Application of Tripolar Concentric Electrodes and Prefeature Selection Algorithm for Brain–Computer Interface

Walter G. Besio, *Senior Member, IEEE*, Hongbao Cao, and Peng Zhou

***Abstract*—For persons with severe disabilities, a brain–computer interface (BCI) may be a viable means of communication. Lapalacian electroencephalogram (EEG) has been shown to improve classification in EEG recognition. In this work, the effectiveness of signals from tripolar concentric electrodes and disc electrodes were compared for use as a BCI. Two sets of left/right hand motor imagery EEG signals were acquired. An autoregressive (AR) model was developed for feature extraction with a Mahalanobis distance based linear classifier for classification. An exhaust selection algorithm was employed to analyze three factors before feature extraction. The factors analyzed were 1) length of data in each trial to be used, 2) start position of data, and 3) the order of the AR model. The results showed that tripolar concentric electrodes generated significantly higher classification accuracy than disc electrodes.**

***Index Terms*—Brain–computer interface (BCI), electroencephalogram (EEG) classification, Laplacian estimation, parameter selection, tripolar electrode.**

I. Introduction

For persons with severe disabilities (e.g., spinal cord injury, amyotrophic lateral sclerosis, brainstem stroke, etc.), a brain–computer interface (BCI) may be the only feasible method for communicating with others and for environmental control. The most common signal employed for BCI has been the scalp-recorded electroencephalogram (EEG) [1], [2]. Unfortunately, the EEG lacks high spatial resolution primarily due to the blurring affects of the volume conductor with disc electrodes. It has also been shown that conventional EEG signals recorded with disc electrodes have reference electrode problems as idealized references are not available with EEG [3]. A common average reference and concentric electrodes have been proposed to resolve the reference electrode problems as discussed by Nunez since concentric electrodes act like closely spaced bipolar recordings [3]. However, in the common average reference recordings, it is possible that components present in most of the electrodes but absent or minimal in the electrode of interest may appear as "ghost potentials" [4].

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Recently, the application of surface Laplacian to EEG was introduced to help alleviate the blurring effects. Surface Laplacian mapping has been shown to enhance the high spatial frequency components and spatial selectivity of the electrical activity located close to the observation point [5]. The Laplacian is the second spatial derivative of the potentials on the body surface which reduces the blurring effect. The application of the Laplacian method to EEG began with Hjorth [6] utilizing a five-point method (FPM). He [5] performed the surface Laplacian with Hjorth's technique derived from an array of disc electrodes measuring surface potentials. Several other approaches have been shown to perform well, including 1) the spline Laplacian algorithm by Perrin *et al.* [7], 2) the ellipsoidal spline Laplacian algorithm by Law *et al.* [8], 3) realistic Laplacian estimation techniques by Babiloni *et al.* [9], [10], and 4) realistic geometry Laplacian algorithms [11].

However, the gains from the aforementioned application of the Laplacian depend on conventional disc electrodes which are based on the same technology Hans Burger used in 1924. There has been little effort put forth on improving the electrodes. To our knowledge, Fattorusso and Tilmant [14] were the first to report the use of concentric electrodes. Concentric electrodes are symmetrical, alleviating electrode orientation problems [15]. They act as high-pass spatial filters reducing the low spatial frequencies, accentuating localized activity increasing the spatial selectivity [5]. Concentric electrodes outperform disc electrodes with higher signal-to-noise ratio (SNR), higher spatial selectivity, and lower mutual information (MI) which should be beneficial for the field of EEG [5]–[16]. Further, McFarland *et al.* concluded that the common average and the Laplacian derivation yield good performance on EEG classification [17]. Babiloni *et al.* demonstrated that surface Laplacian transformation of EEG signals can improve the recognition scores of imagined motor activity [18].

Since the tripolar concentric electrode has shown significant improvements over disc electrodes, in this paper a comparison of classification of left/right hand imagery was performed between signals from disc electrodes and tripolar concentric electrodes. Two bipolar signals were acquired from each tripolar concentric electrode and then combined to estimate the Laplacian [19]. An autoregressive (AR) model [20] for feature extraction was built. A Mahalanobis distance based linear classifier [21] was used for classification, which was previously established for BCI classification by Cincotti *et al.* [22].

