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A new pre-whitening transform domain LMS algorithm and its application to speech denoising

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A B S T R A C T

In this paper, we propose a new pre-whitening transform domain LMS algorithm. The main idea is to introduce a pre-whitening using a simple finite impulse response decorrelation filter of order one before applying the transform to reinforce its decorrelation. The resulting algorithm has the advantage of using any transform even with low decorrelation. This advantage can be exploited to consider transforms having lower computational and structural complexities than those of the classical transforms. For this purpose, we also investigate the use of other transforms, namely the parametric Fourier and Hartley transforms. This investigation is accomplished by studying the eigenvalue spreads obtained by a given parametric transform and then finding the value of the parameter corresponding to the minimum eigenvalue spread, which is equivalent to the best mean square error (MSE) convergence behavior. This approach provides new attractive transforms for the proposed algorithm. Moreover, we consider the adaptive speech denoising as an application to evaluate the performance of the proposed algorithm. The comparisons between the proposed and conventional algorithms for different transforms are performed in terms of the computational complexity, MSE convergence speed, reached steady state level, residual noise in the denoised signal, steady state excess MSE, misadjustment and output SNR.

1. Introduction

The least mean square (LMS) algorithm is the mostly used in the adaptive filtering for its simplicity and robustness [1]. However, it has a slow convergence in the case of highly correlated input signals [2,3]. This is due to the fact that the autocorrelation matrix of the input signal has a large eigenvalue spread. To overcome this problem by reducing the eigenvalue spread, whitening or decorrelated adaptive algorithms have been proposed for time-domain LMS [4–6]. In [4], the authors proposed a joint decorrelation of both the input and error signals. The decorrelation is achieved in the time domain using an adaptive decorrelation filter based on the concept of prediction. The resulting decorrelated normalized LMS (NLMS) structure has the advantage of improving the mean square error (MSE) convergence speed and steady state compared to the conventional LMS and NLMS algorithms. The decorrelation of the input signal can also be achieved by an orthogonal transformation followed by power normalization [7]. These two operations have led to a new configuration named transform-domain LMS (TDLMS) adaptive filters, which outperform the time-domain LMS adaptive filters in terms of the MSE convergence speed and steady state [8–10]. The orthogonal transforms such as the discrete Fourier transform (DFT), the discrete Hartley transform (DHT) and the discrete cosine transform (DCT) have been used in the TDLMS [7]. The resulting adaptive filters have been named as DFT–LMS, DHT–LMS and DCT–LMS, respectively [11]. The convergence speed of these filters depends on the used transform [8,11,12]. In general, the DCT–LMS filter presents a convergence performance better than those of the DFT–LMS and DHT–LMS filters [11]. This is mainly due to the fact that the DCT is suboptimal in terms of decorrelation [13,14]. Therefore, it is highly desirable to use in the TDLMS adaptive filters a transform having better decorrelation. However, the existing transforms are fixed and hence it is not possible to increase their decorrelation ability. Since the introduction of a decorrelation in the time-domain LMS has brought interesting improvements, it is important to investigate the introduction of such a decorrelation in the TDLMS. However, to the best of author's knowledge, this investigation has not been reported in the literature.

One of the applications of LMS adaptive filters is speech ;denoising. It is a very crucial operation to enhance the quality and intelligibility of the voice and reduce communication fatigue in modern communication systems such as mobile phones, hands-free

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telephony and voice-controlled systems, which are generally used in noisy environments [15]. Most of the audio frequency acoustic noises, such as computer fan noise and noise from people and cars, have low-frequency spectra and hence are colored [15,16]. These noises often corrupt the speech signal, which is also colored. Therefore, it is important to consider colored noises in designing speech denoising techniques.

In this paper, we propose a new pre-whitening TDLMS (PW-TDLMS) algorithm. It maintains the structure of the conventional TDLMS algorithm and introduces a pre-whitenning before applying the transform. This is a novel and interesting strategy to reinforce the decorrelation of the used fixed transform in the TDLMS. The proposed pre-whitening is achieved by using a simple finite impulse response (FIR) decorrelation filter of order one based on a fixed prediction concept. The resulting PW-TDLMS has the advantage of using any transform even with low decorrelation. For this purpose, we investigate the use of other transforms such as the parametric DFT and DHT transforms [17] and study the performance of the proposed PW-TDLMS algorithm in terms of MSE convergence speed and steady state. We carry out this comparative study by considering adaptive speech denoising as an application of the proposed algorithm and show the simulation results of the proposed PW-TDLMS and TDLMS for different transforms. Moreover, we compute the eigenvalue spread of the autocorrelation matrix obtained after applying the parametric DFT or DHT transform and power normalization in the case of highly correlated Markov-1 noise, which is equivalent to the first order autoregressive (AR) process [11], for different values of the independent parameter of the transform. The transform with the value of the parameter corresponding to a good compromise between the eigenvalue spread and computational complexity is selected for the proposed PW-TDLMS. It should be noted that the eigenvalue spreads in the case of the DCT and classical DFT and DHT transforms are known in the literature [9,11,18].

