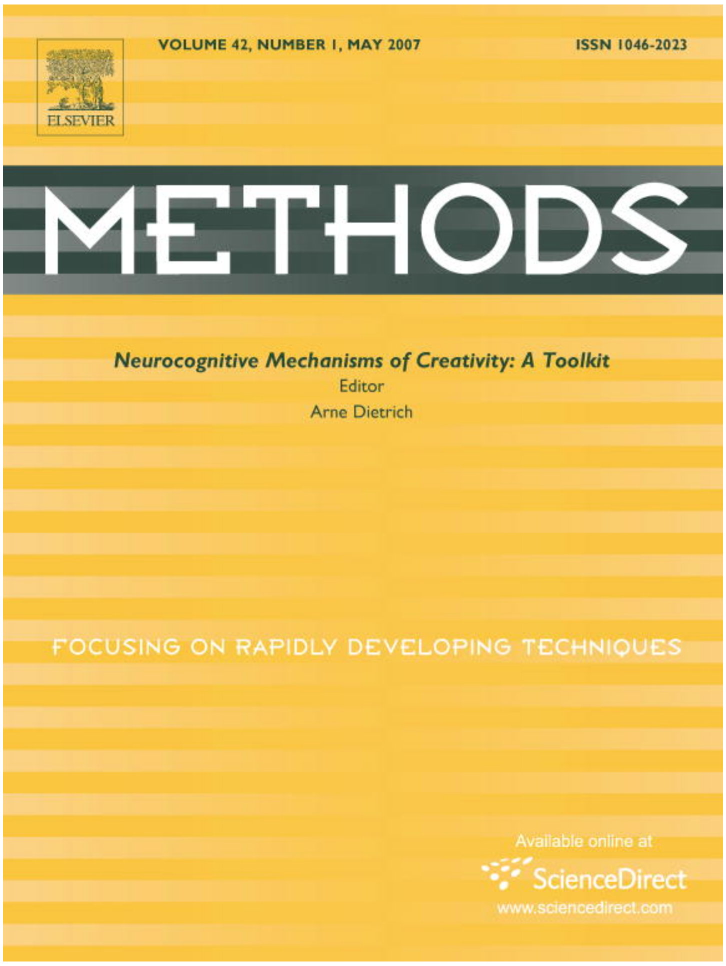
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Cognitive neuroscience of creativity: EEG based approaches

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Abstract

Cognitive neuroscience of creativity has been extensively studied using non-invasive electrical recordings from the scalp called electroencephalograms (EEGs) and event related potentials (ERPs). The paper discusses major aspects of performing research using EEG/ERP based experiments including the recording of the signals, removing noise, estimating ERP signals, and signal analysis for better understanding of the neural correlates of processes involved in creativity. Important factors to be kept in mind to record clean EEG signal in creativity research are discussed. The recorded EEG signal can be corrupted by various sources of noise and methodologies to handle the presence of unwanted artifacts and filtering noise are presented followed by methods to estimate ERPs from the EEG signals from multiple trials. The EEG and ERP signals are further analyzed using various techniques including spectral analysis, coherence analysis, and non-linear signal analysis. These analysis techniques provide a way to understand the spatial activations and temporal development of large scale electrical activity in the brain during creative tasks. The use of this methodology will further enhance our understanding the processes neural and cognitive processes involved in creativity.

Keywords: Creativity; Cognitive neuroscience; EEG; ERP; Filtering; Artifact rejection; Spectral analysis; Coherence

1. Introduction

Creativity is an important aspect of cognition and research on creativity has focused on various processes that constitute or are associated with creativity. Some recent researchers have argued that creativity is not special and ordinary cognitive processes and underlying neural mechanisms are also utilized in creativity [1]. Problem solving tasks or open-ended tasks are used in creativity research that try to measure various parameters including fluency, flexibility, originality, and elaboration. Studies on higher cognitive processes show that the prefrontal cortex is activated during effortful problem solving tasks [2]. While intelligence is not highly correlated with creativity, certain aspects or types of intelligence like fluid intelligence may be highly correlated with creativity. Imaging research looking at the neural activation during intelligence tasks has shown that the lateral frontal cortex is activated [3].

