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·Method·

A novel single-trial event-related potential estimation method based on compressed sensing

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ABSTRACT

Cognitive functions are often studied using event-related potentials (ERPs) that are usually estimated by an averaging algorithm. Clearly, estimation of single-trial ERPs can provide researchers with many more details of cognitive activity than the averaging algorithm. A novel method to estimate single-trial ERPs is proposed in this paper. This method includes two key ideas. First, singular value decomposition was used to construct a matrix, which mapped single-trial electroencephalographic recordings (EEG) into a low-dimensional vector that contained little information from the spontaneous EEG. Second, we used the theory of compressed sensing to build a procedure to restore single-trial ERPs from this low-dimensional vector. ERPs are sparse or approximately sparse in the frequency domain. This fact allowed us to use the theory of compressed sensing. We verified this method in simulated and real data. Our method and dVCA (differentially variable component analysis), another method of single-trial ERPs estimation, were both used to estimate single-trial ERPs from the same simulated data. Results demonstrated that our method significantly outperforms dVCA under various conditions of signal-to-noise ratio. Moreover, the single-trial ERPs estimated from the real data by our method are statistically consistent with the theories of cognitive science.

Keywords: compressed sensing; event-related potentials; single-trial electroencephalography; singular value decomposition

INTRODUCTION

Event-related potentials (ERPs) hidden in electroencephalographic recordings (EEG) are powerful indices of cognitive brain functions. When participants are exposed to specific external stimuli, potentials that are time-locked to the stimulus onset are evoked[1]. The EEG recorded under these conditions is commonly modeled as a linear combination of ERPs and spontaneous EEG. The most commonly-used method to estimate ERPs is to calculate an average across an ensemble of trials[2]; this is considered to eliminate spontaneous EEG activity. Obviously, the average cannot provide information on the trial-to-trial variability of ERPs. This variability is measurable[3] and meaningful in cognitive science[4]. For example, a study[5] of the P300 by single-trial analysis pointed out that people with schizophrenia have a smaller P300s; another study[6] based on single trials revealed different sub-types of response in late ERPs components; and EEG-fMRI single-trial coupling has been used to investigate the neuronal generators of the early posterior negativity in response to emotional auditory stimuli[7]. A previous study[8] also provided evidence that single-trial ERPs can be used to accurately classify the differences between experimental conditions. In their search for richer indicators of cognitive functions, researchers have been committed to finding better means by which single-trial ERPs can be estimated accurately.

A number of techniques have been developed to estimate single-trial ERPs. The matched-filter proposed by Woody in 1967 is based on a signal model in which the trial-to-trial change of amplitude and latency is depicted[9]. Subsequent researchers expanded Woody's thinking to advance this field so that maximum likelihood could be used to estimate the amplitudes and latencies for each trial[10-14]. A method based on Bayesian theory[15] used second-order *a priori* statistical information in the EEG to estimate single-trial ERPs. Some researchers assume that EEG sources are independent, so Independent Component Analysis has been used to estimate single-trial ERPs[16-18]. Another study proposed a classification-based framework and derived a specialized algorithm for single-trial ERPs estimation from this framework[19]. On the other hand, analyses of the characteristics of signals in the frequency domain have been exploited to design procedures to estimate single-trial ERPs[20-26]. Wavelet and Fourier transformations usually underlie these procedures. Recently, a new approach based on the principle of projecting the signal and noise onto their respective signal and noise coefficient subspace was reported[27].

In single-trial ERPs estimation and related fields, the sparsity of ERPs has drawn attention and been used to develop new methods of ERPs estimation and representation. Sparse component decomposition has been applied to estimate ERPs[24]. A framework based on compressed sensing (CS), a special computing technology for sparse signals, was introduced for the representation of multichannel, multiple-trial EEG[28]. A classification method based on sparse representation of EEG signals and ell-1 minimization has been suggested for building motor imagery-based brain-computer interface systems[29, 30]. In the present study, we started with the sparsity of ERPs in the frequency domain to build a novel method based on CS for single-trial ERP estimation.

CS was developed in a theoretical framework based on the theory of optimal recovery, the theory of n-widths, and information-based complexity[31]. In recent years, CS has attracted considerable attention in applied mathematics, computer science, and electrical engineering by suggesting that it may be possible to surpass the traditional limits of sampling theory. CS builds upon the fundamental fact that we can represent many signals using only a few non-zero coefficients in a suitable base or dictionary. Nonlinear optimization can then enable the recovery of such signals from very few measurements[32].

