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Title: A method for discrimination of noise and EMG signal regions recorded during rhythmic behaviors

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Corresponding Author: Dr. Christine E. Wall, Ph.D.

Corresponding Author's Institution: Duke University

First Author: Rex Ying, B. S.

Order of Authors: Rex Ying, B. S.; Christine E. Wall, Ph.D.

Abstract: Analyses of muscular activity during rhythmic behaviors provide critical data for biomechanical studies. Electrical potentials measured from muscles using electromyography (EMG) require discrimination of noise regions as the first step in analysis. An experienced analyst can accurately identify the onset and offset of EMG but this process takes hours to analyze a short (10-15 s) record of rhythmic EMG bursts. Existing computational techniques reduce this time but have limitations. These include a universal threshold for delimiting noise regions (i.e., a single signal value for identifying the EMG signal onset and offset), pre-processing using wide time intervals that dampen sensitivity for EMG signal characteristics, poor performance when a low frequency component (e.g., DC offset) is present, and high computational complexity leading to lack of time efficiency. We present a new statistical method and MATLAB script (EMG-Extractor) that includes an adaptive algorithm to discriminate noise regions from EMG that avoids these limitations and allows for multi-channel datasets to be processed. We evaluate the EMG-Extractor with EMG data on mammalian jaw-adductor muscles during mastication, a rhythmic behavior typified by low amplitude onsets/offsets and complex signal pattern. The EMG-Extractor consistently and accurately distinguishes noise from EMG in a manner similar to that of an experienced analyst. It outputs the raw EMG signal region in a form ready for further analysis.

Duke University
DURHAM
NORTH CAROLINA
27708

EVOLUTIONARY ANTHROPOLOGY
Room 206B Biological Sciences Building
Campus Box 90383

Telephone: (919) 668-2543
Lab Phone: (919) 660-7284
Facsimile: (919) 660-7348

October 4, 2016

Farshid Guilak, Editor-in-Chief
Journal of Biomechanics
St. Louis Shriner's Hospital
Washington University
St. Louis, Missouri

Re: BM-D-16-00490 Revision 1

Dear Farsh:

I am writing to submit the revised manuscript entitled "A method for discrimination of noise and EMG signal regions recorded during rhythmic behaviors" for re-review as a Short Communication. We apologize for taking 3 months to complete the revisions. Rex Ying was in China over the summer and returned to the U.S. last week to start graduate school. He was unable to communicate with me on the revisions while in China.

Reviewer #1 considered this a minor revision, and Reviewer #2 had no comments. We addressed all of the comments of Reviewer #1 and made all but one of the requested changes.

The only requested change we didn't make is that we continue to cite Figures 1B and 1C on lines 87-88, and cite Figures 3A (and 3B) on line 134. With the addition of new figure captions, we think that these are the appropriate figure citations, but we will change these if they are still unclear (see Comment 8 below).

The revisions are detailed in the Revision Notes.

We appreciate the opportunity to revise this manuscript, and the opportunity to extend the revision date. We look forward to hearing from you concerning the outcome of the re-review.

Sincerely,

Christine E. Wall, Ph.D.
Research Professor

Referee Suggestions

Ying and Wall, J Biomechanics
Title: A method for discrimination of noise and EMG signal regions recorded during rhythmic behaviors

Professor Tom Roberts, Brown University, Ecology and Evolutionary Biology,
Thomas_Roberts@brown.edu

Professor Emeritus Allan Thexton, University College London
A.thexton@btinternet.com

Dr. Nicolai Konow, Research Associate, Concord Field Station, Harvard University
konow@fas.harvard.edu

Revision Notes:

The following list and the locations of revised text are annotated by line. The sequence of revisions follows the sequences of requested changes.

1. L49-88: We switched the second and third paragraphs of the Introduction

2. L64-66: We modified this sentence from: "We compare the performance of the EMG-Extractor to that of an experienced analyst (By_Eye Method) and the Thexton (1996) method." to: "We compare the performance of the EMG-Extractor to two commonly used methods: visual identification by an experienced analyst and the Thexton (1996) method."

3. L180-182: Sentences on Lines 66 and 67 of the original were moved to the Discussion.

4. L70-74: The awkward wording has been re-written and is more clear.

5. L70-74: The definitions have been combined.

6. L97: We have clarified the reference to Figure 2. It now correctly reads Fig. 2 since the reader should refer to all three panels (A, B, C) of Fig. 2 at this point in the text.

7. L97: Changed "this distributions" to "this distribution"

8. L87-88 and L134: Figures 1B and Figure 1C refer to the output of the EMG-Extractor for the entire sequence. Figures 3A and 3B are blow-ups of one or two bursts that show the silent period clearly.

9. L100-101: Now reads "Based on the estimated noise region in the pre-processing step, we build a model of the transitions for both the entire input signal and for the noise regions only."

10. L105: Changed to " Σ_n "

11. L114: added comma after "Therefore"

12. L115: added "the"

13. L222: italicized Brain, Beh., Evol.

14. Tables 1 and 2: modified to use a common number of decimal places for all numbers

15. Figures 1B and 1C: The y-axes are now present as black lines.

16. Figure 1C: A figure caption was added.

17. Figure 2C and L97: A figure caption was added. Figure 2C is now cited in the paper on L97.

18. Additional Figures: We originally submitted 3 additional files as potential cover illustrations. In this revision, we have included only 1 additional file for consideration as a cover illustration. This is a color image of Figure 2A showing the frequencies of the transition matrix generated by the EMG-Extractor.

In addition, although not requested by a reviewer, we have made sure to standardize our language by always referring to the noise region as the “noise region” throughout the manuscript. In the original submission, we referred to this by either noise region or noise sequence(s).

Short Communication

Title: A method for discrimination of noise and EMG signal regions recorded during rhythmic behaviors

Rex Ying[1] and Christine E. Wall[2]

[1] Department of Computer Science, Duke University, Durham, NC 27708, U.S.A.

[2] Department of Evolutionary Anthropology, Duke University, Durham, NC 27708, U.S.A.

Corresponding Author: Christine E. Wall, Research Professor, Department of Evolutionary Anthropology, Duke University, Campus Box 90383, Durham NC 27708, U.S.A.
Telephone: 1-919-668-2543
Fax: 1-919-660-7348
Email: cw19@duke.edu

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Abstract

Analyses of muscular activity during rhythmic behaviors provide critical data for biomechanical studies. Electrical potentials measured from muscles using electromyography (EMG) require discrimination of noise regions as the first step in analysis. An experienced analyst can accurately identify the onset and offset of EMG but this process takes hours to analyze a short (10-15 s) record of rhythmic EMG bursts. Existing computational techniques reduce this time but have limitations. These include a universal threshold for delimiting noise regions (i.e., a single signal value for identifying the EMG signal onset and offset), pre-processing using wide time intervals that dampen sensitivity for EMG signal characteristics, poor performance when a low frequency component (e.g., DC offset) is present, and high computational complexity leading to lack of time efficiency. We present a new statistical method and MATLAB script (EMG-Extractor) that includes an adaptive algorithm to discriminate noise regions from EMG that avoids these limitations and allows for multi-channel datasets to be processed. We evaluate the EMG-Extractor with EMG data on mammalian jaw-adductor muscles during mastication, a rhythmic behavior typified by low amplitude onsets/offsets and complex signal pattern. The EMG-Extractor consistently and accurately distinguishes noise from EMG in a manner similar to that of an experienced analyst. It outputs the raw EMG signal region in a form ready for further analysis.

