THE EFFECT OF PARAMETRIC PHYSICAL ATTRIBUTES OF 2D SHAPES ON SHAPE RECALL AND ON CLASSIFIYING SHAPES AS NATURAL OR UNNATURAL

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BY

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PLAGIARISM

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29,09,2021

ABSTRACT

Previous research in the visual perception domain has shown the interaction between some attributes of shapes and how humans perceive them differently when those attributes are changing. However we felt there are not enough resources in the literature regarding the geometrical parameters of 2D shapes. Also about the naturalness classification in visual perception, there are studies focusing on the natural scenes but again, the knowledge of the naturalness perception according to the 2D geometrical shape parameters is pretty limited. In this study we aimed at combining these two subdomains and providing quantitative findings about how the geometrical parameters like edge count, concavity, naturalness and uniformity are affecting the memory performance and naturalness classification for a shape. We designed a behavioural experiment to test different shapes with different values of those parameters and presented these shapes to participants in a recall task and a naturalness survey. Then we ran some correlation analysis between those values and memory performance and naturalness rating. We found out that edge count and concavity significantly affects the memory performance for a shape. Another finding was that our judgement of a shape being natural or artificial is affected by the edge count, concavity level and roundness level of a shape. Lastly, we observed that the memory performance is worse for the shapes that are rated as natural.

Key words: shape perception, naturalness perception, edge count, concavity, roundness, uniformity

ÖZET

Görsel algı alanında yapılmış çalışmalar şekillerin bazı özelliklerindeki değişimlerin bu şekillerin insan beyninde nasıl algılandığını etkilediğini ortaya koymuştur. Fakat geometrik özelliklerin şekil algısına etkisi konusunda henüz yeterince çalışılmamış ve sonuç bulunamamıştır. Aynı zamanda doğallık algısı konusunda da literatürde doğal görsellerin özellikleri ve nasıl algılandıkları konusunda çalışmalar olmasına rağmen iki boyutlu şekillerin doğal olarak değerlendirmesine sebep olan geometrik özellikler henüz yeteri kadar anlaşılamamıştır. Bu çalışmada bu iki alanın birlikte incelenmesi ve kenar sayısı, içbükeylik, yumuşak hatlılık ve düzgünlük gibi özelliklerin şekillerin görsel algısını ve doğallık algısını nasıl değiştirdiğine yönelik sayısal veriler sunulması amaçlanmıştır. Çalışmada bu amaca yönelik davranışsal bir deney tasarlanmış ve uygulanmıştır. Deneyde yukarıda bahsedilen özelliklerin farklı değerleriyle şekiller yaratılmış ve bu katılımcıların bu şekilleri yeniden yaratıp ne kadar doğal bulduklarını oylamaları istenmiştir. Daha sonra toplanan veri korelasyon analizinde kullanılmış ve özelliklerin değerleriyle şekillerin hatırlanma performansı ve doğallık puanı karşılaştırılmıştır. Bulunan sonuçlar özellikle kenar sayısı ve içbükeyliğin bir şeklin algılanmasını ve hatırlanmasını etkilediğini göstermiştir. Bir diğer bulgu şekillerin doğan olarak değirlendirmesinde kenar sayısı içbükeylik ve yumuşak hatlılığın etkisinin olduğudur. Son olarak doğal olarak değerlendirilen şekillerin hafıza performanslarının daha düşük olduğu gözlemlenmiştir.

Anahtar kelimeler: şekil algısı, doğallık algısı, kenar sayısı, içbükeylik, yumuşak hatlılık, düzgünlük

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1. INTRODUCTION

Among senses, vision is mostly considered as one of the most impactful sense in human perception (OBrien, Miller-Kuhaneck, 2020). As we can define the procedural order of the human cognitive system to be as attention - perception - memory, it can also be said that visual perception mechanisms are crucial for the whole human cognitive system as a starting point. Capabilities of visual perception make us able to extract complex information from the outer environment. However the most crucial contribution of visual perception is not to get and save the visual stimuli in the memory but making us organize, structure and interpret it (OBrien, Miller-Kuhaneck, 2020).

1.1 Visual Perception

The visual perception mechanism starts by receiving the visual stimuli from the environment by the anatomy of the eye. According to the type of the stimuli, different receptor cells are getting triggered. By the complex connections between eye receptor cells and occipital lobe, which is the area in the brain that specialized to interpret visual stimuli, these receptors cause firing of some related neurons according to the nerve connection network. Lastly, firing of the neurons on the occipital lobe triggers the neurons that will cause the network connection which will lead to storing that visual information in the cognitive system by sensory - short term - long term and working memory.

The capacity of human memory is limited. There are about one billion neurons in the human brain and on average one neuron connects with 1000 other neurons, which will make a total connection of above trillions. If one neuron would only store one memory instance then there will be a huge memory problem in our brains. Because the total storage space would be a few gigabytes, which equals to a USB drive. However neurons combine in a way that each one interacts with others and this mechanism increases the capacity to around 2.5 petabytes from a USB drive (Namaziandost, & Ziafar, 2020). Since the memory capacity is not infinite, our brain is evolved and structured to store the information effectively by selecting the important, relevant stimuli and interpreting and summarizing these stimuli instead of storing all the raw data. Even though this system is working so efficiently, the mechanisms of this summarization are not always perfect. For some occasions, the summarization rules and heuristic ways can lead to wrong deductions. The basis of modern understanding on the way we are making perceptual decisions about what we receive from the outer environment and where to attend comes by the consideration of the optimal ways to do these behaviours. Even though statistical computation provides good results in order to find the optimal solutions for a perceptual question, optimization needs excellent knowledge of priors and mostly complex computation. But in the light of the literature, it can be said that optimal value for a perceptual task can be found or at least approximated in a simpler way with the heuristic approaches of the human cognitive system (Gardner, 2019). One explanation to this heuristic approach can be by Gestalt principles while "Gestalt" meaning shape or form in German. Gestalt principles which also known as Gestalt laws are the rules of the organization of perceptual scenes. They were presented by a group of scientists called Gestalt psychologists in the early 1900's stating that when we see the outer world, we mostly perceive pretty complex scenes that consist of smaller elements that can even be composed of smaller parts on a background. Gestalt principles are providing ways to answer the question of "How do we accomplish such a remarkable perceptual achievement, given that the visual input is, in a sense, just a spatial distribution of variously colored individual points?". The aim of the Gestalt principles is to understand and formulate how the perceptual visual input got organized into unitary forms and groups generating regularities (Wertheimer, 1938). Since the visual perception is biased, it could be affected by many factors. In the next sections there are some explanations and examples for the implications of the biases on the perception of 2D or 3D shapes / objects.

1.1.1 3D Visual Perception

Even though the third dimension theoretically makes the visual perception mechanisms much more complex, visual perception is evolved to detect the cues of the third dimension for survival purposes. Some most common aspects of 3D perception are depth, motion, surface and shadow. The 3D objects vary on shading, image intensity, optical texture gradients, surface contours and line drawings depicting the edges and vertices of objects. According to findings in the study of Todd, qualitative aspects of 3D structure which can be reliably determined from visual information act like a base of perceptual representation of 3D shapes (Todd, 2004). Visual features like occlusion contours and high curvature edges which are mostly stable over the direction of view can be a data structure form for the representation of those qualitative properties. About the location of the activity for 3D shape perception, recent neuroimaging studies have shown that the neural processing of 3D shapes mostly exist throughout the ventral and dorsal visual pathways (Todd, 2004). The significance of object features in visual perception has long been acknowledged. A well-known theory from Biederman elaborating on how crucial the distinct visual parts are for the environment perception. According to Biederman, object recognition is dependent on the individual structure components and their general configuration within the context of the whole (Biederman, 1987). In the study about object recognition by components, Biederman found out that as the count of individual objects presented for a shape, object recognition performance has improved as can be seen in Figure 1 (stimuli example) and Figure 2 (results) *(Biederman, 1987).*

Figure 1

Object Recognition by Components, Stimuli Example (Biederman, 1987)

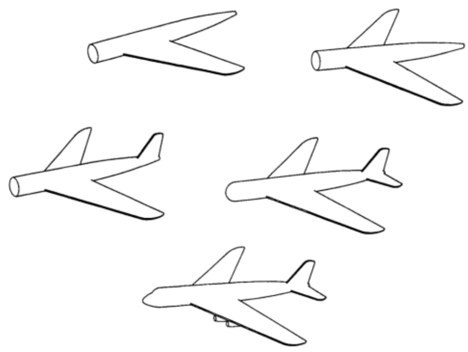
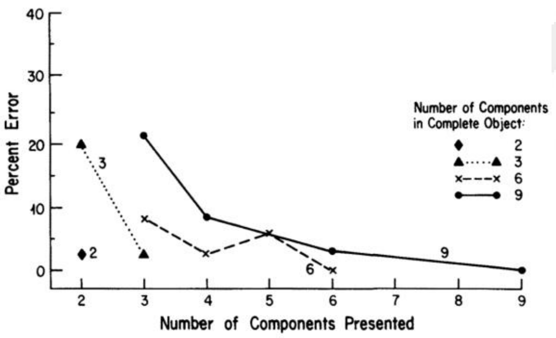


Figure 2

Object Recognition by Components, Results (Biederman, 1987)



The theory behind those studies is called recognition by components and is focused on structural geometric shapes. Later research however provided evidence that for visual perception, recognition of the components is actually not necessary and in most cases, humans evaluate the image by the general features instead of evaluating components separately. Thus the features may be interpreted as any compositional unit of a visual stimulus, including contours (Loffler, 2008), colors or textures or minimal elements of contrast, such as Gabor patches (Dong, & Ren, 2015). The circle of Zhang demonstrates the wide variation by adopting the broad conceptualization of visual features as any discrete components of an image that are detected independently of each other (Zhang et al., 2015).

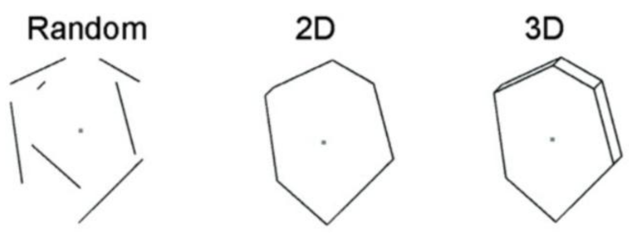
1.1.2 2D Visual Perception

2D stimuli can be claimed as a representation of the actual 3D environment. While the whole environment is hard to boil down to a 2D summary, individual objects are suitable for a 2D representation. Especially when their volume is high or their distance is far so that the receiving angle of the stimuli is more or less the same. Previous research showed that shape is a crucial information when reconstructing a 3D object from a 2D image in the human cognitive system (Matsuno, & Tomonaga, 2007). When summarizing the environment by 2D shapes, humans use heuristics again instead of an optimal 3D modeling. Thus a 2D perception of the environment is also not perfect or optimal but efficient. Understanding how we are making those judgments can be helpful to understand the underlying of the visual perception mechanisms. In section 1.1.2.1 we will go deeper to the attributes of 2D shapes to understand their relations with each other and their relation to visual perception in general.

Being able to group elements in a complex visual scene is one of the extraordinary capabilities of the visual system for humans. By this mechanism, our cognitive system can successfully simplify the description of an image. We can for example describe a bunch of parallel lines as a pattern instead of 14 lines, moreover in this case we would not even specify the features of the lines like location, length or orıentation but we focus on the pattern. This kind of grouping mechanism can actually be seen in the neuron activity level as well. As an example, if there is an element has some shared properties like orientation and length the neuron response on the primary visual cortex can be surpassed by the grouping mechanism. This kind of pattern context effect in the V1 area can be thought to be mediated by both local connections and interactions in the brain with higher areas (Murray et al., 2002). A study proved some differences in the perception of 2D and 3D shapes by using neuroimaging showing that the neural activation is different when the stimuli is a random stimuli, a proper 2D shape and a proper 3D shape. An example stimuli classification can be seen in Figure 3 (Murray et al., 2002). According to this study, LOC (lateral occipital complex) is a higher visual area critical for object shape perception (Murray et al., 2002). Findings of Murray et al. suggest that exposure to a shape stimuli increases the activity on LOC. Moreover it has shown that LOC activity is higher for proper shapes rather than the random line and the activity even increases when the stimulus is a 3D object instead of a 2D object (Murray et al., P, 2002). Reduced activity might be interpreted as a negative statement however it may afford several behavioral advantages. For example, by selectively decreasing activity in V1 for grouped elements, ungrouped or novel elements may be more readily detected. A practical example to that would be being able to detect the fruits between leaves. If we brain activity would be higher for leaves in this case, there might not be enough sources to detect the important stimuli, which is the fruit.

Figure 3

Stimuli Classification by Type in the Study of Murray et al (Murray et al., 2002).



A single 3D object will project infinity of different image configurations on the retina. Also the orientation object to the viewer is an infinite variable which will increase the number of 2D projections exponentially. This object can actually be occluded by other objects or texture fields, just like it is being viewed behind foliage. Thus the representation of the object is not necessarily a full-colored and texture image but it can be a simplified 2D line drawing instead (Sigman et al., 2001).

