SUBSPACE METHODS FOR MULTI-MICROPHONE SPEECH DEREVERBERATION

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ABSTRACT

A novel approach to speech dereverberation is presented. The method is based on construction of the null space of the data matrix in the presence of colored noise, using the GSVD technique. The special Sylvester structure of the filtering matrix, related to this subspace, is exploited for deriving a LS estimate for the acoustical filters. Other, less robust but computationally more efficient methods are derived based on the same structure. A preliminary experimental study supports the potential of the method.

1. INTRODUCTION

In many speech communication applications, the recorded speech signal is subject to reflections on the room walls and other objects on its way from the source to the microphones. The resulting speech signal is then called reverberated. The quality of the speech signal might deteriorate severely and this can even cause a degradation in intelligibility. Subsequent processing of the speech signal, such as speech coding or automatic speech recognition might be rendered useless in the presence of reverberated speech. The most successful methods for dereverberation are based on multi-microphone measurements. Beamforming methods which steer a beam towards the direction of arrival of the desired signal (or more generally, towards the transfer function of the desired signal) can reduce the amount of reverberation but can not eliminate it completely. Spatio-temporal methods, consisting of application of spatial averaging and cepstrum domain processing are presented by Liu *et al.* [1]. Other methods are based on the structure of the correlation matrix of the measurements (e.g. Moulines *et al.* [2] and Gürelli and Nikias [3]). The methods presented in this contribution are also based on the structure of the correlation matrix. We will start by deriving a method for constructing the null space in the presence of colored noise. Then, the special structure of the filtering matrix will be exploited to derive a LS approach for acoustical transfer function(ATF) estimation as well as some suboptimal procedures. The derivation of the algorithm is followed by a preliminary experimental study.

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2. PROBLEM FORMULATION

Assume a speech signal is received by M microphones in a noisy and reverberating environment. Then, for $m = 1, \ldots, M$; $t = 0, 1, \ldots, T$,

$$z_m(t) = a_m(t) * s(t) + n_m(t) = \sum_{k=0}^{n_a} a_m(k) s(t-k) + n_m(t) \quad (1)$$

Where, $z_m(t)$ is the $m-$th received signal, $n_m(t)$ is the noise signal received in the $m-$th microphone, $s(t)$ is the desired speech signal and $T+1$ is the number of samples observed. $*$ denotes the convolution operation. We further assume that the acoustical transfer functions (ATFs) relating the speech source and each of the M microphones can be modeled as an FIR filter of order n_a, $\mathbf{a}_m^T = [a_m(0), a_m(1), \ldots, a_m(n_a)]$. Define also the $Z-$transform of each of the M filters as,

$$A_m(z) = \sum_{k=0}^{n_a} a_m(k) z^{-k}.$$

The goal of the dereverberation problem is to reconstruct the speech signal $s(t)$ from the noisy observations $z_m(t)$. This goal may be achieved by first estimating the ATFs, $\mathbf{a}_m(t)$.

3. ALGORITHM DERIVATION

We will start our discussion dealing with a special case of the problem and then proceed to the general case.

3.1. Two microphone noiseless case - preliminaries

In this section we will lay the foundations of the algorithm by noting that the the desired ATFs are embedded in the null space of the signals' data matrix.

The two microphone noiseless case is depicted in Figure 1. The noiseless signals, denoted by $y_m(t)$, are given in Eq. 2, as can be seen from the left-hand side of the Figure.

$$\begin{aligned} y_1(t) &= a_1(t) * s(t) \\ y_2(t) &= a_2(t) * s(t). \end{aligned} \quad (2)$$

Clearly, as can be seen from the right-hand side of Figure 1, the following identity holds.

$$[y_2(t) * a_1(t) - y_1(t) * a_2(t)] * e_l(t) = 0 \quad (3)$$

where, $e_l(t), l = 0, 1, 2, \ldots$ are arbitrary and unknown filters, the number of which and their order will be discussed in the sequel. Define the $(\hat{n}_a + 1) \times (T + \hat{n}_a + 1)$ single

$$\mathcal{Y}_m = \begin{bmatrix} y_m(0) & y_m(1) & \cdots & & y_m(\hat{n}_a) & y_m(\hat{n}_a+1) & \cdots & y_m(T) & 0 & \cdots & 0 \\ 0 & y_m(0) & y_m(1) & \cdots & \vdots & \vdots & & \cdots & y_m(T) & 0 & 0 \\ \vdots & 0 & \ddots & \ddots & & & & & & \ddots & \vdots \\ 0 & & & \ddots & \vdots & & \ddots & & 0 & \ddots & \\ 0 & & \cdots & 0 & y_m(0) & y_m(1) & \cdots & y_m(\hat{n}_a) & \cdots & & y_m(T) \end{bmatrix} \quad (4)$$

