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EXPLORING THE PERCEIVED COMPLEXITY OF 3D SHAPES: TOWARDS A SPATIAL VISUALIZATION VR APPLICATION

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ABSTRACT

The objective of this work is to explore the perceived complexity of 3D shapes used in spatial visualization tasks and leverage Machine Learning to create a model that can predict this perceived complexity using the visual features of the shapes. This could help automate the process of generating 3D shapes for a Virtual Reality (VR) application designed to help develop spatial visualization skills. Spatial visualization skills are important skills needed in the STEM fields. While VR has been used to help develop these skills, most of the existing applications do not necessarily tailor their content to the skills level of individuals. Automatically generating shapes can help VR applications tailor spatial visualization tasks to the skills level of users. However, in order to do this, it is important to first understand how humans perceive the complexity of 3D shapes, and how this relates to their performance in spatial visualization tasks. The results of this work indicate that while participants perceived complexity of 3D shapes is correlated to their performance in spatial visualization tasks that use the same 3D shapes, this perceived complexity by itself is not enough to predict their performance in such tasks. Moreover, the results indicate that certain visual features of 3D shapes can help explain the perceived complexity of the shape as well as the performance of individuals in spatial visualization tasks that implement those 3D shapes.

Keywords: Spatial Visualization, Complexity, VR, Symmetry

1. INTRODUCTION

Spatial Visualization skills are described as the ability to mentally manipulate, rotate, twist or invert 3D objects [1]. It is a complex process that involves both visual abilities and the formation of mental images [2]. They are one of the most important skills in STEM fields. These skills are especially critical for engineers of all disciplines, as engineers communicate largely via graphical means [3]. Furthermore, studies have shown that these skills are correlated to students' performance, confidence, motivation, and reasoning [4] [5]. Unfortunately, many students in STEM fields significantly lack spatial skills when they begin their studies [6]. Moreover, standard instruction and class coursework at the introductory level might not be enough to thoroughly develop these skills [7].

Virtual Reality (VR) technology has started to be used more and more in education as it enables students to find out answers, explore, and build their own knowledge [8]. VR has already been used to teach and develop spatial visualization skills with promising results [9]. Even though VR educational applications can motivate students to learn new concepts and develop new skills, it has been shown that students can have different levels of expertise which can directly impact their state of flow in a given application [12]. It has been found that students best execute the tasks whose difficulty aligns with their skills level [10-12]. Unfortunately, most of the existing VR applications for spatial visualization skills are designed following a “one-size-fits-all” approach which only enables users to interact with a limited set of 3D shapes that are not necessarily tailored to their skill level [13]. Consequently, after a couple of trials and/or interaction with the VR applications, students could easily lose their attention and get demotivated [14].

A way to overcome these limitations is to automatically generate new content that students can interact with. Specifically, for VR applications designed to help develop spatial visualization skills, automatically generating new 3D shapes and tailoring the shapes based on students' skill levels could improve users’ state of flow and their motivation. One potential solution to achieve this would be to leverage Procedural Content Generation methods based on Reinforcement Learning approaches to generate new content, as presented in previous work [15-17]. Specifically, 3D shapes of different complexities can be automatically generated for students to interact with while developing their spatial visualization skills. However, to create a model based on Reinforcement Learning approach capable of generating 3D shapes of different complexities, a uniform system to algorithmically quantify the perceived complexity of 3D shapes must be created. This is important since any Reinforcement Learning approach would need to have a reward function to generate an action policy. Moreover, this reward function needs to consider the perceived complexity of a given shape to create an action policy that generate shapes of different complexities based on student skill level.

Several studies have proposed computing complexity at the pixel level by predetermined mathematical formulas [18]. Nevertheless, these metrics might not necessarily capture the human-perceived complexity of 3D shapes used to develop spatial visualization skills, but rather focus on the topological definition of a shape. Hence in this work, an experiment is conducted to analyze the perceived complexity of 3D shapes in spatial visualization tasks, and Machine Learning models are used to correlate visual features of the 3D shapes to their complexity.

