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Research Article

Frequency-Domain Adaptive Algorithm for Network Echo Cancellation in VoIP

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We propose a new low complexity, low delay, and fast converging frequency-domain adaptive algorithm for network echo cancellation in VoIP exploiting MMax and sparse partial (SP) tap-selection criteria in the frequency domain. We incorporate these tap-selection techniques into the multidelay filtering (MDF) algorithm in order to mitigate the delay inherent in frequency-domain algorithms. We illustrate two such approaches and discuss their tradeoff between convergence performance and computational complexity. Simulation results show an improvement in convergence rate for the proposed algorithm over MDF and significantly reduced complexity. The proposed algorithm achieves a convergence performance close to that of the recently proposed, but substantially more complex improved proportionate MDF (IPMDF) algorithm.

1. INTRODUCTION

The popularity of voice over internet protocol (VoIP) coupled with an increasing expectation for natural communication over packet-switched networks has called for improvement in VoIP technologies in recent years. As network systems migrate from traditional voice telephony over public switch telephone network (PSTN) to packet-switched networks for VoIP, improving the quality of services (QoS) for VoIP has been and will remain a challenge [1, 2]. As described in [1], several factors that can affect the QoS for VoIP include the choice of speech coder-decoders (codecs) [3], algorithmic processing delay [4], and packet loss [5], where the algorithmic delay is one of the significant factors for determining the budget for delay introduced by network echo cancellers. The problem of network echo is introduced by the impedance mismatch between the 2- and 4-wire circuits of a network hybrid [6], which occurs in VoIP systems, where analog phones are involved in PC-to-phone or phone-to-phone connections [7], where "PC" represents all-digital terminals. Acoustic echo, on the other hand, occurs when hands-free conversations are conducted [8]. Transmission and algorithmic processing cause the echo to be transmitted back to the originator with a delay, hence impeding effective communication. As a result, network echo cancellation for IP networks has received increased attention in recent years. For effective network echo cancellation (NEC), adaptive filters such as shown in Figure 1 have been employed for the estimation of network impulse response. Using the estimated impulse response, a replica of the echo is generated and subtracted from the far-end transmitted signal. The main aim of this work is therefore to address the problem of (NEC) with reduced complexity and low algorithmic delay through the use of adaptive algorithms.

In VoIP systems, where traditional telephony equipment is connected to the packet-switched network, the resulting network impulse response such as shown in Figure 2 is typically of length 64–128 milliseconds. This impulse response exhibits an "active" region in the range of only 8–12 milliseconds duration, and, consequently, it is dominated by "inactive" regions, where magnitudes are close to zero making the impulse response sparse. The "inactive" region is principally due to the presence of bulk delay caused by unknown network propagation, encoding, and jitter buffer delays [7]. One of the first algorithms which exploits this sparse nature for the identification of network impulse

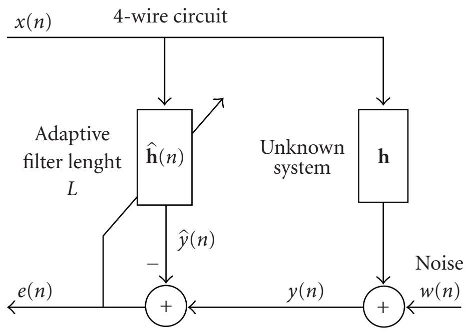


Figure 1: Network echo cancellation.

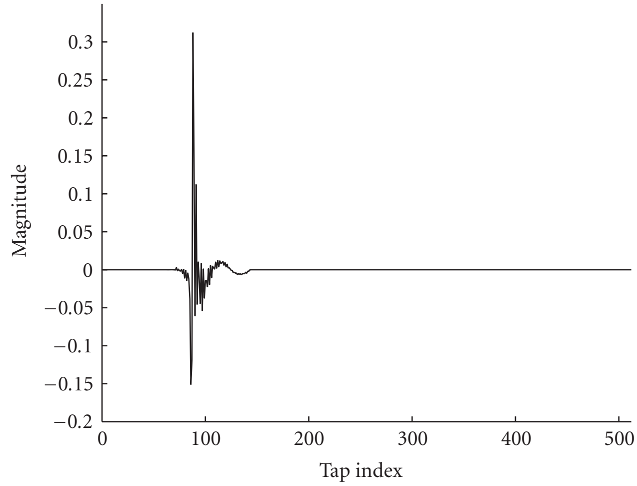


Figure 2: A sparse network echo impulse response, sampled at 8 kHz.

responses is the proportionate normalized least-mean-square (PNLMS) algorithm [9], where each filter coefficient is updated with a step-size which is proportional to the coefficient magnitudes. The PNLMS algorithm is then shown to outperform classical adaptive algorithms with a uniform step-size across all filter coefficients such as the normalized least-mean-square (NLMS) algorithm for NEC application [9]. Although the PNLMS algorithm achieves fast initial convergence, its rate of convergence reduces significantly. This is due to the slow convergence of filter coefficients having small magnitudes. To mitigate this problem, subsequent improved versions such as the improved PNLMS (IPNLMS) [10] and the improved IPNLMS [11] algorithms were proposed. These algorithms share the same characteristic of introducing a controlled mixture of proportionate (PNLMS) and nonproportionate (NLMS) adaptation. Consequently, these algorithms perform better than PNLMS for sparse impulse responses.

The increase in VoIP traffic in recent years has resulted a high demand for high density NEC in which it is desirable to run several hundred echo cancellers in one processor core. Defining L as the length of the impulse response, the PNLMS and IPNLMS algorithms require approximately $\mathcal{O}(3L)$ and $\mathcal{O}(4L)$ number of multiplications per sample iteration respectively compared to $\mathcal{O}(2L)$ for the substantially slower converging NLMS algorithm. Hence, in order to reduce the computational complexity of PNLMS and IPNLMS, the sparse partial update NLMS (SPNLMS) algorithm was recently proposed [12], which combines two adaptation strategies: sparse adaptation for improving rate of convergence and partial-updating for complexity reduction. For the majority of adapting iterations, under the sparse partial (SP) adaptation, only those taps corresponding to tap-inputs and filter coefficients both having large magnitudes are updated. However, from time to time the algorithm gives equal opportunity for the coefficients with smaller magnitude to be updated by employing MMax tap-selection [13]. This only updates those filter taps corresponding to the $M < L$ largest magnitude tap-inputs. It is noted that partial update strategies have also been applied to the filtered-X LMS (FxLMS) algorithms as described in [14, 15]. Other ways to reduce the complexity of adaptive filtering algorithm include the use of a shorter adaptive filter to model only the active region of the sparse impulse responses as described in [16].

It is well known that frequency-domain adaptive filtering such as the fast-LMS (FLMS) algorithm [17] offers an attractive means of achieving efficient implementation. In contrast to time-domain adaptive filtering algorithms, frequency-domain adaptive algorithms incorporate block updating strategies, whereby the fast-Fourier transform (FFT) algorithm [18] is used together with the overlap-save method [19, 20]. However, one of the main drawbacks of these frequency-domain approaches is the delay introduced between the input and output, which is generally equal to the length of the adaptive filter. Since reducing the algorithmic processing delay for VoIP applications is crucial, frequency-domain adaptive algorithms with low delay are desirable especially for the identification of long network impulse responses. The multidelay filtering (MDF) algorithm [21] has been proposed in the context of acoustic echo cancellation for mitigating the problem of delay. This algorithm partitions an adaptive filter of length L into K blocks each of length N. As a result, the delay of MDF algorithm is reduced by a factor of K compared to FLMS. The benefit of low delay for MDF over FLMS in the context of NEC has been shown in [22].

