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MÉTHODE DE GRADIENT DESCENTE EN LOCALISATION UTILISANT LA PUISSANCE DU SIGNAL RECUE POUR UNE ESTIMATION PRÉCISE

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Abstract

In this work we propose an improved RSS-based localization technique for wireless network based on the gradient descent optimization algorithm, usually received signal strength (RSS) is susceptible to the noise factor, and the gradient descent method can be affected by the initialization plus the local minimum issue, influencing the estimated distance accuracy of the node. For this reason, the first part in this work will be; demonstrating the effect of the initialization technique on the localization accuracy. Results have shown that the selection of the initialization step has an efficient impact on the accuracy of the target nodes location estimation. Second, to show the big importance of gradient descent in localization domain over the trilateration technique, and that by reducing the number of needed anchor nodes. Furthermore, a new objective function is defined as the sum of the difference between the real and estimated power. By applying gradient descent technique on this objective function, the positions of unknown nodes are estimated. Generally, to localize a node, a specific number of anchors (reference nodes) is required, this number of needed anchors will increase in the presence of noise factor. Results have shown that, using our improved proposition, the number of needed anchors is reduced despite the existence of the noise aspect. A comparison with other techniques is made to show the effectiveness of the proposed approach. Finally, in the last part of this work, we address the problematic of the unknown path loss exponent factor in the RSS-based localization technique. The proposed approach shows an accurate estimation of nodes position even in unknown path loss condition.

Résumé

Dans ce travail, nous proposons une technique de localisation améliorée basée sur le signal reçu (RSS) pour un réseau sans fil, basée sur l'algorithme d'optimisation gradient descente, l'intensité du signal reçu étant généralement sensible au facteur de bruit et la méthode gradient pouvant être affectée par l'initialisation. En plus, le problème local minimum influence la précision de distance estimée entre les nœuds. Pour cette raison, la première partie de ce travail sera: démontres l'effet de la technique d'initialisation sur la précision de la localisation. Les résultats ont montré que la sélection de l'étape d'initialisation a un impact fort sur la précision de l'estimation de l'emplacement des nœuds. Deuxièmement, montrer la grande importance de la technique gradient dans le domaine de localisation par rapport à la technique de trilatération, en réduisant le nombre de nœuds d'ancrage nécessaires. En outre, une nouvelle fonction objective est définie comme la somme des différences entre la puissance réelle et la puissance estimée. En appliquant la technique gradient sur cette fonction objectif, les positions des nœuds sont estimées. Généralement, pour localiser un nœud inconnu, un nombre spécifique d'ancres (nœuds de référence) est requis, ce nombre d'ancres nécessaires augmentera en présence d'un facteur de bruit. Les résultats ont montré que, grâce à notre proposition améliorée, le nombre d'ancres nécessaires est réduit. Une comparaison avec d'autres techniques est faite pour montrer l'efficacité de l'approche proposée. Enfin, dans la dernière partie de ce travail, nous exposons la problématique du facteur d'atténuation du signal dans la technique de localisation basée sur RSS. L'approche proposée conduit à une estimation précise de la position des nœuds même dans des conditions d'affaiblissement inconnues.

Glossary of Abbreviations

Global Positioning System	**GPS**
Time of arrival	**TOA**
Time difference of arrival	**TDOA**
Angle of arrival	**AOA**
Received Signal Strength Indicator	**RSSI**
Path loss exponent	**PLE**
Gradient descent	**GD**
Wireless Sensor Network	**WSN**
Approximate Point In Triangulation	**APIT**
Distance vector-Hop	**DV-HOP**

General introduction

Commonly, Global Positioning System (GPS) represents the famous technique in localization in outdoor environment, despite all the advantages that GPS offer, it is still inefficient for indoor localization where the signal of GPS cannot be flexible because of the different types of obstacles. For this reason, two common types of localization have been widely used; The range free techniques, where the absolute range information or angle between two pair of nodes is not needed, and the range-based techniques such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and Received Signal Strength Indicator (RSSI). Range based techniques are characterized by being more accurate compared to range-free, where the information on distance/angle between nodes are required.

Among range-based techniques, RSS is widely accepted to be used in wireless network, especially in indoor environment, it consists of calculating the distance using the RSS measurements between the receiver and the transmitter node. Using RSS measured at the receiver, distance estimation between transmitter and receiver can be very easy and suitable. However, RSS based method is susceptible to the noise and interference factor, that will affect the estimated distance accuracy. Since obtaining an accurate location of the target sensor is the goal of all localization technique, many researches have focused in their studies on the optimization part in localization, optimization algorithm has shown an attractive solution in localization domain compared with the previous mentioned techniques. Amongst all optimization methods, gradient descent (GD) has concerned many researchers in optimization localization domain.

Note that, in this work we are using the wireless sensor network as an example of wireless network since it can be used in localization domain. Nerveless, the study will be focused on localization domain by having an accurate localization technique.

Problematic

1. Localization is considered one of the important issues in Wireless Networks for example in Wireless Sensor Network (WSNs), especially for the applications requiring the accurate position of the sensed information.
2. Most of localization techniques suffer from diverse problems in indoor areas, affecting the accuracy of the target nodes location.
3. Although GPS (global positioning system) is a popular location estimation system, it does not work indoors because it uses signals from GPS satellites. But using indoor localization in wireless networks instead of GPS makes localization possible.
4. Gradient descent can be affected by the initialization and the local minimum problem.
5. Propagation conditions play a key role affecting the RSS-based accuracy.

Objective:

- The objective will be, having an accurate position of the target sensor. In order to achieve this goal, we have tried in our study to combine gradient descent optimization technique with the RSS-based method using a non-random initialization technique.
- Prove the effectiveness of our developed algorithm by comparing it with other techniques.
- Make an accurate estimation of the unknown path loss exponent factor in RSS-based techniques in addition to location estimation.

Structure of Thesis and Contribution

Basically, wireless devices are capable of monitoring different phenomena in the physical world due to there physical diversity, for example WSN can be implemented in different types of applications, some of these applications require knowing the accurate location of the target sensor. For this reason, chapter 1 discuses different techniques for localization, and shows the importance of localization in wireless network.

Generally, the main goal in every localization technique will be having an accurate position of the deployed nodes. To achieve this, many researchers have tried to combine different localization techniques to obtain new one that can offer a good solution in complex areas. Gradient descent optimization technique has showed an attractive solution in localization domain compared with the traditional techniques. Nevertheless, gradient descent accuracy can be affected by the local minimum problem or the initialization factor, to resolve this problem, in chapter 2 our plan will be showing the impact of initialization in gradient descent on the localization accuracy, where 3 types of initialization were tested and compared. In addition, the importance of using gradient descent in localization domain over traditional localization techniques will be shown in terms of reducing the number of anchor nodes.

After resolving initialization issue and presenting the importance of gradient descent in localization domain, chapter 3 introduce an improved RSS-based localization technique in a wireless sensor network based on the gradient descent optimization algorithm in a noisy propagation model. To realize the performance of our adopted method, results has been compared to other techniques.

Finally, the path loss exponent factor affects in a huge way the RSS – based technique, and it is considered as a study case for many researches. If we took an example in a complex environment, the path loss exponent can vary due to different physical phenomena. For this reason, in order to see the effectiveness of our proposed approach, we increased the complexity by applying our algorithm in unknown path loss condition, to make an estimation for the target nodes location and the unknown path loss exponent factor.

CHAPTER 1

LOCALIZATION IN WIRELESS NETWORK

1-1 Introduction to Wireless Network

Wireless devices link physical world with the digital world via several techniques, and that is by gathering information and analyzing it about the studied object before converting this information to an easy form that can be proceeded. One of the famous approaches for localization in wireless network, is the wireless sensor network.

In the last few years, wireless sensor network had become one of the dominant technologies that can be used in different fields. WSN can be defined as a collection of low cost and power sensors that can communicate wirelessly, each node in this network can since, process and has the ability to communicate with its peer [1].

1-2 WSN applications

One of the main advantages of sensors is there physical diversity, we have several types and forms of sensors, temperature, pressure, optical, acoustic, mechanical, vibration, position, chemical, humidity. Adding that, in the next few years the needs of wireless sensor network technology will increase more, and it is expected to form the core of the future intelligent network. For this reason, wireless sensor network can be included in different sorts of applications. [1-2-3-4]:

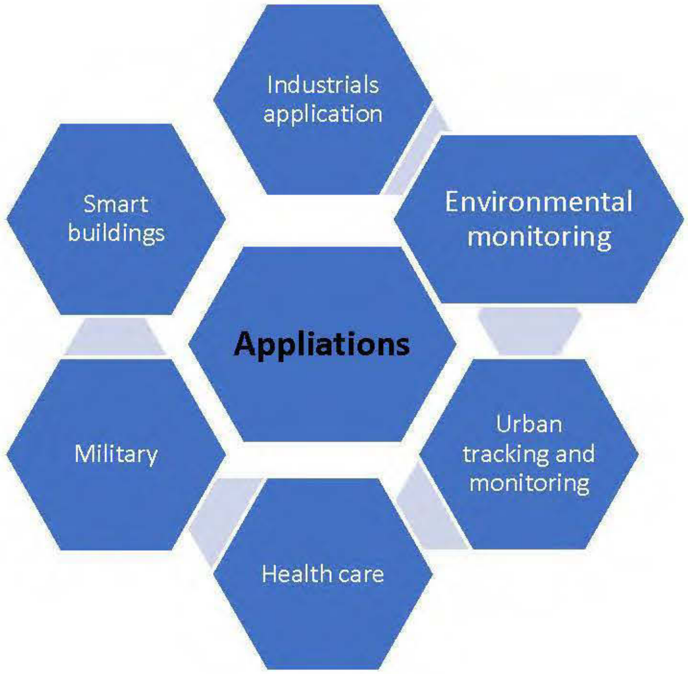

Figure 1-1:Wireless Sensor Network applications.

Wireless sensor networks can be an essential part of military applications, the self-organization, fast deployment and low-cost characteristics of sensor networks make them very desirable for this application domain, like control, communications, computing, intelligence, surveillance, investigation and targeting systems. Since sensor networks are based on the dense deployment and low-cost sensor nodes, destruction of some nodes by aggressive attacks does not affect a military operation which makes wireless sensor networks a recovering approach for battlegrounds [4-5].

Many environmental applications of WSN include tracking the movements of birds, small animals, and insects; adding that, these applications may be implemented also in forest, example; fire detection, precision agriculture and flood detection, to monitor environmental conditions and ensure the security of the forests [4-5].

WSN can be the way of saving lives for many patients. Since now, WSN is implemented in many health caring applications, like tracking and monitoring doctors and patients inside a hospital, and that is by using special sensors that will be attached to the patient and each sensor has a specific task [4-5].

Furthermore, WSN can be used in smart home applications like home automation where the deployed sensors allow end users to manage home devices locally and remotely more easily.

1-3 Importance of Localization in wireless network

Some of WSN applications consist of distributing sensors in a random way, for example several applications consist of dropping thousands of sensors from an airplane in harsh environment (amazon forest), or in case of complex application, sensors may be distributed in mine environment, some of these distributed sensors may be damaged, but a huge number of them will be able to work and communicate with the sink normally. Hence, knowing the sensors location is necessary to recuperate from them significant information. Consequently, localization has become an interesting topic for many researchers.

One of the famous approaches that has been mostly used in localization is the global positioning system (GPS), the main idea of GPS hinges on a method called triangulation or trilateration, it needs to get message from three satellites at least to work properly; in order to apply triangulation a GPS receiver measure the distance between itself and each satellite. Despite all the advantages that GPS offer, it's still unsuitable in indoor areas and will not be a good choice due to different physical phenomena (attenuation, multipath …) that can affect signal propagation.

1-4 Localization types

Since the GPS cannot offer a good solution for all wireless applications, two common types of localization have been widely used; The range free techniques (hop count, APIT, centroid….), where the significant range information between the sensor nodes is not needed, and the range-based techniques that use propagation signal information such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and Received Signal Strength Indicator (RSSI). Range based techniques are characterized by being more accurate compared to range-free. Most of localization techniques consist of using multiple anchors or reference nodes, nodes that we know their real position [6-7]:

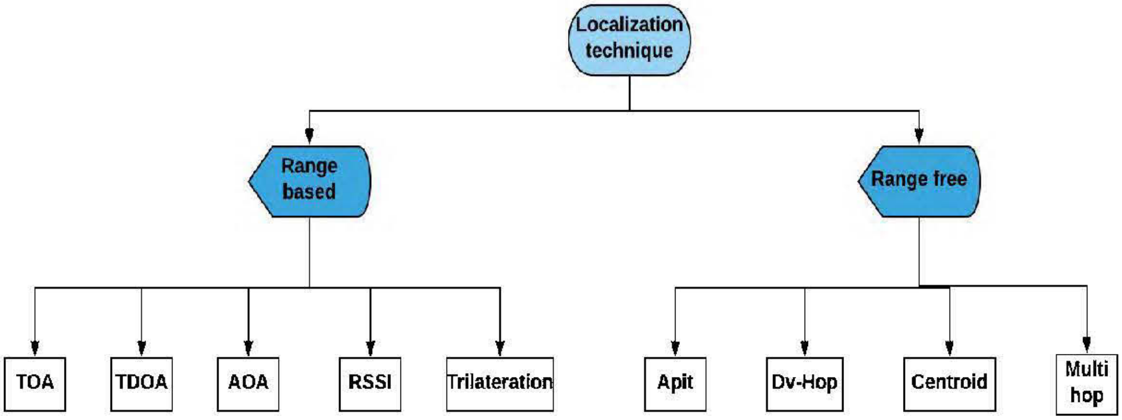

Figure 1-2: Localization techniques

1-5 Range based localization

This type is characterized by being more accurate compared to range-free, where the information on distance/angle between sensor nodes are required, adding an extra hardware requirement.

1-5-1 Time based localization

Time of Arrival (TOA): TOA (also called time of flight method) based on the concept where the distance between two sensors can be calculated using the measured signal propagation time and the known signal velocity. Note that there is two types of TOA, one-way TOA and two-way TOA.

1-5-2 Based on One-way TOA

This method measures the one-way propagation time represented as the difference between the sending time and the signal arrival time, One-way TOA requires highly accurate synchronization of the clocks for the sender and the receiver

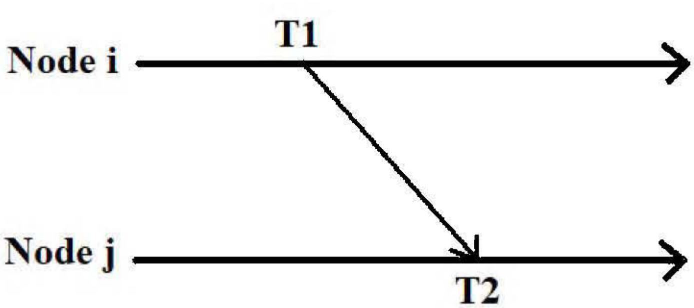

Figure 1-3: One-way time of arrival.

$$d_{i,j=}(t_2 - t_1) \times v \qquad (1)$$

$d_{i,j}$: represent the distance between node i and node j.

t_1: represent the sending time of the signal.

t_2: represent the receiving time of the signal.

v: represent the signal velocity.

1-5-3 Based on Two-way TOA

The two-way time of arrival method is preferred, where the round-trip time of a signal is measured at the sender device as shown in figure 1-4.

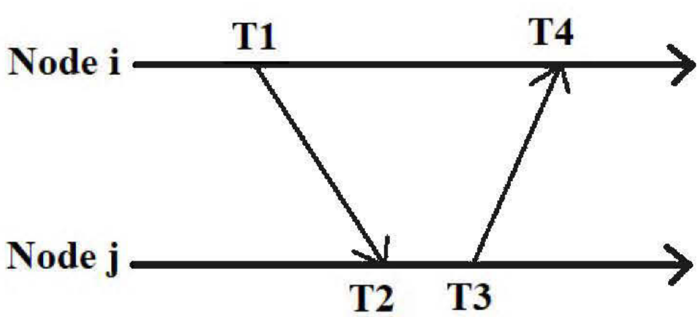

Figure 1-4: Two-way time of arrival.

$$d_{i,j=} \frac{(t_4 - t_1) - (t_3 - t_2)}{2} \times v \qquad (2)$$

Where t_3 and t_4 represent the sending and receiving times of the response signal. Note that with one-way localization, the receiver node calculates its location, while in the two-way approach, the sender node calculates the receiver's location. Therefore, a third message will be necessary in the two-way approach to inform the receiver of its location.

Two-way TOA is preferred, where the round-trip time of a signal is measured at the sender sensor [8].

1-5-4 Based on Time Difference on Arrival (TDoA)

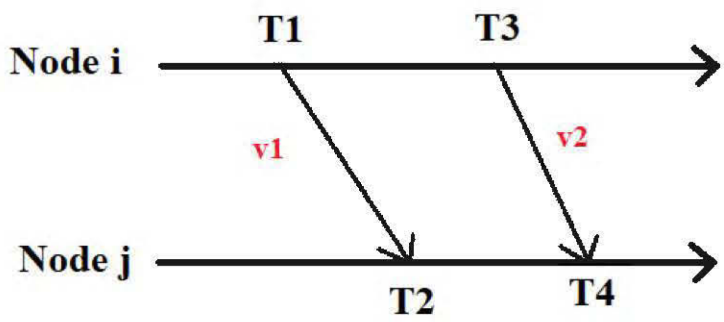

Figure 1-5: Time difference of arrival.

TDoA is based on:

1. The difference in the times at which a single signal transmitted from a single node is received at three or more nodes.
2. The difference in the time where numerous signals is received at three or more nodes.

In the first case the synchronization between receiver nodes is needed, adding that it is frequently used in cellular networks [6].

The second case can be more flexible and used in WSNs where the sensor nodes must be equipped with extra hardware capable of sending two types of signal simultaneously, these signals must have different propagation speed, the receiver is then able to determine its location similar to the ToA approach. For example, the first signal could be a radio signal (carried at $T1$ and received at $T2$) followed by a different type of signal (acoustic signal). Therefore, the receiver can determine the distance as:

$$\boldsymbol{d}_{i,j=} = (v_1 - v_2) \times (t_4 - t_2 - t_{wait}) \quad (3)$$

$$t_{wait} = t_3 - t_1.$$

Advantage of TDoA: the clock synchronization of the clock for the sender and the receiver is not needed.

Disadvantages: the need for additional hardware, for example, a microphone, speaker etc [6-8].

1-5-5 Based on Angle of Arrival (AoA)

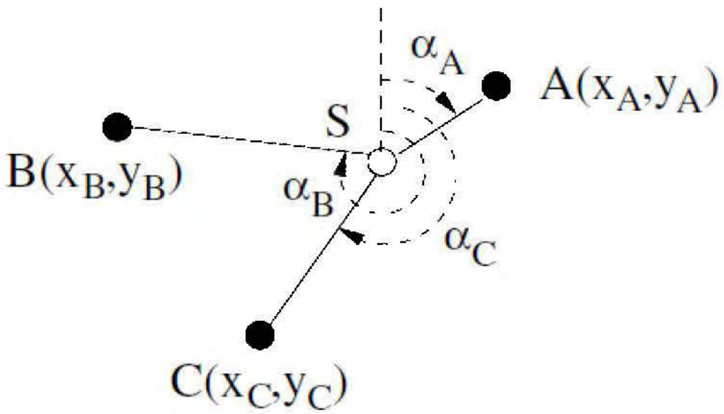

Figure 1-6: Angle of arrival (AoA).

Angle-of-arrival is used to determine the direction of signal propagation, using an array of antennas or microphones. As shown in Figure 1-6, a sensor node S with an unknown location, $(x_s\ , y_s\ )$, receives signals from sensor nodes A, B, and C with known locations, $(x_A,\ y_A)$, $(x_B,\ y_B)$, and $(x_C,\ y_C)$. After that, node S estimates the AoA of each node, α_A, α_B, and α_C, AoA measurements are then combined with the locations of nodes A,B and C to estimate the position of node S. Mention that, the AoA technique accuracy is affected by the measurement accuracy.

Nevertheless, this technique needs a high complexity antenna array for direction measurement, which increases the cost. Furthermore, antenna arrays need a certain spacing to provide spatial diversity and to accurately measure the AoA. Finally, AoA techniques also suffer from multi-path and scattering as well as NLoS conditions. Since the direction of arrival is used for localization, the error due to NLoS components of the received signal may be even more severe compared to that of RSSI- techniques [6].

1-5-6 Based on RSSI-Finger printing:

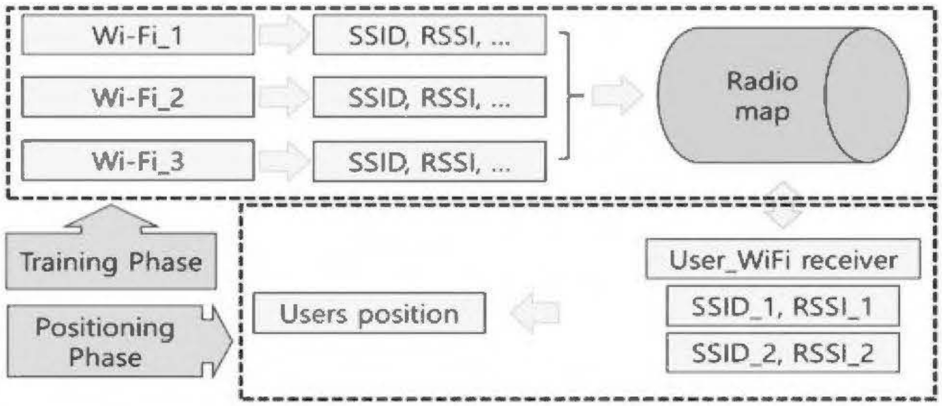

Figure 1-7: Finger printing localization [9].

Consists of two phases, training phase (off line / calibration phase) and positioning phase (online phase), in training phase a radio map will be created using the coordinates of references nodes to prevent the time-consuming process of the actual process. In other words, at this stage, the RSS will be collected from all access point (AP).

In poisoning phase, the location of the target mobile user will be measured using the RSS values from several access point, after that the obtained values will bel compared with the data stored in the radio map [10].

The positioning distance D_j between the stored RSS value RSS_{offine} and the online collected RSS value RSS_{online} at the j_{th} anchor point is given by:

$$D_j = \sum_{i=1}^{N} \sqrt{(RSS_{offine} - RSS_{online})^2} \tag{4}$$

Where i represent the number of sensor nodes ranging from 1 to N.

