Localizing Functional Activity in the Brain Through Time-Frequency Analysis and Synthesis of the EEG

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Multichannel electroencephalograms (EEG's) are processed using time-frequency (TF) analysis and synthesis techniques to geometrically localize neuroelectric generators of specific activity contained within the observed EEG. The TF domain techniques are utilized to separate the signals of interest from the remainder of the EEG, by allowing the definition of regions of interest which contain the signals for which we desire to localize the underlying neuronal generators. This approach essentially introduces a filtering technique which allows the distortionless separation of the signals of interest from all other components recorded. The source of the functional activity in the brain is estimated and mapped numerically by a least-squares approach. We have applied these techniques to identify the anatomical location of the sleep spindle, a component of the EEG observed during sleep, which is of importance in understanding the generation of sleep and sleep patterns.

I. Introduction

A problem of major significance, in both basic and clinical neuroscience, is the localization of functional areas responsible for the generation of electrical activity in the human brain. The solution of this problem will allow important questions concerning areas of the brain in which information is processed to be answered noninvasively, and the identification of so-called "eloquent areas" of the brain will allow these areas to be protected during surgery. In this paper, we first briefly provide a background in electrophysiology, including fundamental units of the nervous system, their functions, their contributions to the observed neuroelectric activity, and methods of electroencephalogram (EEG) acquisition. Then, previous signal processing methods applied to the EEG are reviewed, with particular emphasis on time-frequency (TF) analysis. We then review techniques for source localization based on mathematical models of a volume conductor and a dipole current source, formulated as the inverse problem of the EEG. Next, we present our approach to the utilization of TF analysis and synthesis techniques to process multichannel EEG data. In this approach, we compute the TF distribution series (TFDS) and assemble the results to form a weighted-average. A region of interest (ROI) in the TF plane, containing the identified signal of interest, is specified with respect to this average, and the TF filtered signal is iteratively reconstructed for each channel of the EEG using a set of Gabor coefficients. Finally, experimental results localizing the underlying generators for sleep spindles are presented. These results demonstrate a significant improvement on the source localization problem using TF technique as compared to traditional methods.

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II. Biological Considerations

It is well known that the variation of the surface potential distribution on the scalp reflects functional activities emerging from the underlying brain [1]. This surface potential variation can be measured by affixing an array of electrodes, which are usually gold-plated, approximately 1 cm in diameter, to the scalp, and measuring the voltages between pairs of these electrodes, which are then filtered, amplified, and recorded. The resulting data is called the EEG. Fig. 1 shows waveforms of a 8-s EEG segment containing five recording channels, while the recording sites are illustrated in Fig. 2.

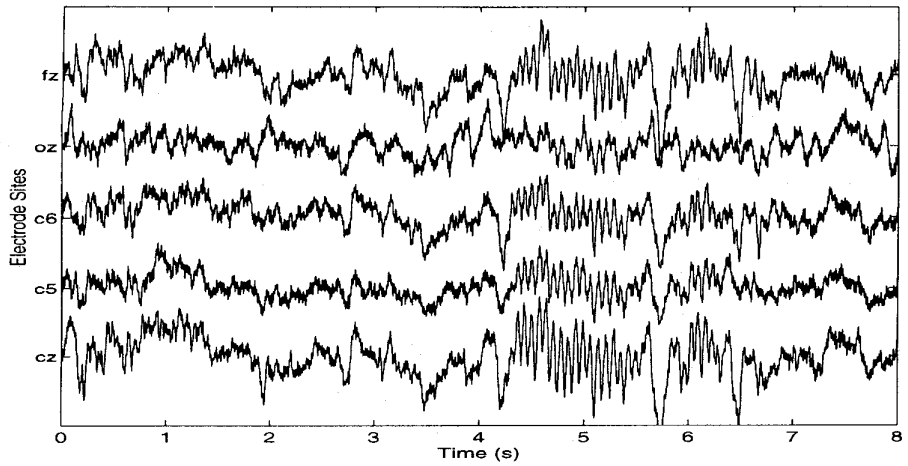

Fig. 1. A segment of a multichannel EEG of an adult male subject during sleep: Only five channels are shown out of a total of 64 channels recorded. This EEG segment belongs to stage two QS demonstrating a sleep spindle between 4 and 7 s.

