Extraction of Sources of Tremor in Hand Movements of Patients With Movement Disorders

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***Abstract*—This paper proposes an efficient method to acquire sources of tremor in patients with movement disorders based on blind source separation of convolutive mixtures. The extracted sources indicated neural activities that might be generated in the central nervous system. Four patients with essential tremor were tested in a set of movement tasks. Subjects wore a data glove that measured finger movements of the hand. The experimental data were then fed to a convolutive-mixture model, which revealed sources that imbibed in them the tremor frequency components of 2–8 Hz. Time–frequency analysis of these sources might be of potential help to clinicians to devise tasks that can manifest visible tremor from patients.**

***Index Terms*—Blind source separation, convolutive mixtures, essential tremor (ET), time–frequency analysis (TFA).**

I. Introduction

QUANTIFICATION of the tremor and the degree of severity of diseases with movement disorders like essential tremor (ET) and Parkinson's disease (PD) is one of the major difficulties in clinical evaluation. At present, clinicians are limited by ordinal rating scales such as unified PD rating scale and Fahn–Tolosa–Marin (FTM) tremor rating scale, because such scales are more subjective and open to examiner's interpretation. Researchers are shifting away from ordinal rating scales and are evaluating tremor based on electromechanically measured parameters like stiffness, rigidity, etc. [1] by utilizing computer-aided tools. The behavioral motor characteristics in these movement disorders are infamously unpredictable, especially in advanced stages of the disease, and any contribution to provide better performance would be appreciated by clinicians.

The current methods to measure tremor include accelerometry, electromyography (EMG), computer tracking, tablets, infrared, video cameras, and laser transducers. Though all these methods are better than Likert scale, which itself is susceptible to problems of sensitivity and reliability, several of them have general drawbacks like bulky machinery (not portable) and time-consuming procedures (e.g., 24- to 72-h-long EMG recordings). Moreover, it has been reported that accelerometric measurements, besides being 1-D, suffer from gravitational artifacts [2], EMG provides only a loose measure of tremor amplitude [3], and digitizing tablets are deficient in sensitivity to measure tremor [4]. Apart from the limitations, all the aforementioned techniques are useful in specific environments in which they are deployed.

In our study, we used a data glove to measure tremor. Data gloves are precise and easy to use in measurement, as they are wearable and assume the shape of the hand. (Note that hands are affected in 95% of ET patients [5].) A similar concept has been already tested previously in [6] where hand and finger movements were precisely quantized using a VPL data glove in chorea, myoclonus, and tremor. Data gloves have also been used by us to measure postural and kinematic information for hand movement analysis in normal subjects [7], [8].

Quantification of tremor has been achieved by numerical methods such as spectral analysis and time–frequency analysis (TFA) [1], [9], [10]. However, these analyses were performed directly on the experimentally recorded data. They might not achieve optimal quantification of tremor, because tremor is spread across parts of limbs, and at a single site of recording, tremor might not be significant. Although ET is a central tremor that originates from a central source, the tremor is distributed across the limbs [5]. Different frequencies of tremor were observed in different limbs [5], [10]. This variation might be due to mechanics of limbs that accentuate tremor differently, although the tremor originates from a single neural source. The distribution of tremor makes it difficult to evaluate, measure, and manage the tremor [5], [11]. In this paper, we base our analysis upon a modeled characteristic of tremor generation. We propose to utilize a technique from the blind source separation for convolutive mixtures to obtain sources of tremor from joint movements of the hand. In contrast to previous methods, our method attempts to isolate the sources of tremor from a raw data of joint movements that contain tremor distributed across multiple joints of the hand in different movement tasks. We believe that these sources will work as miniature windows to view movement disorders.

II. Methods

A. Model

We model the joint movements of the hand as convolutive mixtures of source signals created in the central nervous system (see Fig. 1). In our model, an impulse originated in the higher level neural system evokes the activation of some circuits in the lower level neural system, then stimulates certain biomechanical

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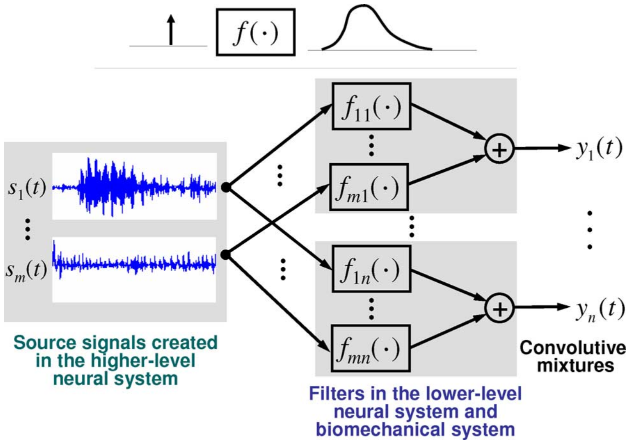