1-5-7 Trilateration

To localize an unknown node, a well-known technique is used; the trilateration where at least 3 anchor nodes (nodes which real positions are known) are necessary to estimate an unknow node's position that will be the intersection of three circles [11]. It is known that the sensor nodes must be positioned somewhere along the circumference of a circle centered at the anchor's position with a radius equal to the sensor–anchor distance.

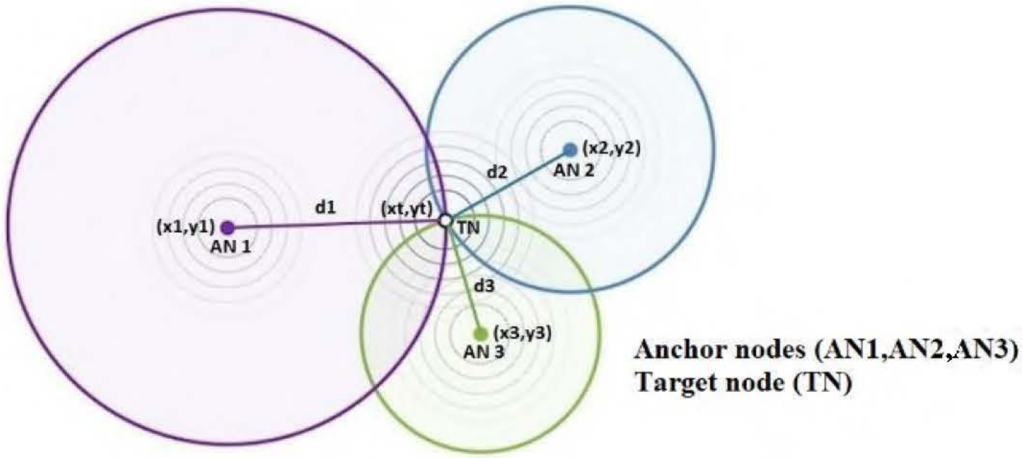

Figure 1-8: localization using trilateration technique [12].

Figure 1-8 illustrates an example in the two-dimensional case. To obtain distance measurements in the case of three dimensions, at least four non-coplanar anchors are required.

Suppose that the locations of the N_α anchor nodes are given by (x_i, y_i) $i = 1, \ldots, N_n$ and that the distances between a regular node (x, y) and these anchor nodes are also known by d_i, $i = 1, \ldots N_\alpha$. Using this information we can obtain the system of nonlinear equations as following that shows the relation between the Anchor/Target position and distance:

$$\begin{cases} (x_1 - \hat{x})^2 + (y_1 - \hat{y})^2 = \hat{d}_1{}^2 \\ (x_2 - \hat{x})^2 + (y_2 - \hat{y})^2 = \hat{d}_2{}^2 \\ \cdot \\ \cdot \\ (x_{N_\alpha} - \hat{x})^2 + (y_{N_\alpha} - \hat{y})^2 = \hat{d}_{N_\alpha}{}^2 \end{cases}$$

where $(\hat{x}, \hat{y})$ are the estimated coordinates of the target node. After linearize the system above, we get [11]:

$$\gamma_{\hat{\alpha}} = -\frac{1}{2} k \qquad (5)$$

$$\hat{\alpha} = [\hat{x}, \hat{y}]^T$$

$$\gamma = \begin{bmatrix} x_1 - x_{N_\alpha} & y_1 - y_{N_\alpha} \\ x_2 - x_{N_\alpha} & y_2 - y_{N_\alpha} \\ \vdots \quad \vdots & \vdots \quad \vdots \\ x_{N_\alpha - 1} - x_{N_\alpha} & y_{N_\alpha - 1} - y_{N_\alpha} \end{bmatrix}$$

$$k_i = \begin{bmatrix} d_1^{*^2} - d_{N_\alpha}^{*^2} + x_{N_\alpha}^2 - x_1^2 + y_{N_\alpha}^2 - y_1^2 \\ d_2^{*^2} - d_{N_\alpha}^{*^2} + x_{N_\alpha}^2 - x_2^2 + y_{N_\alpha}^2 - y_2^2 \\ \vdots \\ d_{(N_\alpha - 1)}^{*^2} - d_{N_\alpha}^{*^2} + x_{N_\alpha}^2 - x_{(N_\alpha - 1)}^2 + y_{N_\alpha}^2 - y_{(N_\alpha - 1)}^2 \end{bmatrix}$$

Since γ is a non-invertible matrix, α can be estimated by the pseudo-inverse of γ as following:

$$\hat{\alpha} = -\frac{1}{2}(\gamma\gamma^t)^{-1}\gamma^t \, k \quad [11] \qquad (6)$$

1-5-8 Based on Received Signal Strength (Path loss model)

RSS technique offers a good solution in indoor areas, it consists of calculating the distance using the RSS measurements between the receiver and the transmitter node, it is considered as a low complex and low energy consumption method [13-14]. Nowadays, RSS ranging is mainly implemented among short range wireless communication systems because RSS measurement is obtained in every RF transceiver [15]. Nevertheless, despite all the advantages of RSS, it is sensitive to the noise factor, that will affect the estimated distance accuracy [6]. In order to understand this technique well, the next section will represent a detailed study about path loss model.

1-5-8-1 Path loss model

Wireless communication is based on different propagation model that predict the behavior of electromagnetic waves, most of these models can be represented as a mathematical formula that give a reliable accuracy for estimation. Despite that, applying these models in real life environment don't give the same result as given by the generic model due to the existence of different environmental characteristics. For this reason it is important to characterize the reel world effect in order to make wireless communication more consistent.

In wireless communication system, the losses of energy that occurred between transmitter and receiver is identified as propagation path loss. Path loss of energy is a main factor in the analysis and design of wireless communication structure. Furthermore, the electromagnetic waves typically cannot directly reach the receiver due to many obstacles that block the line of sight path. Multipath fading, occurs when a transmitted signal divides and takes more than one path to a receiver and some of the signals arrive out of phase, resulting in a weak or fading signal.

There are many factors that can affect the signal propagation [16].

- Reflection.
- Diffraction.
- Scattering.
- Doppler Effect.

a) Reflection

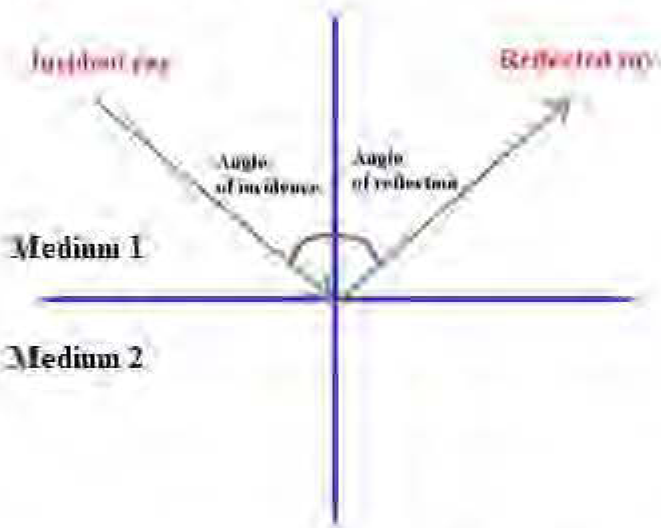

Figure 1-9: Wave reflection.

Reflection is the abrupt change in the direction of propagation of a wave that strikes the boundary between two different media (change in the index of crossed environments). Common example includes the reflection of light, sound and water waves.

b) Diffraction

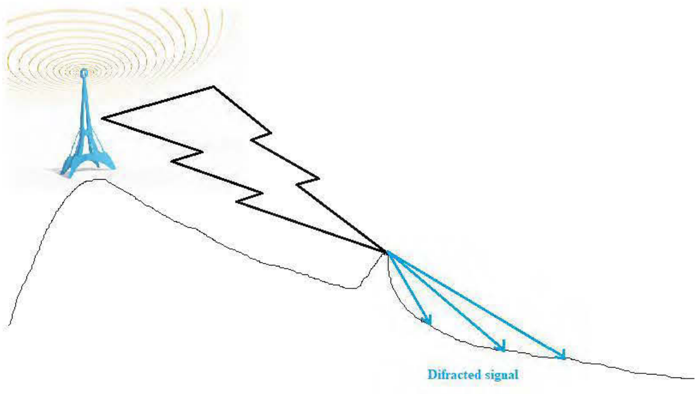

Figure 1-10: Wave diffraction.

When diffraction happens, the signal encounters an edge or a corner, whose size is larger than the wavelength of the signal.

c) Scattering

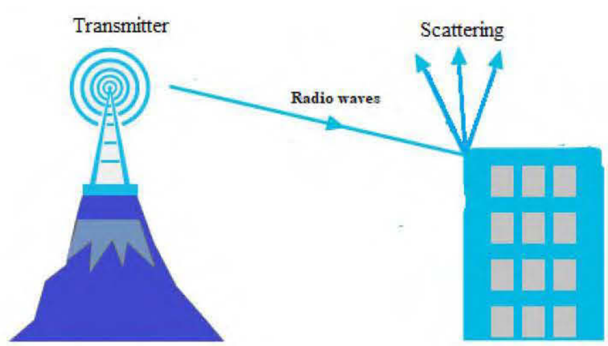

Figure 1-11: Wave scattering.

Scattering occurs when the signal encounters small objects their size are smaller than the wavelength of the signal. A simple example, when the sun's rays pass through clouds, the light is deflected off of its straight path and scatters in many direction

d) Doppler effect

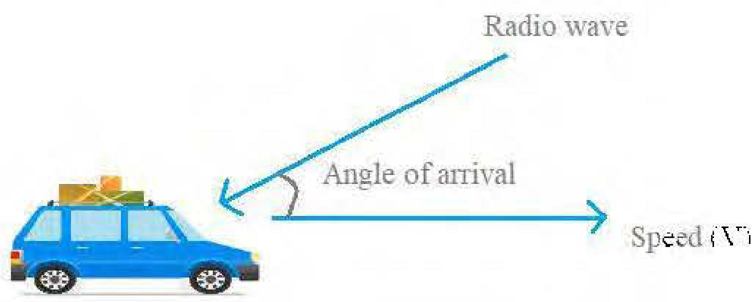

Figure 1-12: Doppler effect.

Doppler Effect, occurs when the transmitter of a signal is moving in relation to the receiver. Therefore, the receiver will not obtain the same transmitted signal since this movement shifts the frequency of the signal [17].

The Doppler shift formula is represented by:

$$F = \frac{V+V_0}{V-V_s} \times \mathrm{f} \tag{7}$$

F: The observed frequency.

f: The actual frequency.

V: Velocity of wave.

V_0:Velocity of the observer.

V_s: Velocity of the source.

e) Friis space model

The relation between the transmitted and the received power can be estimated using Friis [11] space equation:

$$\frac{p_r}{p_t}(d) = \frac{G_r G_t \lambda^2}{(4\pi d)^2 L} \tag{8}$$

p_r: Represent the received power by the antenna at distance *d*.

p_t: Represent the transmitted power of the antenna.

G_r: Represent the gain of the receiver antenna.

G_t: Represent the gain of the transmitter antenna.

D: Represent the distance between the transmitter and the receiver.

L: Represent the system loss factor.

f) Path loss model

Generally, the power of electromagnetic waves decreases related to the increasing of the traveled distance between the sender and the receiver, this law determines the dissipation of energy during signal travelling to the receiver in a direct line of sight or through multi path. In both cases the energy dissipation will be related to the power function described in equation below.

$$Pr_d = \mathrm{Pr}_{d0} - 10 \times n \times Log10\left(\frac{d}{d_0}\right) + X_\sigma \ \text{(dbm)} \tag{9}$$

- Pr_d represent the received power at distance d.
- Pr_{d0} represent the power received at distance d_0.
- n is the path loss exponent.
- d is the distance between the sender and the receiver.
- X_σ represents a normal or gaussian random variable in db.

Path loss function can be affected by many parameters, path loss exponent factor (PLE) is considered to be the most important features. Usually PLE depend on the types of the environments, for this reason we find that, the value of PLE in underground situation is different to the PLE in a free space environment or in underwater atmosphere. Furthermore, the existence of different styles of obstacles can affect in a huge way the path loss equation and make the measurements mush harder [18].

Table 1: Path loss exponent in different environments variation [18].

Environment	Path loss exponent
Free Space	2
Urban area cellular radio	2.7 to 3.5
Shadowed urban cellular radio	3 to 5
In building line-of-sight	1.6 to 1.8

Obstructed in buildings	4 to 6
Obstructed in factories	2 to 3

After presenting a comprehensive study about range-based localization, next we introduce the second type of localization technique, the range free techniques.

1-6 Range free

The different techniques used in range-based approaches are based on measuring the distance and / or angle. On the other hand, "range-free" algorithms are more economical in hardware as they are content with connectivity information related to the radio scope instead distance or angle measurements. The following sections describe range free different algorithms.

1-6-1 Approximate Point In Triangulation (APIT)

APIT is an anchor-based range free localization algorithm which locate the location of unknown node by triangular area method. This method relies on the presence of several anchor nodes that know their own positions. Any combination of three anchor points constitutes a triangular region and the presence of a node inside or outside such a region allows a node to refine it possible position [19]. The signal strength between the nodes and the anchors can be used to estimate which node is closest to the anchor, then if no neighbor (1,2,3,4) of node M is near neither far from the three anchors A,B,C simultaneously, M supposes that it is inside the triangle A,B,C (figure 1-13). Otherwise M assumes he is outside the triangle (figure 1-14).

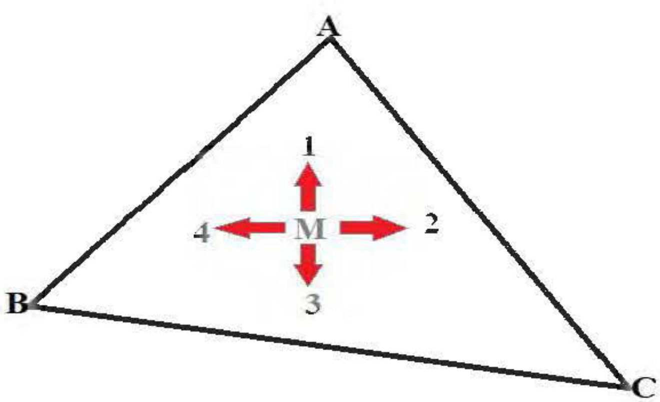

Figure 1-13: APIT (inside case).

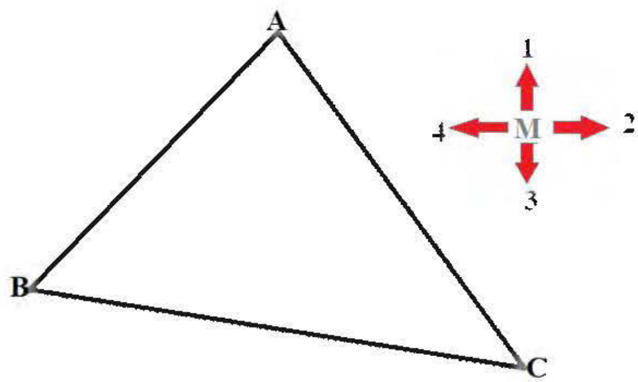

Figure 1-14: APIT (outside case).

The situation is different in this part, for example the neighbor 4 is close to all three anchor nodes than node M, while node 2 is away from the anchor nodes than the M node, hence the M node concludes that it is outside the triangle A.B.C.

In this scheme, a node can make bad decisions, for example in the inner case, if the distance measurements from node 4 indicate that it is farther from the node **B** that the node M (because of an obstacle between the anchor B and the node 4), the node M would conclude it must be outside the triangle ABC [19].

The advantage of APIT lies in its simplicity and the facility of implementation. Nevertheless, the APIT requires a high density of anchor nodes.

1-6-2 Distance Vector-hop (DV-HOP)

DV-HOP is an example of a location algorithm based on a distributed connectivity that estimates the position of the node "S" with the support of at least three anchor nodes, where the errors of localization can be reduced by increasing the number of anchor nodes. Each anchor propagates its location to all other nodes in the network using the concept of the distance vector exchange (DV), where the nodes in a network exchange periodically their routing tables with their neighbors at a single hop [20], each node holds a table *Xi, Yi,* n_i, where *Xi, Yi* is the location of node *i*, n_i is the minimum hop count between this node and another node i. when anchor node gets the distances to other anchors, then it determines an average size of a hop C_i (called the correction factor) which can be calculated as follows:

$$C_i = \frac{\sum \sqrt{(X_i - X_j)^2 + (Y_i - Y_j)^2}}{\sum n_i} \tag{10}$$

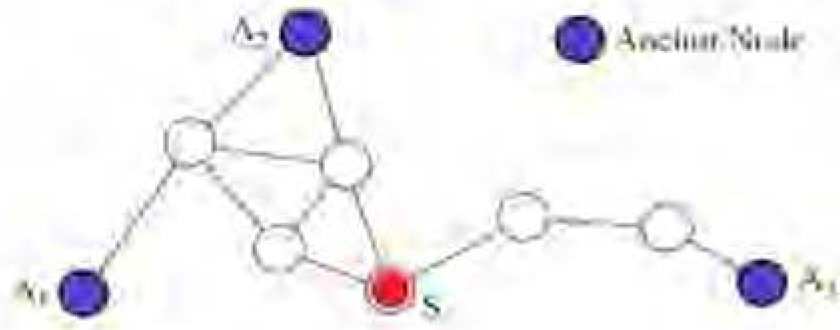

Figure 1-15: Dv-hop technique.

To better understand this technique, we take this example which is illustrated in Figure. 1-15. In this example, we have three anchor nodes A_1, A_2, A_3. For anchor A_1, the Euclidean distances between anchor A_1 of anchors A_2 and A_3. are $d_{A_1-A_2} = 50$ m and $d_{A_1-A_3} = 110$ m, respectively. In addition, the numbers of the hops separating the anchor A1 from the anchors A2 and A3 are two and six hops successively. The correction factor for A1 is then calculated by $\frac{50+110}{2+6} = 20$ m, which represents the estimated average distance of a hop. In the same way, we calculate the correction factor for A_2 as $\frac{50+80}{2+5} = 18.57$ m. Once all the anchors are sharing their own average size of a hop, they diffuse them through the network to the nodes in range.

1-6-3 Centroid

In centroid localization algorithm [21], node's location is computed on the basis of numerous anchor node positions. The centroid localization algorithm uses the location (X_i , Y_i) of anchor nodes.

$(\hat{X}, \hat{Y})$ represent the estimated position of sensor node.

N is the number of anchor nodes.

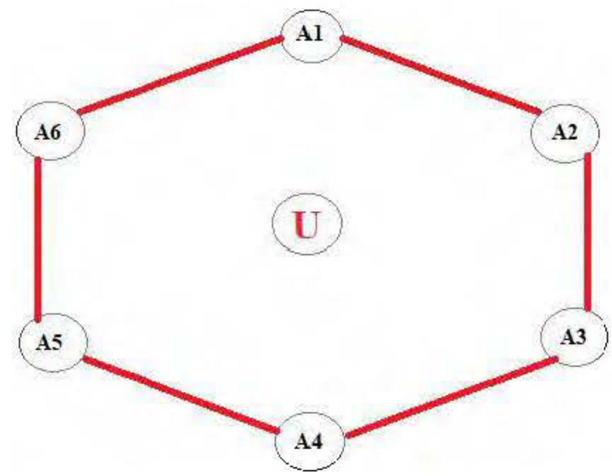

Figure 1-16: Centroid.

The idea of centroid algorithm is to take a number of nodes around the target node as shown in figure 1-16, where A represent the anchor node and U is the Unknown node [21].
After receiving the information from several anchor nodes, the unknown node estimates its position by using following formula:

$$(\hat{x}, \hat{y}) = (\frac{X_1 + \cdots + X_N}{N}, \frac{Y_1 + \cdots + Y_N}{N}) \quad (11)$$

1-6-4 Multi-Hop

Multi Hop techniques rely on a network connectivity graph. The multidimensional scaling (MDS) uses counectivity information considering the nodes are within the communication range.

A number of localization techniques have been reported which use Multidimensional scaling. It is a set of data analysis techniques which display distance like data as geometric structure. This method is used for visualizing dissimilarity data. It is often used as a part of data exploratory technique or information visualization technique. MDS based algorithms are energy efficient as communication among different nodes is required only initially for obtaining the inter-node distances of the network. Once all distances are obtained, further computation for finding positions does not need communication among nodes.

This scheme is represented by the following three steps [11-21]:

- Estimate the distance between each pair of nodes.
- Deriving the locations using MDS to fit the estimated distance.
- Optimization is done by putting the known locations into account.

1-7 Range free and range-based technique comparison.

The accuracy of localization algorithm depends on multiple factors such as precision, scalability and computation cost..., The localization outlines can be classified on the basis of certain measures such as: presence of anchor, computational model, and communication range measurements. All localization techniques have their own merits and limitations, making them suitable for different applications [21]. The comparison between several range free localization technique is summarized in table 2. In addition, the comparison between range-based technique will be shown in table 3. Nevertheless, the summary of comparison between range based and range free technique is shown in table 4.

Table 2: Range free technique comparaison [21].

Technique	Accuracy	Cost	Scalability
APIT	Good	High	Yes
DV-HOP	Good	Medium	No
Multi-Hop	Good	High	No
Centroid	reasonable	Low	Yes

Table 3: Range base technique comparaison [21].

Technique	Accuracy	Cost	Hardware size	Energy efficiency	Complexity
TOA	Medium	High	Large	Less	High
TDOA	High	Medium	Average	High	High
AOA	Low	High	Large	Medium	High
RSSI	Medium	Low	Small	High	Low

Table 4: Range based and range free comparison [21].

Techniques / Characteristic	Range based	Range free
Cost	More	Less
Power consumption	More	Less
Additional hardware	Yes	No
Accuracy	**85-90%**	**70-75%**

In this work, the goal will be having an accurate result, for this reason we will be focusing on range-based techniques since it can be more accurate compared to range free techniques, basically the accuracy of the localization in range-based is related in a huge way with the environmental characteristic, for example the AoA technique cannot be a good choice in complex area since it suffer from multi-path and scattering as well as NLoS conditions, in addition, the Time of arrival techniques require a high synchronisation, so it is hard for this technique to be implemented in complex area. In other hand, RSS is used by many researchers since its less complex compared to the others. Some researchers have focused on optimization algorithms that have shown a significant result localization domain, specially in complex applications. Hence, our goal in this work is to use the gradient descent optimization technique and combine it with the RSS technique.