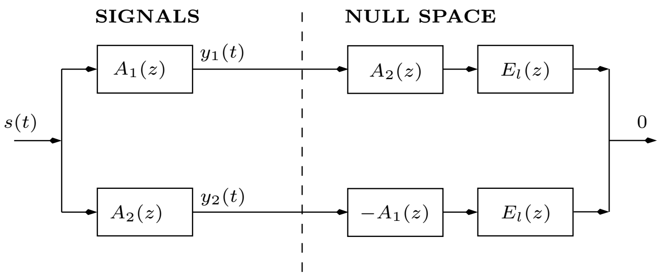

Figure 1: Null space in the two microphone noiseless case.

channel data matrix $\mathcal{Y}_m$, given in Eq. 4 at the top of the page. We assume that the inequality $\hat{n}_a \geq n_a$ holds, i.e., the ATFs order is always overestimated. Define also the two-channel data matrix,

$$\mathcal{Y} = \begin{bmatrix} \mathcal{Y}_2 \\ -\mathcal{Y}_1 \end{bmatrix}.$$

The $2(\hat{n}_a+1) \times 2(\hat{n}_a+1)$ correlation matrix of the data is thus given by $\hat{R}_y = \frac{\mathcal{Y}\mathcal{Y}^T}{T+1}$.

Now, following [3] and [2], the null space of the correlation matrix can be calculated by virtue of the eigenvalue decomposition. Let λ_l ; $l = 0, 1, \ldots, 2\hat{n}_a + 1$ be the eigenvalues of the correlation matrix $\hat{R}_y$, then by sorting them in ascending order we will have,

$$\begin{array}{ll} \lambda_l = 0 & l = 0, 1, \ldots, \hat{n}_a - n_a \\ \lambda_l > 0 & \text{otherwise} \end{array} . \quad (5)$$

Thus, as proven by Gürelli and Nikias [3], the rank of the null space of the correlation matrix is $\hat{n}_a - n_a + 1$. We note that the singular value decomposition (SVD) of the data matrix, $\mathcal{Y}$, might be used instead of the eigenvalue decomposition for determining the null space. The SVD is generally regarded as a more robust method.

Denote the null space vectors (eigenvectors corresponding to zero eigenvalues or singular values) by $\mathbf{g}_l$ for $l = 0, 1, 2, \ldots, \hat{n}_a - n_a + 1$. Then, splitting each null space vector into two parts of equal length $\hat{n}_a + 1$ yields,

$$\mathcal{G} = \begin{bmatrix} \mathbf{g}_0 & \mathbf{g}_1 & \cdots & \mathbf{g}_{\hat{n}_a - n_a} \end{bmatrix} = \quad (6)$$
$$\begin{bmatrix} \tilde{\mathbf{a}}_{1,0} & \tilde{\mathbf{a}}_{1,1} & \cdots & \tilde{\mathbf{a}}_{1,\hat{n}_a - n_a} \\ \tilde{\mathbf{a}}_{2,0} & \tilde{\mathbf{a}}_{2,1} & \cdots & \tilde{\mathbf{a}}_{2,\hat{n}_a - n_a} \end{bmatrix}.$$

Each of the $\hat{n}_a$+1-long vectors represents an $\hat{n}_a$ order filters,

$$\tilde{A}_{ml}(z) = \sum_{k=0}^{\hat{n}_a} \tilde{a}_{ml}(k) z^{-k}$$
$$l = 0, 1, \ldots, \hat{n}_a - n_a \; ; \; m = 1, 2.$$

From the above discussion, the null space filters are given by,

$$\tilde{A}_{ml}(z) = A_m(z) E_l(z) \quad (7)$$
$$l = 0, 1, , \ldots, \hat{n}_a - n_a \; ; \; m = 1, 2.$$

Thus, the zeros of the filters $\tilde{A}_{ml}(z)$ extracted from the null space of the data, contain the roots of the desired filters as well as some extraneous zeros. This observation was proven by Gürelli and Nikias [3] as the basis of their EVAM algorithm. It can be stated in the following lemma (for the general M channel case):

