Localization for Fire Rescue Applications by Using Wireless Sensor Networks

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Abstract

Localization in Wireless Sensor Networks (WSNs) is very important. It can be used in various applications one of these applications is the Fire Rescue system. Localization means the determination of geographical locations of sensor nodes, consequently detecting the event location and to initiate a prompt action whenever necessary. The localization process passes with three phases which are distance and/or angle estimation phase, position phase, and algorithm phase. There are many techniques can be used in each phase, some of these techniques that may add additional devices, cost, power consumption, or delay to the network. This paper studied the most popular localization algorithms for WSN in each phase then demonstrated their problems with some suggestions for their solutions. Finally, the suitable Localization techniques for different categories of fire rescue system application will be recommended.

Keywords: *Wireless Sensor Networks, Localization Algorithms, Position Estimation, Fire Rescue.*

1. Introduction

WSNs consist of many sensors deployed in a certain area to monitor or detect an event(s) depending on the used application. WSNs are composed of hundreds, possibly thousands, of tiny low-cost and smart devices called Sensor Nodes (SN) that are capable of measuring various physical values they can detect temperature, sound, pressure, etc., this sensors are deployed in large numbers, and they are communicating with each other and organizing themselves in order to cooperatively achieve a desired task It can provide opportunities for monitoring and controlling homes, cities, and the environment. WSNs can be used in many applications such smart home [4], precision agriculture [35], habitat monitoring [6], environmental monitoring [6], animal migratory patterns [27], volcano monitoring [39], structural monitoring [13], vehicle tracking [22];[34], traffic control [14] and natural disaster detection [16].

The main challenges of a WSN design and implementation are power consumption constrain for nodes using batteries, scalability to large scale of deployment, Ability to withstand harsh environmental conditions and ease of use. An important aspect in most of the sensor networks application is the localization of the individual nodes, localization capability is a highly desirable characteristic of wireless sensor networks in environmental monitoring applications such as bush fire surveillance, water quality monitoring and precision agriculture, and other applications. The measurement data are meaningless without knowing the location from where the data are obtained. Moreover, location estimation may enable a myriad of applications such as intrusion detection, road traffic monitoring, health monitoring, reconnaissance and surveillance. Localization enables the efficient routing: A typical sensor network has large number of nodes which communicate at very short distance (a few meters). The data sensed by a node has to be communicated to the central unit through several other nodes. Thus multi-hop routing is a must. In order to impellent multi-hop routing it is necessary that nodes are of their locality, namely, they know their relative position with respect to their neighbors. Consequently localization becomes very important. Localization helps also in saving WSN energy, for example; in case of deploying a sensor network for pollution monitoring, the neighbor sensor nodes will have data which will not be dramatically different from each other. Thus to save power it makes sense to combine the data from neighboring nodes and then communicate the combined, reduced data set, thereby conserving power (since communication takes lot more power than local processing). In order to do this local data fusion, we will need the location information. Localization useful in locating the source of the data: In many applications, an event based sensor network is used. Here, the nodes are normally in sleep mode and when an event occurs (say sudden vibrations take place) the nodes are awakened. The nodes than sense and transmit the data. Such data requires a location stamp and therefore localization becomes necessary. From the previous examples we see that localization is indeed a necessity for sensor networks. Moreover, localization techniques vary depending on applications. [30]. Localization systems can be divided into three distinct components as shown in Fig. 1:

Distance/angle estimation: This component is responsible for estimating information about the distances and/or angles between two nodes. This information will be used by the other components of the localization system. *Position computation:* This component is responsible for computing a node's position based on available information concerning distances/angles and positions of reference nodes, reference nodes are nodes which it is positions is known.

Localization algorithm: This is the main component of a localization system. It determines how the available information will be manipulated in order to allow most or all of the nodes of a WSN to estimate their positions.

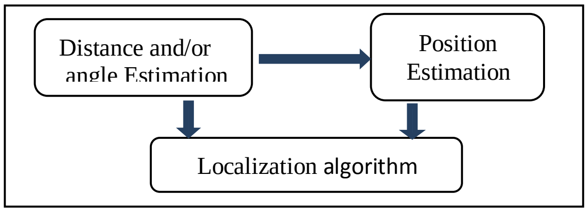

Fig. 1 Localization systems components.

The rest of this paper is organized as follows. In section 2, Fire rescue environment is described. In section 3 Angle estimation techniques are explained. Section 4 describes an overview about distance estimation techniques. A classification about position estimation techniques are presented in Sections 5. Localization algorithm phase is explained in section 6. Using wireless sensor networks for fire rescue applications and the importance of localization in this application is tabulated in section 7. Conclusions and future work are introduced in Section 8, 9 respectively.