CHAPTER 2

GRADIENT DESCENT OPTIMIZATION APPROACH AND IMPACT OF INITIALIZATION

2-1 Optimization

In practice, solving a mathematical optimization problem involves finding the best solution to a problem that has been expressed in a particular mathematical form that involves one or more criteria. This or these criteria are expressed in the form of a mathematical function, called an objective function. The optimal solution or the better solution is to find an extreme value, also called extremum - that is to say a maximum or a minimum - to this objective function.

In order to solve an optimization problem, it is important to identify which category this problem belongs to. Indeed, the algorithms developed are designed to solve a given type of problems and are not very effective for another types. The classification of optimization problems varies. For example, there are:

The problems of continuous optimization versus discrete optimization problems

In some cases, the decision variables are discrete, most often in the form of integers or binaries. The optimization problem is said to be discrete. On the contrary, in continuous optimization problems, variables can take any value, they are real. Continuous optimization problems are usually easier to solve. An optimization problem mixing continuous variables and discrete variables is called mixed.

Optimization problems with and without constraints

It is important to distinguish between problems where constraints exist on the decision variables. These constraints can be simply bounding and go up to a set of equality and inequality type equations. It is sometimes possible to eliminate a replacement equality constraint in the objective function. Naturally, problems with constraints are more complicated to solve and use dedicated algorithms.

Mono-objective or multi-objective optimization problems

Single objective problems are defined by a single objective function. Multi-objective problems exist when a compromise is to be sought between several contradictory objectives. It may be possible (but not necessarily effective) to reformulate a multi-objective problem with a single objective function in the form of a combination of different objectives or by transforming objectives into constraints.

Deterministic or stochastic optimization problems

Deterministic optimization problems consider that the data are perfectly known, whereas in stochastic optimization problems, this is not the case; for example, a stochastic approach may be relevant in the case where the variables of a problem are the future sales of a product. In this case, uncertainty can be introduced into the model.

2-2 Optimization technique in localization

Generally, there are many optimization algorithms that can be used in different sorts of applications, in optimization localization domain the most two famous algorithms are Newton and the Gradient descent.

2-2-1 Newton method

Newton's method (sometimes called Newton-Raphson method) uses first and second derivatives of the objective function. Given a starting point (initialization), construct a quadratic approximation of the objective function that matches the first and second derivative values at that point. We then minimize the approximate (quadratic function) instead of the original objective function. The minimizer of the approximate function is used as the starting point in the next step and repeat the procedure iteratively. Newton method can be impractical for high-dimensional problems because it requires inverting the Hessian matrix, but many highly effective optimizations algorithms can be viewed as approximations to Newton's method. This technique is characterized by being complexes.

2-2-2 Gradient descent method

In terms of localization and for the simplicity, most of researchers prefer to use the gradient descent optimization technique instead of using newton or other technique, hence, this work will be based on gradient descent (GD) algorithm. The core of GD hinges on the concept of minimizing a specific target function by iteratively moving in the direction of the optimum value.

Principally gradient descent method can be described in 3 mathematical steps:

1. Take a random point x_0 and start from this point. This step can be named the initialization step.
2. Compute the derivative of the objective function f $\frac{df}{dx}$ (the slope).
3. Walk in the direction opposite to the slope: x_{i+1}=x_i−K×$\frac{df}{dx}$ (x_i) Here K represent the step size, and the *minus* sign enables us to go in the opposite direction.

   So, for example for i=*0*, the first iteration will be:

   x_{0+1}=x_0−K×$\frac{df}{dx}$ (x_0)

   x_0 represent the initial value from the first step, after that we repeat step 3 till convergence.

In this work we have used two objective functions, the first will be described in this chapter as the difference between the real and estimated distance, and the second target function will be represented in chapter 3 as the difference between the real and estimated power based on the path loss model.

2-3 Gradient Descent in localization

Since in this work the objective functions is based on a logarithmic equation, the target function will not be a normal quadratic function. For this reason, the next section will show the way of how the gradient descent will be applied in this work.

Figure 2-1. Gradient descent in localization

The initialization represents the starting point. By moving iteratively, we can reach the optimum value that will be in our case the location (coordinates) of the target nodes. Gradient descent accuracy can be affected by the local minimum problem or the initialization factor. A local maximum is any peak, when the rate of change switches from positive to negative, and local minimum is any trough, when the rate of change switches from negative to positive. In order to resolve this problem a non-random initialization technique will be used to avoid falling into these problems.

2-4 Gradient descent related work in localization

Many researches have focused in their studies on the optimization part in localization, that have shown a significance results compared with traditional localization techniques.

Among all optimization methods, gradient descent has concerned most of researchers in optimization localization domain, [22] presents a gradient-based fingerprinting for indoor localization, that can be more adaptive to the time variant indoor wireless signal, [23] presents a distributed gradient descent localization, where GD was combined with vector push sum gossip algorithm to compute sums, in order to achieve fast convergence. Other researchers have focused on the secure side of gradient descent localization, [24] presents a secure localization algorithm that can resist to malicious attacks by merging gradient descent with a selective pruning technique, additionally, this same method was improved in [25] to eliminate ambiguous information, where the usual nodes can collaborate to reduce localization errors. Furthermore, while using gradient descent algorithm we should start by initial values, may assigned randomly, nevertheless, one of the most issue in gradient descent is falling into the local minimum issue, for that in order to avoid such type of problem [10] presents an initialization method were a selected K nearest neighbor was useful to get an appropriate initial point of the gradient descent. Work in [26] two gradient methods were introduced, gradient method A (GDA) and gradient method B (GDB), in both, the inter sensor distance was supposed to be known, and the target function represented as the sum of the squared error between the given and estimated distance, the idea is to minimize the target function. In GDA method, the initialization was done randomly based on the weighted distance. The difference between the two methods is that in A the gradient was applied on the weight changing on each iteration in order to obtain the optimum weight that will give us the location of the unknown node, while in B the gradient was applied on the estimated coordinates, in addition, in both of these methods, the number of used reference nodes is considered to be high in such small area.

The idea in this chapter is to show the importance of using gradient descent in localization domain in term of reducing the required anchor nodes, and that is by comparing the number of anchor node used in trilateration technique with the gradient descent method used in this chapter, second, to show the importance of a good initialization in node's localization. For that, we combine two methods (GDA and GDB) mentioned in [26], and that by using the initialization used in GDA and applying it on GDB, while the gradient will be made on the coordinates and not on the weights.

This initialization technique was compared to a non-random initialization method, and that is to show the importance of non-random initialization and how it can affect the results accuracy.

2-5 Block diagram of the algorithm

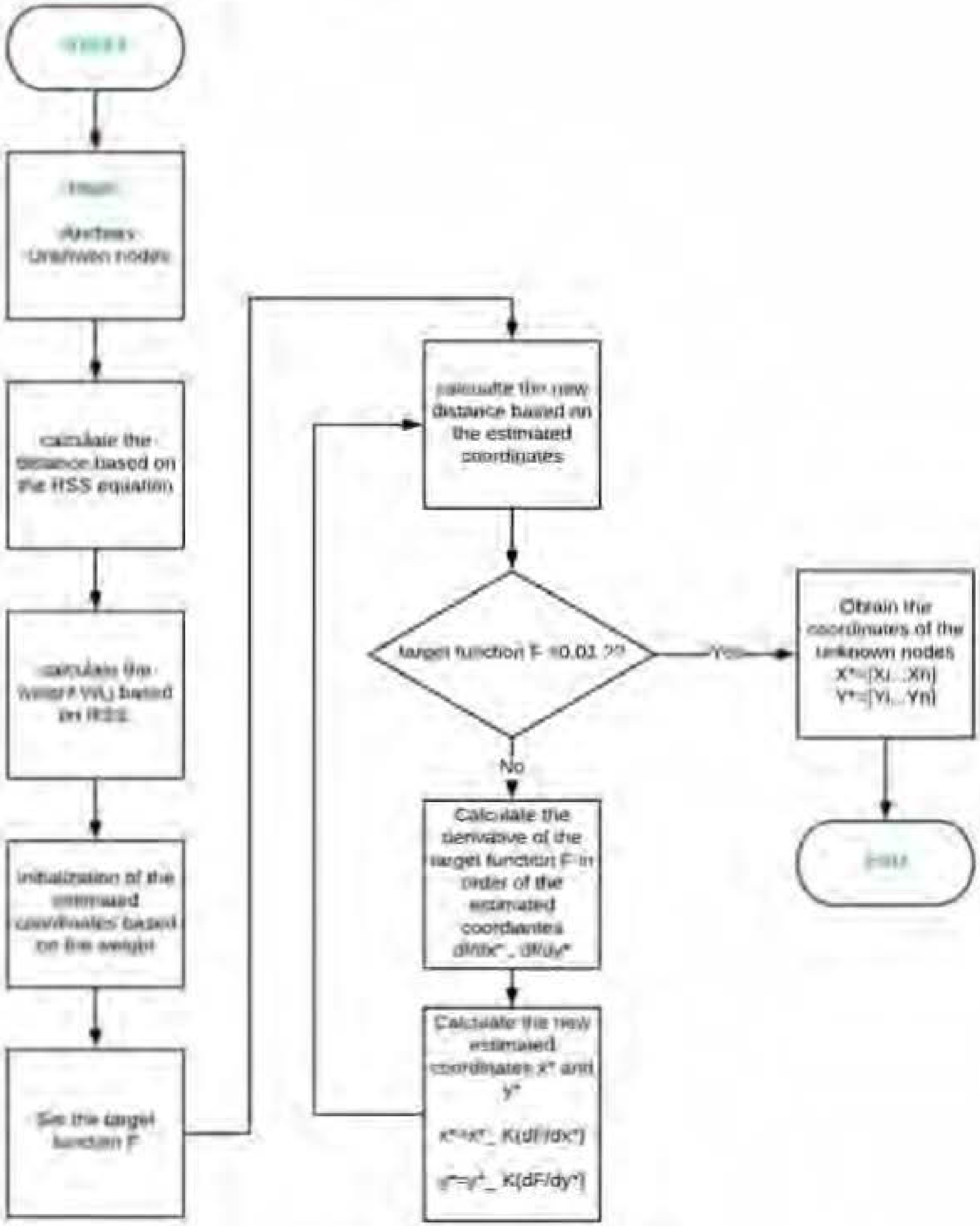

Figure 2-2: Block diagram for gradient descent methodologies.

As a first step, we will create a network, this network will contain as input 2 anchor nodes, and the unknown nodes. The distribution of these nodes will be based on a random way. The goal is to apply our algorithm on this network in order to obtain the accurate location of the distributed nodes. The second step will be calculating the distance based on RSS value represented by the equation 13. After having the distance, we will move to the initialization step, that means the starting points $(\hat{x}_0, \hat{y}_0)$, the initialization will be based on the weighted distance presented in equation 20, 21 below. Next the target function will be set as the difference between the real and estimated distance (equation 14). After that, the estimated distance will be calculated based on the estimated coordinates (equation 15). In order to obtain the location of the unknown nodes, a condition will be applied on the target function F, if the condition true we will obtain a vector of the unknown node's location $(\hat{x}_i, \hat{y}_i)$, if not the , the derivative of the target function will be calculated with respect to $\hat{x}_i$ and $\hat{y}_i$ (equation 22, 23). After that, the new estimated coordinates will be calculated (equation 24), the last two steps will be repeated to achieve the condition goal, and obtain and the end the location of the unknown nodes.

2-6 Distance estimation

As a first step, the calculation of the distance between the anchors and the unknown node will be based on the equation of the received power below.

$$Pr_{i,j} = \mathrm{Pr}_{d0} - 10 \times n \times Log10\left(\frac{d^*_{i,j}}{d_0}\right) \tag{12}$$

Where the distance can be calculated as follow using [10]:

$$d^*_{i,j} = d_0 \times 10^{\left(\frac{Pr_{d0} - Pr_{d^*_{i,j}}}{10n}\right)} \tag{13}$$

$Pr_{i,j}$ represent the received power by the ith node from the jth anchor.

Pr_{d0} represents the received power at distance d_0, n is the path loss exponent and $d^*(i,j)$ is the distance between target node i and anchor j.

2-7 Objective function and Coordinates estimation

The objective function now will be represented by the sum of the squared errors between the distance obtained from equation 13 and the estimated distance $\hat{d}$ changing in each iteration. [26]

$$F = 0.5 \times \sum_{\substack{i,j=1 \\ i \neq j}}^{N,M} \left(d^*_{i,j} - \hat{d}_{i,j}\right)^2 \tag{14}$$

$d^*_{i,j}$ is the distance obtained by equation 13, and $\hat{d}_{i,j}$ is the estimated distance based on the estimated coordinate that will change on each iteration:

$$\hat{d}_{i,j} = \sqrt{\left(x_j - \hat{x}_i\right)^2 + \left(y_j - \hat{y}_i\right)^2} \tag{15}$$

$\hat{x}_i$ and $\hat{y}_i$ represent the estimated coordinates of the unknown node to be localized.

x_j and y_j represent the coordinates of the anchor nodes.

With $i = (1 \ldots\ldots, N)$ with N number of nodes and $j = (1 \ldots, M)$, with M the number of anchors.

The goal of the algorithm is to obtain the location of unknown nodes coordinates at the last iteration, and that will be by minimizing the objective function (equation14) through Gradient descent. GD is used to find the best coordinate $\hat{x}$ and $\hat{y}$ that minimize the target function. In order to do that, we should start by an initial coordinate; it can be assigned randomly but it is important to start by a suitable value in order to avoid local minima issue and obtain an accurate result.

This work will show a good initialization, that will be compared in the simulation with the random initialization techniques:

2-8 Initialization techniques

a. Random initialization (RI)

First initialization is based on [26].

$$\hat{x}_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \tag{16}$$

$$\hat{y}_1 = \left(v_{1,2} \times d_{1,2}\right) + \left(v_{1,3} \times d_{1,3}\right) + \cdots \left(v_{1,M} \times d_{1,M}\right) \tag{17}$$

Here the weights w and v are given randomly using uniform law.

$d_{1,j}$ is the distance between the unknown node 1 and the anchor j. xe_1 and ye_1 represent the coordinates of the unknown node 1.

Note that the position of N nodes $(\hat{x}_1, \hat{y}_1), (\hat{x}_2, \hat{y}_2) \ldots\ldots (\hat{x}_N, \hat{y}_N)$ are all the target coordinates to be find.

b. Another random initialization (ARI)

Another initialization method based on [10] is used also in this work. Where the weight will not be multiplied with the inter node distance, but with the coordinates of the anchor nodes.

$$\hat{x}_1 = (w_{1,2} \times x_2) + (w_{1,3} \times x_3) + \cdots (w_{1,M} \times x_M) \tag{18}$$

$$\hat{y}_1 = (w_{1,2} \times y_2) + (w_{1,3} \times y_3) + \cdots (w_{1,M} \times y_M) \tag{19}$$

Where x_2, x_3, x_M, y_2, y_3 and y_M represent the coordinates of the anchor nodes and the weight is given randomly

c. Weighted initialization (WI)

The third initialization will be based on RSS and the non-random weight [10], this technique hinges on the concept of using a weighted initialization based on the RSS value between the anchor and the target nodes. This method will lead us to go in the right direction during several iteration steps in the gradient descent. Since we are using two anchors only, it is possible to have some problems like the local minimum problem or space distance problem, that means we can have the same distance from the anchor to the unknown nodes in different locations, leading the condition applied on the target function to be true. In addition, starting by a bad initialization point can be an issue and facilitate falling into these previous problems affecting the location accuracy. In order to avoid these problems, we show the effectiveness of using a weighted distance based on the RSS value.

$$\hat{x}_1 = (w_{1,2} \times d_{1,2}) + (w_{1,3} \times d_{1,3}) + \cdots (w_{1,M} \times d_{1,M}) \tag{20}$$

$$\hat{y}_1 = (w_{1,2} \times d_{1,2}) + (w_{1,3} \times d_{1,3}) + \cdots (w_{1,M} \times d_{1,M}) \tag{21}$$

$d_{1,j}$ is the distance between the unknown node 1 and the fixed anchor j.

$$w_{1,j} = \left| \frac{1}{Pr_{1,j}} \right|$$

Using a non-random weighted distance will make the derivative to go in the correct direction of the optimum value.

$Pr_{1,j}$ represent the received power between the unknown node 1 and the fixed anchor j with j=1…M.

2-9 Derivation

After the initialization step, we derive the objective function in (14) with respect to $\widehat{x}_i$ and to $\widehat{y}_i$.

$$\frac{dF}{d\,\widehat{x}_i} = \sum_{\substack{j=1,\\ i=1\\ j<i}}^{N,M} (\,\widehat{d}_{i,j} - d_{i,j}{}^{*})\left(\frac{\widehat{x}_i - x_j}{\widehat{d}_{i,j}}\right) \tag{22}$$

$$\frac{dF}{d\,\widehat{y}_i} = \sum_{\substack{j=1,\\ i=1\\ j<i}}^{N,M} (\,\widehat{d}_{i,j} - d_{i,j}{}^{*})\left(\frac{\widehat{y}_i - y_j}{\widehat{d}_{i,j}}\right) \tag{23}$$

with $i = 1 \ldots N$ (N number of nodes), and $j = 1,..M$.

Then, we apply gradient on the coordinates in order to minimize the objective function and obtain the position of the unknown nodes.

$$\begin{bmatrix} \widehat{x}_i \\ \widehat{y}_i \end{bmatrix} = \begin{bmatrix} \widehat{x}_i \\ \widehat{y}_i \end{bmatrix} - k \begin{bmatrix} \frac{dF}{d\,\widehat{x}_i} \\ \frac{dF}{d\,\widehat{y}_i} \end{bmatrix} \tag{24}$$

k the step size ($0 < k < 1$).

The derivative will be calculated until reaching the convergence of the target points $\widehat{x}_i$ and $\widehat{y}_i$, and that by reaching the minimum of the objective function.

2-10 Simulation

The goal of the simulation is to see the advantage of using gradient descent in localization domain. In addition, to show the importance impact of initialization on localization accuracy.

2-10-1 Comparison between Gradient descent and trilateration

Simulations are done using MATLAB. The first part of the simulation result is described by figures below presenting a comparison between the gradient method and trilateration technique, showing the efficiency of our proposed method, in an environment of area= 45 m×45 m. The network was generated using a uniform law in MATLAB.

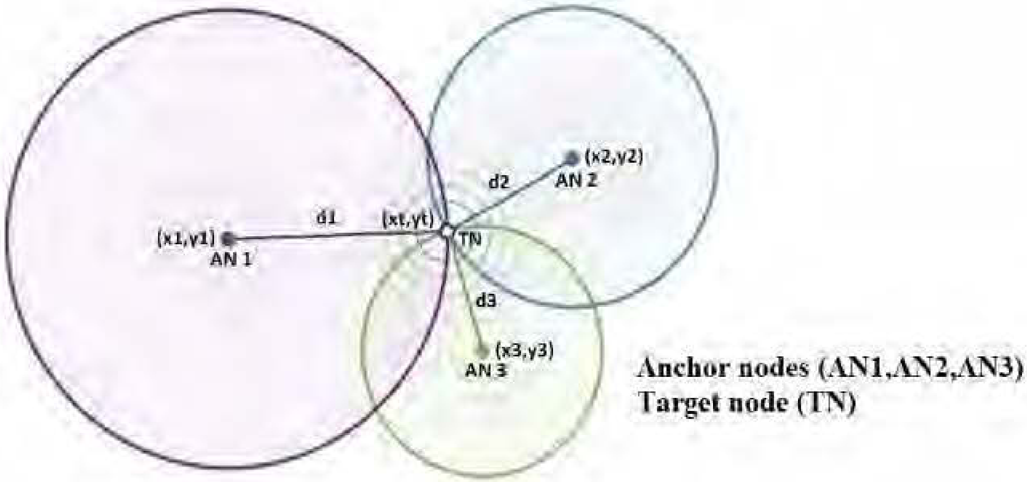

Figure 2-3: localization using trilateration technique.

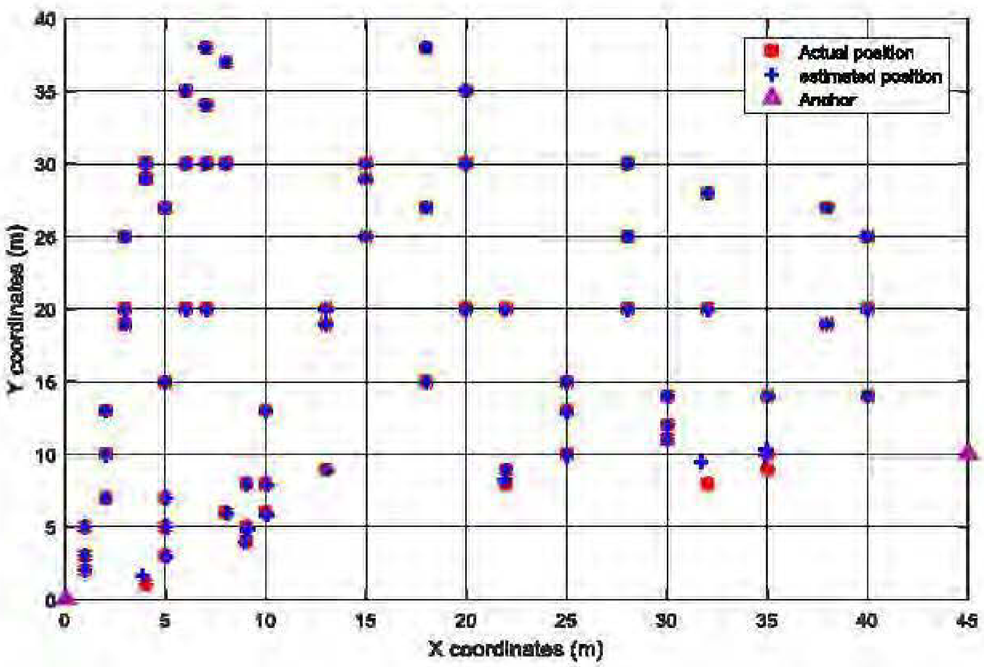

Figure 2-4: Localization of 70 points using gradient descent.

