A Compressive Sampling Approach For Brain-Machine Interfaces Based on Transcranial Doppler Sonography: A Case Study of Resting-State Maximal Cerebral Blood Velocity Signals

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***Abstract*—Transcranial Doppler sonography was recently proposed as an approach for brain-machine interfaces. However, monitoring maximal cerebral blood flow velocity signals for extensive time periods can generate large volumes of data for processing. In this paper, a compressive sensing (CS) approach is proposed based on a time-frequency dictionary formed by modulated discrete prolate spheroidal sequences (MDPSS). To test the proposed scheme, we examined maximal cerebral blood flow velocity signals acquired from 20 healthy subjects during a resting state. The results of our analysis clearly depicted that these signals can be accurately reconstructed using only 30% and 50% of original samples. Hence, the proposed MDPSS-based CS approach is a valid tool for diminishing the number of acquired samples during brain-machine operations using transcranial Doppler sonography.**

***Index Terms*—Brain-machine interface, transcrannial Doppler sonography, compressive sampling, modulated discrete prolate spheroidal sequences.**

I. Introduction

Cerebral blood flow is related to cerebral metabolism and brain function [1] and it can be demonstrated that mental and motor activities result in an increased cerebral blood flow in the feeding bed arteries, especially because of increased regional demand for O_2, glucose and other metabolites [2], [1]. Functional transcranial Doppler (fTCD) is an inexpensive, noninvasive imaging modality that can be utilized to monitor the hemodynamic characteristics of major cerebral arteries in normal and pathologic conditions [3]. A major advantage of fTCD is a high temporal resolution and therefore has been used in many psychophysiologic studies involving various cognitive tasks, which demonstrated that mean cerebral blood flow velocity (CBFV) obtained from fTCD data increases when users are doing a cognitive activity compared with baseline periods [4], [5], [6]. Furthermore, it is important to characterize the resting-state cerebral blood flow velocity (CBFV) using fTCD as the resting-state activity of the brain can influence the consequent mental tasks. This is a particularly important issue as fTCD is becoming an important clinical tool to study cerebral blood flow and was a recently proposed as a viable option for brain-to-computer interfaces [7], [8].

However, brain-machine interfaces require long-term, continuous monitoring of maximal cerebral blood flow velocity signals. However, these signals are calculated on the raw Doppler sonography signals (e.g., [9]), which are usually sampled at high frequencies (e.g., at several kHz). Such a high sampling frequency produces millions of data points within minutes which need to processed almost in real-time. Therefore, approaches based on compressive sensing (CS) (e.g., [10], [11], [12], [13]) have gained considerable attention for continuous monitoring of various physiological signals (e.g., [14], [15]). Following our previous developments, we developed a CS approach based on a time-frequency dictionary formed from modulated discrete spheroidal sequences (MDPSS) [16], [17]. Using the proposed approach, we analyzed transcranial Doppler signals acquired from twenty healthy subjects during a resting state. The results showed that the accurate results can be obtained using a limited number of original samples.

II. Methods

A. Data acquisition

We analyzed the data acquired from twenty able-bodied participants (10 females; 21.5 ± 1.86 years old (19-26 years old); 67.9 ± 14.2 kg ($50.4 - 99.9$ kg); 174 ± 9.69 cm ($157 - 191$) cm; body mass index: 22.3 ± 2.94 (17.7-29.1)). The protocol was approved by the Institutional Review Board at the University of Pittsburgh and further details about the data collection protocol and participants can be found in [9].

