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Recursive least-squares learning algorithms for neural networks

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Advanced Signal Processing Algorithms, Architectures, and Implementations
Franklin T. Luk
San Diego, CA | July 08, 1990

Abstract

abstract

This paper presents the development of a pair of recursive least squares (ItLS) algorithms for online training of multilayer perceptrons which are a class of feedforward artificial neural networks. These algorithms incorporate second order information about the

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training error surface in order to achieve faster learning rates than are possible using first order gradient descent algorithms such as the generalized delta rule. A least squares formulation is derived from a linearization of the training error function. Individual training pattern errors are linearized about the network parameters that were in effect when the pattern was presented. This permits the recursive solution of the least squares approximation either via conventional RLS recursions or by recursive QR decomposition-based techniques. The computational complexity of the update is $O(N^2)$ where N is the number of network parameters. This is due to the estimation of the $N \times N$ inverse Hessian matrix. Less computationally intensive approximations of the iLS algorithms can be easily derived by using only block diagonal elements of this matrix thereby partitioning the learning into independent sets. A simulation example is presented in which a neural network is trained to approximate a two dimensional Gaussian bump. In this example RLS training required an order of magnitude fewer iterations on average (527) than did training with the generalized delta rule (6 1 BACKGROUND Artificial neural networks (ANNs) offer an interesting and potentially useful paradigm for signal processing and pattern recognition. The majority of ANN applications employ the feed-forward multilayer perceptron (MLP) network architecture in which network parameters are "trained" by a supervised learning algorithm employing the generalized delta rule (GDI) [1 2]. The GDR algorithm approximates a fixed step steepest descent algorithm using derivatives computed by error backpropagation. The GDII algorithm is sometimes referred to as the backpropagation algorithm. However in this paper we will use the term backpropagation to refer only to the process of computing error derivatives. While multilayer perceptrons provide a very powerful nonlinear modeling capability GDR training can be very slow and inefficient. In linear adaptive filtering the analog of the GDR algorithm is the least-mean-squares (LMS) algorithm. Steepest descent-based algorithms such as GDR or LMS are first order because they use only first derivative or gradient information about the training error to be minimized. To speed up the training process second order algorithms may be employed that take advantage of second derivative or Hessian matrix information. Second order information can be incorporated into MLP training in different ways. In many applications especially in the area of pattern recognition the training set is finite. In these cases block learning can be applied using standard nonlinear optimization techniques [3 4 5].

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Topics

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