Lemma 3.1 *Let $\tilde{\mathbf{a}}_{ml}$ be the partitions of the null space eigenvectors into M vectors of length $\hat{n}_a + 1$, with $\tilde{A}_{ml}(z)$ their equivalent filters. Then, all the filters $\tilde{A}_{ml}(z)$ for $l = 0, \ldots, \hat{n}_a - n_a$ have n_a common roots, which constitutes the desired ATFs $A_m(z)$, and $\hat{n}_a - n_a$ different extraneous roots. These extraneous roots are common for all partitions of the same vector, i.e., $\tilde{A}_{ml}(z)$ for $m = 1, \ldots, M$.*

Under several regularity conditions (stated, for example by Moulines *et al.* [2]), the filters $A_m(z)$ can be found.

In matrix form Eq. 7 may be written in the following manner. Define the $(\hat{n}_a+1) \times (\hat{n}_a - n_a + 1)$ Sylvester filtering matrix (recall we assume $\hat{n}_a \geq n_a$),

$$\mathcal{A}_m = \underbrace{\begin{bmatrix} a_m(0) & 0 & 0 & \cdots & 0 \\ a_m(1) & a_m(0) & 0 & \cdots & 0 \\ \vdots & a_m(1) & \ddots & & \vdots \\ a_m(n_a) & \vdots & \ddots & \ddots & 0 \\ 0 & a_m(n_a) & & \ddots & a_m(0) \\ \vdots & 0 & & & a_m(1) \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & \cdots & 0 & a_m(n_a) \end{bmatrix}}_{\hat{n}_a - n_a + 1} . \quad (8)$$

Then,

$$\tilde{\mathbf{a}}_{ml} = \mathcal{A}_m \mathbf{e}_l, \quad (9)$$

where, $\mathbf{e}_l^T = \begin{bmatrix} e_l(0) & e_l(1) & \ldots & e_l(\hat{n}_a - n_a) \end{bmatrix}$ are vectors of the coefficients of the arbitrary unknown filters. Thus, the number of different filters (as shown in Eq. 7) is $\hat{n}_a - n_a + 1$ and their order is $\hat{n}_a - n_a$. Using Fig 1 and Eq. 3 and denoting,

$$\mathcal{E} = \begin{bmatrix} \mathbf{e}_0 & \mathbf{e}_1 & \cdots & \mathbf{e}_{\hat{n}_a - n_a} \end{bmatrix},$$

we conclude

$$\mathcal{G} = \begin{bmatrix} \mathcal{A}_1 \\ \mathcal{A}_2 \end{bmatrix} \mathcal{E} \triangleq \mathcal{A}\mathcal{E}. \quad (10)$$

We note, that in the special case when the ATFs' order is known, i.e. $\hat{n}_a = n_a$, there is only one vector in the null space and its partitions $\tilde{\mathbf{a}}_{m0}$; $m = 1, \ldots, M$ are equal to the desired filters $\mathbf{a}_m$ up to a (common) scaling factor ambiguity. In the general case $\hat{n}_a > n_a$ the real M ATFs $A_m(z)$ are embedded in $\tilde{A}_{ml}(z)$; $l = 0, 1, \ldots, \hat{n}_a - n_a$.

The special structure depicted in Eq. 10 forms the basis of our suggested algorithm.

3.2. Two microphone noiseless case - algorithm

Based on the special structure of Eq. 10 and in particular on the Sylvester structure of $\mathcal{A}_1$ and $\mathcal{A}_2$ we will now derive an algorithm for finding the ATFs $A_m(z)$.

Note that $\mathcal{E}$ in Eq. 10 is a square and arbitrary matrix, implying that its inverse usually exists. Denote this inverse by $\mathcal{E}^i = \mathrm{inv}(\mathcal{E})$. Then.

