

Is it Positive or Negative? On Determining ERP Components

Peter beim Graben* and Stefan Frisch

Abstract—In most experiments using event-related brain potentials (ERPs), there is a straightforward way to define—on theoretical grounds—which of the conditions tested is the experimental condition and which is the control condition. If, however, theoretical assumptions do not give sufficient and unambiguous information to decide this question, then the interpretation of an ERP effect becomes difficult, especially if one takes into account that certain effects can be both a positivity or a negativity on the basis of the morphology of the pattern as well as with respect to peak latency (regard for example, N400 and P345). Exemplified with an ERP experiment on language processing, we present such a critical case and offer a possible solution on the basis of nonlinear data analysis. We show that a generalized polarity histogram, the word statistics of symbolic dynamics, is in principle able to distinguish negative going ERP components from positive ones when an appropriate encoding strategy, the half wave encoding is employed. We propose statistical criteria which allow to determine ERP components on purely methodological grounds.

Index Terms—Coherence, component definition, event-related potentials (ERP), half wave encoding, symbolic dynamics, word statistics.

I. INTRODUCTION

THERE is a broad consensus in research with event-related brain potentials (ERPs) that ERP components are not defined in an absolute way, but always as a deflection of voltage averages in one (experimental) condition relative to another (control) condition [1]. An N400 component in response to a semantic anomaly, e.g., is a more negative going waveform in one (e.g., semantically anomalous) condition compared to another (e.g., semantically coherent) condition [2]. Thus, the assumption that a component is defined in a subtractive way and that an appropriate control condition is essential is inherent in the definition of ERP components [1].

In ERP research, experimental and control condition are usually determined on theoretical grounds, but such a determination is not always unequivocal, as illustrated in a German language processing experiment done by Frisch *et al.* [3]. They investigated the opposing influence of two well-known processing strategies in sentences such as shown in (1) and (2) at the top of the next page.

The pronoun *sie* (*she*) in the second clause in both sentence examples is ambiguous with respect to its grammatical function

since it can either be the subject or the object of the clause. The ambiguity is resolved on the following argument *der/den Wanderer* (*the wanderer*) which is unambiguously marked for either object (1) or subject (2). Psycholinguistic theory allows opposing predictions with respect to the question which of these two disambiguations is easier. According to a general *subject preference strategy* based on some notion of sentence complexity [4], the pronoun should be preferentially analyzed as the subject [as in (1)]. Thus, the disambiguation toward the *object* [as in (2)] should be harder to process, i.e., should induce a revision of the initial choice (*reanalysis*). By contrast, *parallel function strategy* [5], according to which the processor attempts to unify the grammatical function of the pronoun and of its antecedent, would predict that the pronoun is preferentially assigned the function of object [such as in (2)], seeing that its antecedent, namely *die Jägerin* (*the huntress*), is object of its own clause. Therefore, a disambiguation of the pronoun toward the *subject* [such as (1)] should be more difficult.

On the disambiguating determiner [underlined in (1) and (2)], Frisch *et al.* [3] found that both conditions differed significantly between approximately 300 and 500 ms (see Fig. 3). However, it is unclear on Fig. 3 whether the pattern in condition (2) is more *negative* going than in (1) (*N400 component*, cf. [7]) or whether the pattern in (1) is more *positive* going than in (2) (*P345 component*, cf. [6]). Which of the two components we actually deal with is hard to decide seeing that i) both components have been found for the revision of a grammatical function preference [6], [7]; that ii) both directions of the effect can be predicted on the basis of psycholinguistic theory; and that iii) neither topography nor latency nor morphology give a criterion in the present case. In the following, we will present a method of nonlinear ERP data analysis which can be used in order to address such a problem. The main idea of our solution is to represent the single ERP epochs by sequences of two symbols, which are either “0” for negative voltages or “1” for positive ones. An ERP component then corresponds to a time window where one symbol dominates the other across all measured trials and where the asymmetry in the distribution of symbols is larger in one condition against the other. We shall formulate some statistical criteria which allow the polarity of ERP components to be defined on purely methodological grounds.

II. SYMBOLIC DYNAMICS OF ERPs

Our approach to ERP data analysis is founded on symbolic dynamics and information theory [8]. In this paper we shall show that a generalization of the well-known *polarity histograms* [9], the *word statistics* of symbolic dynamics, provides criteria to decide the above-mentioned problem, namely discriminating between experimental and control conditions

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Nachdem der Fischer die Jägerin getroffen hatte, begrüßte sie den Wanderer
 After [the fisherman]_{SUBJ} [the huntress]_{OBJ} met had greeted she_{AMB} [the wanderer]_{OBJ}
 “After the fisherman had met the huntress, she greeted the wanderer” (1)

Nachdem der Fischer die Jägerin getroffen hatte, begrüßte sie den Wanderer
 After [the fisherman]_{SUBJ} [the huntress]_{OBJ} met had greeted she_{AMB} [the wanderer]_{SUBJ}
 “After the fisherman had met the huntress, the wanderer greeted her” (2)

on purely methodological grounds. To avoid confusion about notions we will distinguish two terms. On the one hand, we reserve the term *ERP component* for a significant contrast between different conditions. On the other hand, we call an absolute polarity effect in only one condition a *polarity deflection*, or, in short, a *deflection*.

A. Coarse-Graining Strategies

To construct a symbolic dynamics from the electroencephalogram (EEG), we consider an ensemble of N EEG epochs $x_i(t)$, where i ($1 \leq i \leq N$) denotes the epoch number and t is the discrete time ranging from 1 to L . The simplest way to obtain a symbolic dynamics is to assign the symbol “0” to time t when $x_i(t) < 0$ while assigning the symbol “1” otherwise. This procedure is called *static encoding* of the time series [10]. In a recent study, we investigated theoretically another encoding algorithm detecting up- and down-going half waves of the signal [11] that is inspired by Lehmann [12], who encoded positive and negative maximal field values of the EEG. Here we shall apply the half wave encoding to real ERP data in order to reduce the content of noise and to get rid of drifting baselines.