The aim of this work is to develop a *low complexity*, *low delay*, and *fast converging* adaptive algorithm for identifying sparse impulse responses presented in the problem of NEC for VoIP applications. We achieve this by incorporating the MMax and SP tap-selection into the frequency-domain MDF structure. As will be shown in this work, applying the MMax and SP tap-selection to frequency-domain adaptive filtering presents significant challenges since the time-domain sparse impulse response is not necessarily sparse in the frequency domain. We first review in Section 2 the SPNLMS and MDF algorithms. We then propose, in Section 3.1, to incorporate MMax tap-selection into MDF structure for complexity reduction. We show how this can be achieved using two approaches and we compare their tradeoffs in terms of complexity and performance. We next illustrate, in Section 3.2, how the sparseness of the Fourier transformed impulse response varies with the number of blocks K in the MDF structure. Utilizing these results, we show how the SP tap-selection can be incorporated into the MDF structure for fast convergence and low delay. The computational complexity for the proposed algorithm is discussed in Section 3.3. In Section 4, we present the simulation results and discussions using both colored Gaussian noise (CGN) and speech inputs for NEC. Finally, conclusions are drawn in Section 5.

2. REVIEW OF THE SPNLMS AND MDF ALGORITHMS

We first review the problem of sparse system identification. With reference to Figure 1, we define tap-input vector $\mathbf{x}(n)$, network impulse response $\mathbf{h}$, and coefficients of adaptive filter $\widehat{\mathbf{h}}(n)$ as

$$\begin{aligned}\mathbf{x}(n) &= [x(n)\cdots x(n-L+1)]^T,\\ \mathbf{h} &= [h_0\cdots h_{L-1}]^T,\\ \widehat{\mathbf{h}}(n) &= [\widehat{h}_0(n)\cdots \widehat{h}_{L-1}(n)]^T,\end{aligned} \tag{1}$$

where L is the length of $\mathbf{h}$ and $[\cdot]^T$ is defined as vector/matrix transposition. The adaptive filter $\widehat{\mathbf{h}}(n)$, which is chosen to be of the same length as $\mathbf{h}$, will model the unknown impulse response $\mathbf{h}$ using the near-end signal

$$y(n) = \mathbf{x}^T(n)\mathbf{h} + w(n), \tag{2}$$

where $w(n)$ is the additive noise.

2.1. The SPNLMS algorithm

The sparse partial (SP) update NLMS (SPNLMS) algorithm [12] utilizes the sparse nature of network impulse response. This algorithm incorporates two updating strategies: MMax tap-selection [13] for complexity reduction and SP adaptation for fast convergence. Although it is normal to expect that adapting filter coefficients using partial-updating strategies suffers from degradation in convergence performance, it was shown in [12] that such degradation can be offset by the SP tap-selection.

The updating equation for SPNLMS is given by

$$\widehat{\mathbf{h}}(n) = \widehat{\mathbf{h}}(n-1) + \mu\frac{\mathbf{Q}(n)\mathbf{x}(n)e(n)}{\|\mathbf{Q}(n)\mathbf{x}(n)\|_2^2+\delta}, \tag{3}$$

where μ is the step-size, δ is the regularization parameter and $\|\cdot\|_2$ is defined as the l_2-norm. As shown in Figure 1, the a priori error is given by

$$e(n) = y(n) - \mathbf{x}^T(n)\widehat{\mathbf{h}}(n-1). \tag{4}$$

The $L\times L$ tap-selection matrix

$$\mathbf{Q}(n) = \operatorname{diag}\{q_0(n)\cdots q_{L-1}(n)\} \tag{5}$$

in (3) determines the step-size gain for each filter coefficient and is dependent on the MMax and SP updating strategies for SPNLMS. The relative significance of these strategies is controlled by the variable $T\in\mathbb{Z}^+$ such that for $\operatorname{mod}(n,T)=0$, elements $q_i(n)$ for $i=0,\dots,L-1$ are given by

$$q_i(n) = \begin{cases}1 & i\in\{\text{indices of the } M_1 \text{ maxima of } |x(n-i)|\},\\ 0 & \text{otherwise},\end{cases} \tag{6}$$

and for $\operatorname{mod}(n,T)\neq 0$,

$$q_i(n) = \begin{cases}1 & i\in\{\text{indices of the } M_2 \text{ maxima of}\\ & \qquad |x(n-i)\widehat{h}_i(n-1)|\},\\ 0 & \text{otherwise}.\end{cases} \tag{7}$$

The variables M_1 and M_2 define the number of selected taps for MMax and SP, respectively, and the MMax tap-selection criteria given by (6) for the time-domain is achieved by sorting $\mathbf{x}(n)$ using, for example, the SORTLINE [23] and short sort [24] routines. It has been shown in [12] that, including the modest overhead for such sorting operations, the SPNLMS algorithm achieves lower complexity than NLMS. To summarize, SPNLMS incorporates MMax tap-selection given by (6) and SP tap-selection given by (7) for complexity reduction and fast convergence, respectively.

2.2. The MDF algorithm

The MDF algorithm [21] mitigates the problem of delay inherent in FLMS [17] by partitioning the adaptive filter into K subfilters each of length N, with $L=KN$ and $K\in\mathbb{Z}^+$. As a consequence of this partitioning, the delay for the MDF is reduced by a factor of K compared to FLMS. To describe the MDF algorithm, we define m as the frame index and the following time-domain quantities given by

$$\mathbf{X}(m) = [\mathbf{x}(mN)\cdots\mathbf{x}(mN+N-1)], \tag{8}$$

$$\mathbf{y}(m) = [y(mN)\cdots y(mN+N-1)]^T, \tag{9}$$

$$\widehat{\mathbf{h}}(m) = [\widehat{\mathbf{h}}_0^T(m)\cdots\widehat{\mathbf{h}}_{K-1}^T(m)]^T, \tag{10}$$

$$\begin{aligned}\widehat{\mathbf{y}}(m) &= [\widehat{y}(mN)\cdots\widehat{y}(mN+N-1)]^T\\ &= \mathbf{X}^T(m)\widehat{\mathbf{h}}(m),\end{aligned} \tag{11}$$

$$\mathbf{e}(m) = \mathbf{y}(m) - \widehat{\mathbf{y}}(m). \tag{12}$$

We also define a $2N\times 1$ tap-input vector

$$\boldsymbol{\chi}(m-k) = [x(mN-kN-N)\cdots x(mN-kN+N-1)]^T, \tag{13}$$

where $k=0,\dots,K-1$ is defined as the block index and the subfilters in (10) are given as

$$\widehat{\mathbf{h}}_k(m) = [\widehat{h}_{kN}(m)\cdots\widehat{h}_{kN+N-1}(m)]^T. \tag{14}$$

