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Comparing EEG Brain Power of Mechanical Engineers in 3D CAD Modelling from 2D and 3D Representations

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Abstract

Using the EEG features extracted from the EEG signals, the presented study investigates differences in the cognitive load posed on engineers while 3D CAD modelling in two different conditions, depending on the visual representations used as stimulus - a 2D and a 3D technical drawing of parts. The results indicate a higher cognitive load during the 2D drawing task. In addition, common indicators of the ongoing spatial information processing were recognised - a suppression of parietal and occipital alpha power, a higher frontal theta, and differences in theta power between the hemispheres.

Keywords: electroencephalography, brain activity, visualisation, computer-aided design (CAD), design cognition

1. Introduction

The creation of virtual three-dimensional (3D) models using computer-aided design (CAD) software solutions is one of the basic engineering activities (McMahon, 2015). From the cognitive perspective, 3D CAD modelling is a higher-level cognitive activity, having its perceptual and production component (Willis et al., 1979). To perform 3D CAD modelling, one must perceive and act upon a stimulus - a visual representation of an object, such as a mental image, a two-dimensional (2D), or a 3D technical drawing. In particular, 3D CAD modelling requires one to (1) interpret information shown in the visual representation, (2) create part's 3D mental representation, (3) break the part down into features, and (4) create a 3D CAD model in a CAD software solution. A substantive amount of literature has researched CAD software solutions, tools, and activities during design due to their importance in everyday engineering practice. The previous studies have often measured participants' external performance of tasks (e.g., time or correctness). Still, cognitive aspects of CAD modelling have been poorly studied due to the lack of objective methods for their monitoring and measuring (Goel et al., 2012; Hay et al., 2020). The most dominant method for understanding designers' thinking and behaviour during design activities has been protocol analysis. However, this method does not measure brain activity directly, making the results hard to validate and prone to the subjectivity of experimenters (Nguyen and Zeng, 2010).
Electroencephalography (EEG) is a non-invasive neuroimaging method proposed for the analysis of processes of thinking and acting relevant for design (Hay et al., 2020). EEG provides a high temporal resolution that may allow continuous monitoring of brain activity. The EEG features extracted from the recorded EEG signals (for instance, a frequency band power) may be used as objective measures of underlying cognitive processes (Gevins and Smith, 2003). Recent EEG studies of design processes and engineers' cognition aimed to shed a light on different characteristics of thinking. EEG studies covered engineers' creativity and explored the cognitive differences between design tasks (such as open and constrained tasks) or activities (e.g., decision-making, ideation, sketching). Moreover, EEG proved to

be useful to highlight differences in design cognition according to the previous experience of engineers (e.g., novice and experts) or background (e.g., mechanical engineers, industrial designers, and architects). Yet, only a few EEG studies focused on visual representations, CAD modelling, and engineers' interaction with virtual models and environments (Maccioni and Borgianni, 2020). These studies (e.g., (Liu et al., 2014) and (Nguyen and Zeng, 2014)) captured EEG signals during CAD activities with the aim of upgrading and adapting the functionalities of the available CAD software solutions and the associated human-computer interaction (HCI) tools to better suit designers' skills and behaviours (their cognitive and affective states). It has been argued that insights gathered through an analysis of engineers' brain activity and inferred cognitive processes (for example, visual perception and spatial thinking) while CAD modelling may be essential in further development of CAD software solutions, design visual representations, and HCI media (Goel et al., 2012). Among the key features to explore, cognitive load - the cognitive demand imposed on humans' limited information-processing resources (Gevins and Smith, 2003) is crucial for an efficient and proficient HCI.
Thus, the goal of the presented study is to investigate differences in the cognitive load that is posed on engineers while 3D CAD modelling based on 2D and 3D technical drawings of parts. In particular, the study aims to answer the following research question:

- Is the cognitive load of 3D CAD modelling different when the engineers process the information from 2D and 3D technical drawings?

