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# Synthetic Images and Creative AI: A discussion on the nature and production of images in the era of deep learning

**Keywords: Synthetic Images, Deep Learning, Artificial Intelligence, Creative AI, Image Science, Vilém Flusser**

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**The emergence of new AI algorithms in recent years, especially those concerning deep learning, brings new challenges to the sphere of art, changing how artists creatively use computer systems. Although AI is not new in the universe of art, the new scenario makes it possible for algorithms to produce new types of automated images. Given this picture, this paper proposes to shed some theoretical and practical lights on the processes employed in the generation of visual art using AI. We start exploring the very nature of computer images, having as a theoretical framework the ideas of Dietmar Kamper (1936-2001), Hans Belting (1935-), Christoph Wulf (1944-), and Vilém Flusser (1920-1991). Next, building on this conceptual exploration, we describe the process of using deep learning techniques to generate self-portraits, which are synthetic images pointing to an external index.**

## 1. Introduction

The emergence of new artificial intelligence (AI) algorithms in recent years, especially those concerning deep learning, brings new challenges to the sphere of art, changing how artists creatively use computer systems. Although AI is not new in the universe of art (Boden 1998, Cohen 1995), the new scenario makes it possible for algorithms to produce new types of automated images. Regardless of what kind of AI is used to generate images, they are all synthetic images, i.e., images that are algorithmically generated or modified by an apparatus, sharing a specific set of features and characteristics. According to Flusser (2011, 2012), apparatuses are instruments programmed to codify abstract scientific concepts into images. Apparatuses abstract scientific discourse, articulating computer programming languages and symbols through calculations to produce synthetic images composed of a series of points that appear superficially as an image. These images are, therefore, mosaic-like structures. The mosaic points are so tiny that, to be perceived as meaningful forms, apparatuses are required to compute, calculate, and group them into images. A clear understanding of synthetic images' nature is critical as they are now ubiquitous, permeating the internet, social media and the art world.

## 2. The Nature of Synthetic Images

We will start by exploring what the German philosopher Dietmar Kamper understands by image. In the article *Bild* (1998) he exposes the concept of image in a systematic way and presents it in a very close conception to what the German art historian Hans Belting (1990) proposes, mainly its differentiation between cult images and art images. In line with Belting, Kamper proposes a distinction between image as a magical presence and image as an artistic representation.

According to Kamper, such ambivalence will run through the entire history of image, even in the current images that seem to escape this double sense. Nevertheless, in the historical journey of image in the West, its destiny was decided in favour of representation, of mimesis, and against its magical aspect. This occurs, says Kamper, in the Greek philosophy in Plato, runs through the Judeo-Christian tradition, is taken up again by modern philosophy, and has its peak in the Enlightenment. However, the denied aspect is still present in all images and can manifest itself at any moment. There is also a third variant – that of images as technical simulations.

In line with Belting, Kamper understands the concept of image as "ambiguous from the beginning, 'image' is, among other things, the presence, representation and simulation of an absent thing" (1998, 210). However, in a complementary way to Belting, Kamper does not think of the problem through art history, but as a psychological and philosophical problem. Belting had already pointed to the birth of image in the rituals of death. In Kamper, this becomes the central problem and the reason why images provoke so much fascination – death both in its sense of physical absence and in its indisputable destiny that haunts existence from the moment of birth. According to Kamper, on the back of images – be they presence, representation or simulation –, the deepest fear of emptiness is hidden.

> Behind the horizon and the objects threaten an abyssal "horror vacui". The material to which the various images correspond is an absence, a void, an elementary scarcity, so to speak, it is the experienced loss of the mother's womb's environment, which permeates throughout life the one of premature birth. That one is born and must die offers the condition for the experience of loss which seems irrecoverable but can be replaced. Images are thus substitutes for what is lacking, for what is absent, without affecting the dignity of what they replace (Kamper 1998, 211).

