Region Based Distributed Sensor Network Signal Processing

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Abstract. A framework for performing signal processing tasks over a distributive, ad hoc wireless sensor network is presented in this paper. A novel target localization method using directional polarized infrared (PIR) sensors is reported in this paper. Traditionally, if a PIR sensor reports a target detection event, the location of the target will be positioned at the intersection of the line-of-sight of the PIR sensor and the road. This coordinate can be computed in advance and stored in a table to be looked up during run time. A potential drawback of this approach is that when more than 1 PIR detection are made at the same time, it would be difficult to choose an appropriate target location. In this work, we developed an empirical PIR localization method. Using ground truth of training data, we associate a pattern of PIR detection to a probability distribution of the potential target locations. We have implemented this algorithm and compared the PIR localization and tracking results using real-life sensor network time series.

1 Introduction

Low-cost miniature sensors will soon become feasible to be deployed in massive amount to monitor large regions over ground surface, underwater, or atmosphere. These sensor nodes will be integrated with miniature power supply, sensors, onboard processors, and wireless radio communication modules, capable of forming a large-scale ad hoc wireless network [4]. Common signal processing tasks performed in a sensor system include event detection, and parameter estimation. While these detection, classification, and tracking algorithms have been well developed for conventional centralized signal processing systems, much less is known for a distributed wireless sensor network system. A distinct feature of such a system is that it contains multiple, physically scattered sensing and processing modules that must collaborate with each other to achieve high performance. Conventional centralized information and data fusion techniques are unsuited for such an application because too much data must be communicated from individual sensors to a centralized fusion center. Instead, a family of novel distributed, localized, and location centric signal processing and information fusion algorithms must be developed to meet this demand.

In this paper, we propose a Table Based approach for the collaborative target Localization of moving vehicles using PIR sensors. The key innovation of this approach is to cross check across the acoustic modality for verification of the presence of a target in the vicinity of the sensor. If a sensor reports a PIR detection and the acoustic modality doesn't confirm it, then it implies that the PIR sensor is providing a false alarm. It comes from the fact that if the acoustic modality doesn't hear anything with in $40m$ then a target can't be present in front of the sensor. Also the spatial separation between multiple reporting nodes is also a very useful criteria of judging the credibility of a region detection. Given we have a single target situation, one of the two reporting sensors can be declared wrong depending upon the distance between the two nodes. These intuitive concepts are verified using real world experimental data recorded at a military training ground using a prototype wireless sensor network. In the rest of this paper, the background of wireless sensor network architecture will be introduced. The UW sensor network signal processing algorithms will be surveyed in section 2 with special attention to the task of target PIR localization. Then the last section shows some of the results that we have achieved using this approach.

2 UW CSP Approach

The idea is to track targets moving through a distributed sensor network using multiple modalities. For this purpose the whole network is partitioned into regions, which can be static or can be dynamically created. Each region has its own sensors, which help in performing collaborative signal processing (CSP). Each of the active sensors within a region performs local energy detections using the acoustic and PIR timeseries. These timeseries are also used to classify targets into different categories by using sophisticated classification techniques. There is also a provision for an unknown class to take care of noise and other interferences. These classification results can be used in performing the attribute data association in the Multi-Target scenario. The detection and classification results are sent to a designated Manager Node of the region, which after receiving the reports from its sensors, within a processing cycle, performs region detection to indicate the presence of a target and hence initiate target localization and tracking processes. An Energy Based Localization (EBL) algorithm is used to estimate the target position at the current time by solving an optimization function on grid points, for acoustic timeseries. The PIR Localization results are the projection of the sensor node coordinates onto the road. The output of the Localizer is used as the observables for the Kalman Filter for tracking.

