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ARTIGO

A COMPUTATIONAL APPROACH FOR ANALYSIS OF ART COMPOSITIONS

UMA ABORDAGEM COMPUTACIONAL PARA ANÁLISE DE COMPOSIÇÕES ARTÍSTICAS

UN ENFOQUE COMPUTACIONAL PARA EL ANÁLISIS DE COMPOSICIONES ARTÍSTICAS

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RESUMO: Novas abordagens emergem da análise de obras com ferramentas computacionais e têm potencial para oferecer diferentes perspectivas para obras recriadas em ambientes digitais. Este estudo visa revelar as relações implícitas entre as composições de Mondrian com diferentes representações visuais. No âmbito do estudo, as composições concluídas entre 1938 e 1943, que possuem uma forte relação geometria-cor, foram discutidas pela primeira vez com uma abordagem baseada em pixels. No método de fragmentação seguido, as semelhanças e diferenças são expressas com dados transferidos de pixels para matrizes numéricas em duas etapas distintas: 1. Entre os artefatos em pares, 2. Entre um artefato e todos os outros artefatos selecionados. A visualização das matrizes foi representada por mapas de cores 2D e mapas de texturas 3D. Esses estilos de interpretação permitem que as composições sejam expressas do geral para o específico e novamente do específico para o geral, ganhando um novo significado.

PALAVRAS-CHAVE: Arte computacional; Análise baseada em pixels; Codificação visual; Mondrian.

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ABSTRACT: New approaches emerging from the analysis of artworks with computational tools have the potential to offer different perspectives to artworks recreated in digital environments. This study aims to reveal the implicit relationships between Mondrian compositions with different visual representations. In the scope of the study, compositions completed between 1938 and 1943, which have a strong geometry-color relationship, were first investigated through a pixel-based approach. In the fragmentation method followed, the similarities and differences are expressed with data transferred from pixels to numerical matrices in two different steps: 1. Between the artifacts in pairs, 2. Between an artifact and all the other selected artifacts. The visualization of the matrices was represented by 2D color maps and 3D texture maps. These interpretation styles allow the compositions to be expressed from general to specific and again, from specific to general, by gaining a new meaning.

KEYWORDS: Computational art; Pixel-based analysis; Visual encoding; Mondrian.

RESUMEN: Los nuevos enfoques que surgen del análisis de obras de arte con herramientas computacionales tienen el potencial de ofrecer diferentes perspectivas a las obras de arte recreadas en medios digitales. Este artículo pretende revelar las relaciones implícitas entre las composiciones de Mondrian con diferentes representaciones visuales. En el ámbito del estudio, las composiciones completadas entre 1938 y 1943, que tienen una fuerte relación geometría-color, se investigaron primero a través de un enfoque basado en píxeles. En el método de fragmentación empleado a seguir, las similitudes y diferencias se expresan con datos transferidos de píxeles a matrices numéricas en dos pasos diferentes: 1) Entre los artefactos en pares, y 2) Entre un artefacto y todos los demás artefactos seleccionados. La visualización de las matrices estuvo representada por mapas de color 2D y mapas de textura 3D. Estos estilos de interpretación permiten que las composiciones se expresen de lo general a lo específico y nuevamente de lo específico a lo general, adquiriendo un nuevo significado.

PALABRAS CLAVE: Arte computacional; análisis basado en píxeles; Codificación visual; Mondrian.