B. Compressive sampling of transcranial Doppler sonography signals

The Shannon sampling theorem states that a bandlimited signal $x(t)$ can be reconstructed from uniform samples $\{x(kT_s)\}$:

$$x(t) = \sum_k x(kT_s) \frac{\sin\left(\Omega_{\max}(t - kT_s)/\pi\right)}{\Omega_{\max}(t - kT_s)/\pi} \qquad (1)$$

where T_s is the sampling period and $\Omega_{\max}$ represents the maximum frequency present in the signal. However, by using the Shannon sampling theorem we rely on bases of infinite support, while we generally reconstruct signal samples in the finite domain [18]. To alleviate this issue, the recently proposed idea of CS converts input signals, embedded in a high-dimensional space, into signals that lie in a space of significantly smaller dimensions [12]. These CS approaches are particularly suited for K-sparse signals, i.e., signals that can be represented by significant K coefficients over an N-dimensional basis. Encoding of a K-sparse, discrete-time signal of dimension N is accomplished by computing a measurement vector y that consists of $M << N$ linear projections of the vector x:

$$y = \Phi x \tag{2}$$

where Φ represents an $M \times N$ matrix and is often refer to as the sensing matrix [12]. Naturally, one can use an l_o minimization framework to solve the above problem, but it is quite impractical in many applications as it is NP-hard [19]. To avoid the computational burden, approaches like thresholding, (orthogonal) matching pursuit and basis pursuits have been proposed [19]. In this paper, we will focus on the matching pursuit [20].

The immediate question here is how to define the sensing matrix Φ, that is the bases used in the recovery of the signal. Most commonly used sensing matrices are random matrices with independent identically distributed (i.i.d.) entries formed by sampling either a Gaussian distribution or a symmetric Bernoulli distribution [21]. Previous publications have shown that these matrices can recover the signal with high probability [21]. However, when dealing with biomedical signals, we would like to "precisely" recover the signals (i.e., with a very small error). Therefore, we propose to use a time-frequency dictionary (also known as frames [22]) based on modulated discrete prolate spheroidal sequences (MDPSS) [16]. MDPSS are defined as

$$M_k(N, W, \omega_m; n) = \exp(j\omega_m n) v_k(N, W; n) \tag{3}$$

where $\omega_m = 2\pi f_m$ is a modulating frequency, N is such that $n = 0, 1, ..., N-1$ and the normalized half-bandwidth, W is such that $0 < W < 0.5$. $v_k(N, W; n)$ are discrete prolate spheroidal sequences (DPSS) defined as the real solution to the system of equations [23]:

$$\sum_{m=0}^{N-1} \frac{\sin[2\pi W(n-m)]}{\pi(n-m)} v_k(m, N, W) = \lambda_k(N, W) v_k(n, N, W) \tag{4}$$

with $\lambda_k(N, W)$ being the ordered non-zero eigenvalues of (4)

$$\lambda_0(N, W) > \lambda_1(N, W), ..., \lambda_{N-1}(N, W) > 0. \tag{5}$$

MDPSS are also doubly orthogonal and are bandlimited to the frequency band $[-W + \omega_m : W + \omega_m]$.

A modulation frequency ω_m is chosen such that

$$\omega_m = W/2 \tag{6}$$

as long as both satisfy:

$$|\omega_m| + W < \frac{1}{2}. \tag{7}$$

Given that exact frequency band is known only with a certain degree of accuracy and usually evolves in time. Therefore, we construct a time-frequency dictionary with the first few bases in the dictionary are the actual traditional DPSS with bandwidth W. Additional bases are constructed by partitioning the band $[-\omega; \omega]$ into K subbands with the boundaries of each subband given by $[\omega_k; \omega_{k+1}]$, where $0 \leq k \leq K-1$, $\omega_{k+1} > \omega_k$, and $\omega_0 = -\omega$, $\omega_{K-1} = \omega$. Hence, each set of MDPSS has a bandwidth equal to $\omega_{k+1} - \omega_k$ and a modulation frequency equal to $\omega_m = 0.5(\omega_k + \omega_{k+1})$. In this paper, we partition the bandwidth in equal blocks to reduce amount of stored pre-computed DPSS. In general, finding the best partitioning approach would be based on a priori knowledge about the phenomenon under investigation.