We next define $\mathbf{F}_{2N}$ as the $2N\times 2N$ Fourier matrix and a $2N\times 2N$ matrix

$$\underline{\mathbf{D}}(m-k) = \operatorname{diag}\{\mathbf{F}_{2N}\boldsymbol{\chi}(m-k)\} = \operatorname{diag}\{\underline{\boldsymbol{\chi}}(m-k)\}, \tag{15}$$

with diagonal elements containing the Fourier transform of $\boldsymbol{\chi}(m-k)$ for the kth block. We also define the following frequency-domain quantities [8]

$$\begin{gathered}
\underline{\mathbf{y}}(m)=\mathbf{F}_{2N}\begin{bmatrix}\mathbf{0}_{N\times 1}\\ \mathbf{y}(m)\end{bmatrix},\qquad \underline{\widehat{\mathbf{h}}}_k(m)=\mathbf{F}_{2N}\begin{bmatrix}\widehat{\mathbf{h}}_k(m)\\ \mathbf{0}_{N\times 1}\end{bmatrix},\\
\underline{\mathbf{e}}(m)=\mathbf{F}_{2N}\begin{bmatrix}\mathbf{0}_{N\times 1}\\ \mathbf{e}(m)\end{bmatrix},\\
\mathbf{G}^{01}=\mathbf{F}_{2N}\mathbf{W}^{01}\mathbf{F}_{2N}^{-1},\quad \mathbf{W}^{01}=\begin{bmatrix}\mathbf{0}_{N\times N} & \mathbf{0}_{N\times N}\\ \mathbf{0}_{N\times N} & \mathbf{I}_{N\times N}\end{bmatrix},\\
\mathbf{G}^{10}=\mathbf{F}_{2N}\mathbf{W}^{10}\mathbf{F}_{2N}^{-1},\quad \mathbf{W}^{10}=\begin{bmatrix}\mathbf{I}_{N\times N} & \mathbf{0}_{N\times N}\\ \mathbf{0}_{N\times N} & \mathbf{0}_{N\times N}\end{bmatrix},
\end{gathered}\tag{16}$$

where $\mathbf{0}_{N\times N}$ is the $N\times N$ null matrix and $\mathbf{I}_{N\times N}$ is the $N\times N$ identity matrix. The MDF algorithm is then given by [21]

$$\underline{\mathbf{e}}(m)=\underline{\mathbf{y}}(m)-\mathbf{G}^{01}\sum_{k=0}^{K-1}\underline{\mathbf{D}}(m-k)\underline{\widehat{\mathbf{h}}}_k(m-1),\tag{17}$$

$$\mathbf{S}(m)=\lambda\mathbf{S}(m-1)+(1-\lambda)\underline{\mathbf{D}}^*(m)\underline{\mathbf{D}}(m),\tag{18}$$

$$\mathbf{P}(m)=\mathbf{S}(m)+\delta\mathbf{I}_{2N\times 2N}=\operatorname{diag}\{p_0(m)\cdots p_{2L-1}(m)\},\tag{19}$$

$$\underline{\widehat{\mathbf{h}}}_k(m)=\underline{\widehat{\mathbf{h}}}_k(m-1)+\mu\mathbf{G}^{10}\underline{\mathbf{D}}^*(m-k)\mathbf{P}^{-1}(m)\underline{\mathbf{e}}(m),\tag{20}$$

where $*$ denotes complex conjugate, $0\ll\lambda<1$ is the forgetting factor and $\mu=\beta(1-\lambda)$ is the step-size with $0<\beta\leq 1$ [21]. Letting σ_x^2 be the input signal variance, the initial regularization parameters [8] are $\mathbf{S}(0)=\sigma_x^2/100$ and $\delta=20\sigma_x^2N/L$. For $N=L$ and $K=1$, MDF is equivalent to FLMS [17].

3. THE SPARSE PARTIAL UPDATE MULTIDELAY FILTERING ALGORITHM

Our aim is to utilize the low delay inherent in MDF as well as the fast convergence and reduced complexity brought about by combining SP and MMax tap-selection for NEC. We achieve this aim by first describing how MMax tap-selection given in (6) can be incorporated into MDF. We next show, using an illustrative example, how the sparse nature of the impulse response is exploited in the frequency domain which then allows us to integrate the SP tap-selection given by (7). The proposed MMax-MDF and SPMMax-MDF algorithms are described by (17), (18), (19), and

$$\underline{\widehat{\mathbf{h}}}_k(m)=\underline{\widehat{\mathbf{h}}}_k(m-1)+\mu\mathbf{G}^{10}\underline{\widetilde{\mathbf{D}}}^*(m-k)\mathbf{P}^{-1}(m)\underline{\mathbf{e}}(m).\tag{21}$$

The difference between (20) and (21) is that the latter employs $\underline{\widetilde{\mathbf{D}}}^*(m-k)$, and we will describe in the following how this $2N\times 2N$ diagonal matrix can be obtained for the cases of MMax and SP tap-selection criterion.

3.1. *The MMax-MDF algorithm*

As described in Section 2.1, the MMax tap-selection given in (6) is achieved by sorting $\mathbf{x}(n)$. In the frequency-domain MDF implementation, however, elements in $\underline{\widetilde{\mathbf{D}}}(m-k)$ are normalized by elements $p_i(m)$ in the vector $\mathbf{P}(m)$ defined in (19). Hence, for the frequency-domain MMax tap-selection, we select taps corresponding to the M_1 maxima of the Fourier transformed tap-inputs normalized by $p_i(m)$ with $i=0,\ldots,2L-1$. For this tap-selection strategy, the concatenated Fourier transformed tap-input across all K blocks is given as

$$\begin{aligned}\underline{\mathbf{g}}(m)&=\left[\underline{\boldsymbol{\chi}}^T(m)\cdots\underline{\boldsymbol{\chi}}^T(m-K+1)\right]^T\\ &=\left[\underline{\chi}_0(m)\cdots\underline{\chi}_{2L-1}(m)\right]^T,\end{aligned}\tag{22}$$

where $\underline{\boldsymbol{\chi}}(m-k)$ is defined in (15) and $\underline{\chi}_i(m)$, $i=0,\ldots,2L-1$ denotes the ith element of $\underline{\mathbf{g}}(m)$. Elements of the $2L\times 2L$ diagonal MMax tap-selection matrix $\mathbf{Q}(m)$ are given by

$$q_i(m)=\begin{cases}1 & i\in\left\{\text{indices of the } M_1 \text{ maxima of } \dfrac{\underline{\chi}_i^*(m)\underline{\chi}_i(m)}{p_i(m)}\right\},\\ 0 & \text{otherwise},\end{cases}\tag{23}$$

for $i=0,\ldots,2L-1$ with $1\leq M_1\leq 2L$. Due to the normalization by $p_i(m)$ in (23), we denote this algorithm as MMax-MDF$_\text{N}$ and define a $2L\times 1$ vector $\underline{\widetilde{\mathbf{g}}}(m)$ containing the subselected Fourier transformed tap-inputs as

$$\underline{\widetilde{\mathbf{g}}}(m)=\mathbf{Q}(m)\underline{\mathbf{g}}(m)=\left[\underline{\widetilde{\chi}}_0(m)\cdots\underline{\widetilde{\chi}}_{2L-1}(m)\right]^T.\tag{24}$$