Figure 2-3 represents the localization using trilateration technique. Generally using trilateration, three anchor nodes is needed to localize the location of the target nodes as figure 2-3 shows. Nevertheless, in figure 2-4, by using only two anchors, we were able to locate all the target points with a high accuracy using gradient descent technique with a WI. This reduction of anchor numbers presents different advantages such as reducing the overloading in the network, adding the cost benefits.

2-10-2 Localization using Gradient descent technique and the effect of initialization

The second part of the simulation shows the impact of initialization on the gradient descent methods in localization.

- We have tested 3 types of initialization.
- For the simplicity and to see the error in the random initialization clearer, we have used 26 nodes from our network, two of them are anchors (note that we can use a greater number of unknown nodes as shown in figure 2-4).
- For the simplicity also, we did not take into consideration the noise factor.
- We have chosen a suitable step size value in our simulations (k= 0.2).
- The path loss exponent factor is equal to 3
- We have used two anchors randomly, Anchor1 (2,9) and Anchor2 (0,0).
- The network is generated using a uniform law.

2-10-2-1 RI localization result

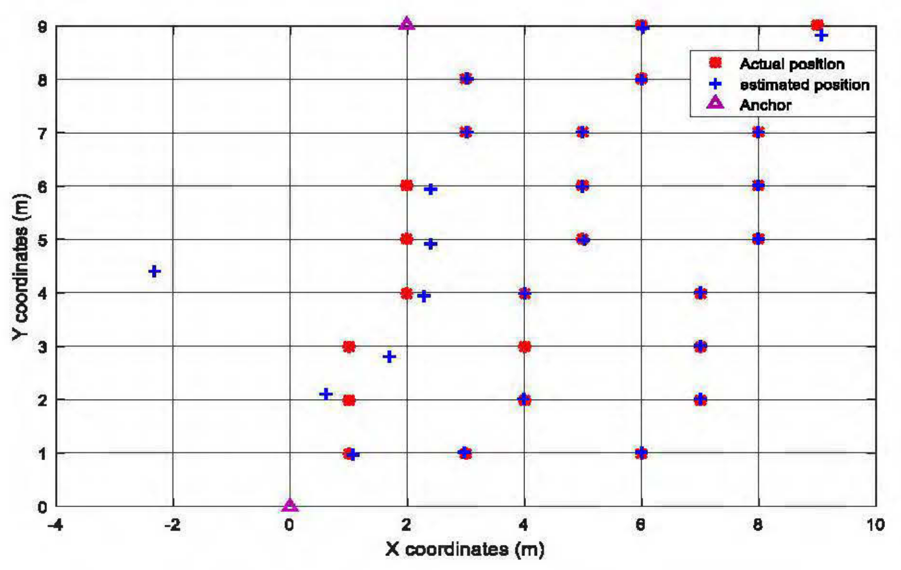

Figure 2-5: Localization of 26 points using RI (first simulation).

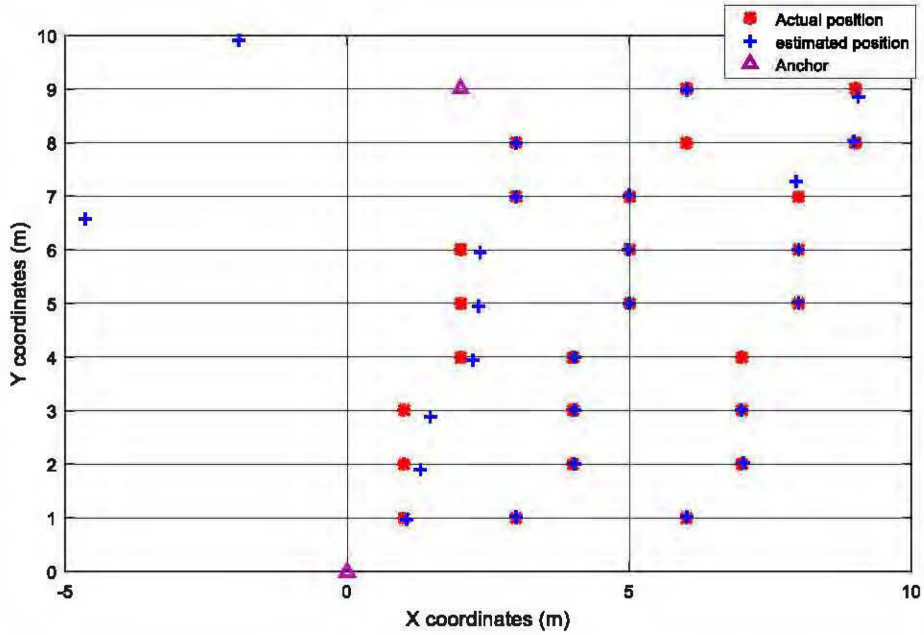

Figure 2-6: Localization of 26 points using RI (second simulation)

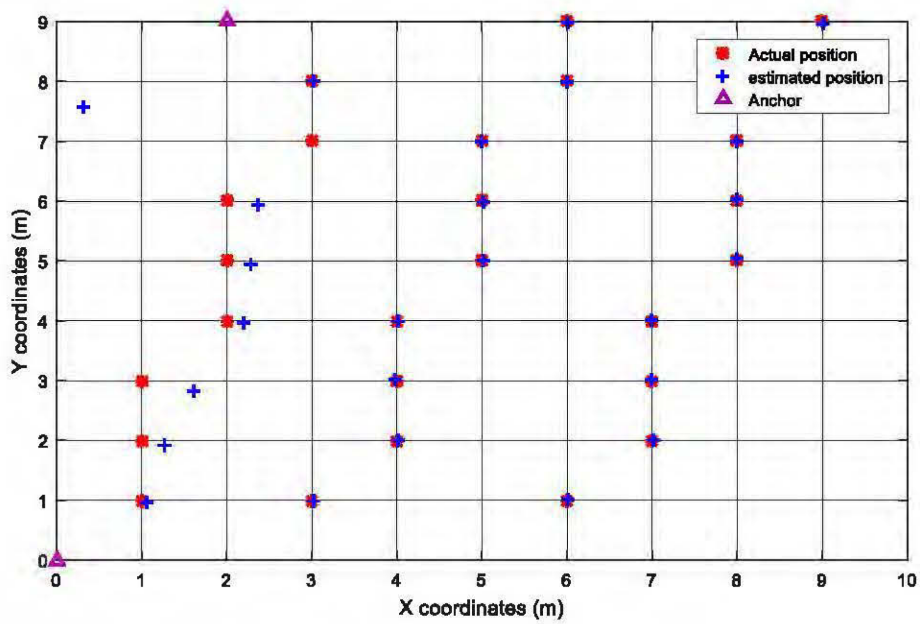

Figure 2-7: Localization of 26 points using RI (third simulation).

2-10-2-2 ARI localization result

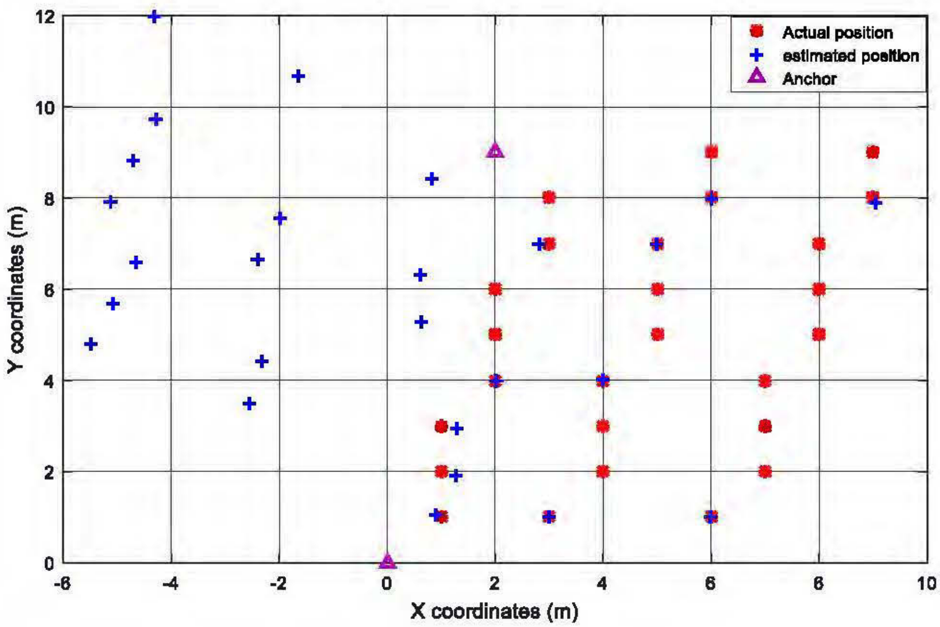

Figure 2-8: Localization of 26 points using ARI.

2-10-2-3 WI localization result

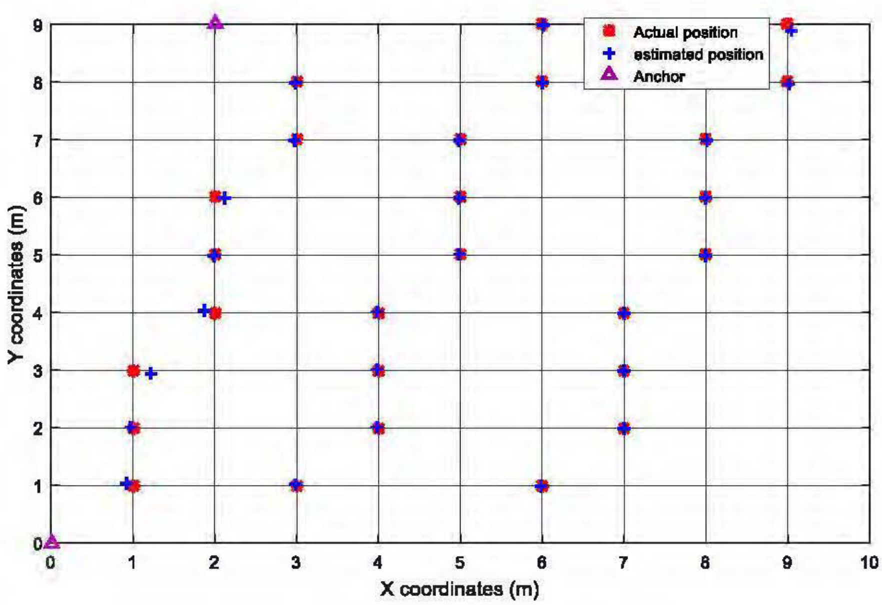

Figure 2-9: Localization of 26 points using WI.

From figure 2-5 to figure 2-8 where a random weight is applied, the used algorithm fails to locate the target points (red and blue points are different) adding that, in RI we have made the simulation many times, from the results we can see the instability of nodes localization, where the unknown nodes location can vary depending on the random initialization value. Nevertheless, in figure 2-9, where a weighted initialization based on RSS is applied, the algorithm can locate the target points with a high accuracy (red and blue points are almost overlapped) mention that, the result in WI will be fixed despite the number of simulations.

2-11 Coordinates error in each initialization

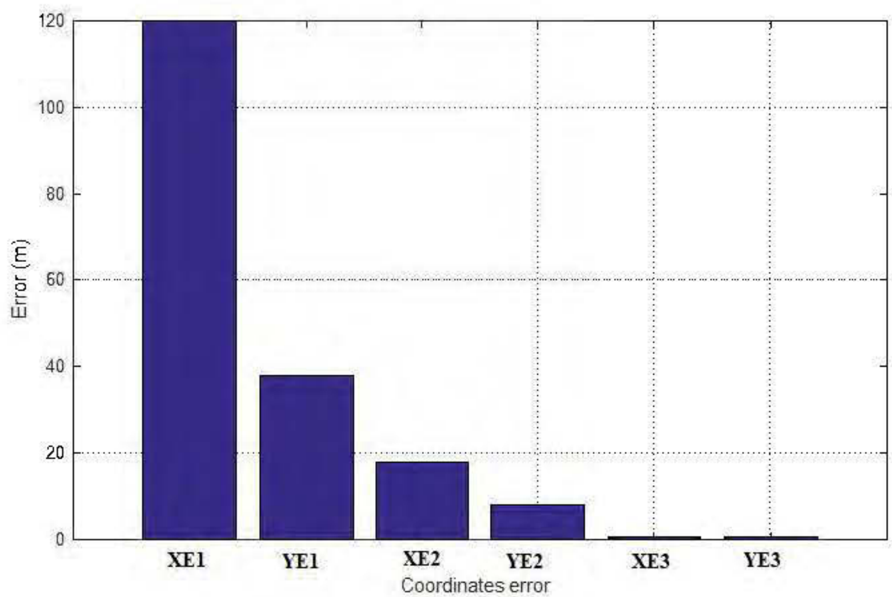

Figure 2-10: Coordinates error in each initialization methods.

1. *XE1 and YE1*: represent the sum error of the difference between the real coordinate (x_N, y_N) and estimated one $(\widehat{x}_N, \widehat{y}_N)$ based on RI.

$$RealX = [x_1 \ldots \ldots . x_i]$$

$$\widehat{x}_N = [\widehat{x}_1 \ldots . . \widehat{x}_i]$$

$$RealY = [y_1 \ldots \ldots . y_i]$$

$$\widehat{y}_N = [\widehat{y}_1 \ldots . . \widehat{y}_i]$$

$XE1 = |\sum(realX - \hat{x}_N)|$

$YE1 = |\sum(realY - \hat{y}_N)|$

2. $XE2$ *and* $YE2$ represent the sum error of the difference between real and estimated coordinates based on random ARI
3. $XE3$ *and* $YE3$ represent the sum error of the difference between real and estimated coordinates based on random WI.

The error between the real and estimated coordinates for a random initialization is big and most of the points was not localized (XE1 YE1 and XE2 YE2). For a non-random initialization the error was small as the figure 2-10 shows (XE3 YE3).

2-12 Time convergence of each initialization method

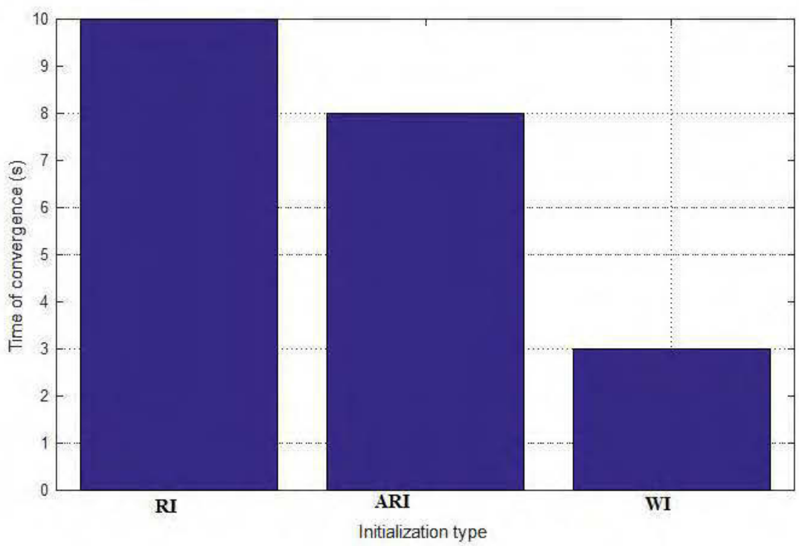

Figure 2-11: Time of convergence of the gradient descent in each initialization method.

Figure 2-11 shows that, using an initialization based on RSS will make the convergence faster than a random initialization, mention that, the time of convergence represents the measuring time from the first iteration to the last iteration that achieve the convergence condition applied on the objective function, also we should light on an important thing. Despite that the convergence using random initialization can be done, however, the estimated positions will not be accurate, due to the space distance error.

2-13 Result using multiple network schemes

In order to see the effectiveness of our gradient descent in localization domain, we will show now different types of simulated networks to see that the gradient descent algorithm here, is not limited to a specific type of network conditions.

The network is generated using uniform law.

First the path loss exponent factor is equal to 3, and we used anchor is Anchor1 (0,0) and Anchor 2 (9,0).

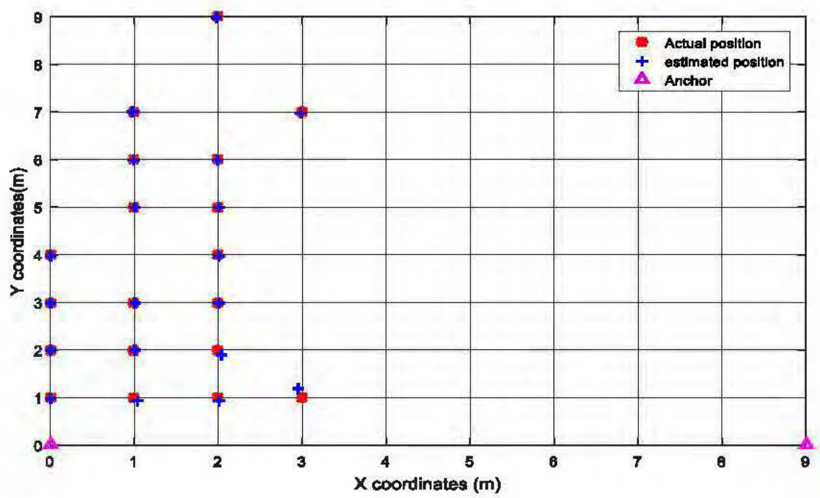

Figure 2-12: Network example 1.

If we change the path loss exponent to n=4 and the anchor to Anchor 1 (0,0), Anchor 2= (10,3).

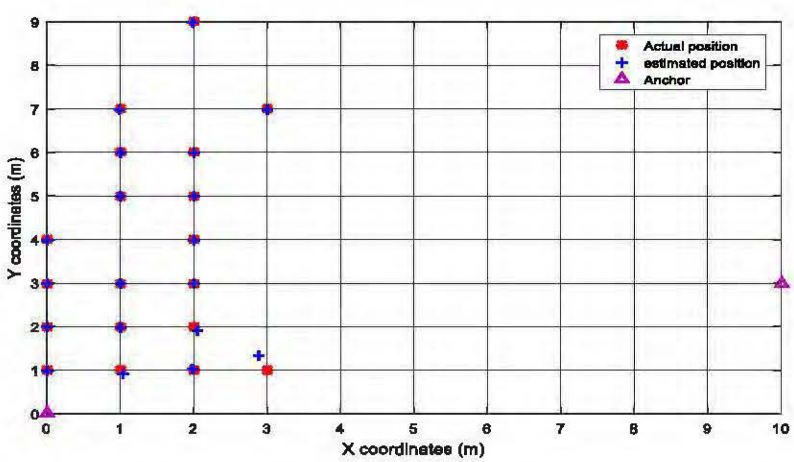

Figure 2-13: Network example 2.

Changing the target coordinates position, and the path loss exponent to n=3.5 and the position of anchors, Anchor1 (2,3) and Anchor2 (8,9).

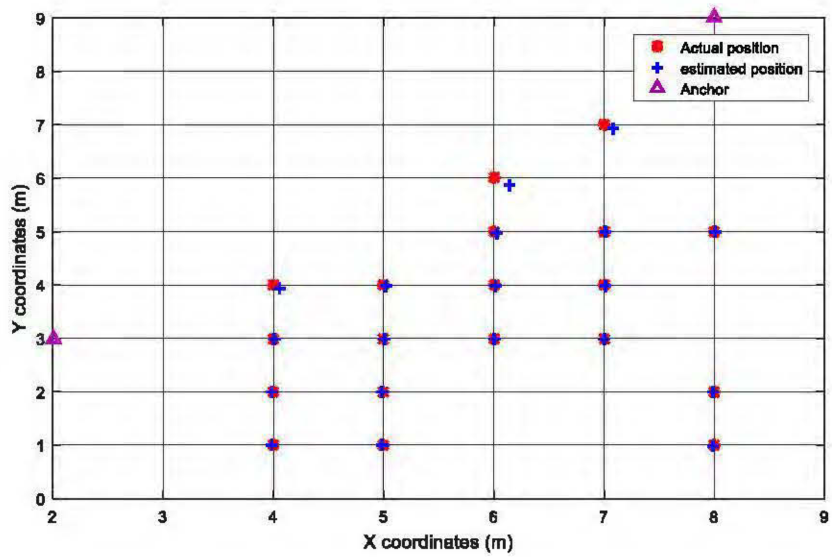

Figure 2-14: Network example 3.

Changing now the target coordinates position and the path loss exponent to 2.5, and the position of anchor to Anchor1 (10,20) and Anchor2 (5,8).

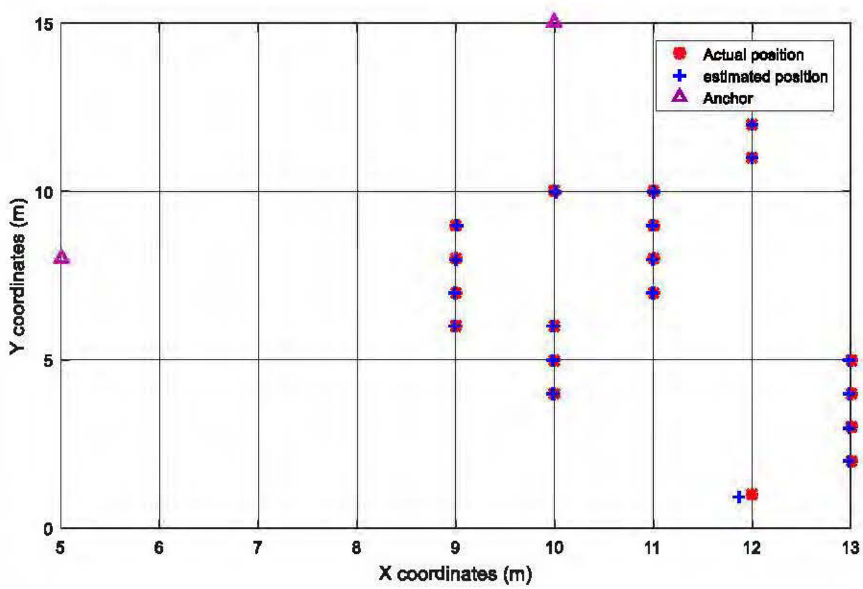

Figure 2-15: Network example 4.

