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Symbolic Pointillism: Computer Art motivated by Human Perception

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Abstract

A new kind of multi-modal image representation that results in computer generated images is introduced. This image representation has been motivated by human visual perception. We call the style of images ‘Symbolic Pointillism’ since it resembles certain impressionist images drawn by the sub–group of Pointillists. However, instead of points, symbolic icons represent condensed and meaningful local information.

1 Introduction

We introduce a new kind of multi-modal image representation that results in computer generated images with considerable aesthetic value (see figure 1, 4 and 5). This image representation is used in the artificial visual system described in (Krüger et al., 2002a,b; Krüger and Wörgötter, 2002; Krüger et al., 2003a; ModIP, 1998—) and is a central pillar of the ongoing European project ECOVISION (ECOVISION:, 2002–2004). This image representation has been motivated by human visual perception (Krüger et al., 2003b). We call the style of images ‘Symbolic Pointillism’ as will be motivated below.

Pointillism is a style of art that was part of the impressionist movement. This movement aimed to paint images not in a realistic way but in a way ‘humans perceive the world’. The sub–group of impressionists called Pointillists (most notably Seurat and Pissarro) decided to base their paintings on small coloured dots (or even small oriented patches). The observer then constructs the image by mixing these dots. Perceived reality is, thus, a concept constructed by the observer.

It is by now known that the human visual system operated on a similar level. First, condensed and meaningful image information (like orientation, colour, distance, form, shape) is generated by localised processors (neurons) (Hubel and Wiesel, 1979; Gazzaniga, 1995). These neurons are highly connected and communicate with each other (Gazzaniga, 1995; Watt and Phillips, 2000). The need to reduce the cost of this communication process drives the condensation to meaningful information in the first place. As the consequence, it is almost as those nerve cells would in the end communicate symbols. It seems to be this specific neuronal communication process by which our perceived ‘reality’ is generated.

Having the aim of building technical systems with similar power and similar structure than the human visual system, we invented an image representation that consists of such abstract, symbolic icons. We include, for example, information about colour, orientation and contrast transition (see figure 2). A communication process is established by grouping related information (as represented by linking lines). In this way our electronically generated paintings visualise internal principles of image processing in the brain.

In section 2, we give a short description of the computation of our image representation as well as its relation to human perception. We then discuss this approach in the context of the modelling of ‘creativity’ in section 3. As a central thesis, we suggest that the understanding and modelling of creativity can be supported by the understanding and modelling of human perception.

2 Computation of ‘Symbolic Pointillist’ Images

In section 2.1, we describe the processing of the basic entities of our images which are symbol–like icons. These icons carry condensed information about multiple aspects of local image structures and organise themselves into groups. In section 2.2, we discuss the specific role of the icons in visual processing.

2.1 Symbolic Icons and Early Visual Feature Extraction

In our artificial system we process an image representation that codes different feature domains.

Position and Orientation: In our icons (see figure 2a) orientation is represented as a local line with appropriate angle. Edge detection and orientation estimation is based on the isotropic linear filter (called monogenic signal (Felsberg and Sommer, 2001)). The monogenic signal performs a *split of identity*: it orthogonally divides a signal into energetic information (indicating the likelihood of the presence of a structure), its geometric information