The $2N\times 2N$ diagonal matrix $\underline{\widetilde{\mathbf{D}}}(m-k)$ for MMax-MDF$_\text{N}$ is then given by

$$\begin{aligned}\underline{\widetilde{\mathbf{D}}}(m-k)=\operatorname{diag}\{\underline{\widetilde{\chi}}_{2kN}(m)\cdots\underline{\widetilde{\chi}}_{2kN+2N-1}(m)\},\\ k=0,\ldots,K-1.\end{aligned}\tag{25}$$

Hence, it can be seen that elements in the vector $\underline{\widetilde{\mathbf{D}}}(m-k)$ are obtained from the kth block of the selected Fourier transformed tap-inputs contained in $\underline{\widetilde{\mathbf{g}}}(m)$ with indices from $2kN$ to $2kN+2N-1$. The adaptation of MMax-MDF$_\text{N}$ algorithm is described by (23)–(25) and (21).

It is noted that the MMax-MDF$_\text{N}$ algorithm requires $2L$ additional divisions for tap-selection due to the normalization by $p_i(m)$ in (23). Hence, to reduce the complexity even further, we consider an alternative approach where such normalization is removed so that elements of the $2L\times 2L$ diagonal tap-selection matrix $\mathbf{Q}(m)$ are expressed as

$$q_i(m)=\begin{cases}1, & i\in\{\text{indices of the } M_1 \text{ maxima of } |\underline{\chi}_i(m)|\},\\ 0, & \text{otherwise},\end{cases}\tag{26}$$

for $i=0,\ldots,2L-1$ and $1\leq M_1\leq 2L$. As opposed to MMax-MDF$_\text{N}$, we denote this scheme as the MMax-MDF algorithm since normalization by $p_i(m)$ is removed. Accordingly, elements in $\underline{\widetilde{\mathbf{D}}}(m-k)$ for MMax-MDF are computed using (24) and (25), where $\mathbf{Q}(m)$ is obtained from (26). Hence, the adaptation of MMax-MDF algorithm is described by (24)–(26) and (21).

As will be shown in Section 4, the degradation in convergence performance due to tap-selection is less in MMax-MDF_N than in MMax-MDF. However, since reducing complexity is our main concern, we choose to use MMax-MDF as our basis for reducing the computational complexity of the proposed algorithm. As will be described in Section 3.2, the proposed algorithm incorporates the SP tap-selection to achieve, in addition, a fast rate of convergence.

3.2. *The SPMMax-MDF algorithm*

We show in this section how the SP tap-selection can be incorporated into the frequency domain. The SP tap-selection defined by (7) was proposed to achieve fast convergence for the identification of sparse impulse responses. We note that the direct implementation of SP tap-selection into frequency-domain adaptive filtering such as FLMS is inappropriate since impulse response in the transformed domain is not necessarily sparse. To illustrate this, we study the effect of $K \geq 1$ on the concatenated impulse response of the MDF structure $\underline{\mathbf{h}}$ defined by

$$\underline{\mathbf{h}} = \mathbb{F}_{2L}\left[\begin{bmatrix}\mathbf{h}_0\\ \mathbf{0}_{N\times 1}\end{bmatrix}^T \cdots \begin{bmatrix}\mathbf{h}_{K-1}\\ \mathbf{0}_{N\times 1}\end{bmatrix}^T\right]^T, \tag{27}$$

where

$$\mathbf{h}_k = \left[h_{kN} \cdots h_{kN+N-1}\right]^T, \tag{28}$$

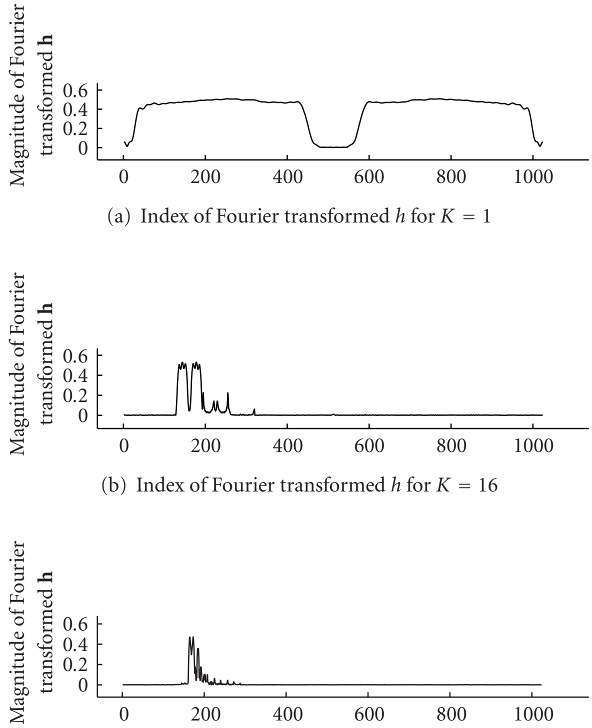
for $k = 0, \ldots, K-1$ is the kth subfilter to be identified and

$$\mathbb{F}_{2L} = \begin{bmatrix}\mathbf{F}_{2N} & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & \mathbf{F}_{2N}\end{bmatrix}_{2L\times 2L} \tag{29}$$

is a $2L \times 2L$ matrix constructed by K Fourier matrices each of size $2N \times 2N$. As indicated in (28), the impulse response $\mathbf{h}$ is partitioned into smaller blocks in the time domain as K increases. Figure 3 shows the variation of the magnitude of $\underline{\mathbf{h}}$ for $K = 1$, $K = 16$ and $K = 64$, where MDF is equivalent to FLMS for $K = 1$. As can be seen from the figure, the magnitude of $\underline{\mathbf{h}}$ is not sparse for $K = 1$. Hence SP tap-selection in the MDF structure will not improve the convergence performance for $K = 1$. For the cases where $K > 1$, the number of taps with small magnitudes in $\underline{\mathbf{h}}$ increases with K, that is, the number of subfilters. In Figure 4, we show how the sparseness of the magnitude of $\underline{\mathbf{h}}$ varies with K using the sparseness measure given by [25, 26]

$$\xi = \frac{L}{L-\sqrt{L}}\left[1 - \frac{\|\underline{\mathbf{h}}\|_1}{\sqrt{L}\|\underline{\mathbf{h}}\|_2}\right], \tag{30}$$

where $\|\cdot\|_1$ denotes l_1-norm and it was shown in [26, 27] that ξ increases with the sparseness of $\mathbf{h}$, where $0 \leq \xi \leq 1$. As can be seen from Figure 4, the magnitude of $\underline{\mathbf{h}}$ becomes more sparse as K increases. As a consequence, we would expect SP tap-selection to improve the convergence rate of MDF for sparse system identification.