ART THROUGH COMPUTATIONAL ANALYSIS

In parallel with the development of the multifunctionality of computers, computational approaches to art gained different perspectives. The position of the artist in the generation, analyses, and evaluation processes has evolved over time into a combination of analog and digital processes working in collaboration with computers. With the advances in computational design tools, methods, and techniques, today it has become possible to analyze artworks and create them directly in the digital environment. However, considering the artworks generated through computational processes, it can be asserted that the artists' contributions mostly remain as defining merely the inputs. In other words, the dialogue between the human artist and the computer offers promises beyond common practice. This dialogue has the potential to contribute to art-based processes, where the simply evaluate and creative side of the human being is combined with the analytical, fast, and multifunctional qualities of computational tools. Efforts on the externalization of the potential paths followed by the artists in the design process provide an important basis for the evaluation and comparison of the works created using creative algorithms. In this sense, the analysis of existing physical works makes an important contribution to understanding the processes in the mind of the artist and basing the algorithms on these outputs (Bourached et al., 2021). Investigations on understanding the background of artwork can bring along a creative thinking process as well as the creation of it. Discussions about how an artwork can be created in a computer environment have been important study fields of artificial intelligence (AI). The development of AI technologies such as machine learning, deep learning, and neural networks offer methods that support the handling of works of art with computational approaches. In literature studies based on computational tools and analysis of artworks, the use of AI technologies comes to the fore. One reason that makes it difficult for an AI system to produce the aesthetic quality of original artwork (Hertzmann, 2018) is the restructuring of mathematical and geometric relations, especially in abstract compositions. While the algorithms developed for existing artworks are important for making these works understandable, new digital art productions based on these algorithms may be the ultimate goal of the programmer and also the program itself. Contemporary artists and programmers using these new approaches focusing on contemporary art mostly neglect the different roles that digital design tools can play (Greenfield, 2006). In this context, only focusing on whether computers can create art, may lead to ignoring the possibilities offered by the digital environment. It is possible to emphasize the potential of generating computational artworks under two items: First, the deconstruction of an existing artwork into pieces, rules and relations can lead to the creation of new designs beyond mere reproduction. Accordingly, it is necessary to seek sub-meanings and original approaches that can be targeted beyond formally imitating compositions.

Analyzing methods based on different components such as color, texture, scale or line in order to understand an artwork form the basis of visual analysis. The decode and encode methods developed within the scope of this study present a visual analysis framework without the aim of producing new artwork. In the scope of visual analysis, artworks can be evaluated as content and structure, meaning and form, or semantics and expression. It is the strength and clarity of expression that supports the semantics in the artwork. The interpretation of the components in an artwork begins with the selective operation of the eye. As a challenging cognitive task, visual analysis of works of art can be achieved with brain and eye coordination in humans. AI, on the other hand, requires a much more complex process to understand the similarities, differences, and relations between them in a work compared to the human system (Shamir & Tarakhovsky, 2012). For this reason, analyses using computer-based tools can both provide decoding methods for new computational approaches and create a new perception state for the human mind with visual encoding results. Determination of the visual objects in the artwork is an important parameter in the analysis of the artwork transferred to digital media. Different methods such as fractal analysis (Bountis et al., 2017; Alvarez-Ramirez et al., 2016), complexity analysis (Lopes & Machado, 2019; Sigaki et al., 2018), or deep learning (DL) (Cetinic et al., 2019; Kim et al., 2019; Smirnov & Eguizabal, 2018) can be used depending on the content in abstract artworks or fine art paintings that closely resemble physical objects. The ability to formulate the repetition and symmetry of geometric forms with their compliance with the rules allows mechanical production (Franke, 1985). Franke stated that as early as 1985, graphical analysis in a computer environment could be expressed from different perspectives with a single parameter change.

Along with the convenience offered by the digital environment, new models with varying degrees of complexity can also be generated by utilizing a computational way of structuring design processes. In this forward-thinking approach based on the relationship between art and mathematics in the digital environment, Franke presented methods for digital decoding by using titles such as Symmetrization, Transformations, Mathematical Functions, and Matrix Calculus (Franke, 1985). Considering these basic mathematical and geometric relations in the artworks, the De Stijl movement can be considered a milestone that can be supported by the context of aesthetic-computational approaches. It is suitable for researching the implicit connections of forms and does not refer to external reality (Novak, 1989). Mondrian, the pioneer of the DeStijl movement, is one of the representatives of works that do not resemble real-world objects but are based on geometric, mathematical, and logical connections. He aimed for plastic mathematics in his art (Rotzler, 1989) and reflected the relations between the components in this way. The elegant and simple approach of Euclidean geometries and the lightness in the combination of primary colors and angular spaces of the De Stijl movement support each other in his artworks (Tufte et al., 1990). The ways of decomposing and combining built within the scope of the study are also based on the goal of understanding the relations between these geometric features.

