

Paraphrasing Magritte's Observation

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Contrast Sensitivity of the human visual system can be explained from certain low-level vision tasks (like retinal noise and optical blur removal), but not from others (like chromatic adaptation or pure reconstruction after simple bottlenecks). This conclusion still holds even under substantial change in stimulus statistics, as for instance considering cartoon-like images as opposed to natural images (Li, Gomez-Villa, Bertalmio, & Malo, 2022).

In this note we present a method to generate original cartoon-like images compatible with the statistical training used in (Li et al., 2022). Following the classical observation in (Magritte, 1929), the stimuli generated by the proposed method certainly *are not* what they represent: *Ceci n'est pas une pipe*. The clear distinction between representation (the stimuli generated by the proposed method) and reality (the actual object) avoids eventual problems for the use of the generated stimuli in academic, non-profit, publications.

Keywords: Visual stimulus generation, Image representation in Surrealism, Cartoon-like images.

1. Introduction

Visual neuroscience based on statistical learning depends on image datasets that simulate the environment that shapes the sensors. Seminal contributions were based on clever observations on few images (Field, 1987), and 2nd-order trends and marginal PDFs on decorrelated domains can be fairly obtained just from hundreds of images (Malo, Ferri, Albert, Soret, & Artigas, 2000). Specific effects such as chromatic adaptation require images with accurate calibration (Gutmann, Laparra, Hyvärinen, & Malo, 2014; Laparra & Malo, 2015; Gomez-Villa, Bertalmio, & Malo, 2020; Malo, 2020). In this context small datasets with radiometrically controlled spectra (Foster, Amano, & Nascimento, 2016; Nascimento, Amano, & Foster, 2016), or tristimulus calibrated images (Laparra, Jiménez, Camps, & Malo, 2012) are fundamental. However, conventional deep-learning is data-intensive and hence larger datasets (with millions of images) are required (Russakovsky et al., 2015).

Open-access academic journals require authors to inform about the copyright status of the images shown in the figures of the papers. In this setting, large datasets of images automatically taken from the internet are great for training models but they are problematic in terms of copyright or data protection: the database maybe publicly available for academic purposes but the specific author of each picture may be unknown. Moreover, if the picture displays people, they should sign the consent to appear in the publication. In practice these images cannot be shown.

In case of natural images, endless arguments with editorial staff are easy to avoid by using whatever picture of the author taken by a close friend (cited with the proper credit), as in (Martinez, Cyriac, Batard, Bertalmío, & Malo, 2018), or the other way around, as in (Webster, 2011).

In this note we present a method to generate original cartoon-like images compatible with the statistical training used in (Li et al., 2022).

2. Method

In order to generate original cartoon-like images ready to be published we propose the following method: (1) deep introspection to internally visualize the main features of the class of scenes one wants to represent, and (2) by-hand drawing to synthesize an image of such mental representation.

Figure 1 illustrates the timeline and intermediate results of the by-hand drawing stage of the proposed method. While waking up that early or coffee is not strictly necessary, but a bit of background in drawing may help to keep the image statistics right so that the synthesized signal *resembles* the target.

It is important to note that given the randomness associated to the internal representation of stage (1) and the noisy nature of stage (2), the proposed synthesis method is unlikely to generate nothing close (in Mean Squared Error terms) to any existing still image of the target class.

More generally, following the classical observation in (Magritte, 1929), the stimuli generated by the proposed method certainly *are not* the objects they represent.

3. Results

Fig. 2 shows the result of the proposed method. Note that the reflection of the images introduced by the careless use of the *selfie* mode of the cellphone alters the appearance of time in the watch of the picture taken at 8:59AM in Fig. 1 but it does not reduce the generality of the result.