Introduction

Animals engage in many rhythmic behaviors, such as chewing, food transport, respiration, and locomotion. Electrical potentials measured from muscles during rhythmic behaviors can be highly variable. The resulting signal may be characterized by: low EMG-to-noise signal ratio, variable DC offset, periods of low amplitude background muscle stimulation (e.g., cross-talk), the presence of multiple EMG bursts within a single behavioral cycle, variation in peak amplitude, variation in burst duration, variation in cycle duration, and low amplitude onset and offset. The accurate quantification of low amplitude EMG (e.g., onset and offset) requires a method to discriminate between signal and noise when both are of low amplitude. The accurate and automated identification of EMG onset and offset is of considerable benefit because hypotheses about CNS-PNS-muscle communication and the evolution of neuromotor control often include predictions concerning the relative timing of EMG onset and offset (Alfaro et al., 2001; German et al., 2009; Herrel and DeVree, 2009; Lauder and Shaffer, 1988; Smith, 1994; Wainwright, 2002).

The Thexton (1996) method has the advantage of distinguishing noise regions based on independent waveform characteristics. This method has been used to compare EMGs of branchial arch muscles during feeding behaviors (Crompton et al., 2008; Konow et al., 2010). The Thexton (1996) method identifies a universal threshold for a given EMG record using a Runs test. A universal threshold on full-wave integrated and rectified signal is a limitation for two reasons. First, it does not distinguish onsets and offsets from noise on the basis of variation in wave characteristics in the neighborhood (i.e., in adjacent points). A more precise criterion to determine EMG onsets and offsets will include the amplitude of a single point, but also signal variation in its neighborhood, and adjacency to other signal points. Second, the integration step uses a large window, and precision in assigning onset and offset is limited by window size.

Here we present a new method to discriminate noise regions from EMG records of muscle recruitment during rhythmic behaviors. The goals are to identify the EMG onset and offset points and remove the noise regions. We use jaw-adductor muscles to exemplify this method. The new method is named EMG-Extractor and is implemented in MATLAB (The

MathWorks, Inc.). The code is available for download at Github (https://github.com/FEEDEXP/EMG-Extractor) or by request. We compare the performance of the EMG-Extractor to two commonly used methods: visual identification by an experienced analyst and the Thexton (1996) method.

Method

Pre-processing

The input signal is a raw signal with rhythmic EMG components and noise components (Fig. 1A). Signal value denotes the amplitude at each time point along the entire input signal. EMG signal regions are between corresponding onsets and offsets. To develop the EMG-Extractor, we used four datasets of raw EMGs of mammalian jaw-adductor muscles during chewing (Vinyard et al., 2005, 2008; Wall et al., 2008). The datasets contain a wide range of variation in signal value and noise characteristics. They are open access in FEED (https://feedexp.org/, trials 332, 701, 761, and 998). The input signal is digitally sampled at a rate of 10 KHz. The method is also applicable to unfiltered data and data sampled at other rates.

The EMG-Extractor first filters the input signal with a low-pass zero-lag Butterworth filter to remove frequency components less than 100 Hz. The second step is to run the Thexton (1996) algorithms to obtain a threshold value that roughly distinguishes the amplitude of the noise region and that of EMG. We then extract these estimates of the noise region by taking those consecutive sequences of instances (signal values) that are below the threshold. This set of instances could include some false positive and false negative instances. We use a zero-lag Root-Mean-Square algorithm with a 1.5 ms window to integrate the signal as part of this step.

Based on the estimated noise region, the EMG-Extractor builds the noise model and performs a set of post-processing steps. The EMG-Extractor then outputs the EMG (Fig. 1(B) and Fig. 1(C)).

Noise model

We build a probabilistic transition model for the input signal, as well as parts of it that are noise, in order to estimate the probability of each signal point being in the noise region given its neighborhood amplitudes and the transition models.

We define a transition on an EMG value x_n as the ordered pair of changes in signal amplitudes $(x_n - x_{n-1}, x_{n+1} - x_n) \in \mathbb{R}^2$. Based on empirical evidence from the datasets, we found that both the transition probabilities of the entire input signal sequence and the noise region are distributed normally for a given sequence conditioned on each amplitude value (Fig. 2). This distribution may vary among different muscles and species, but are invariant in different parts of a single input signal (i.e., a channel containing EMG and noise), i.e. both the noise region and the EMG in one signal sequence are stationary.

Based on the estimated noise region in the pre-processing step, we build a model of the transitions for both the entire input signal and for the noise region only. Let S be a random variable for a transition in the signal sequence in general, and N be a random variable for a transition in the noise region, then

$$T_s \sim N(\mu_s,\, \Sigma_s^2)$$

$$T_n \sim N(\mu_n, \Sigma_n^2)$$

Where μ_s and μ_n are the means of the entire signal sequence and the noise sequence, regarded as the sample mean in signal space and noise space, and Σ_s and Σ_n are the 2-by-2 covariance matrices of T_s and T_n respectively.

Let I_k be the event that the k-th signal value belongs to the noise region. Let $\mathrm{A_k}$ be the amplitude of the k-th signal value. Let the realization of $\mathrm{A_k}$ and T_k be $\mathrm{a_k}$ and t_k respectively. We propose that event I_k is related to not only the current signal value $\mathrm{a_k}$, but also the transition t_k. Using the Bayes' Theorem, for the k-th signal value,

$$\Pr[I_k \mid T_k = t_k, A_k = a_k] = \frac{\Pr[T_k = t_k, \mathrm{A_k} = \mathrm{a_k} | I_k] \Pr[I_k]}{\Pr\ [T_k = t_k, \mathrm{A_k} = \mathrm{a_k}]}$$

In the numerator, $\Pr[T_k = t_k, \mathrm{A_k} = \mathrm{a_k} | I_k]$ can be computed based on the noise distribution; $\Pr[I_k = 0]$ is omitted because this term is independent of the the k-th signal value, and thus the same for all k. In the denominator, $\Pr\ [T_k = t_k]$ can be computed using the signal distribution. Therefore, we obtain an un-normalized posterior probability of the k-th signal point being in the noise region given its value.

Given the following signal sequence, we obtain the un-normalized posterior that takes a relatively large value for signal points in the noise region, and much smaller value for signal points in the EMG.

Post-processing

Given the posterior computed by the noise model, we detect the noise region by considering the neighborhood window of size 41 points (4.1 ms with a sampling rate of 10 KHz) around each signal point, with 20 points on each side of the signal point. We compute n_l, the number of signal points with high posterior value on the 20-point window to the left of the signal point, and n_r, the number of signal points with high posterior value on the 20-point window to the right of the signal point. An onset is characterized by having a large number of signal points with high posterior values on the left 20-point window, but a small number of such points on the right 20-point window. An offset is similarly characterized by a small number of signal points with low posterior values on the left and high posterior values on the right.

A threshold H is used here to determine the sensitivity of detection of onsets and offsets. For each signal point, we compute the value $n_r - n_l$, so the onset is the first positive value above H after a sequence of 0's, and the offset is the last negative value below $-H$ before a sequence of 0's. We also define an "allowed gap" in the EMG. This allows for a region within an EMG burst to contain a silent period of length less than or equal to the allowed gap interval and consisting of signal values that are not different from a noise region (Fig. 3(A) and Fig. 3(B)). Similarly, we remove orphan spikes (Fig. 3(B)) whose lengths are below a length threshold.

