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Blind Estimation of Signal to Noise Ratio Using Time-Delay Radial Basis Connectionist Models

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Abstract: Signal-to-noise ratio (SNR) is an important parameter in mobile communication channels and is widely used in system performance evaluations. In this paper, the SNR of a communication channel is estimated using a radial basis function (RBF) neural network with a time-delay structure. In the proposed model, there is no need to have any prior knowledge of transmitted symbols for estimating SNR. This feature is one of the benefits of the proposed estimation model, as compared to transmitted data aided (TxDA) estimators. The performance index of the system, in terms of normalized mean squared error (NMSE) criterion, reaches 0.001 which is sufficient for systems which are based on link adaptation techniques in practical applications. The performance of the proposed time-delay RBF (TD-RBF) neural estimator is better than some other SNR estimation techniques, e.g. squared signal-to-noise variance (SNV) and second-fourth order moments (M_2M_4) estimators in the range of 18dB$\leq$SNR$\leq$30dB and maximum likelihood (ML-TxDA) and signal-to-variation ratio (SVR) estimators in the range of 8dB$\leq$SNR$\leq$30dB. The computational complexity of the proposed estimator is low, as compared to other classic estimation methods with low to moderate complexity, as well.

Key words: Estimation · Signal-to-noise ratio · Time-delay · Radial basis neural networks

INTRODUCTION

Nowadays, in modern telecommunication technology, e.g. third generation mobile communication systems, radio resource management is achieved by dynamic methods. Thus, the parameters of the system, like modulation and coding parameters or power control parameters, are determined and changed based on the dynamic conditions of telecommunication channel. This approach, which is mentioned as link adaptation or adaptive modulation and coding (AMC), improves the performance of the system as compared to classic and static systems and provides better usage of channel capacity in mobile communications [1]. In this way, it is necessary to have sufficient knowledge about the present conditions of channel [2] to determine the parameters of system, e.g. modulation and coding parameters [3].

The fading channel causes random power fluctuations and therefore performance degradation in the receiver [4-7]. A telecommunication channel can be characterized by different parameters such as instantaneous gain, channel frequency response, instantaneous traffic, signal-to-noise ratio (SNR) and fading parameters such as Doppler shift. Among these channel parameters, SNR is one of the most important parameters for mobile applications [8, 9].

Currently, there are different methods to estimate the SNR of a channel, e.g. iterative methods [10], high order momentums [11-14], limited time series [15] and linear prediction [16]. In order to assess the effectiveness of new proposed models for SNR estimation, it is usual to compare their performance with other classic SNR estimation methods, e.g. maximum-likelihood (ML), squared signal-to-noise variance (SNV), second-fourth order moments (M_2M_4) and signal-to-variation ratio (SVR) [17, 18]. Selecting a suitable method for SNR estimation often leads to a trade-off between system complexity and the exactness of estimation.

In this paper, a time-delay radial basis function (TD-RBF) neural network is used to estimate SNR of the channel. This paper is organized as follows. In Section 2, the blind estimation is described. The structure of proposed neural-based estimator model is detailed in Section 3. The simulation and empirical results are reported in Section 4. Conclusions are also drawn in Section 5.

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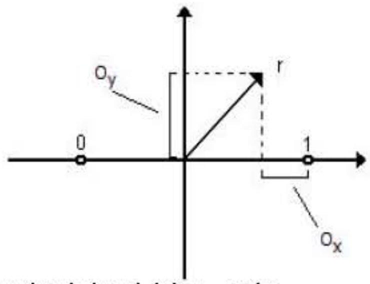

Fig. 1: Phasor diagram representing received signal {r}, o_x and o_y

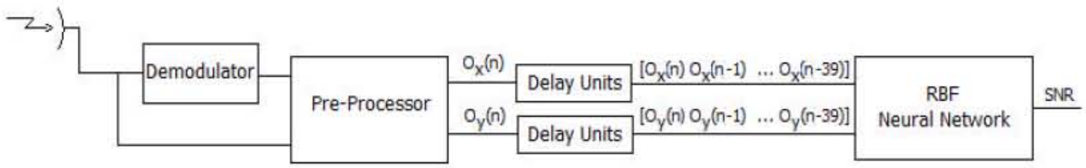

Fig. 2: Block diagram of the proposed SNR estimator system

BLIND ESTIMATION

In some of the classic SNR estimation methods, it is necessary to transmit agreed data, which is already known by the receiver. The estimator uses this data to predict SNR of the channel. For example, in one of these methods, the receiver estimates SNR of the channel by comparing the agreed data with received data and calculates the bit error rate (BER) of channel. Then, the receiver calculates SNR of the channel by a formal equation that relates SNR and BER. These methods which use transmitted data aided (TxDA) technique to estimate the SNR are not efficient for continuous and dynamic SNR estimation, because in these methods it is necessary to assign some part of the channel capacity to send agreed data [17].