(a) Index of Fourier transformed h for $K = 1$

(b) Index of Fourier transformed h for $K = 16$

(c) Index of Fourier transformed h for $K = 64$

FIGURE 3: Variation of the magnitude of $\underline{\mathbf{h}}$ of length $2L$ with $L = 512$ for (a) $K = 1$, (b) $K = 16$, and (c) $K = 64$.

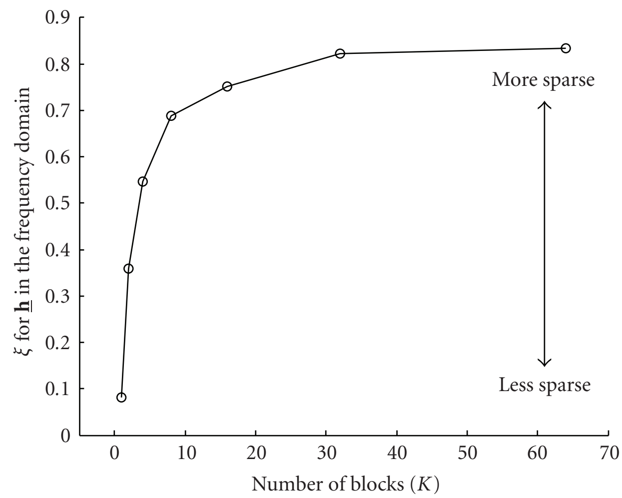


FIGURE 4: Sparseness of the magnitude of $\underline{\mathbf{h}}$ against K.

Although integrating SP tap-selection can be beneficial in the frequency domain, it requires careful consideration since as can be seen from (13), the length of the input frame $\boldsymbol{\chi}(m-k)$ is $2N$ compared to L for the adaptive filter. This causes a length mismatch between $\underline{\boldsymbol{\chi}}(m-k)$ and $\hat{\mathbf{h}}(m)$. We overcome this problem by concatenating all frequency-domain subfilters, $\underline{\hat{\mathbf{h}}}_k^T(m)$, $k = 0, \dots, K-1$ to obtain $\underline{\hat{\mathbf{h}}}(m)$, which is of length $2L$, that is,

$$\begin{aligned} \underline{\hat{\mathbf{h}}}(m) &= \left[\underline{\hat{\mathbf{h}}}_0^T(m) \cdots \underline{\hat{\mathbf{h}}}_{K-1}^T(m)\right]^T \\ &= \left[\underline{\hat{h}}_0(m) \cdots \underline{\hat{h}}_{2L-1}(m)\right]^T. \end{aligned} \tag{31}$$

Since SPMMax-MDF aims to obtain fast convergence with low complexity, our approach of achieving SP tap-selection is then to select $1 \leq M_2 \leq 2L$ elements from $|\underline{\chi}_i(m)\underline{\hat{h}}_i(m)|$ for $i = 0, \dots, 2L-1$, where elements $\underline{\chi}_i(m)$ can be obtained from $\underline{\mathbf{g}}(m)$ defined in (22). Elements of the $2L \times 2L$ diagonal tap-selection matrix $\mathbf{Q}(m)$ are therefore given by

$$q_i(m) = \begin{cases} 1 & i \in \{\text{indices of the } M_2 \text{ maxima of} \\ & \qquad |\underline{\chi}_i(m)\underline{\hat{h}}_i(m)|\}, \\ 0 & \text{otherwise,} \end{cases} \tag{32}$$

for $i = 0, \dots, 2L-1$. Employing (32), the diagonal matrix $\underline{\tilde{\mathbf{D}}}(m-k)$ in (21) for the SP tap-selection can be described by (24) and (25).

It should be noted that additional simulations performed using selection criteria by sorting $|\underline{\chi}_i^*(m)\underline{\chi}_i(m)\underline{\hat{h}}_i(m)/p_i(m)|$ showed no significant improvement for SPMMax-MDF as it was found that the sparseness effect of $|\underline{\hat{h}}_i(m)|$ dominates the selection process compared to the term $\underline{\chi}_i^*(m)\underline{\chi}_i(m)/p_i(m)$, which results in selecting the same filter coefficients for adaptation as would be selected using (32). In addition, normalization by $p_i(m)$ incurs an extra $2L$ divisions, which is not desirable for our VoIP application. As a final comment, since the number of the "active" coefficients of $\underline{\mathbf{h}}$ reduces with increasing K, we choose M_2 to be

$$M_2 = \frac{(2-a)L}{K} + aL. \tag{33}$$

This enables M_2 to reduce with increasing K hence allowing adaptation to be more concentrated on the "active" region. A good choice of a has been found experimentally to be given by $a = 1$. The proposed SPMMax-MDF algorithm is described in Algorithm 1.

3.3. Computational complexity

Although it is well known, from the computational complexity point of view, that $N = L$ is the optimal choice for the MDF algorithm, it nevertheless is more efficient than time-domain implementations even for $N < L$ [8]. As shown in Algorithm 1, the proposed SPMMax-MDF computes $\underline{\tilde{\mathbf{D}}}(m-k)$ using tap-selection matrix $\mathbf{Q}(m)$, which is defined by (26) and (32) for $\text{mod}(m, T) = 0$ and $\text{mod}(m, T) \neq 0$, respectively. We show in Table 1 the number of multiplications and divisions required for MDF, MMax-MDF, MMax-MDF$_\text{N}$, and SPMMax-MDF to compute the term $\underline{\tilde{\mathbf{D}}}^*(m-k)\mathbf{P}^{-1}(m)\underline{\mathbf{e}}(m)$. We have also included the recently proposed IPMDF algorithm [22] for comparison. It should be noted that for MMax and SP tap-selection in (26) and (32), no additional computational complexity is introduced since $|\underline{\chi}_i(m)|$ and $|\underline{\chi}_i(m)\underline{\hat{h}}_i(m)|$ can be obtained from (18) and (17), respectively. For MMax-MDF$_\text{N}$, however, computing the selected filter coefficients for adaptation using (23) incurs additional number of divisions. The complexity for each algorithm for an example case of $L = 512$, $T = 8$, $M_1 = 0.5 \times 2L$, and $K = 64$ is shown in Table 2. It can be seen that the complexity of the proposed SPMMax-MDF is approximately 50% of that for the MDF. Compared to MMax-MDF, SPMMax-MDF requires only an additional 2% of multiplications and divisions. However, as will be shown in Section 4, the performance of SPMMax-MDF is better than MMax-MDF. Finally, the complexity of SPMMax-MDF is 33% and 25% of that for the IPMDF algorithm in terms of multiplications and divisions, respectively.

Table 1: Complexity of algorithms.

Algorithm	Multiplication	Division
MDF	$2L$	$2L$
IPMDF	$3L$	$4L$
MMax-MDF	M_1	M_1
MMax-MDF$_\text{N}$	M_1	$M_1 + 2L$
SPMMax-MDF	$[M_1 + (T-1)M_2]/T$	$[M_1 + (T-1)M_2]/T$

Table 2: Complexity for the case of $L = 512$, $T = 8$, $M_1 = 0.5 \times 2L$, and $K = 64$.

