Differentiation of speech-induced artifacts from physiological high gamma activity in intracranial recordings

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Abstract

There is great interest in identifying the neurophysiological underpinnings of speech production. Deep brain stimulation (DBS) surgery is unique in that it allows intracranial recordings from both cortical and subcortical regions in patients who are awake and speaking. The quality of these recordings, however, may be affected to various degrees by mechanical forces resulting from speech itself. Here we describe the presence of speech-induced artifacts in local-field potential (LFP) recordings obtained from mapping electrodes, DBS leads, and cortical electrodes. In addition to expected physiological increases in high gamma (60-200 Hz) activity during speech production, time-frequency analysis in many channels revealed a narrowband gamma component that exhibited a pattern similar to that observed in the speech audio spectrogram. This component was present to different degrees in multiple types of neural recordings. We show that this component tracks the fundamental frequency of the participant's voice, correlates with the power spectrum of speech and has coherence with the produced speech audio. A vibration sensor attached to the stereotactic frame recorded speech-induced vibrations with the same pattern observed in the LFPs. No corresponding component was identified in any neural channel during the listening epoch of a syllable repetition task. These observations demonstrate how speech-induced vibrations can create artifacts in the primary frequency band of interest. Identifying and accounting for these artifacts is crucial for establishing the validity and reproducibility of speech-related data obtained from intracranial recordings during DBS surgery.

Introduction

Invasive brain recordings performed in awake patients undergoing clinically indicated neurosurgeries provide a unique opportunity to study speech production with better spatial and temporal precision than noninvasive neuroimaging methods. One of the advantages of intracranial recordings is a much higher signal-to-noise ratio (SNR) and larger measurable frequency range. This allows examination of frequency bands above 70 Hz that are typically unattainable with noninvasive methods due to volume conduction effects and a sharp attenuation in power at higher frequencies when passing the skull (Mukamel and Fried, 2012). Many assume that a higher SNR in the intracranial recordings makes them less susceptible to artifacts frequently observed in noninvasive recordings, such as electro-myographic artifacts due to eye, jaw, lip and tongue movement (Flinker et al., 2018; Lachaux et al., 2003; Llorens et al., 2011). Comprehensive quantitative examination of the quality of the signal and identification of potential sources of artifacts in intracranial recordings, however, have received very little attention. Several types of artifacts found in scalp EEG have been described in intracranial recordings, such as eye movement artifacts in fronto-anterior regions (Ball et al., 2009), and facial and mouth movement artifacts in electrodes close to temporal muscles (Otsubo et al., 2008). This suggests that movement artifacts can contaminate intracranial LFP recordings acquired to study of the neural control of speech production.

Neural activity in the high gamma frequency band (60-200 Hz) tracks specific features of speech perception and production. For example, increased power in the high gamma frequency range has been observed in the superior temporal gyrus in response to auditory stimuli (Crone et al., 2001; Hamilton et al., 2018; Mesgarani et al., 2014), and in Broca's and motor cortices during speech production (Edwards et al., 2010; Flinker et al., 2015; Mugler et al., 2018). High gamma activity recorded from the Rolandic cortex (pre and postcentral gyri) has been shown to track articulatory and/or acoustic features of speech sounds (Bouchard et al., 2013; Cheung et

al., 2016; Chrabaszcz et al., 2019; Conant et al., 2018). Some recent advances have even made it possible to reconstruct speech from the brain's activity in the high gamma band (Anumanchipalli et al., 2019; Martin et al., 2019), pointing at its potential utility for brain-computer interfaces (BCI) to develop speech prostheses. Contamination of the neural signal with audio acoustics therefore is a potential barrier to decoding the true electrophysiological correlates of speech production.

Given the impact that speech dysfunction can have in patients with movement disorders, and the fact that the role of subcortical regions in speech production are not well understood, we recently developed a strategy to simultaneously record from the cortex and the subcortical implantation target during DBS surgery. With the patient's consent, it is possible to temporally place an electrocorticography (ECoG) electrode strip on the surface of the brain, a technique that has been used safely in over 500 patients (Panov et al., 2017; Sisterson et al., 2021). Here, we report the systematic identification and quantification of speech-induced artifacts in several types of intracranial electrophysiological recordings obtained using a speech production task performed during DBS implantation surgery. We show that this artifact is caused by mechanical vibrations induced by the produced speech, and that it can also be found in a 'blank' headstage pin not connected to any electrode. The results presented in this study encourage careful assessment of possible audio-induced artifacts in intracranial recordings obtained during speech production research. Additionally, we provide suggestions for data collection and analysis that may reduce the potential for false discoveries.

Materials and Methods

Participants

Participants were English-speaking patients with Parkinson's disease (21M/8F, age: 65.6±7.1 years, duration of disease: 6.1±4.1 years) undergoing awake stereotactic neurosurgery for

85   implantation of DBS electrodes in the subthalamic nucleus (STN). Dopaminergic medication

86   was withdrawn the night before surgery. All procedures were approved by the University of

87   Pittsburgh Institutional Review Board (IRB Protocol #PRO13110420) and all patients provided

88   informed consent to participate in the study.

89   **Behavioral task**

90   Participants performed a syllable repetition task intraoperatively. Subjects heard consonant-

91   vowel (CV) syllable triplets through earphones (Etymotic ER-4 with ER38-14F Foam Eartips)

92   and were instructed to repeat them. Triplets were presented at either low (~50dB SPL) or high

93   (~70dB SPL) volume using BCI2000 (Schalk et al., 2004) presentation software. The absolute

94   intensity was adjusted to each participant's comfort level, keeping the difference between low

95   and high-volume stimuli fixed at 25dB SPL. Participants were instructed to repeat the low-

96   volume syllable triplets at normal conversation level and the high-volume triplets at increased

97   volume, "as if speaking to someone across the room". The syllables were composed of a

98   combination of either of the 4 English consonants (/v/, /t/, /s/, /g/) and either of the 3 cardinal

99   vowels (/i/, /a, /u/), resulting in 12 unique CV syllables. A total of 600 triplets were constructed

100 which were divided among 5 presentation lists, with each session composed of 120 triplets. No

101 syllable was repeated within a triplet. Syllable position and phoneme occurrence within a triplet

102 and intensity level (low or high) within each session were balanced. The produced audio was

103 recorded with an PRM1 Microphone (PreSonus Audio Electronics Inc., Baton Rouge, LA, USA)

104 at 96 kHz using a Zoom-H6 portable audio recorder (Zoom Corp., Hauppauge, NY, USA). The

105 average number of trials per session was 106 (range: 14-120). The duration of the utterances

106 was of 1.3 ± 0.3 s (mean ± standard deviation pooled across subjects), with a median within-

107 subject standard deviation of 0.14 s.

Neural recordings

As part of the standard clinical DBS implantation procedure, functional mapping of the STN was performed with microelectrode recordings (MER), acquired with the Neuro-Omega recording system (Alpha-Omega Engineering, Nof HaGalil, Israel) using parylene-insulated tungsten microelectrodes (25 µm in diameter, 100 µm in length). LFPs were recorded from stainless steel macroelectrode rings (0.55 mm in diameter, 1.4 mm in length) located 3 mm above the tip of the microelectrode. The microelectrodes were oriented on the microtargeting drive system using three trajectories of a standard cross-shaped Ben-Gun array with 2 mm center-to-center spacing (Central, Posterior, Medial). The MER and LFP signals were recorded at a sampling rate of 44 kHz. The neural signal was referenced to the metal screw holding one of the guide cannulas used to carry the microelectrodes. Prior to initiating MER mapping, one or two subdural electrocorticography (ECoG) strips with 54 or 63 contacts each (platinum 1 mm disc contacts arranged in a 3x18 or 3x21 layout, with 3 mm center to center spacing, PMT Cortac Strips models 2110-54-001 and 2011-63-002) were placed through the standard burr hole. ECoG strips were targeted to the left superior temporal gyrus (covering the ventral sensorimotor cortex) and left inferior frontal gyrus. Signals from ECoG electrodes and DBS leads were acquired at 30 kHz with a Grapevine Neural Interface Processor equipped with Micro2 Front Ends (Ripple LLC, Salt Lake City, UT, USA). Recordings were referenced to a sterile stainless-steel subdermal needle electrode placed in the scalp, approximately at the location of Cz in a standard EEG montage.

Two or three sessions of the syllable repetition task were performed by each subject when the microelectrode was positioned at different depths within the STN. The clinical setup evolved during the collection of this dataset between subjects 22 and 23, transitioning from a traditional stereotactic frame to the use of robotic stereotactic assistance (Faraji et al., 2020).

132 This change resulted in modification of the stereotactic frame's mechanical coupling to the

133 electrode micro-drive.