Fig. 1. Hypothesized model for generation of hand movement. (Top) Impulse response of a filter. (Bottom) A movement profile of the hand can be modeled as convolutive mixtures of source signals originated in the higher level neural system passing through the corresponding filters residing in the lower level neural system and connected biomechanical system.

structures, and eventually creates a stereotyped angular change at each finger joint of the hand. This process can be simplified to the production of an impulse response of a filter [see Fig. 1 (top)]. The filter characterizes the related neural–biomechanical structures that trigger the movement of a specific finger joint in response to an impulse in the higher level neural system. We assume that all the filters are linear and their impulse responses have finite durations. Thus, a movement profile of the hand can be modeled as the superposition of the impulse responses of some neural source signals (trains of impulses) passing through the corresponding filters residing in the lower level neural system and connected biomechanical system [see Fig. 1 (bottom)]. Although the neuromuscular system is nonlinear, considering a linear approximation might give useful insight of the system. Moreover, it has been suggested that motor behavior of vertebrates can be well approximated by linear combination of tiny modules of movement called movement primitives [12]. However, our model is mainly targeted at estimation of tremor and cannot account for the characteristics and dynamics of the system under some nonlinear conditions such as output saturation (e.g., maximum force generation) and hysteresis (e.g., rigidity).

Our model can be expressed by the following equation:

$$y_k(t) = \sum_{i=1}^{m} s_i * f_{ik}(t), \qquad k = 1, \ldots, n \tag{1}$$

where "$*$" represents convolution; $y_k(t)$ represents the angle of the kth joint of the hand at time t, k ranges from 1 to n, and n is the total number of the considered joints of the hand; $s_i(t)$ represents the time sequence of the ith source signal created in the higher level neural system, i ranges from 1 to m, and m is the total number of sources; and $f_{ik}(\cdot)$ represents the finite impulse response of the filter through which the ith source acts on the kth joint of the hand.

We will use the aforementioned model to extract sources of tremor in hand movements of patients with ET. We assume that in ET, the tremor sources and sources responsible for voluntary movement control can be approximately viewed as independent with each other. This assumption is supported by: 1) the relative independence of ET from peripheral mechanical reflex mechanisms [13] and 2) existence of central sources responsible only for tremor. Studies have revealed cortical and thalamic involvement in the generation of ET [14], occurrence of rest tremor in ET [15], thalamic neuronal activity correlated with ET [16], and a strong correlation between tremor in ET and cerebral activity [17]. Although the severity of tremor may depend on the effort to make a movement, the timing of the tremor can be considered independent to that of the voluntary movement. Therefore, it is a reasonable approximation that the tremor sources are statistically independent of the sources for command signals of movement control. Based on this, we can apply the techniques for blind source separation of convolutive mixtures.

Fig. 2. Two tasks of subject 2 wearing CyberGlove: writing letter A (left) and drawing Archimedes spiral (right). Tremor is witnessed while drawing the spiral.

B. Experiment

Four subjects, two males (aged 42 and 70 years) and two females (aged 40 and 71 years) with ET were tested in a series of tasks. These subjects recorded 4, 3, 3, and 3 (on a scale of 4) on FTM tremor scales, respectively. All these subjects were informed about the nature of the study and signed institutionally approved consent forms. The experimental setup included a CyberGlove for the right hand, equipped with 22 sensors that could measure angles at all the finger joints of the hand at a sampling frequency of 64 Hz. Subjects wore this data glove during all the tasks of the experiment. Before the beginning of the experiment, joint sensors were individually calibrated for each of the subjects. Start and stop of the tasks were indicated to subjects by system beeps. The tasks designed for these experimental purposes were motivated by motor examination and daily activities. Tasks included opening and closing the fist naturally, opening and closing the fist at a faster rate, opening fist followed by adduction of fingers followed by abduction of fingers followed by closing the fist, repeating the previous task faster, finger tapping, untying shoe laces, drawing Archimedes spiral, drawing pentagon clockwise and then anticlockwise, drawing letter A, reaching and grasping a cup on the table, and finally signing signatures. Two of the tasks for subject 2 are illustrated in Fig. 2.