To make a fair comparison between the two electrode configurations, the maximum classification ratio was searched for

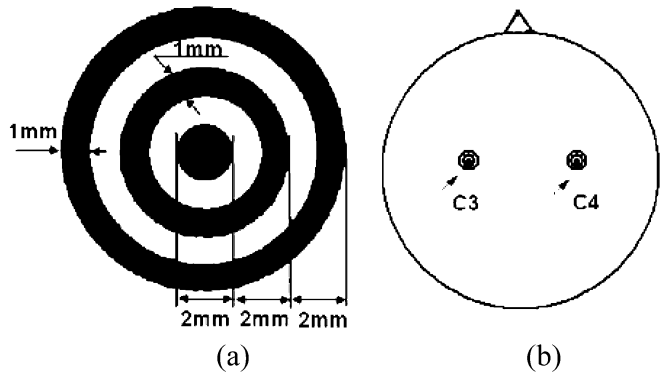

Fig. 1. (a) Configuration and dimensions of a tripolar concentric electrode and (b) positions of the electrode on the scalp surface.

each data set. An exhaust search algorithm was utilized to find the best factors for each subject that generated the highest classification ratio. The results showed that signals from tripolar concentric electrodes generated significantly higher classification ratio compared to signals from disc electrodes.

II. Methods

A. Data Recording

EEG signals of twelve healthy subjects ($\mathrm{males} = 9, \mathrm{females} = 3$, aged from 23 to 30) were recorded using two tripolar concentric electrodes [23] (Fig. 1). All experiments were conducted in accordance with Louisiana Tech University institutional review board approved protocol. Two sets of signals were recorded from each subject with tripolar concentric electrodes [Fig. 1(b)]. The scalp was prepared once with the abrasive Nuprep (D.O. Weaver & Co., Aurora, CO). Then approximately 1.0 mm of Ten-20 electrode paste (D.O. Weaver & Co.) was applied to each electrode prior to placing it on the scalp at C3 and C4 of the 10/20 International Electrode Placement System as shown in Fig. 1(a). The skin-to-electrode impedance was approximately 2 KΩ for each subject. Preconditioning was provided with custom built pre-amplifiers ($\mathrm{gain} = 10$) along with a Grass 15LT Bipolar AC Amplifier System (Grass Technologies, West Warwick, RI) for a total gain of 500 K (0.5–30 Hz). The data were acquired (14 bit) using a DI-720 data acquisition system (DATAQ Instruments, Akron, OH) with a sampling rate of 125 samples/s per channel.

For signal data set one, two bipolar signals were recorded from each electrode (P1–P3 and P2–P3, where P1, P2, P3 were the signals from the outer ring, middle ring, and center disc, respectively). For signal data set two, the outer ring, middle ring and center disc of the electrodes were shorted to make a virtual disc electrode; one signal was recorded from each virtual disc electrode with respect to the reference electrode on the forehead.

Fig. 2 is a timing diagram of the protocol followed for acquiring trials of the signals. Each trial started with a visual fixation on a cross displayed for two seconds on a computer monitor followed by a warning beep alerting the subject that a cue was about to be presented. After the cue, the subjects were required to imagine a left/right hand-lifting movement according to the cue. A random pause was selected such that the length of each trial was between 8 and 9 s. For each subject, 480 trials were recorded, approximately 240 each of left and right hand related signals. Half of the total trials for each subject were used for model training, and half for testing. The trials contaminated with eye and head movements were removed. Approximately 160–200 artifact free trials including both left and right hand related signals were recognized for each subject.

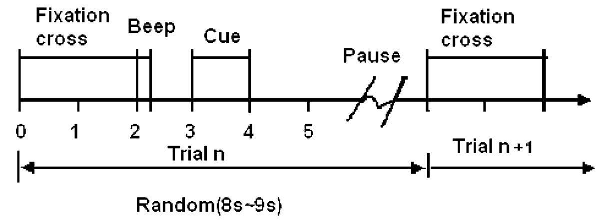

Fig. 2. Timing diagram of the events during the experimental protocol.

TABLE I
Range and Incremental Step of Each Factor Tested

	Range	Increment
LOD	0.1~3.0 s	0.05
SPD	4.5~7.4 s	0.05
AR Order	3~15	1

B. Data Preprocessing and Tripolar Algorithm

For data set one, two channels of bipolar signals were acquired from the tripolar concentric electrodes and postprocessed with a tripolar algorithm for Laplacian estimation [19]

$$\mathrm{S} = 16 * (\mathrm{P2} - \mathrm{P3}) - (\mathrm{P1} - \mathrm{P3}) \tag{1}$$

where S was the signal. For data set two, the recorded signals were used directly after filtering. An AR model was developed for feature extraction [20] with a Mahalanobis distance based linear classifier for classification [21], [22].

