AN EFFICIENT FAST STEREO ECHO CANCELER BY PAIRWISE OPTIMAL WEIGHT REALIZATION TECHNIQUE

Masahiro YUKAWA Noriaki MURAKOSHI Isao YAMADA

Dept. of Communications & Integrated Systems, Tokyo Institute of Technology,
S3-60, Tokyo, 152-8552, Japan.
E-Mail: {masahiro,noriaki,isao}@comm.ss.titech.ac.jp

ABSTRACT

This paper presents a novel stereophonic acoustic echo canceling scheme. The proposed scheme is based on the ideas of "simultaneous use of two different states of inputs [Yukawa & Yamada, IEICE 2004]" and "an accelerating weight technique named POWER [Yukawa & Yamada, EUSIPCO 2004]". The two states generate two solution sets, of which the intersection is expected to be fairly small and to contain the true impulse response of echo paths. The POWER technique and the simultaneous use of the inputs find a good direction to the intersection, realizing thus fast convergence. Numerical examples demonstrate that the proposed scheme significantly improves the convergence behavior compared with conventional methods in system mismatch (i.e., normalized coefficients error) and Echo Return Loss Enhancement (ERLE).

1. INTRODUCTION

The objective of this paper is to examine the applicability, to a real world problem, of the weighting technique named *Pairwise Optimal WEight Realization (POWER)* [1, 2], which was originally proposed for accelerating the *adaptive Parallel Subgradient Projection (PSP) algorithms* [3]. We examine the effect of the POWER technique in its application to Stereophonic Acoustic Echo Cancellation (SAEC) problem, which is well-known to be one of the most challenging problems.

The SAEC problem has become a major issue when we design high quality hands-free systems such as advanced teleconferencing. A simple system model for SAEC is illustrated in Fig. 1. In SAEC, the normal equation, to be solved for minimization of the residual echo, is often ill-conditioned or has infinitely many solutions depending on the transmission paths because of highly cross-correlated input signals, which is called non-uniqueness problem [4–8]. A great deal of effort has been devoted to resolve the non-uniqueness problem; e.g., [4–7]. The adaptive filter should keep close to the true echo paths in order to avoid relapses of influential echo with changes of transmission/echo paths. Therefore, *fast and accurate* track of the echo paths is strongly required. Moreover, an adaptive algorithm employed for SAEC must be realized with low computational complexity, since all 4 acoustic paths from 2 loudspeakers to 2 microphones should be identified simultaneously by adapting 4 echo cancelers. Establishing such an efficient algorithm is the major interest in the study of the SAEC problem [8].

Although a variety of preprocessing techniques have been proposed for resolving the non-uniqueness problem [4–7], we focus on the one proposed in [7] for simplicity. The technique in [7] alternates two states of inputs periodically, which leads to alternation of two solution sets, and thus, accurate echo path identification is attained; see Fig. 2. To accelerate the speed of convergence, an efficient SAEC scheme, based on *the Adaptive Projected Subgradient Method (APSM)* [9, 10], was proposed [11], which simultaneously utilizes both states by using the adaptive PSP techniques [3] at each iteration. In [11], uniform weights are employed for the computation of the parallel projection, and further acceleration is expected by some strategic weight design; see Fig. 2.

In this paper, we propose an efficient fast SAEC scheme that further develops the method in [11] by the use of the POWER weighting technique. First, we present a theorem that provides an efficient way to compute the projection onto the intersection of two

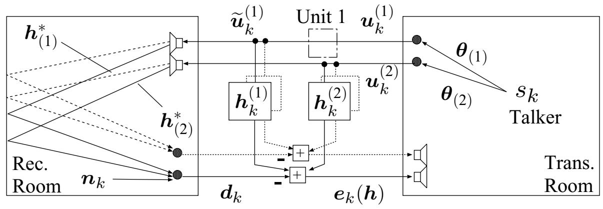

Figure 1: Stereophonic acoustic echo cancelers; Unit 1 is a preprocessing unit. Without the unit, this figure illustrates a standard system for SAEC. $\widetilde{\boldsymbol{u}}_k^{(1)}$ is the input periodically delayed by the preprocessing unit.

closed half-spaces[1], which are characterized by three vectors. The resulting weights turn out to be optimal in the sense of a solution to a certain *worst case optimization problem*; see Sec. 3.1. Then, we present the proposed scheme, which exploits the theorem (POWER) just once after taking respective uniform averages of projections with current and previous state data; see Fig. 4. Because of this simple construction, the scheme is more efficient in computation than the original POWER technique proposed in [1]. Numerical examples demonstrate that the proposed scheme significantly improves the convergence behavior compared with some conventional methods in system mismatch (i.e., normalized coefficients error) and Echo Return Loss Enhancement (ERLE). All results are shown without proves due to lack of space; proves are given in [2].

