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Hiding in Plain Sight: Enabling the Vision of Signal Rich Art

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Abstract

Digital watermarking technologies are based on the idea of embedding a data-carrying signal in a semi covert manner in a given host image. Here we describe a new approach in which we render the signal itself as an explicit artistic pattern, thereby hiding the signal in plain sight. This pattern may be used as is, or as a texture layer in another image for various applications. There is an immense variety of signal carrying patterns and we present several examples. We also present some results on the detection robustness of these patterns.

Introduction

Digital watermarking is the technology of adding a unique digital identifier to digital media, such as audio, images or video. This embedded information may be used in a variety of applications, such as digital signatures, copyright, counterfeit resistance, user interaction, and product serialization.

In this paper we focus on digital watermarking for images. This is typically implemented using amplitude modulation of a host image: a signal with a small amplitude is added to each pixel in the host image, so that the changes are nearly imperceptible. The signal is designed with a lot of redundancy and error correction coding, so that the digital identifier may be accurately recovered from the embedded image after typical image processing degradations such as blur and noise (image resampling, sensor noise, etc.). When the image is captured by a mobile phone camera or a point of sale scanner, we can also expect a general perspective transform distortion, including, rotation, scale, shear and translation. Typical two-dimensional signaling methods, such as QR codes, have a dedicated signal for signal synchronization in the presence of such geometric distortions.

A common assumption in watermarking and steganography is that the signal must look like background noise to be visually imperceptible. However, in many applications, we may want to enhance an image by adding an explicit artistic background texture in a part of the image or over the whole image. Figure 1 shows an example. If this texture also carries a unique identifier, it will serve the same purpose as a watermark signal.

Figure 1 Example of an image with multiple artistic patterns in the background. Here either the pattern of vertical lines or the colored squares may be used to covertly carry a signal without changing the appearance of the image.

There is a widespread use of artistic patterns as background elements in packaging, advertising and other applications. The patterns are used to communicate a certain quality, say 'naturalness' for organic food products, or a technical idea (Fraunhofer spectral lines) in the website banner for this conference. However, these patterns only have an aesthetic purpose and do not carry a digital signal.

In consumer packaging, the value of a brand and its quality perception is extremely sensitive to the printed colors. Even minor changes to the colors may not be permissible and print process constraints like spot colors pose a challenge to embedding a traditional watermark on some packages. As an alternative, adding an explicit signal carrying artistic pattern helps to preserve the color integrity of the brand and enable new interactive applications with the product packaging.

Related Work

There are many examples of artistic enhancements of barcodes and QR codes [4] [5]. However, the underlying barcode or QR code is still quite visible. An alternative visible, but artistic signaling protocol called artCodes [6] exists, but it has limited payload capacity and the detection is not robust in the presence of noise.

The concept of signal rich art was introduced in a visionary paper [1], which described several ways in which a watermark may be used as a design element in applications. Reference [3] describes a particular idea for use in videoconferencing.

Signal Rich Art

We present a new approach to watermarking: we algorithmically generate artwork in which the signal is an intrinsic part of the artistic pattern. If the pattern is used to artistically enhance a target image or looks like a natural part of the image, it allows us to embed the watermark signal with high covertness as well as high detection robustness.

These patterns may be generated using classical signal processing tools as well as more recent neural network based style transfer methods. We call these patterns signal rich art, or SRA for short.

We will present a few examples of signal carrying patterns to illustrate the variety of methods that may be used to generate signal rich art. We will also describe ways to measure the signal embedding strength.

Methods

There are many ways of generating a watermark signal. In this paper we will assume the signal is created as a tile that may replicated to mark an image of any size. Each signal tile has two signals, a synchronization signal and an information payload signal. The synchronization signal is a fixed pattern that allows us to estimate a linear transform composed of rotation, scale and translation. This may also be sufficient to cover perspective transforms since they look like linear transforms locally. The payload signal is encoded with an error correction code and repetition for noise robustness. These synchronization and payload signal patterns are nearly orthogonal spatially. The addition of these two signals produces our watermark signal tile. For further details, see [2].

We present examples of SRA generated using three methods: 1) algorithmic 2) deep learning and 3) stylization filters. In all the examples below, the watermark ID can be decoded using the free Digimarc Discover app available for both Apple and Android devices, in the respective app stores. After running the app, hold the camera approximately four to six inches from the image for optimal detection.

Algorithmic

For the algorithmic method, we use the MATLAB toolbox. One approach to generate SRA is from maps used to visualize different aspects of the watermark signal. For example, a pattern may be generated from a contour map of the signal. We may also mark the locations of the local minima, with an additional keep out region constraint so the points are evenly distributed. This produces a sparse dot patterned image as shown in Figure 2, from which the watermark is still recoverable, due to the redundancy in the encoding.

