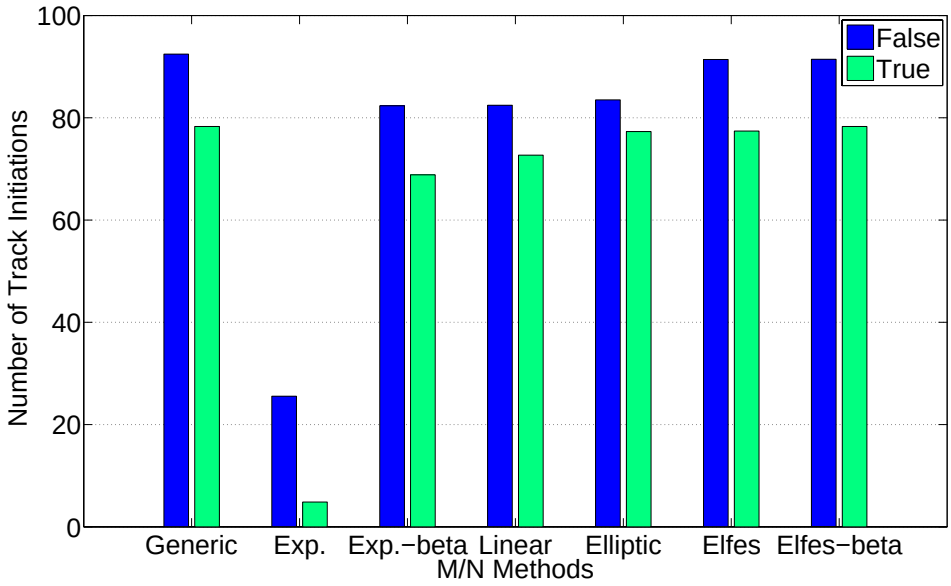


Figure 5.12. True and false track initiation comparison among the M/N methods in high clutter while the gate size is seven meters

5.3. Comparison of The Track Initiation Methods with Randomly Moving Targets in Cluttered Environments

In this section, we examine the changes of the number of true and false track initiations while the targets are randomly moving in the simulation area. The layout of the randomly moving targets can be seen in Figure 5.13. The figure also illustrates the tracking process of a sensor node for two targets. All the simulation parameters utilized in the scenario are the same as Table 5.2. We suppose to scrutinize the effect of probability of false alarm differentiations to our M/N logic track initiation models for the random moving targets.