2. Localization for Fire Rescue Applications by Using Wireless Sensor Networks

Fire rescue is one of the most important public safety activities. A typical scenario of the fire rescue process is depicted as follows. After a fire department gets a fire alarm call, it will send a fire rescue team to the fire field. Normally, a fire rescue team consists of one incident commander vehicle, two engine vehicles, one ladder vehicle, and the most important role, a set of firefighters, who are grouped as squads associating with one of the above vehicles. During the process of fire rescue, the incident commander is in charge of the whole fire rescue situation, including monitoring the fire field and making real-time schedule on firefighter assignment. The two engine vehicles carry water which will be used in the case when water is lack near the fire field. And the ladder vehicle holds the utilities like ladders that are needed by the firefighters. The firefighters are organized into different squads based on their specialty and fight cooperatively to eliminate fire in the fire field. This fire rescue operation mode has several shortages. First of all, the incident commander could not have a clear view of neither the status of firefighters after the rescue work starts nor the accurate situation of the fire field, so that it is difficult for him to make an optimized schedule. Second, the fire fighters in the fire field do not know the dangerous situation around him in time, which increases the danger to the firefighter as well. Finally, it is inflexible for the fire departments headquarter located far away from the fire field to get fresh and timely fire rescue information, which is particularly important for big cities which might have multiple fires at the same time. More real-time information about the firefighter and fire field is wanted by the incident commander and the fire department. First, the incident commander needs the real-time location information of firefighters, because the firefighters keep moving according to the fire situation during the process of fire rescue. Having the location information, the incident commander can make better schedule, e.g., he can find firefighters with some specialty and send them to where they are needed. In addition to the information about firefighters, the fire field information is also very useful for the incident commander to judge the real situation of the fire rescue and make real time decision and schedule. Thus, the WSN could be used to collect the environment information of the fire field, including the humidity and temperature of the fire field, the wind speed, the density of the smoke, and so on. Furthermore, the information about some vital events in the fire field need to be monitored as well, e.g., the death of the firefighters and the dramatic changing of the environment parameters, such as temperature, chemical and biological leak. Based on this information, the incident commander and fire department will have a clear view of the fire situation and make effective schedule to fight the fire. Not only does the incident commander sitting near the fire field need the information collected by the WSN, but also the officers sitting in the fire department, which is located far away from the fire field. In a big city like New York, there may be several fires happened at the same time, so the officers in the fire department need to make schedule on how to control these fires effectively and concurrently. Thus the real-time information from different fire fields is needed by the fire department, and the optimized schedule will be made based on this global information. Web based service is one of the most convenient ways to provide these information to these officers. By doing so, the real-time information from each fire field is wrapped as a web-enabled service, accessible through regular Web browsers. Because the fire department is located far away to the fire field, the traditional Internet will act as the bridge to connect the fire field and fire department. First, the web-enabled service should provide the information that the fire department interested via the network, e.g., it continuously reports the live situation of each fire field. Second, it will automatically generate some events to the fire department to ask aid when more firefighters or vehicles are needed. Moreover, the collected data can bestride and analyzed later to find some good rescue models to support the future fire fight.

3. Angle Estimation

Angle estimation based on AOA techniques estimates the angle at which signals are received depending on either amplitude or phase. It can be divided into two subclasses; technique that uses the receiver antenna's amplitude response and technique that uses the receiver antenna's phase response.

3.1. Technique uses the receiver antenna's amplitude response

It considers that the beam of the receiver antenna is rotated, and the direction corresponding to the maximum signal strength is taken as the direction of the transmitter, from Fig. 2 if the arrow is referring to the transmitter direction which is in direction with maximum signal strength [23].

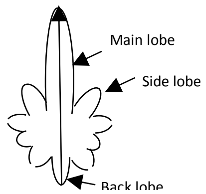

Fig. 2 Receiver antenna pattern with varying amplitude.

A technical problem to be faced and overcome arises when the transmitted signal has varying signal strength, the receiver cannot differentiate the signal strength variation due to the varying amplitude of the transmitted signal and the signal strength variation caused by the anisotropy in the reception pattern, from Fig. 1 if the side lobe strength is almost equal to the main lobe strength this problem will occur [23]. To deal with the problem we can use a second non-rotating and Omni directional antenna at the receiver. By normalizing the signal strength received by the rotating anisotropic antenna with respect to the signal strength received by the non-rotating Omni directional antenna, the impact of varying signal strength can be largely removed.

3.2 Technique uses the receiver antenna's phase response

It derives the AOA measurements from the measurements of the phase differences in the arrival of a wave front; it typically requires a large receiver antenna relative to the wavelength of the transmitter signal or an antenna array. Fig. 3 shows an antenna array of N antenna elements, the adjacent Antenna elements are separated by a uniform distance d.

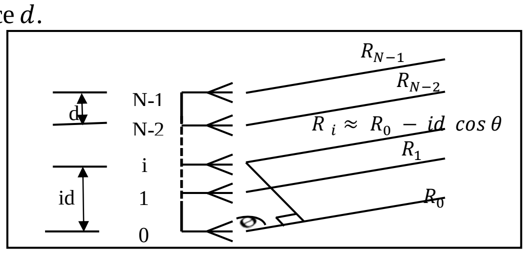

Fig. 3 Antenna array used in AOA measurement.

The distance between a transmitter far away from the antenna array and the i[th] antenna element can be approximated by

$$R_i \approx R_0 - id\ cos\,\theta \qquad (1)$$

Where Θ is the bearing of the transmitter with respect to the antenna array. The transmitter signals received by adjacent antenna elements have a phase difference of: $2\pi \frac{\mathrm{d}\cos\theta}{\lambda}$. This allows obtaining the bearing of the transmitter from the measurement of the phase difference [23].

AOA measurement either by using the receiver antenna's amplitude response or by using the receiver antenna's phase response works quite well for high SNR but may fail in the presence of strong co-channel interference and/or multipath signals. The accuracy of AOA measurements is limited by the directivity of the antenna, by shadowing and by multipath reflections. The multipath component may appear as a signal arriving from an entirely different direction and can lead to very large errors in AOA measurements [23], [5]. Multipath problem in AOA can be solved by using the Maximum Likelihood (ML) algorithms. ML methods will estimate the AOA of each separate path in a multipath environment.

4. Distance Estimation

Distance estimation techniques used to estimate the range between nodes, it can be divided into four subclasses; distance estimation based on one-way propagation time measurements, distance estimation based on round-trip propagation time measurements, distance estimation based on time-difference-of-arrival measurements, and distance estimation using received signal strength measurements.

4.1. One-way propagation time measurements

One-way propagation time measurements measure the difference between the sending time of a signal at the transmitter and the receiving time of the signal at the receiver to determine the distance between the transmitter and the receiver, the distance between the transmitter and the receiver regardless the processing delay time can be given by $d = c\times\| t_T - t_R \|$, where t_T is the transmitting time and t_R is the receiving time, this processing happens at the receiver. This technique requires the local time at the transmitter and the local time at the receiver to be accurately synchronized. This requirement may add to the cost of sensors by demanding a highly accurate clock and/or increase the complexity of the sensor network by demanding a sophisticated synchronization mechanism. This disadvantage makes one-way propagation time measurements a less attractive option than measuring round-trip time in WSNs. A solution for this problem is by using a combination of RF and ultrasound hardware on each transmission, a transmitter sends an RF signal and an ultrasonic pulse at the same time. The time difference between the receipt of the RF signal and the receipt of the ultrasonic signal is used as an estimate of the one way acoustic propagation time. This can be used to adjust clock on both the transmitter and the receiver.

