Multisensor fusion of environment measures using Bayesian Networks

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Abstract - *Autonomous mobile robots usually require a large number of sensor types and sensing modules. There are different sensors, some complementary and some redundant. Integrating the sensor measures implies several multisensor fusion techniques. These techniques can be classified in two groups: low level fusion, used for direct integration of sensory data; and high level fusion, which is used for indirect integration of sensory data.*

We have developed a system to integrate indirect measures of different sensors. This system allows us to use any type of sensor which provides measures of the robot's environment. It is designed as a Belief Bayesian Network. The method needs that the user creates a low level fusion module and an interface between that module and our fusion system.

Keywords: multisensor data fusion, mobile robots, bayesian networks.

1. Introduction

Data fusion refers to an essential technology in the problem of the information treatment to improve the quality of sensing systems, data bases, communications, etc. Data fusion technology is used by military applications [1] to efficiently collect, extract, manage, and distribute information to several systems at all levels of command. Data fusion is also broadly used by non-military environments, such as, robotics, traffics control, medical diagnosis, remote sensing, etc. Examples of these applications can be found in [2], [3], etc.

Data fusion uses various data sources to provide a better understanding of the phenomenon taken into consideration. The information proceeds from two types of data sources: sensors of the same type (equal sensors) and different type of sensors. In the first case, data from sensors of the same type are integrated, such as, ultrasonic transducers of a ultrasonic system [4], chambers of stereoscopy vision, sonar ([5], [6], for example), etc. In the second case, usually named multisensor data fusion, [7] [8], different sensor observations to construct our environmental model are used.

We have focused on fusion, or integration, of multiple sensing data in robot applications (a review of different techniques for sensor fusion in robot applications can be found in [9]). When a mobile robot operates (usually in real time) in a uncertain or unknown dynamic environment is necessary to provide a perception system to determine reliably the absence or presence of an object in the vicinity of the robot. Perception function for a mobile robot needs to consider integrating the data from a variety of different external sensors so that the environment can be quickly perceived.

Mobile robot designers use different types of sensors due to the advantages and limitations of each sensing type, such us limitations in a particular environment, technical or economical factors, or range and scan rate. The limitations of each type of sensor are solved using redundant sensors and/or complementary sensors. There are lots of multisensor data algorithms that solve the problem of perception of a mobile robot, but generally they are conditioned by the sensors used in each case.

We have developed a simple and effective method that permits to merge measures of various sensors environment without the need of large modifications or adjustments in our fusion system. In this way, the same system can make use of some given sensors which can be increased, decremented or changed at any moment. This permits, without important changes, to accomplish the study, or development, of different sets of sensing systems depending on the availability on the sensors, the environment or, the application of the mobile robot.

Of course, all generalisation requires a greater degree of abstraction and so a loss of the observed information, but that is supplied through the improvement that is produced upon integrating information of different sources.

Several architectures are used in multisensor information fusion, [10], [11], we have chosen a distributed sensor network with different abstraction levels: (1) the treatment of raw data will be accomplished by the user. The user can use any typical techniques and the result of all observations will be provided to the fusion system so that it will be merged with the observed data by other sensors. (2) the decision-level identity fusion system will be designed through Bayesian networks ([12], [13]) where the estimates of the sensors will be integrated. The user can design the information to merge, the manner of merging it and, the information that the system finally will provide.

The organisation of this paper is the following. In next section the structure of the fusion system is described. In section 3 we show which operations are necessary to use the Bayesian networks in the fusion of the uncertain information originated from each one of the used sensors. In section 4 an example on how to integrate environment information of two sensors of a mobile robot (vision and ultrasonic) is presented. Finally, the fusion system is designed and is accomplished with our robot. It follows a simple real trajectory in our laboratory to show the improvement in the belief of detected targets starting from the fusion of the individual measures.