134 After the functional mapping phase patients were implanted with one of the DBS leads

135 models shown in Table 1:

136 ● Medtronic 3389: Platinum/Iridium, 4 cylindrical macroelectrodes, contact length 1.5 mm,

137 1.27 mm in diameter, 0.5 mm axial electrode spacing (Medtronic, Minneapolis, MN,

138 USA).

139 ● St. Jude 6172 short: Platinum/Iridium, directional lead with two central rings split in three

140 contacts, 8 contacts total, length 1.5 mm, axial spacing 0.5 mm, lead diameter 1.27 mm,

141 outer tubing material polycarbonate urethane (Abbott Neuromodulation, Austin, TX,

142 USA).

143 ● Boston Scientific DB-2202-45: Platinum/Iridium, directional lead with two central rings

144 split in three contacts, 8 contacts total, length 1.5 mm, axial spacing 0.5 mm, lead

145 diameter 1.3 mm, outer tubing material polyurethane (Boston Scientific Neuromodulation

146 Corp, Valencia, CA, USA).

147 After the leads were successfully implanted, a final session of the speech task was performed

148 by some participants, providing LFP data from DBS leads. A summary of recording types and

149 the corresponding acquisition specifications is provided in Table 1. A schematic illustration of

150 the intraoperative intracranial recording setup is shown in Figure 1.

151 **Vibration sensor**

152 A shielded piezoelectric vibration sensor (model SDT1-028K, TE Connectivity Company) was

153 fixed to the stereotactic frame using a sticky pad for the duration of one experiment. This sensor

154 was selected for its flat transfer function at frequencies above 30 Hz. The signal from the sensor

155 was captured without amplification as an analog input to the Grapevine system

| Data type	Acquisition system	Model/Manufacturer	Sampling rate	Number of recordings
DBS Lead	Grapevine	Medtronic 3389; St. Jude 6172 short; Boston Scientific DB-2202-45	30 kHz	4 or 8
Micro	Neuro-Omega	Alpha Omega	44 kHz	3
Macro	Neuro-Omega	Alpha Omega	44 kHz	3
ECoG	Grapevine	PMT 2110-54-001; PMT 2011-63-002	30 kHz	54 to 126
Presented audio	Grapevine	BCI2000	30 kHz	1
Produced audio	Grapevine	PRM1 PreSonus Microphone; Zoom-H6 audio recorder	96 kHz	1
Vibration sensor	Grapevine	SDT1-028K, TE Connectivity Company	1 kHz	1

156   **Table 1**. Acquisition system specifications for neural and physiological signals.

157   **Electrode localization**

158   DBS electrodes were localized using the Lead-DBS localization pipeline (Horn and Kühn, 2015).

159   Briefly, a preoperative anatomical T1-weighted MRI scan was co-registered with a postoperative

160   CT scan. The position of individual contacts was manually identified based on the electrode

161   artifact present in the CT image and constrained by the geometry of the implanted DBS lead.

162   This process rendered the coordinates for the leads in each subject's native space. Based on

163   the position of the lead and the known depth and tract along which the lead was implanted in

164   each hemisphere, the positions of the micro and macro recordings from the functional mapping

165   were calculated using custom Matlab scripts (github.com/Brain-Modulation-Lab/Lead_MER).

166   The position of the ECoG strips was calculated from an intraoperative fluoroscopy image as

167   described in (Randazzo et al., 2016). Briefly, the cortical surface was reconstructed from the

168   preoperative MRI using the FreeSurfer image analysis suite

169   (http://surfer.nmr.mgh.harvard.edu/). A model of the skull and the stereotactic frame was

170   reconstructed from the intraoperative CT scan using OsiriX neuroimaging viewing tool

171   (https://www.osirix-viewer.com/). The position of the frame's tips on the skull and the implanted

172   DBS leads were used as fiducial markers. The models of the pial surface, skull and fiducial

173   markers were co-registered, manually rotated and scaled to align with the projection observed in

174   the fluoroscopy image. Once aligned, the position of the electrodes in the ECoG strip was

175   manually marked on the fluoroscopy image and the projection of those positions to the convex

176   hull of the cortical surface was defined as the electrodes' locations in the native brain space.

177   The coordinates were then regularized based on the known layout of the contacts in the ECoG

178   strip (github.com/Brain-Modulation-Lab/ECoG_localization). All coordinates were then

179   transformed to the ICBM MNI152 Non-Linear Asymmetric 2009b space (Fonov et al., 2011)

180   using the Symmetric Diffeomorphism algorithm implemented in the Advanced Normalization

181   Tools (Avants et al., 2008). Anatomical labels were assigned to each electrode based on the

182   HCP-MMP1 atlas (Glasser et al., 2016) for cortical electrodes, and the Morel (Niemann et al.,

183   2000) and DISTAL (Ewert et al., 2018) atlases for subcortical electrodes.

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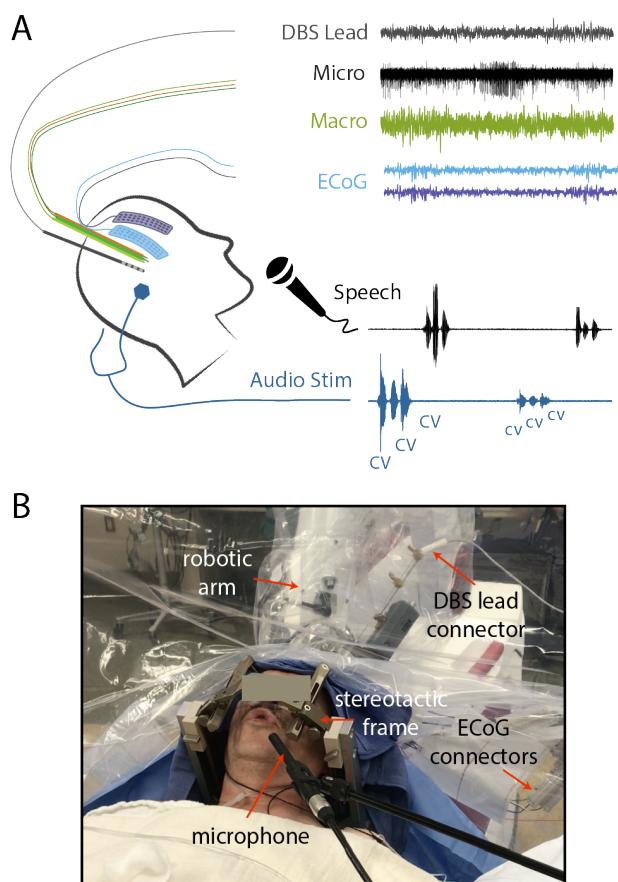
Figure 1: Intraoperative intracranial recording setup and speech task.
A. Schematic representation of intracranial electrodes and syllable triplet repetition task. During the mapping phase of the DBS implantation surgery ECoG strips were temporarily placed through the burr hole, allowing simultaneous recording of cortical and subcortical LFPs and MER from the STN. Participants were instructed to repeat aloud CV syllable triples at a volume matching the auditory stimuli. **B.** Photograph of a participant performing the speech task.

Phonetic coding

Phonetic coding of each participant's produced speech was performed by a trained team of speech pathology students. Using a custom Matlab GUI (github.com/Brain-Modulation-Lab/SpeechCodingApp), onset and offset times, IPA transcription, accuracy and disorder characteristics of each produced phoneme were coded. Speech onsets were marked based on acoustic evidence of key speech features. Voice segments, such as vowels, were marked at the first visible glottal pulse, indicating the onset of vocal fold vibration. Unvoiced phonemes were marked based on the characteristic noise features for that phoneme. For example, the

199   rapid increase of high frequency energy denoted the onset of plosive consonants. A broadband

200   spectrogram was utilized to maximize visualization of key speech features. All coders completed

201   a course in speech science to ensure knowledge of important speech features and were trained

202   in coding procedures by a speech language pathologist.

203   **Electrophysiological data preprocessing**

204   Data processing was performed using custom code based on the FieldTrip (Oostenveld et al.,

205   2011) toolbox implemented in Matlab, available at (github.com/Brain-Modulation-Lab/bml).

206   Recordings from the Grapevine, Neuro-Omega and Zoom-H6 systems were temporally aligned

207   based on the stimulus and produced audio channels using a linear time-warping algorithm.

208   Continuous alignment throughout the entire recording session was achieved with sub-

209   millisecond precision. Data was low-pass filtered at 250 Hz using a 4th order non-causal

210   Butterworth filter, down-sampled to 1 kHz and stored as continuous recordings in FieldTrip

211   datatype-raw objects in mat containers. This frequency range is well-suited for analyses in the

212   canonical frequency bands normally used to explore cognitive functions. All annotations,

213   including descriptions of each session (duration, type of subcortical recording, depth of the MER

214   recordings), details of the electrodes (active time intervals, channel names, coordinates in

215   native and MNI space, anatomical labels), phonetic coding at the phoneme, syllable and triplet

216   level, and times of stimulus presentation were stored in annotation tables.