Improvement via Feedback

The next step is to implement a method to improve the noise model and eliminate small bursts of EMG or noise (Fig. 3(C)) while avoiding erosion of low amplitude EMG signal associated with onset and offset. We start with the preliminary estimation of noise from Thexton's (1996) method which contains both false positives and false negatives. To improve the noise model, we use the noise region identified in the post-processing step, which are more accurate, to build a new noise model, and generate the corresponding posterior to obtain a new set of onsets and offsets. We observe that one or two rounds of this improvement via feedback removes ambiguous EMG. We also observe that the process converges rapidly, producing the same results after the second round of feedback. In practice, the EMG-Extractor performs feedback for only one round. This is to limit the width of the noise distribution. It has the effect of removing unwanted small bursts classified as EMG in the Thexton (1996) method while maintaining the sensitivity to onset and offset point.

Comparisons to other methods and statistics

The performance of the EMG-Extractor is compared to that of an experienced analyst (By_Eye method) and the Thexton (1996) method for forty-four chewing cycles from trials 332 and 701. For the By_Eye method, an analyst (CEW) determined onset and offset by locating the point where a change occurs such that the signal amplitude goes above or below the largest amplitudes in the noise region, and then visually scanning the neighboring signal for waveforms that subjectively appear to have the characteristics of muscle action potentials. The By_Eye method is subjective, but incorporates information about the neighboring signal and is based on expert knowledge of the visual characteristics of EMG.

We use the replicated goodness-of-fit test in BIOMstat 4.10 (Applied Biostatistics, Inc.) [H_0: the onset and offset points are homogeneous across methods and therefore could have been the outcome of the same method] to test for patterning in Onset Order and Offset Order. We derive three variables: the absolute, pairwise difference among methods in the onset and offset (Onset Difference and Offset Difference) and the EMG Duration (= Offset Time – Onset Time). The Kruskal-Wallis and pairwise Wilcoxon tests are used to test for significant differences (JMP 12, SAS Institute, Inc.).

Results

From the onset and offset points, the EMG-Extractor obtains a series of EMG regions separated by noise regions (Fig. 1(B) and Fig. 1(C)). For each EMG region, the boundary is exactly the onset and offset identified from the posterior. The replicated goodness-of-fit tests on Onset Order and Offset Order are highly significant (Table 1). Mean Onset Difference and Offset Difference are, on average, within several ms of one another but there are three significant pairwise comparisons (Table 2). EMG Duration does not differ significantly among the methods (Table 2).

Discussion

The heterogeneity tests indicate that the methods are not homogeneous. The Thexton (1996) method consistently yields the earliest onset (Onset Order = 1) and offset (Offset Order = 3) (Table 1). This leads to patterning in Onset Difference, Offset Difference, and EMG Duration, and variation in the magnitudes of Onset Difference and Offset Difference in the pairwise comparisons (Table 2). EMG Duration is approximately 23 ms shorter using the Thexton (1996) method whereas the EMG-Extractor and By_Eye methods yield nearly identical mean values.

The advantages of the EMG-Extractor are that it does not use a universal threshold for delimiting noise regions (cf. Thexton, 1996) or pre-processing using wide time intervals that dampen sensitivity for EMG characteristics (cf. Choi and Principe, 1994). It allows the evaluation of onset and offset at a narrow time scale because it does not use a window for integration to assign noise and EMG values. It also discriminates low frequency components (cf. Marple-Horvat and Gilbey, 1992) and avoids high computational complexity (cf. Choi and Principe, 1994). A limitation of the EMG-Extractor is that it requires prior knowledge of the distribution of noise and signal amplitudes and transitions, although in practice, a normal distribution based on sample mean and variance or discrete distribution based on the signal samples works well in most cases. However, when the signal contains too few sample points, these distributions are less accurate to describe the signal and noise data.

Conflict of interest statement

The authors assert that there are no conflicts of interest of any type.

Acknowledgements

The authors thank Emma Santoianni for help digitizing and formatting the EMG datasets. The authors thank Robert E. Druzinsky, Rebecca Z. German, Christopher J. Vinyard, and Susan H. Williams for discussions on EMG analysis. The authors also thank Allan Thexton (King's

College London, emeritus, Department of Physiology) for his encouragement on the FEED project. The EMG data are in the open access Feeding Experiments Enduser Database (FEED, https://feedexp.org/). Sources of funding: NSF-ABI 1062333, NSF-SBR 9420764, NSF-BCS 0094522.

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Table 1. Replicated Goodness-of-Fit (Heterogeneity) tests on Onset Order and Offset Order. The EMG-Extractor typically results in the second or third onset and the first or second offset in comparison to By_Eye and Thexton (1996).

Onset Order	**First Onset = 1**	**Second Onset = 2**	**Third Onset = 3**

By_Eye	11	10	23
Thexton	32	9	3
EMG-Extractor	1	25	18
Heterogeneity G = 66.992, p < 0.00001			
Offset Order	**First Offset = 3**	**Second Offset = 2**	**Third Offset = 1**
By_Eye	11	32	1
Thexton	0	1	43
EMG-Extractor	33	11	0
Heterogeneity G = 172.5555, p = 0			

Table 2. Statistical comparison of the absolute values of the variables Onset Difference, Offset Difference, and EMG Duration in msec. Variables are determined using EMG-Extractor, By_Eye, and Thexton. The smallest mean difference in Onset Difference is between EMG-Extractor and Thexton methods. The smallest mean difference in Offset Difference is between EMG-Extractor and By_Eye methods. EMG Duration is not significantly different among the methods, and is most similar between the EMG-Extractor and By_Eye methods. The significance level is p < 0.00555 after comparison-wise adjustment.

	Onset Difference (msec)	**Onset Difference (msec)**	**Onset Difference (msec)**
	(EMG-Extractor to By_Eye)	**(By_Eye to Thexton)**	**(EMG-Extractor to Thexton)**
mean	4.7	6.4	3.9
sd	6.1	5.3	7.7
n	44	44	44
Kruskal-Wallis Test	**p < 0.0001**		
Pairwise Comparisons:			
(EMG-Extractor - By_Eye) v. (By_Eye - Thexton)	ns		
(EMG-Extractor - By_Eye) v. (EMG_Extractor - Thexton)	ns		

(By_Eye - Thexton) v. (EMG-Extractor - Thexton)	**$p < 0.0001$**		
	Offset Difference (msec)	**Offset Difference (msec)**	**Offset Difference (msec)**
	EMG-Extractor to By_Eye	**By_Eye to Thexton**	**EMG-Extractor to Thexton**
mean	3.4	4.6	6.0
sd	2.9	4.3	3.2
n	44	44	44
Kruskal-Wallis Test	**$p < 0.0001$**		
Pairwise Comparisons:			
(EMG-Extractor - By_Eye) v. (By_Eye - Thexton)	ns		
(EMG-Extractor - By_Eye) v. (EMG_Extractor - Thexton)	**$p < 0.0001$**		
(By_Eye - Thexton) v. (EMG-Extractor - Thexton)	**$p = 0.0012$**		
	EMG Duration (msec)		
	EMG-Extractor	**Thexton**	**By_Eye**
mean	579.1	556.3	579.9
sd	158.0	165.0	146.6
n	44	44	44
Kruskal-Wallis Test	ns		

FIGURE CAPTIONS

Ying and Wall

Figure 1A. A raw input signal.

