IEEE BIBE 2020

EEG noise model in cortical source localization of ICA-derived source scalp projection maps

Zeynep Akalin Acar
Swartz Center for Computational Neuroscience
Institute for Neural Computation
University of California San Diego
La Jolla CA 92093-0559
zeynep@sccn.ucsd.edu

Scott Makeig
Swartz Center for Computational Neuroscience
Institute for Neural Computation
University of California San Diego
La Jolla CA 92093-0559
smakeig@ucsd.edu

***Abstract*—In this work, we introduce a novel approach to estimating the noise covariance matrix of ICA-derived source scalp projection maps, and show that it is useful for estimating cortical source distributions in source-resolved EEG brain imaging. To determine spatial noise characteristics for individual independent component (IC) maps (found by AMICA decomposition), we used RELICA (Bootstrap-ICA) to generate 50 similar bootstrap decompositions for the same EEG data set. This allowed us to identify clusters of bootstrap ICs for IC maps associated with the brain effective sources in the full EEG data decomposition. This, in turn, made it possible to estimate the statistical stability of the related whole-data ICs. We used the Sparse Compact Smooth (SCS) algorithm for cortical source localization. When noise covariance matrix was initialized using RELICA-component cluster covariance maps, we observed an improvement of in source localization. The peaks of the patch sources moved an average of 14.6 mm (range 2–20 mm) and in, some cases, were localized in different sulci or gyri.**

***Index Terms*—EEG, cortical source localization, noise, ICA, NFT, RELICA.**

I. Introduction

There are three main challenges for improving the accuracy of EEG source imaging: 1. Better head modeling: Determining and dealing with error and uncertainty in the electrical head model. 2. Better Source modeling: Understanding and incorporating the temporal dynamics of the sources into the EEG inverse problem. 3. Better Spatial models: Incorporating the observation that the neural current sources projecting coherently to the scalp need not be confined to a single voxel of a cortical model but rather, may be expected to be a smooth distribution over a compact set of voxels. Another important element of EEG source dynamics is the expected time-variation of the effective sources, where the sparsity variation exhibits locality, periodicity, etc. Here, we focus on spatial source modeling and illustrate how correctly modeling spatial uncertainty in ICA-decomposed EEG component processes can improve the accuracy of their localization.

The volume conductor model used, and the source localization method itself are the two major determinants of any EEG source localization approach. Our previous work on the NFT forward problem head modeling toolbox [1], and our more recent work on simultaneous conductivity and source location estimation (SCALE) has focused on improving electrical head modeling [2], [3]. There have been numerous proposed approaches for solving the EEG inverse problem using either parametric or linear distributed source localization methods [4]–[6]. Since the EEG inverse problem is ill-posed, a priori assumptions are required to constrain the space of solutions, such as the number of sources and anatomical and neurophysiological constraints including smoothness, sparsity, spatial extent, etc. [7]. Parametric methods represent the brain sources by oriented equivalent dipoles placed inside the model brain volume, while linear distributed methods constrain the sources of the brain to be in gray matter and oriented perpendicular to the cortex, and typically estimate a spatial source distribution that fits the data [8].

The compact current sources assumption in EEG implies a spatial sparsity assumption. However, effective sources cannot be point sources (within a single cortical model voxel); they should have some further spatial extent, resulting in the need to extend the source model. For parametric models this may mean introducing additional parameters such as equivalent dipole number, size, or pattern symmetry. For distributed algorithms, the lead field matrix can encode the source model (e.g., a patch basis [9]) in addition to the head geometry and electrical properties of the head for each voxel.

In this work we apply the SCS (Sparse Compact Smooth) algorithm [10] to generate distributed source images of the scalp projection maps obtained from near-dipolar EEG effective sources found by independent component analysis (ICA) decomposition [11] of sufficient high-density EEG data. In SCS solutions, we obtain compact source distributions with low residual error. The distribution weights of most cortical voxels are close to zero, with from one to a few clusters of high-intensity voxel weights representing the active source areas. The contribution of the very large number of low-weighted voxels to the solution should be negligible. Here we demonstrate that for SCS, this rewards use of a data-driven source map noise model.