217   An automatic data cleaning procedure was used to remove segments of data with

218   conspicuous high-power artifacts. First, a 1 Hz high-pass 5th order non-causal Butterworth filter

219   was applied to remove low frequency movement related artifacts. The power at frequencies in

220   different canonical bands (3 Hz for δ, 6 Hz for θ, 10 Hz for α, 21 Hz for β, 45 Hz for γ_L and 160

221   Hz for γ_H) was estimated by convolution with a Morlet wavelet with a width parameter of 9. For

222   each frequency, the maximum power in 1-s time bins was calculated, log-transformed and the

223   mean ($\bar{x}$) and standard deviations (σ) of the distribution were estimated using methods robust to

224   outliers. A time bin was defined as artifactual if its maximal log-transformed power in any band

225   exceeded $\bar{x} + 3\sigma$ for that band. Note that this resulted in thresholds at least 10-fold higher than

226   the mean power. Channels were entirely discarded if more than 50% of the time-bins were

227   classified as containing artifacts. Blocks of channels sharing a head-stage connector were

228   entirely discarded if more than 50% of those channels were defined as artifactual.

229   For each trial, 3 different behavioral epochs were defined: stimulus presentation or

230   listening epoch - the 1.5-s long window during which syllable triplets were presented auditorily;

231   speech production epoch - the variable time during which subjects repeated the syllable triplet;

232   baseline epoch - a 500-ms time window centered between speech offset of one trial and

233   stimulus onset of the following.

234   **Electrophysiology data analysis**

235   **Time-frequency plots.** Time-frequency analyses for neural and audio data were performed

236   using the Short Time Fourier Transform (STFT) method with a 100 ms Hanning window and a

237   frequency step of 2 Hz, based on multiplication in the frequency domain as implemented by

238   FieldTrip. Trials were aligned to speech onset and Z-scored relative to a 500-ms baseline

239   epochs included in every trial. Frequencies up to 250 Hz were used for this analysis as that

240   covers the canonical frequency bands normally used to explore cognitive functions.

241   **Spectrogram correlation analysis.** To index the degree of similarity between the audio

242   spectrogram and the time-frequency spectrogram of a neural channel calculated by the STFT

243   method, a correlation between these two matrices was calculated. This correlation was

244   computed as the normalized sum of the element-by-element products of the two matrices.

245    $$r = \frac{\sum_m \sum_n (A_{m,n} - \bar{A})(B_{m,n} - \bar{B})}{\sqrt{\sum_m \sum_n (A_{m,n} - \bar{A})^2 \times \sum_m \sum_n (B_{m,n} - \bar{B})^2}}$$ (Equation 1)

246   where A represents the audio spectrogram and B the time-frequency spectrogram of data at a

247   given neural channel.

248   **Coherence analysis.** Phase relationship between the audio signal and the neural signal at a

249   given channel was quantified using a metric of inter-trial phase consistency (ITPC) (Cohen,

250   2014). First, the audio and the neural signals were band-pass filtered between 70 and 240 Hz

251   using a 5th order non-causal Butterworth filter. This frequency range contains the fundamental

252   frequency of the voice in humans and the narrowband component studied in this work. A notch

253   filter was applied to remove line noise and its harmonics. For each individual epoch of interest

254   (noted by the index e), and neural channel (X) a complex value φ_e was calculated following

255    $\varphi_e = \frac{1}{|X_e||A_e|} \sum_k S_{e,k} \, A_{e,k}$ (Equation 2)

256   where $S_e = X_e + iH(X_e)$ is the analytic signal, $H(X_e)$ is the Hilbert transform of the neural data

257   for the epoch e , and A_e is the audio signal for that epoch. The sum is taken for every sample *k*

258   within the epoch. $|X_e|$ and $|A_e|$ are the Euclidean norms of the neural and audio signals for

259   epoch e. The absolute value and phase of φ_e represents the degree of correlation and phase

260   relationship between the neural and the audio channels for epoch e. If there is inter-trial phase

261   consistency, the mean value of φ across trials (noted as $\langle\varphi\rangle$) will be significantly different from 0.

262   To quantify this, the ITPC index was defined as

263    $ITPC = \frac{|\langle\varphi\rangle|}{StdErr(\varphi)}$ (Equation 3)

264   where the standard error of φ is defined as $StdErr(\varphi) = \sqrt{\sum_e |\varphi_e - \langle\varphi\rangle|^2}/N$, and the sum is

265   taken over the *N* epochs considered for the neural channel of interest. Note that this metric was

266   calculated independently for the speech production, listening and baseline epochs.

267   **Significance threshold for coherence index.** To define a threshold of significance for the

268   coherence index, a Monte Carlo simulation was performed to obtain the distribution of

269 coherence index under the null hypothesis of no consistent phase relationship between the

270 neural and the audio channels. To this end, a random time jitter uniformly distributed between -

271 100 and 100 ms was applied to the neural data before calculating each φ_e value. 22000

272 independent randomizations were calculated using data from all electrodes in the dataset. This

273 analysis resulted in a significant threshold for the coherence index of 3.08 that corresponds to

274 the 99.99 percentile of the distribution. Thus, a coherence index greater than 3.08 suggests

275 significant correlation of inter-trial phase consistency between the audio and the neural signal.

276 **Objective assessment of acoustic contamination.** A recent study by Roussel et al. 2020,

277 comparing intracranial recordings collected from human subjects during speech perception and

278 production at five different research institutions found that spectrotemporal features of the

279 recorded neural signal are highly correlated with those of the sound produced by the

280 participants or played to participants through a loudspeaker. The method proposed by Roussel

281 et al. for quantifying the extent of acoustic contamination in an electrophysiological recording

282 was applied to the data using the open source toolbox developed by the authors (Roussel et al.,

283 2020) (https://doi.org/10.5281/zenodo.3929296). Briefly, the method correlates the power of the

284 neural data and audio across different frequency bins, thus creating a correlation matrix for

285 every combination of frequencies of the two channels. Significantly higher correlation

286 coefficients at matching frequencies of the two channels (i.e. on the diagonal of the matrix),

287 compared to non-matching frequencies, is considered to be evidence of acoustic contamination.

288 A permutation test is used to determine the significance threshold. The method was applied to

289 data from individual electrodes, and the False Discovery Rate was adjusted according to

290 (Benjamini and Hochberg, 1994).

291 **Testing the spatial distribution of coherence over the brain.** We used hierarchical

292 bootstrapping (Saravanan et al., 2020) to test whether any particular brain region displayed an

293 average coherence that was significantly different from the rest of the brain. Specifically, we

294 built a null distribution of average coherence across the brain by calculating the mean

295 coherence across the brain accounting for subjects as one hierarchical level but ignoring brain

296 regions within subjects. We then calculated the average coherence for the 15 brain regions (as

297 parcellated by the MMP1 atlas) that had coverage in 10 or more subjects, with 3 or more

298 electrodes per subject. Each distribution was again built using subjects as the hierarchical level

299 and electrodes were restricted to those within that particular brain region. Bootstrapping was

300 performed weighing each subject by the number of electrodes present in that region. The

301 distributions were then all compared to the null and the significance threshold was adjusted

302 using an FDR correction for 15 comparisons. Resampling number ($N_{bootstrap}$) was set to 10,000

303 for all bootstrap samples.

Results

304

Narrowband high gamma component in neural recordings during speech production

305

306 We averaged spectrograms time-locked to the speech onset across trials for each audio and

307 neural channel. Representative examples of the averaged spectrograms for each recording type

308 are provided in Figure 2. Figure 2A shows the spectrogram for the produced audio, in which the

309 fundamental frequency (F0) of the participant's voice (at around 120 Hz) and its first harmonic

310 (at around 240 Hz) can be easily discerned as an increase in power at the corresponding

311 frequencies. The 3 peaks of power in the spectrogram at different times correspond to the three

312 produced syllables. A similar narrowband component occurring around the frequencies of the

313 participants' F0 also appeared in some electrodes during the speech production epoch. For

314 example, this narrowband component can be readily observed in the time-frequency plot for one

315 ECoG electrode shown in Figure 2B, but not for another ECoG electrode from the same subject

316 shown in Figure 2C. Thus, while both electrodes show an increase in speech-related gamma

317　activity, the increase in gamma activity in the electrode in Figure 2B is remarkably similar to the

318　narrowband component in the audio spectrogram (Figure 2A), overlapping with it in frequency,

319　time, and overall shape. Similar narrowband components in the high gamma frequency range

320　were also identified in some of the LFP recordings extracted from the micro electrodes (Figure

321　2D), macro electrodes (Figure 2E) and from the DBS leads (Figure 2F). Thus, this narrowband

322　speech-related component can be observed in different electrophysiological recordings

323　collected simultaneously with different acquisition devices.

