INTERSPEECH 2019
September 15–19, 2019, Graz, Austria

Phase synchronization between EEG signals as a function of differences between stimuli characteristics

L. ten Bosch[1], *K. Mulder*[1,2], *L. Boves*[1]

[1]Radboud University Nijmegen, The Netherlands
[2]Max Planck Institute for Psycholinguistics, The Netherlands

{l.tenbosch, l.boves}@let.ru.nl, Kimberley.Mulder@mpi.nl

Abstract

The neural processing of speech leads to specific patterns in the brain which can be measured as, e.g., EEG signals. When properly aligned with the speech input and averaged over many tokens, the Event Related Potential (ERP) signal is able to differentiate specific contrasts between speech signals. Well-known effects relate to the difference between expected and unexpected words, in particular in the N400, while effects in N100 and P200 are related to attention and acoustic onset effects. Most EEG studies deal with the amplitude of EEG signals over time, sidestepping the effect of phase and phase synchronization. This paper investigates the relation between phase in the EEG signals measured in an auditory lexical decision task by Dutch participants listening to full and reduced English word forms. We show that phase synchronization takes place across stimulus conditions, and that the so-called circular variance is narrowly related to the type of contrast between stimuli.

Index Terms: phase synchronization, EEG, lexical decision, circular variance, phase locking value

1. Introduction

EEG signals and Event Related Potentials (ERP) derived from EEG signals are widely used in psycholinguistics. EEG/ERPs are assumed to provide a rich source of information about the online processing of stimuli unfolding over time. However, the neurophysiological source(s) of EEG signals are still not well understood [1, 2]. EEG activity related to a stimulus may be (a) invoked, i.e., super-imposed upon and independent of the ongoing electrical activity in the brain, (b) induced, i.e., EEG changes are caused by phase (de-)synchronization, or (c) a combination of the two. The conventional interpretation that links the structure in ERPs and their timing to underlying cognitive processes is most straightforward when EEG signals corresponds to induced activity [2].

Also, different cognitive processes may be related to different frequency bands of EEG signals. According to [3], acoustic-phonetic processing is related to phase synchronization in the theta band (4-8 Hz, the modulation frequency band most important for speech intelligibility [4]). Decision processes are related to frequencies below 4 Hz [5], while semantic processing is mainly related to power in the alpha band (812 Hz) [6]. Apart from the frequency band, EEG signals reveal different effects in different time windows. For instance, the early N100 component (occurring around 100 ms after spoken word onset) and the P200 component are associated with early acoustic processing, attention, and working memory activation. The time window ranging from approximately 200 to 400 ms after word onset, may show whether targets are congruent or incongruent to primes (first exposure), especially over posterior electrode sites [7, 8]. Friedrich et al. [7] linked these match/mismatch effects to the P350, a positive component peaking around 350 ms after word onset associated with lexical identification. The reduction of this P350 component in the match condition was interpreted as facilitated lexical identification.

In later time windows (ranging from approximately 400 to 1000 ms after word onset), the N400 is a frequently observed ERP component in different language-related tasks (see [9] for a comprehensive review of the discussions about the interpretations of the results of independent experiments). In lexical priming paradigms, the N400 is reduced (i.e., less negative amplitudes were found) for targets that better match their primes (e.g.,[10]). In [11] and [8] the N400 was sensitive to a match in word stress (although the polarity of the effects was not compatible with the expected direction from the N400 literature for all experiments).

This paper is a first step towards a procedure for processing and statistically analyzing EEG signals that will allow us to combine effects in ERPs, as well as phase synchronization and power in several frequency bands. To make it possible to compare and integrate results obtained with different representations, we aim at signal processing techniques that yield time signals, comparable to ERPs. In addition, we aim to develop processing methods that are maximally transparent, so that they can be used by other researchers without the need to rely on complex tool boxes. For this paper we use a set of EEG signals recorded in a complex experiment on auditory lexical decision in a second language [12, 13]. The design of that experiment had three nested factors. The first factor relates to the position of an unstressed syllable in a multi-syllabic word: it can be before 'pre-stress' or after 'post-stress' the syllable with word stress. The second factor has the levels 'cognate' and 'control', while the third factor has the levels 'fully articulated' or 'reduced'. Results of an analysis of reaction times and error rates [13] show that there are complex interactions between the three main factors. It appears that, especially for the reduced stimuli, there is a large difference between the pre-stress and post-stress conditions.

