Efficient Detection and Localization of Assets in Emergency Situations

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Abstract

Environment monitoring is a vital tool in emergency situations, as it allows directing evacuation strategies and attempts to avoid injuries. In this paper, we present Compressed Sensing (CS) applied to Radio Frequency (RF) Tomography in a wireless sensor network as a new approach to track assets in emergencies and disasters. RF tomography refers to the inferring of information about an environment via capturing and analyzing RF signals transmitted between sensor nodes. On the other hand, CS provides efficient methods to analyze this information.

Our approach involves gathering characteristics about the monitored environment through the wireless sensor nodes deployed around the area. Assuming few assets exist in the environment, they can be detected and located using information from those nodes. The paper will discuss details of how emergency situations can be monitored using our technique, and will discuss the major benefits our technique provides over other techniques such as video monitoring. Simulations will show how the technique detects different assets, and will examine the performance parameters such as noise level and available RF signals. Finally, the paper demonstrates how our approach can lengthen valuable network battery life during emergencies.

Keywords**:**

Emergency control, safety measurements, compressed sensing, RF tomography

1. Introduction

Detecting and locating assets in emergency situations is always an essential issue for security and safety personnel. Tracking assets includes being able to locate humans as well as obstructions. Imagine a situation where a fire has started on a floor in a hospital, or any building. Due to the fire, some and obstructions may block certain paths to the exit. The ability to detect the location of these objects, allows security personnel to locate and evacuate people quickly.

In typical situations, few obstructions might suddenly disrupt a monitored environment. This paper provides a feasible and cheap emergency solution to detect and locate those few obstructions. In emergency situations, humans are the primary assets to keep track of. People must be reliably led to safe locations away from the disaster's location. Our approach can be well applied to locating obstructions in earthquake or fire situations. During this kind of disasters, large physical objects are moved and may cause path obstructions to survivors. With such a monitoring system, security workers can better guide the rescue operation with the least cost of injuries. In addition, people trapped in certain areas may well be discovered as they form an obstruction in front of signals of the sensor network.

Detection and estimating of location is the objective of RF tomography in this scenario. RF tomography is the process of inferring characteristics about a medium via analyzing wireless RF signals that traverse that medium. Each link between two nodes provides received signal strength (RSS) value, which is used to deduce characteristics about the path. Further extension to this approach is incorporating compressed sensing in the processing of sensor data. Compressed sensing is a sampling technique, used in signal processing, which allows the efficient recovery of data from a sparse signal.

The concepts of compressed sensing of RF tomography come together in this paper to provide a viable solution to medical and health institutions. In this paper, we provide an approach which describes the application related to medical and emergency situations. Throughout the paper, we provide some insight into the theory behind the approach, and the simulations which characterize the performance of the system. Section 2 will discuss our technique of applying RF tomography and compressed sensing in emergency situations. Section 3 will introduce RF tomography and compressed sensing in more detail and relate them to our objective in this paper. Section 4 will formulate the problem in a clear manner, and discuss some aspects in looking for the solution. Finally Section 5 will present some simulation results that are required to prove the validity of the design and gain an insight into its performance.

Related Work

The concepts of compressed sensing and tomography have been introduced to medical and health issues in more than one occasion. Compressed sensing/sampling (CS) has recently had acquired increasing interest in various areas of research and development. CS theory was applied to image compression [10], networked data [11] and other engineering areas and has also attracted some important medical care applications such as Magnetic Resonance Imaging (MRI) [12], where theory helps suppress artifacts in angiography, coronary imaging, brain imaging, and dynamic heart imaging.

Tomography in general has had many applications in medical and monitoring aspects. Computerized tomography, for instance, is used to accurately generate medical images for different parts of the body [13]. RF tomography has been applied to the ground penetrating radar to detect and identify hidden underground objects deeply buried [9].

2. Efficient RF Tomography for Emergency Situations

RF tomography enables security workers to monitor areas through changes in wireless characteristics in the medium. There are several reasons behind selecting RF tomography as a suitable approach in asset detection and localization. RF signals traverse through humans, walls, and other types of obstructions due to their frequency. In addition, this type of tomography is a much cheaper solution compared to other complicated tomography used in medical applications. In our approach, significantly less accuracy is required since the goal is localization and detection, not person identification. As shall be shown in the simulations and results section, the accuracy constraint can be considerably relaxed without significantly affecting the performance of the design.