2. PROBLEM FORMULATION

Throughout the paper, the following notations are used ($k \in \mathbb{N}$: time index, superscript T: transposition):

- speech vector: $\boldsymbol{s}_k \in \mathbb{R}^L$ ($L \in \mathbb{N}^* := \mathbb{N} \setminus \{0\}$)
- i-th transmission path: $\boldsymbol{\theta}_{(i)} \in \mathbb{R}^L$ ($i = 1, 2$)
- i-th input: $u_k^{(i)} := \boldsymbol{s}_k^T \boldsymbol{\theta}_{(i)} \in \mathbb{R}$ ($i = 1, 2$)
- i-th input vector: $\boldsymbol{u}_k^{(i)} := [u_k^{(i)}, \cdots, u_{k-N+1}^{(i)}]^T \in \mathbb{R}^N$ ($N \in \mathbb{N}^*$)
- preprocessed 1-st input: $\widetilde{\boldsymbol{u}}_k^{(1)} \in \mathbb{R}^N$; see Fig. 1
- input vector: $\boldsymbol{u}_k := \begin{bmatrix} \widetilde{\boldsymbol{u}}_k^{(1)} \\ \boldsymbol{u}_k^{(2)} \end{bmatrix} \in \mathscr{H} := \mathbb{R}^{2N}$
- input matrix: $\boldsymbol{U}_k := [\boldsymbol{u}_k, \cdots, \boldsymbol{u}_{k-r+1}] \in \mathbb{R}^{2N \times r}$ ($r \in \mathbb{N}^*$)
- i-th echo path: $\boldsymbol{h}_{(i)}^* \in \mathbb{R}^N$ ($i = 1, 2$)
- estimandum: $\boldsymbol{h}^* := [\boldsymbol{h}_{(1)}^{*\,T}, \boldsymbol{h}_{(2)}^{*\,T}]^T \in \mathscr{H}$
- adaptive filter (echo canceler): $\boldsymbol{h}_k := [\boldsymbol{h}_k^{(1)T}, \boldsymbol{h}_k^{(2)T}]^T \in \mathscr{H}$
- noise: $\boldsymbol{n}_k := [n_k, n_{k-1}, \cdots, n_{k-r+1}]^T \in \mathbb{R}^r$
- output: $\boldsymbol{d}_k := \boldsymbol{U}_k^T \boldsymbol{h}^* + \boldsymbol{n}_k \in \mathbb{R}^r$
- residual error function: $\boldsymbol{e}_k(\boldsymbol{h}) := \boldsymbol{U}_k^T \boldsymbol{h} - \boldsymbol{d}_k \in \mathbb{R}^r$

Here, $\mathscr{H} (:= \mathbb{R}^{2N})$ is a real Hilbert space equipped with the

[1]Given $\boldsymbol{v} \in \mathscr{H}$ ($\mathscr{H}$: real Hilbert space) and a closed subspace $M \subset \mathscr{H}$, the translation of M by $\boldsymbol{v}$ defines the *linear variety* $V := \boldsymbol{v} + M := \{\boldsymbol{v} + \boldsymbol{m} : \boldsymbol{m} \in M\}$. If $\dim(M^\perp) = 1$, V is called *hyperplane*, which can be expressed as $V = \{\boldsymbol{x} \in \mathscr{H} : \langle \boldsymbol{a}, \boldsymbol{x} \rangle = c\}$ for some $(0 \neq)\boldsymbol{a} \in \mathscr{H}$ and $c \in \mathbb{R}$. $^{-} := \{\boldsymbol{x} \in \mathscr{H} : \langle \boldsymbol{a}, \boldsymbol{x} \rangle \leq c\}$ is called a *closed half-space* with its boundary V.

This work was supported in part by JSPS grants-in-Aid (178440).

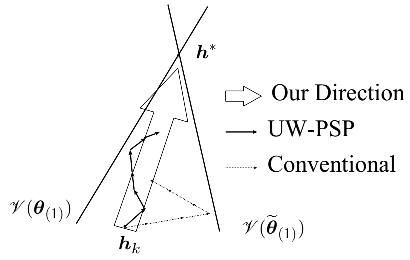

Figure 2: A geometric interpretation of existing methods and the direction of this paper.

inner product $\langle \boldsymbol{x}, \boldsymbol{y} \rangle := \boldsymbol{x}^T \boldsymbol{y}$, $\forall \boldsymbol{x}, \boldsymbol{y} \in \mathscr{H}$, and its induced norm $\|\boldsymbol{x}\| := \left(\boldsymbol{x}^T \boldsymbol{x}\right)^{1/2}$, $\forall \boldsymbol{x} \in \mathscr{H}$. For any nonempty closed convex set $C \subset \mathscr{H}$, the *projection operator* $P_C : \mathscr{H} \to C$ is defined by $\|\boldsymbol{x} - P_C(\boldsymbol{x})\| = \min_{\boldsymbol{y} \in C} \|\boldsymbol{x} - \boldsymbol{y}\|, \forall \boldsymbol{x} \in \mathscr{H}$. The notation $|S|$ stands for the cardinality of a set S.