4.2. Round-trip propagation time measurements (RTT)

It also known as time of arrival (TOA) [38], it measures the difference between the time when a signal is sent by a sensor and the time when the signal returned by a second sensor is received at the original sensor. Since the same clock is used to compute the round-trip propagation time, there is no synchronization problem. The major error source in round-trip propagation time measurements is the delay required for handling the signal in the second sensor. This internal delay is either known via a priori calibration, or measured and sent to the first sensor to be subtracted. The performance of TOA based ranging depends on the availability of the direct path (DP) signal. In its presence, for example, short distance line - of - sight (LOS) conditions, accurate estimates are feasible. The challenge, however, is ranging in non - LOS (NLOS) conditions, which can be characterized as site - specific and dense multipath environments. These environments introduce several challenges. The first corrupts the TOA estimates due to the multipath components (MPCs), which are delayed and attenuated replicas of the original signal, arriving and combining at the receiver shifting the estimate. The second is the propagation delay caused by the signal traveling through obstacles, which adds a positive bias to the TOA estimates. The third is the absence of the DP due to blockage, also known as undetected direct path (UDP). The bias imposed by this type of error is usually much larger than the first two and has a significant probability of occurrence due to cabinets, elevator shafts, or doors that are usually cluttering the indoor environment [16].

4.3. Time-difference-of-arrival measurements (TDOA)

It measures the TDOA of a transmitter signal at a number of receivers with known location information to estimate the location of the transmitter. In [23] The TDOA between a pair of receivers i and j is given by:

$$\Delta t_{ij} \triangleq t_i - t_j = \frac{1}{c}\left(\|r_i - r_t\| - \|r_j - r_t\| \right), i \neq j \quad (2)$$

From Eq. (2) if Δt_{ij} is measured sor$_t$ can be estimated. Fig. 4 shows the localization using time-difference-of-arrival measurements where t_i and t_j are the time when a signal is received at receivers i and j respectively, C is the light speed.The most widely used method in measuring the TDOA of a signal at two receivers at separate locations is the generalized cross correlation method, where the cross correlation function is given by:

$$\rho_{i,j}(\tau) = \frac{1}{T}\int_0^T s_i(t)s_j(t-\tau)\,dt \quad (3)$$

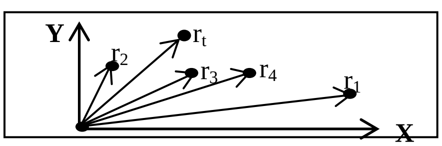

Fig. 4 localization using time-difference-of-arrival measurements.

Cross correlation method steps is shown in Fig. 5. From [17] the TDOA is given by:

$$\Delta t_{ij} = arg\ max\ (\rho_{i,j}(\tau)) \quad (4)$$

TDOA system requires sensors to be accurately synchronized among each other. Cross-correlating signals of a pair of sensors (r_i ,r_j) yields the requested TDOA by detecting the peak position. For an accurate estimation of the cross-correlation, the used time window per time difference estimation should be much larger than the maximum delay: T >>τ_{max}.[17] .

The cross-correlation function can also be obtained from an inverse Fourier transform of the estimated frequency domain cross-spectral density function. Frequency domain processing is often preferred because the signals can be filtered prior to computation of the cross-correlation function. The cross correlation approach requires very accurate synchronization among receivers but does not impose any requirement on the signal transmitted by the transmitter. The accuracy and temporal resolution capabilities of TDOA measurements will improve when the separation between receivers increases because this increases differences between times-of-arrival. Closely spaced multiple receivers may give rise to multiple received signals that cannot be separated. For example, TDOA of multiple signals that are not separated by more than the width of their cross-correlation peaks (whose location on the time-delay axis corresponds to TDOA) usually cannot be resolved by conventional TDOA measurement techniques. Yet another factor affecting the accuracy of TDOA measurement is multipath problem [5].

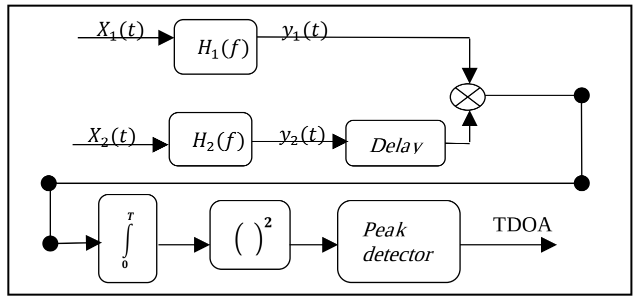

Fig. 5 Block diagram of generalized cross correlation method.

4.4. Multipath Problem

Overlapping cross-correlation peaks due to multipath often cannot be resolved. Even if distinct peaks can be resolved, a method must be designed for selecting the correct peak value, such as choosing the largest or the first peak [23].

Multipath problem can be solved by using an ultra-wide band (UWB) signals for accurate distance estimation. A UWB signal is a signal whose bandwidth to center frequency ratio is larger than 0.2 or a signal with a total bandwidth of more than 500 MHz, UWB can achieve higher accuracy because its bandwidth is very large and therefore its pulse has a very short duration. This feature makes fine time resolution of UWB signals and easy separation of multipath signals possible [23].

4.5. Distance estimation using received signal strength measurements

It estimates the distances between neighboring sensors from the received signal strength measurements. These techniques are based on a standard feature found in most wireless devices, a Received Signal Strength Indicator (RSSI). They are attractive because they require no additional hardware, and are unlikely to significantly impact local power consumption, sensor size and thus cost. In free space, the RSSI varies with the inverse square of the distance d between the transmitter and the receiver.

$$\text{RSSI} = P_r(d) = \frac{P_t G_t G_r \lambda^2}{(4\pi)^2 d^2},\ \boldsymbol{d} = \sqrt{\frac{P_t G_t G_r \lambda^2}{(4\pi)^2 P_r(d)}} \quad (5)$$

where P_t is the transmitted power, G_t is the transmitter antenna gain, G_r is the receiver antenna gain and λ is the wavelength of the transmitter signal in meters. The free-space model however is an over-idealization, and the propagation of a signal is affected by reflection, diffraction and scattering. Of course, these effects are environment (indoors, outdoors, rain, buildings, etc.) dependent. However, it is accepted on the basis of empirical evidence that it is reasonable to model the RSS=P_r(d) at any value of d at aparticular location as a random and log-normally distributedrandom variable with a distance-dependent mean value, That is,

$$\text{RSSI } [dBm] = P_r(d)[dBm] = P_t - PL(d_0)\text{-}10n_p \log_{10}(\frac{d}{d_0}) + X_\sigma \quad (6)$$

