

Role of Machine Learning in Configuration Management of Ad Hoc Wireless Networks

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ABSTRACT

In this work, we show that machine learning, e.g., graphical models, plays an important role for the self-configuration of ad hoc wireless network. The role of such a learning approach includes a simple representation of complex dependencies in the network and a distributed algorithm which can adaptively find a nearly optimal configuration.

Categories and Subject Descriptors

I.6.5 [Model Development]: Modeling methodologies

General Terms

Distributed Automated Management

1. INTRODUCTION

Self-configuration is for the network to achieve a desired network configuration by the cooperation of individual nodes. A key requirement is to find an optimal local algorithm so that the desired global configuration be achieved. Although many algorithms and protocols provide promising results, it is unclear when optimal self-configuration is available in a fully distributed fashion. This work intends to address the following questions: (a) How to quantify the optimality of a configuration? (b) When and how can the local adaptation results in a globally optimal configuration?

We show that graphical models provide a simple and explicit representation of inter-dependencies in a network configuration. Such a representation shows when and why a local management results in a nearly optimal global configuration.

2. PROBLEM FORMULATION

Consider an ad hoc wireless network with N nodes, with positions, $\underline{X} = \{X_1, \dots, X_N\}$. Let σ_{ij} be random activity of link (i, j) , referred to as a “communication dipole,” $\sigma_{ij} = 1$ if node i is transmitting to node j ; and $\sigma_{ij} = -1$, otherwise. A network configuration is a combination of both node positions and link activities, i.e., $G(\underline{\sigma}, \underline{X})$, and an optimal configuration includes an optimal physical topology ($\underline{X}^*$) with maximal channel reuse ($\underline{\sigma}^*$) under management constraints. The optimal configuration ($\underline{\sigma}^*, \underline{X}^*$) is defined as the most likely configuration that maximizes the likelihood function,

i.e., $\arg \max_{(\underline{\sigma}, \underline{X})} P(\underline{\sigma}, \underline{X} | \underline{\sigma}_0, \underline{X}_0)$, where $(\underline{\sigma}_0, \underline{X}_0)$ is the initial configuration.

Self-configuration is to obtain an optimal distributed algorithm characterized by local rules, $g_i(\cdot)$, for $1 \leq i \leq N$, $(\hat{X}_i(t+1), \hat{\sigma}_{ij}(t+1)) = \arg \max_{(X_i(t+1), \sigma_{ij}(t+1))} g_i(X_i(t+1), \sigma_{ij}(t+1) | X_{N_i}(t), \sigma_{N_i}(t))$, where N_i and σ_{N_i} are the neighbors of node

i and dipole σ_{ij} , and $|\prod_{i=1}^N g_i(\cdot) - P(\underline{\sigma}, \underline{X} | \underline{\sigma}_0, \underline{X}_0)| < \delta$ for a given $\delta > 0$.

3. PROBABILISTIC NETWORK MODEL

To quantify the goodness of a network configuration, we obtain the likelihood $P(\underline{\sigma}, \underline{X} | \underline{\sigma}_0, \underline{X}_0)$ which will be obtained from $P(\underline{\sigma} | \underline{X}, \underline{\sigma}_0, \underline{X}_0)$ and $P(\underline{X} | \underline{\sigma}_0, \underline{X}_0)$.

Assuming the traffic demand is all-to-all for simplicity, the management constraint for $\underline{\sigma}$ is then to maximize the spatial channel reuse. Thus, $P(\underline{\sigma} | \underline{X}, \underline{\sigma}_0, \underline{X}_0) = P(\underline{\sigma} | \underline{X})$. Each feasible communication configuration of a network can be represented with the total energy of the network, which is referred to as “configuration Hamiltonian,” then characterized by the total negative power $-\sum_{ij} P_{ij}$, and denoted as $H'(\underline{\sigma} | \underline{X})$, which is

$$\begin{aligned} & -\sum_{ij} P_i l_{ij}^{-4} \eta_{ij} + \sum_{ij} \sum_{mn \in N_{ij}^I} (2\sqrt{P_i P_m} l_{ij}^{-2} l_{mj}^{-2} - P_m l_{mj}^{-4}) \eta_{ij} \eta_{mn} \\ & - \sum_{ij} \sum_{mn \in N_{ij}^I} \sum_{uv \in \{N_{ij}^I, N_{mn}^I\}} 2\sqrt{P_m P_u} l_{mj}^{-2} l_{uj}^{-2} \eta_{ij} \eta_{mn} \eta_{uv} \\ & + R_I(\underline{\sigma}, \underline{X}) + R_3(\underline{\sigma}, \underline{X}) + \beta \cdot \sum_{ij} \|\text{SINR}_{ij} - \text{SINR}_{th}\|, \end{aligned} \quad (1)$$

