A Spectral Mapping Method for EMG-based Recognition of Silent Speech

Matthias Janke, Michael Wand and Tanja Schultz

Cognitive Systems Lab, Karlsruhe Institute of Technology
Karlsruhe, Germany

Abstract. This paper reports on our latest study on speech recognition based on surface electromyography (EMG). This technology allows for *Silent Speech Interfaces* since EMG captures the electrical potentials of the human articulatory muscles rather than the acoustic speech signal. Therefore, our technology enables speech recognition to be applied to silently mouthed speech. Earlier experiments indicate that the EMG signal is greatly impacted by the mode of speaking. In this study we analyze and compare EMG signals from audible, whispered, and silent speech. We quantify the differences and develop a spectral mapping method to compensate for these differences. Finally, we apply the spectral mapping to the front-end of our speech recognition system and show that recognition rates on silent speech improve by up to 12.3% relative.

1 Introduction

Automatic Speech Recognition (ASR) has matured to a point where it is successfully applied to ubiquitous applications and devices, such as telephone-based services and mobile personal digital assistants. Despite their success, speech-driven technologies still face two major challenges: recognition performance degrades significantly in the presence of noise, and confidential or private communication in public places are jeopardized by audible speech. Both of these challenges are addressed by Silent Speech Interfaces (SSI). A Silent Speech Interface is an electronic system enabling to communicate by speech without the necessity of emitting an audible acoustic signal.

In this paper, we present our most recent investigations in electromyographic (EMG) speech recognition, where the activation potentials of the articulatory muscles are directly recorded from the subject's face via surface electrodes[1]. This approach has two major advantages: firstly, it is able to recognize silent speech, where not even a whispering sound is uttered. Secondly, the required technology is mobile, lightweight, and comes at very reasonable costs.

The use of EMG for speech recognition dates back to the mid 1980s, when Sugie and Tsunoda published a first study on Japanese vowel discrimination [1]. Competitive performance was first reported by [2], who achieved an average word error rate of 7%

[1] Strictly spoken, the technology is called *surface electromyography*, however we use the abbreviation *EMG* for simplicity.

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on a 10-word vocabulary of English digits. A good performance could be achieved even when words were spoken non-audibly, i.e. when no acoustic signal was produced [3], suggesting this technology could be used to communicate silently. While the former approaches used words as model units, [4] successfully demonstrated that phonemes can be used as modeling units for EMG-based speech recognition, paving the way for large vocabulary continuous speech recognition. Recent results include advances in acoustic modeling using a clustering scheme on *phonetic features*, which represent properties of a given phoneme, such as the place or the manner of articulation. In [5], we report that a recognizer based on such *bundled phonetic features* performs more than 30% better than a recognizer based on phoneme models only.

While reliable automatic recognition of silent speech is currently heavily investigated and recent performance results come within useful reach, little is known about the EMG signal variations resulting from differences in human articulation between audible and silent speech production. Therefore, this paper studies the variations in the EMG signal caused by *speaking modes*. We distinguish *audible EMG*, i.e. EMG signals recorded on normally pronounced speech, *whispered EMG*, i.e. EMG signals recorded on whispered speech, and *silent EMG*, i.e. signals from silently mouthed speech.

Maier-Hein [6] was the first to investigate cross-modal speech recognition performance, i.e. models were trained on EMG signals from audible speech and tested on EMG signals from silent speech, and vice versa. The results suggested that the EMG signals are impacted by the speaking mode. Also, it was found that performance differences were lower for those speakers who had more practice in speaking silently while using the system.

Since the capability to recognize silent speech is the focus of Silent Speech Interfaces in general, and EMG-based speech recognition in particular, we consider it very crucial to investigating how the difference between speaking audibly or silently affects the articulation and the measured EMG signal. Furthermore, it is of very high interest to the silent speech research community how to compensate for these differences for the purpose of speech recognition.