There have been several proposals that general intelligence and executive functions are implemented in a common neural circuitry and depend on the prefrontal cortex [4,5]. Executive functions include mechanisms requiring mental processes such reasoning, decision-making and, importantly, performing operations on mental representations in absence of external referents. Consistent with the present idea, the lateral cortex plays a key role in executive functions [6] as being critical for working memory functions and behavioral inhibitory mechanisms [7] that are essential for goal-directed behavior. These top-down processes have been studied using human electrophysiology to reveal changes in P300 component whenever multiple internal memory representations are required to be made by working memory [8], although there is no clear consensus regarding the neural source of this component [8,9]. Activation of the prefrontal cortex has also been reported with effortful problem solving [2]. Given the possible importance of executive functions in creativity, these studies indicate that the prefrontal cortex plays a significant role in creative tasks [10].

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A number of studies on the neural mechanisms of creativity have looked at the role of hemispheric asymmetry [11–14]. It has been hypothesized that creativity might be primarily a right hemisphere function. However, these laterality studies are too simplistic and the recent trend is to focus on the large scale interaction of neural networks in the brain and specific functional roles of cortical areas in explaining the distinct modes or processes underlying creativity [10,15,16]. Different brain areas may get activated dependent on the nature of the creative process and the type of problems that are solved by creative thought processes. Open-ended problems may show a larger activation in the temporal, parietal, and occipital areas in which knowledge is stored. It is also possible that solutions to open-ended problems may be associated with the synchronization of a large number of areas in the brain. It has also been argued that deliberate closed problem solving may show a larger activation in the dorsolateral prefrontal cortex [10].

Creativity research has been performed using different methodologies including behavioral experiments and brain-based techniques [17]. In the past forty years an important methodology to investigate neurocognitive processes including creativity has been electroencephalography (EEG). Techniques using EEG form part of the burgeoning research in the interdisciplinary area of cognitive neuroscience [18]. Like other areas of research in cognitive science, creativity research has also employed this methodology with reasonable success. Compared to other techniques in cognitive neuroscience, EEGs offer certain advantages and complement the research performed with brain imaging and other neurocognitive methodologies. The temporal resolution of EEG provides an opportunity to explore the temporal development of cognitive processes and their underlying brain activities. This enables us to study differences in macroscopic electrical activity in the brain resulting from the interaction of neural activity in different areas of the brain performing specific cognitive tasks.

An important aspect of performing creativity research using EEG/ERP paradigms is the nature of the creative task. The tasks that has been employed span a wider range including verbal (e.g., producing compound words) and non-verbal (e.g., spontaneous mental creation of drawings) tasks. Compound remote associate problems have also been used. Here the feedback from observers was used to differentiate between insight solutions from non-insight solutions [19,20]. Others have used tasks of unusual situations, which may lead to insightful problem solving [21]. Verbal tasks in which stories have to be created using words from dissimilar categories have also been used to study creativity [22]. The EEG/ERP experiments performed with such tasks enable us to understand the brain activity underlying these tasks. This paper explores the EEG methodology in detail.

2. EEG recording

Electroencephalograms (EEGs) are electrical signals recorded from the scalp. They are a non-invasive measure of brain electrical activity which are represented as changes in potential difference between different points on the human scalp. EEG is a record of electric field potentials that arise primarily from excitatory and inhibitory postsynaptic potentials. EEG recorded without any external stimuli is called spontaneous EEG (or just plain EEG) and EEG recorded as a response to external stimuli is called an event related potential (ERP). Typical amplitudes in EEG waveforms are of the order of 50–200 μV. Event related potentials (ERPs) typically are of much smaller amplitude than EEG and are usually in the order of a few μV. ERPs are typically obtained by averaging EEG obtained from multiple presentations of the same stimulus and task conditions. ERPs are used to assess brain function and observe electrophysiological manifestations of cognitive activities including creativity. In general, ERPs are typically described in terms of components based on polarity and latency. The positive and negative peaks in ERPs that are obtained after sampling and averaging of time-locked events can be described in terms of their characteristic scalp distribution, polarity and latency [23,24].