Algorithm	Multiplication	Division
MDF	1024	1024
IPMDF	1536	2048
MMax-MDF	512	512
MMax-MDF$_\text{N}$	512	1536
SPMMax-MDF	519	519

4. RESULTS AND DISCUSSIONS

We present simulation results to illustrate the performance of the proposed SPMMax-MDF algorithm for NEC using a recorded network impulse response $\mathbf{h}$ with 512 taps [12], as shown in Figure 2. The performance is measured using normalized misalignment defined as

$$\eta = \frac{\|\mathbf{h} - \hat{\mathbf{h}}(n)\|_2^2}{\|\mathbf{h}\|_2^2}. \tag{34}$$

We used a sampling frequency of 8 kHz and white Gaussian noise (WGN) $w(n)$ was added to achieve a signal-to-noise ratio (SNR) of 20 dB. The following parameters for the algorithms are chosen for all simulations [22]: $T = 8$, $\lambda = [1 - 1/(3L)]^N$, $\mathbf{S}(0) = \sigma_x^2/100$, $\delta = 20\sigma_x^2 2N/L$. Step-size control variable β has been adjusted for each algorithm so as to achieve the same steady-state performance.

We first compare the variation in convergence of MMax-MDF$_\text{N}$ and MMax-MDF with M_1 using step-size control variables $\beta = 0.7$ and $\beta = 0.6$ for MMax-MDF$_\text{N}$ and MMax-MDF, respectively. We used a CGN input generated

$$\delta = 20\sigma_x^2 N/L,$$
$$\lambda = \left[1 - \frac{1}{3L}\right]^N,$$
$$\mu = \beta(1-\lambda),\ 0 < \beta \leq 1,$$
$$\mathbf{S}(0) = \sigma_x^2/100,$$
$$\hat{\mathbf{h}}_k(m) = [\hat{h}_{kN}(m)\hat{h}_{kN+1}(m)\cdots\hat{h}_{kN+N-1}(m)]^T,$$
$$\hat{\underline{\mathbf{h}}}_k(m) = \mathbf{F}_{2N}\begin{bmatrix}\hat{\mathbf{h}}_k(m)\\ \mathbf{0}_{N\times 1}\end{bmatrix},$$
$$\underline{\mathbf{g}}(m) = [\underline{\chi}_0(m)\underline{\chi}_1(m)\cdots\underline{\chi}_{2L-1}(m)],$$
$$i = 0, 1, \ldots, 2L-1,$$
MMax tap-selection for $\bmod(m,T) = 0$,
$$q_i(m) = \begin{cases} 1 & i \in \{\text{indices of the } M_1 \text{ maxima of } |\underline{\chi}_i(m)|\}, \\ 0 & \text{otherwise}, \end{cases}$$
SP tap-selection for $\bmod(m,T) \neq 0$,
$$M_2 = (2-a)L/K + aL,$$
$$q_i(m) = \begin{cases} 1 & i \in \{\text{indices of the } M_2 \text{ maxima of } |\underline{\chi}_i(m)\underline{\hat{h}}_i(m)|\}, \\ 0 & \text{otherwise}, \end{cases}$$
$$\tilde{\underline{\mathbf{g}}}(m) = \mathbf{Q}(m)\underline{\mathbf{g}}(m) = [\tilde{\underline{\chi}}_0(m)\cdots\tilde{\underline{\chi}}_{2L-1}(m)]^T,$$
$$\tilde{\underline{\mathbf{D}}}(m-k) = \operatorname{diag}\{\tilde{\underline{\chi}}_{2kN}(m)\cdots\tilde{\underline{\chi}}_{2kN+2N-1}(m)\},$$
$$\underline{\mathbf{e}}(m) = \underline{\mathbf{y}}(m) - \mathbf{G}^{01}\textstyle\sum_{k=0}^{K-1}\underline{\mathbf{D}}(m-k)\hat{\underline{\mathbf{h}}}_k(m-1),$$
$$\mathbf{S}(m) = \lambda\mathbf{S}(m-1) + (1-\lambda)\underline{\mathbf{D}}^*(m)\underline{\mathbf{D}}(m),$$
$$\mathbf{P}(m) = \mathbf{S}(m) + \delta\mathbf{I}_{2N\times 2N},$$
$$\hat{\underline{\mathbf{h}}}_k(m) = \hat{\underline{\mathbf{h}}}_k(m-1) + \mu\mathbf{G}^{10}\tilde{\underline{\mathbf{D}}}^*(m-k)\mathbf{P}^{-1}(m)\underline{\mathbf{e}}(m).$$

Algorithm 1: The SPMMax-MDF algorithm.

by filtering zero-mean WGN through a lowpass filter with a single pole [12]. It can be seen from Figure 5 that for each case of M_1, the degradation in convergence performance due to tap-selection is less for the MMax-MDF$_\text{N}$ than the MMax-MDF. However, as shown in Tables 1 and 2, MMax-MDF$_\text{N}$ incurs $2L$ additional divisions compared to the MMax-MDF algorithm.

We next compare the convergence performance of SPMMax-MDF with MDF and IPMDF using CGN input for $K = 1$ in Figure 6. We have used $T = 8$ and $\beta = 0.6$ for all algorithms. We have also used $M_1 = 0.5 \times 2L$ since it was shown in [28] that by such setting, a good balance between complexity reduction and performance degradation due to MMax tap-selection can be reached. As can be seen from the figure, the performance of SPMMax-MDF is close to that for the MDF since for $K = 1$ which results in $M_2 = 2L$ according to (33). Consequently, under the condition of $\bmod(m,T) \neq 0$, all the $2L$ filter coefficients are updated, while under the condition of $\bmod(m,T) = 0$, $M_1 = 0.5 \times 2L$ coefficients are updated. As a result of this, and consistent with any partial update algorithms presented in [28], the performance of SPMMax-MDF approaches that for the MDF. Compared to IPMDF, SPMMax-MDF only requires approximately 63% and 47% of the number of multiplications and division, as indicated in Table 1.

We show in Figure 7 the convergence performance of SPMMax-MDF, MDF, and IPMDF for $K > 1$ using CGN input. As before, we have used the same step-size control variable of $\beta = 0.6$ for all algorithms except for the cases of SPMMax-MDF, where $\beta = 0.8$ is used to archive the same steady-state performance. It can be seen that for $K = 64$, the proposed SPMMax-MDF algorithm achieves faster rate of convergence in terms of normalized misalignment compared to the more complex MDF during adaptation. Since, as shown in Figure 4, ξ increases with K, it can therefore be expected that such improvement can be increased when larger K is employed. In addition, as the delay for MDF is reduced by a factor of K compared to FLMS, the proposed SPMMax-MDF can archive further delay reduction for larger K and thus is desirable for NEC. For the case of $M_1 = 0.5\times 2L$ and $K = 64$, the number of multiplications and divisions required for each algorithm is shown in Table 2.