$$\mathcal{G}\mathcal{E}^i = \mathcal{A} \qquad (11)$$

Denote the columns of $\mathcal{E}^i$ by, $\mathcal{E}^i = \left[\begin{array}{cccc} \mathbf{e}_0^i & \mathbf{e}_1^i & \cdots & \mathbf{e}_{\hat{n}_a - n_a}^i \end{array}\right]$. Eq. 11 can be rewritten as,

$$\tilde{\mathcal{G}}\mathbf{x} = \mathbf{0} \qquad (12)$$

where, $\tilde{\mathcal{G}}$ is defined as,

$$\tilde{\mathcal{G}} = \begin{bmatrix} \mathcal{G} & \mathcal{O} & \cdots & \cdots & \cdots & \mathcal{O} & -\mathcal{I}^{(0)} \\ \mathcal{O} & \mathcal{G} & \mathcal{O} & \cdots & \cdots & \mathcal{O} & -\mathcal{I}^{(1)} \\ \vdots & \mathcal{O} & \ddots & & & \vdots & \vdots \\ \vdots & \vdots & & \ddots & \ddots & \vdots & \vdots \\ \vdots & \vdots & & \ddots & \ddots & \mathcal{O} & \vdots \\ \mathcal{O} & \mathcal{O} & \cdots & \cdots & \mathcal{O} & \mathcal{G} & -\mathcal{I}^{\hat{n}_a - n_a} \end{bmatrix} \qquad (13)$$

and the vector of unknowns is defined as,

$$\mathbf{x}^T = \left[\begin{array}{cccccc} \mathbf{e}_0^i & \mathbf{e}_1^i & \cdots & \mathbf{e}_{\hat{n}_a - n_a}^i & \mathbf{a}_1 & \mathbf{a}_2 \end{array}\right]$$

$\mathbf{0}$ is a vector of zeros: $\mathbf{0}^T = \left[\begin{array}{cccc} 0 & 0 & \cdots & 0 \end{array}\right]$.

We used the following expressions: $\mathcal{O}$ is a $2(\hat{n}_a + 1) \times (\hat{n}_a - n_a + 1)$ all-zeros matrix and $\mathcal{I}^{(l)}$; $l = 0, 1, \ldots, \hat{n}_a - n_a$ is given by,

$$\mathcal{I}^{(l)} = \left[\begin{array}{c|c} \begin{array}{c} \mathcal{O}_{l \times (n_a+1)} \\ \mathcal{I}_{(n_a+1) \times (n_a+1)} \\ \mathcal{O}_{(\hat{n}_a - n_a - l) \times (n_a+1)} \end{array} & \mathcal{O}_{(\hat{n}_a+1) \times (n_a+1)} \\ \hline \mathcal{O}_{(\hat{n}_a+1) \times (n_a+1)} & \begin{array}{c} \mathcal{O}_{l \times (n_a+1)} \\ \mathcal{I}_{(n_a+1) \times (n_a+1)} \\ \mathcal{O}_{(\hat{n}_a - n_a - l) \times (n_a+1)} \end{array} \end{array}\right]$$

A non-trivial (and exact) solution for the set of equations may be obtained by finding the eigenvector of the matrix $\tilde{\mathcal{G}}$ corresponding to its zero eigenvalue. The ATF coefficients are given by the last $2(n_a + 1)$ terms of this eigenvector. This method will be useful in the presence of noise.

3.3. Two microphone noisy case

Recall that $\mathcal{G}$ is a matrix containing the eigenvectors corresponding to zero eigenvalues of the noiseless data matrix. In presence of additive noise, the noisy observations $z_m(t)$, given in Eq. 1, can be stacked into a data matrix fulfilling

$$\mathcal{Z} = \mathcal{Y} + \mathcal{N},$$

where, $\mathcal{Z}$ and $\mathcal{N}$ are noisy signal and noise-only signal data matrices, respectively, defined in a similar way to Eq. 4. Now, for long observation time the following approximation holds, $\hat{R}_z \approx \hat{R}_y + \hat{R}_n$ where, $\hat{R}_z = \frac{\mathcal{Z}\mathcal{Z}^T}{T+1}$ and $\hat{R}_n = \frac{\mathcal{N}\mathcal{N}^T}{T+1}$ are the noisy signal and noise-only signal correlation matrices, respectively. Now, Eq. 12 would not be accurate anymore. A reasonable approximation, although not exact, would be to transform Eq. 12 into the following least squares (LS) problem,

$$\tilde{\mathcal{G}}\mathbf{x} = \boldsymbol{\varepsilon}.$$

The eigenvector corresponding to the smallest eigenvalue will reveal the desired LS solution for the vector $\mathbf{x}$ and hence for the desired ATFs. The null space matrix determination for both the white noise case and the colored noise case will be addressed in the sequel.