1.1.2.1 Geometric Attributes of 2D Shapes and Shape Perception

Representing the object shape is one of the main functions of the visual system. Among the visual properties of the objects, object shape has an important role in human visual perception as it is a strong determinant for isolating an object in a scene from it's environment (Matsuno, & Tomonaga, 2007). The theories related with shape perception are mostly focused on curvatures, symmetries and axis structure (Spröte et al., 2016). For a 2D shape, one of the major perceptual properties has been considered especially to be curvature. As Yu and Dyer explained, our physiological system can compute rigid transformations by its own. These transformations have been used extensively in shape matching and object recognition as well as for shape modeling in both 2D to 3D and 3D to 2D (Yu, & Dyer, 2001). For recognizing an object, interpreting an image and for shape perception, Local two-dimensional curvature is a visual cue which is highly helpful and impactful. There is a question raised by Langley about if our cognitive system is less or more sensitive to the geometric properties of visual curves and this question still remains debatable. (Dresp-Langley, 2015). Results of Spröte et al. suggests that shape perception does not only simply detect local features like depth, orientations, surface curvatures but it also involves some constructive processes. These constructive processes contribute by grouping local features in a purely geometrical way into complete objects. Actually this view contradicts with the highly flexible nature of perceptual organization as well as the high level computational difficulties involved in shape parsing and representation and potential cognition involvement in shape representation (Spröte et al., 2016). There are also studies with findings that the visual-cognitive system decomposes both familiar and unfamiliar objects into components with distinct causal origins. We can see this trend in the perceptual differences in intrinsic concavities and bites. Moreover there is a relation between those casual interpretations and symmetry, especially for computing the back and the front of the objects (Spröte et al., 2016). According to the study findings of Spröte et al., participants in an experiment were eligible to suppress concavity information caused by bites when expressing the information about an object's front and back as well as the symmetry (Spröte et al., 2016). The effect of context on shape interpretation can be seen in Figure 4 and effect of context on axis perception can be seen in Figure 5 (Spröte et al., 2016).

Figure 4

Effect of Context on Shape Interpretation (Spröte et al., 2016)

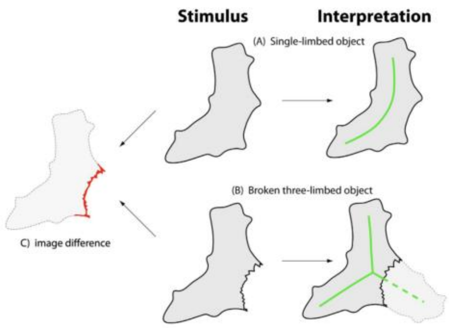
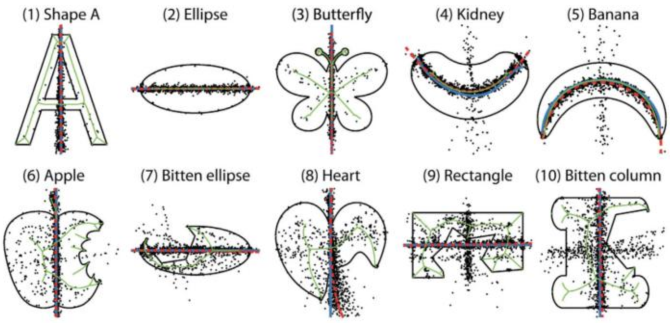


Figure 5

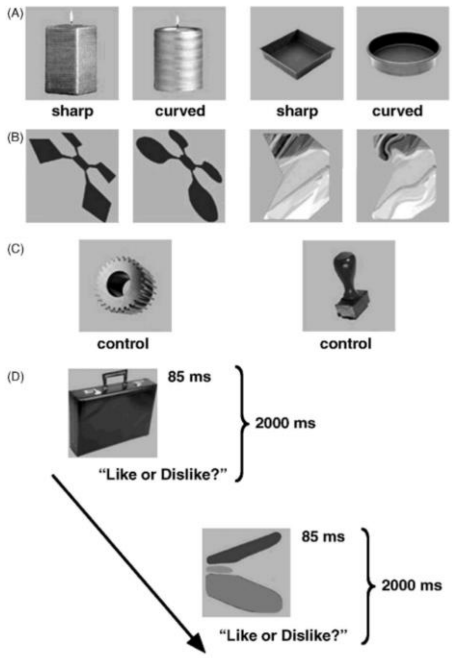
Effect of Context on Axis Perception (Spröte et al., 2016)



Thus curvature plays a crucial role in interpreting a shape or object. However the degree of curvature is also a decision point that can affect preference and memory. In a previous study it had been shown that curvature has an advantage on human preference over shapes and curvy shapes are causing a lower activation in Amygdala compared to sharper shapes (Bar, & Neta, 2007). Sample shapes that are used in this study can be seen in Figure 6 (Bar, & Neta, 2007).

Figure 6

Sample Sharp and Curved Shapes (Bar, & Neta, 2007)



Another crucial factor for shape perception in addition to the concavity and curvature is the edge detection. According to Yang et al., for image segmentation edge detection is one of the basic computation metrics, moreover it is not only involved in image segmentation but also in feature extraction and image matching. However the accuracy of the current detection algorithms are questionable since they are using a convolution operation in the spatial domain which can easily lead to losing the overall characteristics of the image (Yang et al., 2013).

For our study, in order to represent shapes by the values of some attributes, we had to choose the abstract physical attributes that would be enough to define a 2D shape. In the light of the previous studies we decided to focus on 4 attributes; edge count, concavity, roundness and uniformity. There are different methods in the literature about generating random 2D shapes with mathematical values. Since in our use case we wanted to edit the shapes by the values of the attributes we chose, we followed a similar method that Sohel presented by using the Bezier curves and Bernstein polynomials for random shape generation (Sohel et al., 2010). Then we made additions to the already existed model and used the mathematical values of our four selected attributes as explained in more detail in section 2.1.2.1.

1.1.3 Evolution of Visual Perception

In the early stages of the perceptual evolution, vertebrate species were using a visual perception mechanism that was dominated by the information most probably transmitted via the retinotectal visual pathway while attention was primarily controlled by the selective network that is located in the midbrain. However as the evolution progressed through the primates retinogeniculate visual pathway which is located in the forebrain started to dominate the visual perception by supplying the information transmission. At the same time, location of attention activities also shifted to the forebrain. For non-primate mammals and the birds, both the retinotectal and retinogeniculate pathways contribute critically to visual information processing, and both midbrain and forebrain networks play important roles in controlling attention. Even though there is an independent evolutionary process going on for birds and mammals for around 300 million years, the computations and processing strategies still share pretty similar characteristics (Knudsen, 2020). It is not surprising that some closer species share some visual perception mechanisms. As mentioned in the previous sections, concavity creates an advantage on shape memory. A study by Matsuno and Tomonaga presented a similar behavior for chimpanzees. According to the findings of this study, chimpanzees showed a better performance for concave shapes in a shape recognition task (Matsuno, & Tomonaga, 2007). Sample stimuli of this experiment can be seen in Figure 7 and the Result summary can be seen in Figure 8

Figure 7

Recognition Task Stimuli Shapes for Chimpanzees (Matsuno, & Tomonaga, 2007)

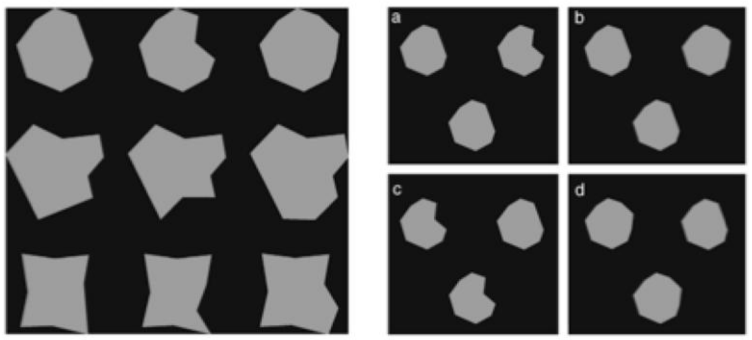
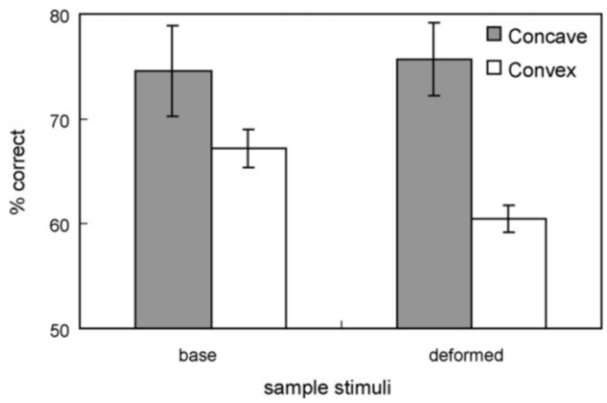


Figure 8

Recognition Task Results for Chimpanzees (Matsuno, & Tomonaga, 2007)



It is an accepted fact that evolution is not favoring the optimal perfect solutions but the best fit solutions instead. We can confidently claim that this is the same for the evolution of visual perception, moreover for the whole cognitive system as well. As Hoffman describes, perception is a product of evolution. Thus, just as our organs like liver and kidneys, the perceptual system is also shaped by natural selection. “For the perceptions of H. sapiens, space-time is the desktop and physical objects are the icons. Our perceptions of space-time and objects have been shaped by natural selection to hide the truth and guide adaptive behaviors. Perception is an adaptive interface. Natural selection is a search procedure that yields satisfactory solutions, not optimal solutions.” (Hoffman, 2018). The sensory pathways of animals are well adapted to processing a very high number of signals from the environment of the animal. A characteristic of the natural stimuli is that an important portion of it is redundant. Thus a processing and simplification is redundant for a natural scene (Atick, 1992).

For a while it has been assumed by the scientists that statistical properties of the exposed stimuli caused a target adaptation for the neurons through both the developmental and evolutionary processes. A famous theory proposed which is called information theory was expected to provide a link to neural responses by the coding efficiency perspective and the environmental statistics. However even though there is a general agreement about it in the literature, there are still not enough concrete and quantitatively precise findings (Simoncelli, & Olshausen, 2001).

If evolution had favoured the best accuracy, all the living organisms would be able to see all the details of the environment with all the aspects possible like color, texture, dimension until the atoms, which will be much above the cognitive capacity of all organisms. However it evolved for best fit, and that is why some species have trichromacy, why some are better in motion detection and why some are using different clues. In summary it would be expected for human visual perception to be evolved for the stimuli that they got exposed to throughout their evolution. Nowadays a human living in cities has a completely different environment from infantry compared to apes. Our knowledge about the perception of natural environments compared to nowadays' artificial environments is pretty limited.

1.2 Naturalness

We can define naturalness as the degree to which the system would change if humans were removed (Anderson, 1991). It is not an independent measure but a comparable one. Hence we can express it by the opposite of being artificial.

1.2.1 Perception of Natural Scenes

Even though the certain classification can be tricky, natural scenes are the scenes with elements found in nature without human interaction. Many studies that successfully detected some common statistical properties of natural images. Understanding the statistics of natural scenes are important because they have crucial implications on target recognition, image denoising and image compression. They can even help understanding the anatomy of the visual system. However, unfortunately natural images have specific and complex structures which kill the chances of explaining them with some simple parametric statistical models like Gaussian models and it is said that the noise in images is more often clutter and the statistics of clutter is not Gaussian at all (Huang, & Mumford, 1991).

Figure 9

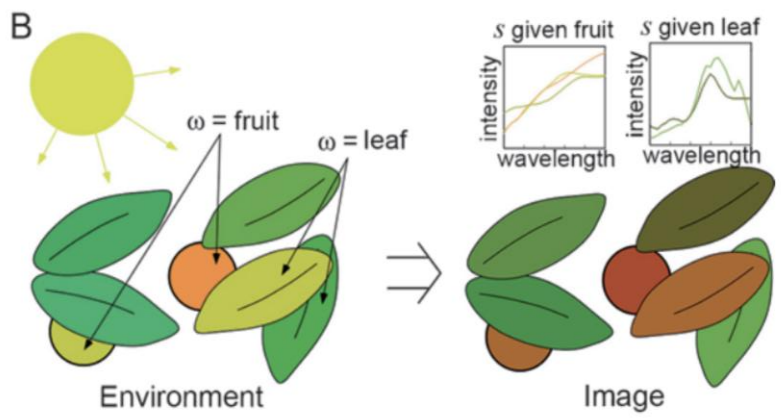
Pixel Distribution in Natural and Artificial Scenes (Huang, & Mumford, 1991)

Studies on natural image statistics mostly focus on the spatial frequency, hue, independent components, gabor filters and wavelets of the natural images. By the evidence from the previous studies, we know that there are some rules that make humans decide if a scene is natural or artificial. For example, Kardan et al. showed the interactive contribution of edge and color related characteristics of a natural scene on defining an image as natural or not. In addition, in the same study, researchers generated a machine learning algorithm to validate the generalizability of their models. They successfully trained a classifier using the same algorithm for distinguishing an image being liked or disliked with a 70% accuracy. Their results claimed that: “There can be low-level visual regularities of natural environments that we are “programmed” to gain benefits from while the benefits can be esthetic pleasure among others lower SED (more non-straight surfaces, borders, and shades), lower hue level (lower hue means more yellow-green content rather than blue-purple content), as well as higher diversity in saturation (scene containing both low and highly saturated colors) predicted more preference, adjusting for the other visual features” (Kardan et al., 2015)

1.2.2 Natural Objects

Natural objects are the objects that exist in the environment without human touch. Just as the natural scenes, natural objects also have their own statistical properties. For example because of the morphological consistency of objects, nearby pixels are pretty similar in the visual appearance for natural images. In these images, the luminosity profile changes gradually in space and only at borders or edges abruptly. Also when we look at the natural images from the color perspective, we observe smoothness and continuity. Thus it can be said that in the natural images, there is a high degree of spatio-temporal and chromatic correlation among pixels. In this case pixel by pixel representation will not be suitable for natural scenes. It is inefficient as it is formed by the photoreceptor mosaic (Atick, 1992).