The goal of the SAEC problem is to cancel the echo all the time; i.e., $\boldsymbol{u}_k^T \boldsymbol{h}^* - \boldsymbol{u}_k^T \boldsymbol{h}_k \approx 0, \forall k \in \mathbb{N}$. Since only $\boldsymbol{u}_k$ and $\boldsymbol{d}_k$ are observable, a common alternative goal is to suppress the residual error; i.e., $\boldsymbol{e}_k(\boldsymbol{h}_k) \approx 0$, $\forall k \in \mathbb{N}$. Due to high correlation between input signals $u_k^{(1)}$ and $u_k^{(2)}$, this problem has infinitely many solutions depending on $\boldsymbol{\theta}_{(1)}$ and $\boldsymbol{\theta}_{(2)}$, which is the so-called non-uniqueness problem [4–8]. Without well-approximating $\boldsymbol{h}^*$, echo relapses by change of transmission paths $\boldsymbol{\theta}_{(1)}$ and $\boldsymbol{\theta}_{(2)}$. Hence, it is strongly desired to keep $\boldsymbol{h}_k$ close to $\boldsymbol{h}^*$.

3. PROPOSED STEREOPHONIC ACOUSTIC ECHO CANCELING SCHEME

Following a useful theorem and a proposition, we present a fast SAEC scheme that efficiently develops the method[2] in [11] by the theorem.

3.1 Projection onto Intersection of Two Half-Spaces

For convenience, let us define, $\forall \boldsymbol{a}, \boldsymbol{b} \in \mathscr{H}$,

$$^-(\boldsymbol{a}, \boldsymbol{b}) := \{\boldsymbol{y} \in \mathscr{H} : \langle \boldsymbol{a} - \boldsymbol{b}, \boldsymbol{y} - \boldsymbol{b} \rangle \leq 0\} \subset \mathscr{H}. \quad (1)$$

$^-(\boldsymbol{a}, \boldsymbol{b})$ is a closed half-space if $\boldsymbol{a} \neq \boldsymbol{b}$. Given an ordered triplet $(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \in \mathscr{H}^3 (:= \mathscr{H} \times \mathscr{H} \times \mathscr{H})$ s.t. $^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b}) \neq \emptyset$, define $\mathscr{P}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) := P_{^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b})}(\boldsymbol{s})$, namely $\mathscr{P}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})$ denotes the projection of $\boldsymbol{s}$ onto $^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b})$ in $\mathscr{H}$. The POWER technique is based on pairwise uses of the following theorem.

Theorem 1 *(Projection onto Intersection of Two Half-Spaces) Given $(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \in \mathscr{H}^3$ s.t. $^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b}) \neq \emptyset$, let $\xi := \|\boldsymbol{a} - \boldsymbol{s}\|^2$, $\zeta := \|\boldsymbol{b} - \boldsymbol{s}\|^2$, and $\eta := \langle \boldsymbol{a} - \boldsymbol{s}, \boldsymbol{b} - \boldsymbol{s} \rangle$. Then, we have*

$$\mathscr{P}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) = \boldsymbol{s} + \mu^* \{\omega^* \boldsymbol{a} + (1 - \omega^*) \boldsymbol{b} - \boldsymbol{s}\}, \quad (2)$$

where

$$\mu^* := \begin{cases} 1, & \text{if } \eta \geq \xi \text{ or } \eta \geq \zeta, \\ \frac{2\xi\zeta - (\xi + \zeta)\eta}{\xi\zeta - \eta^2}, & \text{if } \eta < \min\{\xi, \zeta\}, \end{cases}$$

$$\omega^* := \begin{cases} 1, & \text{if } \eta \geq \zeta, \\ 0, & \text{if } \eta \geq \xi, \\ \frac{\zeta(\xi - \eta)}{2\xi\zeta - (\xi + \zeta)\eta}, & \text{if } \eta < \min\{\xi, \zeta\}. \end{cases}$$

Now, let us define the operator $\mathscr{Q} : [0, 1] \times [0, \quad) \times \mathscr{H}^3 \to \mathscr{H}$ by

$$\mathscr{Q}(\omega, \mu, \boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) := \boldsymbol{s} + \mu \{\omega \boldsymbol{a} + (1 - \omega) \boldsymbol{b} - \boldsymbol{s}\}. \quad (3)$$

By (2) and (3), we see that $\mathscr{P}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) = \mathscr{Q}(\omega^*, \mu^*, \boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})$. An optimality of ω^* and μ^* is shown below; see also Fig. 3.

