GAMMA ACTIVITY IN THE HUMAN EEG

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Detection of change is one of the most prominent obligations of the human brain. Such changes can occurr in any of the many sensory modalities, e.g. visual (seeing), auditory (hearing), somatosensory (feeling), olfactory (smelling) or gustatory (tasting). When you show a little kid the same red card over and over, he will loose interest in it—the response habituates. But as soon as you show him a blue card instead, the new stimulus will immediately result in all kinds of responses signaling increased attention (Squire and Kandel, 1999, p. 29). This pattern of habituation/attention makes a lot of sense, since you don't want to be confronted with all of those perceptions that stay constant over time. Instead, you want to focus on those that change suddenly and might indicate the need for a sudden response, e.g. an unexpected sensation of heat at your hand will make you withdraw it. This is the automatic or bottom-up type of attention. In addition, there is selective or top-down attention, which one can voluntarily focus onto parts of a picture, certain voices in a conversation, etc. In previous chapters, we have seen how these types of processes lead to MMN and P300 components in the ERP. Here, I will demonstrate that gamma activity in the human electroencephalogram (EEG) also reflects processes of attention.

1 Oscillations in the EEG

EEG analysis has long been among the main methodologies to investigate the functional behaviour of the human and animal brain. While physicians focus their interest mostly onto the continuous EEG, psycholgists usually average EEG responses to certain stimuli resulting in so-called event-related potentials (ERPs). What remains unmentioned is that often both types of electrophysiological measures (continuous EEG and ERP) can also be investigated in the frequency domain. It has been demonstrated that looking at only certain frequencies can sometimes yield much better insights into functional correlations of these signals (Başar et al., 1999). This can be achieved by selectively filtering out those parts of the signal which oscillate at a given frequency. In principle, every signal can be decomposed into a number of sinusoidal oscillations of different amplitudes. Such a decomposition is usually computed via the Fourier tranform, yielding the oscillations that constitute the signal (see, e.g. Dumermuth, 1977).

1.1 It all started with the alpha rhythm

Oscillations were the very beginning of EEG research when the German neurophysiologist Berger (1929) found oscillations of approximately 10 Hz (10 cycles per second) to be recordable on the human scalp. He coined the term alpha frequency for activity in this frequency range by using the first letter of the greek alphabet.

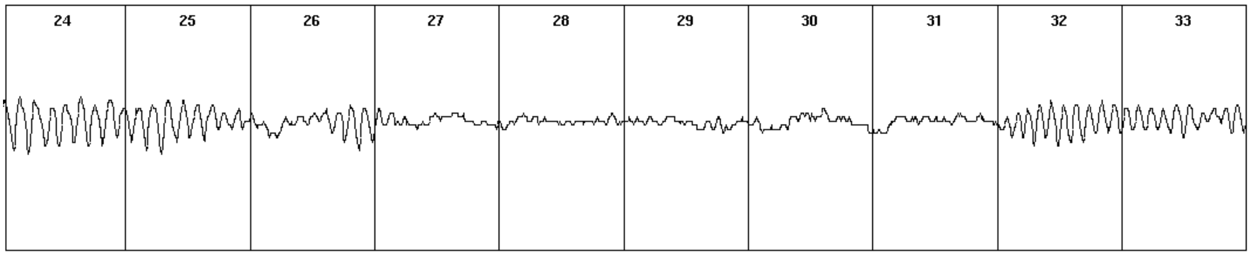


Figure 1: Ten seconds of continuous EEG recorded with eyes closed showing slow alpha activity (7-8 Hz) in seconds 24 and 25. Eye-opening in seconds 26 to 31 results in suppression of alpha activity and subsequently leads to speeded alpha of 10-11 Hz in seconds 32 and 33.

Berger then used the letter beta for the second type of rhythmic activity that he found in the human EEG. This is nowadays considered to be the frequency range of roughly 12 to 30 Hz. Following the consecutive ordering of the naming of the frequencies, Adrian (1942) called oscillations around 40 Hz found after odour stimulation in the hedgehog gamma waves. In their overview on gamma-band activity, Başar-Eroglu et al. (1996b) called this the first stage of gamma research. In this taxonomy, the second stage was initiated by Freeman (1975), who found 40 Hz to play a key role in perceptual models of the rabbit's olfactory bulb. At this stage, gamma activity was found also in the human brain and in evoked potentials. The third phase started with the work of Galambos et al. (1981) which made gamma oscillations generally accepted in studies of human perception. The real break-through making gamma research a broad field of research came when (Gray et al., 1989) showed that synchronous firing of single neurons in the 40 Hz range was able to solve the binding problem (see below). At that time the fourth and so far most prominent phase of gamma research began. According to Karakaş and Başar (1998), we are now in the fifth phase which is marked by the enormous amount of different paradigms and methods applied to solve the 'gamma puzzle'.

1.2 Gamma activity and its functional roles

1.2.1 Binding

Neurons in primary cortices usually code simple features of perceived stimuli. Real-world objects are commonly composed of various such features which are distributedly represented by different neurons in the brain. The activity of all neurons which code the features of one object have somehow to be bound together by the brain in order to perceive a coherent object. The so-called binding problem arises when multiple objects are perceived at one time and their single features could potentially be bound in the wrong way—leading to illusory conjunctions. Mechanisms of binding and attention are needed to solve this binding problem.