The sources of EEG noise include: environmental noise (AC power lines, other EM noise, subject movement, etc.), ECG, EMG, EOG, and skin potentials. Although ICA decomposition can separate out sources of EMG, EOG, ECG, and (in favorable circumstances) environmental noise [12], there may still be residual uncertaintly in the IC scalp projection maps of the effective brain sources included in the decomposition.

While noise occurring in EEG data has been studied [7], [13], how to model the noise characteristics of individual IC scalp maps generated by an ICA decomposition of the whole data is unclear. In this work, we first compared the two distributed source localization methods available in the NFT toolbox, and investigated the effect of the SCS scalp map uncertaintly model by plotting the residual variance from the IC scalp map of the back-projected scalp projection of the SCS-derived, threhold-masked source spatial distribution for different noise parameters. We then used RELICA to generate large number of bootstrap ICs for the dataset, which we then grouped based on similarity. We computed the noise characteristics of each returned component cluster to build a spatial uncertainty model for every IC scalp map associated with a brain effective source process.

II. Methods and Results

A. Head and source model

To generate realistic head tissue models we can use the NFT toolbox to model scalp, skull, CSF, and brain tissue model compartments [1]. NFT is a MATLAB toolbox for generating realistic head models from available data (MRI and/or electrode locations) and for computing numerical solutions for solving the forward problem of electromagnetic source imaging. After generating a head model and forward problem solution, equivalent dipole source localization and/or distributed source localization can be performed using the scalp maps associated with independent component sources of multi-channel EEG data compatible with generation in the brain (most often, brain cortex). Distributed source localization uses Freesurfer [14] routines to generate a high-density cortical source space and co-registers this source space with the NFT-generated head model. It then generates a complete set of cortical-surface conformal Gaussian patches of different scales (3, 6, and 10 mm in diameter) and performs distributed source localization for a given source EEG scalp map using either 1) the Sparse, Compact, Smooth (SCS) method [2], [10], or 2) a patch-based sparse Bayesian (SBL) method [15], [16].

Figure 1 shows the tissue surface and cortical source space meshes for a participant as well as the co-registered scalp locations of the 128 scalp electrodes.

B. Overview of Distributed source localization

In distributed source localization methods, two types of solution conditions are commonly enforced or encouraged, spatial source (a) smoothness, and (b) sparsity. Minimum Norm Estimates (MNE), LORETA, and other linear regulation-based methods encourage source smoothness [17], while Sparse Bayesian Learning (SBL) algorithms encourage source sparsity [18]. In reality, neuronal networks of the brain, and specifically within the cortex, exhibit a quasi *small world* property in which neurons synchronize mainly with their immediate neighbors through short-distance connections, with relatively few long-range connections that are capable of supporting long-distance field synchrony [19]. Therefore, the current sources making relatively strong effective contributions to scalp EEG signals should be generated in locally spatially coherent field activity across a both spatially compact and locally smooth cortical source patch. To objectify these source properties, we use the SCS source localization method [2], [10]. In Figure 2, we compare patch-based Sparse Bayesian Learning (SBL) and SCS source localization methods for cortical distributed source localization that estimate distributed cortical source areas that are implemented in the NFT toolbox. They both give compact high-resolution source distributions, however, SCS returned better fitting and more sparse solutions (Figure 2).

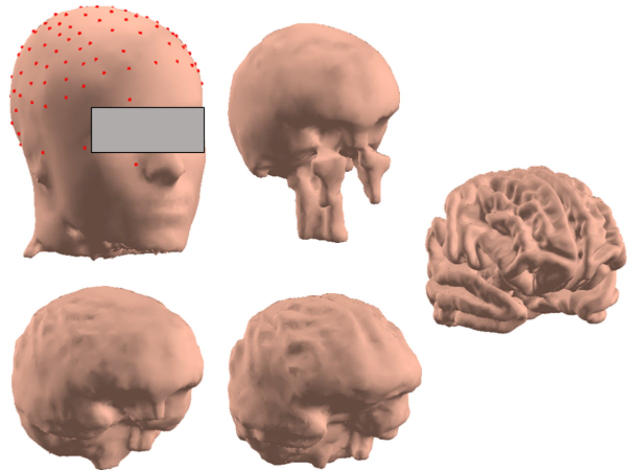

Fig. 1. (Left above) Scalp, skull, (left, below) CSF and brain surface meshes used to create a finite element method (FEM) head model for one participant. Note the (upper left) 128 scalp-measured ("digitized") scalp electrode locations, co-registered to the MR head image. (Right) The high-resolution Freesurfer cortical source space for this participant.