[2] In [11], two schemes were proposed; one is based on the parallel projection by simultaneous use of data and the other is based on the selective projection by min-max criteria. In this paper, we focus on the former scheme.

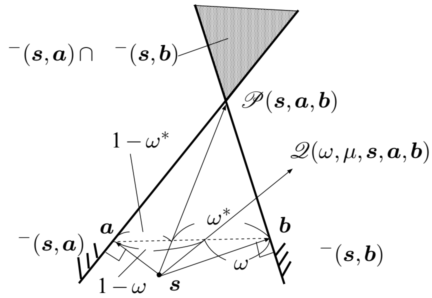

Figure 3: A geometric interpretation of Theorem 1 and Proposition 1. Given $(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \in \mathscr{H}^3$, (ω^*, μ^*) of $\mathscr{P}(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})$ $[= \mathscr{Q}(\omega^*, \mu^*, \boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})]$ is *the best* among all $(\omega, \mu) \in [0, 1] \times [0, \quad)$ of $\mathscr{Q}(\omega, \mu, \boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b})$.

Proposition 1 *(Optimality of ω^* and μ^*) Given $(\boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) \in \mathscr{H}^3$ s.t. $^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b}) \neq \emptyset$, let $\phi(\omega, \mu, \boldsymbol{z}) := \|\boldsymbol{s} - \boldsymbol{z}\|^2 - \|\mathscr{Q}(\omega, \mu, \boldsymbol{s}, \boldsymbol{a}, \boldsymbol{b}) - \boldsymbol{z}\|^2$. Then, (ω^*, μ^*) in Theorem 1 are optimal in the sense of*

$$(\omega^*, \mu^*) \in \underset{(\omega, \mu) \in [0, 1] \times [0, \quad)}{\operatorname{argmax}} \left[\min_{\boldsymbol{z} \in {}^-(\boldsymbol{s}, \boldsymbol{a}) \cap {}^-(\boldsymbol{s}, \boldsymbol{b})} \phi(\omega, \mu, \boldsymbol{z}) \right]. \quad (4)$$

Intuitively, (ω^*, μ^*) achieves a worst case optimization, or, in other words, (4) implies that (ω^*, μ^*) is a solution to the *max-min problem* of maximizing, over ω and μ, the minimum of $\phi(\omega, \mu, \boldsymbol{z})$ over $\boldsymbol{z}$.

Since an extension of Theorem 1 to more general number of (more than two) closed half-spaces is computationally expensive, the POWER technique exploits Theorem 1 in a pairwise manner for more than two closed half-spaces. For saving the computational complexity, the proposed scheme just exploits Theorem 1 once an iteration unlike the one in [1].

3.2 Proposed Scheme

It is reported that the non-uniqueness problem is mitigated by reducing the correlation between input signals $u_k^{(1)}$ and $u_k^{(2)}$, and such reduction can be achieved by generating multiple states of inputs in one of two channels with some preprocessing [4–7]. In this paper, we utilize a simple but effective one named *input sliding technique* [7]. The input sliding technique generates two states of inputs with some modification in Unit 1 in Fig. 1 artificially; one uses no modification and the other uses one-sample-delayed input signal in channel 1, $[u_{k-1}^{(1)}, u_{k-2}^{(1)}, \cdots, u_{k-N}^{(1)}]^T$. It is not hard to see that the latter modification is equivalent to the change of $\boldsymbol{\theta}_{(1)}$ into $\widetilde{\boldsymbol{\theta}}_{(1)} := [0, \boldsymbol{\theta}_{(1)}^T]^T$. This implies that the two states have different solution sets, say $\mathscr{V}(\boldsymbol{\theta}_{(1)})$ and $\mathscr{V}(\widetilde{\boldsymbol{\theta}}_{(1)})$, since a solution set depends on transmission paths in the SAEC problem; e.g., [5]. The technique switches the state of inputs every $Q/2$ iterations, where $Q \in \mathbb{N}^*$ denotes the cycle period.

Figure 2 illustrates a geometric interpretation of "a conventional method in [7]" and "the method in [11] with the uniform weights", which we call Uniformly Weighted PSP (UW-PSP). The conventional method approaches the solution set corresponding to the current state of inputs in each half-period (The dotted arrows show its behavior during a cycle period). On the other hand, thanks to the simultaneous use of data from both states, the UW-PSP finds a better direction to $\boldsymbol{h}^*$. This paper aims to achieve even better direction by the POWER technique.

