Noise Reduction in Car Speech

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This paper presents properties of chosen multichannel algorithms for speech enhancement in a noisy environment. These methods are suitable for hands-free communication in a car cabin. Criteria for evaluation of these systems are also presented. The criteria consider both the level of noise suppression and the level of speech distortion. The performance of multichannel algorithms is investigated for a mixed model of speech signals and car noise and for real signals recorded in a car.

Keywords: beamforming, adaptive array processing, signal processing, microphone arrays, speech enhancement.

1 Introduction

This paper presents some possible ways of speech enhancement in a car cabin. This task is a very important for speech control of devices in a car or for mobile communication. Both of these applications contributes to greater traffic safety.

Multichannel methods of digital signal processing can be successfully used for speech enhancement. This class of methods outperforms single channel methods and achieves greater noise suppression.

2 Spatial filtering

A microphone array is a basic part of multichannel processing. A uniformly spaced microphone array is the simplest arrangement. The input acoustic signal is sampled in space due to microphone spacing and in time. It is possible to distinguish the signals coming from different directions thanks to spatial sampling.

An input multichannel signal $x[n]$ can be described as a mixture of the desired signal and interference. Most multichannel systems are described under several assumptions. A model of a multichannel signal is introduced. First, the microphone array is focused to the Direction Of Arrival of the desired signal (DOA). Second, it is assumed that the source signal is far enough from the array. The input acoustic signal can be assumed to be a plane wave [9]. The input signal at the m-th channel can be expressed as

$$x_m[n] = s[n] + u_m[n], \tag{1}$$

where $s[n]$ denotes the n-th sample of the desired signal, and $u_m[n]$ denotes the noise and interference at the m-th sensor.

3 Interference in multichannel systems

Three types of interference are usually considered in a multichannel system. A criterion for classification is the coherence function $\Gamma(e^{j\omega T})$. This function expresses the reciprocal dependency (correlation) of particular signals in individual frequency bands. The Coherence Function $\Gamma_{ij}(e^{j\omega T})$ of two signals is defined by the relation [14]

$$\Gamma_{ij}(e^{j\omega T}) = \frac{\phi_{ij}(e^{j\omega T})}{\sqrt{\phi_{ii}(e^{j\omega T})\phi_{jj}(e^{j\omega T})}}, \tag{2}$$

where $\phi_{ii}(e^{j\omega T})$ denotes the Power Spectral Density (PSD) of a signal in the j-th channel and $\phi_{ij}(e^{j\omega T})$ the CrossPower Spectral Density (CPSD) of signals in the i-th and the j-th channel. The Magnitude Squared Coherence (MSC), defined as

$$MSC(e^{j\omega T}) = \left|\Gamma_{ij}(e^{j\omega T})\right|^2, \tag{3}$$

is also often used.

The type of interference is distinguished according to the shape of MSC$(e^{j\omega T})$. Three types of interference are recognized: spatial coherent, spatial incoherent and diffusive interference.

3.1 Spatial coherent interference

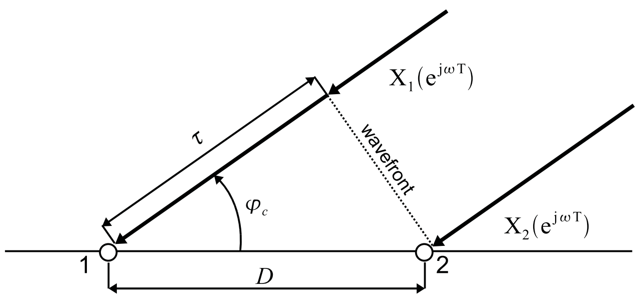

Fig. 1: An array of two sensors

First, let us consider a plane wave reaching an array of two microphones under angle φ_c. This situation is illustrated in Fig. 1. The spectrum of the signal at sensor 2 is $X_2(e^{j\omega T})$. The wavefront reaching sensor 1 is attenuated by a constant A and delayed by

$$\tau = \frac{D}{c}\cos\varphi_c, \tag{4}$$

where c denotes the propagation speed of an acoustic signal and D denotes sensor spacing. The spectrum of the signal at sensor *1* is given by

$$X_1(e^{j\omega T}) = A\,X_2(e^{j\omega T})\,e^{-j\omega T}. \tag{5}$$

Substituting (5) into (2) results in an expression for the coherence function:

$$\Gamma_{12}(e^{j\omega T}) = \frac{A\,\phi_{22}(e^{j\omega T})\,e^{-j\omega T}}{\sqrt{A^2\,\phi_{22}(e^{j\omega T})\phi_{22}(e^{j\omega T})}} = e^{-j\omega\frac{D}{c}\cos\varphi_c}. \quad (6)$$