Nonetheless we have gathered information about the statistical properties of natural scenes and the characteristics of the scenes that are considered as natural for humans, we are behind on the classification of natural for the objects and shapes. When elements are perceived as belonging to the same object in natural scenes, they are mostly grouped. Shape of an object is a feature that is only represented in higher stages of the visual system, thus any effect of perceived shape on lower areas would require feedback processes (Murray et al., 2002). As Murray et al. says, some properties of the scenes can be boiled down to the properties of 3D objects and 2D shapes. Thus understanding what makes a shape natural can help understanding the general perception about naturalness. Geisler also suggested that there are similarities as well as differences for the actual natural environments versus natural images by focusing on the wavelength (Geisler, 2008). As can be seen in Figure 10, wavelength distinction is not as clear in a natural scene compared to the actual environment. This implies the crucial role of 2D representation and shape detection for visually perceiving



the natural environment

Figure 10

Wavelength Difference for a Natural Image Versus Actual Environment (Geisler, 2008)

1.3 Aim of The Study

Visual perception is one of the most commonly researched topics in the cognitive science and neuroscience domains. However we actually don’t know much about how we visually perceive 2D shapes, and how as humans we differ from other species about processing the shapes that we see. We don't know how and why our superior shape perception evolved. We don't know for what kind of shapes that we are exposed to caused these adaptations. In this study we wanted to understand the optimal shapes that humans can perceive and remember. Also we want to understand what kind of shapes that humans perceive as natural. If we would understand the optimal values of geometric attributes, and the cross relations between those attributes for a 2D shape to be remembered and to be classified as natural, we would be able to understand the specific mechanisms for superior human shape perception and for what kind of shapes and for what reason it evolved.

Much of the previous research has shown the relation between the attributes of shapes and how humans perceive them differently when those attributes are changing. Most studies in the area successfully showed the correlation between memory and attributes like contour, spatial frequency and texture. Also there are many studies focusing on the attributes of 3D shapes like luminance, smoothness, angle, depth and polarity. However our knowledge on the relation between memory and geometric attributes of 2D shapes like edge count, concavity, roundness and uniformity is pretty limited. Also there are not enough articles that are showing the effect of geometric attributes of 2D shapes into classifying shapes as being natural or artificial. We believe there is a lot to be done and understood yet in this area. The aim of our study is to provide statistical correlations between the attributes: edge count, concavity, roundness, uniformity, and memory performance and naturalness perception.

1.3.1 Hypotheses

Specific research questions of this study are: Is there a positive or negative correlation between geometrical attributes of 2D shapes (edge count, concavity, roundness, uniformity) with the memory performance for the shapes? Is there a positive or negative correlation of the values of the attributes with perceiving a shape as natural or artificial? What are the optimal values of each attribute for the human vision to comprehend and recall shapes? Is the memory performance better or worse for the shapes rated as natural?

In order to validate the hypotheses of the study we designed a behavioural experiment where we display shapes with different physical attributes to the participants. We then asked them to recall the shape by manipulating the values of the attributes. As a last task we asked participants to rate how natural they consider this shape on a scale from 1-5.

2. EXPERIMENT

2.1 Methods

2.1.1 Participants

Total count of participants in the experiment was 20, all those participants were in the range of 18-35 years old with an average of 24.8 and either university graduates or students. None of them reported any illness, psychological or physical disorders. All participants were given a gift card and undergraduate students were given a course credit in addition.

2.1.2 Stimuli and Procedure

2.1.2.1 Creating Shapes with Geometric Attribute Values

As mentioned in section 1.1.2.1, we defined 4 parameters as edge count, concavity, roundness and uniformity to define a 2D shape. We used a mathematical model that takes the values of the parameters as the input and generates a 2D shape as the output. As the base of this model, we used Bernstein Polynomials as seen in equation (1) and Bezier curves as seen in equation (2).

$$\begin{aligned} d_{k,j}^{n}(\bar{a}) &= \frac{1}{\rho_n}\binom{n}{k}\sum_{i=1}^{j} p_{k,i}\,\bar{p}_{n-k,j-i} \\ &= \frac{1}{\rho_n}\binom{n}{k}\sum_{i=0}^{j}(-1)^{j-i} p_{k,i}\sum_{h=j-i}^{n-k} p_{n-k,h}\binom{h}{j-i}. \end{aligned} \tag{1}$$

$$\begin{aligned} \ddot{B}_{k}^{n}(t;\bar{a}) = &\sum_{i=n-k}^{n-1}\alpha_{n,i}\left(\sum_{j=n-k}^{n-1}\alpha_{i,j}B_{n-k}^{j}(1-t;\bar{a}) - \sum_{j=i+k-n}^{i-1}\alpha_{i,j}B_{i+k-n}^{j}(t;\bar{a})\right) \\ &- \sum_{i=k}^{n-1}\alpha_{n,i}\left(\sum_{j=i-k}^{i-1}\alpha_{i,j}B_{i-k}^{j}(1-t;\bar{a}) - \sum_{j=k}^{i-1}\alpha_{i,j}B_{k}^{j}(t;\bar{a})\right). \end{aligned} \tag{2}$$

We extended these mathematical formulas to have the parameter values as the input. These inputs adjust the vectors that form a shape so we became able to create a desirable shape according to the values of the parameters. Each section below has the details of how we formulated the mathematical model for each attribute. In order to have reasonable experiment duration, we selected a discrete value set for each parameter instead of a continuous range.

2.1.2.1.1 Edge Count

For the edge count we defined 4 possible values to be used as 5-6-7-8. The reason we came up with those options is that we had to limit the total number of options as the total number of trials are limited. Thus we wanted to select the option set which will create the maximum diversity among shapes.

2.1.2.1.2 Concavity

In the literature concavity and convexity are mostly mentioned as the opposites of each other, thus a curve is considered as either concave or convex. However in our study we are not looking at the local curves but we are looking at the whole shape instead. Hence as one edge gets concave, the other edge becomes convex and the concavity measure for us in this study is also the measure of convexity. Thus as the value of the concavity increases, shapes get away from neutral and become both convex and concave. However, the way we adjust the concavity is by decreasing the vector length of some edges. As an outcome we generate a concave edge when we increase the value of the concavity. The formula that we used for vector length manipulation is: (X2 , Y2) = (X1 * concavity value, Y1 * concavity value). But an important question there was to decide how many and which edge vectors should be manipulated. We decided to make the edge selection definitive and we defined a rule for it. We assigned indexes to each edge according to their vector angle and ordered them ascending by angle. For example the edge on the top right corner of the shape would have 1 as the index. Then we took the edge count of the shape: E and selected E / 2 as the count of edges to be manipulated. Lastly we manipulate the edges as they become one normal - one concave until we reach E / 2 concave edges. Total scale of the concavity parameter is between 0-1 and the discrete options we selected are 1.5, 4 and 8.

2.1.2.1.3 Roundness

Roundness is the curvature degree of the Bezier curve. So if the value of the roundness is 0, then the connections between edges are straight and the edges are sharp. The input scale of the roundness is 0-1. For the different kinds of shapes that are shown to the participants, we used the discrete values of roundness as 0.1, 0.5 and 0.9.

2.1.2.1.4 Uniformity

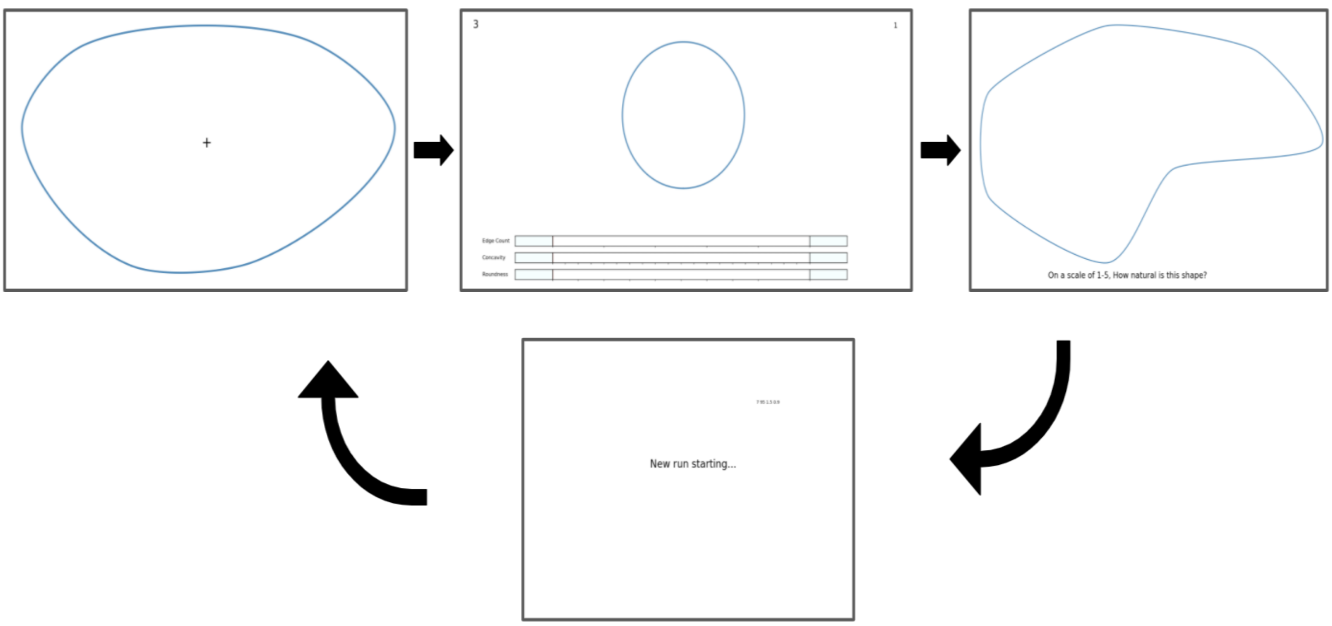
Uniformity is the only hidden variable of the experiment. It can be considered as the opposite of randomness. If we had not involved uniformity in the experiment, all shapes would be perfect shapes. For example a shape with 6 as the edge count, 0 as the concavity and 0 as the roundness would be a geometrically perfect hexagon. But we designed the experiment to have a higher variety of shapes and also we wanted to understand if uniformity of a shape is affecting the naturalness perception. Total scale of uniformity is between 0 - 100 while 0 has high randomization and 100 has no randomization at all. The technique that we use for randomization is manipulating the length of the vectors. We are setting the vector length of each edge as the value of the uniformity + random value. So as the uniformity increases, length of vectors will be equal, or decreased only by a rule for concavity. The discrete values that we selected for these parameters are 1, 50 and 95.

2.1.2.2 Procedure

In order to test the performance of the different shapes, we designed a behavioral experiment. In this experiment, we were generating shapes with different values of our four parameters; edge count, concavity, roundness and uniformity. Our hypotheses are on two topics; memory performance and naturalness perception. Thus we required two tasks from participants. First task was on memory performance and the second task was on natural perception. The details of those tasks are given in the sections below. We generated a shape for each and every combination of 4 parameter values. Which makes a total of 4 (edge count) * 3 (concavity) * 3 (roundness) * 3 (uniformity) = 108 distinct shapes and there was an experiment run for each shape. For each run, the main flow of the experiment is showing the shape for a limited time then recall task and then naturalness task.

Figure 11

Experiment Flow



2.1.2.2.1 Apparatus

The experiment was held in the computer engineering laboratory of the university for 16 of the 20 participants. For the other 4 participants, it is held in a residential room with the same computer setup as in laboratory. Laboratory was isolated so that there was no noise or distraction. Lighting of the laboratory was random according to the experiment time of the day but it was always bright enough to easily detect every object. Screen size for the experiment was 320x220 mm and the horizontal distance from the participant eye to the screen was 600 cm. Computer background was black and the stimuli background was white. Experiment is programmed using Python 3.5 on Pycharm. A standard F type keyboard and a standard mouse has used in the experiment. All participant data was stored anonymously and a voluntary participation form has signed by participants.

2.1.2.2.2 Noise Shapes

When displaying the shapes, we wanted to avoid the recency effect and sensory memory effect. So we added some noise shapes before and after showing the actual shape (will be mentioned as the target shape from now on). Noise shapes were generated with the same method that target shapes are created. The only difference is that instead of selecting discrete possible parameter values, these shapes could get any value between the value scale of the parameter. As the visual stimuli, we showed 8 shapes in total to the participants. In each run, among those 8 shapes there was only 1 target shape and the other 7 are noise shapes. The display order of the target shape among 8 total shapes was random between indexes 3, 4, 5, 6. We did not show the target shape as the first or second shape to make sure that the participant is not blindsided to the target. Also we did not show it as the last two shapes to avoid the recency effect. The reason that the shape is not shown in a defined same index in each run but we randomize instead is that we did not want participants to neglect the noise shapes and get prepared for the target shape. For participants to detect the target shape, we draw it with the thick border which has double line width compared to noise shapes. At the beginning of the experiment, participants are instructed to try to remember the shape with the thick border.

