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# Cumulant analysis in wavelet space for studying effects of aging on electrical activity of the brain

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ABSTRACT

Multiresolution wavelet analysis with thorough processing of decomposition coefficients using a set of cumulants is proposed as a way to improve the characterization of complex dynamics based on experimental data. The application of this approach for quantification the effects of aging in the responses of the electrical activity of the brain to fine motor tasks (clenching the fist) is considered. It is shown that young and elderly adults have significant differences in reactions to this type of movements carried out by the dominant and non-dominant hand. The characterization of inter-group distinctions using the skewness and kurtosis of the probability distribution of the wavelet decomposition coefficients outperforms the diagnostics of age-related differences based on standard deviation of this distribution.



## 1. Introduction

Multiresolution wavelet analysis (MWA) is one of the most popular methods for studying complex processes at multiple scales [1–3]. It decomposes a signal using two sets of conjugate mirror filters to get independent information in the form of wavelet-coefficients that describe the signal in non-overlapping frequency bands. This tool is especially useful if the results of the analysis should include not only knowledge of specific frequencies/amplitudes, but also their behavior over time. The latter extends the applicability of MWA to different types of nonstationary processes. Its advantages over Fourier-based methods, as well as various fields of application, are described in many books and research papers, e.g. [4–9]. The most important features of MWA are associated with the use of localized basic functions that improve the analysis of experimental data containing artifacts or extreme events. The algorithm makes it possible to analyze signals without their preliminary processing (detrending, noise reduction), since band-pass filtering is involved at each stage of signal decomposition.

Fluctuations in the signal cause corresponding changes in the decomposition coefficients, and a good measure of their variability is the variance or standard deviation (SD). This measure has been used in various studies, in particular, to search for precursors of engine destruction [10], diagnose heart rate failures based on RR-intervals [11], quantify processes of multi-particle production [12], identify and classify specific oscillatory patterns in neurophysiological data sets [13–15], etc. However, this measure reflects only a part of information about the wavelet-coefficients, which may be insufficient for diagnostic purposes. Recently, it has been discussed how a more thorough analysis of the decomposition coefficients can improve the characterization of complex processes, and an enhanced approach has been proposed [16] combining MWA with detrended fluctuation analysis, subsequently verified using both simulated and experimental data [16,17]. This approach is well suited for relatively long datasets, since pyramidal decomposition of the signal reduces the number of detail wavelet-coefficients as the resolution level increases, and each successive level is associated with a halved set of coefficients. When dealing with rather short signals, the latter may be not enough to consider a wide range of scales and quantify power-law correlations. In such cases, a statistical analysis of the coefficients using moments or cumulants may be preferable. In particular, it is shown that transitions between synchronous and asynchronous oscillations in coupled Lorenz systems are better recognized from noisy sequences of return times using the kurtosis of the distribution of wavelet coefficients compared to SD [18].

This circumstance suggests that more thorough processing of complex signals in wavelet space using, for example, cumulant analysis

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may be preferable to improve the characterization of experimental measurements, especially for relatively short datasets. Based on this idea, here we apply an enhanced version of MWA to characterize age-related differences in brain electrical activity during fine motor tasks. Aging is a reason of numerous chronic changes in the human body, including violations of biological and physiological processes resulting in different disabilities [19–22]. It affects the electrical activity of the brain leading to serious diseases. For diagnostic purposes, it is important to identify the early (latent) stages of brain diseases from mild disorders which are related to healthy aging. Therefore, the search for precursors of the early stages of diseases and risk factors is an important problem. Healthy aging affects the impairment of cognitive and motor functions, leading to delays in reactions, reduced motor control [23–26], etc. When performing fine motor tasks, the electrical activity of the brain in elderly adults may involve additional areas of the brain [27–30] that is explained by a compensatory mechanism [31,32]. For this reason, distinctions between young and elderly adults are expected. Besides the differences associated with the position of the electrodes, there is another age-related change, namely, a reduction of distinctions in the responses for the dominant and non-dominant hand when carrying out fine motor tasks. In our work, we study the possibility of diagnosing this type of age-related effects based on enhanced MWA for the case of tasks consisting of clenching the hand into a fist. The considered approach can also be applied, e.g. to characterize the dynamics of complex networks of various nature [33,34].