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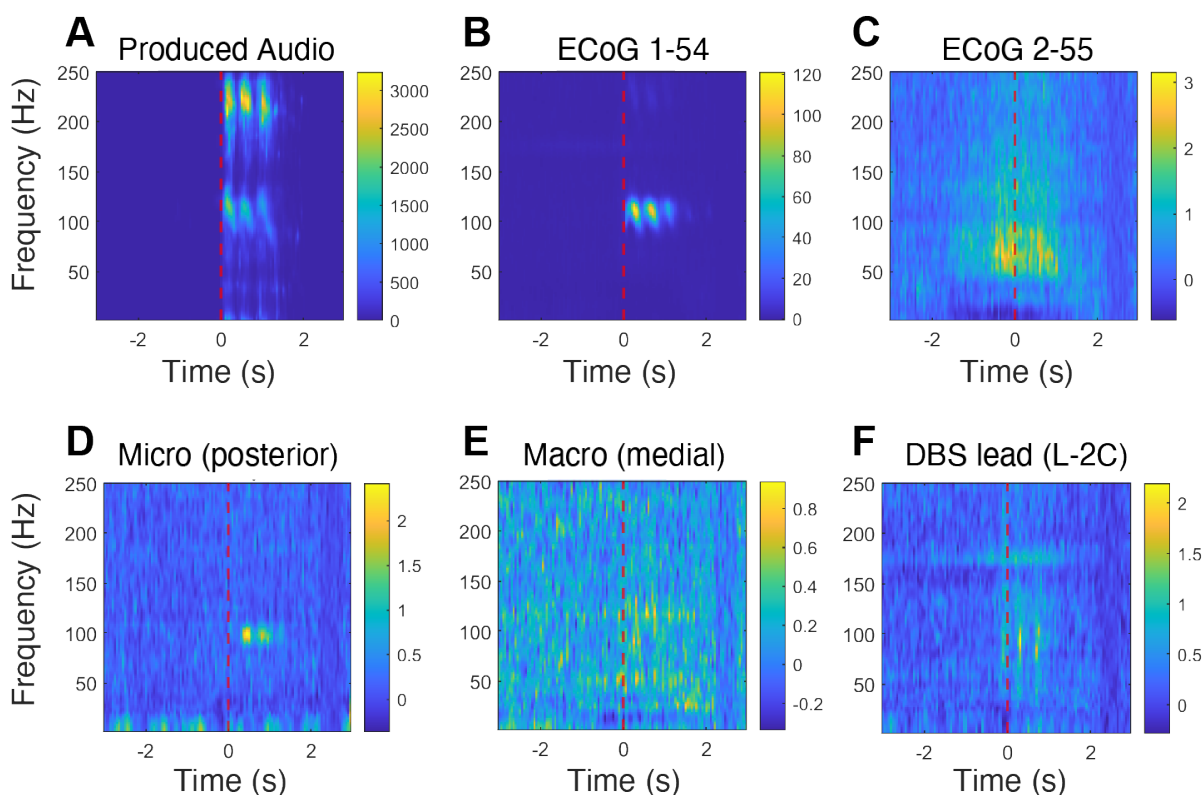
**Figure 2: A speech-related narrowband component in the high gamma frequency range
was observed across different types of neural recordings.**
Time-frequency plots for the audio and different neural channels from subject DBS3014. The
red vertical dashed line represents speech onset time, which was used to time-lock the data
across trials. **A.** Average spectrogram of the produced speech audio, z-scored to baseline. **B.**
ECoG contact 1-54, showing a prominent narrowband high gamma component during the
speech production epoch. **C.** ECoG contact 2-55, showing a broadband activation during
speech production (note that this activity begins before speech onset). **D.** Spectrogram for LFP
signal extracted from the posterior micro electrode targeting the left STN. **E.** Spectrogram for

334 LFP signal from the medial macro ring targeting the left STN. **F.** Spectrogram for the left DBS

335 lead contact.

The narrowband high gamma component correlates with the fundamental frequency of the voice

338 Because of the striking similarity between the neural data and speech spectrogram, we set out

339 to quantify the identified narrowband high gamma component and its relationship with the

340 produced audio further, using different analytical approaches. First, we asked whether the

341 observed overlap in the frequency range between the narrowband component and the produced

342 speech audio was consistent across participants. To this end, we calculated the Welch power

343 spectrum of the audio and neural data during the speech production epochs (Figure 3A),

344 identified at which frequencies peak power within the F0 range (70-240 Hz) occurs in both types

345 of spectra, and correlated the obtained frequency values. For each subject, we used data from

346 single trials of the LFP signal extracted from one of the micro channels of the subcortical

347 mapping electrodes, selected for having a prominent narrowband high gamma component.

348   As can be seen in Figure 3B, there is a strong correlation (Spearman's ρ=0.98, p-value

349 $< 10^{-6}$, intercept = 1.4±5.1 Hz, slope = 0.99±0.4) between the fundamental frequency of the

350 voice and the peak frequency of the narrowband component across participants. Furthermore,

351 the relation not only is linear, but also has a slope not significantly different from 1, meaning that

352 the frequency of peak high gamma power in the neural data corresponds to the fundamental

353 frequency of the voice.
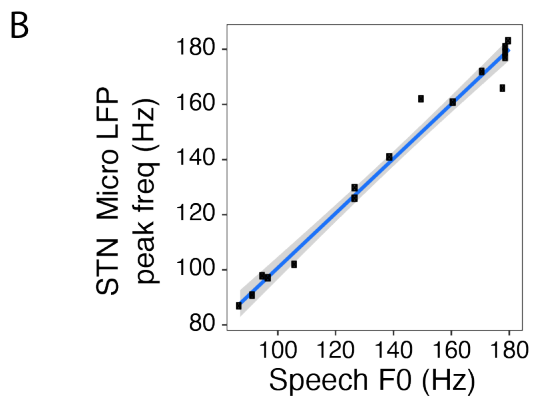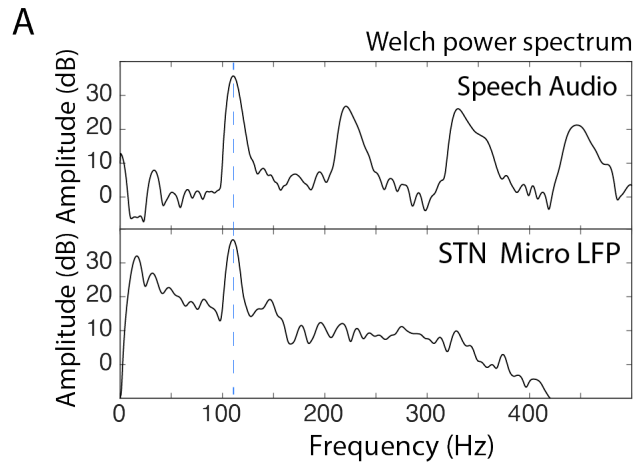
Figure 3: The frequency of peak power of the high gamma narrowband component correlates with the fundamental frequency of the voice across participants.
A. Welch power spectrums for the produced speech audio (top) and the LFP signal extracted from the micro tip of the subcortical mapping electrode by low-pass filtering at 400 Hz (bottom). The vertical dashed blue line represents the frequency of peak power identified in each spectrum. **B.** Correlation of the frequency of peak power in the range of 70-200 Hz between the audio and neural data. Blue line represents the best linear fit to the data; gray ribbon represents the confidence interval of the fit.

Spectrogram cross-correlation between audio and neural data

To further characterize the distribution of this narrowband component across electrodes and

recording sessions, we developed two different and complementary measures of similarity

between the neural signal and the audio signal. The first metric consists of correlating the time-

frequency spectrogram of a neural channel across times and frequencies with the spectrogram

368   of the produced audio. A schematic representation of the method is shown in Figure 4A. For

369   each subject, the correlation coefficient between the spectrogram of the produced audio and the

370   spectrogram of neural recordings was calculated (Equation 1). We found widespread correlation

371   between spectrograms obtained from intracranial recordings and spectrograms of the produced

372   audio, reaching correlation coefficients of up to 0.8 (Figure 4B). The strength of correlations was

373   variable across subjects, recording sessions, and electrodes. Also note that strong correlations

374   were present in different types of intracranial recordings, albeit with a varying consistency.