In this paper, we proposed a special single-trial ERPs estimation method built upon the sparsity of ERPs in the frequency domain. Elimination of spontaneous EEG is a difficult problem because it is always much stronger than the ERPs. Almost all ERPs estimation methods assume that ERPs are irrelevant to spontaneous EEG. We also adopted this assumption in the process of constructing this new method. We started with this assumption to seek a solution for eliminating spontaneous EEG by a de-noising matrix obtained by singular value decomposition (SVD) of spontaneous EEG. Further, a sensing matrix in CS was obtained by multiplying this de-noising matrix by the basis of the inverse Fourier transform. Our method can be briefly described in three steps: (1) obtain a de-noising matrix by SVD of spontaneous EEG and a sensing matrix by multiplying the de-noising matrix by that basis, (2) eliminate spontaneous EEG by the de-noising matrix obtained in the first step, and (3) recover single-trial ERPs by the sensing matrix using the theories of CS.

METHODS

Signal Model and Problem Formulation

A trial EEG recorded from the scalp is here written as $E^k \in \mathbb{R}^{T\times N}$, where k represents the index of the trial, N the number of channels, and T the number of sampling points for a trial. When EEG is recorded in the ERPs experimental paradigm, ERPs exist in the EEG, which is considered to be a linear combination of spontaneous EEG and ERPs. So, we have

$$E^k = B^k + S^k \tag{1}$$

where B^k denotes the spontaneous EEG of the kth trial and S^k the ERPs of the kth trial; certainly B^k, $S^k \in \mathbb{R}^{T\times N}$ too. We denote a column vector of E^k, B^k, S^k as e, b, s, respectively. Clearly, $e = b + s$. The average, commonly used to estimate ERPs, can be expressed as

$$\overline{S} = \lim_{K\to\infty} \frac{1}{K}\sum_{k=1}^{K}(B^k + S^k) \tag{2}$$

where it is expected that $\lim_{K\to\infty} \frac{1}{K}\sum_{k=1}^{K} B^k = 0$ and $\overline{S}$ is the average of all S^k, the variability of which is ignored here. In actual settings, K usually ranges from 80 to 200. The broad applications of average estimation in cognitive science

show that $\bar{S}$ is not a bad approximation of S^k [1, 2, 33]. Seeking to find every S^k, we consider that $\bar{S}$ is still valuable.

Given the task is to estimate all S^k from E^k, what is known is clearly not enough. Most estimates of ERPs, including averaging and a variety of single-trial estimation methods[2, 9-26], build upon the assumption that ERPs are irrelevant to spontaneous EEG. Here, we also made this assumption. Since $\bar{S}$ is an acceptable approximation of S^k and B^k is irrelevant to S^k, $\tilde{B}^k = E^k - \bar{S}$ can be considered an acceptable approximation of B^k. Furthermore, the column vectors of B^k are relevant to each other and they jointly reflect the status of spontaneous EEG in a trial. That is, we can find a projection from B^k, by which a column vector of B^k corresponding to a channel from the kth trial can be transformed to another vector in which most entries are very weak. This implies a solution to attenuate spontaneous EEG for estimation of single-trial ERPs. In the actual case, B^k is unknown. It is reasonable to use $\tilde{B}^k$ as a substitute for B^k.

We explored the projection described above by SVD of $\tilde{B}^k$. According to the principle of SVD, we have $\tilde{B}^k = U\Delta V$, where $U \in \mathbb{R}^{T\times T}$, $V \in \mathbb{R}^{N\times N}$, and Δ is a $T \times N$ rectangular diagonal matrix with non-negative real numbers on the diagonal, which are called singular values. Each column vector of U corresponds to a singular value in Δ. When b is projected to a column vector of U, the singular value corresponding to it represents the power of b on it. Usually, the singular values decay rapidly if they are sorted in descending order. That is, the power of b concentrates on only a few dimensions if b is projected to the space determined by U. We can obtain a de-noising matrix $D^k \in \mathbb{R}^{M\times T}$, where $M<N<<T$, by transposing some column vectors of U corresponding to the small singular values. For the sake of simplification, we denote the above procedure with the notation SV_M, that is $D^k = SV_M(\tilde{B}^k)$, where the subscript M is a parameter of de-noising. It may be expected that every entry of $\eta = D^k b$ is close to 0. So, we have

$$\begin{aligned} y &= D^k e \\ &= D^k s + D^k b \\ &= D^k s + \eta \\ &\approx D^k s \end{aligned} \tag{3}$$

where $e \in \mathbb{R}^{T\times 1}$ is the known measurement result and $D^k \in \mathbb{R}^{M\times T}$ is obtainable, so $y \in \mathbb{R}^{M\times 1}$ is a computable approximation of $D^k s$. Now, estimation of single-trial ERPs has been formalized as a problem of determining s by known y and D^k. Here, D^k is not a square matrix and not invertible. The problem of equation is still difficult. The next step of our method is built on CS.