Thus an expression for $\mathrm{MSC}(e^{j\omega T})$ reveals full coherency

$$\mathrm{MSC}(e^{j\omega T}) = \left|\Gamma_{12}(e^{j\omega T})\right|^2 = 1. \quad (7)$$

3.2 Spatial incoherent interference

In case of spatial incoherent interference, the coherence computed from samples obtained at two different points in space is equal to zero in the whole frequency band, because $E[X_1^*(e^{j\omega T})X_2(e^{j\omega T})] = 0$. X_1 and X_2 denote the spectra of two interferences and the asterisk denotes complex conjugate. Incoherent noise is represented by electrical noise in microphones.

3.3 Spatial diffuse interference

A reverberant environment is often encountered where many reflections occur. The delayed reflected signal reaches the array together with the direct wave. The characteristics of the delayed signal (magnitude and phase) depend on the acoustic properties of the given environment, e.g. a car cabin. This type of interference is very often present in real environments, and it is called spatial diffuse interference.

Diffuse noise can be modelled by an infinite number of independent sources distributed on a sphere [3]. A formula for coherence derived from this model is given by

$$\Gamma_{12}(e^{j\omega T}) = \frac{\sin\left(\frac{\omega D}{c}\right)}{\frac{\omega D}{c}}, \quad (8)$$

where ω denotes angular frequency and D and c have been defined above. A shape for diffuse noise is depicted in Fig. 2. The shapes are depicted for microphone spacing D = 5cm, 10 cm and 20 cm. An analysis of equation (8) and Fig. 2 shows that the closer together the microphones are placed, the wider the main lobe of MSC is.

