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Bio-inspired cluster-based routing for wireless sensor networks

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Abstract—To cope with ever-increasing size and complexity of information networks, self-organization based networking technologies draw increasing attention. In this paper, we consider incorporating two control mechanisms operating on different layers and having different objectives, i.e. clustering and routing, in a wireless sensor network. While each self-organization based control autonomously accomplishes the targeted objectives, it does not necessarily mean the desired performance is obtained.

Therefore, we introduce a mechanism of mutual interactions among clustering and routing to improve the performance as the whole system. Simulation results show that sharing one parameter between clustering and routing.

1. Introduction

The rapid growth of wireless networks in size and complexity makes traditional and conventional mechanisms unsuccessful. To cope with emerging problems, self-organization based networking technologies draw increasing attention. Many successful attempts have been made, especially taking an approach to be inspired by self-organizing behavior of biological systems, e.g. [1]. However, most of them only consider application of a single biological model to a single networking problem. Apparently, a single control mechanism cannot satisfy diverse requests on networking and communication in a functional aspect ranging from the lowest physical layer to the highest application layer of a layered reference model and in a structural aspect from M2M wireless networks of tiny devices to large-scale optical backbone networks. Therefore, we need to consider incorporating multiple self-organization based networking technologies, but much has not been known about appropriate combination to achieve consistent, stable, robust, and adaptive control as a whole.

In this paper, we consider incorporating two self-organization based networking technologies operating on different layers and having different objectives. They are clustering and routing in a wireless sensor network (Fig. 1). Wireless networks are one of active areas of application of self-organization based control algorithms, because characteristics of unstable, unreliable, and bandwidth-limited wireless communication make conventional and firm control infeasible.

Clustering makes clusters of sensor nodes, where each cluster has one representative node called cluster head (CH) and cluster members (CMs). Sensing data are gathered at a CH from CMs and then sent to a sink node, i.e. collection point of all sensing data, by the CH through inter-cluster data forwarding. Since a CH consumes more energy than CMs for reception and transmission of sensing data, roles of CH and CM should be rotated to balance energy consumption among nodes. Therefore, a primary concern of clustering is balance of energy. On the contrary, routing, in charge of establishment and maintenance of paths from CHs to a sink, aims at lower delay and higher ratio of data gathering.

As a basic algorithm of self-organization based clustering and routing, we use a mathematical model of biological adaptation, called the attractor selection model [2]. The model explains how an *E.coli* cell adapts to dynamically changing nutrient condition of the environment. Each cell autonomously regulates gene expression and synthesizes appropriate nutrient to compensate deficiency of nutrients in the environment. In [3], we applied the attractor selection model to routing in mobile ad-hoc networks and verified that our proposal outperformed a conventional mechanism and other bio-inspired mechanism in robustness, adaptability, and performance. We can expect that attractor selection-based clustering and routing autonomously and adaptively accomplish the targeted objectives, i.e. energy balance and data gathering performance.

However, we need to consider the fact that clustering and routing intrinsically depend on each other. Paths that routing establishes heavily depend on the structure of clusters, which a clustering mechanism constructs. At the same time, inter-cluster communication determined by a routing mechanism puts an additional burden on CHs whose energy consumption changes depending on the location that a CH exists in a path. As a consequence of independent and autonomous behaviors of clustering and routing aiming at maximization of their individual objectives, there is a chance that they can find good solutions leading to the near global optimization. However, convergence would take time. In reality, they are more likely to interfere each other and a whole system never converges. It considerably degrades the performance and shortens the lifetime of a wireless sensor network. Therefore, in this paper, we introduce a mechanism of mutual interactions among clustering and routing. In our proposal, they are combined by sharing some control parameters. Differently from so-called cross-layer architecture [4], where optimization is performed by taking into account states and parameters of multiple layers at once, clustering and routing are loosely coupled while leaving autonomy of mechanisms in our proposal.

2. Attractor selection model

The attractor selection model is in the form of a stochastic differential equation combining a function $f(x)$, an activity α ($0 \leq \alpha \leq 1$), and a noise term η. The dynamics of system state x is given by the following equation.

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

The state x can be either of a scalar or a vector. The function $f(x)$ corresponds to a potential function defining attractors. An attractor is a stable state where a dynamic system governed by $dx/dt = f(x)$ converges and stably stays. The activity α is a scalar which expresses the goodness of the current state x. When the state x is appropriate for the current condition, the activity α is high. Multiplication of $f(x)$ and α reinforces or weakens the potential energy of attractors. Together with the noise term η, a system exhibits adaptive behavior.