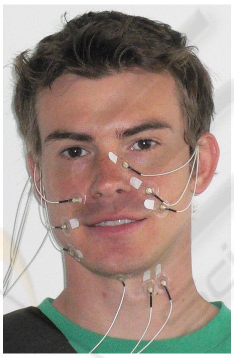
In [7] we performed first experiments on cross-modal recognition of continuous speech based on units which were smaller than words. We showed that the difference between audible and silent speaking modes has a significant negative impact on recognition performance. We also conducted preliminary experiments on comparing the differences between recordings of audible and silent EMG and postulated a correlation between signal energy levels and cross-modal recognition performance. The current study is a continuation of these initial experiments. Here, we investigate the spectral content of the EMG signals of audible, whispered and silent speech, showing that there is a correlation between similar spectral contents and good recognition performance across different speaking modes. We then present a *spectral mapping* method which serves to reduce the discrepancies between spectral contents in different speaking modes. We perform additional experiments on whispered speech, since this speaking mode can be seen as an in-between of audible and silent speech: On the one hand, it is generally softer than audible speech and does not involve any vocal chord vibration, on the other hand, whispered speech still provides acoustic feedback to the speaker.

The remainder of the paper is organized as follows: In section 2 we describe the data corpus which we used for this study. Section 3 documents our EMG-based speech recognizer. Section 4 specifies our analytic experiments, and in section 5 we apply the results to our EMG-based speech recognizer. Section 6 concludes the paper.

2 Data Corpus

For our experiments, we recorded a corpus of EMG signals of audible, whispered, and silent speech of seven male speakers and one female speaker, aged between 24 and 28 years. Each speaker recorded between one and six sessions. The recording protocol was as follows: In a quiet room, the speaker read 50 English sentences for three times, first audibly, then in whispered speech, and at last silently mouthed. In each part we recorded one BASE set of 10 sentences which were identical for all speakers and all sessions, and one SPEC set of 40 sentences, which varied across sessions. In each session, these sentence sets were the same for all three parts, so that the database covers all three speaking modes with parallel utterances. The total of 50 BASE and SPEC utterances in each part were recorded in random order. In all recognition experiments, the 40 SPEC utterances are used for training, and the 10 BASE utterances are used as test set.

For EMG recording we used a computer-controlled 6-channel EMG data acquisition system (Varioport, Becker-Meditec, Germany). All EMG signals were sampled at 600 Hz and filtered with an analog high-pass filter with a cut-off frequency at 60Hz. We adopted the electrode positioning from [6] which yielded optimal results. Our electrode setting uses five channels and captures signals from the levator angulis oris, the zygomaticus major, the platysma, the anterior belly of the digastric and the tongue. In the audible and whispered parts, we parallely recorded the audio signal with a standard close-talking microphone connected to an USB soundcard.



Speaker	# Sessions	Average Session Length in [sec] (Training/Testing)		
		audible	**whispered**	**silent**
1	3	190/54	222/62	198/55
2	6	162/44	164/45	163/46
3	1	189/52	197/53	221/57
4	2	169/44	168/43	184/48
5	1	182/49	193/51	185/48
6	1	151/43	151/94	156/42
7	1	188/51	189/52	189/49
8	1	158/41	164/44	170/44
TOTAL	16	2753/751	2876/837	2863/775

Fig. 1. Electrode positioning (left), properties of the data corpus (right).

The collected data is intended to be comparable to the *EMG-PIT* corpus of EMG recordings of audible and silent speech [5]. However, the EMG-PIT corpus lacks whispered recordings, which we perceived as essential for our investigation. Figure 1 shows the electrode positioning and the final corpus of utterances which we used for this study.

3 The EMG-based Silent Speech Recognizer

For all recognition experiments we apply our EMG speech recognition system based on three-state left-to-right fully continuous Hidden-Markov-Models [5], which are used to model phonetic features (PFs) representing phoneme-based properties. The modeling details are not required for the understanding of the remainder of this paper and are therefore omitted. The interested reader is refered to [5].

3.1 Feature Extraction

Figure 2 gives an example for a raw EMG signal (one channel) of the utterance "We can do it". At the bottom of the signal the phoneme alignment is displayed.