2. LITERARY REVIEW

2.1 Virtual Reality in Education

Apart from gaming and entertainment, VR has found a broad variety of applications, including but not limited to health, education, and sports [19-21]. Specifically, in education, researchers have found that VR helps develop feelings of presence and immersion, which in the long run, can help construct engaging learning situations with a long-lasting impact on students [22].

Moreover, VR can help students to connect distinct educational concepts to their personal experiences [23]. VR supports students to develop a deep-rooted, mental model of the knowledge acquired. Developing mental models is known to be the main foundation of knowledge, as the student cognitively engages with the learned material [24]. The most important feature that distinguishes VR from other education-supportive tools is the sense of presence it creates in an immersive environment [25]. VR not only helps improve students' engagement but could also provoke a stronger interest in a new subject [26].

As VR technology has evolved, the cost of a headset has steadily decreased, thus increasing the economic accessibility of the devices for different socio-economic groups [27]. Unfortunately, creating meaningful VR experiences is still a major barrier, which could also prevent overcoming the issues that arise from the "one-size-fits-all" design approach. This is because, even though VR has the capability to engage students, presenting the same type of content to students, who have distinct levels of experience and knowledge, won't have a uniform impact across students. Consequently, it is important, as with any pedagogical system, to tailor the content to the students' skill levels.

Research has already started exploring how Procedural Contented Generation (PCG) methods can be leveraged to help automate the creation of VR content in educational applications [17, 28, 29]. Some of the authors' prior work has explored how to leverage Reinforcement Learning (RL) and PCG methods to help automatically create content for VR educational applications [15-17]. However, an important aspect of any RL based-method is the reward function used to help train the RL agent, which has to align with the action policy the researchers want the RL agent to generate. This work takes initials steps to help solve this problem, specifically for VR applications design to help develop spatial visualization skills, by exploring how humans perceive the complexity of 3D shapes, and how this relates to their performance in spatial visualization tasks.

2.2 Virtual Reality and Spatial Visualization Skills

Spatial visualization is a complex process that involves both visual abilities and the formation of mental images. Because of the importance of spatial visualization across many disciplines, it has been studied by a wide variety of fields in science, education, and cognitive psychology [30]. Spatial intelligence is defined as the set of skills that assist us to understand spatial relations, visual-spatial tasks, and also, receive a better orientation of objects in space [31]. Furthermore, spatial ability is often correlated to good academic performance in the engineering curriculums [16]. VR technology is found to be useful for learning and developing these skills because it can provide a "first-person" experience and visualize 3D objects in a 3D virtual environment [32].

Several studies have shown that VR can help improve spatial visualization skills [33]. A study with a group of senior university students, presented in [34], was conducted to test the impact of a VR spatial visualization application had on students' spatial visualization skills. The results pointed out that students who participated in the VR environment showed higher improvement in spatial visualization skills compared to those that did not use the VR application. While VR has been shown to help develop students' spatial visualization skills by allowing students to complete and practice spatial visualization tasks in a 3D virtual environment, it has been also shown that students can have different levels of expertise that can directly impact their state of flow in a given application. The Flow theory of motivation indicates that students would be more engaged to execute the tasks whose difficulty aligns with their skills level [12]. Unfortunately, most of the existing VR applications designed to help develop spatial visualization skills are designed following a "one-size-fits-all" approach which only enables users to interact with a limited set of 3D shapes that are not necessarily tailored to their skill level.

In order to make sure that each student using a VR application designed to help develop spatial visualization skills interacts with tailored content to maximize flow, the complexity of the 3D shapes used in the spatial visualization tasks should be

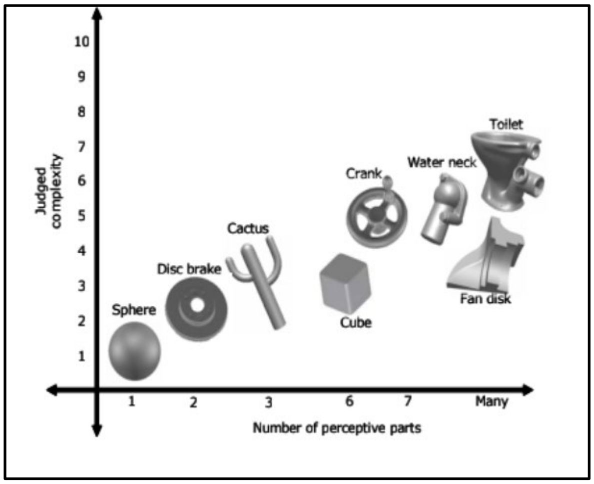


FIGURE 1. NUMBER OF PERCEPTIVE PARTS vs COMPLEXITY FROM [38]