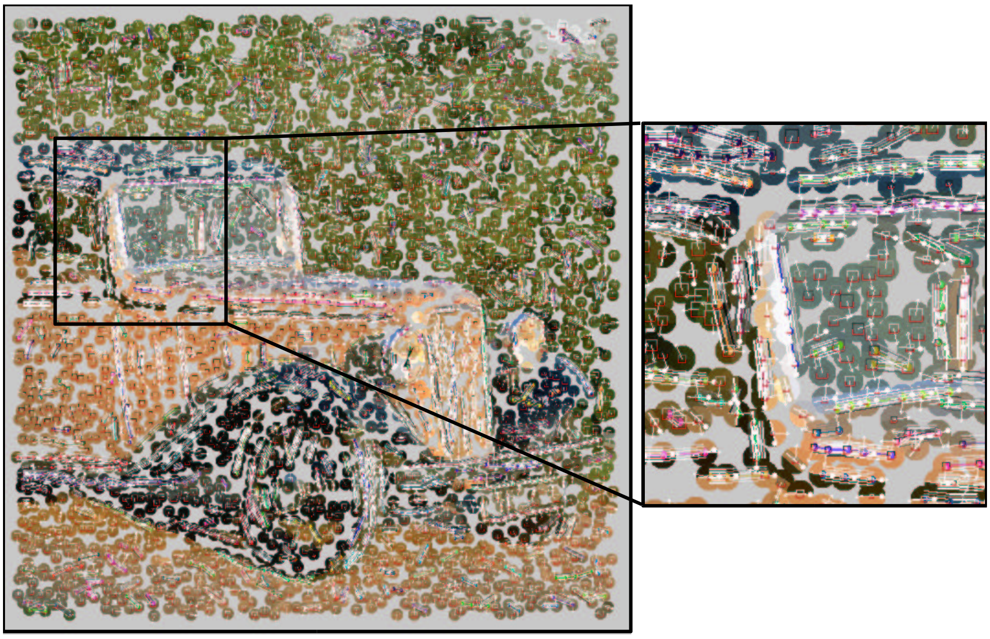

Figure 1: Symbolic Pointillism: A computer generated image and an enlarged frame.

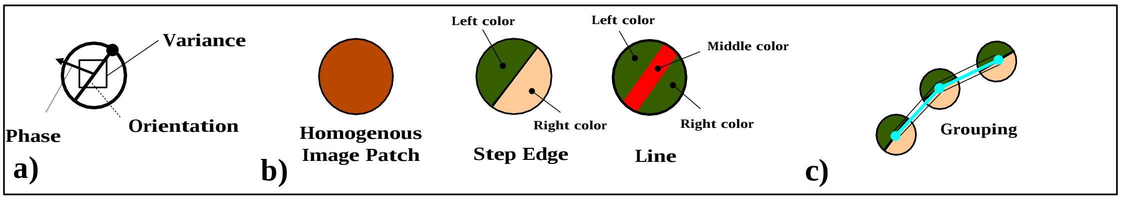

Figure 2: a,b: Icons as basic elements of ‘Symbolic Pointillism’. c: Grouping is represented by linked lines.

(orientation) and its contrast transition. We look for energy maxima in the position–orientation space. We use hexagonally arranged patches with a diameter of approximately 15 pixels. To avoid the occurrence of very close line–segments produced by the same image structure we demand that line segments have a certain minimal distance.

Contrast Transition: The contrast transition is displayed by a small arrow (see figure 2a). Using contrast transition, we can for example distinguish between lines and step edges (see figure 2b). Contrast transition is coded in the phase at a local maximum in the (x, y, o) feature space (Kovesi, 1999). It refers to the kind of grey level structure existent at the local image patch (as dark/bright edge, or bright line on dark background). The continuum of contrast transition can be expressed by the continuum of phases. Therefore, it allows for a coding different kinds of edge–like structures by one parameter.

Colour: Colour is processed by integrating over image patches in coincidence with their edge structure. In case of a line we have in addition a colour value in a middle strip that carries colour information (see figure 2b). To code the modality color at intrinsically one–dimensional image structures we perform a Gaussian integration in the RGB color space over the left and right part (’left’ and ’right’ defined by the associated line segment) of the image patch (see figure 2). Since the distribution of phases indicates the dominance of edges (Krüger and Wörgötter, 2002), this kind of integration corresponds to the most likely model of intrinsically one–dimensional structures.

Energy and Orientation Variance: The ‘homogeneous-ness’, ‘edge–ness’ or ‘junction–ness’ of a local signal patch can be computed from the variance of the local orientation and the energy in this area. The variance is displayed as the diameter of a square (see figure 2a) while the local energy is displayed as the grey value of the upper part of this square.