In this paper, in order to prevent this loss of capacity, blind SNR estimation is used [19, 20]. This method is a received data aided (RxDA) SNR estimation of the channel with no need to send agreed data by the transmitter.

PROPOSED MODEL STRUCTURE

The neural model which is used in this study is a radial basis function (RBF) neural network with a time-delay structure (TD-RBF). In this paper, the modulation is assumed to be BPSK. It is obvious that this method can be generalized to the other digital modulation schemes [22].

In this study, in order to estimate SNR of the channel, two sets of data are used for training the neural model (phasor diagram depicted in Fig. 1): O_x; the difference of *Re*{received data} and *Re*{modulator output} and O_y; the difference of *Im*{received data} and *Im*{modulator output}.

The proposed SNR estimator model uses these two sets of data (O_x and O_y) and their time-delayed versions in its estimation (Fig. 2). As shown in Fig. 2, a packet of 40 time-delayed values of the first dataset (O_x) and a packet of 40 time-delayed values of the second dataset (O_y) are the inputs of the neural estimator model.

RESULTS

Training data is provided for SNRs in the range of 1dB to 30dB with the steps of 1dB. This range of SNR is suitable I n practical applications. For each value of SNR, simulation of a communication channel with additive white Gaussian noise (AWGN) is repeated 21 times for 7 different initial states of pseudo-random noise generation by Ziggurat algorithm [23]. It is noted that in this algorithm, a sequence of pseudo-random noise is generated from a specified recursive sequence. Choosing different numbers, as the first number (initial state) of this sequence, leads to different pseudo-random sequences. So, the total number of training data is 4410 ($30\times21\times7$) packets and each packet contains 80 data. This data is used for training the neural SNR estimator model.

To achieve an error margin of 0.05 at the level of packets, that is equivalent to 0.000625 at the level of data in packets, the number of hidden layer neurons is set to 125 in our experiments.

In order to test the system, 1260 packets are used that are generated in different SNRs and initial states of pseudo-random noise. This test data is generated for SNRs in the range of 1dB to 30dB with the steps of 1dB.

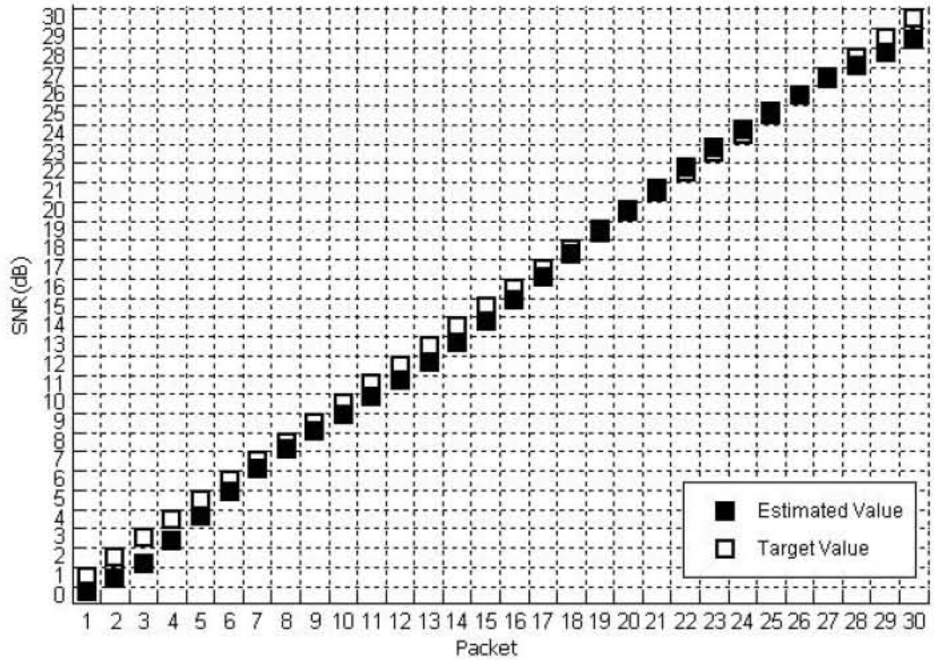

Fig. 3: Estimated values of SNR for 30 packets of test data in the range of 1dB-30dB