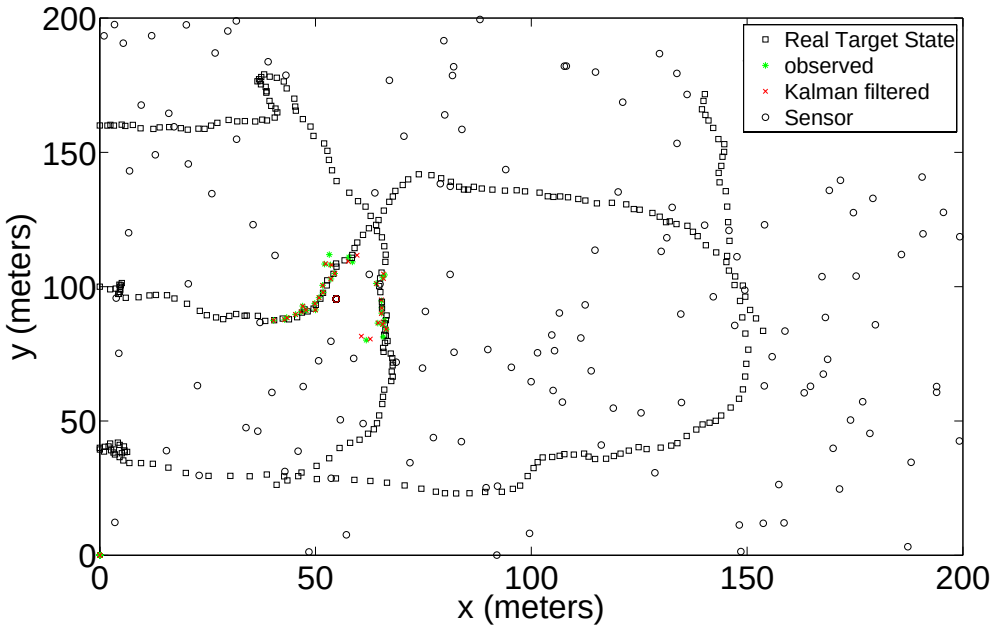
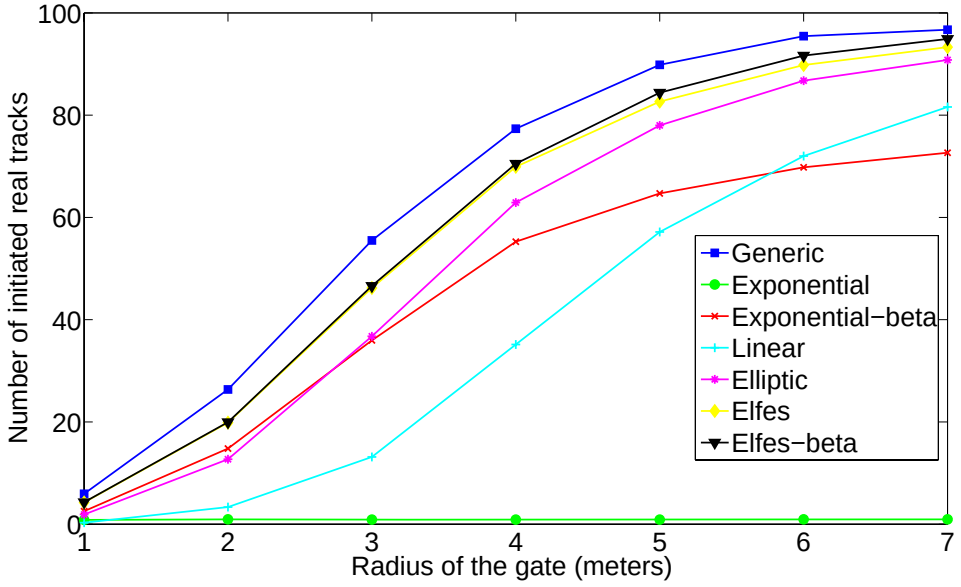
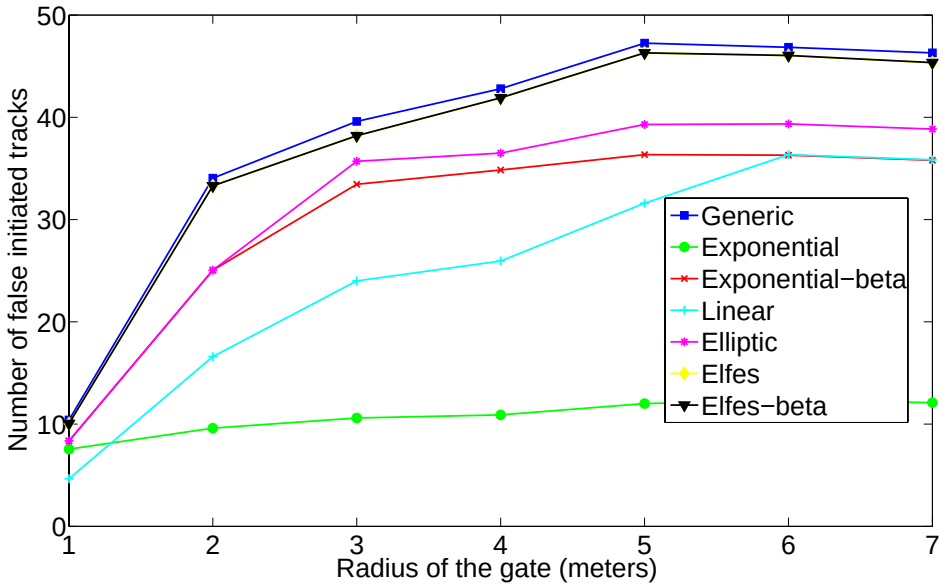


Figure 5.13. Scenario layout for random moving targets

When the movement pattern of the targets are changed to random, no significant change has been detected in the initiation pattern of the M/N initiation models. However, as the randomly moving targets are roaming more on the network area, more sensors can detect the targets which lead to an approximately 23 per cent increase in the number of real true track initiations.