Christoph Wulf (2004), Kamper's writing partner in several books on historical anthropology, has elucidated the three categories mentioned above more extensively.

### 2.1. Image as a Magical Presence

Wulf explains that the magical cult image has the characteristic of being a producer of presence; it does not refer to something outside of it, as is the case with the mimetic image, but points to itself, to its presence in the present. This occurs with the mortuary, cult and, in some cases, artistic images. Based mainly on Belting's studies, Wulf exposes the deepest and most archaic sense of the images: they are the answers to the fear of death. According to Belting (2014), mortuary images – painted skulls, mannequins, and masks – dating up to 7000 BC. highlight the human capacity to overcome physical absence by symbolic presence, i.e., the absence of the body by the presence of the image. As in the case of the Golden Calf, there are also other cult images reported by the Old Testament, which are producers of presence through the association of the divine with images, when images are the embodiment of the divine and, therefore, inseparable from it. This is the spatiotemporal coincidence of the divine with images. Wulf also mentions artistic images, especially particular works of modern art, whose production of presence occurs because they refer only to themselves and not to something external to them, as in the case of mimetic images and in the artworks of Mark Rothko and Barnett Newman (Wulf 2004).

## 2.2. The Image as an Artistic Representation

The second type of image characterized by its artistic representation and ability to mimic the world. It is not a matter of copying or resemblance to the represented, but, according to Wulf, in the production of appearance: "the mimetic act creates images of art and poetry, making visible something that otherwise could not appear" (Wulf 2004, 236). Wulf uses Plato's theory to substantiate the representation problem and shows it as being of ancient interest to philosophy. As is already common knowledge, Plato was against poetry and artistic representation, justifying his aversion by understanding that poets and painters make artificial appearances of things, not the things themselves. Still, according to Wulf's reading, the result is "the creation of an aesthetic realm separated from reality and therefore unaffected by questions of truth" (Wulf 2004, 236). Since images mimic the world and constitute a world of appearances, they are not under the same norms as things in the real world and are, therefore, dangerous. The point here is that such images can exert a powerful fascination over the people who come to mimic them. It happens not only because real things can be mimicked, but appearances, that is, images, too. In line with Wulf, the philosopher Gernot Böhme (2004) states that Plato's image theory is still the fundamental basis of the whole West-Central image theory.

The question of mimetic representation gains more relevance to the study of images in an anthropological sense when thought of in relation to the body. Wulf argues that representation belongs to one of the most elementary forms of the human condition and that one of its central themes is the body. Since the earliest times of humankind, the creation of images has the body as the main object of representation. The body is both a product and a producer of images. This overlap is evident in the first natural exogenous images. Shadow and reflection are images produced by the body exposed to light, and its theme is the body itself. The paradoxical condition of human existence, problematized by Helmuth Plessner (1975) in the formula of having a body (*Körper haben*) and being a body (*Leib sein*), is repeated in the experience with the image: we have images, and we are images.

According to Belting, "whenever people appear in the image, bodies are represented. Therefore, images of this kind have a metaphorical meaning: they show bodies, but they mean people" (2014, 117). Images have accompanied human existence since ancient times. Today there is an increase in them thanks to the new media and the imaging devices that offer every layperson the possibility of creating images. That is also why studies in anthropology and philosophy have become increasingly concerned with them.

### 2.3. The Image as a Technical Simulation

The images that surround us today are mostly characterized by their abstract nature and circulation in complex electronic media. Wulf points out that such images circulate on media that radically reconfigure space and time. The electronic media allow overcoming the limitations imposed by the circulation of images in more traditional media.