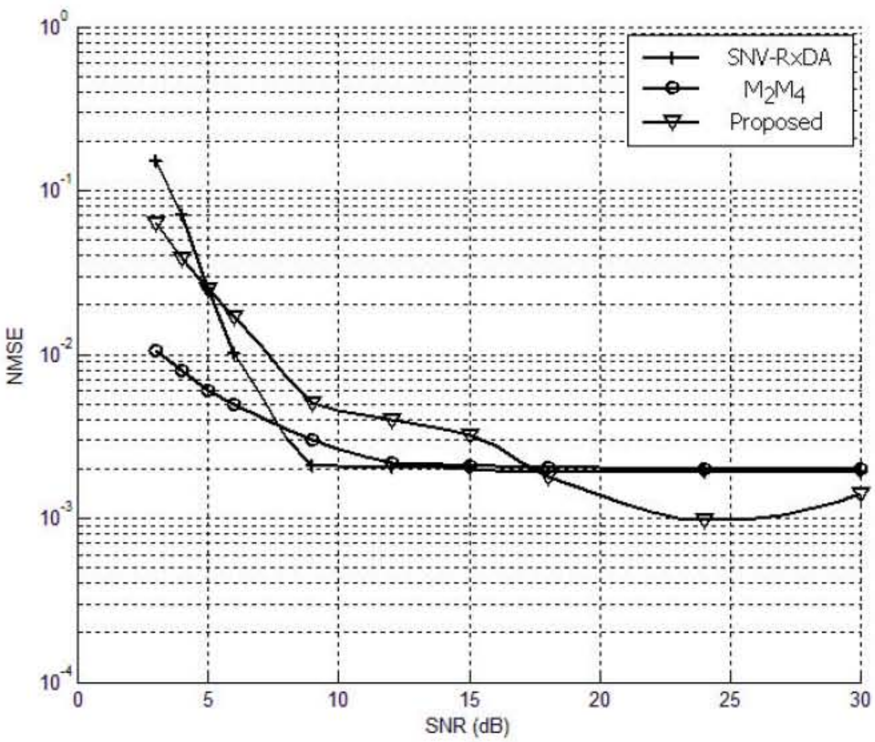

Fig. 4: Comparison of NMSE in SNR estimation by SNV, M_2M_4 and proposed methods

The specifications of pseudo-random noise are also different for the training and test datasets.

To show the performance in the test phase, 30 randomly selected test packets are used. The estimated SNR values in this experiment are shown in Fig. 3 by filled boxes. The target values in this experiment are shown in Fig. 3 by the blank boxes, as well.