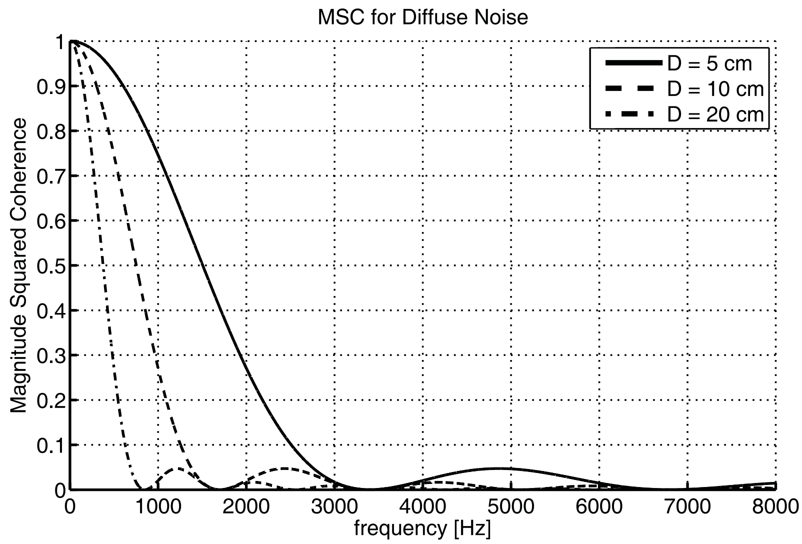

Fig. 2: MSC for diffuse noise and different microphone spacing

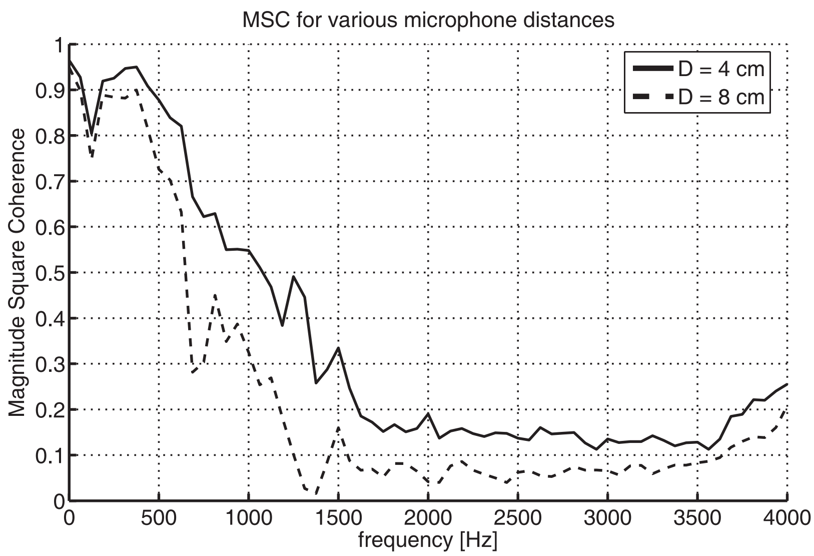

Fig. 3: MSC for noise in a car cabin and different microphone spacing

An analysis of noise recorded in a car cabin revealed interference of a diffuse nature. Fig. 3 depicts the shapes of MSC for various distances of microphones. The shapes are very close to the model of diffuse noise.

4 Processing in the frequency domain

Algorithms of multichannel processing can be implemented in the time or frequency domain. The basic algorithms, e.g. GSC [7], operate in the time domain. A speech signal cannot be supposed stationary, so adaptive algorithms are used. The coefficients of adaptive filters are usually controlled by the LMS algorithm. However, advanced algorithms require processing in the frequency domain.

A block diagram of processing in the frequency domain is depicted in Fig. 4. First, the input signal is divided into quasi-stationary overlapping segments. Moreover, each segment is weighted by a Hamming window. A typical segment length is 16 ms. Second, a short time spectrum is computed. Third, the short-time spectra are processed. An input signal is finally obtained using the inverse Fourier transform and the Overlap and Add (OLA) method [14].

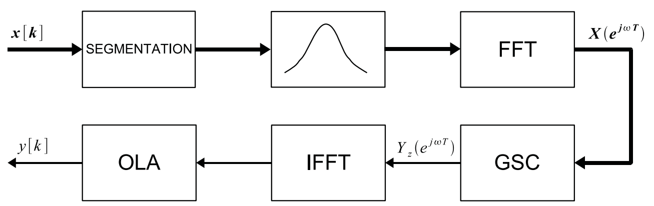

Fig. 4: Block diagram of processing in the frequency domain

Weight adaptation is performed block by block. The adaptation is performed according to Minimum Mean Square Error (MMSE). The advantage of this approach is that the weights in each frequency band change according to the power of the noise in a particular band.

5 Beamforming algorithms

The performance of four algorithms will be presented in this paper. Their principles will be explained in this section. The following algorithms will be presented: Beamformer with Adaptive Postprocessing (BAP) [16], Generalised Sidelobe Canceler (GSC) [7], Linearly Constrained Beamformer (LCB) [5] and Modified Coherence Filtering (MCF) [10].

5.1 BAP

Delay And Sum beamformer (DAS) is the first block of BAP [16]. The output of this block Y_b is an average of the input channels. Weights w_i are equal to $1/M$. BAP improves the DAS beamformer by using a Wiener Filter (WF) behind the DAS structure, Fig. 5. The main contribution of WF is in improving the suppression level of uncorrelated interferences. The derivation for the weights of WF can be found in [15]. Weights in the frequency domain are obtained as

$$W(e^{j\omega T}) = \frac{\phi_{xs}(e^{j\omega T})}{\phi_{xx}(e^{j\omega T})}, \tag{9}$$

where $\phi_{xx}(e^{j\omega T})$ denotes the Power Spectral Density (PSD) of the signal $x[k]$ (input of WF), and $\phi_{xs}(e^{j\omega T})$ is the Cross-Power Spectral Density (CPSD) of the signals $x[k]$ and $s[k]$ (output of WF). It is assumed that the interferences are uncorrelated ($E[U_i(e^{j\omega T})U_j(e^{j\omega T})]=0$ for all $i \neq j$) and the desired signal is uncorrelated with the interferences ($E[S(e^{j\omega T})U_j(e^{j\omega T})]=0$ for all i). $S(e^{j\omega T})$) is a spectrum of the desired signal and $U_i(e^{j\omega T})$ is a spectrum of the interference at the i-th sensor. Under these assumptions it holds

$$\phi_{xs}(e^{j\omega T}) = \phi_{sx}(e^{j\omega T}) = \phi_{ss}(e^{j\omega T}). \tag{10}$$

Weights of WF can now be expressed as

$$W(e^{j\omega T}) = \frac{\phi_{ss}(e^{j\omega T})}{\phi_{xx}(e^{j\omega T})} \tag{11}$$

In the case of the BAP structure, the PSDs in relation (11) are estimated by averaging the signal in a particular channel [13]

$$\hat{\phi}_{ss} = \frac{2}{M(M-1)} \sum_{i=1}^{M-1} \sum_{k=i+1}^{M} \mathrm{Re}\left\{X_i(e^{j\omega T})^* X_k(e^{j\omega T})\right\}, \tag{12}$$

$$\hat{\phi}_{xx}(e^{j\omega T}) = \frac{1}{M}\left|\sum_{i=1}^{M} X_i(e^{j\omega T})\right|^2, \tag{13}$$

where $X_i(e^{j\omega T})$ is a spectrum of the input signal.