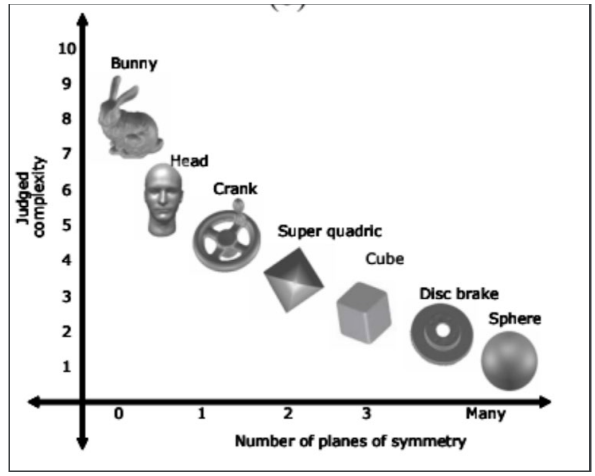


FIGURE 2. NUMBER OF PLANES OF SYMMETRY vs COMPLEXITY FROM [38]

aligned with the student's skill level. While several researchers have proposed ways to measure shape complexity, perceived complexity represents a broad term that can be challenging to measure algorithmically. Moreover, the perceived complexity of shapes in spatial visualization tasks might differ from the perceived complexity of 3D shapes used in other contexts.

2.3 Measuring Complexity

3D representations are unique because they can characterize important visual properties that can guarantee the accurate identification of objects [36]. Previous studies have found a significant correlation between the value of complexity and the visual determinants of shapes, including but not limited to angular variation, symmetry, curvature, clutter, openness, organization, and number of elements [37].

For example, in [38] a study was conducted to explore how the number of elements and symmetry of 3D shapes correlated to the perceived complexity of the shapes. First, 3D objects were segmented based on the number of distinct elements, and a survey was given to participants so they can decide whether a shape was more complex than another. It was discovered that participants describe objects with a greater number of parts to be more complex. Figure 1, from [38] figure 1d, shows the relation between the number of perceptive parts and the perceived complexity from the participants' responses. Shapes with more perceived distinct elements, like the "toilet" and "fan disk", were perceived as more complex by participants. In addition, the 3D objects were segmented based on the axes of symmetry (i.e., in how many axes is the object symmetrical). The results show that shapes that were more symmetrical were perceived as less complex. As shown in Figure 2, from [38] figure 1e, objects with no symmetry had high complexity ratings. This indicates that perceived complexity is inversely proportional to the object's symmetry. For example, a sphere, disk brake, and cube were rated less complex.

Based on their findings, the authors of [38] presented a complexity metric that used algebraic expressions and surface kernels to measure complexity. The expressions had a goal to represent a shape in its implicit form. However, this way of mathematical representation has a major limitation in predicting the interaction or dependency between its components. Moreover, this metric might not necessarily capture the human-perceived complexity of 3D shapes used to develop spatial visualization skills, but rather focus on the topological definition of a shape.

Besides symmetry and the number of elements, studies have shown that perceived complexity is related to the variation in the curvature of objects; with sharper and unexpected variations contributing to increased complexity. Specifically, it has been observed that the average complexity rating for surfaces increases with an increase in variation of surface curvature [39]. This increase of variation of surface curvature could be related to the symmetry of the object's surface, as presented in Fig. 2. Research done with building blocks in children. has shown that the number of building blocks used to make shapes were significantly and positively correlated with the level of complexity [40]. Even though significant progress has been achieved to measure the perceived complexity of 3D shapes, it is still unclear how humans perceive the complexity of 3D objects in spatial visualization tasks, and how it can be measured algorithmically.