Figure 1B. The output of the EMG-Extractor for the raw input signal in Fig. 1(a). The black region is the extracted EMG, defined by a series of onset and offset points. The grey region is the noise region removed by the EMG-Extractor algorithms.

Figure 1C. An enlarged view of Fig. 1(b) showing EMG bursts 6, 7, and 8. The black region is the extracted EMG, and the grey region is the noise region.

Figure 2A. The frequencies (plotted on the z-axis) of the values of the transition matrix of the noise region visualized as a surface. The first component of each of the transitions is plotted on the x-axis. The second coordinate of the transition matrix is plotted on the y-axis. The larger the absolute value of a transition, the less likely it is in a noise region. The absolute values of most of the transitions are small, resulting in a peak close to the origin. Transitions with large absolute values occur less often.

Figure 2B. The frequencies (plotted on the z-axis) of the values of the transition matrix of the input signal visualized as a surface. The first coordinate of the transition matrix is plotted on the x-axis. The second coordinate of the transition matrix is plotted on the y-axis. EMG typically consists of a number of transitions with very large absolute values compared to the transitions in the noise region. This results in a larger variance of the distribution.

Figure 2C. This figure shows that there are transitions with large absolute values although we can only see a central peak in Fig. 2(b). Each point (x, y) in the plot shows the presence of a transition (x, y) in the signal sequence. These transitions are important landmarks of EMG signals.

Figure 3A. EMG separated by short silent periods (black arrows). Silent periods occur frequently in the jaw adductors of humans and other species. The EMG preceding and following the silent period occurs in the same cycle of the rhythmic behavior (e.g., during the same jaw adducting phase). As discussed in the Materials and Methods, the EMG-Extractor defines an “allowed gap” that allows for a region within an EMG burst to contain a silent period of length less than or equal to the allowed gap interval and consisting of a sequence of signal values that are not different from a noise region.

Figure 3B. An example of two orphan spikes (defined as EMG bursts of exceptionally short duration that are not part of the rhythmic behavior of interest). A silent period (black arrow) is also present in the rhythmic EMG burst on the left.

Figure 3C. An example of low amplitude, rhythmic signal interspersed between EMG recorded for the rhythmic behavior of interest (e.g., the jaw adducting phase). This type of low amplitude signal is not of interest for further analysis and may include EMG and/or noise. These bursts may be due to cross-talk from overlying or nearby muscles. If they are not known to be caused by cross-talk, then the method of noise reduction implemented in the EMG-Extractor can be modified to retain these bursts as EMG.

Figure 1A
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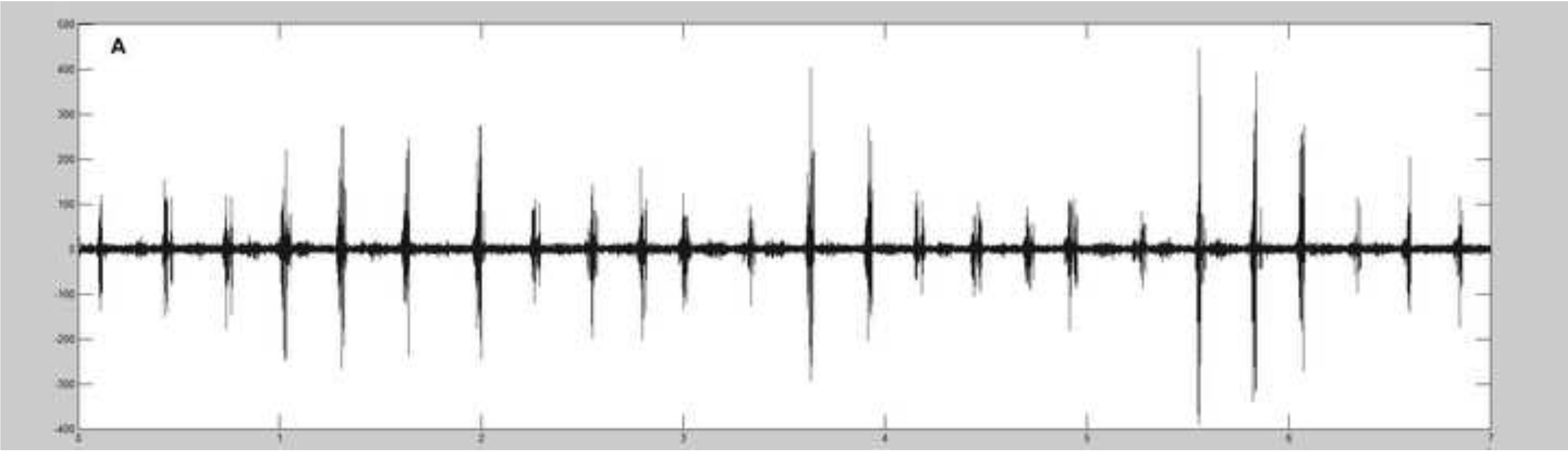

Figure 1B revised

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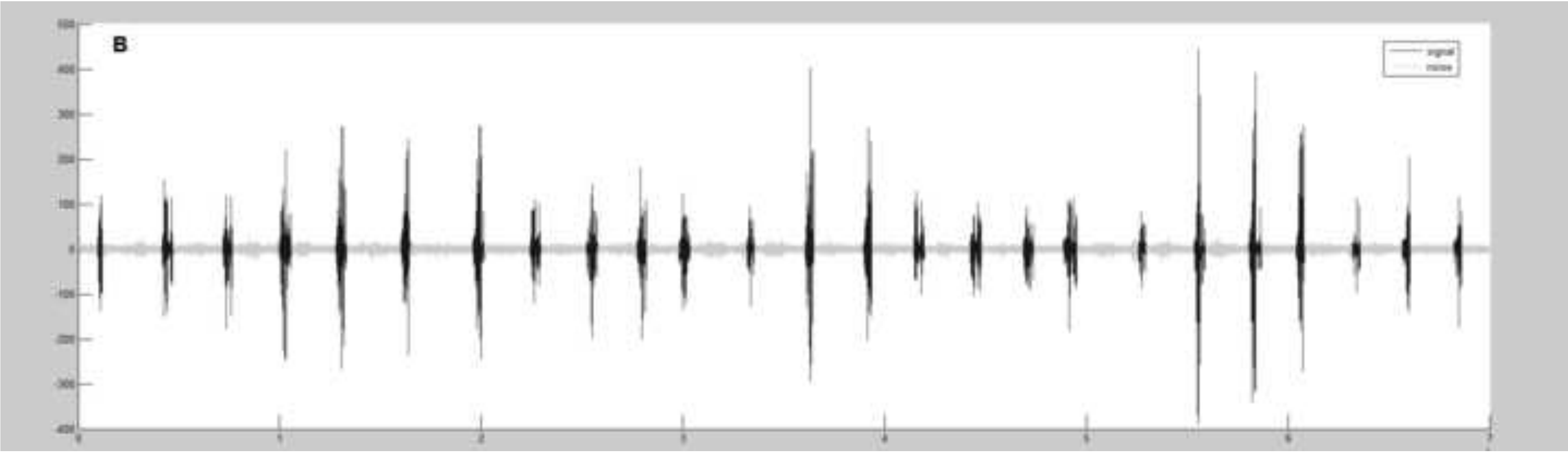