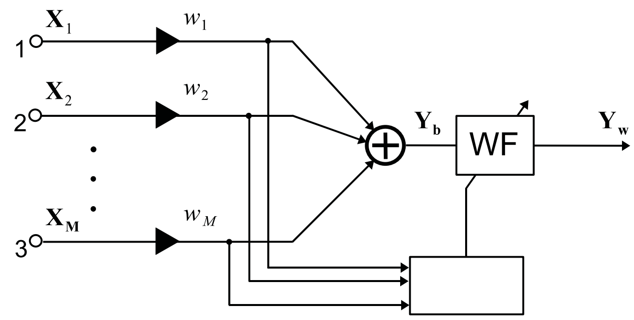

Fig. 5: BAP

5.2 GSC

The Structure of GSC [7] is depicted in Fig. 6. It is equal to the Adaptive Beamformer [6]. The system consists of the DAS beamformer and the Adaptive Noise Canceler (ANC). ANC serves to suppress the coherent interference.

The weights of ANC filters are in accordance with Wiener theory [7]. A formula for optimal weights is given by

$$H_i(e^{j\omega T}) = \frac{\phi_{Y_i Y_b}(e^{j\omega T})}{\phi_{Y_i Y_i}(e^{j\omega T})}, \quad i = 1, \ldots, M-1. \tag{14}$$

$\phi_{Y_i Y_b}(e^{j\omega T})$ denotes the CPSD of signals Y_i and Y_w, the meaning of which is obvious from Fig. 6. $\phi_{Y_i Y_i}(e^{j\omega T})$ is the PSD of Y_i.

The Proper function of the ANC is given by perfect separation of the desired signal from the input signal. Let us denote any coherent signal incident on the array from any

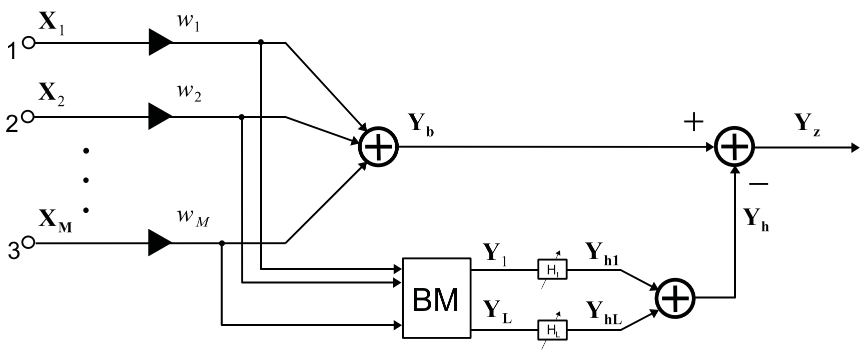

Fig. 6: GSC

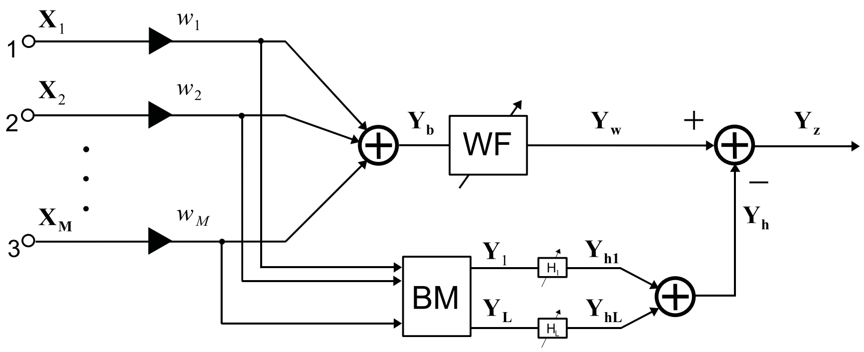

Fig. 7: LCB

direction except DOA as coherent interference. Under this assumption, an interference can be separated from the input signal by an appropriate combination of input channels $x_i[k]$. This separation is arranged by the Blocking Matrix (BM). The most commonly used BM differentiates neighbouring channels. BM consists of M columns, and $(M-1)$ rows, and looks like this [7]:

$$\mathrm{BM} = \begin{pmatrix} 1 & -1 & 0 & \cdots & 0 & 0 \\ 0 & 1 & -1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & -1 \end{pmatrix}. \tag{15}$$

5.3 LCB

LCB utilizes GSC and BAP beamformers [5]. The structure of LCB is depicted in Fig. 7.