With the large α a system stays the current attractor stably. When the environmental condition changes and α becomes small, a system moves out of an attractor and takes random walk being driven by the noise term. When a system eventually approaches a new attractor, which is appropriate for the current condition, the activity begins to increase. As a consequence the system state is entrained to the new attractor. In summary, the attractor selection model is a meta-heuristic algorithm to find a good solution defined as an attractor. It combines deterministic nonlinear dynamics and random search with mediation of the activity as feedback.

3. Attractor selection-based clustering

Each node i maintains activity α_{i_C} and a state vector $\vec{x_i} = \{x_{i,1}, x_{i,2}, ..., x_{i,M}\}$ where M corresponds to the number of nodes in its vicinity plus one for node i itself. $x_{i,1}$ is a state value of node i. At the regular clustering interval of T_c, all nodes conduct the following process. Node i first evaluates the clustering activity α_{i_C} by using the following equation.

$$\alpha_{i_C} \leftarrow \rho_C \alpha_{i_C} + (1-\rho_C)\frac{\min_{k\in CH_i} r_k}{\max_{j\in N_i} r_j}, \tag{2}$$

where N_i is the set of neighbor nodes additionally including node i, $r_j = \frac{ResidualEnergy_j}{Capacity_j}$ is the ratio of residual energy to the capacity, CH_i is the set of CHs and node i. For the purpose of advertisement of energy condition as well as neighbor discovery and maintenance, each node broadcasts hello messages at regular intervals of T_h. ρ_C ($0 \leq \rho_C \leq 1$) is a smoothing coefficient.

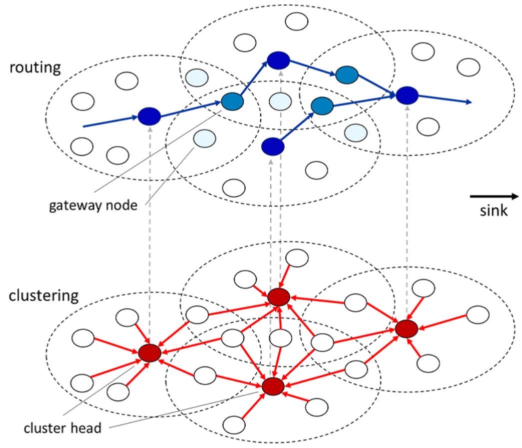

Figure 1: Layers of clustering and routing control

Next, node i updates the state vector $\vec{x_i}$ by,

$$\frac{dx_{i,j}}{dt} = \frac{\alpha_{i_C}\left(\frac{1}{\sqrt{2}} + \beta\alpha_{i_C}^{\gamma}\right)}{1 + x_{i,max}^2 - x_{i,j}^2} - \alpha_{i_C} x_{i,j} + \eta_{i,j} \quad (1 \leq j \leq M), \tag{3}$$

where $x_{i,max} = \max\{x_{i,j}\}$, $\beta = 20$, and $\gamma = 10$. The term $\eta_{i,j}$ is Gaussian white noise with mean 0 and variance 1.

Then, node i sets its backoff timer t_i as

$$t_i = T_{max}\sqrt{1 - x_{i,1}}, \tag{4}$$

where T_{max} is the maximum waiting time of CH election. When the backoff timer t_i expires, node i broadcasts a cluster-head claim (CHC) message to all of its neighbors and becomes a CH. Hearing the CHC message, other nodes in the range of broadcasting cancel their backoff timers and become CMs of CH i.

If non-CH node j receives several CHC messages during $T_{max} + T_g$ from the beginning of the current clustering process, it becomes a gateway node (GW). It mediates inter-cluster message forwarding. GW j multicasts a gateway claim (GWC) message to neighbor CHs to inform its existence. At $T_u > T_{max} + T_g$ from the beginning of the current clustering process, all nodes update lists of CHs and GWs used for routing based on a result of clustering.

4. Attractor selection-based routing

At regular intervals of T_d, sensing data are gathered from all nodes to a sink. First each of all CMs and GWs sends sensing data to its designated CH. At T_a from the beginning of the current data gathering, CH i aggregates received sensing data together with its own and selects a GW to send the aggregated data.