To answer the research question, the study focuses on the differences between CAD modelling in two different conditions, depending on the visual representations used as stimulus. Both 2D and 3D drawings contain spatial information needed to create the 3D CAD part models (such as size, shape, and scale). However, 2D drawings provide spatial information using one or more 2D views (for example, front, right, and top views). Consequently, one must allocate additional cognitive resources to mentally manipulate 2D information presented in 2D drawing and perceive it in 3D (Fajen and Phillips, 2013). Hence, a higher cognitive load is expected when engineers create 3D CAD models from 2D than 3D drawings. In the experimental part of the conducted study, engineers' brain activity was continuously monitored while creating 3D CAD models of parts to confirm or reject the above-stated assumption.
The rest of the paper is organised as follows: study background and work related to measuring EEG signal during activities that incorporate visual processing are given in Sect 2. The methodology is described in Sect 3. The presented results (Sect. 4) and the limitations of the conducted study are discussed in Sect 5. Finally, the conclusions and avenues for future work are presented in Sect 6.

2. Background and related work

An overview of EEG features used for measuring cognitive load across domains is firstly presented in Sect. 2.1. The following section explains several factors that affect the cognitive load of tasks encountering visual processing of information. Finally, to clarify the status of the topic in the design domain, Sect. 2.3 brings the studies that measured engineers' EEG signals while perceiving or creating visual representations of a design.

2.1. EEG features for measuring cognitive load

EEG signals are continuously recorded from the electrodes attached to one's scalp. Depending on the location of the electrodes, EEG signals can be recorded from four brain lobes: frontal (F), parietal (P), temporal (T), and occipital (O). EEG spectrum contains five main, functionally distinct frequency bands: delta (1 - 3 Hz), theta (4 - 7 Hz), alpha (8 - 13 Hz), beta (13 - 30 Hz), and gamma (30 - 100 Hz). The frequency bands have been associated with cognitive states and processes. One EEG feature often used when inferring one's cognitive states and processes from EEG signals is an average power of frequency bands (Klimesch et al., 2005). The frequency band power stands for the contribution of the frequency band to the overall power of the signal. In previous studies across domains, the cognitive load has been persistently correlated with changes in the power of alpha and theta frequency bands. In particular, an increase in theta and a decrease in alpha bands have been noticed during tasks that impose a high cognitive load (Gevins and Smith, 2003; Nguyen and Zeng, 2014). Such effects have been noticed for various tasks - including those that comprise the visual processing of spatial

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information (Nguyen and Zeng, 2014). In addition, the cognitive load has been measured as a ratio of theta and alpha power. For example, Holm et al. (2009) suggested measuring cognitive load through a cognitive load index (CLI), defined as a ratio between average frontal theta (measured from the channel Fz) and parietal alpha (measured from the channel Pz). Using the proposed cognitive load metrics, Dan and Reiner (2017) compared the CLIs of two visually demanding tasks (learning the paper folding - i.e. origami based on the presented instructions) of different complexity levels. Similarly, Cowan et al. (2018) measured the cognitive load as a theta and alpha power ratio, where a greater ratio indicated a higher cognitive load.

2.2. Internal factors affecting the cognitive load in visual processing tasks

The cognitive load of task performance changes with the difficulty of the cognitive task (Gundel and Wilson, 1992). The task difficulty is defined by the task complexity and conditions under which it is performed (Galy et al., 2012). EEG studies that compared tasks of different difficulty levels, defined by task complexity, often tried to confirm the stated dissimilarities with cognitive load implied from EEG features. In these studies, the task complexity levels were often based on the number and type of actions needed to perform the task. In addition, the standardised loading tasks (e.g., the Sternberg item recognition paradigm) and subjective tests (e.g., NASA Task Load Index) were often employed to test the difficulty levels. For instance, Gundel and Wilson (1992) reported that higher difficulty of tasks related to visual processing of information presented on computer screen resulted in the reduction of parietal and occipital alpha activity (due to the amount of visual scanning) and the increase of theta activity in the left frontal electrodes (related to the amount of general mental processing). Furthermore, the studies aimed to clarify whether a difference in cognitive load posed by a task exists when performed in two conditions that require allocating different amounts of cognitive resources for information perception and elaboration. For example, when different types of information are presented or media are used to present information. As for the information types, Gerlič and Jaušovec (1999) revealed a difference in brain activity when subjects processed information from multimedia (video and picture) and text presentations in the task of learning the presented information. Processing the information presented by the multimedia increased the activity (higher alpha power magnitude) of the occipital and temporal lobes. In contrast, the text presentation increased the activity of the frontal lobes. Furthermore, Rugg and Dickens (1982) reported a significantly lower alpha and higher theta power while performing psychometric visuospatial and verbal tasks (compared to the rest condition). Also, theta power in the right hemisphere was significantly higher during the visuospatial than the verbal task (Rugg and Dickens, 1982).

