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Implementing innovative gaze analytic methods in design for manufacturing: a study on eye movements in exploiting design guidelines

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Abstract

Design guidelines aim to raise awareness of possibilities and limitations in manufacturing. The guidelines intend to support engineers and students to exploit the potential of manufacturing processes and to overcome the challenges of design for manufacturing. However although there are studies which show the benefit of guidelines, it remains unclear how this benefit is achieved or why it is missing. The aim of the present paper is to analyze the visual behavior of engineers and students while working with a design guideline. Gaze stationary and transition entropy are eye tracking metrics that quantitatively describe visual behavior. These metrics have been implemented in fields such as medicine and arts, but not yet in engineering. We conducted a study with 16 engineers and 20 students, who work with a design guideline and then solved an engineering design task. Their performance was classified by the manufacturability and the manufacturing effort of the design outcome, and their scanning patterns were analyzed using innovative eye tracking metrics. The results show that high performing engineers have a significant lower stationary entropy, while high performing students tend to have both high stationary and high transition entropies. While we were not able to show clear group differences, to predict the performance only through visual scanning behavior, gaze entropy remains a feasible metric for interest and curiosity. Furthermore, we adopt a Target Based Analysis for design methods to further investigate in the benefit of design guidelines.

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Keywords: design for manufacturing; gaze analytic; design methods

1. Introduction

Engineering design is a knowledge-based discipline [1, 2]. Design guidelines are a means of sharing knowledge and information [3]. They contain general recommendations and manufacturing restrictions, and provide examples of recommended and not recommended solutions [4]. This makes design engineers aware of important aspects at an early stage of product development [4, 5]. Still, it remains unclear how the benefit of design guidelines is achieved or why the benefit is still missing.

Previous studies examined the benefit of guidelines with eye tracking technology and investigated in how novice and expert design engineers benefit from design guidelines [6, 7]. Eye-Tracking is increasingly used in design research, also to investigate in differences in analysis and interpretation of technical systems by expert and novice engineering designers [8]. In these studies, traditional eye tracking metrics such as fixation count and fixation duration were employed. Although the analysis of these metrics can lead to interesting results, incorporating more innovative and complex methods may provide additional, valuable information [9, 10]. For instance, fixation count and fixation duration do not provide sufficient information about scanning behavior or visual attention distribution. Gaze entropy offers the calculation and allows quantification of attention distribution, scanning behavior, and extent of exploration. Additionally, it is possible to associate gaze entropy with qualities such as curiosity and interest [11, 12].

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Gaze stationary and transition entropy are recently developed eye movement metrics [9] that allow a quantitative comparison of participants' visual behavior. Stationary entropy is a measure for visual attention distribution [11]. It describes how dispersed the fixations of an individual are. Transition entropy is a measure for visual attention switching behavior [12]. It describes the extent to which an individual redirects his or her visual attention towards different regions of the visual field as described in 3.6.

Stationary and transition entropy have been implemented in numerous studies in different fields, including medicine and clinical psychology [9, 13–16]. The visual attention distribution is also important in the engineering context when working with design guidelines, because it is about information processing. The classic eye tracking metrics are not sufficient to investigate the benefit. Therefore we incorporated these innovative metrics in our study in order to compare participants' visual behavior.

We conducted an experiment in which experienced and novice participants worked with the design guideline and were classified based on their performance in a design task. Our aim was to examine the differences between low and high performers and to understand how they interacted with the design guideline.

2. Related work

2.1. Design guidelines

Butenko et al. [4] stated that design guidelines are a well-known and established form of knowledge documentation in both industry and science. Their findings reveal that design guidelines must meet certain requirements regarding the quality of the documented knowledge and the availability of relevant information. The results from Reimlinger et al. [3] show that design guidelines could be further developed with the help of eye-tracking technology and have a positive impact on design engineers' performance.

Previous studies have explored how novices and experts can benefit from design guidelines [6, 7]. Reimlinger et al. [5] analyzed how novice and expert engineers interact with a design guideline. Their results show that novice engineers perform better when they interact more intensively and frequently with the guideline. In contrast, expert engineers achieve better results with less intense and less frequent interaction with the guideline

The main metric used in these studies was dwell time. A dwell is defined as one visit in an area of interest, and dwell time indicates the duration of that visit [17]. Although this metric allows to make comparisons between participants, it does not provide information about visual scanning behavior and visual attention distribution during the interaction with the guideline. The use of metrics like gaze entropy could provide additional insight into participants' visual behavior.