EEG systems typically employ at least one computer for stimulus presentation and collection of behavioral data and another computer for collection of EEG data. The EEG data is obtained by placing electrodes on the scalp. Typical clinical EEG systems employ around 20 electrodes and the electrodes are arranged according to the 10–20 system (Fig. 1). High density EEG systems used for research currently employ anywhere from 64 to 256 electrodes. Electrode impedances are usually kept below 5 kΩ. Ag/AgCl or tin electrodes are normally used for recording EEG signals from the scalp. One of the electrodes is used as a reference electrode and standard locations for the reference electrode include the tip of the nose, the ear lobes and

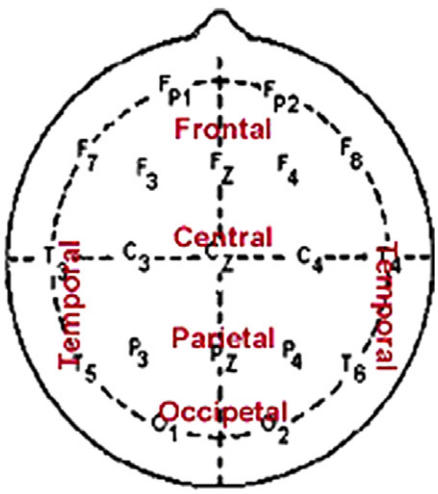

Fig. 1. Scalp electrode positions based on the 10–20 system.

locations near the temples on both the sides of the head. The EEG signal obtained is dependent on the reference electrode and there is no placement of reference electrode that is unproblematic. There is no position that can be considered "at infinity" so that the reference electrode can be treated as an "inactive" electrode compared to an "active" electrode which is close to a neural source [25]. There is no distinction between a reference electrode or recording electrode and the choice of an appropriate reference electrode may depend on electrode locations as well as the sources of the electrical signal in the brain. Two fairly common choices for a reference are the linked-mastoids reference and the common average reference. There are two types of linked-mastoids references, namely, the physical linked-ears reference and the mathematical linked-ears reference. In the physical linked-ears reference, the two ears are linked by a physical wire. In the other type, a particular ear is used as a reference for all electrode locations, including the other ear, and EEG signals at all the electrode locations are mathematically derived. In the common average reference, the signals from all the electrodes are averaged and used as reference.

The analog EEG signal is typically filtered using an analog band-pass filter with a lower cutoff typically at 0.5 Hz and a higher cutoff above 50 Hz. Sometimes a notch filter is used to reduce interference of the power line frequency (50 or 60 Hz). The analog signals obtained through the electrodes are amplified and then converted into digital signals using an analog-to-digital converter. Some important parameters concerning an amplifier are the gain, resolution, range, common-mode rejection, and input impedance. Dynamic range specifies the range within which the EEG signal is obtained without distortion (clipping or saturation). Range is typically in the mV range while EEG signals are typically within a few hundred μV. The gain should be large enough so that the EEG signal can be brought to within the dynamic range of the amplifier. Resolution depends on the number of bits given by the AD converter. Most current AD converters have 12–24 bit resolution. Common-mode rejection refers to the ability to reject a signal that is simultaneously applied to both of the inputs of a differential amplifier. Recommended common-mode rejection ratios are any signal above 100 dB. Input impedance is typically in the GΩ range. The sampling frequency depends primarily, on the maximum frequency present or of interest in the signal. According to Nyquist criterion, if $f_{\max}$ is the maximum frequency, then the sampling frequency should be at least twice that of $f_{\max}$. A better criterion is to keep the sampling frequency at least 2.5 times that of $f_{\max}$. Sampling frequency is typically set to at least 250 Hz since the frequency content of the EEG signal of interest to cognitive neuroscience researchers occur mostly in the range of 1–50 Hz although there are recent studies looking at frequencies of 100 Hz or more. ERP signals typically have a bandwidth of 0.5–20 Hz. Most current systems employ a sampling frequency of 1000 Hz. The digital EEG data obtained after sampling and quantization is analyzed using commercial software that is usually packaged along with the recording system or standard computing software like MATLAB (The Mathworks, Inc.).