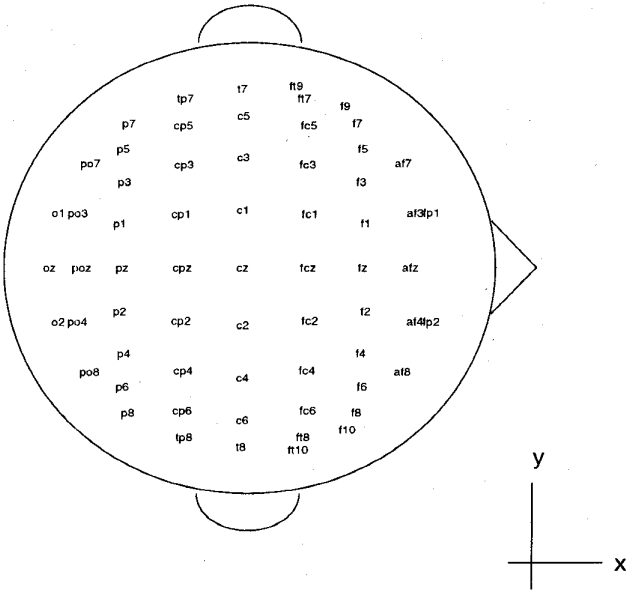

Fig. 2. Locations of electrodes: 64 recording electrodes utilized in our experiments are shown with symbols commonly used in neurophysiological studies. The viewpoint is directly above the vertex of the head (Electrode Cz).

The brain is composed of *neurons* and supporting tissues called *glia* [1]. Abstractly, a neuron is probably the most diverse, in terms of form and size, of all cells in the body; however, all neurons have in common the functional properties of integration, conduction, and transmission of nerve impulses. The neuron consists of three parts: 1) a dendritic branching through which input information is transferred to the cell, 2) a body (or soma) which serves to integrate this information, and 3) an axon, which is a segment transferring information to other neurons. Each neuron is in contact through its axon and dendrites with other neurons, so that each neuron is an interconnecting segment in the network of the nervous system.

The *synapse*, a specialized site of contact between neurons, is of prime significance in the integrative activities of the nervous system. Electric potentials are produced at the synaptic junctions which reflect communication between neurons, and unidirectional conduction is determined at these sites, resulting in functional polarity for sequences of neurons such that excitation can only be transmitted from the axon of one neuron to the dendrites or soma of the next. Stimulation of the synaptic input sites on the soma and dendrites generally evokes a graded potential which spreads decrementally to reach the initial segment of the axon where an action potential may be produced. The dendrites and the soma are not adapted for long-distance transmission, as is the axon, but rather for integrating synaptic activity. In addition to the fast action potentials observable from single neurons in any domain of cortical or subcortical tissue, slower wave processes may also be seen. The EEG is thought to be the synchronized subthreshold dendritic potentials produced by the synaptic activity of many neurons summed [2].

Compact groups of neurons, called nuclei, are anatomically identifiable within the central nervous system. Tracts of axons connecting these nuclei can be traced from region to region and it is to such relatively complex nuclear regions that the various functions of the nervous system are related, and which are the putative sites of generators for the EEG observed on the scalp.

The EEG recorded from the scalp in man typically has amplitudes from 10 to 100 μV and a frequency content from 0.5 to 40 Hz. Signals of 10–30 μV are considered low amplitude and potentials of 80–100 μV are considered high amplitude. The spectrum of the EEG is traditionally divided into four dominant frequency bands: δ-band (0–4 Hz), θ-band (4–8 Hz), α-band (8–13 Hz), and β-band (13–30 Hz). An alert person displays a low amplitude EEG of mixed frequencies, while a relaxed person produces large amounts of sinusoidal waves, in the 8–13 Hz frequency range, which are particularly prominent at the back of the head.

The EEG has been a primary tool in the study of sleep which is important in both basic neuroscientific research and the clinical diagnosis of many neurological disorders. In the adult human, sleep is classified into several stages on the basis of brain, muscle, and eye activity, although the boundary between stages cannot be clearly defined. Quite sleep (QS), rapid eye movements (REM), and occasional momentary wakings occur in a periodic sequence throughout the night, taking approximately 90 min in the adult human [3].

QS stage may be further differentiated into four substages. As an individual goes to sleep, α-activity is replaced by a lower amplitude, mixed frequency voltage (stage one QS), which within minutes has superimposed 1–2-s bursts of 12–14 Hz activity called sleep spindles (stage two QS), the activity investigated in this research. Several minutes later high-amplitude slow waves (0.5–3 Hz) appear and mark the onset of stage three QS. After about 10 min these slow waves dominate the EEG and the deepest stage of sleep, stage four is reached. After a return through these stages, REM sleep occurs, approximately 90 min after sleep onset [3].

The notion of sleep stages in terms of frequency features described above has been accepted as a general rule in the EEG community in the study of sleep. However, in many individuals, the EEG does not follow this rule closely. Significant fluctuations can occur over a short period of time due to rapid changes in the underlying neuroelectric activity in the brain (see Fig. 1). For a signal with rapidly varying spectral attributes which cannot be modeled adequately by traditional means, difficulty often arises in understanding the signal since it cannot be well separated from the background EEG. In Sections V and VI we will investigate this problem using TF techniques.