Next, we utilize matching pursuit[20], [22], to approximate the signal. The algorithm begins with initial approximation for the signal, $\widehat{x}$, and the residual, R:

$$\widehat{x}^{(0)}(m) = 0 \tag{8}$$

$$R^{(0)}(m) = x(m) \tag{9}$$

where m represent the M time indices that are uniformly or non-uniformly distributed. Then, the matching pursuit builds up a sequence of sparse approximation by reducing the norm of the residue, $R = \widehat{x} - x$. At stage k, it identifies the dictionary atom that best correlates with the residual and then adds to the current approximation a scalar multiple of that atom, such that

$$\widehat{x}^{(k)}(m) = \widehat{x}^{(k-1)}(m) + \alpha_k \phi_k(m) \tag{10}$$

$$R^{(k)}(m) = x(m) - \widehat{x}^{(k)}(m) \tag{11}$$

where $\alpha_k = \langle R^{(k-1)}(m), \phi_k(m) \rangle / \left\| \phi_k(m) \right\|^2$. The process continues till the norm of the residual $R^{(k)}(m)$ does not exceed required margin of error $\epsilon > 0$: $||R^{(k)}(m)|| \leq \epsilon$ [20]. The stopping approach considered here is that the normalized mean square error should be below a certain threshold value, γ:

$$\frac{\left\| x - \widehat{x}^{(k)} \right\|_2^2}{\|x\|_2^2} \leq \gamma \tag{12}$$

Using these steps, a matching pursuit approximates the signal using L bases as

$$x(n) = \sum_{l=1}^{L} \langle x(m), \phi_l(m) \rangle \phi_l(n) + R^{(L)}(n) \tag{13}$$

where ϕ_l are L bases from the dictionary with the strongest contributions.

Therefore, the steps for the algorithm are as follows:

1) Assume values for N, W and K.
2) Approximate the peak frequency, f_p, for the block of length N.
3) Set the modulation frequency $\omega_m = W/2 + f_p$. If $\omega_m + W > 0.5$, set $W = 0.5 - \omega_m$.

TABLE I

A SUMMARY OF STATISTICAL FEATURES EXTRACTED FROM THE RAW AND ENVELOPE CBFV SIGNALS. AN ASTERISK DENOTES MULTIPLICATION BY 10^{-4}. † = STATISTICAL DIFFERENCES BETWEEN THE SIGNAL BASED ON 30% SAMPLES AND ORIGINAL SIGNALS/SIGNALS WITH 50% SAMPLES. σ = STANDARD DEVIATION; ξ = SKEWNESS; γ = KURTOSIS; CC_{L-R} = CROSS-CORRELATION COEFFICIENT.

	Original		30% samples		50% samples	
	L-MCA	R-MCA	L-MCA	R-MCA	L-MCA	R-MCA
σ	14.2 ± 3.70	12.5 ± 3.47	$17.6 \pm 4.4.74$	15.2 ± 4.52	14.2 ± 3.69	12.5 ± 3.44
ξ	0.76 ± 0.27	0.81 ± 0.27	$1.52 \pm 0.47^{\dagger}$	$1.54 \pm 0.48\dagger$	0.76 ± 0.27	0.80 ± 0.26
γ	3.44 ± 0.64	3.47 ± 0.72	$6.95 \pm 3.15^{\dagger}$	$7.13 \pm 2.54^{\dagger}$	3.47 ± 0.63	3.44 ± 0.61
CC_{L-R}	0.98 ± 0.01		0.96 ± 0.03		0.98 ± 0.01	

TABLE II

A SUMMARY OF FREQUENCY FEATURES EXTRACTED FROM THE ORIGINAL AND COMPRESSED SAMPLED BASED CBFV SIGNALS. f_p = PEAK FREQUENCY; f_c = SPECTRAL CENTROID; BW = BANDWIDTH.

