Resource Constrained Position Estimation for Wireless Sensor Networks

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Abstract: Positioning information plays an important part in analyzing and understanding the data obtained from wireless sensor networks, as it facilitates the formation of a coherent picture of the environment. Traditionally the preserve of computationally intensive techniques such as GPS, the limited computation and storage capabilities of wireless sensor networking necessitate an alternative approach. This paper proposes an algorithm adapted for wireless sensor networks and presents the implementation issues that have necessitated such an approach.

1. Introduction.

Wireless sensor networks are networks of large numbers of devices that sense the environment in a distributed manner, whilst retaining autonomous control. These devices are characterised by their small size, low cost and limited computational. The purpose of the general sensor network initiative is to create an intelligent, self-organising network using these simple devices distributed in an ad-hoc fashion [1]. The main advantage of these systems is arguably their self-organising capabilities. Device autonomy allows adaptation to environmental changes. Consequently the network as a whole is reliable and robust to device failure. Additionally, the large number of devices provides finer granularity observation than with previous monolithic sensing techniques.

The distributed nature of these phenomena presents a problem for algorithm designers because processes external to each individual node need to be considered. To overcome this, it is necessary that the algorithms are distributed in nature, to enable the different local circumstances influence the network. The limited resources available to each node necessitate simple algorithms. With distributed algorithms typically being complex and computationally expensive [2], these requirements are conflicting. Biological models help resolve this conflict as they are made up of sets of simple rules working together to exhibit complex behaviour [3]. This work is presented with particular emphasis on the characteristics required from a node localization algorithm within a wireless sensor networking context.

2. Iterative Averaging.

This is a simple algorithm used to determine coarse granularity node position estimates in a sensor networks, using information obtained from radio transmissions between nodes. Two classes of nodes are assumed to exist within the network. Position Aware nodes (PA) are nodes that know their absolute position, either from pre-programmed coordinates or an attached GPS module. Position Determining nodes (PD) do not know their position and thus need to make estimations of their positions. The algorithm proposes that all PDs set their position estimates to the average of all position estimates received from all one hop neighbours i.e. if a node receives more than one estimate, it averages the values obtained, using (1). If a node receives just one position estimate from its neighbours, it sets its position estimate to this value, until such a time as it receives additional position estimates from other neighbouring nodes. This process continues iteratively position estimates stop changing significantly. Intuitively, we infer for the above that nodes with few neighbours will have large errors in position estimates.

$$(x, y) = \frac{\sum_{i=1}^{N} \omega_i x_i}{N}, \frac{\sum_{j=1}^{N} \omega_j y_j}{N} \qquad (1)$$

3. Design considerations.

This work is carried ut within the context of the SECOAS[4] project. The algorithm is implemented on a PIC18F452, a 10 MIPS (100 nanosecond instruction execution), 77 single word instruction, CMOS FLASH-based 8-bit microcontroller, with 256 bytes of EEPROM [5]. The interface between the algorithm and the hardware is a message oriented operating system (kOS), which abstracts the low-level functions and presents the algorithms with a simple self-scheduling design, affording application writers the opportunity to choose their execution time. Compared to pre wireless sensor networking platforms, applications are presented with rather limited resources and the approach taken to design algorithms for these networks needs to take the platform into consideration. As such, the algorithms need to have a small footprint and utilise simple computations to obtain the necessary results. Additional to the device limitations, we also have the challenges posed by the environment. In this situation, the nodes are placed in a highly dynamic environment (the ocean). Consequently, the positions will be changing rapidly as depicted in Figure 1, necessitating an algorithm that converges quickly and utilises minimal resources so that sampling the environmental changes; the primary objective of deploying the network is not hampered by network configuration tasks.