Let $P_0(d_0)[dBm] = P_t - PL(d_0)$ (7)

Then

$$\text{RSSI } [dBm] = P_r(d)[dBm] = P_0(d_0)[dBm] - 10n_p \log_{10}(\frac{d}{d_0}) + X_\sigma \quad (8)$$

Where$P_t$is the transmit power of the sender in dBm, $PL(d_0)$ is the power loss in dBm at a reference distanced_0.$P_0(d_0)[dBm]$ is a known reference power value in $dB\ milli\ watts$ at a reference distance d_0 from the transmitter, n_p is the path loss exponent that measures the rate at which the RSS decreases with distance and the value of n_p depends on the specific propagation environment, $X_\sigma$is a zero mean Gaussian distributed random variable with standard deviation σ and it accounts for the random effect of shadowing. It is possible to conclude from Eq. (8) that given the RSS measurement P_{ij} between a transmitter i and a receiver j, a maximum likelihood estimate of the distance, d_{ij}, between the transmitter and the receiver is:

$$\hat{d}_{ij} = d_0 \left(\frac{P_{ij}}{P_0 d_0}\right)^{-1/n_p} \quad (9)$$

Using Eq. (8) and Eq. (9), the estimated distance $\hat{d}_{ij}$can be related to the true distance:

$$\hat{d}_{ij} = d_{ij}10^{-\frac{X_\sigma}{10n_p}} = d_{ij}10^{-\frac{ln(10)X_\sigma}{10n_p\, ln(10)}} = d_{ij}e^{-\frac{X_\sigma}{\eta n_p}} \quad (10)$$

Where: $\eta = \frac{10}{ln(10)}$

The expected value of $\hat{d}_{ij}$ is:

Thus the maximum likelihood estimate in Eq. (8) is a biased estimate of the true distance and an unbiased estimate is given by:

$$E(\hat{d}_{ij}) = \frac{1}{\sqrt{2\pi}\sigma}\int_{-\infty}^{\infty} d_{ij}e^{-\frac{X_\sigma}{\eta n_p}}e^{-\frac{X_\sigma}{2\sigma^2}}\, dX_\sigma = d_{ij}e^{\frac{\sigma^2}{2\eta^2 n_p^2}} \quad (11)$$

Thus the maximum likelihood estimate in Eq. (9) is a biased estimate of the true distance and an unbiased estimate is given by:

$$\hat{d}_{ij} = d_0 \left(\frac{P_{ij}}{P_0 d_0}\right)^{-1/n_p} e^{-\frac{\sigma^2}{2\eta^2 n_p^2}} \quad (12)$$

5. Position Estimation

Position estimation techniques use angle or distance estimation techniques to estimate nodes positions. Several methods can be used to compute the position of a node, trilateration and probabilistic approaches methods are included in this section.

5.1 Trilateration

Trilateration is the process of finding the position of a node in space based on its distance to three anchors as shown Fig. 6. Let the positions of the three fixed anchors be defined by vectors: $\vec{n}_0$, $\vec{n}_1$, and $\vec{n}_2 \in \mathcal{R}^2$. Further, let $\vec{p} \in \mathcal{R}^2$ be the position vector to be determined. Consider three circles, centered at each anchor, having radii of d_i meters, equal to the distances between $\vec{p}$ and each anchor $\vec{n}_i$. These geometric constraints can be expressed by the following system of equations:

$$\left\|\vec{p} - \vec{n}_0\right\|^2 = d_0^2\ , \quad (13)$$
$$\left\|\vec{p} - \vec{n}_1\right\|^2 = d_1^2, \quad (14)$$
$$\left\|\vec{p} - \vec{n}_2\right\|^2 = d_2^2\ . \quad (15)$$

Since

$$\left\|\vec{p}-\vec{n}_i\right\|^2 = (\vec{p} - \vec{n}_i) . (\vec{p} - \vec{n}_i) = \left\|\vec{p}\right\|^2 - 2\vec{n}_i . \vec{p} + \left\|\vec{n}_i\right\|^2 ,$$

Eq.s (13) , (14) and (15) can be rewritten as follows:

$$\left\|\vec{p}\right\|^2 - 2\vec{n}_0 . \vec{p} + \left\|\vec{n}_0\right\|^2 = d_0^2, \quad (16)$$
$$\left\|\vec{p}\right\|^2 - 2\vec{n}_1 . \vec{p} + \left\|\vec{n}_1\right\|^2 = d_1^2, \quad (17)$$
$$\left\|\vec{p}\right\|^2 - 2\vec{n}_2 . \vec{p} + \left\|\vec{n}_2\right\|^2 = d_2^2\ . \quad (18)$$

Subtracting the second and third equations from the first, results in the following two equations:

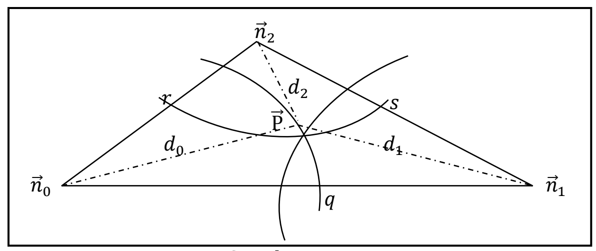

Fig. 6 Trilateration.

$$2(\vec{n}_1 - \vec{n}_0) .\vec{p} = d_0^2 - d_1^2 - \left\|\vec{n}_0\right\|^2 + \left\|\vec{n}_1\right\|^2 , \quad (19)$$
$$2(\vec{n}_2 - \vec{n}_0) .\vec{p} = d_0^2 - d_2^2 - \left\|\vec{n}_0\right\|^2 + \left\|\vec{n}_2\right\|^2 , \quad (20)$$