2. System of measures fusion of environment

The principal purpose of our system is to be general. Here, we use *general* in the sense that it will be valid for any sensor used to observe the robot's environment, provided that some instructions are followed: defining the model cause-effect of the bayesian net, and designing the necessary interface between the assessed information of the sensor and the one used by the network in order to accomplish their fusion. Fulfilling these instructions correctly the fusion system can be used with any type of sensor that will be capable of estimating the features of the objects that are considered interesting for the system. These features do not need to be estimated all by apiece of the sensors, but they can even cover complementary spaces (in this case it would not exist fusion, but integration).

The architecture suitable for this multisensor fusion system will be processes distributed in a network. Each process represents a fusion node. These nodes of fusion can be either virtual sensors, represented by *sensor node* in the figure 1, or nodes of fusion of features, represented by *fusion node* in the figure 1.

Thus, the system consists of the following parts:

- *Physical sensors:* correspond to the real sensors. They observe values of its environment to detect all the objects surrounding the robot. Their observations are raw data that should be processed and interpreted.
- *Drives and interfaces*: they are the routines that permit to read and to handle the data that are obtained directly from the sensors. They include data alignment, manipulation of data, A/D signal processing, etc.
- *Low level fusion*: a treatment of the data received is accomplished to obtain the sought characteristics. Here, any data fusion algorithm can be used to integrate physical sensors that belong to this node, figure 1. This level knows the physical model of the sensor and reduces the number of measures of all receivers of the same type to a set of valid estimates, performs data association, updates observed entities, etc.
- *Sensor Node*: In this node the results of the user fusion system are converted to understandable assessment by the distributed Bayesian network. For this, the results obtained in the previous level are taken and prepared in the necessary format to be merged with similar inferences of other sensors. It corresponds to the interface between the raw data fusion and the decision-level identity fusion of multiple sensors.

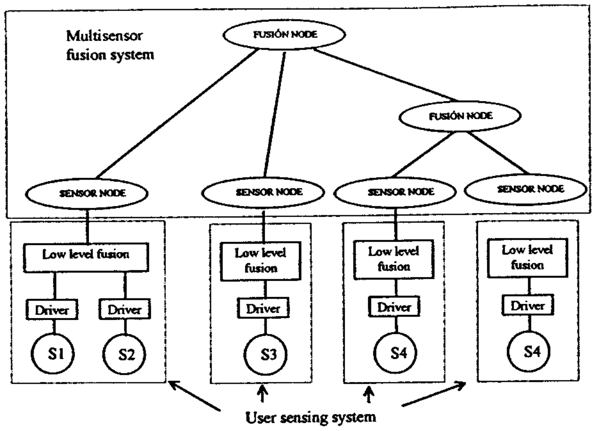

Figure 1. Multisensor fusion system.

- *Fusion Node*: each one accomplishes the fusion of some different assessments about some interesting characteristics from each sensor. This fusion is performed using a Bayesian inference through a belief Bayesian network. It is explained in the following section.

3. Distributed Bayesian Network

We have implemented a Bayesian network with a distributed sensor network. The topology of the sensor network is obtained from the Bayesian network used to define the dependence model of sensors. Each net node, see figure 2, corresponds to one of these two types: a virtual sensor that transforms data of sensor in assessment (sensor node); and a cause node, or feature node that merges assessments of sensor which can influence the credibility of other sensors (fusion node).

The user is free of designing the network of the system. The structure of the network, that will depend on each sensor and on how the designer uses it, will show the relationship between each node and its dependency with respect to the others. Nodes represent variables and arcs represent probabilistic dependencies between these variables. For example, if our robot makes use of a photometer, two cameras (stereoscopic vision) and ultrasonic transducers around it, we could design a Bayesian network as is shown in the figure 2. There, three nodes can be seen which correspond to our three sensors; and also two fusion nodes that represent causes, factors, or symptoms that provoke a determined measure in each sensor. Thus, the intensity of the light will influence the measure of the photometer and the stereoscopic vision, but also the measure of the photometer can be used to modify the credibility of the vision sensor. For example, a poor illuminating or not homogeneous light indicates a bad quality of the images. The upper fusion node represents the occupation state of a cell of our occupancy grid, which is used to store the result of the fusion of assessments of sensors about each cell of the environment.