	Original		30% samples		50% samples	
	L-MCA	R-MCA	L-MCA	R-MCA	L-MCA	R-MCA
f_p	1.11 ± 0.26	0.88 ± 0.41	1.11 ± 0.27	0.88 ± 0.41	1.11 ± 0.26	0.88 ± 0.41
f_c	6.89 ± 4.36	5.72 ± 3.17	8.87 ± 4.09	8.04 ± 2.93	6.92 ± 4.36	5.77 ± 3.21
γ	9.31 ± 3.62	8.61 ± 3.13	11.1 ± 2.11	11.0 ± 1.87	9.35 ± 3.62	8.67 ± 3.15

TABLE III

A SUMMARY OF FREQUENCY FEATURES EXTRACTED FROM THE ORIGINAL AND COMPRESSED SAMPLED BASED CBFV SIGNALS. WE = WAVELET ENTROPY; a_{10} = RELATIVE ENERGY AT THE TENTH APPROXIMATIVE DECOMPOSITION LEVEL.

	Original		30% samples		50% samples	
	L-MCA	R-MCA	L-MCA	R-MCA	L-MCA	R-MCA
WE	0.11 ± 0.03	0.10 ± 0.04	0.16 ± 0.05	0.15 ± 0.05	0.11 ± 0.03	0.11 ± 0.04
a_{10}	98.7 ± 0.49	98.8 ± 0.49	98.7 ± 0.49	98.8 ± 0.49	98.7 ± 0.48	98.8 ± 0.49

4) Carry out the matching pursuit procedure using a K-band dictionary.
5) Continue steps (1)-(4) until a brain-machine interface is running.

C. Feature extraction

In this paper, we considered the same features as previous contributions (e.g., [9]). These are features in time, frequency and time-frequency domains.

D. Statistical tests

To test for statistical differences on the extracted features, we used non-parametric tests such as the Kruskal-Wallis (e.g., [24]) and the Mann-Whitney test (e.g., [25]) test.

III. RESULTS

As illustrative examples of the proposed scheme, we considered recovering maximal cerebral blood flow velocity signals based on 30% and 50% of original samples. Our goal was to examine the characteristics of recovered signals in comparison to the original signals.

Samples signals from left middle cerebral arteries (L-MCA) and right middle cerebral arteries (R-MCA) are shown in Fig. 1. A visual inspection of the samples signals clearly shows that the recovered signals based on 50% samples are almost identical to the original signals. The signals recovered based on 30% samples also achieved very high resemblance to the original signals.

The visual observations were further confirmed by the comparative analysis of the features extracted from the original signals, signals recovered from 30% of samples and signals recovered from 50% of samples. These results are summarized in Tables I-III. Kurtosis and skewness are the only statistical features which exhibited statistical differences between signals recovered from 30% of samples and the original signals/signals recovered from 50% samples. These differences stem from irregular spikes that occur during the recovery process as

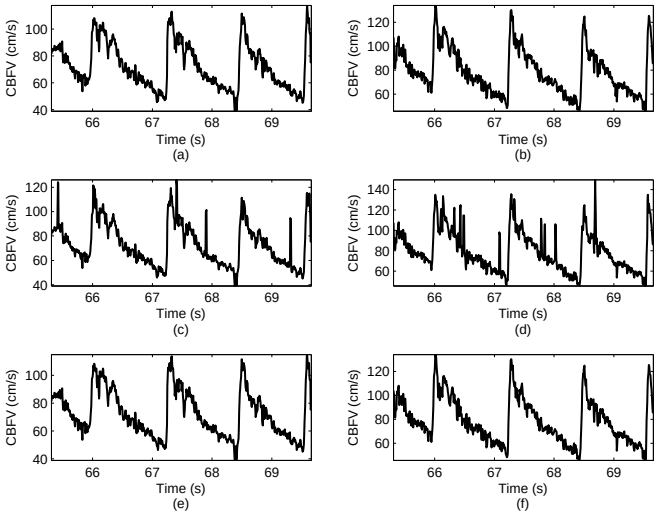

Fig. 1. Samples signals: (a) a sample L-MCA signal; (b) a sample R-MCA signal; (c) a sample L-MCA signal recovered with 30% samples; (d) a sample R-MCA signal recovered with 30% samples; (e) a sample L-MCA signal recovered with 50% samples; (f) a sample R-MCA signal recovered with 50% samples.

shown in Figs. 1 (c) and (d).

