The Artists who Forged Themselves: Detecting Creativity in Art

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Abstract

Creativity and the understanding of cognitive processes involved in the creative process are relevant to all of human activities. Comprehension of creativity in the arts is of special interest due to the involvement of many scientific and non scientific disciplines. Using digital representation of paintings, we show that creative process in painting art may be objectively recognized within the mathematical framework of self organization, a process characteristic of nonlinear dynamic systems and occurring in natural and social sciences. Unlike the artist identification process or the recognition of forgery, which presupposes the knowledge of the original work, our method requires no prior knowledge on the originality of the work of art. The original paintings are recognized as realizations of the creative process which, in general, is shown to correspond to self-organization of texture features which determine the aesthetic complexity of the painting. The method consists of the wavelet based statistical digital image processing and the measure of statistical complexity which represents the minimal (average) information necessary for optimal prediction. The statistical complexity is based on the properly defined causal states with optimal predictive properties. Two different time concepts related to the works of art are introduced: the internal time and the artistic time. The internal time of the artwork is determined by the
span of causal dependencies between wavelet coefficients while the artistic time refers to the internal time during which complexity increases where complexity refers to compositional, aesthetic and structural arrangement of texture features. The method is illustrated by recognizing the original paintings from the copies made by the artists themselves, including the works of the famous surrealist painter René Magritte.

1 Introduction

Digital image analysis methods have advanced in the past decade at an accelerated pace and the interdisciplinary interaction of scientists involved in the formulation and application of these methods, on one side, and art experts on the other, has opened up new possibilities for the advancement of knowledge of interest to both groups. The impetus for such advancement is certainly due to the availability of high resolution images of rich colour representation, among other things. One of the most interesting and intriguing problems related to the use of art image processing tools and methods is the artist identification in the sense of indisputable attribution of the artist to the work of art [1], [2], [3], [4], [5]. In order to achieve this goal, experts often rely on a combination of technical data obtained by the use of sophisticated equipment for mechanical, chemical and optical inspection of the art works and the visual inspection by art scholars supplemented by information provided by art historians. Recently, image processing techniques have appeared which analyse the higher-level features of the painting, such as texture and brush strokes using 2-dimensional wavelet transform or its complex counterpart [5], a technique which is relevant for our approach presented here. Although these techniques are sophisticated and in the early stage of development, and in spite of encouraging results, there are certain weaknesses that leave ample room for improvement. In general, all image processing methods require the original work of art or the training set of original paintings in order to make the comparison with the works of doubtful origin or uncertain authorship.

Our approach is based on the premise that the creativity is a process of artist’s self-organization on the mental level reflected in the self-organization of forms, patterns, textures and brush strokes of the painting which determine the aesthetic quality of the artwork. Recognition of creativity as self-
organization has appeared a few times in the literature, notably in [6], [7] and in a fascinating book by Rudolph Arnheim [8]. Arnheim writes: "The actual functioning of a painting or a piece of music is all mental, and the artist’s striving toward orderliness is guided by the perceptual pulls and pushes he observes within the work while shaping it. To this extent, the creative process can be described as self-regulatory. However, here again, as in the physiological mechanism mentioned above, it is necessary to distinguish between the balancing of forces in the perceptual field itself and the "outside" control exerted by the artist’s motives, plans and preferences. He can be said to impose his structural theme upon the perceptual organization. Only if the shaping of aesthetic objects is viewed as a part of the larger process, namely the artist’s coping with the tasks of life by creating his works, can the whole of artistic creativity be described as an instance of self-regulation". Arnheim wrote this work in 1971 under a strong influence of Gestalt psychology and before the concept of self-organization was scientifically interpreted in the works of Prigogine on far-from-equilibrium dynamical systems [11]. More recently, Zausner has written: "Creating and viewing visual art are both nonlinear experiences. Creating a work of art is an irreversible process involving increasing levels of complexity and unpredictable events" (italics by the present authors). Increasing complexity in time is our apprehension of self-organization and represents our main guiding principle in the analysis and comparison of the works of art.

2 Complexity, self-organization and the wavelet decomposition method

The central concept in our framework [12] is self-organization which is a ubiquitous concept related to the organization and dynamics of complex systems. In general, self-organization denotes a spontaneous emergence of structures and organized behavior without any external influence in systems consisting of a large number of interconnected elements. In general, due to the feedback relations between constitutive components, the dynamics of self-organizing systems is non-linear. Self-organization indicates a spontaneous increase in structural entanglement (complexity) of a system over time. Since there is no unique definition of complexity there are a number of ways to characterize it depending on the context and scientific interest. Our approach has
been influenced by the method of computational mechanics, developed by J. Crutchfield and his collaborators, which focuses on the measure of organization in the systems and on qualitative and quantitative description of structure and patterns \cite{14}, \cite{15}. According to this program the organization of a process is its causal architecture embodied in the key concept, the \( \epsilon \)-machine, which reveals the structure of connections between causal states in the temporal domain. The (statistical) complexity of a process is defined as the minimal information necessary for optimal prediction, according to the proposition in \cite{16}, where the term ”the true measure of complexity” was used. An operational and practical formalization of this definition, in our framework, is based on the wavelet decomposition of the data with the causal architecture embodied in the wavelet-machine \cite{12}.

