Array-based Electromyographic Silent Speech Interface

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Abstract: An electromygraphic (EMG) *Silent Speech Interface* is a system which recognizes speech by capturing the electric potentials of the human articulatory muscles, thus enabling the user to communicate silently. This study is concerned with introducing an EMG recording system based on multi-channel *electrode arrays*. We first present our new system and introduce a method to deal with undertraining effects which emerge due to the high dimensionality of our EMG features. Second, we show that Independent Component Analysis improves the classification accuracy of the EMG array-based recognizer by up to 22.9% relative, which is a first example of an EMG signal processing method which is specifically enabled by our new array-based system. We evaluate our system on recordings of audible speech; achieving an optimal average word error rate of 10.9% with a training set of less than 10 minutes on a vocabulary of 108 words.

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1 INTRODUCTION

Speech is the most convenient and natural way for humans to communicate. Beyond face-to-face talk, mobile phone technology and speech-based electronic devices have made speech a wide-range, ubiquitous means of communication. Unfortunately, voice-based communication suffers from several challenges which arise from the fact that the speech needs to be clearly audible and cannot be masked, including lack of robustness in noisy environments, disturbance for bystanders, privacy issues, and exclusion of speech-disabled people.

These challenges may be alleviated by Silent Speech Interfaces, which are systems enabling speech communication to take place without the necessity of emitting an audible acoustic signal, or when an acoustic signal is unavailable (Denby et al., 2010).

Over the past few years, we have developed a Silent Speech Interface based on surface electromyography (EMG): When a muscle fiber contracts, small electrical currents in form of ion flows are generated. EMG electrodes attached to the subject's face capture the potential differences arising from these ion flows. This allows speech to be recognized even when it is produced silently, i.e. mouthed without any vocal effort.

So far, all EMG-based speech recognizers have relied on small sets of less than 10 EMG electrodes attached to the speaker's face (Schultz and Wand, 2010; Maier-Hein et al., 2005; Freitas et al., 2012; Jorgensen and Dusan, 2010; Lopez-Larraz et al., 2010). The technology is based on standard Ag-AgCl gelled electrodes as used in medical applications. This setup imposes some limitations, for example, small shifts in the electrode positioning between recordings are difficult to compensate, and it is impossible to separate superimposed signal sources, thus single active muscles or motor units cannot be discriminated. In this paper, we present first results on using *electrode arrays* for the recording of EMG signals of speech. We establish a baseline procedure to allow an existing state-of-the-art EMG-based continuous speech recognizer (Schultz and Wand, 2010) to deal with the increased number of signal channels, and we present a first application of the EMG array methodology, namely, we show that application of Independent Component Analysis (ICA) reduces the Word Error Rates of the recognizer.

In the future, we expect EMG array technology to allow a much more fine-grained EMG-based recognition of articulatory activity than can be achieved with separate-electrode systems: The multi-channel signal will allow us to perform source separation methods, as presented in this paper, and should offer the possibility to extract and model certain articulatory patterns which are part of the human speech process. In terms of practical usage, the setup time for the new system is significantly shorter than for the old separate-electrode system, since the electrode at-

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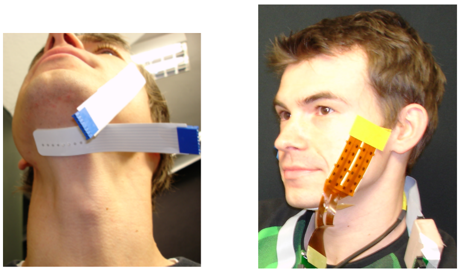

Figure 1: EMG array positioning for setup A (left) and setup B (right).

tachment process is much shorter than for separate-electrode systems.

The remainder of this paper is organized as follows: In the following section 2, we describe our new recording system, and section 3 contains a description of the underlying decoding system. Section 4 presents our experiments, and the final section 5 concludes the paper.

2 RECORDING SYSTEM SETUP AND CORPUS

For EMG recording we used the multi-channel EMG amplifier *EMG-USB2* produced and distributed by *OT Bioelettronica*, Italy (`http://www.otbioelettronica.it/`). The EMG-USB2 amplifier allows to record and process up to 256 EMG channels, supporting a selectable gain of 100 - 10000 V/V and a recording bandwidth of 3 Hz - 4400 Hz. For line interference reduction, we used the integrated DRL circuit (Winter and Webster, 1983). The electrode arrays were acquired from *OT Bioelettronica* as well. Electrolyte cream was applied to the EMG arrays in order to reduce the electrode/skin impedance.