The half waves of a signal are time intervals between succeeding inflection points. The algorithm detects inflection points of time series by computing the ratio of averaged secant slopes over their variances within a sliding time window of length T_1 . This parameter selects a kind of low-pass filter. In a first step one computes the *secant slope function*

$$u(t) = \frac{1}{T_1} \sum_{k=1}^{T_1/2} \frac{x(t+k) - x(t-k)}{k} \quad (3)$$

$$v(t) = \frac{1}{T_1 - 1} \sum_{k=1}^{T_1/2} \left[\frac{x(t) - x(t-k)}{k} - u(t) \right]^2 + \left[\frac{x(t+k) - x(t)}{k} - u(t) \right]^2 \quad (4)$$

$$w(t) = \frac{u(t)}{v(t)}. \quad (5)$$

Secondly, one can smooth $w(t)$ by a further moving rectangular low-pass filter of length T_2

$$\bar{w}(t) = -\frac{1}{T_2} \sum_{k=-(T_2-1)/2}^{(T_2-1)/2} w(t+k). \quad (6)$$

And finally, the inflection points of the original signal are given by the extrema of $\bar{w}(t)$. Its monotonic branches then correspond to the half waves of the time series. Monotonicity is tested by

using a lookahead window of length l . Thus, the positive half waves of the signal are encoded by sequences of “1”s while the negatives half waves are sequences of consecutive “0”s. The lengths of these sequences are the durations of the corresponding half waves. Fig. 4 in Section IV illustrates how the algorithm actually works.

By using one encoding rule we obtain an array $(s_{i;t})_{i \leq N; t \leq L}$ of symbols “0” and “1”. This array can be considered as a set of rows $E = \{s_i | s_i \in \{0, 1\}^L, 1 \leq i \leq N\}$ where $\{0, 1\}^L$ denotes the L -th Cartesian power of the alphabet $\{0, 1\}$. A subset of the ensemble is called *n-cylinder* at time t , when there is a common building block $[a_{k_1}, \dots, a_{k_n}]_t = \{s_i \in E | s_{i;t+l-1} = a_{k_l}, l = 1, \dots, n\}$ of n letters starting at t [8]. The symbol sequence $w = (a_{i_1}, \dots, a_{i_n}) \in \{0, 1\}^n$ is called *n-word*. The probabilities of cylinder sets of experimental data can be estimated by their relative frequencies

$$p(a_{k_1}, \dots, a_{k_n} | t) = \frac{\#([a_{k_1}, \dots, a_{k_n}]_t)}{N} \quad (7)$$

where “ $\#(\cdot)$ ” denotes the set theoretic cardinality function counting the number of occurrence of the word a_{k_1}, \dots, a_{k_n} across all measured EEG trials. Considering all cylinders of given length n at given time t together, we call the resulting distribution $\{([a_{k_1}, \dots, a_{k_n}]_t, p(a_{k_1}, \dots, a_{k_n} | t)) | t, n \text{ fixed}\}$ *word statistics* of order n . For a simple static encoding of EEG epochs the word statistics of order $n = 1$ is the polarity histogram in ERP research [9].

B. Modeling the Symbolic Dynamics of ERPs

When using the half wave encoding, the word statistics provides a measure of coherence of the ERP across all measured trials analogous to the linear intertrial coherence [13]. Overlapping positive half waves occurring in almost all epochs at the same time, for example, lead to a large relative frequency $p(1^n | t)$, for words containing n consecutive “1”s at a certain instance of time. In order to make quantitative judgements about the distribution of words we present a simple model of the symbolic dynamics.

Let us assume that a positive half wave (our model “ERP”) of duration $d = 2b + 1$ samples starts at time $-b$ and ends at time $+b$. Let us further assume that this d -word 1^d is embedded into a bi-infinite string of zeros. The corresponding bi-infinite symbolic sequence is then given by

$$s = \underbrace{\dots 00 \dots 00}_{-\infty \text{ to } -b-1} \underbrace{11 \dots 11}_{-b \text{ to } +b} \underbrace{\dots 00 \dots 00}_{+b+1 \text{ to } +\infty}. \quad (8)$$

Next, we consider a “reading frame” of length $n < d$ moving through the string s from left to right where t denotes its current

position on the left. Then we have to discriminate five different cases.

The frame is left from the “ERP”

$$t < -b - n + 1. \quad (9)$$

The frame and the “ERP” are overlapping from the left

$$-b - n + 1 \leq t < -b. \quad (10)$$

The frame is swallowed by the “ERP”

$$-b \leq t < b - n + 1. \quad (11)$$

The frame and the “ERP” are overlapping from the right

$$b - n + 1 \leq t < b. \quad (12)$$

The frame is right from the “ERP”

$$t \geq b. \quad (13)$$

When the reading frame moves through the “ERP,” the n -words belong to three different classes. Let us discuss the case $n = 4$ for an example. There are 16 4-words: “0000,” “0001,” “0010,” “0011,” “0100,” “0101,” “0110,” “0111,” “1000,” “1001,” “1010,” “1011,” “1100,” “1101,” “1110,” and “1111” falling into the classes of i) *forbidden words*, ii) *singular words*, and iii) *sustaining words*. The words “0010,” “0101,” or “1011,” e.g., are forbidden. They cannot be generated by the reading frame at all, hence, their probabilities $p(a_{k_1} a_{k_2} a_{k_3} a_{k_4} | t) = 0$ for all t . The singular words occur in the cases (10) and (12). For example, the word “0001” appears only when $t = -b - n + 1$, the word “0011” appears singularly when $t = -b - n + 2$, and so on. The probabilities of these words are vanishing at almost every time, except at those times when they are actually generated by the reading frame. Thus, e.g., $p(0011|t) = 1$ for $t = -b - n + 2$ and zero everywhere else. The sustaining words are created by the reading frame in the cases (9), (11), and (13). The probability $p(0000|t) = 1$ for all t obeying either $t < -b - n + 1$ or $t \geq b$. By contrast, the probability $p(1111|t) = 1$ for $-b \leq t < b - n + 1$; Fig. 1(a) illustrates this model for $b = 10$ and $n = 4$.