The wavelet transform in the one-dimensional case (1-D), decomposes the signal in terms of the shifted (in space or in time) and dilated (scaled) versions of a wavelet function, which can be considered as a motive or template. The signal then represents a superposition of these wavelet templates with appropriate weights, which are known as wavelet coefficients. In two dimensions wavelets acquire an additional attribute of orientation, namely horizontal, vertical or diagonal. Three additional orientations may be generated by the complex wavelet transform. An image under consideration may be represented as a superposition of wavelet templates on a grid with appropriate coefficients. Figure 1 illustrates the 1-D wavelet and the 2-D wavelet which consists of three wavelets, namely horizontal, vertical and diagonal. In the dyadic representation of scale and time (or space), which is the standard practice, each wavelet coefficient has 2 (1-D) or 4 (2-D) successors on a finer scale forming a binary tree structure (1-D) or quad-tree (2-D) respectively, represented in Fig. 2.

Since the interdependence (causal relationship) of the nodes takes place
Figure 2: Left: Statistical model of the one-dimensional wavelet transform. Each coefficient (coloured node) is modeled as a mixture with the hidden state variable (white node). The standard domain of the wavelet transform is time (horizontal axis) - frequency (vertical axis) which in our model transforms to the space-time domain. Hidden states are linked to each other vertically across scales to yield the Hidden Markov tree. Right: Statistical model of the two-dimensional wavelet tree (quad-tree). Nodes of the same colour belong to the same scale.
vertically through the tree according to persistence property \[13\], we consider

the time axis as directed from the coarsest to the finest scale although in a con-

ventional approach this axis represents frequency or scale. The domain of the

one-dimensional temporal signal is considered as spatial (intrinsic for images)

so that by introducing \textit{diffeomorphism invariance} the wavelet tree becomes

the spatio-temporal tree. The wavelet decomposition is sparse implying that

the number of large coefficients is small and the number of small coefficients

is large. The large coefficients, which we call yang, convey information on

singularities (1-D case) or edges (2-D case) and the small, yin coefficients,

contain information on smooth parts of the signal or the image. The major-

ity of the image energy is contained in the yang coefficients, although the yin

coefficients also store significant energy, just because there are many of them.

Usually the energy of the yin coefficients is only one order lower than the

total energy of the yang coefficients while sometimes it may even surpass the

yang energy. Thus, the yin and yang coefficients of the wavelet decomposition

are in a kind of dynamic balance, justifying our choice of terminology. As a

consequence of the wavelet decomposition each coefficient has an associated

probability distribution indicating its frequency of occurrence. Usually, the

probability distributions, which are unknown ("hidden"), are modelled with

two zero-mean Gaussian distributions whose mixture is sufficient to model

the overall non-Gaussian distribution of wavelet coefficients. To each of the

two distributions corresponds a more frequently occurring (yin) state or a

less frequently occurring (yang) state. The locations in the image contain-

ing sharp edges correspond to the less frequent, but more energy containing

yang coefficients, thus having a wider distribution at every scale. The loca-

tions with prevailing smooth features correspond to the narrow distribution

since the corresponding yin coefficients are more frequent although less en-

ergy containing. The corresponding hidden states \( S \) are labelled as 1 and 2,

respectively (Fig.3).

In simple terms, the hidden state of the 2-state model associated with

each coefficient shows whether the template wavelet overlaps an edge or not.

Naturally, it is possible to allocate probability distributions to a larger num-

ber of states, if required. These states are modelled by the so called Hidden

Markov Tree Model (HMTM), characterized by the matrix whose entries are

probabilities of transition from one state to another. The probabilities of

the hidden states along with the probabilities of transition from one state to

another and the variances of the two distributions for each scale and orienta-

tion represent the parameters of the HMM which are jointly evaluated by the
Figure 3: Two-state, zero-mean Gaussian mixture model for wavelet coefficients. Each wavelet coefficient is modeled with a hidden state variable S and a random variable D. The Gaussian conditional pdf’s for a low-variance state 1 (left) and a high-variance state 2 (middle) and the overall non-Gaussian pdf (right) are shown.

Expectation Maximization (EM) algorithm given the observed values of the wavelet coefficients. Two important properties of the wavelet coefficients are persistence and clustering implying respectively that the large or small values of the coefficients tend to propagate across scales (in the vertical direction of the (quad) tree) and the adjacent coefficients (in the horizontal direction) tend to share the same properties. Due to the persistence property which determines hierarchical causal dependencies, we chose the direction of persistency propagation as the time axis, although in the conventional approach this is the frequency axis. At first glance, such practice suggests that we consider causality in a very weak sense, implying that the outcome consistently proceeds from the cause which completely determines it. However, mathematical framework, briefly explained earlier in nontechnical terms, clearly reveals a probabilistic aspect of causality.