where $\eta_{ij} = (\sigma_{ij} + 1)/2$, N_{ij}^M is the neighboring dipoles within MAC range of an active dipole σ_{ij} ; and the dipoles outside the MAC range, denoted as N_{ij}^I , are allowed to be active concurrently, resulting in interference. Relevant interference neighbors are those whose power exceeds a threshold, i.e., $P_{th} \leq P_m \cdot l_{mj}^{-4}$. The minimum region that covers all relevant interference neighbors is referred to as “interference range.” The interference outside the inference range is denoted with a remainder $R_{I_{ij}}(\underline{\sigma}, \underline{X})$. With $R_I(\underline{\sigma}, \underline{X}) = \sum_{ij} R_{I_{ij}}(\underline{\sigma}, \underline{X})$, being the total contribution due to interference outside the interference range.

The total energy $H'(\underline{\sigma} | \underline{X})$ can now be related to probability $P(\underline{\sigma} | \underline{X})$ using an analogy between communication activities in ad hoc wireless networks and particles in statistical physics [2]. The probability distribution of particle systems obeys the Maxwell-Boltzmann distribution [2]. As a result, for a configuration Hamiltonian, the corresponding Boltzmann distribution is $P(\underline{\sigma} | \underline{X}) = \exp^{-H'(\underline{\sigma} | \underline{X})} / \sum_{\underline{\sigma}} \exp^{-H'(\underline{\sigma} | \underline{X})}$.

We now obtain the probability distribution of node positions $P(\underline{X} | \underline{\sigma}_0, \underline{X}_0)$, assuming that current node positions are conditionally independent of initial conditions, i.e., $P(\underline{X} | \underline{\sigma}_0, \underline{X}_0)$

$= P(\underline{X}|\underline{X}_0)$. With no management purposes, nodes' movement can be characterized by a two-dimensional random-walk around fixed positions, i.e., $\underline{X}_0$, where $P(\underline{X}|\underline{X}_0)$ is a multi-variate Gaussian distribution with an exponent $H(\underline{X}|\underline{X}_0) = (\underline{X} - \underline{X}_0)^T \cdot (\underline{X} - \underline{X}_0) / 2\sigma^2$, and the variance of node movement σ^2 . Management constraints make nodes move cooperatively to achieve a pre-defined constraint, e.g., 1-connected topology. The 1-connectivity can be achieved by a Yao-like graph, which can be implemented with

$$C(X_i, X_j) = \begin{cases} 0 & , \frac{|l_{ij} - l_{th}|}{l_{th}} < \epsilon_0 \text{ or } j \notin N_i^\theta \\ |l_{ij} - l_{th}| & , \text{otherwise} \end{cases} \quad (2)$$

where ϵ_0 is a small constant, l_{th} is a threshold, and N_i^θ is the set of the nearest neighboring nodes of node i for every angle θ ($\theta=90^\circ$ in this work). The extended Hamiltonian for the topology is $H'(\underline{X}|\underline{X}_0) = H(\underline{X}|\underline{X}_0) + \sum_i \sum_{j \in N_i^\theta} \zeta \cdot C(X_i, X_j)$, where ζ is a weighting constant.

With the derived Hamiltonians, the overall configuration Hamiltonian results in $H'(\underline{\sigma}, \underline{X} | \underline{\sigma}_0, \underline{X}_0) = \varsigma_\sigma \cdot H'(\underline{\sigma}|\underline{X}) + \varsigma_X \cdot H'(\underline{X}|\underline{X}_0)$, where ς_σ and ς_X are scaling constants, adjusting the Hamiltonians with different scales [2].

4. GRAPHICAL REPRESENTATION

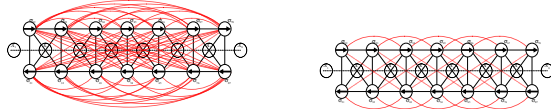
To determine the optimality of self-configuration, it suffices to examine whether the obtained likelihood function is factorizable over cliques. This can be done using the probabilistic graphical models widely studied in machine learning [1]. Specifically, a set of random variables, e.g., $\underline{X}$, is called Gibbs Random Field (GRF) if it obeys Gibbs distribution, $P(\underline{X}) = Z_0^{-1} \exp \frac{-H(\underline{X})}{T}$ [2].

