

## Chapter 4

# INFORMATION FUSION PROPERTIES OF THE LOCALISATION SYSTEM

Information fusion in WSNs is crucial for location discovery, and several location-discovery algorithms have used information fusion techniques to enhance and simplify the position computation process. This chapter provides an overview of such techniques; it distinguishes between distributed and localised algorithms and specifies three conditions to be complied with by localised algorithms. Several approaches can be used by localised information-fusion algorithms to satisfy these three conditions. The chapter will show how ALWadHA, defined in the previous chapter, uses several techniques to implement information fusion. Simulation results confirm that these techniques lead ALWadHA to achieve the most important objectives of information fusion: improving accuracy, reducing communication overheads and saving energy.

### 4.1 INFORMATION FUSION

Sensor nodes may be deployed to gather relevant data, either to provide a better understanding of the behaviour of the monitored entity, or to detect the occurrence of possible events. Information fusion is concerned with the way in which the data, once gathered, can be processed to enhance its relevance. The basic idea of information fusion is the combining of disparate data (either raw data or processed estimates) to improve accuracy and achieve more specific estimates than individual estimates could deliver.

Dasarathy [66] defines information fusion as “encompassing the theory, techniques, and tools conceived and employed for exploiting the synergy in the information acquired from multiple sources (sensor, databases, information gathered by human[s], etc.) such that the

resulting decision or action is in some sense better (qualitatively or quantitatively, in terms of accuracy, robustness, etc.) than would be possible, if these sources were used individually without such synergy exploitation”. This definition is depicted in Figure 4.1.

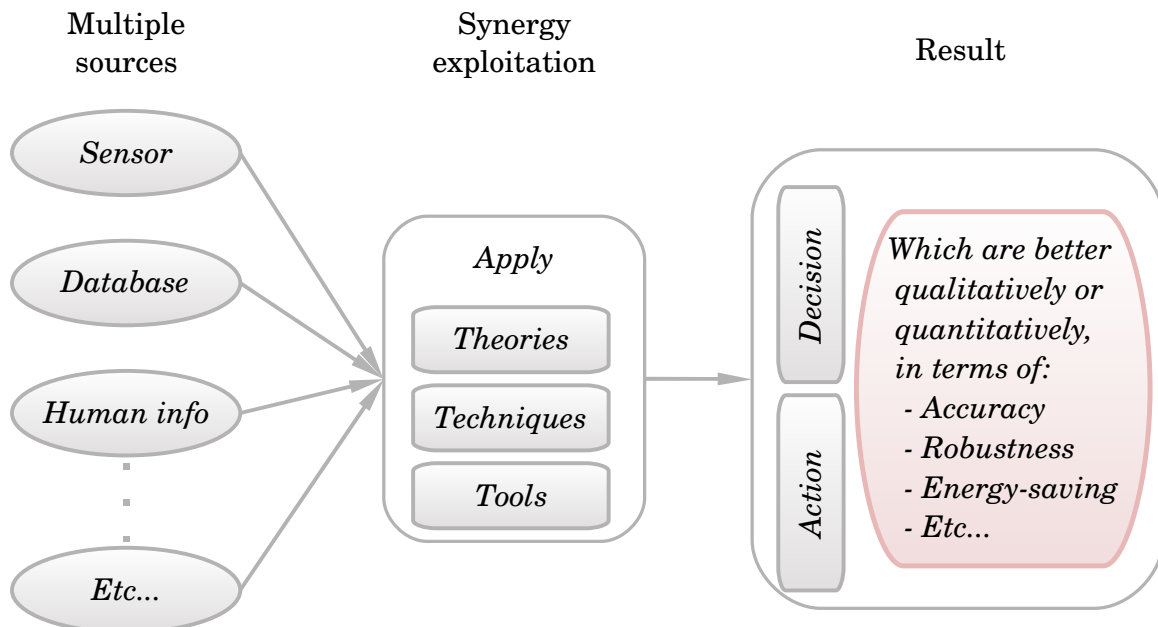


Figure 4.1. The definition of information-fusion

There are many objectives of information fusion. It can be used to compose a comprehensive view from the partial views provided by different nodes; fuse overlapping measurements to get more accurate information; and combine complementary data to allow inferences (e.g. a node can fuse the location of, and the estimated distance to, the neighbour references to obtain its position). Information fusion can reduce the overall communication load in the network and thus conserve energy and prolong the lifetime of the entire network. The minimum requirements for WSNs would be the improvement of accuracy and energy saving [67].

Two approaches to location fusion can be adopted: *centralised fusion* and *decentralised (distributed) fusion*. Theoretically, a centralised fusion system should outperform a distributed one, because the central unit has global knowledge in the sense that all measured data is available. However, this system also requires that all the raw data (or processed estimate) be transmitted from the nodes to the central unit. Such a high volume

of communications might not be practical and might consume too many system resources.

In a decentralised or distributed fusion system, each node has its own processing facility, which cuts out the requirement for any central fusion or central communication facility. In this approach, each node estimates its position and the fusion occurs locally at each node, based on local observation and the information received from neighbouring nodes. The main advantages of a decentralised fusion system are that it reduces the communications overheads and thus overcomes the problem of limited communication bandwidth. It avoids the effect of centralised computational bottlenecks, which makes this approach scalable. It is also adaptable to dynamic changes in the network structure and to the addition or loss of sensing nodes. In view of the nature of WSNs, with their limited resources and bandwidth, these advantages make the distributed algorithms preferable to centralised algorithms.

Localised algorithms are a special type of distributed algorithm in which only a subset of nodes in the WSN is invoked for a specific task (e.g. sensing, tracking, reasoning, communication and computation) [17]. Localised algorithms dramatically reduce redundant processing and communication, and thus save power and prolong the lifetime of the network, which could make them the best solution for WSNs. However, choosing the proper subset of nodes to participate efficiently in a specific task is not a minor problem. Their scalability, robustness and energy-effectiveness have attracted several researchers to use localised algorithms to develop various protocols for WSNs, such as directed diffusion [68], Sensor Protocols for Information via Negotiation [69] and Collaborative Signal and Information Processing [70]. Meguerdichian *et al.* [17] developed a generic localised algorithm for location discovery in WSNs.

#### 4.1.1 Information fusion and localisation systems

As explained in Section 2.2.1, localisation systems consist of three major components: distance/angle estimation, position computation and a localisation algorithm [18]. In order to explain the general role of information fusion within localisation, two supplementary components were added: a localised algorithm and an information-fusion technique, as shown in Figure 4.2.