Sensing Matrix

CS is a method for sparse signals with complete theories. Mathematically, a signal $x \in \mathbb{R}^{T\times 1}$ can be said to be m-sparse when it has at most m non-zeros and $m<<T$[31, 32]. Intuitively, s in this paper should be a sparse signal or an approximately sparse one because most entries of s are close to zero except those surrounding a few peaks, which are called components in cognitive science and related areas[1, 2, 34]. But, this is not straightforward according to the mathematical definition of sparse signals. When s is transformed from the time domain to the frequency domain by Fourier transformation, only $m \approx 16$ entries among all 400 entries of the s vector in the frequency domain are not equal to zero, and other entries are equal to or very close to zero. The sparsity of s is clearly revealed by Fourier transformation.

The sparsity of EEG as well as ERPs has been widely discussed and exploited by many researchers. One paper[28] described the sparsity level of EEG signals based on the analysis of 750-sample EEG recordings from a control participant performing a continuous performance task. Others[29, 30] developed a classification scheme for motor imagery-based brain-computer interface systems by a combination of sparse representation of EEG and a common spatial pattern. A further study[24] designed a decomposition method based on the sparsity of ERPs and EEG, by which multiple signals could be separated by learning in a mixed dictionary with a matching pursuit algorithm, for ERPs estimation.

In this study, we used the sparsity of ERPs in the frequency domain to construct the single-trial ERPs estimate. According to the principle of Fourier transformation, we may have $s = \Phi x$, where $\Phi \in \mathbb{C}^{T\times T}$ corresponds to a discrete inverse Fourier transform, Φ is irrelevant to x, $x \in \mathbb{C}^{T\times 1}$, and most entries of x are equal to or near zero. To proceed, we defined $A^k = D^k\Phi$, $A^k \in \mathbb{C}^{M\times T}$, where D^k is derived from $\tilde{B}^k$ being irrelevant to x, and Φ is also irrelevant to x. Equation (3) can be further written as follows:

$$\begin{aligned} y &= D^k e \\ &= A^k x + \eta \end{aligned} \tag{4}$$

Algorithm 1. COSE, single-trial ERPs estimation

Input: EEG of K trials E^k, $k = 1,\cdots,K$.

Output: ERPs of channel j of K trials s^k, $k = 1,\cdots,K$.

1: initialize de-noising parameter M, sparsity level m, channel index j, inverse Fourier transformation matrix Φ.

2: $\bar{S} = \frac{1}{K}\sum_{k=1}^{K} E^k$

3: $k = 1$

4: **while** $k <= K$ **do**

5: $e = COL_j(E^k)$, $\tilde{B}^k = E^k - \bar{S}$, $D^k = SV_M(\tilde{B}^k)$, $y = D^k e$, $A^k = D^k\Phi$.

6: $x_0 = 0$

7: **while** stopping criterion is not met **do**

8: $x_1 = H_m(x_0 + A^T(y - Ax_0))$, $x_0 = x_1$.

9: **end while**

10: $s^k = \Phi x_1$

11: $k = k + 1$

12: **end while**

In equation (4), e is measured data, D^k is determined *via* $SV_M(\tilde{B}^k)$, y and A^k are computable, and only x is to be determined. Clearly, the task in this study can be accomplished if x is determined well.

In terms of other studies[31, 32], x is an m-sparse signal to be determined, A^k is a sensing matrix, η is noise, and y is the measurement of x. According to the theory of CS, for determining x it is required that $M \geq 2m$. Always, m ranges from 10 to 20. EEG is usually recorded with 64, 128, or 256 electrodes, that is, $N = 64$, 128, or 256. M is slightly smaller than N. So, $M \geq 2m$ is completely met here. Signal recovery algorithms of CS are good for obtaining x from y and A^k.

Algorithm of Estimation

Generally, a variety of ℓ_1 minimization or "greedy" algorithms for signal recovery in CS areas are applicable to our goal in the study. Here, a greedy algorithm named iterative hard thresholding (IHT)[32] was modified as the core of our single-trial ERPs estimation. This is called COSE, an abbreviation of compressed sensing, by which we emphasize the importance of compressed sensing in our method. COSE is shown as Algorithm 1.

In Algorithm 1, $COL_j(\cdot)$ represents an operator that takes the jth column of the matrix, $H_m(\cdot)$ denotes a hard thresholding operator on a vector that sets all entries to zero except for the m entries of this vector with the largest magnitude. The stopping criterion in line 7 can consist of either a limit on the number of iterations or a requirement that $y \approx Ax_1$ in some sense.

dVCA

Comparison between COSE and dVCA[11] will be made in the next section to demonstrate the advantages of our method. Here, dVCA is briefly described in this context. The dVCA algorithm consists of the following steps.