The Kalman filter uses different Measurement Covariance Matrices for the different type of Localization results. These are estimated by using the training data that we have for that particular sensor network setup. It is required to have prior knowledge about the sensor model and the levels of uncertainties one should expect in the observations. The Process Covariance Matrix also needs

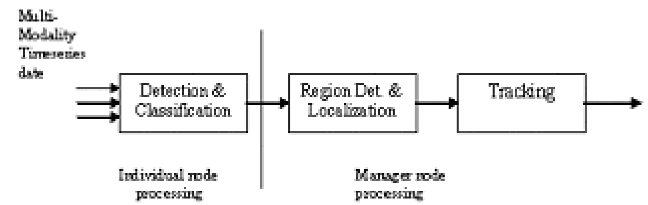

Fig. 1. UW CSP Block Diagram

to be initialized depending upon the underlying Target Dynamic Model that governs the motion of the vehicle through the sensor network.

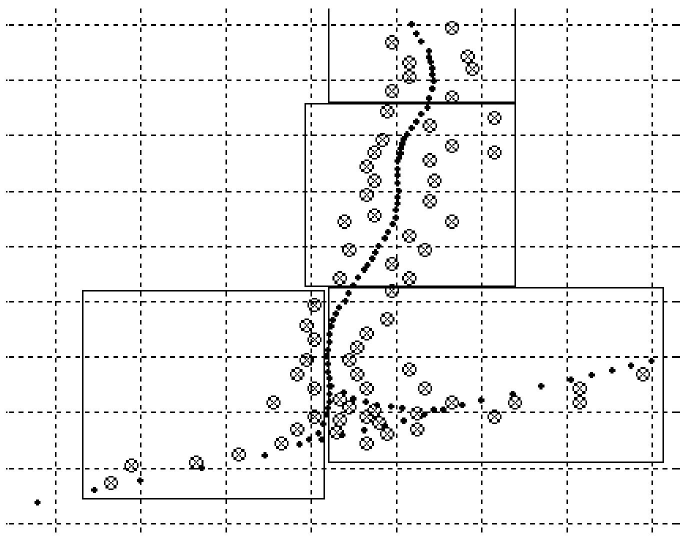

Fig. 2. Sensor Network Divided into Regions and sensors deployed around the road.

As the target is about to leave the current region, next tentative region is activated. A Track Data structure is maintained at the manager node, which holds these matrices and is passed onto the next region, when a track handover takes place. In this way the target moves through the sensor network and the regions are created.

3 Basics of PIR Detection/Localization

Infrared radiation exists in the electro-magnetic spectrum at a wavelength that is longer than visible light. Infrared radiation cannot be seen but it can be detected. Objects that generate heat also generate infrared radiation including animals and the human body whose radiation is strongest at a wavelength of $9.4mm$. The Pyroelectric (PIR) sensor is made of a crystalline material that generates a surface electric charge when exposed to heat in the form of infrared radiation. When the amount of radiation striking the crystal changes, the amount of charge also changes and can then be measured with a sensitive FET device built into the sensor. Our PIR sensor has two sensing elements connected in a voltage-bucking configuration. This arrangement cancels signals caused by vibration, temperature changes and sunlight. A body passing in front of the sensor will activate first one and then the other element as shown in figure 2, whereas other sources will affect both elements simultaneously and be cancelled. The radiation source must pass across the sensor in a horizontal direction when sensor pins 1 and 2 are on a horizontal plane so that the elements are sequentially exposed to the IR source.