2. Method

The phase of a frequency component of a wide-band signal can be obtained in various ways. Perhaps the most straightforward is using the complex Fourier Transform, but in most situations we are not interested in the phase of a single frequency. Yet, phase only makes sense in narrow frequency bands. One way of decomposing a wide-band signal into narrow frequency bands is by using a filter bank. We used that approach by building band pass filters that span the theta range (4 - 8 Hz) and the alpha range (8 - 12 Hz). The phase pattern of the output of the band pass filters was obtained from the analytic signal $s_a(t)$ of the EEG signal $s(t)$ by computing

$$s_a(t) = \mathcal{F}^{-1}(\mathcal{F}(s).2U) = s + iy \qquad (1)$$

http://dx.doi.org/10.21437/Interspeech.2019-2443

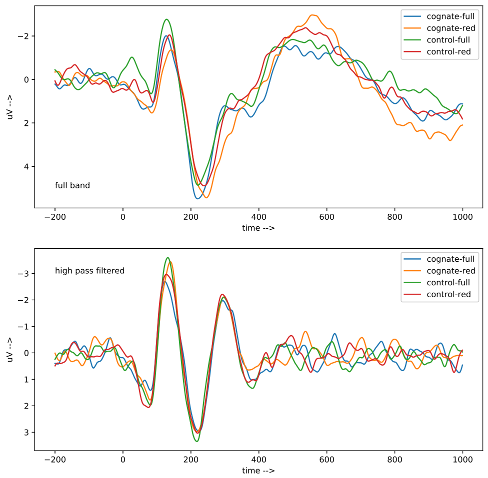

Figure 1: *The effect of high pass filtering on the shape of ERPs. Top panel: High pass cut-off frequency 0.1 Hz; bottom panel: cut-off frequency 4 Hz.*

where $\mathcal{F}$ is the Fourier transform, U the unit step function, and y the Hilbert transform of s.

Another way of obtaining the phase pattern of frequency components of a wide band signal is by using a wavelet transform [14, 15]. The wavelet transform can be interpreted as applying a bank of Finite Impulse Response filters with different center frequencies. To separate amplitude and phase, complex-valued Morlet wavelets can be used. Morlet wavelets are obtained by multiplying a function $f_\omega(t) = e^{i2\pi\omega t}$ with a Gaussian envelope. The number of periods in the complex exponential is fixed. As a consequence, the duration of the wavelets becomes shorter as the frequency ω increases.

2.1. Power versus phase synchronization

The long-term average spectrum of EEG signals shows a 1/f shape. As a consequence, the average of EEG signals time-aligned at the start of a stimulus, which is how ERPs are constructed, will be dominated by the very low frequencies. The effect is demonstrated in Fig. 1. The upper panel shows the ERPs for the four conditions in the pre-stress condition obtained from the full-band signals. The lower panel shows the corresponding results for signals that were high-pass filtered with a cut-off frequency of 4 Hz. It can be seen that ERP components that come later than approximately 250 ms have disappeared in the high pass filtered version. This confirms the finding in [3] that the N100/P200 complex is due to phase synchronization in the theta band.