Figure 1C revised
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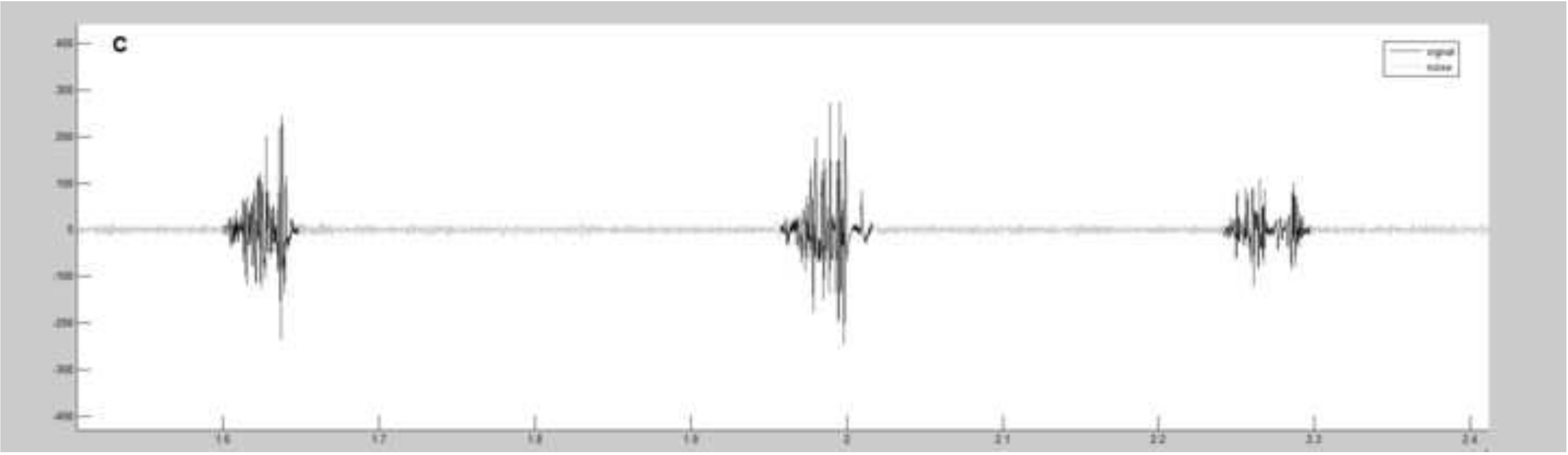

Figure 2A
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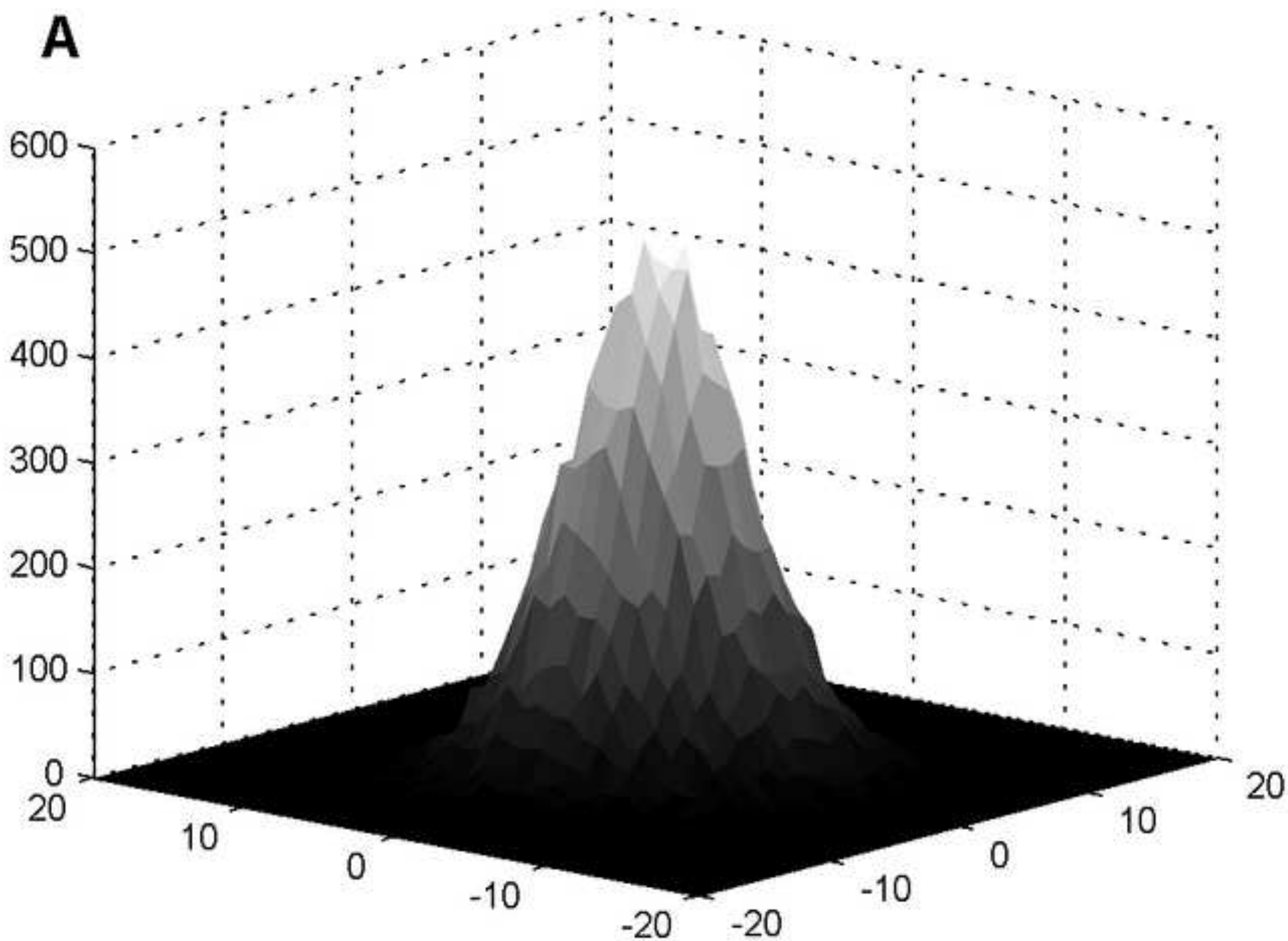