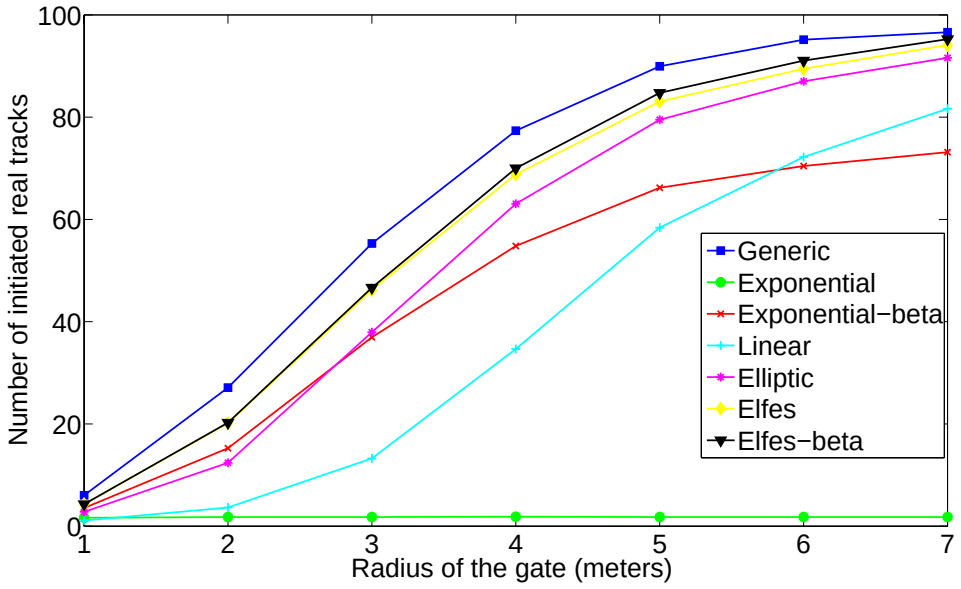


(a)

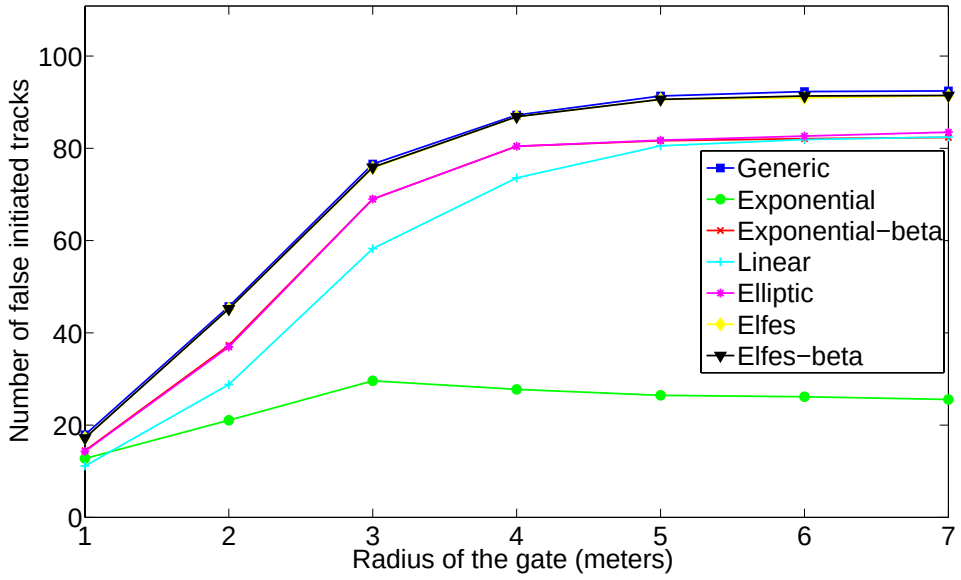


(b)

Figure 5.14. In normal cluttered environments with roaming targets (a) True track initiations according to various gate radius and (b) False alarm track initiations according to various gate radius



(a)



(b)

Figure 5.15. In high cluttered environments with roaming targets (a) True track initiations according to various gate radius and (b) False alarm track initiations according to various gate radius

When we examine the performances of the M/N initiation models for the gate radius equal to seven meters for the randomly moving target scenario, it can be noticed that the performance of the elliptic model is similar for the false alarm track generation case as the same clutter generation parameters are utilized. There is 16 per

cent reduction in the false generated tracks with the elliptic model as in the linearly moving target's scenario. However, the reduction in the number of true track initiations becomes six per cent which is four times bigger than the linearly moving target's scenario.