2.3. EEG features of visual information processing in design activities

The creation and the review of virtual models have been rarely studied in design neurocognition (Maccioni and Borgianni, 2020), resulting in the lack of findings on EEG features of visual information processing in design activities. Alternatively, EEG features as indicators of engineers' cognitive load may be extracted from the studies that explored engineers' cognition during design tasks in general. However, only a few studies segmented design tasks into design activities relatable to the visual processing of information and CAD modelling. One such example is the study conducted by Nguyen et al. (2010) that analysed designers' cognitive processes during conceptual design. The scholars compared the cognitive resources spent on the design task activities (problem analysis, solution evaluation, solution generation, and solution expression). Some of these activities may be related to processing of visual information (e.g., problem analysis or solution evaluation) and creation of a design solution representation (e.g., solution expression). It was suggested that, while solving the design task, the participants spent more cognitive resources in visual thinking during the solution generation than evaluation step, which was inferred from the lower occipital alpha power. In addition, high frontal theta was related to higher consumption of cognitive resources due to visual attention. The current lack of the similar studies led to the conclusion that a methodology for using EEG as a design research method for studying effects of design visual representation types and media on engineers' spatial thinking during design activities (such as CAD modelling) is yet to be defined. The work presented in the following sections does not offer such a methodology, but it provides a basis to ground on in further studies. Through the methodology explained in the next section, the conducted

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study seeks to determine which EEG features are particularly represented when engineers engage in spatial information visual processing tasks and whether they imply cognitive load using the metrics from the previous studies.

3. Research methodology

The design of the experiment carried out to answer the research question was guided by already published experimental studies concerned with the electrophysiological investigation of human behaviour in design (for instance, Li et al. (2021) and Vieira et al. (2020)). The experimental procedure (Sect 3.2) enables the exploration of differences in engineers' brain activity during two 3D CAD modelling tasks (Sect 3.3). While the experimental setup (Sect 3.4) is originally developed for this research question, the data pre-processing (Sect 3.5) elaborates and adapts the pipeline suggested by Li et al. (2021) so that it produces results for data analysis (Sect 3.6).

3.1. Participants

The study recruited 20 subjects to participate in the experiment. The inclusion criteria were: being a mechanical engineer, being experienced with CAD modelling in SolidWorks®, right-handedness, and absence of neurological disorders. In addition, the participants were instructed to refrain from coffee and caffeine beverages at least two hours before the experiment.

3.2. Experimental procedure

The participants were first introduced to the equipment and the experimental procedure. Next, participants were asked to sign a consent. In the third step, the EEG headset was set up. When the contact and EEG data quality were satisfactory, the participants continued to the CAD modelling tasks. The parts and the tasks were the same for all the participants. The tasks were not time limited. Each participant was asked to create 3D CAD models of three parts, further explained in the following subsection. All the participants started with an introductory CAD modelling task. After the introductory task, participants were instructed to create 3D CAD models of two parts based on their drawings. Half of the participants first created a 3D CAD model of part 1 (based on its 2D drawing) and continued to part 2 (based on its 3D drawing). The order was reversed for the other half of the participants. The randomized division was motivated by the goal to bypass the potential bias of the previous task and cognitive fatigue as its consequence. Each task was preceded and followed by a baseline. For the baseline, participants were asked to stare at the cross presented at the monitor display until it disappeared (20 seconds). After the experimental part of the experiment, the questionnaire on demographics and prior-experiment experience related to CAD modelling and technical documentation was sent to the participants.

3.3. 3D CAD modelling tasks

During the CAD introductory task, participants were guided through seven modelling steps to create a 3D CAD model of a simple part (presented in Figure 1 at the top). This task consisted of seven actions - creation of three sketches and usage of four features. The resulting model contained a cuboid, a cylinder, a through hole, and chamfers. The introductory task was not used for the comparisons of the EEG signal power and cognitive load. Instead, it was a warm-up task to familiarize the participants with the interaction devices and CAD environment.