(1) Choose the averaged result of EEG of K trials as the initial estimate of the ERPs component waveform.

(2) For all components and trials, estimate the single-trial latency shift.

(3) Update the ERPs waveform component by component.

(4) For all components and trials, estimate single-trial amplitudes.

(5) If the stopping criterion is met, end. Otherwise, go to step (2).

RESULTS

Simulated Data

We designed a procedure to build simulated EEG

containing known ERPs by referring to the literature[11, 22, 24]. In this procedure, simulated EEG was synthesized by the superposition of spontaneous EEG and simulated ERPs waveforms including several components. Eight university student volunteers (identified as S1 to S8) were randomly selected in order to acquire spontaneous EEG. They were 19–25 years old, half were female, and their hearing and sight were normal. A 64-electrode EEG instrument was used to record EEG at 1 000 Hz. The real 64-channel EEG of participants in the resting state was viewed as spontaneous EEG.

The spontaneous EEG of each participant was cut into 72 segments, each of which spanned 400 ms. The 72 segments corresponded to 72 trials. A simulated ERPs waveform containing two components is shown as the "real" curve on the right in Figure 1. A group of simulated ERPs waveforms for 72 trials were generated by adjusting the amplitudes and latencies of the two components. In detail, the single-trial amplitudes of the two components were Gaussian-distributed with means –1 and 9 and standard deviation 0.5, their latencies were Gaussian-distributed with means 168 and 274 and standard deviations 10 and 15. Superposition of spontaneous EEG segments and simulated ERPs waveforms was carried out to construct a group of simulated EEG corresponding to 72 trials. The signal-to-noise ratio (SNR) of this group of simulated EEG was –10 according to $\mathrm{SNR} = 20 \cdot \log\left(\frac{\sigma_s}{\sigma_n}\right)$, where σ_s represents the standard deviation of simulated ERPs and σ_n the standard deviation of the spontaneous EEG. We produced other 9 groups of simulated EEG for each participant by increasing the mean of amplitudes of the two components. They were –3 and 11, –5 and 13, –7 and 15, –9 and 17, –11 and 19, –13 and 21, –15 and 23, –17 and 25, and –19 and 27. The SNRs of the other 9 groups were –8, –6, –4, –2, 0, 2, 4, 6, and 8.

We estimated single-trial ERPs from each simulated EEG by COSE and dVCA. Also, the average of each group of simulated EEG was computed for comparison. Two randomly-selected examples of estimation results are given in Figure 1. Both examples showed that "averaged" is not equal to "real", which makes it clear that "averaged" is just an approximation of single-trial ERPs. COSE resembled "real" much more than dVCA. This is an indication of the advantage of COSE over dVCA.

When the amplitudes are transformed to gray-scale, a group of ERPs waveforms can be drawn as an image. All estimation results of the two groups of simulated EEG are presented as gray-scale images in Figure 2. Visual inspection showed that COSE images were much more similar to their real counterparts than dVCA images. These results demonstrated that COSE works much better than dVCA in the two groups of simulated EEG.

Next, we compared the real and estimated values of COSE and dVCA for the amplitudes and latencies of components of each simulated trial (Fig. 3). The data

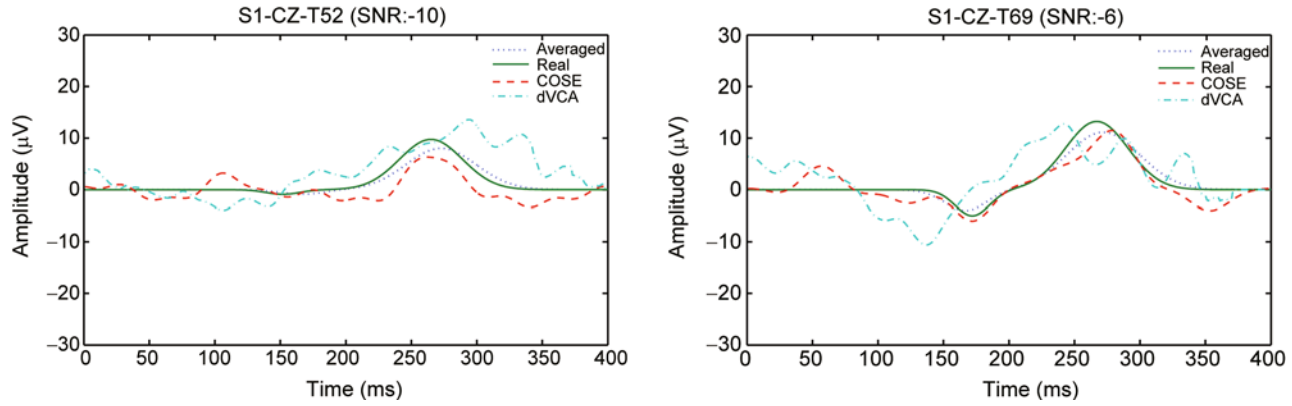

Fig. 1. Examples of waveforms of real ERPs and ERPs estimated by averaging, COSE, and dVCA. The "real" curve is the actual ERPs waveform in simulated EEG. The "averaged" curve is the average of 72 trials. The "COSE" curve is the result estimated by COSE. The "dVCA" curve is the result estimated by dVCA. The left panel is from trial 52 of simulated EEG from S1 in which the SNR is –10. The right panel is from trial 69 of simulated EEG from S1 in which the SNR is –6.