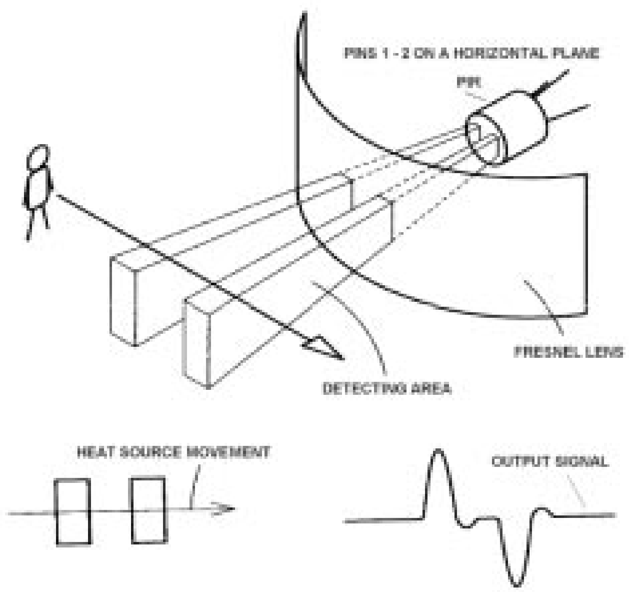

Fig. 3. The PIR sensor with the expected output signal

So as soon as the target crosses the PIR sensor we get the shown output signal. But the signal is not noise free. Generally, the distribution of the signal energy is unknown because the target type is unknown at the time of detection. Moreover, the presence of a target is often a rare event; hence accumulating target signal statistics is a difficult task. Therefore, conventional hypothesis testing methods such as maximum likelihood ratio test will not be applicable. Instead, we employ a $constant \quad false \quad alarm \quad rate \quad (CFAR) \quad detection$ method to detect the presence of a target from the energy time series. Note that without the presence of a target, the received signal (the noise energy) has a Gaussian distribution. If $\mu(n)$ is the mean of received energy $y(n)$ and $\sigma(n)$ is the variance at time n, then we may set a threshold

$$\theta(n) = \mu(n-1) + C.\sigma(n-1) \tag{1}$$

to devise a detection function $D(n)$ for each received energy $y(n)$:

$$D(n) = 1 \quad if y(n) > \theta(n); \qquad 0 \;\; else \tag{2}$$

In equation 1, C is a constant chosen to yield a constant false alarm probability

$$P_{FA} = \frac{1}{\sqrt{2\pi}} \int_{u=C}^{\infty} exp(-\frac{u^2}{2}) du \tag{3}$$

Note that P_{FA} is a constant independent of the time varying mean and variance estimate of $y(n)$. For PIR sensor, the constant C in equation 1 is chosen to be 10 empirically.

Now for localizing the detected target we have used the road coordinates and sensor coordinate information. The simplest way of doing it is to find the perpendicular projections of the sensor nodes on the road and designate those points to be the target locations when that particular sensor reports a detection event. This is shown in the figure 4.

This approach can be implemented as a pre-computed table and whenever a node reports a detection, its corresponding position in the table gives the localized result. But this technique is prone to a few of problems even in the presence of single target within the sensor network.

First of all if multiple sensors detect a single target, the position estimate becomes ambiguous. These multiple reporting sensors can be widely spaced apart as well. Secondly one can get a lot of false detections due to a number of factors. This can be caused by any heat generating body crossing the sensor, while data acquisition is being done. A bad sensor can also result in numerous false detections. One should come up with a way to counter these spurious detections intelligently.