Cognitive load was compared among two CAD modelling tasks that differed in the visual representation from which information needed to create the parts' models were processed. In one condition, the 2D drawing, and in the other, the 3D drawing represented the part (see Figure 1). Nevertheless, the tasks were of the same complexity level, defined by the type and the number of features the resulting 3D CAD models were consisted of (Rosso et al., 2020). The following are the features of the parts: a cuboid, a fillet, a chamfer, a through hole, a slot, and three through slots. One could create 3D CAD models with the same number of actions (creation of sketches and usage of features). However, participants were not restricted either with the type or the number of features during the experiment.

3.4. Experimental setup

EEG data were gathered with 14-channel device Emotiv EPOC+. According to the international 10-20 system, the locations from which sensors captured continuous brain activity were: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4. The EEG device was wirelessly connected to a high-performance computer (through Bluetooth Low Energy). EEG data were collected with a sampling frequency of 128 Hz. According to the Nyquist-Shannon sampling theorem, such sampling frequency is adequate for analysing the frequency bands relevant for the study - theta (4 - 7 Hz) and alpha (8 - 13 Hz) bands. The experiment was conducted using one high-performance computer, two 23.8" monitor screens, and interaction devices (a keyboard and mouse). The resolution of the monitors was 1920 x 1080 pixels with a refresh rate of 60 Hz. The PsychoPy (Peirce et al., 2019) window with the instructions and the tasks was presented on the left monitor, while the SolidWorks® window was opened on the right monitor. Both screens were recorded for the entire duration of the experiments. In addition, a video camera captured a participant's face with the primary aim to support the artefact detection.

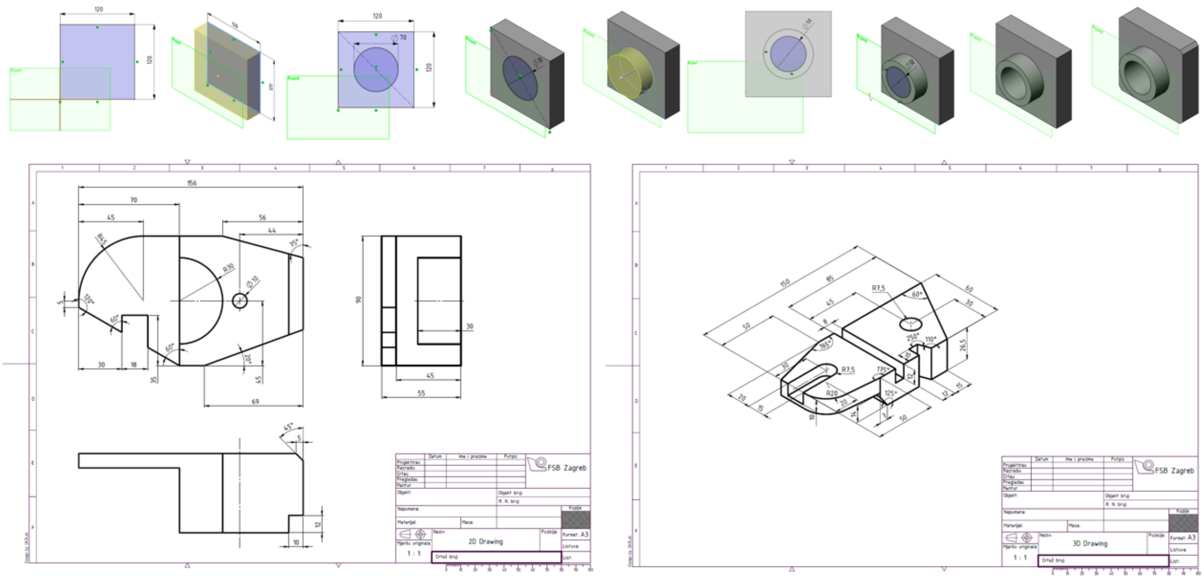

Figure 1. Parts for 3D CAD modelling based on the steps (top), the 2D drawing (left bottom), and the 3D drawing (right bottom)