For the sake of routing, independently of the role, i.e. CH, GW, or CM, node i maintains another set of activity α_{i_R} and state vector $\vec{y_i} = \{y_{i,2}, y_{i,3}, ..., y_{i,M}\}$. They are evaluated and used only when node i is either of CH or GW.

Furthermore, evaluation of the attractor selection model is performed once per data gathering cycle. Now consider the behavior of a CH. A GW also conducts the similar process where GW and CH are interchanged in the following descriptions.

When there is a single GW having the smallest hop counts to a sink (HoTS) among neighbor GWs, it is selected as a next hop without evaluating the attractor selection model. Here, we assume that HoTS is initialized and maintained by using regularly exchanged hello messages or periodic flooding of control messages. When there are two or more GWs with the smallest HoTS, CH i first evaluates the routing activity α_{i_R} using the following equation.

$$\alpha_{i_R} \leftarrow \rho_R \alpha_{i_R} + (1-\rho_R)\frac{\min d}{d_{latest}}, \qquad (5)$$

where d_{latest} is the delay in the latest data gathering and $\min d$ is the minimum delay in the past data gathering. So that CHs and GWs can obtain delay information, at each T_f from the beginning of the current data gathering, a sink sends a feedback message by flooding. A feedback message contains a list of reception time of all data messages it received in the previous period of T_f. ρ_R $(0 \leq \rho_R \leq 1)$ is a smoothing coefficient.

Next, CH i updates a state vector as,

$$\frac{dy_{i,j}}{dt} = \frac{\alpha_{i_C}\left(\frac{1}{\sqrt{2}} + \beta\alpha_{i_C}^{\gamma}\right)}{1 + y_{i,max}^2 - y_{i,j}^2} - \alpha_{i_R} y_{i,j} + \eta_{i,j} \quad (1 \leq j \leq M). \qquad (6)$$

Differently from clustering, CH i only updates state values of neighbor GWs. Then, CH i sends an aggregated data message to a GW with the largest state value.

When CH i receives a data message to forward from a neighbor GW, it first evaluates the attractor selection model if it is not done in the current data gathering cycle and selects a GW with the largest state value as a next hop. In message forwarding, a GW from which it received a message is excluded from next-hop candidates unless it is only neighboring GW.

5. Incorporation of clustering and routing

In [5], we consider interaction between layered routing mechanisms in a hierarchical wired network. Each of interdomain and intra-domain routing mechanisms performs autonomous and adaptive routing based on the attractor selection model. To have explicit mutual interactions, they share activity values among layers by additionally multiplying the activity of the other layer to function $f(x)$ in Eq. (1). With such coupling, a routing mechanism of each layer tries to maximize both activities. In this paper, we take the same approach.

Since clustering takes into account only energy balancing, there is possibility that disconnected cluster structure is formed. Whereas there is a variety of coupling, we consider routing-aware clustering. It is accomplished by replacing α_{i_C} with $\alpha_{i_C}\alpha_{i_R}$ in Eq. (3). As a result of the loose coupling, it is expected that clustering is performed so as to guarantee the connectivity by maximization of objectives of both of clustering and routing.

6. Evaluation

We evaluate the proposal from viewpoints of data gathering ratio, data gathering delay, and energy consumption. The data gathering ratio is defined as the ratio of the number of sensing data which a sink receives in data gathering interval T_d to the number of data messages that all nodes except for a sink sent in T_d. The data gathering delay is defined as time taken for a data message to reach a sink from a CH. Finally, the energy consumption is evaluated by the fairness index [6], which is defined as $(\sum_{i=1}^{n} r_i)^2/(n\sum_{i=1}^{n} r_i^2)$. n is the number of nodes.

We randomly distributed 20 immobile nodes in the region of $500\times1000\ m^2$. Nodes communicate with each other within the range of 250 m by IEEE 802.15.4. Simulations are conducted by using OMNet++ [7] and each simulation time is 20000 s. Other parameters are set as $T_{max} = 0.5s$, $T_f = 2s$, $T_d = 5s$, $T_h = es$, $T_c = 1000s$, $T_u = 1.5s$, $T_g = 0.05s$, $T_a = 0,4s$.

We here and after call a scenario where clustering and routing independently operate "Independent" and a combination of routing-aware clustering and routing "Coupled".