The implementation of RF tomography would typically require a set of wireless sensor nodes located in an environment under surveillance, as seen in Fig. 1. The sensors' primary task is to perform RSS measurements throughout time, which is considered a cheap operation, as it does not require heavy computation or networking among the nodes. RSS measurements are passed to a more powerful central server which handles the data analysis.

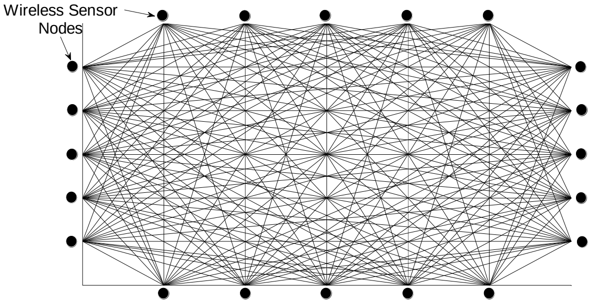

Figure 1: Twenty sensors nodes deployed around a region for detecting and locating assets. Each line represents the signal path between two wireless nodes

One hidden benefit in deploying the wireless sensor network for monitoring is the fact that the nodes typically depend on batteries as a power source. This is especially important in the case of power outages in emergencies and disasters. Moreover, this saves the need of a wired infrastructure which could also be unusable in disaster scenarios.

Efficient RF tomography is the result of combining the efficiency of compressed sensing and the detection ability of RF tomography. RF signals travel throughout humans and obstructions, and allow monitoring in light and dark conditions, which is a major advantage over video monitoring. Video monitoring typically requires considerable processing power and network bandwidth.

The effect of compressed sensing plays an important role in emergency conditions as well. The fact the CS emphasizes efficiency and battery life in the design, which makes it even more attractive for deployment. Moreover, because of the compressed nature of the technique, it works in the absence of several links or nodes. This is especially important when some nodes are destroyed in a fire or earthquake.

3. Compressed Sensing

Compressed Sensing/Sampling (CS) [2][3][4] is a modern efficient approach for recovering signals with sparse components. An m-sparse, in general, signal is a signal that contains maximum of m nonzero elements. A signal of total size n and exactly m non-zero components $(m << n)$ requires traversing all signal elements to determine the few useful components. CS provides a convenient way to determine the m elements from k observations of the original signal.

In this paper, we assume that few changes occur in the environment, so that changes have sparse representations. The objective of CS is to reconstruct a signal of size n containing few nonzero elements signals with significantly less measurements. This reconstruction occurs with a certain success probability which as more measurements are acquired. Prior knowledge of the sparsity of a vector p, allows us to reconstruct it from a set of measurements v by solving an optimization problem. In its simplest form, CS attempts to find the sparsest vector $\hat{p}$ by solving

$$\hat{p} = \arg\min_{p} \|p\|_1 \text{ subject to } v = Ap \tag{1}$$

where **A** is the measurement matrix, and $\|p\|_1$ is the ℓ_1-norm defined as: $\|p\|_1 = \sum_{i=1}^{n} |p_i|$.

The measurement matrix **A** plays a very important role in the reconstruction process. In compressed sensing theory, the measurement matrix should generally satisfy an incoherence property to be reliably used for reconstructing sparse signals. More formally, the matrix should satisfy the Restricted Isometry Principle (RIP) [3].

The optimization problem in (1) turns out to be a convex optimization problem, which has efficient solvers. A typical solution involves running a linear program, also referred to as *Basis Pursuit* [6], which requires, on average, $O(m\log(n))$ measurements. The efficiency and benefits of applying CS have attracted a lot of research towards it lately, allowing for smarter algorithms and cheaper designs. Next, we shall give better insight into RF tomography and the theory that lies behind it.