EVALUATING MONDRIAN COMPOSITIONS WITH COMPUTATIONAL APPROACHES

Along with Mondrian's developing view of art, his abstract works have followed a unique path over time (de Silva Garza & Lores, 2005). The works, in which blue, red, and yellow are used in remarkable simplicity, reflect Mondrian's characteristic compositional style even at first sight. The use of white, which highlights the figure-ground relationship in the composition, is supported by black lines that intersect each other at right angles. The relationship between form, position, line, and color elements, which have a clear and balanced relationship, creates this characteristic style (Cleveland, 2008). This dynamism in the style is preserved by the harmony achieved by these elements in the composition (Park, 2020). The sharp geometries and distinct colors in the compositions have made algorithmic interpretation possible.

Expressing an artist's style with algorithms through computational design and generative approaches is one of the ways of producing art reproductions (Zhang et al., 2012). Different analysis methods and computer-aided design tools can be used in computational studies on Mondrian compositions (Feijs, 2019). One of the best examples of the studies carried out in this context is the Monica program, which can generate random compositions based on Mondrian's style. The algorithm of the program produces an unconstrained evolutionary algorithm other than the main style it will imitate (de Silva Garza & Lores, 2004; de Silva Garza & Lores, 2005). These random decisions are affected by the digital blending and diversification of the original style-like rectangles in terms of color, size, and position. Classifying the elements in Mondrian compositions, considering the geometric elements and their properties separately, and evaluating them with different algorithms are also steps that can be followed in the analysis process. Fejis (2004) has developed a program to create new reproductions in the digital environment and interpreted geometry like planes, lines, and a combination of both. In his later work, he sub-segmented the compositions with extra green lines, which are distinctive in compositions, in addition to black lines to calculate the complexity values, and accepted the intersections of these two lines as analysis parameters (Feijs, 2020).

With the development of artificial intelligence technologies, calculations have been automated and analyzes have been made through more comprehensive algorithms. One of the machine learning algorithms, which distinguishes the original Mondrian works through the use of color intensities, is also based on the purpose of creating trained generative models (Andrzejewski et al, 2010). Also, there are studies that research the representation of two-dimensional composition in three dimensions. Mondal researched the embodiment of the composition components in three dimensions with the Grasshopper, Chingree plugin by defining rules over the shape grammar (Mondal, 2019). Computational geometric visualizations using the KD-tree data structure are involved in research on the representation of Mondrian tables (LeFevre et al, 2006; Roy & Teh, 2008, Wang et al, 2015) on a three-dimensional cube (Skrodzki & Polthier, 2018). Although the use of geometries and colors in the three-dimensional cubes produced is with an approach similar to the Mondrian style, the proportion in the distribution of colored rectangular elements does not directly coincide with the composition (Skrodzki & Polthier, 2018). In another study focusing only on rectangular components by disabling colors in the compositions, researchers create an analysis method for Mondrian compositions using neural network models (Lee & Liu, 1998). These approaches, especially derived from the concept of artificial intelligence, can offer a framework for rapid explorations in creative design processes (Gero, 1994).

Due to developments in programming languages and two-dimensional and three-dimensional digital design tools, Mondrian has been an interdisciplinary subject on which study has been conducted continuously. The digital reflection of the Mondrian style is mostly followed through components such as line thickness, positions of colors, and dimensions of geometries. Developed computer programs and analysis methods also work in this context in the direction of de-structuring compositions. However, the purpose of this study is to create a comparison algorithm for the common language of existing works, rather than suggesting a new application or method for reproductions. The proposed pixel-based decoding and matrix-based encoding presented in this study are a combination of analog and digital approaches for a simple comparison. As one of the decoding methods that reach a quantitative result, it is based on the principle of vertical and horizontal examination of a geometric whole (Klee & Moholy-Nagy, 1953). In the developed algorithm, the components in the works are not handled one by one. Regardless of line-area, color-space, pixels were calculated as the smallest geometric building blocks.

DECODING FRAMEWORK OF THE STUDY

Tufte (1990) on how to use colors in the representation of knowledge; stated that the human eye, which can reach hundreds of thousands of colors, sometimes can produce negative results for encoding information because of the use of even more than 20 colors. Different reflections and small nuances can be seen in different periods in the dominant styles in the compositions of an artist. The general similarities and differences in composition can be discerned even by the naked eye. However, it is also possible to make more objective and exploratory evaluations by expressing these comparisons quantitatively. In this study, five Mondrian works of art completed between 1938 and 1943 were selected (Figure 1), taking into account the algorithmic representation of the color and line arrangement in a certain time period. The general-to-specific decomposition logic followed in the study coincides with the subjective analysis model, which is based on the ability to follow the general composition style through small parts of a work (Thompson, 1977). Although the term geometric decoding corresponds to a broad method, it is defined with a clear framework in the study. Small pieces mentioned in the artworks discussed within the scope of the study are calculated as decoding composition with fragments, and decoding fragments with pixels.