Because the additive noise in the data can be mostly reduced by the half wave encoding [11], we have to consider the problem that ERPs are generally not reliably time-locked to the stimuli, but jittering around a mean latency time [8], [11], [14]. In our model this kind of noise will shift the “ERP” sequence randomly along the time axis, yielding a stochastic process along the trial dimension

$$s_\tau = \underbrace{\dots 00 \dots 00}_{-\infty \text{ to } -b-1+\tau} \quad \underbrace{11 \dots 11}_{-b+\tau \text{ to } +b+\tau} \quad \underbrace{00 \dots 00 \dots}_{+b+1+\tau \text{ to } +\infty} \quad (14)$$

with distribution $(t, p_\tau(t))$, zero mean and variance σ_τ^2 . Then, the impact of the latency jitter is described by the convolution sums of the word statistics with the distribution of the latency times which are evaluated by convolution integrals in continuous time for the sake of convenience [8], [11].

For a mathematical treatment of the sustaining words we suppose the latency jitter to be uniformly distributed with variance $\sigma_\tau^2 = a^2/3$, $a > 0$ and a probability density function ρ_τ obeying

$$\rho_\tau(t) = \begin{cases} \frac{1}{2a}, & t \in [-a, a] \\ 0, & t \notin [-a, a] \end{cases}. \quad (15)$$

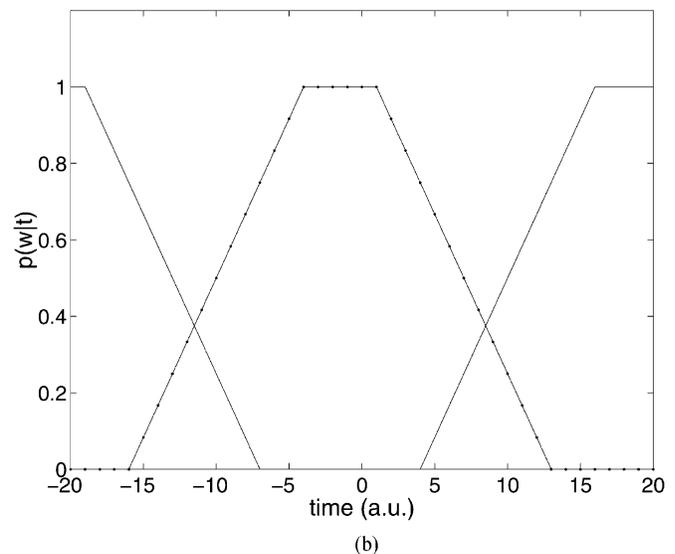
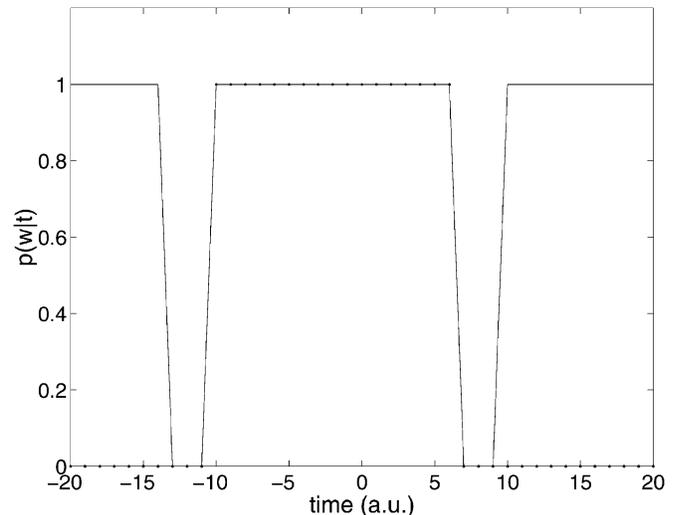


Fig. 1. Word statistics for $n = 4$ of the ERP model. (a) without latency jitter ($a = 0$); (b) with latency jitter $a = 6$. Solid: $p(0000|t)$, solid-dotted: $p(1111|t)$.

The probabilities of the words 0^n and 1^n are obviously step functions

$$p(0^n|t) = \begin{cases} 1, & t < -b - n + 1 \text{ or } t \geq b \\ 0, & \text{else.} \end{cases} \quad (16)$$

$$p(1^n|t) = \begin{cases} 1, & -b \leq t < b - n + 1 \\ 0, & \text{else.} \end{cases} \quad (17)$$

In order to get the probabilities $\tilde{p}(w|t)$ in the presence of latency noise, one has to compute the convolutions of $p(w|t)$ with the probability density function ρ_τ of the jitter [11]

$$\tilde{p}(w|t) = \int_{-\infty}^{\infty} p(w|t-t') \rho_\tau(t') dt'. \quad (18)$$

Inserting (15) into (18) yields

$$\tilde{p}(w|t) = \frac{1}{2a} \int_{t-a}^{t+a} p(w|u) du. \quad (19)$$

In the following one has to consider two different cases for each of the distributions $p(0^n|t)$ and $p(1^n|t)$, respectively. The resulting probabilities of the sustaining words are piecewise linear functions (30)–(33) which are presented in the Appendix.

The probabilities of the sustaining words “0000” and “1111” for latency noise of strength $a = 6$ are shown in Fig. 1(b).

For the words of length $n = 1$ the probabilities $\tilde{p}(0|t)$ and $\tilde{p}(1|t)$ always add to one according to the normalization constraint: $\tilde{p}(0|t) + \tilde{p}(1|t) = 1$. Interestingly, we can derive a similar relation for our model of the latency jitter even for longer words. Let us assume for the sake of simplicity that $a = b$ and determine the sum $f(t) = \tilde{p}(0^n|t) + \tilde{p}(1^n|t)$. Then we have to consider case 1 for the distribution of 0^n and case 2 for the distribution of 1^n . Summing up (30) and (33) yields

$$f(t) = \begin{cases} 1, & t < -2a - n + 1 \\ \frac{1-t-n}{2a}, & -2a - n + 1 \leq t < -2a \\ \frac{2a-n+1}{2a}, & -2a \leq t < 2a - n + 1 \\ \frac{t}{2a}, & 2a - n + 1 \leq t < 2a \\ 1, & t \geq 2a, \end{cases} \quad (20)$$

i.e., within the interval $[-2a, 2a - n + 1]$ the probabilities of the sustaining words add up to a *latency constant*

$$2K = \frac{2a - n + 1}{2a} \quad (21)$$

which eventually depends on the parameters n and a .