3. METHOD

The objective of this work is to explore how the complexity of 3D shapes in spatial visualization tasks can be measured, and how the complexity of these 3D shapes is related to humans' perceived complexity. Hence in this work, an experiment is conducted to analyze the perceived complexity of 3D shapes in spatial visualization tasks, and Machine Learning models are used to correlate visual features of the 3D shapes to their

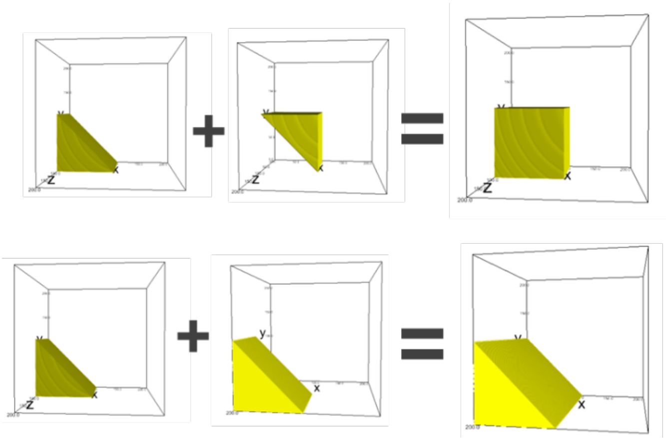


FIGURE 3. WEDGES AND VOXEL SYSTEM REPRESENTATION

complexity. Details about the 3D shapes used and experiments conducted are explained next.

3.1 3D Shapes Generation

To algorithmically generate 3D shapes, like those present in the Purdue Spatial Visualization test [41], a system of wedges and voxels was implemented. Figure 3 shows a representation of this system. There are a total of 8 voxels arranged in a cube configuration. This means, that the biggest 3D shape that can be generated would have 2 voxels of length on any axis. Moreover, each voxel is composed of 12 different wedges that can be enabled or disabled to generate different 3D shapes. These 12 wedges come from having a wedge (i.e., cube cut in diagonal) in each of the three axes that can be rotated 90 degrees at least four times (i.e., 3*4=12). To have a complete voxel, at least two complementary wedges need to be enabled (as shown at the top of Fig. 3). A video of the 3D shape generation can be seen here https://youtu.be/2jBeVD8TEwE.

A subset of 3D shapes, with no curvatures, from the Purdue Spatial Visualization Test [41] were recreated for this work (see Figure 4 for an example). Specifically, a total of 21 shapes (i.e., 70% of the shapes) present in the Purdue test, do not contain any curvatures. To help participants rate the "perceived-complexity" of the 3D shapes, a series of videos were created in which a subset of the shapes are shown rotating in the different axis. To help convey the 3D features of the shapes via a 2D display (i.e., computer display), the faces of the shapes were colored, as shown in Fig. 4.

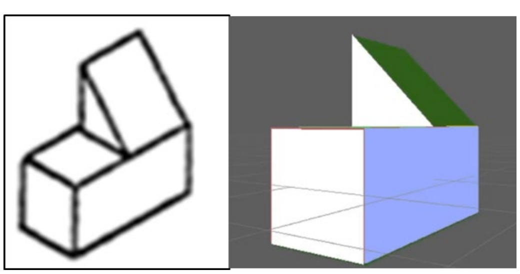


FIGURE 4. 3D SHAPES DESIGN

3.2 Measuring Perceived-Complexity

To understand how people perceive the complexity of different 3D shapes, participants were recruited via Amazon Mechanical Turk (AMT) [42]. AMT has been used extensively in behavioral research since it offers low-cost access to a large and diverse pool of participants, and studies have found no significant differences in the response consistency between internet and laboratory participants [43] [44].

Participants were asked to complete 3 different surveys. (1) *Subset of Purdue Spatial-Visualization test*: in which participants were asked to complete the questions of the Purdue test that related to shapes that did not contain any curvatures. (2) *Rate the*