Oscillatory activity in the gamma-frequency range (30 – 80 Hz) has been found to reveal correlates with processes that are able to solve such problems. In particular, neurons in the animal brain which oscillate at about 40 Hz are believed to represent the binding of different features of one object to form a single coherent percept (Eckhorn et al., 1988; Engel et al., 1992; Gray et al., 1989). When one bar (object) is moved across the receptive fields of two neurons in cat visual cortex (c.f. Figure 2) the responses of these two neurons are synchronous (i.e. they spike at the same time) and are in the gamma frequency range. When two bars move in the same direction (and are usually perceived as one interrupted object) the neurons still fire with some degree of synchrony. But for two bars moving in opposite directions, which will be perceived as two individual objects, the neural discharges are no longer synchronous.

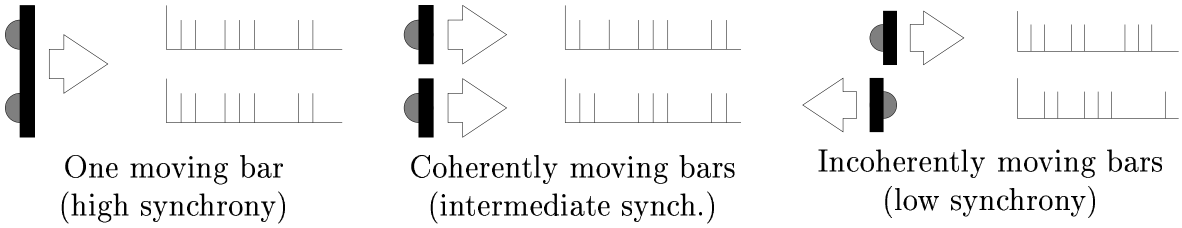


Figure 2: Black bars moving across the receptive fields (gray) of neurons in cat visual cortex and the neuronal response.

Similar findings have been reported from the human EEG, showing higher induced gamma activity for one bar than for two incoherently moving bars (Müller et al., 1997). For this reason it is assumed that gamma activity in the human EEG is associated with visual binding. It has been found for illusory contours (Kanizsa figures, c.f. Section 4) where the inducer disks need to be bound together for the perception of the figure Tallon et al. (1995); Tallon-Baudry et al. (1996); Herrmann et al. (1999). Induced gamma activity has also been reported when subjects suddenly see a meaningful object in a formerly non-meaningful stimulus, as for Dalmatian dogs (Tallon-Baudry et al., 1997) or rotating faces (Keil et al., 1999).

1.2.2 Attention

Another function which is probably reflected by gamma activity is that of attention. Tiitinen et al. (1993) demonstrated that the gamma response around 50 ms after auditory tone pips was larger when subjects were instructed to attend to the ear where the stimulus occurred (attended condition) as compared to when they were instructed to attend to the other ear (unattended condition). Similar findings in the visual domain revealed increased gamma activity over occipital cortex for attended versus unattended flickering lights (Müller et al., 1998). Data from experiments with different Kanizsa figures which intend to differentiate binding and attention processes also support the notion that attention is a main source for gamma activity (Herrmann et al., 1999; Herrmann and Mecklinger, 2000a,b). These experiments will be introduced in Section 4.

1.3 Further roles of gamma activity

In addition to the two most prominent functional correlations of gamma activity, there are also a number of other processes that have been brought into contex with gamma activity. Jokeit and Makeig (1994) and Müller et al. (1998) have shown how gamma activity correlates with reaction-times of fast and slow responders. Başar-Eroglu et al. (1996a) related gamma activity with the formation of a stable percept in a multi-stable pattern (e.g. a Necker cube) by showing that, before a pattern reversal, there is more gamma activity than during the stable perception of one of the two percepts. Miltner et al. (1999) has demonstrated how associative learning results in coherence of gamma activity in visual and motor areas when motor responses to light stimuli are learned.

Reviews related to the functional relevance of gamma oscillations in humans and animals can be found in Başar-Eroglu et al. (1996b). The following journal articles give comprehensive reviews concerning the relation of gamma activity to human visual perception (Tallon-Baudry and Bertrand, 1999) and attentional mechanisms (Müller et al., 2000).

2 Types of gamma activity

2.1 Phase-locking

According to a classification of different types of gamma activity by Galambos (1992), there are *spontaneous*, *induced*, and *evoked* gamma rhythms, all of which are differentiated by their degree of phase-locking to the stimulus.[1]

Spontaneous activity is completely uncorrelated with the occurrence of an experimental condition.

Induced activity is correlated with experimental conditions but is not strictly phase-locked to the onset of it.

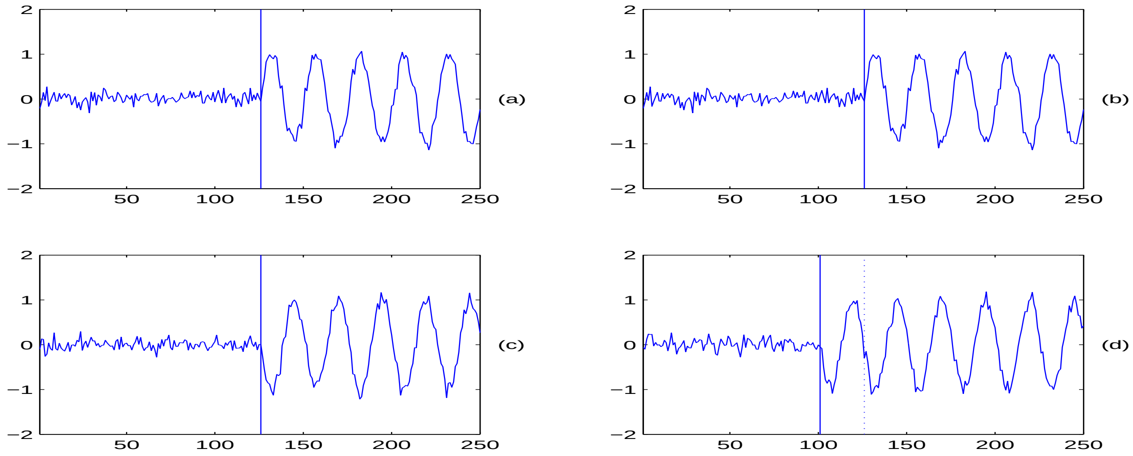
Evoked activity is strictly phase-locked to the onset of an experimental condition.