III. EEG Signal Processing

Signal processing techniques have also been extensively applied to the EEG. Early studies using computational methods to analyze sleep signals were reported by Sclabassi *et al.* [4], [5] whose methods were primarily dependent on the Fourier transform to estimate the spectra of the EEG, assuming that the observed data was stationary over short periods of time (on the order of 2–4 s). Techniques based on spectral analysis of the EEG were discussed in detail by Jervis *et al.* [6], where important aspects of designing sliding windows and computing predictive statistical measures were presented. Although Fourier transform based methods have been improved considerably over years of research, and the frequency band classification referenced above, which summarizes the spectral content of the EEG, provides a convenient basis for EEG analysis and comparison, these methods are not effective when the EEG exhibits significant nonstationarities. This drawback has been addressed by many investigators [7], [8].

Recently, advanced signal processing methods, such as wavelet transforms [9], [10] and TF analysis [11]–[13], have been applied to the EEG and other physiological signals. A comprehensive survey of this development has been provided by Lin and Chen [8] where the fundamental background of TF techniques and their applications to the EEG and evoked potentials, as well as other biological signals, are extensively reviewed. Aiming to characterizing the evolution of time-varying spectrum of the EEG, Blanco *et al.* [14] reviewed TF distributions based on the Gabor transforms. Features of the signals are extracted from the TF distributions and then used in a pattern classification process. This technique produced encouraging results in the study of spectral variation in epileptic seizures. Other interesting applications of TF techniques to the EEG was reported by Nayak *et al.* [15] in the detection of depth of anesthesia during surgery. They showed that the depth was characterized by TF features which, under certain anesthetic conditions, are superior to those derived from the traditional Fourier analysis. Alternative types of TF distributions, such as the pseudo Wigner distribution, have been found effective in providing high-resolution details of event-related potentials (ERP's) which are observed from averaged EEG trails [16], [17]. The Page and Rihazcek distributions have also been applied to the EEG and ERP's [18], [19], as has the Choi–Williams distribution [20], which provides a higher resolution than the spectrogram and fewer interfering cross-terms than the pseudo-Wigner distribution. The Choi–William distribution has also been used to analyze the electrocorticogram (ECoG) which is recorded from the surface of the cortex, rather than the scalp [20]. The cross TF distributions which measure the TF coherence of a pair of signals have been used for analyzing multichannel EEG [16], [17] and for identifying epileptic seizures [20].

IV. EEG-Based Source Localization

Most previous applications of signal processing to the EEG have focused on finding temporal and spectral properties of the signal to permit testing of hypotheses relating to changes in these measures with respect to different groups or experimental conditions. In an alternative problem, however, one is focused on localizing the particular neuronal structure responsible for the generation of particular observed activity [21]–[26]. In this approach, the geometric space of the head is the domain of interest for localizing a source of functional activity; i.e., a set of densely packed, activated neurons, based on the observed signals from the scalp. This problem has been formulated as *the inverse problem* [22]. Theoretically, a system has an inverse if and only if its input/output relationship is unique; however, this is not the case in this problem since different sources may produce identical waveforms at any recording site. Therefore, the inverse problem is generally ill-posed and the solutions are not unique.

Models of the head, including its geometry and conductivity, are required to solve the inverse problem. The simplest model [27] includes a dipolar current source in a spherical volume conductor with shells of isotropic conductance. More complex models employ more than one

dipole, more realistic head shapes, and nonhomogeneous conductivity values [28], [29]. A forward solution for any given model can be obtained using the following differential equation [30]

$$\mathrm{div}(\sigma(\mathbf{r})\mathrm{grad}\psi(\mathbf{r})) = s(\mathbf{r}), \quad \text{for } \mathbf{r} \in \Omega \tag{1}$$

where "div" and "grad" denote, respectively, the operators of divergence and gradient, Ω represents the space of the head, $\psi(\mathbf{r})$ is the potential function of location $\mathbf{r}$, $\sigma(\mathbf{r})$ is the conductivity tensor (generally anisotropic), and $s(\mathbf{r})$ is the current source density function. When σ and s are known and certain boundary conditions are imposed, ψ may be solved analytically for a layered spherelike volume conductor excited by a dipolar current source [30]. In more realistic models, an analytic solution does not exist and the problem must be solved by using the finite boundary or finite element method which requires considerable computation.

In the next step a numerical optimization is utilized to compare the computed scalp voltages obtained from the forward solution against the measured EEG. Assuming the dipole is unconstrained, i.e., free in translation and rotation inside the head, this optimization minimizes the following residual variance

$$R = \frac{\sum_{c=1}^{N_c}[V(c) - v(c)]^2}{\sum_{c=1}^{N_c} v(c)^2} \tag{2}$$

where $V(c)$ and $v(c)$ are, respectively, the theoretical and actually measured scalp voltages for channel c, and N_c is the number of channels. Traditional optimization algorithms, such as the simplex algorithm and steepest descent, are often employed to determine a total of six parameters for the optimal source dipole, three for the location vector, and three for the directional current components [22].

V. Time-Frequency Methods

Most source analyses for the EEG are performed in the time and spatial domains where the measured potential values are used to find the equivalent dipoles [21]–[24]. There also exist techniques based on the frequency domain features of the EEG, where the discrete Fourier transform is applied to the EEG traces before applying the source localization algorithms on the calculated potential maps [31], [32]. In the case where only a subset of the Fourier coefficients is used in this procedure, an effect of bandpass filtering results. Obviously, this method is not suitable for the case of nonstationary EEG, where the patterns of interest cannot be represented by a bandpassed signal.