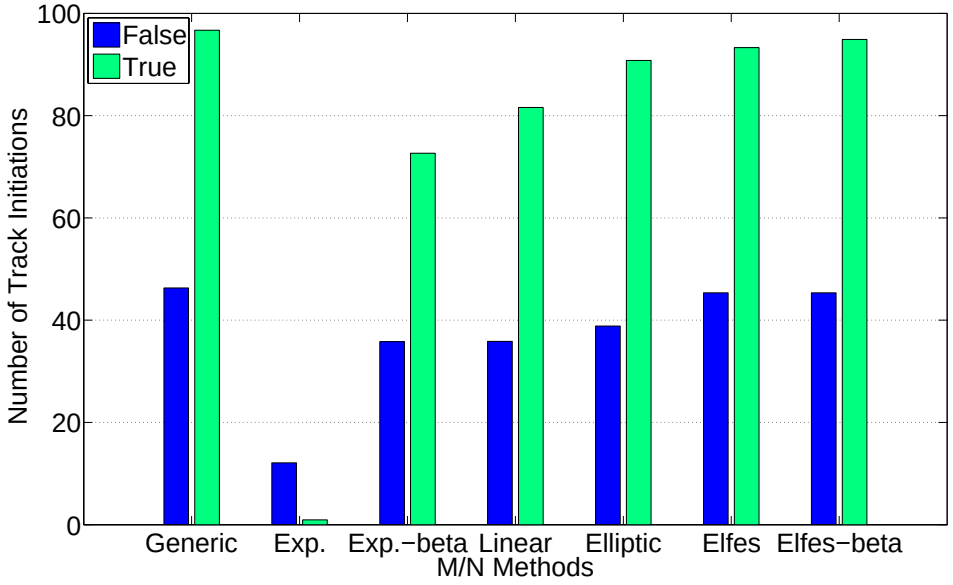


Figure 5.16. True and false track initiation comparison among the M/N methods in normal clutter while the gate size is seven meters

The high cluttered scenario for randomly moving target's when the gate radius is seven meters is illustrated in Figure 5.17. The numbers of the false track initiations are overwhelmingly increased as in the linearly moving target scenario. Moreover, the true track initiation number is decreased by five per cent while the number of false alarm initiations are decreased 10 per cent according to the generic model. The decline in the true track initiations are five times bigger than the linearly moving target scenario.

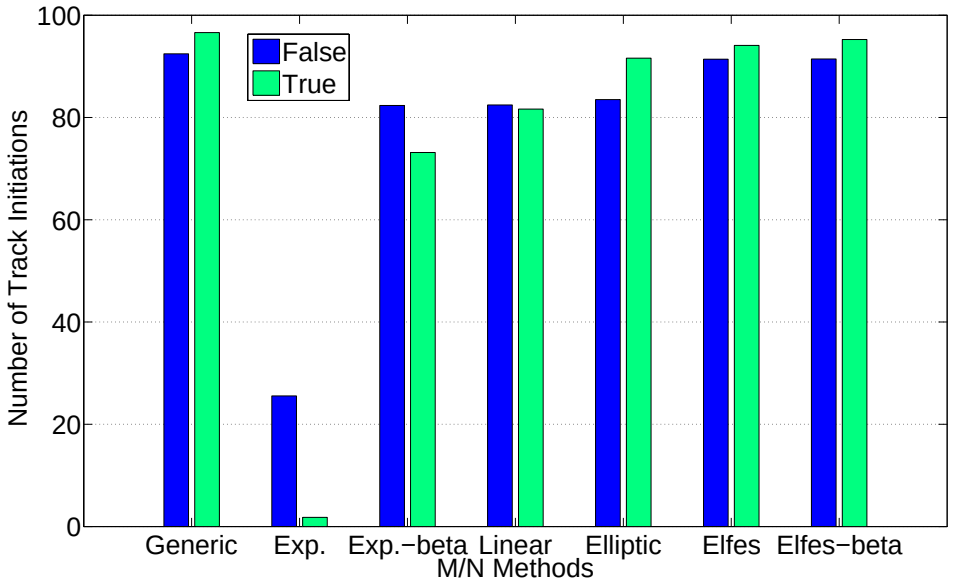


Figure 5.17. True and false track initiation comparison among the M/N methods in high clutter while the gate size is seven meters

5.4. Effect of Various M/N Logics on Track Initiation Process

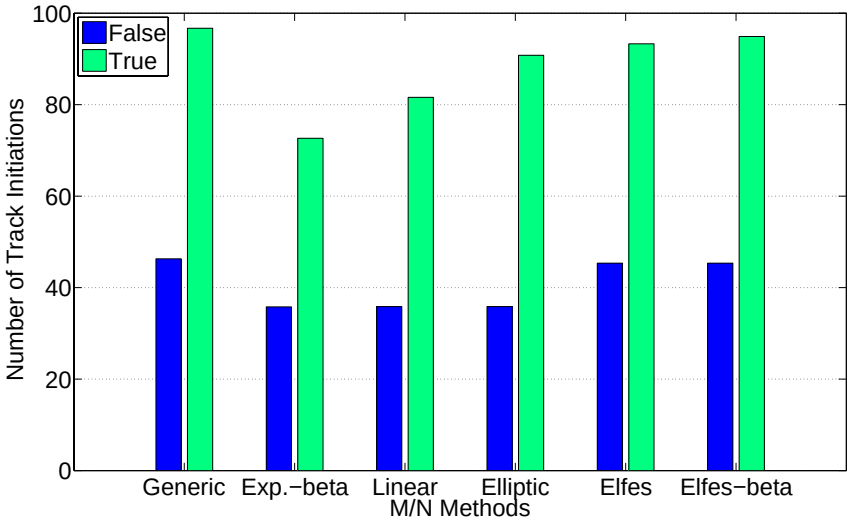
In this section, we will try to observe the performance changes while the M/N logic's numerator is altering. The numerator part of the M/N logic determines whether the initiation logic will approve the tentative track as a new track. When the numerator augments, the initiation time will increase comparatively. However, as the initiation constraint becomes difficult, the number of true track initiations degrades as well. All of the simulations in this section are executed with the randomly moving target scenario illustrated in Figure 5.13. The clutter level for the simulations is assumed to be in normal condition in which the probability of false alarm is P_{fa}=0.2.