4. RF Tomography

Tomography is the process of acquiring cross-sectional images of an object through transmission or reflection of data passing through the object [13]. In RF Tomography, this data is the sensor wireless link power. Radar imaging systems have also been used to monitor areas. However, techniques behind radar imaging systems are based on scattering, while RF tomography is based on attenuation of wireless signals. One advantage of this concept is that the received power on links is on the order of $1/d^2$, whereas scattered power is on the order of $1/d^4$ [1], where d denotes distance.

Links traversing different obstructions undergo different levels of signal attenuation, depending on the obstruction's nature. Analysis of those links allows us to infer about objects' locations and properties. As more links cross over the same object, more information is available to solve for the location of the object. Wireless signals propagating along a certain path between two sensors lose power. The ensemble mean of signal power at a distance d is given by [8]:

$$\overline{P}(d) = P_t - P_0 - 10 n_p \log_{10}\left(\frac{d}{d_0}\right) \text{ dBm} \tag{2}$$

where P_t is the transmitted power, P_0 is the power observed at a certain distance d_0, and n_p is the path loss exponent which controls how fast power is lost along a path. For instance, n_p is around 2 for free space [13], and varies with different environments. Received power on a wireless link between nodes i and j can generally be represented as in [1]:

$$P_{ij} = \overline{P}(d) - Z_{ij} \tag{3}$$

$$Z_{ij} = X_{ij} + Y_{ij} \tag{4}$$

where Z_{ij} is referred to the fading loss which is the sum of shadowing loss X_{ij} and non-shadowing loss Y_{ij}. Thus the knowledge of Z_{ij} of a certain link allows determining whether or not an obstruction lies on the path.

The Network Shadowing (NeSh) Model

Authors in [7] introduced a joint network shadowing (NeSh) model that describes the characteristics of correlative links in a wireless environment. Experiments and results in [7] have supported the validity of the model compared to the other existing models. The importance of the model is that it provides a better statistical representation of links than other models; hence it was meaningful to be included in our approach.

Link path losses are modeled as a function of the underlying path loss field *p(x)*, assumed to be an isotropic and wide-sense stationary Gaussian field. The total shadowing loss witnessed by a link ℓ can be determined by integrating *p(x)*:

$$X_{ij} = \frac{1}{\sqrt{d_{ij}}} \int_{x_i}^{x_j} p(x)\, dx \tag{5}$$

where the factor $1/\sqrt{d_{ij}}$ acts as a normalizing factor, more on this in [1]. For simplicity, shadowing due to an obstruction is assumed to be constant along the path traversed through the object.

The non-shadow fading effect represented by Y, is assumed to be a zero mean, Gaussian random variable with variance σ_Y^2. The Gaussian distribution of Y in [1] follows from a valid assumption of wideband frequency sensor node operation.

After going through some of the important theoretical aspects of the paper, our problem can be nicely formulated in the next section.

5. Problem Formulation

The main contribution of this paper is combining concepts of RF tomography and compressed sensing to produce an efficient design useful in hospitals and emergency situations. The monitored area is divided into a grid of pixels. Each pixels carries information about the amount of attenuation over its area. This information can be displayed in grayscale, where the darker intensity corresponds to more change in attenuation. So the values in *v* are obtained as a linear combination, by matrix **A**, of the pixel values *p* along each link. The entries in **A** are defined as:

$$a_{ij} = \frac{1}{\sqrt{d_i}} \begin{cases} d_{o_{ij}} & \text{if link } i \text{ traverses pixel } j \\ 0 & \text{otherwise} \end{cases} \tag{6}$$

where d_i is the distance is traveled by link *i*, and $d_{o_{ij}}$ is the overlap distance that link *i* travels through pixel j. The factor $1/\sqrt{d_i}$ parallels that in (5). The number of rows in **A** is number of existing links, and the number of columns is the number of pixels. The compressed aspect of our paper lies in selecting a compressed set of links, i.e. rows of the matrix **A**.