Another problem is present in source localization schemes related to noise contamination in the nonstationary EEG. As discussed above, the EEG is a complex signal reflecting integrated neuroelectric activity. Some of this activity is related to the event of interest, while some may be considered to be noise interference. The EEG is often contaminated by other biological and environmental noise as well, such as muscle activity, the electrocardiogram, 60 Hz components from the power line, variation in electrode contact impedance, and electromagnetic emissions. The solutions obtained to the inverse problem, without filtering the EEG, could be at best, highly variable, and at worst, meaningless. Traditional bandpass filtering may be applied when the signal and noise do not share the same frequency bands; however, this is seldom the situation.

TF analysis provide us with a powerful alternative for isolating signal components of interest from contaminating noise components. Noise can be identified much more easily in the joint TF domain than in either the time or frequency domain alone. While noise tends to spread widely in the TF plane, the signal is often concentrated, though its TF profile may be complex in shape. This suggests that a solution to the problem of separating signal components of interest from the contaminated EEG is to transform the EEG into the TF domain, isolate the patterns that reflect the event of interest, and then reconstruct the signal using these patterns by TF synthesis. This approach has been adopted in our study on contaminated, nonstationary EEG recordings.

A. Time-Frequency Analysis

Multiple channels of the EEG (64 in our case) must be acquired to obtain a sufficient sampling of the potentials distributed on the scalp in order to solve the source localization problem. If we calculate and store the TF distribution for each channel of the EEG for consequent analyses, the size of the intermediate data would be overwhelming. This problem is approached by obtaining the weighted average over a TF distribution for each channel to produce a single distribution. Such an approach not only reduces the data size, but also suppresses noise present in individual channels because the noise is often less correlated among channels than the signal. The TF components of the noise have both polarities, which tend to cancel each other during averaging.

An important concern, however, must be addressed to warrant the use of averaging. In the case where the signal components in different channels of the EEG did not exhibit similar TF characteristics, a smearing of the useful components would occur. We investigated this problem by considering the propagation of the EEG in relationship to the dielectric properties of the head volume conductor. In most cases, the spectral energy of the EEG above 30 Hz is insignificant [1]. Below this frequency, the dielectric properties of the volume conductor are negligible [21]. Therefore, the signal observed in any channel of the EEG corresponding to a compact, stable source must have a similar waveform and arrival time at all recording sites on the scalp, despite the difference in amplitude due to the distance between the source and electrode. Consequently, the signal's TF characteristics must be similar in all channels.

We thus compute the TF distribution for each channel and average the results across the channels by

$$P(t,\omega) = \sum_{c=1}^{N_c} \frac{\hat{S}_c}{S_c} \cdot P_c(t,\omega) \tag{3}$$

where $P_c(t,\omega)$ and $P(t,\omega)$ are, respectively, the TF distributions for the cth channel and their weighed average, and $\hat{S}_c$ and S_c are, respectively, the energy within the frequency band of interest and the total energy for the signal in channel c. The inclusion of weights in (3) allows a prediscrimination of the noise by emphasizing the channels where the signal is strong. In order to estimate the energy ratio $\frac{\hat{S}_c}{S_c}$, we applied a bandpass filter to all channels of the EEG with fixed cutoffs which were deemed to be sufficiently wide to cover all possible frequencies of the signal (to be discussed further in Section VI).

Many types of TF distributions can be employed as $P_c(t,\omega)$ in (3). The Wigner–Ville distribution (WVD) possesses many useful properties and has excellent joint TF resolution; however, it suffers from cross-terms which appear as highly oscillatory artifacts in the TF plane [33]. The oscillation of these cross-terms suggested to us to decompose the WVD, utilizing the Gabor transform [14], [34], into a set of two-dimensional (2-D) localized, harmonically related coefficients, and then remove the high-order harmonics which mainly contribute to cross-terms in the WVD. Although this approach seems to be applicable, the Gabor coefficients are inner products of the WVD and 2-D dual functions, which are expensive to compute. An alternative approach is to utilize one-dimensional (1-D) Gabor expansion with respect to the input signal, and then construct a 2-D expansion of the WVD using the resulting coefficients. Let $s(t)$ be the input signal. We have

$$s(t) = \sum_{m,n} C_{m,n} h_{m,n}(t) \tag{4}$$

where $C_{m,n} = \int_{-\infty}^{\infty} s(t) g^*_{m,n}(t)\, dt$ is the set of Gabor coefficients, and "*" denotes the complex conjugate. This expansion is valid only when $h_{m,n}(t)$ and $g_{m,n}(t)$ are provided by a pair of windows which serve as dual basis functions [34], [35].

