

# Shortest Paths in Sensor Snow

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## Abstract

We propose to deploy and exploit a large number of non-mobile inexpensive distributed sensor and communication devices (called Smart Sensor Snow) to obtain information and guide mobile robots over a wide geographic area. Sensors may be of diverse physical natures: acoustic, IR, seismic, chemical, magnetic, thermal, etc. We have previously described solutions for three major issues: (1) sensor distribution patterns, (2) local sensor frames, and (3) autonomous robot sensor snow exploitation techniques. In this paper, we propose the use of level set theory to solve shortest path problems in smart sensor snow.

## Smart Sensor Snow

In our previous work, we discussed how to design sensors which were deployed (e.g., by hand or by a robot).

The major reason for this is the ability to have a large number of sensors in a wide area while maintaining a small number of sensors (e.g., only a few sensors) which are used for other purposes. The sensors can also be used to provide a spatial map of the area, e.g., a map of the area which is used for navigation. This is how planned and unplanned sensors can be used. Very often, the sensors are used for navigation. Following the practice of the sensor snow,

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## Abstract

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## 1 Introduction

We have been working on a distributed computational and sensing framework (*Smart Sensor Snow*) to enhance mobile robot robustness and capabilities [1]. In that paper we presented an approach to exploiting a large number of spatially distributed sensors. This involves the capability of identifying each sensor, determining distances between them, and having them report various sensed information. Algorithms were given to specify application-specific spatial patterns in the sensor device set, determine local or global coordinate frames, and to use those to support mobile robot behaviors for robots that communicate with the sensor devices.

Another major issue of interest is the capability to plan optimal paths through the task terrain; e.g., the fastest route to the maximum concentration of a chemical spill. We describe a method here for a distributed computation which results in shortest paths, and is based on level set theory [3].

## 2 Smart Sensor Snow

In our previous work, we showed how a set of smart devices which were dropped (e.g., by helicopter or plane)

onto a large-scale geographic area could autonomously execute various algorithms and determine: (1) useful coordinate frames of reference, (2) global spatial patterns (calculated asynchronously and locally), and (3) useful task behaviors based on these frames and patterns.

The overarching goal of the sensor snow paradigm is to provide sensory information (sensed values, gradients, etc.) within a wide spatial area where clusters of sensors are used to identify and locate events or actions in the environment. We have shown how this can be used by mobile robots to achieve high-level tasks.

We have also shown how to use the Turing reaction-diffusion mechanism [2, 4] to generate patterns in the sensor snow. The pattern is the result of each sensor device running the equations locally while diffusing to its neighbors. Such patterns provide frameworks for robot navigation, etc.

Finally, we have given techniques for mobile robots to exploit the sensor devices effectively, when each sensor has:

- a measure of the density of sensors around it
- a measure of the distance to a sensed event
- the direction to a sensed event
- the direction toward sensor rich areas (i.e., a gradient of sensor density)
- pattern values for various useful patterns in the application (each pattern could be represented as a bit in a concatenated word).

The mobile robots use this information to navigate or to approach or retreat from an event while maintaining some asserted relations (e.g., stay in sensor rich area, stay a fixed distance from other robots, etc.). The sensors may also be able to provide a spatial mailbox (or communication medium) between robots by storing some bits of information. We have performed simulations of such activities and the behaviors are very interesting. Figure 1 represents two mobile robots following the gradient of the sensed value.

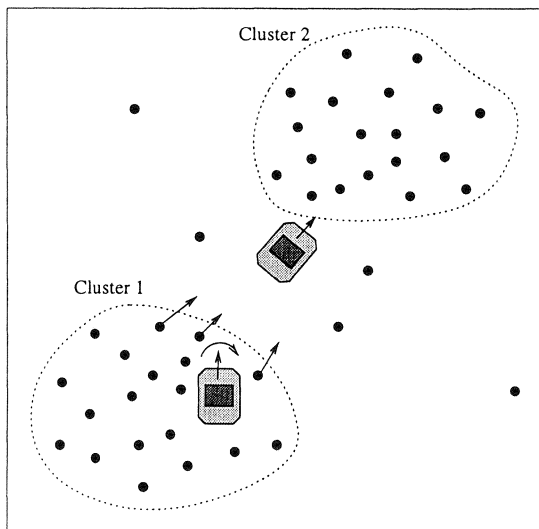


Figure 1: Robots following the gradient.

### 3 Shortest Paths in Sensor Snow

Our focus in this paper is on constrained mobile robot navigation; this means that we would like to determine optimal paths from the mobile robot to a target location with the following conditions:

- the computation should be distributed in the sensor devices
- the computation should be able to incorporate constraints (e.g., in the form of a speed function tied to the nature of the terrain)
- the computation should be robust.

It is possible to achieve this by using the level set technique proposed by Sethian (p. 181):

As a simple example, imagine a starting point A and a finishing point B in the plane, and a collection of subsets of the plane which represent obstacles:  $\Omega_j, j = 1 \dots N$ . The shortest path under a speed function  $F(x, y)$  from A to B which avoids these obstacles can be found by computing the solution to the Eikonal equation:

$$|\nabla T| = \frac{1}{F(x, y)}$$

where  $F(x, y)$  is reset to a very small number  $\epsilon$  at those  $(x, y)$  which belong to one of the subsets. Once the solution is found, back propagation from B to A along the gradient constructs the optimal path.