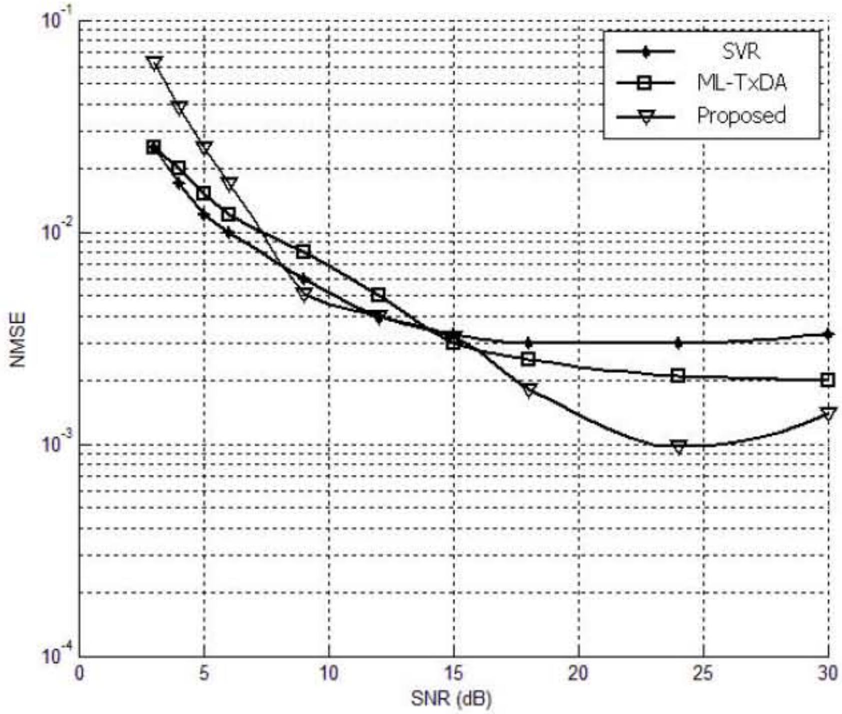

Fig. 5: Comparison of NMSE in SNR estimation by SVR, ML-TxDA and proposed methods

As shown in Fig. 3, the estimator has not the same performance for different SNRs. The best performance is achieved in the range of 17dB≤SNR≤27dB. In order to assess the quality of estimation in different values of SNR, the normalized mean squared error (NMSE) is calculated for the test packets.

The performance of the proposed model, in terms of NMSE averaged over 1260 packets, is compared to four classic estimation methods: squared signal-to-noise variance (SNV), second-fourth order moments (M_2M_4), signal-to-variation ratio (SVR) and maximum-likelihood (ML) (Fig. 4 and Fig. 5).

As shown in Fig. 4, the proposed model has better performance than SNV and M_2M_4 estimators in the range of 18dB≤SNR≤30dB. The proposed model has better performance than SRV and ML-TxDA estimators in the range of 8dB≤SNR≤30dB, as well (as shown in Fig. 5). By increasing the SNR values, the NMSE of estimation decreases and becomes 0.001 in the range of 20dB≤SNR≤30dB.

CONCLUSIONS

In this paper, a radial basis neural network with time-delay structure was used to estimate signal-to-noise ratio in a dynamic communication channel. In this way, estimation was performed by a blind method, which was the advantage of the proposed estimator as compared to TxDA estimators. The error performance of this model was investigated and compared to four classic methods for different SNR values (Fig. 6).

As shown in Fig. 6, the normalized mean squared errors of estimation were averaged over different SNR ranges for the proposed model and four different methods. The simulation results showed that the proposed time-delay radial basis function (TD-RBF) connectionist model performed better than other methods in the range of SNR≤16dB. The error performance of the proposed model, in terms of NMSE, was between 0.0005 and 0.005 in the range of SNR≤8dB, which is suitable in practical applications. By employing a connectionist model, the computational complexity of the proposed model, as compared to classic methods [24], was reduced too (Table 1).

Table 1: Computational complexity of four classic estimators and the proposed model [24]

Estimation method	Computational complexity
ML-TxDA	Low to moderate
M_2M_4	Low to moderate
SNV-RxDA	Low
SVR	Low to moderate
Proposed TD-RBF connectionist model	Low

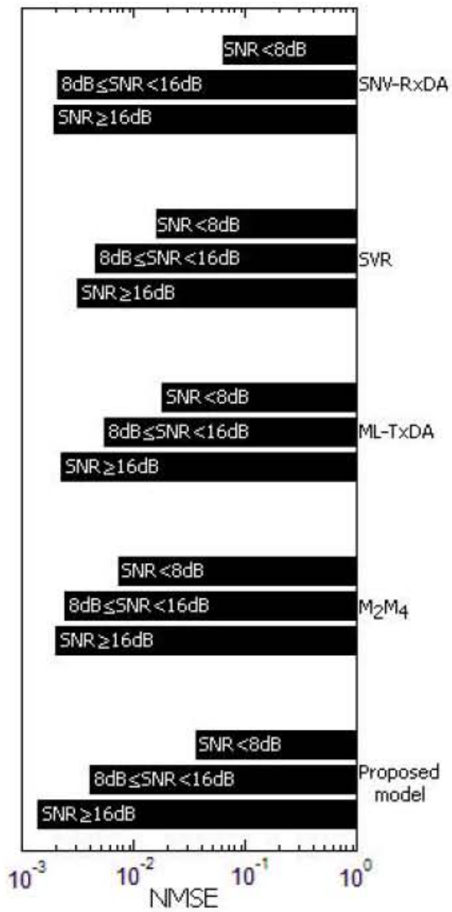

Fig. 6: NMSE averaged over 3 ranges of SNR values-Four classic estimation methods and the proposed model

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