The sparse dot patterned watermark may be extended to a halftone-like watermark pattern by modulating the number of dots in an area and the size of the dots, both of which are tunable parameters, to cover the whole range of grayscale values. We start with a watermarked grayscale image and create a local sparse mark using minima, but vary the size and number of dots depending on the local grayscale value, thereby obtaining a signal carrying halftone-like image, shown in Figure 3 and Figure 4. This idea may be extended to create signal carrying halftone color images.

Figure 2 Signal carrying artwork obtained by marking the locations of the local minima of the watermark signal, with keep out criteria around each point to achieve a more uniform distribution.

Figure 3 The idea of a sparse watermark pattern may be extended to create a halftone reconstruction of an image in which the watermark signal is an intrinsic part of the halftone dot pattern. We may obtain a local grayscale variation by modulating the dot size or dot density in an area. In this image we have used both (see next image for image details). This image was printed on a 8' x 10' wall poster as an interactive artwork exhibit at the AdobeMax conference in 2018.

Figure 4 Image detail showing the local grayscale variation using a combination of dot size and dot density modulation

Given any sparse distribution of points, there is a well-defined and unique Delaunay triangulation of the points, shown in Figure 5, which has pleasant visibility characteristics as well. The Delaunay triangulation has a dual graph called the Voronoi graph, shown in Figure 9, which is also a suitable SRA pattern. This pattern appears in natural objects such as leaves, foam, insect wing patterns and reptilian skin. The familiar natural look of the pattern provides high covertness.

An additional advantage of the SRA patterns we have described so far is that they may all be generated as vector artwork, which helps us overcome the challenge of device DPI and image scale variability in printing and deployment. Furthermore, vector artwork can also be easily embedded in websites since all browsers can render SVG files.

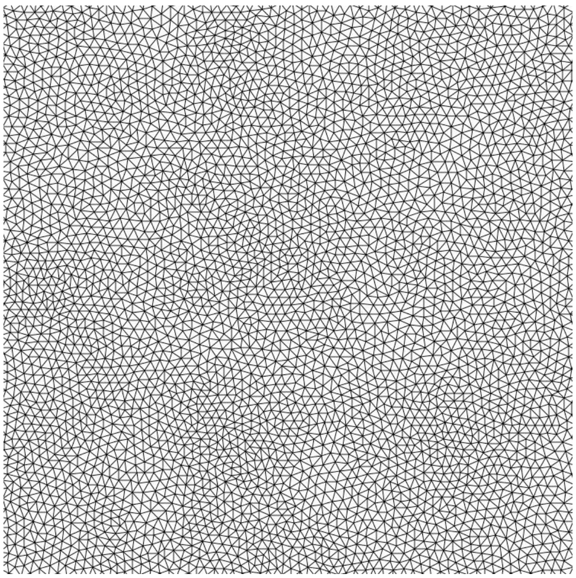

Figure 5 Delaunay triangulation embed obtained by connecting the dots of the sparse dot patterned SRA. The lines boost the signal by enhancing the local minima (dark pixels) in the downsampled image.

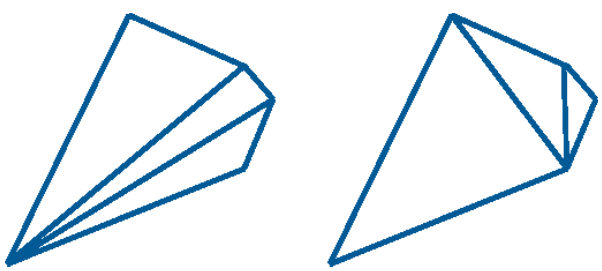

Figure 6 Intuitive explanation for the choice of the Delaunay triangulation over other triangulation options for signal embedding. The figure above shows two triangulation options out of five options for a random set of five points. The Delaunay triangulation on the right produces more uniformly sized triangles, which improves the visual appearance versus a random triangulation (left) which has more 'skinny' triangles and is less pleasing aesthetically.

