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A MULTI-NOISE MULTI-CHANNEL ANC SYSTEM USING RELATIVE TRANSFER MATRIX-BASED APPROACH

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ABSTRACT

Remote microphone-based virtual sensing (RM-VS) methods are used in active noise control (ANC) systems to avoid the physical presence of microphones inside the region of interest (ROI). Conventionally, this is achieved by estimating an observation filter to obtain the primary noise signals at virtual microphones inside the ROI, with the physical microphones recording outside the ROI. In this paper, we present a novel structure of the RM technique, where we estimate the relative transfer matrix (ReTM) between the signals at virtual microphones and physical microphones with both noise sources and secondary sources active. This ReTM can be directly applied to the recorded residual error signals during noise control, as opposed to the conventional observation filter which is typically applied to the estimated primary noise signals. Simulation results show that the proposed ReTM-based approach achieves similar performance to the conventional RM method in a stationary environment, while being more robust to changes in the secondary paths.

Index Terms— Multi-channel active noise control, Relative transfer matrix, Remote Microphone Technique.

1. INTRODUCTION

Active noise control (ANC) reduces unwanted primary noises with secondary source signals for low-frequency noises [1, 2]. The multi-channel filtered-x least mean square (FxLMS) is the most widely used ANC algorithm to reduce noise for a region of interest (ROI) with multiple reference sensors, error microphones, and secondary sources [3–5]. Conventionally, the residual signals in the ROI during noise control are measured by error microphones placed inside the ROI. However, this will pose limitations on the space and usage of the ROI.

To address this limitation, the remote microphone (RM) technique is proposed to use physical microphones outside the ROI monitoring the residual noise inside the ROI. The ANC performance with the RM technique has been evaluated in active headrest systems [6, 7] and head-mounted ANC system [8]. An observation filter is applied to primary noise signals measured at the monitoring microphones to estimate the primary noise signals at the virtual microphones. This filter can be obtained either through statistical calculations of correlation matrices [9, 10] or obtained adaptively [11, 12]. Earlier RM technique in ANC application considered filter design under single primary source [9], which are later extended to multiple primary sources [13, 14]. Recently, Shi *et al.* [11] proposed to use an additional filter to determine the spatial mapping between the physical monitoring microphone and virtual microphone under secondary sources. By individually estimating the primary noise signals and secondary signals at the virtual microphones with the two filters, residual signals at the ROI can be estimated.

The observation filter, considered as the spatial acoustic relationship between two microphones in response to a noise source, can also be referred to as the relative transfer function (ReTF) [15]. ReTF has a favourable characteristic in that it is independent of the source's signal and can be estimated with measured microphone signals. However, this characteristic fails to hold when additional sources are active. Recently, the ReTF has been extended to a Relative Transfer Matrix (ReTM) which derives the spatial mapping between two multi-channel microphone groups in response to multiple sources [16]. In addition to its ReTF properties, ReTM is also robust when the trained source signals change or even become inactive.

Motivated by this work, we propose a ReTM-based approach for a multi-noise multi-channel ANC system. We combine the estimation of ReTM between virtual and monitoring microphone groups under both primary noise sources and secondary sources in a single tuning stage. We formulate and show the ReTM can be used at two different paths during the noise control stage.

2. PROBLEM FORMULATION

Consider a multi-noise multi-channel ANC system as shown in Fig. 1. Let there be J primary noise sources with one reference sensor placed close to each primary noise source, M physical monitoring microphones placed outside of the ROI and V virtual microphones located inside the ROI. We express all signals in the short-time Fourier transform (STFT) domain with f and t denoting frequency bin and time-frame index, respectively. Let $\boldsymbol{x}(f,t)$ be $J \times 1$ vector of reference