3.5. Data pre-processing

The EEG data processing was conducted in Matlab with the EEGLAB toolbox (Delorme and Makeig, 2004). An original script for data processing was developed according to the pipelines described by Li et al. (2021) and Vieira et al. (2020). In the first step, DC offset specific for Emotiv EPOC+ devices was removed with the infinite impulse response (IIR) filter. Secondly, frequencies outside the range of 4 - 45 Hz were removed with the finite impulse response (FIR) filter. After that, muscle artefacts were removed with the blind source separation (BSS) technique based on canonical correlation analysis (CCA) (De Clercq et al., 2006). In the next step, EEG data was divided into theta (4 - 7 Hz) and alpha (8 - 13 Hz) sub-frequency bands using the FIR filter. This was followed by removing the windows (length of 3 s, shift of 1/128 s) with an average transformed power (POW) exceeding the threshold of 100 µV. In this way, any 3s long epoch of the EEG data identified to contain artefacts (even after the filtering) was discarded. After the threshold was applied, POW was calculated as the mean (M) of the squared values of microvolts per second ($\mu V^2/s$). In the final pre-processing step, POW values were normalized for each subject according to the expression for task-related power (TRP) estimation:

$$\mathrm{TRP}_{ij} = \frac{\mathrm{POW}_{ij}(\mathrm{task})}{\mathrm{POW}_{ij}(\mathrm{baseline})}. \tag{1}$$

POW in the numerator is the average transformed power of an electrode i from a subject j during a task (CAD modelling based on 2D or 3D drawing). POW in the denominator is the average transformed

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power of an electrode i from a subject j during a baseline (fixation cross) recorded before each task. Data were segmented into epochs to separate each task and baselines.

3.6. Data analysis

Data analysis was conducted using the R language. Descriptive statistics encompassed the calculation of the M as a measure of central tendency and standard deviation (SD) as a measure of variability. In addition, inferential tests enabled the calculation of differences in POW values and CLI between the tasks. The analysis encompassed a comparison of the tasks based on total signal and band power values. Means of the power were compared between the tasks considering all the 14 channels (cumulatively), each channel individually, and the hemispheres.

The POW was calculated for each electrode across the tasks. Total signal power included the frequencies from 4 to 45 Hz. The analysis further concentrated on alpha and theta band power since they are often used in the related literature (see Sect. 2) as indicators of cognitive load. Finally, the cognitive load was calculated as an index of relative power in alpha and theta frequency bands. Specifically, as suggested by Holm et al. (2009), the CLI was calculated as a ratio between the means of frontal theta and posterior alpha power for each participant and both tasks. T-test was used for comparisons of variables when both assumption of normality (as tested by Shapiro-Wilk test; $p < 0.05$) and equity of variances (as tested by Levene test; $p < 0.05$) were met. If the normality assumption was violated, Wilcoxon rank-sum test was used to test the differences between the variables. In cases when the equality of variances was violated, Welch's t-test was used. In addition, the effect size of differences in mean power and CLI between 3D CAD modelling based on the 2D and 3D drawing was calculated with Cohen's d. Ranges of the effect size were defined as follows: negligible ($d < 0.2$), small ($0.2 \leq d < 0.5$), medium ($0.5 \leq d < 0.8$), and large ($d > 0.8$).

4. Results

A brief description of the participants' demographics is offered in Sect. 4.1. This is followed by the total signal power and band (alpha and theta) power distributions for each task, presented in Sect. 4.2. Finally, the CLI values for each participant and task are presented in Sect. 4.3.

4.1. Participants

Data gathered from three participants were discarded; one participant reported diagnosed neurological issues, the other left-handedness, while the EEG data from the third discarded participant were highly contaminated. Hence, here presented results are based on the sample of 17 male right-handed mechanical engineers. The participants aged from 25 to 30 with the M of 27.31 and the SD of 1.61. All the participants were experienced in using SolidWorks® and all of them completed at least one (the same) SolidWorks® course as a part of their studies.

4.2. Total and band power distribution

The average total signal power (considering all the 14 channels) was slightly higher for the CAD modelling task based on the 2D (M = 1.07, SD = 0.15) in comparison to the 3D (M = 1.06, SD = 0.13) technical drawing. However, the t-test showed that the difference was not statistically significant (p = 0.6867). The difference in the means across all 14 channels was negligible (d = 0.11). Furthermore, visual inspection of the radar graph presented in Figure 2 (on the left) indicates that the highest differences in total signal power were between the channels positioned in the frontal lobe. Indeed, the small effect size of differences between the means was confirmed for four channels in this lobe (FC5, FC6, F4, AF4). These channels are bolded in the radar graph. In addition, right hemisphere was more activated both during the 2D (left: M = 1.02, SD = 0.51; right: M = 1.11, SD = 0.44) and 3D (left: M = 1.01, SD = 0.48; right: M = 1.12, SD = 0.38) task. The difference in the activation between the hemispheres was statistically significant for CAD modelling based on the 3D drawing (p = 0.01132).