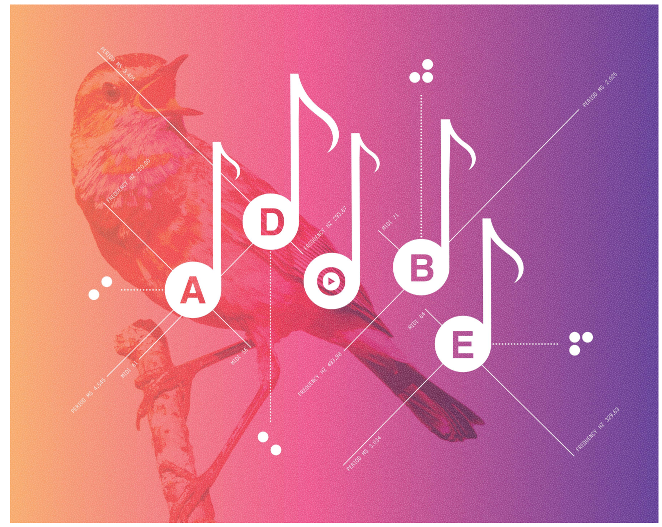

Figure 7 Example showing the Delaunay triangulation SRA used as an aesthetic background pattern, thereby hiding the watermark signal in plain sight. Artwork detail shown in the next figure. This image was printed on a 8' x 10' wall poster as an interactive artwork exhibit at the AdobeMax conference in 2018.

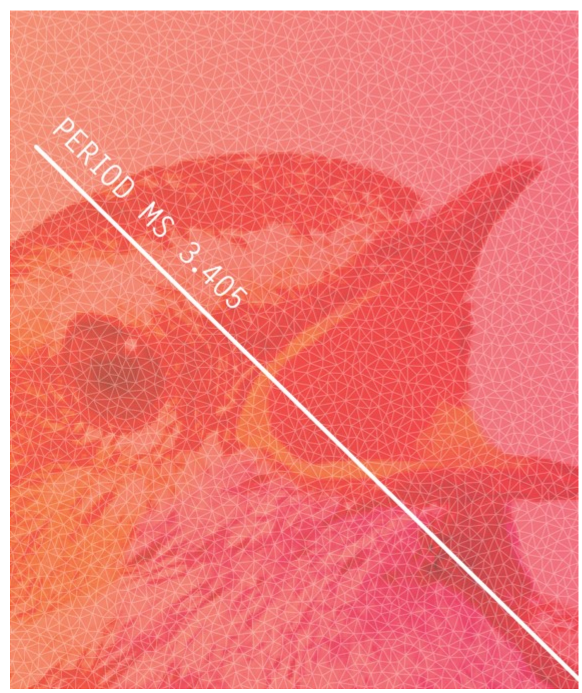

Figure 8 Artwork detail showing the Delaunay SRA used as an artistic background pattern.

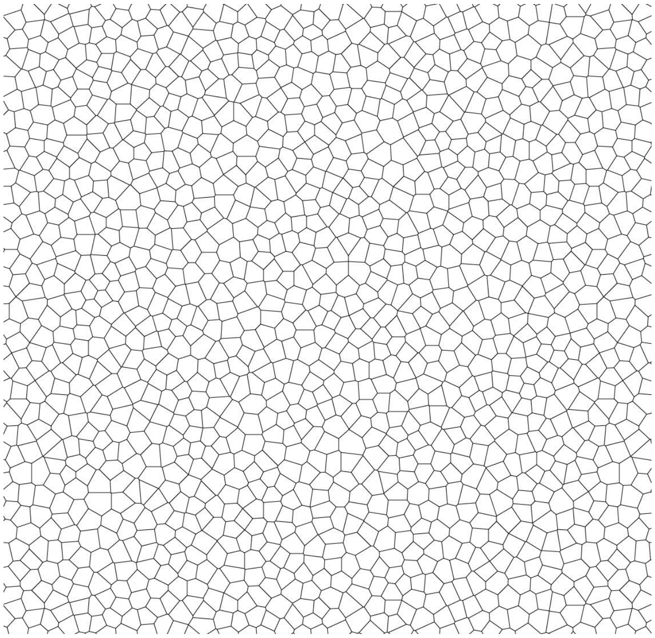

Figure 9 SRA created from a Voronoi plot of local signal maxima. The Voronoi cells re-produce the local maxima in the downsampled image, thereby allowing us to decode the watermark signal.