Figure 8 shows the performance of the algorithms obtained using a male speech input. Parameters used for

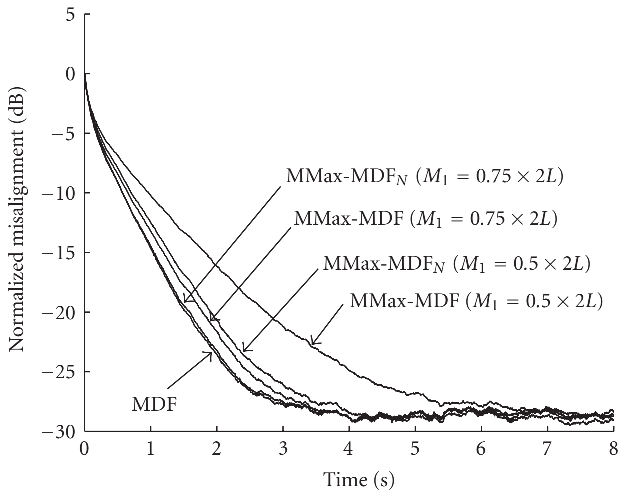


Figure 5: Variation of performance with M_1 for MMax-MDF$_N$ and MMax-MDF.

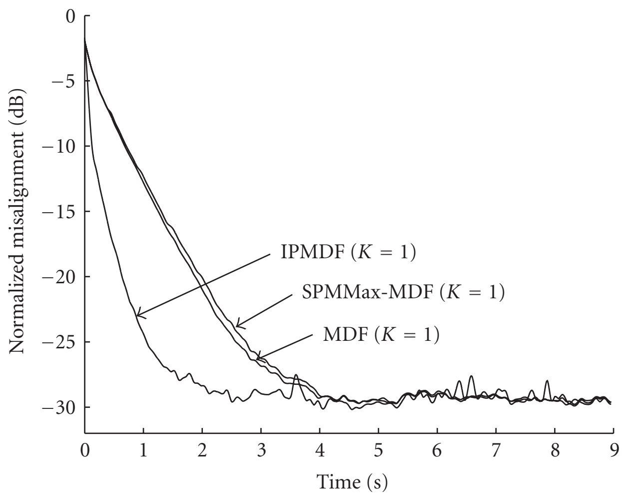


Figure 6: Performance of SPMMax-MDF using CGN input for $T = 8$, $M_1 = 0.5 \times 2L$, $K = 1$.

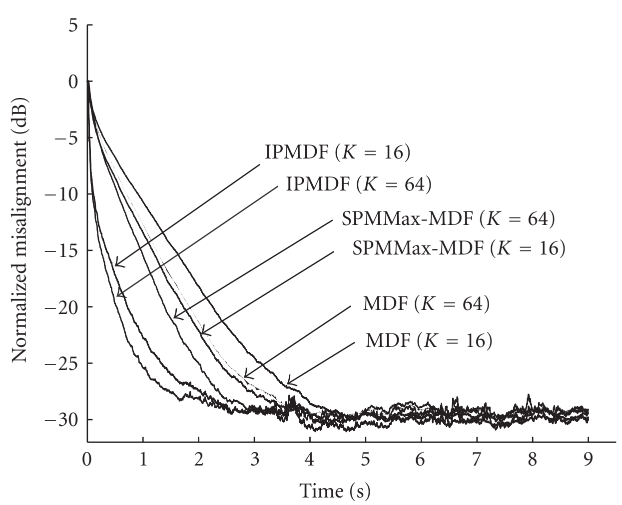


Figure 7: Performance of SPMMax-MDF for CGN input with $T = 8$ and $M_1 = 0.5 \times 2L$.

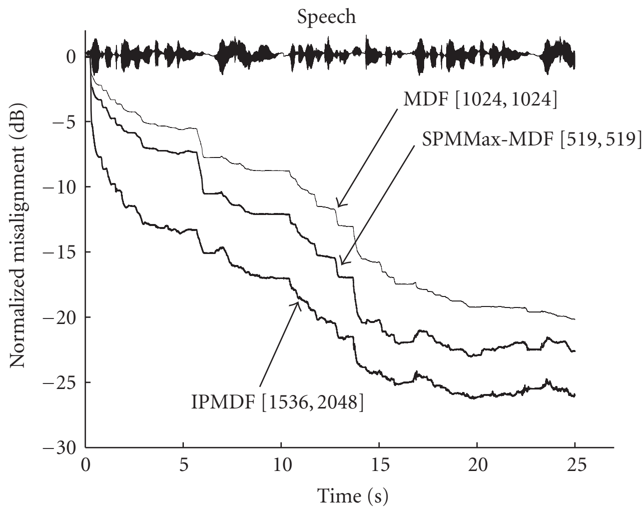


Figure 8: Performance of SPMMax-MDF using speech input for $T = 8$, $M_1 = 0.5 \times 2L$, $K = 64$, and the computational complexity required for each algorithm.

each algorithm are the same as that for the previous simulations except that for SPMMax-MDF, where we have used $\beta = 1$ to achieve the same steady-state performance. The computational complexity required for each algorithm is also shown in the figure between square brackets, where the first and the second integers represent the number of multiplications and divisions, respectively. It can be seen that SPMMax-MDF achieves approximately 5 dB improvement in terms of normalized misalignment with lower complexity in comparison to MDF. In addition, the performance of our low cost SPMMax-MDF algorithm approaches that of IPMDF.

5. CONCLUSIONS

We have proposed SPMMax-MDF for network echo cancellation in VoIP. This algorithm achieves a faster rate of convergence, low complexity, and low delay by novelly exploiting both the MMax and SP tap-selection in the frequency domain using MDF implementation. We discussed two approaches of incorporating MMax tap-selection into MDF and showed their tradeoff between rate of convergence and complexity. Simulation results using both colored Gaussian noise and speech inputs show that the proposed SPMMax-MDF achieves up to 5 dB improvement in convergence performance with significantly lower complexity compared to MDF. In addition, the performance of our low cost SPMMax-MDF algorithm approaches that of IPMDF. Since the MDF structure has been applied for acoustic echo cancellation (AEC) [21] and blind acoustic channel identification [29], where the impulse responses are nonsparse, the proposed SPMMax-MDF algorithm can also be potentially applied to these applications for reducing computational complexity and algorithmic delay.

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After many years of exciting research, the field of multimedia information retrieval (MIR) has become mature enough to enter a new development phase—the phase in which MIR technology is made ready to get adopted in practical solutions and realistic application scenarios. High users' expectations in such scenarios require high dependability of MIR systems. For example, in view of the paradigm "getting the content I like, anytime and anyplace" the service of consumer-oriented MIR solutions (e.g., a PVR, mobile video, music retrieval, web search) will need to be at least as dependable as turning a TV set on and off. Dependability plays even a more critical role in automated surveillance solutions relying on MIR technology to analyze recorded scenes and events and alert the authorities when necessary.

This special issue addresses the dependability of those critical parts of MIR systems dealing with semantic inference. Semantic inference stands for the theories and algorithms designed to relate multimedia data to semantic-level descriptors to allow content-based search, retrieval, and management of data. An increase in semantic inference dependability could be achieved in several ways. For instance, better understanding of the processes underlying semantic concept detection could help forecast, prevent, or correct possible semantic inference errors. Furthermore, the theory of using redundancy for building reliable structures from less reliable components could be applied to integrate "isolated" semantic inference algorithms into a network characterized by distributed and collaborative intelligence (e.g., a social/P2P network) and let them benefit from the processes taking place in such a network (e.g., tagging, collaborative filtering).