C. Exhaust Search Algorithm for Factor Selection

Since all the factors were within a known range, an exhaust search algorithm was used to analyze the factors for the best classification. The event related potential (ERP) due to viewing the arrow (cue) was 3.0–4.5 s (Fig. 2) [24]. To avoid overlapping, imagined movement related signals with the ERP, the imagined movement related EEG between 4.5 and 7.5 s was selected. Therefore, the range of length of data (LOD) was set for 0.1–3.0 s in each trial, and the range of the start position of data (SPD) was 4.5–7.4 s. Extreme AR orders (AR Order) have been shown not to best fit the signal [12]. Thus, the range of AR Order was 3–15. The range and incremental step of each factor tested are listed in Table I.

The exhaust search algorithm was performed for LOD, SPD, and AR Order to find the factors that generated the highest classification ratio (CR) for the signals from the tripolar concentric electrodes and virtual disc electrodes, respectively. The CR was defined in (2), where the total trials recognized were approximately 160–200 for each subject

$$\mathrm{CR} = \frac{\text{Correctly recognized trials}}{\text{Total trials recognized}}. \tag{2}$$

TABLE II
CLASSIFICATION RATIOS FOR EACH SUBJECT FROM TRIPOLAR CONCENTRIC ELECTRODES AND VIRTUAL DISC ELECTRODES, RESPECTIVELY

Subjects	CRs of tripolar	CRs of virtual disc
1	73.89	59.23
2	84.23	72.45
3	80.18	61.09
4	80.16	70.06
5	81.43	69.84
6	77.60	60.05
7	75.77	71.23
8	73.49	69.01
9	79.88	73.34
10	82.48	71.39
11	77.87	70.13
12	77.75	68.32
Mean	78.73	68.01

D. Statistical Analysis

ANOVA was performed to compare the CRs for the signals generated from the tripolar concentric electrodes and virtual disc electrodes. Statistics are reported as mean $\pm$ standard deviation with P-values designated to test significance.

III. RESULTS

A. Influence of Different Electrodes on the CRs

The CRs for data set one (tripolar) and data set two (virtual disc) were $78.7\pm3.3\%$ and $68.0\pm5.0\%$, respectively (Table II). There was a significant difference between the CRs of data set one using the signals from tripolar concentric electrodes compared to the CRs of data set two using signals from the virtual disc electrodes (ANOVA, $\mathrm{P} = 2.9{*}10^{-6}$).

B. Influences of LOD, SPD, and AR Order on the CRs

Fig. 3 shows the influence of (a) LOD, (b) SPD, and (c) AR Order on the CR for subject 1, which was indicative of all the subjects. The CRs varied similarly with the factors in the other subjects. In Fig. 3, it can be seen that the maximum CR was achieved with the signals from the tripolar concentric electrodes.

IV. DISCUSSION

With tripolar concentric electrodes, there was a 16% improvement in the mean CR of the signals compared to that of the signals from virtual disc electrodes. Using the Laplacian of the potentials has been shown to be effective in EEG classification [17], [18]. Since the tripolar concentric electrodes directly acquire Laplacian potentials and are easily combined with simple mathematics (1), they may be suitable for use in real-time BCI applications.

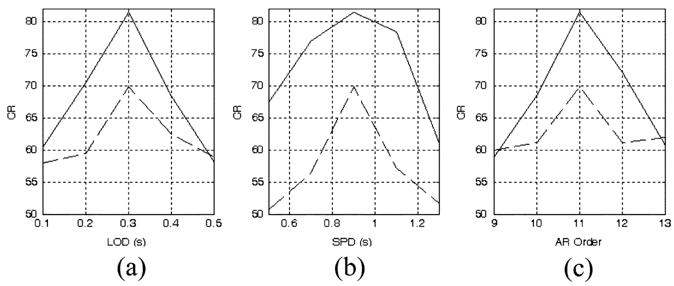

Fig. 3. Influences of LOD, SPD, and AR Order on the CR of subject 1. The solid traces are from data set one (tripolar concentric electrode) and the dashed traces are from data set two (virtual disc electrode). (a) Influence of LOD. (b) Influence of SPD. (c) Influence of AR Order.