375

Figure 4: Spectrogram correlation between audio and neural data.
A. A schematic representation of the spectrogram correlation approach. The electrode
spectrogram (top) is multiplied by the audio spectrogram (middle) to give the cross-spectrogram
(bottom). **B.** Correlation coefficients (Equation 1) for each electrode (represented on the y-axis),
and each recording session (represented on the x-axis). Panels are defined by subject and
electrode type. Tiles in gray correspond to electrodes not present in the montage or which were
removed after the artifact rejection.

Consistent phase relationship between audio and neural data

The method described above compares similarity of time-frequency resolved *power* between neural and audio data but does not take into account the phase information of the signals. Therefore, we developed a complementary metric to quantify the *phase* relationship between the neural data and the produced audio, that is, a measure of coherence or inter-trial phase consistency (ITPC) with the produced audio. This metric is based on dot products of the analytic signal of the neural channel and the produced audio, as schematized in Figure 5A. For each epoch, a complex value representing the magnitude of the correlation and the phase relationship of the neural signal with the audio is obtained (Equation 2). If the mean of these complex values is significantly different from zero, this serves as evidence of a consistent phase relationship between the neural data and the produced speech (Figure 5B). We used the absolute value of the mean of these complex values, normalized by their standard error, as an index of coherence (Equation 3). This method is computationally efficient and well suited for narrowband signals as the one we are characterizing (see details in Methods Section). We calculated a significance threshold using a Monte Carlo simulation in which we applied random time jitters before calculating the coherence index (see details in Methods Section).

As observed in Figure 5C, there is widespread coherence across many subjects and all electrode types during the speech production epoch. Around 50% of the analyzed electrodes show significant coherence with the audio during the speech production epoch (Table 2). Importantly, no significant coherence with the speech audio was observed during the baseline or listening epochs (Table 2). Coherence of the neural signals with the stimulus audio in all behavioral epochs, including the listening epoch, was negligible (Table 2). This suggests that only the process of producing speech sounds was contaminating the neural signal.

The distribution of the coherence indices across electrodes for each recording session can be classified as i) having no or little coherence between neural channels and the produced speech (e.g. subjects 06, 03, 21); ii) having homogenous coherence across electrodes, (e.g.

409   subjects 02, 04); and iii) having heterogeneous coherence across electrodes (e.g. subjects 14,

410   28). While for the homogeneous case both the amplitude of the coherence ($|<\varphi>|$) and the

411   phase relationship with the produced speech are similar across the neural electrodes, in the

412   heterogeneous recording sessions these values may change substantially across electrodes

413   (Figure 5D).

414

Figure 5: Inter-trial phase consistency (ITPC) reveals significant coherence of neural data with the produced speech audio.
A. An ITPC index is derived from multiplying the band-pass filtered analytic neural signal (blue and orange lines for real and imaginary parts) with the produced speech signal (black line) using the internal product, resulting in a complex value φ for each trial. **B.** An example φ values plotted on the complex plane (real part of φ on the x axis and imaginary part on the y axis) for three behavioral epochs: baseline (green circles), listening (blue squares), and speech production (red triangles). The ITPC index is related to the average value of $< \varphi_e >$, represented as a red arrow for the speech production epoch. For the baseline and listening epochs the $< \varphi_e > = 0$, indicating no phase consistency between the neural and the audio data. The circled point in the bottom left quadrant of the plot corresponds to the traces shown in

panel A. **C.** ITPC indices from the speech production epoch plotted for each electrode, recording session, and subject. Each row corresponds to an electrode; each column - to an individual session; panels are defined by subject and data type. Tiles in gray correspond to electrodes that were not present in the montage or which were removed after artifact rejection. White tiles represent electrodes that do not show significant coherence indices **D.** Phase consistency of the neural data with the produced audio across contacts of the ECoG strips. In each polar plot, the angle between the radial lines and the horizontal axis represents the phase relation with the produced audio of an ECoG electrode. Red asterisks mark ECoG strips with homogeneous coherence, defined as those with at least 90% of the electrodes' phases within 90º of each other.

The speech acoustic component can be detected in the neural data by different

quantification methods

The spectrogram correlation index (Figure 4) and the coherence index (Figure 5) are highly

correlated with each other, as can be observed in Figure 6A (Spearman's $\rho = 0.7$, $p < 1e\text{-}6$). In

applying the method proposed by Roussel et al. (2020), the power of the neural data was

correlated with the audio across different frequency bins to create a correlation matrix (Figure

6B). High correlation coefficients on the diagonal of this matrix indicate acoustic contamination

(see details in the Methods Section). Electrodes classified as contaminated based on this

method are indicated by red triangles in Figure 6A. As can be observed, these points tend to

have high spectrogram correlation index and coherence index above the significant threshold

(Figure 6A). This result suggests that all three methods have similar sensitivity in identifying

speech-related artifacts in our dataset.
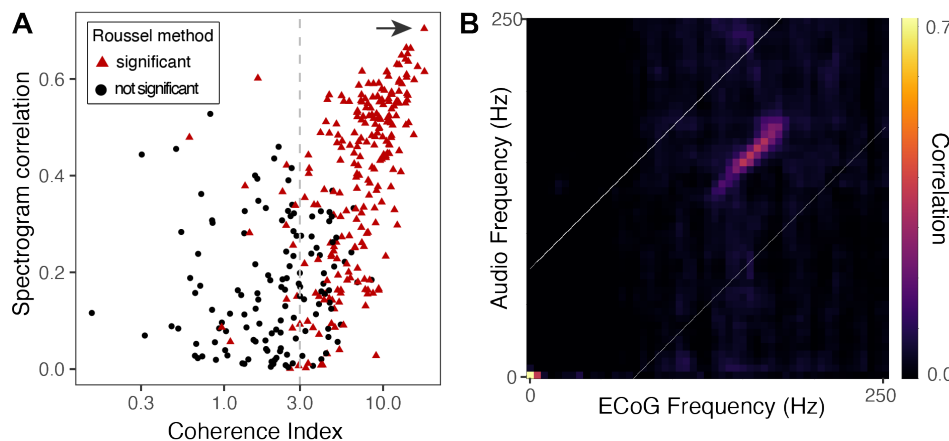
Figure 6: The spectrogram correlation index and the coherence index show strong correlation with each other and high consistency with the Roussel et al. method's outcome.
**A.** Relationship between the spectrogram correlation index and the coherence index for ECoG electrodes for one representative subject (DBS3024). Red triangles indicate electrodes with significant 'acoustic contamination' as assessed by the method developed by Roussel et al., 2020. **B.** Detection of acoustic contamination by the Roussel method is based on the cross-frequency correlation matrix, which indicates degrees of correlation of power across time for different frequencies of the neural and audio data. The shown matrix corresponds to ECoG electrode 2-31, indicated by an arrow in panel A.

Audio	Produced speech audio				Stimulus audio			
Method	Coherence			Roussel	Coherence			Roussel
Epoch	baseline	listening	speech	all	baseline	listening	speech	all
ECoG	0.2±0.1%	0.2±0.1%	52±6%	54±5%	0.4±0.3%	0.2±0.1%	1.4±0.7%	2.2±0.5%
Macro	0%	0%	42±8%	25±5%	0%	0%	0%	4±2%
Micro	0%	0%	56±7%	96±7%	0%	0%	0%	0.6±0.8%
DBS Lead	0%	0%	47±10%	59±10%	6±6%	7±6%	10±8%	12±8%
Blank	10±4%	12±5%	65±8%	71±6%	2±2%	15±8	3±2%	12±7%

Table 2. Percentage (± standard error) of electrodes showing significant similarity between neural data and the produced speech audio or stimulus audio, as established by the coherence method and the Roussel et al.'s method. The coherence method was run independently for the baseline, listening and speech production epochs. The Roussel et al. 2020 method used the entire duration of the session. Hierarchical bootstrapping was used to estimate the standard error.