*Node location*

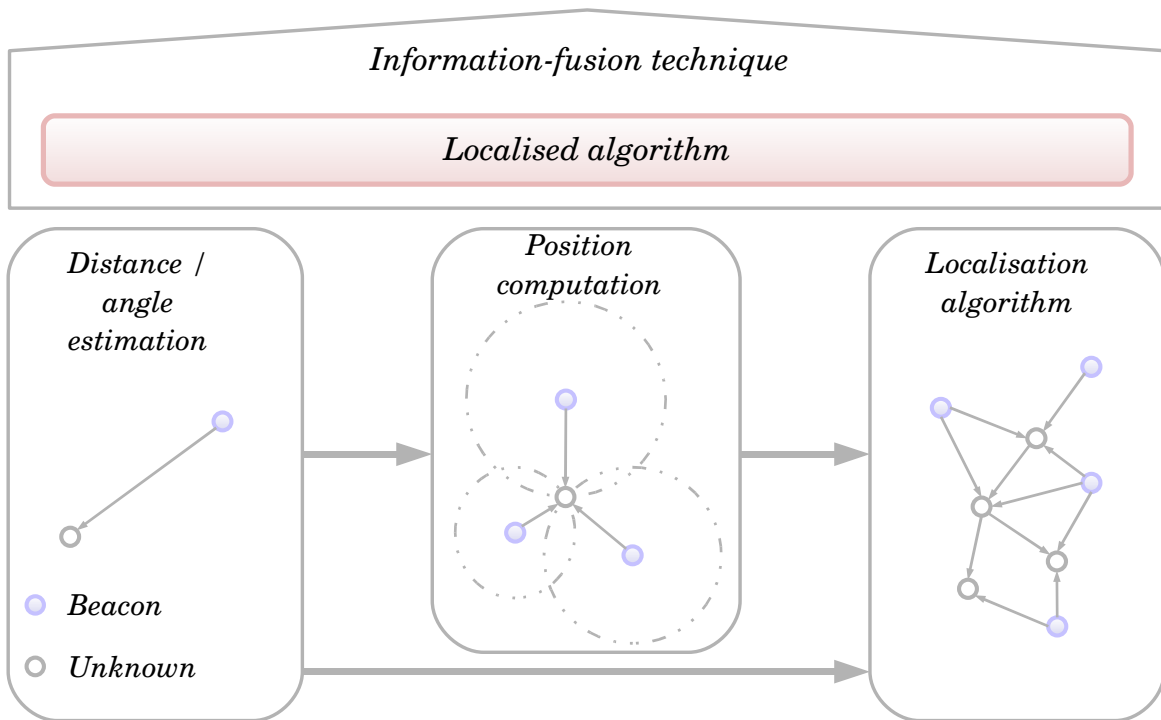


Figure 4.2. Components of localisation systems

Several information-fusion techniques have been used by various localisation algorithms to attain certain objectives, such as enhancing the accuracy of position estimation, reducing the required communication and computational requirements, and saving energy.

#### 4.2 INFORMATION-FUSION TECHNIQUES FOR LOCATION DISCOVERY

Certain information-fusion techniques (such as Bayesian inference, maximum likelihood, least squares (LS), moving average filter, Kalman Filter, particle filter and occupancy grid) have been used by localisation algorithms to enhance the performance of the position discovery process. This section will explain these techniques briefly and mention some localisation algorithms using them. More details about these techniques can be found in [67].

- **Bayesian inference:** Bayesian inference offers a formal way to combine evidence according to the rules of probability theory. The uncertainty of systems can be represented in terms of conditional probability, which estimates the degree of belief

in the  $[0, 1]$  interval, where 1 represents absolute belief while 0 represents absolute disbelief. The authors of [71] propose a localisation algorithm using Bayesian inference to process information from one mobile beacon. The unknown node uses the beacon's position and the RSS measurement to construct a constraint on its position estimate, and then it applies Bayesian inference to compute its new position estimate.

- **Maximum likelihood:** When the state being estimated is not the outcome of a random variable, then the MLE technique can be used. The likelihood function can be defined as the probability density function of the observation sequence given the true value of a certain state. Several localisation algorithms [29, 36, 41, 57, 58, 72] use MLE to estimate the position of unknown nodes by minimising the difference between the measured distances and the estimated distances, assuming that the unknown node has an adequate number of beacons. The MMSE from a set of distance measurements can be used to find the MLE of the unknown node's position.
- **Least squares:** The LS technique is a mathematical optimisation technique that searches for a function that best fits a set of input measurements. This is achieved by minimising the sum of the square error between points generated by the function and the input measurements [67]. Li *et al.* [73] propose the use of least median squares (LMS) as an improvement over LS for achieving robustness to attacks. However, LS outperforms LMS in the absence of attacks. In view of the measurement noise and error propagation that are introduced by the iterative techniques, Liu *et al.* [24] propose a robust least square (RLS) technique for localisation, which considers the error at each iteration. The authors show that RLS is more stable than LS in the presence of measurement noise.
- **Kalman filter:** The Kalman filter was proposed by Kalman [74] in 1960. Since then it has been the subject of extensive research and applications. The Kalman filter is a set of mathematical equations that provides an efficient computational solution of the least-squares method. The filter is a popular information-fusion method, because it supports estimations of desired states even when the precise nature of the modelled system is unknown. The Kalman filter technique has been applied in several distance estimation and location-discovery algorithms [75-77].

- **Particle filter:** The particle filter is recursive implementations of statistical signal processing known as sequential Monte Carlo methods [78]. The Kalman filter provides an effective solution to the linear Gaussian filtering problem. However, for a non-linear model, or non-Gaussian noise, the particle filter should be used. The authors of [79] show that particle filters allow great flexibility when addressing the problem of positioning, and they can be used in non-linear and non-Gaussian applications. Several algorithms [80-83] use the particle filter for refinement of node position estimates or for obtaining node location.
- **Moving average filter:** The moving average filter [84] is a very simple filter to use and to understand, making it the most commonly used in digital signal processing. This filter is also optimal for reducing random noise while retaining a sharp step response. Blumenthal *et al.* [54] propose a new distance estimation method using an exponentially weighted moving average filter to flatten the resulting sequence of distance estimates and to filter outliers. The filter uses multiplying factors to give different weights, which change exponentially, to different beacon locations based on the estimated distances.
- **Occupancy grid:** The occupancy grid is a multidimensional random field that maintains stochastic estimates of the occupancy state of the cells in a spatial lattice [85]. The basic idea of the occupancy grid is to represent a multidimensional map of the environment as evenly square or cubic cells which have random variables indicating the presence of an obstacle at that cell. The cell's probability of being occupied can be computed using Bayesian theory or fuzzy set theory [86], based on information provided by several sources. Wongngamnit and Angluin [87] propose a new robot localisation algorithm using the occupancy grid concept. Readers can find more information about using the occupancy grid for positioning estimation in [88].