3. EEG preprocessing

The digitized EEG signals are typically preprocessed to identify the artifacts that may be present in the signal. It is important for an EEG researcher studying creativity or any other cognitive process to understand the different types of artifacts that affect EEG. Typically EEG epochs contaminated with artifacts are rejected even though some methods are available for artifact correction. Even with artifact rejection, EEG signals are affected by noise which is then removed using digital filtering.

3.1. Artifact rejection

EEG signals are typically affected by the presence of various artifacts. Artifacts include power line interference, muscle activity, blinks, eye-movements, skin potentials and so on. Two possible ways to handle artifacts is to either reject the trials which contain the artifact or employ techniques to estimate and remove the artifacts. While rejection of trials with artifacts may result in better estimation, the number of artifact-free trials needs to be considered when choosing this alternative. If a sufficient number of such trials are not available, a poor estimate of ERPs will result. There are three major possible sources of artifacts: instrumentation artifacts, eye movement artifacts, and overlap from adjacent trials [26]. Overlap from adjacent trials typically occurs at fairly high stimulus presentation rates (more than one stimulus per second). The effect of overlap can be reduced by introducing a temporal jitter (varying the duration) between stimuli and then averaging the waveforms obtained with different inter-stimulus durations. Other methods include estimating the overlap or including *no-stim* trials [27–30]. High stimulus presentation rates are fairly unusual in creativity research and overlap may not be a significant problem in creativity research.

Electrical noise present during the recording can be reduced by employing filters to remove the noise especially if the noise contains higher frequencies, as we are interested in lower frequencies. A possible arrangement that will decrease electrical noise is to use a Faraday cage [24]. Artifacts due to instrumentation consist of both high-frequency artifacts as well as drifts (low frequency artifacts). Loose electrode connections can also cause artifacts and this can be eliminated by checking the connections. Sometimes a pulse-wave artifact can be seen due to blood pulse-waves affecting the electrode connections. A major source of artifact is power line interference which is easily picked up by loosely connected electrodes. Slow wave drifts will alter the baseline of EEG waveforms. They may also result in amplifier saturation.

Another major source of noise in EEG data is eye-movements. Eye movement produces electrical interference that causes a large change in the EEG waveform. Blinks (eye-lid movements) and eye-movements produce substantially larger amplitude in the frontal electrodes than in the posterior electrodes. One possible way to eliminate blinks is to use the Electrooculogram (EOG) signal obtained by placing electrodes near the eyes. Participants in experiments are typically instructed to fixate and minimize blinks. A threshold can be used to eliminate epochs which contain larger than threshold differences between the minimum and maximum peaks in the EOG signal. A typical eye blink response consists of a peak in the order of 50–100 μV and lasts somewhere between 200 and 400 ms. In addition, the polarity is opposite for electrodes below the eye when compared to electrodes above the eye during an eye blink response. This can be used to distinguish between a blink response and a genuine EEG signal. A number of correction techniques have been proposed for blink artifacts including regression, dipole source modeling and independent component analysis [29].

Eye-movements cause voltage changes that are reflected in the EEG signals. While there are different types of eye-movements, most of the eye-movements of interest in a typical ERP experiment are saccades. The amount of deflection caused by saccades is proportional to the size (in degrees) of the saccade at least up to 15°. Any epoch with greater than 1° saccade is typically rejected. In addition to eye-movement artifacts, muscle activity and cardiac activity can produce artifacts in the EEG. Artifacts due to muscle activity contain high frequencies and can be removed using low-pass filtering. The electrical signal generated due to cardiac activity is usually picked up by the mastoid electrodes and is usually not a great problem for EEG analysis. Another source of artifacts is the presence of periodic noise. For example, the alpha rhythm is an artifact that may affect ERP analysis. One possibility is to introduce jitter, that is, vary the interval between stimulus presentations. One can also evaluate the alpha power for an epoch and then reject the epoch if the alpha power exceeds a threshold. It is recommended that the best way to handle artifacts is to minimize the occurrence of artifacts in the first place. While some techniques for artifact correction are available, it is not clear how reliable they are and most of the time epochs with artifacts are rejected.