For this work, only two sensing electrodes were used to acquire the EEG. With basic signal processing, the CRs comparable to those produced with more complex signal processing were achieved [13]. Knowing that signal sources for imagery are primarily localized to sensorimotor cortex, clustering concentric electrodes around those areas may produce more useful features and higher CR. With more complex signal processing, the CR of the signals from tripolar concentric electrodes can possibly be increased further.

There is evidence that not all of the imagery signals come from a single area [25]. Wang *et al.* reported methodology that included coactivated areas of the brain during imagery [26]. They found that a three conventional electrode configuration over C3, FCz, and C4 outperformed a conventional 30-electrode system. They suggested that the signals at FCz act as a reference to derive stronger differences in the left and right signals from C3 and C4. The coactivated areas may have been one possibility why McFarland *et al.* found that a larger Hjorth-type Laplacian had higher SNR than a smaller configuration [17]. The coactivated area may have been outside of the surface area of the smaller Laplacian configuration. By placing tripolar concentric electrodes at the C3 and C4 locations, they were approximately 6.0 cm apart similar to the spacing of the larger Laplacian used by McFarland. With the electrode distance of 6.0 cm, the spatial differences of the EEG signal were acquired between the two electrodes. Tripolar concentric electrodes could also be placed similarly to Wang *et al.* [26] to acquire signals from coactivated areas.

V. SUMMARY

1) The CRs of signals using tripolar concentric electrodes were significantly better than those of signals using virtual disc electrodes.
2) With concentric electrodes, improvements in the CRs comparable to Burke *et al.* [12] were achieved without performing complex feature extraction and classification algorithms.
3) Each individual had a specific LOD, SPD, and AR Order, which gave the best classification accuracy.
4) When building the BCI model for analysis of EEG, it may be beneficial to consider subject variances with the factors individually customized before feature extraction.

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REFERENCES

[1] J. R. Wolpaw, N. Birbaumer, W. J. Heetderks, D. J. McFarland, P. H. Peckham, G. Schalk, E. Donchin, L. A. Quatrano, C. J. Robinson, and T. M. Vaughan, "Brain—Computer interface technology: A review of the first international meeting," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 164–173, Jun. 2000.

[2] G. Pfurtscheller, C. Neuper, C. Guger, W. Harkam, H. Ramoser, A. Schlögl, B. Obermaier, and M. Pregenzer, "Current trends in graz brain-computer interface (BCI) research," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 216–219, Jun. 2000.

[3] P. L. Nunez, R. B. Silberstein, P. J. Cadiush, J. Wijesinghe, A. F. Westdorp, and R. Srinivasan, "A theoretical and experimental study of high resolution EEG based on surface Laplacians and cortical imaging," *EEG Clin. Neurophys.*, vol. 90, pp. 40–57, 1994.

[4] J. E. Desmedt, V. Chalklin, and C. Tomberg, "Emulation of somatosensory evoked potential (SEP) components with the 3-shell head model and the problem of 'ghost potential fields' when using an average reference in brain mapping," *Electroenceph. Clin. Neurophysiol.*, vol. 77, pp. 243–258, 1990.

[5] B. He, "Brain electrical source imaging: Scalp Laplacian mapping and cortical imaging," *Crit. Rev. Biomed. Eng.*, vol. 27, pp. 149–188, 1999.

[6] B. Hjorth, "An on-line transformation of EEG scalp potentials into orthogonal source derivations," *EEG Clin. Neurophysiol.*, vol. 39, pp. 526–530, 1975.

[7] F. Perrin, O. Bertrand, and J. Pernier, "Scalp current density mapping: Value and estimation from potential data," *IEEE Trans. Biomed. Eng.*, vol. BE-BME-34, no. 4, pp. 283–288, Apr. 1987.

[8] S. K. Law, P. L. Nunez, and R. S. Wijesinghe, "High-resolution EEG using spline generated surface Laplacians on spherical and ellipsoidal surfaces," *IEEE Trans. Biomed. Eng.*, vol. 40, no. 2, pp. 145–153, Feb. 1993.

[9] F. Babiloni, C. Babiloni, F. Carducci, L. Fattorini, P. Onorati, and A. Urbano, "Performances of surface Laplacian estimators: A study of simulated and real scalp potential distributions," *Brain Topogr.*, vol. 8, no. 1, pp. 35–45, Sep. 1995.