SCS is designed to generate sparse, compact cortical source distributions for a given independent component (IC) scalp map decomposed using Independent Component Analysis (ICA) from a high-density EEG data recording. For a spatially sparse and maximally compact source, we expect that most relevant information about spatial location of the generating cortical region should be in the *peak* weighted voxels of the estimated source distribution; setting low-weighted source voxels to zero should not result in a large change in the residual variance (RV)remaining in the IC scalp map when the cortical source model projection is regressed out. RV is a measure of how well any source distribution estimate accounts for the given data scalp map (0% RV indicating a perfect fit).

Recently, we observed that applying an apparently reasonable threshold to the SCS estimates of the source distributions to mask-out low-valued source voxels resulted in solutions with a relatively poor, high RV (Figure 3) fit of the masked source distribution scalp projection to the IC scalp map. To obtain a better fit we needed to retain low-value voxel values in the source distribution covering a good portion of the cortical surface, unfortunately not a neurophysiologically

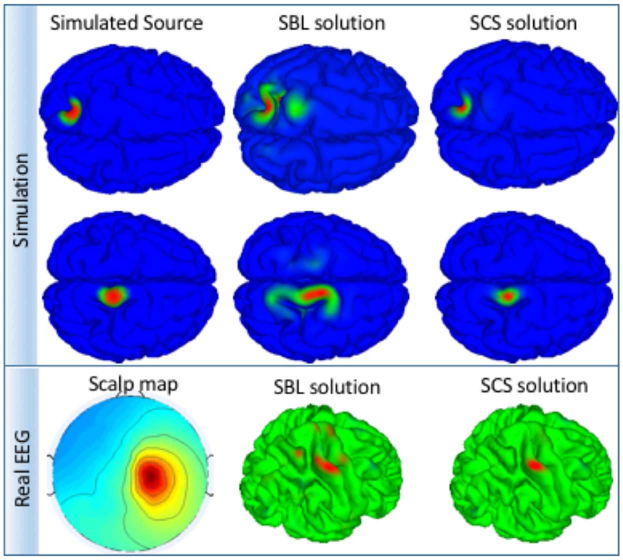

Fig. 2. Source localization results for patch-based SBL and SCS algorithms. The first two rows show simulation results and last row shows source localization results using the scalp potential distribution (scalp map) for one maximally independent brain component of a human EEG dataset.

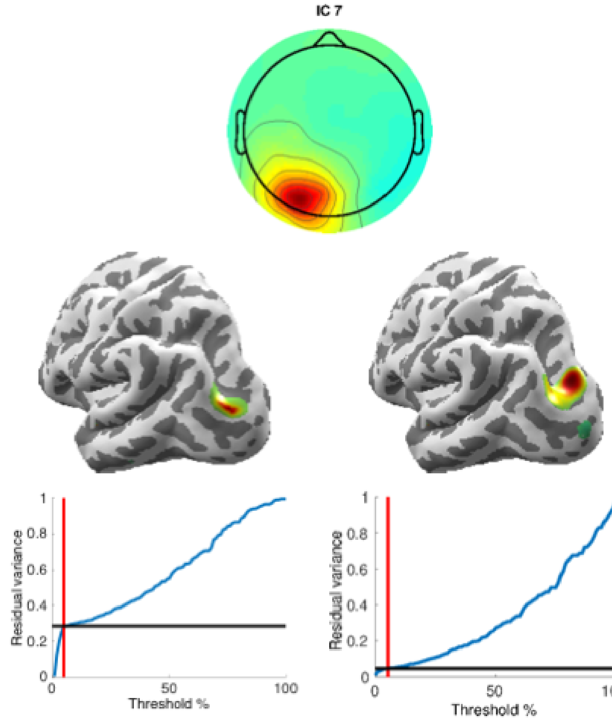

Fig. 3. (top) The scalp map for an IC used for source localization. The middle row shows SCS-computed cortical source distributions (left) obtained using the default noise model, or (right) the noise model obtained by using the RELICA stochastic ICA decomposition method of [20], [21]. The bottom row shows RV vs. threshold value (as percent of the maximum) used to sparsify the spatial source distribution (as shown in the displayed cortical surface maps). Vertical red lines show the threshold values used, horizontal black lines the RV, the percentage of the IC scalp map unaccounted for by the imaged cortical source distribution. Using an improved estimate of IC scalp map uncertainty gave a more plausible result.

plausible solution. Exploring this problem further, we noticed that the SCS default initial noise model we had been using (a simple identity noise covariance matrix) did not reflect the actual uncertainty in the IC scalp map estimates produced by ICA decomposition. After some exploration, we were able to significantly improve the SCS results wherein applying a masking threshold to further sparsify the estimated source distributions no longer resulted in high-RV (imprecise) fits to the respective IC scalp maps.

