Self-Organizing Networks of Unmanned Aerial Vehicles

Abstract. A sensor network is a collection of sensor nodes organized in cooperative network. In this paper we present a method that allows the self organization of a network of UAV's, deployed to monitor traffic in a motorway, allowing real-time adjustment of the network.

1 Introduction

A sensor network is a collection of sensor nodes organized in cooperative network. Inexpensive, low-power communication devices can be deployed throughout a physical space, providing dense sensing, close to physical phenomena (Culler, Deborah *et al.* 2004).

Unmanned Aerial Vehicles (UAVs) constitute a specific case of mobile sensors which have been used, with success, in different applications such as fire detection (Merino, Caballero *et al.* 2005), agricultural monitoring (Herwitz, Dunagan *et al.* 2003) or traffic surveillance (Kaaniche, Champion *et al.* 2005). In the remainder of this paper we will present a method that allows the self organization of a network of UAVs, deployed to monitor traffic in a motorway, allowing real-time adjustment of the network.

Proposed method

For our purposes we will assume a mobile geosensor network that is deployed to perform car detection on a motorway. The sensor network is composed by several UAVs equiped with a camera and a radio transceiver. It is not our purpose to study the car detection or the communication issues since extensive work has been made in this field (Todorovic and Nechyba 2004; Kaaniche, Champion et al. 2005).

The method proposed in this paper takes into account the car density at each moment, in each place. Our goal is to control the sensor network so that the number of vehicles in the field of view of the sensors, at each instant, is maximum. In this case, sensors should not share their field of view with others, since in that case they would be redundant.

The basic idea of a Self-Organizing Map (SOM) (Kohonen 2001) is to map the data patterns onto a n-dimensional grid of neurons or units. That grid forms what is known as the output space, as opposed to the input space where the data patterns are. This mapping tries to preserve topological relations, i.e., patterns that are close in the input space will be mapped to units that are close in the output space, and vice-versa. So as to allow an easy visualization, the output space is usually 1 or 2 dimensional.

In our application, we use a 1-dimensional SOM. Each SOM unit represents an UAV, and the weights of the unit represent the coordinate of the UAV along the motorway. Each vehicle is a data point, characterized by it's coordinates along the motorway. The SOM is repeatedly being trained, using the currently sensed vehicles as data points. Each training phase produces new coordinates for the positions of the units, hence for the coordinates of the UAV. Since there is a limited maximum speed for the UAVs, and their fields of view must not intersect, the calculated positions are adjusted to take these constraints into consideration. In the next training phase, the data points are the vehicles sensed by the UAVs in their new positions.

2 Experimental evaluation

To measure the effectiveness of the proposed method, we must define a metric by which it can be assessed, and a benchmark method with which we may compare it.

Since the objective is to monitor as best as possible the points of interest (in this case, the cars that use the motorway), an obvious metric is the number of cars observed by the sensors (UAVs), divided by the total number of cars in the motorway. We call this ratio the coverage level (CL).

As for a comparison benchmark, we chose a method for defining patrol itineraries that simply puts each sensor moving back and forth in its predefined designated zone. These designated zones are simply the result of dividing the total area of interest into as many equal parts as available sensors. We call this method the baseline method, since it the simplest method that covers all the area with equal probability.

We developed a simulator written in MATLAB. This simulator generated car positions based on a "car traffic simulator" that may be parameterized as needed. Each car may have starting and ending position, as well as speed given by any desired distribution. In our simulations we used uniformly distributed starting and ending positions, and constant speeds. In figure 1 we present a comparison between the SOM and the baseline method. This figure also presents the percentage of cars detected during a period of time.