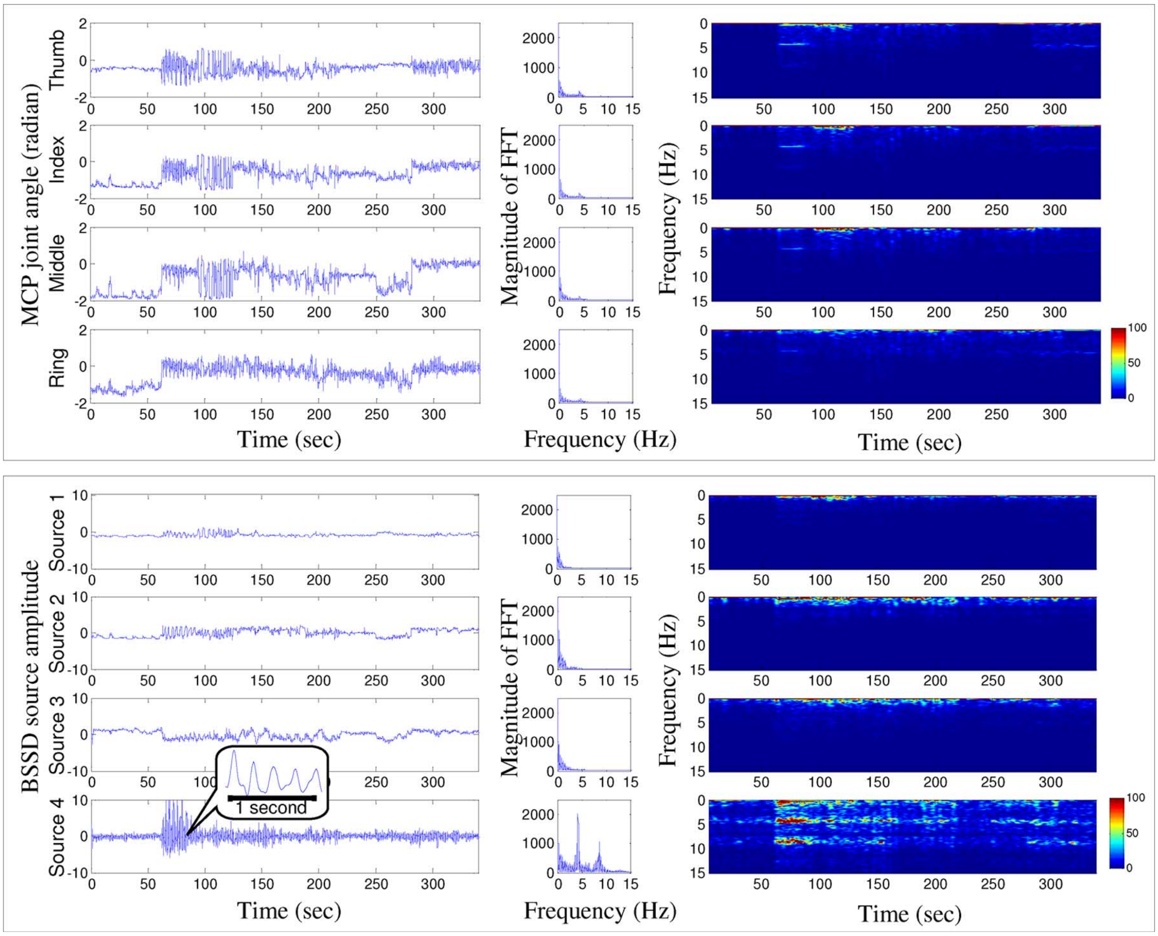

Fig. 3. (Top) Four MCP-joint movement data (left), corresponding frequency spectra (middle), and time–frequency spectra (right) of subject 1. A color legend with red (high power) to blue (low power) is provided at the bottom right corner. (Bottom) Sources obtained when BSSD was implemented for convolutive mixtures (with major tremor in source 4) and corresponding frequency spectra and time–frequency spectra.

C. Data Analysis

We performed the following steps for data analysis.

First, CyberGlove through a PC interface measured the joint angles during different tasks of the experiment. Data collected from the data glove were processed in MATLAB to obtain joint angles of the fingers of the hand.