The paper is organized as follows. Section 2 describes the MWA algorithm with its proposed extension. This section also provides information about the experiments and related datasets considered in our study. The main results describing the effectiveness of the enhanced MWA for quantifying age-related distinctions in the performance of fine motor tasks and their discussion are given in Section 3. Section 4 summarizes the concluding remarks.

## 2. Methods and experiments

### 2.1. Multiresolution wavelet analysis

MWA uses a pyramidal decomposition algorithm with two sets of filters: low-pass filters $\varphi_{j,\ k}$ composed of the dilated and translated scaling function $\varphi(t)$, and high-pass filters $\psi_{j,\ k}$ constituted by the related transformations of the wavelet-function $\psi(t)$

$$\varphi_{j,k}(t) = 2^{j/2}\varphi\left(2^j t-k\right), \qquad \psi_{j,k}(t) = 2^{j/2}\psi\left(2^j t-k\right). \tag{1}$$

The signal $x(t)$ at some resolution level $j_m$ is decomposed as

$$x(t) = \sum_k s_{j_m,k}\varphi_{j_m,k}(t) + \sum_{j\geq j_m}\sum_k d_{j,k}\psi_{j,k}(t). \tag{2}$$

where $s_{j,k}$ and $d_{j,k}$ are the approximation and detail coefficients, respectively. Their amount changes between decomposition levels: the number of $d_{j,k}$ is halved at the transition from level $j$ to $j+1$, and decomposition can be performed until this number becomes less than the support length of the wavelet function. Orthogonal functions of the Daubechies family $D^n$ are usually applied [3], and the choice of $\psi(t)$ is made depending on the research aim, e.g., function with a higher rank $n$ are more regular, possess a larger number of vanishing moments that is important to process signals with polynomial trends (the latter will be ignored), but such functions have a larger support length, require more time for signal processing, and their selection is not always the best choice. In many applications, the $D^8$ wavelet is used as a good compromise between the support length and the regularity of the basic function.

Signal variations lead to fluctuations in the detail coefficients $d_{j,k}$, and their variability depending on the resolution level gives important information about the signal features. Due to this, the SD of detail wavelet-coefficients is often used as an informative measure

$$\sigma_j = \sqrt{\frac{1}{J}\sum_{k=1}^{J}\left[d_{j,k}-<d_{j,k}>\right]^2}, \quad \langle d_{j,k}\rangle = \sum_{k=1}^{J} d_{j,k}, \tag{3}$$

where $J$ is the number of $d_{j,k}$ at the resolution level $j$.

### 2.2. Enhanced MWA

Although the above approach has demonstrated its efficiency in solving many research problems, e.g. [10–15], let us point out its restriction. In general, this approach is based on only one measure of the probability distribution of the detail wavelet-coefficients, namely the variance or SD. The width of the distribution is an important characteristic of the set $d_{j,k}$, however, it does not take into account the symmetry property, the probability of large values ("tails" of the distribution), etc. In other words, limiting to one measure may not be enough for the quantification of signal features in wavelet space. In recent studies, we proposed to use an approach combining MWA with detrended fluctuation analysis to characterize power-law correlations in $d_{j,k}$ coefficients and showed how this approach expands the ability to diagnose changes in the dynamics of complex systems [16,17]. When dealing with relatively short datasets, the number of $d_{j,k}$ for large $j$ is often not enough to study long-range correlations. In this case statistical analysis of $d_{j,k}$ based on moments or cumulants may be preferable. Here we propose to apply cumulant analysis in wavelet space to take into account not only the second cumulant (variance), but also the third one (skewness)

$$A(j) = \frac{\mu_j^3}{\sigma_j^3}, \quad \mu_j^3 = \frac{1}{J}\sum_{k=1}^{J}\left[d_{j,k}-\langle d_{j,k}\rangle\right]^3. \tag{4}$$

and the fourth cumulant (kurtosis or excess kurtosis)

$$E(j) = \frac{\mu_j^4}{\sigma_j^4}-3, \quad \mu_j^4 = \frac{1}{J}\sum_{k=1}^{J}\left[d_{j,k}-\langle d_{j,k}\rangle\right]^4. \tag{5}$$