By solving the following linear system,$\vec{p}$ (expressed as a column vector) can be determined:

$$A = \begin{pmatrix} \vec{n}1 & \vec{n}0 \\ \vec{n}2 & \vec{n}0 \end{pmatrix} \quad (21)$$

$$\vec{b} = \begin{pmatrix} d_0^2 - d_1^2 - \|\vec{n}0\|2 + \|\vec{n}1\|2 \\ d_0^2 - d_2^2 - \|\vec{n}0\|2 + \|\vec{n}2\|2 \end{pmatrix} \quad (22)$$

$$2A\ .\vec{p} = \vec{b} \quad (23)$$

More generally, to determine $\vec{p} \in \mathcal{R}^N$, N + 1 fixed anchors are required: $\vec{n}_0$, . . . ,$\vec{n}_N \in \mathcal{R}^N$. Additionally, the distances between $\vec{p}$ and the N + 1 fixed anchors need to be known. These geometric constraints may be expressed by the following set of equations:

$$\left\|\vec{p} - \vec{n}_i\right\|^2 = d_i^2\ ,\ 0 \le i \le N \quad (24)$$

Using a similar reasoning as before, subtracting equations 2, . . . , N + 1 from the first, results in the following system of N linear equations:

$$A = \begin{pmatrix} \vec{n}_1 - \vec{n}_0 \\ \vdots \\ \vec{n}_N - \vec{n}_0 \end{pmatrix} \quad (25)$$

$$\vec{b} = \begin{pmatrix} d_0^2 - d_1^2 - \|\vec{n}_0\|\text{^}2 + \|\vec{n}_1\|\text{^}2 \\ d_0^2 - d_N^2 - \|\vec{n}_0\|\text{^}2 + \|\vec{n}_N\|\text{^}2 \end{pmatrix} \quad (26)$$

$$2A.\vec{p} = \vec{b}\ . \quad (27)$$

Assuming that the distances between the fixed anchors are known, but the anchors absolute positions are unknown, it is possible to construct a generic coordinate system for locating$\vec{p}$. Consider three fixed anchors: $\vec{n}_0$, $\vec{n}_1$, and $\vec{n}_2 \in \mathcal{R}^2$, such that only the distances between each pair of anchors are known. One possible way to define these vectors is described next:

$$\vec{n}_0 = \begin{pmatrix}0\\0\end{pmatrix} \qquad \vec{n}_1 = \begin{pmatrix}q\\0\end{pmatrix} \qquad \vec{n}_2 = \begin{pmatrix}\vec{n}_{2x}\\\vec{n}_{2y}\end{pmatrix} \qquad (28)$$

By expanding $\|\vec{n}_2 - \vec{n}_1\|^2$, the following is obtained:

$$\|\vec{n}_2 - \vec{n}_1\|^2 = (\vec{n}_2 - \vec{n}_1) \cdot (\vec{n}_2 - \vec{n}_1) = \|\vec{n}_2\|^2 - 2\vec{n}_1.\vec{n}_2 + \|\vec{n}_1\|^2 . \qquad (29)$$

Rearranging Eq. (29) in terms of $\vec{n}_1.\vec{n}_2$, yields the following:

$$\vec{n}_1.\vec{n}_2 = ½ (\|\vec{n}_1\|^2 + \|\vec{n}_2\|^2 - \|\vec{n}_2 - \vec{n}_1\|^2) ,$$
$$= ½ (q^2 + r^2 - s^2) \qquad (30)$$

The components of vector $\vec{n}_2$ can now be determined as follows:

$$\begin{pmatrix}q\\0\end{pmatrix} . \begin{pmatrix}\vec{n}_{2x}\\\vec{n}_{2y}\end{pmatrix} = ½ (q^2 + r^2 - s^2), \qquad (31)$$
$$q . \vec{n}_{2x} = ½ (q^2 + r^2 - s^2) , \qquad (32)$$
$$\vec{n}_{2x} = 1/2q (q^2 + r^2 - s^2), \qquad (33)$$
$$\vec{n}_{2x}{}^2 + \vec{n}_{2y}{}^2 = r^2 \qquad (34)$$
$$\vec{n}_{2y} = \pm\sqrt{r^2 - \vec{n}_{2x}^2} \qquad (35)$$

Assuming that $n_{2y} \geq 0$, then $\vec{n}_2$ is given by:

$$\vec{n}_2 = \begin{pmatrix} 1/2q\ (q2 + r2 - s2) \\ \sqrt{r^2 - \vec{n}_{2x}^2} \end{pmatrix} \qquad (36)$$

Provided vectors $\vec{n}_1$ and $\vec{n}_2$ are not collinear, i.e. $n_{1x} \neq 0$ and $n_{2y} \neq 0$, they form a basis for this two-dimensional vector space, and $\vec{p}$ can be determined by substituting $\vec{n}_1$ and $\vec{n}_2$ into linear system [32].

The main problem with this technique is that it relies on exact measurements to determine a position without taking into consideration error in distance measurement. To solve this problem a good path loss model should be used.

5.2. Probabilistic approaches

The uncertainty in distance estimations has motivated the appearance of probabilistic approaches for computing a node's position. An example of a probabilistic approach is proposed in [33], where the errors in distance estimations are modeled as normal random variables. When an unknown node receives a packet from a reference node, it can be in any place around the reference node with equal probabilities. When another packet is received from another reference node, the unknown node computes its position again as depicted in Fig. 7. When new position information is received from other nodes, it becomes possible to identify the probable location of the unknown node, as depicted in Fig. 8. The main drawbacks of this approach are the high computational cost and the space required to store the information [26].

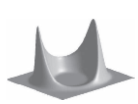

Fig. 7 Position estimation after receiving packets from two reference nodes. [33]

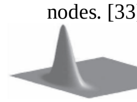

Fig. 8 Position estimation after receiving packets from three reference nodes. [33]

Every unknown node estimates its own position using a probability density function (pdf) $f_{X,Y}(x,y)$ of the two-dimensional coordinate variable (X,Y). Therefore, the probability of an unknown being placed at the coordinate (x_ζ , y_ζ) is:

$$Prob(x_\zeta, y_\zeta) \approx \int_{y_\zeta - \Delta y}^{y_\zeta + \Delta y} \int_{x_\zeta - \Delta x}^{x_\zeta + \Delta x} f_{X,Y}(x,y)dxdy \qquad (37)$$

Where $x_{min} \leq x \leq x_{max}$ and $y_{min} \leq y \leq y_{max}$.