2.2. Gaze entropy

Additional insight in participants' visual behavior is possible with stationary and transition entropy, as developed by Krejtz et al [12], as described in 3.6. Di Stasi et al. [16] studied the effects of task complexity on surgeons' gaze entropy, surgical performance, and perceived task complexity. The main finding was that stationary entropy increased linearly with task complexity. Krejtz et al. [12] studied the eye movements of participants who observed classical art paintings. The results reveal that participants' curiosity had an effect on transition entropy, but it did not affect stationary entropy significantly. The type of artwork affected both stationary and transition entropy. Some paintings depicted people and objects, while others were entirely abstract. This shows that gaze entropy is stimuli-dependent.

Transition entropy was also used in real time for truck drivers. Ebeid and Gwizdka [18] developed an algorithm that gives truck drivers real-time feedback based on their visual attention. The algorithm computes transition entropy in real time and shows this value on a computer screen, letting drivers know whether their attention is low, optimal, or chaotic.

Chanijani et al. [19] implemented an entropy-based analysis of gaze data to assess the skill level of students who solved physics problems. The students were classified in three groups based on their expertise: novices, intermediates, and experts. The study found that novices tend to switch more between AOIs and therefore have a higher transition entropy. Identifying this type of differences can help to improve the scanning behavior of low performing participants.

In the present study, we expected high performers to show greater interest in the guideline and thus to distribute their attention more evenly among areas of interest compared to low performers. This would be indicated by high stationary entropy values. This hypothesis follows the findings of Krejtz et al. [11], who stated that stationary entropy can be thought of as a measure of interest.

Additionally, we predicted that high performers would exhibit a more exploratory behavior in comparison to low performers. According to Krejtz et al. [12], an exploratory character of visual attention is indicated by a higher transition entropy. Therefore, we expected high performers to have a higher transition entropy than low performers

3. Materials and methods

3.1. Participants

The study was conducted with 36 participants. 20 participants were Master's students majoring in mechanical engineering. 16 participants were design engineers from ten industrial companies in Germany, specialized in mechanical design with experience in designing sheet metal products. All participants provided written informed consent.

3.2. Procedure and task description

Each participant was attended individually and all participants were provided with the same procedural requisites and information. The moderator's influence was minimized by using the experiment software OpenSesame v.3.2.6 [20], which had all the relevant information.

The experiment consisted of five steps: (1) Pre-survey, (2) Interaction with the guideline, (3) Task description, (4) Task processing, (5) Post survey. The aim of the task was to develop a bracket angle optimized for manufacturability and manufacturing effort. For this purpose, the task was to reduce the amount of parts, the process steps, and the amount of welding joints. The function of the component was to carry a load of 80 kg. The placement of mounting holes and the material had to remain unchanged. The participants were asked to create one or more concepts and had to select one final concept after concept generation. The task had to be conducted using pen and paper only.

3.3. Hardware and software

A computer monitor was used to present the engineering problem Blank paper and pens were provided for the participants to draw their concepts. A mouse and a keyboard were provided as input for the questionnaire. The Tobii Pro Glasses 2 were used as the eye-tracking device to record eye movements at 100 Hz. The software Tobii Pro Lab was used for fixation and saccade detection with a Velocity-Threshold Identification (I-VT) classification algorithm [21]. Python code was implemented for the analysis of the eye-tracking data [22].

3.4. Data analysis

Performance was evaluated based on manufacturing effort. This criterion can be divided into three categories based on the required costs. Based on a preliminary study, the authors asked service providers for proposals regarding the costs for the most frequently occurring concepts. The average of these costs ranged from a (1) low manufacturing effort category to a (2) medium and to a (3) high manufacturing effort for the reference product of the task description. High performing participants were able to design concepts with low manufacturing effort.

Due to technical problems with the eye tracking device, the eye tracking data of 5 participants were removed from the analysis. In total, there were 31 valid recordings.

For each page and each participant, two entropy values (transition and stationary) were calculated. In total, there were 702 entropy values, which means that participants read an average of 11.3 out of 13 pages of the guideline. To be able to make comparisons across different groups and pages, all entropy values were normalized [19]. In order to test the differences between the groups, we used the Mann–Whitney U test [23]. A p-value below .05 was considered to be statistically significant, and the effect size was calculated [24].

3.5. Stimuli

Eye tracking data were collected during the interaction with the design guideline. The guideline consisted of 13 pages. Each page was divided into several areas of interest (AOIs). An AOI outlines a region in the stimulus that contains interesting information, and is used to quantify the amount of fixations in that particular region [17]. The selection of AOIs was made according to one strategy proposed by Holmqvist et al., namely stimulus-generated AOIs, as shown in Fig. 1 [17].