In the design of the Bayesian network, the user only needs to introduce either the reliability/sensibility model of each sensor, or the relationships cause-effect. This model can include all the deterministic variables that the user wishes to consider, but lots of variables imply a greater degree of the complexity of the model, and an increase of the difficulty to obtain a correct model. In our case we will use a dependent model on the distance of the object (or cell) to the robot. The precision of the vehicle position is known with a precision greater than our grid, therefore the distance for each cell is well known so, the nodes of sensors can be conditioned with respect to this variable without incurring in excessive mistakes.

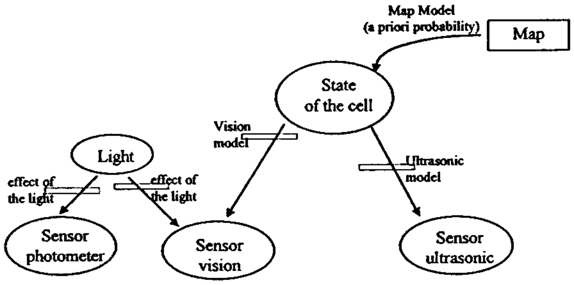

Figure 2. Example of a Belief Bayesian network model

To accomplish the fusion of vision and ultrasonic data is necessary to define the conditional probability distribution that describes the relationship between sensor nodes and theirs parents (fusion nodes). These probabilities are function of the distance between the sensors and the observed cell. This is:

$$\begin{aligned} P(+u \mid +e) &= f_u(r) \\ P(-u \mid -e) &= f_u(r) \end{aligned} \tag{1}$$

where u stands for the ultrasonic sensor and e for the state of the observed cell. The signs (+ and –) represent the affirmative case (detected object or occupied cell) and the negative case (object not detected or empty cell).

Vision sensor follows similar expressions:

$$P(+v \mid +e) = f_v(r)$$
$$P(-v \mid -e) = f_v(r) \qquad (2)$$

With these functions, the probabilistic model cause-effect between the ultrasonic and vision sensor nodes and the fusion node of each cell can be built. That is, in the ultrasonic sensor, we obtain the next matrix of conditional probabilities,

$$M(occ \mid ultras) = \begin{pmatrix} P(+x \mid +u) & P(-x \mid +u) \\ P(+x \mid -u) & P(-x \mid -u) \end{pmatrix} \qquad (3)$$

This process is continued to obtain the other necessary cause-effect relationships. In any case, studies about the behaviour of each sensor and the whole system should be made in order to tune in correctly the network. Table 1 shows how the conditional probabilities, sensibility and specificity are widely known.

Table 1. Conditional probabilities of a sensor s.

	Expression	Conclusion
True positive (sensibility): To accept the hypothesis when it is true	$P(+s \mid +e)$	There is a object
False positive: To accept the hypothesis when it is false	$P(+s \mid -e)$	Failure: mistake of 1ª kind
False negative: To reject the hypothesis when it is true	$P(-s \mid +e)$	Failure: mistake of 2ª kind
True negative (specificity): To reject the hypothesis when it is false	$P(-s \mid -e)$	There is no object

Following the using of the Bayesian network will be shown. We will use two sensors: ultrasonic transducers and stereoscopic vision sensors. These sensor are examined to obtain the model necessary for the Bayesian network of our fusion system. This designed fusion system is tested in a real experiment.

4. Experimental results

As an example of the utilisation of our multisensor fusion system, the method followed to accomplish various fusion environment measures in our mobile robot is showed briefly. The experiment is accomplished with real measures of two different sensors: stereoscopic vision (vision sensor) and a belt of ultrasonic transducers (ultrasonic sensor).

As it has been indicated previously, first we should design the dependency cause-effect of our sensors and the conditional probability distributions. Figure 3 shows the designed fusion system. That is, the Bayesian network where the relationships cause-effect between variables are taken into account. The estimates of both sensors are considered independent.

