World Academy of Science, Engineering and Technology
International Journal of Electronics and Communication Engineering
Vol:9, No:10, 2015

Indoor Localization Algorithm and Appropriate Implementation Using Wireless Sensor Networks

Adeniran Ademuwagun, Alastair Allen

***Abstract*—The relationship dependence between RSS and distance in an enclosed environment is an important consideration because it is a factor that can influence the reliability of any localization algorithm founded on RSS. Several algorithms effectively reduce the variance of RSS to improve localization or accuracy performance. Our proposed algorithm essentially avoids this pitfall and consequently, its high adaptability in the face of erratic radio signal. Using 3 anchors in close proximity of each other, we are able to establish that RSS can be used as reliable indicator for localization with an acceptable degree of accuracy. Inherent in this concept, is the ability for each prospective anchor to validate (guarantee) the position or the proximity of the other 2 anchors involved in the localization and vice versa. This procedure ensures that the uncertainties of radio signals due to multipath effects in enclosed environments are minimized. A major driver of this idea is the implicit topological relationship among sensors due to raw radio signal strength. The algorithm is an area based algorithm; however, it does not trade accuracy for precision (i.e the size of the returned area).

***Keywords*—Anchor nodes, centroid algorithm, communication graph, received signal strength (RSS).

I. Introduction

LOCALIZATION is the process of estimating the position or spatial coordinates of wireless sensors. Localization techniques using wireless sensor networks (WSN) are employed to estimate the location of devices within a network of sensors of relatively known positions using inter-sensor measurements such as distance, time difference of arrival, angle of arrival and connectivity [1], [2]. Sensors with a priori known location information are called anchors, and the anchor locations can be estimated using GPS, coordinate systems or geographical mapping also know as finger printing [3], [4] of a physical environment. However, in our case study we are focused on using coordinate system and connectivity in an enclosed environment.

Localization using WSN relies on measurements; inter-nodal distance measurements between anchors using the coordinate system and the knowledge of the enclosed geographical area. Other factors that influence localization using WSN are the network architecture, the average node degree (i.e the average number of neighbours per sensor), the distribution of sensors in the area and the geometric shape of the network area. The aforementioned factors are key to the choice of algorithm to be employed and the accuracy of the estimated location. The measurements, using a typical WSN localization system can be related to the coordinates of sensors using the following generic formula:

$$\boldsymbol{S} = \boldsymbol{h}(\boldsymbol{U}) + \boldsymbol{e} \tag{1}$$

where $\boldsymbol{S}$ is the vector of all the measurements, $\boldsymbol{U}$ contains the true coordinate vectors of sensors whose locations are to be estimated and $\boldsymbol{e}$ is the vector due to measurement errors [5]. The wireless signal strength received by a sensor from another sensor is a monolithically decreasing function of their distance. This relationship between the received signal strength and distance is modelled by the following log-normal equation [5]:

$$\mathbf{P}_r(\boldsymbol{d})[\boldsymbol{dBm}]=\mathbf{P}_0(\boldsymbol{d}_0)[\boldsymbol{dBm}]\text{-}\mathbf{10n}_p\mathbf{log}_{10}\frac{d}{d_0}+\boldsymbol{X}_\sigma \tag{2}$$

where $P_0(d_0)$ [dBm] is a reference power in dB milliwatts at a reference distance d_0 from the transmitter, n_p is the path loss exponent that measures the rate at which the received signal strength decreases with distance, and X_σ is a zero mean Gaussian distributed random variable with standard deviation σ and it accounts for the random effect caused by shadowing. Both n_p and σ are environment dependent. The path loss exponent n_p is typically assumed to be a constant.

Most of the existing localization algorithms use some forms of RSS-distance profiling based localization techniques [6]-[8]. RSS profiling-based localization techniques works by first constructing a form of map of the signal behaviour of each anchor node within the coverage area. The map is obtained either off-line by a priori measurements or online using sniffing devices deployed at known locations [6]. This technique can also be referred to as Fingerprinting or signal mapping. Another method is the geometric methods, which is carried out by employing trilateration, triangulation or hyperbolic methods for localization using WSN [9], [10].