Second, Fourier transforms of the time series of joint angles in each task were calculated, and after a detailed perusal, only four of the joints that contribute to major tremor were included for further separation of tremor sources. Other joints were ignored to save computation for blind source separation. An example of four joints selected for subject 1 was shown in Fig. 3 (top). Note that these selected joints were different for different subjects. However, the joints included only metacarpophalangeal (MCP) and proximal interphalangeal (PIP) joints. It was reported that hand tremor was observed to be prominent in MCP and PIP joints only [18]. Distal interphalangeal (DIP) joints were not considered as their movements were dependent to a great extent on movements of their parent PIP joints. Moreover, it was empirically observed in our analysis that including additional joints did not account for significant improvement as the joints selected already contained the major tremor component.

Third, all the tasks were cascaded to form a long sequence of tasks, and this sequence was processed with an algorithm for blind source separation of convolutive mixtures through deflation (BSSD) by Castella *et al.* [19]. The algorithm was iterative blind source separation using kurtosis real-valued contrast function of cumulants. Kurtosis is a classic measure of non-Gaussianity, and non-Gaussianity is used to indicate independence [20]. The kurtosis contrast function allows us to extract one non-Gaussian and independent source from the mixture at a time. After one source is extracted, its contribution is subtracted from the observations. This process (called deflation) is repeated to extract all the sources. By using filters with finite impulse response, the whole problem becomes finding a least square solution to a linear regression problem [19].

So as to justify the independence among the extracted sources, we calculated and compared the values of kurtosis for the normalized source signals and joint angle profiles. The kurtosis of a normalized random variable y, where $E\{y\} = 0$ and $E\{y^2\} = 1$, is defined by $E\{y^4\} - 3(E\{y^2\})^2 = E\{y^4\} - 3$. As just mentioned, kurtosis can indicate non-Gaussianity and independence [20]. A larger absolute value of kurtosis of y implies a higher non-Gaussianity of y. According to the central limit theorem, a sum of independent random variables tends to

TABLE I
KURTOSIS VALUES OF THE NORMALIZED JOINT ANGLE PROFILES AND EXTRACTED SOURCE SIGNALS

Subject	Kurtoses of four joint-angle profiles				Kurtoses of four source signals			
1	4.77	2.21	1.84	2.54	6.14	1.76	1.86	**23.9**
2	2.57	2.47	2.53	1.77	1.65	7.01	1.67	**19.4**
3	2.16	1.51	1.60	1.58	10.3	3.15	1.98	**19.4**
4	4.13	3.68	3.84	2.35	2.06	3.46	8.86	**13.5**

have a probability distribution closer to Gaussian than any of the original variables. In other words, an isolated independent source signal tends to have higher non-Gaussianity than the experimentally recorded data, which are mixtures of independent source signals. Therefore, maximizing non-Gaussianity, measured by the absolute value of kurtosis, has been used in independent source separation [20].

Various filter lengths were tried, and best observed filter length was used that revealed tremor synchronous with Fourier transform of the experimental data. These filter lengths were obtained based on the following criteria. A tiny finger movement, evoked by an impulse from transcranial magnetic stimulation (TMS), was about 200–300 ms [21]. At a sampling frequency of 64 Hz, filter lengths about 12–18 will correspond to this movement. Since a TMS impulse itself has nontrivial duration, the movement evoked by a TMS impulse should last longer than the movement triggered by an ideal impulse. Therefore, the filter lengths that we used (typically 10–15 in length) were slightly shorter than 12–18.

Fourth, TFA was performed. As a result of source separation, for each subject, four sources were obtained from the experimental observations. Of the four sources, only one source had substantial component of tremor. The tremor-containing sources were analyzed by fast Fourier transform (FFT) based TFA using the function *spectrogram* in MATLAB. For comparison, TFA was also performed on the raw joint movement profiles. A Hamming window of length 512 and a 512-point short-time FFT were used as parameters.

III. RESULTS

An example of the joint movement profiles (subject 1) was shown in Fig. 3 (top). To the left of the figure are joint movement profiles of the MCP joints of the thumb and index, middle, and ring fingers. In order to make the tremor more visible, the frequency spectra of the same time domain series were plotted in the middle column of Fig. 3 (top).