Information fusion can play two roles in the localisation algorithms: a supporting role and a leading role. In the supporting role, information fusion acts as a tool to assist the localisation algorithms, by using one of the information fusion techniques to assist in the location discovery. In the leading role, the localisation algorithms are designed to support an information-fusion application. One or multiple information-fusion techniques may be executed to accomplish the application's objectives. Rather, these techniques are

responsible for guiding the location discovery process and the fusion process simultaneously. This means the localisation algorithm should be designed with two objectives: location discovery and achieving information fusion.

### 4.3 LOCALISED INFORMATION-FUSION ALGORITHMS

The basic idea of using localised algorithms is not only to request and process information to estimate position locally, but also to use data only from nodes that are likely to contribute to rapid and accurate formation of the final position estimate [17]. In other words, the localised algorithms used for location discovery should consider the following three conditions:

- **Firstly**, request and process information with regard to the localisation algorithm only locally; i.e. report the location of the unknown but do not send the raw data to a centralised entity for processing.
- **Secondly**, only a subset of nodes takes part in the position estimation process.
- **Thirdly**, only the references that are most likely to contribute to accurate position computation of an unknown are selected.

Developing practical localised information-fusion algorithms for WSNs is very important and a challenging task for a number of reasons [17]: The communication delay in WSNs is significantly greater than that of other traditional networks, since communication consumes more energy than sensing and computation; dynamic changes occur in WSNs due to nodes dying or extra deployment; and nodes are not always able to participate in every task (e.g. due to lack of energy, obstacles, etc.). A WSN is resource constrained in terms of resources such as processing, communication and energy. Finally, security issues might require that only a subset of nodes take part in a task, thereby simplifying the task of ensuring that all nodes participating in the process are authentic.

Localised location discovery requires only the position estimates from a subset of the unknown's neighbours, and need not involve all other nodes in the network. This makes the system-wide location-discovery task a good candidate for distributed algorithms.

However, not all distributed localisation algorithms proposed in the literature can be considered as localised algorithms. In fact, most of these algorithms satisfy only the first two of the three conditions mentioned above. To satisfy the third condition, localised information-fusion algorithms should select only references that are likely to contribute to accurate position estimates (i.e. use only a subset of available references to compute the position instead of using all of them). In this type of algorithm, information fusion plays a leading role, since it not only assists in the position estimation process, but also accomplishes fusion's objectives (such as energy saving and accuracy improvement).

Different approaches have been used to select a subset of references. Selecting a subset of references with low error is the approach followed by [38, 39]. Cheng *et al.* [37] simply choose the nearest three references to estimate nodes' position. In other approaches [41, 56], the node selects a subset of references based on a malicious-node removal approach, where the node tries to detect and prevent the malicious nodes from participating in its location estimate. Albowicz *et al.* [40] propose a localisation algorithm for choosing a reliable subset of references based on a reference consistency approach. Lieckfeldt *et al.* [13] consider the impact of geometry to select a subset of references. Costa *et al.* [42] propose a localisation algorithm that selects a subset of references based on a noisy distance measurement in order to avoid the biasing effect of a noisy environment. Section 2.3 discussed these approaches in more detail, while Section 2.4 compared them and highlighted the advantages and disadvantage of these approaches.

A researcher developing practical localisation algorithms for WSNs may take into account several design objectives, including self-organising properties, robustness, energy efficiency, localised information fusion and security. However, selecting the most accurate subset of references is not enough to fulfil all of these design objectives; in addition this subset could be the same as, or a little smaller than, an all-references set. The ALWadHA algorithm, as mentioned above, uses a method that selects almost the minimum possible number of references to achieve an accurate position estimation. This selection method is based on the low-error approach. The rest of this chapter extends the investigation of the ALWadHA algorithm. It shows the impact of using a proper localised selection method on achieving several design objectives, enhancing the performance of localisation systems and making information fusion play a leading role.



#### 4.4 THE THREE FILTERS OF ALWADHA

The ALWadHA algorithm uses three types of filters to satisfy the three conditions required for it to be considered as a localised algorithm. These filters also help to achieve other design objectives, such as energy efficiency (by reducing the computation and communication overheads), accuracy, robustness and security. These three filters also make information fusion play a leading role, not only a supporting role. Figure 4.3 illustrates these three filters. The first filter is used by the known nodes to decide if they will respond to the “location request” packets -- in other words, act as references -- while the other two filters are used by the node itself to select the proper subset of references.

##### 4.4.1 Filter one

This filter is used by a known node, which has received a “location request” packet, to decide if it will act as a reference node and send a “location response” packet. A known node should satisfy two conditions in order to act as reference node. Firstly, its probability of accuracy should be more than a specific value ( $P_{res}$ ). Secondly, its probability of accuracy should be more than the required accuracy level sent by the requesting node ( $L_{acc}$ ). Applying this filter at known level rather than at node level will reduce the cost of communication, since instead of eliminating those references with a low probability of accuracy at node level, those knowns will not send their responses and this will reduce the messages propagated through the network. This filter does not require any interaction between neighbouring knowns; rather it works on the available information. The requesting node will receive “location responses” packets only from  $R$  set of references where  $R \subseteq (K \cup B)$ .

##### 4.4.2 Filter two

The node applies this filter to select a subset of references  $S$ , where  $S \subseteq R$  based on the references' location error. The probability of accuracy of the subset  $S$  should be greater than a certain value ( $P_{min}$ ). As shown in Figure 4.3, the node applies this filter twice firstly to select a subset  $S^0$ , where  $S^0 \subseteq R$  in order to estimate an initial position ( $\hat{z}'$ ) and secondly, to select a subset  $S$ , where  $S \subseteq \bar{R}$ , and  $\bar{R}$  is the output set of filter three in

order to estimate the refined position  $(\hat{z})$ .