The frequency and time-frequency features are almost identical for the recovered signals and the original signals as demonstrated in Tables II and III. Specifically, signals recovered from 30% of samples had slightly higher average values for spectral centroids and bandwidths than the original signals and signals recovered on 50% samples. However, these differences were not statistically different.

Signals recovered from 30% of samples also had slightly higher average values for the wavelet entropy, though not statistically significant.

IV. Discussion

The presented results depicted that compressive sampling schemes can be utilized in acquiring of maximal cerebral blood flow velocity signals. As these signals were previously used in brain-machine interfaces (e.g., [7], [8]), compressed sampling schemes may greatly reduce the number of data points acquired during a typical session.

We only considered the resting-state signals in the current manuscript. Hence, our future efforts should consider signals acquired during cognitive tasks. In particular, it would be interesting to understand if the cognitive tasks affect the recovery accuracy of the maximal cerebral blood flow velocity signals.

It should be mentioned that further improvements in the recovery accuracy can be achieved by optimizing the MDPSS dictionary used in the recovery process. In particular, one may arrange the level divisions in a particular way to exactly cover the signal bandwidth. We recently showed that the only a few samples are needed to recover the signal exactly when the dictionary is optimized with respect to the signal acquired [26].

V. Conclusions

In this paper, we investigated the compressive sampling approach for signals stemming from TCD machines. Our results showed that the maximal cerebral blood flow velocity can be exactly recovered with only 50% of original samples. Accurate results are also obtained with only 30% results. These findings showed us compressive sensing schemes can be a valuable tool for brain-machine interfaces based on transcranial Doppler sonography.

References

[1] O. B. Paulson, S. G. Hasselbalch, E. Rostrup, G. M. Knudsen, and D. Pelligrino, "Cerebral blood flow response to functional activation," *Journal of Cerebral Blood Flow and Metabolism*, vol. 30, no. 1, pp. 2–14, Jan. 2010.

[2] S. Ogawa, T. M. Lee, A. R. Kay, and D. W. Tank, "Brain magnetic resonance imaging with contrast dependent on blood oxygenation," *Proceedings of the National Academy of Sciences*, vol. 87, no. 24, pp. 9868–9872, Dec. 1990.

[3] R. Aaslid, T.-M. Markwalder, and H. Nornes, "Noninvasive transcranial Doppler ultrasound recording of flow velocity in basal cerebral arteries," *Journal of Neurosurgery*, vol. 57, no. 6, pp. 769–774, Dec. 1982.

[4] R. E. Kelley, J. Y. Chang, N. J. Scheinman, B. E. Levin, R. C. Duncan, and S. C. Lee, "Transcranial Doppler assessment of cerebral flow velocity during cognitive tasks," *Stroke*, vol. 23, no. 1, pp. 9–14, Jan. 1992.

[5] S. Knecht, B. Drager, M. Deppe, L. Bobe, H. Lohmann, A. Floel, E.-B. Ringelstein, and H. Henningsen, "Handedness and hemispheric language dominance in healthy humans," *Brain*, vol. 123, no. 12, pp. 2512–2518, Dec. 2000.

[6] B. Rey, M. Alcaniz, J. Tembl, and V. Parkhutik, "Brain activity and presence: a preliminary study in different immersive conditions using transcranial Doppler monitoring," *Virtual Reality*, vol. 14, no. 1, pp. 55–65, Mar. 2010.

[7] A. J. B. Myrden, A. Kushki, E. Sejdić, A.-M. Guerguerian, and T. Chau, "A brain-computer interface based on bilateral transcranial Doppler ultrasound," *PLoS ONE*, vol. 6, no. 9, pp. e24 170–1–8, Sep. 2011.

[8] A. Myrden, A. Kushki, E. Sejdić, and T. Chau, "Towards increased data transmission rate for a three-class metabolic brain-computer interface based on transcranial Doppler ultrasound," *Neuroscience Letters*, vol. 528, no. 2, pp. 99–103, Oct. 2012.

[9] E. Sejdić, D. Kalika, and N. Czarnek, "An analysis of resting-state functional transcranial Doppler recordings from middle cerebral arteries," *PLoS ONE*, vol. 8, no. 2, pp. e55 405–1–9, Feb. 2013.

