Gallery of Fluid Motion

Painting fluid motion using convolutional neural networks: An album of fluid motion 2.0

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In 1982, Milton Van Dyke published *An Album of Fluid Motion* [1], a unique collection of over 300 black-and-white photographs illustrating a diverse set of fluid phenomena. Although often categorized as a form of art, photography is arguably the most common technique used in experimental fluid mechanics research. Over the years, many photography methods, such as shadowgraphy [2], schlieren imagining [3], chronophotography [4], long exposures [5], and high-speed frame acquisition [6], have been utilized for flow visualization and as tools to study phenomena that are hidden from the human eye.

Now imagine if these visualizations served not just their scientific purpose but became the inspiration of an artistic masterpiece. What if Van Gogh, instead of looking to the night sky outside of his window at the Saint-Paul asylum, was able to look at other parts of nature for inspiration, such as a shock wave or flow instability? In this work, a convolutional neural network (CNN) is used to merge the contents of a scientific image with the style of an artistic picture, giving a glimpse into the artist's expression of classical fluid mechanics phenomena.

Convolutional neural networks are famously known for their application in image recognition [7]. Their success hinges on the ability of the network to encode the content of the image via the successive action of the network's layers, which act as filters. The output of deeper layers represents more basic, global content of the image and contains less information on the actual pixel colors [8]. For example, the placement of edges identified by an edge filter, perhaps outlining droplets in a spray, is a good representation of the image content. On the other hand, the artistic style of an image should correspond to qualities like brush stroke texture and not to the global placement of features. Remarkably, textural information is encoded by correlations between the CNN's filters and can be separated from the content information [8].

In this work, synthetic images are generated by combining the content of scientific photographs and the style of artistic paintings following the method described in [8] and implemented in an open source code [9]. Specifically, the pixels of an initially random image were updated to minimize the weighted sum of the content error between the synthetic image and photograph and

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FIG. 1. Selection of paintings generated by the algorithm for five different combinations of photographs and artworks. Photographs are taken from *An Album of Fluid Motion* [1]: (a) 94. *Kármán Vortex Street behind a Circular Cylinder at* R = 140 by S. Taneda, (b) 149. *Breakup of a Liquid Sheet* by N. Dombrowski, (c) and (e) 198. *Atomization from a Nozzle* by E. Klein, and (d) 265. *Cylinder at* M = 3.6 *in Air* by A. C. Charters. Artworks: (a) *Mural* by Jackson Pollock, (b) *Recollection of the Past* by Leonid Afremov, (c) *Luxe, Calme et Volupté* by Henri Matisse, (d) *Guernica* by Pablo Picasso, and (e) *The Starry Night* by Vincent van Gogh. https://doi.org/10.1103/APS.DFD.2018.GFM.P0004

the style error between the synthetic image and painting. These errors are defined as the difference between the filter outputs and filter correlations produced by feeding each image pair through the network, respectively. Figure 1 shows the synthetic images generated by the method for five different combinations of photographs and artworks. Photographs are taken from *An Album of Fluid Motion* [1]. With the help of artificial intelligence, these prints are transformed to reach their full artistic potential, opening new avenues for insights and inspiration.

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