2.2. Phase synchronization

In our analysis of the phase synchronization, the phase locking value (PLV) plays a central role ([16]). PLV is computed as follows: Let $x_1(t)$ and $x_2(t)$ be two different EEG signals of equal length. In our analysis pairs of EEG signals are chosen from the same electrode, but different epochs, in the same condition or from conditions to be contrasted. Given these two real-valued signals, we compute their so-called *relative phase* $\Delta\phi_{1,2}(t)$:

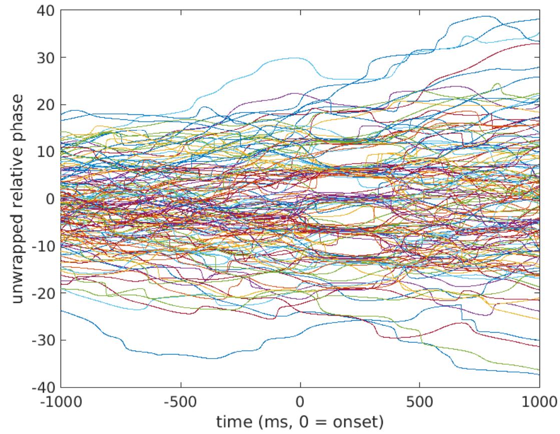

Figure 2: *Phase synchronization visible between 100 ms and 400 ms after word onset. Word onset is at* $t = 0$.

$$\Delta\phi_{1,2}(t) = \arg \frac{z_1(t)\overline{z}_2(t)}{|z_1(t)\overline{z}_2(t)|} \tag{2}$$

in which z_1 and z_2 denote the complex signals that are derived from x_1 and x_2 via the Hilbert transform, $|z|$ denotes the norm of z, and $\overline{z}$ denotes the complex conjugate of z. For each t, $\Delta\phi(t)$ is a real number. This step produces a real signal of the same length as $x_1(t)$ and $x_2(t)$[1].

$\Delta\phi$ denotes the local phase difference (in radians), i.e. all values modulo 2π are indistinguishable. Fig. 2 shows $\Delta\phi(t)$ as a function of time t after phase unwrapping (unwrap() in Matlab) for 150 pairs of EEG signals, in which the two input signals x_1 and x_2 are averages of 20 EEG traces randomly chosen from two contrasting conditions. The horizontal axis shows time in ms; word onset is at $t = 0$; the vertical axis shows the phase. At around $t = 100$, the relative phases appear to pass over 'bridges' that are 2π spaced apart vertically – these 'bridges' actually represent the same bridge. This bridging effect is a phase synchronization between groups of EEG signals. The synchronization emerges around 100 ms after word onset and fades away again at around 400 ms after onset.

Considered as a set of real numbers, the mean, standard deviation and variance of $\Delta\phi(t)$ do not make any sense. However, the narrowing effect of the bridge can be quantified by showing that the *circular variance* [17] decreases substantially between 100 ms and 400 ms. To that end, each point on a relative phase graph is mapped on the complex unit circle $\{|z| = 1\}$ in the complex plane C, by[2] $x \mapsto e^{ix}$. For each t, its expectation is the *phase locking value* PLV:

$$\mathrm{PLV}_{m,n}(t) = \mathcal{E} e^{i \cdot \Delta\phi_{m,n}(t)} \tag{3}$$

Equation 3 maps a distribution of real numbers (the values of the $\Delta\phi$ functions at time t) via the mapping $\exp(\mathrm{i}\Delta\phi(t))$ to $\mathrm{PLV}(t)$ (a complex number within the unit circle, dependent on t). Via the equality

$$\int_{-\inf}^{\inf} \cos(x) \exp\left(-\frac{1}{2}\frac{x^2}{\sigma^2}\right) dx = \exp(\frac{-\sigma^2}{2}) \tag{4}$$

[1] A similar expression can be used to derive the relative phase of two signals using wavelet transforms.

[2] here, $i = \sqrt{-1}$.

if follows that the *norm* $|\text{PLV}(t)|$ of $\text{PLV}(t)$ is related to the so-called *circular variance* $\sigma_c^2(t)$ of the values $\Delta\phi(t)$, via

$$\sigma_c^2(t) = -2 \cdot \log(|\text{PLV}(t)|) \tag{5}$$

There is a direct relation between this σ_c^2 and the value of k in the von Mises distribution, one of the distributions that plays a role in circular statistics ($k = 1/\sigma_c^2$) [17, 18].