C. Polarity Statistics

In this section, we utilize the findings of Sections II-A–II-B in order to present our solution for defining the polarity of ERP components on purely methodological grounds. As mentioned above, overlapping half waves of definite polarity across all measured trials increase the coherence of the symbolically encoded EEG which is reflected by the word statistics that should significantly deviate from the uniform distribution. Let us assume again that a positive polarity deflection should be proven.

In a first step we only consider the statistics of words of length $n = 1$. Then, the positive deflection gives rise to a large relative frequency of the symbol “1,” $\tilde{p}(1|t)$. Assuming that the ERP trials are statistically independent, the symbolic dynamics of the ensemble of size N at time t is given by a Bernoulli experiment of N realizations with the *a priori* probability $P_1(t)$ of the outcome “1” at time t . Hence, the absolute frequency of the symbol “1,” $N\tilde{p}(1|t)$ obeys a binominal distribution with parameter $P_1(t)$. Now we shall test the null hypotheses that this word statistics is the uniform distribution, i.e., $P_1(t) = 0.5$ for all times t . For ensemble size $N > 36$ the test quantity $T = \sqrt{N}(2\tilde{p}(1|t) - 1)$ is approximately normal distributed with zero mean and variance one. Let α be a level of significance, e.g., $\alpha = 0.05$. We define

$$\tilde{p}(1|t) > S(N, \alpha): \text{positive deflection} \quad (22)$$

$$\tilde{p}(0|t) > S(N, \alpha): \text{negative deflection} \quad (23)$$

where

$$S(N, \alpha) = \frac{1}{2} \left[\frac{1}{\sqrt{N}} \Phi^{-1} \left(1 - \frac{\alpha}{2} \right) - 1 \right]$$

with Φ^{-1} as the inverse distribution function of the standard Gaussian distribution, i.e., $\Phi^{-1}(x)$ is the x -quantile of the Gaussian.

The symbol statistics is easily affected by the latency jitter in the EEG. Therefore, using the higher order word statistics

is much more reliable [11]. Our simple model allows a statistical test for polarity to be derived in the presence of latency noise. Without any jittering the probabilities of the sustaining words (16) and (17) are step functions which assume the values one or zero when the respective words are observed or not. We call the latency jitter of the model *moderate* if the standard deviation of the noise is small in comparison to the duration of the deflection; formally: $a \leq b$. In this case we may estimate the putative latency constant K by the time average of $f(t) = \tilde{p}(0^n|t) + \tilde{p}(1^n|t)$ over a certain interval $[T_a, T_b]$

$$\bar{K} = \frac{1}{T_b - T_a} \int_{T_a}^{T_b} \frac{f(t)}{2} dt. \quad (24)$$

The standard deviation of \bar{K} ,

$$\sigma_K = \sqrt{\frac{1}{T_b - T_a} \int_{T_a}^{T_b} \left(\frac{f(t)}{2} - \bar{K} \right)^2 dt} \quad (25)$$

asserts how good the assumption of moderate latency jitter is. As a criterion for defining a polarity deflection we propose

$$\tilde{p}(1^n|t) > \bar{K} + 2\sigma_K: \text{positive deflection} \quad (26)$$

$$\tilde{p}(0^n|t) > \bar{K} + 2\sigma_K: \text{negative deflection} \quad (27)$$

with significance $\alpha \approx 0.05$. These definitions allow the polarity of a deflection to be determined in an absolute way, that is, in a single condition without referring to a control condition.

Finally, one has to decide whether a polarity deflection leads in fact to an ERP component. To this aim, we applied the n -word statistics of all subjects to an analysis of variance (ANOVA) with CONDITION as a within-subjects factor. Then, differences in the asymmetries of the symbol distributions between conditions allow us to tell the experimental from the control condition. The experimental condition is expected to have a larger deviation of the word statistics compared to the control condition, i.e., the asymmetry of the word statistics should be larger in the experimental condition than in the control condition. This criterion to discriminate experimental and control conditions fails in only one case: when (22) and (23) or (26) and (27), respectively, yield a significant positive deflection in one as well as a significant negative deflection in the other condition. In this case, neither condition can be identified as the control condition.

Employing the ANOVA does also provide the answers to some further questions: Which word length should be tested? And would the criteria (22)–(27) result in a multiple hypothesis testing requiring some Bonferroni correction [15]? According to our simple model we shall see that the latter is not necessary. Let us consider once more (30)–(33). Again assuming moderate latency noise with $a = b$ we derive two recursion formulas for the word statistics

$$\begin{aligned} \tilde{p}(0^n|t) &= \tilde{p}(0^{n+1}|t) \\ &+ \begin{cases} 0, & t < -2a - n + 1 \\ \frac{1}{2a}, & -2a - n + 1 \leq t < -n + 1 \\ 0, & t \geq -n + 1 \end{cases} \quad (28) \end{aligned}$$

$$\begin{aligned} \tilde{p}(1^n|t) &= \tilde{p}(1^{n+1}|t) \\ &+ \begin{cases} 0, & t < -n + 1 \\ \frac{1}{2a}, & -n + 1 \leq t < 2a - n + 1 \\ 0, & t \geq 2a - n + 1 \end{cases} \quad (29) \end{aligned}$$

