AN EXPERIMENTAL STUDY ON TRANSFERRING DATA-DRIVEN IMAGE COMPRESSIVE SENSING TO BIOELECTRIC SIGNALS

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ABSTRACT

The emerging area of bioelectric signal compressive sensing(CS) has shown great potential in health care applications. However, improving the reconstruction accuracy of compressively sensed bioelectric signals remains a challenging problem. In recent years, data-driven image CS methods have achieved significant improvements in reconstruction accuracy over conventional model-based image CS methods. In this paper, we conduct an experimental study on transferring existing data-driven image CS methods to bioelectric signals. Through our investigation of five critical factors affecting the reconstruction performance of bioelectric signals, we conclude that existing data-driven image CS methods can be transferred to ECG signals with high reconstruction accuracy. Our experimental results show that transferred data-driven image CS methods can achieve up to 8.08-2.73 SNR improvement over the reference method on ECG signal reconstruction across compression ratios of 2-8x.

Index Terms— compressive sensing, bioelectric signal, deep learning

1. INTRODUCTION

The emerging area of bioelectric signal compressive sensing(CS) has shown great potential in health care applications[1]. Most existing CS reconstruction methods of bioelectric signals are model-based methods built upon handcrafted signal priors[2, 3]. Since the model of bioelectric signals is not yet well understood, the handcrafted signal priors may not sufficiently reflect the actual data distribution of signals, leading to limited reconstruction performance of model-based methods, which is a challenging problem that hinders real-world applications.

In recent years, data-driven image CS methods[4, 5, 6, 7] have achieved great success in reconstructing images sensed even at high compression ratios. By utilizing neural networks to learn a signal prior from data as well as directly reconstruct the signals in an end-to-end fashion, the reconstruction accuracy of data-driven image CS methods has significantly improved over that of conventional model-based image CS methods[8, 9, 10] as shown in [11].

In this paper, we propose to address the problem by transferring existing data-driven image CS methods to bioelectric signals to improve reconstruction accuracy. We identify and investigate five critical factors that affect the reconstruction performance of transferred methods: 1. dimensionality of convolutional layers. 2. pre-training on images. 3. length of signal samples. 4. network structures. 5. bioelectric signal types. By conducting experiments on three public datasets of ECG, EEG, and EMG signals with four existing data-driven image CS methods, we draw the conclusion that existing data-driven image CS methods can be transferred to ECG signals with high reconstruction accuracy. Our experiment results show that transferred data-driven image CS methods can achieve up to 8.08-2.73 SNR improvement over the reference method on ECG signal reconstruction across compression ratios of 2-8x.

Our contributions are summarized as follows:

- We propose a novel approach to address the problem of limited reconstruction accuracy in bioelectric signals by transferring data-driven image CS methods to this domain. The proposed approach shows a significant reconstruction accuracy improvement over the reference method on ECG signals.
- To the best of our knowledge, we are the first to empirically study the problem of transferring data-driven image CS methods to bioelectric signals. By investigating five critical factors that impact the reconstruction performance of transferred methods, we derive the optimal conditions to maximize the reconstruction performance of transferred methods.

2. RELATED WORK

Most existing CS reconstruction methods on bioelectric signals are model-based. [2] provides a detailed review on ex-

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isting model-based CS reconstruction methods for bioelectric signals. [3] provides a more recent review on existing CS reconstruction approaches for EEG signals. [12] provides a thorough survey on existing deep-learning-based CS reconstruction methods in various domains. To the best of our knowledge, the most recent study on applying neural networks to bioelectric signals is [13]. [13] employs a neural network to first estimate the support of a reconstructed signal then estimate the coefficients by pseudo-inversion. Our work differs from [13] in the fact that we reconstruct signals in an end-to-end manner using neural networks.

3. EXPERIMENTS

We investigate five critical factors that affect the reconstruction performance of a transferred data-driven image CS method: 1. dimensionality of convolutional layers. 2. pretraining on images. 3. length of signal samples. 4. network structures. 5. bioelectric signal types.

We conduct experiments on three public datasets corresponding to three types of bioelectrical signals: MITBIH[14] for ECG signals, BCI-IV 2a(EEG)[15] for EEG signals and NinaPro D3(EMG)[16] for EMG signals. Each dataset consists of multiple records corresponding to multiple subjects. Each record is represented as a multi-channel time series. We first divide the records into training sets, validation sets, and testing sets, as shown in Table 1. Then, each channel of a time series is further segmented into signal samples of equal length. As such, we transform each raw dataset consisting of signal records into a dataset consisting of signal samples of equal length. The details of the composed dataset are shown in Table 1. The reconstruction accuracy is measured as averaged signal-to-noise ratios (SNR) over a testing set.