Furthermore, the average alpha power across all the channels was higher for the CAD modelling task based on the 2D drawing (M = 0.97, SD = 0.09) when compared with the 3D drawing task (M = 0.94, SD = 0.1). The difference was statistically significant at the confidence level of 90% (p = 0.05091). The effect size of the difference between the means was medium (d = 0.57). Visual inspection of the radar graph presented in Figure 2 (in the middle) reveals a suppressed alpha power in the right parietal (channel P8) and the occipital (channels O1 and O2) lobes during both tasks. The effect sizes between the alpha power means for the channels P8 and O2 were small, as presented in Table 1. In addition, the alpha power from the channels F7, AF4, and FC6 was higher during the CAD modelling based on the 2D drawing. The analysis revealed a small effect size of differences in the alpha power means for FC6. No significant differences were found in the alpha power between the hemispheres.

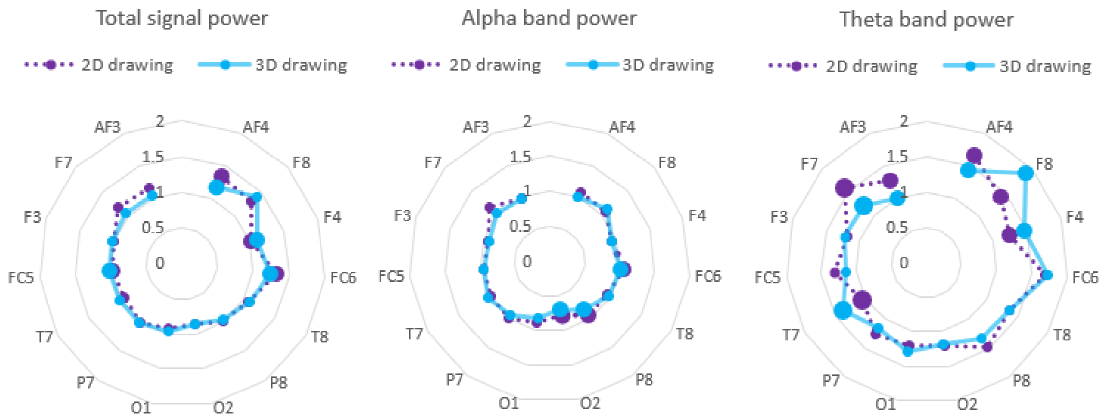

Figure 2. Total signal power (left), alpha power (middle), and theta power (right) in linear scale

The average theta power across all the channels was slightly higher for the CAD modelling task based on the 2D (M = 1.34, SD = 0.19) than the 3D (M = 1.32, SD = 0.23) technical drawing. This difference was not statistically significant ($p = 0.7224$), and the weffect size of the difference in the means across all 14 channels was negligible ($d = 0.04$). Differences in theta power between the tasks were further analysed for each channel individually. The results revealed the small effect size in a difference of the theta power means for the channels in the frontal (AF3, F4, F8, and AF4) and the right parietal lobes (P8). In addition, the effect size was medium for the channels F7 and T7. For channel F7, the statistically significant difference was found at the confidence level of 90% ($p = 0.053$). Furthermore, difference in activation between the left (2D: M = 1.24, SD = 0.57; 3D: M = 1.13, SD = 0.51) and the right (2D: M = 1.42, SD = 1.01; 3D: M = 1.45, SD = 0.5) hemispheres was statistically significant both for the 2D drawing ($p = 0.05443$) and the 3D drawing ($p = 9 \cdot 10^{-5}$) task. For the latter, the difference in the effect size was small, as calculated by Cohen's d ($d = 0.36$). Higher theta power can be noticed in the frontal lobe for both tasks, as it is common during cognitive activities.