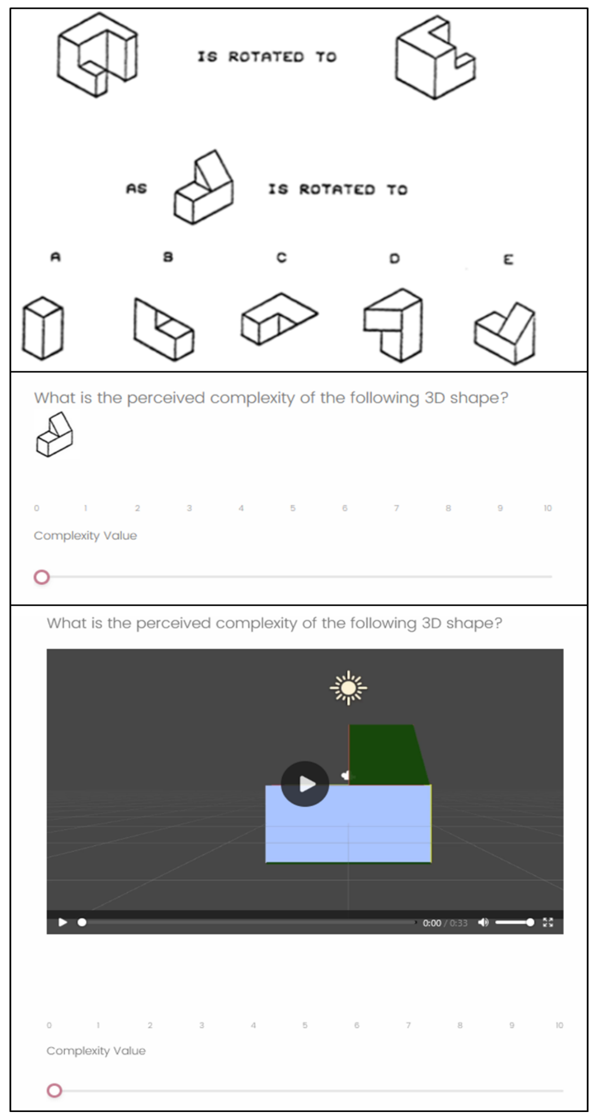


FIGURE 5. SURVEYS TO ASSES PERCIVED COMPLEXITY

perceived complexity of shapes via 2D images: for this survey participants were shown 2D images of the same shapes as in survey one, and asked to rate their perceived complexity using a slider bar ranging from 0 (less complex) to 10 (more complex). (3) *Rate the perceived complexity of shapes via videos showing the 3D shapes rotating*: for this survey participants were shown videos showing some of the 3D shapes as in surveys one and two rotating, and asked to rate their perceived complexity using a slider bar ranging from 0 to 10. Figure 5 shows an example of a question of each of the surveys relating to the same 3D shape.

To reduce potential individual biases, for both surveys 2 and 3, participants were told to use a "cube" as a reference point and consider it as a 3D shape with a complexity of 0. Moreover, the order of the surveys and the shapes participants were exposed to, was randomized to reduce any potential order effects. Lastly, a series of quality control questions and checkpoints were used. For example, for survey 2, participants were also presented a cube, and based on the instruction, they were required to record this shape as having a complexity of 0. Moreover, the time spend on the instructions page and on each question of the surveys was used for quality control.

3.3 Complexity Metric & Features

Based on previous literature, a complexity metric and a series of complexity features were generated. This was to help explore the relationship between the perceived complexity of the 3D shapes analyzed in this work and their visual features. Figure 6, shows a visualization of the complexity metric. This metric aims to algorithmically measure complexity based on the symmetry of 3D shapes. All the 3D shapes explored in this study were replicated using the shape generation system introduced in section 3.1. For each shape, a moving cutting plane in each of the x, y, and z axes was used to scan the shape. This sweep allows to potentially capture complexity arising from internal parts of the 3D shape (e.g., if a shape has a whole) and to account for the difference in the shape along an axis (i.e., the front different than the back). For each of the cutting planes, the voxel area used to generate the 3D shape was identified. This is to help the metric to be size and translation invariant (i.e., a shape should have the same complexity no matter its size or location). Subsequently, the pixel level Euclidian difference between areas of the shape that were divided by each of the 4 potential lines of symmetry was calculated. The difference was then normalized to have values between 0-1.