We experiment with four existing data-driven image CS methods: ReconNet[4], DR2-Net[5], LAPRAN[7] and ISTA-Net[6]. The methods are implemented based on the source code released by the original authors and the source code from OpenICS[11] toolbox. Unless particularly specified, the training strategies are consistent with the strategies proposed by the original authors of the methods.

3.1. Dimensionality of Convolutional Layers

Since bioelectrical signals are mostly represented as 1D time-series data, we first investigate whether a 1D CNN is more applicable than a 2D CNN for signal reconstruction. We use ReconNet to conduct the reconstruction experiments on ECG signals at four compression ratios from 2 to 16. The sample length is set to 1024.

ReconNet can be directly trained to reconstruct square images. To feed 1D signal samples into ReconNet, the 1D signal samples of length 1024 are first reshaped into 32x32 tensors. The reconstruction outputs are reshaped back to 1D vectors of length 1024 for processing. To construct a 1D CNN, we replace the existing 2D convolutional layers in ReconNet with 1D convolutional layers. Specifically, each 2D convolutional layer in ReconNet of size nxn with padding size of $\frac{n-1}{2}$ is converted to an 1D convolutional layer of size n^2 with padding size of $\frac{n^2-1}{2}$ to ensure the output size remains the same as input size. As such, each sensed signal sample can be directly fed into 1D CNN for reconstruction. We denote the constructed 1D CNN network as ReconNet-1D.

The experimental results are shown in Table 2. ReconNet and ReconNet-1D have roughly the same reconstruction accuracy on all compression ratios. The average SNR difference of ReconNet over ReconNet-1D is 0.27 dB. The experimental results show that converting a 2D CNN to a 1D CNN does not bring consistent reconstruction accuracy improvements. Thus, we conclude that this conversion is not necessary for improving reconstruction accuracy.

Table 1. Details of the composed datasets. **Record Index**: the indices of records in the original dataset. **Percent**: the proportion of each type of dataset. **Total**: Total number of samples in each composed dataset. The sample length is set to 1024.

Dataset	Type	Record Index	Percent	Total
MITBIH	Train	The rest	71%	60864
	Val	101, 104, 105 122, 203, 212 231, 233, 234	19%	
	Test	112, 113, 205 221, 222	10%	
BCI-IV 2a	Train	The rest	66%	293900
	Val	A07E, A07T A08E, A08T	23%	
	Test	A09E, A09T	11%	
NinaPro D3	Train	The rest	74%	674676
	Val	S9_E{1-3}_A1 S10_E{1-3}_A1	17%	
	Test	S11_E{1-3}_A1	9%	

Table 2. The reconstruction accuracy comparison between the 1D CNN and 2D CNN on ECG signals. **CR**: compression ratio. **1D**: ReconNet-1D. **2D**: ReconNet.

CR	2	4	8	16
1D	18.45	16.84	13.12	9.48
2D	19.86	17.52	12.11	9.50

3.2. Pretraining on Images

We then investigate whether pretraining on image datasets can bring improvements in reconstruction accuracy. We use MNIST[17] and CIFAR10[18] as the pretrain datasets. The

Table 3. The reconstruction accuracy comparison between pretrained networks and networks trained from scratch on ECG signals. **CR**: compression ratio. **Scratch**: networks trained on the ECG dataset from scratch. **CIFAR10/MNIST**: networks pretrained on CIFAR10/MNIST then finetuned on the ECG dataset.

CR		2	4	8	16
ReconNet	Scratch	21.18	20.38	15.07	10.41
	CIFAR10	19.92	18.04	13.27	9.98
	MNIST	18.51	16.70	12.83	9.64
DR2-Net	Scratch	25.83	20.92	14.90	10.82
	CIFAR10	24.97	20.73	14.20	10.75
	MNIST	23.36	19.99	14.03	10.65

Table 4. The reconstruction accuracy comparison over different sample lengths.

Sample Length	16	64	256	1024
ReconNet	21.99	19.18	15.15	14.74
DR2-Net	21.14	20.42	15.61	13.24

experimented methods are ReconNet and DR2-Net. The sample length is set to 1024. The compression ratios are 2-16x. The experiment results are in Table 3.