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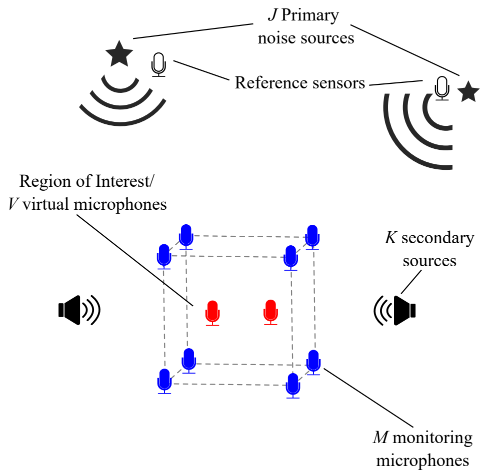


Fig. 1: ANC system setup: There are multiple noise sources individually measured by a reference sensor, multiple secondary sources (loudspeakers) and two microphone groups.

signals, $\boldsymbol{y}(f,t)$ be $K \times 1$ vector of secondary source signals, $\boldsymbol{e}_{\mathrm{V}}(f,t)$ be $V \times 1$ vector of virtual microphone signals, and $\boldsymbol{e}_{\mathrm{M}}(f,t)$ be $M \times 1$ vector of monitoring microphone signals. We can express these signals as

$$\boldsymbol{e}_{\mathrm{M}}(f,t) = [\boldsymbol{P}_{\mathrm{M}}(f)\,\boldsymbol{S}_{\mathrm{M}}(f)][\boldsymbol{x}(f,t)^T\,\boldsymbol{y}(f,t)^T]^T, \tag{1}$$

$$\boldsymbol{e}_{\mathrm{V}}(f,t) = [\boldsymbol{P}_{\mathrm{V}}(f)\,\boldsymbol{S}_{\mathrm{V}}(f)][\boldsymbol{x}(f,t)^T\,\boldsymbol{y}(f,t)^T]^T, \tag{2}$$

where $(\cdot)^T$ is the transpose operator, $\boldsymbol{P}_{\mathrm{M}}$ and $\boldsymbol{P}_{\mathrm{V}}$ are the primary channel response matrices to the monitoring and virtual microphones with sizes $M \times J$ and $V \times J$, respectively. $\boldsymbol{S}_{\mathrm{M}}$ and $\boldsymbol{S}_{\mathrm{V}}$ are the secondary channel response matrices to the monitoring and virtual microphones with sizes $M \times K$ and $V \times K$, respectively.

An ANC system with remote monitoring microphones typically have a tuning stage to learn an observation filter $\boldsymbol{O}_{\mathrm{VM}}(f)$ between the noise signals received at the physical microphones and the virtual microphones without the secondary source signals, i.e.,

$$\boldsymbol{P}_{\mathrm{V}}(f)\boldsymbol{x}(f,t) = \boldsymbol{O}_{\mathrm{VM}}(f)\boldsymbol{P}_{\mathrm{M}}(f)\boldsymbol{x}(f,t). \tag{3}$$

During the control stage, the residual signal can hence be estimated by

$$\begin{aligned}\hat{\mathbf{e}}_{\mathrm{V}}(f,t) = \boldsymbol{O}_{\mathrm{VM}}(f)\left(\boldsymbol{e}_{\mathrm{M}}(f,t) - \boldsymbol{S}_{\mathrm{M}}(f)\boldsymbol{y}(f,t)\right)\\ + \boldsymbol{S}_{\mathrm{V}}(f)\boldsymbol{y}(f,t),\end{aligned} \tag{4}$$

without microphones inside the ROI.

In (4), the estimation of $\hat{\mathbf{e}}_{\mathrm{V}}$ requires knowing $\boldsymbol{S}_{\mathrm{V}}$ and $\boldsymbol{S}_{\mathrm{M}}$ in addition to the observation filter $\boldsymbol{O}_{\mathrm{VM}}$. Due to the absence of virtual microphones during the control stage, $\boldsymbol{S}_{\mathrm{V}}$ can only be measured offline in tuning stage. Any potential change in $\boldsymbol{S}_{\mathrm{V}}$ cannot be monitored during the control stage.