[10] M. Vetterli, P. Marziliano, and T. Blu, "Sampling signals with finite rate of innovation," *IEEE Transactions on Signal Processing*, vol. 50, no. 6, pp. 1417–1428, Jun. 2002.

[11] D. L. Donoho, "Compressed sensing," *IEEE Transactions on Information Theory*, vol. 52, no. 4, pp. 1289–1306, Apr. 2006.

[12] W. Dai and O. Milenković, "Subspace pursuit for compressive sensing signal reconstruction," *IEEE Transaction on Information Theory*, vol. 55, no. 5, pp. 2230–2249, May 2009.

[13] K.-K. Poh and P. Marziliano, "Compressive sampling of EEG signals with finite rate of innovation," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, p. 12 pages, 2010, article ID 183105.

[14] E. Sejdić, A. Can, L. F. Chaparro, C. M. Steele, and T. Chau, "Compressive sampling of swallowing accelerometry signals using time-frequency dictionaries based on modulated discrete prolate spheroidal sequences," *EURASIP Journal on Advances in Signal Processing*, vol. 2012, pp. 101–1–14, May 2012.

[15] E. Sejdić and L. F. Chaparro, "Recovering heart sounds from sparse samples," in *Proc. of 38th Annual Northeast Bioengineering Conference (NEBEC 2012)*, Philadelphia, PA, USA, Mar. 16–18, 2012, pp. 107–108.

[16] E. Sejdić, M. Luccini, S. Primak, K. Baddour, and T. Willink, "Channel estimation using DPSS based frames," in *IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP 2008)*, Las Vegas, Nevada, USA, Mar./Apr. 31–4, 2008, pp. 2849–2852.

[17] J. Oh, S. Senay, and L. F. Chaparro, "Signal reconstruction from nonuniformly spaced samples using evolutionary Slepian transform-based POCS," *EURASIP Journal on Advances in Signal Processing*, vol. 2010, 2010, article ID 367317, 12 pages.

[18] S. Senay, L. F. Chaparro, and L. Durak, "Reconstruction of nonuniformly sampled time-limited signals using prolate spheroidal wave functions," *Signal Processing*, vol. 89, no. 12, pp. 2585–2595, Dec. 2009.

[19] H. Rauhut, K. Schnass, and P. Vandergheynst, "Compressed sensing and redundant dictionaries," *IEEE Transactions on Information Theory*, vol. 54, no. 5, pp. 2210 –2219, May 2008.

[20] S. G. Mallat and Z. Zhang, "Matching pursuits with time-frequency dictionaries," *IEEE Transactions on Signal Processing*, vol. 41, no. 12, pp. 3397–3415, Dec. 1993.

[21] E. J. Candes and M. B. Wakin, "An introduction to compressive sampling," *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21–30, Mar. 2008.

[22] J. Kovačević and A. Chabira, "Life beyond bases: The advent of the frames (part I)," *IEEE Signal Processing Magazine*, vol. 24, no. 4, pp. 86–104, Jul. 2007.

[23] D. Slepian, "Prolate spheroidal wave functions, Fourier analysis, and uncertainty - V: The discrete case," *The Bell System Technical Journal*, vol. 57, no. 5, pp. 1371–1430, May/Jun. 1978.

[24] W. H. Kruskal and W. A. Wallis, "Use of ranks in one-criterion analysis of variance," *Journal of the American Statistical Association*, vol. 47, no. 260, pp. 583–621, Dec. 1952.

[25] H. B. Mann and D. R. Whitney, "On a test of whether one of two random variables is stochastically larger than the other," *The Annals of Mathematical Statistics*, vol. 18, no. 1, pp. 50–60, Mar. 1947.

[26] E. Sejdić and L. F. Chaparro, "Time-frequency representations based on compressive samples," in *Proc. of 21st European Signal Processing Conference (EUSIPCO'13)*, Marrakech, Morocco, Sep. 9–13, 2013, accepted.