We used two different EMG array configurations for our experiments, see figure 1. In *setup A*, we unipolarly recorded 16 EMG channels with two EMG arrays each featuring a single row of 8 electrodes, with 5 mm inter-electrode distance (IED). One of the arrays was attached to the subject's cheek, capturing several major articulatory muscles (Maier-Hein et al., 2005), the other one was attached to the subject's chin, in particular recording signals from the tongue. A reference electrode was placed on the subject's neck.

In *setup B*, we replaced the cheek array with a larger array containing four rows of 8 electrodes, with 10 mm IED. The chin array remained in its place. In this setup, we achieved a cleaner signal by using a *bipolar* configuration, where the potential difference between two adjacent channels in a row is measured. This means that out of 4×8 cheek electrodes and 8 chin electrodes, we obtain $(4+1) \cdot 7 = 35$ signal channels.

For both setups, we chose an amplification factor of 1000, a high-pass filter with a cutoff frequency of 3 Hz and a low-pass filter with a cutoff frequency of 900 Hz, and a sampling frequency of 2048 Hz. The audio signal was parallely recorded with a standard close-talking microphone. We used an analog marker system to synchronize the EMG and audio recordings, and according to (Jou et al., 2006), we delayed the EMG signal by 50ms compared to the audio signal.

The text corpus which we recorded is based on (Schultz and Wand, 2010). We used two different text corpora for our recordings: Each session contains a set of ten "BASE" sentences which is used for testing and kept fixed across sessions. Furthermore, each session contains 40 test sentences, which vary across sessions. For reference, we call this basic text corpus "Set 1". A subset of our sessions has been extended to 160 different training sentences and 20 test sentences, where the 20 test sentences consist of the BASE set repeated twice. This enlarged text corpus is called "Set 2".

The recording proceeded as follows: In a quiet room, the speaker read English sentences in normal, audible speech. The recording was supervised by a member of the research team in order to detect errors (e.g. detached electrodes) and to assure a consistent pronunciation. The training and test sentences were always recorded in randomized order. Thus we finally have four setups to investigate, namely, setups A-1 and A-2 (with 16 EMG channels) and B-1 and B-2 (with 35 EMG channels). At this point we remark that the results on the four setups are not directly comparable, since the number of training sentences, the set of speakers and the number of sessions per speaker differ. Also, our experience indicates that even for one single speaker, the recognition performance may vary drastically between sessions, possibly due to variations in electrode positioning, skin properties, etc. However, it is certainly plausible to compare the effects of different feature extraction methods on the recognition performance of *each* of the setups, which is the purpose of this paper. It should also be noted that the test sets of the four setups exhibit identical characteristics in terms of perplexity and vocabulary.

The following table summarizes the properties of our corpus.

Setup	# of Speakers / Sessions	Average data length in sec.		
		Training	Test	Total
A-1	3 / 6	144	37	181
A-2	2 / 2	528	74	602
B-1	6 / 7	149	42	191
B-2	4 / 4	570	83	653