The meaning of phase-locking is explained by the signals in Figure 3. It is important to note that phase-locking, but not time-locking, is the crucial parameter which determines whether or not activity is cancelled out or summed up when multiple signals are averaged. If averaging signals with temporal relations as in Figure 3 a and b or c and d, they will add up due to their phase-locking to the virtual stimulus at time point 125. If, on the other hand, signals are time-locked but not phase-locked, as in Figure 3 a and c, or neither time- nor phase-locked, as in Figure 3 b and d, signals will cancel out in the average.

2.1.1 Spontaneous gamma activity

Some spurrious oscillations in the gamma frequency range happen to be present in the human EEG without correlation to experimental conditions during and in between stimulation periods. This activity is considered to be spontaneous and usually cancels out completely if an averaged ERP is computed across enough stimulus repetitions. The activity is probably due to cognitive processes that do not relate to the task at hand.

[1] Galambos also specified *emitted* rhythms in response to omitted stimuli which are not important for the topic at hand.



Signal:	Relation:	Average:
a + b	time-locked and phase-locked	add up
a + c	time-locked but not phase-locked	cancel out
c + d	not time-locked but phase-locked	add up
b + d	neither time- nor phase-locked	cancel out

Figure 3: Signals have to be phase-locked, not time-locked to sum up across multiple epochs.

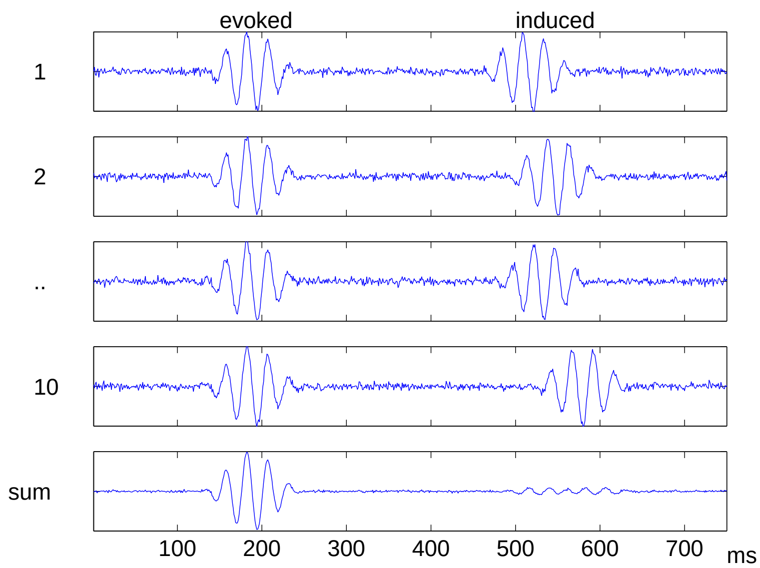


Figure 4: If oscillations occurr at the same latency after stimulus onset with the same phase relative to stimulus onset in multiple trials (rows 1-4) they are considered evoked by the stimulus (left). If, on the other hand, latency or phase jitter relative to stimulus onset, the oscillations are considered to be induced by the stimulus (right). Evoked activity sums up in the average (bottom row) while induced activity is nearly cancelled out.

2.1.2 Induced gamma activity

If oscillations occurr after each stimulation but with varying onset times and/or phase jitter, they are considered as being induced by the stimulus rather than evoked and are not visible in the averaged ERP. This is illustrated in Figure 3 (right). Special methods have to be applied to record this type of activity (see Section 3). This type of gamma activity is assumed to reflect cognitive processes of binding and figure representation.

2.1.3 Evoked gamma activity

Oscillatory activity in EEG can be phase-locked to the onset of an experimental stimulus, i.e. it starts at approximately the same latency after stimulus onset for every repetition of the stimulus (c.f. Figure 3, left). In this case the activity is called evoked, adds up and is visible in the averaged ERP. This type of activity is usually evoked by any kind of sensory stimulation, like auditory, visual or somatosensory stimulation.

2.2 Latency

2.2.1 Early gamma activity

Another differentiation of different types of gamma activity can be made according to the latency at which it occurrs after stimulus onset. Early gamma activity usually peaks around 100 ms after stimulus onset and is evoked by the stimulus. It reflects early processes of stimulus encoding and attention.

2.2.2 Late gamma activity

Tallon-Baudry et al. (1996, 1997) have shown that gamma activity also peaks at a later time. This late gamma activty is usually induced by the stimulus and reflects perceptual and cognitive processes.

3 Methods for gamma analysis

The analysis of gamma frequencies (and other frequencies) within EEG data requires some precautions when data is recorded as well as specific frequency analysis tools, both of which shall be introduced here.