There is a huge amount of evidence that the above–mentioned modalities are processed in early stages of visual processing in so called ‘hyper–columns’ (see, e.g., (Hubel and Wiesel, 1979; Jones and Palmer, 1987; Gazzaniga, 1995)). However, it is not only a local image processing that is going on in early visual processing. As mentioned above, there occurs an extensive communication within visual brain areas as well as across these areas. The communication process leads to a binding to groups (v.d.Malsburg, 1981; Watt and Phillips, 2000) of local entities. In (Krüger and Wörgötter, 2002), we have described a process in which such a binding develop based on statistical measurements in natural scenes. These sta-

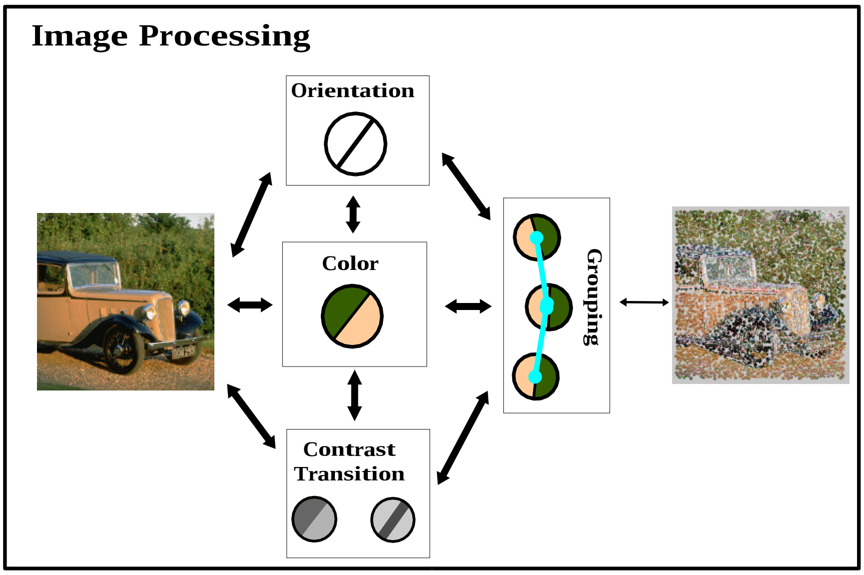

Figure 3: Different stages of image processing: First basic features in different domains (orientation, color, contrast transition) are being processed which are then grouped. Feature processing in the different domains as well as grouping is closely intertwined.

tistical measurements start a self–emergence process in which groups organise themselves. In our images, icons of the very same group are represented by links of very same colour (see figure 2c). The complete image processing is schematically displayed in figure 3.

2.2 Symbols as Carrier of condensed Information

All the low level features described in section 2.1 face the problem of an extremely high degree of vagueness and uncertainty (Aloimonos and Shulman, 1989). However, the human visual systems acquires visual representations which allow actions with high precision and certainty within the 3D world under rather uncontrolled conditions. The human visual system can achieve the needed certainty and completeness by integrating visual information (see, e.g., (Hoffman, 1980)) that occurs for example in the displayed grouping processes.

However, integration of information makes it necessary that local feature extraction is subject to modification by contextual influences and this communication has necessarily to be paid for with a certain cost. This cost can be reduced by limiting the amount of information transferred from one place to the other, i.e. by reducing the bandwidth. Therefore our symbolic icons represent a *condensed* description of a local image patch, which however contains the relevant information: Although a usual image patch has a dimension of, e.g., $15 \times 15 = 225$ pixel values, the output of our symbolic icons has less than 10 values.

3 Creativity and Human Perception

As described in section 2, our computer program produces images that display a certain amount of aesthetic value. People tend to find the images appealing, especially when they are displayed in a large format. Three images have been displayed (with a size of 1m^2 each) in ‘The Lighthouse’, a well known museum for modern art and design in Glasgow. A larger exhibition is on the way. Some images have been sold to a public institution. So they carry also financial value. But possesses our computer program creativity?

There is at least one aspect that may lead to a negative judgement plausible: Our computer program ‘paints’ natural objects and does not create ‘paintings’ using its ‘imagination’. However, it has some understanding of visual structures in general and this understanding is displayed in the images by the design of the icons and their grouping. Therefore, the generated ‘painting’ is not a reproduction of nature but a significant *restructuring* of the perceived image. In this way, our computer program shows *its own style*.

We see the ability to be confronted, to process and to a certain amount understand visual input as an important property which is linked to creativity: It was this confrontation with the natural world that has been dominated the work of most artists and even in most abstract paintings general rules about aesthetic are applied that (with high likelihood) have their origin in certain statistical or geometric regularities in natural scenes (Mumford and Gidas, 2001; Krüger, 1998).