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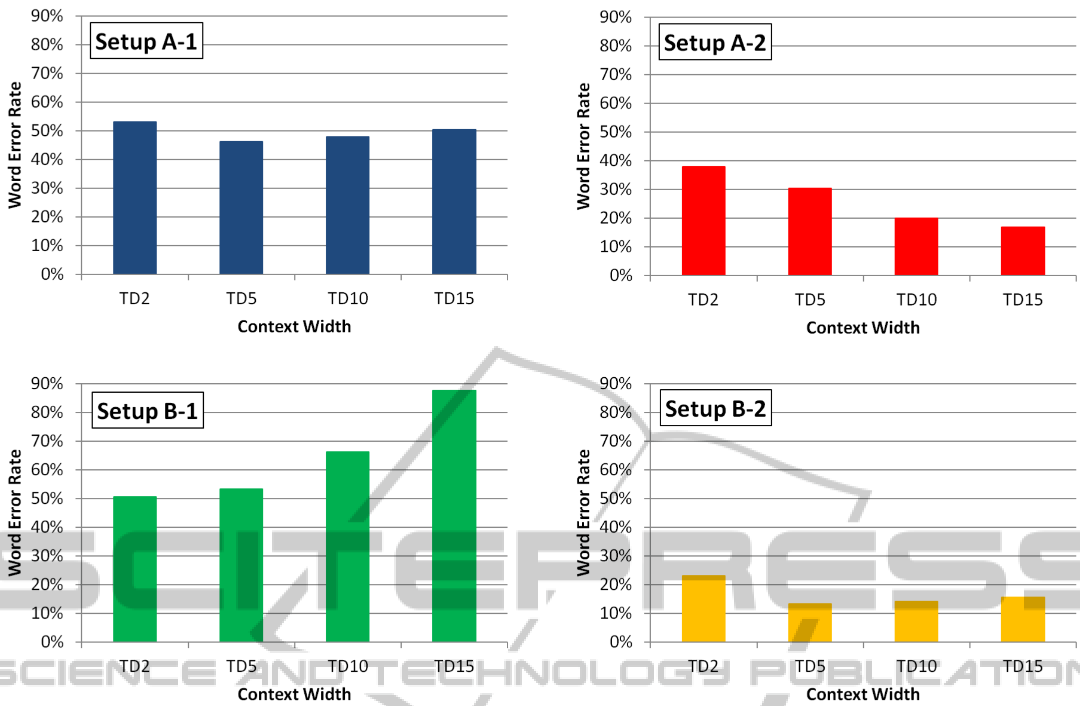

Figure 2: Word Error Rates for the baseline system with different stacking context widths (no PCA or ICA).

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3 FEATURE EXTRACTION, TRAINING AND DECODING

The feature extraction is based on *time-domain features* (Jou et al., 2006). We first split the incoming EMG signal channels into a high-frequency and a low-frequency part, after this, we perform framing and compute the features, as follows:

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 $w[n]$ is defined as

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

The high-frequency signal is $p[n] = x[n] - w[n]$, and the rectified high-frequency signal is $r[n] = |p[n]|$. The final feature $\mathbf{TD}n$ is defined as follows:

$$\mathbf{TD}n = S(\mathrm{TD0}, n), \text{where } \mathrm{TD0} = [\bar{\mathbf{w}}, \mathbf{P_w}, \mathbf{P_r}, \mathbf{z_p}, \bar{\mathbf{r}}],$$

i.e. a stacking of adjacent feature vectors with context width $2 \cdot n + 1$ is performed, with varying n. This process is performed for each channel, and the combination of all channel-wise feature vectors yields the final $\mathbf{TD}n$ feature vector. Frame size and frame shift are set to 27 ms respective 10 ms.

In all cases, we apply Linear Discriminant Analysis (LDA) on the TDn feature. The LDA matrix is computed by dividing the training data into 136 classes corresponding to the begin, middle, and end parts of 45 English phonemes, plus one silence phoneme. From the 135 dimensions which are yielded by the LDA algorithm, we always retain 32 dimensions, which is in line with previous work (Jou et al., 2006; Schultz and Wand, 2010) and thus allows to compare our performance with the results on single-electrode systems. Preliminary experiments with a higher number of retained dimensions did not show any significant improvement. As shown in section 4.2, it may be necessary to perform Principal Component Analysis (PCA) before computing the LDA matrix, see section 4.2 for further details. In the experiments described in section 4.3, Independent Component Analysis (ICA) is applied *before* the feature extraction step, on the raw EMG data.

The recognizer is based on three-state left-to-right fully continuous Hidden-Markov-Models. All experiments used bundled phonetic features (BDPFs) for training and decoding, see (Schultz and Wand, 2010) for a detailed description. In order to obtain phonetic time-alignments as a reference for training, the parallely recorded acoustic signal was forced-aligned with