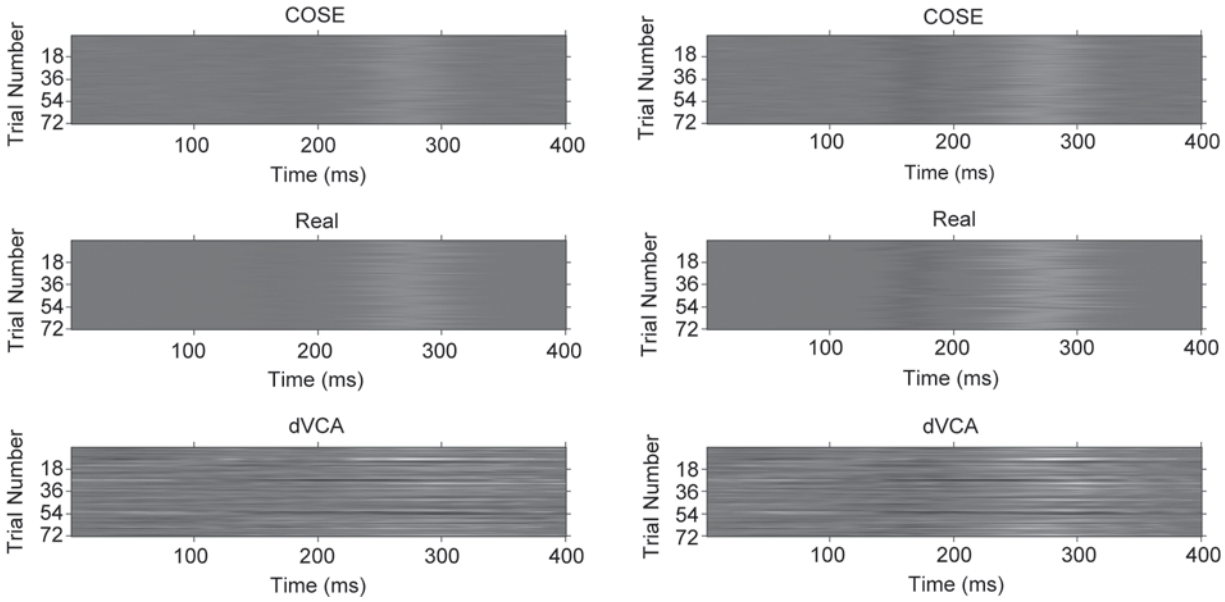

Fig. 2. Groups of ERPs waveforms presented as gray-scale images by transforming amplitude to gray scale. Left panels, images from S1 with SNR = –10; right panels, S1 with SNR = –6. Upper panels, estimates by COSE; middle panels, the real waveforms; bottom panels, estimates by dVCA.

demonstrated that the effectiveness of estimating the latencies of both components by COSE was much better than that of dVCA (Fig. 3, right panels; since both axes are the same scale, good performance is indicated by clustering along the diagonal). For amplitude, we used different scales for the horizontal and vertical axes in order to contain as many dVCA results as possible (Fig. 3, left panels). In this situation, better performance is indicated when data points cluster near the horizontal. The data showed that results of components estimated by COSE were good, while dVCA was not satisfactory. These results demonstrated the good performance of COSE and the advantage of COSE over dVCA.

We built ten groups of simulated EEG for each of the eight participants. All estimated results for amplitudes are shown in Figure 4 and for latencies in Figure 5. The data showed that the correlations of real and estimated values of COSE were higher than those corresponding to dVCA in each group of all subjects for Components 1 and 2, and for amplitudes and latencies. Higher correlation implies better performance and the data showed the superiority of COSE over dVCA. In addition, a trend for the correlation to increase with SNR was revealed for dVCA; this trend was also present for COSE though not obvious. This suggests that SNR plays an important role in the performance of single-trial ERPs estimation. Generally, the SNR of ERPs in real EEG is low. The ability of a method to adapt to a low SNR is very important. The advantages of COSE over dVCA in the groups with a low SNR highlight important points.