Table 1. Cohen's *d* (the effect size) between the channel mean power for the tasks

	AF3	F7	F3	FC5	T7	P7	O1	O2	P8	T8	FC6	F4	F8	AF4
Total	0.07	0.18	0.05	0.21	0.05	0	0.02	0.05	0.06	0.04	0.22	0.26	0.01	0.3
Alpha	0.09	0.19	0.06	0.01	0.01	0.07	0.08	0.27	0.22	0.17	0.23	0.04	0.05	0.1
Theta	0.43	0.53	0.08	0.11	0.5	0.13	0.1	0	0.23	0.03	0	0.3	0.42	0.27

4.3. CLI comparison

During both tasks, average theta power (2D: M = 1.34, SD = 0.19; 3D: M = 1.32, SD = 0.23) was higher than average alpha power (2D: M = 0.97, SD = 0.09; 3D: M = 0.94, SD = 0.1) when considering all the channels. The differences were statistically significant both for the 2D ($p = 3 \cdot 10^{-6}$) and the 3D task ($p = 7 \cdot 10^{-6}$). Also, the large effect size was large in both cases (2D: $d = 1.91$; 3D: $d = 2.54$).

The CLI was calculated as the ratio of mean theta power from the channels positioned in the frontal lobe (AF3, AF4, F7, F8, F3, F4, FC5, FC6) and mean alpha power from the channels positioned in the parietal lobe (P7 and P8). These channels are bolded on the radar graphs presented in Figure 3 (in the middle and on the right side). The results of the descriptive analysis revealed a difference in the mean CLI of the CAD modelling based on the 2D drawing (M = 1.46, SD = 0.47) and the 3D drawing (M = 1.38, SD = 0.48). However, the difference was not statistically significant ($p = 0.6149$), and the effect size in a

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difference of the CLI means was negligible ($d = 0.12$). The distribution of the CLI across the participants is presented in Figure 3 on the left. The CLI was higher when CAD modelling based on the 2D drawing for 65% (11/17) of the participants.

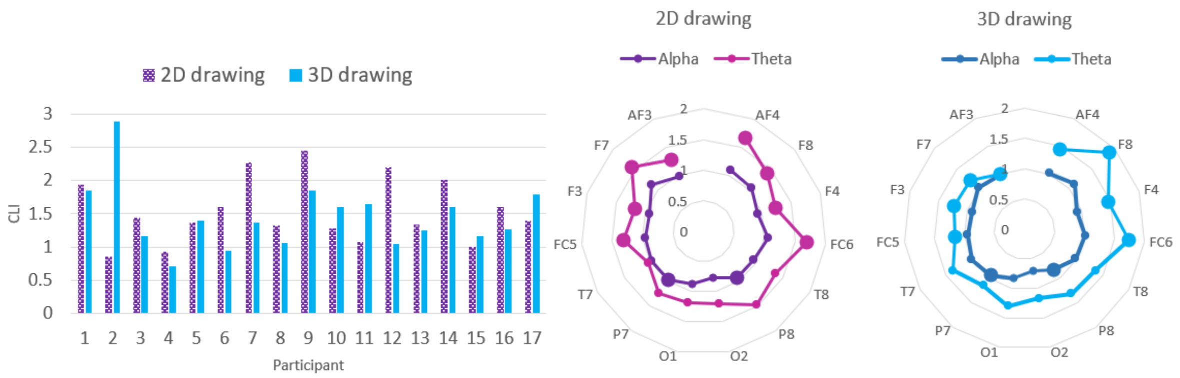

Figure 3. CLI distribution across the participants (left), alpha power distribution for 2D drawing task (middle), theta power distribution for 3D drawing task (right)

5. Discussion

The initial study results help to clarify the differences between 3D CAD modelling in two conditions - based on the 2D and the 3D drawings. The technical drawings were used as stimuli, while the complexity of tasks was kept the same (as explained in Sect. 3). It was hypothesized that CAD modelling based on the 2D drawing would pose a higher cognitive load on engineers. The reason behind that expectation lies in need for allocation of more cognitive resources to perceive end elaborate spatial information contained in 2D visual representation (Fajen and Phillips, 2013). The hypothesis was confirmed since the mean CLI of the CAD modelling based on the 2D drawing was higher than for the 3D drawing. However, the difference was not statistically significant, and the effect size of the difference was negligible. It has been argued that CAD modelling as a higher-level cognitive activity has a perceptual and production component (Willis et al., 1979). Hence, it may be that differences are not statistically significant at the level of an entire activity but are for the individual components. Further studies should disseminate CAD modelling activity into epochs representing perceptual and production components to investigate this possibility.