C. *Characterizing spatial IC map variability*

While it is straightforward to identify noise characteristics of a scalp channel EEG recording at each channel, and from there to generate a spatial noise covariance matrix for the scalp data set, here we are running SCS on IC scalp maps derived from the data set. Therefore, it had not been clear to us how to determine spatial noise characteristics for individual (fixed) IC maps. To generate variability statistics for each map, we needed more data. Here, we used RELICA (Bootstrap-ICA) to generate 50 similar bootstrap decompositions of the same recording, then constructed clusters of similar returned ICs across decompositions. For many ICs in the original whole-data decomposition (about 50, in this process), the correlations between the whole-data IC maps and its bootstrap replicates were very high. This process allowed us to identify well-defined clusters of bootstrap ICs for the (effective brain source) IC maps we used for source localization. This, in turn, made it possible to estimate the statistical stability/uncertainty of these whole-data IC scalp maps.

Figure 4 shows three ICs (top row) and their corresponding bootstrap variability (as normalized variance maps, bottom row) obtained from measuring scalp map variability in the associated bootstrap IC clusters. It is interesting to note from the figure that variability across bootstrap decompositions of one of the scalp activity peaks in the IC17 scalp map (right) is high, suggesting its bilateral dual-source patch characteristic is temporally unstable. While the IC7 scalp map (upper left) shows only a trace of a right-hemisphere activation, the associated bootstrap variance map (lower left) shows that that dual-symmetric source participation is temporally unstable. Together, IC7 and IC17 appear to form a bilateral IC subspace whose complex dynamics can be explored using ICA decomposition of bootstrap selections from the whole data.

When we used the variance of ICs across the bootstrap clusters as the noise covariance matrix in SCS, the IC localization results improved significantly, as shown by the significantly reduced thresholded RV values in Figure 3 above. For an EEG experiment data set for which ICA decomposition returned 9 brain ICs, using RELICA-based noise covariance matrix improved the source localization. The goodness of fit of their modeled scalp channel projections to the targeted IC source maps improved by up to 50%. The new sources were localized between 2-20 mm (average 14.6 mm) away from the sources localized with the default noise model.

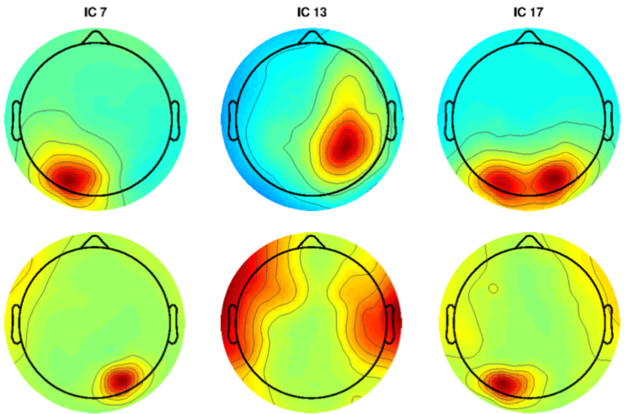

Fig. 4. Some IC scalp maps (top row) and their corresponding RELICA-based bootstrap variance maps (bottom row).