In this paper, we aim to optimize the tuning stage of the remote microphone technique using a ReTM-based approach to model both the noise signals and the secondary paths together, which provides the ANC system more tolerance on secondary path changes during the control stage.

3. RELATIVE TRANSFER MATRIX-BASED ANC

In this section, we first review the definition of ReTM, then formulate an ANC system with a new tuning stage to obtain the necessary ReTM, and apply the matrix filter in the control stage.

3.1. The Relative Transfer Matrix

The ReTM is defined as the spatial mapping between the two microphone groups [16]. The ReTM $\boldsymbol{R}_{\mathrm{VM}}(f)$ between the recorded signals at the physical microphone group and the virtual microphone group is given by

$$\boldsymbol{e}_{\mathrm{V}}(f,t) = \boldsymbol{R}_{\mathrm{VM}}(f)\boldsymbol{e}_{\mathrm{M}}(f,t). \tag{5}$$

Using (1), (2) and (5), the theoretical definition of the ReTM [16] is given by

$$\boldsymbol{R}_{\mathrm{VM}}(f) = [\boldsymbol{P}_{\mathrm{V}}\,\boldsymbol{S}_{\mathrm{V}}][\boldsymbol{P}_{\mathrm{M}}\,\boldsymbol{S}_{\mathrm{M}}]^{\ddagger}, \tag{6}$$

where $(\cdot)^{\ddagger}$ is the pseudo-inverse, assuming validity. We use a correlation-based approach [16] to approximate the $\boldsymbol{R}_{\mathrm{VM}}(f)$ where

$$\boldsymbol{R}_{\mathrm{VM}}(f) \approx \boldsymbol{\mathcal{P}}_{\mathrm{V,V}}(f)\boldsymbol{\mathcal{P}}_{\mathrm{M,V}}{}^{\ddagger}(f), \tag{7}$$

where the cross-correlation $\boldsymbol{\mathcal{P}}_{\mathrm{M,V}} \triangleq \mathbb{E}\{\boldsymbol{e}_{\mathrm{M}}(f,t)\boldsymbol{e}_{\mathrm{V}}{}^*(f,t)\}$ and auto-correlation $\boldsymbol{\mathcal{P}}_{\mathrm{V,V}} \triangleq \mathbb{E}\{\boldsymbol{e}_{\mathrm{V}}(f,t)\boldsymbol{e}_{\mathrm{V}}{}^*(f,t)\}$ matrices, and $(\cdot)^*$ is the conjugate transpose. The expectation $\mathbb{E}(\cdot)$ is found by averaging over T time frames using

$$\boldsymbol{\mathcal{P}}_{\mathrm{MV}}(f) \cong \frac{1}{T}\sum_{t=1}^{T}\boldsymbol{e}_{\mathrm{M}}(f,t)\,\boldsymbol{e}_{\mathrm{V}}^*(f,t), \tag{8}$$

and $\boldsymbol{\mathcal{P}}_{\mathrm{V,V}}(f)$ can be obtained in a similar way.

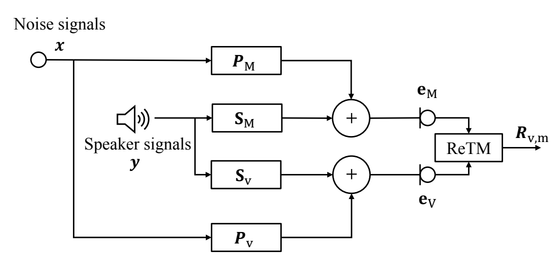


Fig. 2: Illustration of tuning stage to obtain ReTM

3.2. ANC with Relative Transfer Matrix

3.2.1. Tuning (Estimation) Stage

Since the ReTM can incorporate all active sound sources in the environment, we consider both the primary noise sources and secondary sources simultaneously in a single tuning stage, as shown in Fig. 2. The number of monitoring microphones should be set as $M \geq K + J$.