The probability $Prob(x_\zeta, y_\zeta) = Prob(X = x_\zeta, Y = y_\zeta)$ (38)

the constants x_{min} , x_{max} , y_{min} and y_{max} are the bounding coordinates of the network, and both Δx and Δy are arbitrarily small values. The higher the probability $Prob(x_\zeta, y_\zeta)$, the more likely that the unknown node is placed at (x_ζ, y_ζ). By using distribution functions from distance or angle Estimation techniques $Prob(x_\zeta, y_\zeta)$ can be estimated. The next procedure is considering RSS technique used in distance estimation.

Initially Calibration Process is needed. During the calibration phase the RSS is measured at different distances between a transmitter and a receiver pair. Let *P* and *D* denote the random variables of RSS (in dB) and distance (in meters), respectively. The mean of the RSS measurements *P*(*d*) and the standard deviation □*P*(*d*) at each distance *D* = *d* can be calculated from the calibration measurements and using Eq. (37)

$$RSS[dBm] = P_t\,[dBm] - PL(d_0)\,[dBm] - 10\alpha\, log_{10}(d/d_0) + X_{\sigma RSS}\,[dBm] \qquad (39)$$

$P(d)$ and $\sigma P(d)$ can be used to generate a mapping from any RSS to a pdf of the distance random variable *D*. Using this mapping which is a log-normal mapping of the RSS measurements, each unknown estimates its position pdf. Initially, each unknown sets its initial estimation to an even distribution over the entire network area, $f_{X,Y}(x,y) = \frac{1}{A}$; where *A* is the total area of the network. Nodes with position information, including both beacons (anchors) and unknowns with updated pdf estimations, send out beacon packets to their neighbors. Upon receiving a beacon packet, an unknown node executes the following algorithm:

- It measures the RSS of the received beacon packet;
- It maps the RSS to a one dimensional pdf using Eq. (48) and generate a pdf constraint $\Psi_{X_C,Y_C}(x,y)$, which is a function of the coordinate random variable (X_C, Y_C);
- It updates the old pdf estimation by intersecting it with the generated constraint;
- Finally, the unknown with the updated pdf estimation will broadcast to all its neighbors.

There are two classes of beacon packets:

- Beacon packets from a beacon, and
- Beacon packets from an unknown.

If the beacon packet is from a beacon *b* placed at (X_b, Y_b), we assume the position of the beacon is accurate (although the scheme may take into account any inaccuracies of the beacon's position). An unknown j within b's transmission range receiving the beacon packet with $RSS_{p_{b,j}}dB$ maps $p_{b,j}$ to a pdf of the distance with mean $\mu_D(p_{b,j})$ and standard deviation $\sigma_D(p_{b,j})$; both $\mu_D(p_{b,j})$ and $\sigma_D(p_{b,j})$ are calculated during calibration stage that should be at first. The unknown j then calculates a pdf constraint as:

$$\Psi_{X_C,Y_C}(x,y|p_{b,j}) = \frac{\varphi(x,y,x_b,y_b)}{\int_{y_{min}}^{y_{max}}\int_{x_{min}}^{x_{max}}\varphi(x,y,x_b,y_b)\,dxdy} \quad (40)$$

$$\varphi(x,y,X_b,Y_b) = \frac{1}{\sqrt{2\pi}\sigma_D^2(p_{b,j})d_{b,j}} e^{-\frac{(\log d_{b,j}-\mu_D(p_{b,j}))^2}{2\sigma_D^2(p_{b,j})}} \quad (41)$$

$$d_{b,j} = \sqrt{(x-x_b)^2+(y-y_b)^2} \quad (42)$$

If the beacon packet is from an unknown node i with pdf estimation $f_{X_i,Y_i}(x,y)$, the unknown j, receiving a beacon packet from i with $RSS_{p_{b,j}}dB$, estimates the pdf constraints as:

$$\Psi_{X_C,Y_C}(x,y|p_{i,j}) = \frac{\varphi(x,y)}{\int_{y_{min}}^{y_{max}}\int_{x_{min}}^{x_{max}}\varphi(x,y)\,dxdy} \quad (43)$$

$$\varphi(x,y) = \int_{y_{min}}^{y_{max}}\int_{x_{min}}^{x_{max}}\varphi(x,y,x_i,x_i)f_{X_i,Y_i}(X_i,Y_i)\,dx_i dy_i \quad (44)$$

where: $\varphi(x,y,x_i,x_i) = \frac{1}{\sqrt{2\pi}\sigma_D^2(p_{i,j})d_{i,j}} e^{-\frac{(\log d_{i,j}-\mu_D(p_{i,j}))^2}{2\sigma_D^2(p_{i,j})}}$ (45)

Assume the original pdf estimation for unknown j is $f^{old}_{(X_i,Y_i)}(x,y)$; a new pdf estimation for unknown j can be calculated by intersecting the pdf constraint described above, either from a beacon or an unknown, with the original estimation, if vector random variables (X_i,Y_i) and (X_C,Y_C) are mutually independent.

$$f_{X_i,Y_i}(x,y) = \frac{f^{old}_{(X_i,Y_i)}(x,y)\Psi_{X_C,Y_C}(x,y|p)}{\int_{y_{min}}^{y_{max}}\int_{x_{min}}^{x_{max}} f^{old}_{X_i,Y_i}(x,y)\Psi_{X_C,Y_C}(x,y|p)dxdy} \quad (46)$$

