Distributed Adaptive Network Performance with Static Topology and Unweighed Communication

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Abstract: Observation of adaptive behaviour and self-organizing in nature has led to using similar concepts in modern network systems. These concepts have been implemented in signal estimation, detection and network optimization. A possible application for signal detection based adaptive networks can be implemented in cognitive radio where it is important to detect the presence of the primary user activity. In this paper, we examine the performance of a distributed adaptive network with static topology and unweighed communication that computes the autocorrelation function of the primary user for further signal detection application in cognitive radio.

Key–Words: Cognitive radio, adaptive signal processing, adaptive networks, diffusion strategy, exponential averaging

1 Introduction

The concept of a cognitive radio networks is to allow secondary users to transmit when the primary user at a frequency band is not transmitting thus using the spectrum much more efficiently. A problem arises when the primary user starts to transmit and the secondary user should be able to detect the primary users activity. It has been proposed to use the method of spectral sensing to determine the activity of the primary user [1].

In order to improve the performance of sensing the primary signal, adaptive network algorithms have been proposed to enhance the detection probability [2]. This is achieved by exchanging estimation information between network agents that communicate with each other. Each node computes its own estimate and improves them by comparing and adding estimation results from other nodes. The communication follows certain rules and a certain topology [3].

Centralized solutions have been proposed to solve the estimation problem. The centralized method uses a central node referred to as “fusion centre” that is connected to all of the nodes and receives all the estimates that the nodes compute. The common estimate computed by the fusion centre is then fed back to all of the nodes in the network [4]. This method would require a node that has high processing power and connections between all nodes. However, in practical applications the network topology is often much more sparse and a method with low-complexity processing is desirable. The redundancy of the centralized solution is also difficult to achieve. In case of failure of the fusion centre the whole network is crippled. Therefore, decentralized solutions have been proposed such as incremental strategies, consensus strategies and diffusion strategies [6], [3].

Incremental strategies define a cyclic path through the nodes and data is optimized over this path. The current node in the cyclic path will receive the estimate from the previous node and adapt and then forward the result to the next node in the defined path. However, the incremental strategy suffers from NP-hard problem and is receptive to link and node failure [3].

Consensus strategy improve over incremental strategies by allowing network agents adapt at each iteration and allow communication between many adjacent nodes. Consensus strategies that rely on the use of two time-scales are unsuitable to use in real-time applications where measurement data continuously streams [6]. Consensus strategies that rely on single time-scale are able to perform well under certain conditions, but tend to suffer from instability. It is also shown that diffusion strategies with constant step size converge better than consensus strategies [6]. Therefore, we will in this paper focus on diffusion strategies.

Diffusion strategies allow the nodes to cooperate
and diffuse information in real-time. There have been proposed two schemes for diffusion - Adapt-then-combine (ATC) and Combine-then-Adapt (CTA). Diffusion methods are robust to link and node failures and are able to continue learning even when the cost function changes with time [3].

In this paper, we are interested in the performance of estimating the autocorrelation function of the primary signal in a adaptive network using an ATC diffusion strategy with unweighted communication between nodes. Estimating the autocorrelation function of the primary signal is useful for detection applications in cognitive radio [5]. The adaptive network will adapt using the exponential averaging algorithm and the step size of the adaptation will be constant to ensure the learning and adaptation of the network. We are going to compare it to the performance of the same network topology with no cooperation between network agents.

In this paper italic letters are used for scalars (e, E), lower case bold letters are denoting vectors (x) and capital bold letters are denoting matrices (G).

The remainder of the paper is organized as follows. Section 2 states the problem and describes the observed cooperative network. In Section 3 we present the results of our simulation study. The final section concludes the paper and summarizes the results of the simulations.

2 Problem Statement

Assume that there is a primary signal \( y(n) \) and a network of secondary agents, who can communicate with each other. The communication of the network agents is possible within a certain range so that each secondary user is connected to a subset of agents. The communication between network agents is lossless and noiseless. The nodes are identical in terms of processing power and physical attributes.

Complex amplitude of the signal received from the primary user at a location of \( k \)-th secondary user is given by

\[
s_k(n) = \beta_k y(n) + v_k(n),
\]

where \( \beta \) is the random channel amplification of the \( k \)-th channel with Gaussian distribution, \( v_k(n) \) is the additive white Gaussian noise (AWGN) at the location of \( k \)-th network agent. The channel amplification \( \beta \) and noise \( v_k(n) \) are independent of the signal \( y(n) \) and are uncorrelated.

Each network agent estimates the autocorrelation function of the primary signal, \( l \)-th lag of which is given by

\[
r_{l,k} = E[s_k(n)s_k^*(n-l)]
   = E[(\beta_k y(n) + v_k(n)) \cdot (\beta_k y^*(n-l) + v_k^*(n-l))]
   = \beta_k^2 E[y(n)y^*(n-l)] + E[v_k(n)v_k^*(n-l)].
\]

Normalizing the autocorrelation function with the zero lag element we arrive at

\[
r_{l,k} = \begin{cases} 
1, & l = 0 \\
\frac{\beta_k^2 E[y(n)y^*(n-l)] + E[v_k(n)v_k^*(n-l)]}{E[y(n)y^*(n)] + E[v_k(n)v_k^*(n)]}, & l > 0.
\end{cases}
\]

The estimate in each node \( k \) is computed at each iteration using the exponential averaging

\[
r_{l,k}(n) = (1 - \mu)r_{l,k}(n-1) + \mu s_k(n)s_k^*(n-l), \quad (4)
\]

where \( \mu \) is a constant step size and \( 0 < \mu < 1 \).