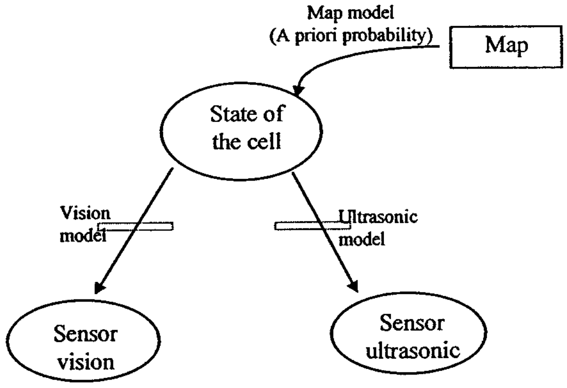

Figure 3. Example of a multisensor fusion Bayesian network.

Now, it is necessary to find the sensibility and specificity model of each sensor. To obtain these models several tests in our laboratory are to be done. Our sensors are tried and observed when they detect a object in different situations. So, a function of the distance between the object and the robot is chosen as a simple model of each sensor. Figure 4 shows the models obtained from laboratory tests, where the probabilities of detecting or not an object with respect to distance between the occupied cell and the robot are presented.

This functions are fitting of each sensor. Normally, object detecting depends on many effects as distance, surface of object, environment noise, etc. We have chosen a function depending on distance to simplify the example. It is necessary to note that always $P(+u \mid +e) > P(+u \mid -e)$ and the same happens with other sensors. Beside, figure 4 draws the following conclusion: ultrasonic sensors detect objects better than vision sensors when the object is near, but if it is far, further than 5 metres, vision sensors are better than ultrasonic sensors.

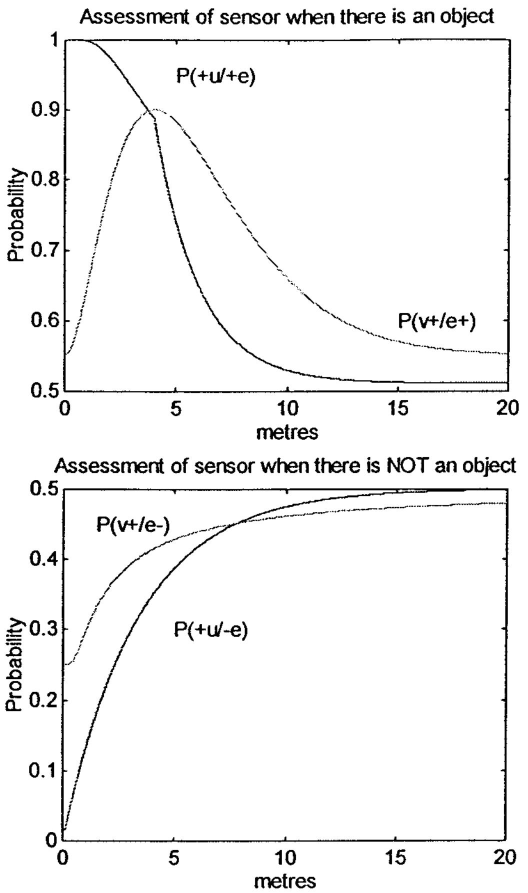

Figure 4. Occupancy Probabilities of sensors.

Note that the difference between sensibility, $P(+u\,|+e)$, and specificity, $P(+u\,|-e)$, represents the quality and precision of sensor, see figure 5. So, a sensor with the difference between sensibility and specificity as large as possible is aimed to get it. That is, it is desirable a sensor with high skill probability (sensibility) and low false positive probability (specificity). However, when sensibility is increased, specificity grows too. So, it is necessary to reach a compromise.

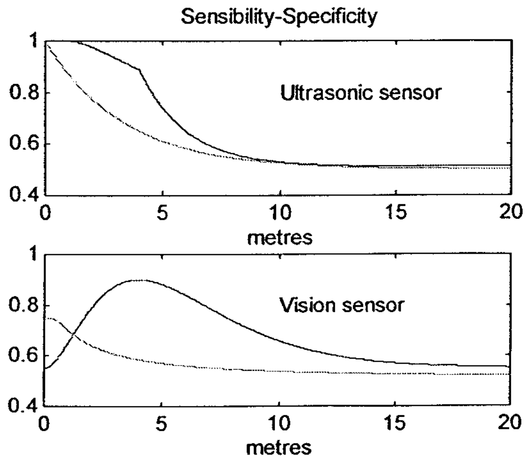

Figure 5. Sensibility and specificity.