3D CAD modelling based on the 2D technical drawing showed a higher mean of neurophysiological activation than the same activity based on the 3D technical drawing. The total and theta power distributions were similar for CAD modelling in both conditions since no statistically significant differences were found when all the 14 channels were considered. On the contrary, differences in alpha power were significantly different. While higher activation was expected for the theta power during the 2D drawing task, it was not for the alpha power. Namely, the lower mean of alpha power band was expected during the 2D modelling task since alpha power is usually lower when one must apply a larger amount of cognitive processing, such as during the mental manipulation of the presented 2D information (Fajen and Phillips, 2013). Nevertheless, a lower alpha power across all the channels during the 3D drawing task may be related to processing a higher amount of information provided in the 3D drawing. Furthermore, the comparison of alpha power between the individual channels revealed the highest suppression in the occipital and parietal lobes for both tasks. This is in line with previous studies that reported suppression of parietal and occipital alpha power due to visual processing of information (e.g., Gundel and Wilson, 1992; Nguyen and Zeng, 2010)). In contrary to the results of the previous studies, the suppression was significantly more marked (lower mean alpha from P8 and O2 channels) during the CAD modelling based on the 3D technical drawing. For example, Gerlič and Jaušovec (1999) reported the higher alpha power of the occipital and temporal lobes yielded when the visual stimulus was presented in 3D. On the other hand, the text presentation increased the alpha activity in the frontal lobes (Gerlič and Jaušovec, 1999). Similarly, the increased alpha power activity at the channels in the frontal lobes (F7, AF4, and FC6) was noticed in the here presented study during the 2D condition.

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When considering theta power, an increase was noticed in the left frontal electrodes during the CAD modelling task based on the 2D drawing (the channel F7). The increase of theta power in that area has been related to the high amount of cognitive processing (Gundel and Wilson, 1992; Nguyen and Zeng, 2010). In addition, significant differences in theta power were found between the left and the right hemispheres for both conditions. A similar effect was related to the visual processing of spatial information in previous studies (Rugg and Dickens, 1982).

5.1. Limitations of the conducted study

The sample of engineers who participated in the conducted study allowed the statistical analysis and provided some statistical evidence. For example, the effect size was small or even medium (as calculated with Cohen's *d*) among specific channels and frequency bands. However, the statistical significance of the differences was not confirmed in all such cases ($p > 0.1$). Furthermore, all three participants whose data were discarded firstly modelled the part presented with the 3D drawing. The resulting dissimilarity in the sample within the groups possibly affected the lack of a clear difference among the tasks.

6. Conclusions and further work

The presented study investigated differences in engineers' cognitive load when creating CAD models of the parts visually presented by the 2D and the 3D technical drawing. EEG features (power of alpha and theta bands) were used as indicators of cognitive load posed on engineers during the CAD modelling tasks. The results indicated slightly higher brain activation and cognitive load during the 2D drawing task. In addition, several effects relatable to previous findings have been noticed. Compared to the baseline, parietal and occipital alpha power were suppressed during both tasks, as common effect of visual processing of information. Furthermore, higher frontal theta and differences in theta power between the hemispheres were found, as another previously reported indicator of ongoing processing of spatial information. These findings have implications for understanding cognitive processing associated with interpretation of 2D and 3D technical drawings and creating virtual 3D models based on it. Hence, the presented work lays the groundwork for the further EEG studies that will investigate a relationship between engineers' spatial thinking, visual representation type and media, and CAD activities from the cognitive perspective. Furthermore, the study outlines several avenues for further work. Firstly, the next studies will leverage EEG's high temporal resolution to analyse shorter epochs of the tasks. For example, to distinguish and analyse the 3D CAD modelling stages listed in the introduction of the presented work. This may result in a better understanding of 3D CAD modelling as a design activity, but also engineers' spatial thinking and skills. In addition, further work will include an analysis of operations and actions during 3D CAD modelling, such as creating and editing a sketch or a feature, constraining, deleting, reversing, and viewing. The presented paper reports only the portion of the captured data. Further studies will strive to investigate a relationship between EEG data and other variables, such as participants' experience and background or performance metrics related to CAD modelling outcome.

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