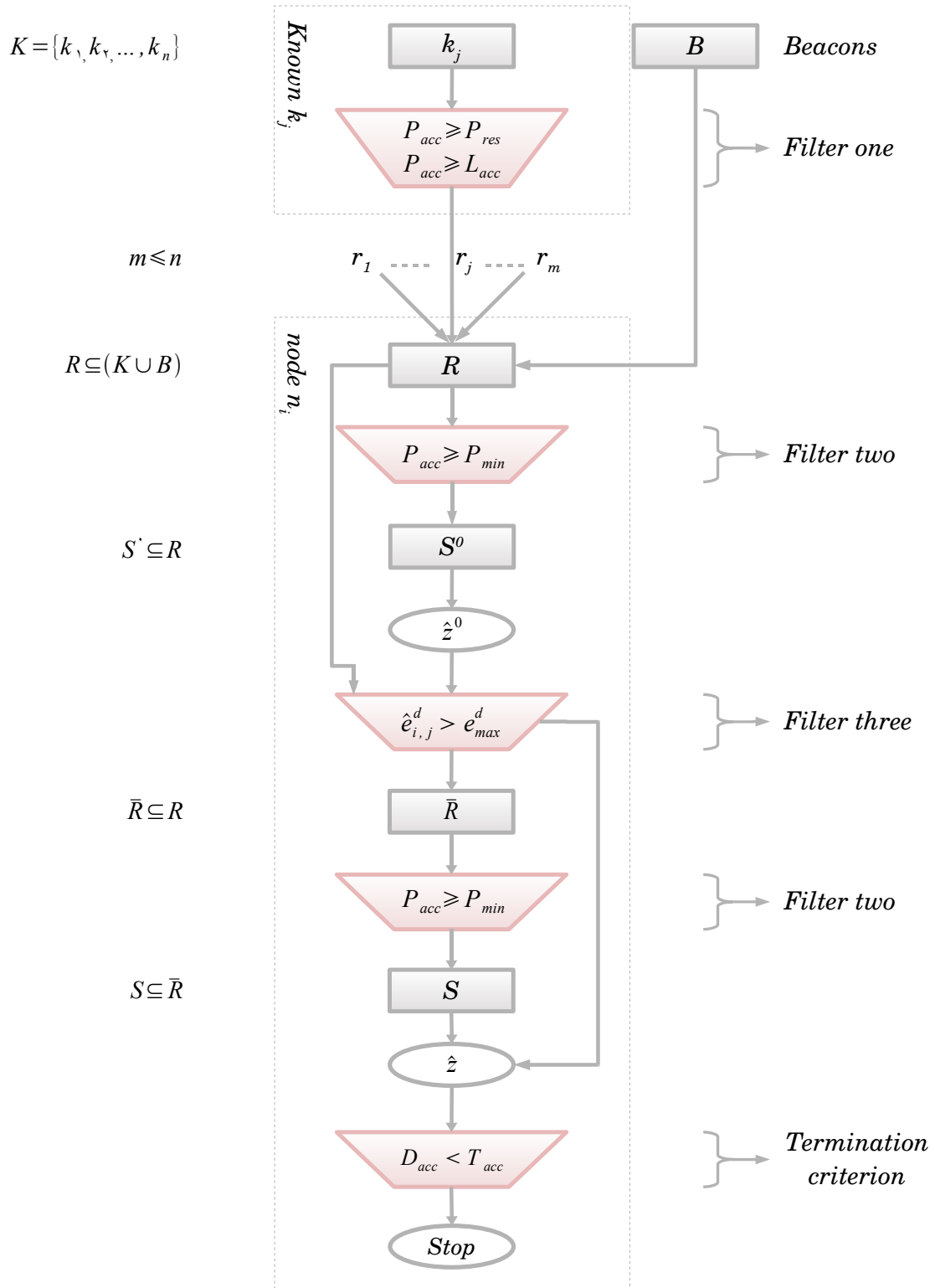


Figure 4.3. The three filters used by ALWadHA

### 4.4.3 Filter three

The node uses the initial position  $(\hat{z}^0)$  to eliminate those references with high distance-measurement error; the result of this filter is  $\bar{R}$ , where  $\bar{R} \subseteq R$ . This filter is only applied if at least one of the references in the subset  $S^0$  has an estimated distance error greater than a certain error value  $(e_{max}^d)$ .

## 4.5 INFORMATION FUSION IN A LEADING ROLE

As mentioned earlier in Section 4.2, information fusion can play two roles in the localisation algorithms: a supporting role and a leading role. In order to distinguish between these two roles in this discussion, the information fusion used by localisation algorithms will be classified into three levels, based on the objectives that can be achieved. In level one, localisation algorithms use one of the information-fusion techniques, explained in Section 4.2, in the position computation. The objective of information fusion on this level is to combine complementary data to allow inferences: the node fuses the location of, and the measured distance to, at least three references to determine its position. On this level, information fusion plays only a supporting role to assist in the location discovery. On level two, information fusion starts to play a leading role by achieving some of the information-fusion objectives: accuracy, robustness, fewer computations and security. However, reducing the communication overhead is not targeted by this level of information fusion. On level three, information fusion also plays a leading role by achieving several objectives. The main objective of information fusion on this level is to reduce the communication overhead in order to enhance the energy efficiency of the localisation algorithm. Developing an efficient localisation algorithm that employs the three levels of information fusion will enhance the performance of this algorithm and assist in achieving several design objectives.

Therefore, as shown in Figure 4.4, the ALWadHA algorithm employs the three levels of information fusion. On level one, the ALWadHA algorithm uses the MLE technique, where the MMSE is used to determine the MLE of the unknown nodes' position. On level two of information fusion, the ALWadHA algorithm uses filter two and filter three. These two filters assist in achieving several objectives, including accuracy, simplicity, robustness,

reduced computation cost, localised algorithm and security. In order to accomplish level three of information fusion, the ALWadHA algorithm follows two approaches. Firstly, the sensor node uses the termination criterion to halt the process of localisation when it has determined its position with good accuracy. This termination criterion reduces the communication overhead by cutting out unnecessary “location request” packets. Secondly, known nodes use filter one to decide if they will act as references based on their accuracy. This filter reduces the communication overhead due to unnecessary “location response” packets. In addition to other objectives, these two approaches enhance the energy efficiency of the ALWadHA algorithm.