The processed data from MATLAB were streamed through the algorithm of BSSD for convolutive mixtures. During the deconvolution procedure, BSSD used filters that were typically 10–15 in length. For subject 1, using a filter length of 10, the obtained sources were shown in Fig. 3 (bottom) along with the frequency spectra. One can clearly witness the source exclusively containing tremor [source 4 in Fig. 3 (bottom)]. Tremor was better appreciated for BSSD when compared to direct spectral analysis. To justify independence of the extracted sources, kurtosis values were calculated for the normalized source signals and joint angle profiles (see Table I). The independence of the tremor source (source 4) can be implied from its kurtosis value (in bold), which is significantly greater than those of the joint angle profiles.

Though analysis of frequency spectrum of the signals provided ready-to-view tremor, it may mislead as the signals are assumed to be stationary. Therefore, in addition to spectral analysis, TFA was carried out for both the joint movement profiles and the extracted sources, considering the signals as nonstationary. The results were shown in the right column of Fig. 3. It can be seen that TFA of the source signals (extracted using our convolutive-mixture model) outperformed TFA done directly on experimental recordings from the joint angle profiles.

In the case of the other three subjects, the extracted sources were displayed in Fig. 4, and TFA implemented for tremor-containing sources was shown in Fig. 5. The filter lengths used for source extraction were 10 for subject 2, 15 for subject 3, and 10 for subject 4, respectively. As noticeably visible, the current model of convolutive mixtures clearly extracted the sources containing tremor. Multiple components of tremor were observed for all the subjects. It is apparent from the TFA that the tremor was relatively more active in some tasks. This variation cannot be observed in the single frequency spectrum [see Fig. 5 (right)] obtained for the entire time series of a source. The variation of tremor seen over time can help clinicians devise better tasks for the tremor to manifest. For instance, in all subjects, dominant tremors were observed in finger tapping, opening and closing the fist, and drawing Archimedes spiral.

IV. DISCUSSION

ET is accentuated by voluntary movement. The current model of convolutive mixtures was able to extract tremor-containing sources from voluntary movements of hand joints. Four statistically independent sources (per subject) were obtained, of which one source was tremor-exclusive. As witnessed in Fig. 3, tremor was better appreciated in the sources extracted using the current model when compared (by using FFT and TFA) with experimentally recorded data. Our method not only proved significant in tremor detection, but also revealed the sources that might indicate neural activities responsible for tremor generated in the central nervous system. We do not claim that the other sources without tremor are exactly the physiological sources for the voluntary movement, but these sources are correlated to the voluntary movement.

1) *Multiple components of tremor:* It is apparent from TFA in Fig. 5 that extracted tremor for all the four subjects had multiple frequency components. This might be due to the sensory feedback that influences the central oscillators [22, Fig. 1]. We observed that subjects had difficulty doing the tasks that needed ample visual guidance. For example, in finger tapping, where subjects had to touch all the fingers with thumb and repeat it as fast as possible, subjects faced difficulty though it appears effortless for normal persons. Multiple components of tremor in ET and other movement disorders were reported by [10]. In multiple sclerosis, similar behavior was observed by [23] where visual guidance was stated as a possible reason.