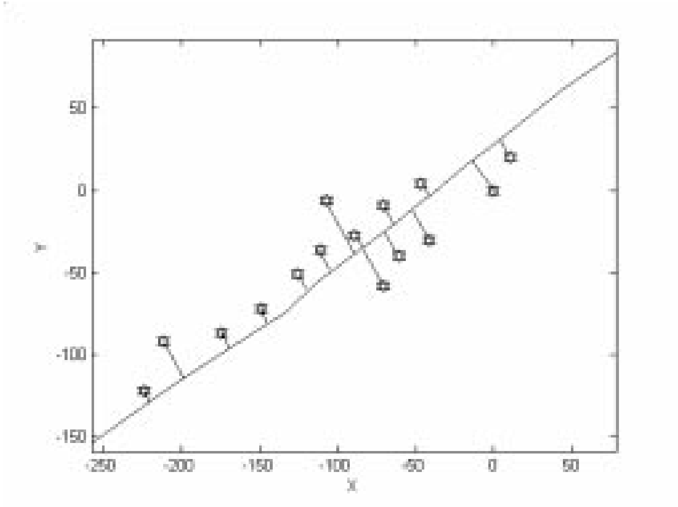

Fig. 4. The perpendicular projections of the PIR sensors on to the road

4 Table Based Approach

We plan to use the Spatial and Multi-Modal information to eradicate the erroneous PIR detections and hence not only give more accurate estimates but also to provides us a probability distribution for the estimate of each PIR detection pattern. We have used the training data to come up with a table based approach, which not only gives us a single position estimate for multiple PIR sensor detections but also promises a confidence level of the estimate by checking across the acoustic modality.

We have seven sets of Sitex02 data for a single vehicle and matching ground truths. These are mainly labeled as AAV3, AAV6, AVV9, DW3, DW6, DW9, DW12. In each set we have a 15 sensor nodes configuration as shown in the 3. Some of these nodes have noisy data at certain time instances. We already know the sensor positions, road coordinates and time stamped ground truths from GPS. The GPS has an error of $\pm$10m in its position estimate. So we accept that our method has a minimum error of this proportion. But this ground truth is not used in the localization process at the run time. It's just for pre-computing the probability density of the PIR localization result and later on in finding the error in our method of position estimation.

The table based approach is implemented by looking at all possible patterns of PIR detections for all sensor nodes and accumulating the ground truths corresponding to each pattern for all the seven sets of data mentioned above.

Table 1. Detection Patterns and the Localized position estimate

Nodes/Pattern	Node 1	Node 2	Node 3	...	Node n	X,Y	Cov Mat
1	1	0	0	...	0	X_1, Y_1	...
2	0	1	0	...	0	X_2, Y_2	...
3	0	0	1	...	0	X_3, Y_3	...
...	...	...	...	...	...	...	...
2^n	0	0	0	...	1	X_{2^n}, Y_{2^n}	...

These ground truths are weighed to get the final position estimate (X, Y) as shown in the 2^{nd} last column. The last column is the Covariance Matrix for the ground truths available for that pattern. In this way we are able to estimate the Measurement Covariance Matrix R which is needed for the Kalman Filter Tracker that we are using. In some cases there will be no (X, Y) estimate available as that particular pattern never happened in the training data.

Similarly, there will be (X, Y) estimates available for some rows with more than one 1 due to some sensors which are quite close to each other. But it's not clear how to weigh the ground truths of those sensors. For right now we assume simple averaging. But this multiple occurrence of 1 can also happen due to noisy detection events. There are a few valid patterns in case of a single vehicle situation and the rest are results of spurious detections. The idea is to put some constraints on the spatial separation of detecting sensor position and the vehicle ground truth. If they are widely spaced apart then it's a false detection. Also if acoustic modality is not showing any detection, it means that the vehicle is at least $30-40$ meters away from the current sensor and the PIR detection is false. We have looked over the data and confirmed these observations.

Using these data sets we have come up with a probability measure of the correctness of the detection decision. So for the situation when we have a positive PIR detection we can arrange the results into a matrix such that

Table 2.

Given PIR Det	Noise	True Target
No Acoustic Det	N1	N2
Acoustic Det	N3	N4

The four possible probabilities of interest are:

$$\begin{gathered}
\text{P(Target/Acoustic Det)} = \text{N4/(N4 + N3)} \\
\text{P(Target/ No Acoustic Det)} = \text{N2/(N2 + N1)} \\
\text{P(Noise/Acoustic Det)} = \text{N3/(N4 + N3)} \\
\text{P(Noise/ No Acoustic Det)} = \text{N1/(N1 + N2)}
\end{gathered}$$

So these probabilities enable us to specify a confidence level of our PIR detection decision.

