

# Toward EEG Sensing of Imagined Speech

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**Abstract.** Might EEG measured while one imagines words or sentences provide enough information for one to identify what is being thought? Analysis of EEG data from an experiment in which two syllables are spoken in imagination in one of three rhythms shows that information is present in EEG alpha, beta and theta bands. Envelopes are used to compute filters matched to a particular experimental condition; the filters' action on data from a particular trial lets one determine the experimental condition used for that trial with appreciably greater-than-chance performance. Informative spectral features within bands lead us to current work with EEG spectrograms.

**Keywords:** EEG, imagined speech, covert speech, classification.

## 1 Introduction

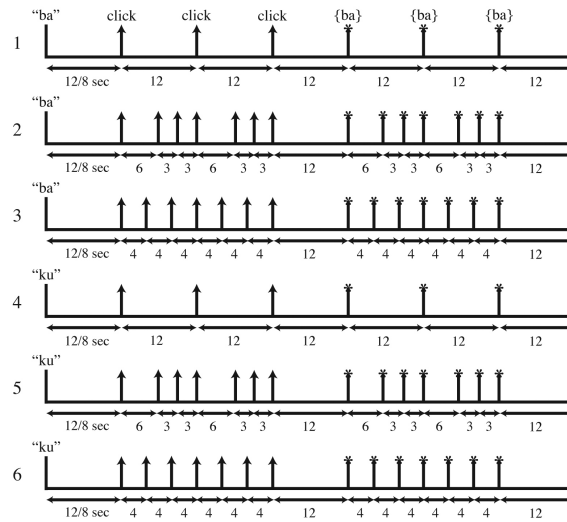
Dewan reported in 1967 [1] that he and several others could transmit letters of the alphabet using EEG recording; their ability to control voluntarily the amplitude of their alpha waves let them send letters using Morse code. Farwell and Donchin [2] used a second method for transmitting linguistic information by EEG; the P300 response to targets let them determine which of a sequence of displayed letters a person had in mind. Finally, Suppes and colleagues [3,4] reported that they were able to classify EEG responses to heard sentences and that there was information available through EEG concerning imagined speech. The work reported here verifies this latter result and develops it further, with the aim of using EEG brain waves to communicate imagined speech.

Classification experiments show that brain-wave signatures of imagined speech lets one distinguish linguistic content, with varying degree of success. These signatures include differences in alpha-, beta- and theta-band activity. Our near-term goal is to use such signatures to design filters that let one distinguish linguistic elements in real time. One application is in further experiments which provide feedback to the thinker as to how recognizable a particular thought is, with the aim of training the thinker to produce brain waves which are more discernible.

The focus within is on the results of a single experiment in which subjects produce in their imagination one of two syllables in one of three different rhythms. Analysis of the data using envelopes within alpha, beta and theta frequency bands, spectral features within single bands, and spectrograms in current work show that EEG provides considerable information on imagined speech in this experimental setting.

## 2 Methods

Four subjects participated in an experiment with six conditions determined factorially through combination of two syllables and three rhythms (see Figure 1). A single experimental session comprised 20 trials for each of the six conditions; conditions were presented in block-randomized order. Each subject participated in six such sessions for a total of 120 trials per condition. EEG was recorded using a 128 Channel Sensor Net (Electrical Geodesics) in combination with an amplifier and acquisition software (Advanced Neuro Technology). The EEG was sampled at 1024Hz and on-line average referenced. Subjects were instructed to keep their eyes open in the dimly-lit recording room and to avoid eye and other movement during the six seconds, following the cue, during which speech was imagined without any vocalization whatsoever.



**Fig. 1.** Timelines for the six conditions, labeled at left, in the imagined speech experiment. Durations are indicated in eighths of a second. The syllable /ba/ was imagined in one of three different rhythms in conditions 1-3; the syllable /ku/ was imagined in conditions 4-6. The condition for each trial was cued during an initial period of duration 4.5 sec ( $12/8 \text{ sec} = 1.5 \text{ sec}$ ;  $3 \times 1.5 \text{ sec} = 4.5 \text{ sec}$ ). During this initial period, subjects heard through Stax electrostatic earphones either a spoken "ba" or a spoken "ku" followed by a train of clicks (arrows) indicating the rhythm to be reproduced. Subjects were instructed to speak in their imagination the cued syllable, illustrated for condition 1 by {ba}, using the cued rhythm and tempo. Desired imagined syllable onset times reproduce the cued rhythm and are indicated by asterisks.

## 3 Analysis and Results

Our aims were to classify single trials offline according to condition and discern condition signatures needed to create online filters. EEG waveform envelopes provide encouraging results when used to classify trials according to experimental condition.