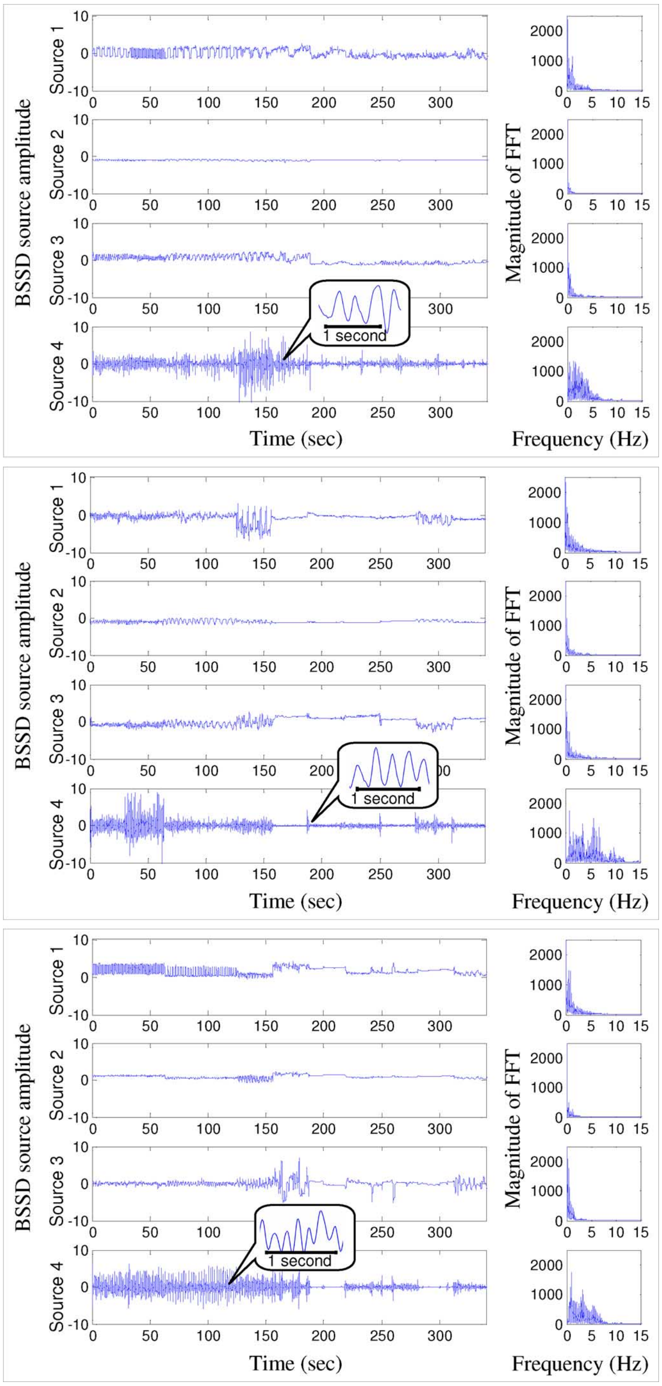

Fig. 4. Four BSSD-extracted sources per subject for subject 2 (top), subject 3 (middle), and subject 4 (bottom). For each subject, the fourth source corresponds to tremor. Frequency spectra are plotted to the right.

2) *Physiological implications of impulse response:* Note that the average length of the selected filters for the four subjects is 11.25 [$=(10+10+15+10)/4$], which implies that the average duration of the impulse responses of these filters is $11.25/64 \times 1000$ ms ≈ 180 ms (sampling rate was 64 Hz). This suggests that a tiny submovement of the hand should last for about 200 ms in response to an ideal impulse in the higher level neural system. Compared with a recent study by Gentner and Classen [21, Fig. 1(A)], our prediction of 200 ms is in the same order as 250 ms, the approximate duration of the fastest hand movement evoked by an impulse from TMS.

3) *Convolutive versus instantaneous mixtures:* In the current model, joint movements are modeled as convolutive mixtures. Can they also be modeled as instantaneous mixtures? To answer this, we carried out blind source separation using independent component analysis (ICA). For ICA, a FastICA algorithm (version 2.5) [24] was used. The sources obtained for subject 1 by ICA were shown in Fig. 6. Obviously, ICA outperformed the spectral analysis done directly on the kinematic profiles of hand movements. In the kinematic profiles, tremor can be seen in all joints, but the tremor components were not prominent in the motion of any one of these joints. ICA was able to redistribute the tremor components in the source signals such that the contrast of tremor was more significant in one of the sources. However, ICA could not completely draw out the tremor sources. In comparison, BSSD was able to extract the tremor sources from other sources. One can appreciate BSSD better as shown in Fig. 3—tremor is more apparent in the BSSD-extracted source.

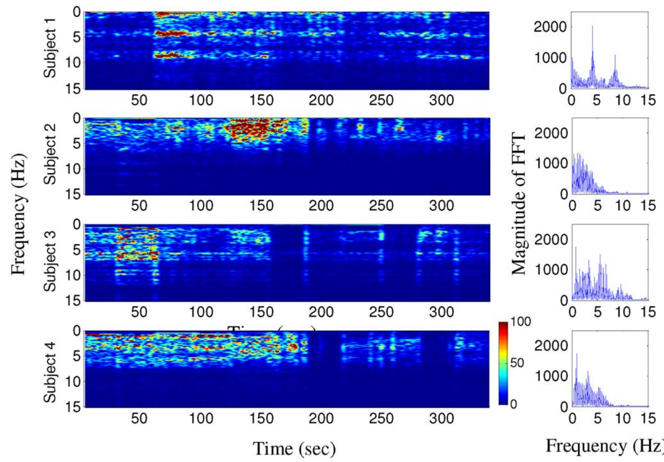

Fig. 5. TFA for all subjects. Corresponding Fourier transforms are shown on the right side. Multiple components of tremor can be witnessed in all subjects. A color legend with red (high power) to blue (low power) is provided.