Another striking feature of images as technical simulations is that they are the result of a high degree of abstraction. According to Wulf, these images "miniaturize the world and make possible an experience of the 'world as image'" (2013, 33). Not only the world but also bodies and things. The process of abstraction turns bodies into body images as we have already seen above. In Kamper, the question is the imprisonment in a world made of such images and the disappearance of what is on its back. In this world "the surface triumphs over all perception! The surface [...] asserts itself worldwide as the only generator of meaning" (Kamper 1994, 63). The disappearance of everything behind the images results in a problem of reference. Not that images no longer have a reference, but that the old "healthy" relationship which existed between image and world, image and body, and all the critical categories associated with them – truth and fiction, reality and illusion, appearance and essence – is in crisis and do little to help understand self-referring media images, that is, images which refer to images.

### 2.4. The Synthetic Image and the Problem of Reference

Flusser advances the discussion by proposing the concept of synthetic image. The Czech-Brazilian thinker elaborated the hypothetical model of the ladder of abstraction (Figure 1) to highlight the image's autonomy in its relation with the world, in an inversion in the vector of meaning found in the new media images, mainly the digital ones. Still in the initial phase of his writings on the subject, mainly between the 1970s and 1980s, Flusser proposed a growing distance from the world as a model for understanding culture's history through communication codes.

The first type of image produced by man had, in this approach, the characteristic of being the first step backwards in relation to the world, preserving its relationship with it. This relationship crisis was explained as a crisis of representation, that is, an inability of images to point to the world in a transparent way, like a kind of window that closes and becomes opaque, pointing only to itself. Thus Flusser characterised this process as "idolatry" – a veneration of images that conceals the world they originally referred to.

Amid this crisis, says Flusser, texts were invented to recover, through explanation, the connection with the world, lost in the images. Later these texts also become opaque and meaningless, and a third hegemonic code was invented to reconnect the mankind with the world. Here the synthetic images emerge, invented to recover the meaning of texts that point to images that mean the world. With each new code, a new step back. The synthetic image is the last step and is linked to the world by a synthesis of the dialectics between concept and imagination. The world remains as the matrix of the image, and the attempt to approach it leads to the paradoxical situation of detachment.

Later, Flusser defined synthetic images as projections and not as abstractions – a change that easily goes unnoticed, but which has great significance for the study of images and media. Considering the image as a projection indicates its ability to create a world and the inversion of orientation vectors.

Synthetic images only retain an illusory resemblance to traditional images. The distinction between the two appears more clearly in the analysis that Flusser proposes from two levels: the superficial, phenomenological, and the profound, scientific. Thus images appear superficially as images, but in-depth they are a combination of programmed points (pixels). Contemporary criticism should stick to these two points, according to Flusser. At the superficial level, the vectors of meaning between the two images point in opposite directions. While the former images are considered abstractions of the world, the latter are projections of models.

From this frozen world of zeros and ones, from this timeless non-place of calculations, there is nowhere else to go back to, only forward. The images that emerge from this advance are not representations, but images of a new type. They are projections against the world and the mankind.

### 2.5. Flusser, Apparatuses, and the Synthetic Images

Flusser (2012) conceptualises images as surfaces which intend to represent something that, in most cases, is external to the image. Thus, images are the product of efforts to abstract two of the four dimensions of space-time, retaining only the dimensions of the plane. This is because an image typically points to something that is out there in space and time. This type of image – designated first order, which abstracts two of the four dimensions of space-time and preserves only the plane – is called "traditional image". To decipher images is to understand this abstraction, concentrating on the resulting planes. The image's meaning is embedded on its surface.