[10] F. Babiloni, C. Babiloni, and F. Carducci, "Spline Laplacian estimate of EEG potentials over a realistic magnet resonance constructed scalp surface model," *EEG Clin. Neurophysiol.*, vol. 98, pp. 363–373, 1996.

[11] B. He, J. Lian, and G. Li, "High-resolution EEG: A new realistic geometry spline Laplacian estimation technique," *Clin. Neurophysiol.*, vol. 112, no. 5, pp. 845–852, May 2001.

[12] D. P. Burke, S. P. Kelly, P. D. Chazal, R. B. Reilly, and C. Finucane, "A parametric feature extraction and classification strategy for brain-computer interfacing," *IEEE Trans. Neural Syst. Rehab. Eng.*, vol. 13, no. 1, pp. 12–17, Mar. 2005.

[13] W. D. Penny, S. J. Roberts, E. A. Curran, and M. J. Stokes, "EEG-based communication: A pattern recognition approach," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 214–215, Jun. 2000.

[14] V. Fattorusso and J. Tilmant, "Exploration du champ electrique precordial a l'aide de deux electrodes circulaires, concentriques et rapprochees," *Arch. Mal Du Coeur*, vol. 42, pp. 452–455, 1949.

[15] D. Farina and C. Cescon, "Concentric-ring electrode systems for noninvasive detection of single motor unit activity," *IEEE Trans. Biomed. Eng.*, vol. 48, no. 11, pp. 1326–1334, Nov. 2001.

[16] K. Koka and W. G. Besio, "Improvement of spatial selectivity and decrease of mutual information of tri-polar concentric ring electrodes," *J. Neurosci. Methods*, vol. 165, pp. 216–272, 2007.

[17] D. J. McFarland, L. M. McCane, S. V. David, and J. R. Wolpaw, "Spatial filter selection for eeg-based communication," *Electroenceph. Clin. Neurophysiol.*, vol. 103, no. 3, pp. 386–394, Sep. 1997.

[18] F. Babiloni, F. Cincotti, L. Lazzarini, J. Millán, J. Mouriño, M. Varsta, J. Heikkonen, L. Bianchi, and M. G. Marciani, "Linear classification of low-resolution EEG patterns produced by imagined hand movements," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 186–188, Jun. 2000.

[19] W. Besio, R. Aakula, K. Koka, and W. Dai, "Development of a tri-polar concentric ring electrode for acquiring accurate Laplacian body surface potentials," *Ann. BME*, vol. 34, no. 3, pp. 426–435, 2006.

[20] W. D. Penny, S. J. Roberts, E. A. Curran, and M. J. Stokes, "EEG-based communication: A pattern recognition approach," *IEEE Trans. Rehab. Eng.*, vol. 8, no. 2, pp. 214–215, Jun. 2000.

[21] P. C. Mahalanobis, "On the generalised distance in statistics," in *Proc. Nat. Inst. Sci. India*, 1936, pp. 49–55, Ch. 12.

[22] F. Cincotti, D. Mattia, C. Babiloni, F. Carducci, L. Bianchi, J. del R Millán, J. Mouriño, S. Salinari, M. G. Marciani, and F. Babiloni, "Classification of EEG mental patterns by using two scalp electrodes and mahalanobis distance-based classifiers," *Methods Inf. Med.*, vol. 41, no. 4, pp. 337–341, 2002.

[23] W. Besio, K. Koka, R. Aakula, and W. Dai, "Tri-polar concentric ring electrode development for Laplacian electroencephalography," *IEEE Trans. Biomed. Eng.*, vol. 53, no. 5, pp. 926–933, May 2006.

[24] S. Sutton, M. Braren, J. Zublin, and E. John, "Evoked potential correlates of stimulus uncertainty," *Science*, pp. 1187–1188, 1965.

[25] P. E. Roland, B. Larsen, and N. A. Lassen, "Supplementary motor area and other cortical areas in organization of voluntary movements in man," *J. Neurophysiol.*, vol. 43, pp. 118–136, 1980.

[26] Y. Wang, B. Hong, X. Gao, and S. Gao, "Design of electrode layout for motor imagery based brain–computer interface," *Electron. Lett.*, vol. 43, no. 10, pp. 557–558, 2007.

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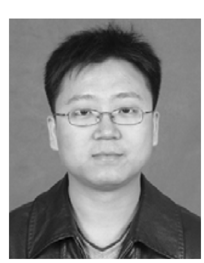

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