3.2. Filtering

After successful artifact rejection, the EEG signal is filtered. Different types of filters are available depending on the frequencies that need to be eliminated. A low-pass filter reduces or removes high frequencies but pass low frequencies. A high-pass filter passes high frequencies but attenuates or removes low frequencies. A band-pass filter passes frequencies within a specified range and a band-stop filter attenuates frequencies within a specified range. It should be noted that filters should be used with care and it may distort the EEG waveforms. In spite of this, filters are commonly used to attenuate the noise in EEG waveforms.

Filters are designed using various parameters. Applying filters changes both the amplitude of the frequencies present in the input signal as well as the phase of each frequency. A filter can be described by using a parameter called half-amplitude cutoff which is the frequency at which the amplitude is cut by 50%. While this is true for a low-pass filter, a high-pass filter may be characterized by their time constants which refer to a value at which the output of the filter is 37% of the starting value. The transition band of a filter can also be characterized by using roll-off which is typically denoted in terms of dB per octave. A filter with 8 dB/octave has a less steeper transition than a filter with 16 dB/octave.

If the lower frequency rhythms of the EEG or ERPs are of interest, then the bandwidth of the filter may be set at 0.01–40 Hz. Specific artifacts like power line noise can be removed using notch filters. Digital filtering can be implemented either in the time-domain or frequency-domain. In the time-domain, a noisy signal containing high-frequency noise can be smoothed using a moving average filter. A typical moving average filter's output is obtained by calculating the weighted average of a given number of EEG samples. In general, the filter's output

$$y(n) = \sum_{i=o}^{N} w_i x(n-i), \tag{1}$$

where $y(n)$ is the filtered signal, $x(n)$ is the given EEG signal, w_i are the filter coefficients and N is the order of the filter. Different filters can be obtained by choosing different sets of filter coefficients. The filter, expressed with a finite set of filter coefficients, is referred to as a finite impulse response (FIR) filter. Filters can also be designed in the frequency domain and different types of filters (Butterworth, Chebyshev, etc.) can be designed to filter the EEG signals [31]. A possible way to apply a frequency-domain filter is to compute the Fourier transform of the EEG signal and then apply the filter in the frequency domain and convert the resulting signal into the time-domain in order to obtain the filtered signal. Alternately, the frequency-domain filter can be converted into the time-domain and then convolved with the noisy EEG signal to get a clean EEG signal. More details on filtering can be obtained from [32] and see [24] for a more detailed discussion on the distortions induced by different types of filters.

4. ERP estimation

Typical estimation of ERPs is based on various assumptions. It is generally assumed that ERPs are synchronized with the stimulus presentation, repeated and identical for each stimulus presentation, statistically independent from the ongoing background EEG activity, and the background EEG is stationary with zero mean. ERPs are obtained by time-locked averaging of EEG signals. Averaging will result in a better estimate with larger number of trials. Noise actually decreases as a function of the square root of the number of trials used for averaging. Another factor that will determine the accuracy of the estimate is the variability in latencies between trials. Some methods have been proposed to reduce the effects of latency variability, namely, area measures, response-locked averages, Woody filter technique, and time-locked spectral averaging [24].

Some of the most common measures to quantify ERP components are the peak amplitude of the component, mean amplitude, and latency of the peak. Mean amplitude is typically measured by specifying a temporal window consisting of the peak amplitude of the component. A component should not be simply equated with peaks that are seen in an ERP waveform. One of the definitions of an ERP component is "scalp-recorded neural activity that is generated in a given neuroanatomical module where a specific computational operation is performed" [24]. Techniques like principal component analysis (PCA) and independent component analysis (ICA) use statistical information obtained from ERP to extract components. Some strategies have been proposed to alleviate the problems associated with the ERP data and the hidden components (see chapter 2 in [24] for more details).

If a particular effect is predicted in a given ERP paradigm, analysis can be restricted to specific electrodes. In a visual P300 paradigm, for instance, amplitudes are higher for the electrodes in the midline parietal regions. Hence Pz may be used for analyzing the P300 components. In the mismatch negativity paradigm, the peak amplitudes are highest for the difference waveform in the midline frontal regions and Fz can be used for analyzing the MMN component. Most creativity studies have focused on the spectral characteristics of EEG and the relationship between the spectral characteristics of EEG signals from different electrodes rather than ERPs themselves. One study that has looked into ERPs generated from auditory and visual tasks is [33]. These authors evaluated the ERP waveforms relating it specifically to intelligence. More regular ERP waveforms, shorter P300 latencies and larger P300 amplitudes, were found with individuals who had higher intelligence scores.