These envelopes were computed for each electrode in the theta (3-8Hz), alpha (8-13Hz) and beta (13-18Hz) frequency bands and used to construct matched filters. These filters work well to classify trials according to condition, yet further results with spectra lead us to explore a finer-grained analysis using spectrograms.

### 3.1 Matched-Filter Classification Using Envelopes

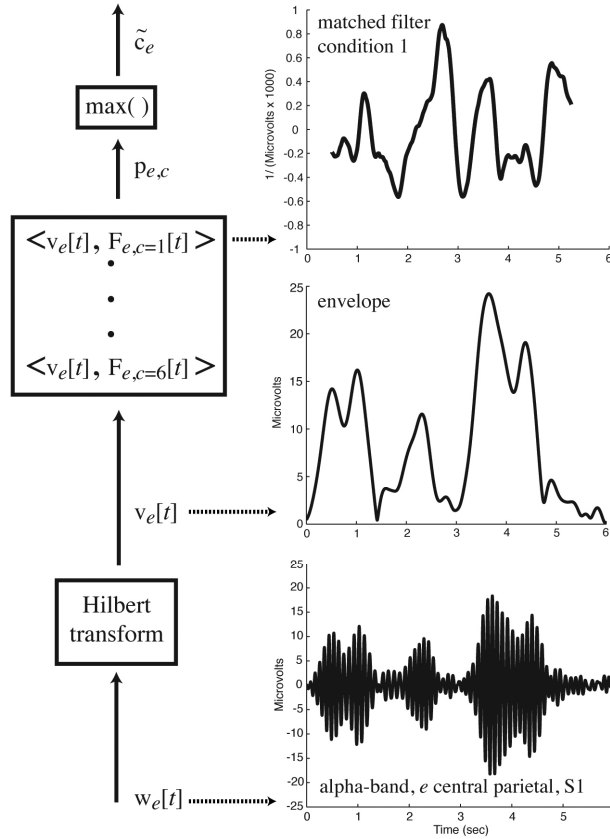
We used waveform envelopes to compute matched filters, one for each of the six conditions (see Figure 2). The inner product of each matched filter with a particular trial’s envelope provides six numbers. The matched filter which gives rise to the largest inner product is the best match, and the condition to which the matched filter corresponds is declared the best guess as to the experimental condition for that trial.

Offline preprocessing steps include

- segment the EEG data to provide time-varying waveforms for each condition, electrode and trial;
- remove from further consideration 18 electrodes most sensitive to electromyographic artifact: those with the lowest positions about the head and spanning locations close to the eyes, low on the temple, at or below the ear, and at or below the external occipital protuberance;
- remove the mean and linear trend from each segmented waveform;
- low-pass filter the detrended, segmented, waveforms to remove 60Hz line noise;
- use thresholds to identify and remove from further consideration filtered waveforms likely contaminated with electromyographic artifact.

Alpha-, beta- and theta-band activity were computed for each electrode and trial using band-pass elliptic filters. These band-pass filtered waveforms ( $w_e[t]$  and bottom right plot in Fig. 2) were Hilbert-transformed to provide corresponding envelopes ( $v_e[t]$  and middle right plot). The envelopes serve as input to the matched-filter classification and as data used to construct the matched filters. An electrode’s average envelopes, found by averaging across trials for each of the six conditions, serve as matched filters with one further step: for each electrode, pseudoinvert the six conditions’ average envelopes to provide six filters ( $F_{ec}[t]$  and top right plot). The inversion of the average envelopes provides filters which return an inner product of one for the corresponding condition’s average envelope and an inner product of zero for all other condition’s average envelopes. Information may be integrated across electrodes by summing the measures  $p_{e,c}$  across electrodes and determining the maximum of the resulting six numbers. Information may be integrated across bands by weighing individual response measures for the three bands by band reliability estimates or by a voting procedure.

Classification results shown in Table 1 show that the beta band (13-18Hz) is, for all but one subject, the most informative frequency band; theta (3-8Hz) and alpha (8-13Hz) are comparable for all subjects but S1. The per-condition classification performance is shown for subject S2 in Fig. 3. Rows refer to a trial’s actual condition, while columns refer to the condition of the matched filter for which the maximal response was obtained. Darker values indicate higher percentages of trials. These dark values describe diagonals, which indicates a match between a trial’s actual condition and the condition with matched filter providing the greatest response.