The simplest form of measurement in WSN are connectivity measurements [11]. In this type of measurement, sensors receive signals from other sensors within its transmission range. These signals can be translated into binary distance measurements, which implies that it is either a sensor is within range or not. A sensor within the transmission range of another sensor defines the proximity between the 2 sensors. Hence, our algorithm seeks to establish in its simplest form that a free node in the neighbourhood of 3 anchors is very close to the 3 anchors and consequently use the centroid of the 3 anchors to estimate the location of the free sensor. However, in reality, where there are likely to be a cluster of more than 3 anchors and the likelihood that the free sensor will receive signals from more than 3 anchors, the challenge is to decide which of the 3 anchors are closest to the free node. This problem is further

Dr. Alastair Allen and Adeniran K. Ademuwagun are with the Department of Engineering, University of Aberdeen, (e-mail: a.allen@abdn.ac.uk, r01aka13@abdn.ac.uk).

compounded when localization is indoors, due to multipath effect of radio wave propagation in an enclosed area. Thus, the need to decipher between the anchors that are close to the free node and the ones that are far away.

In this paper, we propose an overview of the position estimation algorithm and its benefits. First, we analyse RSS characteristics using some data samples collated from indoor experiments with MicaZ, second discus the algorithm and lastly, the novelty of the research.

II. RSS as a Connectivity Indicator

It is often too difficult to model RRS relationship with distance conditions that would be generally applicable for most indoor environmental conditions. The inverted-F antenna installed in the ChipCon CC2420 radio is non-isotropic. Hence, simple radio models that assume a perfect, spherical radio range will not accurately predict or describe real-world radio characteristics [12]. Consequently, simple connectivity became the object of the indoor experiments conducted using 8 MicaZ sensors. Four sensors, each cluster covering a geographical space of about $16m^2$ and each cluster about $5m$ apart. Using Matlab, the 15 data RSS sample readings concurrently taken from 2 different locations was modelled as a 200 data sample experiment. Each data sample was the average reading of the 3 best RSS values from each cluster. This is so because, only 3 anchors will be required for localization.

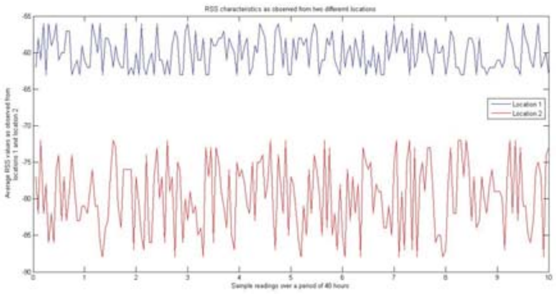

Fig. 1 RSS Characteristics as concurrently observed from 2 different locations in an indoor environment

Fig. 1 is the plot of the RSS values at the locations, while Fig. 2 is a scatter plot indicating the density of RSS reading at each location. An analysis of the plot shows that the deviation of the cluster of anchors closer to the reference sensor was lower than the deviation of the cluster of anchors farther from the reference sensor (2.317 and 4.795 for the closer and farther clusters respectively). Also the range between the maximum and minimum RSS values between the clusters closer to the reference sensor was 7dBm as compared with 16dBm for the clusters farther away from reference sensor. These values should be expected because range estimation error, when it can be quantified, is typically proportional to range such that short range measurements are more accurate within a few meters than longer range measurements. RSS measurement for ranging is a near versus far technique that can provide fairly accurate information about proximity but less accurate with

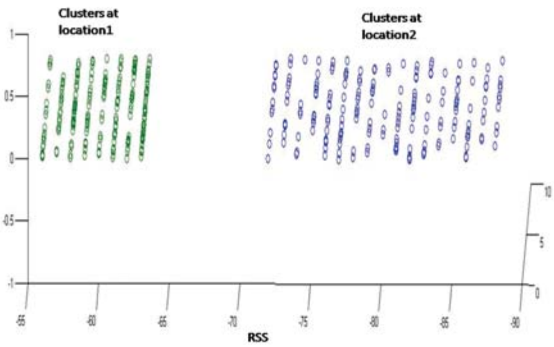

Fig. 2 Scattered plot indicating RSS density at each location

regards to true range. This connectivity variation forms the basis of our algorithm. A knowledge of distance is not essential in this algorithm, what is important is that the algorithm provides information about the relative positions of objects of interest within a known enclosed geographical space.