5. EEG/ERP signal analysis

EEG/ERP signal processing is performed for various reasons. Signal analysis helps in reducing subjectivity in the analysis of EEG/ERP data. It also helps in extracting features that may characterize brain or cognitive functions underlying creativity. As seen in the previous section, signal processing is also used to reduce noise in the data. Furthermore, signal processing is used to reduce the data for further analysis or storage and allows the cognitive scientist to develop models of cognitive functions. After computing relevant features/parameters (spectral powers, coherence values, etc.) using signal processing, statistical analysis is performed. Typically, an Analysis of Variance (ANOVA) is performed with task related conditions and electrodes as variables. It is to be noted that one of the significant problems associated with performing ANOVA in EEG/ERP studies is the violation of the sphericity assumption. A typical way this violation is corrected is by using the Greenhouse Geisser procedure [24]. The EEG signal processing can be performed in the time-domain or frequency-domain. The most common analysis techniques that have been used so far in creativity research are spectral analysis and coherence analysis.

5.1. Spectral analysis

One of the significant methods used to investigate EEG is to explore the spectral characteristics (rhythms) of EEG signals. One of the important properties of EEG signals to be kept in mind when performing the analysis is the stationarity of EEG signal. A signal is stationary if its statistical properties are time-invariant and EEG signals are typically stationary only for short intervals. Spectral analysis provides information about the presence of different frequencies in EEG that reflects the general arousal levels of the brain. There are certain major rhythms in the brain as reflected through spectral analysis of EEG. The alpha rhythm (8–13 Hz) occurs during wakefulness and is observed when a person is in a relaxed state with the eyes closed. Alpha rhythm is reduced during task requiring attention and mental effort. Alpha can be further subdivided into $\alpha 1$ (between 8 and 10 Hz) and $\alpha 2$ (between 10 and 13 Hz). The beta rhythm (greater than 13 Hz and typically less than 30 Hz) is found with increased alertness and focused attention. It is associated with sensory processing and voluntary movements. The beta rhythm can also be subdivided into $\beta 1$ (between 13 and 18 Hz) and $\beta 2$ (between 18 and 30 Hz).The gamma band consists of frequencies greater than 30 Hz, and oscillations around 40 Hz have been implicated in binding [34]. The theta rhythm (4–8 Hz) is usually present at higher percentages in infancy and childhood and has recently been implicated in encoding and retrieval of information [35]. The delta rhythm (0.5–4 Hz) is present during deep sleep.

Spectral analysis is typically performed with EEG segments by computing the Discrete Fourier Transform (DFT). DFT of the given EEG signal $x(n)$ is given by

$$X(k) = \sum_{n=0}^{N-1} x(n) \exp\left(-j\frac{2\pi}{N}kn\right) \quad k = 0, 1, 2, \ldots, N-1, \tag{2}$$

where N is the number of EEG samples taken for analysis. The DFT is typically computed using the Fast Fourier Transform algorithm (FFT) which computes the Fourier transform coefficients $X(k)$ quickly. Power values are calculated using FFT for specific frequency bands which are then used for further analysis. Other methods are also available to compute the spectral characteristics of EEG signals. They include non-parametric and parametric methods for spectral analysis. One possible function that can be used for EEG analysis is the autocorrelation function. The autocorrelation function can be computed by using the formula

$$R(\tau) = \frac{1}{N} \sum_{n=0}^{N-|\tau|+1} x(n)x(n+\tau). \tag{3}$$

The autocorrelation function contains information about the expected frequency content of the random process. If the signal $x(t)$ contains a periodic component, then $R(t)$ will also contain a periodic component with the same period. The power spectral density (PSD) function can be used to provide spectral information, and the PSD is defined as the Fourier transform of the autocorrelation sequence. Spectral analysis can also be performed by using models, typically linear stochastic models. The most popular model is the autoregressive model (AR). AR modeling is used extensively in modeling random signals like EEGs [36]. AR analysis models the EEG signal as the output of a linear system driven by white noise of zero mean and unknown variance [37]. AR models have the form