In Figure 5.18, three types of the $M/5$ logic is compared in terms of true and false alarm track initiations. While the best performance is obtained with the elliptic track initiation counter weighting model in the previous simulations, we decide to check the situation in different $M/5$ logics.

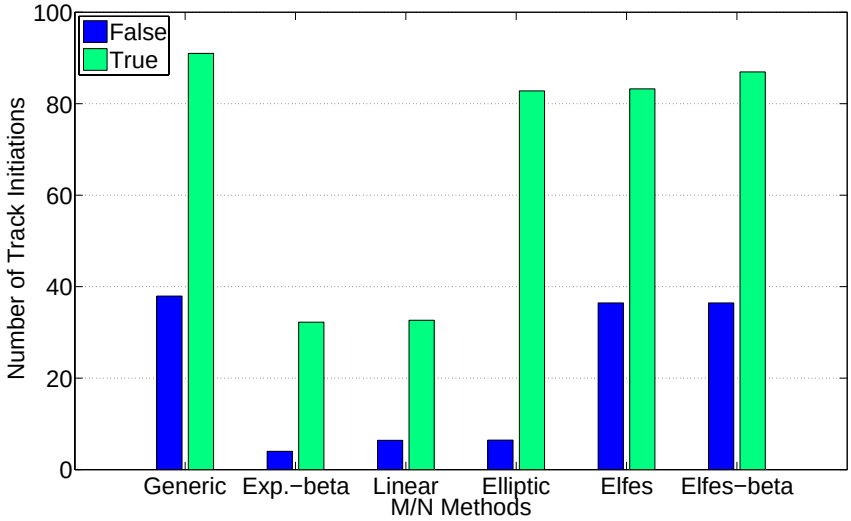
As we know from Section 5.3 that the *3/5* elliptic model decreases the true track initiations only six per cent while a 16 per cent decline in the false initiated tracks is achieved. The performance improvement gained with the elliptic model is far better in *4/5* initiation logic. In Figure 5.18(b), it is clear that the elliptic track initiation logic exhibits a significant contribution in terms of alleviating the false alarm track initiations. Moreover, it diminishes the false track initiations nearly six times with respect to the generic *M/N* track initiation logic. Only 17 per cent of the false initiated tracks remain while the 91 per cent of the true tracks are sustained. However, when the track initiation logic becomes *5/5*, all the effect of the elliptic model vanishes, as expected.

For a more conservative initiation logic, we try *M/7* to observe the performances of the initiation methods. In Figure 5.19, the elliptical model again shows a significant performance improvement while it decreases the false initiated tracks and preserves the true track initiations in a plausible level. Especially in *6/7* initiation logic, elliptical model reduces the false initiated tracks nearly 10 times better than the generic track initiation method. In addition to that, 85 per cent of the true initiated tracks are sustained by the *6/7* elliptic track initiation model. Thus, it is clear that as the numerator of the *M/N* logic ascends, the elliptical method shows better performance on reducing the false track initiations, except the *N/N* level.