As Table 3 shows, pretrained networks have consistently lower reconstruction accuracy than the same networks trained from scratch. On average, the network pretrained on MNIST/CIFAR10 has 1.73dB/0.96dB lower reconstruction SNR than the same network trained from scratch. Thus we conclude the pretraining data-driven image CS methods for transferring to bioelectric signal reconstruction is not necessary.

3.3. Length of Signal Samples

We further investigate how sample length of signals affects the reconstruction accuracy of transferred methods. The comparison is conducted with ReconNet and DR2-Net on the ECG dataset. Four different sample lengths are tested: 16, 64, 256, and 1024. All samples are first reshaped to square 2D tensors to adapt to the input size of networks. The compression ratios we tested are 2-16x.

The experiment results of ReconNet are plotted in Fig 1. The average reconstruction accuracy across different sample lengths is in Table 4. As Fig 1 shows, lower sample length leads to consistently higher reconstruction accuracy at all compression ratios. On average, the reconstruction SNR at sample length of 16 is 7.57 dB higher than it at sample length of 1024. This is strong evidence that one should always use the lowest possible sample length when transferring data-driven image CS methods to bioelectric signals.

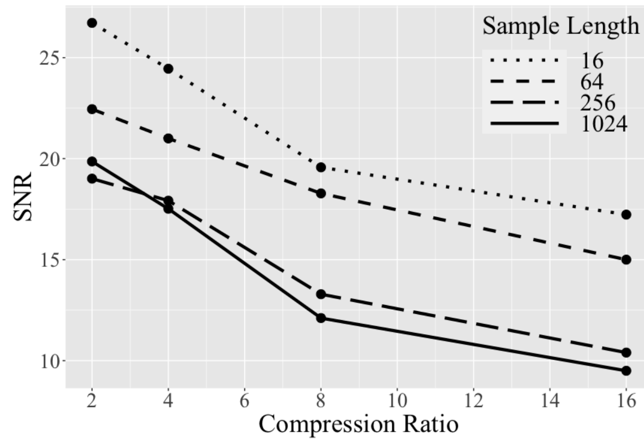

Fig. 1. The reconstruction accuracy comparison between different sample lengths on the ECG dataset. Network: ReconNet.

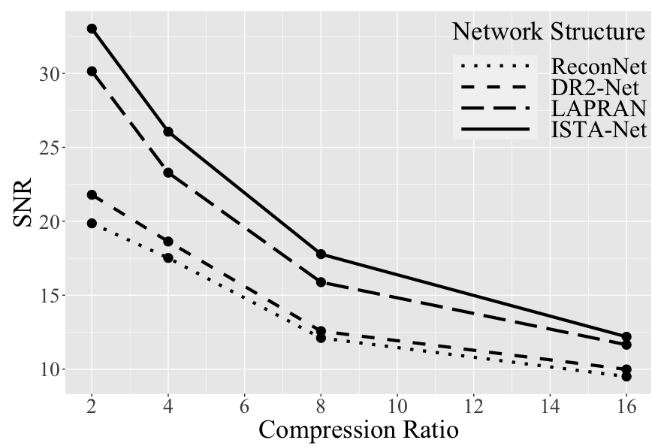

Fig. 2. The reconstruction accuracy comparison between different network structures.

3.4. Network Structures

The network structures have the highest impact on the reconstruction accuracy among all previous factors we investigate. We set the sample length to 1024 and experiment with four different network structures: ReconNet, DR2-Net, LAPRAN and ISTA-Net on ECG dataset. The experiment results are plotted in Fig 2.

As shown by Fig 2, ISTA-Net consistently outperforms all other network structures at all compression ratios. At the compression ratio of 2, the reconstruction SNR of ISTA-Net is 33.03 dB, which is the highest SNR among all the data-driven image CS methods we experimented with. To reveal the true impact of neural networks, we compare ISTA-Net against CTSMD[19] which is the state-of-the-art approach without neural networks for ECG signal CS reconstruction. As shown in Table 5, ISTA-Net achieves an average SNR im-

Table 5. The reconstruction accuracy comparison between ISTA-Net and CTSMD method.

CR	2	4	8
CTSMD	24.95	20.01	15.05
ISTA-Net	33.03	26.06	17.78

Table 6. The reconstruction accuracy comparison between ReconNet, DR2-Net, and DCT-LBCS methods on EEG and EMG datasets.