$$x[k] + \sum_{i=1}^{M} a_i x[k-i] = n[k], \tag{4}$$

where $x[k]$ is the EEG signal, $n[k]$ is zero mean white noise, a_i's are the AR coefficients, and M is the AR order. Various algorithms like the Yule–Walker method and the Burg algorithm have been used to compute the AR coefficients [37]. Burg algorithm minimizes the sums of squares of both forward and backward prediction errors. No windowing is necessary in the Burg algorithm and it typically performs better than Yule–Walker method. The Burg algorithm has been used with EEG and an order of 10 is found to be good for EEG.

Spectral analysis of EEG has been employed extensively in creativity research [19–21]. In a study on creativity, spectral analysis was performed with EEG obtained from tasks that included insight and it was found that insight preparation in comparison with timeout preparation was associated with less alpha power (i.e., greater brain activity) in the 9–10 Hz range especially in mid-frontal cortex and left anterior-temporal cortex [19]. However, non-insight preparation in comparison with timeout preparation showed decrease in alpha power in the 8–9 Hz range in the occipital cortex [19]. In contrast, other studies have shown an increase in alpha power associated with creative tasks [20,21]. EEG alpha band power was determined for two verbal creativity tasks [20]. The spectral power in the alpha band was computed by using FFT with a 90% overlap and a Hanning window (10 s long). Task related power changes were computed using the following formula

$$\mathrm{TRP}(\log \mathrm{Pow}_i) = \log[\mathrm{Pow}_{i\,\mathrm{activation}}] - \log[\mathrm{Pow}_{i\,\mathrm{reference}}], \tag{5}$$

which showed task related increase in alpha power especially with responses deemed more original. These results are also consistent with findings from other studies [20]. The change in alpha power may depend on the nature of the creative task and the employment of attentional resources specific to different types of creative tasks [38].

5.2. Cross-correlation and coherence analysis

Two standard techniques used to identify the relationship between EEG signals from two different electrodes are cross-correlation and coherence. Cross-correlation function between two digital EEG signals $x(n)$ and $y(n)$ as a function of shift d is computed as

$$\theta_{xy}(d) = \sum_{n} x(n)y(n+d). \tag{6}$$

Cross-spectral density is obtained by computing the Fourier transform of the cross-correlation function. A peak in the cross-spectral density function at a particular frequency typically denotes that the two EEG signals exhibit the same rhythm. Coherence analysis can be used to obtain relationships between two different signals in terms of spectral analysis. Given EEG signals from any two electrodes, the normalized coherence spectrum is given by

$$\Gamma_{xy}(f) = \left[\frac{|S_{xy}(f)|}{S_{xx}(f)S_{yy}(f)}^{2}\right], \tag{7}$$

where $S_{xx}(f)$ is the power spectral density of EEG signal from one electrode, $S_{yy}(f)$ is the power spectral density of EEG signal from another electrode and $S_{xy}(f)$ is the cross spectral density between EEG signals from two electrodes. Typically coherence values between electrodes are computed for specific frequency bands (alpha, beta, theta, and delta). Higher coherence values are supposed to indicate higher cooperative processing different regions. Coherence analysis has been used in a number of creativity studies [39]. In one study, coherence analysis was employed to look at differences between trained musicians and non-musicians [37]. These authors found differences in coherence values for different music related tasks such as imagining music and composing.

5.3. Time–frequency analysis

Time–frequency and wavelet analyses simultaneously look at EEG signals using both time and frequency or time and scale, respectively. In time–frequency analysis, amplitudes are plotted as a function of both time and frequency. As discussed earlier, the EEG signal at best is quasi-stationary for brief epochs. For some applications, normal EEG can be assumed to be stationary only for a few seconds at a time. In addition, we are interested in changes in frequency content in EEG signals with time. In wavelet analysis, different scales are used to perform analysis. Wavelet transform describes signals in terms of coefficients, representing their energy content in specified time–frequency region. This representation is constructed by means of decomposition of the signal over a set of functions generated by translating and scaling one function, wavelet ψ. A large number of transforms are available to perform time–frequency analysis and wavelet analysis. In creativity research, time–frequency analysis has been employed in a limited manner. For example, Grossman–Morlet wavelets were used in [20]. These are Gaussian distributions in both time and frequency. With the use of these time–frequency waveforms, differences in alpha as well as gamma power during insight solutions compared to non-insight solutions was found [20]. The use of time–frequency transforms enabled the researchers to see that these alpha and gamma power differences were present at different times with significant alpha power differences at −1.3 and 0.5 s before the insight solution and significant gamma differences starting just 300 ms before the insight solution.