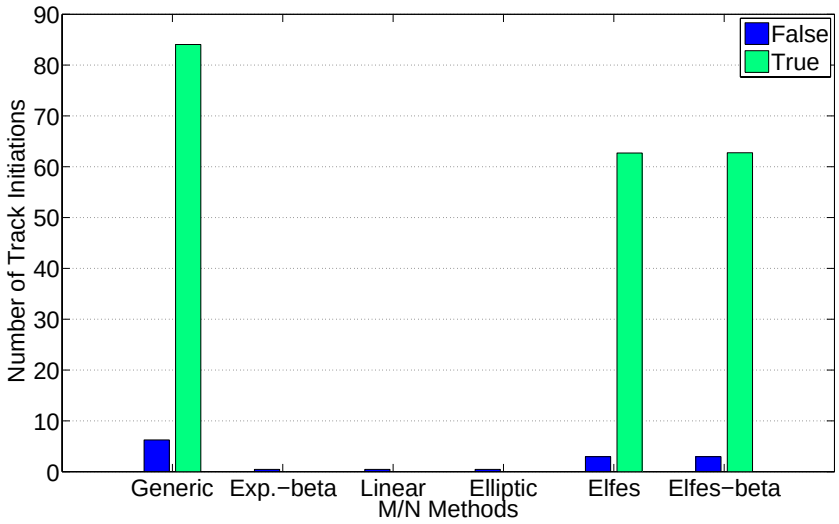
As we know that a typical initiation confirmation criteria can be three out of four as stated in [85], we decide to test *M/4* logics as well. In the previous simulations, we have scrutinized three out of five initiation criteria. If it is crucial to reduce the initiation time, *M/4* logic can be used for this purpose. In Figure 5.20, the comparison of *M/4* logic can be observed. Similar to the *6/7* elliptic track initiation logic, the *3/4* elliptic track initiation logic in Figure 5.20(b) exhibits a great contribution on the false initiated track mitigation process. The elliptical model achieves to minimize the false initiated tracks nearly 6.5 times better than the generic *3/4* initiation logic can do. Moreover, the true track initiations are only decreased seven per cent according to the generic model.



(a)

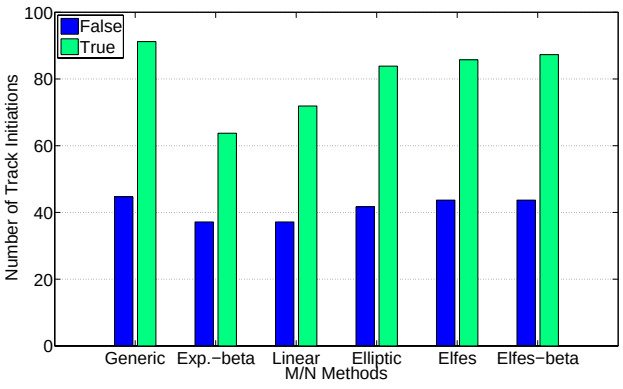


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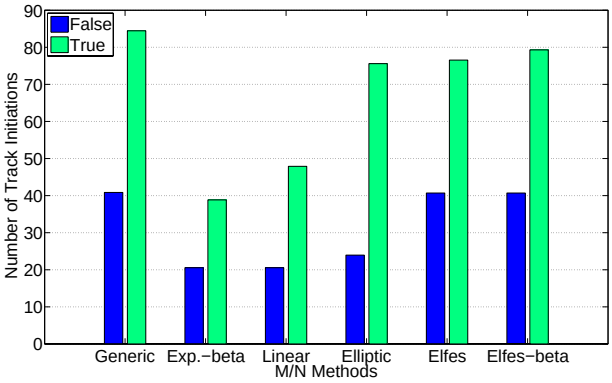


(c)

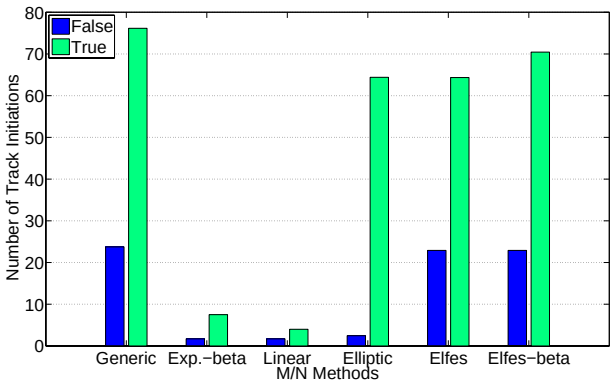
Figure 5.18. (a) 3/5, (b) 4/5 and (c) 5/5 Initiation logic



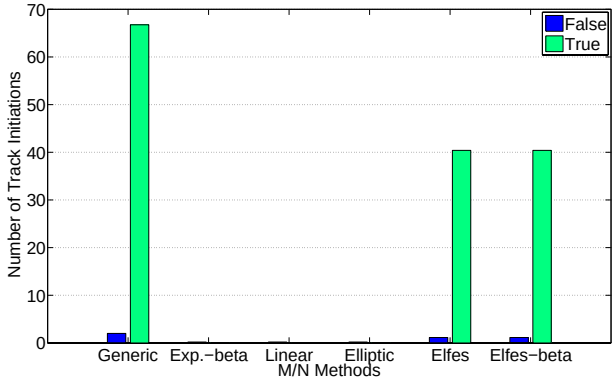
(a)