Geometric decoding, handled by fragmentation, has been used as an analysis tool for the part-whole relationship in the composition and directly to the proportion of the whole composition. The comparison matrixes created from the selected artworks represented the pixel-based values of the works according to each decoding. Matrixes have numerical expressions of the composition, but they are also visualizable data about the style. The visualized data created according to the similarities and differences are the results of an empirical method for the encoding process.

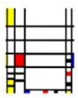
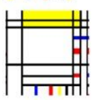
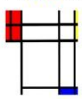
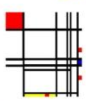
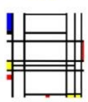
	Selected Compositions		Year	Dimension [cm]
No. 1		Trafalgar Square	1939 - 1943	145,5 x 120
No. 2		Place de la Concorde	1938 - 1943	102,5 x 103
No. 3		Composition of Red, Blue, Yellow and White: Nom III	1939	69,5 x 63
No. 4		Composition No 8, with Red, Blue, and Yellow	1939 - 1942	75 x 68
No. 5		Composition No 10, with Blue, Yellow and Red	1939 - 1942	79,5 x 73

Figure 1. Selected Mondrian compositions completed between 1939 - 1943.

Source: Authors.

The relevant matrices were prepared using P5.js in the pixel-based calculation process. The perception of colors by the eye and the differentiation of colors by the algorithm produced different results. For this reason, we increased the readability of the R, G, and B values in the pictures in the digital environment and aimed to avoid the effects of different pixel values. We took the height value of each artwork as 500 pixels in order to divide the images into fragments in the number specified by the user. Because we kept the original aspect ratio of the images, the width pixels of the compared works differed from each other. Regarding fragmentation, both pixel values and ratios to overall composition were calculated and printed with this algorithm. The matrix-based calculations are based on the output of the compared pixels. These calculations proceeded with the same logic in the fragmentation method and the differences between the matrices were calculated to compare the pictures. In the compared matrices, each color was shown in a different column. Since it does not matter whether the output is positive or negative in matrix operations performed over mutual pixel value differences, the results were taken as absolute values.

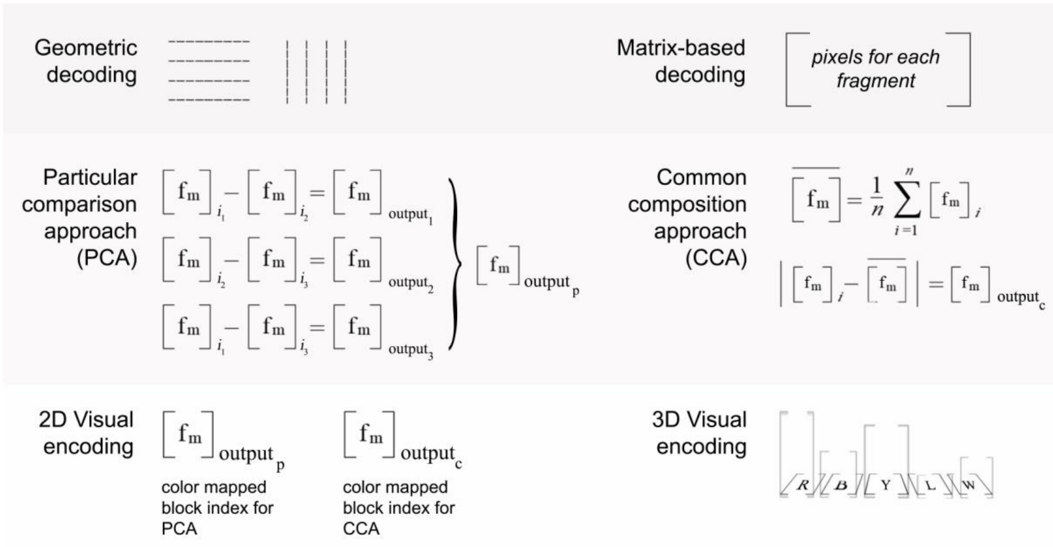


Figure 2. The process from geometric decoding to visual encoding. n is the number of artworks selected, *i* is the index processed. For each selected artwork, f_m represents the fragmentation matrixes.