Instead of a weighted least-square error estimator for reconstruction of the signal, we employ the basis pursuit approach. As mentioned earlier, CS works best under the satisfaction of the sparsity requirement. In monitoring situations, it is usually the case that few changes occur in certain areas in the medium, thus only few data measurements would be required to discover the changes. However, in realistic situations measurements are often perturbed by measurements errors and noise. Measurements in vector *v* now become

$$v = Ap + n \tag{7}$$

The inaccuracy introduced in the measurements requires consideration in the reconstruction algorithm. So the optimization now solves a slightly different problem than (1). Our task now becomes finding the solution $\hat{p}$ which best explains v within a tolerance range. The problem now becomes

$$\hat{p} = \arg\min_{p} \|p\|_1 \text{ subject to } \|Ap - v\|_2 \le \varepsilon \tag{8}$$

The variable ε is closely related to the level of inaccuracy. The value of ε is set to the root of the noise power, which in effect is the standard deviation of noise statistics. The problem in (8) can be solved as a basis pursuit de-noising problem [6] by transforming it into a second order cone problem. The effect of error was examined in [5], and it has been shown that the reconstruction error behaves according to the inequality

$$\|\hat{p}-p\|_2 \le C\varepsilon \tag{9}$$

, where C is a constant.

The algorithm described in [1] can now be tailored to include our approach in this paper. The main algorithm becomes:

- Compute the difference in power for each link between nodes i and j defined as: $v=\overline{P_{ij}}-P_{ij}$, where $\overline{P_{ij}}$ is the averaged power value over initial RSS measurements
- Use ℓ_1 minimization to reconstruct the change in attenuation witnessed over each pixel from the vector v. Store the result in vector $\hat{p}$
- Convert $\hat{p}$ into a vector $\tilde{p}$ in the range [0,1], using a simple transformation that divides all values by their maximum value, and sets negative values to zero

6. Simulations and Results

Simulations are crucial to determine the validity of the design. The primary focus is on the accuracy of results obtained by a compressed set of measurements. Of course, accuracy in this case refers to correctly detect and locate the perturbation in the medium. The recovered values $\hat{p}$ from (8) are mapped onto a vector $\tilde{p}$ whose values are in [0,1]. This allows an easy representation of $\tilde{p}$ on a grayscale as in Fig. 2.

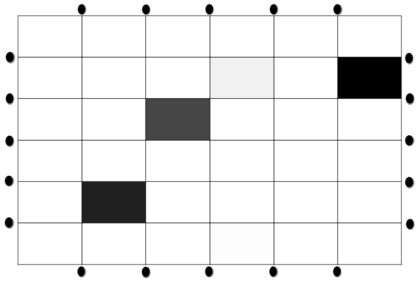

Figure 2: Monitored area showing the discovery of 3 obstructions located at the dark pixels

The area under simulation is a square area surrounded by 20 wireless sensor nodes, transmitting to each other. Each of these sensors can communicate with 15 other sensors, yielding (20×15)/2=150 wireless links. Fig. 2 demonstrates how our approach monitors an environment. The figure shows dark pixels at 3 different positions. Darker pixels correspond to a higher amount of attenuation. These dark pixels naturally correspond to existing obstructions at these locations. With this map, personnel can easily locate obstructions and direct evacuations.

Next, we examine the effect of noisy measurements on the performance of the design. To measure the error caused by noise, accuracy of the system is compared to the noiseless case. For this, we employ a mean squared error (MSE) measure between perfect and reconstructed pixel values. We try to monitor the same obstructions as in Fig. 2 with noise added to the measurements. Performance results are plotted in Fig. 3.

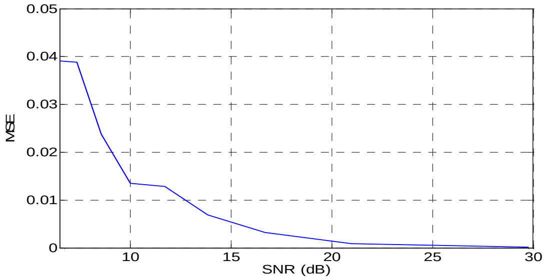

Figure 3: Plot of MSE versus SNR. The plot demonstrates how the accuracy varies with noise level

As expected the noise level is reflected on the accuracy of measurements. Higher SNR results in a more accurate detection and localization. MSE values do not change dramatically with low noise, which means that significant levels of noise do allow the detection of certain obstructions using the reconstruction algorithm. Of course, low SNR values lead to inaccurate measurements, but some obstructions may be correctly located.