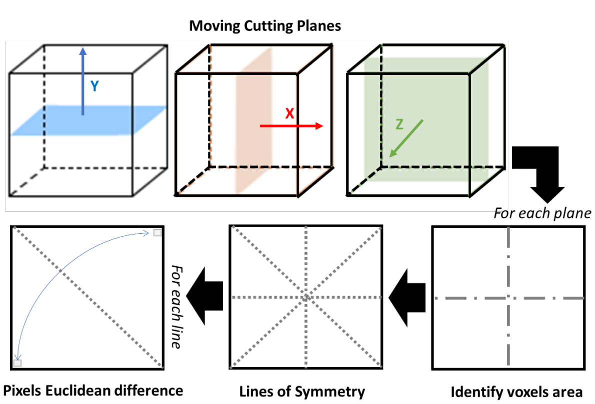


FIGURE 6. VISUALIZATION OF COMPLEXITY CALCULATION

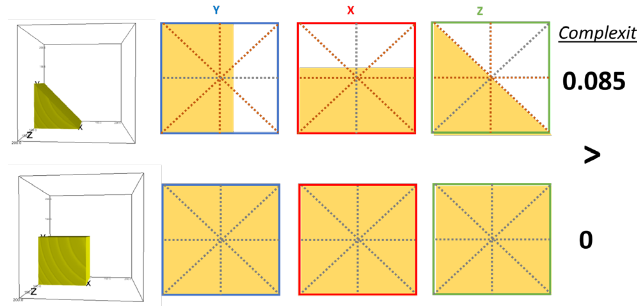
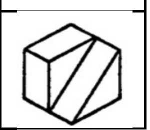
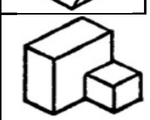
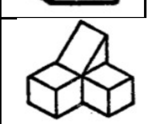


FIGURE 7. COMPLEXITY CALCULATION EXAMPLES

A 3D shape with a complexity of 0 would indicate a 3D shape than in all its axes, any cutting plane you take would have a total of 4 lines of symmetry (i.e., symmetrical horizontally, vertically, and both diagonals). A 3D shape that would have a complexity of 0 would be a cube. Fig.7 shows an example representation of the complexity metric for a cube and a wedge. As shown in Fig. 7, any cutting plane of the cube would have all 4 lines of symmetry, while the wedge would only have 1 (i.e., gray dotted lines). This is why the complexity value of the wedge is greater than the cube.

TABLE 1. COMPLEXITY METRIC AND FEATURES EXAMPLE

Complexity metric	Number of voxels	Number of complete voxels	Number of incomplete voxels	Incline planes.	3D shape image
0.195	7	5	2	1	
0.159	5	5	0	0	
0.179	3	1	2	2	
0.221	4	3	1	1	

In addition, several visual features that related to the number of elements and surface variation of the 3D shape were calculated. Specifically, (i) the total number of voxels used (e.g, number of building blocks), (ii) the total number of complete voxels used (e.g., number of cubes), (iii) the total number of incomplete voxels (e.g., number of non-cubes), and (iv) number of different incline planes. Feature (ii) and (iii) would add up to the feature (i). Table 1 shows a series of figures with their respective complexity metric and complexity features.

4. RESULTS

With the objective to better understand how the visual features of 3D shapes relate to their perceived complexity, an experiment was conducted via AMT. Participants were compensated US$0.5 for their participation, with an additional US$1 bonus, if they passes all the quality control questions and checkpoints. A total of 200 participants were recruited. However, only the data of 53 participants that passed the quality control questions and checkpoints were analyzed in this work. On average, participants took 27.16 minutes to complete all the surveys.

A total of 21 different 3D shapes from the Purdue Test were used for surveys (1) *Subset of Purdue Spatial-Visualization test* and (2) *Rate the perceived complexity of shapes via 2D images* (see section 3.2, and Fig. 5). However, for the survey (3) *Rate the perceived complexity of shapes via videos showing the 3D shapes rotating*, only 5 shapes were used.

The results indicate that there was a strong and significant positive correlation between the perceived complexity reported via the 2D images and the videos of the 3D shapes (ρ=0.988, p-value<0.01). This shows that when asked to rate the perceived complexity of 3D shapes, participants provided similar responses no matter if they were exposed to a 2D image or video of the 3D shape. This indicates that when it comes to the perceived complexity of the shapes used in this study, 2D images and videos might have conveyed the same amount of information. However, this might not hold when comparing shapes shown in Virtual Reality since previous studies indicate that different communication channels can transfer different level of information [45]. Nevertheless, it is hypothesis that the relative difference in complexity of 3D shapes should not vary significantly between the different communication channels used (e.g., a cube would be perceived as less complex than any other shape no matter is presented via a 2D image, video or in VR).