The direct branch composed of BAP suppresses incoherent interference. The lower branch consisting of ANC is responsible for coherent interference suppression.

The greatest difference between GSC and LCB is the way in which the weights of the ANC filters are computed. In LCB they are computed from signals at the outputs of BM and WF. The relation for calculating ANC filters has to be written as

$$H_i(e^{j\omega T}) = \frac{\phi_{Y_i Y_w}(e^{j\omega T})}{\phi_{Y_i Y_i}(e^{j\omega T})}, \ i = 1, \ldots, M-1. \tag{16}$$

$\phi_{Y_i Y_w}$ denotes the CPSD of signals Y_i and Y_w the meaning of which is obvious from Fig. 7.

5.4 Coherence Filtering

Coherence Filtering differs from the other multichannel systems. It is a representative of double channel methods. The idea of this method [2] is based on the fact that the coherence function of the spatially coherent desired signal is close to one, and the coherence of the incoherent interference is close to zero.

The authors of [10] propose a modification to Coherence Filtering. The Coherence Filter is included in the BAP structure, see Fig. 8. The coefficients of the Modified Coherence Filter (MCF) $C(k)$ are computed as follows

$$C(k) = \begin{cases} \mathrm{W(k)}, & \text{if } \ |\Gamma(k)| > T \\ |\Gamma(k)|^{\alpha}, & \text{if } \ |\Gamma(k)| \le T \end{cases} \tag{17}$$

where $W(k)$ denotes an estimated frequency response of the Wiener filter, equation (9), and T denotes the threshold.

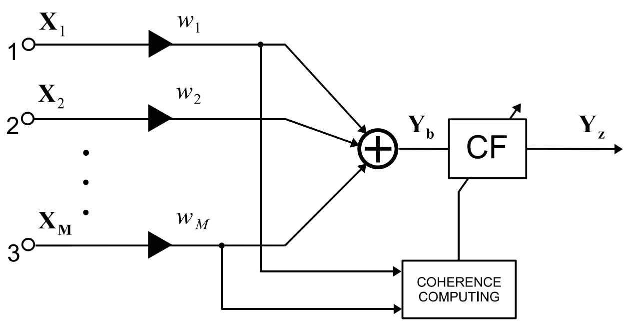

Fig. 8: Structure of a Modified Coherence Filter

6 Testing procedure

It is very difficult to separate the desired signal and noise when the level of noise suppression is evaluated. Separation of the desired signal and noise is crucial for an assessment of the properties of the algorithms. The following approach has been chosen for testing the algorithms. The desired signal and interference are recorded separately. The input mixture $x[n]$ is obtained before processing, so that the SNR is defined. The recordings of utterances in a standing car with the engine switched off are assumed to be the desired signal. Noise is represented by recordings of noise in a moving car without the presence of speech. A block diagram of the testing procedure is depicted in Fig. 9. The input signals $s[n]$ (desired signal) and $u[n]$ (noise) are mixed with defined SNR to make $x[n]$.

The output signal $y[n]$ originates by processing the input mixture. During processing, the coefficients of the adaptive filters are set. Using these coefficients, clear signals $s[n]$ and $u[n]$ are also processed. This processing results in output signals y_s[n] and $y_u[n]$. These signals carry information about the influence of the system on the desired signal and interference.

7 Criteria for system evaluation

The criteria for assessing the level of speech enhancement can be classified into two classes, objective and subjective. The subjective criteria are represented by listening tests. Listening tests are very difficult. It is necessary to gather several qualified listeners. The test also consumes a great deal of time. However, these tests can show how the output signals are perceived by human subjects. Objective criteria give exact information and are not influenced by external factors, e.g. the mood of the listener. The following criteria will be used for evaluating the algorithms: Noise Reduction (NR), Log Area Ratio (LAR), Signal to Noise Ratio Enhancement (SNRE) and spectrograms. All of the criteria will be computed from quasi-stationary segments of the signal.