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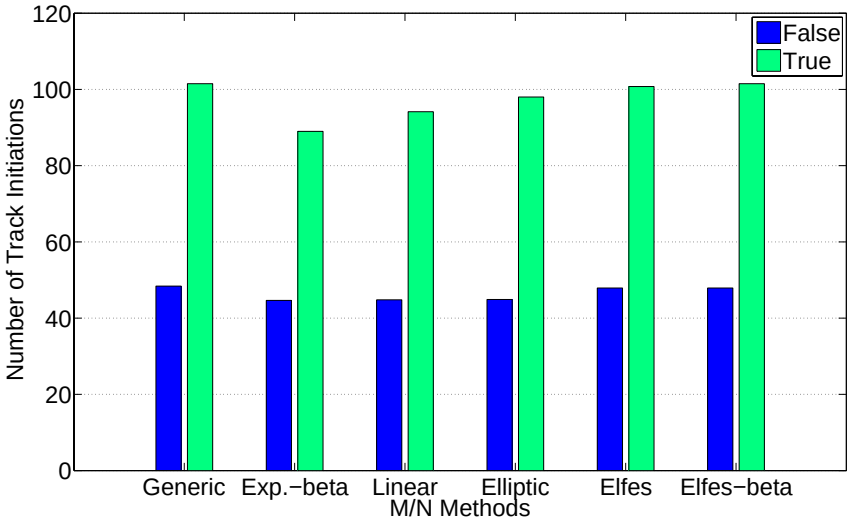


(c)

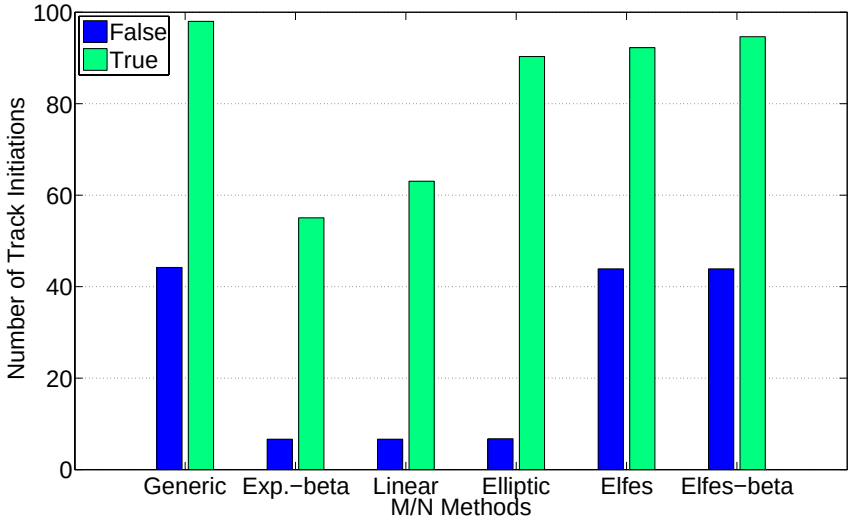


(d)

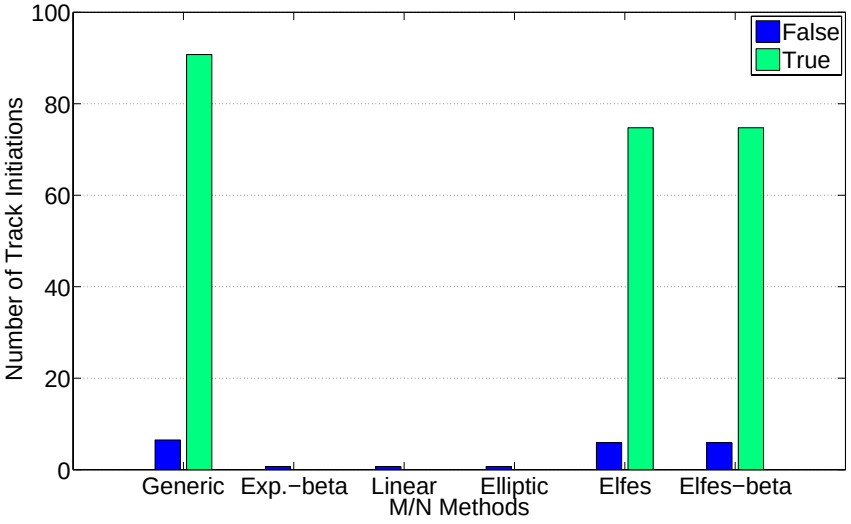
Figure 5.19. (a) 4/7, (b) 5/7, (c) 6/7 and (d) 7/7 Initiation logic



(a)



(b)



(c)