3.1 Recording gamma activity

Two important parameters for the recording equipment have to be set to the right values in order to properly record gamma activity:

The sampling rate has to be set to a value which is at least twice the frequency that should be analyzed (four times is better and is required by some software). I.e. if gamma activity up to 80 Hz shall be analyzed, a minimum sampling rate of 160 Hz is needed and 320 is recommended.

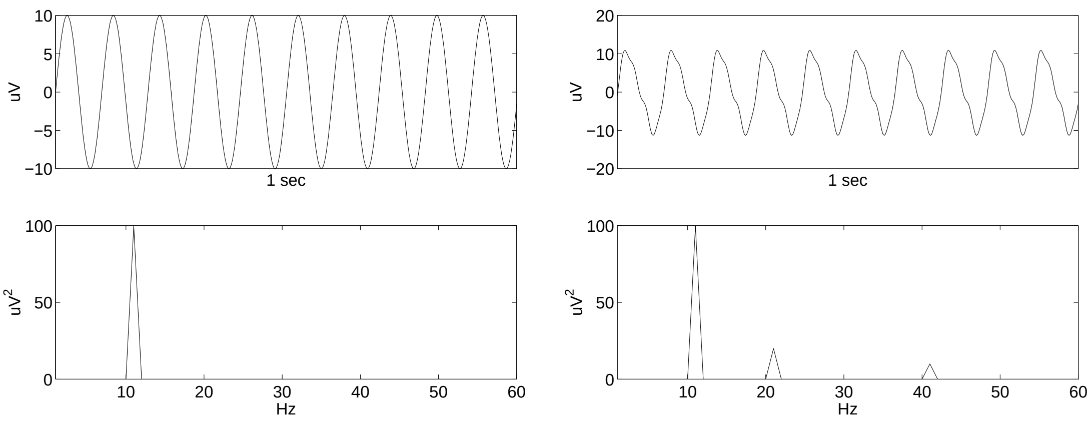
The low-pass filter , which is usually integrated in the analog amplifier to prevent aliasing errors when digitizing analog data, needs to be set to a value higher than the highest frequency that shall be analyzed. This is a trivial statement but is often overlooked by many EEGers trying to record gamma activity for the first time. (Also, it should be noted that the lower 3dB edge frequency is the critical value of a low-pass filter, and not its middle frequency.)

3.2 Potential artefacts

Of course, all artefacts which contaminate traditional ERP averages should be excluded from gamma analysis as well. But, in addition, the rejection of at least two other artefacts is especially crucial for analysing gamma activity.

3.2.1 Harmonics of alpha

A potential problem when recording gamma activity is the appearance of harmonics of alpha activity. Whenever an oscillation is not purely sinusoidal but has some other shape (e.g. more triangular or square) it leads to so-called harmonic frequencies at integer multiples of that frequency. For non-sinusoidal alpha activity at around 10 Hz, one such harmonic can be in the gamma range (Jürgens et al., 1995). Figure 5 (left) shows how a pure sine wave of 10 Hz leads to exactly one spectral peak at 10 HZ, but even a slight change of its shape (right) can lead to harmonic peaks at 20 and 40 Hz. Therefore, it should be investigated whether the gamma activity really behaves independantly of the alpha activity and that the alpha activity does not show the identical effects. Different latencies and different topographical distributions can serve to discriminate the two.



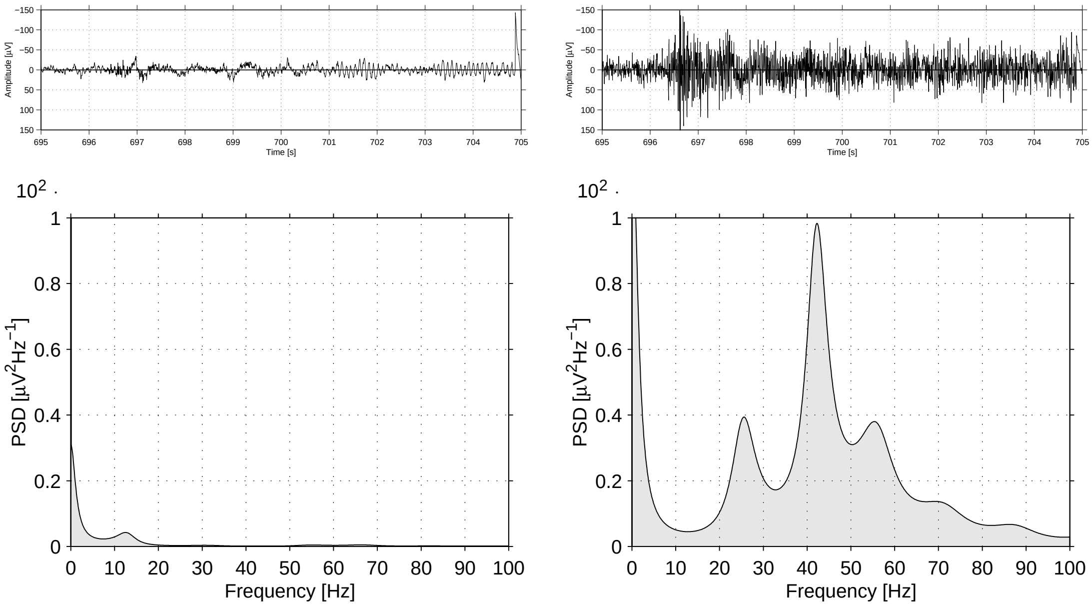
10 Hz sine wave and spectrum   Distorted 10 Hz wave and spectrum

Figure 5: A sinusoidal 10 Hz wave leads to exactly one spectral frequency response at 10 Hz (left). A distorted sine wave will lead to additional harmonic frequencies in the spectrum (right).