The advantage of modeling joint movements as convolutive mixtures over instantaneous mixtures can also be supported by the kurtosis values (indicating independence) calculated for source signals extracted by BSSD and ICA, respectively. The kurtosis values of the four source signals extracted by ICA were 1.76, 8.66, 3.65, and 5.54, which are all significantly smaller than 23.9, the kurtosis value of the tremor source extracted using BSSD.

ICA has been an efficient technique and been used to separate experimental functional MRI (fMRI) in PD [25]. The effectiveness of ICA for fMRI data may be due to the fact that the fMRI data directly reflect the neural activities in the brain, which can be well approximated by instantaneous mixtures of some independent source signals. However, when these source signals mix together after passing through the spinal cord and the peripheral

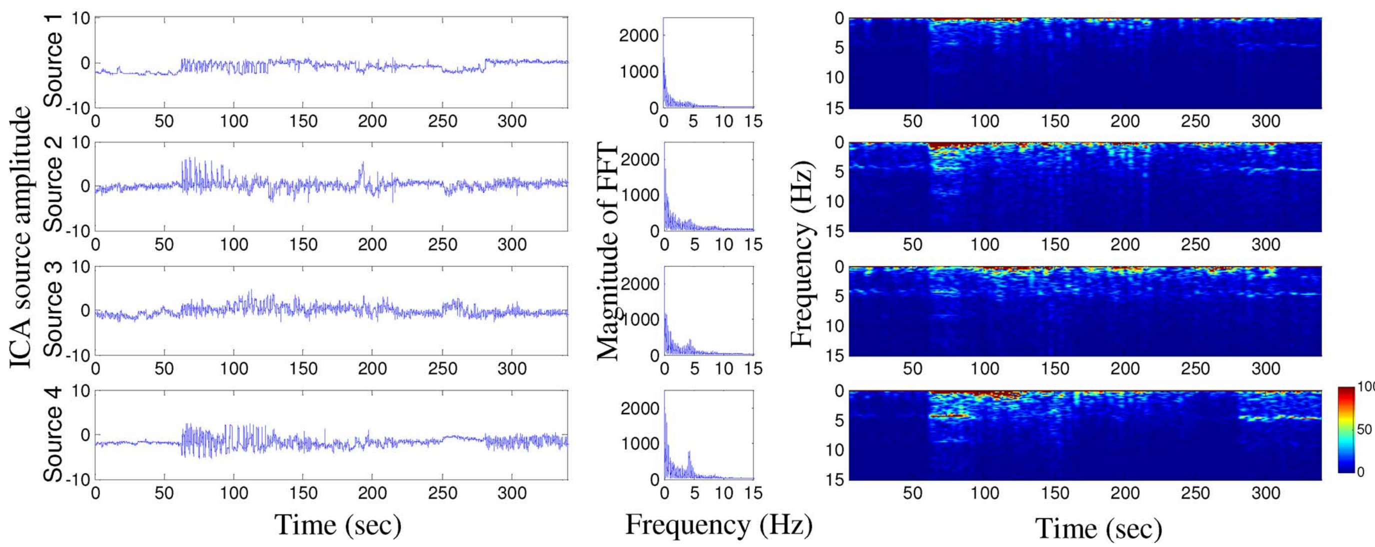

Fig. 6. Sources obtained using ICA when modeled as instantaneous mixtures for subject 1 (with major tremor in source 4). Corresponding frequency spectra are plotted in the middle column and time–frequency spectra to the right. Though better than direct spectral analysis [Fig. 3 (top)], ICA falls behind BSSD [comparing with Fig. 3 (bottom)].

nervous and biomechanical structures, the approximation of instantaneous mixture is no longer accurate, and thus ICA does not work for this scenario. In contrast, BSSD was effective to detect tremor sources and extract them from hand movements, because it took into account the dynamics of the peripheral structures and the possible distortion of the source signals by these structures, as discussed in the model of Section II-A. Therefore, modeling the movement profiles as convolutive mixtures resulted in better extraction of tremor than as instantaneous mixtures.

4) *Comparison with contemporary methods:* Spectral analysis is popularized for quantification of tremor [5]. FFT-based methods have been used frequently because they are computationally inexpensive, but these methods assume the input signals as stationary. Welch's periodogram-based method was used in [3], where power spectral density was estimated for the entire task, ignoring temporal variation of tremor within the task. Our method employing TFA overcomes the aforementioned limitations, and the variation of tremor can be seen over time in TFA. TFA was used previously by other investigators as well, but was implemented directly on the experimentally recorded data from muscle activities [10]. In contrast, our method performed TFA on the tremor sources extracted from the raw experimental data of joint movements. The advantage of using our method was clearly evident in Fig. 3.