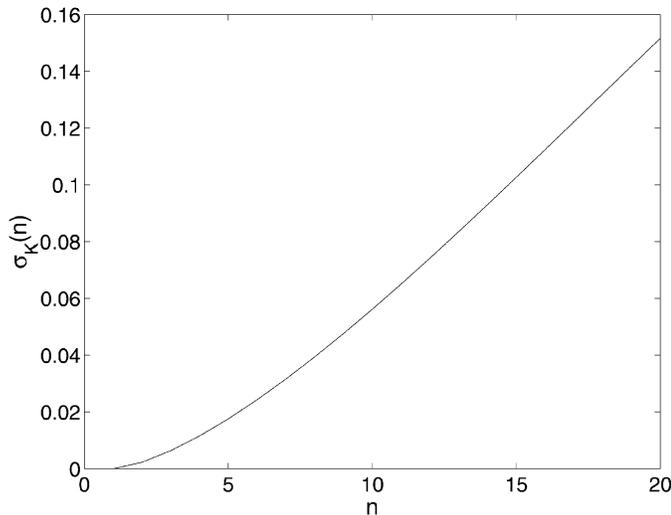


Fig. 2. Monotonic dependence of the standard deviation σ_K (25) on the word length n . Parameters: $a = b = 10$.

From (20) it follows furthermore, that also $2K(n) = 2K(n+1) + 1/(2a)$ for $t \in [-2a, 2a - n]$. Therefore, by (28) and (29) the word statistics differ from \bar{K} by the same amount for all n . Computing the standard deviation of \bar{K} due to (25) yields that σ_K is monotonically increasing with n (see Fig. 2 for $a = b = 10$). We conclude that any sustaining word probability obeying the deflection defining criterion (26) or (27) for some length n^* also obeys the criterion for all $n \leq n^*$. As n^* we choose the length of the longest words surviving the ANOVA between conditions. Thus, it is sufficient testing only the word probabilities for one length n^* .

III. METHOD

In this section, we apply our criteria for assessing ERP deflections. For this purpose, we use the data from the language processing experiment discussed in Sect. I, which gives a good example for an ERP difference whose interpretation is highly ambiguous. The methodological issues concerning participants, materials, procedure, ERP recordings and statistical analysis of the voltage averages are extensively described in [3].

For the present paper, the EEG data of Frisch *et al.* [3] were symbolically encoded using the half wave algorithm (3)–(6) with parameters $T_1 = 52$ samples, $T_2 = 17$ samples and $l = 4$ samples. All encoded trials of all subjects were collected into the grand EEG ensemble. From this, the relative frequencies of the symbol “1,” $\tilde{p}(1|t)$, and the relative frequencies of the words “1111,” $\tilde{p}(1111|t)$, 1^8 , $\tilde{p}(1^8|t)$, 1^9 , $\tilde{p}(1^9|t)$, and 1^{10} , $\tilde{p}(1^{10}|t)$ (positive half wave coherence) for both conditions were determined by (7).

The mean latency constant \bar{K} (24) and its standard deviation σ_K (25) are empirically estimated by

$$\bar{K} = \frac{1}{T_b - T_a} \sum_{t=T_a}^{T_b} \frac{f(t)}{2}$$

and

$$s_K = \sqrt{\frac{1}{T_b - T_a - 1} \sum_{t=T_a}^{T_b} \left(\frac{f(t)}{2} - \bar{K} \right)^2}$$

over the whole sampling duration: $T_a = 0$ ms, $T_b = 1200$ ms.

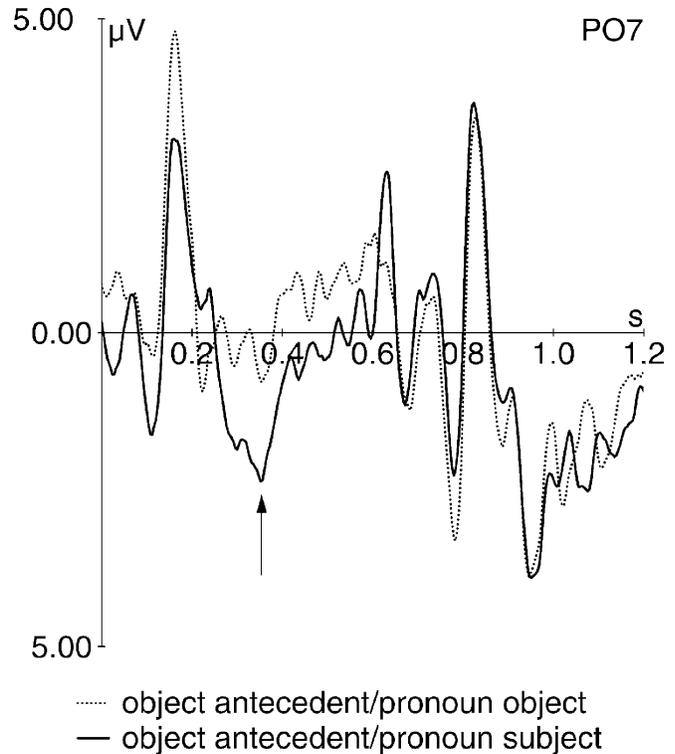


Fig. 3. Average ERPs on the critical disambiguating determiner at electrode PO7. Solid line: condition (1), dotted line: condition (2). The questionable effect is marked by an arrow: positivity (P345) or negativity (N400)?

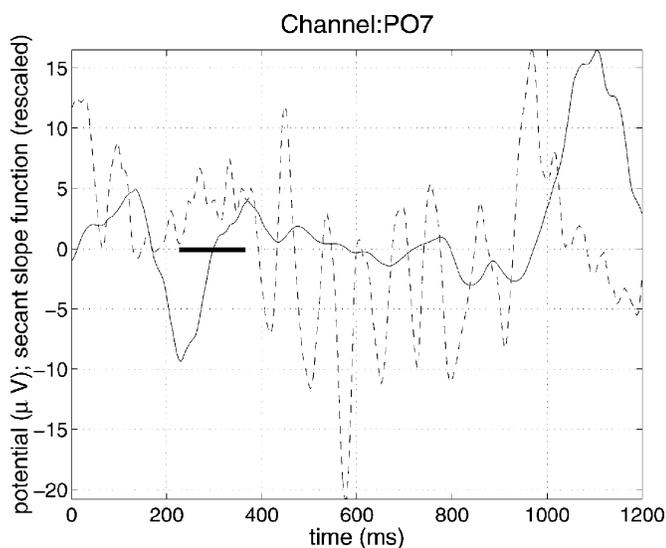
For further analysis, the word statistics for each subject were determined separately. Subsequently, an ANOVA with a two-level within-subjects factor CONDITION was employed. For the present paper, electrode PO7 (following the nomenclature of the *American Electroencephalographic Society*, [16]) was selected as the voltage average differences were most pronounced over left-posterior electrode sites (see, also, [3]).