The benefit of compressed sensing is well observed when there are few available sensors and wireless links is low. This can occur when disasters destroy some of the sensors or completely block some of the links. To demonstrate the power of the reconstruction algorithm, we simulate the same obstruction scenario in Fig. 2 with a varying number of links used.

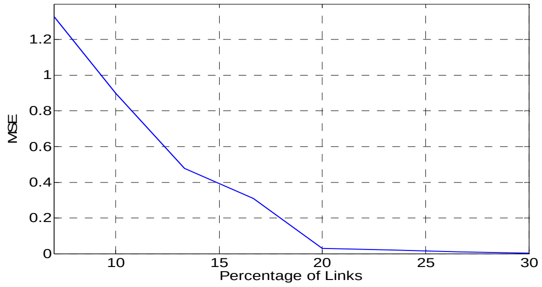

Figure 4: Variation of MSE as more links/nodes are added at SNR=20 dB

Links in this simulation were uniformly selected among all other links to show that the approach works well without any prior knowledge of existing obstructions. Of course, one can argue that some prior knowledge of obstruction positions should allow better selection of links, and hence better performance of the system. Fig. 4 shows how the MSE varies as more links/nodes are added to the system.

As the figure shows, when more than 15% of the links are available, there is no considerable gain in the accuracy of the detection, as these links add redundant information. We can also observe that at a low 7% percentage of links (12 sensors are only working) results are not dramatically off. This shows that compressed sensing lengthens a network's battery life in emergency situations. Saving network battery is obviously of great importance in critical conditions. Network resources can then be used for more time to guide emergency personnel. Fig. 5 shows how the obstructions are monitored for different percentage of links used.

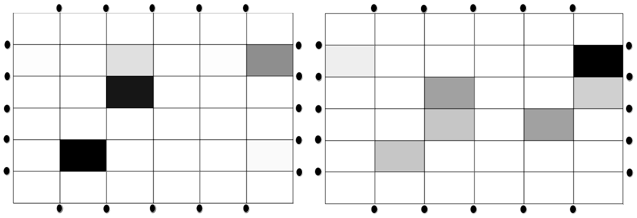

Figure 5: Using a percentage links and nodes (15% on the left and 7% on the right) at SNR=20 dB

As Fig. 5 shows, some error is introduced since less links are available. This error appears as false obstructions detected, in addition to the main obstructions. Even in the 7% case, obstructions can still be detected, and security personnel can still use this information.

Finally the probability of detection was examined in our system. Obstructions correspond to pixels at least two deviations away from the mean of recovered pixel values. Fig. 6 summarizes our results for a scenario similar to Fig. 2.

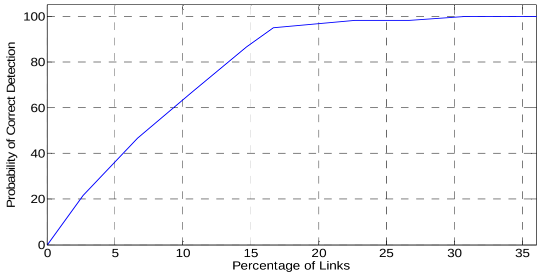

Figure 6: Probability of Correct Detection at SNR = 20 dB

Even at a very low number of available links (5%), assets can be successfully detected with 36% probability. The curve demonstrates the robustness of compressed sensing in emergency situations.

7. Conclusions and Future Work

In this paper we have applied RF tomography and compressed sensing to emergency situations. The advantages of the technique over other techniques have been discussed, along with an overview of the theory and assumptions that lie behind our approach. Simulations have provided better insight into how emergency situations can be monitored from data sent by the sensors. Performance of the design was also examined through investigating the effects of noise and number of sensors.

Our future direction in this area involves generalizing the design to more complicated environments and sensor node deployments. Moreover, it would be interesting to investigate the problem of finding optimal positions for the sensors in a given environment. We are also planning to test the design in real environments and compare results with our simulations.

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