Using (4), the WVD of $s(t)$, $W_s(t,\omega)$, is given by

$$W_s(t,\omega) = \sum_{m,m',n,n'} C_{m,n} C^*_{m',n'} W_{h,h'}(t,\omega). \tag{5}$$

When $h_{m,n}(t)$ is particularly chosen as a modulated and time-shifted Gaussian, the cross-WVD, $W_{h,h'}(t,\omega)$, is a 2-D Gaussian in the TF plane [36] having the following explicit form

$$\begin{aligned} W_{h,h'}(t,\omega) = 2 \sum_{m,m',n,n'} & \exp[jp\omega_0 T] \\ & \times \exp\left[-\frac{(t-t_0)^2}{\sigma^2} - \sigma^2(\omega-\omega_0)^2\right] \\ & \times \exp[-j(pT\omega - q\Omega t)] \end{aligned} \tag{6}$$

where

$$t_0 = \frac{m+m'}{2}T, \quad \omega_0 = \frac{n+n'}{2}\Omega,$$
$$p = m - m', \quad q = n - n'$$

and T and Ω are, respectively, the time and frequency sampling steps [36]. The TFDS, a cross-term reduced WVD, is defined as a partial sum of (5), i.e.,

$$\mathrm{TFDS}_D(t,\omega) = \sum_{d=0}^{D} \left[\sum_{|p|+|q|\le d} C_{m,n} C^*_{m',n'} W_{h,h'}(t,\omega) \right] \tag{7}$$

with D being defined as the order of the TFDS. For $D = 0$, the TFDS is a nonnegative distribution similar to the spectrogram which has low TF resolution but weak cross-terms. As D goes to infinity, the TFDS converges to the WVD which has a high TF resolution but strong cross-terms. In the case of the EEG, the choice of D equal to three or four provides a good compromise.

The computation of TFDS is extremely efficient since $C_{m,n}$ is no more than a sampled short-time Fourier transform and the Gaussian $W_{h,h'}(t,\omega)$ is known in advance [34].

B. Time-Frequency Synthesis

In order to incorporate *a prior* knowledge about the TF features of the signal, the average TF distribution, $P(t,\omega)$ in (3), is rendered as an image which is then utilized to identify the boundary of the TF component (a ROI) of the signal for which we are interested in identifying the generator. The coordinates of the boundary are converted into a binary mask. This mask is used for selecting the ROI in each channel of the TF distribution which is then utilized to reconstruct the noise-free signal.

A problem arises in this reconstruction. It has been shown that, after modifying the values of an arbitrary TF distribution of a signal, the result is, in general, not representable [12], i.e., there may not exist any signal that would produce the masked TF distribution given by the ROI. However, it is possible to construct a signal whose TF distribution is, in the least-square error (LSE) sense, closest to the desired one [11], [12], [37]. LSE-based TF synthesis has been extensively studied. Theories and algorithms based on the WVD [37], spectrogram [38], [39], and the more general forms [11]–[13], [40] have been developed. Although these techniques are applicable to the EEG case, they are based on the entire values of the underlying TF distribution (represented as a large matrix) which are considerably redundant in terms of signal representation. As a result, the computational load is heavy for the EEG having a large number of channels.

In the TFDS case the computation becomes less cumbersome. We take the advantage of the linear form of (4) and work on the Gabor coefficients instead of the TF distribution. First, the noisy signal s_0 is mapped to the joint TF domain via the Gabor transformation G to obtain the Gabor coefficients $c_0 = Gs_0$. If we do not alter the Gabor coefficients, the original signal s_0 can be recovered by the Gabor expansion E, that is, $s_0 = EGs_0$, because $EG = I$ resulting from the biorthogonality of the Gabor transform,

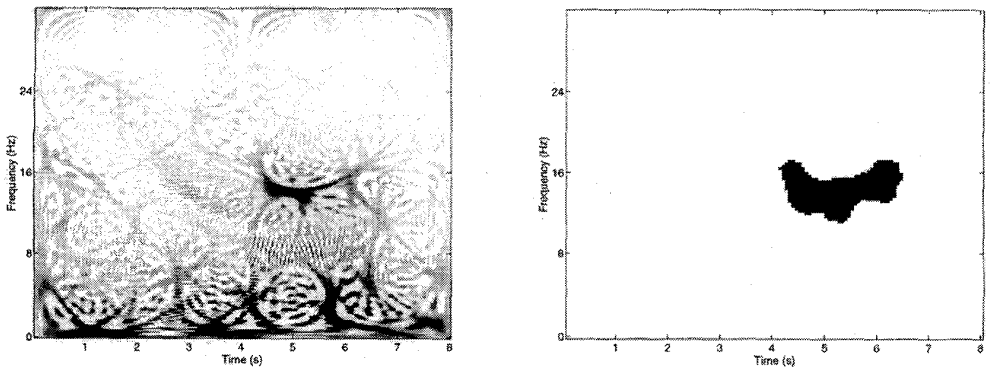

Fig. 3. (a) The weighted average of 64 TFDS's for the EEG shown in Fig. 1. The sleep spindle signal can be observed. (b) The ROI containing the sleep spindle signal in (a).

where I is the identity matrix. When the modification mask is applied, the modified Gabor coefficients may no longer correspond to a valid signal, i.e., $Gs_1 \neq MGs_0$, where M denotes the mask matrix and $s_1 = EMGs_0$. However, if we apply the same mask matrix to Gs_1 and compute the next waveform s_2, and continue this process i times, we obtain $(EMG)^i s_0 = s_i$. In this integrative projection process, s_i is convergent as long as matrix EMG satisfies the conventional convergence conditions for its power matrices [41]. The relationship between the eigenstructures of EMG and the mask matrix M is rather complicated; however, for various binary M tested by us, the numerical results have always been convergent.