3.3.1. White noise case

In the case of spatio-temporal white noise - i.e. $\hat{R}_n \approx \sigma^2 I$, where I is the identity matrix - the first $\hat{n}_a - n_a + 1$ eigenvalues in Eq. 5 will be σ^2 instead of zero. The corresponding eigenvectors will remain intact. Thus, the algorithm will not change.

3.3.2. Colored noise case

The case of colored noise was addressed in [2],[3]. We suggest an alternative method which is computationally more efficient, as no pre-whitening of the noise correlation matrix is involved. We suggest to use the generalized eigenvalue decomposition of the measurement correlation matrix, R_z and the noise correlation matrix R_v (usually, the latter is estimated from speech-free data segments). Then the null space matrix $\mathcal{G}$ is formed by choosing the generalized eigenvectors related to the generalized eigenvalues of value 1. The subsequent steps of the algorithm remain intact. Alternatively, we can use the generalized SVD of the corresponding data matrices.

3.4. Multi microphone case ($M > 2$)

In the multi microphone case a reasonable extension would be based on channel pairing (see [3]). Each of the $\frac{M \times (M-1)}{2}$ pairs fulfills,

$$[y_i(t) * a_j(t) - y_j(t) * a_i(t)] * e_l(t) = 0.$$

Thus, the data matrix would be constructed as follows,

$$\mathcal{Z} = \begin{bmatrix} \mathcal{Z}_2 & \mathcal{Z}_3 & \cdots & & \mathcal{Z}_M & \mathcal{O} & \cdots & \mathcal{O} & \cdots & \mathcal{O} \\ -\mathcal{Z}_1 & \mathcal{O} & \cdots & & & \mathcal{Z}_3 & \cdots & \mathcal{Z}_M & & \mathcal{O} \\ \mathcal{O} & -\mathcal{Z}_1 & & & & -\mathcal{Z}_2 & & \mathcal{O} & & \vdots \\ \vdots & \mathcal{O} & \ddots & & & & & \vdots & & \mathcal{O} \\ & \vdots & & \ddots & & & & \mathcal{O} & & \mathcal{Z}_M \\ \mathcal{O} & \mathcal{O} & \cdots & & -\mathcal{Z}_1 & \cdots & & -\mathcal{Z}_2 & \cdots & -\mathcal{Z}_{M-1} \end{bmatrix}, \qquad (14)$$

where $\mathcal{O}$ here is an $(\hat{n}_a + 1) \times (T + \hat{n}_a + 1)$ all-zero matrix.

3.5. A suboptimal method - estimates averaging

We will now exploit the special structure of the filtering matrix $\mathcal{A}$ to derive a computationally more efficient method (although less robust) to estimate the ATFs. We rely on the fact that each column of the Sylvester matrix is a delayed version of the previous one. Thus, extraction of each of the columns can be exploited in the noisy case to produce an estimate of the ATFs. Averaging of the estimates may be applied to increase robustness. We will use rotations of the null space matrix given by Eq. 10 for this purpose. Define, the $K \times K$ row rotation matrix,

$$J_K = \begin{bmatrix} 0 & 0 & \cdots & 0 & 1 \\ 1 & 0 & \cdots & & 0 \\ 0 & \ddots & 0 & \cdots & 0 \\ \vdots & 0 & \ddots & & \vdots \\ 0 & \cdots & & 1 & 0 \end{bmatrix}.$$

It is obvious that left multiplication of a K-row matrix by J_K^k will rotate its rows downwards k times, while right multiplication of a K-columns matrix by $(J_K^k)^T$ will rotate its columns rightwards. Lemma 3.2 can now be used to extract an estimate of the ATFs.

Lemma 3.2 *Apply QR decomposition to the transpose of the k-times row rotated null space matrix. The last row of the "R" matrix is equal to the last but k row of the filtering matrix up to a scaling factor.*

Proof: Rotate the $2(\hat{n}_a+1)\times(\hat{n}_a-n_a+1)$ null space matrix $\mathcal{G}$ not more than $\hat{n}_a-n_a+1$ times. Then, $\mathcal{G}^R = J^k_{2(\hat{n}_a+1)}\mathcal{G} = J^k_{2(\hat{n}_a+1)}\mathcal{A}\mathcal{E}$. Exploiting the orthogonality of the matrices J_K we have, $\mathcal{G}^R = J^k_{2(\hat{n}_a+1)}\mathcal{A}J^T_{\hat{n}_a-n_a+1}J_{\hat{n}_a-n_a+1}\mathcal{E}$. Then,

$$(\mathcal{G}^R)^T = (J_{\hat{n}_a-n_a+1}\mathcal{E})^T(J^k_{2(\hat{n}_a+1)}\mathcal{A}J^T_{\hat{n}_a-n_a+1})^T \qquad (15)$$