Changing the path loss exponent to n=3 and the anchor to Anchor 1(8,9), Anchor 2(14,13)

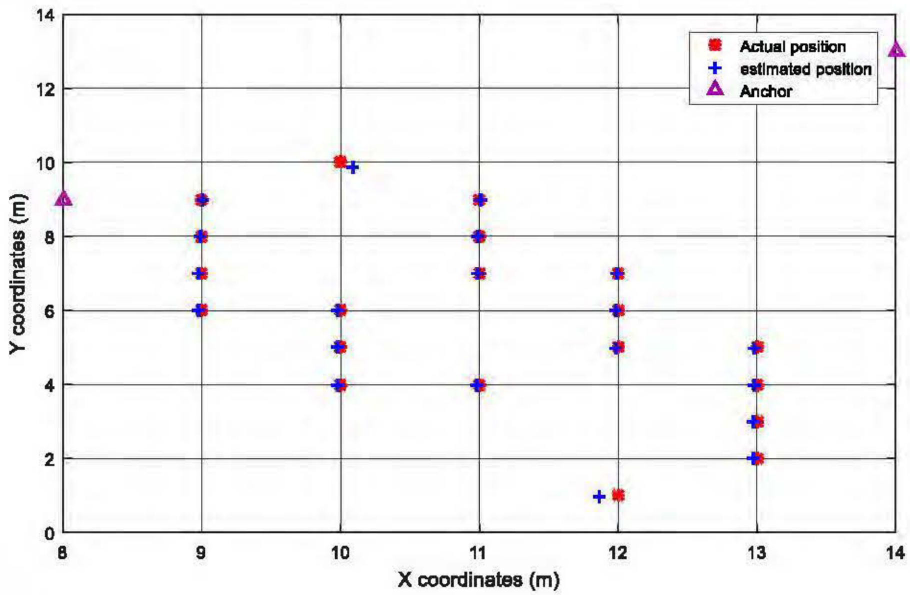

Figure 2-16: Network example 5.

Changing the target coordinates position and the anchors, Anchor 1(8,10) Anchor2 (20,10) with path loss exponent equal to 3

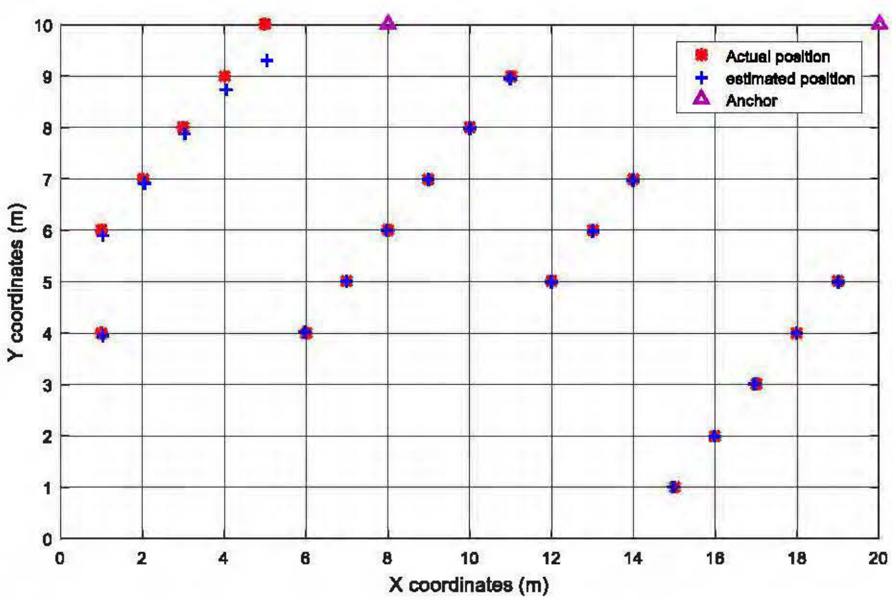

Figure 2-17: Network example 6.

Changing the target coordinates position and the anchors, Anchor 1(20,10) Anchor2 (6,15) with path loss exponent equal to 4.

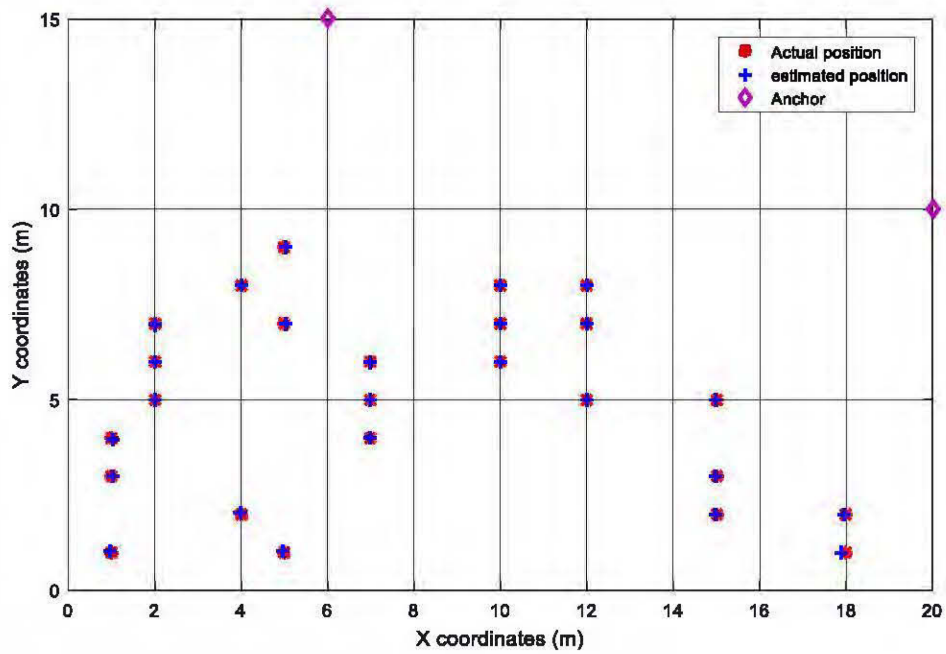

Figure 2-18: Network example 7.

Changing the target coordinates position and the anchors, Anchor 1(45,20) Anchor2 (0,0) with path loss exponent equal to 3.

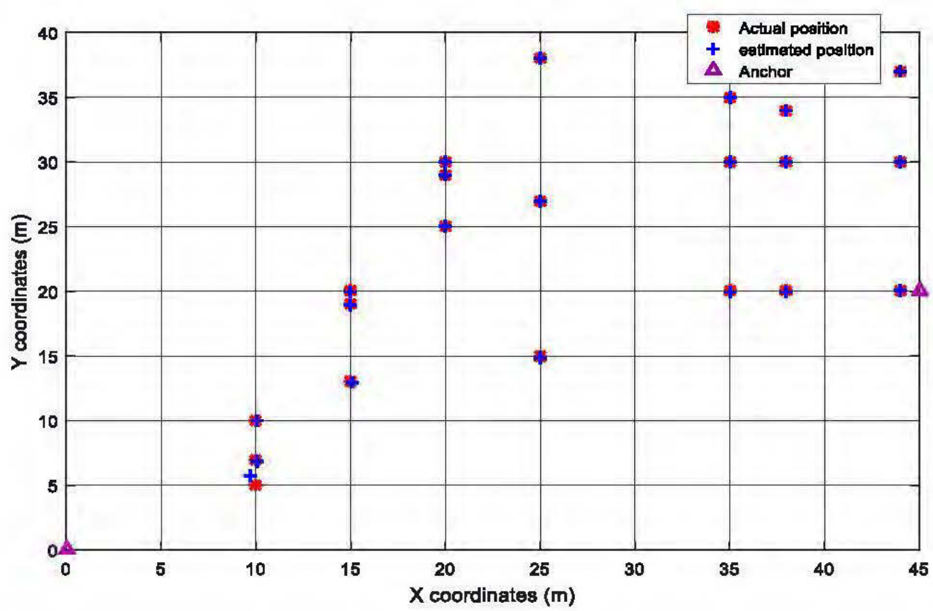

Figure 2-19: Network example 8

The results show that, all the simulated network give an accurate result of the target nodes location even if we expand the size of the network or change network conditions, we can see the actual and estimated position points are overlapped in different scenarios.

Conclusion

In this chapter, we present the importance of the gradient descent method where the number of reference nodes can be confined in a specific area. In addition, we show the significance impact of the initialization technique affecting the accuracy of the location estimation. As a result, we conclude that a smart initialization based on RSS measurements is important to reduce errors in positions estimation.

After showing the importance of gradient descent in localization domain, in the next chapter we introduce a novel gradient descent technique based on RSS value, where the objective function will be based on the difference between the real and estimated power. In order to see how the complexity can affect the proposed technique, the noise factor will be added to the path loss model.

CHAPTER 3

GRADIENT DESCENT PROPOSED APPROACH

3-1 Introduction

After resolving in chapter 2 the initialization issue and realise the importance of gradient descent in localization domain, in this chapter we propose a new localization technique based on the RSS measurements between the anchor and the target node in a noisy model, means that, the noise factor will be added with the RSS. Generally RSS is susceptible to the noise factor that is related with the type of environment of the study area, affecting the estimated distance between the nodes. Commonly, to localize a target node, a specific number of anchors is required, this number of needed anchors will increase in the presence of noise factor, in addition, the localization will be affected by the path loss condition and specifically with the path loss exponent factor. Hence, in this chapter we propose a new gradient descent method based on RSS- based localization technique. In order to see the effectiveness of the algorithm, two scenarios will be presented, first one, will be in known path loss conditions, and the second will be in unknown path loss conditions, means that the complexity of localization will be important.

3-2 Proposed method for localization with known path loss conditions

The gradient descent localization technique in this chapter is based on finding the partial derivative of the target function with respect to the node's coordinates.

3-2-1 Block diagram

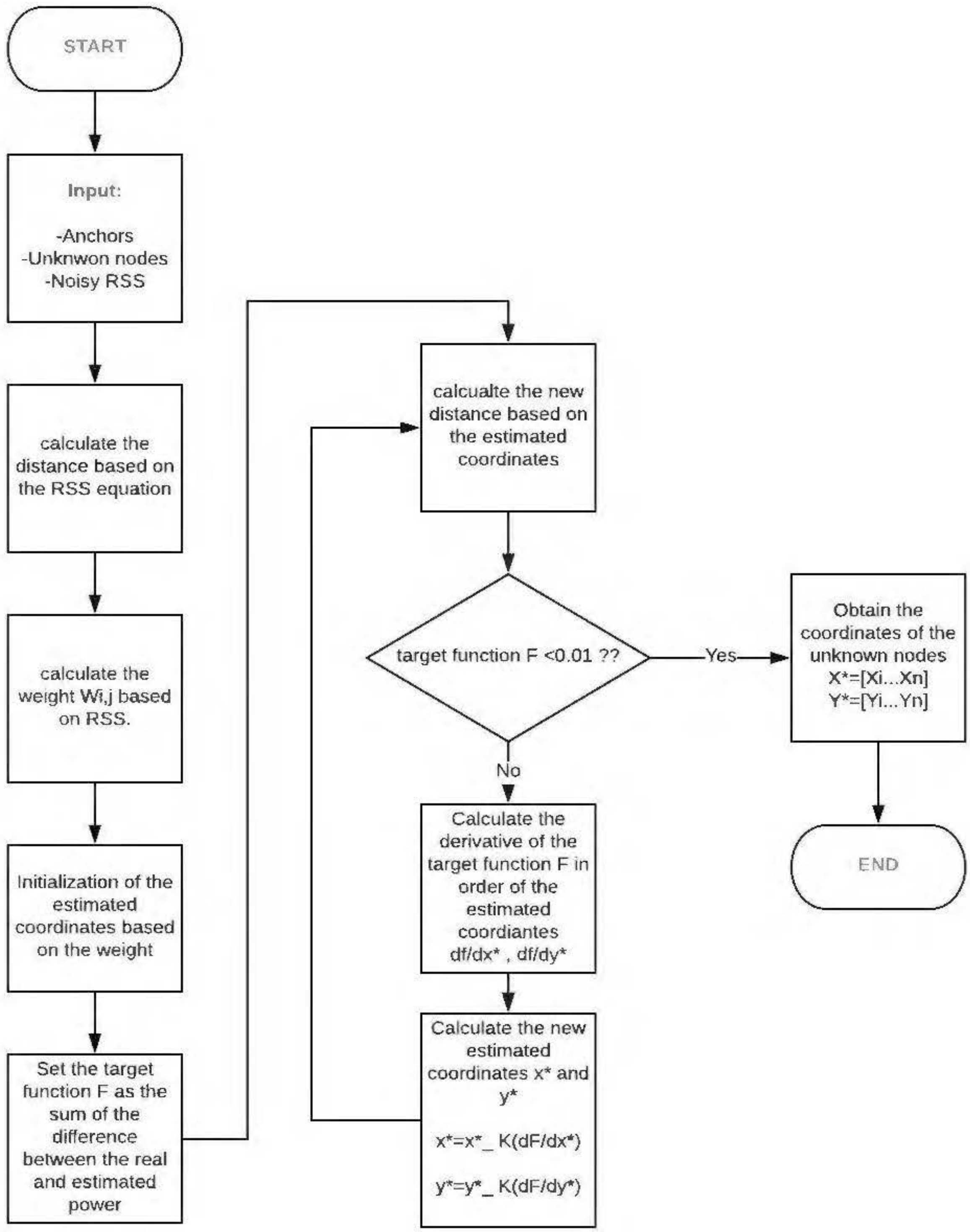

Figure 3-1: Block diagram in known path loss condition.

As a first step, we will create a network, this network will contain as input the anchor nodes, and the target nodes. The distribution of these nodes will be based on a random way following a uniform law. The goal is to apply our algorithm on this network in order to obtain the accurate location of the distributed nodes. The second step will be, calculating the distance based on the noisy RSS value, means that the noise factor will be added to the path loss model as equation 26 shows. After having the distance, we will move to the initialization step, representing the starting points $(\hat{x}_0, \hat{y}_0)$, the initialization will be based on the weight presented in equation 20-21. Next, the target function will be set as the difference between the real and estimated power (equation 25). After that, the estimated distance will be calculated based on the estimated coordinates (equation 15). In order to obtain the location of the target nodes, a condition will be applied on the target function F, if the condition true we will obtain a vector of the unknown node's location $(\hat{x}_i, \hat{y}_i)$, if not, the derivative of the target function will be calculated with respect to $\hat{x}_i$ and $\hat{y}_i$ (equation 28, 29). After that, the new estimated coordinates will be calculated (equation 24), the last two steps will be repeated in order to achieve the condition goal and obtain at the end the location of the target nodes

Consider a WSN of N unknown nodes and M anchors deployed on $L \times L$ area. The target function F will be represented as the difference between the real and the estimated power between the anchors and the target point:

$$F = 0.5 \times \sum_{i,j=1}^{N,M} \left(Pr_{(i,j)} - \widehat{p}_{r_{(i,j)}}\right)^2 \tag{25}$$

$$Pr_{(i,j)} = Pr_{\,d0} - 10 \times n \times Log_{10}\left(\frac{d_{i,j}}{d_0}\right) + X\sigma \tag{26}$$

$$\widehat{p}_{r_{(i,j)}} = Pr_{\,d0} - 10 \times n \times Log_{10}\left(\frac{\hat{d}_{i,j}}{d_0}\right) \tag{27}$$

$Pr_{(i,j)}$ represents the noisy received power.

$\widehat{p}_{r_{(i,j)}}$ represents the received power by the i^{th} node from the j^{th} anchor, based on the estimated coordinates.

Pr_{d0} is the received power at distance d_0 (d_0=1 m),.

n is the path loss exponent.

X_σ is the normal or gaussian random variable.

$\hat{d}_{i,j}$ is the estimated distance between unknown node i and anchor j given as

$$\hat{d}_{i,j} = \sqrt{\left(x_j - \hat{x}_i\right)^2 + \left(y_j - \hat{y}_i\right)^2}$$

$\hat{x}_i$ and $\hat{y}_i$ represent he estimated coordinates of the unknown nodes to be localized.

x_j and y_j represent the coordinates of the anchor nodes. With $i = (1 \ldots \ldots, N)$ and $j = (1 \ldots, M)$.

We have N nodes with unknown location $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$. The known information is the power between each unknown node and the anchors, note that the power will be affected by the noise factor. The steps of the algorithm are given below:

1) Initialization of the coordinates.

$$\hat{x}_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right)$$

$$\hat{y}_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right)$$

2) Calculate the distance

$d_{1,j}$ is the distance between the target node 1 and the anchor j. Note that, since the power is known, the distance $d_{1,j}$ can be calculated using the following equation.

$$d_{1,j} = d_0 \times 10^{\left(\frac{-Pr_{d0} + Pr_{d_{1,j}}}{10n}\right)}$$

The weight $w_{1,j}$ is defined as:

$$w_{1,j} = \left|\frac{1}{Pr_{1,j}}\right|$$

$Pr_{1,j}$ represent the received power by the target node 1 from the fixed anchor j with j=1…, M.

3) Compute the derivative of the target function with respect to $\hat{x}_i$ and $\hat{y}_i$.

$$\frac{dF}{d\hat{x}_i} = \sum_{i=1,j=1}^{N,M} \frac{T}{log_{10}\left(\hat{d}_{i,j}{}^2\right)} \quad (28)$$

$$T = -\left[5n \times \left(2x_j - 2\widehat{x}_i\right) \times (Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}\left(\widehat{d}_{i,j}\right)}{Log10}\right))\right]$$

$$\frac{dF}{d\widehat{y}_i} = \sum_{i,j=1}^{N,M} \frac{H}{log_{10}\left(\widehat{d}_{i,j}{}^2\right)} \tag{29}$$

$$H = -\left[5n \times (2y_j - 2\,\hat{y}_i) \times (Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}(\hat{d}_{i,j})}{Log10}\right))\right]$$

4) Update the new value of $\hat{x}_i$ *and* $\hat{y}_i$ as follow.

$$\begin{bmatrix} \widehat{x}_i \\ \widehat{y}_i \end{bmatrix} = \begin{bmatrix} \widehat{x}_i \\ \widehat{y}_i \end{bmatrix} - k \begin{bmatrix} \dfrac{dF}{d\widehat{x}_i} \\ \dfrac{dF}{d\widehat{y}_i} \end{bmatrix}$$

(k the step size ($0 < k < 1$)

5) Repeat step 2 till $\hat{x}_i$ *and* $\hat{y}_i$ converge.

3-3 Proposed approach in unknown path loss conditions

As we have mentioned before, the value of the path loth exponent is considered to be the most important factor in the RSS-based equation. Hence, in order to see the complexity of our proposed approach. In this section we will make an estimation of the PLE in addition to the unknown node's coordinates using our proposed approach, were the objective function will be applied not only to find the coordinates of the target nodes, but also to find the value of the unknown path loss exponent. Hence, the estimated power will be represented as follow:

$\widehat{p}_{r(i,j)}$ represent the estimated power between the i[th] node and the j[th] anchor, based on the estimated coordinates.

$$\widehat{p}_{r(i,j)} = Pr_{\,d0} - 10 \times \widehat{n} \times Log_{10}\left(\frac{\widehat{d}_{i,j}}{d_0}\right) \tag{30}$$

3-3-1 Block diagram

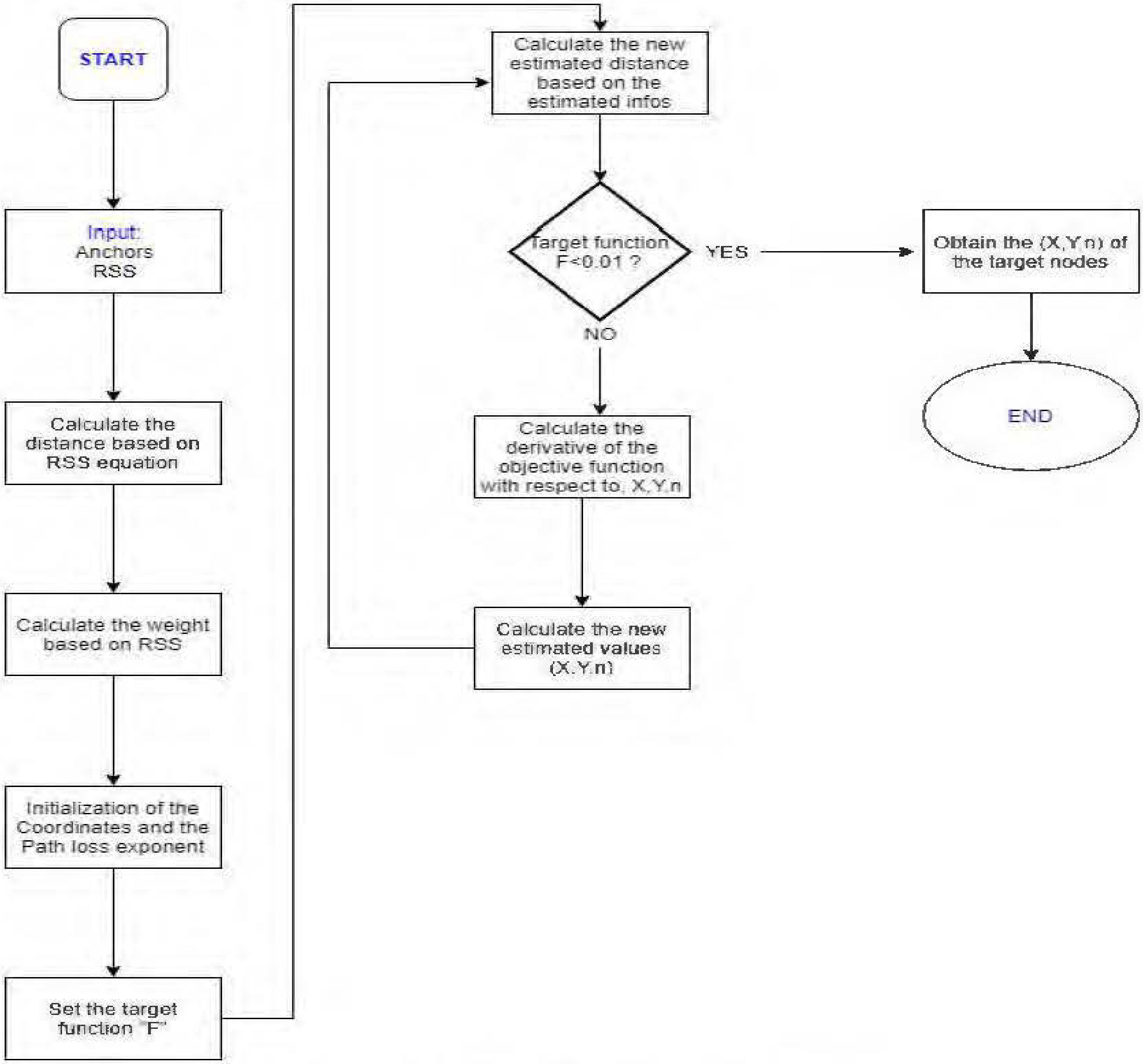

Figure 3-2:Block diagram in unknown path loss condition.