### 2.3. Experimental studies

The experiments were carried out in Innopolis University (Kazan, Russia). Two groups of healthy right-handed volunteers were considered each consisting of 10 participants. The first group included young volunteers aged 19–33 years (7 men and 3 women), and the second group consisted of elderly adults (55–72 years old, 4 men and 6 women). The participants signed a written informed consent and were informed about the details of the experiments. They also confirmed the absence of neurological diseases such as tumors, traumatic brain injuries, etc. Experimental procedures were carried out according to the Helsinki Declaration and protocols approved by the local Ethics Committee of the Innopolis University.

EEGs were recorded from 31 electrodes by means of an "Encephalan-EEG-19/26" electroencephalograph (Medicom MTD, Taganrog, Russia) with a sampling rate of 250 Hz. The positions of the electrodes were selected following the international 10–10 scheme. At the stage of data preprocessing, a Butterworth bandpass filter was used whose cut-off frequencies were selected at 1 Hz and 100 Hz, and a 50 Hz notch filter was applied.

During the experiment, the volunteers sat on a chair with their hands on the table desk. The baseline EEG (relaxation, eyes open) was recorded for 5 min, then a series of 30 motor tasks per each hand was performed. Within the task, the volunteer clenched his/her hand into a fist after an audio signal (a beep) and keep it clenched until the next signal. Depending of the duration of the beep, movement by the left

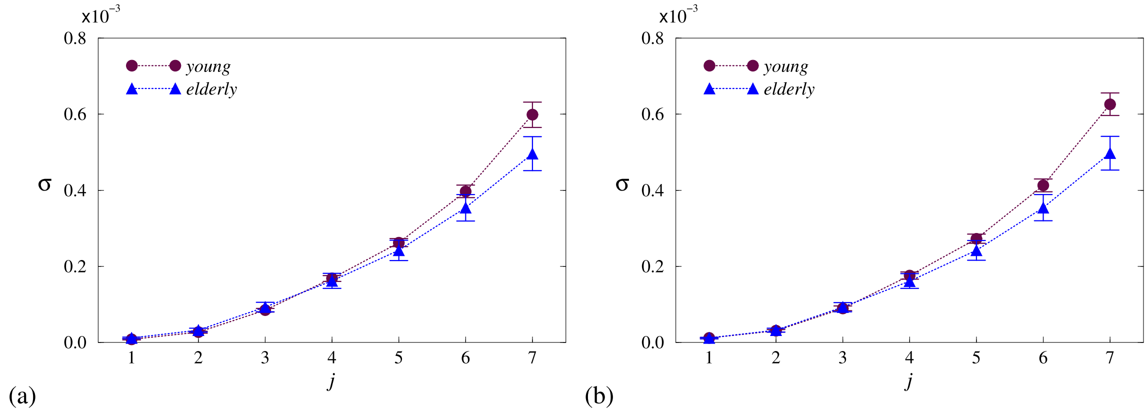


**Fig. 1.** Standard deviations of detail wavelet-coefficients versus the resolution level for EEG segments related to hand-to-fist clenching in two groups of volunteers: (a) left, and (b) right hand movements. Results are given as mean ± SE.

hand (LH) (a short signal, 0.3 s) or the right hand (RH) (a prolonged signal, 0.75 s) was done [35,36]. A random selection of tasks (LH or RH) was applied avoiding adaptation (training). EEG segments related to each task were extracted for further analysis. We used segments involving 2 s of the baseline EEG preceding the motor task, 4–5 s of the tasks itself (during this period of time, the volunteer clenched the hand and held the fist in a clenched state), 6–8 s of unclenching, and a pause before the next task. The extracted segments were centered at the start of the first signal. In the course of visual inspection, EEG segments less corrupted by artifacts were chosen (15 hand-to-fist clenching for each hand).