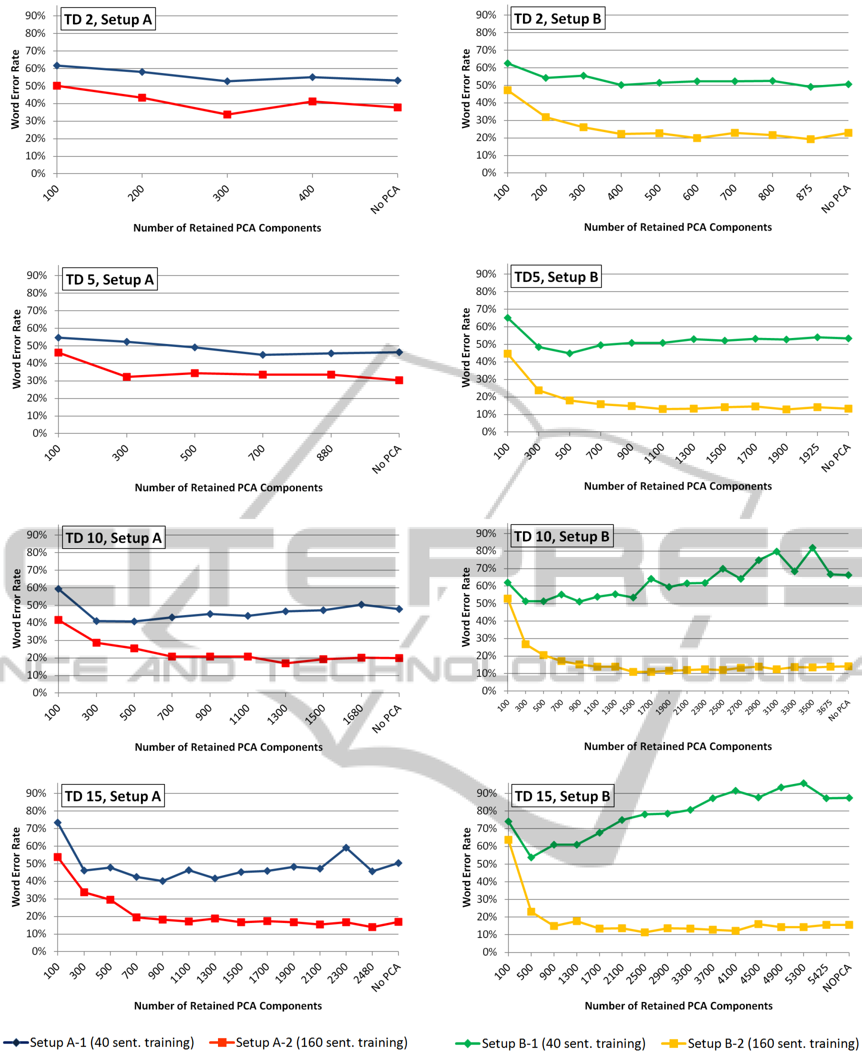

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Figure 3: Word Error Rates for different PCA dimension reductions. Observe that the feature space dimension before the PCA step increases from left to right and from top to bottom.

an English Broadcast News (BN) speech recognizer. Based on these time-alignments, the HMM states are initialized by a merge-and-split training step (Ueda et al., 2000), followed by four iterations of Viterbi training.

For decoding, we used the trained acoustic model together with a trigram Broadcast News language model. The test set perplexity is 24.24. The decoding vocabulary was restricted to the words appearing in the test set, which resulted in a test vocabulary of 108 words. Note that we do *not* use lattice rescoring for our experiments.

4 EXPERIMENTS AND RESULTS

In this section we first outline our baseline system, based on (Schultz and Wand, 2010), and then describe the modifications to the feature extraction process which are necessary to deal with a large number of channels. In the final part, we apply Independent Component Analysis (ICA) to the raw EMG data and show that it can increase the recognition accuracy.

4.1 Baseline Recognition System

Our first experiment establishes a baseline recognition system. We use our recognizer, as described in section 3, and feed it with the EMG features from the

Table 1: Optimal Results and Parameters with and without PCA.

Setup	A-1	A-2	B-1	B-2
Best Result without PCA ("Baseline")	46.3%	17.0%	50.5%	13.4%
Optimal Stacking Width without PCA	5	15	2	5
Optimal Number of Dimensions without PCA	880	2480	875	1925
Best Result with PCA	40.1%	13.9%	44.9%	10.9%
Optimal Stacking Width with PCA	15	15	5	10
Optimal Number of Dimensions with PCA	900	2480	500	1500
Relative Improvement by PCA Application	13.4%	18.2%	11.1%	18.7%

array recording system. Figure 2 shows the Word Error Rates for different stacking widths, averaged over all sessions of the four setups.

We now consider the optimal context widths for the four setups. This has been investigated e.g. by (Jou et al., 2006), where a context width of 5 was used, and by (Wand and Schultz, 2010), where it was shown that increasing the context width to 15 frames, i.e. 150 ms, still brings some improvement.