The goal is to apply our algorithm in order to obtain the accurate location of the distributed nodes in addition to the path loss exponent factor. The initialization step, present the starting points $(\hat{x}_1, \hat{y}_1, \hat{n}_1)$. Next, the target function will be set as the difference between the real and estimated power (equation 25). After that, the estimated distance will be calculated based on the estimated coordinates (equation 15). In order to obtain the location of the unknown nodes, a condition will be applied on the target function F, if the condition true we will obtain a vector of the unknown node's variables $(\hat{x}_i, \hat{y}_i, \hat{n}_i)$, if not, the derivative of the target function will be calculated with respect to $\hat{x}_i, \hat{y}_i$ and $\hat{n}_i$ (equation 28,29,31). Next, the new estimated coordinates and PLE will be calculated (equation 32), the last two steps will be repeated in order to achieve the condition goal and obtain at the last iteration the location and the PLE of the target nodes

Steps:

1) Initialization of the coordinates $(\hat{X}, \hat{y})$ and of the path loss exponent $\hat{n}$.

$\hat{n}_1=2$ (the first iteration will start with $\hat{n}_1 = 2$ since we know that the real value of n in free space is 2)

2) Compute the derivative of the target function with respect to $\hat{n}_i$, $\hat{x}_i$ *and* $\hat{y}_i$.

The derivation of $\hat{x}_i$ and $\hat{y}_i$ will be the same as the derivation in equation 28, 29.

Derivation of the path loss exponent:

$$\frac{dF}{d\hat{n}_i} = \sum_{i,j=1}^{N,M} \frac{(10 \times \log(\hat{d}_{i,j}) \times \left(p_{r_{i,j}} - p_t + (10 \times \hat{n}_i \times \log(\hat{d}_{i,j}))\right)) \Big/ \log(10)}{log10} \tag{31}$$

3) Update the new value of $\hat{n}_i$, $\hat{x}_i$ and $\hat{y}_i$ as follow.

$$\begin{bmatrix}\hat{x}_i\\ \hat{y}_i\\ \hat{n}_i\end{bmatrix} = \begin{bmatrix}\hat{x}_i\\ \hat{y}_i\\ \hat{n}_i\end{bmatrix} - k\begin{bmatrix}\frac{dF}{d\hat{x}_i}\\ \frac{dF}{d\hat{y}_i}\\ \frac{dF}{d\hat{n}_i}\end{bmatrix} \tag{32}$$

(k the step size ($0 < k < 1$).

4) Repeat step 2 till $\hat{n}_i, \hat{x}_i$ *and* $\hat{y}_i$ converge.

In order to see the accuracy of our proposed approaches, in the next chapter we will show the simulation results in known and unknown path loss conditions for different networks.

CHAPTER 4

SIMULATION AND RESULTS

4-1 Simulation in known path loss conditions

In the simulation part, the improved gradient descent technique presented in this work was compared with GDB/GDA mentioned in [26]. The scenario is described as follows:

- There are totally 50 nodes randomly located in a square area of *10 m×10 m*. This environment was taken in order to compare our work with the results in [26].
- In order to localize the 50 unknown nodes, we used 4 anchor nodes.
- The RSS values between the anchors and the unknown nodes is considered to be known.
- The noise of the RSS measurement is generated by a Gaussian distribution generator in MATLAB.
- The true locations of the 50 nodes are shown in Fig 4-1.

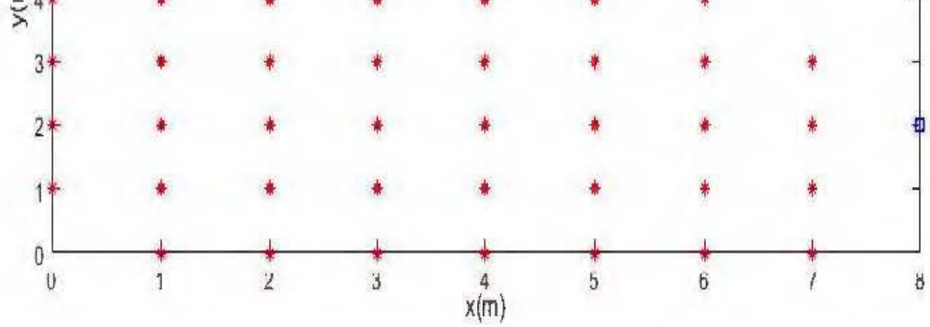

Figure 4-1: Real location of the nodes in the network.

With the presence of the noise element, the locations of the 50 nodes are estimated by GDA/GDB and our improved localization methods, their results are shown in Fig 4-2 Below. The abscissa shows different noise levels. Standard derivation is set to by 0.3, 0.6, 0.9, …, 2.7, 3db. The accuracy of the localization technique can be judged by the error per node calculated as:

$$E = \frac{\sum_{i=1}^{N}\sqrt{(x_{i-} - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N} \tag{33}$$

x_i, y_i: represent the coordinates of the true coordinates.

$\hat{x}_i$, $\hat{y}_i$: represent the final estimated coordinates at the end of the simulation.

N represent the total number of nodes.

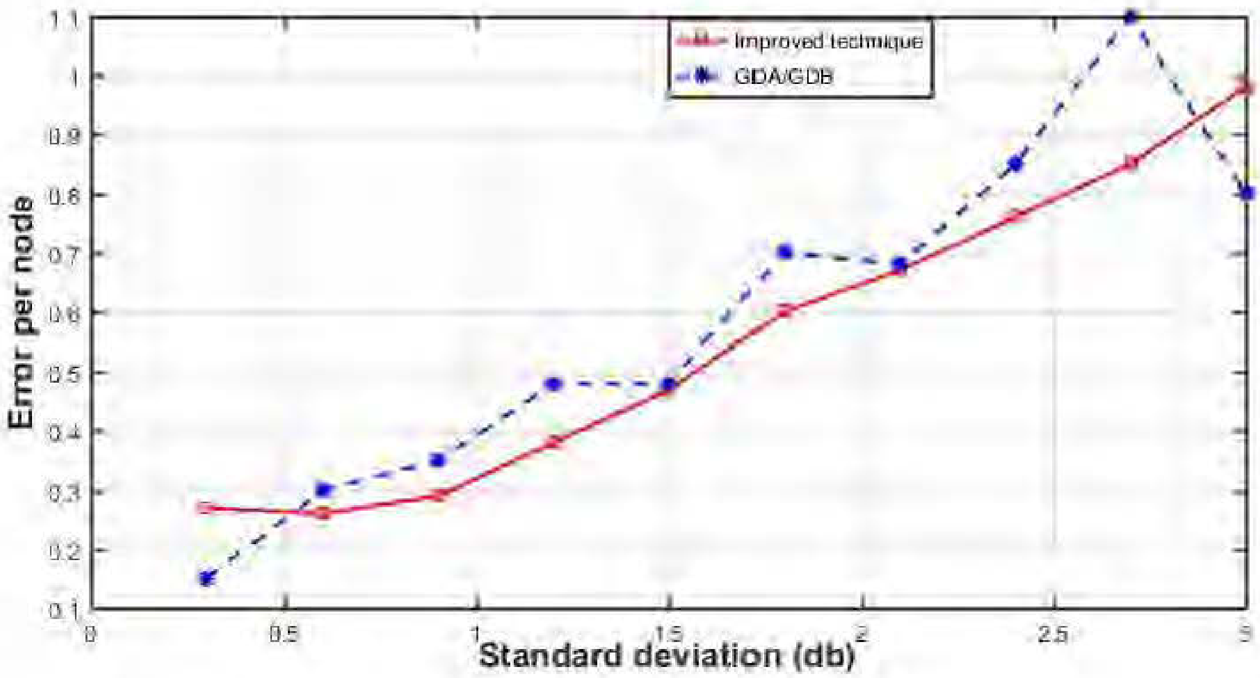

Figure 4-2: Accuracy of the methods with the increasing of noise factor.

The dash line represents the error per node in GDA/GDB localization technique mentioned in [26] related to the variation of the noise factor changing from 0.3 to 3db. The localization of the unknown nodes was done using 10 anchors.

The solid line represents the error per node in our improved method. Using our algorithm, only 4 anchors were used to localize the unknown nodes in the network. Obtained result shows that our proposed approach is better than GDA/GDB technique. Also, by using our technique, an important reduction of anchor's number is very beneficial on the network, and that by decreasing the network overloading, taking an example; many applications consist of using thousands of unknown sensor nodes, for that using the minimum number of needed anchors will be a good choice to localize them with the presence of minimum overload on the network. Adding also, the hardware cost will be reduced.

4-1-1 Conclusion

From the comparison with the GDA/GDB localization method, the proposed gradient descend algorithms can reach better accuracy in the presence of noise factor using a smaller number of anchor nodes.

4-2 Simulation in unknown path loss conditions.

In this section, the path loss exponent factor will be considered to be unknown, and the goal will be estimating the nodes location in addition to the PLE factor values. In order to see the flexibility of the algorithm we will show different network. The estimated path loss exponent should be equal to 3 between each per of nodes at the convergence in network 1, 2 and 3. And equal to 4 in network 4.

4-2-1 Network one

- There are totally 50 nodes randomly located using a uniform law in a square area of *15 m×15 m*.
- The RSS values between the anchors and the unknown nodes is considered to be known.
- Three anchors located at (9,15), (0,0) and (15,9) are used.
- The PLE factor is unknown.

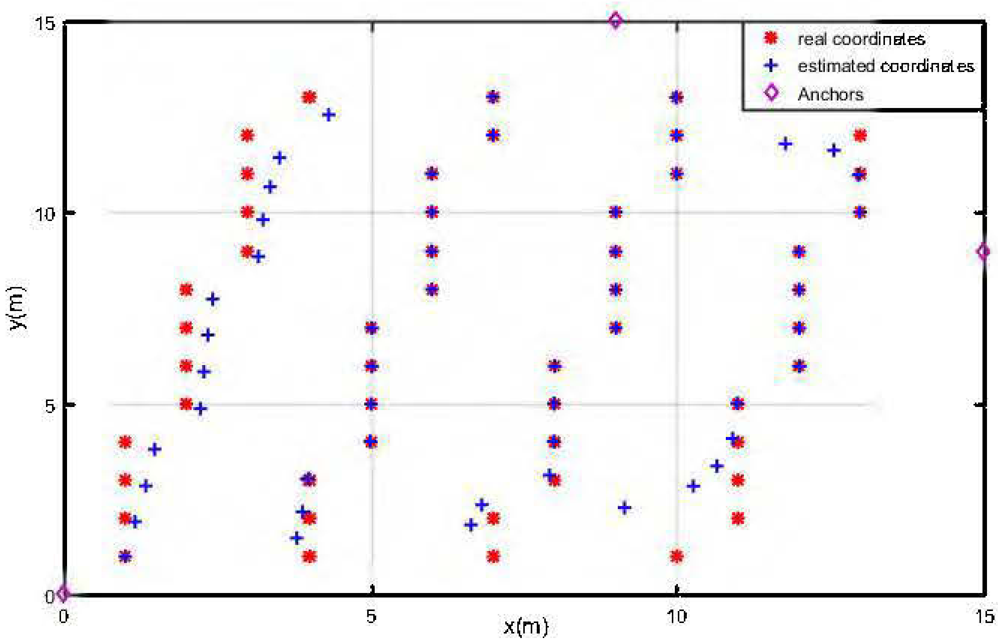

Figure 4-3: Localization of 50 nodes in network one.

Figure 4-3 represents the localization using our improved technique. We were able to locate 50 unknwon points with a high accuracy by using our improved gradient descent method.

Error per node:

$$E = \frac{\sum_{i=1}^{N} \sqrt{(x_{i-} - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N} = 0.0333$$

With N=50.

Furthermore, we were able to estimate the path loss exponent factor values with high accuracy. The MATLAB result are shown below:

$\hat{n}_i =$

2.9992	3.0039	3.0118	3.0205	3.0095	3.0142	3.0198	3.0271	3.0121	3.0195	3.0319
3.0515	3.0371	3.0205	3.0054	3.0007	3.0003	2.9992	3.0003	3.0005	2.9992	2.9993
2.9991	2.9990	2.9990	2.9984	3.0489	3.0198	3.0076	3.0010	3.0007	2.9992	2.9992
2.9991	2.9991	2.9991	2.9991	2.9992	3.0001	3.0967	3.0712	3.0319	3.0080	3.0013
2.9987	2.9990	2.9990	2.9991	3.0001	3.0019					

Result shows that, all the estimated values are almost equal to the real value of the path loss exponent.

The average error of the path loss exponent can be represented as follow:

$$AE = \frac{\sum_{i=1}^{N}(n_r - \hat{n}_i)}{N} = 0.0134$$

n_r: represent the real value of the path loss exponents.

$\hat{n}_i$:represent the values of the estimated path loss exponent at convergence.

N: is the total number of nodes in the network (N=50).

4-2-2 Network 2

- There are totally 50 nodes randomly located using a uniform law in a square area of *20 m×20 m*.
- The RSS values between the anchors and the unknown nodes is considered to be known.
- Three anchors located at (0,0), (20,10) and (10,20) are used.
- The PLE factor is unknown.

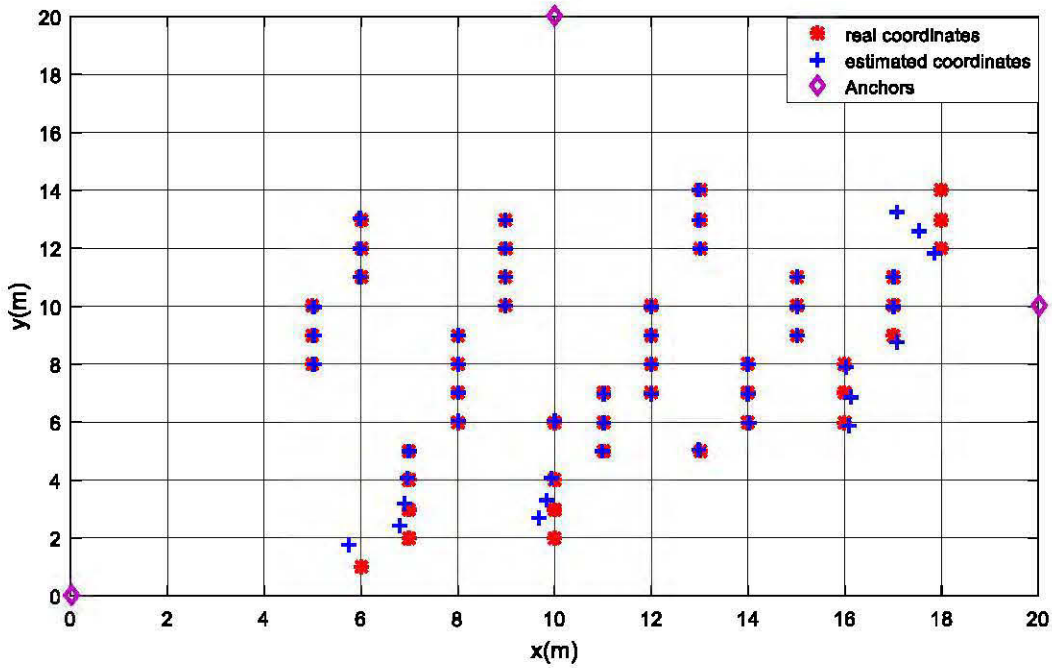

Figure 4-4: Localization of 50 nodes in network 2.

$$E = \frac{\sum_{i=1}^{N} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N} = 0.015$$

$\hat{n}_i$=

3.0001	2.9995	2.9995	2.9995	2.9996	2.9996	2.9996	3.0585	3.0335	3.0160
3.0080	3.0021	3.0001	2.9995	2.9995	2.9995	2.9996	2.9996	2.9996	3.0585
3.0335	3.0160	3.0080	3.0021	3.0006	3.0004	3.0007	3.0005	2.9994	2.9996
2.9996	2.9996	2.9997	2.9998	3.0085	3.0019	3.0007	2.9993	2.9995	2.9996
2.9999	3.0001	3.0079	3.0031	2.9991	2.9993	2.9996	3.0003	3.0050	3.0518

$$AE = 0.015$$

4-2-3 Network 3

- There are totally 50 nodes randomly located using a uniform law in a square area of *45 m×45 m*.
- The RSS values between the anchors and the unknown nodes is considered to be known.
- Three anchors located at (45,20), (20,45) and (0,0) are used.
- The PLE factor is unknown.

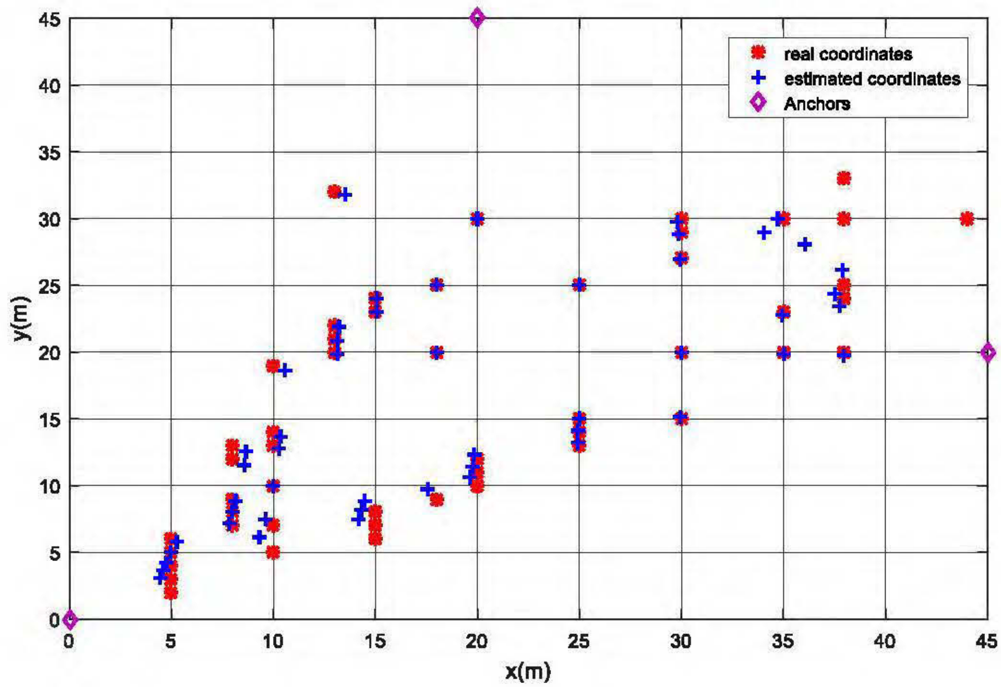

Figure 4-5: Localization of 50 nodes in network 3.

$$E = \frac{\sum_{i=1}^{N} \sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N} = 0.099$$

$\hat{n}_i =$

3.0059	3.0023	3.0005	2.9998	3.0004	3.0003	3.0001	3.0002	3.0025		3.0035
3.0015	3.0066	3.0019	3.0000	3.0009	3.0043	3.0010	3.0012	3.0061	3.0013	3.0004
3.0005	3.0120	3.0084	3.0056	3.0058	3.0000	3.0000	2.9998	3.0049	3.0031	3.0018
3.0020	3.0011	3.0005	2.9999	3.0003	3.0006	3.0012	2.9999	2.9998	3.0095	2.9993
2.9997	3.0501	3.0036	3.0258	3.0017	2.9989	3.0977				

$$AE = 0.05$$

4-2-4 Network 4

- There are totally 50 nodes randomly located using a uniform law in a square area of *20 m×20 m*.
- The RSS values between the anchors and the unknown nodes is known.
- Three anchors located at (0,0), (20,15) and (15,20) are used.
- The PLE factor is unknown.

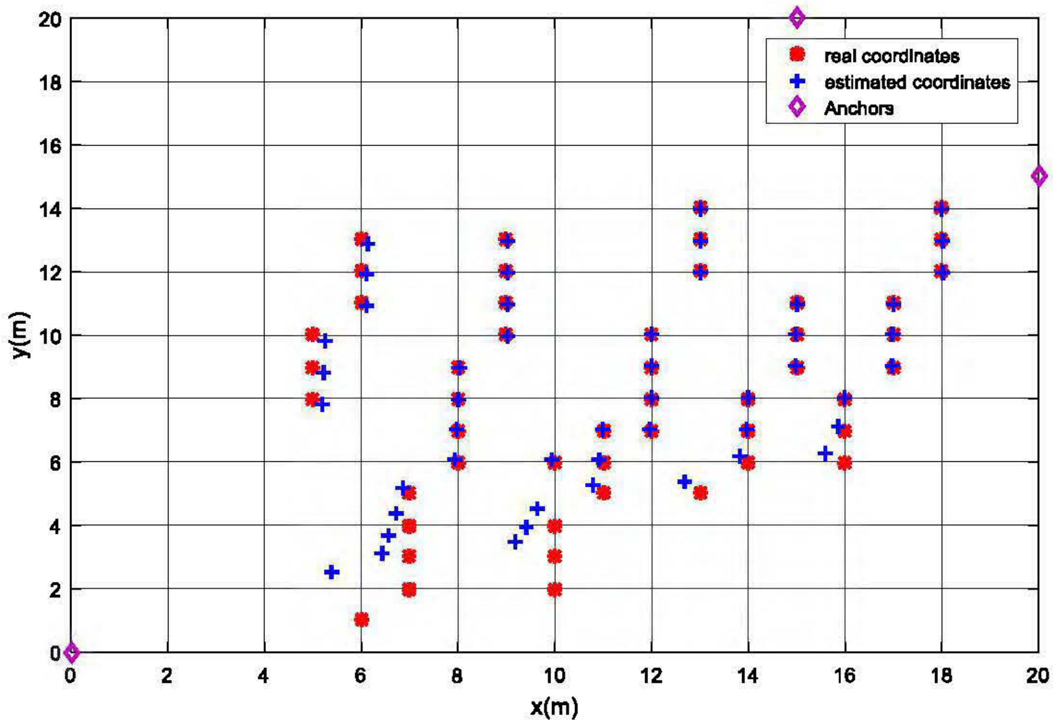

Figure 4-6: Localization of 50 nodes in network 4.

$$E = \frac{\sum_{i=1}^{N} \sqrt{(x_{i-} - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2}}{N} = 0.069$$

$\hat{n}_i$=

4.0052	4.0075	4.0099	4.0041	4.0054	4.0075	4.0554	4.0407	4.0214	4.0093	4.0030
4.0014	4.0002	3.9993	4.0002	4.0002	4.0003	4.0005	4.0007	4.0436	4.0717	
4.0031	4.0230	4.0126	4.0041	4.0008	4.0041	4.0011	4.0007	4.0005	4.0003	

3.9991	3.9992	3.9991	4.0211	4.0109	4.0025	4.0010	4.0010	4.0008	3.9992
4.0261	4.0090	4.0015	4.0014	4.0011	3.9990	3.9989	3.9990	3.9990	

$$AE = 0.0497$$

All the estimated values are almost equal to the real value of the path loss exponent n_r=4.