Figure 2B
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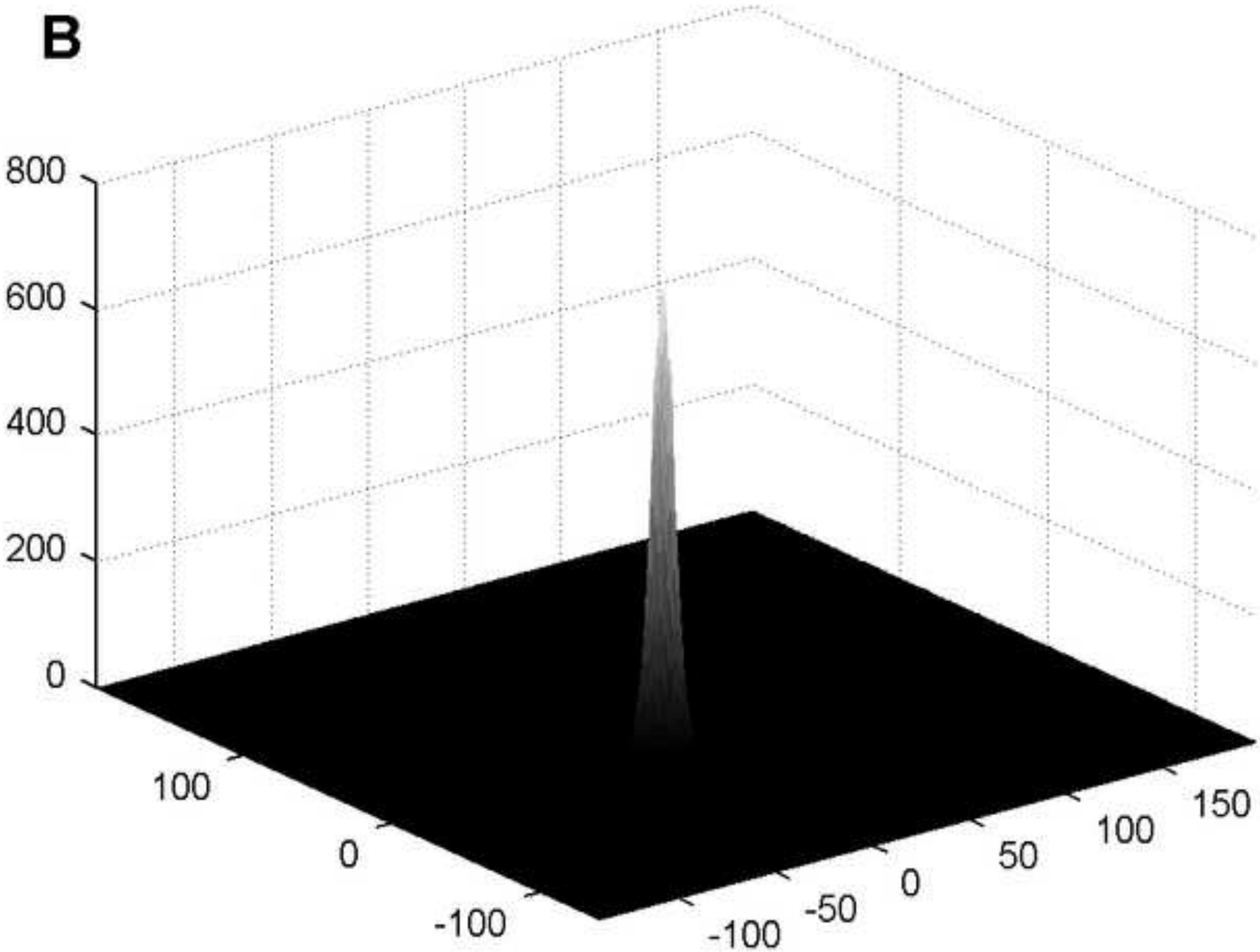

Figure 2C
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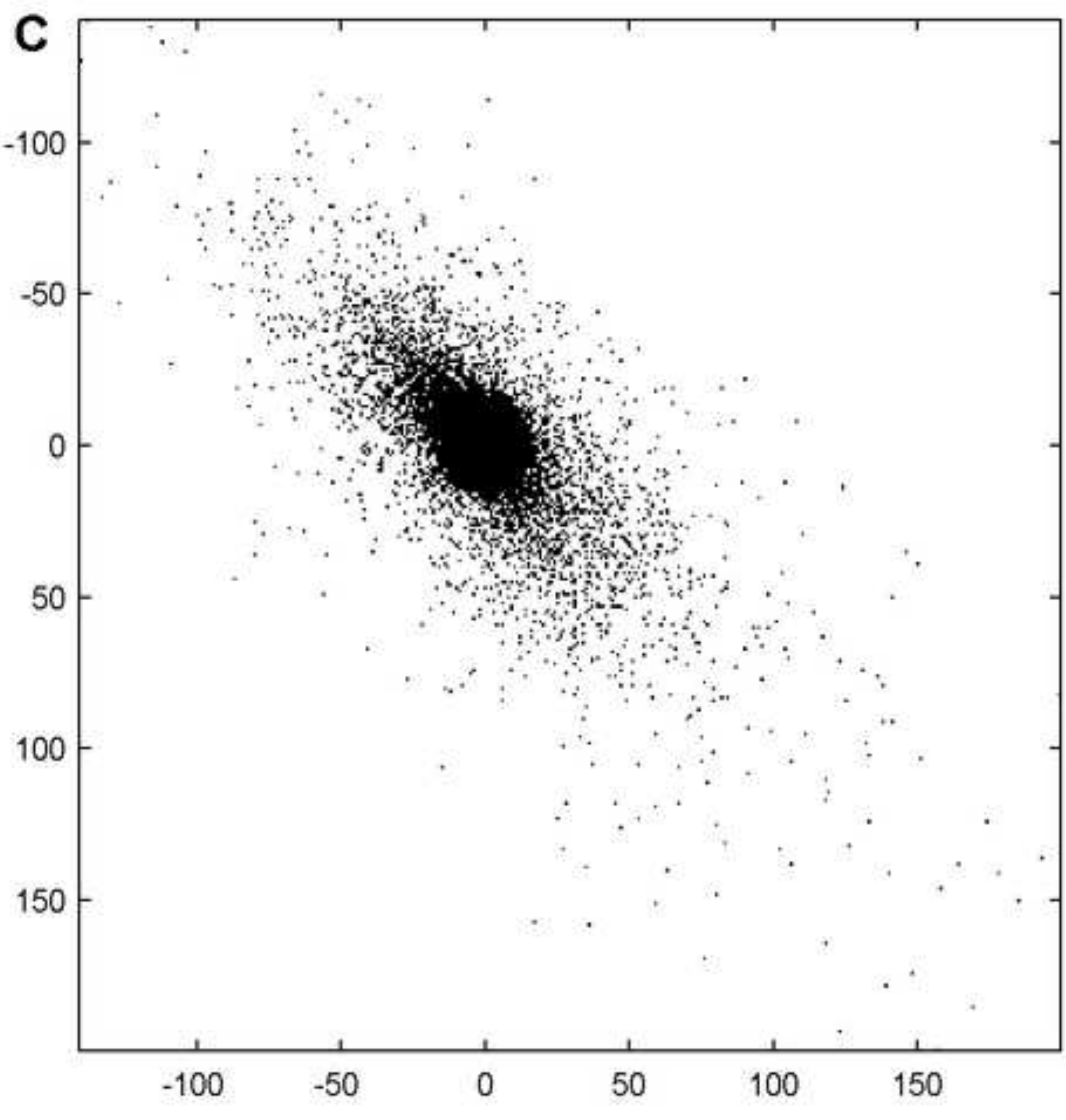