III. Localization Algorithm

This is a proximity based algorithm because only the anchors above a certain RSS threshold will be considered in the localization process. The algorithm comprises three main phases; selection of reference anchor nodes, isolation of the three anchor nodes to be used in localization, which we also refer to as the 'polling phase', and localization of the non-reference or free node. The focus will be on the local network topology, which is the communication graph formed by the anchors in the proximity of the node to be localized, rather than the global topology. The local topology or the communication graph will be formed by a set of active links between some anchors and the node to be localized. The network topology will consider a graph **G = (V,E)** to represent communication network. Where **V** is the set of all anchor nodes in the communication graph and **E** the edge linking the free node to the anchors or linking anchors to anchors.

The first step of the algorithm is that the free node ranks the RSS values from the anchors in its proximity. The second step is to select the first 3 anchors with the strongest link to the free node. However, a condition must be met during this phase; given that **V** is the set of all nodes in the communication graph and there is an edge $(v_1,v_2)\in\mathbf{E}\subseteq V^2$ if and only if anchors v_1 and v_2 can directly communicate with each other. Any asymmetric link is discarded in this algorithm because of lack of bidirectional communication. Consequently, the three anchors in the localization process must have bidirectional links with each other. The last phase will estimate the position of the free sensor through a simple centroid estimate as given in the equation below:

$$(X_{est}, Y_{est}) = \left(\frac{X_1 + \cdots + X_N}{N}, \frac{Y_1 + \cdots + Y_N}{N}\right) \tag{3}$$

The algorithm will be employed in processing the location of a free node at the position X in the communication graph of Fig. 3.

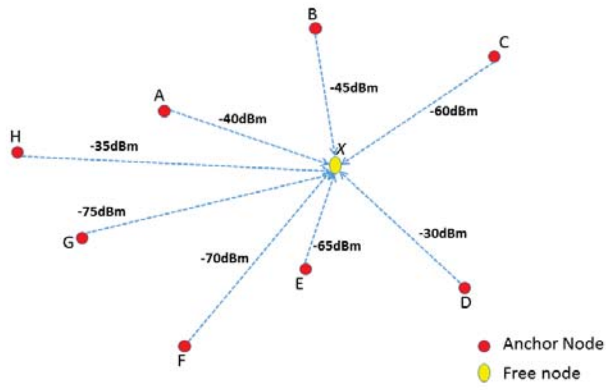

Fig. 3 A communication graph of anchors and a free node

Fig. 3 is a communication graph of set of anchors ABCDEFGH, while X is the location of the free sensor to be localized. The free sensor tabulates RSS signals from anchors in its vicinity as indicated in the yellow diagonal boxes in Table I. The second phase, which we call the polling

TABLE I
SENSOR X TABULATES OF RSS VALUES FROM ANCHORS IN ITS VICINITY

	X	A	B	C	D	E	F	G	H
	A	-40	-50		-35				-45
	B	-51	-45		-65				-25
	C			-60					
	D	-65	-50		-30				-30
	E					-65			
	F						-70		
	G							-75	
	H	-50	-65		-40				-35

phase, is where the free node select the 3 anchors with the highest average among the anchors that have bidirectional links with each other as in Table II. In this case, looking at anchor A; anchor A reads the RSS of anchors B,C and D as $-50dBm$, $-35dBm$ and $-45dBm$ respectively. However, anchor A cannot read anchors C,E,F and G or their RSS value is below the required threshold, hence their readings are discarded. Likewise, anchor H, reads A,B,D as $-45dBm$, $-25dBm$ and $-30dBm$ respectively but can also not read anchors C, E, F and G. Hence, in this instance, anchors ABD have the highest RSS combination average among the anchors with bidirectional RSS link (i.e. anchors ABDH) with each other. This is indicated in Table III.

In the third and final phase, there are two iterative steps, first the centroid (X) of the selected three anchors (i.e. anchors

TABLE II
NODES ABDH ARE ANCHORS WITH BIDIRECTIONAL LINKS WITH EACH OTHER

	X	A	B	C	D	E	F	G	H
-130	A	-40	-50		-35				-45
-141	B	-51	-45		-65				-25
	C			-60					
-145	D	-65	-50		-30				-30
	E					-65			
	F						-70		
	G							-75	
-150	H	-50	-65		-40				-35

TABLE III
ANCHORS ABD ARE SELECTED 'VOTED' FOR THE LOCALIZATION PHASE

	X	A	B	C	D	E	F	G	H
-130	A	-40	1		1				1
-145	B	1	-45		1				1
	C			-60					
-145	D	1	1		-30				1
	E					-65			
	F						-70		
	G							-75	
	H	1	1		1				-35

ABD) is calculated using the coordinates of the selected anchors, as shown in Fig. 4.