In addition, we want to draw the reader's attention to a problem that is inherent when EEG data is interpreted: When no difference in EEG data is found between two experimental conditions one may not conclude that there is no difference in the underlying brain processes. It may very well be that the electric responses of the brain processes are different but do not propagate all the way through brain and skull to the EEG electrodes.

3.2.2 Electromyography

Another potential confound of gamma activity in the human EEG is electromyography (EMG). If subjects sit uncomfortably or chew during an EEG session and thereby innervate their muscles, EMG activity will be recorded by the EEG electrodes. This high-frequency activity (30–80 Hz) can be mistaken for gamma activity. Therefore, all epochs which are subsequently averaged be visually observed by an EEG expert for the ocurrence of such EMG artefacts. Trials containing EMG or EOG artefacts should be excluded from further analysis.



No EMG artefact   EMG artefact

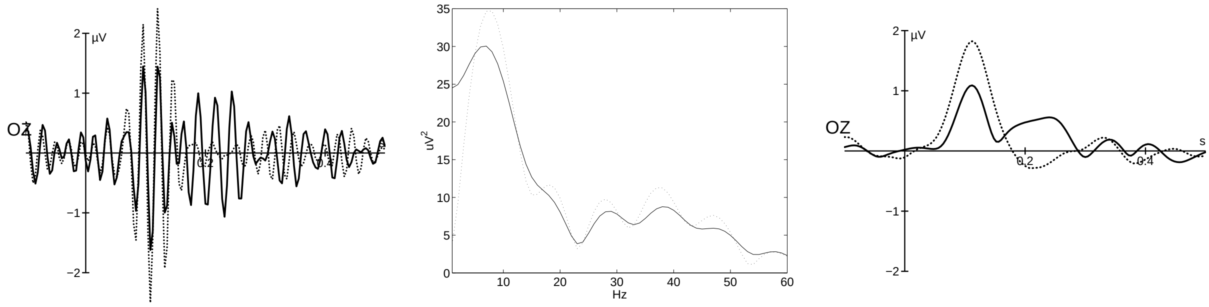
Figure 6: Clean EEG data and its frequency spectrum (left) and an epoch with EMG contamination leading to frequency peaks around 40 Hz.

Figure 6 shows ten seconds of clean EEG and the corresponding frequency spectrum with a 0 Hz and a 12 Hz peak (left). EMG activity can easily be detected in the time domain (right) but may be mistaken for gamma activity in the spectrum.

3.3 Different ways of frequency analysis

Numerous different ways exist to extract only oscillations of a specific frequency from ERP data. Among the most popular are filtering, Fourier transformation and wavelet analysis.

Figure 7 shows the results of the three methods to extract frequency information. On the left, the result of filtering an ERP with a band-pass filter (35–45 Hz) is shown. A clear



Filter (35–45 Hz) FFT Wavelet transform

Figure 7: Three possibilities to extract frequency information from ERP data: a 35–45 Hz filtered ERP (left), the FFT spectrum of the epoch 50..150 ms (middle) and the wavelet transform of the ERP (right).

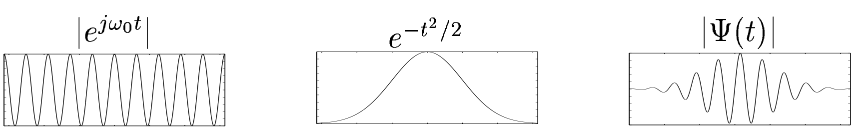
burst of 40 Hz activity is visible aroung 100 ms. This oscillatory activity is enhanced for the dotted as compared to the solid condition. The middle part of Figure 7 depicts the Fourier spectrum of the interseting time interval from 50..150 ms. Again, an increase of activity for the dotted condition can be noticed aroung 40 Hz. On the right, the absolut values of the wavelet transform of the ERP is shown for a 40 Hz wavelet. The difference between conditions is very prominent and can be observed at every point in time due to the lack of oscillations in the signal. The wavelet transform can be thought of as the envelope of the filtered ERP. Since the wavelet transform is ideally suited for frequency analysis of ERP, we will introduce it in some detail in the following.

3.4 The wavelet transform

In order to compute a wavelet transform, the original signal needs to be convolved with a so-called wavelet. In the case of the Morlet wavelet used here it is calculated according to the formula

$$\Psi(t) = e^{j\omega_0 t} \cdot e^{-t^2/2}$$

where ω_0 is 2π times the frequency of the unshifted and uncompressed mother wavelet. Figure 8 shows how these mathematical terms construct a wavelet.



a) b) c)

Figure 8: Multiplying a sinusoidal function (a) and an envelope function (b) results in a wavelet (c).

Convolving wavelets with signals results in a new signal (the convolution) which can be interpreted as the similarity of the wavelet and the signal. Wavelets can be compressed by a factor a to get wavelets of different frequencies (substitute t by t/a). The mother wavelet ($a = 1$) has the same frequency as the sampling frequency (f_s) of the signal. Wavelets of lower frequencies are computed by increasing a (e.g. for $a = f_s$ the wavelet has a frequency of 1 Hz).