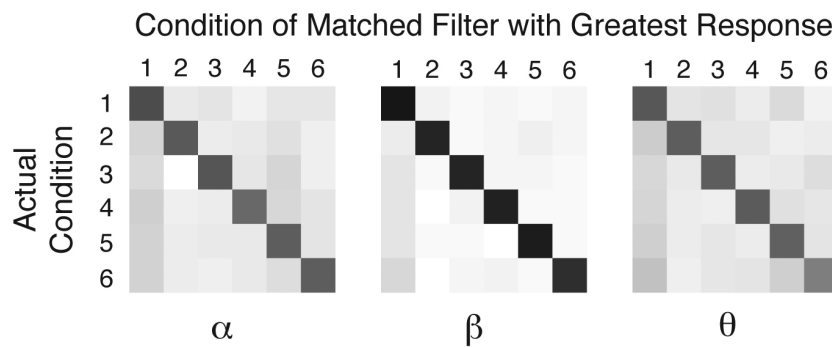


**Fig. 2.** Preprocessed and band-pass-filtered waveform  $w_e[t]$ , recorded by electrode  $e$ , is Hilbert-transformed to provide envelope  $v_e[t]$ . Shown at bottom right is the preprocessed waveform from an electrode with mid-parietal location from subject S1 for a trial during which {ba} is spoken in imagination at times 1.5, 3.0 and 4.5 sec (condition 1). Shown at middle right is the corresponding envelope. The inner product  $\langle, \rangle$  of this envelope with each matched filter  $F_{e,c}[t]$ , one filter per condition per electrode, provides six numbers  $p_{e,c}$ . These six numbers measure how well the particular trial's envelope matches the filter for each condition. The maximum of these six numbers is used to determine the most likely condition  $\hat{c}_e$ . Shown at top right is a matched filter for condition  $c = 1$ .

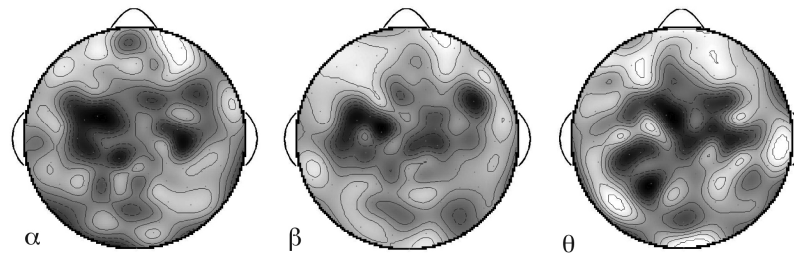
The distributions of classification performance across the scalp are similar across the four subjects; those for subject S4 are shown in Figure 4. The most informative electrodes lie largely near the top of the head (vertex) where electromyographic artifacts have their least influence. These distributions of information differ significantly from the distributions of envelope amplitude, which follow well-known patterns for alpha activity (parietal) and theta activity (frontal).

**Table 1.** Classification performance using matched filters for envelopes in three frequency bands. The fraction of correctly-classified trials (720 trials per subject, identified in the left column) is indicated. The chance performance level in this classification among six conditions is 1/6 (0.17).

	alpha	beta	theta
S1	0.38	0.80	0.63
S2	0.63	0.87	0.59
S3	0.44	0.68	0.46
S4	0.64	0.62	0.59



**Fig. 3.** Classification matrices for subject S2. Values along the diagonals indicate correct classification, while non-white values off the diagonal indicate errors. The black gray-value in the middle panel (beta-band) for actual condition 1 and matched filter condition 1 (top left square) represents 91% of the trials; lighter shades indicate smaller values (through white indicating 0%). Perfect performance would be indicated by all off-diagonal entries set to white.



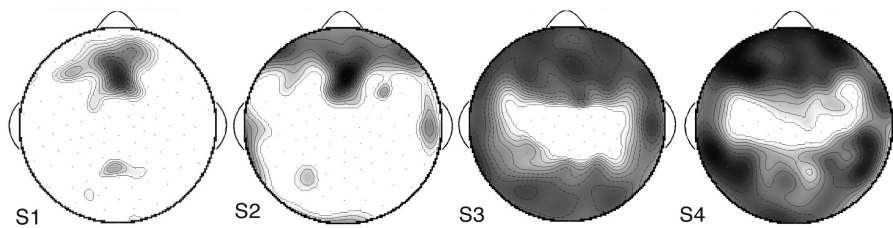
**Fig. 4.** Distributions of classification performance across the scalp for alpha ( $\alpha$ ), beta ( $\beta$ ) and theta ( $\theta$ ) bands for subject S4. Darker values indicate the positions of electrodes providing better classification performance.