Figure 3A
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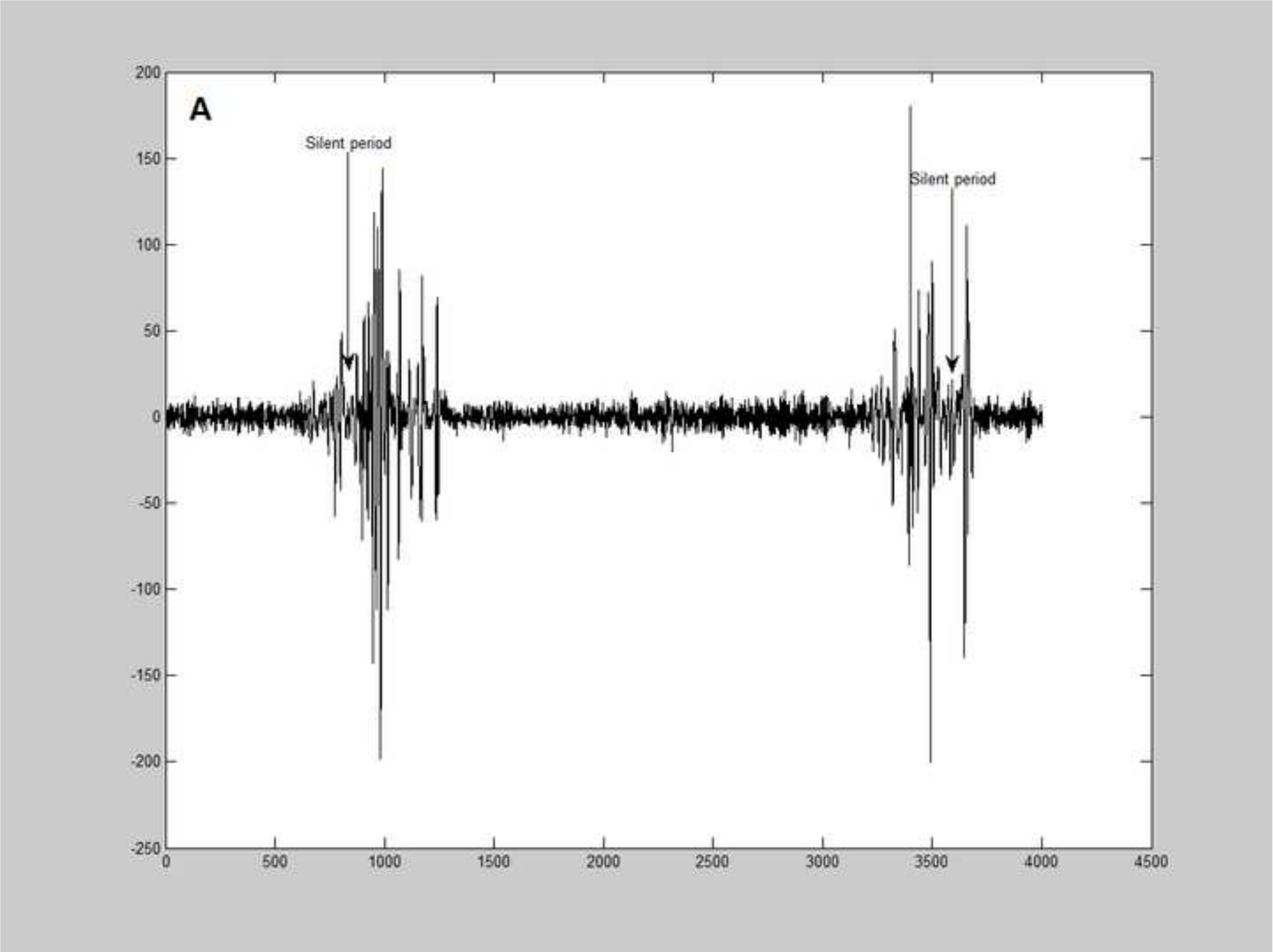

Figure 3B

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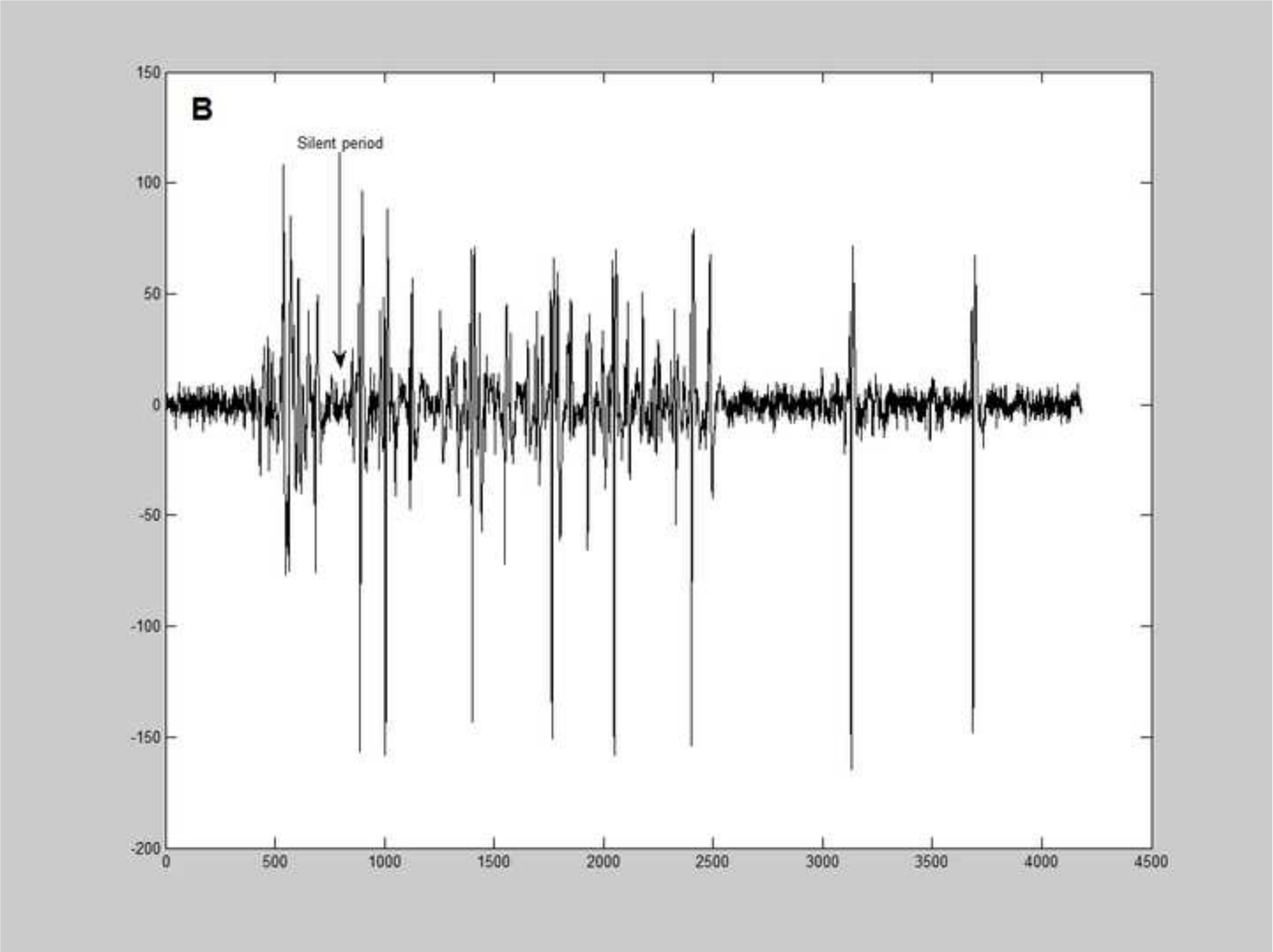