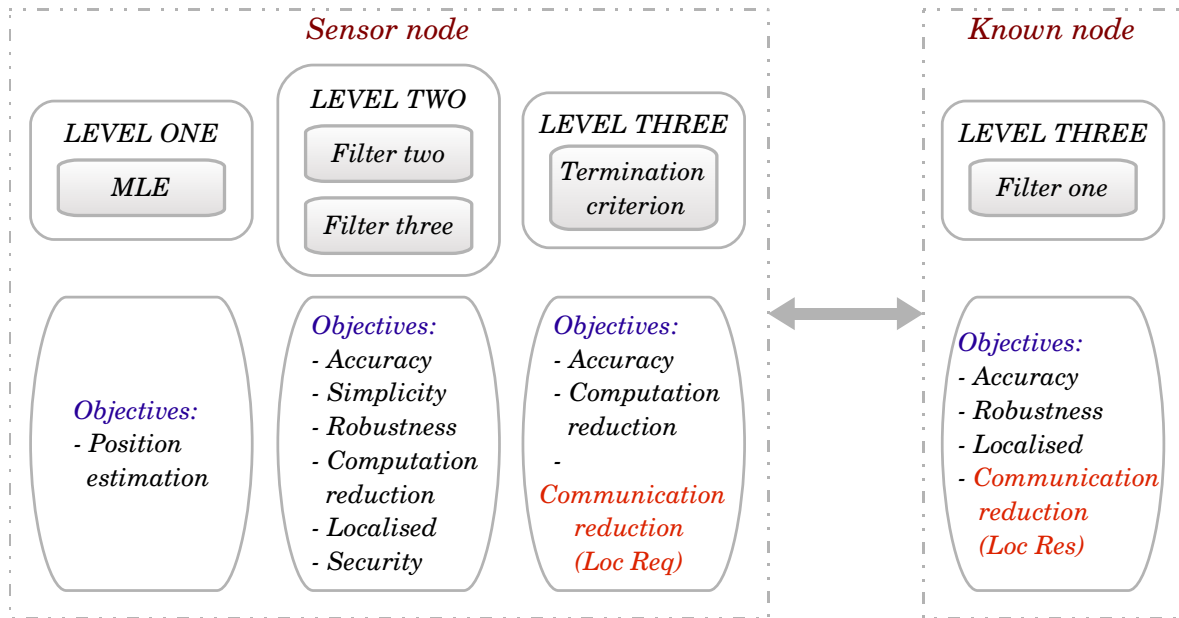


Figure 4.4. The three levels of information-fusion used by ALWadHA algorithm

#### 4.6 SIMULATION

This section will evaluate the ALWadHA algorithm using the same grid and random deployment as described in Section 3.3.3. Several experiments were performed to evaluate the performance of the ALWadHA algorithm compared with other localisation algorithms. The performance of each algorithm was evaluated based on the following metrics: The localisation error at each iteration, number of “location request” packets, number of “location response” packets and the energy consumed.

#### 4.6.1 Localisation error vs number of iterations

Refinement algorithms, such as M\_Refine, NDBL and ALWadHA algorithms, perform several iterations of position estimation. In this section, the mean error is shown as a ratio of transmission range at each iteration. CRLB, M\_Single and the Nearest algorithms are based on a single-estimation approach, in which the node estimates its position only once. The mean error at a specific iteration  $I$  is equal to the summation of location error of knowns that estimate their location at iteration  $I$ , divided by the number of these knowns, and then it is divided by the transmission range as follows:

$$Mean\ error_I = \left( \frac{1}{n} \sum_{i=1}^n \|\hat{z}_i - z_i\| \right) \frac{1}{r_{tx}} 100\% \quad (4.1)$$

where  $n$  is the total number of knowns that estimate their position at iteration  $I$ . Figure 4.5 shows that in the ALWadHA algorithm the nodes perform at the most six iterations before they establish their final position. This shows that the ALWadHA algorithm not only uses a low number of references, but requires a low number of iterations to get an accurate position; which also reduces the computation cost dramatically. In the grid deployment (Figure 4.5.a), the mean error using the ALWadHA algorithm at the sixth iteration is equal to 1.18%, using an average number of references equal to 3.42, while after 32 iterations the mean error of the M\_Refine algorithm is equal to 3.14%, using an average of 12.46 references. Figure 4.5.b shows that none of the other algorithms could achieve the same level of accuracy that the ALWadHA algorithm achieves within only five iterations.

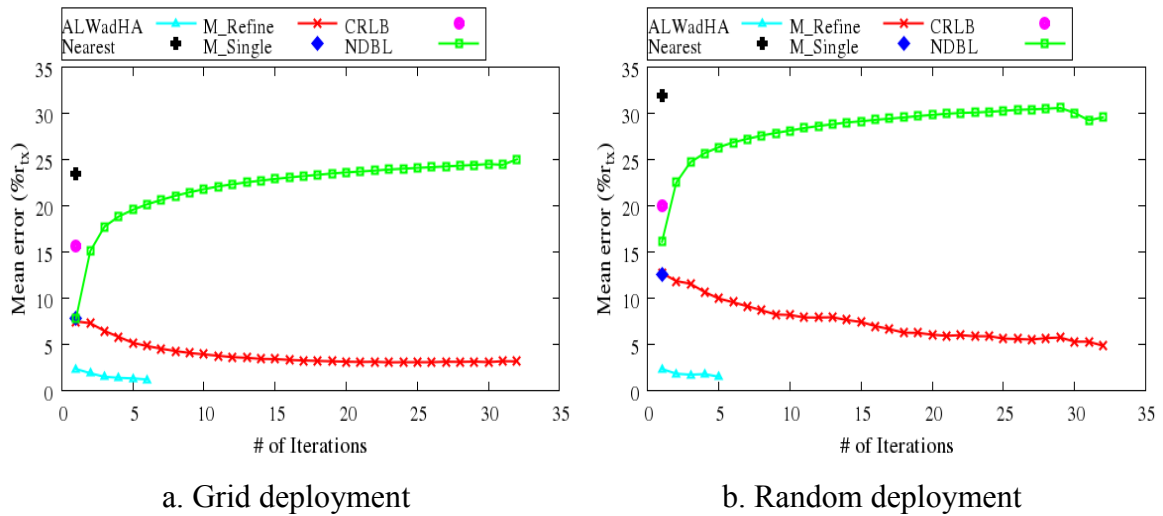


Figure 4.5. The mean error at each iteration

#### 4.6.2 Number of “location request” packets

The node starts the localisation process by broadcasting a “location request” packet; if it cannot estimate its position it will again broadcast another “location request” packet after a specific time (for instance 5 seconds). In the refinement algorithms the node increases this time after each estimation. Figure 4.6 shows that the ALWadHA algorithm broadcasts a lower number of “location request” packets compared with CRLB, M\_Refine and NDBL algorithms because of the termination criterion that has been followed by the ALWadHA algorithm. The M\_Single and the Nearest algorithms require a low number of “location request” packets because they are based on the single-estimation approach, in which the node estimates its position only once.