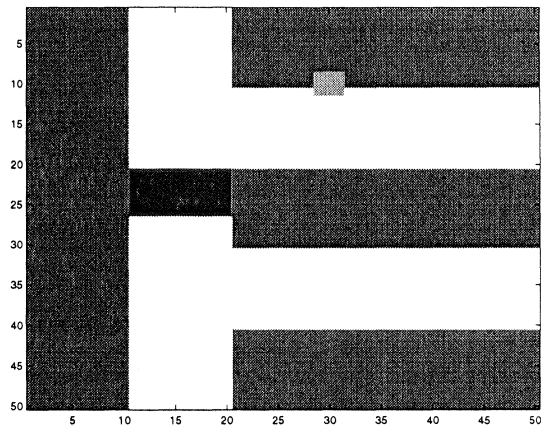


Figure 2: Speed Function  $F$  with Robot

The function  $F(x, y)$  gives the speed (i.e., maximum possible robot speed) at location  $(x, y)$  in the terrain. The function  $T(x, y)$  gives the time of arrival of the mobile robot were it to take the fastest possible path to  $(x, y)$  from its current position.

In general, the function  $T$  depends on the mobile robot's location and must be computed. Once  $T$  is known, the gradient of  $T$  can be computed, and then the optimal path is found by following the opposite of the gradient of  $T$  from the target back to the robot. Our insight is that this computation is easily done by the distributed sensor devices. Let's consider an example.

Figure 2 shows a function  $F(x, y)$  where speed is greater on roads (white regions), lower off-road (gray regions), and one part of the vertically-oriented road is blocked (black region;  $F = 0$  in that region). The mobile robot (light gray square) is in the upper part of the map. The mobile robot communicates to the nearest sensor device which sets its  $T$  value to zero. The Eikonal equation is then solved (although we use a slightly modified version of the fast marching algorithm which we have found faster and more robust), and the function  $T$  is determined (see Figure 3). In the figure, intensity is proportional to distance; the blocked zone is white and cannot be entered.

Figure 4 shows the contour plot of  $T$ . The gradient is reversed and followed from the target to the robot; the computed path is shown overlayed on the  $F$  function in Figure 5. As can be seen, the robot follows the fastest parts of the terrain where possible.

Several issues require further elucidation. First, the distributed Eikonal equation computation is accomplished as follows:

- each node initially is set to a value of infinity
- when all a node's neighbors that are used in the computation of its own value change from infinity to a

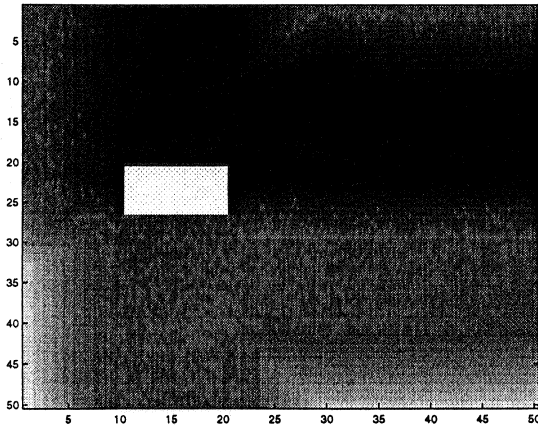


Figure 3: Time of Arrival Function  $T$

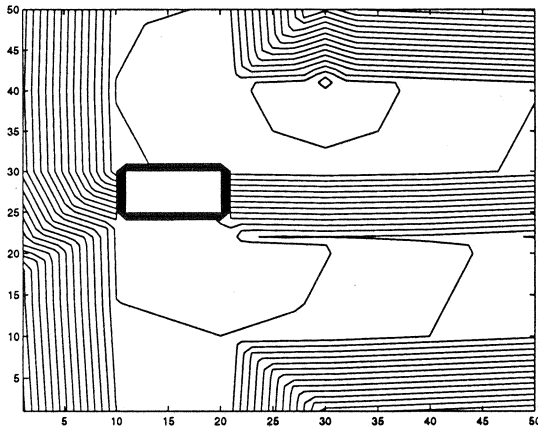


Figure 4: Contours of  $T$

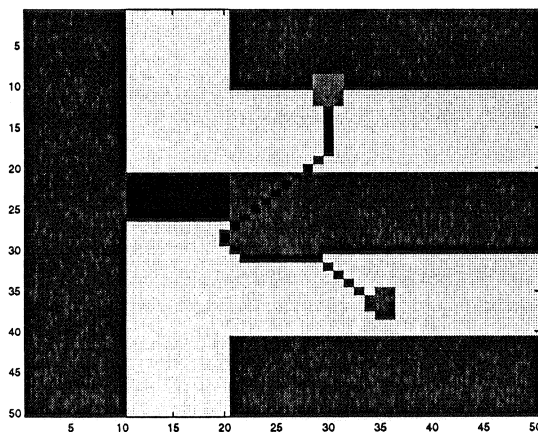


Figure 5: Shortest Path

known value, then the node's computation proceeds

- the node then passes its value to its neighbors which require the value (i.e., we use the *upwind* scheme).

This proceeds until all nodes have a value (this requires time proportional to the diameter of the sensor device grid). The  $F$  values must be set; several possibilities exist:

- registration of local sensor device coordinate frames with a global frame of reference (e.g., a map)
- distributed sensor devices measure the hardness of the local terrain and assign an  $F$  value
- as they explore the terrain, the mobile robots set  $F$  values in the sensor devices.

Our method assumes  $F$  is known.

Once  $T$  is calculated,  $\nabla T$  can be computed locally. Reversing the gradient is accomplished by reversing the sign of the gradient. To determine the shortest path, we simply follow the gradient from the target back to the robot. (Our method follows the minimum time of arrival value back to the robot.)

## 4 Conclusions and Future Work

We have expanded our Smart Sensor Snow framework to allow the distributed computation of shortest paths in the grid. This is achieved by solving the Eikonal equation using level set methods.

Future work involves the evaluation of this technique on non-uniform grids, as well as further complete simulations involving all aspects of smart sensor snow combined with multiple mobile robots working on high-level tasks.

## References

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