Source: Authors.

Particular Comparison Approach (PCA): PCA is based on the calculation of the numerical difference between pixel values by creating binary combinations of any number of paintings. The contrast values obtained in PCA calculations allow the comparison of two paintings in terms of pixel-based similarity.

Common Composition Approach (CCA): CCA employs the arithmetic average of each calculated matrix. The difference of the matrix of a selected painting from this common composition matrix shows the similarity and difference degrees of the painting with the common language on a pixel basis. Gray-scale color mapping has been applied in order to present a clearer comparison of matrix-based calculations.

Fragmentation is calculated separately horizontally and vertically. In the fragmentation method, the composition was considered as a whole and in each painting, the user was allowed to create as many horizontal or vertical fragments as desired. The user is able to decode the picture from the band gaps of equal width, and fragments, by dividing the picture into two-part or hundreds. The width of the fragments in the selected direction is determined by the user input. In this study, in order not to create too dense fragments or too little sensitivity, this input was taken as 20 to create an average of 25 fragments with 500-pixel stability. Although the colors were sharpened digitally, the R, G, B values were calculated as ± 50 in the algorithm, since there could be a lot of difference in the colors of the pixel values adjacent to the lines.

VISUAL ENCODING OF THE OUTPUTS

Expressing only numerical values in matrix calculations is not an optimized solution for distinguishing visual similarities and differences between the artworks. For this reason, a three-layer visualization experiment was conducted as visual encoding. First, color mapping was generated with a gray hue according to the numerical value of each matrix cell. Further to the color mapping, these visually obtained color-mapped matrices were superimposed to obtain a colored map. As a third step, a three-dimensional representation of the superimposed output map was created. In the first encoding process, the largest numerical value was accepted as 255 and the smallest was 0 in the cells because of the normalization applied in accordance with the RGB values. The greater the color difference in the compared pixels, the darker the color in the matrix. In the matrices, the dominant colors in Mondrian compositions, red, blue, yellow, black and white, are represented by the symbols R, B, Y, L and W, respectively.

Specifying a smaller input value by the user will result in a more precise comparison fragment. The gray-scale matrix encoding of the first three images prepared using the PCA is given in Figure 3 (f_{output} p). The numbers 0-24 on the left show the fragments separated according to the input value is considered 20. The matrix comparison values in the vertical direction for each fragment number show the difference for each horizontal fragment of painting No. 1 and 2, 2 and 3, and 1 and 3, respectively. According to this visual encoding, it is seen that the difference between painting No. 1 - 2 and painting numbers 2 - 3 is quite high in the first 5 fragments. Since the binary differences in cell lines 10, 11 and 12 are quite less, the gray in these parts is close to white. When all the color pixels in the comparison matrix are added together, the highest difference is seen in paintings No.1 and No.2, and the least difference is between No. 1 and No.3.