Convolving the signal and the shifted and compressed wavelet leads to a new signal

$$s_a(b) = A \quad \int \overline{\Psi}\left(\frac{t-b}{a}\right) \cdot x(t) \quad dt$$

where $\overline{\Psi}$ is the conjugate of the complex wavelet and $x(t)$ is the original signal. These new signals $s_a(b)$ are computed for different scaling factors a. For the experiments in Section 4, we calculated the gamma activity by using a wavelet which was compressed to 40 Hz. The scaling factor $A = 1/\sqrt{a}$ is used to scale the wavelet prior to convolution.

To represent phase-locked (evoked) activity, the wavelet transform is computed on the average over the single trials, i.e. the ERP. This is denoted by the formula WTAvg (Wavelet Transform of Average). Since the wavelet transform returns complex numbers, the absolute values are calculated.

$$\text{WTAvg} = \left| A \quad \int \overline{\Psi}\left(\frac{t-b}{a}\right) \cdot \frac{1}{n} \sum_{i=1}^{n} \text{eeg}_i(t) \quad dt \right|$$

The baseline of the raw data in a time interval prior to stimulation (e.g. -200..0 ms) needs to be subtracted from each EEG epoch prior to averaging. Also, after calculating the gamma activity, the frequency-specific baseline activity at 40 Hz can be subtracted to yield values which indicate gamma amplitude relative to baseline. When wavelet convolutions are computed, the convolution peaks at the same latency as the respective frequency component in the raw data. But, the width of the peak will be smeared. Therefore, the baseline should be chosen to precede the stimulation by half the width of the wavelet (i.e. 150 ms for 6 25 ms cycles of a 40 Hz wavelet) to avoid the temporal smearing of post-stimulus activity into the interval directly preceding the stimulus. To avoid distortions by the rectangular window function which results from 'cutting out' a single epoch from continuous raw data, the convolution should start and end one wavelet length before the baseline and after the end of the investigated time interval, respectively.

The convolution of an EEG with a wavelet results in a new signal, as depicted in Figure 9 (left). These wavelet convolutions can be computed for multiple frequencies and the amplitudes of the convolutions can then be color- or gray-scale-coded in one single diagram. This is shown in Figure 9 (right) and is called a time-frequency representation.

The above time-frequency representation (WTAvg) contains only that part of the activity which is phase-locked to stimulus onset. In order to also compute the activity which is not phase-locked to stimulus onset (and is therefore canceled out in the average), the sum of evoked and induced activity can be computed. To calculate the sum of all activity at one frequency, the absolute values of the wavelet transforms of the single trials are averaged (AvgWT). This means that each single trial is at first transformed and the absolute values

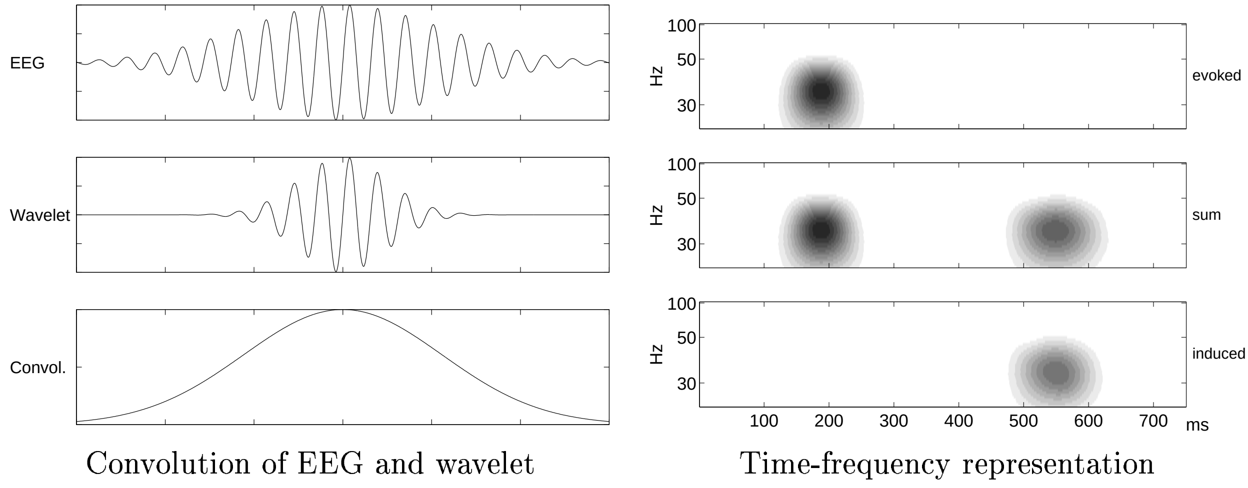


Figure 9: Left: Convolving an EEG (top) with a moving wavelet (middle) results in a the convolution (bottom). Multiple such convolutions can be mapped in a time-frequency representation. This is shown for the evoked gamma activity (top) of the example in Figure 4, the sum of evoked and induced gamma activity (middle) and isolated induced gamma activity (bottom).

are averaged subsequently.

$$\text{AvgWT} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{1}{\sqrt{a}}\quad\int\overline{\Psi}\left(\frac{t-b}{a}\right)\cdot x_i(t)\quad dt\right|$$

This new time-frequency representation contains all activity of one frequency that occurred after stimulus onset, no matter whether it was phase-locked to the stimulus or not. As above, the 40 Hz activity in a pre-stimulus interval (e.g. -400..-150 ms) can be subtracted in order to get a relative measure.