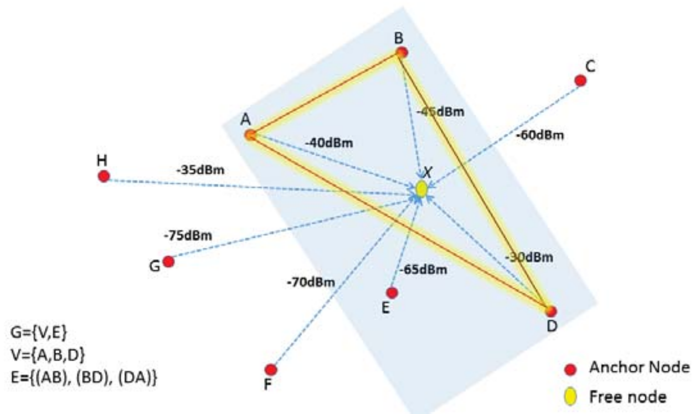

Fig. 4 Anchors ABD are used to calculate the centroid X

The second step is to use the new coordinate (X) in conjunction with the 2 anchors with the higher RSS average (anchors AB in this case) to calculate a new and final centroid, X', as shown in Fig. 5.

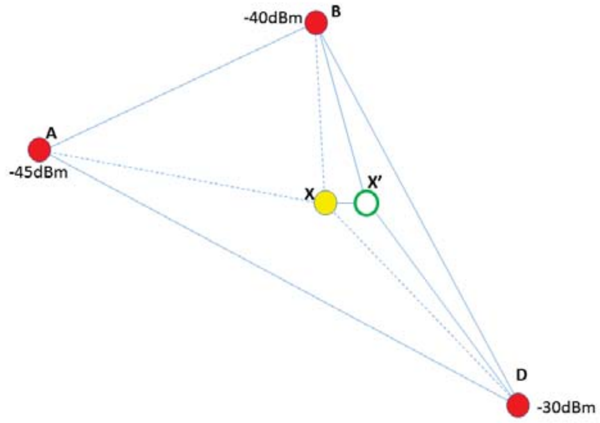

Fig. 5 Position X and anchors BD to calculate the final iterative position X'

In this algorithm, we introduce an error coefficient $\pm E$ for a more accrute estimation. For instance an object could have its actual distance at 4units, an error of 0.25units will suggest that the object is within 3.75units and 4.25units from the anchor. The error on either side of the actual position may not be uniform, it could be different or random, say (E_1, E_2)units. If the actual distance of the free node from an anchor is D units, then the range interval of the localized node is (D-E_1)units to (D+E_2)units. Hence, the best estimated area or position is achieved on the second iteration and it is given by πE^2, where E is ranging error. The choice of 2 iterative steps is subjective, it is limited to reduce the processing demand on the microcontroller.

IV. Novelty of the Algorithm

The major novelty of the algorithm are as follows:

- We observed that concurrently analysing a cluster of 3 anchors as against a single anchor, provides a workable information, such as the distinction between anchors in close proximity to the free node and anchors that are far away from the free node. Our approach also provides an alternative to using RSS as a benchmark for distance estimation, which often comes up with the conlusion that RSS is an unreliable indicator for localization [13]- [15].
- This method also eliminates (subject to further experimentations) anchors that are outliers, i.e anchors that appear to be in close proximity to the free node due to multipath effect, while they are actually further from the free node. Intuitively, the bidirectional link between the anchors ensures that outlier anchors are eliminated from participating in the localization process.
- It is also intuiteve that the algorithm will be effective under low power operations, hence save the lifespan of the anchors. A low power operation will eliminate anchors that are far afield of the free sensor, thus, limiting the size of communication network that will be formed, hence, reducing the processing time required for localization.

V. Conclusion

Analysing the RSS from a single anchor with respect to distance, produces inconsistent RSS-distance relationship, particularly in enclosed environment. However, concurrently examining in group, a combination of 3 anchors among anchors that are evenly distributed within an enclosed environment, produces a more reliable information, from which the location of a free node can be estimated.