In the tuning stage, we play white noise from the secondary sources while all noise sources are active and place

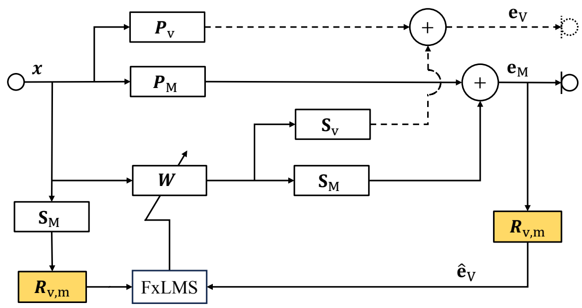


Fig. 3: Illustration of control stage using ReTM to estimate signals at the virtual microphone positions and FxLMS as adaptive algorithm for ANC

physical microphones at both virtual and monitoring microphone positions. Then, $\boldsymbol{R}_{\mathrm{VM}}(f)$ is estimated, using a short segment of $\boldsymbol{e}_{\mathrm{V}}(f,t)$ and $\boldsymbol{e}_{\mathrm{M}}(f,t)$ via (7) and (8).

Note that the ReTM is different to the observation filter in the conventional remote microphone technique (3), which only estimates the primary noise signals at the virtual microphone positions. As seen from (6), $\boldsymbol{R}_{\mathrm{VM}}(f)$ contains the transfer functions from both the primary and secondary sources to the virtual microphone positions. Thus it can map either primary or secondary or both signals together to the virtual microphones. In the next section, we show how to use $\boldsymbol{R}_{\mathrm{VM}}(f)$ in two different roles in the control stage.

3.2.2. Control Stage

The proposed control stage with the conventional FxLMS adaptive algorithm for ANC is illustrated in Fig. 3 where there are no physical microphones at the virtual microphone locations. We use the ReTM function at two different paths as highlighted in Fig. 3 and described below.

Using the estimated $\boldsymbol{R}_{\mathrm{VM}}(f)$ during the tuning stage and monitoring microphone signals $\boldsymbol{e}_{\mathrm{M}}(t,f)$, we estimate the error signal at the virtual microphones as

$$\begin{aligned}\hat{\boldsymbol{e}}_{\mathrm{V}}(f,t) &= \boldsymbol{R}_{\mathrm{VM}}(f)\boldsymbol{e}_{\mathrm{M}}(t,f) \\ &= \boldsymbol{P}_{\mathrm{V}}(f)\boldsymbol{x}(f,t)+\boldsymbol{S}_{\mathrm{V}}(f)\boldsymbol{y}(f,t),\end{aligned} \tag{9}$$

where the second line follows from (1) and (6).

In conventional remote microphone technique, the reference signal vector is filtered by the secondary channel response to the virtual microphones $\boldsymbol{S}_{\mathrm{V}}$. However, the secondary channel can change over time but cannot be updated as there are no physical microphones at the virtual locations during the control stage. Unlike $\boldsymbol{S}_{\mathrm{V}}$, the secondary channel to monitoring microphones may be updated using existing online secondary path modelling techniques [17]. We assume the perturbation to the learned ReTM is minimal since it is a relative difference of any change to the environment. Thus, in the proposed structure, we filter the reference signal vector $\boldsymbol{x}(f,t)$ by $\boldsymbol{S}_{\mathrm{M}}(f)$ and the estimate ReTM $\boldsymbol{R}_{\mathrm{VM}}(f)$ before feeding to the FxLMS algorithm.