5.3. Spring-Relaxation Technique

The concept of spring-relaxation technique is explained be considering the following example. The example consists of five beacons and a sensor whose location is to be determined. In the concept of spring-relaxation technique, the considered example is equivalent to having a moving particle (i.e., sensor) attaching with five springs. For each spring, while its one end attaches to the particle, its another end is nailed by a pin (i.e., beacon) at a fixed location. Fig. 9 depicts the described example. In the illustration, the black rings are the beacons or the pins in fixed locations, and white ring is the sensor or the particle in its initial guessed location. The natural length of a spring is the length where the spring is in the rest state. When the length of a spring becomes shorter (resp. longer) than its natural length, the spring is compressed (resp. stretched) and forces are produced at each end of the spring. The particle attached to a set of springs receives forces from them when they are compressed or stretched. The net force applies on the particle is the vector sum of all received forces. When the particle begins at a particular location with nonzero net force, the net force moves the particle to a new location and the net force changes accordingly. The particle continues to move until the net force becomes zero, and the particle comes to rest. This resting location, indicated by the grey ring in Fig. 9, is also the final stopping location of the particle. Localization using spring-relaxation technique does not have real springs connecting the particles and pins. It uses the concept to simulate the movements of the particle under the spring forces computed, and find the final stopping location, which is the estimated location of the particle. From Hooke's law, the magnitude of the force F from each spring $F = k(L_0 - L)$ (47)
where L_0 is the natural length of the spring, L is the current length of the spring, and k is the spring constant. The difference which $L_0 - L$ describes is the stretch or compression of the spring. Let $\vec{F}$ be the force vector applied on a particle by a spring, and $\overrightarrow{F_{net}} = \sum\vec{F}$ be the net force applying on the particle by all the attached springs. By Newton's first and second law, we have the relationship:

$$\overrightarrow{F_{net}} = \frac{d(m\vec{v})}{dt} \quad (48)$$

where m is the mass of the particle and $\vec{v}$ is the instantaneous velocity of the particle due to the net force. The instantaneous displacement of the particle can be determined by: $\vec{D} = \int \vec{v}dt = \iint \frac{\overrightarrow{F_{net}}}{m}dt^2$ (49)
The instantaneous displacement will cause a change in force applied by each spring on the particle. This change in force leads to a new net force on the particle which then changes the instantaneous displacement of the particle again. As this process continues, the particle moves and will eventually rest at an equilibrium location where the net force is zero.

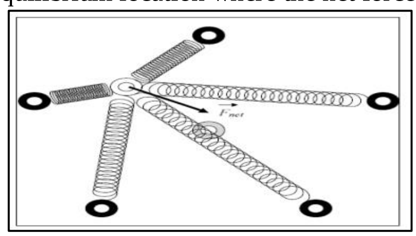

Fig. 9 Example of five beacons and a sensor. [39]

6. Localization Algorithm

It determines how the available information will be manipulated in order to allow most or all of the nodes of a WSN to estimate their positions.

6.1. Localization based on RSS algorithm

In [37].The distance estimation phase is the initial step performed when locating a node's position in space using RSS profiling techniques. By estimating distances to neighbors with known coordinates, a node can determine its own position using positioning algorithms. Once a node determines its position, it becomes an anchor node and can then help other neighbors find their positions. Alternatively, nodes attached to GPS-devices can rely on this instrument for obtaining coordinates, without needing to estimate distances to their neighbors. [38]
The received signal strength (RSS) technique does not require any hardware in addition to the radio transceiver. Knowing the transmitted signal's power and path-loss model, the inter-node separation can be calculated. RSS based localization systems do not require hardware components in addition to the radio transceiver. Moreover, no dedicated packets need to be sent over the network for such systems to function. However, RSS measurements are very unreliable, even when both sender and receiver are stationary. Ranging errors of ± 50% have been observed, leading to inaccurate distance estimates. Hence, it is important to understand the sources of error before relying on this technique for locating nodes.
Multipath and shadowing are two major phenomena affecting the reliability of RSS measurements. Different magnitude signals arriving out of phase at the receiver cause

constructive and destructive interference. Spread spectrum radios effectively mitigate this problem by averaging the received power over multiple frequencies. Shadowing effects are caused by obstructions (e.g. thick vegetation, walls, furniture) that attenuate the signal's strength. Additionally, not all RSSI circuits are factory calibrated, resulting in device-dependent RSS measurements for the same signal strength. The actual signal power can be different from the transceiver's intended transmission power, causing further discrepancies in RSS measurements. Various techniques have been proposed for mapping RSS measurements to distance estimates. The basic formula used in RSS localization is given by the formula:

$$RSS[dBm] = P_t[dBm] - PL(d_0)[dBm] - 10\alpha \log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma_{RSS}}[dBm] \quad (50)$$

where RSS is the received signal strength in units of decibels with respect to milli watts (dBm). In Eq. (50), d is the true distance from the sender to the receiver, $\alpha = n_p$ is the path-loss exponent, P_t is the transmit power of the sender in dBm, $PL(d_0)$ is the power loss in dBm at a reference distance d_0. The quantity $X_{\sigma RSS}$ in dBm is a random variable representing the noise in the measured RSS and is often assumed to be a zero-mean Gaussian random variable with variance σ_{RSS}. The source of the noise $X_{\sigma RSS}$ in measured RSS can come from both time varying and time-invariant sources. Time varying errors, such as interference, can be averaged out by taking multiple measurements corresponding to the same distance. Time-invariant errors, Such as shadowing due to heterogeneity in the medium resulting from objects such as walls or buildings can cause the signal to degrade contrary to the path-loss model. These errors cannot be averaged out by taking multiple measurements, as the path loss model cannot be specifically designed for each wireless channel in each deployed network. It is observed that the random effects of shadowing are appropriately modeled by assuming the error $X_{\sigma_{RSS}}$ is Gaussian. In a WSN performing RSS-based localization according to traditional techniques, each node measures an RSS value corresponding to each neighboring beacon node. This measured value RSS is mapped to a distance estimate $\hat{d}$. This mapping from RSS to $\hat{d}$ requires an expression for the distance $\hat{d}$ as a function of RSS and can be obtained by solving (20) for, yielding:

$$d = k10^{(P_t - RSS + X_{\sigma_{RSS}})/(10\,\alpha)} \quad (51)$$

Where k is a constant incorporating both $PL(d_0)$ and $\alpha \log_{10}(d_0)$.