2.1.2.2.3 Fixation Task

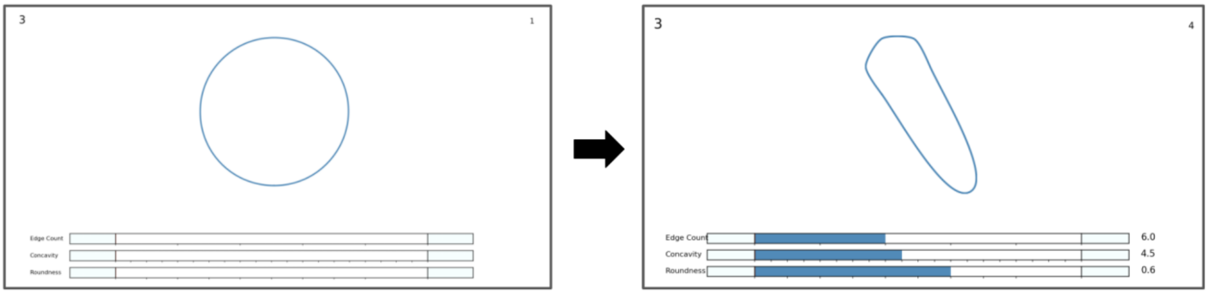
In order to avoid participants not paying attention / not looking at the shapes after the target shape, we added a basic fixation task to the experiment. We placed a fixation point at the center of the shapes which is shaped as a + sign. Fixation change occurred based on color. In the duration of displaying each shape, fixation color is changed from black to red with a probability of 20%. We instructed participants to press the space key on the keyboard when they see the fixation change. We did not measure the performance of the fixation task as the reason we placed it was to keep the attention on the participants on the noise shapes. Display duration of both the noise and target shapes were 200 milliseconds and there were no blank screens between.

2.1.2.2.4 Recall Task

For each run, after the display section ended for the 1 target and 7 noise shapes, a recall task began for the participants. In this task, participants tried to regenerate the target shape by manipulating the values of edge count, concavity and roundness on a slider scale. Right after the display section ended, participants got exposed to a screen with an initial circle shape and 3 sliders (Figure 12). Participants have 8 seconds for the recall task.

Figure 12

Recall task



As the participants moved the slider by using the mouse, the parameter values changed and the shape changed accordingly. By playing the values of those sliders, participants tried to have a shape which is as close to the target shape as possible. The scale and the increments of the slider was on 4 - 9 scale with the increment of 1 for edge count, 0 - 10 scale with the increment of 0.5 for concavity and 0 - 1 scale with the increment of 0.1 for the roundness. Default parameter value on the initial screen was 4 for edge count and 0 for the other parameters. Uniformity was not in the recall task because it was a hidden variable. After the duration of 8 seconds passed, the screen closed with the last values and the responses were recorded. The rotation of the shape could change among target shape and regenerated shape. Participants were informed about it in the introduction and told not to pay attention to the rotation of the shape.

Figure 13

Shape Change on Edge Count Value

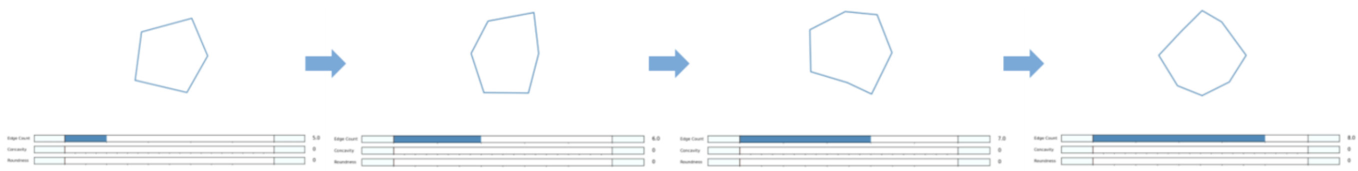


Figure 14

Shape Change on Concavity Value

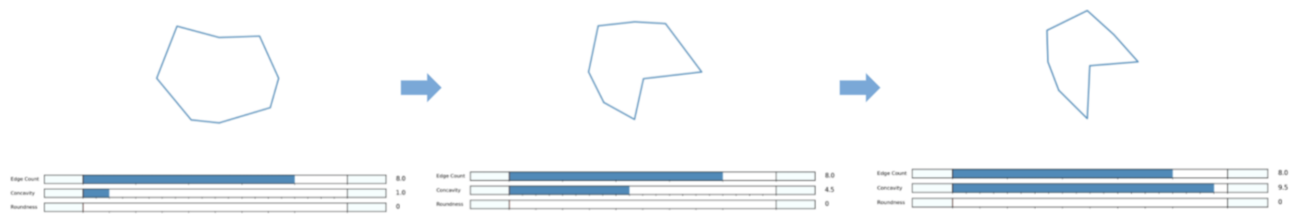
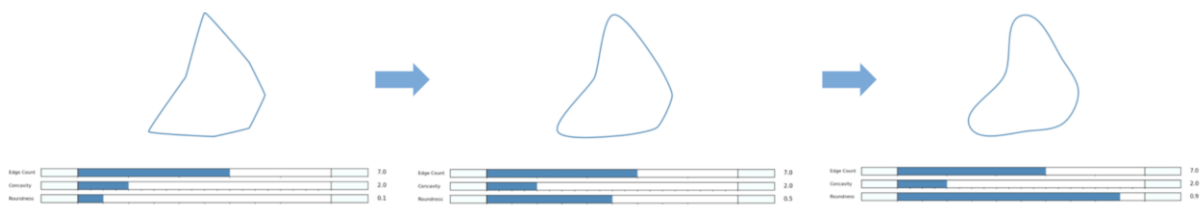


Figure 15

Shape Change on Roundness Value



2.1.2.2.5 Naturalness Task

Right after the recall task ended, the naturalness task began. In this part of the experiment, a shape was shown to the participants and participants were asked to rate how natural they think the shape is on a scale from 1 - 5 as 5 being very natural and 1 being not natural. A single shape was shown in this task and the shapes were mixed up in the order so the shape on the recall task was not the same with the shape of the naturalness task in the same run. There was not a time limit for the naturalness task and participants gave their response by pressing 1-2-3-4-5 buttons on the keyboard when they decided. After the naturalness task was done, the response was saved and the next run started after 2 seconds of a screen with the text “Next run is starting” on a white background.

2.1.2.2.6 Tutorial

There was no grouping among participants in the experiment so all the participants had gone through the same process and same stimuli for the experiment. Each session had 108 shapes and took around 25 minutes on average. We decided to make 3 identical sessions with each participant in order to increase the significance of the analysis. Each session was exactly the same and participants had a break of 10 minutes between sessions. Total experiment time was around 1hour 40 minutes on average including the experiment brief and tutorial. Before starting the experiment, participants were briefed about the topic of the experiment, what are the tasks and what is expected from them. Then there was a tutorial of 10 runs for 10 sample target shapes. Tutorial runs were exactly the same as the real experiment runs. After the tutorial, the experiment supervisor started the experiment. From the moment that experiment was started, participants were not instructed anymore and continued the experiment on the computer until the session ended.

2.1.3 Data Tables - Analysis

Responses of the participants have saved automatically by the Python program. As the independent measures, we stored the participant number, session number, parameter values, display index and the fixation performance as a boolean for each shape including noise shapes along with the target shapes. Also in a separate table we stored the same information above but only for the target shapes. In addition, we stored the responses for each parameter from the recall task. Lastly we had a separate table for the naturalness task with participant number, shape index, parameter values and the naturalness response from the participants. In addition to the independent measures, we created calculated measures for the performance. First measure is the match percentage for each parameter. It is calculated by the formula: 100 - ((|Actual Value - Response| / Scale length) * 100). Lastly in order to measure the overall memory performance, we took the average of match percentages for all 3 parameters. The trials that participants had not made any change in the sliders are marked as pass trials and they are excluded from the analysis.

2.2 Results

We categorized our results and correlation analysis into three main topics. In the first section we focused on the effect of each parameter on the memory performance. In the second section the effect of parameters on naturalness perception is analyzed. Lastly we checked the correlation between memory performance and naturalness rating.

For the analysis tool we used Tableau for the basic charts and tables with means and standard deviations. For the statistical analysis we used JASP. We did our first analysis on finding correlation coefficients between each independent variable and dependent variables, which are memory performance and naturalness rating, by using 2-tailed Pearson Correlation test on JASP. For the second analysis we also want to see the interaction between independent variables and their multi dimensional effect on dependent variables, thus we used Repeated Measures ANOVA analysis on JASP.

2.2.1 Memory Performance on Recall Task

2.2.1.1 Single Parameter Comparison

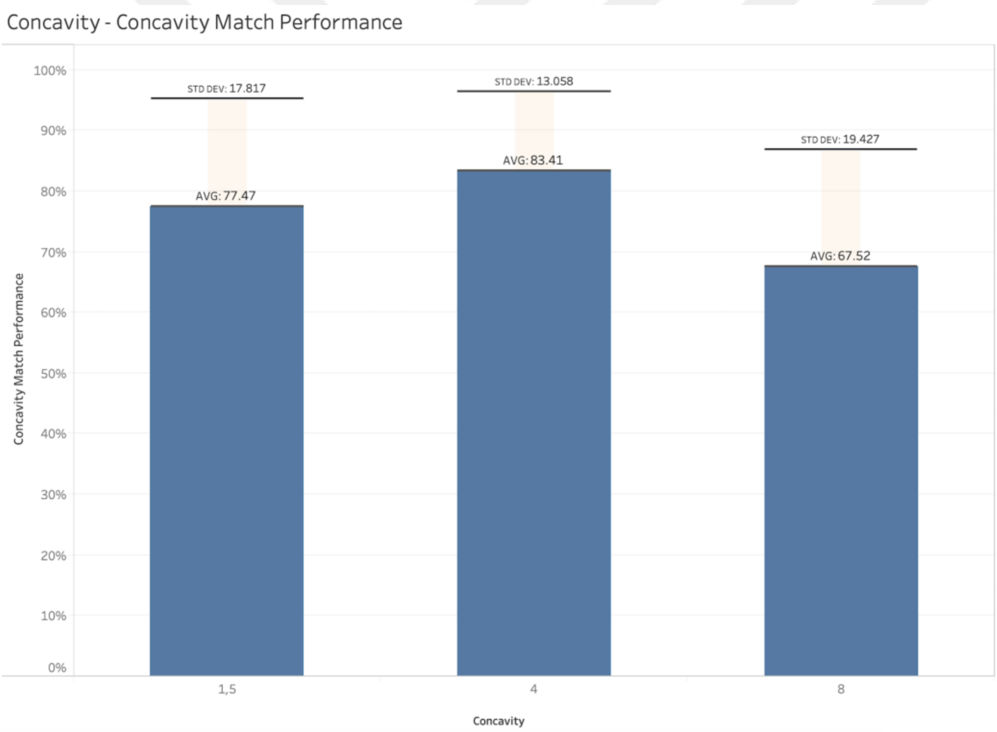
For single parameter comparison, we checked the correlation between the actual parameter value of a shape and the match performance measure for the same parameter. Our aim was to understand if the memory performance for a parameter changes with the value of that same parameter.

2.2.1.1.1 Concavity - Concavity

For concavity memory performance (M = 76.110 SE = 18.213) and concavity value, the observed increase was not continuous as the performance increased when concavity values increased from 1.5 (M = 77.47 SE = 17.817) to 4 (M = 83.41 SE = 13.058) but then decreased from 4 to 8 (M = 67.52 SE = 19.427). The increase was statistically significant on 0.01 level with the Pearson correlation coefficient of -0.219.

Figure 16

Concavity – Concavity Results



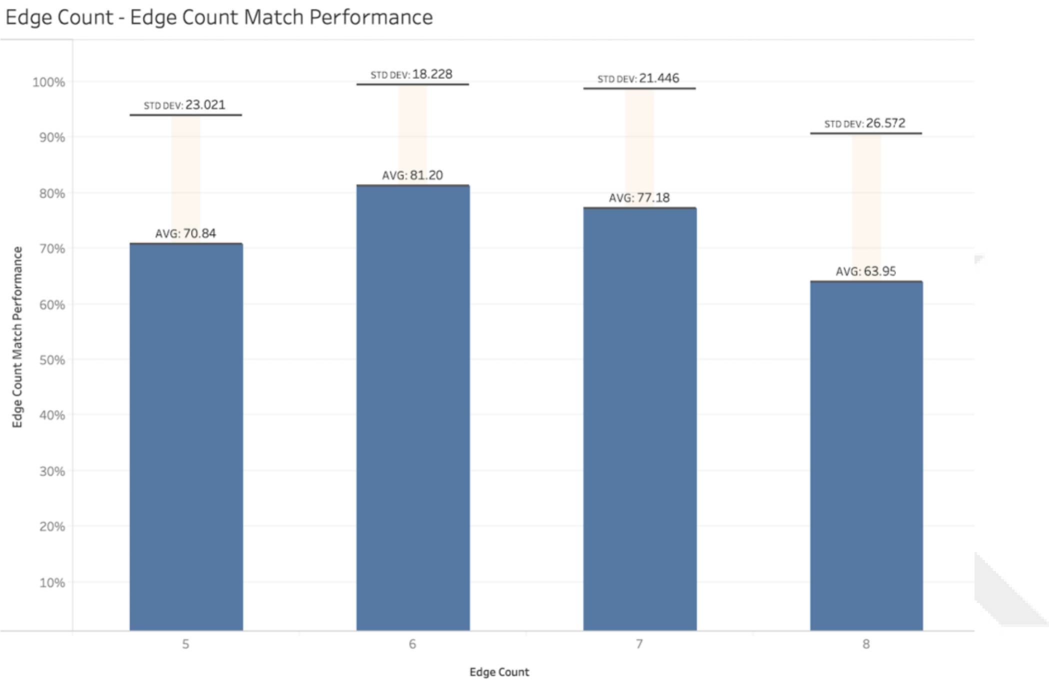
2.2.1.1.2 Edge Count - Edge Count

For edge count memory performance (M = 73.291 SE = 23.442) and edge count value, there was not a continuous correlation as the performance increased from 5 (M = 70.84 SE = 23.021) to 6 (M = 81.20 SE = 18.228) but then decreased continuously from 6 to 8 (M =

63.95 SE = 26.572). The increase was statistically significant on 0.01 level with the Pearson correlation coefficient of -0.130.