Coherence indices for cortical recording sites are independent of anatomic location

Next, we asked if there is any spatial structure of the coherence index within the cortex. To this end, we performed a hierarchical bootstrapping analysis accounting for the nested nature of the data (electrodes within anatomical regions within subjects) and found that none of the cortical regions (as defined by the Multi Modal Parcellation 1 in Glasser et al., 2016) show values of coherence significantly higher than the average distribution over the entire brain (see methods for detail). All cortical electrodes with their corresponding coherence values are plotted on a standard brain in Figure 7. Electrodes with high coherence with the produced audio do not cluster on any specific neuroanatomical region.
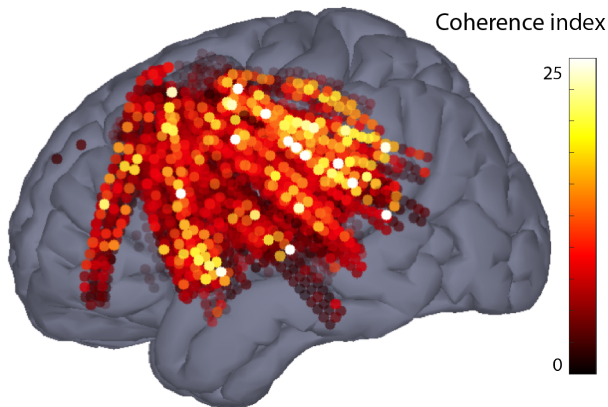
Figure 7: Increased Inter-trial Phase Consistency is not specific to any cortical region.
Localizations of cortical ECoG electrodes for the entire subject cohort (n = 29) plotted in MNI space (MNI152 Nonlinear Asymmetric 2009b, (Fonov et al., 2011)). The color of the points represents the average coherence between neural and produced audio data for that electrode.

Speech-related vibrations can be detected in non-neural data

The experiments described above demonstrated that some neural recordings show time-frequency patterns similar to the produced audio recordings. This suggests that there is contamination of the electrophysiological neural data with the speech audio signal. If this is the case, we expect to find the same kind of contamination in "blank" electrodes not in contact with the brain. Most of the ECoG strips used in our experiments contained 63 contacts laid out in a 3 x 21 arrangement (Figure 8A). These contacts were connected to the amplifier's front-end

486 through 4 cabrio-type connectors, each containing 16 pins. This resulted in the last pin of the 4th

487 cabrio connector (#64) not connected to any electrode on the brain. Instead, the wire connected

488 to this pin runs the length of the cable and ends within the silicon rubber matrix of the ECoG

489 strip. We recorded the signal from this "blank" pin as it provides a control for all non-neural

490 sources of noise affecting the neural signal. Using the same time-frequency method as before,

491 we analyzed the recorded signal from this blank ECoG headstage pin. As can be observed in

492 Figure 8B, a narrowband component similar to that observed in some neural recordings is also

493 present during speech production in the recordings from the blank headstage pin. It is

494 interesting to note that the frequency of peak power recorded from this pin is slightly lower than

495 the fundamental frequency of the voice (Figure 8C), although the component has the same

496 timing and overall pattern (note the power increase around the first harmonic of the F0). As

497 shown in the bottom row of the Figure 5C, labeled 'Blank', signals from the blank headstage

498 pins show significant coherence with the produced speech audio in the same recording

499 sessions that showed strong coherence with the produced speech audio in other electrode

500 types (see also Figure 4B and Table 2).

501 These results strongly suggest that the source of the observed narrowband component

502 is not neural. Among possible sources of this component are speech-induced vibrations of the

503 stereotactic frame, cables, connectors and/or acquisition chain. To address this question, we

504 attached a piezoelectric vibration sensor to the stereotactic frame (Figure 8D) during data

505 collection in one subject (subject DBS3029). The recorded signal from the piezoelectric sensor

506 was analyzed in the same way as other types of recordings. A strong narrowband component

507 was observed at the time corresponding to the production of the first syllable, in the same

508 frequency range as the fundamental frequency of the voice (Fig. 8E). The attenuated power

509 observed during the time of the production of the second and the third syllables might be due to

510 the fact that in this particular participant speech intensity decreased across the produced

511 syllable triplet, as seen in the audio spectrogram in Figure 8F.
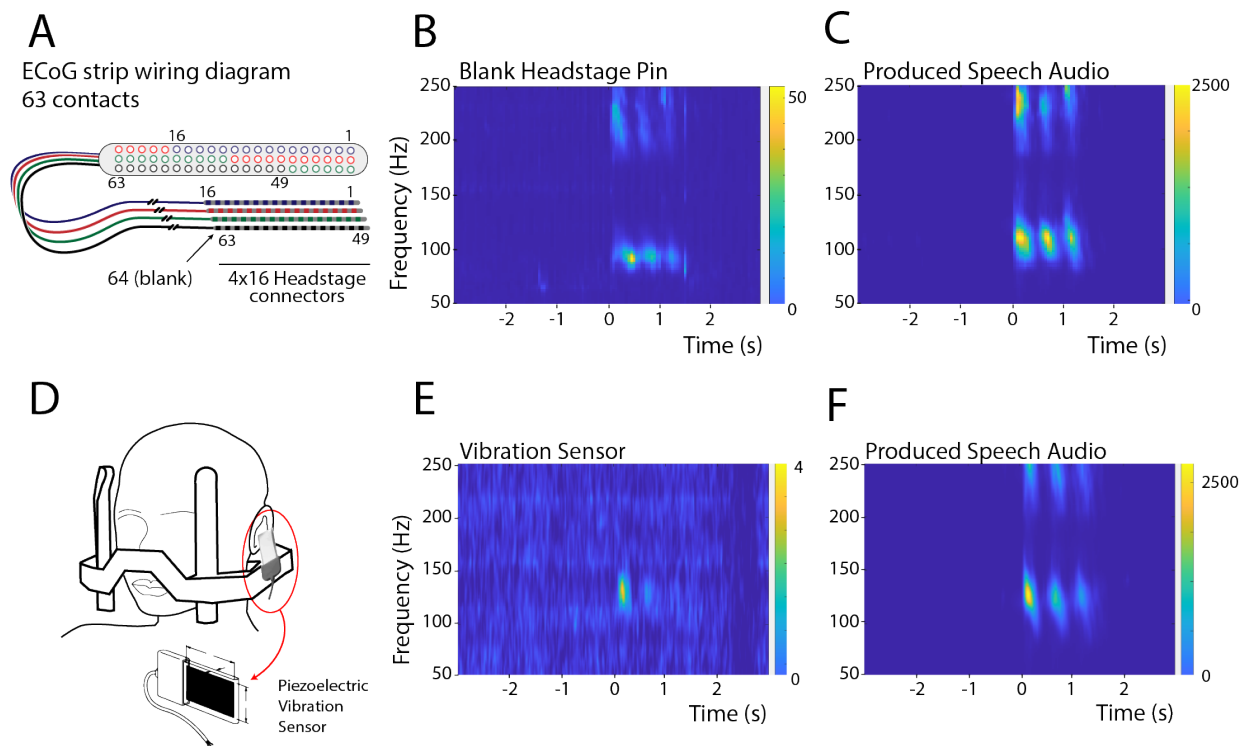
Figure 8: The narrowband component is present in non-neural recordings.
A. A schematic of the ECoG electrode strip showing the electrode contact and connector layout. 4 cables of 16 wires are used for the 63 electrodes, resulting in one headstage pin not connected to any electrode on the brain (marked as contact #64). **B.** Time-frequency plot of the signal recorded from the blank headstage pin (subject DBS3020). **C.** Spectrogram of the produced speech audio for the same subject as in B. **D.** A schematic representation of the montage of the vibration sensor on the stereotactic frame. **E.** Time-frequency plot of the signal recorded from the vibration sensor (subject DBS3029). **F.** Spectrogram of the produced speech for the same subject as in E. In panels B-C and E-F, zero marks the onset of the speech production.

Discussion

We identified the presence of a narrowband high gamma component in the neural signals recorded from patients undergoing DBS implantation surgery that is consistent with a mechanically induced artifact. This component is widespread across many electrode types and was the most prominent feature in many electrode recordings. It occurs almost exclusively during cued speech production epochs and it has spectral and temporal characteristics strikingly

similar to the produced speech audio. Indeed, a recent work shows the presence of acoustic contamination on ECoG recordings (Roussel et al., 2020). In the environment of DBS surgery, speech-induced vibrations conducted by the skull and stereotactic frame can impinge on the electrodes and/or signal acquisition chain affecting the recorded signal.

Several results support the interpretation that the observed narrowband high gamma component is an artifact due to speech-induced vibrations. First, the frequency of peak power of the narrowband component tracks the fundamental frequency of the voice across participants (Figure 3). Second, the narrowband high gamma component is almost exclusively present during the cued speech production epoch, but not the listening epoch (Table 2). Thirdly, the time-frequency resolved power from the neural recordings strongly correlates with the produced audio spectrogram (Figure 4). Fourth, significant inter-trial phase consistency between the produced audio and the neural data suggests similarities not only across the frequency domain, but also the temporal domain (Figure 5). Fifth, most of the recordings that we classified as contaminated in our analysis were also classified as having acoustic contamination by the recently proposed method in Roussel et al. (2020) (Figure 6 and Table 2). Sixth, there was no significant cortical localization of the ITPC index (Figure 7). Finally, the narrowband high gamma component was also detected in "blank" pins of the headstage connector not connected to any electrode (Figure 8B) and in the recording from a vibration sensor attached to the stereotactic frame (Figure 8E). Taken together, these results strongly suggest the presence of speech-induced vibration artifact.