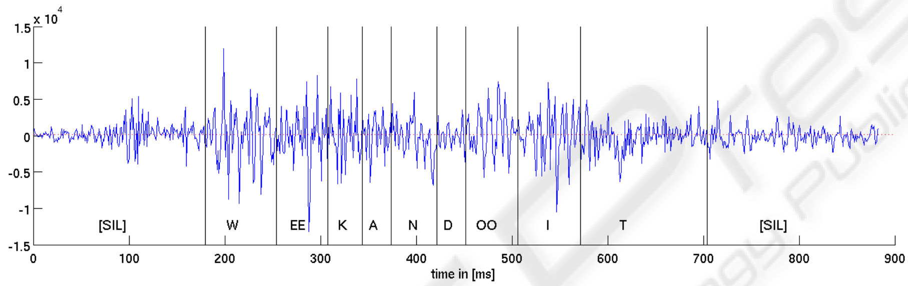


Fig. 2. Example for the EMG signal (channel 1) of the utterance "We can do it".

The feature extraction is based on *time-domain features* [4]. Here, for any given feature $\mathbf{f}$, $\bar{\mathbf{f}}$ is its frame-based time-domain mean, $\mathbf{P_f}$ is its frame-based power, and $\mathbf{z_f}$ is its frame-based zero-crossing rate. $S(\mathbf{f}, n)$ is the stacking of adjacent frames of feature $\mathbf{f}$ in the size of $2n+1$ ($-n$ to n) frames.

For an EMG signal with normalized mean $x[n]$, the nine-point double-averaged signal $w[k]$ is defined as

$$w[n] = \frac{1}{9}\sum_{n=-4}^{4} v[n], \quad \text{where} \quad v[n] = \frac{1}{9}\sum_{n=-4}^{4} x[n].$$

The rectified high-frequency signal is $r[n] = |x[n] - w[n]|$. In baseline experiments with audible EMG, the best word error rate is obtained with the following feature, which we use in this study as well:

$$\mathbf{TD15} = S(\mathbf{f2}, 15), \text{where } \mathbf{f2} = [\bar{\mathbf{w}}, \mathbf{P_w}, \mathbf{P_r}, \mathbf{z_r}, \bar{\mathbf{r}}].$$

As in [7], frame size and frame shift were set to 27 ms resp. 10 ms. In all cases, we apply LDA on the TD15 feature to generate a final feature with 32 coefficients.

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3.2 Cross-modal Initialization

Initializing an EMG-based Continuous Silent Speech recognizer is a challenging task since in order to initialize acoustic models representing sub-word units (phonemes or phonetic features), one needs a *time-alignment* of the training material, i.e. information about the phoneme boundaries in the training utterances. Our previous works on *audible* EMG data used a conventional speech recognizer on the parallel-recorded audio stream in order to create such a time-alignment and then forced-aligned the training sentences. However, this method is infeasible for silent EMG, and information on the phoneme boundaries is not readily available.

We employ two kinds of initialization methods for the silent EMG recognizer [7]. Both methods rely on the existence of a "base recognizer", which must be trained in advance on audible or whispered EMG by using the parallel-recorded audio stream. These methods are as follows:

Cross-modal Testing. We directly use the base recognizer to decode the silent EMG test set.

Cross-modal Labeling. We use trained models from the base recognizer to create a time-alignment for the silent EMG data. Then we forced-align the silent EMG data and do a full training run. This means that we create specific acoustic models for silent EMG.

For decoding, we use the trained acoustic model together with a trigram Broadcast News language model giving a perplexity on the test set of 24.24. The decoding vocabulary is restricted to the words appearing in the test set, which results in a test vocabulary of 108 words.

4 Spectral Analysis of Audible, Whispered and Silent EMG

4.1 Spectral Density Comparison

As a first experiment, we computed the power spectral density (PSD) of the EMG recordings of each session on a per-utterance and per-channel basis and then averaged over the utterances of each session and each speaking mode. For the PSD computation, we used Welch's method [8], which works as follows:

- The input signal is divided into an integer number of segments with a 30 samples window length with 67% overlap.
- Each segment is windowed with one Hamming window to reduce spectral distortion.

Thus for each session we obtained the average spectral contents of the audible, whispered, and silent EMG recordings. Since the EMG signals were sampled with 600 Hz, the frequency range is between 0 and 300 Hz.

The left-hand side of figure 3 shows the average power spectral density of EMG channel 1 for the three sessions of Speaker 1, who has moderate experience in speaking silently. The curve shapes look similar, but the amplitudes differ for the speaking modes.