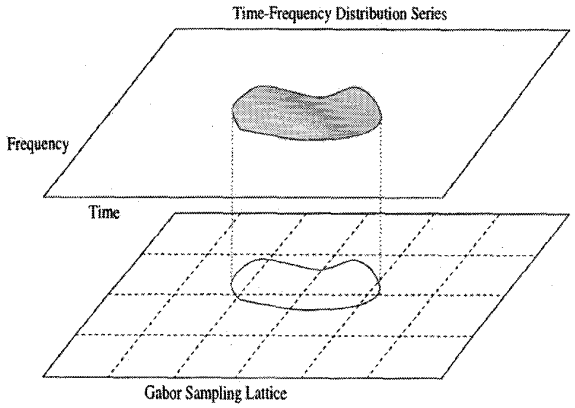

Fig. 4. The ROI specified in the TF plane is projected to the grid of the Gabor coefficients. This projection matches the locations of the corresponding TF elements such that the Gabor coefficients can be modified to reconstruct the signal.

VI. Localization of Spindle Signals in Sleep

As an example we present a study based on sleep spindles recorded from three healthy adult subjects. As previously described, sleep consists of states for which the brain waves are quite different. Spindles occur during stage two sleep, which occupies more than 50% of the total sleep time in a typical adult. Computer detection of sleep spindles using TF techniques has been reported by Durka and Blinowska [42], where the wavelet transform based matching pursuit algorithm was applied. They showed that the spindles were separable from other components in the EEG in the TF plane; however, due to the limitation of the number of entries in the dictionary of the TF atoms, it is apparent that the fine details of sleep spindles were not extracted as well using the Gabor transform approach [Fig. 3(a)].

It has been hypothesized [43] that the spindle activity is related to the thalamus (a relay nucleus located near the center of the head) with propagation to the cortex via thalamocortical projections. Animal studies [44] have been performed which suggest that sleep spindles are generated in the thalamus. However, the invasive procedures utilized in these studies cannot be applied to human subjects. In our approach we use TF techniques to test the hypothesis that the thalamus is indeed the site of the spindle generator in the human.

We recorded spontaneous EEG (sampled at 256 Hz) from three sleep-deprived male subjects aged 26, 28, and 39 using a 64-channel amplification and acquisition system. To avoid aliasing, an analog bandpass filter with cutoff frequencies of 0.1 Hz and 70 Hz were utilized before digitization. Electrodes were placed at the sites defined in the International 10–20 System [2] and at the midpoints between these standard electrode sites (Fig. 2). Sleep spindles were identified and notated by a trained sleep scorer. A total of 38 segments of EEG containing sleep spindles were identified and selected for this study. Each segment contained 64 channels of data with 2048 samples per channel. In order to reduce the border effect in the process of computing TF distributions, we positioned the spindle signal near the center of each segment. The segmented data were then downsampled by a factor of four after digital low-pass filtering (cutoff frequency 25.6 Hz, well above the maximum sleep spindle frequency). A set of typical traces of the EEG (recorded from five of the electrode sites) is shown in Fig. 1.

The TFDS for $D = 3$ was computed for each trace and averaged over all 64 channels using (3). This value was determined empirically by repeated calculations of test spindle segments. The weights for this average were

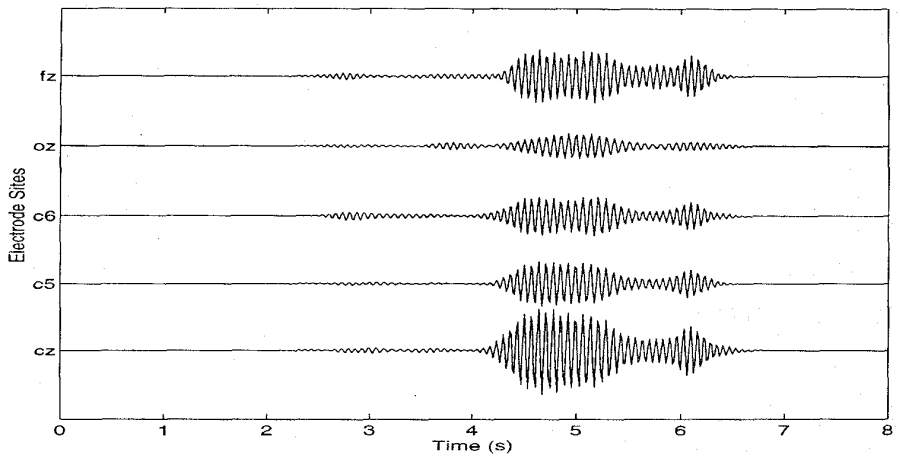

Fig. 5. Results of five channels of the reconstructed sleep spindle using TF analysis and synthesis of the raw EEG shown in Fig. 1. A comparison between these two figures indicates that the background noise is effectively removed by the TF technique.