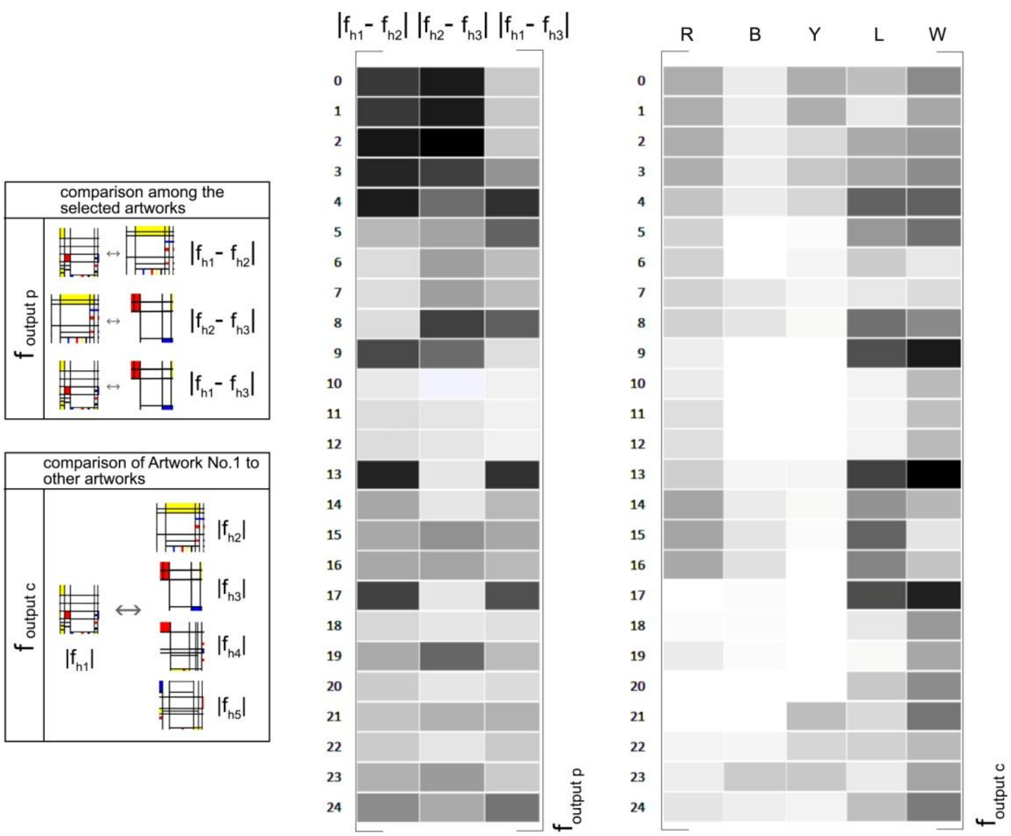


Figure 3. User input is taken as 20 and f_{hi} shows for horizontal fragments. On the left matrix, $f_{outputp}$ is the result of a particular comparison among the selected picture 1, 2, and 3. On the right, $f_{outputc}$ shows the result of the comparison of No.1 and the matrix value derived from CCA.

Source: Authors.

The f_{output} c shown on the right in Figure 3 is a visual prepared with the fragmentation method and CCA. It is obtained as a result of comparing artwork No.1 with the matrix results of the common language. Fragments were created in the horizontal direction. The cells that are very close to white on the grayscale prove that the similarity is high in comparison with the common composition. Particularly in the use of blue and yellow, painting No.1 is quite similar to the other four paintings between fragments 9 and 21. This result confirms the total white difference in Figure 3 and also represents its distribution over fragments.

Fragments were recalculated by turning them to the vertical axis for the targeted superposition of the second encoding process. While calculating the horizontal fragments, the height value was taken equal, and the widths in the paintings were different from each other. Figure 4 shows the output of the vertical fragment comparison. The first 6 fragments contain dark tones that are a result of the differentiation between the compared paintings. The middle parts of the vertical fragments of the three paintings have a more balanced distribution than the horizontal fragments and the different ratios are closer to each other. The resulting image of vertical fragmentation is $f_{output}c$, on the right in Figure 4. The use of black and white color is similar to the common matrix in the 6 - 18 while the fragments in the beginning and end parts of the composition differ greatly in the 3rd, 21st, and 22nd fragments. In general comparison, visual encoding of vertical and horizontal fragments resulted in close color gradation in CCA. In the horizontal decode matrix, the upper cells have more contrast, while the vertical matrix has contrast both above and below it. Intermediate tones in the middle are more difficult to compare with the naked eye.