7. Wireless Sensor Fire Rescue Network (WSFRN) Architecture

The architecture of the proposed Wireless Sensor Fire Rescue Network (WSFRN) Architecture is shown in Fig. 10. In the WSFRN, the vehicles and firefighters are equipped with sensors which forma self-organized heterogeneous wireless sensor network. In the incident commander's vehicle, a powerful laptop connected with a powerful sensor acts as the gateway of WSN. The ladder vehicle and the two engine vehicles are loaded with sensors having GPS equipped. These vehicles can act as the landmark for the whole WSN because they will have relatively stable location, i.e., other sensors can calculate their location based on the location of these vehicles. Each firefighter in the sensor field carries a sensor, such as MICA2 or MICAz from Crossbow [29] attached with available sensor board which can sense interested parameters, acting as the active badge for each firefighter. The active badge records all the information expected by the incident commander and fire department (for later analysis), such as the firefighter information, the fire field environment information and emergent events, as listed in the Fig. 10. The role of each active badge (i.e., sensor) has two-fold: sensing the data and forwarding the packets. After the fire fight team starts their work, the sensors attached to vehicles and firefighters are self-organized into a WSN via wireless communication. Then, the sensors start to operate according to their pre-installed program. For example, the sensors attached to firefighters will collect the information of firefighters, sample the environment parameters, and generate the vital events happened in the fire field, as shown in the right part of Fig. 10. These data will be reported to the sink by the multi-hop routing protocol and further delivered to the fire department via Internet. Then, both the incident commander and the officers in the fire department have the accountability and real-time information from the fire field, which is abstracted and presented by the powerful pre-installed software in the sink or fire department. By doing so, the whole fire field is monitored and the status of each firefighter is clear to the incident commander and fire department. Based on this, the incident commander and fire department will make optimized fire schedule according to the suggestion of the intelligent software. The location, especially the real-time location, of firefighters in a fire scene is a very important and valuable piece of information. Given this piece of information, the incident commander could have a clear view of the distribution of deployed firefighters, and make real-time decisions. Moreover, location information is very useful for other protocols in WSN as well. Most research topics in WSN, e.g., fault tolerant routing, aggregation, event detection and tracking, and so on, directly or indirectly lend on accurate location information provided by the underlying localization service. Admittedly, location in the fire rescue application is not a trivial task given the fact that firefighters are moving very fast and randomly in a real rescue operation as well as the inherent ad-hoc feature of Fire Net. Localization in WSN has been extensively studied in the literature [1]; however, as a reality check, few of practical localization algorithms are deployed in the real applications, and practical localization, especially mobile localization, is still a challenge from the perspective of real deployment. Intuitively, Global Positioning System (GPS) is a pretty good positioning system at outdoors; however, it is not accurate enough for indoor tracking. Moreover, most of existing localization solutions did not take the mobility into consideration, i.e., they always assume the location of sensors is static, which is obviously not the case in Fire Net. The few mobile localization algorithms such as [38] do not consider the moving speed and the dynamics of the system. Therefore, we argue that the localization protocol for a WSN in fire rescue application needs to address the following issues: mobility, heterogeneity, locality, robustness, feasibility, and accuracy, each of which is described as follows.

1) Mobility The fast movement of firefighters makes the localization a big challenge in a timely fashion.

2) Heterogeneity Due to the heterogeneity of the sensors used in Fire Net, the localization algorithm should take these diverse platforms into consideration, e.g., the computing devices on some vehicles/equipment, such as laptops or tablets, could be integrated with GPS support which provides some reference points for further location resolving, while on the other side, the sensors carried by firefighters would be very simple and possess only limited computing resource and energy support.

3) Locality Each sensor has limited computing power, memory, and communication range, thus only a completely localized algorithm is applicable in Fire Net, where each sensor interacts with its neighbors only.

4) Robustness Sensors in Fire Net are working in a very harsh and highly failure-prone environment. Robustness is a key requirement of the localization algorithm, i.e., the failure of some sensors should not affect the calculation of other sensors location.

5) Feasibility The localization algorithm has to be practical enough so that its computing cost could be affordable by the limited hardware/software supporting of those tiny sensors.

6) Accuracy the real scheduling by the incident commander and fire department is based on the accurate location of firefighters. Accurate positioning in a static environment is already nontrivial; it becomes more challenge in such a highly dynamic environment.

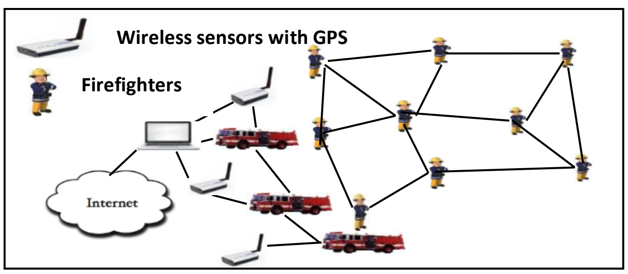

Fig. 10 Fire rescue network.

Table 1 highlights the Advantages and disadvantages of the most suitable localization techniques for fire rescue systems using WSN Round-trip propagation time and RSS.

Table 1: Advantages and disadvantages of RTT and RSS techniques

Technique	Advantages	Disadvantages	Comment
TOA	-More accurate	- Hardware is complex - Accuracy is sensitive to the multipath condition and the system bandwidth - Performance of TOA technique depends on the availability of the direct path (DP) signal	- It also known as time off arrival (TOA). - Suitable for outdoor localization
RSS	- More practical - Simple to implement - No additional hard ware are required - Insensitive to the multipath condition and the bandwidth of the system - Localization error is independence of the system bandwidth	- Lower accuracy and precision - High density of anchors or reference points is needed - Extensive training and computationally expensive algorithms are required.	- Performance of RSS techniques depends on the accuracy of the model used for the estimation of the RSS

8. Conclusion

TDOA methods are impressively accurate under line-of-sight conditions. But this line-of-sight condition is difficult to meet in some environments. Furthermore, the speed of sound in air varies with air temperature and humidity, which introduce inaccuracy into distance estimation. Acoustic signals also show multi-path propagation effects that may impact the accuracy of signal detection TDOA also needs synchronization. AOA techniques provide more accurate localization result than RSSI based techniques but the cost of hardware of very high in AOA. However Angle-Of-Arrival measurements techniques and distance related measurements techniques can be used to determine the location of sensor nodes, RSS can be considered the most suitable localization technique for WSN because no additional hardware need to be added (rotating antenna, antenna array, synchronization equipment's) and is unlikely to significantly impact local power consumption which is a very important issue in WSN, sensor size and thus cost. Table.1 highlights the advantages and disadvantages of the most suitable techniques for WSN Round-trip propagation time and RSS. [38],[27].

9. Future Work

In this paper the localizations process phases and its importance in fire rescue process are described in near future enhancing the localization accuracy and saving energy consumption will be introduced.

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