IV. RESULTS

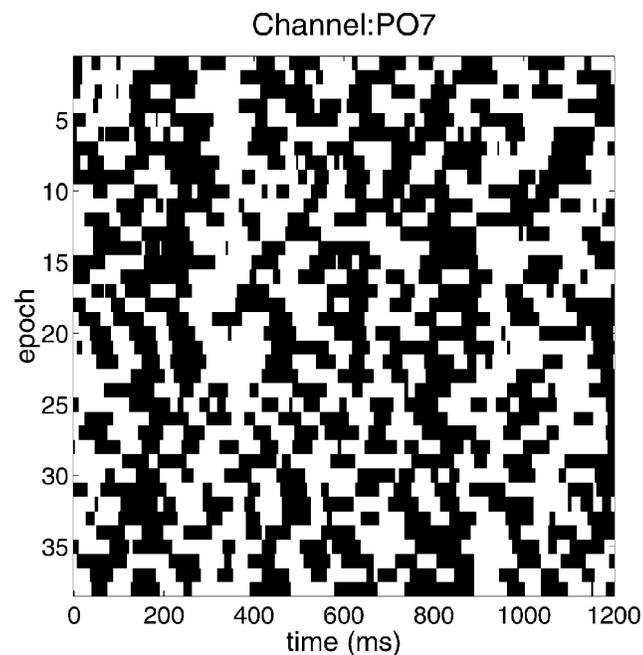
First, we present the traditional voltage average ERPs which have been reported in [3] at electrode PO7 in Fig. 3. The arrow points to the problematic effect: is there a positivity (P345) or rather a negativity (N400)?

The half wave encoding is illustrated in Fig. 4. Fig. 4(a) shows one selected ERP epoch of condition (1) together with its secant slope function (3)–(6). The bar, starting with a local minimum of the secant slope function which corresponds to an inflection point of the low-pass filtered EEG signal with positive slope and ending with a local maximum of the secant slope function where an inflection point of the signal with negative slope is being observed, denotes the time span which is filled up with “1”s by the algorithm. The result is depicted in Fig. 4(b) where the symbolically encoded time series have been piled up in order to visualize intertrial coherence. Coherent half waves of a given, say positive, polarity lead to patterns of vertical (white) stripes which are quantified by the word statistics (7).

Fig. 5(a) displays the instantaneous relative frequencies of the symbol “1” at electrode PO7 for each condition. As in Fig. 1, there is a clear difference between the two conditions. On the basis of the present analysis, however, the question of whether the effect is an N400 for condition (2) compared to (1) or a P345



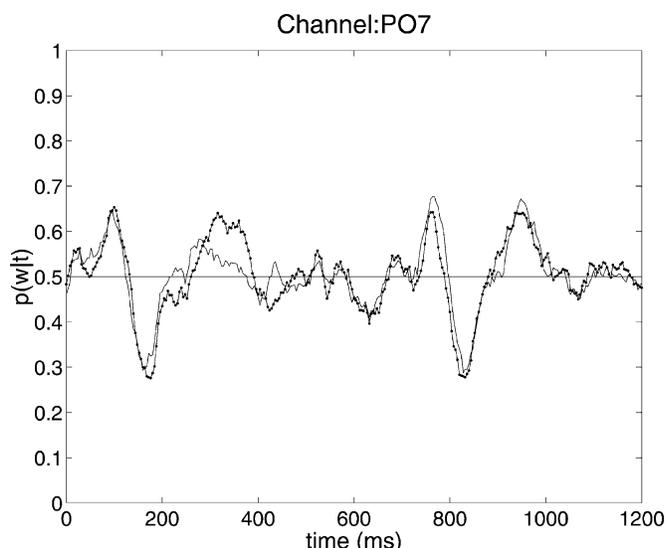
(a)



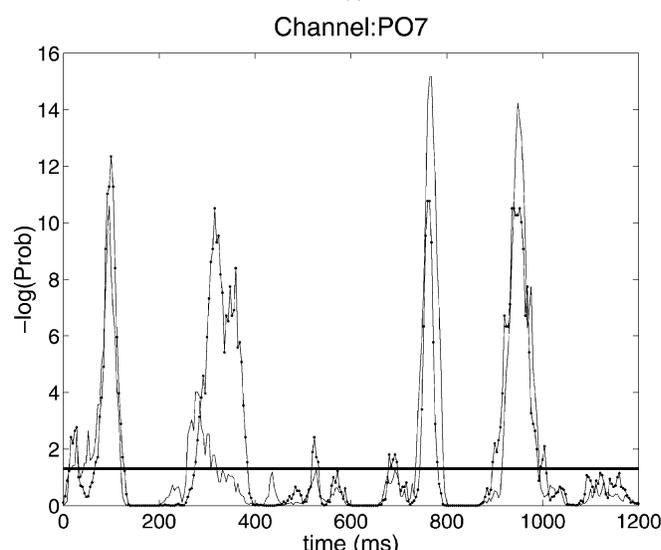
(b)

Fig. 4. Illustration of the half wave encoding algorithm applied on a single ERP epoch (trial 4 of subject #11 for condition (1)). (a) Solid: the (rescaled) secant slope function (3)–(6) computed from the EEG time series (dashed) using parameters $T_1 = 52$ samples, $T_2 = 17$ samples and $l = 4$ samples. The maxima and minima of the secant slope function correspond to the inflection points of signal. Intervals between the maxima and minima of the secant slope function reflect the half waves of the signal. The bar denotes a positive half wave around 350 ms. (b) The symbolically encoded ensemble of ERP epochs for condition (1) (subject #11). Black areas denote “0,” white “1”. The coherent positive half waves in the 350 ms window lead to a vertical white stripe in this time range.