Figure 5.20. (a) 2/4, (b) 3/4 and (c) 4/4 Initiation logic

6. CONCLUSIONS

Our first intention is to develop a better collaboration logic for the target tracking phenomena in WSNs. The intense research on the collaboration logic is to find a new sensor selection strategy that can lead to allow the most informative sensor nodes to transmit their data. Thus, we can decrease the target localization error throughout the network while alleviating the redundant power consumption issues. In this respect, we designed a fuzzy inference system to determine which sensor to collaborate its target state information with the network. According to the simulations that we have tried, we saw that the Euclidian distance metric shows slightly the same performance with the maximum mutual information metric. When we scrutinize the sensor information ranking lists of these two metrics, we see that the order of the sensors is quite different. Thus, how can be the results of these two metrics has nearly the same performance. This occasion inclined us to join these two metrics in a smart way to gain the advantages of each one in order to build a better sensor selection measure. Therefore, we decided to try a fuzzy logic inference system to merge these metrics as an output ruler.

Consequently, we attained nearly the same performance with the fuzzy inference system metric versus the maximum mutual information metric. The hardest problem in the fuzzy logic is to thoroughly understand and precisely define the problem, and then we must be able to evaluate and fine-tune the results. We tried numerous trials via changing the fuzzy rule weights and values, but we could not achieve a significant improvement on the tracking quality of the sensor nodes. The reason why we could not beat the maximum mutual information and the Euclidean distance metrics lies on the familiar behavior of the input membership values of the fuzzy inference system: Euclidean distance and mutual information metrics. Both metrics generates almost the same performance on average localization error comparison. If the results of the metrics on the average error localization were diverse and complementary, fuzzy inference system would yield better performance than the Euclidean distance and mutual information metrics.

Actually, there is a rule of thumb that if we have an analytical solution for a problem, the fuzzy logic inference system would not give a better result in most of the cases. That vision would guide us to utilize the fuzzy inference logic in appropriate issues.

The second objective of this thesis is to find a new *M/N* track initiation logic in cluttered environments for WSNs while it is not computation consumptive and relatively good in sparse cluttered environments. In generic *M/N* logic, the consecutive detections inside the gate are valued with identical weights and the initiation counter is increased by one all the time. However, if the newly detected observations in the gate are usually away from the center of the predicted target position while the performance of the tracking filter is precise enough, the intended track may not be a real target. Thus, we should adjust the initiation counter weights of the tentative tracks according to the distance measure while utilizing *M/N* logic for the track initiation decision. For this purpose, we envisaged six different weighting schemes named as exponential, linear, elliptic, Elfes and two beta versions of the exponential and Elfes models.

According to the simulations, elliptic track initiation counter weighting model exhibits promising results. In *4/5* elliptic track initiation logic, a significant contribution in terms of alleviating the false alarm track initiations is achieved while the number of false initiated tracks is reduced nearly six times regarding the number of false track initiations with the generic model. As a more conservative track initiation logic, *6/7* elliptic initiation logic shows an impressive performance that it reduces the false initiated tracks nearly ten times regarding the generic track initiation method while the downturn in the true track initiations are only 15 per cent according to the generic model. If timing is crucial according to the application, more quick initiator, elliptic *3/4*, can be utilized where it yields nearly 6.5 times less false initiated tracks than the generic model and it brings only seven per cent decline in true initiations. Thus, it is acknowledged that an increase in M parameter of the *M/N* logic drives for a better performance in terms of alleviating the number of false initiated tracks. However, it produces a tradeoff with the delay of the authentication decision. We should constitute a balance among these issues and try to decrease the number of false alarm

track initiations as well.

6.1. Remarks and Future Directions

In a target tracking application of WSNs, targets usually can be detected by more than one sensor node. While a distributed WSN collaboration architecture is utilized, a little decrease in the true track initiations would not be too much critical for the entire system. As there will be some other sensor nodes that would detect the same target, the decrease in the number of true track initiations would be compensated via collaboration among the sensors. That phenomena reveals the importance of our contribution to the target track initiation issue.

In all track initiation cases, the generic M/N initiation logic exhibits better true track initiation performance than the other M/N-based track initiation counter weighting models. However, in cluttered environments, the advantage of the generic M/N track initiation logic deteriorates as the number of false initiated tracks grows significantly. As a future work, an adaptive track initiation logic in terms of changing the M/N-based track initiation counter weighting models according to the environmental clutter level, would bring an optimized number of true track initiations while keeping the false track initiations at the possible lowest degree. Meanwhile, determining the clutter level of the environment emerges as another research issue. Moreover, for enhancing the performance of the adaptive track initiation logic, weighting model can be adjusted with respect to the speed of the target while it would provide better adjustment for the weighting values.

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