## 3. Results and discussion

### 3.1. MWA

Systems with time-varying dynamics often show an increasing dependence of $\sigma_j$. On small scales, changes in the local mean value and other types of nonstationary behavior usually do not have an essential effect on the probability distribution of detail wavelet-coefficients, since short data segments can be interpreted as parts of a stationary process, and characteristics estimated from these segments may vary strongly in only a few cases, such as short-term events (artifacts or failures of recording equipment). When passing to each next level of resolution (from $j$ to $j+1$), the segments length doubles, and becomes comparable with the entire time series at the end of the pyramidal decomposition procedure. As a result, transients and other slow nonstationary components can have a stronger influence, and the variance of $d_{j,k}$ grows. The time-varying dynamics of physiological systems is not necessarily due to recording equipment or inappropriate experimental procedures. Often, it reflects responses to a change in the state of the system, which are important for diagnostic purposes, and such types of nonstationary behavior should not be excluded from data analysis. The fine motor tasks considered in this study are an example of a case when time-varying EEG dynamics is expected, and the subject of the study is differences in the responses of young and elderly adults. Since the time intervals associated with the hand-to-fist clenching significantly exceed the sampling step, we expect the variance of $d_{j,k}$ to increase with $j$.

Fig. 1 confirms this expectation for two groups of volunteers. Here, a two-step averaging was done: the first step is averaging over all individual tasks and channels for every participant, and the second step is group averaging (mean value ± SE). In addition to the growing dependences of $\sigma_j$, let us note that higher resolution levels are more appropriate for detecting age-related effects. This may be explained by the consideration of more suitable time intervals for highlighting differences: large time scales (comparable to the execution of the task itself) are more informative for studying responses in brain electrical activity than much shorter time intervals related to very small parts of the task. Fig. 1 is an illustration of the distinctions between the responses in groups of volunteers to movements by dominant and non-dominant hand. In both cases, inter-group separation is observed, e.g., for $j = 7$ (the Mann-Whitney test, $p < 0.05$). Distinctions for individual participants are shown in Fig. 2, where the symbols mark the values of $\sigma_j$ associated with fine motor tasks performed by the left and right hand. Each symbol corresponds to a value averaged over 15

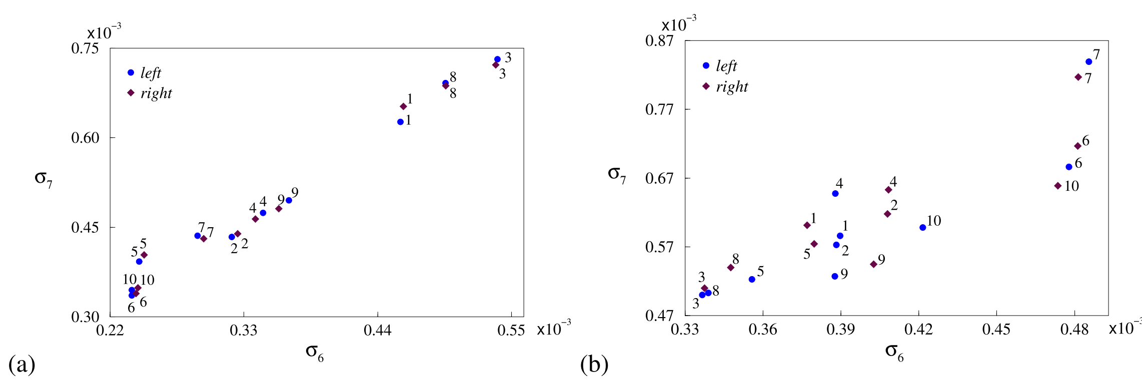


**Fig. 2.** Standard deviations of detail wavelet-coefficients on the plane ($\sigma_6$, $\sigma_7$) for elderly (a) and young (b) volunteers. Elderly volunteers show less distinctions in the characteristics for movements by the left and right hand.