In order to simplify the model a standard procedure known as tying within the scale is used, so that variance and transition parameters are the same at each scale of the wavelet transform. Such procedure enables application to a limited number of images (e.g. one or two) without the need of a training set. Also, it makes the model less image specific since it rules out an a priori assumption on existence of smooth regions or edges at certain spatial locations. As shown in [12], the hidden states are actually the causal states which are sufficient for prediction purposes, where prediction refers to the discovery of structure in the signal or in the image. In analogy with [17], the local statistical complexity is defined as the entropy of the local causal state.
and the global complexity is evaluated as the entropy of the whole hidden (quad-)tree formed by the hidden states. The local complexity has a specific physical interpretation in the sense that it is higher if the distribution of the hidden yang and yin states in the node of the wavelet tree is more uniform. In that case, there is a higher probability of the yang coefficient appearance based on the persistence property contained in the nodes at the immediate neighbouring scales meaning that the information stored in them will be preserved. It is important to stress that the yin and yang states are statistics of the complete tree of the wavelet coefficients, so that separation into the future and the past becomes irrelevant to our interpretation of causality. In spite of idiosyncracy of this method with respect to the treatment of the past and the future, a similar conceptual framework appeared already in physics. Namely, in the Feynman-Wheeler picture of classical electrodynamics the radiation reaction of an electrically charged particle is considered as an interaction with other particles in both the past and the future [18] [19]. In contrast to the conventional approach where the future action of the particle may be determined by conditions at the present moment, in the Feynman-Wheeler electrodynamics the future behaviour of the particles cannot be predicted by specifying initial positions and velocities, but additional information on the past and future behavior of the particles is required.

One of the crucial aspects of any wavelet based signal or image processing technique is the choice of the optimal template (wavelet basis) so that according to a certain predefined criterion it optimally corresponds to the image. Our choice of the optimal wavelet basis is the one which maximizes global statistical complexity. This criterion has been very successful in determining and predicting properties of dynamical systems through the analysis of times series [12], [20], and here we extend the application of this criterion in the context of art works where the relationship between complexity and self-organization occurs naturally. Hence, at the same time the method determines the optimal wavelet for each particular image which, in turn, recognizes self-organization as a process which increases local complexity in time evaluated as the maximal length of the interval at which the complexity function increases monotonically. An additional, special feature of this method is that it may be concurrently used for noise reduction based on excellent denoising properties of wavelet based HMM [21].
3 Complexity, cognitive neuroscience and visual art

As mentioned earlier, the fundamental course of our approach is based on the importance of prediction and the information required for optimal prediction. In order to gain deeper understanding of the basic ideas and direction of our approach, it is significant to supplement it and contrast it to the recently proposed predictive coding model of perception, an important new direction of research in cognitive neuroscience \[22\], \[23\], \[24\]. According to this model the brain does not passively register sensory input to which it is subjected, but actively participates by making predictions based on experience. At every level of visual hierarchy, which encompasses cortical structures of varying complexity, predictions are made and propagated to lower levels (top-down) where they are compared to the representation in the subordinate, lower levels. The signals from the lower levels propagate in the opposite direction (bottom-up). This comparison generates a prediction discrepancy or prediction error which propagates to higher cortical levels where it regulates the neuronal representation of sensory input and changes the prediction. This self-organizing process takes place until the prediction error is minimized leading to the generation of the most likely causal input. It should be stressed that the prediction here refers to the prediction of sensory effects from their cause and not the prediction of sensory states in the future, i.e. forecasting. Each level in the cortical hierarchy has a twofold function. First, it enables prediction based on the information obtained from the lower level and second, it encodes the mismatch between the generated prediction and the bottom-up evidence (the prediction error) which is propagated to the next higher level of the cortical hierarchy where further reduction of the prediction error takes place. This hierarchical model is characterized by transfer of empirical priors or constraints on the lower levels by the higher ones, thus it is often attributed as the Bayesian brain model. As a result of this hierarchical cortical process, the visual system organizes the perceptual input in patterns, thus defining a structure which enables predictability of visual representations. Reduction of prediction error, equal to the free-energy in the model of Friston \[24\], arises from the tendency of the brain and the whole body to retain homeostasis, an equilibrium state. However, a perception of the work of art is significantly different from the perception of ordinary things and events. Namely, art requires complete involvement, which transcends
simple observation so that the observer acquires an active role as an accomplice or as a contender. The role of emotions is also very important since in the ordinary perception the mismatch between expectations and reality usually arouses negative emotion. It is undeniable that repeated presentations in the works of art cause more fluent and economical cortical processing due to increased predictability (reduced prediction error), however that does not automatically imply positive emotional arousal. An active observer, and particularly an art connoisseur, expects to depart the default brain mode of preferred predictability when observing the work of art and expects a reward, a gratification in the form of a resolution of the prediction error which results in a pleasurable aesthetic experience. Thus, an unpredictable visual representation, causing a short-lived prediction error can be very effective in causing pleasurable aesthetic experience, while redundancy of predictive patterns may be boring and unemotional. It is not surprising that very often artists, intuitively and sometimes precisely and according to a strict plan, combine both predictable and unpredictable patterns in order to exert an aesthetic impact. A good example of this practice are the works of M.C. Escher, who induced prediction errors by combining repeated two-dimensional patterns with optical illusions which suggest a higher-dimensional departure from recurrent patterns. His artworks are also demonstrate how pleasurable aesthetic experience may emanate even from a long-term predictive error. Predictable perceptual forms and patterns may be periodically or intermittently disconnected by patches that compel the viewer to complete the visual experience, as practiced for example, by surrealist painters. Predictable patterns may also be completely destroyed or fragmented in order for new patterns and forms to appear. Resolution of prediction errors takes place in the mind of the viewer and since paintings are static art forms it induces dynamics which is stimulating and very often aesthetically pleasing. It is not surprising that art viewers and appreciators expect prediction errors and enjoy in resolving them while artists consciously create them and sometimes use them as a kind of personal trade-mark. The interplay of predictive patterns and unpredictable interruptions and the proportion of their occurrence determines to a large degree the aesthetic experience and gratification and has a strong impact on the emotional interpretation of the work of art. An interesting view of the relationship between art and the predictive coding model from the aspect of Gestalt psychology is given in [?], [?].