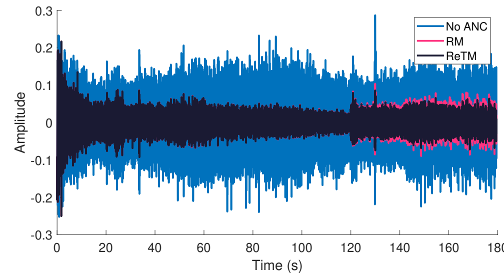


Fig. 4: Residual noise at the virtual microphone location during the control stage with ANC off, the proposed method (ReTM), and the conventional method (RM) with three scenarios of noise sources.

Following [18], the generalized multiple-reference multiple-output FxLMS algorithm is given by

$$\boldsymbol{W}_j(f,t+1)=\boldsymbol{W}_j(f,t)-\mu\boldsymbol{x}_j(f,t)\boldsymbol{S}_{\mathrm{V}}(f)^T\boldsymbol{e}_{\mathrm{V}}{}^*(f,t)\,, \tag{10}$$

where $\boldsymbol{W}_j$ is $K\times 1$ vector and μ is the step size. In the proposed method, we replace $\boldsymbol{e}_{\mathrm{V}}(f,t)$ by (9) and $\boldsymbol{S}_{\mathrm{V}}(f)$ by $\boldsymbol{R}_{\mathrm{VM}}(f)[\mathbf{0}\,\boldsymbol{S}_{\mathrm{M}}]$.

Note that the usage of secondary sources in this paper in the tuning stage is different from the auxiliary filter based virtual sensing methods [19, 20]. Although the auxiliary filter based methods use both primary noise and secondary sources in the tuning stage, the secondary source signals need to be adapted for auxiliary filter training. Our proposed method does not require the adjustment of the secondary source signals. Hence, we argue that the proposed method is an improvement to the conventional RM techniques, but not a direct use of the auxiliary filter based virtual sensing methods.

4. SIMULATION RESULTS

In this section, we conduct simulations to compare the noise reduction performance of our proposed ReTM-based ANC system and the conventional RM-based ANC system.

We conduct an ANC system with $J=2$ noise sources at $[0.6,0.8,1]$ m and $[2.17,1.15,0.05]$ m, $K=2$ secondary loudspeakers at $[0,\pm 0.3,0]$ m, and $M=8$ monitoring microphones at $[\pm 0.15,\pm 0.15,-0.15]$ m, $[0,\pm 0.212,0.15]$ m and $[\pm 0.212,0,0.15]$ m, in a simulated room of size $[8,7,4]$ m and $T_{60}=500$ ms. The impulse responses are obtained using the image source method [21]. For the tuning stage, we place $V=6$ of microphones at $[0.05,\pm 0.10,0]$ m, $[-0.05,\pm 0.10,0]$ m and $[0,\pm 0.10,0]$ m to obtain the necessary ReTM mapping. The last pair of microphones at $[0,\pm 0.10,0]$ are used to examine the performance of ANC algorithms. We use two broadband factory noise signals of length 100 s from the NOISEX-92 dataset [22] with 8 kHz sampling rate.

We use 60 s of the factory noise signals for the primary sources for the tuning stage. Both the secondary sources emitted random noise during the tuning stage of comparable am-

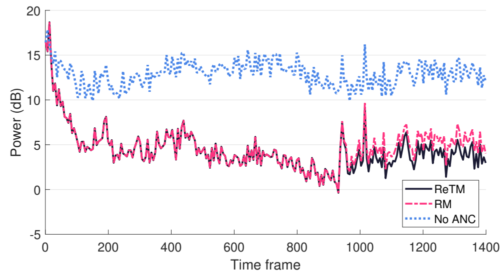


Fig. 5: Power spectrum averaged over $20 - 600$ Hz at the virtual microphone location during the control stage with ANC off, the proposed method (ReTM), and the conventional method (RM) with three scenarios of noise sources.

plitude to the primary noise signals at the microphones.