On the other hand, synthetic images are produced by apparatuses, which are, as we described earlier, products of applied scientific text. The most noteworthy feature of computer-generated synthetic images is that they are the outcome of programming logic, resulting from computational language processing within digital apparatuses. They are indirect products of texts, which grants them special historical and ontological statuses from traditional images. All AI-generated images fit this paradigm, located after the development of specific and highly abstract scientific theories. The traditional image performs the first-degree abstraction, abstracting two dimensions from the concrete phenomenon, leaving only the plane. The synthetic image works in a more sophisticated manner, being a third-degree abstraction because it abstracts one of the traditional image's dimensions engendering texts that are a second-degree abstraction. The synthetic image is not made up of planes or surfaces, but rather by algorithmically calculated points. Thus, it is null-dimensional. The escalation of abstraction that brought us synthetic images is nothing more than an escalation of subtraction, consisting of the progressive and relentless removal of objects' dimensions, from three to two, to one and then to zero. Synthetic images do not occupy the same ontological level as traditional ones since they are new phenomena with no past parallel. Figure 1 illustrates the Flusserian ladder of abstraction, from the concrete world to synthetic images. For a more in-depth discussion about the Flusserian ladder of abstraction, see Heilmair and Poltronieri (2013) and Poltronieri (2014).

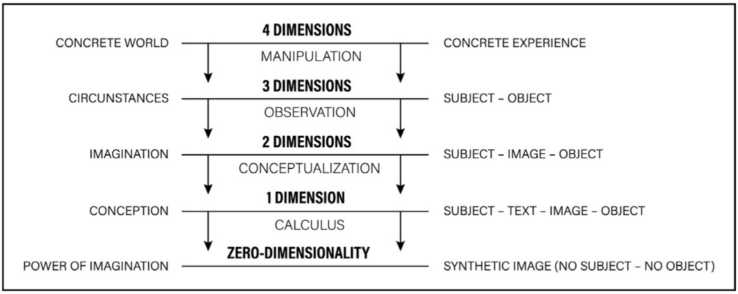


**Fig. 1.** The Flusserian Ladder of Abstraction.

Traditional images – such as realistic paintings – extract surfaces from volumes found in the real world, whereas synthetic ones are surfaces composed of calculated points. For example, when an artist paints the Eiffel Tower, she takes the actual tower as a model – a 3D volumetric object in Paris – and abstracts it onto the surface of a canvas or paper. This is the first degree of abstraction. When a machine learning algorithm generates an AI image of the same Eiffel Tower, the operation starts by feeding abstract equations with many images used to train the AI model. The expected outcome is the generation of new synthetic images depicting the famous Parisian tower. The high and sophisticated level of abstraction found in the synthetic images is one of the reasons that make AI-generated images so hard to explain, as these images are surfaces pointing directly to the mathematical formulas and abstract concepts behind the AI algorithms, rather than an index to something concrete in the real world.

Thus, a substantial effort is required to understand AI-generated images. Science seeks to apprehend the world in its generalizations, attempting to deal with its generalities abstractly. AI synthetic images are products of these abstract generalizations, conveying all this sophisticated conceptual thinking. They are automatically produced through the mediation of highly specialized codes and mathematical formulas. Synthetic images aim to masquerade themselves as real, intending for perfection, a final stage of improvement, representing the idealization of an impossible, but desired world.

Traditional images are created from the human hand's action, equipped with some tool – brushes, pencils, stones, pens – which transfers elaborate mental symbols onto some tangible medium, which constitutes the image's surface. Decoding these images implies knowing what was going on in the human agent's mind who dreamt up the symbols and transferred them to their hand, from there to the tool, and then to the surface.

In the case of synthetic images, the situation is not as evident. Nonetheless, synthetic images are just as symbolic as all other images and must be deciphered and criticized by those who wish to understand their meaning. There is both an apparatus and a human agent that manipulates them. The "apparatus-operator" system, however, is too complex to be understood and penetrated. It is a black box, where we see only the inputs and the outputs. The outputs are indexes of abstract symbols: the programming logic that encodes the apparatuses' algorithms. As the result of algorithms encoded into codes, codes into text, and texts into images, synthetic images are, ultimately, metacodes of algorithms. Imagination – the ability to encode texts (abstractions) into images – is the starting point of synthetic images. To decipher these images is to rebuild the abstract thought that gave rise to them. When the deciphering is correctly accomplished, the conceptual world emerges again as the synthetic image's universe of meanings. Therefore, what we see when contemplating synthetic images is not the "world", but certain concepts regarding the world and every criticism of the synthetic images should make this box more transparent (Flusser 2012). Therefore, understanding the nature and ideology of AI ideas and algorithms is pivotal to criticize AI-generated images.