Cognitive Experiment Data

Besides simulated data, our method was further verified with real data from a cognitive experiment based on sensory gating, which is a normal function of brain. The brain filters redundant information by this function to adapt to a new environment and maintain the integrity of cognitive function[35]. Sensory gating is related to cognitive processes such as attention and working memory and works to protect cognition[36]. The paired-click paradigm, a standard means of researching sensory gating, was inserted into delayed-response tasks with different memory loads in three experiments. In Experiment 1, the participants were asked to maintain a resting state. In Experiment 2, a randomly-selected image of a face was set as the stimulus of a trial and the participants were trained to maintain a state of low-load object working memory. In Experiment 3, two randomly-selected faces were set as the high memory load and the participants were also trained to maintain an object

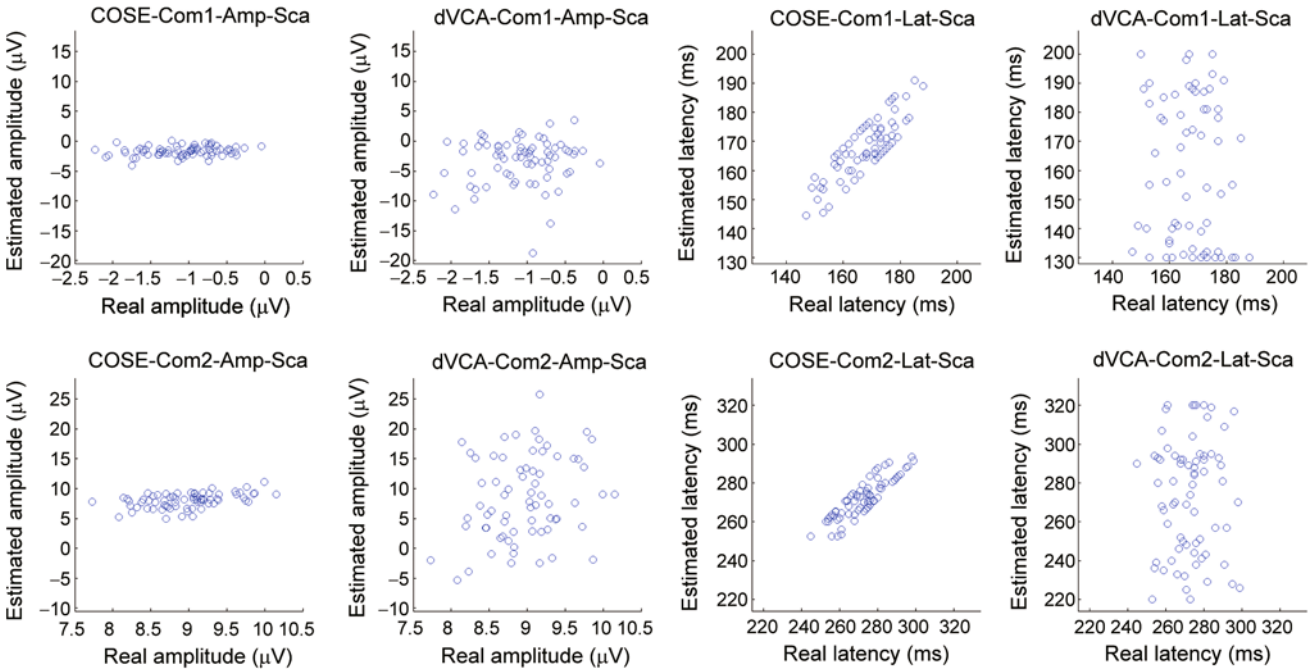

Fig. 3. Scatter diagrams of data from S1 with SNR = –10. Horizontal axis, real value; vertical axis, estimated value. Each point includes information of the real and estimated values of a component of a trial. Left panels, scatter diagrams of component amplitudes; right panels, scatter diagrams of component latencies. The title "COSE-Com1-Amp-Sca" denotes that this is a scatter diagram of the amplitudes of Component 1 estimated by COSE; other titles are similar.

working memory state, but with a high load. In Experiments 2 and 3, the participants were asked to remember the faces and make a judgment as to whether the probe faces were the same as the target ones by clicking a computer mouse. The three experiments corresponded to three different states of the participants. In each state, they were all given stimuli of two consistent 10-ms sounds (frequency, 1 000 Hz; intensity, 85 db; inter-stimulus interval, 500 ms; inter-test interval, 6-8 s; selected according to the paired-click paradigm). EEG was recorded from the participants in the different states. The real EEG was the superposition of ERPs and spontaneous EEG. The three experiments consisted of 80 trials for each participant. Normally, the ERPs evoked by the first sound is stronger than that by the second sound; i.e., sensory gating occurs. We verified COSE by judging whether the results in these real EEG were consistent with this phenomenon.