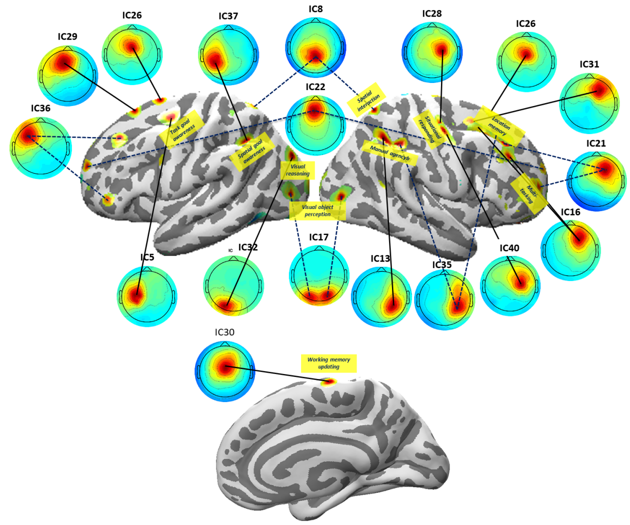

Fig. 5. SCALE/SCS-estimated source distributions and matching whole-data IC scalp maps (connected by line segments) for 17 of 45 brain IC effective sources drawn from 1-4 model AMICA decompositions of 128-channel data recorded during a complex (STRUM) multiscreen videogame playing task session, superimposed on the participant's semi-inflated cortical surface mesh constructed using the NFT toolbox from the participant MR head image. Dashed connecting line segments show ICs localized to two, presumably anatomically well-connected source areas.

D. EEG-based functional parcellation of the cortical surface

By computing noise models for the IC maps for which bootstrap statistics were available, and using an experimentally determined noise coefficient for the remaining ICs, we used SCS to generate source images for data from a participant in a complex (STRUM) videogame task (Figure 5). We have annotated the figure, for exploratory interest, by noting functional associations obtained from a brief survey of the fMRI data for the estimated IC cortical surface source areas. The associated cognitive functions are consistent with cognitive requirements of the STRUM task which involved performing several simultaneous and/or temporally interleaved tasks including driving a vehicle through a virtual city based on animated 3-D scene cues (in a central monitor), a video map display (in a left monitor), and a top-down active satellite image (in a right monitor), plus side tasks, warning messages, and alerts presented in pop-up windows on all three screens.

III. Discussion

While Independent Component Analysis removes or isolates noise from the signal and isolates independent brain activity, it had been unclear to us how to model uncertainty in the individual component scalp maps. Here, we introduced a method to estimate the noise covariance matrix of ICA-derived source scalp projection maps to solve EEG cortical source localization problem using the SCS algorithm. This improved the source localization: The new sources have a better goodness of fit (lower RV) which is not sensitive to thresholding (setting low valued sources to zero). The source locations moved by an average of 14.6 mm and, in some cases, the identified source patches even moved to a neighboring sulcus or gyrus. While we applied this method to one participant's data in this work, it can be applied to other participant data with any task paradigm.

We used RELICA to compute a bootstrap ensemble of similar ICs, estimated from bootstrap versions of the same data, which allowed us to estimate the noise covariance matrix for each component. We used these noise characteristics to improve the SCS source localization. however, this approach can be used with other source localization methods including expectation-maximization (EM) algorithms [24], generalized least-squares methods, or SBL algorithms, as well as after separating effective brain sources using ICA decomposition, where noise covariance matrix estimate can be used in SCS source localization.

Acknowledgment

This work was supported by a grant from the US National Institutes of Health (R01-NS047293, R01-EB023297), by a gift to UCSD from The Swartz Foundation (Old Field, NY), and by the Army Research Laboratory under Cooperative Agreement Number W911NF-10-2-0022.

References

[1] Z. Akalin Acar and S. Makeig, "Neuroelectromagnetic forward head modeling toolbox." *J. of Neuroscience Methods*, vol. 190, pp. 258–270, 2010.

[2] Z. Akalin Acar, C. Acar, and S. Makeig, "Simultaneous head tissue conductivity and EEG source location estimation." *NeuroImage*, vol. 124, pp. 168–180, 2016.

[3] Z. Akalin Acar and S. Makeig, "Evaluation of skull conductivity using scale head tissue conductivity estimation using eeg," *submitted to NeuroImage*, 2020.

[4] C. M. Michel, M. M. Murray, G. Lantz, L. Gonzales, S. Spinelli, and R. G. de Peralta, "EEG source imaging." *Clin. Neurophysiol*, vol. 115, no. 10, pp. 2195–2222, 2004.

[5] M. Jatoi, N. Kamel, A. Malik, I. Faye, and T. Begum, "A survey of methods used for source localization using eeg signals." *Biomedical Signal Processing and Control*, vol. 11, pp. 42–52, 2014.