In addition, the results from survey (1) *Subset of Purdue Spatial-Visualization test*, indicates that, on average, the number of correct responses of a 3D shape was only negatively correlated to its perceived complexity reported when using a 2D image of the shape (i.e., survey 2 responses) (ρ=-0.439, p-value<0.05). This indicates, that participants, on average, performed worse in the Purdue Spatial visualization test questions that involved 3D shapes that were reported as more complex. Nonetheless, this correlation could be considered weak, which indicates that asking participants to report their perceived complexity of a 3D shape might not capture enough information to explain their performance on a spatial-visualization task that involves the same 3D shape.

Figure 8 shows a correlation matrix between participants' responses on the surveys, and the complexity metric and features introduced in this work. The number of incomplete voxels and incline planes of a 3D shape was positively correlated with the perceived complexity of the shapes reported when using 2D images and videos. This indicates that 3D shapes with more incline planes are perceived as more complex. This could be explained by the variability that incline planes introduce to the

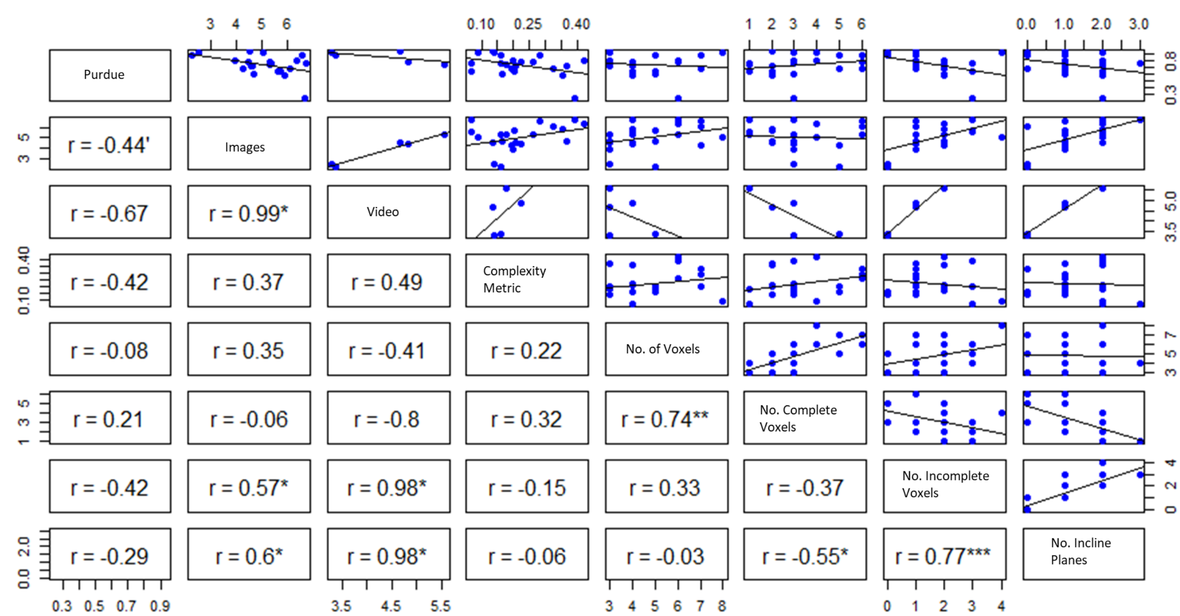


FIGURE 8. CORRELATION MATRIX
*p-values: <0.05, * <0.01, **<0.001, ***<0.001*

surface of 3D shapes, as shown in previous studies (see section 2).