5.4. Non-linear analysis

Various parameters like correlation dimension, Lyapunov coefficients, etc. that describe certain non-linear characteristics of EEG signals have been computed and used in EEG analysis [40]. Methods that can be used to perform non-linear multivariate analysis on EEG signals have been proposed in addition to linear multivariate analysis [41]. We have already looked at the use of coherence to study the relationship between EEG signals. Given certain disadvantages, other measures based on non-linear analyses for estimating interdependency between EEG signals from different electrodes have been proposed [15]. Three indices based on generalized synchronization, mean phase coherence and phase synchrony based on entropy were computed to study phase synchronization in artists and non-artists in a creative task involving mental creation of drawings. They found that synchronization was more in the alpha and the higher frequency bands for non-artists while synchronization was more common in the delta band for artists. An effect of hemispherical asymmetry was also obtained with more synchronization in the right hemisphere for artists. Alpha synchronization has also been found in the frontal areas in a divergent thinking task [42]. Differences in phase synchronization have also been found in EEG studies with musicians and non-musicians [43]. They found higher phase synchrony for musicians especially in the gamma band. These results show the importance of gamma band frequencies for creativity which have also been implicated in binding and consciousness [34].

5.5. PCA and ICA

PCA finds directions of maximal variance in Gaussian data (second-order statistics). PCA is performed by computing a d-dimensional μ (mean) and the $d \times d$ covariance matrix. The eigen vectors and eigen values are computed. The components corresponding to k largest eigen values are chosen for further analysis. PCA is used for (1) reducing the amount of data to be analyzed, (2) providing information about ERP components that may not be easily identifiable using the ERP waveforms, and (3) describing the EEG or ERP data more effectively. More information on applying PCA to ERP signals can be seen in [44,45]. Other alternate techniques have also been developed based on computing eigen values [45]. Other methods are also used to compute components in EEG or ERP signals. For example, ICA finds directions of maximal independence in non-Gaussian data by using higher-order statistics [46]. ICA has been used for filtering artifacts as well as extracting relevant information related to cognitive processes [47]. Some of the analyses including spectral analysis, coherence analysis, PCA and ICA can be performed using the EEGLAB toolbox [48] which runs in MATLAB (The Mathworks, Inc.).

5.6. Source localization

Source localization aims to identify neural sources/dipoles that may underlie the EEG signals obtained by recording from the scalp [24,49]. Localizing the dipoles from the observable EEG voltage signals is called the inverse problem and is very difficult to solve. Usually the number of dipoles are not known and a possible way is to assume a certain number of dipoles, obtain the scalp voltage signals for the given set of dipoles, compare the EEG signals predicted by the model with the observed EEG signals and make changes to the dipole model until the predictions of the model and the actual observations match. The most commonly used technique that utilizes this approach for localizing dipoles is the brain electrical source analysis (BESA). Another major approach is low resolution brain electromagnetic tomography (LORETA) which models the EEG electrical activity as a resultant of a number of voxels [50]. The inverse solution produced by LORETA emphasizes a 3D distribution of sources that maximizes similarity of orientation and strength between neighboring voxels. So far not many creativity studies employing EEG have used source localization techniques.

6. Concluding remarks

A predominant paradigm of research in cognitive neuroscience is EEG/ERP. This paradigm has been extensively used in creativity research. EEG and ERP designs are useful in understanding the temporal evolution of cognitive processes and various analysis techniques including spectral analysis, coherence analysis and other types of analysis have been used in creativity research employing EEG. The development of high density EEG systems along with the development of sophisticated techniques for EEG data analysis points to a promising future for creativity research using this methodology.

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