The goal of this special issue is to gather high-quality and original contributions that reach beyond conventional ideas and approaches and make substantial steps towards dependable, practically deployable semantic inference theories and algorithms.

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- Evaluation of semantic inference dependability using standard dependability criteria
- Matching user/context requirements to dependability criteria (e.g., mobile user, user at home, etc.)
- Modeling synergies between different semantic inference mechanisms (e.g., content analysis, indexing through user interaction, collaborative filtering)
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Call for Papers

Computing platforms that are embedded within larger systems they control, called embedded systems, are inherently very complex as they are responsible for controlling and regulating multiple system functionalities. Often embedded systems are also safety-critical requiring high degree of reliability and fault tolerance. Examples include distributed microprocessors controlling the modern cars or aircrafts and airport baggage handling system that track and trace unsafe baggage. To address this growing need for safety and reliability, formal techniques are increasingly being adapted to suit embedded platforms. There has been widespread use of synchronous languages such as Esterel for the design of automotive and flight control software that requires stronger guarantees. Languages like Esterel not only provide nice features for high-level specification but also enable model checking-based verification due to their formal semantics. Other semi-formal notations are also being proposed as standards to specify industrial embedded systems using, for example, the newly developed IEC61499 standard for process control. This standard primarily focuses on component-oriented description of embedded control systems. The goal of this special issue is to bring together a set of high-quality research articles looking at different applications of formal or semiformal techniques in specification, verification, and synthesis of embedded systems.

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Special Issue on Distributed Video Coding

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Distributed source coding (DSC) is a new paradigm based on two information theory theorems: Slepian-Wolf and Wyner-Ziv. Basically, the Slepian-Wolf theorem states that, in the lossless case, the optimal rate achieved when performing joint encoding and decoding of two or more correlated sources can theoretically be reached by doing separate encoding and joint decoding. The Wyner-Ziv theorem extends this result to lossy coding. Based on this paradigm, a new video coding model is defined, referred to as distributed video coding (DVC), which relies on a new statistical framework, instead of the deterministic approach of conventional coding techniques such as MPEG standards.

DVC offers a number of potential advantages. It first allows for a flexible partitioning of the complexity between the encoder and decoder. Furthermore, due to its intrinsic joint source-channel coding framework, DVC is robust to channel errors. Because it does no longer rely on a prediction loop, DVC provides codec independent scalability. Finally, DVC is well suited for multiview coding by exploiting correlation between views without requiring communications between the cameras.

High-quality original papers are solicited for this special issue. Topics of interest include (but are not limited to):

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- Channel statistical modeling and channel coding
- Joint source-channel coding
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Special Issue on FPGA Supercomputing Platforms, Architectures, and Techniques for Accelerating Computationally Complex Algorithms

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Field-programmable gate arrays (FPGAs) provide an alternative route to high-performance computing where fine-grained synchronisation and parallelism are achieved with lower power consumption and higher performance than just microprocessor clusters. With microprocessors facing the "processor power wall problem" and application specific integrated circuits (ASICs) requiring expensive VLSI masks for each algorithm realisation, FPGAs bridge the gap by offering flexibility as well as performance. FPGAs at 65 nm and below have enough resources to accelerate many computationally complex algorithms used in simulations. Moreover, recent times have witnessed an increased interest in design of FPGA-based supercomputers.

This special issue is intended to present current state-of-the-art and most recent developments in FPGA-based supercomputing platforms and in using FPGAs to accelerate computationally complex simulations. Topics of interest include, but are not limited to, FPGA-based supercomputing platforms, design of high-throughput area time-efficient FPGA implementations of algorithms, programming languages, and tool support for FPGA supercomputing. Together these topics will highlight cutting-edge research in these areas and provide an excellent insight into emerging challenges in this research perspective. Papers are solicited in any of (but not limited to) the following areas:

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  - Novel architectures of supercomputers, including coprocessors, attached processors, and hybrid architectures
  - Roadmap of FPGA-based supercomputing
  - Example of acceleration of large applications/ simulations using FPGA-based supercomputers
- FPGA implementations of computationally complex algorithms
  - Developing high throughput FPGA implementations of algorithms
  - Developing area time-efficient FPGA implementations of algorithms
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EURASIP Journal on Wireless Communications and Networking

Special Issue on OFDMA Architectures, Protocols, and Applications

Call for Papers

Orthogonal frequency-division multiple access (OFDMA) technologies are currently attracting intensive attention in wireless communications to meet the ever-increasing demands arising from the explosive growth of Internet, multimedia, and broadband services. OFDMA-based systems are able to deliver high data rate, operate in the hostile multipath radio environment, and allow efficient sharing of limited resources such as spectrum and transmit power between multiple users. OFDMA has been used in the mobility mode of IEEE 802.16 WiMAX, is currently a working specification in 3GPP Long Term Evolution downlink, and is the candidate access method for the IEEE 802.22 "wireless regional area networks." Clearly, recent advances in wireless communication technology have led to significant innovations that enable OFDMA-based wireless access networks to provide better quality-of-service (QoS) than ever with convenient and inexpensive deployment and mobility.

However, regardless of the technology used, OFDMA networks must not only be able to provide reliable and high quality broadband services, but also be implemented cost-effectively and be operated efficiently. OFDMA presents many of the advantages and challenges of OFDM systems for single users, and the extension to multiple users introduces many further challenges and opportunities, both on the physical layer and at higher layers. These requirements present many challenges in the design of network architectures and protocols, which have motivated a significant amount of research in the area. Also, many critical problems associated with the applications of OFDMA technologies in future wireless systems are still looking for efficient solutions. The aim of this special issue is to present a collection of high-quality research papers that report the latest research advances in this field from physical and network layers to practical applications. Original papers are solicited in all aspects of OFDMA techniques including physical layer issues, architectures, protocol designs, enabling technologies, theoretical studies, practical applications, and experimental prototypes. Topics of interest include, but are not limited to:

- Adaptive coding and modulation
- Signal processing for OFDMA
- Interference control techniques
- Bandwidth and resources allocation
- Efficient MAC protocol development
- Routing algorithms and congestion control schemes
- MAC and network layer management
- Cross-layer design and optimization
- Cooperative and game theoretic analysis
- Quality of service provisioning
- Network modeling and performance analysis
- Security and privacy management
- Broadband Wireless Access
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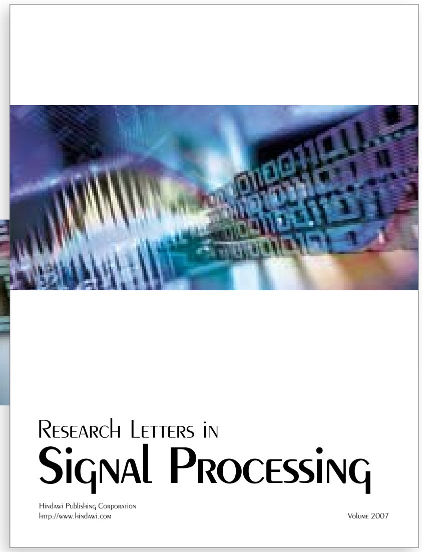

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