3. Experiment

3.1. Materials

The data for this paper come from an experiment in which native speakers of Dutch made lexical decisions on spoken English words. The experiment was designed to investigate three main factors: (1) presence/absence of a strongly reduced syllable, (2) the position of the reduced syllable before or after the syllable carrying primary stress, (3) the cognate status of the target words (for details, see [12, 13]).

Forty advanced learners of English (mean age = 20.9 years, SD = 2.2) participated. They were highly proficient in English as evidenced by their scores on the LexTALE proficiency task (mean = .83, SD = .37) [19]. Participants had to decide as quickly and accurately as possible whether the aurally presented stimulus was a real English word. For several different reasons the data of 11 participants were discarded for the EEG signal analysis, which leaves us with 29 participants.

An experiment consisted of 900 stimuli, half of which were existing words. The target items in the pre-stress condition were 68 Dutch-English cognate items and 68 English non-cognate items; in the post-stress there were 46 cognates and controls. An item was considered a cognate if it had the same meaning in English and Dutch and the Levenshtein distance (not considering word stress) between the Dutch and the English pronunciations was < 5 (mean 3.71 for the post-stress stimuli and 3.3 for the pre-stress stimuli). The cognates and non-cognates had similar log subtitle word frequencies (SUBTLWF [20]; mean log frequency for cognates and non-cognates in the post-stress task: 4.94 and 4.45, respectively. The filler items were 44 disyllabic, 48 trisyllabic and 22 foursyllabic real words with varying position of word stress. The pseudo words were generated by means of Wuggy [21].

The stimuli were recorded by a male native speaker of British English following the same procedure as in [12]. The duration of the schwa was manually measured with the speech analysis software package Praat [22]. Schwa was absent in all reduced forms and had an average duration of 68 ms in the full forms.

3.2. EEG recordings

EEG data were collected from 59 AgAg CI electrodes positioned according to the 1020 standard system. Bipolar horizontal and vertical electrooculograms (EOG) were recorded for ocular artifact rejection. The left mastoid served as the reference electrode and an additional electrode was placed on participants right mastoid for re-referencing offline. Electrode impedances were kept below 5 kΩ. The EEG was recorded continuously with a band-pass filter of 0.02100 Hz and digitized with a sampling frequency of 1000 Hz.

3.3. EEG data analysis

We first re-referenced the EEG data offline to the average of the left and right mastoids, and filtered the data with a 0.135 Hz band-pass filter. We then segmented the data into epochs from -2 s to 2 s relative to the onset of the words. We removed a small number of epochs because of large artifacts. In this paper we only analyze the EEG signals pertaining to the target stimuli. The main goal is to see to what extent phase coherence in several frequency bands can distinguish the eight sets of target stimuli.

3.4. Computation of phase synchronization

The phase $\phi(t)$ of the EEG signals was computed, using the analytic signal and the wavelet approaches. In the analytic signal approach we designed band pass 4^{th} order Butterworth filters (the effective order is double, because we used forward-backward filtering to make sure that the filters have zero phase) with pass bands between 4 Hz and 8 Hz (theta band), and between 8 Hz and 12 Hz (lower alpha band). We applied wavelet decomposition with complex Morlet wavelets with center frequencies of 6 Hz and 10 Hz (i.e., in the middle of the pass bands of the Butterworth filters). Here, we limit ourselves to an analysis of the central electrodes, *AFz, Fz, FCz, Cz, CPz, Pz, POz*.

It appears that the expectation operator in eq. (3) is essential. The relative phase of pairs of individual EEG signals is impossible to interpret. Therefore, we used the following procedure for obtaining $PLT_{m,n}(t)$: We started by collecting the EEG signals of all 29 participants per condition in one set. From that set, we created 40 disjoint subsets of 15 signals, which were then averaged. These 40 average signals take the role of (m, n) in eq. (3). We calculated circular variances for all $(40 \cdot 39)/2$ combinations within each condition. We also calculated circular variances for (m, n) taken from $(8 \cdot 7)/2$ pairs of conditions, and computed the PLVs of those randomly formed signal pairs. This procedure was repeated for each of the EEG sensors of interest, and for each of the frequency bands of interest. The procedure was performed for the phase estimates obtained with the Hilbert transform and with the wavelet transform. All subsequent results were very similar for the Hilbert and wavelet transforms; therefore, here we only deal with the results of the Hilbert transform approach.