Our observations for the four distinct setups presented in this study are very different: For *setup A-1*, with 16 channels and 40 training sentences, the Word Error Rate (WER) varies between 46.3% and 53.2%, with the optimum reached at a context width of 5 (i.e. TD5). For the B-1 setup, with 35 channels but the same amount of training data, the optimal context width appears to be TD2 with a WER of 50.5%, and for wider contexts, which increases to 87.6% for the TD15 stacking.

For the setups with 160 training sentences, the recognition performance is generally better due to the increased training data amount. With respect to context widths, we observe a behavior which vastly differs from the results above: For 16 EMG channels (setup A-2), the optimal context width is TD15, with a WER of only 17.0%. For setup B-2, TD5 stacking is optimal, with a WER of 13.4%.

The behavior described in this section is quite consistent across recording sessions. This means that even though the corpora for the four setups are different, we have observed a deep inconsistency with respect to the optimal stacking width, which leads us to the series of experiments described in the following section.

4.2 PCA Preprocessing to avoid LDA Sparsity

Machine learning tasks frequently exhibit a challenge known as the "Curse of Dimensionality", which means that high-dimensional input data, relative to the amount of training data, causes undertraining, diminishes the effectiveness of machine learning algorithms, and reduces in particular the generalization capability of the generated models. The maximal feature space dimension which allows robust training depends on the amount of available training data.

The dimensionality of the feature space in our experiments depends on the number of EMG channels and the stacking width during feature extraction. From the results of section 4.1, we observe

- that for both setups A and B, increasing the amount of training data increases the optimal context width
- and that for both the 40-sentence training corpus (set 1) and the 160-sentence training corpus (set 2), the optimal context width with setup B is lower than the optimum for setup A.

This strongly suggests that the "Curse of Dimensionality" is the cause of the discrepancy we observed. However, since the LDA algorithm *always* reduces the feature space dimensionality to 32 channels, the GMM training itself is not affected by varying feature dimensionalities.

We assumed that the deterioration of recognition accuracy for small amounts of training data and high feature space dimensionalities is caused by the LDA computation step. It has been shown that when the amount of training data is small relative to the sample dimensionality, the LDA within-scatter matrix becomes sparse, which reduces the effectivity of the LDA algorithm (Qiao et al., 2009). This may be the case in our setup, since with only a few minutes of training data, we may have a sample dimensionality before LDA of up to $35 \cdot 5 \cdot 31 = 5425$ for the 35-channel system with a TD15 stacking.

The following set of experiments deals with coping with the LDA sparsity problem. From these experiments we expect an improved recognition accuracy and, in particular, a more consistent result regarding the optimal feature stacking width. In these experiments, we allowed an additional PCA dimension reduction step before the LDA computation, as advocated for visual face recognition (Belhumeur et al., 1997). This step should allow an improved LDA estimation, however, if the PCA cutoff dimension is chosen too low, one will lose information