Participants S1–S4 took part in Experiments 1 and 2, and S5–S8 in Experiments 1 and 3. During these experiments, NeuroScan was used to record and precondition the EEG: the AC filter was set to 0.1–100 Hz, and the data sampling rate was 1 000 Hz; the reference electrode was on the nasion, and the resistances of all electrodes were <5 kΩ. About 60 single-trial EEGs were obtained in each session, since precoditioning usually rejected some single trials.

COSE was applied to estimate single-trial ERPs from all real EEG. Subsequently, the amplitude of N100, a component often measured in studies of sensory gating, was determined from each single-trial ERPs estimation and matched according to the relation of the first sound and second sound. The Wilcoxon signed-rank test was carried out on the pairs of amplitudes for all experiments on each participant. As shown in Table 1, means corresponding to the 1st sound were larger than those to the 2nd sound (P <0.05). This is fully consistent with the principle of sensory gating[35]. The results of these cognitive experiments support the utility of COSE, our single-trial ERPs estimation method based on compressed sensing.

DISCUSSIONS

ERPs have been important tools of research on cognitive

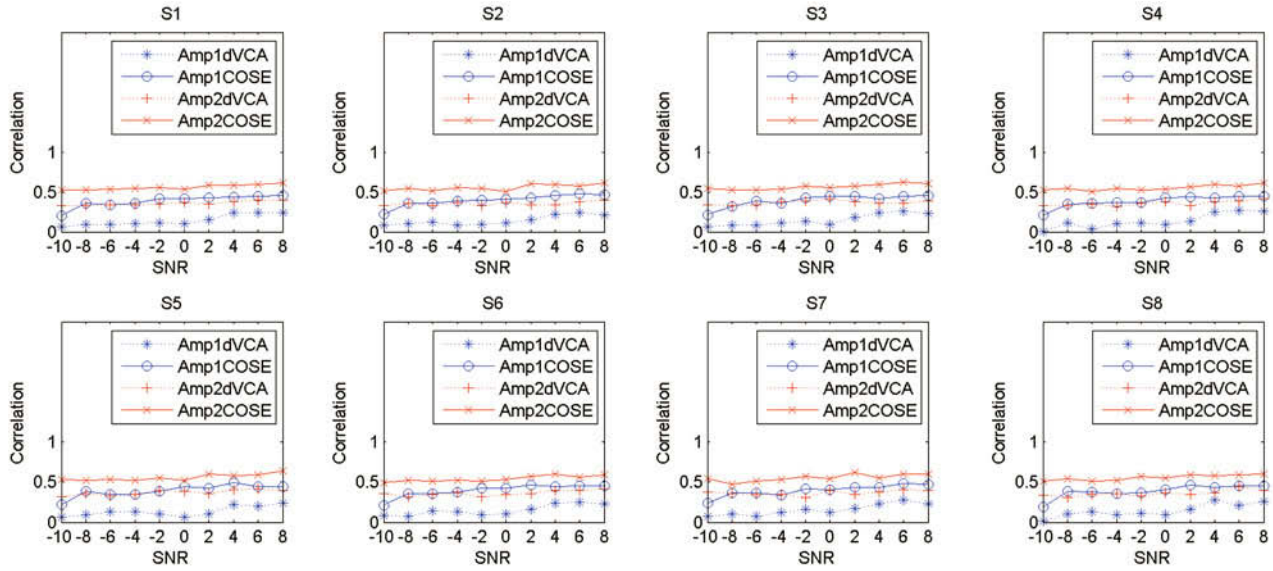

Fig. 4. Correlation of amplitudes. The correlation coefficient of real and estimated amplitudes was calculated for each component of each group of all subjects. The symbol '*' represents the correlation coefficient of a group of Component 1 real amplitudes and amplitudes estimated by dVCA. The horizontal coordinate is the SNR of the group and the vertical coordinate the correlation coefficient. 'o', '+' and 'x' have same implications, but correspond respectively to Component 1 estimated by COSE, Component 2 estimated by dVCA, and Component 2 estimated by COSE. Blue indicates Component 1 and red Component 2. The solid lines indicate COSE and the dotted lines dVCA. Each sub-graph displays the results from one participant (S1–S8).