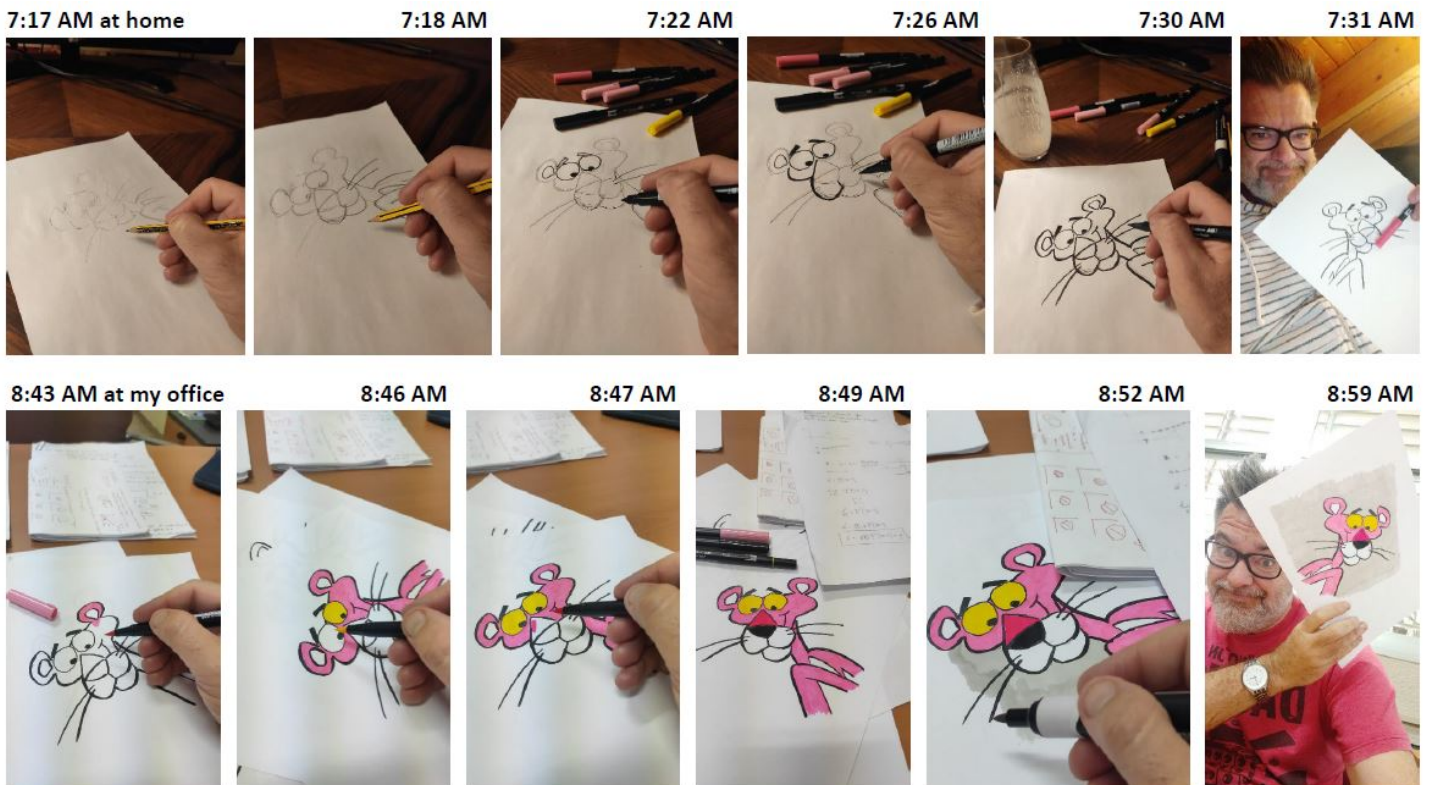


Figure 1: By-hand drawing stage of the proposed method. Performance by the author executed by feb. 8th 2022 in the case of a popular cartoon. He took pictures of himself along the process to illustrate intermediate results. The author holds the copyright of these pictures and explicitly consents that the pictures that display his face appear in this publication.