Now, let us explain the proposed scheme, which starts with the computation of certain projections as shown below. Define the stochastic property set

$$C_k(\rho) := \left\{ \boldsymbol{h} \in \mathscr{H} : g_k(\boldsymbol{h}) := \|\boldsymbol{e}_k(\boldsymbol{h})\|^2 - \rho \leq 0 \right\}, \quad (5)$$

where $\rho \geq 0$. Since the projection onto $C_k(\rho)$ requires, in general, huge computational complexity, we employ an approximating projection onto the closed half-space $H_k^-(\boldsymbol{h}) := \{\boldsymbol{x} \in \mathscr{H} :$

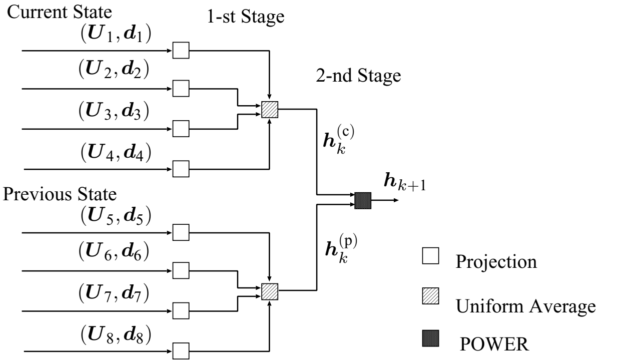

Figure 4: Simple system models with eight parallel processors to implement the proposed scheme. $\mathscr{I}_k^{(c)} = \{1,2,3,4\}$, $\mathscr{I}_k^{(p)} = \{5,6,7,8\}$.

$\langle \boldsymbol{x} - \boldsymbol{h}, \ \ g_k(\boldsymbol{h})\rangle + g_k(\boldsymbol{h}) \le 0\} \supset C_k(\rho)$, which has the following simple closed-form expression:

$$P_{H_k^-(\boldsymbol{h})}(\boldsymbol{h}) = \begin{cases} \boldsymbol{h} + \frac{-g_k(\boldsymbol{h})}{\| \ \ g_k(\boldsymbol{h})\|^2} \ \ g_k(\boldsymbol{h}), & \text{if } \boldsymbol{h} \notin H_k^-(\boldsymbol{h}), \\ \boldsymbol{h}, & \text{otherwise}. \end{cases}$$

Here, $\ \ g_k(\boldsymbol{h}) = 2\boldsymbol{U}_k \boldsymbol{e}_k(\boldsymbol{h})$ and $P_{H_k^-(\boldsymbol{h})}(\boldsymbol{h}) \cong P_{C_k(\rho)}(\boldsymbol{h})$; see [3]. It should be remarked that $P_{H_k^-(\boldsymbol{h})}(\boldsymbol{h})$ requires $O(N)$ complexity. For given $q \in \mathbb{N}^*$, define the control sequences $\mathscr{I}_k^{(c)} := \{k, k-1, \ldots, k-q+1\} \subset \mathbb{N}$ and

$$\mathscr{I}_k^{(p)} := \begin{cases} \emptyset, & 0 \le k \le Q/2, \\ \mathscr{I}_{k-Q/2}^{(c)}, & k > Q/2. \end{cases}$$

Here, $\mathscr{I}_k^{(c)}$ and $\mathscr{I}_k^{(p)}$ are index sets from the current state and the previous (or other) state, respectively. The proposed scheme is given as follows.

Scheme 1

Suppose that a sequence of closed convex sets $(C_\iota(\rho))_{\iota \in \mathscr{I}} \subset \mathscr{H}$ is defined as in (5)*, where $\mathscr{I} := \bigcup_{k\in\mathbb{N}} \left(\mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}\right)$. Let $\boldsymbol{h}_0 \in \mathscr{H}$ be an arbitrarily chosen initial vector. Then, define a sequence $(\boldsymbol{h}_k)_{k\in\mathbb{N}} \subset \mathscr{H}$ through the following two stages.*

1-st Stage: Uniformly Averaged Directions

$$\boldsymbol{h}_k^{(g)} := \begin{cases} \boldsymbol{h}_k + \mathscr{M}_k^{(g)} \left(\sum_{\iota \in \mathscr{I}_k^{(g)}} w_k^{(g)} P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right), \\ \quad \text{if } \mathscr{I}_k^{(g)} \neq \emptyset, \\ \boldsymbol{h}_k, \ \text{otherwise}, \end{cases}$$

$$\forall k \in \mathbb{N}, \ \forall \mathrm{g} \in \{\mathrm{c}, \mathrm{p}\}, \quad (6)$$

where $w_k^{(g)} := \frac{1}{|\mathscr{I}_k^{(g)}|} = \frac{1}{q}$ ($\forall \iota \in \mathscr{I}_k^{(g)}$) and

$$\mathscr{M}_k^{(g)} := \begin{cases} \dfrac{\sum_{\iota \in \mathscr{I}_k^{(g)}} w_k^{(g)} \left\| P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}{\left\| \sum_{\iota \in \mathscr{I}_k^{(g)}} w_k^{(g)} P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}, \\ \quad \text{if } \boldsymbol{h}_k \notin \bigcap_{\iota \in \mathscr{I}_k^{(g)}} H_\iota^-(\boldsymbol{h}_k), \\ 1, \quad \text{otherwise}. \end{cases}$$