There are three important features of the predictive coding model that should be contrasted with our self-organization model. First, the predictive
coding model is a general model of perception which explains how the brain retains its non-equilibrium steady state when subjected to visual stimuli. Second, the resolution of the prediction error is necessary for the brain to retain its steady state and the role of emotions may not be of importance in completing the visual experience. Third, the resolution takes time and this perceptual synthesis time or ”time of contemplation” [27], is a time experienced and created by the viewer. Our framework, which we may refer to as the creativity model, is concerned with the work of art which represents an authentic reflection of the self-organizing cognitive and emotional processes taking place in the artist’s brain. Thus, we indirectly map the creative process of the artist’s brain into a self-organizing wavelet tree along with the statistical properties of the wavelet coefficients. The brain of the artist in the act of creation is almost without exception, not in equilibrium which leads to innovation and the emergence of new ideas. Apparently the artist is trying to remain in such a state until various possibilities of artistic expression are explored or until the emergent ideas are actualized in the painting. The prediction errors which may be manifested in the content, arrangement of forms, aesthetic arrangements, colour juxtapositions, texture, design, etc., are deliberately created in order to induce a specific aesthetic and emotional impact on the observer and to induce the creative process of art contemplation. However, the emotional and aesthetic feedback upon the artist is also of great relevance, thus the artist creates and resolves the predictive errors according to his mental and emotional state. Finally, there is a specific form of time associated with the work of art, essentially with its texture, best described by the term ”the intrinsic time of the work of art” [27], which we may be detected within our framework. To quote Souriau, ”There is no longer a question of a simple psychological time of contemplation, but of an artistic time inherent in the texture itself of a picture or a statue, in their composition, in their aesthetic arrangement. Methodologically the distinction is basic, and we come here (notably with Rodin’s remark) to what we must call the intrinsic time of the work of art. The significance of these words (valid for any of the arts) is particularly clear and striking when we deal with the representational arts, as in the normal case with painting and sculpture (and also for literature, the theater, etc.)”. The psychological time mentioned by Souriau although mathematically intriguing is beyond the current analysis and will be addressed elsewhere (M. R & M. M., in preparation). In our HMM wavelet model of self-organization, we distinguish two different concepts of time. The first, referred to as the internal time is recognized as the
progression of causal dependency among wavelet coefficients extending from the coarsest to the finest scale. The internal time axis is graphically represented as the vertical axis of the one-dimensional and the two-dimensional (quad-tree) presented in Fig. 3. The second concept of time is related to the smooth increase of local complexity and is completely determined by the compositional and aesthetic arrangement of texture features of the image. Since it coincides with the "intrinsic time of the work of art" of Souriau we refer to it as the \textit{artistic time}, and it actually represents one time frame of the internal time. In the next section this concept will be illustrated and presented in more detail.

4 Self-organization and complexity in the wavelet analysis of paintings

Although there are many measures of complexity, it is generally agreed that the things which are completely random or completely uniform (or orderly) are not complex. As a matter of fact, these two opposite aspects of the disorder have zero complexity and the real complexity lies between them. The maximal complexity corresponds to disorder lying somewhere close to halfway between these two extrema. In the excerpt from \cite{8}, presented earlier, Arnheim mentions that the creation and communication of the artistic idea is all mental; and we add here that the same is true of the reception and understanding of this idea by the audience. Hence, the artistic process creates a two-way information channel which contains encoded and decoded symbols, where a symbol, in the context of paintings, encompasses colours, texture, paints, brush strokes, forms, patterns, etc. Based on the information exchanged in this channel, we find it appropriate to adopt the concept and the first law of aesthetic complexity \cite{28} which states that: "The aesthetics of artistic forms and designs depend on their complexity. Too condensed coding makes a decryption of a work of art impossible and is perceived as chaotic by the untrained mind, whereas too regular structures are perceived as monotonous, too orderly and not very stimulating". Accordingly, the more complex a pattern is in terms of artistry and symbolisation, the more difficult is its decryption. A fast or easy decryption may cause boredom while a difficult decryption may lead to irritation and confusion. Hence the concept of aesthetic complexity may be perceived as the general form of complexity.
In our statistical complexity approach we are focused on discovering causal relationships: how one symbol leads to or brings about another symbol, thus establishing a direct relationship between complexity, self-organization and creativity in art. In order to illustrate our method we present the analysis results of two data sets, one of which was previously analysed using different techniques and which is freely available for download \cite{29}.