5) *Correlation between tremor and voluntary movement:* For subject 1 (see Fig. 3), the tremor source had a low-frequency component (0.3 Hz, correlated to finger tapping) during the time period from 60 to 90 s. We separately analyzed the finger tapping task by BSSD. As illustrated in Fig. 7 (top), frequency spectra of joint movement profiles indicated coexistence of frequencies due to task as well as tremor in all joints. However, when processed through BSSD, one can clearly appreciate the separation of task frequency and tremor frequency in spectra of the second

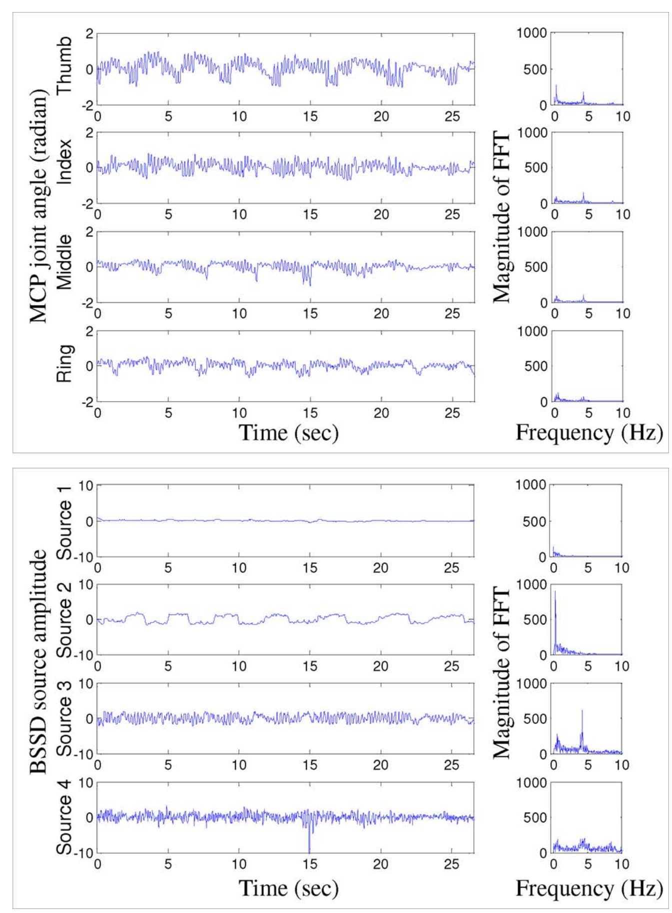

Fig. 7. (Top) Four MCP-joint movement data (left) and corresponding frequency spectra (right) of subject 1 during the finger tapping task. (Bottom) Sources obtained when BSSD was implemented for convolutive mixtures (with major tremor in source 3 and tapping movement in source 2) and corresponding frequency spectra.

and third sources, respectively [see Fig. 7 (bottom)]. Although there was appreciable separation, task frequency was not completely eliminated in the third source, which corresponded to tremor. This implies that the tremor-containing sources included components correlated with voluntary movement. One possible reason is that the current model requires the sources to be statistically independent with each other. However, this cannot be completely satisfied in ET where the amplitude of the tremor may depend on the effort in achieving a task. The correlation between the tremor and voluntary movement was previously observed by [26] and [27] in ET. Nevertheless, as we mentioned in Section II-A, the timing of tremor can be independent of the voluntary movement—as in the case of rest tremor in ET [15].

V. CONCLUSION

Our method was based on a convolutive-mixture model of tremor generation, and was able to attribute tremor to a central source manifested across multiple joints of the hand. Compact representation of sources of tremor, one per subject, was extracted that contained the information of tremor variation across a variety of movement tasks. Clinicians can appreciate this method as this compact representation (a single source of tremor) will ease the diagnosis of the tremor avoiding the trouble of tediously going through numerous experimental data. However, the current method is limited for clinical purposes targeted at quantification of tremor and may not be applicable for home-based rehabilitation as it is. The method presented is also applicable to PD as there is evidence of neural sources responsible for tremor. It is reported that in PD, central oscillators are responsible for tremor generation [28]. The current approach is to be extended over a large group of subjects with various movement disorders. We view these as future scope of this research.

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