4-2-5 Conclusion

By having only, the received power, we showed that, the proposed gradient descend algorithms can reach an important accuracy in estimating the location of the target nodes, adding the high precision in estimating the path loss exponent factor. Furthermore, we have shown that, the proposed approach is not limited to a specific type of network, mention that, if we increased the effect of noise factor to be important, the error will increase, hence, in order to avoid having a bad accuracy we can increase the number of anchor nodes or as a future work we can work on having an optimum step size that will help us beside the weighted initialization to have a better accuracy with the presence of an important noise factor.

CHAPTER 5

CONCLUSION

5-1 General conclusion

In this work, we proposed a new localization technique based on gradient descent algorithm combined with RSS-based technique, Gradient descent can be affected by several constraint like the local minimum problem, means that, it can fall in a wrong extremum. In addition, initialization can also be a problem, starting by a bad point can affect the accuracy of the localization or facilitate falling into local minimum issue. Hence in order to apply gradient descent in our proposed approach the first goal was to resolve these problems that can affect the accuracy of the localization, for this reason in chapter 3, these problems was resolved by presenting a specific type of a good initialization based on the weight, in order to reduce there effects and obtain accurate results. Furthermore, the importance of gradient descent was shown by comparing it with the trilateration technique, we showed that the number of anchor nodes can be reduced.

Next, after presenting the importance of gradient descent in localization domain and resolving several issues that can face the algorithm. In chapter 4, we have proposed an improved gradient descent technique based on the difference between the real and estimated power in a noisy propagation model. Despite the noise factor, our algorithm has shown significant results in terms of obtaining a good accuracy using a lesser number of anchors comparing with other techniques.

Basically, the path loss exponent factor affects in a huge way the RSS – based technique due to different physical phenomena. In order to see the effectiveness of our proposed approach, we increased the complexity by applying our proposed technique in unknown propagation conditions, means that, the path loss exponent factor will be considered to be unknown. Result has shown that, by applying the proposed algorithm, we can make an accurate estimation not only for the coordinates of the target nodes, but also for path loss exponent factor.

List of publication

IEEE International Symposium on Antennas and Propagation and USNC- URSI Radio Science Meeting

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Tittle: Impact of Initialization on Gradient Descent Method in Localization Using Received Signal Strength

ACTEA: Association of Career& Technical Education Administrators

Tittle: Gradient Descent Localization Algorithm Based on Received Signal Strength Technique in a Noisy Wireless Sensor Network

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APPENDIX

First Article

Impact of Initialization on Gradient Descent Method in Localization Using Received Signal Strength

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Abstract. In this article we present a localization technique based on received signal strength (RSS) combined with the gradient descent optimization method. The goal of this article is to show the importance of gradient descent in localization domain over the trilateration technique, and that by reducing the number of needed anchor nodes. Furthermore, we demonstrate the effect of the initialization technique on the localization accuracy. Results have shown that the selection of the initialization type (4 types of initialization were tested) has an efficient impact on the accuracy of the target sensors location estimation.

1 Introduction

In the last few years wireless sensor network (WSN) had become one of the dominant technologies that can be used in different fields (outdoor and indoor). WSN can be defined as a collection of low cost and power sensors that can communicate wirelessly, each node in this network can since, process and have the ability to communicate with its peer, in order to share and exchange meaningful information[1], furthermore, WSN has gained a lot of interest in many application such as tracking system, underwater surveillance, health caring and so on [1-2-3], most of these applications consist of distributing sensors in a random way, hence, knowing the sensors location is necessary to recuperate from them significant information. Consequently, localization has become an interesting topic for many researchers.

One of the famous approaches that has been mostly used in localization is the global positioning system (GPS), despite all the advantages that GPS offer, it's still unsuitable in indoor places and will not be a good choice due to different physical phenomena (attenuation, multipath …) that can affect signal propagation. For that, two common types of localization have been widely used: range free techniques[4-5] (hop count, pattern matching, centroid….), where the absolute range information or angle between two pair of node is not needed, and range based techniques such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival(AOA), Received Signal Strength Indicator (RSS), where the information on distance/angle between nodes are required. RSS technique offers a good solution in an indoor environment compared to other methods, it consists of calculating the distance using the RSS measurements between the receiver and the transmitter node, it is considered as a low complex and low energy consumption method [4-5]. Nevertheless, RSS still susceptible to the noise and interference factor, that will affect the estimated distance accuracy. Hence, some researchers have used optimization algorithms like gradient descent, newton Raphson [6] and other techniques, that have shown an attractive solution in localization domain compared with the previous mentioned algorithms.

Furthermore, to localize an unknown node, a well-known technique is used; the trilateration where at least 3 anchor nodes (nodes which real positions are known) are necessary to estimate an unknow node's position.

For that, in this article our goal will be showing the impact of initialization in gradient descent on the localization accuracy, where 4 types of initialization were tested and compared. Also, we have shown the benefits of the gradient descent technique in localization domain by showing its advantage over trilateration in terms of reducing the number of needed anchors.

The remaining of this paper will be organized as follow, in the section 2 we will briefly describe some related works. In section 3, gradient descend method and 4 types of initialization will be explained, in section 4 we present the simulation results with a comparison between the initialization techniques. In the last section we wrap up with a conclusion.

2 Related works

Localization and optimization algorithm have become a good combination to obtain a better result compared to the traditional localization methods. Between all optimization techniques, gradient descent (GD) has gained a lot of popularity in localization domain, the main idea of GD depends on the concept of finding the optimum value by using the derivative of the objective function. Many localization studies were done based on gradient descent, in [7] an improved indoor positioning method was done based on fingerprinting method, and a K nearest neighbor (KNN) was applied to obtain a good initial point of the gradient descent algorithm. In [8] another modified gradient method was done in radio localization system; the proposed algorithm has shown a good result compared with Foy method. In other hand, some researchers have focused on the safe side of gradient localization, [9] presents a secure localization algorithm that can resist malicious attack by combining gradient descent with a selective pruning method, furthermore, this same technique was modified in [10] to remove misleading information, where the ordinary nodes can cooperate to reduce localization errors.

Other researches have focused on smart initialization in localization. Usually, the initial value can be implemented randomly, however sometimes gradient descent can fall into the local minima issue [11]. For that selecting a suitable initial point can play an important role in avoiding this problem and has an important influence on the accuracy of localization [7]. In [12] two gradient methods were introduced, gradient method A(GDA) and gradient method B(GDB), in both, the inter sensor distance was supposed to be known, and the target function represented as the sum of the squared error between the given and estimated distance, the idea is to minimize the target function. In GDA method, the initialization was done randomly based on the weight. The difference between the two methods is that in A the gradient was applied on the weight changing on each iteration in order to obtain the optimum weight that will give us the location of the unknown node, while in B the gradient was applied on the estimated coordinates.

The idea in our work is to show the importance of using gradient descent in localization domain in term of reducing the required anchor nodes, and that is by comparing the number of anchor node used in trilateration technique with the gradient descent method used in this article, second, to show the importance of a good initialization in node's localization. For that, we combine these two methods (GDA and GDB), and that by using the initialization used in GDA ($x_1 = (w_{1,2} \times d_{1,2}) + (w_{1,3} \times d_{1,3}) + \cdots$) [12] and applying it on GDB, while the gradient will be made on the coordinates and not on the weights.

This initialization technique was compared to a non-random initialization method [7], and that is to show the importance of non-random initialization and how it can affect the results accuracy.

3 Gradient descend method

3.1 Distance Estimation:

The distance can be calculated based on the RSS values between the anchor and the unknown nodes.

As a first step, the calculation of the distance will be based on the equation of the received power below:

$$Pr_{i,j} = \mathrm{Pr}_{d0} - 10 \times n \times Log10\left(\frac{d_{i,j}^{*}}{d_0}\right) \quad (1)$$

Where the distance can be calculated as follow using [13]:

$$d_{i,j}^{*} = d_0 \times 10^{\left(\frac{Pr_{d0} - Pr_{d_{i,j}^{*}}}{10n}\right)} \quad (2)$$

$Pr_{i,j}$ represent the power between the i[th] node and the j[th] anchor.

Pr_{d0} represents the power of the transmitter at distance d_0, and n is the path loss exponent (2< n <6), and $d^*(i,j)$ is the distance between unknown node i and anchor j.

3.2. Coordinates estimation

The objective function now will be represented by the sum of the squared errors between the distance obtained in (2) and the estimated distance (de) changing in each iteration. [12]

$$F = 0.5 \times \sum_{\substack{i,j=1 \\ i \neq j}}^{N,M} \left(d_{i,j}^* - de_{i,j}\right)^2 \qquad (3)$$

$d_{i,j}^*$ is the distance obtained by equation (2), and $de_{i,j}$ is the estimated distance based on the estimated coordinate that will change on each iteration:

$$de_{i,j} = \sqrt{\left(x_j - xe_i\right)^2 + \left(y_j - ye_i\right)^2} \qquad (4)$$

xe_i and ye_i represent the estimated coordinates of the unknown node to be localized.

x_j and y_j represent the coordinates of the anchor nodes.

With $i = (1 \ldots\ldots, N)$ with N number of nodes and $j = (1 \ldots, M)$, with M the number of anchors.

The goal of the algorithm is to obtain the location of the unknown coordinates at the end, and that will be by minimizing the objective function (3). Gradient descent is used to find the best coordinate xe and ye that minimize the target function. In order to do that we should start by an initial coordinate, it can be assigned randomly but it is important to start by a suitable value in order to avoid local minima issue and obtain an accurate result.

This article will show multiple way of a good initialization, that will be compared in the simulation with the random initialization techniques:

3.3 Initialization techniques

a. Initialization 1:

First initialization is based on [12]

$$xe_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \qquad (5)$$

$$ye_1 = \left(v_{1,2} \times d_{1,2}\right) + \left(v_{1,3} \times d_{1,3}\right) + \cdots \left(v_{1,M} \times d_{1,M}\right) \qquad (6)$$

Here the weights w and v are given randomly.
$d_{1,j}$ is the distance between the unknown node 1 and the anchor j. xe_1 and ye_1 represent the coordinates of the unknown node 1.

Note that the position of N nodes $(xe_1, ye_1), (xe_2, ye_2) \ldots\ldots (xe_N, ye_N)$ are all the target coordinates to be find.

b. Initialization 2:

The second initialization will be based on RSS and the non-random weight [7]:

$$xe_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \qquad (7)$$

$$ye_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \qquad (8)$$

$d_{1,j}$ is the distance between the unknown node 1 and the fixed anchor j.

$$w_{1,j} = \left|\frac{1}{Pr_{1,j}}\right| \qquad (9)$$

$Pr_{1,j}$ represent the received power between the unknown node 1 and the fixed anchor j with j=1…M.

c. Initialization 3:

Another initialization method based on [7] is used also in this article. Where the weight will not be multiplied with the inter sensor distance, but with the coordinates of the anchor nodes.

$$xe_1 = \left(w_{1,2} \times x_2\right) + \left(w_{1,3} \times x_3\right) + \cdots \left(w_{1,M} \times x_M\right) \qquad (10)$$

$$ye_1 = \left(w_{1,2} \times y_2\right) + \left(w_{1,3} \times y_3\right) + \cdots \left(w_{1,M} \times y_M\right) \qquad (11)$$

Where x_2, x_3, x_M, y_2, y_3 and y_M represent the coordinates of the anchor nodes and $w_{1,j}$ represent the non-random weight based on RSS equation (9).

d. Initialization 4:

Same as initialization 3 but the weight is given randomly (it's not calculated based on RSS value).

3.4 Derivative

After the initialization step, we derive the objective function in (3) with respect to xe_i and to ye_i. [12]

$$\frac{dF}{dxe_i} = \sum_{\substack{j=1, \\ i=1 \\ j<i}}^{N,M} \left(de_{i,j} - d_{i,j}{}^*\right)\left(\frac{xe_i - x_j}{de_{i,j}}\right) \qquad (12)$$

$$\frac{dF}{dye_i} = \sum_{\substack{j=1, \\ i=1 \\ j<i}}^{N,M} \left(de_{i,j} - d_{i,j}{}^*\right)\left(\frac{ye_i - y_j}{de_{i,j}}\right) \qquad (13)$$

with $i = 1 \ldots N$ (N number of nodes), and $j = 1, .. M$ (M number of anchors).

Then, we apply gradient on the coordinates in order to minimize the objective function and obtain the position of the unknown nodes. [12]

$$\begin{bmatrix} xe_i \\ ye_i \end{bmatrix} = \begin{bmatrix} xe_i \\ ye_i \end{bmatrix} - k \begin{bmatrix} \frac{dF}{dxe_i} \\ \frac{dF}{dye_i} \end{bmatrix} \quad (14)$$

k the step size ($0 < k < 1$).

The derivative will be calculated until reaching the convergence of the target points xe_i and ye_i, and that by reaching the minimum of the objective function. The steps can be summarized as follow:

1) Calculate the distance based on RSS values using equation (2).
2) Initialization of the unknown coordinate. The different mentioned initialization technique will be applied and compared.
3) Calculate the derivative in order of the unknown coordinates xe_i and ye_i. (12) (13)
4) Calculate the new value of xe_i and ye_i using (14)
5) Update the new values of xe_i and ye_i obtained in equations (14)
6) The convergence will be depending on the condition applied on the objective function in equation (3).

4 Simulations

Simulations are done using MATLAB. The first part of the simulation result is described by figures below presenting a comparison between the gradient method and trilateration technique, showing the efficiency of our proposed method, in an environment of area= *10m×10m*.

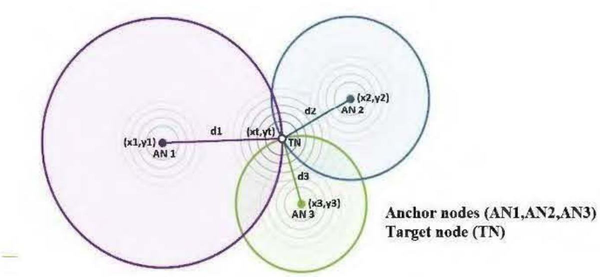

Fig.1.localization using trilateration technique [14].

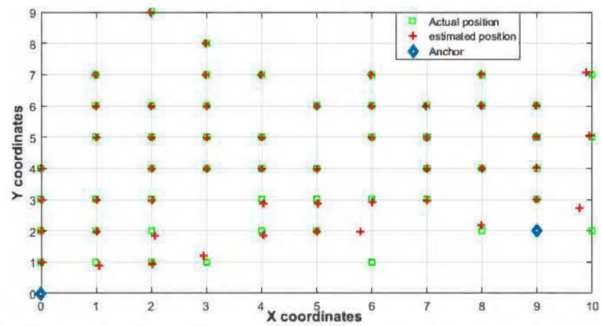

Fig. 2. Localization of 55 points using gradient descent.

Figure 1 represents the localization using trilateration technique. Generally using trilateration, three anchor nodes is needed to localize the unknwon location of the target sensors as figure 1 shows. Neverless, in figure 2, by using only two anchors ,we were able to locate 55 unknwon points with a high accuracy by using gradient descent technique. This reduction of anchor numbers presents different advantages such as reducing the overloading in the network, adding the economic benefits.

The second part of the simulation shows the impact of initialization on the gradient descent methods in localization.

- We have tested 4 types of initialization.
- For the simplicity and to see the error in the random initialization clearer, we have used 20 nodes, two of them are anchors (note that we can use more nodes).
- For the simplicity also, we did not take into consideration the noise factor.
- We have chosen a suitable step size value in our simulations.
- The random initialization was done using MATLAB function *rand*.
- We have used two anchors Anchor1(2,9) and Anchor2(0,0)

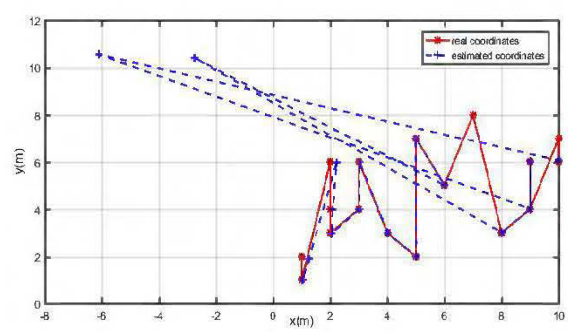

Fig. 3. Localization of 20 points using initialization 1.

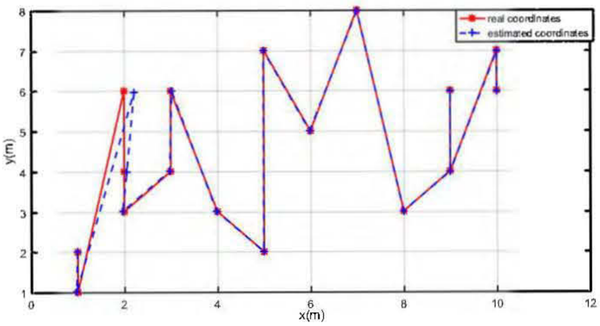

Fig. 4. Localization of 20 points using initialization 2.

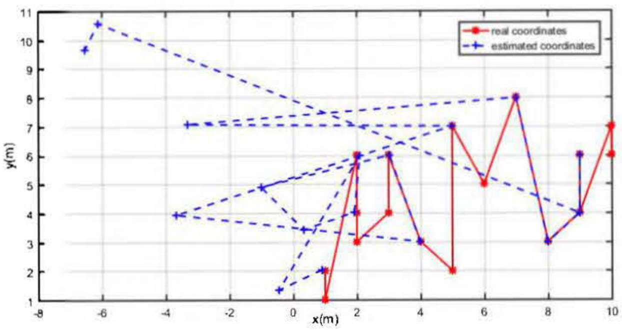

Fig. 5. Localization of 20 points using initialization 4.

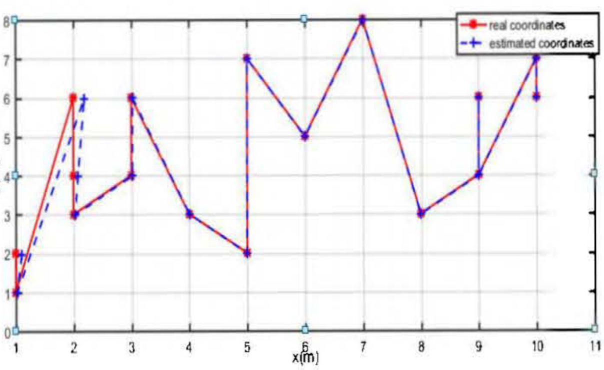

Fig. 6. Localization of 20 points using initialization 3.

In fig.3 and fig.5 where a random weight is applied, the used algorithm fails to locate target points (red and blue curves are different). Nevertheless, in fig.4 and fig.6, where a non-random weight based on RSS is applied, the algorithm can locate the target points with a high accuracy (red and blue curves are almost overlapped).

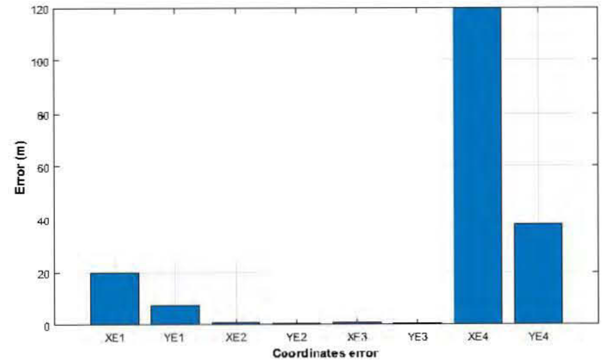

Fig. 7. Coordinates error in each initialization methods.

4. *XE1 and YE1*: represent the sum error of the difference between the real coordinate (x_N, y_N) and estimated one (xe_N, ye_N); Based on initialization 1.

$$RealX = [x_1 \dots\dots x_N] \ (N{:}\, nb\ of\ node)$$

$$Xe = [xe_1 \dots\dots xe_N]$$

$$RealY = [y_1 \dots\dots y_N]$$

$$Ye = [ye_1 \dots\dots ye_N]$$

$$XE1 = |\sum(realX - Xe)|$$

$$YE1 = |\sum(realY - Ye)|$$

5. $XE2$ *and* $YE2$ represent also the sum error of the difference between real and estimated coordinates based on random initialization 2.
6. $XE3$ *and* $YE3$ based on Initialization 3.
7. $XE4$ *and* $YE4$ based on Initialization 4.

The error between the real and estimated coordinates for a random initialization is big and most of the points was not located (XE1 YE1 and XE4 YE4). For a non-random initialization the error was small as the Fig.7 shows (XE2 YE2 and XE3 YE3).

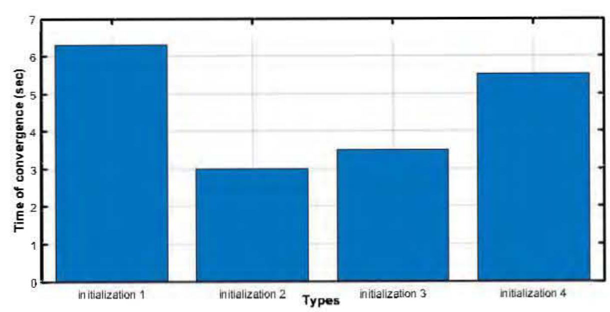

Fig. 8. Time of convergence of the gradient descent in each initialization method.

Figure 8 shows that, using an initialization based on RSS will make the convergence faster than a random initialization, also we should light on an important thing. Despite that the convergence using random initialization can be done, however, the estimated positions will not be accurate (fig 3 and fig 5).

5 Conclusion

In this article, we present the importance of the gradient descent method where the number of reference nodes can be reduced in a specific area. In addition, we show the significance impact of the initialization technique affecting the accuracy of the location estimation. As a result, we conclude that a smart initialization based on RSS measurements is important to reduce errors in positions estimation.