To better understand how the complexity metric and features introduced in this work might correlate to the perceived complexity of a shape, a set of Machine Learning models were trained. The independent variables of the models were the (i) complexity metric introduced in section 3.3, (ii) the number of voxels used to create the 3D shape, (iii) number of complete voxels, (iv) number of incomplete voxels, and (v) number of incline planes of the 3D shape. The dependent variables tested were the (i) average perceived complexity reported by participants when exposed to a 2D image of the shape (i.e., survey 2 responses) and (ii) the average correct response of participants on the Purdue Spatial Visualization Test (i.e., survey 1 responses). The responses of survey 3 were not explored given the low number of shapes analyzed (i.e., only 5 shapes).

A Support Vector Machine algorithm using a polynomial kernel was used to train the models. Moreover, a 10-fold cross-validation approach was used to assess the performance of the models. To help compare the model, both dependent variables were normalized in a range between 0-1. The results indicate that the model that had the average correct response of the Purdue test (i.e., spatial-visualization tasks) as a dependent variable had an average Mean Absolute Error (MAE) of 0.997 (SD= 0.005). Moreover, the model that had the perceived complexity as a dependent variable had had an average MAE of 0.9769 (SD= 0.073). While the model that has the average perceived complexity as a dependent variable had less error, the difference between both models' MAE was not statistically significant. When looking at the most important features, the number of incomplete voxels, the complexity metric used in this work, and the number of voxels used, raised to the top 3 for both models. This is supported by the correlation results shown in Fig. 8, suggesting that symmetry, number of elements, and surface variability are important factors that impact perceived complexity, as in previous studies (see sections 2), but also the performance of individuals in spatial visualization tasks.

5. CONCLUSION & FUTURE WORKS

Spatial visualization is an important skill needed in STEM fields. While VR has been used to help develop these skills, most of the existing applications do not necessarily tailor their content to the skills level of individuals. Automatically generating 3D shapes using Procedural Contented Generation method based on Reinforcement Learning approached [15-17] could help VR applications tailor spatial visualization tasks to the skills level of users. However, to do this, it is important to first understand how humans perceive the complexity of 3D shapes, and how this relates to their performance in spatial visualization tasks.

The results of this work indicate that while participants perceived complexity of 3D shape is correlated to their performance in spatial visualization tasks that use the same 3D shape, this perceived complexity by itself is not enough to predict their performance in such tasks. Moreover, the results indicate that certain visual features of 3D shapes might help explain the perceived complexity of the shape as well as the performance of individuals in spatial visualization tasks that implement those 3D shapes. These are promising results that suggest that computational models might be able to measure the perceived complexity of 3D shapes, particularly as it relates to spatial visualization tasks, by analyzing the visual features of the shapes.

This work lays the foundation that could help develop Reinforcement Learning-based methods to automatically generate 3D shapes of a given desired complexity. This by leveraging the Procedural Content Generation methods shown in in [15-17] and utilizing the 3D shape generation method and complexity metrics introduce in this work as part of the training environment and reward function of a Reinforcement Learning agent respectively. This could help VR application tailor their spatial visualization tasks to a user's unique skill level. This would ultimately help develop students' spatial visualization skills by increasing their motivation and state of flow while interacting with such applications.

However, this work has several areas of improvement. One of the biggest limitations of this work is that it did not explore 3D shapes with curvatures. As a result of this, a limited set of 3D shapes was explored, since only 21 shapes did not contain any curvatures from the Purdue Spatial Visualization test. While only 30% of the shapes presented in the Purdue test, contain shapes with curvatures, future work will explore the complexity of 3D shapes with curvatures, and test a wider range of 3D shapes that are not necessarily on the Purdue Spatial Visualization test. Moreover, the performance of individuals in the Purdue Spatial Visualization test, which is explored in this work, is not only dependent on the complexity of the shape used, but also on the skill level of the user and the rotations exemplified on the spatial-visualization task (e.g., see the top of Fig. 5). Hence, future studies will aim to control for these factors by increasing the number of participants, presenting a wider range of spatial visualization tasks with 3D shapes with multiple rotations, and assessing participants' skill levels. Similarly, another factor that could impact the perceived complexity of 3D shapes and the performance in spatial visualization task, is the communication channel used. For example, showing a 3D shape via a 2D display is not the same as showing the same 3D shape via a Virtual Reality headset. Hence, if the goal is to help design a VR application to develop spatial visualization skills, the impact of visualizing 3D shapes in 3D virtual environments need to be consider.

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