The first data set considered here consists of 7 high-resolution images of paintings by the Dutch artist Charlotte Caspers. She was commissioned by Ingrid Daubecheis and the members of the Machine Learning and Image Processing for Art Investigation Research Group at Princeton University to paint 7 paintings of relatively small size (approximately 25 cm x 20 cm) of different styles and using different materials \cite{29}. Within the next few days she has also painted a copy for each painting using the same paints, brushes and grounds and under the same lighting conditions. For the presentation of our method and the results of the analysis, it is of interest to mention the remark of I. Daubecheis \cite{29} that C. Caspers spent close to 2 times more time on creating each copy as compared to the original, indicating that "painting a copy is a more painstaking process than the spontaneous painting of an original". The copies were of such high quality that the artist was convinced that it would not be able to distinguish copies from originals. The high-resolution digital images were downloaded from the home site of the Princeton group\footnote{http://web.math.princeton.edu/ipai/index.html}.

In the so called RGB (Red, Green, Blue) colour space, each pixel in a colour image is represented by red, green and blue components. Each component may be treated as a separate image and for each painting we perform the analysis for each colour separately. The wavelet transform was applied in a twofold manner, namely on the whole painting and on all the patches of size 512 x 512 pixels, applying overlapping where necessary due to the dimension of the painting. The top nine scales of the transformation are used to form the causal structure which represents the cornerstone of our method. Note that all of the methods for artist authentication based on the wavelet decomposition apply the opposite practice, namely they use the coefficients at the few finest scales which contain the majority of coefficients. The templates from the standard orthogonal and biorthogonal wavelet families are used: Haar (haar), Daubechies (db2), Symlet (sym3), Coiflet (coif1), Biorthogonal (bior1.3), Reverse Biorthogonal (rbior1.3) and Discrete Meyer (dmey). The
wavelet transform has a layered structure, where each layer corresponds to a particular scale. Each layer consists of the slightly blurrier version of the image and the wavelet transforms along the three directions (horizontal, vertical and diagonal) which need to be complemented with detail information in order to reconstruct the original image. Parameters of the HMM model are evaluated for two, three, four and five hidden states, however, we have found no substantial difference between results for the two-state and for the higher states, so that only paradigmatic results for the two-state case are presented. The local complexity is evaluated as the Shannon entropy of the hidden variables in each node (coefficient) and the global entropy is evaluated as the entropy of the whole wavelet tree. The crucial importance of the global entropy is that it measures the increase of complexity in time so that self-organization of various degrees may be recognized, for example weak and strong self-organization may be defined accordingly. Higher global entropy implies stronger self-organization requiring more information for prediction while the weaker self-organization has the opposite attributes. Few of the paintings from this set and their images are presented in Figs. 4, 5 and 6.

The two dimensional wavelet-transform acts as an orientation microscope, which detects discontinuities of images such as point singularities (contour vertices) or orientation features such as edges, borders, segments or interwoven, mikado type edges. In Fig 7 we present local complexity of the painting
Figure 5: The second set of paintings by Charlotte Caspers, based on the use of acrylic paint. The brush strokes on a commercially primed canvas are visibly accentuated. Both soft and hard brushes were used.

Figure 6: The third set of paintings by Charlotte Caspers painted with oil paints and soft brushes on a chalk-ground. The technique is similar to the 15-th century Flemish paintings.
Figure 7: Local complexity of the paintings shown in Fig. 4. Each color corresponds to a different wavelet: black (Haar), red (db2), yellow (sym3), green (coif1), magenta (bior1.3), purple (rbior1.3) and blue (dmey).

and its copy presented in Fig 4 as an illustration of some of the representative characteristics of this quantity. Continual, smooth increase of local complexity indicates self-organization and the corresponding time during which the self-organization takes place we refer to as the time of self-organization. In most of the cases considered, local complexity corresponding to the original painting has smoother characteristics and displays longer self-organization for the majority of wavelets than in the case of a copy. For example, the rbior1.3 wavelet displayed in blue colour, exhibits the long-term self-organization which spans almost 5 time units in the case of the original painting (left) while it displays self-organization only during one time unit in the case of a copy (right). From the aspect of local complexity the optimal wavelet is the one which displays the lengthiest self-organization, time-wise. However, as mentioned earlier global complexity quantifies self-organization for the whole wavelet tree and represents the most important measure of complexity and self-organization.