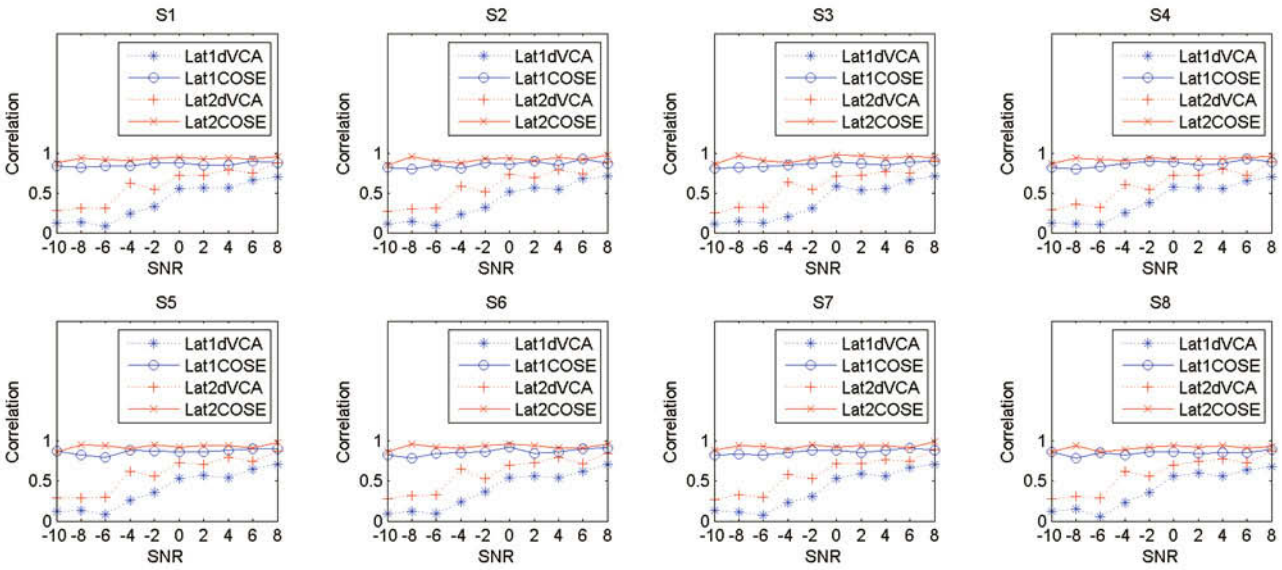

Fig. 5. Correlation of latencies, as in Fig. 4.

functions for a long time. However, they are usually estimated by averaging. Clearly, estimation of single-trial ERPs can reveal much more about cognitive activities in the brain. However, estimation of single-trial ERPs is difficult. Research on this issue can be traced back at least to 1967[9], and a variety of methods have been proposed and tried. In recent years, various ways to improve the estimation of single-trial ERPs have been developed[15, 19, 27].

Table 1. Cognitive experiment results.

Subject	Experiment 1			Experiment 2 or 3		
	1st sound	2nd sound	*P* value	1st sound	2nd sound	*P* value
S1	3.11 ± 2.1	1.93 ± 2.5	0.017	2.61 ± 2.5	1.19 ± 1.8	0.011
S2	2.95 ± 2.0	1.77 ± 2.3	0.011	2.53 ± 2.3	1.03 ± 1.9	0.010
S3	3.25 ± 2.3	1.65 ± 2.6	0.009	2.91 ± 2.6	1.02 ± 1.9	0.009
S4	3.11 ± 2.3	1.77 ± 2.7	0.012	2.92 ± 2.4	1.16 ± 1.7	0.013
S5	3.27 ± 2.2	1.72 ± 2.5	0.008	2.53 ± 2.6	0.76 ± 1.6	0.009
S6	3.15 ± 2.5	1.75 ± 2.4	0.009	2.37 ± 2.7	0.67 ± 1.7	0.011
S7	3.02 ± 2.1	1.73 ± 2.2	0.013	2.57 ± 2.5	0.62 ± 1.5	0.010
S8	3.12 ± 2.0	1.69 ± 2.6	0.015	2.39 ± 2.5	0.53 ± 1.8	0.009

The unit of measurement in the "1st sound" and "2nd sound" columns is μV. The data in "*P* value" columns are the *P* values of the Wilcoxon signed-rank test on matched amplitudes of 1st and 2nd sounds.

Here, we sought a new solution to estimate single-trial ERPs, starting with the fact that ERPs are sparse or approximately sparse in the frequency domain. Compressed sensing, which recently emerged as a computing technology for sparse signals, was suitable for single-trial ERPs estimation in our research. We built a method on compressed sensing, in which singular value decomposition was also used.

We designed a procedure to construct simulated data, in which our method and dVCA were compared. The results showed that our method worked well and was clearly better than dVCA. The real data were from cognitive experiments designed to assess sensory gating. The results of our method with the real EEG were fully consistent with the findings of cognitive science. The cognitive experiments provide evidence for the utility of our method.

An ERPs waveform consists of only a few peaks, which implies their sparsity, although this is not straightforward in the time domain. Here, we disclosed the sparsity of ERPs through Fourier transformation. However, there may be other approaches to accomplish this for ERPs, such as wavelet transformation. This is a direction of advancing research.

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