Similarly, once we are doing PIR localization on a set of a data, we can find out the Sensitivity and Specificity of those detection results. For this particular setup we can similarly come up with a matrix:

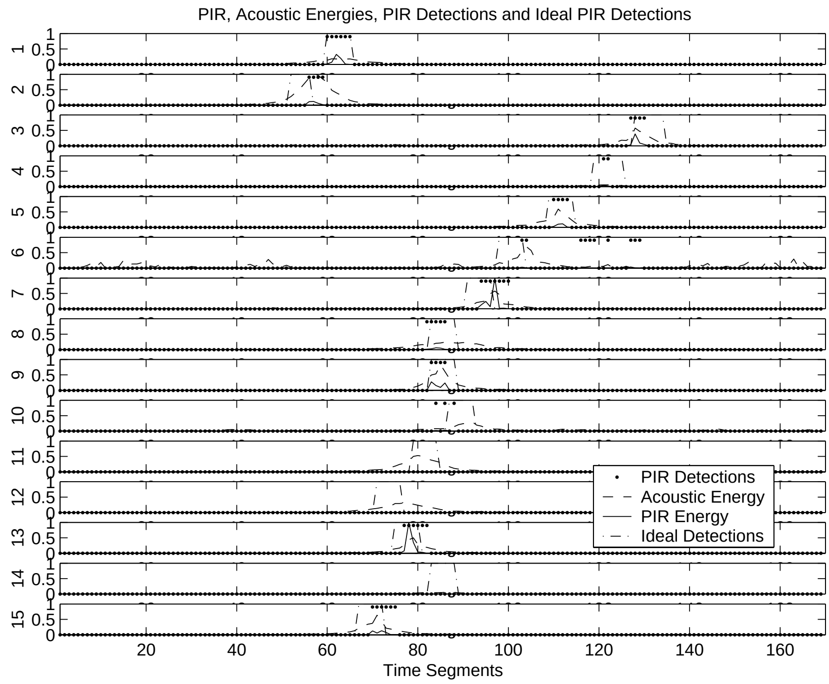

Fig. 5. PIR, Acoustic Energies, PIR Detections and Ideal Detections for the 15 sensor nodes of AAV3 data set. It's clear that at later stage the PIR shows false detections for sensor 6, but its negated by Acoustic Modality.

Table 3.

	Noise	True Target
No PIR Det	N1	N2
PIR Det	N3	N4

Now we have

$$\text{Sensitivity} = \text{N4x100} \,/\, (\text{N4} + \text{N2})$$
$$\text{Specificity} = \text{N4x100} \,/\, (\text{N4} + \text{N3})$$

These are a good measure of looking at the detection results as they don't consider the False detections due to noise. The goal is to achieve 100 percent of these measures.

5 Results

We have used these techniques for the different data sets interchangeably. I have observed some very good improvements against large PIR localization errors, besides reducing the small ones as well. The histograms below show the Localization errors with and without the Table Based Approach. It's clear that the spatial constraint has removed the large errors and small errors are also reduced

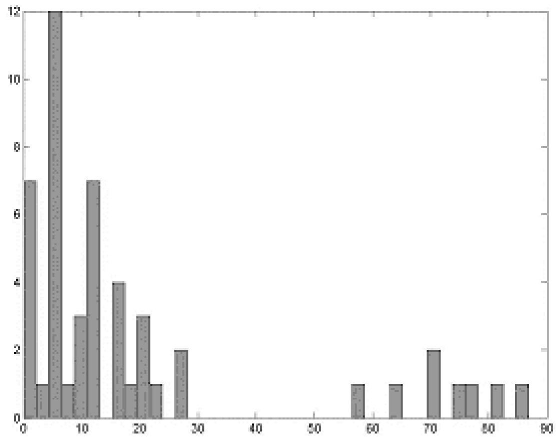

Fig. 6. Histogram of PIR Localization error (meters) using traditional methods.