Before showing the fusion of our two sensors in a real environment, it is necessary to test the fusion system to well tune in our design. Figure 6 shows the bayesian network working well with simulated measures. It shows that estimation of fusion system is better than each simple sensor estimation.

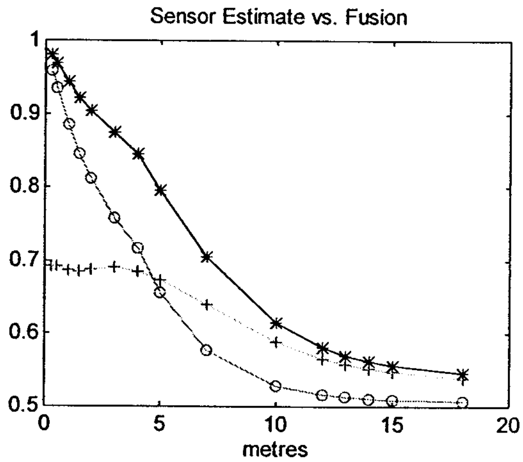

Figure 6. Fusión of occupancy probability (o ultrasonic, + vision, * fusion of both)

Finally, our perception fusion system is tested in a real case. An experiment is executed in our laboratory, figure 7. Our robot is moved through the laboratory, and then vision and ultrasonic sensors detect obstacles around the robot. The trajectory carried out by our robot is showed in figure 7.

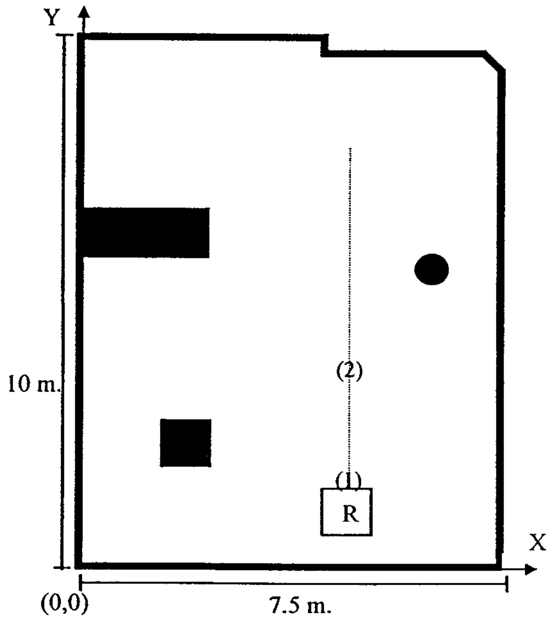

Figure 7. Laboratory map and robot trajectory.

The fusion system accepts measures and merges them at concrete periods of time. In the example, the robot fusion system merges measures of sensors at 0.5 metres on its trajectory. Vision sensor needs great processing of the captured images, so it spends more time. Thus, system fusion uses 16 environment scans of ultrasonic sensor compared to 4 images of vision sensor.

In figure 8, the assessments of vision and ultrasonic sensors are showed. They are obtained in the same positions of the robot. The fusion system uses a occupancy grid [5] to store the accumulated occupied probabilities. The pictures represent the cells that the sensor believes to be occupied in the moment of the measure.

Figure 8a shows estimates of ultrasonic sensor for the positions 1 and 2 indicated in figure 7. This sensor take measures around the robot, but its range is short. Figure 8b represents estimates of vision sensor in the same positions as in the ultrasonic sensor. It has a great range, but it only can observe the front of robot.