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Article 2:

A new Gradient Descent Positioning Method in Wireless Sensor Network Based on Received Signal Strength

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Abstract—In this article, we propose a new localization technique in a wireless sensor network (WSN), using the gradient descent optimization algorithm, combined with the Received Signal Strength (RSS) method. In this work, a new objective function is represented as the sum of the difference between the real and estimated power. By applying gradient descent technique on this objective function, the positions of unknown nodes are estimated. Simulation results have shown the efficiency of our proposed method in accurately localizing numerous unknow nodes, using an RSS- based technique.

Keywords—Wireless Sensor Networks; Localization; Optimization; Indoor localization, RSS.

I. INTRODUCTION

WSN can be defined as a group of small, low cost sensor devices, having the ability to communicate wirelessly to exchange information. Furthermore, location estimation is an essential factor for all the applications that have been using WSN technology such as, agriculture, health caring, disaster monitoring [1-2]. Hence, this network will not be effective without knowing the accurate sensor node's position. For that, the importance of localization has attracted a lot of researchers.

Two common types of localization techniques had been widely used, range-based and range-free [3]. Most of these techniques, hinge on a set of anchors or reference nodes (nodes which their real positions are known) to identify the position of the unknown nodes. Between all localization methods, Received Signal Strength (RSS), is considered one of the famous approaches that can be used in indoor environment. It consists in calculating the distance based on the power measurements between two sensor nodes, RSS can be defined as a low cost, low complex method, adding that it does not require an external hardware [3]. Despite all the advantages that RSS offer, it is still susceptible to the noise and interference factor, that will affect the estimated distance accuracy [3]. Subsequently, some researchers have focused on optimization algorithm that have shown an attractive result compared with the traditional localization methods. In this article we propose a new localization method based on gradient descent algorithm combined with RSS technique, where the target function will be represented as the sum of the difference between the real power and estimated one.

II. GRADIENT DESCENT LOCALIZATION

Among all optimization methods, gradient descent (GD) has attracted many researchers, the main idea of GD depends on the concept of minimizing a specific target function by iteratively moving in the direction of the optimum value, sometimes it is easy for GD to fall into local minima issue, for that in [4] a selected K nearest neighbor was applied to get a suitable initial point of the gradient descent. In [5] two gradient descent methods were applied; GDA and GDB, they have shown a good performance compared to the existing localization algorithms. In most of GD localization the objective function is represented as the sum of the squared error between the real and estimated distance. Nevertheless, to avoid local minima issue, we have used in this work the initialization munched in [4].

III. Proposed METHOD

Consider a WSN of N unknown nodes and M anchors deployed on $L \times L$ area. The target function F will be represented as:

$$F = 0.5 \times \sum_{i,j=1}^{N,M} \left(Pr_{(i,j)} - Pr^{*}_{(i,j)}\right)^2 \qquad (1)$$

Where $Pr_{(i,j)}$ represent the known received power, and $Pr^*_{(i,j)}$ represent the estimated power between the i[th] node and the j[th] anchor, based on the estimated coordinates.

$$Pr^*_{(i,j)} = Pr_{\,d0} - 10 \times n \times Log_{10}\left(\frac{d^*_{i,j}}{d0}\right) \quad (2)$$

$Pr_{\,d0}$ is the power of the transmitter at distance $d_0(d_0$=1m), n is the path loss exponent (2< n <6), and $d^*(i,j)$ is the estimated distance between unknown node i and anchor j given by:

$$d^*(i,j) = \sqrt{\left(x_j - x^*_i\right)^2 + \left(y_j - y^*_i\right)^2} \quad (3)$$

x^*_i and y^*_i represent the estimated coordinates of the unknown nodes to be localized. x_j and y_j represent the coordinates of the anchor nodes. With $i = (1 \ldots\ldots, N)$ and $j = (1 \ldots, M)$.

We have N nodes with unknown location $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$. The known information is the power between each unknown node and the anchors. The steps of the algorithm are given below based on [5]:

1) *Initialization of the coordinates based on [4-5]:*

$$x^*_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \quad (4)$$

$$y^*_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \quad (5)$$

$d_{1,j}$ is the distance between the unknown node 1 and the anchor j. Note that, since the power is known, the distance $d_{1,j}$ can be calculated normally. The weight $w_{1,j}$ is defined as:

$$w_{1,j} = \left|\frac{1}{Pr_{1,j}}\right| \quad (6)$$

$Pr_{1,j}$ represent the received power between the unknown node 1 and the fixed anchor j with j=1…, M.

2) *Compute the derivative of the target function with respect to x^*_i and y^*_i.*

$$\frac{dF}{dx^*_i} = \sum_{i=1,j=1}^{N,M} \frac{A}{log_{10}\left({d^*_{i,j}}^2\right)} \quad (7)$$

$$A = -\left[5n \times \left(2x_j - 2x^*_i\right) \times \left(Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}\left(d^*_{i,j}\right)}{Log10}\right)\right)\right].$$

$$\frac{dF}{dy^*_i} = \sum_{i,j=1}^{N,M} \frac{C}{log_{10}\left({d^*_{i,j}}^2\right)} \quad (8)$$

$$C = -\left[5n \times \left(2y_j - 2\,y^*_i\right) \times \left(Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}\left(d^*_{i,j}\right)}{Log10}\right)\right)\right].$$

3) *Update the new value of x^*_i and y^*_i as follow.*

$$\begin{bmatrix} x^*_i \\ y^*_i \end{bmatrix} = \begin{bmatrix} x^*_i \\ y^*_i \end{bmatrix} - k \begin{bmatrix} \frac{dF}{dx^*_i} \\ \frac{dF}{dy^*_i} \end{bmatrix} \quad (9)$$

(k the step size $(0 < k < 1)$

4) *Repeat step 2 till x^*_i and y^*_i converge.*

IV.SIMULATION

In the simulation, we use two anchors located at (0,0) and (2,9) to estimate the position of 50 unknown nodes in a square area of *10m×10m*.

For the simplicity we do not take into consideration the noise factor. Adding that, the power between the unknow nodes and the anchors is known.

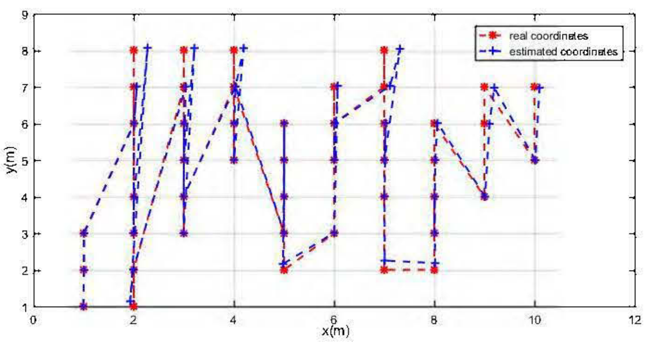

Fig. 1. Localization *of 50 node in a square* in a square area of *10m×10m*.

Fig. 1 shows the estimated coordinates in blue, vs the real coordinates in red. As shown, almost all the unknow points can be located with a high accuracy, (the red and blue curves are almost overlapped). The error percentages on coordinates estimations are calculated as:

$\% ERROR_x = \sum_{i=1}^{N}\left|\frac{x_i - x^*_i}{x_i}\right| \times 100 = 0.77\%$ (x_i:real coordinates; x^*_i estimated coordinates)

$\% ERROR_y = \sum_{i=1}^{N}\left|\frac{y_i - y^*_i}{y_i}\right| \times 100 = 0.4711\%$ (y_i: real coordinates; y^*_i: *estimated coordinates*)

Obtained values show the efficiency of this approach in localizing all nodes, using only two anchors with very low error values.

V.CONCLUSION

In this article we present a new target function in a gradient descend – RSS based method consisting in using the sum of the difference between the given and estimated power. Results shows that we can accurately locate many unknown nodes using only 2 anchors.

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Article 3

Gradient Descent Localization Algorithm Based on Received Signal Strength Technique in a Noisy Wireless Sensor Network

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***Abstract*—In this article we propose an improved RSS-based localization technique in a wireless sensor network based on the gradient descent optimization algorithm in a noisy propagation model, usually RSS is susceptible to the noise factor affecting the estimated distance of the sensor network. Generally, to localize an unknown node, a specific number of anchors (reference nodes) is required, this number of needed anchors will increase in the presence of noise factor. Results have shown that, using our improved technique, the number of used anchors is reduced despite the existence of the noise aspect. A comparison with other techniques is made to show the effectiveness of our proposed approach.**

Keywords*—Wireless sensor network, localization technique, optimization technique, gradient descent algorithm.*

I. INTRODUCTION

Wireless sensor network (WSN) is now considered one of the top technologies that can be used in different environments, it consists of multiple small and low cost, sensors having a limited processing and computing resources. Furthermore, each sensor in this network can sense different types of physical phenomenon, these sensors operates as a mesh network, having the ability to exchange information between them. Several types of WSN exist; Terrestrial WSNs, Underwater WSNs, Multimedia WSNs, Mobile WSNs, and Underground WSNs. The main advantages of WSN that, it is easily operated and deployed, and it can be used in harsh environments where wired networks cannot be effectively installed [1]. For that, WSN can be used in different applications such as military or environmental application (health caring, underwater surveillance, tracking system, mine) [2]. Nearly, in all WSN application the information received by the sensor will not be meaningful unless the location of the sensor node is known. Hence, due to the significant role of localization in WSN, it has become the most important constraint that attracted many researchers.

Commonly, Global Positioning System (GPS) represent the famous technique in localization in outdoor environment, despite all the advantages that GPS offer, it is still inefficient for indoor localization where the signal of GPS cannot be flexible because of the different types of obstacles. Two common types of localization have been widely used; The range free techniques [3-4] (hop count, pattern matching, centroid….), where the absolute range information or angle between two pair of nodes is not needed, and the range-based techniques such as time of arrival (TOA), time difference of arrival (TDOA), angle of arrival (AOA), and Received Signal Strength Indicator (RSSI). Range based techniques are characterized by being more accurate compared to range-free, where the information on distance/angle between nodes are required [5]. Most of localization techniques consist of using at least three anchors or reference nodes (node that we know their real position) to localize the unknown nodes.

Among range-based techniques, RSSI is widely accepted to be used in WSN, especially in indoor environment, it consists of calculating the distance using the RSS measurements between the receiver and the transmitter node. Using (RSS) measured at the receiver, distance estimation between transmitter and receiver can be very easy and suitable. Nowadays, RSS ranging is mainly implemented among short range wireless communication systems because RSS measurement is obtained in every RF transceiver. Therefore, no additional components and power consumption are necessary [6]. However, RSS based method is susceptible to the noise and interference factor, that will affect the estimated distance accuracy. Since obtaining an accurate location of the target sensor is the goal of all localization technique, optimization algorithm has shown an attractive solution in localization domain compared with the previous mentioned techniques.

For this reason, we propose an improved localization method using the gradient descent optimization algorithm in a noisy propagation condition.

II. RELATED WORK

Many researches have focused in their studies on the optimization part in localization, that have shown a significance results compared with traditional localization techniques. In [7] a localization optimization algorithm of maximum likelihood estimation was made based on received signal strength, result have shown that, the proposed recursive algorithm provides a better performance compared to the traditional maximum likelihood method, in [8] a new proposed indoor localization method was done based on newton Raphson optimization algorithm that was compared with newton gaussian and trilateration techniques and have shown a better accuracy. On the other hand, [9] presents an optimal stochastic newton Raphson technique with measurement noise rejection capabilities. Numerical results have shown that the proposed algorithm provides significant improvement compared to the traditional newton Raphson method.

Amongst all optimization methods, gradient descent (GD) has concerned most of researchers in optimization localization domain, the core of GD hinge on the concept of minimizing a specific target function by iteratively moving in the direction of the optimum value, [10] presents a gradient-based fingerprinting for indoor localization, that can be more adaptive to the time variant indoor wireless signal, [11] presents a distributed gradient descent localization, where GD was combined with vector push sum in order to achieve fast convergence. Other researchers have focused on the secure side of gradient descent localization, [12] presents a secure localization algorithm that can resist to malicious attacks by merging gradient descent with a selective pruning technique, additionally, this same method was improved in [13] to eliminate ambiguous information, where the usual nodes can collaborate to reduce localization errors. Furthermore, while using gradient descent algorithm we should start by initial values that may assigned randomly, nevertheless, one of the most issue in gradient descent is falling into the local minimum issue, for that in order to avoid such type of problem [14] presents an initialization method were a selected K nearest neighbor was useful to get an appropriate initial point of the gradient descent. Work in [15] presents two gradient descent method GDA and GDB, were the inter-sensor distance was supposed to be known. In both techniques the objective function was represented as the sum of the squared errors between the given distance measurements and the distance calculated based on the estimated location of the nodes.

In this article we propose an improved RSS based localization technique based on the gradient descent optimization technique, the target function in this work will be represented as the difference between the real noisy RSS and the estimated power based on the estimated coordinates.

III. PROPOSED METHOD

The gradient descent localization technique in this article is based on finding the partial derivative of the target function with respect to the node's coordinates.

Consider a WSN of N unknown nodes and M anchors deployed on $L \times L$ area. The target function F will be represented as the difference between the real and the estimated power:

$$F = 0.5 \times \sum_{i,j=1}^{N,M} \left(Pr_{(i,j)} - Pr^*_{(i,j)}\right)^2 \quad (1)$$

$$Pr_{(i,j)} = Pr_{d0} - 10 \times n \times Log_{10}\left(\frac{d_{i,j}}{d_0}\right) + X\sigma \quad (2)$$

$$Pr^*_{(i,j)} = Pr_{d0} - 10 \times n \times Log_{10}\left(\frac{d^*_{i,j}}{d_0}\right) \quad (3)$$

$Pr_{(i,j)}$ represents the known noisy received power.
$Pr^*_{(i,j)}$ represents the estimated power between the ith node and the jth anchor, based on the estimated coordinates.
Pr_{d0} is the power of the transmitter at distance d_0 (d_0=1m),.
n is the path loss exponent (2< n <6).
X_σ is the normal or gaussian random variable.
$d^*(i,j)$ is the estimated distance between unknown node i and anchor j given as

$$d^*(i,j) = \sqrt{\left(x_j - x^*{}_i\right)^2 + \left(y_j - y^*{}_i\right)^2} \qquad (4)$$

$x^*{}_i$ and $y^*{}_i$ represent the estimated coordinates of the unknown nodes to be localized.

x_j and y_j represent the coordinates of the anchor nodes. With $i = (1 \ldots\ldots, N)$ and $j = (1 \ldots, M)$.

We have N nodes with unknown location $(x_1, y_1), (x_2, y_2), \ldots, (x_N, y_N)$. The known information is the power between each unknown node and the anchors, note that the power will be affected by the noise factor. The steps of the algorithm are given below based on [15]:

5) *Initialization of the coordinates*

$$x^*{}_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \quad (5)$$

$$y^*{}_1 = \left(w_{1,2} \times d_{1,2}\right) + \left(w_{1,3} \times d_{1,3}\right) + \cdots \left(w_{1,M} \times d_{1,M}\right) \quad (6)$$

$d_{1,j}$ is the distance between the unknown node 1 and the anchor j. Note that, since the power is known, the distance $d_{1,j}$ can be calculated using the following equation.

$$d_{1,j} = d_0 \times 10^{\left(\frac{-Pr_{d0} + Pr_{d_{1,j}}}{10n}\right)} \qquad (7)$$

The weight $w_{1,j}$ is defined as:

$$w_{1,j} = \left|\frac{1}{Pr_{1,j}}\right| \qquad (8)$$

$Pr_{1,j}$ represent the received power between the unknown node 1 and the fixed anchor j with j=1…, M.

6) *Compute the derivative of the target function with respect to $x^*{}_i$ and $y^*{}_i$.*

$$\frac{dF}{dx^*{}_i} = \sum_{i=1,j=1}^{N,M} \frac{T}{log_{10}\left(d^*_{i,j}{}^2\right)} \qquad (9)$$

$$T = -\left[5n \times \left(2x_j - 2x^*{}_i\right) \times (Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}\left(d^*_{i,j}\right)}{Log10}\right))\right].$$

$$\frac{dF}{dy^*{}_i} = \sum_{i,j=1}^{N,M} \frac{H}{log_{10}\left(d^*_{i,j}{}^2\right)} \qquad (10)$$

$$H = -\left[5n \times (2y_j - 2\,y^*{}_i) \times (Pr_{(i,j)} - Pr_{d0} + \left(\frac{10nLog_{10}\left(d^*_{i,j}\right)}{Log10}\right))\right].$$

7) *Update the new value of $x^*{}_i$ and $y^*{}_i$ as follow.*

$$\begin{bmatrix} x^*{}_i \\ y^*{}_i \end{bmatrix} = \begin{bmatrix} x^*{}_i \\ y^*{}_i \end{bmatrix} - k \begin{bmatrix} \frac{dF}{dx^*{}_i} \\ \frac{dF}{dy^*{}_i} \end{bmatrix} \qquad (11)$$

(k the step size $(0 < k < 1)$

8) *Repeat step 2 till $x^*{}_i$ and $y^*{}_i$ converge.*

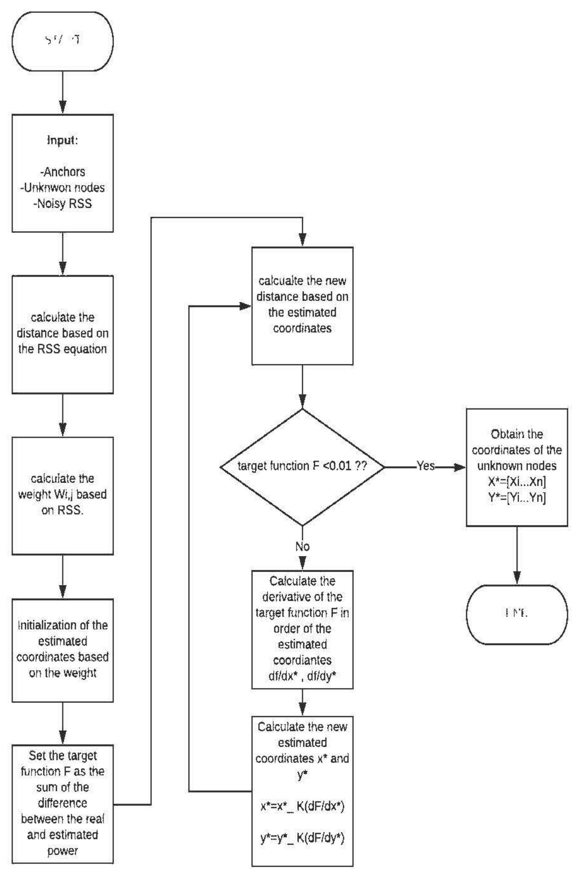

Figure 1:Flow chart describe the steps of the algorithm.

IV. SIMULATION

In the simulation part, the improved gradient descent technique presented in this paper was compared with GDB/GDA mentioned in [15]. The scenario is described as follows:

- There are totally 50 nodes randomly located in a square area of $10m \times 10m$.
- In order to localize the 50 unknown nodes, 4 nodes are used to be anchors.
- The RSS values between the anchors and the unknown nodes is considered to be known.
- The noise of the RSS measurement is generated by a Gaussian distribution generator in MATLAB, using the function *normrnd*.
- The true locations of the 50 nodes are shown in Fig 2.

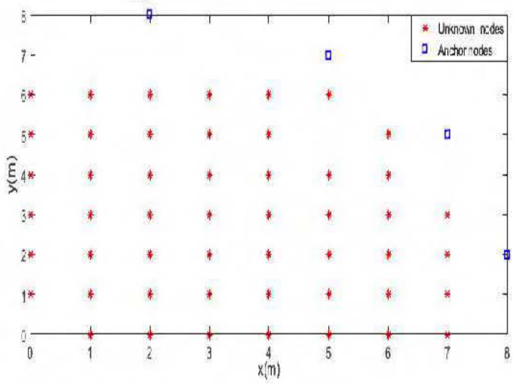

Figure 2. true location of the nodes in the network.

With the presence of the noise element, the locations of the 50 nodes are estimated by GDA/GDB and our improved localization methods, their results are shown in Fig.3 Below. The abscissa shows different noise levels. Standard derivation is set to by 0.3, 0.6, 0.9, …, 2.7, 3db. The accuracy of the localization technique can be judged by the error per node calculated as :

$$E = \frac{\sum_{i=1}^{N}\sqrt{(x_i-x_i^*)^2+(y_i-y_i^*)^2}}{N} \tag{12}$$

x_i, y_i: represent the coordinates of the true coordinates.

x_i^*, y_i^*: represent the final estimated coordinates at the end of the simulation.

N represent the total number o f nodes.

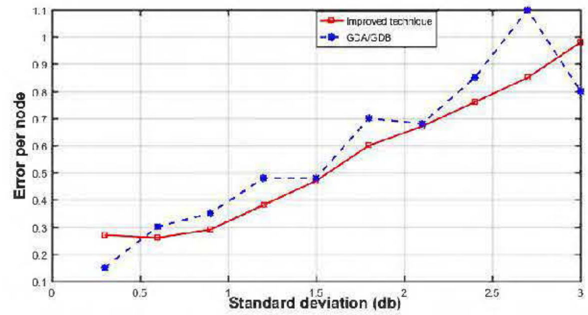

Figure 3. Accuracy of the methods with the increasing of noise factor.

The dash line represents the error per node in GDA/GDB localization technique mentioned in [15] related to the variation of the noise factor changing from 0.3 to 3db. The localization of the unknown nodes was done using 10 anchors.

The solid line represents the error per node. In our improved method only 4 anchors were used to localize the unknown nodes in the wireless sensor network. Obtained result shows that our proposed approach is better than GDA/GDB technique. Also, by using our technique, an important reduction of anchor's number is very beneficial on the WSN, and that by decreasing the network overloading, taking an example; many applications consist of dropping thousands of unknown sensor nodes, for that using the minimum number of needed anchors will be a good choice to localize them with the presence of minimum overload on the network. Adding also, the hardware cost will be reduced.

V. CONCLUSION

In this article, we present an improved localization technique in a wireless sensor network based on gradient descend algorithm and the RSS based method in a noisy propagation model. From the comparison with other localization method, the proposed gradient descend algorithms can reach better accuracy in the presence of noise factor using a less number of anchor nodes.

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