CR		2	4	8
EEG	DCT-LBCS	17.06	13.56	9.44
	ReconNet	12.105	7.70	4.06
	DR2-Net	12.87	8.80	4.29
EMG	DCT-LBCS	22.09	9.00	4.23
	ReconNet	14.31	4.96	2.66
	DR2-Net	15.01	5.65	2.14

provement of 5.62 dB over CTSMD at compression ratios of 2-8x. This is strong evidence that data-driven image CS methods can be generally transferred for bioelectric signal reconstruction.

3.5. Bioelectric Signal Types

Finally, we study how the type of bioelectric signals affects the reconstruction performance of a transferred method. We conduct experiments on ECG, EEG, and EMG signals with ReconNet and DR2-Net. The sample length is set to 16. Due to the fact that EEG and EMG signals are geometrically more complicated and less periodic than ECG signals, as shown in Fig 3, the reconstruction accuracy on EEG and EMG signals are largely reduced compared with the reconstruction accuracy on ECG signals. We take DCT-LBCS[20] as the state-of-the-art approach without neural networks on EEG and EMG signal reconstruction. The comparison results are in Table 6.

As shown in Table 6, ReconNet and DR2-Net have an average of 5.39/4.46 dB and 4.7/4.17 dB reconstruction SNR reduction than the reference method DCT-LBCS on EEG/EMG dataset, respectively. We further visually compare the reconstruction quality of ECG, EEG, and EMG signals. As shown in Fig 3, EEG and EMG signals have much more geometrical details(in terms of the number of peaks and valleys) than ECG signals. Reconstruction errors mostly occur in geometrically complicated areas. Based on the experimental results, we conclude that existing data-driven image CS methods are insufficient to be transferred for EEG and EMG signal reconstruction.

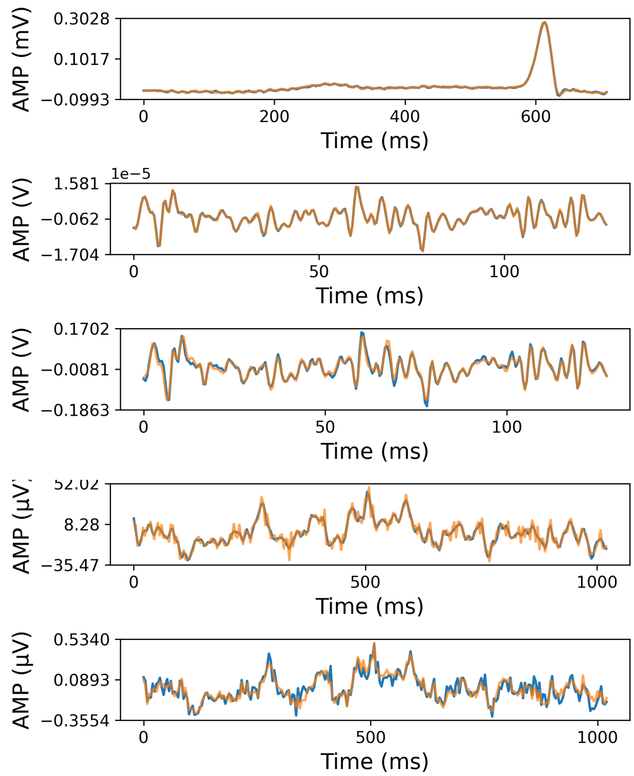

Fig. 3. Visual quality comparison of reconstructed signals. The compression ratio is 2. Blue/Orange line: original/reconstructed signal. **From top to bottom: 1.** ECG signal reconstructed with DR2-Net. SNR: 26.63 dB. **2.** EMG signal reconstructed with DCT-LBCS. SNR: 21.05 dB. **3.** EMG signal reconstructed with DR2-Net. SNR: 12.67 dB. **4.** EEG signal reconstructed with DCT-LBCS. SNR: 8.45 dB **5.** EEG signal reconstructed with DR2-Net. SNR: 7.66 dB

4. CONCLUSION

In this paper, we conduct an experimental study on transferring data-driven image CS methods to bioelectric signals to address the problem of low reconstruction accuracy. By identifying and conducting experiments to study five critical factors that affect the reconstruction performance of transferred methods, we conclude that data-driven image CS methods can be generally transferred to ECG signals with high reconstruction performance. On EEG and EMG signals, existing data-driven image CS methods are insufficient to reconstruct geometric details at fine granularity. We leave the study of improving reconstruction accuracy of data-driven image CS methods on EEG and EMG signals to future work.