It is useful to consider and compare global complexity characteristics in different orientations, so the global complexity values are presented corresponding to horizontal, vertical and diagonal directions. The mean value of these orientational complexities is the most important quantity which we simply refer to as the global complexity. First, we present typical results of the analysis performed on the whole painting and Table 1 displays orientational complexities and the global complexity for the red component of the paintings presented in Fig. 4.
Table 1: The global complexity and the orientational complexities evaluated for the entire paintings of Fig. 4. The colour in the RGB colour space is red. The optimal wavelet is denoted in bold.

| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|---------|------|-----|------|-------|---------|----------|------|
| Original | 0.7765 | 0.6258 | 0.6763 | 0.7435 | 0.7644 | 0.7921 | **0.8134** |
| Copy    | 0.7804 | 0.7178 | 0.7496 | 0.6298 | 0.7841 | **0.7856** | 0.5674 |
| Diagonal complexity |
| Original | 0.8992 | 0.6500 | 0.7196 | 0.8945 | 0.8895 | 0.9492 | **0.9534** |
| Copy    | 0.8977 | 0.8052 | 0.8170 | 0.8933 | 0.8922 | **0.9034** | 0.7852 |
| Horizontal complexity |
| Original | 0.7845 | 0.7222 | 0.8130 | 0.7754 | 0.7486 | 0.7832 | **0.8278** |
| Copy    | 0.7896 | 0.8365 | **0.8188** | 0.8045 | 0.8044 | 0.7342 | 0.8026 |
| Vertical complexity |
| Original | 0.6459 | 0.5053 | 0.4962 | 0.5607 | 0.6552 | 0.6439 | **0.6591** |
| Copy    | 0.6537 | 0.5117 | 0.6129 | 0.4191 | **0.6450** | 0.6191 | 0.6149 |

The optimal wavelet corresponds to the maximum global complexity and is marked in bold. In Table 2, the global and directional complexities are presented for the red component of the paintings presented in Fig. 5. Similar results are obtained for the green and blue components and are not shown here.

These Tables capture paradigmatic characteristics of all paintings from this set with respect to self-organization and complexity. First, the global complexity corresponding to the optimal wavelet of original paintings is always larger than the reciprocal global complexity of copies. Second, the optimal wavelet may be the same for all orientations, including the global self-organization indicator although this is not the rule. It is natural to agree that the complexity of the painting may be different in different directions depending on, for example, artist’s technique or the thematic content. For example, in Table 1 the discrete Meyer wavelet persists as an optimal wavelet for the original painting for all directions as well as for the global complexity, while the optimal wavelet for the copy is the same (rbior1.3) only for the diagonal direction and for the global complexity. This inconsistency is also an important indicator of the lack of self-regulating flow of ideas which ma-
Table 2: The global complexity and the orientational complexities evaluated for the entire paintings of Fig. 5. The colour in the RGB colour space is red. The optimal wavelet is denoted in bold.

| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|---------|------|-----|------|-------|---------|---------|------|
| Original | 0.4515 | 0.4284 | 0.4368 | 0.4240 | 0.4438 | 0.4339 | 0.3875 |
| Copy | 0.4177 | 0.4453 | 0.3936 | 0.4027 | **0.4244** | 0.3954 | 0.3890 |

| Diagonal complexity |
|---------------------|
| Original | 0.5123 | 0.4601 | 0.4594 | 0.4445 | **0.5151** | 0.4306 | 0.4314 |
| Copy | 0.4753 | 0.46163 | 0.41101 | 0.4073 | **0.4868** | 0.4091 | 0.4242 |

| Horizontal complexity |
|-----------------------|
| Original | **0.4179** | 0.3945 | 0.3988 | 0.3921 | 0.3976 | 0.4147 | 0.3368 |
| Copy | 0.3759 | **0.4171** | 0.3175 | 0.3554 | 0.3400 | 0.3342 | 0.3279 |

| Vertical complexity |
|---------------------|
| Original | 0.4242 | 0.4303 | 0.4523 | 0.4355 | 0.4168 | **0.4566** | 0.3942 |
| Copy | 0.4019 | **0.4551** | 0.4521 | 0.4452 | 0.4464 | 0.4428 | 0.4148 |

The second approach is based on the analysis of patches of size 512 x 512 pixels, and in general we have found that the distinction between originals and copies is more apparent than in the case when the whole painting is subject to the wavelet HMM analysis. Tables 3 and 4 present global complexity results for one of the patches of paintings in Fig. 4 and 5 respectively.

For all patches and all the paintings from the set the mean global complexity of an original painting is larger than the corresponding value of a copy. We have found that in a few cases the horizontal or the vertical complexity of a copy may be larger than the analogous value of an original, however the
Table 3: The global complexity evaluated for one patch of the size 512 x 512 pixels of the paintings shown in Fig. 4. The colour of the RGB spectrum is red.

| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|---------|------|-----|------|-------|---------|----------|------|
| Original | 0.5470 | 0.5508 | 0.5543 | **0.5648** | 0.5187 | 0.5332 | 0.4831 |
| Copy    | 0.5116 | 0.5382 | 0.5091 | **0.5326** | 0.5010 | 0.5049 | 0.4236 |

Table 4: The global complexity evaluated for one patch of the size 512 x 512 pixels of the paintings shown in Fig. 5. The colour of the RGB spectrum is red.

| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|---------|------|-----|------|-------|---------|----------|------|
| Original | 0.5772 | **0.5900** | 0.5807 | 0.5797 | 0.5775 | 0.5696 | 0.4878 |
| Copy    | 0.2686 | 0.2883 | 0.2967 | 0.2931 | 0.2610 | **0.3079** | 0.2832 |

contributions of other two orientational complexities prevail and the mean global complexity is always larger for an original.