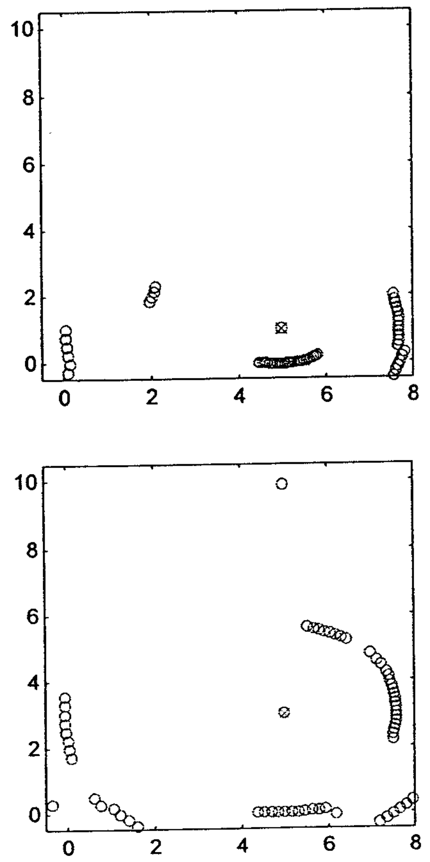

Figure 8a. Assessments of ultrasonic sensor in (1) and (2) positions.

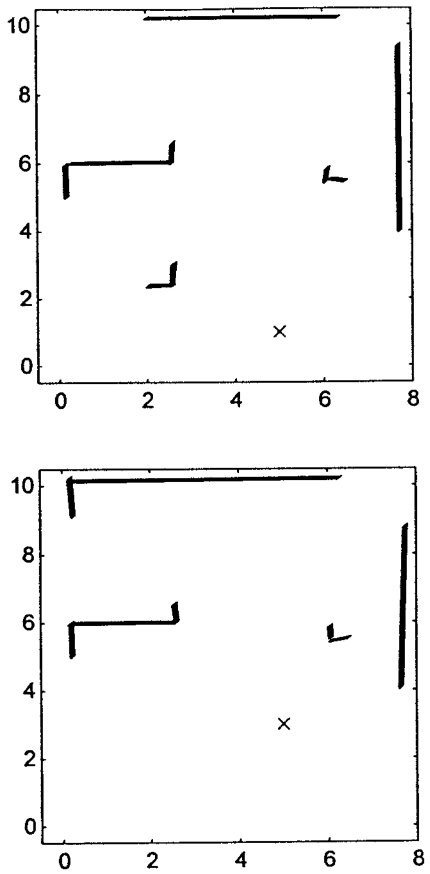

Figura 8b. Assessments of vision sensor in (1) and (2) positions.

Neither a map nor another priori knowledge is used by the bayesian network of our fusion system in this example. It allows to emphasise the fusion process of our sensor data. Of course, fusion system permits to update cells from measures of an only sensor. Figure 9a presents the map obtained only from fusion of ultrasonic sensor measures.

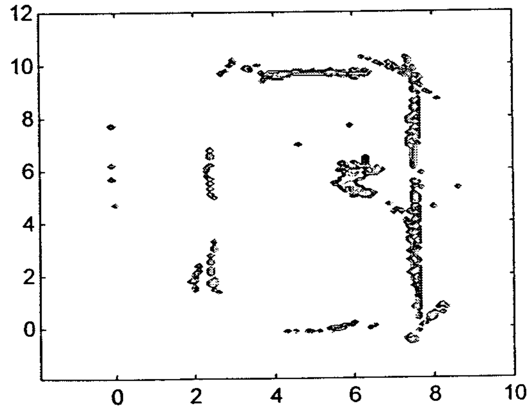

Figure 9a. Laboratory map obtained using fusion of ultrasonic measures.

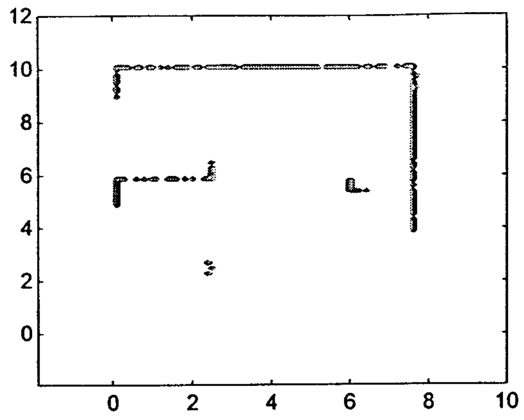

Figure 9b. Laboratory map obtained using fusion of vision measures.