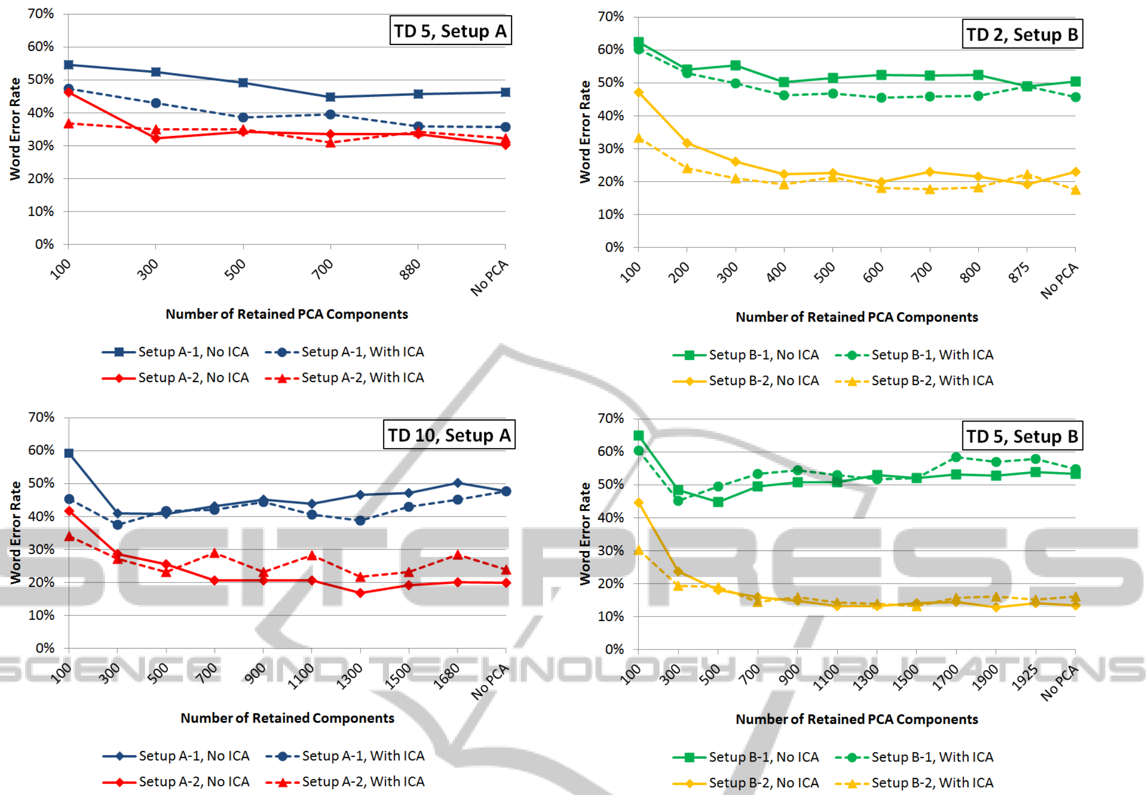

Figure 4: Word Error Rates after ICA application, for the four different setups and varying context widths.

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which is important for discrimination.

The computation works as follows: On the training data set, we first compute a PCA transformation matrix. We apply PCA and keep a certain number of components from the resulting transformed signal, where the components are, as usual, sorted by decreasing variance. Then we compute an LDA matrix of the PCA-transformed training data set, finally keeping 32 dimensions. The resulting PCA + LDA preprocessing is now applied to the entire corpus, normal HMM training and testing is performed, and we use the Word Error Rate as a measure for the quality of our preprocessing.

Figure 3 plots the Word Error Rates of our recognizer for setups A and B and different stacking widths versus the number of retained dimensions after the PCA step. In all cases, we jointly plot the WERs for training data sets 1 and 2.

The figures show that the PCA step indeed helps to overcome LDA sparsity. For example, in the A-1 setup, the optimal context width without PCA application is 5, yielding a WER of 46.3%. With PCA application, the optimal number of retained PCA dimensions *for the* TD5 *context width* is 700, yielding a WER of 44.8%. However, we can still do better: With a vastly increased context width of 15, we get the best WER of 40.1%, at a dimensionality after PCA application of 900.

This is also true for the other four setups, see table 1 for an overview. In all cases, we obtain WER reductions of more than 10% relative, and also, in all cases the optimal context width increases.

So far, we have found the optimal context width for the EMG speech classification task to lie around 10 to 15 frames on each side, which makes a context of around 200-300 ms. It may be possible to try even wider contexts, however, close examination of the results in figure 3 show that between the context widths of 10 and 15, the respective results with optimal PCA dimensionality are rather close for each of the four setups.

4.3 ICA Application

Having established a baseline recognizer, we now turn our attention to applications of array technology. One well-established means of identifying signal sources in multi-channel signals is *Independent Component Analysis (ICA)* (Hyvrinen and Oja, 2000). ICA is a linear transformation which is used to obtain independent components within a multi-channel signal; the underlying idea is that the statistical independence be-

Table 2: Best Results with and without ICA.

Setup		A-1	A-2	B-1	B-2
Without PCA	Best Result without ICA	46.3%	17.0%	50.5%	13.4%
	Best Result with ICA	35.7%	16.2%	44.2%	12.1%
	Relative Improvement	22.9%	4.7%	12.5%	9.7%
With PCA	Best Result without ICA	40.1%	15.15%	44.9%	10.9%
	Best Result with ICA	35.7%	12.40%	40.8%	11.8%
	Relative Improvement	11.0%	18.2%	9.1%	-8.3%

tween the estimated components is maximized.