## 3. Synthetic Deep Self-Portraits

It is deep feasible to create the self-portrait images – part of Poltronieri's "Selfie Apparatus" series of artworks – because of the recent advances in the field of deep learning.[1] To create this series, a type of deep learning neural network called Generative Adversarial Network (GAN) was employed. GANs are becoming ubiquitous, with applications ranging from the designing of new anime characters for game and animation industries (Jin et al. 2017), and video and music generation (Vondrick et al. 2016, Yang et al. 2017) to medical uses, such as anomaly and tumour detection (Schlegl et al. 2017).

1. As there is a vast literature on deep learning (Goodfellow et al. 2016, LeCun et al. 2015, Schmidhuber 2015), this will not be a topic that we will address in this paper.

Technically speaking, GANs are a class of deep neural networks used in unsupervised learning, composed of a pair of competing networks: a generator and a discriminator, which aim to generate realistic data – images, in our case – from some prior distribution. A GAN is trained, i.e., it learns, by alternately optimizing two objective functions. Throughout the training, the generator learns to produce samples resembling real images, and the discriminator, also known as a critic, learns during the training to better discriminate between real and AI-generated data. The generator does not have access to the training data, producing samples from random noisy inputs generated from a latent computational space. In turn, the discriminator takes as input two images: one real image from the dataset used to train the network and the one generated by the generator. The discriminator must learn to recognize which of the two images was algorithmically generated. A negative loss is given to the generator if the discriminator recognizes the AI-generated image. On the other hand, the discriminator gets penalized if it fails to recognize which one of the two images is not real.

GANs can be viewed as a two-player game where both players aim to minimize their losses, and the solution to this zero-sum game is a state of equilibrium where neither player can improve their loss unilaterally. At equilibrium, the discriminator should not tell the difference between the images generated by the generator and the actual images in the training set, leading the generator to generate synthetic images that come from the same distribution as the training set. Usually, GANs produce sharp images, though still in quite low resolutions and with somewhat limited variation (Karras et al. 2017). Figure 2 shows the global concept of a GAN.[2]

2. Our aim is not to provide an extensive explanation on how GANs work, let alone to discuss their technical details. More information about GANs can be found in Langr and Bok (2019), and Foster (2019).

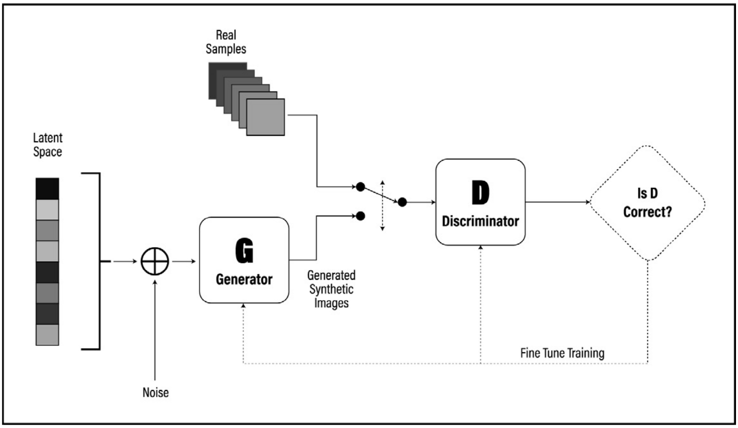


Fig. 2. Diagram exemplifying the concept of a GAN.

Our project consisted of training a GAN to generate new self-portraits of one of us. The first step, creating a dataset of actual self-portraits, was done over about three months, and consisted in collecting more than 25.000 selfies in different contexts, environments, and situations, using the frontal camera of an iPhone X in the square mode. Although 25.000 images could sound like an extensive collection, it is far from being an ideal amount. It was, however, enough for our purposes. Figure 3 presents a collection of images taken from the original selfies.