in the other direction can be answered. Considering electrode PO7 reveals a high frequency of the symbol “1” between 200 and 400 ms for condition (1) (solid-dotted line) indicating that more than 60% of all trials have overlapping, i.e., coherent, positive half waves. According to (22) we define a positive polarity deflection in this time range when the probability to reject the null hypothesis erroneously is less than $\alpha = 0.05$. Fig. 5(b) shows the negative logarithm of the error probability of the first



(a)



(b)

kind for both conditions. $\alpha = 0.05$ corresponds to a threshold of 1.3 that must be reached by the graph in order to argue for a positive deflection. This is obviously the case for both conditions (1) (solid-dotted line) and (2) (solid line) in the time between 200 and 400 ms. By contrast, there is no evidence for a negativity since only “0”s would indicate a coherent negative half wave, hence, the possibility to observe an N400 is to be precluded.

In Fig. 6, we present the higher word order statistics. Fig. 6(a) shows the relative frequencies of the 4-words “1111” for both conditions [(1): solid-dotted line and (2): solid line] and additionally the time averaged latency constant \bar{K} (horizontal line) with error bars indicating two standard deviations of \bar{K} . According to (26) a positive deflection can be recognized when the relative word frequencies $\hat{p}(1111|t)$ cross the error bars from below. Similarly, Fig. 6(b) displays the estimated probabilities

kind for both conditions. $\alpha = 0.05$ corresponds to a threshold of 1.3 that must be reached by the graph in order to argue for a positive deflection. This is obviously the case for both conditions (1) (solid-dotted line) and (2) (solid line) in the time between 200 and 400 ms. By contrast, there is no evidence for a negativity since only “0”s would indicate a coherent negative half wave, hence, the possibility to observe an N400 is to be precluded.

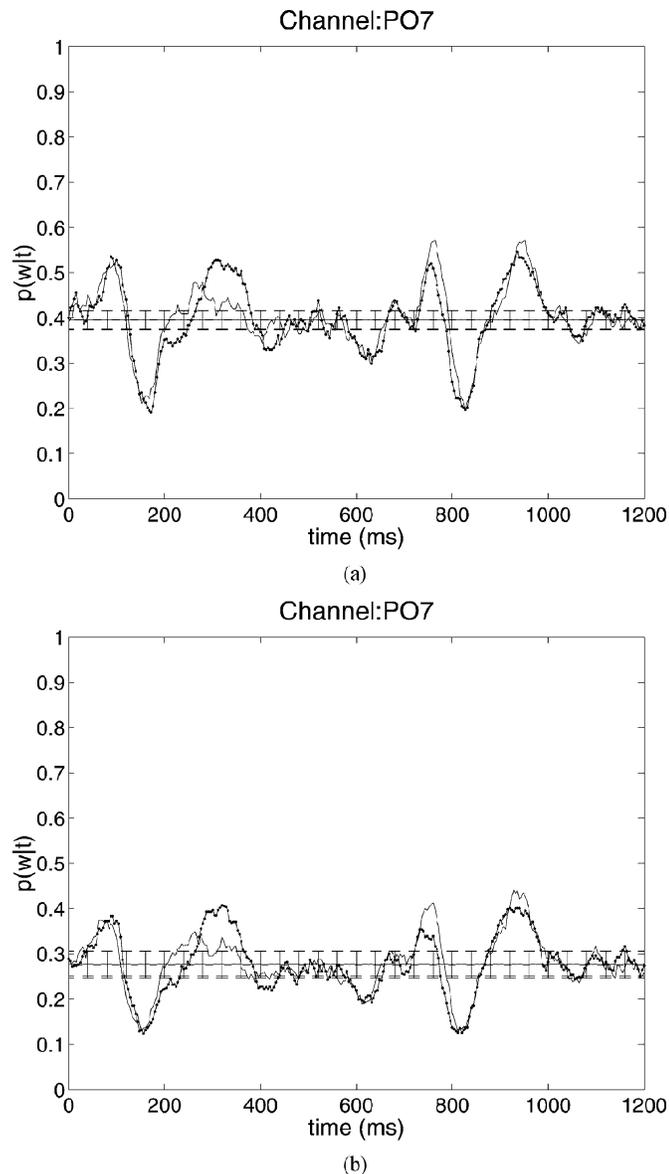


Fig. 6. Symbolic dynamics of the half wave encoding with the same parameters. (a) Relative frequencies of the word “1111” for the conditions (1): solid-dotted line and (2): solid line. (b) Relative frequencies of the word 1^8 for the same conditions. Also shown is the time averaged latency constant \bar{K} (horizontal line) with error bars indicating two standard deviations of \bar{K} .

of the sustaining 8-words 1^8 for both conditions together with the time averaged latency constant \bar{K} with error bars as above. As can be clearly seen the estimates of $\hat{p}(1111|t)$ and $\hat{p}(1^8|t)$ cross the $2s_{\bar{K}}$ threshold for both conditions, thus indicating a positive deflection in the time range around 200 and 400 ms. Again, there is no evidence for a negative deflection in this time. Note further that the criterion defining a positive deflection is barely met by condition (2) for the 8-word statistics, thus demonstrating the increased reliability of the method using high word orders.

We performed the ANOVA on the single-subject word statistics of the half wave encodings in the time window between 300 to 400 ms for the word lengths: $n = 1$, $n = 4$, $n = 8$, $n = 9$, and $n = 10$, where only the relative frequencies of the sustained positive deflections ($w = 1$, $w = 1111$, $w = 1^8$, $w = 1^9$, $w = 1^{10}$) were examined.