Figure 17

Edge Count – Edge Count Results

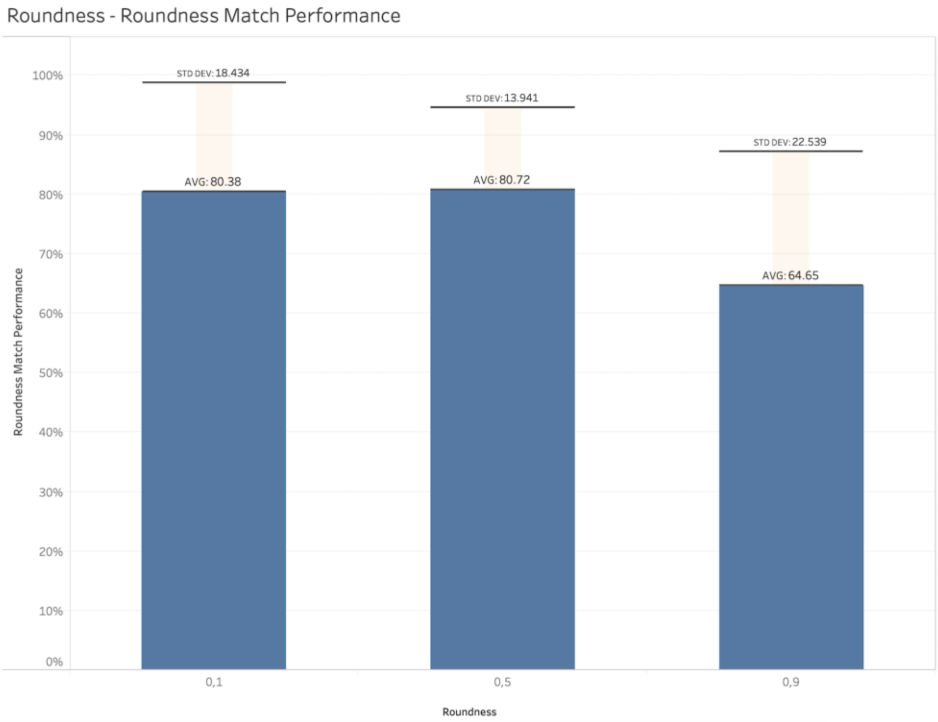


2.2.1.1.3 Roundness - Roundness

For roundness memory performance (M = 75.224 SE = 20.126) by roundness value, a significant decrease was observed in memory performance when roundness value has increased from 0.1 (M = 80.38 SE = 18.434) to 0.5 (M = 80.72 SE = 13.941) and to 0.9 (M = 64.65 SE = 25.539).

Figure 18

Roundness – Roundness Results



2.2.1.2 Dual Parameter Comparison

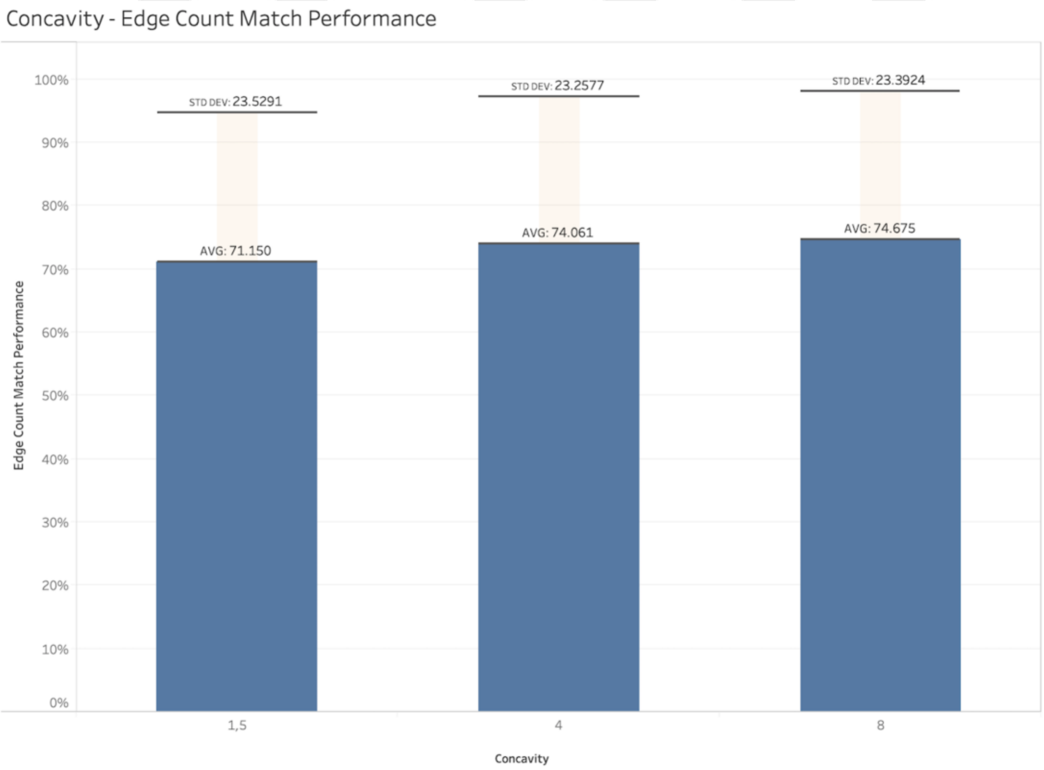
For the dual parameter comparisons, we checked the cross correlations between the actual parameter values of a shape and the match performance measure for a different parameter. Our aim in doing that was to understand the effect of a parameter to detect and memorize the values of other parameters.

2.2.1.2.1 Concavity - Edge Count

As can be seen in the figure below, edge count memory performance (M = 73.291 SE = 23.442) has increased as the concavity value increased from 1.5 (M = 71.150 SE = 23.529) to 4 (M = 74.061 SE = 23.258) and 8 (M = 74.675 SE = 23.392). Positive correlation between concavity and edge count memory performance was significant at 0.01 level with the correlation coefficient of 0.062.

Figure 19

Concavity – Edge Count Results

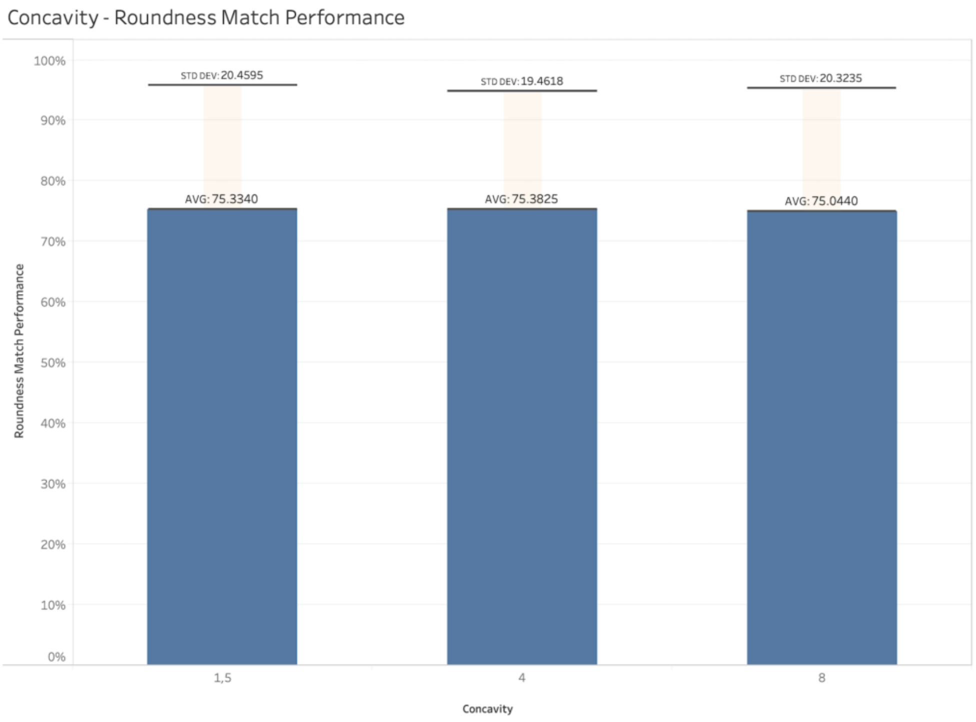


2.2.1.2.2 Concavity - Roundness

Roundness memory performance (M = 75.224 SE = 20.126) decreased as the concavity value increased from 4 (M = 75.382 SE = 19.461) to 8 (M = 75.044 SE = 20.325). However the correlation is not statistically significant.

Figure 20

Concavity – Roundness Results

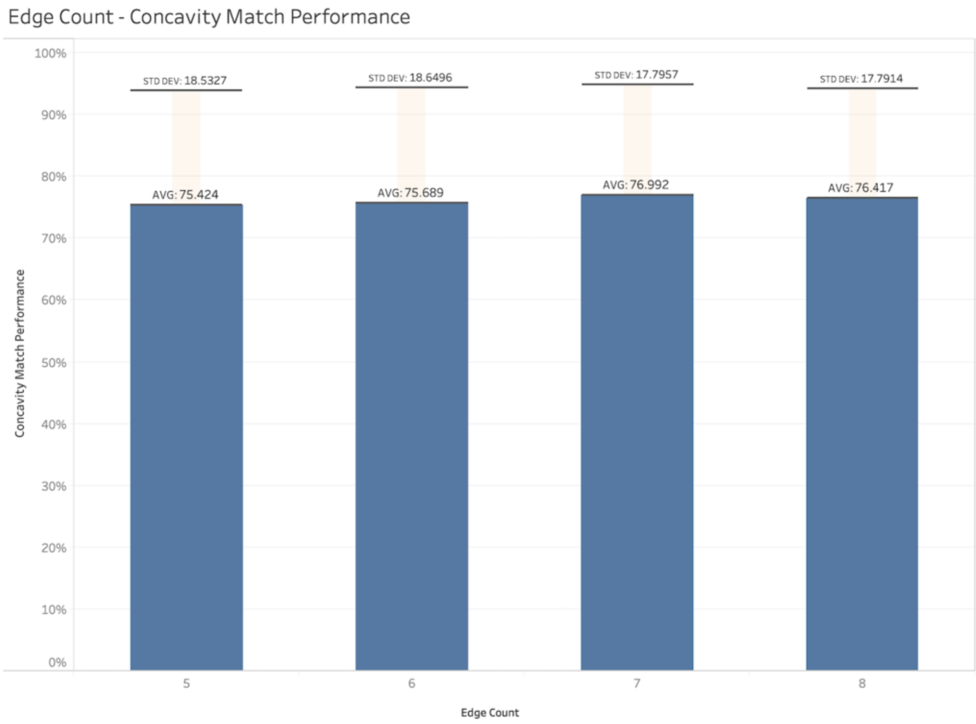


2.2.1.2.3 Edge Count - Concavity

There was a significant increase on concavity memory performance (M = 76.110 SE = 18.213 when edge count value has increased up to 7 (M = 72.992 SE = 17.796) from 5 (M = 75.424 SE = 18.533) and from 6 (M = 75.689 SE = 18.650), but when edge count value reached 8 (M = 76.417 SE = 17.791), there was a decrease in the concavity memory performance. Even though the correlation is not continuous, it was still significant at 0.05 level with the correlation coefficient of 0.035.

Figure 21

Edge Count – Concavity Results

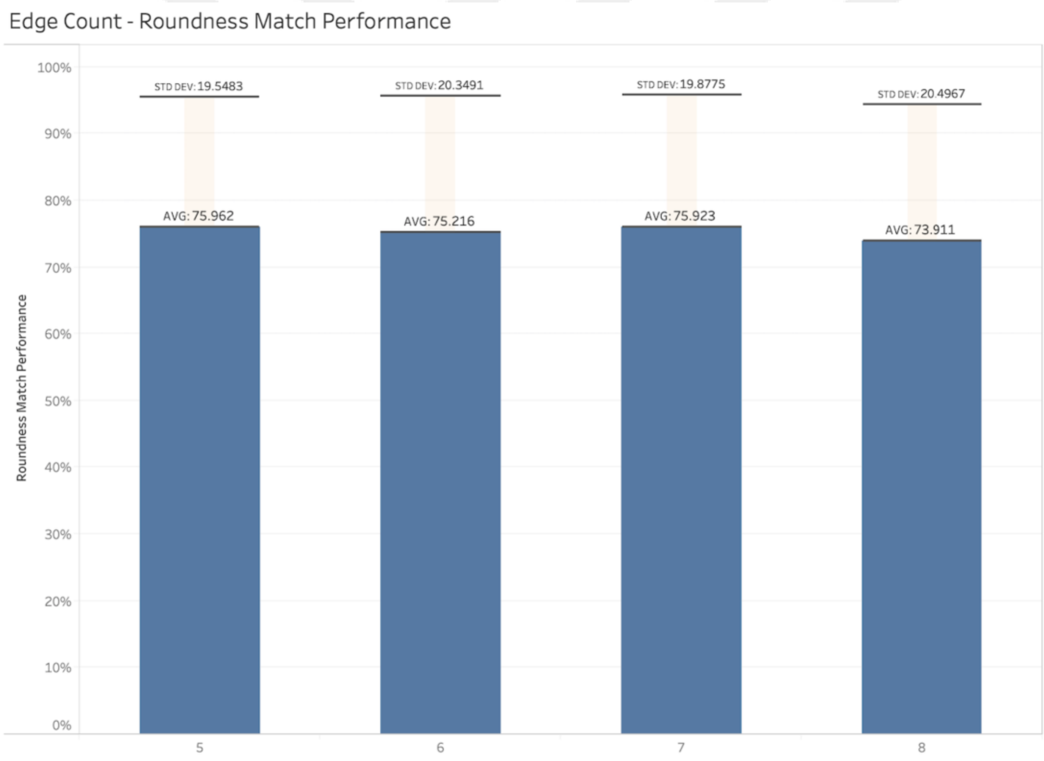


2.2.1.2.4 Edge Count - Roundness

For edge count value and roundness memory performance (M = 75.224 SE = 20.126), neither a positive or negative correlation has observed. The only finding was roundness memory performance being higher for odd number of edge count which are 5 (M = 75.962 SE = 19.548) and 7 (M = 75.923 SE = 19.878) compared to even number of edge count which are 6 (M = 75.216 SE = 20.349) and 8 (M = 73.911 SE = 20.497).