The algorithm proposed in this article, relies on this technique to consistently isolate the 3 anchors that are in close proximity to a free node, or any sensor of interest, for the purpose of localization. This process is able to isolate the need for the direct correlation between RSS and distance and replace it with a proximity concept that will enable us localize an object within a certain region with a consistent level of accuracy. The algorithm is an area based algorithm.

References

[1] YoungMin Kwon, Kirill Mechitov, Sameer Sundresh, Wooyoung Kim, and Gul Agha. Resilient localization for sensor networks in outdoor environments. In *Distributed Computing Systems, 2005. ICDCS 2005. Proceedings. 25th IEEE International Conference on*, pages 643–652. IEEE, 2005.

[2] Neal Patwari, Alfred O Hero III, Matt Perkins, Neiyer S Correal, and Robert J O'dea. Relative location estimation in wireless sensor networks. *Signal Processing, IEEE Transactions on*, 51(8):2137–2148, 2003.

[3] Hüseyin Akcan and Cem Evrendilek. Gps-free directional localization via dual wireless radios. *Computer Communications*, 35(9):1151–1163, 2012.

[4] Mussa Bshara, Umut Orguner, Fredrik Gustafsson, and Leo Van Biesen. Fingerprinting localization in wireless networks based on received-signal-strength measurements: A case study on wimax networks. *Vehicular Technology, IEEE Transactions on*, 59(1):283–294, 2010.

[5] Guoqiang Mao and Barış Fidan. Introduction to wireless sensor network localization. *Localization Algorithms and Strategies for Wireless Sensor Networks*, pages 1–32, 2009.

[6] Parameshwaran Krishnan, AS Krishnakumar, Wen-Hua Ju, Colin Mallows, and SN Gamt. A system for lease: Location estimation assisted by stationary emitters for indoor rf wireless networks. In *INFOCOM 2004. Twenty-third AnnualJoint Conference of the IEEE Computer and Communications Societies*, volume 2, pages 1001–1011. IEEE, 2004.

[7] Phongsak Prasithsangaree, Prashant Krishnamurthy, and Panos K Chrysanthis. On indoor position location with wireless lans. In *Personal, Indoor and Mobile Radio Communications, 2002. The 13th IEEE International Symposium on*, volume 2, pages 720–724. IEEE, 2002.

[8] Teemu Roos, Petri Myllymäki, and Henry Tirri. A statistical modeling approach to location estimation. *Mobile Computing, IEEE Transactions on*, 1(1):59–69, 2002.

[9] Nirupama Bulusu, Vladimir Bychkovskiy, Deborah Estrin, and John Heidemann. Scalable, ad hoc deployable rf-based localization. In *Proceedings of the Grace Hopper Conference on Celebration of Women in Computing*, volume 31, 2002.

[10] Guoqiang Mao. *Localization Algorithms and Strategies for Wireless Sensor Networks: Monitoring and Surveillance Techniques for Target Tracking: Monitoring and Surveillance Techniques for Target Tracking*. IGI Global, 2009.

[11] Vaidyanathan Ramadurai and Mihail L Sichitiu. Simulation-based analysis of a localization algorithm for wireless ad-hoc sensor networks. In *Proceedings of the International Conference on Wireless Networks, Las Vegas, NV*, 2003.

[12] Michael Allen, Sebnem Baydere, Elena Gaura, and Gurhan Kucuk. Evaluation of localization algorithms. *Localization Algorithms and Strategies for Wireless Sensor Networks. IGI Global*, 2009.

[13] Ambili Thottam Parameswaran, Mohammad Iftekhar Husain, Shambhu Upadhyaya, et al. Is rssi a reliable parameter in sensor localization algorithms: An experimental study. In *Field Failure Data Analysis Workshop (F2DA09)*, page 5, 2009.

[14] Qian Dong and Waltenegus Dargie. Evaluation of the reliability of rssi for indoor localization. In *Wireless Communications in Unusual and Confined Areas (ICWCUCA), 2012 International Conference on*, pages 1–6. IEEE, 2012.

[15] Zaher Merhi, Michel Nahas, Samih Abdul-Nabi, Amin Haj-Ali, and M Bayoumi. Rssi range estimation for indoor anchor based localization for wireless sensor networks. In *Microelectronics (ICM), 2013 25th International Conference on*, pages 1–4. IEEE, 2013.