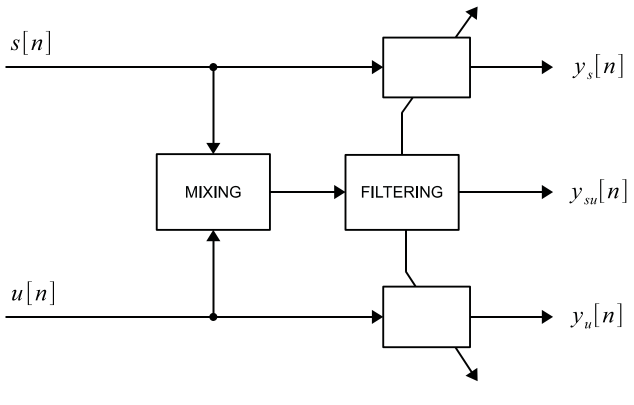

Fig. 9: Block diagram of the testing procedure

7.1 Noise reduction

NR expresses the ability of an algorithm to reduce noise. NR is defined as

$$\mathrm{NR}(e^{j\omega T}) = \frac{\Phi_{uu}(e^{j\omega T})}{\Phi_{y_u y_u}(e^{j\omega T})}, \tag{18}$$

where $\Phi_{uu}(e^{j\omega T})$ is the PSD of the interference at the input of the system, and $\Phi_{y_u y_u}(e^{j\omega T})$ is the PSD of the interference processed by the system. The assumption for NR calculation is that no desired signal is present at the input of the system. NR considers only the influence of the system on the interference. It does not consider the influence on the desired signal. This criterion has to be combined with other criteria.

7.2 Log Area Ratio

LAR [12] takes into account the influence of the system on the desired signal and speech intelligibility. An advantage of this criterion is its high correlation with listening tests [4]. A presumption when using this criterion is the presence of speech. LAR is calculated on the basis of the partial correlation coefficients (PARCOR) of the auto regressive model [8]. Computing LAR requires a clear speech signal $s[n]$ and an output signal $y_s[n]$. The computing is performed in the following steps:

1. Estimation of PARCOR coefficients $k(p, l)$ of the signal segment. Index p denotes the p-th PARCOR coefficient and l the signal segment. The order of the model is chosen as $P = 12$. A Burg algorithm can be used for estimating the coefficients [8].
2. Calculation of area coefficients
$$g(p, l) = \frac{1 + k(p, l)}{1 - k(p, l)}, \quad p = 1, \ldots, 12, \tag{19}$$
where $k(p, l)$ is a p-th PARCOR coefficient of the l-th segment. (PARCOR coefficients $k(p, l)$ are marked in some sources [11] as a negative of reflection coefficients.)
3. Calculation of LAR for block l
$$\mathrm{LAR}(l) = \sum_{p=1}^{12} 20 \left| \log_{10} \frac{g_s(p, l)}{g_y(p, l)} \right|. \tag{20}$$

LAR expresses the “distance” of the model of signal $s[n]$ from the model of signal $y[n]$. The lower LAR is, the less the speech is distorted.

7.3 SNRE

SNRE is very often used for evaluating systems for speech enhancement. The value of SNRE is also calculated segment by segment. SNRE is obtained as the difference of $\mathrm{SNR}_{\mathrm{out}} - SNR_{\mathrm{in}}$. Signals $s[n]$ and $u[n]$ are used for calculating $\mathrm{SNR}_{\mathrm{in}}$ and $y_s[n]$ and $y_u[n]$ are user for calculating $\mathrm{SNR}_{\mathrm{out}}$.

8 Database of car speech

A database of car speech and car noise has been created for developing and verifying of multichannel systems performing speech enhancement. The database creation procedure was chosen to fulfill the requirements of the testing procedure described in section 6. The signals were recorded in a Škoda Fabia. A microphone array of 12 sensors with constant spacing of 4 cm was used. The desired signal was represented by reproduced recordings of female and male utterances. Noise signals were recorded under various conditions. More details about the database are summarized in [1].

9 Experiments

Two approaches were used to verify the algorithms presented in this paper. First, a model of the desired signal and noise recorded in a car were used as an input mixture. A model of the desired signal was created by copying the clear speech signal into all channels. The purpose of this approach is to verify the performance of the algorithm. The influence of the properties of the microphone array is not considered. Breaking the assumptions mentioned in section 3 introduces additional delays of signals between the individual microphones. Additional delays can be due to the fact that the acoustic signals cannot be represented by plane waves, and due to array imperfections. Solving these problems is a separate issue.