Although we cannot rule out the presence of physiological neural activity with the exact same spectral and timing characteristics as the observed narrowband high gamma component, we favor the interpretation that the narrowband component identified in this work is mainly, if not completely, due to the vibration artifact. It is worth mentioning that broadband gamma activity can be detected in many electrodes (see example in Figure 2C), including some that also show the vibration artifact.

555   These results are in line with a recent report by Roussel et al. (2020), in which the

556   authors show evidence for acoustic contamination of ECoG recordings. The authors analyze

557   multiple-center datasets collected in epilepsy patients in an extra-operative setting, finding that

558   both produced, and stimulus audio can affect ECoG recordings. Our work extends these

559   findings, showing that the same kind of contamination can occur not only in the ECoG

560   recordings, but can also affect other types of invasive neural recordings, such as those collected

561   in the context of DBS implantation surgery. In addition, there are two key differences to note

562   between our results and those of Roussel et al. First, we only observe contamination when the

563   patient is speaking, but not during auditory stimulus presentation. This difference may be due to

564   the use of headphones in our recording setup as opposed to the loudspeaker in the work by

565   Roussel et al., who found that acoustically isolating the speaker reduced contamination of the

566   neural signal. Second, in our recordings the affected signals are those corresponding to the F0

567   and to a lesser extent its harmonics. This could be explained by the fact that the stereotactic

568   frame imposes some additional mechanical constraints, thus changing the way the vibration

569   propagates.

570   Despite the fact that intracranial recordings in general are less prone to artifacts than

571   extracranial recordings, it is recognized that the patient's speech induces vibrations that affect

572   MER. For example, a patent for a new micro-electrode design from AlphaOmega mentions that

573   "*various mechanical noise and vibration, such as motor vibration, motion of the electrode within*

574   *the tissue or voice of the subject, are detected by the electrode that acts essentially as*

575   *microphone and is erroneously combined with the neural signal that is being recorded*" (Alpha

576   Omega Technologies, 2020). Therefore, a common practice has been to analyze the recordings

577   only when the patient is not speaking. The introduction of "microphonic free" microelectrodes

578   with improved shielding that reduces the effects of vibrations on the recordings, allows acquiring

579   single unit activity while the patient is speaking (Alpha Omega Technologies, 2020). Besides the

580   clear clinical advantage, this has opened the possibility of studying single unit activity of DBS

581 target structures during speech production. Although the quantifications of single-unit firing can

582 be reliably performed with these electrodes (Lipski et al., 2017, 2018), in light of our results it is

583 clear that mechanical vibrations affect other intracortical recordings including those obtained

584 with macro contacts on the shaft of the micro electrodes, recordings from ECoG strips and

585 recordings from the clinically implanted DBS leads.

586 Interestingly, neural signals with similar characteristics to the narrowband high gamma

587 component described in this work have been reported in the literature. The Frequency Following

588 Response (FFR) in the auditory brainstem is a potential with spectrotemporal features

589 resembling the stimulus audio that reflects sustained neural ensemble activity phase-locked to

590 periodic acoustic stimuli (Bidelman, 2018; Marsh and Worden, 1968; Marsh et al., 1970; Rose et

591 al., 1966). This brainstem response to auditory stimuli can be recorded from scalp electrodes by

592 averaging over hundreds of trials, a technique that has become a powerful diagnostic tool in

593 audiology and neurology known as the Auditory Brainstem Response (Hall, 1992; Jewett et al.,

594 1970). In recent years several works based on scalp EEG, sEEG and MEG have reported

595 cortical FFRs (Behroozmand et al., 2016; Bidelman, 2018; Coffey et al., 2016).

596 In our data, there are two features that argue against the narrowband component being

597 a true FFR. First, it only occurs during speech production and not during auditory stimulus

598 presentation. Second, the narrowband artifact is not localized to the auditory cortex, or to any

599 other cortical region (Figure 7). In light of the results presented in this work and similar results

600 recently published by Roussel et al, it is clear that caution should be taken when interpreting

601 cortical FFR, due to the fact that this signal is exactly what would be expected if there was an

602 artifact (e.g., vibration at electrodes or connectors, electromagnetic induction by speakers,

603 electrical crosstalk in the amplifier or connectors).

604 Other reported sources of artifacts affecting intracranial recordings, including artifacts

605 due to eye blinking (Ball et al., 2009) and other facial muscle contraction (Otsubo et al., 2008),

606 have spectral characteristics distinct from the narrowband component described in this work;

607 they show broadband spectrums that do not match that of the produced audio and are not

608 expected to track the fundamental frequency of the voice or correlate with the power of the

609 speech audio across time.

610 Acknowledging the existence of this speech-induced vibration artifact is an important first

611 step to avoid overinterpreting spurious features of the data. Many important questions related to

612 high-level cognitive processes, including the neural control of speech production, can only be

613 answered by acquiring recordings that are likely to be affected by the described artifact, but

614 several steps can be taken to identify it. First, methods that correlate the audio signal with the

615 neural data can be used to detect the presence of acoustic contaminations. Second, recording

616 from open headstage pins provides a control for non-neural sources affecting the signal. Third,

617 vibration sensors can detect mechanical vibrations along the recording system that might affect

618 the signal. Furthermore, invasive recordings for BCI applications are likely to be affected by

619 speech-induced vibrations, compromising the decoding performance. Therefore, it is necessary

620 to develop source separation methods to remove speech-related artifacts from the neural data

621 in order to reliably quantify underlying neural activity.

622 Identifying and mitigating artifacts in intracranial recordings from awake patients is

623 fundamental to achieving reliable and reproducible results in the field of human systems

624 neuroscience. This, in turn, will lead to an improved understanding of the neural physiology and

625 pathophysiology of uniquely human cognitive abilities.

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Author Contributions

W.J.L. and R.M.R. designed the experiment and performed the recordings. A.B., A.C., C.D.-H. and W.J.L. reconstructed the electrode localizations and preprocessed the electrophysiological data. A.C. and C.D.-H. overviewed the phonetic coding. A.B., A.C., V.P., V.S., C.D.-H. analyzed data. A.B. and A.C. wrote the manuscript. All authors discussed the results and implications and commented on the manuscript at all stages. The authors declare no competing financial interests.

References

Alpha Omega Technologies. (2020). Reduced Larsen Effect Electrode.

Anumanchipalli, G.K., Chartier, J., and Chang, E.F. (2019). Speech synthesis from neural decoding of spoken sentences. Nature 568, 493–498.

Avants, B.B., Epstein, C.L., Grossman, M., and Gee, J.C. (2008). Symmetric diffeomorphic image registration with cross-correlation: Evaluating automated labeling of elderly and neurodegenerative brain. Med Image Anal 12, 26–41.

Ball, T., Kern, M., Mutschler, I., Aertsen, A., and Schulze-Bonhage, A. (2009). Signal quality of simultaneously recorded invasive and non-invasive EEG. Neuroimage 46, 708–716.

Behroozmand, R., Oya, H., Nourski, K.V., Kawasaki, H., Larson, C.R., Brugge, J.F., Howard, M.A., and Greenlee, J.D.W. (2016). Neural correlates of vocal production and motor control in human Heschl's gyrus. J Neurosci 36, 2302–2315.

650 Benjamini, Y., and Hochberg, Y. (1994). Controlling the false discovery rate: a practical and
651   powerful approach to multiple testing. Journal of the Royal statistical society: series B
652   (Methodological), *57(1), 289-300.*

653 Bidelman, G.M. (2018). Subcortical sources dominate the neuroelectric auditory frequency-
654   following response to speech. Neuroimage *175*, 56–69.

655 Bouchard, K.E., Mesgarani, N., Johnson, K., and Chang, E.F. (2013). Functional organization of
656   human sensorimotor cortex for speech articulation. Nature *495*, 327--332.

657 Cheung, C., Hamiton, L.S., Johnson, K., and Chang, E.F. (2016). The auditory representation of
658   speech sounds in human motor cortex. Elife 5, e*12577*.

659 Chrabaszcz, A., Neumann, W.-J., Stretcu, O., Lipski, W.J., Bush, A., Dastolfo-Hromack, C.A.,
660   Wang, D., Crammond, D.J., Shaiman, S., Dickey, M.W., et al. (2019). Subthalamic
661   nucleus and sensorimotor cortex activity during speech production. J Neurosci *39*, 2698--
662   2708.

663 Coffey, E.B.J., Herholz, S.C., Chepesiuk, A.M.P., Baillet, S., and Zatorre, R.J. (2016). Cortical
664   contributions to the auditory frequency-following response revealed by MEG. Nat
665   Commun 7, 1*1070*.