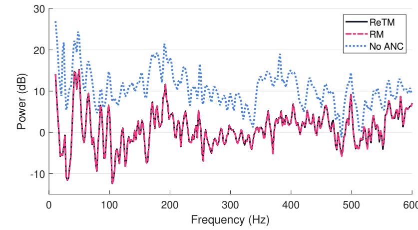
We conducted three scenarios in the control stage. First, we use the same 60 s of noise signals from the tuning stage as the noise signals at primary sources. Second, we changed the noise signals to another 60 s of noise signals which was unexposed during the tuning stage. Finally, we change the secondary sources position to $[0, \pm 0.35, 0]$ m, and use another 60 s of unexposed noise signals.

We present the time domain signals of the three scenarios at one of the virtual microphones with ANC system off, RM-based conventional method, and the proposed ReTM method in Fig. 4. We can see that the proposed ReTM approach has a similar residual noise as the conventional RM method in the first 120 s when there is no secondary path change. After 120 s, a change in secondary source positions resulted in changes to the secondary paths and we observe that both methods show an increase in residual error, and the error increased with the conventional method is more than the proposed method. This can be attributed to the proposed method estimating $\boldsymbol{S}_{\mathrm{V}}$ with $\boldsymbol{S}_{\mathrm{M}}$ and ReTM, and the estimation can adapt partially with assumed accurate estimations of $\boldsymbol{S}_{\mathrm{M}}$.

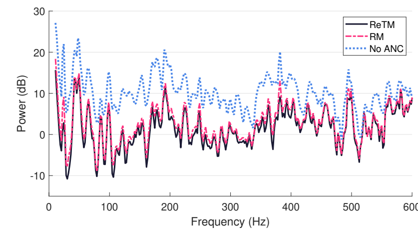
The averaged residual noise power over $20 - 600$ Hz for each time frame of the three scenarios at the virtual microphone location is shown in Fig. 5. We observe that the RM and ReTM residual signal power overlap for the first two scenarios (up to 940 time frame). For the last scenario, both the RM and ReTM method provides higher residual noise level than the two former scenarios, with our ReTM approach having constantly lower residual power than the conventional RM approach. This follows the same trend as in Fig. 4.

To further examine the effect of changing secondary speaker position, we look into the average residual power at the virtual microphone across the frequency of interest in scenarios 2 and 3, respectively, as shown in Fig. 6. We notice a minimal difference between the ReTM method and the RM method in Fig.6a over all frequencies. After changing secondary source position in Fig.6b, this difference in residual power is more noticeable at the lower frequency < 400 Hz.

Overall, our simulations demonstrate the proposed ReTM obtained in the tuning stage with secondary sources all active



(a) Scenario 2: Without secondary paths change



(b) Scenario 3: With secondary paths change

Fig. 6: Power spectrum averaged over time frames (a) before secondary paths and (b) after secondary paths change at the virtual microphone location during the control stage with ANC off, the proposed method (ReTM), and the conventional method (RM).

behaves similarly to the conventional observation filter tuned only with primary noise sources. When there is no changes in the environment, our method can achieve a similar noise reduction performance with the conventional RM method in a stationary environment. With small perturbations in the secondary paths, the ReTM-based ANC system is more robust due to having accurate information on the monitoring secondary paths. However, we note that our ReTM is dependent on the acoustic environment and the noise reduction will deteriorate quickly if the secondary paths significantly changes.

5. CONCLUSION

In this paper, we proposed a ReTM-based approach to estimate the virtual microphone signals from the measured monitoring signals in a multi-noise multi-channel ANC system. The ReTM is trained in a single stage with both primary and secondary sources active. We show that the same ReTM can be used to both filter the residual signals at the physical microphones, and filter the reference signals for the adaptive ANC algorithms. The proposed method can achieve a similar noise reduction performance with the conventional RM method in a stationary environment, and shows its robustness when changes to the secondary paths occur. For future works, we aim to conduct experiments with changing environment, such as moving furniture, to further examine the proposed method, and a more in-depth analysis of the robustness of ReTM against different changes of acoustic paths.

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