Other authors refer to this sum of evoked and induced activity simply as induced activity Tallon-Baudry and Bertrand (1999). This may be a legitimate approximation, since the absolute amount of evoked activity is small compared to the much higher absolute values of the summed activity. To obtain only that activity which is not phase-locked to stimulus onset, the evoked activity (WTAvg) needs to be subtracted from the sum of evoked and induced activity (AvgWT). For this to be done, it is required that absolute measures are subtracted (no baseline correction in the frequency domain) to obtain AvgWT-WTAvg.

4 Sample experiment

Gamma and attention

In order to test whether gamma activity is related to top-down processes of attention, we carried out two experiments with the same stimuli but different tasks for the subjects. All electrophysiological responses which stay identical across both experiments reflect bottom-up processes and are not affected by top-down task requirements. The P300 would be a typical candidate for such a top-down component in the ERP, as we saw in a previous chapter. If, on the other hand, a response changes from Experiment 1 to Experiment 2, it must reflect a top-down process.

Figure 10 shows the four stimuli which were used for the two experiments. Two of the stimuli represent Kanizsa figures (a and b) while the other have similar physical properties but do not constitute illusory figures. The difference is that the pac-men are rotated in such a way that none of the pac-men can be bound together to shapes by collinear line segments. Therefore, the two experiments are suited to differentiate between binding and attention, since one stimulus is defined as target (to test attention) but two of them require binding for the perception of an illusory figure. In Experiment 1, the Kanizsa square (Figure 10 a) was defined as the target and had to be counted by the subjects (Herrmann et al., 1999). In Experiment 2, the non-Kanizsa square was defined as target and had to be counted as well (Herrmann and Mecklinger, 2000a).

a) b) c) d)

Figure 10: The four stimulus types used in the experiment: a) Kanizsa square (target), b) Kanizsa triangle, c) non-Kanizsa triangle, d) non-Kanizsa square.

Figure 11 shows the ERPs in response to the four different stimuli. As expected, the Kanizsa square evokes the largest P300 in Experiment 1, since it was counted. In Experiment 2, the non-Kanizsa square evoked the largest P300. The P300 is the only ERP component which represents a top-down process in these experiments. In Experiment 2, the amplitude is suppressed and the latency is prolonged, which indicates that the task is harder than in Experiment 1.

The order of amplitude on the P1 and N1 components stayed constant across the two experiments. From this we can conclude that P1 and N1 reflect bottom-up processes of coding the sensory input. The P1 amplitude is mainly affected by the number of pac-men in a figure. Triangles evoke larger P1 amplitudes than the squares which may be due to less extinction of the unsymmetric shapes in the two hemispheres. Intersetingly, the Kanizsa figures evoke larger N1 amplitudes than do the non-Kanizsa figures. This indicates that the illusory figures are in fact processed by the subjects.

Figure 12 shows the topographical distribution of the early evoked gamma activity (50..150 ms) for the four different stimuli that were used in Experiment 1. The Kanizsa square, which was defined as target and counted by the subjects, clearly shows stronger activation than the other three stimuli. This target effect could possibly mean that the early evoked gamma activity reflects a top-down mechanism of attention. Even though the four stimuli were designed in two dimensions (figureness and number of pac-men) to differentiate between binding and attention, there could still be a confoundation with the target being a Kanizsa figure at the same time. Therefore, we conducted the second eperiment, where the non-Kanizsa square was defined as the target. We expected the new target (non-Kanizsa square) to evoke the most early evoked gamma activity, as did the Kanizsa square

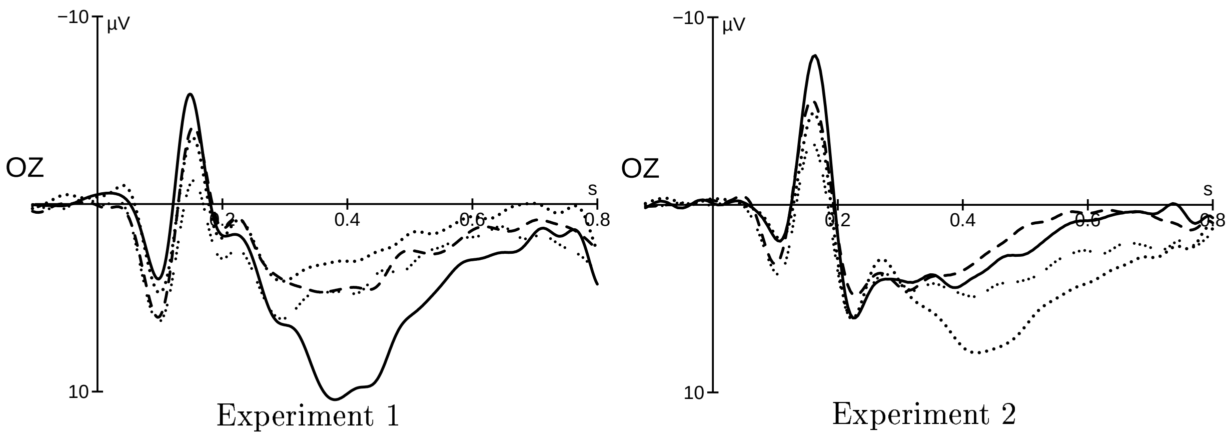


Figure 11: ERPs of electrode OZ for Experiments 1 and 2. P1 and N1 components are independent of task requirements. The P3 component is affected by the task change between experiments and is delayed in latency and reduced in amplitude. Kanizsa square (solid), Kanizsa triangle (dashed), non-Kanizsa square (dotted) ans non-Kanizsa triangle (intermittently dotted).

in Experiment 1.