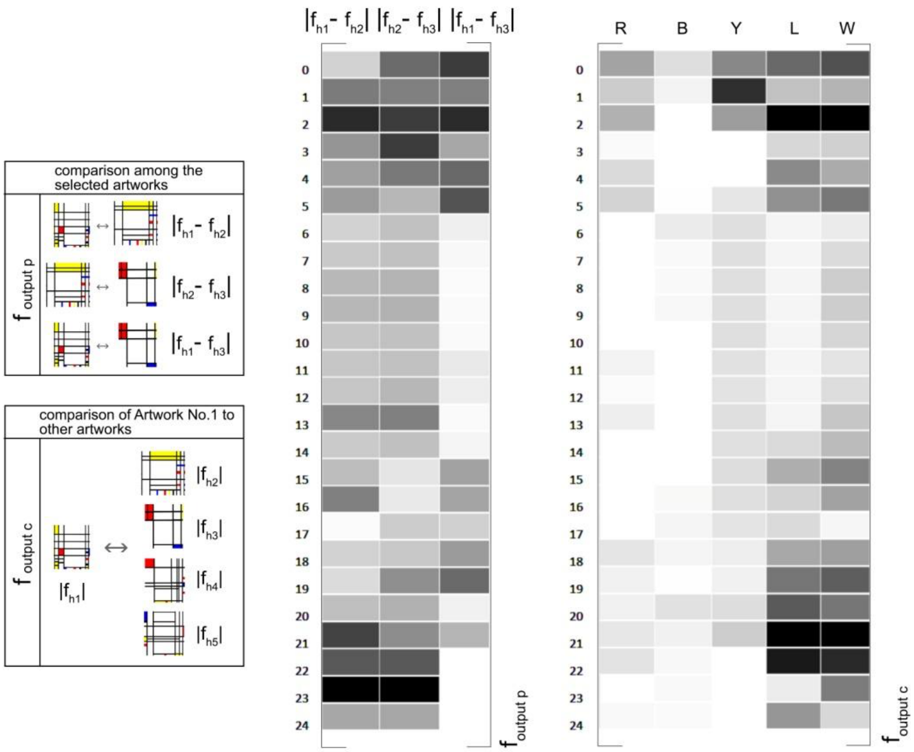


Figure 4. Output matrixes show the implementation of the specified method with vertical fragments.

Source: Authors.

The $f_{outputc}$ matrixes present the horizontal and vertical similarities separately. As a result of the superposition of these two data, Figure 5 was generated. By overlaying these discrete matrices, comparing intersecting cells on a fragment basis was becoming possible. Grayscale mapping outputs were used instead of performing a matrix calculation again. A red color overlay is applied to the grayscale output that represents the horizontal fragment differences. The blue color is assigned to the visual of the vertical fragment. In these two different colors the superposition table and the purple color scale was automatically created according to the intensity of the colors.

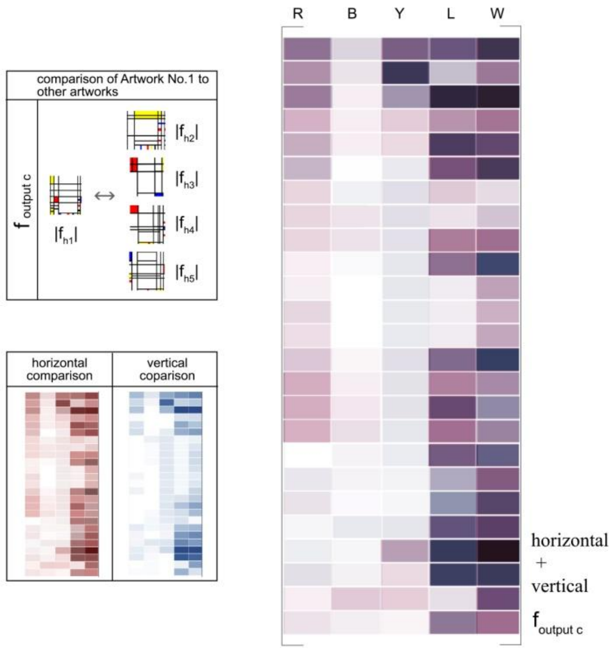


Figure 5. The superposition of the horizontal fragment output with red color overlay, and vertical fragment output with blue color overlay.

Source: Authors.

In the first two layers of the visualization, grayscale mapping and color overlaying were applied as a 2D encoding. As a third layer of visual encoding, the vertical and horizontal comparison matrix-based color maps are expressed in 3D. In the first two steps, only the change of similarities and differences based on applied color can be created. However, the original colors in Mondrian's paintings could not be used in these visualizations. In the modeling study carried out at this stage, the values in the matrix were directly assigned as the Z index value. The resulting 3D pattern can show each respective R, B, Y, L, and W colors. Both the color and also the difference between the related color in the paintings can be represented in the 3D model (Figure 6).

Finding the similarity between each picture is a valid step to catch the geometric approach. In addition, the exploratory process of the work expands with new textures and layers offered by visual encoding studies. The contrast created by the decode starting from the pixel and reaching the fragment cells and the whole picture has the potential to turn into a concept design model. The first two layers, which are only open to a visual evaluation in two dimensions, have turned into an output that can be rotated, axonometrically examined, or even touched in this step.