This speaker has an average Word Error Rate (WER) of 32.3% on audible EMG, while the Cross-Modal Labeling experiment gives a WER of 87.8% on silent EMG. Whispered speech is recognized with 51.2% WER. The right-hand side of figure 3 charts the PSD of a speaker well practiced in speaking silently, with good recognition rates for all speaking modes. The shape of the PSD curves is very similar to those of speaker 1, and the ratio between the energy contents per frequency is much closer to one than for speaker 1. Also note that the average signal energy is an order of magnitude higher than for speaker 2. For speaker 2 the WERs are 34.3% for audible EMG (which is about the same as for speaker 1), but only 6.1% for whispered EMG, and 26.3% for silent EMG. The good performance for whispered speaking mode might be related to the higher energy.

Except for some recordings which contained 50 Hz power line noise, the PSD shapes look quite similar across channels. Based on physiological differences and individual articulation charateristics the maximal values of the PSD differ. The maximum PSD on channel 1 varies between 0.017 and 0.22 for the eight speakers.

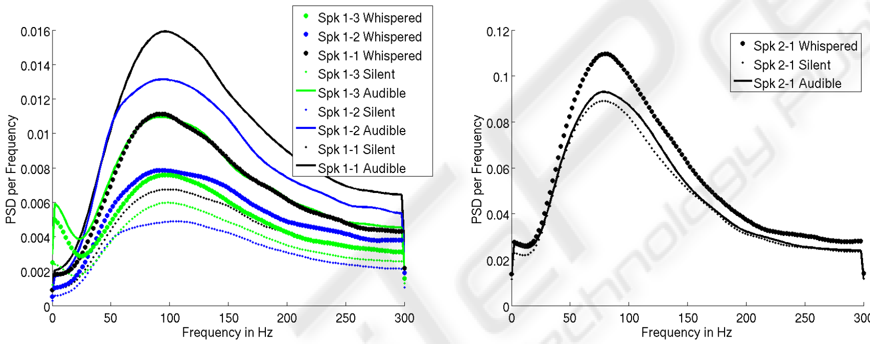

Fig. 3. PSD (Channel 1) of three Sessions of Speaker 1 (left) and Session 1 of Speaker 2 (right) with audible, whispered and silent speech.

These examples suggest that the recognition rates on silent speech and the similarity of the PSD curves are related to each other. In order to quantify this statement, we performed the following computations, individually for each session:

1. We computed the ratio of audible EMG and silent EMG PSD of each channel for each frequency bin and took the mean of this ratio over the frequency bins. This gives a value representing the spectral energy discrepancy between audible and silent EMG.
2. We calculated the WER difference between audible EMG and silent EMG (Cross-Modal Labeling Experiment) as a measure for the disparity of EMG recognition performance on audible and silent speech. Note that except for one session, all speakers perform better results with audible than silent speech.

A scatter plot of these values for each of the 16 sessions and for EMG channel 1 is shown in figure 4. The correlation coefficient is 0.67 and indicates that speakers with high spectral energy difference between speaking modes tend to have a high difference in audible and silent speech recognition performance. The scatter plots for EMG channels 2 to 6 show quite similar characteristics, the correlation coefficients for the other channels are 0.44 for channel 2, 0.66 for channel 3, 0.74 for channel 4, and 0.75 for channel 6. In some recordings of sessions 1-2, channel 2 shows noticeable power line noise, which appears in the PSD graph as a high peak centered around 50 Hz. This explains why the correlation coefficient for channel 2 is much lower than for the other channels: When session 1-2 is removed from the computation, the correlation coefficient for channel 2 increases to 0.72.

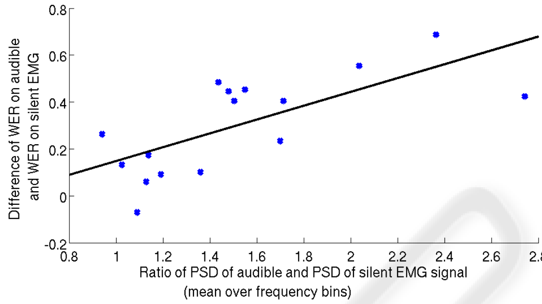

Fig. 4. Scatter plot comparing the ratio between power spectral density (PSD) of audible EMG and PSD of silent EMG and the difference of word error rates (WER) on silent and audible EMG for each session, with regression line. The PSD is for EMG channel 1 only and was maximized over frequency bins. The WER for silent EMG is from the "Cross-Modal Labeling" system.