**Table 1**
The average number of EEG channels with significant inter-group distinctions for three values of $p$. Here, we compared the values of $\Delta\sigma_6$, $\Delta A_6$, $\Delta E_6$ for detail wavelet coefficients related to fist clenching. Advantages of using $\Delta A_6$ and $\Delta E_6$ for detecting the effects of aging are obvious.

| Measure | Confidence level | | |
|---|---|---|---|
| | $p < 0.05$ | $p < 0.01$ | $p < 0.001$ |
| $\Delta\sigma_6$ | 6 | 2 | 1 |
| $\Delta A_6$ | 19 | 14 | 11 |
| $\Delta E_6$ | 19 | 15 | 8 |

recurring tasks and all channels. Numbers are used to identify results with each volunteer. According to Fig. 2, much stronger distinctions between the characteristics of EEG for movements by the left and right hand are observed in young adults. Elderly volunteers are characterized by nearly similar values of $\sigma_j$ for such movements, i.e., they have distinctly smaller differences between the responses to motor tasks performed by the dominant and non-dominant hand. Thus, $\Delta\sigma_j = \sigma_j^{left} - \sigma_j^{right}$ can be used to quantify inter-group distinctions. Further, we will compare $\Delta\sigma_j$ and analogous measures for other cumulants, namely, $\Delta A_j = A_j^{left} - A_j^{right}$ and $\Delta E_j = E_j^{left} - E_j^{right}$.

### *3.2. Enhanced MWA*

Despite the above analysis clearly shows age-related differences between the responses to movements of the left and right hand (Fig. 2), their quantitative assessment can be better provided if the $d_{j,k}$ coefficients are more thoroughly processed. Cumulants make it possible to obtain a more informative description of various features of the probability distribution, including its symmetrical properties, the behavior of "tails", i.e., the probability of large values, etc. Moreover, differences can vary depending on the electrode position, and this circumstance should also be taken into account.

At the first stage, we compared the effectiveness of cumulants in detecting the aging effects based on the Student's $t$-test and searched for the maximum $t$-value that quantifies inter-group differences between the characteristics of EEG segments in wavelet space related to movements by the left and right hand for all EEG-channels and resolution levels, i.e., for $\Delta\sigma_j$, $\Delta A_j$, $\Delta E_j$, $j\in[1,7]$. Larger values of $t$ are obtained for skewness ($\Delta A_j$) and kurtosis ($\Delta E_j$), 10.32±0.46 and 7.26±0.37, respectively versus 2.38±0.23 for $\Delta\sigma_j$, and therefore, the assessment of these cumulants reveals more significant differences between the probability distributions of $d_{j,k}$ for EEG recordings in young and elderly adults when comparing fine motor tasks carried out by the dominant and non-dominant hand. This is also confirmed by the estimation of the average number of channels where such differences are significant (Table 1). The results are given for three values of $p$ and the 6-th level of resolution. These results do not mean that the variance or SD is inappropriate measures to describe the effects of aging. Our main conclusion is that analysis based on various features of the wavelet coefficients is preferable for diagnostic purposes.

In order to relate the identified differences between the characteristics of responses to movements by the dominant and non-dominant hand to specific areas of the brain, we also considered their distributions in relation to the position of the electrode. These results are shown in Fig. 3. In accordance to this figure, we can conclude that main differences for $\Delta A_6$ and $\Delta E_6$ are observed in frontal lobe (its parts responsible for motor control, concentration, planning and problem solving) and have a rather strong reflection if parietal lobe (body awareness). For $\Delta\sigma_6$, the distinctions are less pronounced. We can conclude, that the observed distinctions do not have a limited region of their reflection and, in particular, can be detected in more than a half of EEG channels. Significant differences ($p < 0.05$) are also found on the next level of resolution ($j = 7$) in 12, 22, and 18 channels for $\Delta\sigma_7$, $\Delta A_7$ and $\Delta E_7$, respectively, i.e. the observed age-related distinctions are more pronounced than for $j = 6$, although the conclusion for the latter level about the absence of a limited region of their detection remains unchanged. The relation between the distinctions and the position of the electrode for $j = 7$ are shown in Fig. 4.