666 Cohen, M.X. (2014). Analyzing Neural Time Series Data. MIT Press.

667 Conant, D.F., Bouchard, K.E., Leonard, M.K., and Chang, E.F. (2018). Human Sensorimotor
668   Cortex Control of Directly Measured Vocal Tract Movements during Vowel Production. J
669   Neurosci *38*, 2955–2966.

670 Crone, N.E., Hao, L., Hart, J., Boatman, D., Lesser, R.P., Irizarry, R., and Gordon, B. (2001).
671   Electrocorticographic gamma activity during word production in spoken and sign
672   language. Neurology 57, 2045--2053.

673 Edwards, E., Nagarajan, S.S., Dalal, S.S., Canolty, R.T., Kirsch, H.E., Barbaro, N.M., and
674   Knight, R.T. (2010). Spatiotemporal imaging of cortical activation during verb generation
675   and picture naming. Neuroimage *50*, 291–301.

676 Ewert, S., Plettig, P., Li, N., Chakravarty, M.M., Collins, D.L., Herrington, T.M., Kühn, A.A., and
677   Horn, A. (2018). Toward defining deep brain stimulation targets in MNI space: A
678   subcortical atlas based on multimodal MRI, histology and structural connectivity.
679   Neuroimage *170, 271–282.*

680 Faraji, A.H., Kokkinos, V., Sweat, J.C., Crammond, D.J., and Richardson, R.M. (2020). Robotic-

Assisted Stereotaxy for Deep Brain Stimulation Lead Implantation in Awake Patients. Oper Neurosurg 19, 444–452.

Flinker, A., Korzeniewska, A., Shestyuk, A.Y., Franaszczuk, P.J., Dronkers, N.F., Knight, R.T., and Crone, N.E. (2015). Redefining the role of Broca's area in speech. Proc National Acad Sci *112*, 2871–2875.

Flinker, A., Piai, V., and Knight, R.T. (2018). Intracranial electrophysiology in language research, in The Oxford handbook of psycholinguistics (2dn ed.). 992–1010.

Fonov, V., Evans, A.C., Botteron, K., Almli, C.R., McKinstry, R.C., Collins, D.L., and Group, the B.D.C. (*2011*). Unbiased Unbiased average age-appropriate atlases for pediatric studies. Neuroimage, 54(1), 313-327.

Glasser, M.F., Coalson, T.S., Robinson, E.C., Hacker, C.D., Harwell, J., Yacoub, E., Ugurbil, K., Andersson, J., Beckmann, C.F., Jenkinson, M., et al. (2016). A multi-modal parcellation of human cerebral cortex. Nature *536*, 171–1*78*.

Hall, J.W. (1992). Handbook of auditory evoked responses. Allyn & Bacon.

Hamilton, L.S., Edwards, E., and Chang, E.F. (2018). A Spatial Map of Onset and Sustained Responses to Speech in the Human Superior Temporal Gyrus. Curr Biol *28, 1860-1871.e4*.

Horn, A., and Kühn, A.A. (2015). Lead-DBS: A toolbox for deep brain stimulation electrode localizations and visualizations. Neuroimage *107, 127--135.*

Jewett, D.L., Romano, M.N., and Williston, J.S. (1*9*70). Human auditory evoked potentials: possible brain stem components detected on the scalp. Science, *167(3924), 1517-1518*.

Lachaux, J.P., Rudrauf, D., and Kahane, P. (2003). Intracranial EEG and human brain mapping. J Physiology-Paris *97, 613–628*.

Lipski, W.J., Wozny, T.A., Alhourani, A., Kondylis, E.D., Turner, R.S., Crammond, D.J., and Richardson, R.M. (2017). Dynamics of human subthalamic neuron phase-locking to motor and sensory cortical oscillations during movement. J Neurophysiol *118*, 1472--1487.

Lipski, W.J., Alhourani, A., Pirnia, T., Jones, P.W., Dastolfo-Hromack, C., Helou, L.B., Crammond, D.J., Shaiman, S., Dickey, M.W., Holt, L.L., et al. (2018). Subthalamic nucleus neurons differentially encode early and late aspects of speech production. J Neurosci 38, 5620–5*63*1.

711 Llorens, A., Trébuchon, A., Liégeois-Chauvel, C., and Alario, F.-X. (2011). Intra-Cranial
712   Recordings of Brain Activity During Language Production. Front Psychol *2, 375*.

713 Marsh, J.T., and Worden, F.G. (1968). Sound evoked frequency-following responses in the
714   central auditory pathway. Laryngoscope 78, 1149–1163.

715 Marsh, J.T., Worden, F.G., and Smith, J.C. (1970). Auditory Frequency-Following Response:
716   Neural or Artifact? Science *169*, 1222–1223.

717 Martin, S., Millán, J. del R., Knight, R.T., and Pasley, B.N. (2019). The use of intracranial
718   recordings to decode human language: Challenges and opportunities. Brain Lang *193*,
719   73–83.

720 Mesgarani, N., Cheung, C., Johnson, K., and Chang, E.F. (2014). Phonetic Feature Encoding in
721   Human Superior Temporal Gyrus. Science *343*, 1006–1010.

722 Mugler, E.M., Tate, M.C., Livescu, K., Templer, J.W., Goldrick, M.A., and Slutzky, M.W. (2018).
723   Differential representation of articulatory gestures and phonemes in precentral and inferior
724   frontal gyri. J Neurosci 38, 9803--9813.

725 Mukamel, R., and Fried, I. (2012). Human Intracranial Recordings and Cognitive Neuroscience.
726   Annu Rev Psychol 63, *511*–537.

727 Niemann, K., Mennicken, V.R., Jeanmonod, D., and Morel, A. (2000). The Morel Stereotactic
728   Atlas of the Human Thalamus: Atlas-to-MR Registration of Internally Consistent Canonical
729   Model. Neuroimage 12, 601–616.

730 Oostenveld, R., Fries, P., Maris, E., and Schoffelen, J.-M. (2011). FieldTrip: Open Source
731   Software for Advanced Analysis of MEG, EEG, and Invasive Electrophysiological Data.
732   Comput Intel Neurosc 2011, 156869.

733 Otsubo, H., Ochi, A., Imai, K., Akiyama, T., Fujimoto, A., Go, C., Dirks, P., and Donner, E.J.
734   (2008). High-frequency oscillations of ictal muscle activity and epileptogenic discharges on
735   intracranial EEG in a temporal lobe epilepsy patient. Clin Neurophysiol *119*, 862–868.

736 Panov, F., Levin, E., Hemptinne, C. de, Swann, N.C., Qasim, S., Miocinovic, S., Ostrem, J.L.,
737   and Starr, P.A. (2017). Intraoperative electrocorticography for physiological research in
738   movement disorders: principles and experience in 200 cases. J Neurosurg *126*, 122--131.

739 Randazzo, M.J., Kondylis, E.D., Alhourani, A., Wozny, T.A., Lipski, W.J., Crammond, D.J., and
740   Richardson, R.M. (2016). Three-dimensional localization of cortical electrodes in deep

741   brain stimulation surgery from intraoperative fluoroscopy. Neuroimage *125, 515–521.*

742 Rose, J.R., Brugge, J.F., Anderson, D.J., and Hind, J.E. (1966). Phase-locked response to low-
743   frequency tones in single auditory nerve fibers of the squirrel monkey. Journal of
744   neurophysiology *30.4: 769-793.*

745 Roussel, P., Godais, G.L., Bocquelet, F., Palma, M., Hongjie, J., Zhang, S., Giraud, A.-L.,
746   Mgevand, P., Miller, K., Gehrig, J., et al. (2020). Observation and assessment of acoustic
747   contamination of electrophysiological brain signals during speech production and sound
748   perception. J Neural Eng *17, 056028.*

749 Saravanan, V., Berman, G.J., and Sober, S.J. (2020). Application of the hierarchical bootstrap
750   to multi-level data in neuroscience. Arxiv.

751 Schalk, G., McFarland, D.J., Hinterberger, T., Birbaumer, N., and Wolpaw, J.R. (2004).
752   BCI2000: a general-purpose brain-computer interface (BCI) system. Ieee T Bio-Med Eng
753   51, 1034–1043.

754 Sisterson, N.D., Carlson, A.A., Rutishauser, U., Mamelak, A.N., Flagg, M., Pouratian, N.,
755   Salimpour, Y., Anderson, W.S., and Richardson, R.M. (2021). Electrocorticography during
756   deep brain stimulation surgery: safety experience from 4 centers within the national
757   institute of neurological disorders and stroke research opportunities in human consortium.
758   neurosurgery.