Each node in the network computes its own normalized autocorrelation function estimate at every iteration. Each node will also receive the normalized autocorrelation function estimates from other adjacent nodes in the network that have a connection with the node. In each node the estimates are then combined according to

\[
r_{l,k}(n) = \frac{\sum_{f=1}^{K} r_{f,k}(n) \cdot p_{f,k}}{\sum_{k=1}^{K} p_{f,k}}, \quad (5)
\]

where

\[
\sum_{f=1}^{K} p_{f,k} \quad \text{is the number of adjacent nodes,}
\]

\( r_{l,k}(n) \) is the average estimate at iteration \( n \),

\[
p_{f,k} = \begin{cases} 
1, & \text{if a connection between nodes is present} \\
0, & \text{if a connection between nodes is not present}
\end{cases}
\]

\( K \) is the number of nodes in the network and \( f \) signifies the node at which the averaging is done.

Substituting the average estimate (5) into the adaptive algorithm (4) we arrive at

\[
r_{l,k}(n) = (1 - \mu)\bar{r}_{l,k}(n-1) + \mu s_k(n)s_k^*(n-l). \quad (6)
\]

Equation (6) expresses the adaptive algorithm at node \( k \). At each iteration each node will thus compute their estimate based on the previous averaged estimate \( \bar{r}_{l,k}(n-1) \) and communicate and receive the computed estimate \( r_{l,k}(n) \) to and from their adjacent nodes to compute the new averaged estimate \( \bar{r}_{l,k}(n) \) (5).
3 Simulation results

Let us assume static topology which is shown in Fig. 1. From the topology it is seen that all of the 9 nodes share their estimate with themselves and communicate with their adjacent neighbours. The communication between nodes is full duplex.

The table of connections is expressed in Tabel 1. Value "1" reflects a connection between nodes and value "0" reflects the absence of a connection between nodes (5). The $f$ and $k$ values signify the connections between certain nodes.

In order to compare the performance of the proposed adaptive network the performance of the non-cooperating network is given in comparison. Assume the same condition and the same topology without any connection between adjacent nodes. The non-cooperative network is shown in Fig. 2.

The non-cooperative network is described below. Each node receives the primary signal (1), computes the autocorrelation function of the received signal (2) and normalizes the autocorrelation function (3). At each iteration $n$ the nodes compute the estimate of the autocorrelation function (4).

A small constant step size $\mu = 0.999$ is selected for the simulations. Each of the nodes channel attenuation $\beta_k$ is generated randomly and the signal to noise ratios for nodes is selected decreasingly with a step size of 2 dB starting from Node 1 to Node 9. The results are averaged over 100 iterations. The following figures Fig. 3, Fig. 4, Fig. 5 and Fig. 6 express the MSE convergence of the cooperative and non-cooperative networks at nodes 5-8 averaged across all of the values of the autocorrelation function.

Observing the figures Fig. 3 and Fig. 4 it can be deducted that the non-cooperating network performs better than the adaptive network. This is due to the fact that the nodes in question have adjacent nodes whose signal to noise ratios are poorer in respect to the observed node.
It is seen from Fig. 5 and Fig. 6 that the performance of the adaptive network is able to perform better than the non-cooperating network. Nodes 7-9 have the lowest signal to noise ratio and benefit from averaging the estimations with the adjacent nodes.

Dependant on the channel amplification $\beta_k$ and the AWGN $v_k(n)$ this algorithm will result in better estimates for the nodes that have adjacent nodes with better than average signal to noise ratio and worse estimates for nodes that have adjacent nodes with worse signal to noise ratio than average. The global convergence averaged across the nodes is given in Fig. 7. Overall the algorithm improves the performance of the network on average, but on a single node level the performance depends on the signal to noise ratio of adjacent nodes.

4 Conclusion

In this paper we have investigated the performance of estimating the autocorrelation function of the primary signal in a adaptive network using an ATC diffusion strategy with unweighed communication between nodes. As an example we used a static topology with 9 nodes and the nodes computed their estimates using the exponential averaging. The results were compared to a identical network with non-cooperating nodes. It is shown that the estimation performance of the nodes in cooperative network is dependent on signal to ratios of the node and its adjacent nodes. Nodes with better signal to noise ratio performed worse than the non-cooperating nodes and nodes with worse signal to noise ratio performed better than the non-cooperating nodes. Overall the algorithm improves the performance of the network on
average, but on a single node level the performance depends on adjacent nodes. The performance of the adaptive network could be improved by weighing the estimates by a local parameter.

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References:


