Biologically Inspired Models for Sensor Network Design

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Abstract

This paper discusses the purposes, requirements and challenges of creating pervasive networks of devices that have sensor technology and embedded computation. The demands placed on these sensor networks suggest that they have to function in a similar way to self-organised biological systems so concepts can be taken from them to design appropriate models for how sensor networks could work. This paper focuses on the reasons why this is possible and gives examples of previously studied biological systems.

1 Introduction

Developments in VLSI have led to an increase in hardware integration and economy of scale that have resulted in devices becoming smaller and cheaper. This makes it possible for them to be deployed in large numbers over an environment for the purpose of performing various sensing tasks [1]. The devices can combine short range wireless communication with micro-sensing, actuation and on-board processing capabilities [2] and in sensor networks they become useful for sensing, computing and manipulating variables from the physical world. Sensor network applications are widespread with uses spanning from geographical monitoring to military operations, thus the aim is to move away from using specialized instrumentation for each environment to construction with reusable building blocks and techniques [3]. Sensor networks need to have:

- Dynamic networking The devices will be deployed densely and rapidly, for example in their thousands from an aircraft. As a result, they need to set up a network dynamically in an ad-hoc manner that would be flexible enough to respond to frequent topological changes. These changes are the result of potential sensor failures or additions that should prompt the network to re-organize itself to deal with the respective loss or gain of a system resource.
- Self-calibration The devices need to calibrate themselves automatically and adapt to their changes in their environment independently. Manual operation of the network could be made difficult by the weather or location so unattended independent operation is imperative. The devices need to divide themselves task of monitoring between themselves while adapting to the resources at their disposal [4].
- Peer to peer communication The devices need to be able to talk between themselves to develop a multi-dimensional view of the sensing environment. A centralized approach would not provide the vast scalability expected from a sensor network, thus distributed and localized algorithm is needed where

information is passed between sensors in the same vicinity [5]. The data can then be compressed and aggregated to give an accurate global representation.

Sensor networks are self-organized systems of nodes that co-ordinate themselves autonomously but their development is hindered by the constraints of the devices used. Firstly, they are power constrained which makes device failure inevitable and energyefficient communication essential. They also have limited computing power preventing sophisticated network protocols from being run and limited bandwidth which constrains the amount of communication [6].

Implementing sensor networks will involve methods that allow the devices to make decisions based on their local environment and their own individual state that would result in the global purpose of the network being fulfilled. This, in fact, occurs in many biological systems which show orderly patterns emerging from seemingly random low-level activities. Ant colonies are an example that show functionality and adaptation on a global scale that result from locally-applied underlying rules and amplified collective behaviour. The observation made from their clustering behaviour is that "a better use of a small brain [is] not to attempt to be an excellent architect" [7]. This suggests that the ants carry out very simple steps without the need for central manager that does more than the rest of the group. The result is the emergence of a pattern from a complex system, the details of which are given in the next section. The cell automata model is discussed in section 3 and the use of a biological model to spread information in an active network is detailed in section 4.

2 Ant Cemetery Construction

The authors in [8] analyzed the large-scale spatial patterns found in the clustering behaviour of ants for evidence of local activation–long-range inhibition (LALI) mechanisms. This is where an elevated local concentration of pattern-forming substance encourages more build up in one area but inhibits the build-up in another area some distance away [7]. Specifically, they observed the way ants, when placed in a circular arena with a homogeneous distribution of corpses around the perimeter, would form cemeteries of the dead ants and derived a mathematical model for the process.

The ants showed a strong tendency to follow the inner walls of the arena, thus reducing the problem to a one-dimensional system. They went on to pick up and drop corpses of dead ants to form several clusters after a few hours but gradually some clusters would grow while others would disappear. This led to a steady state with a stable number of clusters being placed at different locations around the perimeter.

The experiments carried out in [8] showed that LALI mechanism applied to individual ant behaviour and that the behaviour followed the mathematical model developed. The actions of the ants were dictated by spatial and temporal variables in their local environment; they are not concerned with what is going on globally and do not need to plan or think ahead. Instead their very simple and initially inefficient individual actions lead to the ordered cemetery formations showing that a waste of time and energy is rewarded by the robustness of the procedure [7].

3 The Cellular Automata Model

The behaviour these biological systems can be emulated by computer simulations called cellular automata which consists of a geometric array of minimalist computing elements, each of which contains a finite state machine that is updated in discrete time steps. The cells determine their next state by examining its' present state and that of its' neighbours and carrying out a set of simple rules. Stephen Wolfram created a simple one - dimensional automaton and found that the system displayed complexity above a certain threshold. He found that if the rules applied to individual cells were made a little more complicated then the whole system would show all of the main types of complex behaviour. Any more complications to the rules would make little change to the level of complexity in the system [9]. The fact that simple rules can generate complex outputs means that it possible for emergence to be an additional consequence and can be applied to technical systems, such as sensor networks, that need to work in the same way.

4 The Firefly-Gossip Protocol

One example of an inefficient algorithm being implemented in a technical system that was developed using borrowed concepts from the behaviour of biological entities is the firefly-gossip protocol developed in [10]. In this case, an efficient way of distributing large amounts of information around a policy-based management system of an active network was needed because of the regular updates made to the system and node policies. The policy distribution needed to be asynchronous, decentralised and reliable.

The protocol needed to meet these requirements and the most appropriate form of information-sharing to base its' design on was gossip. This weak consistency protocol involves propagating updates via delayed point-to-point communications between nodes in batches. The design was also influenced by the behaviour of fireflies which when isolated emit flashes of light at regular intervals but in a group alter their internal timers to flash at the same rate as their neighbours i.e. synchronization. Fireflies achieve this state through passing messages between individuals and their neighbours in the local environment. The synchronization of flashing is analogous to the synchronization of the rate of updates in an active network and this with gossip gave a technical solution.



The nodes had a flash interval that determined when the node was next going to talk to its' neighbours and this was allowed to reach a maximum value to limit the average flash interval increase due to the new policy addition. Figure 1 shows the maximum flash interval being varied from 10 to 70 epochs to observe the effect on the average flash interval when a policy is added to the network of 100 nodes at a time of 300 epochs.

Figure 1: Graph showing mean flash interval against time

The graph shows the network can respond to the addition of a new policy by reducing the flash interval and as the policy spreads, the flash interval increase until it reaches the maximum and stays steady.

5 Conclusion

There are many examples of self-organization, emergence and complexity in biology that involve lower-level entities making local decisions and inadvertently affecting the global state. This approach needs to be applied to many areas of computation but the focus in this paper is on sensor networks. The mathematical analysis of self-organizing systems such as ant colonies and previous work on cell automata show that an appropriate biological model can be applied to sensor networks to encourage them to learn how to deal with the tasks given to it. The small calculating machines in the network need only to carry out very simple rules and any inefficiency encountered most likely will be compensated by the results.

6 References

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