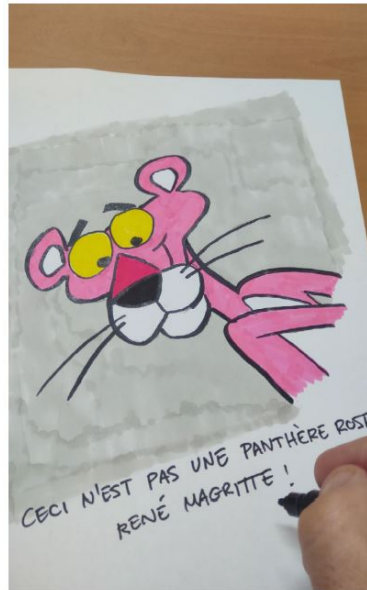


Figure 2: Result of the proposed method together with a reference to (Magritte, 1929). This image depicting the result of the proposed method was also taken by the author and he supports its publication here as well as any use of this image for academic non-profit purposes. In order to compare this result with the original result of René Magritte, please visit <https://en.wikipedia.org/wiki/File:MagrittePipe.jpg>

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References

- Field, D. J. (1987, Dec). Relations between the statistics of natural images and the response properties of cortical cells. *J. Opt. Soc. Am. A*, 4(12), 2379–2394.
- Foster, D. H., Amano, K., & Nascimento, S. M. (2016). Time-lapse ratios of cone excitations in natural scenes. *Vision research*, 120, 45–60.
- Gomez-Villa, A., Bertalmio, M., & Malo, J. (2020). Visual information flow in wilson-cowan networks. *J. Neurophysiol.*, 123(6), 2249–2268.
- Gutmann, M. U., Laparra, V., Hyvärinen, A., & Malo, J. (2014). Spatio-chromatic adaptation via higher-order canonical correlation analysis of natural images. *PLoS ONE*, 9(2), e86481.
- Laparra, V., Jiménez, S., Camps, G., & Malo, J. (2012). Nonlinearities and adaptation of color vision from sequential principal curves analysis. *Neural Computation*, 24(10), 2751–2788.
- Laparra, V., & Malo, J. (2015). Visual aftereffects and sensory nonlinearities from a single statistical framework. *Frontiers in Human Neuroscience*, 9, 557.
- Li, Q., Gomez-Villa, A., Bertalmio, M., & Malo, J. (2022). Contrast sensitivity functions in autoencoders. In *Journal of Vision. Preprint* <https://arxiv.org/abs/2103.00481>.
- Magritte, R. (1929). La trahison des images: Ceci n'est pas une pipe. In *Los Angeles County Museum of Art*. https://en.wikipedia.org/wiki/The_Treachery_of_Images.
- Malo, J. (2020). Spatio-chromatic information available from different neural layers via gaussianization. *J. Math. Neurosci.*, 10(18), 10.1186/s13408-020-00095-8.

- Malo, J., Ferri, F., Albert, J., Soret, J., & Artigas, J. (2000). The role of perceptual contrast non-linearities in image transform quantization. *Image and Vision Computing*, 18(3), 233-246.
- Martinez, M., Cyriac, P., Batard, T., Bertalmío, M., & Malo, J. (2018). Derivatives and inverse of cascaded linear+nonlinear neural models. *PLoS ONE*, 13(10), doi:10.1371/journal.pone.0201326.
- Nascimento, S. M., Amano, K., & Foster, D. H. (2016). Spatial distributions of local illumination color in natural scenes. *Vision Research*, 120, 39–44.
- Russakovsky, O., Deng, J., Su, H., Krause, J., Satheesh, S., Ma, S., et al. (2015). Imagenet large scale visual recognition challenge. *Int. J. Comput. Vis.*, 115, 211–252.
- Webster, M. A. (2011, 05). Adaptation and visual coding. *Journal of Vision*, 11(5), 3-3.