The second set of images consists of two paintings by Rene Magritte, known under the title "La saveur des larmes" ("The flavour of tears"). The paintings are presented side by side in Fig. 8. One is an original, but which one? And which one is a copy? One is in the Barber Museum of Fine Arts in Birmingham, UK and the other in the Musées Royaux des Beaux Arts de Belgique in Brussels. The canvases are both dated 1948 and since Rene Magritte was a Surrealist with an exquisite sense of humour he might have been enjoying a charming and probably profitable joke. Magritte may well have seen his forgeries as part of the conflict between the real and the unreal, as the tension between these two realms was one of the hallmarks of the Surrealist movement. Magritte is known to have played a joke with the audience when he hung his forgery of Max Ernst’s painting "The Forest" in place of the original in 1943. Giorgio de Chirico, another famous surrealist, in his later years created what he called "self-forgeries" of the paintings from his earlier period. He would backdate them with an intention to make fun of the art critics as a revenge for their critique of his later works.

Art experts now consider that both canvases are Magritte originals, and assume he forged his own work to make money during the war years. The
existence of both paintings was unknown until 1983 when one of the canvases turned up at an auction in New York while the other remained in Europe. The two versions of the same painting are identical by all means and the experts agree that even the holes made by a caterpillar are exactly the same on the two canvases. Even the inscriptions on the back of the paintings are the same and undiscernible. So, which one of the two canvases may be considered as an original? We show that indisputably one of them has more indicators of creative artistic idea transferred on canvas, then the other so we claim with utmost confidence, that only one of them is the result of self-regulatory creative work. The other is a copy by the original artist. In order to distinguish them in the text we refer to them as ”The flavour of tears 1” and ”The flavour of tears 2”. As an illustration, in Tables 5 and 6 we present a comparison of global and orientational complexities of the two paintings for the dominant colours of the RGB spectrum, namely the blue and the green colour respectively. Similar results leading to the same conclusions are obtained for the red colour, and are not presented here. The analysis is preformed on the entire painting.

It can be immediately noticed that the Symlet (sym3) is the optimal
| Global complexity: "The Flavour of Tears 1 and 2"; colour: blue |
|---------------------------------|---|---|---|---|---|---|---|
| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
| 1 | 0.1845 | 0.2804 | **0.3186** | 0.2612 | 0.1950 | 0.2225 | 0.2780 |
| 2 | 0.1795 | 0.2427 | **0.2905** | 0.2807 | 0.1918 | 0.1979 | 0.2711 |

| Diagonal complexity |
|----------------------|
| 1 | 0.1849 | 0.4275 | **0.5211** | 0.3706 | 0.1824 | 0.2241 | 0.3917 |
| 2 | 0.1668 | 0.3201 | **0.3707** | 0.2778 | 0.1682 | 0.1581 | 0.3448 |

| Horizontal complexity |
|-----------------------|
| 1 | 0.2010 | 0.2048 | 0.2088 | 0.2066 | 0.2018 | **0.2293** | 0.2087 |
| 2 | 0.2138 | 0.2247 | 0.2179 | **0.2250** | 0.2123 | 0.2113 | 0.2016 |

| Vertical complexity |
|---------------------|
| 1 | 0.1677 | 0.2088 | 0.2298 | 0.2063 | 0.1708 | 0.2141 | **0.2335** |
| 2 | 0.1578 | 0.1831 | **0.1878** | 0.1760 | 0.1596 | 0.1755 | 0.1688 |

Table 5: The global complexity and the orientational complexities evaluated for the Magritte’s paintings. The colour in the RGB colour space is blue. The optimal wavelet is denoted in bold.

| Global complexity: "The Flavour of Tears 1 and 2"; colour: green |
|---------------------------------|---|---|---|---|---|---|---|
| Wavelet | haar | db2 | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
| 1 | 0.1907 | 0.2836 | **0.3209** | 0.2663 | 0.1908 | 0.2264 | 0.2840 |
| 2 | 0.1746 | 0.2396 | **0.2560** | 0.2251 | 0.1747 | 0.1802 | 0.2442 |

| Diagonal complexity |
|----------------------|
| 1 | 0.2013 | 0.4322 | **0.5219** | 0.3816 | 0.1987 | 0.2367 | 0.4049 |
| 2 | 0.1620 | 0.3195 | **0.3691** | 0.2812 | 0.1637 | 0.1556 | 0.3585 |

| Horizontal complexity |
|-----------------------|
| 1 | 0.2085 | 0.2074 | **0.2271** | 0.2192 | 0.1994 | 0.2265 | 0.2126 |
| 2 | 0.2113 | 0.2222 | **0.2154** | 0.2145 | 0.2009 | 0.2089 | 0.2043 |

| Vertical complexity |
|---------------------|
| 1 | 0.1722 | 0.2114 | 0.2237 | 0.2080 | 0.1741 | 0.2160 | **0.2346** |
| 2 | 0.1504 | 0.1771 | **0.1834** | 0.1697 | 0.1515 | 0.1762 | 0.1699 |