Our GAN of choice was developed by NVIDIA and is known as “Progressive Growing of GANs for Improved Quality, Stability, and Variation” (Karras et al.

2017). It has already been outperformed by a new GAN architecture called "StyleGAN" (Karras et al. 2018), also developed by NVIDIA. The original selfies straight out of the iPhone are 2320x2320 pixels. The problem with this resolution is that GANs cannot generate hi-res resolution images at their actual stage of development. This is currently one of the main setbacks of this technology. The majority of GAN generate images are 256x256 pixels. This restriction is related, among other factors, to the GPU (Graphics Processing Unit) used to train the network. Deep learning is very computationally intensive, but CPUs (Central Processing Units) are not the best choice for these algorithms' mathematical computation. Most of the deep learning computations involve matrix and vector operations, the same type of computations GPUs are designed for. Besides that, GPUs usually have hundreds of simpler cores, can run thousands of concurrent hardware threads and maximize floating-point throughput. GPUs are the heart of deep learning, as the model training process is composed of simple matrix calculations, the speed of which can be significantly enhanced if the computations can be massively carried out in parallel.

**Fig. 3.** Four original selfies taken from the 25.000 images dataset used to train our GAN.

Another downside of GANs is that GPUs are expensive, and their energy consumption is very high. To train our network, we used an NVIDIA GeForce GTX 2080ti, with 11GB of memory, allowing us to train the network to generate 512x512 pixels synthetic images, later resized to 4724x4724 pixels using another deep learning network (Champandard 2016). Before starting the training process, our dataset images were resized to 512x512 pixels. Our GPU is not the best one available, but it was the best consumer NVIDIA GPU when we trained the GAN.

The training was completed in about 28 days, with the system running 24x7 and the GPU using almost 100% of its processing capacity all the time. Karras et al. (2015) state that a single hi-end GPU could train a 1024x1024 network for CelebA-HQ in about two weeks. CelebFaces Attributes Dataset (CelebA), is a large-scale face attributes dataset with more than 200K celebrity images and can be employed as the training and test sets for face attribute recognition, face detection, and landmark or facial part localization (Liu et al. 2014). This dataset's images are significantly varied in terms of resolution and visual quality, ranging from 43x55 to 6732x8984 pixels. The CelebA-HQ is a high-quality version of the CelebA dataset, consisting of 30.000 images at 1024x1024 resolution. (Karras et al. 2015).

Dataset building and training time are the biggest bottlenecks in the process of generating images with GANs. For the sake of comparison, the new NVIDIA StyleGan takes 41 days to train using the Flickr-Faces-HQ (FFHQ) dataset – a high-quality 70.000 images dataset of human faces – at 1024x1024 resolution using one Tesla V100 GPU and six days to train the same dataset and resolution using eight Tesla V100 GPUs in parallel. These are high-end GPUs, costing about $6,000.00 each. The GPU used in our setup costs, at the time of writing, about $1,200.00.

After the training, the GAN could generate new, virtually endless, AI selfie images, which we divided into two series: "Selfie Apparatus " (figure 4) and "Twisted Selfie Apparatus" (figure 5), comprised of synthetic glitched images that the network generates from time to time. From the artistic point of view, these images are the most interesting ones, as they present image manipulations and distortions that happened by chance inside the neural network black box.

**Fig. 4.** Four GAN generated self-portraits, part of the "Selfie Apparatus" series.

**Fig. 5.** Four glitched GAN generated self-portraits, part of the "Twisted Selfie Apparatus" series.

Images from the "Selfie Apparatus" and "Twisted Selfie Apparatus" series have been exhibited in shows in China, the UK, Brazil, and Canada, and are part of an ongoing practice-based research project about the role of chance in computer art that has been developed by the authors for more than ten years.