3.5. Computation of the power in frequency bands

We estimated the instantaneous power of the EEG signals in the theta and alpha bands by taking the absolute value of the Hilbert transform.[3] To make it possible to analyze the power data in the same way as the phase synchronization data, we followed the same procedure: we created 40 random sets of EEG signals, of which we computed the Hilbert transform. This yields 40 instantaneous power traces for each of the eight conditions.

4. Regression analyses

To investigate to what extent the circular variance (v_c) as a function over time can be explained in terms of three main factors (full/reduced, prestress/poststress, cognate/control), a regression model was applied with v_c as dependent variable. The best model (also smallest AIC) is shown in Table 1.

This model is based on 2,690,240 data points, covering the time interval 100-300 ms after word onset. The average circular variance (denoted 'ave', averaged over all tokens) and the frequency band (on intercept: the theta band (4-8 kHz)) were

[3]This is reminiscent of the definition of instantaneous power as the product of voltage and current in AC circuits.

Table 1: *The regression model predicting the circular variance in terms of stimulus contrasts. The model is trained on 100-300ms after word onset.*

```
model = lm(cv ~ band + ave + STR + CS +
        FR + STR:CS + CS:FR + STR:FR)
```

	Estim	SE	t value	p	
(Int)	-1.601	0.013	-122.01	< 2e-16	***
band8-12	3.270	0.002	1346.28	< 2e-16	***
ave	1.000	0.004	271.26	< 2e-16	***
STR	0.035	0.008	-4.47	7.3e-06	***
CS	0.076	0.008	-9.63	< 2e-16	***
FR	0.022	0.008	2.82	0.00479	**
STR:CS	0.126	0.006	19.67	< 2e-16	***
CS:FR	-0.012	0.006	-1.91	0.05561	.
STR:FR	-0.055	0.006	-8.55	< 2e-16	***

```
Adjusted R-squared:  0.7374
F-statistic: 2.359e+05 on 8 and 671991 DF
p-value: < 2.2e-16
```

control predictors. Predictors of interest denote *contrasts* between conditions: STR $= 0$ (on intercept) refers to the *same* stress condition, while STR $= 1$ corresponds to opposing conditions (prestress vs. poststress). Similarly: CS $= 0$: same cognate status, CS $= 1$: different cognate status, and FR refers to full vs. reduced. The β's of STR, CS and FR are significantly positive, indicating that the circular variance is significantly *increased* compared to intercept condition when stimuli are compared which indicates a *lower* phase synchronization (i.e., a lower von Mises k). The positive β for `band8-12` means that the phase synchronization in the alpha band –as expected– is much lower than in the theta band. The interactions are all significant, meaning that the contributions do not linearly add if these condition contrasts occur in combination. Since the model is already quite complex (including condition *contrasts* as predictors), this model is based on site Cz only.

We also built `lmer` models to investigate which differences in EEG *power* can be modelled. Results are shown in Table 2. Observe that this is a different type of model than the model shown in Table 1: this model uses conditions as predictors of interest, while the model in Table 1 estimates phase differences in terms of condition *contrasts*. The power model has the predictors of interest postpre (0 = poststress, 1 = prestress), concog (control = 0, cognate = 1) and redfull (reduced = 0, full = 1). Significant effects could only be found in a short time interval following stimulus onset. The contribution of the theta ('the') band (abbreviated 'bandthe' in the table) differs significantly from the alpha band. All three main predictors of interest are significant. Also sites are significant, compared to the site AFz on intercept. The model shown is the best one found: other models with interactions between sites and stimulus conditions did not converge.