Figure 2 and 3 show the data gathering ratio of Independent and Coupled in a set of simulation runs, respectively. Whereas there are sudden drops in the data gathering ratio due to disconnected cluster topology, Coupled achieves the stably higher data gathering ratio in the latter half of simulation time than Independent. As a result, the fairness index of energy decreases from 0.9903 (Independent) to 0.9893 (Coupled), but the sacrifice is small.

Next Fig. 4 compares the data gathering delay. They differ little from each other because organized cluster topology does not differ much as far as it guarantees the connectivity. Within each data gathering interval, the data gathering delay fluctuates very much. It is because of stochastic behavior of the attractor selection model. We can expect that the delay converges to a smaller value when we have a longer data gathering interval giving the sufficient time for convergence. We can also accelerate convergence by using smaller γ in Eq. (3).

Finally, Fig. 5 illustrates the data gathering ratio averaged over 10 simulation runs. Because of the small number of simulation runs, the data gathering delay fluctuates but fluctuation is smaller in Coupled. It means that incorporating clustering and routing by loose coupling leads to stable data gathering.

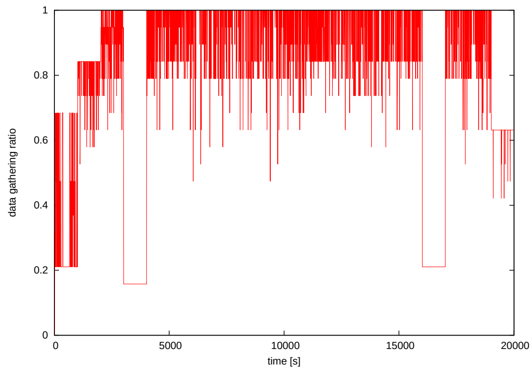

Figure 2: Data gathering ratio (Independent)

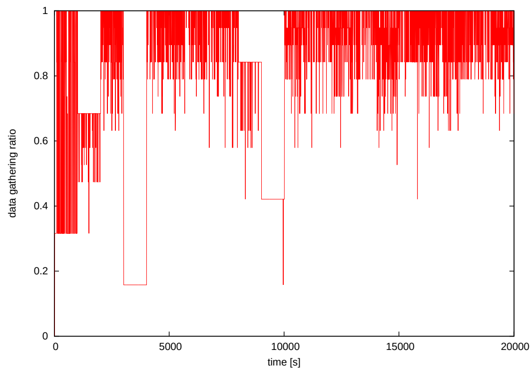

Figure 3: Data gathering ratio (Coupled)

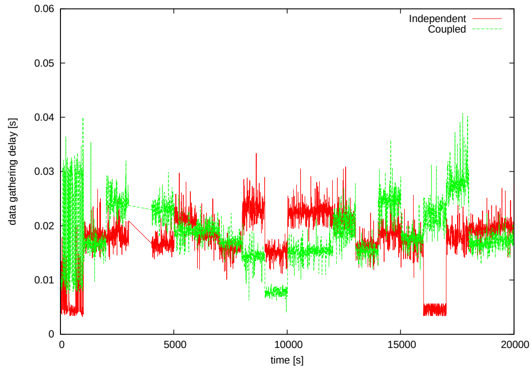

Figure 4: Data gathering delay

7. Conclusion

In this paper, we propose incorporation of self-organization based clustering and routing for a wireless sensor network. To achieve better performance, we introduce explicit but loose mutual interaction among those control mechanisms. We conducted simulation experiments and verified our proposal. We plan to consider further performance improvement by fine-tuning of control mechanisms. Furthermore, we will investigate other scenarios such as interaction between self-organization based mechanisms operating on the same layer. Then, we will derive a design principle of combination of multiple self-organization based networking technologies from the obtained results.

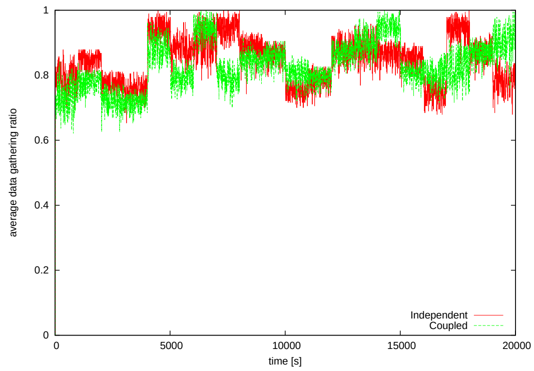

Figure 5: Average data gathering ratio

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