Figure 22

Edge Count – Roundness Results

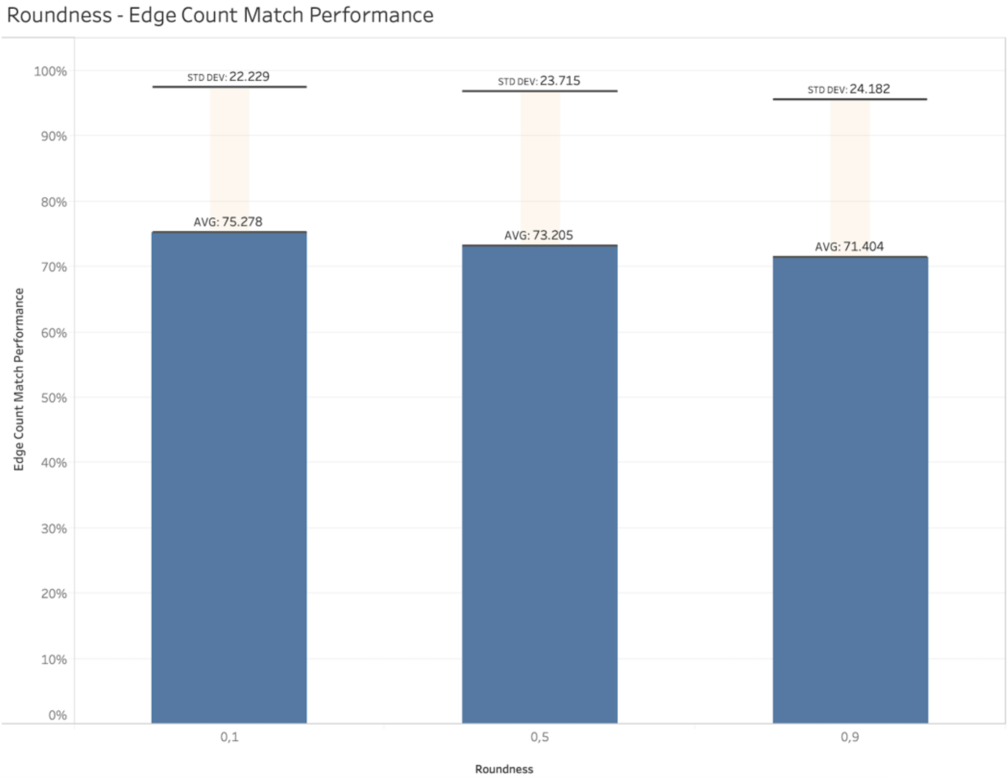


2.2.1.2.5 Roundness - Edge Count

There was a statistically significant negative correlation between roundness and edge count memory performance (M = 73.291 SE = 23.442). Edge count memory performance decreased when roundness value increased from 0.1 (M = 75.278 SE = 22.229) to 0.5 (M = 73.205 SE = 23.715) and to 0.9 (M = 71.404 SE = 24.182). Correlation coefficient was 0.070 and it was significant at level 0.01.

Figure 23

Roundness – Edge Count Results

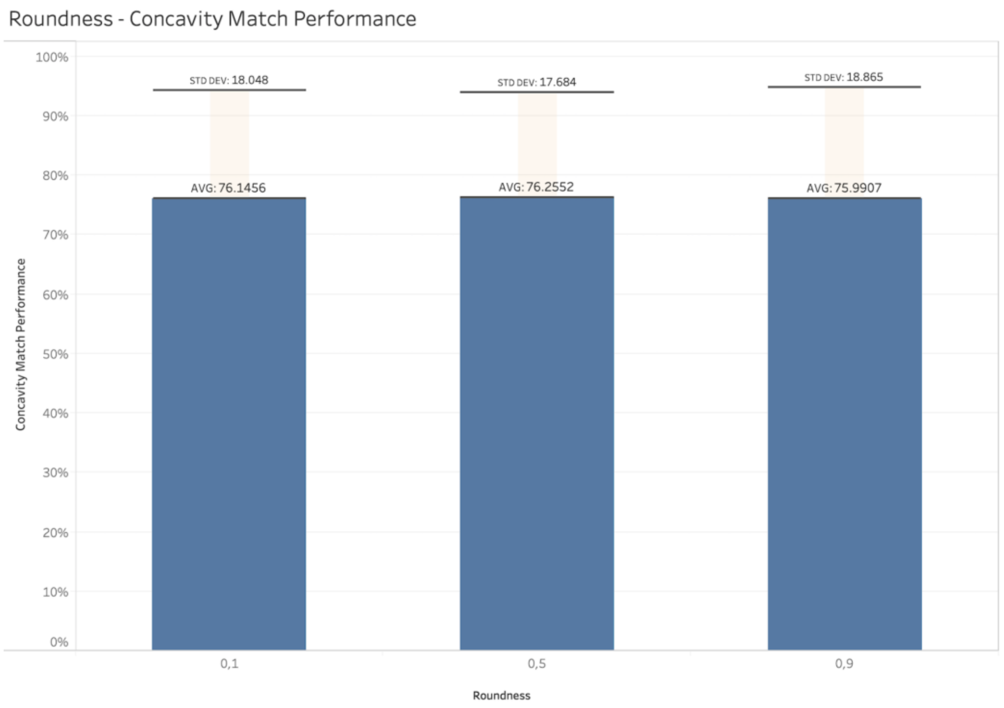


2.2.1.2.6 Roundness - Concavity

Concavity memory performance (M = 76.110 SE = 18.213) increased as the roundness value increased from 0.1 (M = 76.146 SE = 18.048) to 0.5 (M = 76.255 SE = 17.684) but when the roundness value increased to 0.9 (M = 75.991 SE = 18.865), concavity memory performance decreased. The decrease was not continuous however it was significant at 0.01 level with a correlation coefficient of 0.059.

Figure 24

Roundness – Concavity Results



2.2.1.2.7 Uniformity

For uniformity value no significant correlation is observed with the memory performance of other three parameters.

2.2.2 Naturalness Perception

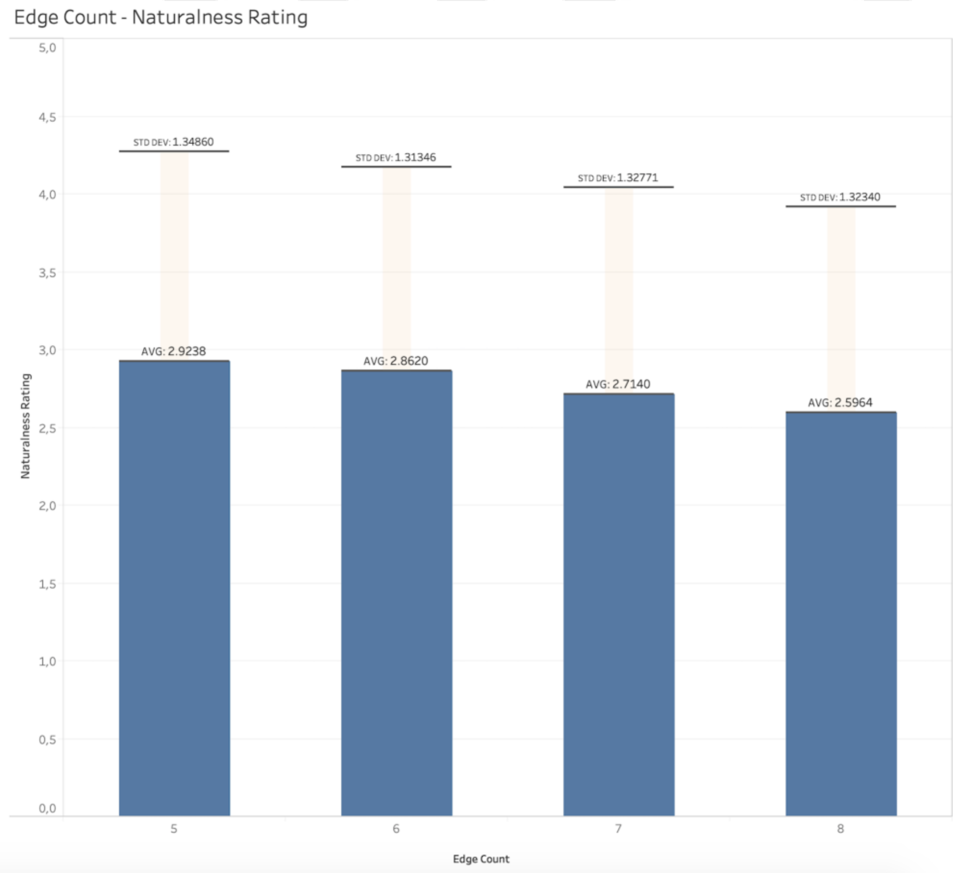
In this section we analyzed the correlation between the values of the parameters and participants ratings about naturalness. The goal was to understand the effect of each parameter on the natural - artificial classification.

2.2.2.1 Edge Count - Naturalness

A strong negative correlation between edge count value and the naturalness perception (M = 2.695 SE = 1.393) has identified. Correlation was continuous for all the values of edge count: 5 (M = 2.923 SE = 1.348), 6 (M = 2.862 SE = 1.313), 7 (M = 2.714 SE = 1.328) and 8 (M = 2.596 SE = 1.323). Correlation coefficient was -0.088 and it was significant at 0.001 level.

Figure 25

Edge Count – Naturalness Rating

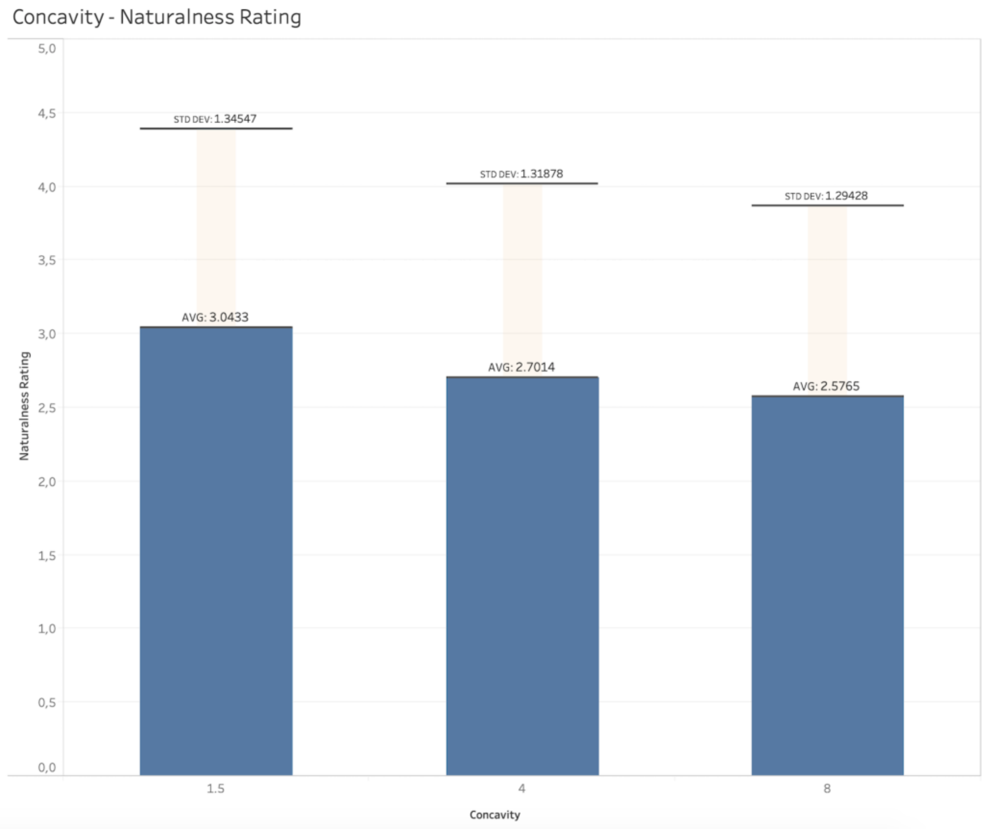


2.2.2.2 Concavity - Naturalness

A strong negative correlation is observed between concavity value and naturalness rating (M = 2.695 SE = 1.393). Naturalness rating decreased significantly as concavity value increased from 1.5 (M = 3.043 SE = 1.345) to 4 (M = 2.701 SE = 1.319) and 8 (M = 2.577 SE = 1.294). Correlation coefficient was -0.129 and it was significant at 0.001 level.