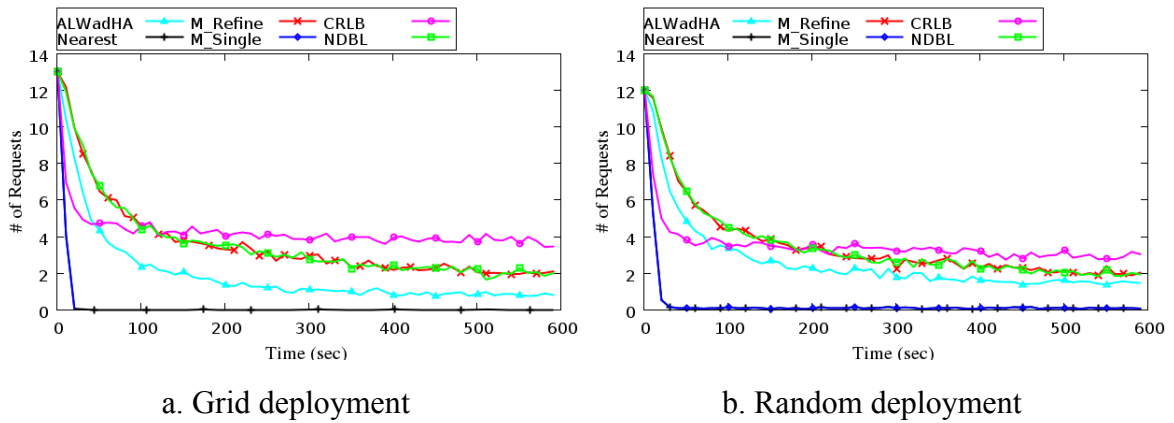


Figure 4.6. Number of “location request” packets

### 4.6.3 Number of “location response” packets

Figure 4.7 shows the number of “location response” packets vs time. This figure shows that the ALWadHA algorithm requires a lower number of “location response” packets than CRLB, M\_Refine and NDBL algorithms, because of the “filter one” that the knows use to decide if they will send their response or not, as explained in Section 4.4.1.

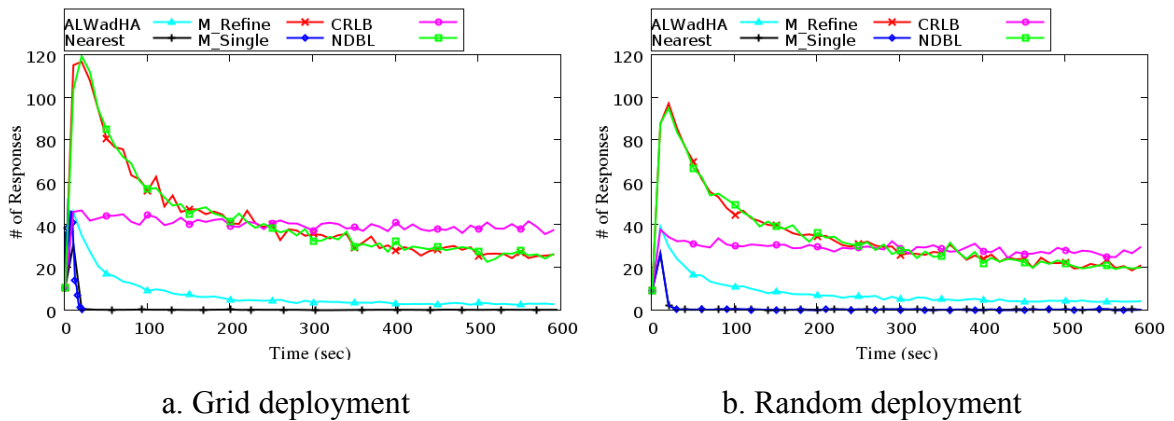


Figure 4.7. Number of "location response" packets

### 4.6.4 Remaining energy

At the beginning of the simulation each node has 2.0 joule. Figure 4.8 shows the average remaining energy vs time, considering only energy consumption due to communication. Since the ALWadHA algorithm requires a lower number of “location request” and “location response” packets, as shown in Figure 4.6 and 4.7, it consumes less energy

compared with the CRLB, M\_Refine and NDBL algorithms. The difference is expected to be higher if the energy consumption due to computation is also included, for two reasons. Firstly, the ALWadHA algorithm uses a lower number of references. Secondly, the ALWadHA algorithm requires a lower number of iterations to get an accurate position estimation (Figure 4.5). These two characteristics could reduce the computation cost dramatically, especially for WSNs. Unlike other algorithms, ALWadHA consumes less energy in the grid deployment, because the higher number of references around each node enables it to reach its final position faster than if the deployment was random, and thus it stops sending the “location request” packets.

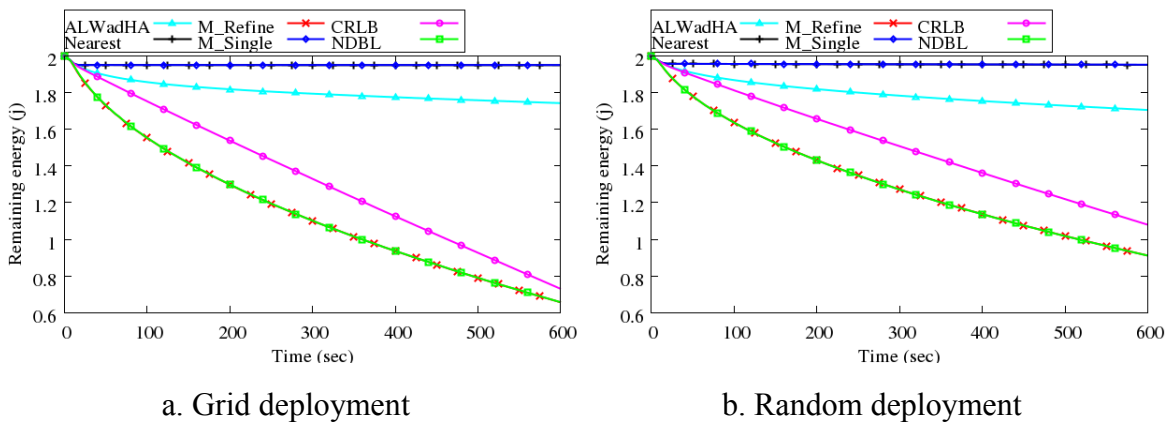


Figure 4.8. Remaining energy

#### 4.6.5 Performance comparison

Table 4.1 shows a performance comparison between the implemented localisation algorithms in both grid and random deployment. The mean error is recorded at the last iteration shown in Figure 4.5. The average number of requests and the average number of responses represent their average during the run time. Finally, the remaining energy at the end of the run time is also listed. The results shown in this table confirm the objectives of employing the third level of information fusion in localisation algorithms. The termination criterion made ALWadHA broadcast a lower number of “location request” packets than other refinement algorithms. At the same time, filter one reduced the number of “location response” packets dramatically. For instance, in the random deployment, using ALWadHA, the average number of “location response” packets is only three packets for each “location request” packet, while in CRLB, M\_Refine and NDBL algorithms there are ten “location



response” packets for each “location request” packet.