AARON, developed by Harold Cohen, was the first

Figure 4: Symbolic Pointillism: Ape.

example of an 'artificial artist' that is able to paint images with considerable aesthetic value. Harold Cohen nevver claimed AARON to be creative. In contrast to our system, AARON was not equipped with the ability to perceive the world. It may well be that future artificial artists make experience in natural environments and develop their work in a process of similar confrontation with nature than many artists do. It may even be that the rules on which exploratory–creativity and transformational–creativity (Boden, 1990) is based upon, need to be learned from rules valid in natural environments. And it is the use, modification and deliberate violation of such well established rules that makes successful artists. In this way, we see our image representation as well as the produced images not only as an accidental 'by–product' of computer vision research but as a step towards artificial artists that are creative, and in this sense, can go beyond AARON.

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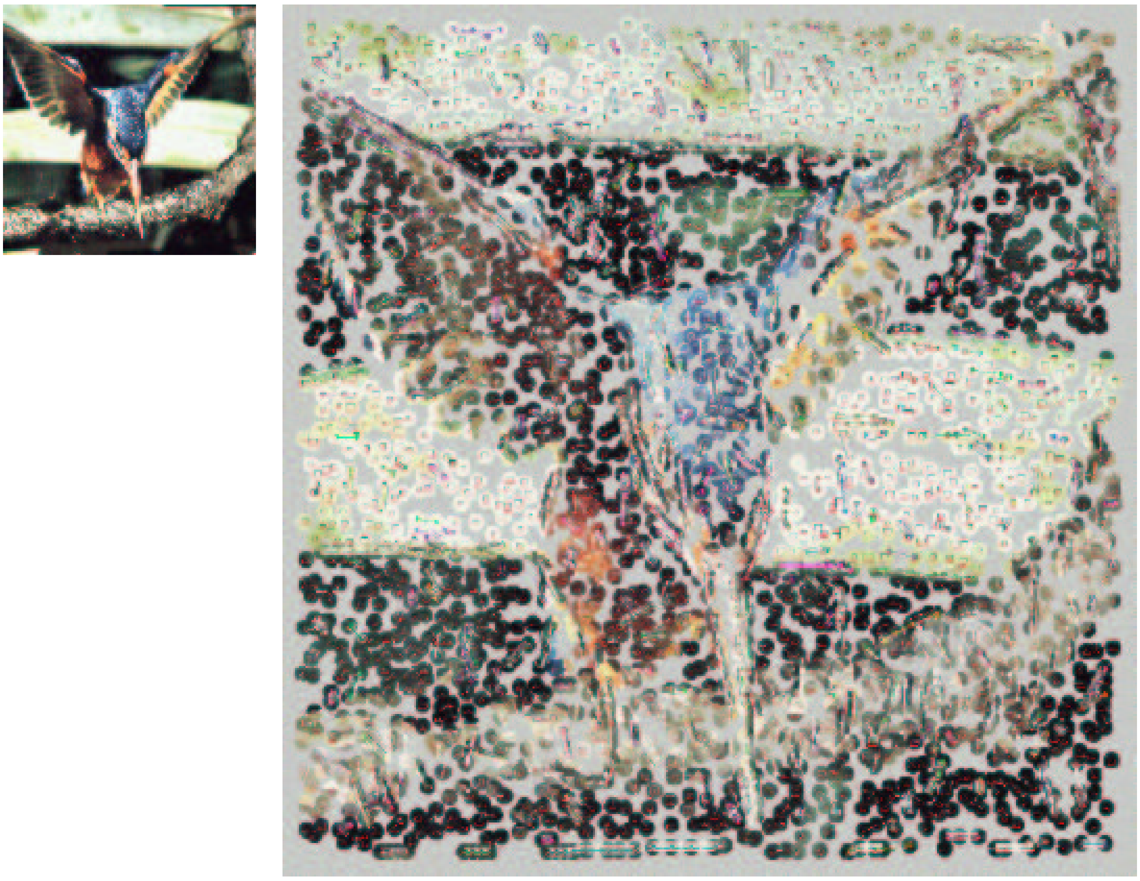

Figure 5: Symbolic Pointillism: Bird.

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