2-nd Stage: Reasonably Averaged Direction by POWER

$$\boldsymbol{h}_{k+1} := \begin{cases} \boldsymbol{h}_k, & \text{if } \eta_k = -\sqrt{\xi_k \zeta_k} \neq 0, \\ \boldsymbol{h}_k + \lambda_k \{\mathscr{P}(\boldsymbol{h}_k, \boldsymbol{h}_k^{(c)}, \boldsymbol{h}_k^{(p)}) - \boldsymbol{h}_k\}, \\ \quad \text{otherwise}, \end{cases}$$

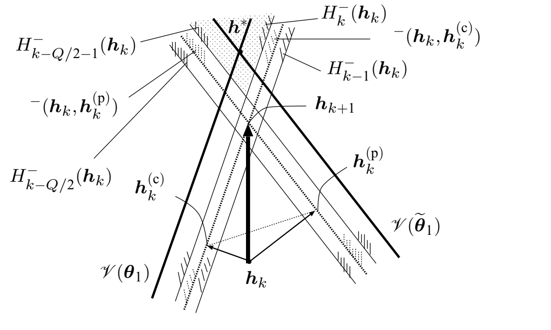

Figure 5: A geometric interpretation of the proposed scheme. $\mathscr{I}_k^{(c)} = \{k, k-1\}$, $\mathscr{I}_k^{(p)} = \{k-Q/2, k-Q/2-1\}$.

$\forall k \in \mathbb{N}$, where $\lambda_k \in [0,2]$ is the step size, $\eta_k := \langle \boldsymbol{h}_k^{(c)} - \boldsymbol{h}_k, \boldsymbol{h}_k^{(p)} - \boldsymbol{h}_k\rangle$, $\xi_k := \|\boldsymbol{h}_k^{(c)} - \boldsymbol{h}_k\|^2$ and $\zeta_k := \|\boldsymbol{h}_k^{(p)} - \boldsymbol{h}_k\|^2$.

A simple system model to implement Scheme 1 is shown in Fig. 4. In (6), each term in the summation can be computed simultaneously with q concurrent processors. This implies that the proposed scheme is inherently suitable for real time implementation with $2q$ concurrent processors. A geometric interpretation of Scheme 1 is illustrated in Fig. 5. For simplicity, we set $q = 2$ and $\lambda = 1$. In the figure, the estimandum $\boldsymbol{h}^*$ (see Sec. 2) is assumed to belong to the dotted area; i.e., $\boldsymbol{h}^* \in \bigcap_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} H_\iota^-(\boldsymbol{h}_k)$. This assumption holds if $C_k(\rho)$ is defined with appropriately chosen ρ; for details, see [3]. We see that the scheme attains a good direction of update.

Next, a simple proposition is given, followed by showing certain optimality of the proposed scheme.

Proposition 2 *For any $\boldsymbol{h}^* \in \bigcap_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} H_\iota^-(\boldsymbol{h}_k)$,*

$$\left\langle \boldsymbol{h}_k - \boldsymbol{h}_k^{(g)}, \boldsymbol{h}^* - \boldsymbol{h}_k^{(g)} \right\rangle \le 0, \ \forall \mathrm{g} \in \{\mathrm{c}, \mathrm{p}\}. \quad (7)$$

Proposition 2 implies that by (1)

$$\boldsymbol{h}^* \in \bigcap_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} H_\iota^-(\boldsymbol{h}_k) \Rightarrow \boldsymbol{h}^* \in \ ^-(\boldsymbol{h}_k, \boldsymbol{h}_k^{(c)}) \cap \ ^-(\boldsymbol{h}_k, \boldsymbol{h}_k^{(p)}). \quad (8)$$

By Proposition 1 and (8), the weights realized in the second stage are "*optimal*" in the sense of a solution to a worst case optimization problem; see under Proposition 1. An explicit formulation of the weights realized by the proposed scheme is presented below.