Table 4.1. Performance comparison

Metrics	Mean error		# of Request		# of Response		Energy	
	Grid	Rand	Grid	Rand	Grid	Rand	Grid	Rand
ALWadHA	1.18	1.47	1.92	2.63	7.06	8.1	1.743	1.705
M_Single	7.77	12.53	0.21	0.3	0.77	0.8	1.950	1.952
M_Refine	3.14	4.83	3.61	3.47	42.96	34.49	0.657	0.912
CRLB	15.65	19.99	4.23	3.46	40.07	28.73	0.732	1.081
NDBL	25.00	29.54	3.62	3.47	42.92	34.49	0.658	0.912
Nearest	23.38	31.86	0.22	0.66	0.81	0.84	1.949	1.951

## 4.7 TOWARDS MORE ENERGY EFFICIENCY

This section will investigate three methods that could be used for making ALWadHA more energy efficient. All the experiments done in this section employed random deployment.

### 4.7.1 Single-estimation approach

In this technique ALWadHA will consider the single-estimation approach instead of using the successive-refinement approach. In this approach the node estimates its position only once and it does not repeat the estimation to enhance the accuracy of positioning. Figure 4.9 shows that this technique (A\_Single) could enhance the energy efficiency of the original algorithm (ALWadHA). On the other hand, the mean error is slightly higher than the original algorithm. However, Figure 3.26 showed that the mean error of the single-estimation algorithms increases dramatically by increasing the distance-measurement error, while the successive-refinement algorithms are more robust than single-estimation algorithms. Therefore, in a noisy environment it is not advisable to use the single-estimation approach, especially if accuracy is a critical issue.

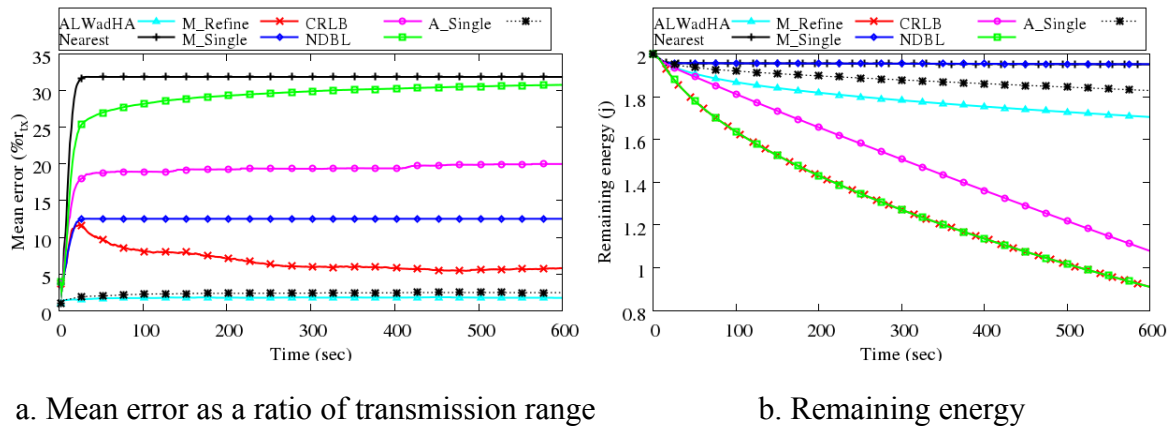


Figure 4.9. ALWadHA based on single-estimation approach

#### 4.7.2 Dynamic power control

The dynamic power control technique can be used to adaptively change the level of transmission power based on the distance between the transmitting and receiving nodes. Instead of continuing to send the packets using the maximum transmission power to cover the entire range, the node dynamically specifies the required transmission power to enable the packet to reach the destination node. The dynamic power control technique is adopted in the proposed localisation system as follows: the node uses the maximum transmission power to broadcast the “location request” packets, to make sure all the references within its transmission range will receive this packet. The references which receive this request estimate the distance to the requesting node using the RSS and then estimate the required transmission power to enable the “location response” packets to reach the requesting node.

Figure 4.10 Shows that the use of this technique by ALWadHA (A\_DPC) does not enhance the energy efficiency very much for several reasons. One reason is that this technique is used only to change the power level for sending the “location response” packets, while the nodes use the maximum transmission power to send the “location request” packets. The nodes' density is low, only 4.75 nodes per  $r_{tx}^2$ , which means the nodes are not close to one another and therefore the transmission power is little lower than the maximum transmission power. As shown in Table 4.1, ALWadHA reduced the average number of “location response” packets dramatically compared with other algorithms (due to filter one), therefore this technique does not greatly affect the energy efficiency of the ALWadHA algorithm. However, this technique could enhance the energy efficiency of the

other localisation algorithms and also reduce the interference.