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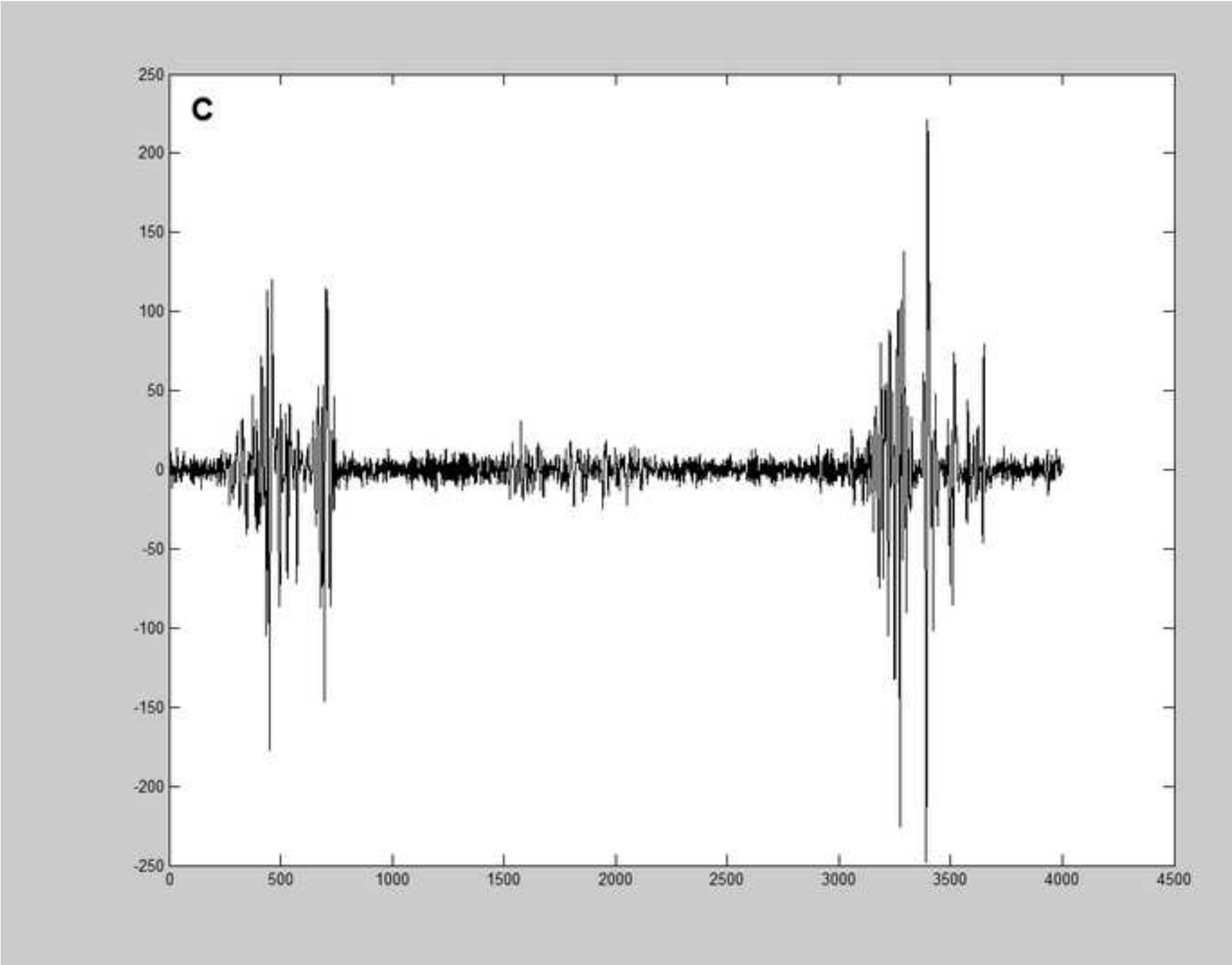

Figure Color Version Fig 2A Potential Cover Illustration

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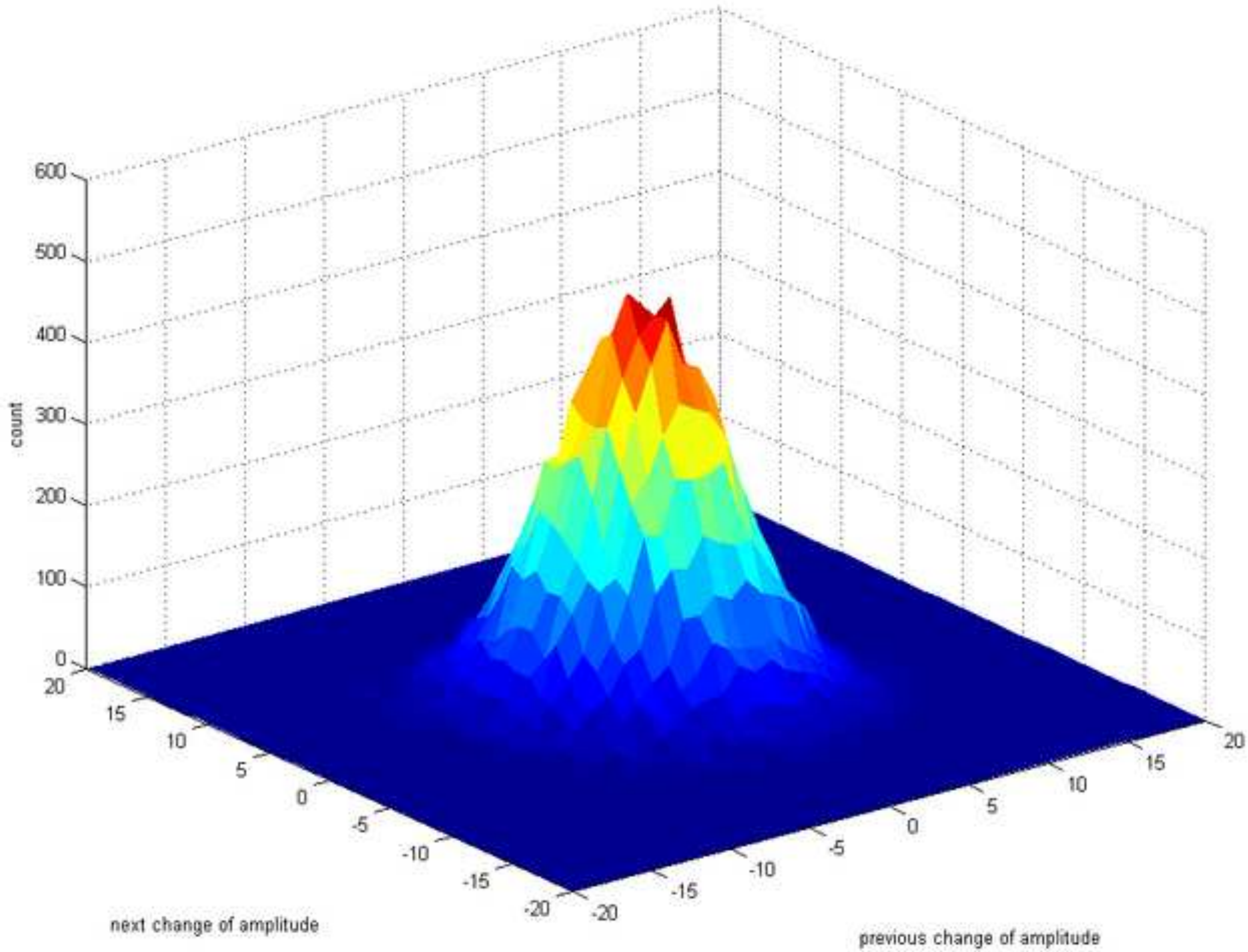
A



Conflict of Interest Statement

Ying and Wall, J Biomechanics
Title: A method for discrimination of noise and EMG signal regions recorded during rhythmic behaviors

The authors assert that there are no conflicts of interest of any type.

This assertion is also included in the manuscript.