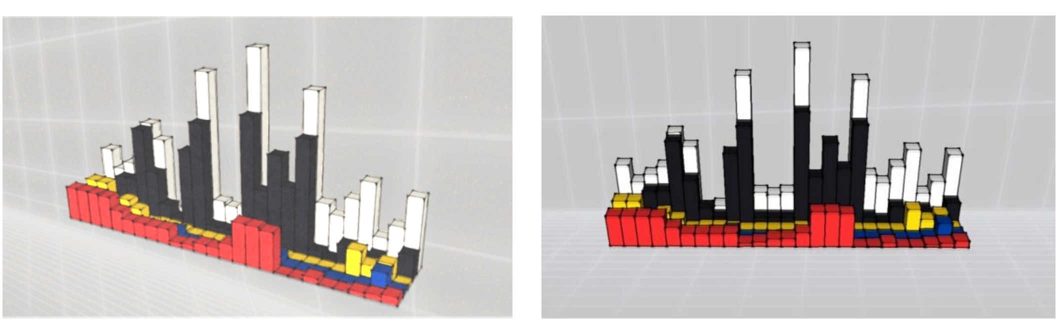


Figure 6. 3D models of 2D color overlay output.

Source: Authors.

The relative similarity between compositions can be calculated based on the percentages of fragment-based color usage differences. In the comparison table of No.1, No.2, and No.3 color differences in vertical fragments, the percentage of total usage differences of R, B, Y, L, W colors in 24 vertical fragments is shown. Figure 7 shows that No.2 artwork is more similar to No.1 in terms of using red in vertical fragments and more similar to No.3 in using yellow. The use of blue, black, and white is quite close to each other in percentage. However, the ratios of the colors used in the comparisons are quite close to each other. This consistency in the use of colors is one of the important implicit values in the distinctiveness of the Mondrian style.

Compared Artworks	R	B	Y	L	W
No.1 - No. 2	%5,3	%2,1	%23,4	%25,2	%44
No.2 - No. 3	%10	%3	%17,2	%26	%43,3

Figure 7. The comparison of color usage in vertical fragments of Artwork No. 2 to No.1 and No.3.

Source: Authors.

DISCUSSION

This study presents a computational comparison method for how Mondrian's composition style can be divided into parts by deduction and how the separated parts can be approached to the original style by induction. Verification of visually distinguishable visual information and revealing implicit comparison information that allows recognizing the style intuitively can also be obtained with this decoding method. Pixels can be evaluated on a more computable scale with fragments determined by the users, and this method offers a responsive frame for comparisons in different scopes. With the flexibility in the decoding method suggested by the research, it is possible to detect the similarities and differences of existing works and to capture the style grammar in the reproduction process in the pixel-based color focus. The results obtained by computer analysis and the new information visualizations produced can also find effective connections in the context of style decoding. The purpose of the decoding process used in the study is to obtain verifiable, quantitative comparison data of artworks. The encoding process aims to create visualizations that support the interpretation of this data in different formats. In this context, instead of creating reproductions of an artist's style through copying or imitating, the focus was on making the existing relationships expressed through visual interpretations.

The reason why the pixel-based approach can be used in this study is the abstract and geometric language in the selected artworks. The strong color and combination of geometry in the Mondrian style paves the way for the use of analysis methods that are open to subjective interpretations. However, this exploratory method may not produce a valid result in context-sensitive paintings. It may not be possible to separate the relationship between color and geometry into parts, as the colors and components that directly reflect a real-world presence will form the basis of the coherence of meaning in the pictures. However, trying similar methods with different artists and different composition styles will bring new results.

Computational design tools that can be used in the production of digital artworks also bring creative new concepts and perspectives. Reciprocally the use of computational analysis methods also has the potential to reinforce current issues such as image processing and machine learning. It is an expected result that innovative approaches fed from different technologies and different methods will contribute to the understanding and interpretation of the other disciplines that include the creative design process, as well as the existing artworks. On the other hand, this study can contribute to novel ideas regarding shape computing. In the future, it is possible to make a more precise comparison by increasing the number of artworks included in the algorithm. In addition, the study offers a developable method for people working in the field of computational design. By changing and improving the algorithm used, it will be possible to create different pixel-based comparison matrices or to develop matrix-independent complex representation tools.

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