The purpose of the second experiment is to show the properties of the whole system. It should show that the properties of the array are significant and that it is worth taking them into account.

Each of the experiments was performed for two different environments. The first environment was a standing car with a running engine, and the second environment was a car moving outside a village (70 km/h). The criteria NR, LAR and SNRE were calculated for segments of 128 samples. An mean value was calculated for each criterion.

The experiments were performed for an array of 4 microphones with 4 cm spacing and SNR_{in} was set to 0 dB. The sample rate was 8 kHz. The parameters of MCF were set to $T = 0.2$ and $\alpha = 2$.

Table 1: Results for a model of a signal, standing car

	LAR	**SNRE**	**NR**
BAP	0.5	1.52	13.37
GSC	0.0	4.95	2.43
LCB	0.5	5.14	14.75
MCF	1.66	2.19	2.33

Table 2: Results for a model of a signal, running car (70 km/h)

	LAR	**SNRE**	**NR**
BAP	0.53	0.9	13.85
GSC	0.0	3.11	–1.46
LCB	0.53	3.22	10.86
MCF	1.83	1.38	2.72

Table 3: Results for a real signal, standing car

	LAR	**SNRE**	**NR**
BAP	4.42	–0.32	13.66
GSC	7.36	–1.8	4.40
LCB	7.62	–1.9	17.24
MCF	6.26	–0.33	2.84

Table 4: Results for a real signal, running car (70 km/h)

	LAR	**SNRE**	**NR**
BAP	4.41	–0.78	14.64
GSC	7.25	–1.47	5.95
LCB	7.52	–1.51	18.95
MCF	6.38	–0.69	4.21

Tables 1 and 2 show the results for a model of the desired signal. The results for a real signal are displayed in Tables 3 and 4.

The experiment with a model of the signal was done for different values of SNR_{in}. The results are summarized in the graphs in Figs. 10, 11 and 12.

10 Conclusion

The experiments enabled a comparison of the methods for speech enhancement presented here. The results are very different for a model of the desired signal and for a real signal. Array imperfections and propagation of signals are the most important influences.

LCB provided the best results for a model of a signal. The experiments showed the importance of using several criteria. BAP achieves low SNRE and high NR according to the results in Table 1. GSC behaves in an opposite way. MCF seems to have the weakest performance. It produced high speech distortion (high values of LAR) and low SNRE and NR. Zero speech distortion is worth noting in the case of GSC. This is due to perfect separation of the desired signal at the input of the ANC filters.