5. REFERENCES

[1] Mahdi Khosravy, Nilanjan Dey, and Carlos A Duque, *Compressive sensing in healthcare*, Academic Press, 2020.

[2] Darren Craven, Brian McGinley, Liam Kilmartin, Martin Glavin, and Edward Jones, "Compressed sensing for bioelectric signals: A review," *IEEE Journal of Biomedical and Health Informatics*, vol. 19, pp. 529–540, 2015.

[3] Dharmendra Gurve, Denis Delisle Rodríguez, Teodiano Freire Bastos Filho, and Sridhar Sri Krishnan, "Trends in compressive sensing for eeg signal processing applications," *Sensors (Basel, Switzerland)*, vol. 20, 2020.

[4] K. Kulkarni, Suhas Lohit, Pavan K. Turaga, Ronan Kerviche, and Amit Ashok, "Reconnet: Non-iterative reconstruction of images from compressively sensed measurements," *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 449–458, 2016.

[5] Hantao Yao, Feng Dai, Dongming Zhang, Yike Ma, Shiliang Zhang, and Yongdong Zhang, "Dr2-net: Deep residual reconstruction network for image compressive sensing," *Neurocomputing*, vol. 359, pp. 483–493, 2019.

[6] Jian Zhang and Bernard Ghanem, "Ista-net: Interpretable optimization-inspired deep network for image compressive sensing," *2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1828–1837, 2018.

[7] Kai Xu, Zhikang Zhang, and Fengbo Ren, "Lapran: A scalable laplacian pyramid reconstructive adversarial network for flexible compressive sensing reconstruction," *ArXiv*, vol. abs/1807.09388, 2018.

[8] Weisheng Dong, Guangming Shi, Xin Li, Yi Ma, and Feng Huang, "Compressive sensing via nonlocal low-rank regularization," *IEEE transactions on image processing*, vol. 23, no. 8, pp. 3618–3632, 2014.

[9] Christopher A Metzler, Arian Maleki, and Richard G Baraniuk, "From denoising to compressed sensing," *IEEE Transactions on Information Theory*, vol. 62, no. 9, pp. 5117–5144, 2016.

[10] Chengbo Li, Wotao Yin, Hong Jiang, and Yin Zhang, "An efficient augmented lagrangian method with applications to total variation minimization," *Computational Optimization and Applications*, vol. 56, no. 3, pp. 507–530, 2013.

[11] Jonathan Zhao, Márk Lakatos-Tóth, Matthew Westerham, Zhikang Zhang, Avi Moskoff, and Fengbo Ren, "Openics: Open image compressive sensing toolbox and benchmark," *Software Impacts*, vol. 9, pp. 100081, 2021.

[12] Alina L. Machidon and V. Pejović, "Deep learning techniques for compressive sensing-based reconstruction and inference - a ubiquitous systems perspective," *ArXiv*, vol. abs/2105.13191, 2021.

[13] Mauro Mangia, Luciano Prono, Alex Marchioni, Fabio Pareschi, Riccardo Rovatti, and Gianluca Setti, "Deep neural oracles for short-window optimized compressed sensing of biosignals," *IEEE transactions on biomedical circuits and systems*, vol. 14, no. 3, pp. 545–557, 2020.

[14] George B. Moody and Roger G. Mark, "The impact of the mit-bih arrhythmia database," *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, pp. 45–50, 2001.

[15] Clemens Brunner, Robert Leeb, Gernot Müller-Putz, Alois Schlögl, and Gert Pfurtscheller, "Bci competition 2008–graz data set a," *Institute for Knowledge Discovery (Laboratory of Brain-Computer Interfaces), Graz University of Technology*, vol. 16, pp. 1–6, 2008.

[16] Manfredo Atzori and Henning Müller, "The ninapro database: A resource for semg naturally controlled robotic hand prosthetics," *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pp. 7151–7154, 2015.

[17] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner, "Gradient-based learning applied to document recognition," *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278–2324, 1998.

[18] Alex Krizhevsky, Geoffrey Hinton, et al., "Learning multiple layers of features from tiny images," 2009.

[19] Kai Xu, Yixing Li, and Fengbo Ren, "A data-driven compressive sensing framework tailored for energy-efficient wearable sensing," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2017, pp. 861–865.

[20] Cosimo Aprile, Johannes Wüthrich, Luca Baldassarre, Yusuf Leblebici, and Volkan Cevher, "Dct learning-based hardware design for neural signal acquisition systems," *Proceedings of the Computing Frontiers Conference*, 2017.