Figure 9b presents the map obtained only from fusion of vision sensor measures. Vision sensor has a opening of 60 degrees and it is located at front of the robot. It cause that the robot back side is not detected by this sensor. Besides, vision sensor needs a lot of processing time. Because of this, less samples of environment objects are taken, that is, the fusion system uses less observations of around robot.

When both sensors are merged a more precise map of our laboratory is obtained (figure 10). In this map of the laboratory two obstacles and a column detected by the robot are showed.

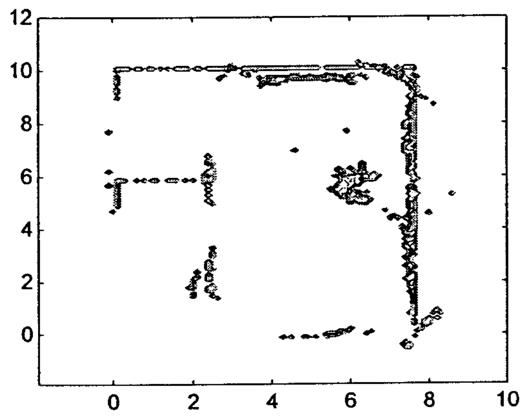

Figure 10. Laboratory map after fusion process

In conclusion, a new high level fusion procedure is designed. It permits the user to use different sensors with a little effort. Precision of estimates are associated with measure error of sensors and size of occupancy grid.

5. References

[1] Llinas, J., and Waltz, E. *Multisensor Data Fusion*. Artech House, Norwood, Massachuusetts, 1990.

[2] Luo, R.C. and Kay, M.G. *Data Fusion and Sensor Integration: State-of-the-art 1990s.* In Data Fusion in Robotics and Machine Intelligence, by Abidi and Gonzalez. Boston, MA, Academic Press, 1992.

[3] Abidi, M.A. and Gonzalez R.C. *Data Fusion in Robotics and Machine Intelligence.* Boston, MA, Academic Press, 1992.

[4] Chang C.C., and Song, K. *Ultrasonic Sensor Data Integration and Its Application to Environment Perception.* Journal of Robotic Systems. 13 (10) pp. 663-677, 1996.

[5] Elfes, A. *Occupancy Grids: A Stochastic spatial Representation for Active robot Perception.* Proceeding of the Sixth Conference on Uncertainty in AI, July 1990.

[6] Rigaud, V., and Marcé L. *Absolute Location of underwater Robotic Vehicles by Acoustic Data fusion.* Int. Conf. on Robotics and Automation. pp. 1310-1315, 1990.

[7] Luo, R.C., and Kay M.G. *Multisensor Integration and Fusion in Intelligent Systems.* IEEE Transactions on Systems, Man, and Cybernetics. 19 (5), pp. 901-931, 1989.

[8] Hall, D. L. *Mathematical Techniques in Multisensor Data Fusion.* Artech House, London, 1992.

[9] Kam M. Zhu X. and Kalata P. *Sensor Fusion for Mobile Robot Navigation.* Proceedings of the IEEE, 85 (1), pp. 108-119. January, 1997.

[10] Kessler et al. *Functional Description of the Data Fusion Process.* Tech. Rep. Office of Naval Technolo. Naval Air Development Ctr. Warminster, PA, Jan. 1992.

[11] Viswanathan R. And Varshney P. K. *Distributed Detection With Multiple Sensors: Part I- Fundamentals.* Proceedings of the IEEE, 85 (1), pp. 54-63. January, 1997.

[12] Pearl, J. *Probabilistic Reasoning in Intelligent systems,* Morgan Kaufmann, San Mateo, California, 1988.

[13] Neapolitan, R. E. *Probabilistic Reasoning in Expert Systems. Theory and Algorithms.* John Wiley & Sons, inc. 1990.