4.2 Comparison based on Phoneme Classes

As a final experiment, we investigated the relationship between the spectral contents of audible and silent speech in more detail. It may be assumed that computing the spectral contents of the EMG signal on a per-utterance basis is a rather coarse way to analyze the highly time-variant EMG signal. Therefore we split up the signals into frames with a length of 27ms and a frame shift of 10ms, which is the same windowing used by the EMG recognizer. We then grouped the frames according to the phonetic features they represented. As our first experiment, we compared the spectral components of vowels and consonants taken from the audible EMG signal and the silent EMG signal. Figure 5 shows the PSDs for consonants and vowels of session 3 of speaker 2.

While the PSD shapes of silent and audible consonants differ only little, there is a noticeable difference in the vowel PSD chart. A reason for the higher vowel PSD in audible EMG could be the fact that (English) vowels are syllable peaks and thus major articulatory targets. When the speaker lacks acoustic feedback while articulating, this might have the consequence that acoustic targets are not fully reached any more, thus causing a less intense vowel articulation. However, further research on this question is necessary.

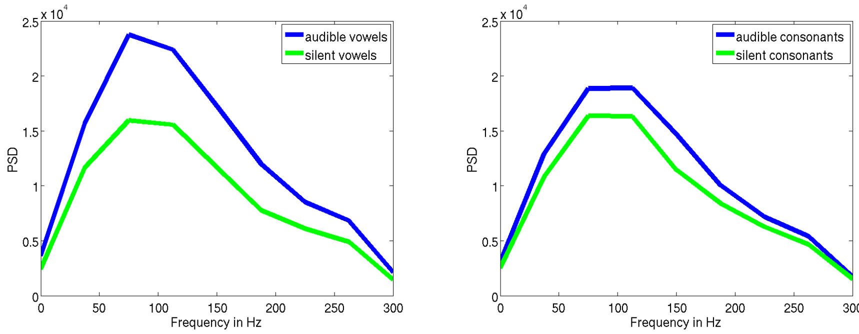

Fig. 5. PSD of EMG signal of audibly versus silently uttered vowels (left) and consonants (right) occurring in session 2-3.

5 Spectral Mapping and Recognition Experiments

With the information we obtained about the relationship between the spectral contents of EMG signals of audible, whispered and silent speech and the recognition performance of the respective cross-modal recognizers, we developed a *spectral mapping* method which is applied to the *silent* EMG signals. This mapping is applied independently to each channel and each session and works as follows:

1. We define a “base speaking mode” (audible or whispered) for this experiment.
2. We compute the PSD ratio between the target silent EMG and the EMG signal of the base speaking mode (as a function of the frequency). The result is averaged over all utterances of one session. We call this ratio *mapping factor*.
3. Each utterance is transformed into the frequency domain by the Fast Fourier Transform (FFT), then each resulting frequency component is multiplied by the corresponding mapping factor, and the resulting frequency representation of the signal is transformed back into the time domain by application of the inverse FFT.
4. After this procedure, the transformed signal is used for the training and testing process as usual. We tested both Cross-Modal Testing and Cross-Modal Labeling on the transformed silent EMG, where the transformation was computed with the same base speaking mode which was also used to train the base EMG recognizer.

The resulting WERs for silent EMG and an audible EMG base system are charted in Figure 6. One can see that particularly for Cross-Modal Testing, spectral mapping indeed yields a large improvement: The average WER without spectral mapping is 62.13%, which by our mapping approach is improved to 54.58%. So we achieved a relative improvement of 12.3%. Note that the improvements for Speaker 2 tend to be slighly smaller, which can be explained by the fact that this speaker is most experienced in speaking silently and tends to have good recognition rates for both silent and audible speech. The Cross-Modal Labeling System yields an average WER of 54.36%; with spectral mapping this is improved by 6.74% relative to 50.7%.

