ADAPTIVE FILTERING OF CYCLOSTATIONARY INTERFERENCE FROM SPEECH

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ABSTRACT: In this paper we propose a new time domain method for separating a periodic interference signal component from speech signal. The method handles also such cases in which the amplitude of a periodic interfering signal fluctuates and when the speech signal occasionally is located in the same frequency band as the interfering signal. The method is applied with success to the filtering of electromagnetic interference produced by a TDMA-based system from speech signal.

1. INTRODUCTION

Electronic equipment often introduces electromagnetic interference to the environment and to the equipment itself. Such a situation occurs for example in a TDMA radio system terminal. A part of the TDMA transmission sent by the transmitter of the terminal falls on the electric circuit of the audio part of the terminal and interferes with the audio signal therein.

Interference can be filtered by means of frequency domain or time domain signal processing. Frequency domain filtering often removes some of the actual signal with the interfering signal if they are within the same frequency band. For reducing periodic interference in the time-domain, coherent averaging may be used where more than one signal sequences are co-phased and summed together for determining the average form of a single signal sequence [1]. The method of averaging model of interference waveform runs into difficulties when the interference amplitude changes strongly and especially if the actual useful signal is present at the same time. Another example with this problem is a filter that learns the interference and reduces the interference from the signal to be processed [2].

Common adaptive filtering algorithms that have found widespread application are the least mean square (LMS), the recursive least square (RLS), and the Kalman filter algorithms [3]. In terms of computation and storage requirements, the LMS algorithm is the most efficient. However, the basic LMS-algorithm suffers from poor performance if signal is nonstationary. In our case the interfering signal is cyclostationary but the amplitude of interference may change also during a speech segment. In addition, the superimposed speech signal adds difficult noise on the interference waveform.

There is a large class of problems involving signals that are not strictly stationary, but have statistics that vary in a periodic or cyclic manner. During a “cycle” the statistics may vary widely, but the variations are the same from cycle to cycle [4]. In cyclostationary adaptive filtering [5] filter tabs should cycle among a set of weight vectors, each one optimum for a relative position within the period of the statistics. Each such weight vector can be adapted independently, using a cyclic update. In our case one cycle is 60 ms, 480 samples at 8 kHz sampling rate, which means quite long convergence time to changes on interference amplitude.

2. CYCLOSTATIONARY INTERFERENCE

Following factors effects to the properties of the interfering signal component induced by TDMA based transmitter:

- The device shielding against the electromagnetic interference,
- TDMA timing effects,
- External effects, e.g. moving the microphone in relation to the transmitter, changes the amplitude of the interference. External effects can not be predicted, so the algorithm should be adaptive.

An example of an interfering signal is shown in figure 1. Such a signal is cyclostationary and the length of one cycle is 13 pulse periods.

Fig. 1. Interfering signal at a frequency of 8 kHz.
The sampling frequency 8 kHz is not a multiple of the recurrence frequency of the interference 216.67 Hz; i.e., the division result between a sample frequency and an occurrence frequency of the signal sequence is not an integer (8000/216.67 ≈ 36.92). The consecutive pulses are therefore sampled in different phases, which is seen as small differences between the pulses. Sampling frequency 9.1 kHz is a multiple of the occurrence frequency of the pulse train (9100/216.67 = 42). Thus no phase shift is seen in the signal. Signal interpolation has, however, too large a time complexity for our purposes.

3. INTERFERENCE CANCELLATION METHOD

3.1 Oversampled model of interference

An over-sampled model of a pulse period is formed from one cycle of cyclostationary signal by arranging the samples taken from the different phases of the pulses in consecutive order to form a new signal representing one pulse period. With a mathematical notation, the signal processing operation is the following. Let us take the consecutive samples

\[ X = [S_1, S_2, \ldots, S_{j-1}, S_j, S_{j+1}, S_{j+2}, \ldots, S_{j+i-1}, S_{j+i}] \]

where \( i \) is the number of samples taken from the signal sequence and \( j \) is the number of signal sequences in the cycle. Any part of the signal sequence can freely be selected as the first sample. Let us now convert vector \( X \) into matrix form, in which the lines correspond to samples taken from different pulse periods. Thus, matrix \( A \) is obtained from vector \( X \):

\[
A = \begin{bmatrix}
S_{1,1} & S_{1,2} & \cdots & S_{1,i-1} & S_{1,j} \\
S_{2,1} & S_{2,2} & \cdots & S_{2,i-1} & S_{2,j} \\
\vdots & \vdots & \ddots & \vdots & \vdots \\
S_{j-1,1} & S_{j-1,2} & \cdots & S_{j-1,i-1} & S_{j-1,j} \\
S_{j,i} & S_{j+1,i} & \cdots & S_{j+i-1,i} & S_{j+i,j}
\end{bmatrix}
\]

When a transpose \( A^T \) is taken from matrix \( A \) and when the transposed matrix \( A^T \) is correspondingly converted into vector mode, vector \( Y \) of the form

\[ Y = [S_{1,1}, S_{1,2}, \ldots, S_{j-1,1}, S_{j,1}, S_{j,2}, \ldots, S_{j+i-1,1}, S_{j+i,1}] \]

is obtained. The signal corresponding to vector \( Y \) is an over-sampled model of a single pulse period.

3.2 Signal separation using oversampled model

Let us now take a closer look at the separation method by means of Figures 2A to 2F that represent an authentic measurement. Figure 2A shows an audio signal of the audio part in the radio system terminal, the audio signal being interfered by a regular pulse train. Figure 2B shows a noisy over-sampled model of the interfering pulse period. In Figure 2C, the over-sampled pulse period model has been filtered in order to reduce noise, which yields a more accurate model. From this oversampled model 13 filtered pulses can be provided by restoring the samples into the original order with the inverse transformation. The filtering may be, for example, band-pass filtering, median filtering, averaging filtering or any known filtering reducing noise. Figure 2D shows an audio signal in the oversampled model resembling noise. The audio signal has remained while the signal in Figure 2C has been removed from the signal in Figure 2B. Figure 2E shows a pulse train that is obtained by restoring the samples in Figure 2C into the original order. Figure 2F shows an audio signal that was obtained by restoring the samples in Figure 2D into the original order.