Figure 26

Concavity – Naturalness Rating

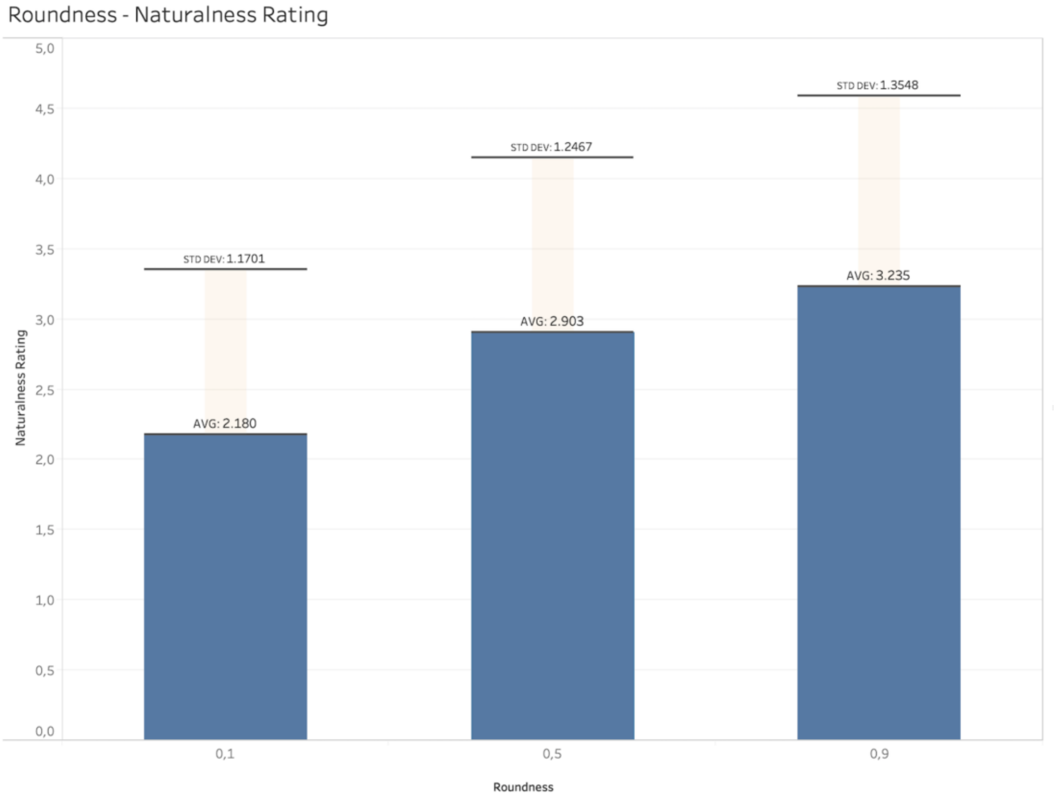


2.2.2.3 Roundness - Naturalness

We also observed a statistically significant correlation between roundness value and naturalness rating (M = 2.695 SE = 1.393). Naturalness rating increased as the roundness value increased from 0.1 (M = 2.180 SE = 1.170) to 0.5 (M = 2.903 SE = 1.247) and 0.9 (M = 3.235 SE = 1.355). Correlation coefficient was 0.304 and it was significant at level 0.001,

Figure 27

Roundness – Naturalness Rating



2.2.2.4 Uniformity - Naturalness

When the value of the uniformity increased, an increase is observed in naturalness value, however the correlation between uniformity and naturalness was not statistically significant.

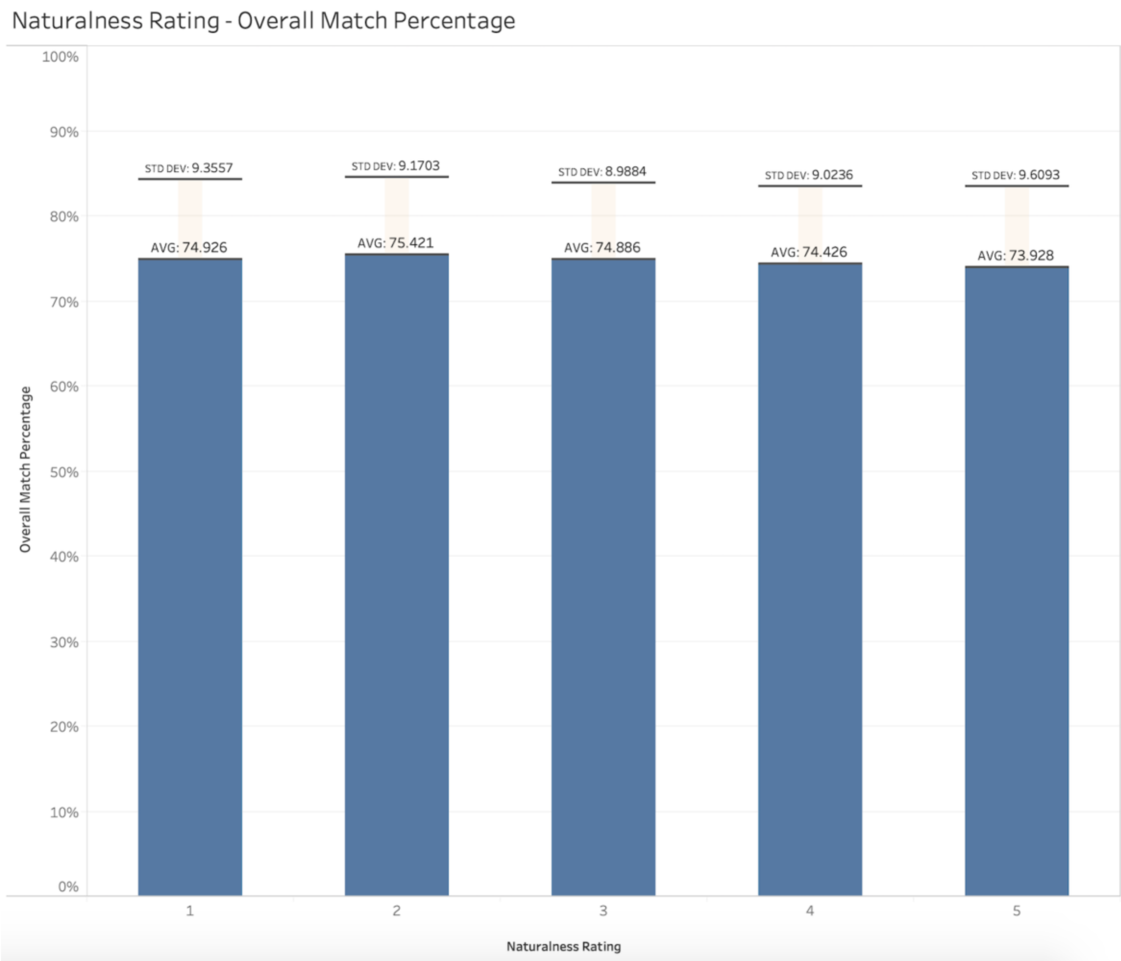
2.2.3 Memory by Naturalness

Our aim in this part was to see if the shapes that are rated as natural have an advantage or a disadvantage over other shapes considering the memory performance. Previous research has shown that viewing images of nature scenes can have a beneficial effect on memory and humans having a preference on natural scenes. Thus the shapes that are rated as natural could have higher match percentages. On the other hand, in the light of the previous studies we know that the cognitive system uses its capacity effectively so it could be evolved that it would focus the sources for the unnatural object among a collection of natural objects in a scene. If this is the case, then the match percentage of the shapes that are rated as natural could be lower compared to others.

We checked the overall memory performance had (M = 74.874 SE = 9.184) by the naturalness rating and there was a negative correlation between them with a -0.051 Pearson correlation coefficient and 0.001 level of significance. However the negative correlation was not continuous as when naturalness rating increased from 1 (M = 74.926 SE = 9.356) to 2 (M = 75.421 SE = 9.170), average match percentage also increased but then it decreased when naturalness rating was 3 (M = 74.886 SE = 8.998), 4 (M = 74.426 SE = 9.024) and 5 (M = 73.928 SE = 9.609).

Figure 28

Average Match Percentage by Naturalness Rating



2.2.4 Result Summary

For the memory performance on recall task, results show that there is a clear negative correlation between edge count match percentage and roundness while there is a positive correlation between edge count match percentage and roundness. For concavity memory performance, there was an increase as edge count increases from 5 and 6 to 7, but then there was a decrease for edge count 8. In order to decrease the complexity, we used overall match percentage in ANOVA analysis, which is the average of three match percentages for each parameter. Table 1 shows the Repeated Measures ANOVA analysis for edge count, concavity and roundness (for section 2.2.1), also Table 2 shows the descriptive summary of the analysis. Uniformity is not placed in this analysis since there were no statistically significant findings for uniformity. In Table 5, the average match percentages of each 3 parameter for each three parameters combination can be seen.

For naturalness rating, all parameter values except uniformity provided a significant correlation. Average naturalness rating increased when roundness increased and concavity and roundness decreased. Repeated Measures ANOVA analysis for all parameters can be seen in Table 3 and descriptive summary can be seen in Table 4. Also in Table 6, the average naturalness rating can be seen by the combination of each three parameters.

For match percentage by naturalness rating, there was a negative correlation but it was not a continuous correlation since overall match percentage increased when naturalness rating increased from 1 to 2.

Table 1

Memory Performance Repeated Measures ANOVA Results

Repeated Measures ANOVA

Within Subjects Effects

Cases	Sum of Squares	df	Mean Square	F	p
Edge Count	2820.018 [a]	3 [a]	940.006 [a]	15.082 [a]	< .001 [a]
Residuals	11031.775	177	62.326		
Concavity	2994.877 [a]	2 [a]	1497.438 [a]	38.344 [a]	< .001 [a]
Residuals	4608.244	118	39.053		
Roundness	4415.839 [a]	2 [a]	2207.920 [a]	42.780 [a]	< .001 [a]
Residuals	6090.088	118	51.611		
Edge Count ✻ Concavity	961.237	6	160.206	6.970	< .001
Residuals	8136.530	354	22.985		
Edge Count ✻ Roundness	136.086	6	22.681	1.170	0.322
Residuals	6860.301	354	19.379		
Concavity ✻ Roundness	112.709 [a]	4 [a]	28.177 [a]	1.301 [a]	0.270 [a]
Residuals	5110.067	236	21.653		
Edge Count ✻ Concavity ✻ Roundness	287.013 [a]	12 [a]	23.918 [a]	1.025 [a]	0.423 [a]

Within Subjects Effects

Cases	Sum of Squares	df	Mean Square	F	p
Residuals	16513.539	708	23.324		

Note. Type III Sum of Squares
[a] Mauchly's test of sphericity indicates that the assumption of sphericity is violated (p < .05).

Table 2

Memory Performance Repeated Measures ANOVA Results - Descriptive

Descriptives

Edge Count	Concavity	Roundness	Mean	SD	N
5	1.5	0.1	75.289	5.897	60
		0.5	75.801	5.474	60
		0.9	74.917	5.275	60
	4	0.1	76.803	5.026	60
		0.5	76.650	5.011	60
		0.9	73.241	5.460	60
	8	0.1	74.280	5.313	60
		0.5	73.472	5.908	60
		0.9	70.028	4.960	60
6	1.5	0.1	77.412	6.419	60
		0.5	77.051	4.905	60
		0.9	75.032	6.739	60
	4	0.1	78.419	5.986	60
		0.5	78.310	5.194	60
		0.9	76.310	6.227	60
	8	0.1	74.843	5.597	60
		0.5	74.611	5.301	60
		0.9	71.880	6.739	60
7	1.5	0.1	76.419	6.353	60
		0.5	76.125	5.469	60
		0.9	72.829	6.460	60
	4	0.1	78.600	5.903	60
		0.5	78.403	4.650	60
		0.9	75.530	5.883	60
	8	0.1	76.329	5.759	60
		0.5	76.231	5.562	60
		0.9	71.861	7.282	60
8	1.5	0.1	73.352	6.061	60
		0.5	73.157	5.612	60
		0.9	69.236	6.022	60

Table 2

Memory Performance Repeated Measures ANOVA Results - Descriptive

Descriptives

Edge Count	Concavity	Roundness	Mean	SD	N
	4	0.1	76.278	5.634	60
		0.5	75.062	7.424	60
		0.9	72.850	5.925	60
	8	0.1	73.854	7.289	60
		0.5	74.157	5.836	60
		0.9	70.428	7.657	60

Table 3

Naturalness Rating Repeated Measures ANOVA Results

Repeated Measures ANOVA

Within Subjects Effects

Cases	Sum of Squares	df	Mean Square	F	p
Edge Count	33.372 [a]	3 [a]	11.124 [a]	18.833 [a]	< .001 [a]
Residuals	101.004	171	0.591		
Concavity	86.559 [a]	2 [a]	43.280 [a]	30.862 [a]	< .001 [a]
Residuals	159.871	114	1.402		
Roundness	413.641 [a]	2 [a]	206.820 [a]	87.851 [a]	< .001 [a]
Residuals	268.382	114	2.354		
Edge Count ✻ Concavity	4.947 [a]	6 [a]	0.825 [a]	2.271 [a]	0.037 [a]
Residuals	124.184	342	0.363		
Edge Count ✻ Roundness	12.113	6	2.019	5.502	< .001
Residuals	125.481	342	0.367		
Concavity ✻ Roundness	10.044 [a]	4 [a]	2.511 [a]	6.585 [a]	< .001 [a]
Residuals	86.947	228	0.381		
Edge Count ✻ Concavity ✻ Roundness	3.308	12	0.276	0.882	0.566
Residuals	213.862	684	0.313		

Note. Type III Sum of Squares

[a] Mauchly's test of sphericity indicates that the assumption of sphericity is violated ($p < .05$).