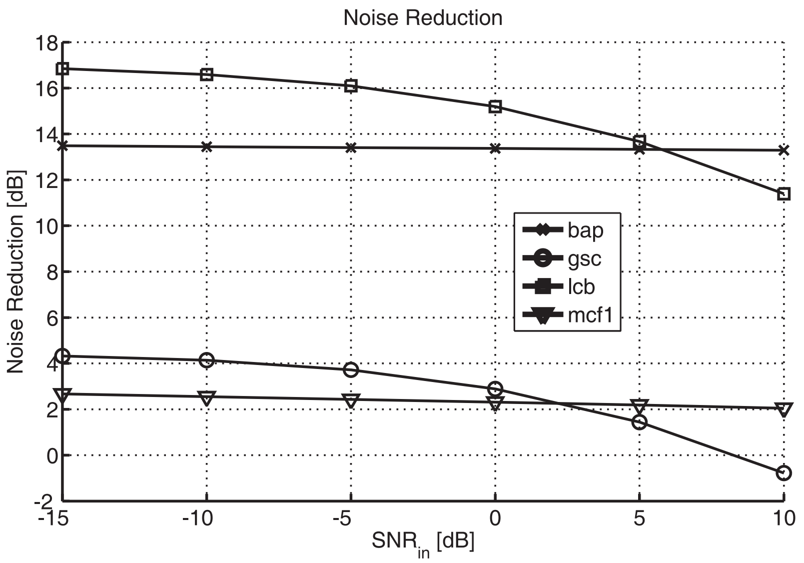

Fig. 10: NR for various SNR_{in}

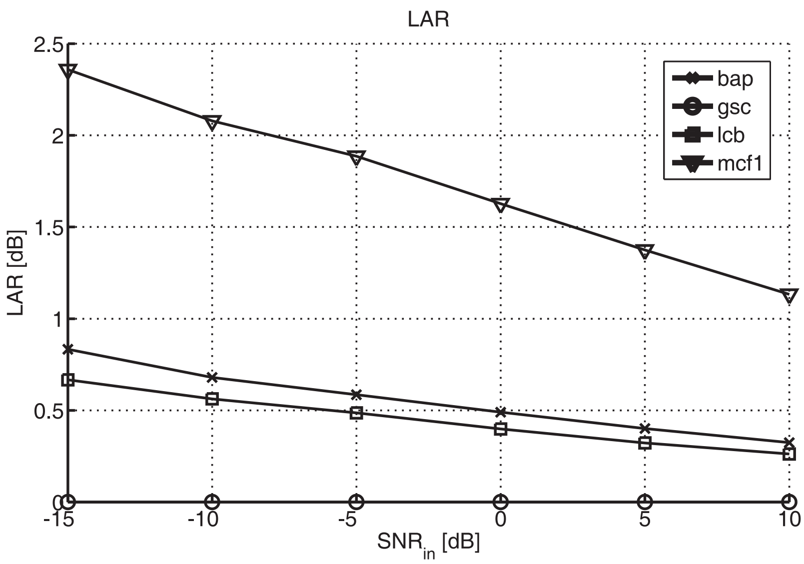

Fig. 11: LAR for various SNR_{in}

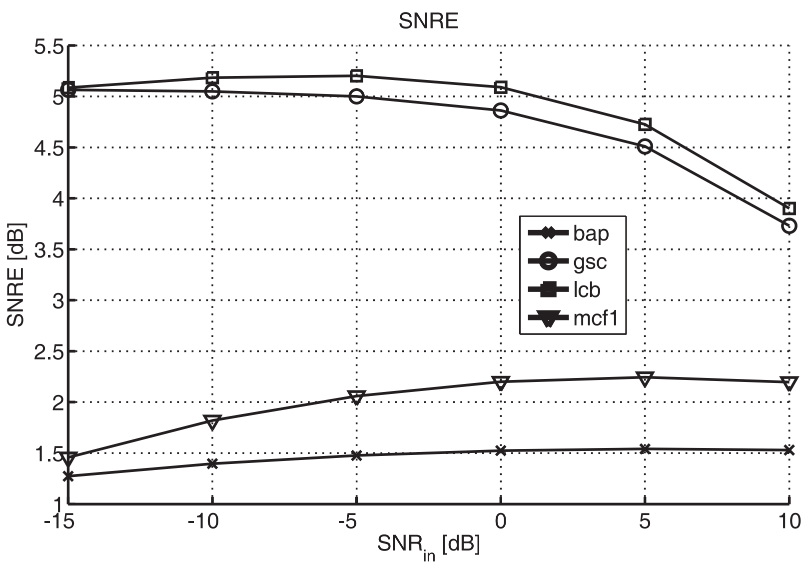

Fig. 12: SNRE for various SNR_{in}

All of the algorithms showed much worse performance for real signals. There is both high speech distortion and low enhancement. There are no so significant differences between a standing car and a moving car. NR for BAP and LCB is an exception. The lowest values of LAR and SNRE are for BAP and MCF.

The second experiment focused on the influence of SNR_{in} on the results. The shape of NR (Fig. 10) reveals strong dependance on SNR_{in} for GSC and LCB. The NR of LCB falls below BAP, and GSC falls below MCF for high values of SNR_{in}.

The shape of SNRE (Fig. 12) shows a very similar trend. BAP and MCF are almost independent of SNRin with respect to both NR and SNRE.

Only BAP, LCB and MCF can be considered when observing LAR (Fig. 11). GSC does not distort speech in the case of a model of the input signal, due to perfect separation of the desired signal. BAP and LCB have the same shape of LAR for the same reason. The highest speech distortion was for MCF. The figure also shows that speech distortion decreases with growing SNR_{in}.

This paper has shown the properties of selected algorithms for speech enhancement in a noisy environment. The experiments with a model of the input signal showed that these methods are capable of speech enhancement. A problem occurred when the methods were used for real signals. The assumptions of proper functionality were broken in this case. The input signals did not match the model that the methods were developed for. It is necessary to focus on compensating the array imperfections and signal propagation in future work.

Acknowledgments

The research described in this paper was supervised by prof. Pavel Sovka. This paper was mainly supported by research activity MSM 6840770012 ”Transdisciplinary Research in Biomedical Engineering II” and GAČR grant 102/08/H008 “Analysis and modelling of biomedical and speech signals” and GAČR grant GA102/08/0707 “Speech Recognition under Real-World Conditions”.

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