The overall improvement for cross-modal labeling is smaller than for cross-modal testing. This may be explained by the fact that cross-modal testing directly applies the

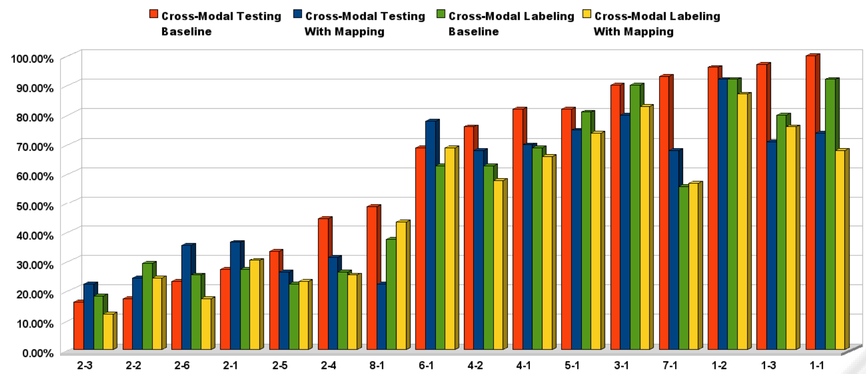

Fig. 6. Word Error Rates for the silent/audible mapped data.

recognizer trained on audible or whispered EMG to silent EMG, whereas cross-modal labeling means that a full training is performed on the silent EMG data, which should lessen the influence of the difference between the speaking modes.

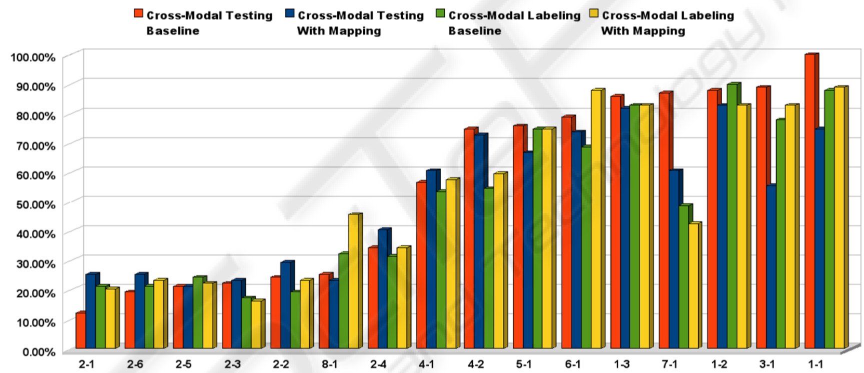

Fig. 7. Word Error Rates for the silent/whispered mapped data.

As a next step, we performed the same set of experiments with *whispered EMG* as the base system. The resulting word error rates can be seen in figure 7. As with the audible EMG base system, spectral mapping improves the resulting WER in the cross-modal testing experiment from 55.88% to 51.07%, which is a relative improvement of 8.6%. However, in the case of Cross-Modal Labeling, the Word Error Rate increases from 50.31% to 52.77%. The resulting Word Error Rates for the spectral mapping experiments are summarized in the following table:

	Cross-Modal Testing		**Cross-Modal Labeling**	
	Baseline	***With Mapping***	***Baseline***	***With Mapping***
audible/silent	62.13%	54.48%	54.36%	**50.70%**
whispered/silent	55.88%	51.07%	**50.31%**	52.77%

In particular, it can be seen that for three out of four experiments, particularly when no spectral mapping is performed, using whispered EMG is superior to using audible EMG as the base signal. This supports our earlier claim that whispered speech is an in-between of audible (normal) and silent speech.

6 Conclusions

Using EMG signals captured from the articulatory muscles, we compared the discrepancies between different speaking modes, analyzing corresponding audible, whispered and silent utterances. We showed that EMG signals from audible speech generally have a higher spectral power than EMG signals from silent speech, and that this power ratio and the Word Error Rate difference between speech recognition on audible and silent EMG correlate with a correlation coefficient of up to 0.75. With this information a mapping from silent to audible/whispered EMG could be achieved, which resulted in 12.3% relative improvement in our audible-to-silent Cross-Modal Testing System.

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