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ONLINE LEARNING ALGORITHM OF DYNAMIC BAYESIAN NETWORKS FOR NONSTATIONARY SIGNAL PROCESSING

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Abstract. *In this paper, we investigate a novel online estimation algorithm for dynamic Bayesian network (DBN) parameters, given as conditional probabilities. We sequentially update the parameter adjustment rule based on observation data. We apply our algorithm to two well known representations of DBNs: to a first-order Markov Chain (MC) model and to a Hidden Markov Model (HMM). A sliding window allows efficient adaptive computation in real time. We also examine the stochastic convergence and stability of the learning algorithm.*
Keywords: Dynamic Bayesian networks, Online estimation, Markov chain, Hidden Markov model, Convergence property

1. **Introduction.** A dynamic Bayesian network (DBN) is a graphical model of stochastic causal systems [1]. The model represents conditional probabilities for random variables of system states based on observation data. These probabilities are the DBN parameters that must be optimally estimated for modeling accuracy and reliable inference.

Although, there is no standard procedure for DBN parameter learning, in general, researchers have used Maximum Likelihood (ML) estimation [2] and the Expectation-Maximization (EM) algorithm [3]. The underlying scheme is to maximize likelihood with respect to the parameter vector for given observation data. These algorithms were successfully utilized for acoustic modeling with finite observation data [4]. However, online learning using these algorithms is difficult because of the heavy computational burden of the optimization routine. Moreover, the EM algorithm can settle at a local minimum and yield suboptimal parameters [3].

Applications of DBN include fault detection/diagnosis [5], control systems [6], probability density estimation [7], etc., where stochastic modeling is warranted. Many of these applications involve nonstationary statistics and a large data set. DBN modeling of such systems requires online learning and adaptation.

Surprisingly, few investigators have addressed online iterative learning. In [8], online learning algorithm for HMMs was explored using gradient optimization for likelihood maximization. The authors also incorporated the algorithm into the EM framework for online EM learning of HMMs. In [9], a recursive parameter estimate for HMMs based on extended least squares and recursive state prediction error minimization was developed. The authors proved that their algorithm was locally convergent and more computationally