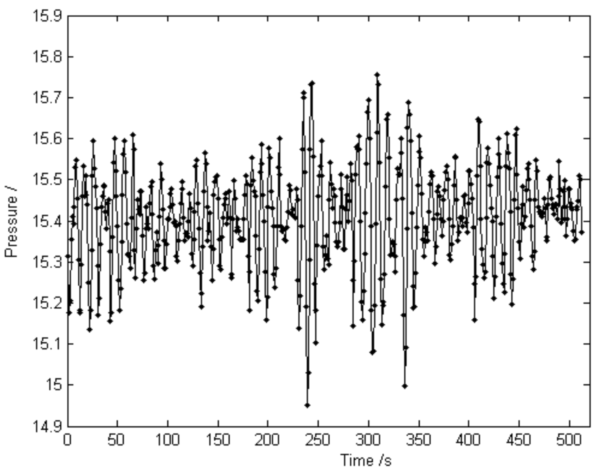

Figure 1 **Variability of ocean wave height. 512 samples of wave height fluctuation at 1 Hz over a time of ~8 minutes [7].**

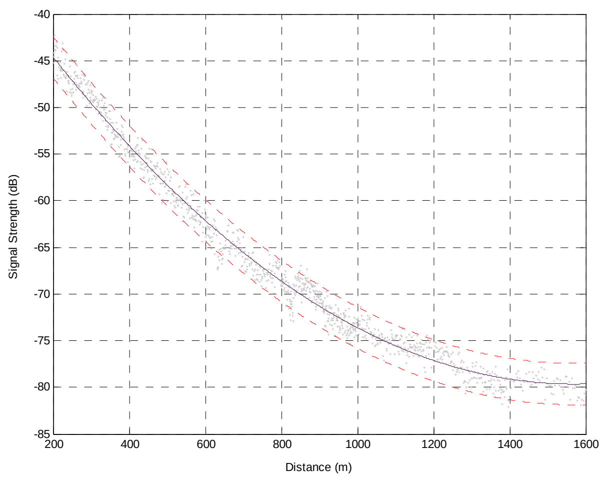

Figure 2 **Relationship between signal strength and distance from propagation tests carried put in the Scroby sands area by University of Essex. The readings are between two 173MHz radio modules placed in the ocean at various distances apart. The centre zero mean line is straddled by dotted lines, showing error bounds at ±2Δ standard deviations, i.e. 95% confidence interval.**

Another problem is the large error in the measurements obtained for utilisation by the algorithms. This method of distance estimation presents a number of challenges. Several repetitions of the same measurement yield different results. This is attributable to the fact that signal strength is not only influenced by the equipment and range of the transmitter and receiver, but also the angle in 3D-space between the sender and receiver nodes and the environment in which the measurements are obtained, i.e. the orientation and proximity of objects in the environment . In our case, the wave height variability means that the angle between the transmitter and receiver will change frequently resulting in high variability of RSSI obtained for any particular distance, making RSSI a very unreliable distance measure. This is corroborated by propagation test data obtained off the coast of Great Yarmouth, as shown in Figure 2. We can see that there is high variability in the obtained RSSI analysis of the data shows that the measurement error is of the order of ±50m.

Given this significant error and the limited resources the IA algorithm was developed. RSSI information is only used loosely for the position estimation. The primary factor in the determination of the position estimates is the finite communication constraint, allowing information to move across the network from one cluster of nodes to the next by a diffusion-like process. IA has been implemented on the kOS platform for testing in an oceanic environment in the SECOAS trials scheduled for August 2004.

4. Results.

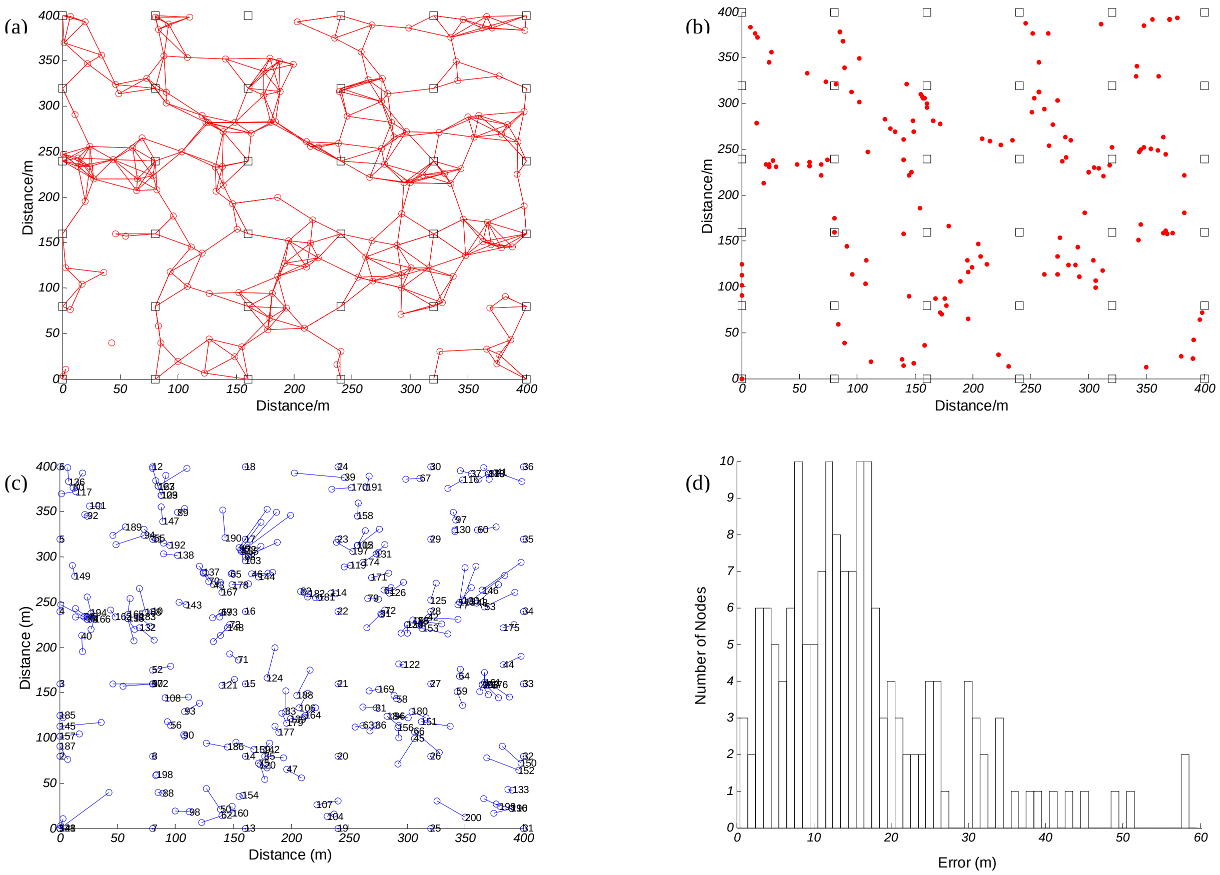

Figure 3:**(a) Simulation results showing initial randomly generated topology for a network of 164 PD nodes in circles, 36 PA nodes in square are positioned in a grid, (b) the final position estimates of the randomly located nodes, (c) linked real and estimated position pairs of all PD nodes, the point with the node id is estimated , (d) Distribution of the errors in the position estimates.**

This section presents the IA simulation results. Figure 3 show the results for a simple network of 200 nodes on a 400x400 grid, with 36 of the nodes being PA nodes. The PA nodes are arranged in a 6x6 grid. The remaining 164 PD nodes are uniformly distributed within the deployment area. All nodes have a communication range of 40m. Figure 3 (a) illustrates the node topology and connectivity within the test network. Initially the 196 PD nodes have no knowledge of their positions and are initialised to position (0,0). On running the algorithm, the PD nodes are able to make position estimates based on the information they receive from their neighbours. Figure 3(b) shows the final position estimates of these nodes, while Figure 3(c) provides real and estimate position pairs for comparison. On closer inspection of Figure 3(c), we observe that the accuracy of the position estimate is related to the proximity to a PA node, the number of neighbouring nodes, the number of PA nodes present within the range of a PD node and the distribution of the neighbouring nodes. This can be better explained by focusing on particular areas of the graph.

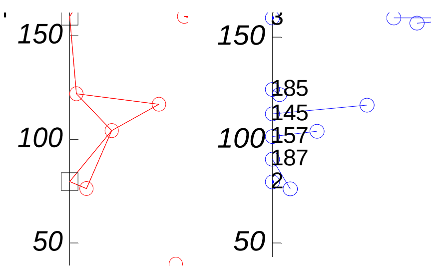

Figure 4 **Close-up of the area around 40-160 on the y-axis for Figures 3 (a) and (c).**

Considering the nodes around 40 to 160 along the y-axis as shown in Figure 4, they only receive information from two PA lying on this axis. The only information they have is that they are close to two nodes with 0 as their x coordinate and their y coordinate must lie somewhere between 80 and 160. Consequently they have no x information but manage to arrange themselves in the correct order in the y direction. This results in a clustering along the y-axis as seen in Figure 4. In contrast to this clustering behaviour that produces highly erroneous position estimates other node configurations perform mush better.

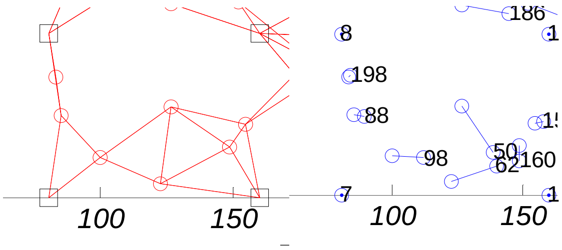

Figure 5 **Close-up of the area around 80-160 on the x-axis for Figures 3 (a) and (c).**

Figure 5 shows nodes close to 80-160 on the x-axis. These nodes have obtained better position estimates, because they are able to obtain information through 'diffusion' from a number of differently positioned PA nodes, resulting in the position estimates providing a better fit to the real data. This results in a network with high variability in positioning accuracy. This is shown graphically in Figure 3(d). The mean error is of the order of 16m. This is in line with theoretical analysis.

The intrinsic error of obtaining estimates from only one PA in an 80m square grid is 32m, as calculated from the standard deviation ($\hat{\sigma}$) of a uniform distribution. In this case, the majority of nodes can estimate their positions by using information from several nodes, resulting in the expectation that the error distribution will have a mean significantly less than this. Figure 3(d) shows that the average error is substantially below the 32m baseline as predicted and therefore, the algorithm performs as expected. We expect weighting using the RSSI information would further improve the performance.

5. Conclusions.

Despite being a relatively new research area, wireless sensor networking has attracted considerable interest and there are several research initiatives in the field [9]-[11]. The issue of node localization in these networks has attracted particular interest due to the value position information adds to the sampled data. There are numerous approaches to the problem. The predominant method is to use range measurements obtained using one of RSS, TDOA, or some combination of these methods. Triangulation or multilateration are then applied to the range values to obtain position estimates [12]-[16]. A qualitative analysis of some of these methods is presented in [17].

The dependence on range measurements presents two problems; (i) error is introduced into the position estimates from the onset, (ii) ranging requires radio usage, resulting in large power requirements. Both these reasons make the above algorithms unsuitable for our application. We require a lightweight algorithm with little dependence on RSSI ranging, both for power considerations, as radio transmission are the single largest power drain on wireless sensor node power resources [18] and because the environmental characteristics (ocean spray) result in unpredictable radio characteristics, making it difficult to obtain distance information from RSS measurements.

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