## Conclusion

Unlike images made up of planes representing something "out there" in space and time, synthetic images are not made up of planes or surfaces, but rather by algorithmically calculated points. When assembled, these points can appear photorealistic and believable. Both "Selfie Apparatus" and "Twisted Selfie Apparatus" series are products of the same GAN, the same artificial neural network that algorithmically defined and assembled the pixels that composed the self-portrait images. Sometimes these images are indistinguishable from a real image, and some others are ghostlike, distortions, a creative abstraction from real objects in the world – the "imaginings" of the algorithm.

GANs have not reached the limits of what they are capable of and will continue to improve for the foreseeable future. It appears inevitable that the art environment will become even more saturated with synthetic images. Indeed, much of contemporary art is at least processed, modified or augmented through some computational process. Fully synthetic images will only rise in preponderance. Though distinct in their internal structure from traditional images, Flusser (2011 and 2012) has argued that synthetic images will be increasingly impossible to distinguish from traditional images without the aid of algorithms. Only algorithms will discern the sub-surface artefacts that are distinctly technical, as synthetic images appear increasingly believable to the viewer.

Such a future scenario seems to replace humans not only in the creative process but also in the decision-making process, as Flusser (2011) has warned. An artificial agent can process millions of images and videos, learn patterns from them and automatically generate new content. As we described, recent developments in neural networks enable a new wave of algorithms capable of learning from patterns identified in large datasets, that can be automatically collected and organized by computers. Hence, AI can be understood, above all, as a revolution in decision making, as a "displacement of critical consciousness from human being to automata." (Flusser 2011, 119)

Due to the complexity of neural networks and the speed at which they produce synthetic new images, it is becoming increasingly impossible to have a "human-in-the-loop" checking all the new images. Our selfie GAN is, after training, capable of generating new images every half second. Flusser (2011) warned that such a revolution in decision making would be the "end of freedom", confronting us with fundamental moral and ethical decisions.

With the constant increase in quality of AI-generated synthetic images, purely visual methods to judge them will rapidly become impractical. It is not only a question related to the technical attributes of the images, but, more importantly, it has also to do with the aesthetic attributes of synthetic images. Soon, the only trustworthy critics and judges of art will be counter-algorithms designed to identify subtle nuances, artefacts and strategies used to produce synthetic images. One of the main reasons for that is the fact that in informatics the informational content of a given scenario is, in principle, precisely determinable, irrespective of the type of information involved (Flusser 2011). Flusser argues that

> The rarity of each element of the situation to be measured (the rarity of each bit of information) can be precisely determined. Furthermore, these measurements can be undertaken at however many levels of a situation one wishes [...] Information does, in fact, consist of so many levels that it is not humanly possible to single out each one and measure it, but artificial intelligences can calculate and compute faster [...] Automatic critics will not only replace but will also have deeper insights than human ones in the foreseeable future. (2011, 118)

This is already the case, even if currently a large proportion of AI-generated synthetic images display artefacts or distortions that, though varying in degree, make identifying them relatively easy. As AI algorithms further develop and become even better at generating automated content, they will increasingly be able to simulate an experience that is entirely algorithmically generated. The collaboration between scientific research and artistic practice has been fruitful in generating insights into AI's role in the visual field and about the level of control we have over the process of generating synthetic images. This opens new horizons for artistic practice and a possible aesthetic future, especially if artists, philosophers, and scientists engage in joint discussions about how synthetic images are generated using neural networks. As Flusser (2011 and 2012) suggested, the critique of synthetic images must be done from both, a superficial symbolic interpretation and a deep algorithmic explanation. Neural networks are particularly tricky because they are obscure, they do not easily reveal the reasoning behind any given decision. AI-generated synthetic images should, therefore, be critiqued primarily in terms of the algorithms that generate them. Failure to develop effective methods for algorithmic critique will entail a failure in understanding how the future of image is being reconfigured.

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