## 4. Conclusion

We discussed how an enhanced version of MWA, which includes a thorough analysis of the decomposition coefficients, is able to improve characterization of complex processes based on experimental data. The proposed way for such an improvement consists in the use of cumulants being the expansion coefficients of the natural logarithm of the characteristic function into the Maclaurin series. Although a set of cumulants provides the same information as a set of moments, their interpretation is more convenient in some cases. The general idea was to show how taking into account the various features of the probability distribution is helpful for diagnostic-related studies. As an example of the experiments chosen to support this idea, fine motor tasks consisting of clenching hands into fists were used in two groups of adult volunteers of different ages. The obtained results show that a simple MWA algorithm with an estimate of the standard deviation of the detail coefficients can clearly describe the effects of aging, but the use of skewness and kurtosis of the probability distribution makes the inter-group separation more pronounced and significant. In particular, these distinctions are revealed for a larger number of EEG channels. Thus, we can conclude that the results of this study can confirm the benefits of enhanced versions of MWA.

## CRediT authorship contribution statement

**G.A. Guyo:** Software, Investigation, Writing – original draft. **A.N. Pavlov:** Conceptualization, Methodology, Writing – original draft. **E.N. Pitsik:** Experiments, Investigation, Visualization. **N.S. Frolov:** Experiments, Investigation, Validation. **A.A. Badarin:** Experiments, Investigation. **V.V. Grubov:** Experiments, Investigation. **O.N. Pavlova:**

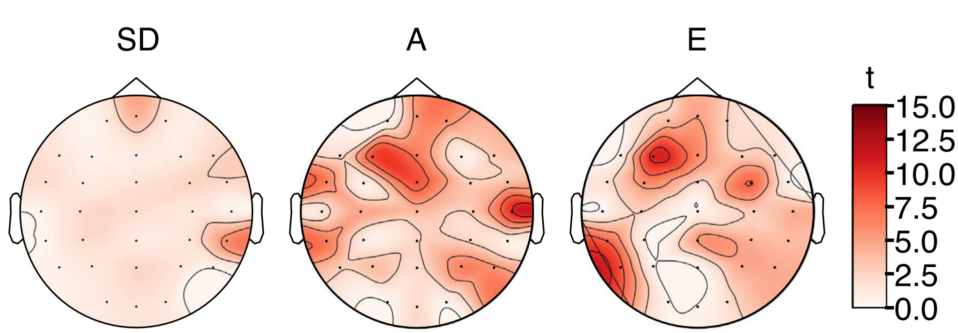


**Fig. 3.** A relation between the inter-group distinctions and the position of the electrode for $\Delta\sigma_6$ (SD), $\Delta A_6$ (A), $\Delta E_6$ (E) according to $t$-value of the Student's test.

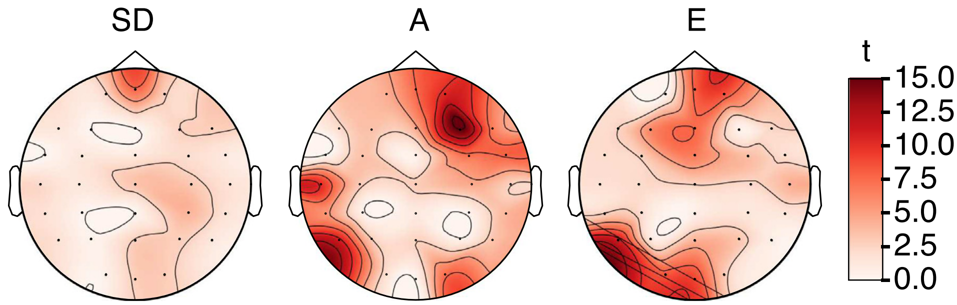


**Fig. 4.** A relation between the inter-group distinctions and the position of the electrode for $\Delta\sigma_7$ (SD), $\Delta A_7$ (A), $\Delta E_7$ (E) according to $t$-value of the Student's test.

Methodology, Formal analysis, Visualization. **A.E. Hramov:** Conceptualization, Writing – review & editing.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.


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