Table 6: The global complexity and the orientational complexities evaluated for the Magritte’s paintings. The colour in the RGB colour space is green. The optimal wavelet is denoted in bold.

wavelet for both colour cases and that the global complexity and the diagonal complexity for the painting 1 are considerably larger than for the painting 2.
Also, the optimal wavelet values for horizontal and vertical directions are also in favour of painting 1 so that we may ascribe to this canvas the attribute of originality in the sense that it represents an outcome of the creative artistic expression. Similar results are obtained when the analysis is performed on patches of size 512 x 512 pixels. Tables 7 and 8 illustrate typical results of this analysis.

**Global complexity**: "The Flavour of tears 1 and 2", patch A, colour: blue

| Wavelet  | haar | db2  | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|----------|------|------|------|-------|---------|----------|------|
| 1        | 0.1888 | 0.2754 | **0.3231** | 0.2564 | 0.1882 | 0.2176 | 0.2717 |
| 2        | 0.1712 | 0.2410 | **0.2545** | 0.2216 | 0.1721 | 0.1800 | 0.2378 |

Table 7: The global complexity evaluated for one, typical patch of the size 512 x 512 pixels of the Magritte’s paintings. The colour of the RGB spectrum is blue.

An interesting feature of these results is that they show remarkable consistency between self-organisation indices for the entire painting and for patches of size 512 x 512 pixels when either of the two dominant colours, blue and green, are analysed. Similar results are obtained for the red colour (not shown) and for patches positioned in the areas dominated by the red colour (drapes on the right hand side of the paintings). Minor departures from this trend were noticed in a small number of cases, and only for horizontal or vertical complexities. The consistency of the results suggests that Magritte was highly skilled in copying his own work and that perhaps he devised a special technique for that purpose, a practice that would be in the spirit of surrealism and surrealists.

**Global complexity**: "The Flavour of tears 1 and 2", patch B, colour: green

| Wavelet  | haar | db2  | sym3 | coif1 | bior1.3 | rbior1.3 | dmey |
|----------|------|------|------|-------|---------|----------|------|
| 1        | 0.1907 | 0.2836 | **0.3209** | 0.2665 | 0.1906 | 0.2276 | 0.2840 |
| 2        | 0.1888 | 0.2754 | **0.3131** | 0.2566 | 0.1882 | 0.2176 | 0.2718 |

Table 8: The global complexity evaluated for one, typical patch of the size 512 x 512 pixels of the Magritte’s paintings. The colour of the RGB spectrum is green.
5 Conclusion

Several writers on art as either theoreticians or practitioners, or both, have rightfully hypothesized that artistic creativity has many properties in accord with nonlinear dynamics, e.g. in [7] and references therein. However, even before the advent of chaos theory and non-equilibrium thermodynamics, it was suggested that self-regulatory and self-organizing processes may be recognized in the works of art. The mind of an artist is an open, dissipative system which absorbs information from the external world and produces entropy which could take the form of an artwork. We suggest here that artistic creativity, generally perceived as aesthetic or pleasing is self-organisation process which could be detected by examining the work of art and we focus our attention on paintings which, unlike other forms of art, are frequently subject to forgeries. When the work of art is created different elements, forms and textures are assembled and juxtaposed in a specific way, creating a higher organization than in the case when the same constituents are by themselves. Self-organizing processes in the brain of an artist create ideas and emotions which, by means of the artist’s brush strokes are transferred on canvas creating ”higher organization of meaning in the work of art”. We show that complexity and self-organisation are numerical quantities which could be used to differentiate between an original, creative, artistic intension and realization from the technical process which produces a copy of the work of art. Although the method shows very good and promising results in recognizing creative process, further improvements are possible. A non-exhaustive list of some of the advantages of the presented framework in comparison with the existing methods for art work analysis and artist authentication are the following:

In order to obtain reliable and conclusive results it is not necessary to use the complex wavelet transform which provides three additional orientations with respect to the ordinary wavelet transform.

A sophisticated analysis of brush strokes is not necessary and it is not necessary to use separate statistical models for texture-based and brush-stroke features.

It is not necessary to know which work of art is original as long there is another art work for comparison from the aspect of originality and creativity.

It is not necessary to have a training set consisting of other works of art of the same artist.

It is not necessary to introduce various distance (dissimilarity) measures
Finally, we regard our work as an important step in integration of artistic and scientific perspectives and an attempt in creating common ground for communication of ideas between arts and sciences.

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