[6] R. Grech, T. Cassar, J. Muscat, K. Camilleri, S. Fabri, M. Zervakis, P. Xanthopoulus, V. Sakkalis, and B. Vanrumste, "Review on solving the inverse problem in EEG source analysis." *J. on Neuroeng. and Rehab*, vol. 5, 2008.

[7] C. Phillips, M. D. Rugg, and F. K. J., “Systematic regularization of linear inverse solutions of the EEG source localization problem.” *NeuroImage*, vol. 17, pp. 287–301, 2002.
[8] S. Baillet and L. Garnero, “A bayesian approach to introducing anatomo-functional priors in the EEG/MEG inverse problem.” *IEEE Trans. on Biomed. Eng.*, vol. 44, pp. 374–385, 1997.
[9] T. Limpiti, B. D. Van Veen, and R. Wakai, “Cortical patch basis model for spatially extended neural activity.” *IEEE Trans. on Biomed. Eng.*, vol. 53, pp. 1740–1754, 2006.
[10] C. Cao, Z. Akalin Acar, K. Kreutz-Delgado, and S. Makeig, “A physiologically motivated sparse, compact, and smooth (SCS) approach to EEG source localization.” in *34th Annual International IEEE EMBS Conference, San Diego*, 2012.
[11] S. Makeig, A. J. Bell, T. Jung, and T. Sejnowski, *Independent component analysis of electroencephalographic data.* MIT Press, Cambridge, 1996, vol. 8.
[12] T. Jung, S. Makeig, M. J. Mckeown, A. J. Bell, T. Lee, and T. J. Sejnowski, “Imaging brain dynamics using independent component analysis.” *Proc. of the IEEE*, vol. 89, pp. 1107–1122, 2001.
[13] J. Koles, “Trends in EEG source localization.” *Electroencep. and Clin. Neurophysiol.*, vol. 106, pp. 127–137, 1999.
[14] A. M. Dale, B. Fischl, and M. I. Sereno, “Cortical surface-based analysis: 1. segmentation and surface reconstruction.” *NeuroImage*, vol. 9, pp. 179–194, 1999.
[15] Z. Akalin Acar, G. Worrell, and S. Makeig, “Patch-based cortical source localization in epilepsy.” in *Proc. of IEEE EMBC*, 2009.
[16] R. Ramirez and S. Makeig, “Neuroelectromagnetic source imaging using multiscale geodesic neural bases and sparse bayesian learning.” in *Proc. of HBM*, 2006.
[17] M. Fuchs, H. Wischmann, and M. Wagner, “Generalized minimum norm least squares reconstruction algorithms.” *ISBET newsletter*, vol. 5, 1994.
[18] D. Wipf and S. Nagarajan, “A unified bayesian framework for MEG/EEG source imaging,” *NeuroImage*, vol. 44, pp. 947–966, 2009.
[19] W. Freeman, “A neurobiological theory of meaning in perception part ii: Spatial patterns of phase in gamma EEGs from primary sensory cortices reveal the dynamics of mesoscopic wave packets.” *Int J of Bifurcation and chaos*, vol. 13, pp. 2513–2535, 2003.
[20] F. Artoni, D. Menicucci, A. Delorme, M. S., and S. Micera, “Relica: a method for estimating the reliability of independent components,” *Neuroimage*, vol. 103, pp. 391–400, 2014.
[21] F. Artoni, A. Delorme, and M. S., “Applying dimension reduction to eeg data by principal component analysis reduces the quality of its subsequent independent component decomposition,” *Neuroimage*, vol. 175, pp. 176–187, 2018.
[22] J. A. Palmer, K. Kreutz-Delgado, B. D. Rao, and S. Makeig, “Modeling and estimation of dependent subspaces.” in *Proceedings of the 7th International Conference on Independent Component Analysis and Signal Separation*, 2007.
[23] J. A. Palmer, K. Kreutz-Delgado, and S. Makeig, “Super-gaussian mixture source model for ICA.” in *Proceedings of the 6th International Symposium on Independent Component Analysis*, J. C. P. Justinian Rosca, Deniz Erdogmus and S. Haykin, Eds. Springer, 2006.
[24] E. e. a. Pirondini, “”computationally efficient algorithms for sparse, dynamic solutions to the eeg source localization problem,” *IEEE Transactions on Biomedical Engineering*, vol. 65, pp. 1359–1372, 2018.