Proposition 3 *(Weight Realization)*
Let $(\boldsymbol{h}_k)_{k\in\mathbb{N}} \subset \mathscr{H}$ be a sequence of filtering vectors generated by Scheme 1. Suppose $\eta_k \neq -\sqrt{\xi_k \zeta_k}$. Then, $\boldsymbol{h}_{k+1}$ is rewritten by

$$\boldsymbol{h}_{k+1} := \boldsymbol{h}_k + \lambda_k \mathscr{M}_k \left(\sum_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} w_\iota^{(k)} P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right),$$

$\forall k \in \mathbb{N}$, where $\lambda_k \in [0,2]$ is the step size and

$$\mathscr{M}_k := \begin{cases} \dfrac{\sum_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} w_\iota^{(k)} \left\| P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}{\left\| \sum_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} w_\iota^{(k)} P_{H_\iota^-(\boldsymbol{h}_k)}(\boldsymbol{h}_k) - \boldsymbol{h}_k \right\|^2}, \\ \quad \text{if } \boldsymbol{h}_k \notin \bigcap_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} H_\iota^-(\boldsymbol{h}_k), \\ 1, \quad \text{otherwise}. \end{cases}$$

Here, the weights

$$w_\iota^{(k)} := \begin{cases} \dfrac{\omega_k^* \mathscr{M}_k^{(c)} w_k^{(c)}}{\alpha_k}, & \forall \iota \in \mathscr{I}_k^{(c)}, \\ \dfrac{(1-\omega_k^*) \mathscr{M}_k^{(p)} w_k^{(p)}}{\alpha_k}, & \forall \iota \in \mathscr{I}_k^{(p)}, \end{cases} \quad (9)$$

satisfy $w_\iota^{(k)} > 0$ *and* $\sum_{\iota \in \mathscr{I}_k^{(c)} \cup \mathscr{I}_k^{(p)}} w_\iota^{(k)} = 1$ *with* $\alpha_k := |\mathscr{I}_k^{(c)}| \omega_k^* \mathscr{M}_k^{(c)} w_k^{(c)} + |\mathscr{I}_k^{(p)}| (1-\omega_k^*) \mathscr{M}_k^{(p)} w_k^{(p)}$ *and* ω_k^* *the weight to calculate* $\mathscr{P}\left(\boldsymbol{h}_k, \boldsymbol{h}_k^{(c)}, \boldsymbol{h}_k^{(p)}\right)$*; see Theorem 1.*

Proof is omitted because it is given by simple algebra. Proofs of Theorem 1 and Propositions 1 and 2 are presented in [12]. Proposition 3 means that the proposed scheme can be written in the form of the method in [11]. We see that the proposed scheme realizes strategic and computationally efficient weight design for the method in [11], since the proposed scheme utilizes the POWER technique just in the second stage (see Fig. 4) and the weights in the second stage are optimal (see the discussion before Proposition 3).

4. NUMERICAL EXAMPLES

This section presents a numerical comparison of the proposed scheme with the UW-PSP, the Affine Projection Algorithm (APA) and the Normalized Least Mean Square (NLMS) algorithm (see, e.g., [13]) with a common preprocessing technique proposed in [7]. Input signals in channel 1 are modified with the cycle $Q = 800$; see Sec. 3.2. The tests are performed, for estimating $\boldsymbol{h}^* \in \mathscr{H} := \mathbb{R}^{512} (N = L = 256)$, under the noise situation of SNR $:= 10\log_{10}(E\{z_k^2\}/E\{n_k^2\}) = 25$dB, where $z_k := \langle \boldsymbol{u}_k, \boldsymbol{h}^* \rangle$ and $E\{\cdot\}$ denote *pure echo (echo without noise)* and expectation, respectively. We utilize a male's speech signal, for $(s_k)_{k\in\mathbb{N}}$, recorded at sampling rate 16kHz. To measure the achievement level for echo path identification as well as that of echo cancellation, we evaluate System Mismatch$(k) := 10\log_{10} \frac{\|\boldsymbol{h}^* - \boldsymbol{h}_k\|^2}{\|\boldsymbol{h}^*\|^2}$, $\forall k \in \mathbb{N}$, ERLE$(k) := 10\log_{10} \frac{\sum_{i=1}^{k} (z_i)^2}{\sum_{i=1}^{k} (z_i - \langle \boldsymbol{u}_i, \boldsymbol{h}_i \rangle)^2}$, $\forall k \in \mathbb{N}$.

For the proposed scheme and the UW-PSP, we set $\lambda_k = 0.4$ and $q = |\mathscr{I}_k^{(c)}| = |\mathscr{I}_k^{(p)}| = 8$, $\forall k \in \mathbb{N}$. The stochastic property sets are designed by $r = 1$ and $\rho = \max\{(r-2)\sigma^2, 0\}\ (=0)$, where σ^2 is the variance of noise; for detailed discussion on the choice of ρ, see [3]. For the NLMS, the step size is set to $\mu = 0.2$. For the APA, the step size is set to $\mu = 1, 0.05$. For numerical stability against observable poor excitation of the speech input signals, certain regularization and threshold are utilized, which is the reason for the observable flat intervals.

Figure 6 depicts the performance of the algorithms in System Mismatch and ERLE. We observed that the proposed scheme achieves dramatically faster convergence than the UW-PSP both in System Mismatch and in ERLE. Moreover, the proposed scheme achieves lower level misidentification of echo paths and higher level ERLE than the other algorithms. Finally, we remark that the increase of computational complexity that accompanies the proposed scheme can be somewhat alleviated by $2q$ concurrent processors.