Now assume a QR decomposition for the first term (although, $\mathcal{E}$ is not known), $(J_{\hat{n}_a-n_a+1}\mathcal{E})^T = QR$. Then, $(\mathcal{G}^R)^T = QR(J^k_{2(\hat{n}_a+1)}\mathcal{A}J^T_{\hat{n}_a-n_a+1})^T = Q\tilde{R}$. Since, $\tilde{R} = R\times(J^k_{2(\hat{n}_a+1)}\mathcal{A}J^T_{\hat{n}_a-n_a+1})^T$ is a multiplication of two upper triangular matrices it is also upper triangular. Since the QR decomposition is unique, Eq. 15 is the QR decomposition of $(\mathcal{G}^R)^T$.
The last row of $(J^k_{2(\hat{n}_a+1)}\mathcal{A}J^T_{\hat{n}_a-n_a+1})^T$ is the k but last row of $\mathcal{A}^T$, provided $k \leq \hat{n}_a - n_a + 1$. R is a square matrix like $\mathcal{E}$. Thus, the last row of the $\tilde{R}$ in the QR decomposition of $\mathcal{G}^T$ will give the desired filters. Note, that due to the special structure of $\mathcal{A}$ there will be $\hat{n}_a - n_a$ leading zeros both in front of the $\mathbf{a}_1$ and $\mathbf{a}_2$ estimates.

3.6. Signal reconstruction

The estimated ATFs can be used in the extended GSC derived by Gannot *et al.* [4]. This GSC based structure enables the use of general ATFs rather than delay-only filters in order to dereverberate the speech signal and to reduce the noise level. It consists of a fixed beamformer branch - which by use of the correct ATFs eliminates the reverberation, a noise reference construction block - which uses the ATF ratios, and a multi-channel Widrow-LMS noise canceller branch.

4. EXPERIMENTAL STUDY

The validity of the proposed method was tested. A 10 Sec long speech sentence (80000 samples) was used. This sentence was filtered with two arbitrary 20 taps filters, and a colored noise signal was added at several levels, to construct the two signals $z_1(t), z_2(t)$ with several SNR values. In applying the algorithm the filter length was overestimated to be $\hat{n}_a = 45$. Since the number of the null space vectors (corresponding to generalized eigenvalues equal to 1) was $L = 25$, we concluded that the real filter length should be $n_a = 20$. This number was used in the construction of the various matrices. The noise correlation matrix was estimated using different segments of the same length of noise only signal. The real and estimated frequency response for the various SNR levels is depicted in Figure 2. The sensitivity to the noise level is clearly indicated. The other suboptimal methods proposed are found to be much more sensitive to the noise level.

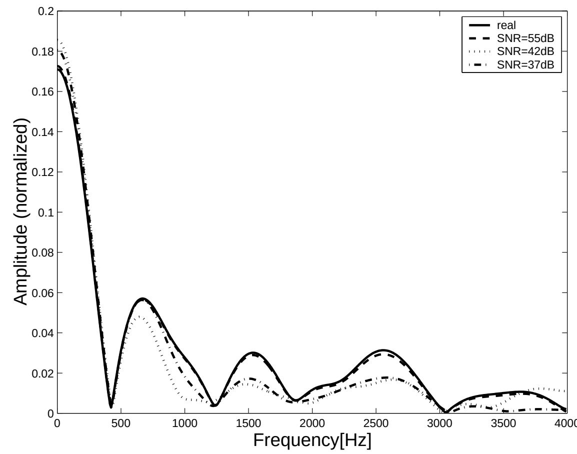

Figure 2: Real and estimated frequency response of an arbitrary ATF.

5. CONCLUSIONS

A method for speech dereverberation - based on null space extraction (applying GSVD to the noisy data matrix) and ATFs estimation (exploiting the filtering matrix structure using LS fitting) - was presented. The LS approach, although imposes a high computational burden, is found to be superior to the cheaper method of averaging several estimates of ATFs, also proposed in this work. Preliminary results, although achieved in high SNR conditions, show the potential of the algorithm. Improvements for the method using partial knowledge of null space is currently under investigation.

6. REFERENCES

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