Since the Boltzmann distribution of a network configuration obeys a Gibbs form, thus from Hammersley-Clifford theorem [2], a network configuration can be represented with two Markov Random Fields (MRFs), i.e., $(\underline{\sigma}|\underline{X})$ and $(\underline{X}|\underline{X}_0)$. The remaining question is if these MRFs are factorizable into small clique potentials [2].

Fig.1 (a) illustrates a one-dimensional network topology.



(a) MAC and Interference Neighborhood on Linear Topology



(b) With $R_I(\underline{\sigma}, \underline{X})$ (c) Without $R_I(\underline{\sigma}, \underline{X})$

Figure 1: Dependence of $(\underline{\sigma}, \underline{X})$

In Fig.1 (b), a link between two dipoles indicates their statistical dependence. Since link activities of all dipoles are mutually dependent, the graph is fully connected. However, the outside interference, $R_I(\underline{\sigma}, \underline{X})$, is relatively small compared to the first three terms in the configuration Hamiltonian of Equation (1). Moreover, the third-order term, i.e., $R_3(\underline{\sigma}, \underline{X})$, is also negligible compared to the second-order term. Hence, the resulting dependence now becomes local as shown in Fig.1 (c). And the system Hamiltonian can be well represented with only the first and second order terms, i.e., α_{ij} and $\alpha_{ij,mn}$, which define an approximation $P^l(\underline{\sigma}|\underline{X})$ with

an exponent $\hat{H}'(\underline{\sigma}|\underline{X}) = -\sum_{ij} \alpha_{ij} \cdot \eta_{ij} + \sum_{mn \in N_{ij}^I} \alpha_{ij,mn} \cdot \eta_{ij} \eta_{mn}$. The approximated MRF, $(\underline{\sigma}|\underline{X})$, is now the well-known second-order Ising model [2]. The following proposition shows the goodness of the approximation.

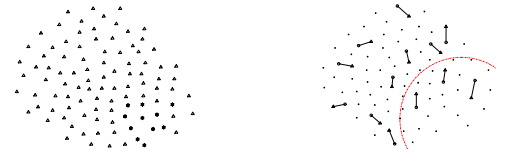
Proposition 1: Let l_{ij} be the distance between a signal source i and destination j of a dipole σ_{ij} ; and l_{mj} be the distance between an interference source m and signal destination j . Then $|\frac{H(\underline{\sigma}|\underline{X}) - H^l(\underline{\sigma}|\underline{X})}{H(\underline{\sigma}|\underline{X})}| \leq O(\max_{ij,mn} l_{ij}^{-2} l_{mj}^{-2})$, for $l_{mj} > l_{ij} > 1$. The proof is straightforward with simple algebra and thus omitted.

Next, for the 1-connected topology, the corresponding Hamiltonian, $H'(\underline{X}|\underline{X}_0)$, shows that the random field, $(\underline{X}|\underline{X}_0)$, is a second-order energy MRF [2]. Therefore, the coupled MRF $(\underline{\sigma}, \underline{X} | \underline{\sigma}_0, \underline{X}_0)$ can be fully described by an Ising model and a second-order MRF together, representing the nested local dependence with random bonds.

5. DISTRIBUTED ALGORITHM

The nearly optimal configuration is the one that maximizes the approximated likelihood function. Maximizing the global likelihood function reduces to maximizing local likelihood at cliques, i.e., for $1 \leq i, j \leq N$, $(\hat{X}_i(t+1), \hat{\sigma}_{ij}(t+1)) = \arg \max_{(X_i(t+1), \sigma_{ij}(t+1))} P^l(X_i(t+1), \sigma_{ij}(t+1) | X_{N_i}(t), \sigma_{N_i}(t))$. Therefore, the nearly optimal local rule $\prod_i g_i() = P^l()$. Stochastic relaxation is an optimal distributed algorithm through Gibbs sampling [1]. Now self configuration is viewed as local optimizations of Hamiltonian on cliques.

An important application of self-configuration is adaptive recovery from failures. Consider node failures from an optimal configuration. There is a trade-off between global optimization of network configuration and failure localization. Fig. 2 (a) shows the self-configured topology from initial



(a) Self-configuration and Failure (b) Self-Recovery

Figure 2: Self-Configuration and Recovery

randomness, where the failed nodes are marked by stars. Due to failure localization, Fig. 2 (b) shows that only nodes and links within the arc are involved in the recovery.

6. CONCLUSION

We find that a random-bond model is the probability distribution of the network configuration where link activities are coupled by random coefficients due to node positions. This model shows that the nested Markov dependence naturally appears in the ad hoc wireless networks. Thus, self-configuration is achieved in a fully distributed fashion through stochastic relaxation.

7. REFERENCES

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