3.6. Gaze entropy

The concept of entropy can be implemented in gaze data analysis. It can be a useful metric to compare participants' visual behavior while performing a task or learning new information through visual stimuli [19]. Entropy is often associated with disorder, with high entropy indicating a disordered system. This idea can be adapted to gaze analysis to determine how "disordered" the visual behavior of a subject is. There are two types of gaze entropy: stationary and transition entropy [12]. Together, these two quantities provide a method for characterizing visual behavior [25].

3.6.1. Stationary entropy

Stationary entropy ($\boldsymbol{H_s}$) is a measure that describes gaze dispersion [16]. It provides information about the distribution of gaze across AOIs. It is calculated using Equation (1).

$$H_s = -\sum_{i=1}^{n} p_i \, \log(p_i) \tag{1}$$

$\boldsymbol{p_i}$ represents the probability of viewing the $\boldsymbol{i^{th}}$ AOI, and $\boldsymbol{n}$ represents the total number of AOIs. The probability $\boldsymbol{p_i}$ is obtained by dividing the number of fixations in an AOI by the total number of fixations. Since probabilities are numbers between zero and one, and the log function has a negative output in this range, a minus sign is introduced. This ensures that $\boldsymbol{H_s}$ always has a positive value.

The maximum value for stationary entropy is equal to $\boldsymbol{\log(n)}$, where $\boldsymbol{n}$ is the total number of AOIs. This value indicates that visual attention was distributed equally among AOIs, i.e. all AOIs have the same number of fixations and thus the same probability [12]. A high stationary entropy value means that the subject did not focus on any particular area, but rather distributed his or her attention more evenly.

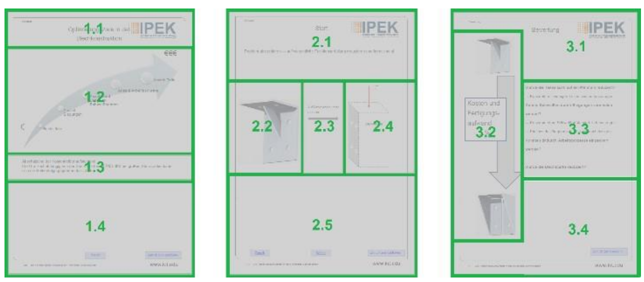

Fig. 1. Selection of AOIs adopted by Holmqvist et al.: stimulus-generated AOIs

The minimum value for stationary entropy, which is equal to zero, is achieved when visual attention is focused entirely on one single AOI, and all fixations are inside this AOI. The probability for this AOI is one, while the probabilities for all the other AOIs are zero. Since $\mathbf{log(1) = 0}$, the value for $\boldsymbol{H_s}$ is also zero. A low stationary entropy value indicates that attention was focused more toward certain regions, meaning that some AOIs have a larger number of fixations than others.

3.6.2. Transition entropy

Information about the scanning pattern of a subject cannot be obtained using stationary entropy, since only the position of fixations is considered and not the order in which they appeared. This information can provide useful insight into the scanning behavior of a subject, since it is not only important to know where a subject focused their attention, but also how his or her attention changed.

Transition entropy ($\boldsymbol{H_t}$) is a measure that describes visual scanning patterns [25]. It indicates to which extent a subject switched between the different AOIs of a stimulus. It is obtained using Equation (2), as proposed by Krejtz et al. [12].

$$H_t = -\sum_{i=1}^{n} p_i \sum_{j=1}^{n} p_{ij}\ log(p_{ij}) \qquad (2)$$

Analogous to stationary entropy, $\boldsymbol{p_i}$ represents the probability of looking at the $\boldsymbol{i^{th}}$ AOI and $\boldsymbol{n}$ the total number of AOIs. The term $\boldsymbol{p_{i,j}}$ represents the probability of viewing the $\boldsymbol{j^{th}}$ AOI given the previous viewing of the $\boldsymbol{i^{th}}$ AOI [9]. In other words, how likely it is that the subject looks at AOI $\boldsymbol{j}$ if he or she is currently looking at AOI $\boldsymbol{i}$. These probabilities are represented in the transition probability matrix, where each row represents a source AOI and each column a destination AOI. To calculate the transition probability matrix, the transitions between AOIs are counted (from AOI1 to AOI2, etc.). Each of these numbers is then divided by the total number of transitions from the source AOI as shown in Equation (3). The resulting values represent the probability of having a transition from one AOI to another.

$$p_{ij} = \frac{n_{ij}}{\sum_j nj} \qquad (3)$$

The maximum value for $\boldsymbol{H_t}$ is equal to $\mathbf{log(}\boldsymbol{n}\mathbf{)}$, where $\boldsymbol{n}$ represents the total number of AOIs. It is obtained when all transitions are equally likely to happen, meaning that all the elements in the transition matrix have the same value. This suggests a random scanning pattern, since fixations do not follow any particular order. A high transition entropy value indicates a more exploratory character of visual attention [12].

