Swarm Implementation for Multiagent MultiMessenger Environmental Low-frequency Sensing

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We are developing a reproducible and measurable approach to the deployment of complex adaptive networks of aerial drones, mobile ground robots, underwater gliders, ROV s and fixed or mobile sensors deposed on the ground or the sea floor. The approach exploits Voronoi maps, multisensory fusion of different kind of chemical and non chemical sensors framed by a multi agent Belief Space Planning methodology.

Our project – integrating resources from the AIFORS Lab at FER, University of Zagreb, Heron@CNR Joint Lab and University of Warsaw- and opportunistically looking for funding at national, European and international level - aims to integrate a new concept of self-organizing sensor networks with a robot swarm acting in an open ended environment.

The extraction of information from the environment and mapping of the environment are organized as two emergent concurrent processes. The network creates nodes as the individual swarm members randomly explore the environment. The process of self-organization and growth of the swarm is controlled by a fitness function based on a function of mutual information among the swarm members. Networked sensors are more densely released into the environment with reference to higher entropy measures locally calculated by the already deployed sensor points. The nodes are created when the fitness function, representing the mutual information between the nodes, is above a 'relevance' threshold. The creation of new nodes evolve in time while the individual agents randomly explore the environment. Any new node attach preferentially to the already existing ones according to their 'fitness '. The agent swarm act as particle swarm optimization (PSO) algorithm which changes, at each time step, the velocity of each particle toward its pbest and lbest locations by means of a random procedure. Particle swarm optimization is a simple algorithm that has been proposed for optimizing a wide range of functions. We apply to the managements of a flock of autonomous agents the behaviour rules supposedly working in natural flocks of birds, and more appropriately in our case, schools of fishes, following the original example from Reynolds. The initially considered, semi-structured, application scenarios are geophysics high resolution tomography applications, the identification, mapping and tracking of slowly changing environmental parameters in 'calm waters' for example at the bottom of sea harbours or small secluded bay. The monitoring robots flock to the 'informational saliency' hot spots. The extensive sensory mini micro bots set up an on field dynamic sensory and communication mesh integrated with the mobile robots and ambient intelligence based the opportunistically deployed sensors.

Reynolds proposed a simple but effective model for the behaviour of swarms, such as a flock of birds or school of fish, which are able to move in a synchronized manner without any central planning or control. This approach has been recently applied to swarm of robots. In our case the Reynolds' algorithm is applied to a flock of environment monitoring robots integrated with a sensor dust. The aim is to opportunistically deploy robots and sensors to acquire more information, and in particular, information that is correlated with the evolving sensory motor network of the swarm. Novel communication strategies are being developed to improve communication bandwidth over state of the art. This will be the topic of future reports.

Multisensory Data Fusion

In summary the system as a whole will perform a simultaneous localization, mapping and time-tracking of a number of 'environmental measures' useful for the characterization of slowly changing underwater environments.

Example of tracked low-frequency 'environmental feature variable' slowly changing over time are given:

1. Acoustic
2. Light Scattering (sensors in the pipe???)
3. Aerosol dispersions
4. Variable optical/acoustic characteristics of medium
5. Variable friction
6. Micro-seismics
7. Micro-winds
8. Electromagnetic
9. Others....

In a first stage we will focus on 1,2,6,8. However, the methodology and the platforms make possible a multi-messenger sensory fusion scheme potentially very effective for noise characterization of the ITF surrounding environment and in perspective of the ITF itseld.
Multisensor data fusion allows to efficiently and effectively merge observations from different kind sensors to build a time varying map description of the environment with respect to the variables of interst .

ANSER II (cit. Durrant-White 2008) is an example of Decentralised Data Fusion system such as that we are implementing. ANSER II models sensors through the likelihood function, and shows how very different data fusion architectures from the 'vanilla' Bayesian form can be implemented..
Decentralised data fusion (DDF) methods exploit the fact that the informational form of the Kalman filter data fusion algorithm can be implemented by simply adding information contributions from the observations coming from the sensors. This allows (thanks to the commutative properties of addition on Vectors and Matrices) the posterior estimates can be optimally integrates with the measures coming from an heterogeneous network of spatially distributed sensors.
The individual sensors are modelled as local-to-the-agent likelihood function. The local Bayesian network nodes share the time and observation updates and exchange mutual information (information gain. As a consequence, the single posterior obtained by merging the timed observations of the nodes is more likely to approximate the ground truth than those of the individual nodes.

The Reynold’s Boid’s model

When the flock algorithms are used as an optimization tool there are several possible improving including dealing with constrained optimization problems, introducing a craziness operator to increase the likelihood of escaping from a local minima, and dynamically changing the inertia value w.
The PSO (Particle Swarm Optimization) is a stochastic population based process depending on the memory of each agent as well as the knowledge gained by the population as a whole.
The population is called the ''swarm' while the single agent is called a 'particle'

Our robot and sensor network will act as an ‘embodied’ PSO.
PSO can be seen comparatively as an example of non-gradient based, probabilistic search algorithms. Other examples are evolutionary algorithms and simulated annealing algorithms.
This class of optimization algorithms have several appealing characteristics.
They are generally easy to implement, can be implemented on a large numbers of parallel processors, are efficient for finding global or near global solutions, they don't need the computation of derivatives.
The main disadvantage is the weak local search capabilities and the computational cost, that in our case is distributed among the robotic agents.

We have implemented a BSP (Belief Space Planning) versiom of Reynolds flocking model.
Reynolds has shown (Reynolds, 1987) that flocking behaviours can be implemented by imposing to the individual agents a surprisingly simple set of rules:

1. Separation - avoid crowding neighbours (short range repulsion)
2. Alignment - steer towards average heading of neighbours
3. Cohesion - steer towards average position of neighbours (long range attraction)

In our system each agent targets the centers of the school of (robot)fishes – (3) - and keep distance among boids (1,2).
Leveraging on the tests reported in Annex I, it has been developed in cooperation by the University of Warsaw and Heron Robots a first iteration prototype mobile robot for geoseismic applications. A new low cost iteration is under development by a cooperation University of Warsaw, AIFORS Lab at FER, University of Zagreb and Heron Robots.

Conclusion and Future work

The system described here integrates a flocking algorithm for the coordination of the robot swarm with a sensory 'dust' distributed in accordance with an

opportunistic strategy based on information gain measures. This strategy is inspired by a model of the evolution of sensory layouts in natural intelligent systems (Bonsignorio, 2007, Olsson, 2004). The swarm organization described here could be in principle more effective than other more classical developments for the same purposes. The flocking algorithm is quite simple, the self organizing mapping of the environment is, in theory, very flexible, while the opportunistic deployment of sensors in the environment could in principle prove very effective. The individual robot 'agents' motion planning will be governed by a Belief Space Planning algorithm.
The field experimentation of such a system will help a better understanding of the cognition processes in a network of physical agents. In turn a better understanding of those processes could drive the development of more intelligent and useful robot swarms.
In [22] we have shown as a suitable BSP control of the individual agent allows to implement robust swarm behaviours in networks of physical agents.
We are studying the integration of signals from Virgo-like Gravitational Wave detectors in the overall multisensory perception platform.

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