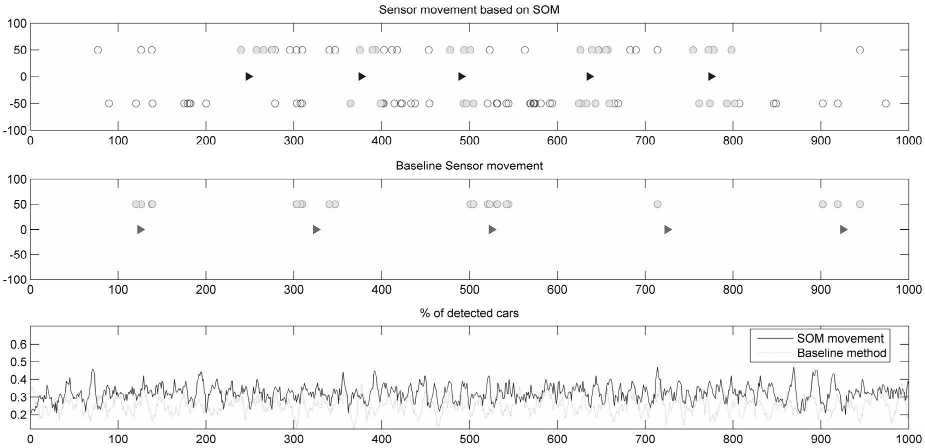

Figure 1: SOM-based and benchmark sensor movement

In figure 2 we present the mean of coverage level evaluated over 20 tests using the SOM and the baseline methods.

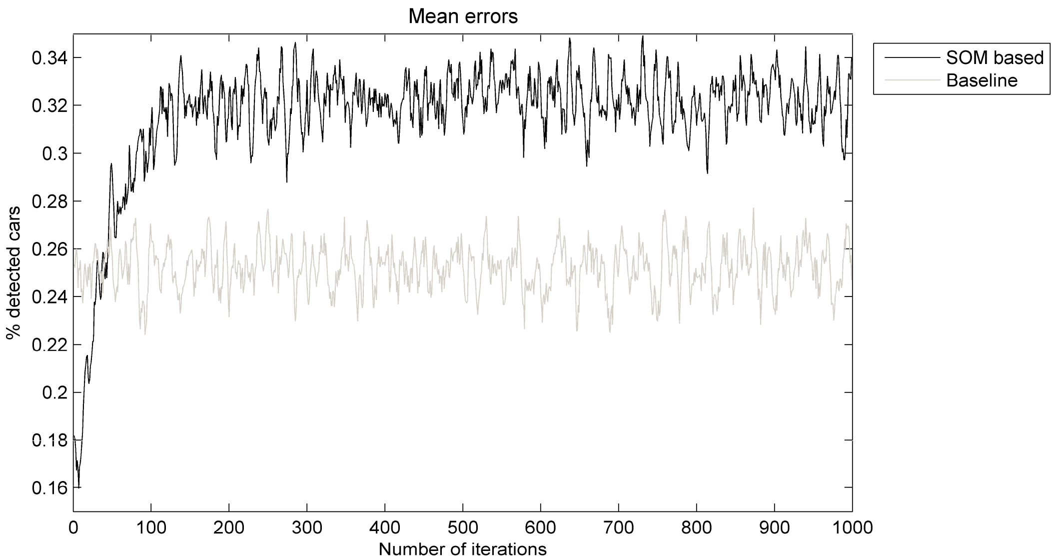

Figure 2: Coverage level between SOM-based and baseline method

The proposed method is significantly better than the baseline, as can be seen in table 1.

Table 1: ANOVA table

Summary

Groups	Count	Sum	Average	Variance
Baseline average	22.00	5.54	0.25	0.00
SOM based average	22.00	6.94	0.32	0.00

ANOVA

Source of variation	SS	df	MS	F	P value	F crit
Between groups	0.04	1.00	0.04	14911.02	0.00	4.07
Within groups	0.00	42.00	0.00			
Total	0.04	43.00				

H0: Baseline and SOM based coverage level are equal

H1: Baseline and SOM based coverage level are statistically different

The test statistic is the F value of 14911.02. Using an α of 0.05, we have that $F_{0.05;\,1,\,42} = 4.07$. Since the test statistic is much larger than the critical value, we reject the null hypothesis of equal error means and conclude that there is a (statistically) significant difference among the number of detected cars between the baseline example and the SOM based tests.

3 Conclusion

In this paper we presented a first approach to the use of Self-Organizing Maps as a geosensor network management system. The working example use in this study was based on motorway traffic monitoring in which the sensors position has to be optimized over a 1-dimensional distribution. The tests show that the proposed method significantly improves the number of cars detected by using the SOM based method.

4 References

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