### 3.2 Spectral Features

Analysis of trials' power spectral densities shows that differences in power within single frequency bands can provide information concerning trial condition. Spectral

differences within a single band are completely invisible to the previous analysis, which grouped together activity at all frequencies within a single band.

Data for subjects S1 and S2 show that, for condition 3, there is a peak in the power spectrum in the range 5-6Hz, relative to baseline power measured at 3.5-4.5Hz. This peak is largely absent for condition 1. This difference between the average power spectra for conditions 3 and 1 is localized to electrodes with front central locations on the scalp (see Fig. 5, leftmost panels). This spectral difference alone, within the theta band, provides ~75% correct two-way classification between these two conditions. The peak and the localized spatial distribution do not exist for subjects S3 and S4 (see Fig. 5, rightmost panels).



**Fig. 5.** Difference between condition 3 and condition 1 theta sub-band spectral power localized primarily to electrodes with front, center locations for subjects S1 and S2; this pattern is not evident for S3 and S4

### 3.3 Spectrographic Analysis

The spectral data suggest several things. The first is that one would do well to represent EEG data spectrographically: record power as a fine-grained function of both frequency and time. The second and third are more cautionary. There is a tremendous amount of trial-by-trial variability in EEG recordings. Adding channels, like further frequency bands of narrow range as in spectrograms, may have the effect of masking signals more effectively. Furthermore, fine subdivision of the frequency domain may reveal individual differences (as in Fig. 5), so that averages across subjects become less meaningful. These caveats notwithstanding, our current work focuses on spectrographic means of identifying imagined speech.

## 4 Discussion

The syllables /ba/ and /ku/ have little semantic content in and of themselves, so that differences in EEG records underlying classification performance are unlikely to reflect semantic contributions to imagined speech production. Furthermore, each experimental trial starts with a period during which the cue to the condition is presented; cue recognition and response planning occur during the cue period and are likely absent during the following period in which EEG recording is made of imagined speech. The EEG recordings analyzed here concern most likely immediate aspects of imagined speech production based on readout from working memory.

EEG electrodes record not only signals from brain cortex but also electromyographic activity. Common sources of the latter are muscles responsible for eye and head movements and other muscles near recording electrodes, like those in the temples and neck. Electrodes atop or close to such muscles are most sensitive to electromyographic activity. The most flagrant such offenders were excluded from analysis in the work reported here. Furthermore, recordings for which EEG signals (detrended and filtered to excluded 60Hz line noise) exceeded 30  $\mu$ V in absolute value were excluded from consideration. This threshold eliminated many (but not all) recordings contaminated with artifact. The most informative electrodes are those positioned on the scalp near the top of the head (Fig. 3), and this suggests that the information is due more to cortical than electromyographic activity.

Subjects were instructed to think the imagined speech without any vocal or subvocal activity: without moving any muscles involved in producing overt speech. This contrasts with what is the most successful method yet for recognizing speech produced without any acoustic signal: surface electromyographic (SEMG) recordings from face and throat muscles. Substantial progress has been made in automatic speech recognition from surface EMG recordings of vocal tract articulators made during both spoken speech [5-10] and subvocalized speech [11-17].

Further non-acoustic methods for extracting imagined speech information potentially include magnetoencephalography (MEG) and invasive methods, like electrocorticography (ECoG), which involve implanted electrodes. While there are no published positive results yet for classification of imagined speech using MEG, its high temporal resolution and moderate spatial resolution (comparable to high-density EEG) suggest its value, as does success in classifying heard speech [18-21]. MEG is most sensitive to cortical signals from surfaces perpendicular to the scalp (in sulci) while EEG is most sensitive to signals from parallel surfaces (gyri) [22], so that the two methods are complementary. While the use of electrodes implanted in the brain is limited to small clinical populations for which these electrodes are indicated in combination with neurosurgery, it can provide very useful information concerning imagined speech [23]. Functional magnetic resonance imaging (fMRI) studies have contributed significantly to our neuroscientific knowledge of language perception and production [24-27]. Yet the poor temporal resolution of fMRI and of functional near-infrared imaging (fNIR) make these unlikely candidates for speech recognition.

EEG is a non-invasive, non-injurious method for probing cortical activity which has a high temporal resolution, moderate spatial resolution ( $\sim$ 2cm), a relatively low cost and which is increasingly portable. We feel that its greatest contribution as a brain-computer interface is likely to be found in circumstances where a human subject is trained to produce activity discernible by EEG [28]. Such training can reduce the variability associated with imagined speech production and also help one emphasize aspects of imagined speech which are most easily discerned by EEG. Our next step is to close the loop by providing real-time feedback concerning imagined speech signals.

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