Figure 13 shows the topographical distribution of the early evoked gamma activity for the stimuli of Experiment 2. The pattern is clearly different—the non-Kanizsa square now evokes the largest gamma response. This is in line with our hypothesis. In addition to what we expected, the Kanizsa square and the non-Kanizsa triangle also evoke some gamma activity. These two stimuli share one of the features of the target stimulus. The Kanizsa square is also a square and the non-Kanizsa triangle is also a non-Kanizsa figure.

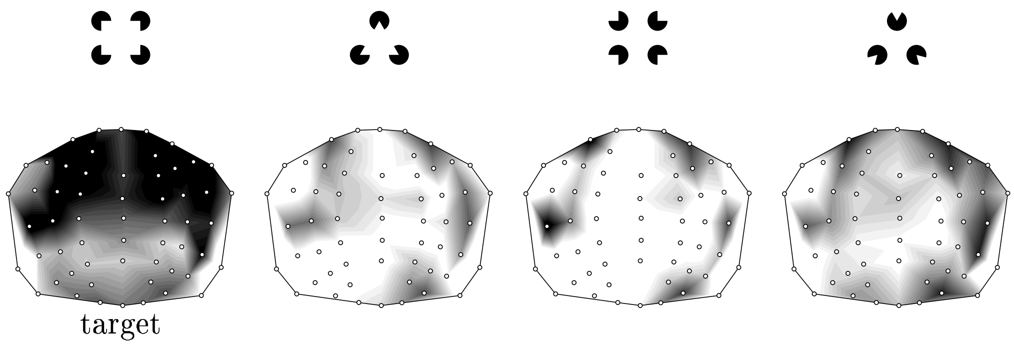


Figure 12: Topographical maps of the early evoked gamma activity for the four stimuli of Experiment 1. The target evokes the highest gamma response.

The results of the early evoked gamma activity demonstrate that, just like the P300 in the ERP, the early evoked gamma activity reflects top-down processes of attention. Compared to the P300 which peaks around 400 ms, the early evoked gamma activity peaks much earlier, i.e. at around 100 ms. It is interseting to note that the order of amplitude of the early evoked gamma activty already resembles the pattern of reaction times about 500 ms before the actual button press (Herrmann and Mecklinger, 2000a).

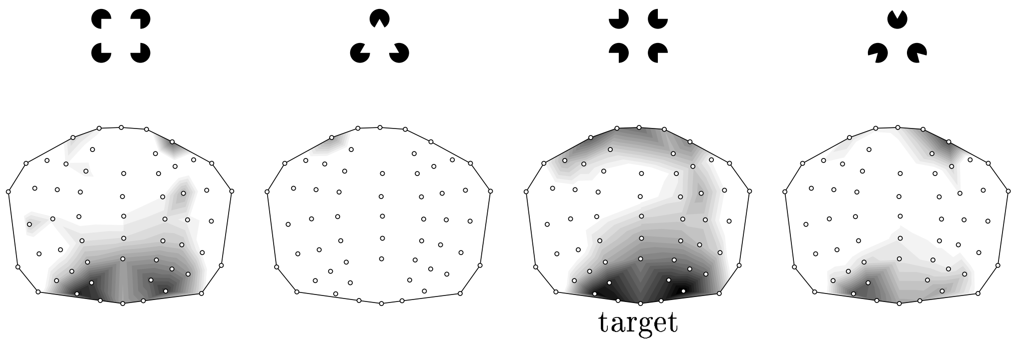


Figure 13: Topographical maps of the early evoked gamma activity for the four stimuli of Experiment 2. Even though the four stimuli are identical to Experiment 1, the change of the task affects the gamma response. The target evokes the largest gamma response.

5 Gamma activity and the detection of change

As we have seen in the previous sections, gamma activity in the human EEG and MEG is related to the detection of change in at east two ways.

5.1 Automatic detection of change

As outlined above, gamma activity is related to binding. In visual search displays which consist of numerous distractor pac-men and one Kanizsa square, the binding of the Kanizsa-forming pac-men leads to an automatic change of the focus of attention (Herrmann et al., 2000).

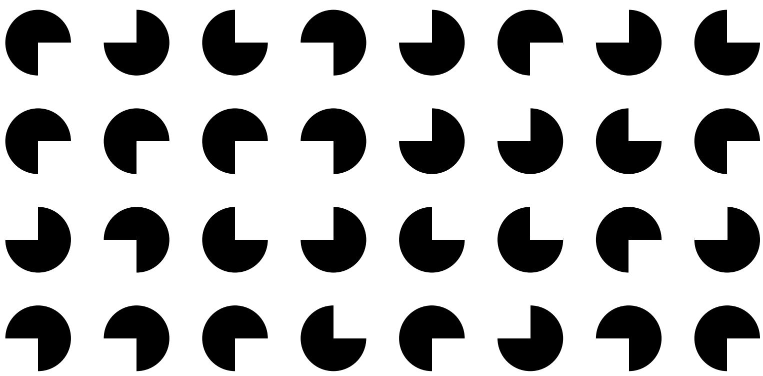


Figure 14: When pac-men are bound together this leads to a pop-out of the resulting Kanizsa square. The associated gamma activity seems to be related to the automatic detection of a change to a meaningful Gestalt among randomly arranged pac-men.

5.2 Voluntary detection of change

Subjects can voluntarily attend to certain aspects of their perceptions, i.e. they can attend to specific figures or to one of their two ears. As we have seen, such top-down processes of attention also lead to an increase in gamma activity and thus reflect a voluntary detection of change.

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