5. Discussion and Conclusion

In this paper we investigate methods for processing EEG signals that allow for easy comparisons between conventional ERPs and representations of instantaneous power and phase synchronization in specific frequency bands. The computation of instantaneous power involves linear filtering (a familiar procedure) in combination with Hilbert transforms. Software for

Table 2: *Predicting power as a function of electrode and experimental factors.*

```
model = lm(power ~ band + elec + ave +
        postpre + concog + redfull + trial,
        data=data2)
```

	Estim	Std.Err.	t value	p
(Interc)	2.2880	3.82e-02	59.80	< 2e-16
bandthe	0.5608	1.95e-03	287.34	< 2e-16
elecFz	0.1985	3.56e-03	55.70	< 2e-16
elecFCz	0.4706	3.56e-03	132.07	< 2e-16
elecCz	-0.0225	3.86e-03	-5.83	5.3e-09
elecCPz	0.2799	3.56e-03	78.53	< 2e-16
elecPz	0.0382	3.56e-03	10.72	< 2e-16
elecPOz	-0.1224	3.56e-03	-34.34	< 2e-16
ave	0.0115	3.84e-03	2.99	0.00274
postpre	-0.2284	1.94e-03	-117.76	< 2e-16
concog	-0.0093	1.94e-03	-4.77	1.7e-06
redfull	0.0532	1.90e-03	27.40	< 2e-16
trial	-0.0002	1.66e-05	-9.36	< 2e-16

```
Adjusted R-squared:  0.1296
F-statistic: 1.173e+04 on 12 and 945,635 DF
p-value: < 2.2e-16
```

Hilbert transform is available in R, Python and Matlab.

Compared to EEG power, computing measures of phase synchronization is, inevitably, much more complicated. For that reason we included a detailed description of the followed procedures. Software for computing circular variance is available in R, Python and Matlab.

We have shown that both the power of the EEG traces and the phase locking value (PLV) between EEG traces provide powerful information to separate auditory stimuli in terms of prestress versus poststress, cognate versus control, and full versus reduced pronunciation. Remarkably, the PLV as applied in this paper is powerful enough to detect phase synchronization between EEG traces from *different* participants related to *different words* with *different* characteristics. The degree of synchronization, quantified as the circular variance over time, shows a steep rise at around 100 ms, and decays about 300 ms later. The most prominent characteristic of the circular variance over time is the value of its minimum; the larger the difference between trial conditions, the higher this minimum and so the lower the von Mises `k` value, and so the smaller the phase synchronization (Table 1). Table 2 showed that instantaneous power values also critically depend on the frequency band and on the electrode sites considered.

Further research is needed to see if there are phase effects that are easier traceable using wavelet transforms [23, 24] than with conventional band pass filters and Hilbert transforms. All statistical analysis is based on the `lme4` package in `R`. The transparency of the processing techniques applied in this paper can lay the basis for independent future experiments that investigate the various interactions in greater detail.

6. Acknowledgements

The data used in this paper are collected in an ERC project awarded to Mirjam Ernestus, Radboud University, Nijmegen.

7. References

[1] S. Makeig, D. S., J. Onton, and A. Delorme, "Mining event-related brain dynamics," *Trends in Cognitive Sciences*, vol. 8, p. 204210, 2004.

[2] A. Burgess, "Towards a unified understanding of event-related changes in the EEG: The firefly model of synchronization through cross-frequency phase modulation," *PLoS ONE*, vol. 7, 2012. [Online]. Available: https://doi.org/10.1371/journal.pone.0045630

[3] H. Luo and D. Poeppel, "Phase patterns of neuronal responses reliably discriminate speech in human auditory cortex," *Neuron*, vol. 54, p. 10011010, 2007.

[4] R. Drullman, J. Festen, and R. Plomp, "Effect of temporal envelope smearing on speech reception," *J. Acoust. Soc. Am.*, vol. 95, p. 10531064, 1994.

[5] T. Hunt, N. Nils Kolling, A. Soltani, M. Woolrich, M. Rushwort, and T. Behrens, "Mechanisms underlying cortical activity during value-guided choice," *Nature Neuroscience*, vol. 15, pp. 470–476, 2012.