The minimum value for $\boldsymbol{H_t}$ is zero, and is achieved when all fixations are inside one single AOI. In this case, there is only one type of transition happening, which is the transition from the $\boldsymbol{i^{th}}$ AOI to the $\boldsymbol{j^{th}}$ AOI, where $\boldsymbol{i = j}$. Consequently, only one element from the transition matrix is different from zero, and it has a value of one. Thus, the value for $\boldsymbol{H_t}$ is zero, since $\mathbf{log(1) = 0}$.

4. Results

The aim of the study was to examine differences between low and high performers using stationary and transition entropy. The results show no clear group differences between low and high performers, as well as between engineers and students.

4.1. Stationary entropy

The results for stationary entropy show no clear group differences between low and high performers of students. High performing students had a higher mean stationary entropy than that of low performing students ($p = 0.323$). Engineers had the opposite behavior as hypothesized. High performing engineers had significantly lower stationary entropy than low performing engineers ($p = 0.0455$). The stationary entropy values for the four groups are shown in Fig. 2 and Table 1.

Table 1. Number of participants (N), mean (M), standard deviation (SD), and median (Md) of stationary entropy

Group	N	M	SD	Md
Low performing engineers	4	0.775	0.113	0.789
High performing engineers	9	0.69	0.139	0.758
Low performing students	11	0.754	0.106	0.783
High performing students	7	0.768	0.12	0.764

4.2. Transition entropy

The results show no clear group differences in transition entropy. On average, high performing students had a higher transition entropy than low performing students. For engineers, the results show the opposite. High performing engineers had a lower mean transition entropy than low performing engineers, indicating that high performers showed a more structured scanning behavior. Fig. 3 and Table 2 show the transition entropy values for low and high performing students and engineers.

Table 2. Number of participants (N), mean (M), standard deviation (SD), and median (Md) of transition entropy

Group	N	M	SD	Md
Low performing engineers	4	0.781	0.061	0.772
High performing engineers	9	0.772	0.09	0.789
Low performing students	11	0.765	0.068	0.76
High performing students	7	0.789	0.073	0.78

5. Discussion

Engineers and students showed no clear different visual behaviors while working with the design guideline, and within these groups, only between low and high performing engineers statistical differences can be found. The obtained results do not confirm our hypotheses.

5.1. Stationary entropy

In order to perform well on the tasks, knowledge about sheet metal part design is necessary. Since the design guideline provides this knowledge, we expected high performers to show greater interest in the guideline. This means that their attention would be more evenly distributed among AOIs and therefore, their stationary entropy should be higher [10, 11]. However, the hypothesis could not be confirmed. Engineers even had the opposite behavior as hypothesized. High performing engineers had significantly lower stationary entropy than low performing engineers ($p = 0.0455$). One possible interpretation of this result is that experienced engineers already possessed the knowledge required for the task, hence they only focused on specific areas containing information that was useful to them. This is consistent with the results from [19], in which experts had significantly lower entropy than novices. Whereas, students can benefit from a design guideline, if they examine its content carefully. Low performing students tend to skip information.

5.2. Transition entropy

Since students lack the expertise and skills of experienced engineers, acquiring new knowledge offered by a design guideline can be advantageous. This is why we expected high performers to have a more exploratory behavior in comparison to low performers, seeking as much information as possible and trying to understand it by finding connections in the material presented in the guideline (e.g. definitions, processes, illustrations, etc.).

The obtained results for students show no clear differences between low and high performers ($p = 0.371$ for students; $p = 0.440$ for engineers). High performing engineers focused more on specific AOIs in comparison to low performing engineers, meaning that there was a smaller number of possible transitions. This would explain why their average transition entropy is lower than that of low performing engineers.

High performing students had, on average, a higher transition entropy than low performing students. A possible explanation could be that high performing students are more curious. They are more interested in acquiring new knowledge, but their low expertise prevents them from finding an efficient strategy to do so, resulting in constant switching between areas of interest.