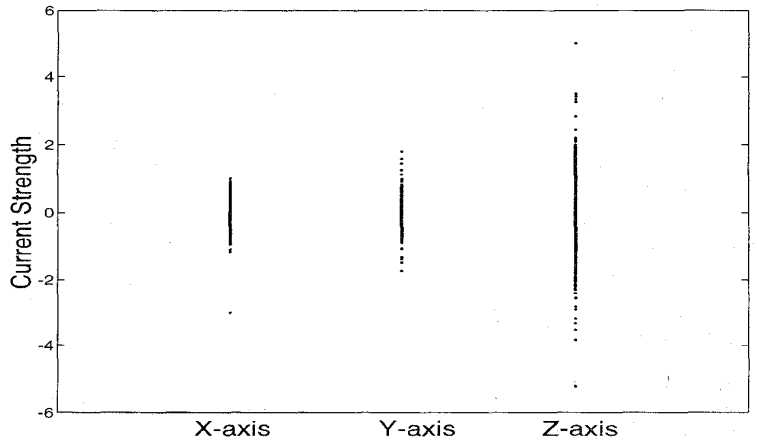

Fig. 6. Histogram of the strength of the dipole current in each of the x, y, and z coordinates. A more spread distribution of the current moment can be observed in the z-axis than in the x- and y-axis. This indicates that the source current of sleep spindles tends to be stronger in parallel to the direction of the vertex of the head.

determined by a bandpass filtering with cutoffs of 10 and 16 Hz, which were the extreme frequencies of sleep spindles within our test data, estimated by visually examining the TFDS of all 38 spindle segments. The Gaussian synthesis window (length 256) was used in the computation of the Gabor coefficients. This window and its dual window with $T = 8$ and $\Omega = 4$ were almost identical [34], [35]. The average TFDS produced for each spindle segment was again examined and the ROI in the TF plane was specified interactively. The averaged TFDS and the ROI corresponding to the signal in Fig. 1 is shown in Fig. 3. The ROI was then proportionally projected to the Gabor sampling lattice as shown in Fig. 4 to produce a binary matrix M which is used in the synthesis process. The synthesized signal computed from Fig. 1 is shown in Fig. 5 where it can be seen that the background EEG activities have been essentially eliminated. We applied the single-dipole source localization algorithm to a total of 2559 time slices from all 38 spindle segments using the homogeneous spherical head model [$\sigma(\mathbf{r}) = 0.0033$ for all $\mathbf{r}$ in (1)]. The source localization results are exemplified in Fig. 7 which corresponds to the single spindle segment shown in Fig. 1. The dipoles localized are overlaid on the subject's MRI sectional image shown in Fig. 7(a). Similar results were obtained from other spindle segments which are summarized in Table 1, where the average source location (column two), standard deviation (column three), and the average residual variance (column four) of the sources for each of the three subjects are shown. Fig. 6 shows the histogram of the calculated strength of the dipole current in each of the three coordinates. It can be observed that, since the energy of the dipole moment for the z-axis (through the vertex of the head) is much larger than other axes, the current of the spindle source tends to flow in the up