Table 4

Naturalness Rating Repeated Measures ANOVA Results – Descriptive

Descriptive

Edge Count	Concavity	Roundness	Mean	SD	N
5	1.5	0.1	2.190	0.974	58
		0.5	3.287	1.034	58
		0.9	3.902	1.054	58
	4	0.1	2.161	0.968	58
		0.5	3.011	0.929	58
		0.9	3.420	1.062	58
	8	0.1	2.218	0.948	58
		0.5	2.974	0.919	58
		0.9	3.259	0.924	58
6	1.5	0.1	2.445	0.959	58
		0.5	3.259	0.953	58
		0.9	3.670	0.957	58
	4	0.1	2.126	0.979	58
		0.5	2.914	0.827	58
		0.9	3.299	0.845	58
	8	0.1	2.233	0.962	58
		0.5	2.810	0.831	58
		0.9	3.014	0.951	58
7	1.5	0.1	2.391	0.959	58
		0.5	3.247	1.069	58
		0.9	3.546	1.066	58
	4	0.1	2.098	0.881	58
		0.5	2.851	0.890	58
		0.9	3.052	0.951	58
	8	0.1	1.894	0.853	58
		0.5	2.595	0.816	58
		0.9	2.862	0.943	58
8	1.5	0.1	2.362	0.937	58
		0.5	3.103	0.963	58
		0.9	3.342	1.026	58
	4	0.1	2.046	0.966	58
		0.5	2.578	0.954	58
		0.9	2.914	0.908	58
	8	0.1	2.014	0.937	58
		0.5	2.454	0.967	58

Table 5

Average Match Percentages by Parameter Values

Edge Count	Concavity	Roundness	Avg. Concavity Match (%)	Avg. Edge Count Match (%)	Avg. Roundness Match (%)
5	1,5	0,1	76,31%	71,11%	80,17%
		0,5	75,89%	72,63%	83,07%
		0,9	77,72%	75,56%	66,22%
	4	0,1	83,19%	73,61%	80,78%
		0,5	83,56%	69,58%	82,06%
		0,9	82,25%	68,75%	64,72%
	8	0,1	67,16%	70,08%	80,22%
		0,5	66,31%	69,03%	82,61%
		0,9	66,33%	67,22%	63,89%
6	1,5	0,1	77,50%	82,50%	83,39%
		0,5	78,53%	81,39%	80,22%
		0,9	80,47%	77,92%	66,00%
	4	0,1	84,47%	82,40%	78,83%
		0,5	84,39%	82,78%	78,17%
		0,9	83,52%	79,75%	66,09%
	8	0,1	63,42%	82,50%	81,39%
		0,5	64,03%	82,78%	79,67%
		0,9	64,97%	78,75%	63,17%
7	1,5	0,1	78,06%	77,64%	81,28%
		0,5	79,47%	73,75%	80,11%
		0,9	76,86%	70,83%	64,94%
	4	0,1	85,03%	78,77%	81,62%
		0,5	83,78%	77,36%	81,61%
		0,9	81,53%	76,67%	66,11%
	8	0,1	69,72%	82,22%	79,61%
		0,5	70,19%	81,25%	82,28%
		0,9	68,33%	76,11%	65,78%
8	1,5	0,1	75,69%	61,25%	79,11%
		0,5	76,61%	53,47%	79,22%
		0,9	76,47%	55,51%	60,06%
	4	0,1	82,83%	70,28%	80,78%
		0,5	83,08%	65,42%	79,89%
		0,9	83,28%	63,47%	63,94%
	8	0,1	70,36%	70,97%	77,39%
		0,5	69,22%	69,03%	79,72%
		0,9	70,17%	66,06%	64,80%

Table 6

Average Naturalness Ratings by Parameter Values

		Roundness		
Concavity	Edge Count	0,1	0,5	0,9
1,5	5	2.206	3.227	3.891
	6	2.392	3.260	3.614
	7	2.391	3.211	3.528
	8	2.356	3.064	3.366
4	5	2.129	3.024	3.418
	6	2.149	2.888	3.273
	7	2.131	2.840	3.062
	8	2.041	2.560	2.875
8	5	2.211	2.943	3.260
	6	2.318	2.790	3.060
	7	1.871	2.564	2.818
	8	1.977	2.477	2.647

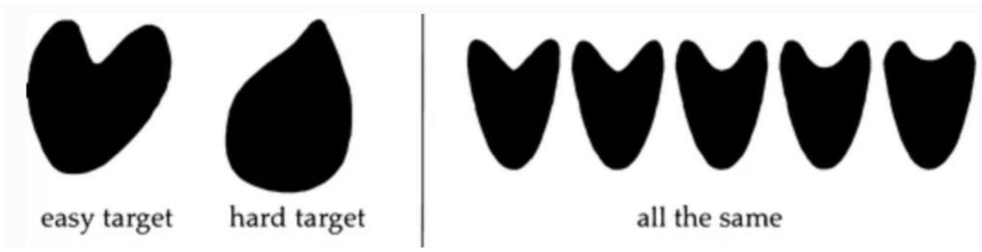
3. DISCUSSION

3.1 Hypotheses and Outcomes

In our study we found that the memory performance drops for edge count and concavity when their values increase. This finding favors simpler shapes with low number of edges and low concavity for the memory performance. Similar findings were found in eye tracking studies about concavity like the study of Bertamini et al. (Bertamini et al., 2012). However in the study of Bertamini et al. the effect of the degree of the concavity had not observed as the results were same for different concavity levels which can be seen in Figure 29. Our results however suggest that degree of concavity also matters for the memory performance.

Figure 29

Effect of Concavity Level for Eye Tracking Study (Bertamini et al., 2012)



Moreover, we have found some evidence supporting the independent components theory as we observed a positive correlation between concavity value and edge count memory performance. Concavity creates independent parts in the shapes, which makes visual perception to perceive components and edges easier and hence remember it better. The study of Bell and Senjowski suggests that independent components are helping to detect edges

(Bell, & Sejnowski, 1997). This creates an expectation towards memory performance of edge count to be higher as the concavity value increases, which is aligned with our results.

Correlation between concavity and edge count was not the only finding about concavity and edge count. Our results showed a significant increase in concavity memory performance when edge count increases up to 7. This finding actually supports the bitten affect theory of Spröte about concavity stating that the perception of concavity becomes stronger when the concave part shares a smaller angular share of the whole shape, as known as the bitten effect (Spröte, & Schmidt, 2016). When edge count increases, angular share of the concave component decreases and it makes it easier to detect, perceive and remember the concavity in a better way. However we also spotted a decrease in concavity memory performance when edge count increase to 8 from 7. Thus there should be an optimal value of this angle for bitten effect. According to our results from discrete values, optimal concave component share is $360° / 7 \approx 50°$. However for this experiment we only worked with 4 discrete values of edge count. Another experiment that focuses on continuous values can lead a more significant number of the optimal angle for bitten effect.

As previous studies also showed similar findings, sharp edges are easier to detect. Our study stands as a proof for the literature since we found a significant negative correlation between roundness value and edge count memory performance. Interestingly we observed the same trend of roundness on concavity as well. Because in our results, concavity memory performance was also negatively correlated with the roundness value. We unfortunately could not find a significant result considering the uniformity correlation of the match performance of other parameters. In Figure 30 and Figure 31, one example of most and least remembered shapes based on overall memory performance can be seen.

Figure 30

Most Remembered Shape Type

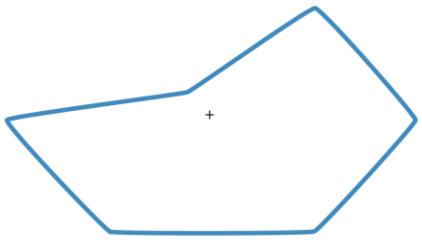
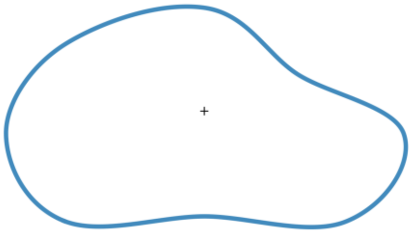


Figure 31

Least Remembered Shape Type



Our finding about naturalness perception being positively correlated with roundness is a validation that the naturalness perception in this experiment is affected by the characteristics of the actual objects in nature as natural objects tend to be more rounded than sharp. Moreover, naturalness rating decreased significantly as concavity value and this outcome is also aligned with the objects in the nature, because due to the entropy rule, organic objects in nature tend to avoid concavities. Thus this can be another validation that there are common aspects between the naturalness perception of 3D objects and 2D shapes as their representation. In Figure 31 and Figure 32, the shapes that are rated as most natural and least natural can be seen.

Figure 32

Shape Type Which has Perceived as Most Natural

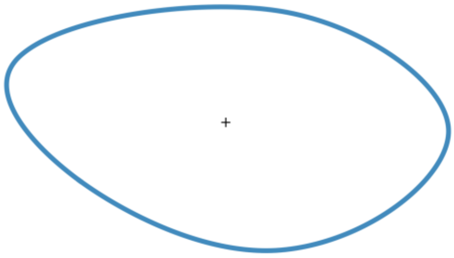
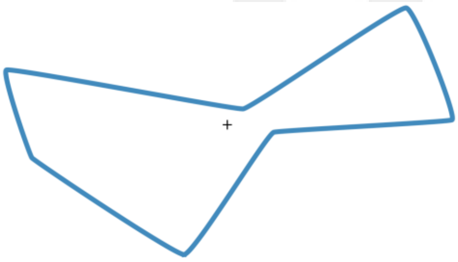


Figure 33

Shape Type Which has Perceived as Least Natural



When it comes to how we make use of our findings to answer our first set of hypothesis, we conclude that edge count, concavity and roundness affects the memory performance for a 2D shape but uniformity does not have any direct impact. While roundness causes a decrease in the memory performance, concavity and edge count have a positive effect because they cause increases on each other's memory performance even though their increase causes decreases in their own memory performance.

Our second hypothesis was if there is a correlation between geometrical attributes of 2D shapes and naturalness perception. The results imply that concavity, edge count and roundness significantly affect the naturalness perception. According to our findings, low edge count, low concavity and high roundness are associated with naturalness in human perception.

If we convert these parameters into 3D shapes, it is apparent that having no edges, being rounded and having no concavities are the common attributes of the organic objects in nature. Main reason of this is the entropy rule, so organic objects are tended to have lower surface / volume ratio, and for the lowest surface / volume ratio, there should be no concavities, no edges and even if there are edges, they should be rounded. Thus we can conclude that naturalness perception of 2D shapes is aligned with the naturalness perception of the 3D objects or the natural environment itself. In addition, these findings also can be a proof that the naturalness perception of humans is directly affected by the properties of organic objects. Since there are quiet many studies in the literature that showed that human having a preference of natural scenes as the study of Kardan (Kardan et al., 2015), if we combine our findings with the previous research, we can say that human have a preference for the organic objects. Our findings then can also be a support for the fruit theory which states that the some visual perception mechanisms evolved to detect fruits among leaves and main cause of human visual perception getting superior to the visual perception systems of other apes is being able to detect fruits.

Our last hypothesis was that memory performance will be lower for the less natural shapes because of the efficient resource allocation mechanism in the human cognitive system. Since we found a significant negative correlation between the naturalness rating and the overall match percentage, our study can support the theory that selective attention occurs because of efficient cognitive resource allocation. Efficient resource allocation systems evolved for survival in nature, so the main gain from them is to neglect to static and unimportant visual stimuli to have enough resources for the unexpected and dangerous stimuli, which is mostly associated with predator detection. Hence from another perspective, our finding of less resources being allocated natural stimuli can also be a support for predator detection theory about visual perception evolution.

3.2 Conclusion

Findings of this study give quantitative support for the theories of independent components, fruit theory, theory of Barenholtz about concavity and sharp edges theory (Barenholtz et al., 2003), bitten effect theory and predator detection theory. Moreover, there were new significant findings proving the effects of the geometrical parameter values over the memory performance of 2D shapes, especially the cross relational effect between edge count and concavity. We also provided a quantitative optimal point of edge count for concavity detection as 7.

About naturalness, literature has studies about natural scenes and some correlations found between attributes like spatial frequency, hue and naturalness perception. However there were no findings about naturalness that focus on the parameters of 2D shapes, especially on their geometrical attributes. In this study we contributed to the literature by finding significant correlations between naturalness perception and high roundness, low edge count and low concavity. Also we provided a proof about natural perception of 3D environment being aligned with 2D shape representations.

We also found support for the impact of efficient resource allocation on selective attention for naturalness on 2D shapes domain.

3.3 Limitations

Recall task setup of experiment caused a limitation for the memory performance of single parameters. In the recall task, there was a general issue about the participants' tendency to select the left or middle option compared to the right option. When we analysed the recall task data, we observed that participants tended to adjust the sliders in the left area of the scale. This was an issue we oversee and took some precautions to minimize the effects of it like adding tails to the sliders. However it is a known issue in the literature and our solution was not completely sufficient to deal with it, thus it blocked us to gather significant findings about single parameter values.

One of our main aims in our research was to provide quantitative optimal values for parameters for the shape perception. However due to the experiment duration limitations, we had to choose 3 or 4 discrete values as the options for the parameter values. If there would be a way to overcome this issue and give unlimited continuous options to participants, then it would be possible to estimate the exact mathematical optimal values for these parameters.

3.4 Possible Future Studies

As the new geometrical attributes like edge count and roundness are introduced, dedicated research on them can be conducted as they have been done for concavity. Also in our study we wanted to test several attributes, so we had to keep the number of options limited to 3 (4 for edge count) because of the duration limitation of the experiment. If there will be individual studies for each attribute, we could be able to detect the specific optimal values for memory performance and naturalness perception. Another enhancement to the study would be to provide relations of the findings with visual evolutionary theories because there is a big potential here as we see in our study that how the perception of the 2D shape parameters are aligned with some evolutionary theories like fruit theory.

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