At electrode PO7, we found a main effect of CONDITION for $n = 1$ ($F(1, 15) = 10.17$, $p < 0.01$), $n = 4$ ($F(1, 15) = 8.73$, $p < 0.01$) as well as for $n = 8$ ($F(1, 15) = 5.02$, $p < 0.05$). The probabilities of longer words do not differ significantly between conditions [$n = 9$ ($F(1, 15) = 4.5$, $p > 0.05$), $n = 10$ ($F(1, 15) = 4.41$, $p > 0.05$)]. Hence, we were able to determine the maximal word length $n^* = 8$ surviving the ANOVA. Since all shorter words also meet the deflection criterion (26), testing multiple hypotheses is not necessary.

This analysis shows that the observed polarity deflections are indeed a positive ERP component in the time window between 300 to 400 ms, i.e., a P345 for the subject-object disambiguation and not an N400 for the object-subject disambiguation.

V. DISCUSSION

In this paper, we have raised the question of whether and how the polarity of an ERP effect can be determined on methodological grounds alone independent of theoretical predictions. On the basis of an ERP experiment on language processing in German [3], we have shown that cases exist in which cognitive theory does not help us to determine which of two conditions is the experimental and which is the control condition. Testing the opposing influence of two strategies for syntactic ambiguity resolution we have found a difference in the ERP pattern which could either be interpreted as an N400, indicating the revision of *subject preference strategy*, or a P345, reflecting the revision of a *parallel function strategy*. Since experimental and control condition could not be determined on theoretical grounds (although such a determination is implicit in component definition, cf. [1]), we have addressed the problem of using a purely “data-driven” way of ERP data analysis.

To this aim, we have introduced a coarse-graining of the EEG raw data leading to a symbolic dynamics. We have applied a recently developed algorithm for detecting up- and down-going, i.e., positive and negative half waves in the EEG [11]. This algorithm maps half waves onto sequences of consecutive “1”s and “0”s by filling up time intervals between successive inflection points, thus abandoning the noisy behavior of the data between those inflection points. After applying this approach an ERP epoch is represented by such sequence of “0”s and “1”s that can be further characterized by the word statistics as generalized polarity histograms. We define a deflection of positive/negative polarity by a disproportion of the relative frequencies of the sustaining words of n consecutive “0”s or “1”s when one of these frequencies is significantly higher than a constant dependent on the latency jitter. These definitions allow to determine the polarity of a deflection in an absolute way. On the other hand, the question of how to determine the control condition relies upon a relative difference in the asymmetries of the word statistics between two conditions. This asymmetry has been further tested by an ANOVA over the word statistics obtained from each subject. Additionally, the ANOVA allows to determine a maximal word length n^* . Then all shorter words will also meet the criteria defining an ERP deflection.

Our criterion to define the polarity of a deflection can be applied in two cases: First, when the asymmetries in both conditions go into the same direction (i.e., they exhibit both more words of one type compared to the other), and second,

$$\begin{aligned} \text{case 1, } a \leq b + \frac{n-1}{2} \\ \tilde{p}(0^n|t) = \begin{cases} 1, & t < -b - n + 1 - a \\ \frac{a-t-b-n+1}{2a}, & -b - n + 1 - a \leq t < -b - n + 1 + a \\ 0, & -b - n + 1 + a \leq t < b - a \\ \frac{a-b+t}{2a}, & b - a \leq t < b + a \\ 1, & t \geq b + a \end{cases} \end{aligned} \quad (30)$$

$$\begin{aligned} \text{case 2, } a > b + \frac{n-1}{2} \\ \tilde{p}(0^n|t) = \begin{cases} 1, & t < -b - n + 1 - a \\ \frac{a-t-b-n+1}{2a}, & -b - n + 1 - a \leq t < b - a \\ \frac{2(a-b)-n+1}{2a}, & b - a \leq t < -b - n + 1 + a \\ \frac{a-b+t}{2a}, & -b - n + 1 + a \leq t < b + a \\ 1, & t \geq b + a \end{cases} \end{aligned} \quad (31)$$

$$\begin{aligned} \text{case 1, } a \leq b - \frac{n-1}{2} \\ \tilde{p}(1^n|t) = \begin{cases} 0, & t < -b - a \\ \frac{t+a+b}{2a}, & -b - a \leq t < -b + a \\ 1, & -b + a \leq t < b - n + 1 - a \\ \frac{b-n+1-t+a}{2a}, & b - n + 1 - a \leq t < b - n + 1 + a \\ 0, & t \geq b - n + 1 + a \end{cases} \end{aligned} \quad (32)$$

$$\begin{aligned} \text{case 2, } a > b - \frac{n-1}{2} \\ \tilde{p}(1^n|t) = \begin{cases} 0, & t < -b - a \\ \frac{t+a+b}{2a}, & -b - a \leq t < b - n + 1 - a \\ \frac{2b-n+1}{2a}, & b - n + 1 - a \leq t < -b + a \\ \frac{b-n+1-t+a}{2a}, & -b + a \leq t < b - n + 1 + a \\ 0, & t \geq b - n + 1 + a \end{cases} \end{aligned} \quad (33)$$

when only one condition exhibits a deflection that turns out to be significant (either negative or positive) while the other one does not. Using this way of analysis, we have found that the relative frequencies of $n = 1, 4$, and 8 consecutive “1”s in the experiment of Frisch *et al.* [3] were significantly higher than the latency constant \bar{K} (indicating coherent overlapping positive half waves) in condition (1). In addition, the statistical analysis revealed a significant contrast between conditions in the way that the relative frequency of $n = 1, 4$, and 8 consecutive “1”s was larger for the revision of a preference based on *parallel function* compared to the revision of a *subject preference*. Therefore, we have been able to decide that the effect found in the language experiment [3] was a P345 component for a disambiguation towards subject-object and not an N400 for disambiguation towards object-subject.

APPENDIX

WORD STATISTICS AND LATENCY JITTER

The probabilities of the sustaining words in the presence of latency jitter (15) for $w = 0^n$, and $w = 1^n$, respectively, are given by (30)–(33) at the top of the page. The convolution integrals (19) of the singular word statistics are all vanishing and have, hence, been neglected.

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