This contradicts the results obtained from Krejtz et al. [12], where highly curious participants exhibited lower transition entropy levels. In the mentioned study, however, participants were looking at different pieces of artwork. The discrepancy between the results is likely due to the nature of the stimuli. Whereas in art curious participants focus on specific areas to appreciate details and to understand the meaning of the artwork, in engineering it is necessary to find connections and to understand relationships between various pieces of information. This is achieved by constantly looking at the different areas shown in the stimulus. Whereas it is challenging to present complex relationships that need to be connected by a novice engineers in a small area. A precise definition and quantification of *curiosity,* and a further examination of different stimuli are required in order to confirm these hypotheses.

5.3. Target Based Analysis of design methods

The design guidelines intend to support engineers and students to exploit the potential of manufacturing processes and to overcome the challenges of design for manufacturing. We were not able to predict the performance of the participants alone with the visual attention distribution. Gaze entropy offers an operationalisation of interest and curiosity. Further influences on the performance have to be considered. Therefore, Bojko presented a framework of Target Search Analysis with a four step procedure for investigating in tasks of a target search [26]. Mussgnug et al. adopted and modified this framework to the Target Based Analysis model for the usability testing of tangible products [27]. Both researcher defined the processing of information and activities as: (1) perception success or findability, (2) comprehension success or recognisability, (3) explain failures or handling and (4) detect problems or prepare/wait.

The improvement of the Target Based Analysis model is necessary for the application of design methods within their iterative and fractile character. We want to adopt and offer quantitative data for steps (1) and (2) but need to investigate in a more detailed analysis for the degree of application of design method activities and furthermore the core dimensions of

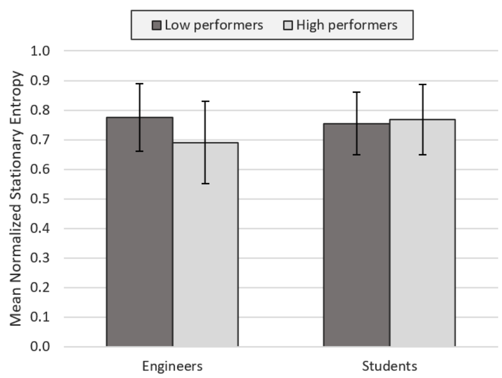

Fig. 2. Stationary entropy of low and high performing engineers and students. A higher stationary entropy indicates a greater interest in the guideline and a more evenly distributed attention among AOIs.

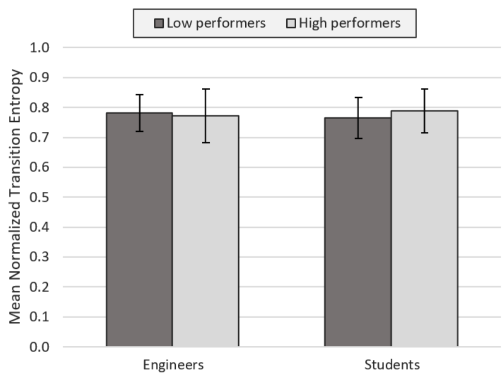

Fig. 3. Transition entropy of low and high performing engineers and students. A higher transition entropy indicates a more exploratory behavior of visual attention distribution, as seeking as much information as possible and trying to understand it by finding connections in the material presented in the guideline.

measuring usability of design methods as effectivity, efficiency and satisfaction [28].

6. Conclusion

Design guidelines support engineers and students in the development of design concepts. Their visual behavior while interacting with design guidelines can be described with innovative eye tracking metrics such as gaze entropy. These metrics provide an insight on how design guidelines support engineers and students. This could support the further development and improvement of design guidelines.

A study was conducted in order to explore the visual behavior of participants who work with a design guideline and its impact on their performance. We were not able to show clear group differences. High performing engineers had significant lower stationary, and tend to have lower mean transition entropy values than low performing engineers, meaning that they exhibited a more focused visual attention and less switching behavior. In contrast, high performing students had higher mean stationary and transition entropy values than low performing students, indicating a more equal distribution of visual attention and a more exploratory behavior.

Possible limitations could be the number of participants and the choice of AOIs in some stimuli. Also, the use of a screen-based eye tracker, rather than a head-mounted one, could provide more reliable and accurate data in the context of this study. Nonetheless, the results suggest that stationary and transition entropy can potentially quantify the extent of support of design guidelines. Furthermore, design guidelines not only intend but actually support engineers and students in exploiting the potential of manufacturing processes and in overcoming the challenges of design for manufacturing.

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