We interpret ICA as a method of (blind) source separation, therefore we apply ICA and then run our recognizer *on the estimated components*; this includes the PCA step and the LDA step. Another method would be to delete undesired sources, e.g. noise, and then back-project the remaining components (Jung et al., 2000). Also, we do not manually remove undesired channels, instead we allow the PCA+LDA step to remove these non-discriminative components. Clearly, this is expected to be only a first step towards a more meticulous application of ICA, in particular, we expect to be able to detect and remove irrelevant noise channels in the future.

The ICA separation matrix is always computed on the training data of the respective sessions. Since in both setups A and B, we have two separate EMG arrays, we run the ICA algorithm on the channels from these two arrays *separately*. We use the Infomax ICA algorithm according to (Bell and Sejnowski, 1995), as implemented in the Matlab EEGLAB toolbox (Makeig, S. et al., 2000).

Figure 4 shows average Word Error Rates for setups A and B, plotted against the PCA cutoff dimension, with and without ICA application. As typical examples of our observations, for setup A we plotted the results for the context widths of 5 and 10, for setup B, we chose the context widths of 2 and 5.

It can be seen that in almost all cases, ICA improves the recognition results consistently across different PCA dimensionalities. The remarkable exceptions are setups B-1 and B-2 with TD5 stacking. Generally, ICA appears to be slightly more helpful in setup A. Table 2 gives an overview of the results of ICA application. It can be seen that the only case where ICA application gives a worse result is the B-2 setup, which is, however, still our best setup altogether.

Finally, we ask the question why the ICA application does not yet always yield satisfactory results. One can visually study the effects of ICA preprocessing by looking at the EMG signals before and after ICA application: Figure 5 gives a typical example of the first second of a recording from corpus A-2; only the signals from the cheek array are shown. One sees that the eight original channels (left) show somewhat similar patterns, including a relatively large amount of pure noise at the beginning, when the speaker has not yet started to articulate.

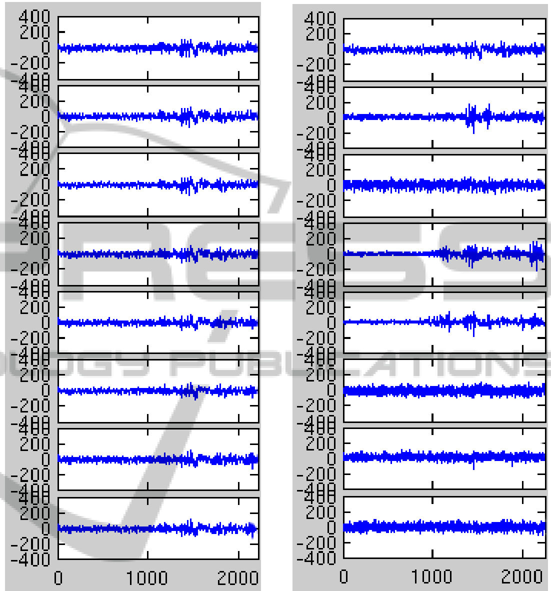

Figure 5: 8-channel EMG signals before ICA application (left) and after ICA application (right).

The ICA-processed signals present a different image: Out of the eight channels, four show white noise throughout the recording, three show starkly different EMG signals, and the first channel appears to show a mixture of noise and content-bearing signal. Note that the ICA implementation changes the scale of the ICA components.

Our current method applies the EMG preprocessing described in section 3 to all these ICA components *indiscriminately*. The fact that the recognition results are better for the ICA-processed signals than for the original EMG data indicates that the PCA+LDA step is able to suppress the noise components and concentrates on the content-bearing channels, however, this method is likely suboptimal. In the future we plan to develop and apply heuristical methods to distinguish content-bearing signals and noise components, so that the latter can be automatically removed.

5 CONCLUSIONS

In this study we have laid the basics of a new EMG-based speech recognition technology, based on *electrode arrays* instead of single electrodes. We have presented two basic recognition setups and evaluated their potential on data sets of different sizes. The unexpected inconsistency with respect to the optimal stacking width led us to the introduction of a PCA preprocessing step before the LDA matrix is computed, which gives us consistent relative Word Error Rate improvements of 10% to 18%, even for small training data sets of only 40 sentences.

As a first application of the new array technology, we have shown that Independent Component Analysis (ICA) typically improves our recognition results. We also have observed that our method of applying ICA does not yet always yield satisfactory results: In one of our setups, we actually observed slightly worse results than without ICA.

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