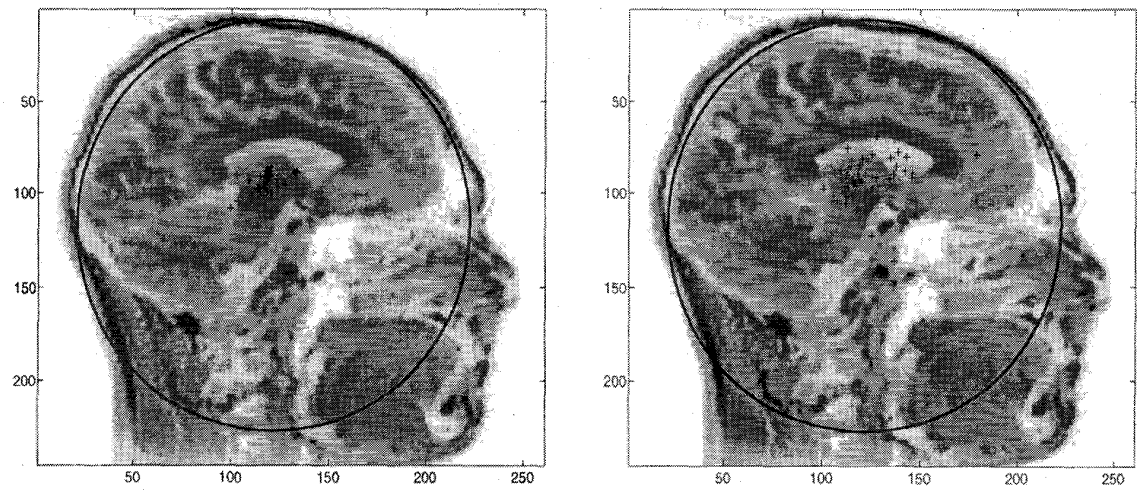

Fig. 7. (a) Localized dipoles (with TF processing) are superimposed with the MRI sectional image of the subject. The dipoles (cross patterns) are concentrated in the neighborhood of thalamus as suggested by the previous animal experiments. The average residual variance for the dipoles in this particular data segment is 3.23%. (b) The same result without TF processing, but with the traditional bandpass filtering (Order-8 Butterworth) between 10 Hz and 16 Hz. It can be observed that the dipole locations are scattered due to the influence of the remaining noise. The average residual variance in this case is 8.52%, 2.6 times larger than the case of using TF processing, indicating a less confident result.

Table 1 Statistics of Sleep Spindle Source Locations for Three Subjects

Subject	Location	Standard Deviation	Residual Variance	Number of Dipoles
1	(0.1007, −0.0064, 0.1961)	(0.1937, 0.1129, 0.1349	6.09%	1042
2	(−0.0303, −0.0055, 0.0948)	(0.1141, 0.0739, 0.1237)	3.35%	444
3	(0.0649, 0.0316, 0.1999)	(0.1533, 0.1064, 0.1265)	5.43%	1073

and down directions. In addition, the grand averages for the three subjects with respect to the dipole locations and their standard deviations are (0.0451, 0.0066, 0.1636) and (0.1537, 0.0977, 0.1284), respectively, which suggest that the source of the sleep spindles is located in the region of thalamus. This result is in a good agreement with the previously reported experimental data and hypothesis [43], [44].

Finally, to compare the TF and the traditional bandpass filtering methods, we localized dipoles for the same spindle segment (shown in Fig. 1). We applied an order-4 Butterworth filter with cutoffs 10 and 16 Hz (determined as described previously) twice to each channel of data in the increasing and decreasing directions in time to cancel the nonlinear phase distortions. The results are plotted in Fig. 7(b) where the patterns are scattered due to the influence of noise which is left in the signal. The average residual variance is 8.52%, 2.6 times larger than that obtained by the TF method (3.23%), indicating a much poorer result.

VII. Discussion

We have reviewed the applications of TF techniques to the study of the EEG and, in particular, to the processing and localization of sleep spindle patterns in the brain. It has been shown that, using the TF filtered scalp potentials, a good fit of the sleep spindle signal to a dipolar source located near the center of the head can be obtained. Our results agree with that obtained from previous animal experiments. We have also found that nonstationary EEG signals, such as sleep spindles, can be effectively filtered and reconstructed in the TF domain as long as they maintain oscillatory profiles with reasonable many of cycles. The synthesized noise-free signal provides a reliable input to source localization or pattern classification algorithms.

Although useful in many cases of EEG analysis, TF techniques cannot be considered as a versatile tool to solve EEG problems. In cases where the signal is relatively stationary, such as in some QS stages without spindles, muscle artifacts, and K-complex patterns [2], traditional methods based on the Fourier transform and parametric approaches, such as autoregressive and moving average modeling, may perform extremely well. In these cases, use of TF techniques, which generally require more computation and storage, may only result in a waste of efforts and computational resource. In other cases where the brain waves exhibit isolated triangular or sharp waves, such as the K-complex and certain epileptic patterns, TF distributions may have difficulty in identifying signal and noise components. In these cases the time-varying spectra of these signals may be either widely spread in the TF plane overlapped with the noise components, or severely packed

in the low frequency region without showing identifiable patterns. In this case, high-resolution time-scale analysis and synthesis approaches, such as wavelet decomposition with a signal-matched functional basis [9], [10] and nonlinear wavelet denoising [45] with a variable soft threshold are highly recommended.

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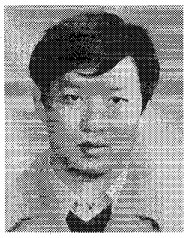

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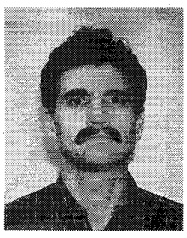

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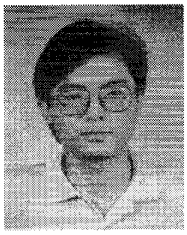

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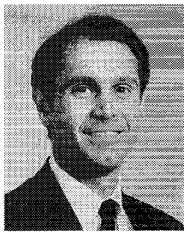

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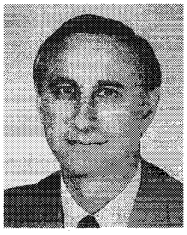

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