Layered Attractor Selection for Clustering and Data Gathering in Wireless Sensor Networks

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1 Introduction

In this paper we propose a clustering scheme for wireless sensor networks (WSN) based on a biologically-inspired mathematical model of a gene network, initially introduced in [1]. The aim of this approach is to establish a robust and resilient clustered network which adapts to and quickly recovers from changes in the environment while keeping the network lifetime as high as possible, in regards to depletion of energy.

The concept is based on adaptive-response by attractor selection (ARAS) in [2]. In this model the notion of attractor selection is defined by a function f, an activity $0 \le \alpha \le 1$, and noise term η . The principal equation of the dynamics of state x is given by the following stochastic differential equation:

$$\frac{dx}{dt} = f(x)\,\alpha + \eta \tag{1}$$

The activity defines how suitable the current (found) solution is and increases as the solution becomes better, and smaller when the solution is not suitable. Hence as the activity becomes smaller, the noise term dominates and allows random selection to take place until a better solution is found (in which case activity will grow again) and the solution converges to the newly found attractor. The main idea is to induce inherent adaptability and resilience in a network rather than pure optimization which traditional methods seek to achieve.

We believe that the notion of attractor selection is an effective way to establish an adaptive system, where any perturbations or events influence the system's current equilbrium state and eventually direct it to a stable attractor, i.e. a new equilibrium state. While the original attractor selection model maximizes a single activity, a WSN needs to achieve multiple objectives at the same time, e.g. selecting highest energy nodes as cluster heads (CHs) and at the same time route aggregated data to high energy gateways (GWs) towards the sink over the clustered WSN. Furthermore, when such a system is subjected to unexpected changes, e.g. node failure/destruction, the system is able to reliably recover itself in a self-organized manner. We introduce the layered attractor model which allows independent objectives to balance each other in order to meet an emergent purpose such as those that occur in biological systems.



Fig. 1 Layered clustering and routing concept.

2 Protocol Details

The following are the assumptions made for the WSN suitable for the proposed clustering and routing model: 1) each node has different energy levels, and some or all nodes have permanent or temporary power source, e.g. solar energy; 2) not all nodes are within transmission range of the sink, i.e. multihop routing of data is inevitable by nodes not within a one-hop range of the sink; 3) GPS is not available; 4) environment influences the function of the network. Specifically, in this paper we consider an environmental sensor network where nodes are equipped with solar-powered charging cells as an example application scenario. Thus, environmental influences are, e.g. the amount of sunlight, shadows cast by clouds or trees.

Figure 1 shows the layered architecture for the proposed protocol. In the figure, the *clustering layer* is in charge of local CH election and cluster management, whereas the *routing layer* is in charge of routing the aggregated data towards the sink. Although each layer has independent objectives, they interact and are ultimately interdependent of each other, and hence affect each other's behavior. This is done through the activity dynamics of the two layers, where the activity of one layer affects the activity of the other layer.

2.1 Clustering Layer

In the clustering layer, attractors correspond to the choice of CH and the activity expresses the balance in energy consumption. Clustering using ARAS, dubbed as CARAS, is based on the following algorithm:

- 1. Node *i* periodically broadcasts its current residual energy e_i to its 1-hop neighbors.
- 2. Node *i* calculates the activity α_i and derives a state vector $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ based on itself and its neighbor

bors' residual energy, where n is the total number of neighbors plus node i. This is defined by

$$\frac{dx_i}{dt} = f(\tilde{e}_i, x_i) \,\alpha_i + \eta_i,\tag{2}$$

where $f(\tilde{e}_i, x_i)$ is the function that defines the attractors, \tilde{e}_i is the current energy of node *i* normalized among all neighbors, α_i is the activity defining the "goodness" of the selection as CH, and η_i is the Gaussian noise. In this paper, the activity for CH selection is defined as the variance of energy in the neighborhood, as

$$\alpha_i = \frac{\beta_i}{n-1} \sum_{j=1}^n (\tilde{e}_j - \tilde{e}_{avg})^2, \tag{3}$$

where \tilde{e}_{avg} represents the average normalized energy of all *n* neighboring nodes including *i* and β_i is defined as

$$\beta_i = \begin{cases} \alpha_j^* & \text{node } i \text{ is a CH} \\ 1 & \text{otherwise} \end{cases}, \quad (4)$$

where α_j^* is the routing activity of GW j, which will be discussed next.

3. Node *i* identifies the index *k* with the maximum vector value.

$$k = \operatorname*{arg\,max}_{i} x_{i} \tag{5}$$

If k is the node itself, it will broadcast a CH claim after a time $T(e_i)$, else it will do nothing.

- 4. Nodes which receive a CH claim will become a member of that cluster, and notify their CHs of their membership.
- 5. Nodes which hear more than one CH claim become GW nodes to those clusters. Such nodes unicast a GW claim to each of their corresponding CHs.
- 6. Data gathering by CHs and forwarding to the sink is done at an interval of t_q . Repeat from Step 1.

2.2 Routing Layer

The second layer based on routing of data to the sink is introduced on top of the clustering layer. In the second layer, a CH chooses a GW node to route the data toward the sink among candidate GWs. Hereafter we call a neighboring cluster closer to the sink a lower cluster and its CH a lower CH. The attractor is the choice of GW for routing. The candidate GWs are those which lead to lower clusters. The routing layer activity is defined as

$$\alpha_j^* = \tilde{e}_j \, \tilde{q}_j, \tag{6}$$

where α_j^* is the activity associated with GW *j*, reflecting its suitability for routing. The new parameter here is the normalized rate of energy charging \tilde{q}_j of CH *j*. Hence the state vector $y_j = (y_{j1}, y_{j2}, ..., y_{jm})$ is derived by the CH, where *m* is the number of candidate GWs for routing to the lower cluster.

$$\frac{dy_j}{dt} = g(\tilde{e}_j, \tilde{q}_j, y_j) \,\alpha_j^* + \xi_j \tag{7}$$

The function $g(\tilde{e}_j, \tilde{q}_j, y_j)$ defines the attractors for GW selection and ξ_j is the noise term for the routing layer. The candidate set for a CH node j in (7) are GW nodes which lead to a lower cluster toward the sink. CH j identifies index w with the maximum vector value. It will then select GW w to route data to the lower cluster.

$$w = \underset{j}{\operatorname{arg\,max}} y_j$$

If α_j^* is high, then the high energy GW, charging the best and leading to the lower cluster, is more likely to be chosen, whereas if α_j^* is low, then one of the GW nodes leading to the lower cluster is chosen with higher randomness. This GW will receive the data and then performs the selection of a lower CH using the same attractor selection method in (7) for forwarding the data. We note that only CHs and GWs take part in routing. Cluster members are only in charge of sending their data to the CH and triggering a reclustering.

3 Conclusion

In this paper we introduced a layered clustering protocol which aims at building a self-organized, resilient and adaptive platform for WSNs. The protocol consists of two independent objectives, namely cluster formation and routing, affected by interdependent properties, namely activity dynamics of each layer. This kind of interaction would make the system resilient and adaptive to changes in the environment, and provide a high energy-saving performance. Future work should aim at careful study of the dynamics of the system and advantages over previous approaches.

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References

- A. Kashiwagi, I. Urabe, K. Kaneko, and T. Yomo. Adaptive response of a gene network to environmental changes by fitness-induced attractor selection. *PLoS ONE*, 1, Dec. 2006.
- [2] K. Leibnitz, N. Wakamiya, and M. Murata. Biologically-inspired self-adaptive multi-path routing in overlay networks. *Communications of the ACM*, 49(3):62–67, Mar. 2006.