Similarly, the four probability measures, as discussed above, about the authenticity of the PIR detection in consultation with Acoustic modality came out to be:

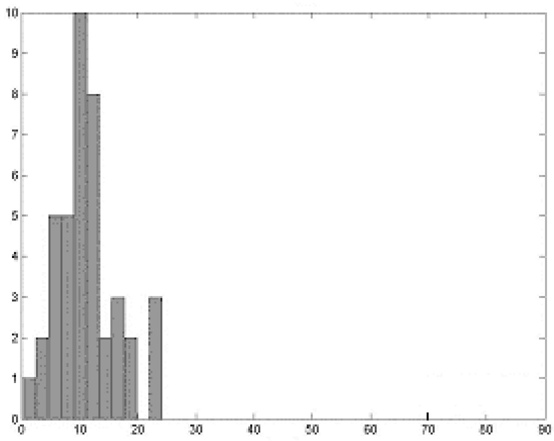

Fig. 7. Histogram of PIR Localization error (meters) using Table Based Approach.

$$P(\text{Target/Acoustic Det}) = N4/(N4 + N3) = 0.6$$
$$P(\text{Target/ No Acoustic Det}) = N2/(N2 + N1) = 0.273$$
$$P(\text{Noise/Acoustic Det}) = N3/(N4 + N3) = 0.4$$
$$P(\text{Noise/ No Acoustic Det}) = N1/(N1 + N2) = 0.727$$

One of the problems that we have faced is the orientation of the PIR sensors. The sensors are supposed to be oriented directly towards the road during the data acquisition. But its not always true, as it happened in our case. Some of the sensors have slight orientation problem. Due to this factor, the Ideal Detections expected do not always exactly match up with the CFAR detections. This is obvious from figure 5. This results in the reduction of the Sensitivity of our Detection Algorithm. The Sensitivity that we obtained for AAV3 data set is 39.6%. There was an improvement in the Specificity when we used our Table Based approach to reject some of the PIR detections. There was an improvement of 7% and the value jumped from 59% to 66% percent.

6 Conclusions

We have presented a framework for performing signal processing tasks over a distributive, ad hoc wireless sensor network. A novel target localization method using directional polarized infrared (PIR) sensors is reported in this paper. Advantages of this proposed approach include higher accuracy, simple implementation, and immune to noise. We have implemented this algorithm and compared the PIR localization and tracking results using real-life sensor network time series. The Table Based Approach has not only provided us more accurate estimates of the target position by putting some constraints but it also promises some future framework for research in this direction. We plan to extend this approach for the case of multiple targets present within the same sensor network. We believe that it can greatly help in automatically indicting the presence of multiple targets in a region, which of course has been one of the main issues in the Sensor Network Signal Processing. The use of PIR Table Based Approach also opens a gateway of research in the direction of Region Detection. If the PIR detections are made more reliable then these can greatly help in reducing the false Acoustic Detections, which occur due to inevitable noisy acoustic time series.

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References

1. Li, D., Wong, K.D., Hu, Y. H., Sayeed, A. M.: Detection, classification and tracking of targets. IEEE Signal Processing Magazine **19** (2002) 17–29
2. Hans J. Keller. Advanced Passive Infrared Presence Detectors as Key Elements in Integrated Security and Building Automation Systems, IEEE, $CH3372-0/93$, 1993.
3. Brooks, R. R., Iyengar, S. S.: Multi-sensor fusion: fundamentals and applications with software. Upper Saddle River, NJ: Prentice Hall PTR (1998)
4. Estrin, D., Girod, L. Pottie, G., Srivastava, M.: Instrumenting the world with wireless sensor network. Proc. ICASSP'2001. Salt Lake City, UT, (2001) 2675–2678.
5. Li, D., Hu, Y.H.: Energy Based Collaborative Source Localization Using Acoustic Micro-Sensor Array. J. Applied Signal Processing, pp. (to appear)
6. H. Poor, An Introduction to Signal Detection and Estimation. New York: Springer-Verlag, 1985, ch. 4.