The reminder of this paper is organized as follows. Section 2 briefly presents the parametric DFT and DHT. In Section 3, we analyze the TDLMS adaptive filter by considering the stability, steady state and convergence performances in the case of a first order AR process. For the convergence analysis, we review the eigenvalue spreads in the cases of the DFT, DHT and DCT, and then find the eigenvalue spreads in the cases of the parametric DFT and DHT. The proposed PW-TDLMS adaptive filter is developed and compared with the conventional TDLMS adaptive filter in Section 4 in terms of the eigenvalue spreads in the cases of the DCT, DFT, DHT, parametric DFT and DHT transforms. Section 5 presents the computational complexities of the DCT–LMS and proposed parametric DHT-based PW-LMS algorithms. In order to compare the performance of the proposed PW-TDLMS with that of the TDLMS for different transforms, we consider in Section 6 the speech denoising application for the cases of speech-like and real speech signals. The simulation results and comparisons are given therein in terms of the MSE convergence speed, reached steady state level, residual noise in the denoised signal, steady state excess MSE, misadjustment and output SNR. Some concluding remarks are given in Section 7.

2. Parametric discrete Fourier and Hartley transforms

The three-parameter DFT transform of a complex sequence $x(k)$ of order $N = 2^r$, $r > 3$, is defined in [17] as

$$X^{a,b,c}(n)=\sum_{k=0}^{N-1} x(k) v_{\mathbf{F}^{a,b,c}}(nk \bmod N),\ 0 \le n \le N-1 \tag{1}$$

where $v_{\mathbf{F}^{a,b,c}}(i)$, $0 \le i \le N-1$, are the entries of the parametric kernel vector given by

$$\mathbf{V}_{\mathbf{F}^{a,\,b,\,c}} = \begin{bmatrix} 1 & \mathbf{V} & c & -j\mathbf{V} & -1 & -\mathbf{V} & -c & j\mathbf{V} \end{bmatrix} \tag{2}$$

with the vector

$$\mathbf{V}=\begin{bmatrix} W_N^1 & \cdots & W_N^{(N/16)-1} & a & W_N^{(N/16)+1} & \cdots & W_N^{(N/8)-1} & b & W_N^{(N/8)+1} & \cdots & W_N^{(3N/16)-1} & -ja^* & W_N^{(3N/16)+1} & \cdots & W_N^{(N/4)-1} \end{bmatrix},$$

$W_N=\exp(-j(2\pi/N))$, $j=\sqrt{-1}$, $(.)^*$ denotes the complex conjugate transpose, and a, b and c are three nonzero parameters. The matrix form of (1) can be written as

$$\mathbf{X}^{a,b,c}=\mathbf{F}_N^{a,b,c}\mathbf{x} \tag{3}$$

where the entries of the three-parameter matrix $\mathbf{F}_N^{a,b,c}$ are $f_N^{a,b,c}(n,k) = v_{\mathbf{F}^{a,b,c}}(nk \bmod N)$, $0 \le n, k \le N-1$. Since the parametric transform defined by (1) or (3) possesses three parameters that can arbitrarily be chosen from the complex plane, a large number of new transforms with different features can be obtained. If the three parameters are chosen as $a=W_N^{N/16}$, $b=W_N^{N/8}$ and $c=W_N^{N/4}$, then the parametric transform reduces to the classical DFT. If the values of the three parameters are arbitrarily chosen from the unit circle, then the parametric transform reduces to a three-parameter unitary transform. An interesting special case of this transform is obtained in [17] when $a=e^{j\alpha}$, with α being an arbitrary real-valued parameter, $b=W_N^{N/8}$ and $c=W_N^{N/4}$. Let $\mathbf{F}_N^{\alpha}$ be the matrix operator of this unitary transform, which is nothing but the classical DFT parameterized by one parameter and then denoted by DFT$^{\alpha}$. The matrix operator $\mathbf{H}_N^{\alpha}$ of the one-parameter DHT is defined in [17] as

$$\mathbf{H}_N^{\alpha}=\mathrm{Re}(\mathbf{F}_N^{\alpha})-\mathrm{Im}(\mathbf{F}_N^{\alpha}) \tag{4}$$

The corresponding transform denoted by DHT$^{\alpha}$ is involutory, i.e., $\mathbf{H}_N^{\alpha}\mathbf{H}_N^{\alpha}=N\mathbf{I}_N$, with $\mathbf{I}_N$ is an identity matrix. It is obvious that $\mathbf{F}_N^{-\pi/8}$ is the classical DFT matrix and thus, $\mathbf{H}_N^{-\pi/8}$ is the classical DHT matrix, and hence, the classical DFT and DHT correspond to DFT$^{-\pi/8}$ and DHT$^{-\pi/8}$, respectively.

3. Transform domain LMS adaptive filter analysis

In the TDLMS adaptive filter presented in Fig. 1, the correlated tap delayed input vector $\mathbf{x}_k=[x_k, x_{k-1}, \ldots, x_{k-N+1}]^T$ is transformed into the vector $\mathbf{u}_k=\mathbf{T}_N\mathbf{x}_k$ using a fixed data-independent orthogonal transform matrix $\mathbf{T}_N$, where N is the filter length. The resulting vector $\mathbf{u}_k$ is less correlated then the vector $\mathbf{x}_k$. The transformed vector is then power normalized using the diagonal matrix $\mathbf{P}_k$ defined in [9,11,19] as

$$\mathbf{P}_k=\mathrm{diag}\left(\left[\sigma_k^2(i), i=0,1,\ldots,N-1\right]\right) \tag{5}$$

where $\sigma_k^2(i)$is the power estimate of the ith input $u_k(i)$, which can