[6] A. Strauß, S. Kotz, M. Scharinger, and J. Obleser, "Alpha and theta brain oscillations index dissociable processes in spoken word recognition," *Neuroimage*, vol. 97, pp. 387 – 395, 2014.

[7] S. Friedrich, C. K.and Kotz, A. Friederici, and T. Gunter, "ERP correlates of lexical identification in word fragment priming," *Journal of Cognitive Neuroscience*, vol. 16, pp. 541 – 552, 2004.

[8] U. Schild, A. B. C. Becker, and C. K. Friedrich, "Processing of syllable stress is functionally different from phoneme processing and does not profit from literacy acquisition," *Frontiers in Psychology*, vol. 5, p. 530, 2014.

[9] M. Kutas and K. D. Federmeier, "Thirty years and counting: Finding meaning in the N400 component of the event-related brain potential (ERP)," *Annual Review of Psychology*, vol. 62, pp. 621–647, 2011.

[10] C. Kutas, M.and Van Petten, "Event-related brain potential studies of language," in *Advances in psychophysiology (Vol. 3)*, P. Ackles, J. R. Jennings, and M. G. H. Coles, Eds. JAI Press, 1988, pp. 139–187.

[11] S. Dufour, D. Bolger, S. Massol, P. J. Holcomb, and J. Grainger, "On the locus of talker-specificity effects in spoken word recognition: an erp study with dichotic priming," *Language, Cognition and Neuroscience*, vol. 32, no. 10, pp. 1273–1289, 2017.

[12] K. Mulder, G. Brekelmans, and M. Ernestus, "The processing of schwa reduced cognates and noncognates in non-native listeners of english," in *Proceedings of the 18th International Congress of Phonetic Sciences [ICPhS 2015]*, 2015.

[13] K. Mulder, L. Wloch, and M. Ernestus, "Effects of cognate status and location of reduced syllables on lexical decisions of Dutch-English bilinguals," submitted.

[14] C. S. Burrus, R. A. Gopinath, and H. Guo, *Introduction to Wavelets and Wavelet Transforms: A Primer*. Pearson Higher Education, 1998.

[15] S. Roux, T. Cenier, S. Garcia, P. Litaudon, and N. Buonviso, "A waveletbased method for local phase extraction from a multi-frequency oscillatory signal," *Journal of Neuroscience Methods*, vol. 160, no. 1, pp. 135–143, 2007.

[16] S. Aydore, D. Pantazis, and R. M. Leahya, "Note on the phase locking value and its properties," *Neuroimage*, vol. 74, pp. 231 – 244, 2013.

[17] C. Ley and T. Verdebout, *Modern Directional Statistics*. CRC Press Taylor & Francis Group, 2017.

[18] D. Best and N. Fisher, "Efficient simulation of the von Mises distribution," *Applied Statistics*, vol. 28, p. 152157, 1979.

[19] K. Lemhöfer and M. Broersma, "Introducing LexTALE: A quick and valid lexical test for advanced learners of english," *Behavior Research Methods*, vol. 44, no. 2, pp. 325–343, 2012.

[20] M. Brysbaert and B. New, "Moving beyond Kučera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English," *Behaviour Research Methods*, vol. 41, pp. 977–990, 2009.

[21] E. Keuleers and M. Brysbaert, "Wuggy: A multilingual pseudoword generator," *Behavior Research Methods*, vol. 42, pp. 627–633, 2010. [Online]. Available: https://doi.org/10.3758/BRM.42.3.627

[22] P. Boersma and D. Weenink, "Praat: doing phonetics by computer," http://www.praat.org/, 2019.

[23] O. A. Rosso, M. T. Martin, A. Figliola, K. Keller, and A. Plastino, "EEG analysis using wavelet-based information tools," *Journal of Neuroscience Methods*, vol. 153, pp. 163–182, 2006.

[24] O. Faust, U. R. Acharya, H. Adeli, and A. Adeli, "Wavelet-based EEG processing for computer-aided seizure detection and epilepsy diagnosis," *Seizure*, vol. 26, pp. 56–64, 2015.