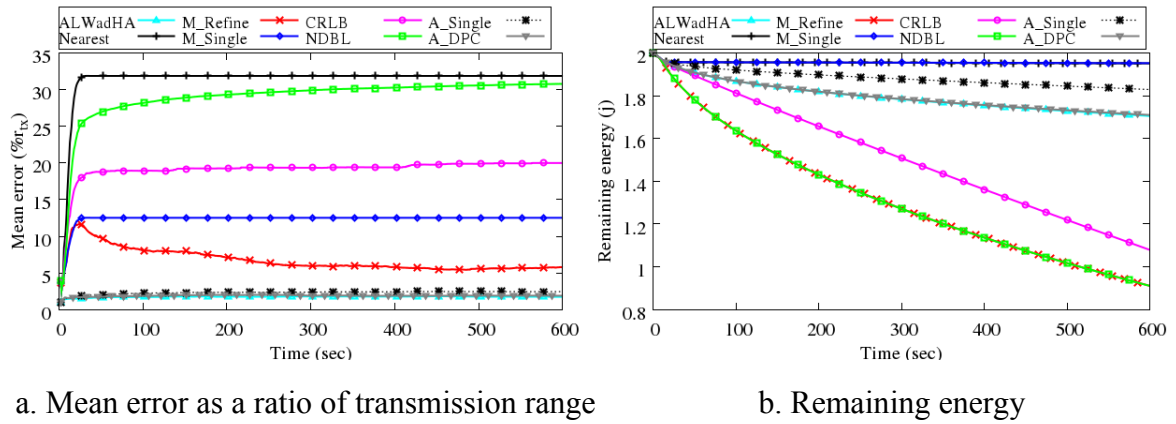


Figure 4.10. ALWadHA with dynamic power control

### 4.7.3 Incremental and exponential requesting rate

One target of a localisation system is to minimise the number of beacons used because of the cost or the difficulty of installing these nodes, which means only some of the nodes will be neighbours of these beacons. Initially, the nearby unknown nodes will be able to determine their position and they could act as references for other unknowns. Therefore, the unknown nodes far from the beacons need more time to determine their position compared with the ones close to them. Using a fixed requesting rate will lead to wasting the energy of sensor nodes, mainly those that are far from the beacons, because at first these will keep sending “location request” packets without getting enough “location response” packets back. Therefore, the requesting rate ( $\Delta t_{req}$ ) is updated after each iteration, either incrementally or exponentially, as follows: if the node has determined its position at a specific iteration (or enhanced the accuracy of the current position), it will increase the requesting rate by one ( $\Delta t_{req} = \Delta t_{req} + 1$ ), otherwise it will multiply the requesting rate by two ( $\Delta t_{req} = 2 * \Delta t_{req}$ ).

As shown in Figure 4.11 ALWadHA, when using the incremental and exponential requesting rate technique (A\_IncExp), consumes less energy than the original ALWadHA and A\_Single; moreover, the accuracy is slightly better. This technique allows the nodes close to the beacons to reach their final estimation faster, which also enhances the position accuracy of other nodes. At the same time it prevents the nodes farther away from

continuing to send useless “location request” packets and thus enhances the energy efficiency of the algorithm.

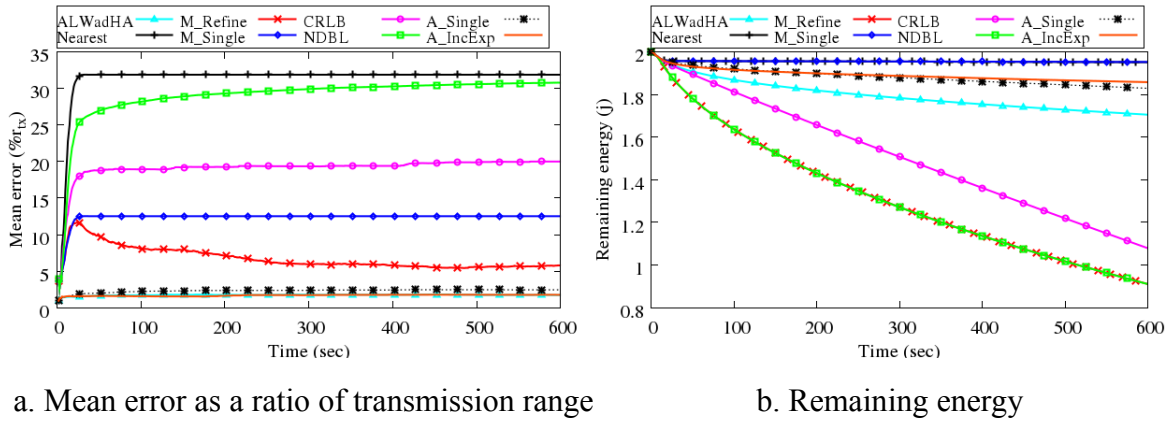


Figure 4.11. ALWadHA based on the incremental and exponential requesting rate

#### 4.7.4 Performance comparison

Table 4.2 shows a performance comparison between the original ALWadHA algorithm and the new techniques. The mean error and the remaining energy are recorded at the end of the run time. ALWadHA using the incremental and exponential technique (A\_IncExp) achieved the best result. A\_IncExp still follows the successive-refinement approach, thus it is still robust even in a noisy environment.

Table 4.2. Performance comparison of the new techniques

Algorithm	Mean error	Remaining energy
ALWadHA	1.797	1.705
A_Single	2.462	1.829
A_DPC	1.900	1.710
A_IncExp	1.773	1.857

#### 4.8 CHAPTER CONCLUSION

WSNs are regarded as resource-constrained networks, therefore this chapter emphasised that localised information-fusion algorithms should be used to provide an accurate position estimate at reduced cost. The localised algorithms should satisfy three conditions, which

are that: information is requested and processed only locally; only a subset of nodes takes part in the position-estimation process; and only the references that are most likely to contribute to accurate position computation of an unknown are selected. In fact, the focus is on the impact and significance of the third condition, which enhances the accuracy of localisation systems.

Several approaches can be used by localised algorithms. A number of design parameters and certain requirements play a vital role in selecting the proper approach. However, selecting a certain approach may not always give the best position estimate (for instance because of its simplicity), and so selecting another approach with a more sophisticated technique for selecting a subset of references is required. The accuracy of position estimation is one of the most important design objectives, thus the ALWadHA algorithm follows the low-error references approach. However, ALWadHA uses several techniques to overcome the drawbacks and limitations of this approach.

The ALWadHA algorithm carefully selects a sufficient number of the best references in order to enhance accuracy at reduced cost. In order to select a proper subset of references it uses three types of filters. The first filter is used by known nodes to reduce the communication load of “location response” packets, while the next two filters are used by the node itself to select the proper subset of references. The second filter is used to handle the location error, while the third filter is used to deal with distance-measurement error. Employing these three filters enables the ALWadHA algorithm to achieve high estimation accuracy using only a low number of references, almost equal to the minimum possible number of references.

The information fusion used in localisation systems was classified into three levels, based on the objectives achieved. On the first level information fusion assists in location discovery. On the second level it achieves several objectives such as accuracy, robustness and security. However, reducing the communication overhead is not targeted on this level, which is the main objective of the third level. The ALWadHA algorithm made use of these three levels. It was shown that using the three levels of information fusion enhances the performance of the ALWadHA algorithm and assists in achieving several design objectives. Selecting the best subset of references will enhance the accuracy and simplicity of the

algorithm. Filtering out those references with high location error or distance-measurement error will increase the robustness of the algorithm. These levels also reduce the computation and communication overhead and thus enhance the energy efficiency of the ALWadHA algorithm. The simulation results confirmed this achievement and showed that ALWadHA required a lower number of iterations to achieve better accuracy (due to level two and level three). It was also shown that ALWadHA required a lower number of “location request” and “location response” packets (due to level three), which reduced communication overheads and therefore enhanced energy efficiency. Finally, three techniques that could be used to enhance the energy efficiency of the ALWadHA algorithm were investigated.