5. CONCLUSION

This paper has presented an efficient fast stereophonic acoustic echo canceling scheme. The proposed scheme has found a good direction of update with low computational complexity thanks to an efficient use of the POWER technique. Numerical examples have verified the efficacy of the proposed scheme. The results suggest the applicability of the POWER weighting technique to a real world problem.

Acknowledgement

The authors would like to express their deep gratitude to Prof. K. Sakaniwa of Tokyo Institute of Technology for fruitful discussions.

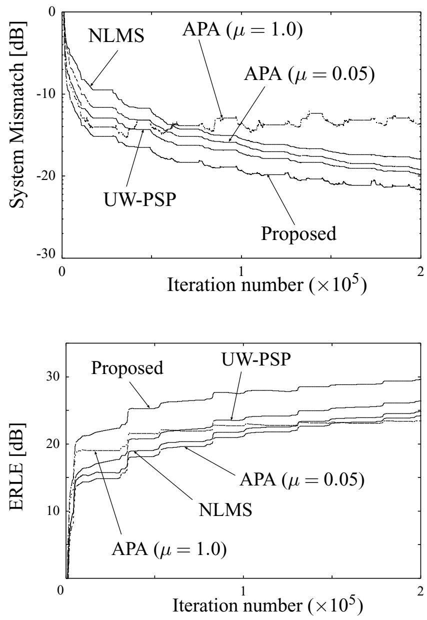

Figure 6: The proposed scheme versus the UW-PSP, the APA and the NLMS algorithms under SNR 25dB with common preprocessing. For the proposed scheme and the UW-PSP, $\lambda_k = 0.4$, $r = 1$, $\rho = 0$ and $q = 8$. For the NLMS, $\mu = 0.2$.

REFERENCES

[1] M. Yukawa and I. Yamada, "Acceleration of adaptive parallel projection algorithms by pairwise optimal weight realization," in *Proc. EUSIPCO*, 2004, pp. 713–716.

[2] M. Yukawa and I. Yamada, "Pairwise optimal weight realization —acceleration technique for set-theoretic adaptive parallel subgradient projection algorithm," submitted for publication.

[3] I. Yamada, K. Slavakis, and K. Yamada, "An efficient robust adaptive filtering algorithm based on parallel subgradient projection techniques," *IEEE Trans. Signal Processing*, vol. 50, no. 5, pp. 1091–1101, 2002.

[4] M. M. Sondhi, D. R. Morgan, and J. L. Hall, "Stereophonic acoustic echo cancellation—an over view of fundamental problem," *IEEE Signal Processing Lett.*, vol. 2, no. 8, pp. 148–151, 1995.

[5] J. Benesty, D. R. Morgan, and M. M. Sondhi, "A better understanding and an improved solution to the specific problems of stereophonic acoustic echo cancellation," *IEEE Trans. Speech Audio Processing*, vol. 6, no. 3, pp. 156–165, 1998.

[6] S. Shimauchi, Y. Haneda, S. Makino, and Y. Kaneda, "New configuration for a stereo echo canceler with nonlinear preprocessing," in *Proc. IEEE ICASSP*, May 1998, pp. 3685–3688.

[7] A. Sugiyama, Y. Joncour, and A. Hirano, "A stereo echo canceler with correct echo-path identification based on an input-sliding technique," *IEEE Trans. Signal Processing*, vol. 49, no. 11, pp. 2577–2587, 2001.

[8] T. Gänsler and J. Benesty, "Multichannel acoustic echo cancellation: what's new?," in *Proc. IEEE International Workshop on Acoustic Echo and Noise Control*, 2001.

[9] I. Yamada, "Adaptive projected subgradient method: A unified view for projection based adaptive algorithms," *The Journal of IEICE*, vol. 86, no. 8, pp. 654–658, August 2003, in Japanese.

[10] I. Yamada and N. Ogura, "Adaptive projected subgradient method for asymptotic minimization of sequence of nonnegative convex functions," *Numer. Funct. Anal. Optim.*, vol. 25, no. 7&8, pp. 593–617, 2004.

[11] M. Yukawa and I. Yamada, "Efficient adaptive stereo echo canceling schemes based on simultaneous use of multiple state data," *IEICE Trans. Fundamentals*, vol. E87-A, no. 8, pp. 1949–1957, Aug. 2004.

[12] M. Yukawa and I. Yamada, "On optimality of power weighting technique for adaptive filtering," Tech. Rep., IEICE, Apr. 2005, SIP2005-7.

[13] S. Haykin, *Adaptive Filter Theory*, Prentice Hall, 3rd edition, 1996.