![Fig. 2. Signal separation using over-sampled model and median-filter (length = 10).](image)

An important feature of the method is that in the over-sampling process the speech signal component most often changes into noise. In this case, the audio signal samples, which are now in a random order, are summed on top of the over-sampled pulse period and appear as noise. An exception occurs when the fundamental frequency \( F_0 \) of speech is the same or very close to the recurrence frequency of the pulse train. This high \( F_0 \) frequency can occur with female speakers or children. In this case, a waveform representing the glottal pulse period of the transformed speech signal is added on the pulse period model. If
this frequency overlap does not occur, the signal components can be distinguished from one another.

### 3.3 Model amplitude adaptation

If the audio signal of the radio system terminal is much stronger than the interfering signal from the same device the additive noise in the over-sampled model is difficult to remove adequately well. In the GSM mobile system the situation can be improved by forming a master model of the pulse period when silence is transmitted instead of speech in a long enough time window (at least one cycle of 13 pulse periods). When speech is then transmitted, the power of the over-sampled model is computed after filtering, and the power is compared to the power of the master model. A scaling factor is computed from the ratio of the power values and the master model is scaled with this factor. The scaled model is a better estimate of the true over-sampled model of the pulse period than the noisier one. This new model is then subtracted from the original noisy model, which, after inverse transformation, produces an enhanced estimate of the speech signal.

The amplitude adaptation is limited, when the signal-to-noise ratio is high and the signal components overlap each other in both the frequency and time domain. We detect this situation by comparing the noisy over-sampled model with the master model. The normalised master model and the noisy model are presented in figure 3. Although some speech component is left in filtered over-sampled model changes in interference power can be detected.

A large difference indicates that a strong audio component is present in the over-sampled signal sequence and then a modified adaptation is performed with the following steps:

1. Synchronisation of noisy and master models. Synchronisation can be realised in different ways depending on the application. In our case we translate the master model in one-sample intervals in both directions in order to find the minimum of the difference signal of models.
2. Master model and noisy model are normalised by dividing each with their maximum amplitudes.
3. The models are subtracted and the energy $E_1$ is computed for the error signal.
4. Energy $E_1$ is scaled with the energy of master model to produce relative energy $E_2$.
5. Weighting coefficients are looked up from Table 1, and the weighted sum is computed of the models to produce an approximation of the interfering pulse period.

<table>
<thead>
<tr>
<th>Table 1: Used weights in amplitude adaptation.</th>
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<tr>
<td>Relative energy $E_2$</td>
</tr>
<tr>
<td>------------------------</td>
</tr>
<tr>
<td>$\geq 0.01$</td>
</tr>
<tr>
<td>$[0.01 - 0.03]$</td>
</tr>
<tr>
<td>$[0.03 - 0.05]$</td>
</tr>
<tr>
<td>$[0.05 - 0.10]$</td>
</tr>
<tr>
<td>$[0.10 - 0.25]$</td>
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<tr>
<td>$[0.25 - 0.5]$</td>
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<td>$[0.5 \rightarrow]$</td>
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### 3.4 Adaptive SNR-threshold controlling adaptation

A disadvantage of the above solution is that the master model cannot be computed from a speech segment, but a non-speech segment is needed. This problem can be remedied by adopting an iterative algorithm for improving the master model initialised from a speech segment. With this method a rough estimate of the interference waveform is readily available and the filtering performance improves over time.

1. A master model is initialised from the first separation result. SNR threshold is initialised.
2. In the following cycles, SNR is computed by dividing the energy of separated speech component with the energy of interference component.
3. If SNR is less than SNR threshold, the master model is updated.
4. If SNR is less than $\alpha \times$SNR threshold, SNR threshold is updated. The function of factor $\alpha$ is to ensure that SNR threshold will not go too low and then prevent the updating of master model.
The master model converges towards the one taken from a non-speech segment because eventually such a segment is met.

4. SIMULATIONS

Simulations were done in Matlab 5.0 environment using authentic audio data including speech and interfering signal. Several different data were measured and also some synthetic data was generated. Filtering results were evaluated with two methods: hearing tests, and visual inspection of reconstructed interference signal and residual error signals. With hearing tests two features were observed: the subjective quality of filtered speech and the extent to which interference is removed. According to our tests, the interference signal, caused by a TDMA transmitter, can be removed nearly completely and the subjective quality of the speech signal remains at a very good level. Even when the amplitude of interference fluctuates considerably the interference can be reduced significantly, see Fig. 4.

5. CONCLUSION

A new method was proposed for separating a periodic interference signal component from speech signal. The method is based on transforming a signal segment to a new space that emphasizes the interfering waveform. The suffled speech signal is noise in that representation and is filtered away to extract the interfering waveform. Inverse transformation of the separated speech component produces an enhanced estimate of the speech signal. The method handles also such cases in which the amplitude of a periodic interfering signal fluctuates and when the speech signal occasionally is located in the same frequency band as the interfering signal. Filtering process can be successfully initiated even during speech segments. Adaptation is possible with good performance within speech segments. The method was applied with success to the filtering of electromagnetic interference produced by a TDMA-based system from speech signal.

6 REFERENCES


Fig. 4. Filtering results, X-axis: Time in samples (x10^4), Y-axis: Amplitude in arbitrary units.