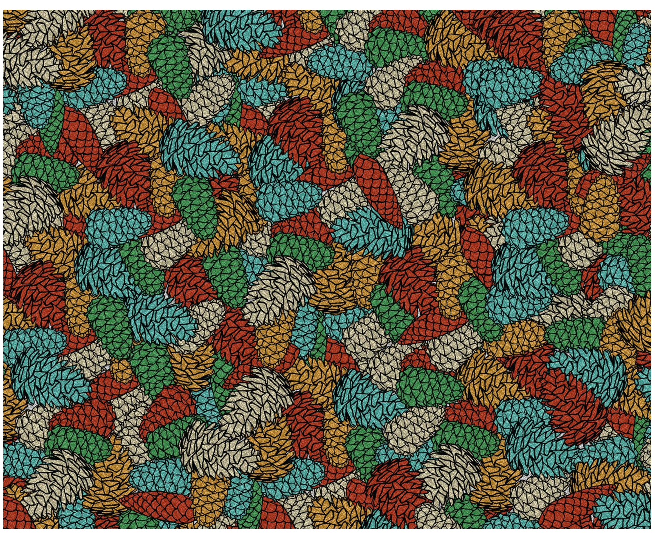

Figure 10 Example showing the Voronoi SRA used as an aesthetic background pattern, thereby hiding the watermark signal in plain sight. Artwork detail shown in the next figure. This image was printed on an 8' x 10' wall poster as an interactive artwork exhibit at the AdobeMax conference in 2018.

Figure 11 Artwork detail showing the Voronoi SRA used as an aesthetic background pattern.

Deep Learning/Style Transfer

For the second method of generating SRA using deep learning algorithms, we use an open source tool called TensorFlow. We apply a deep learning algorithm called Style Transfer [7], in which any target image (called the content image in this context) may be rendered in the painting style of a given artist. To generate SRA, we use the watermark signal as the content image and the input style image may be a painting or any pattern. Then the style transfer algorithm produces a signal carrying pattern in which the fine details of the pattern intrinsically communicate the watermark information, without further modulation. Examples are shown in Figure 12 and Figure 13. At a high level, we may think of this approach as cutting up the style image into smaller pieces and reproducing the content image as a seamless patchwork of these pieces based on the best local correlation.

Typically, in style transfer, we use a pre-trained neural network at the core of the style transfer algorithm. In our experiments, we used the pre-trained VGG-16 neural network. The style transfer algorithm attempts to minimize a loss function which is the sum of two loss functions, namely the content loss and the style loss. The content loss is simply the Euclidean distance between the mixed image P^l and the content image F^l in the layer l of the network,

$$L_{content} = \sum_{i,j}(F_{ij}^l - P_{ij}^l)^2 \qquad (1)$$

where i, j are the pixel coordinates. Further, this loss is summed over all the layers of interest in the network. This is close to the objective of the watermark detector, which is trying to maximize the correlation between the watermark signal and the embedded image. The style loss is defined in terms of second order correlations in the data and tries to minimize the Euclidean distance between the Gram matrix

$$G_{ij}^l = \sum_k F_{ik}^l F_{kj}^l \qquad (2)$$

of the mixed image G^l, and style images A^l in the layer l of the network,

$$L_{style} = \sum_{i,j}(G_{ij}^l - A_{ij}^l)^2 \quad (3)$$

and this is also summed over all the layers of interest. Finally, the optimization program iterates several times over the mixed image and the network response to minimize the loss function. The iterations are seeded with a random noise-like image, and as the loss reduces after a few iterations, the mixed image begins to resemble the local characteristics of the style image more and more while also maintaining a high correlation with the content image. This achieves the goal of transferring an artistic style to any picture.

Automatic Grading Method

There are a number of tunable parameters in the algorithmic as well as the deep learning based SRA algorithms. These parameters affect the readability of the watermark signal and the visual appearance of the generated pattern. For instance, in the style transfer algorithm described in [8], some of the design choices are: 1) the number of network layers to use, 2) number of iterations and 3) relative weight of the content and style loss. It is useful to have an automatic grading method, so that we may search the parameter space for good signal readability and then we only need a subjective evaluation of the signal carrying texture for those optimal parameter settings.

We have created an automatic grading method as follows. The watermark signal should be readable in the presence of typical image processing distortions such as camera capture, noise from sensors and lossy compression (JPEG). We model these distortions by attacking the image with blur and noise and measuring the average detection rate at increasing levels of blur and noise. We may compare the blur and noise level at which detection drops off with some baseline images watermarked the standard way, using pixel amplitude modulation. If the watermark detects at a rate better than 90% at a set of baseline blur and noise levels, we consider the embedding robust.

Specifically, we looked at two detection rates, based on common applications of the Digimarc barcode. One is the POS (point of sale) detection rate, which is based on a 660nm illumination source and noise and blur equivalent to a Datalogic POS camera. The second detection rate is based on a model which assumes white light illumination and noise and blur equivalent to an iPhone 6 camera.

The automatic grading method has been applied to discover some robustly embedded patterns, which are also interesting to look at, using a variety of input style images and the style transfer method. Figure 12 shows an example.

Our grading method also showed that a different style transfer algorithm called ‘Fast Style Transfer’ [9] produces well-embedded patterns without any need for parameter tuning. Some examples are shown in Figure 13.

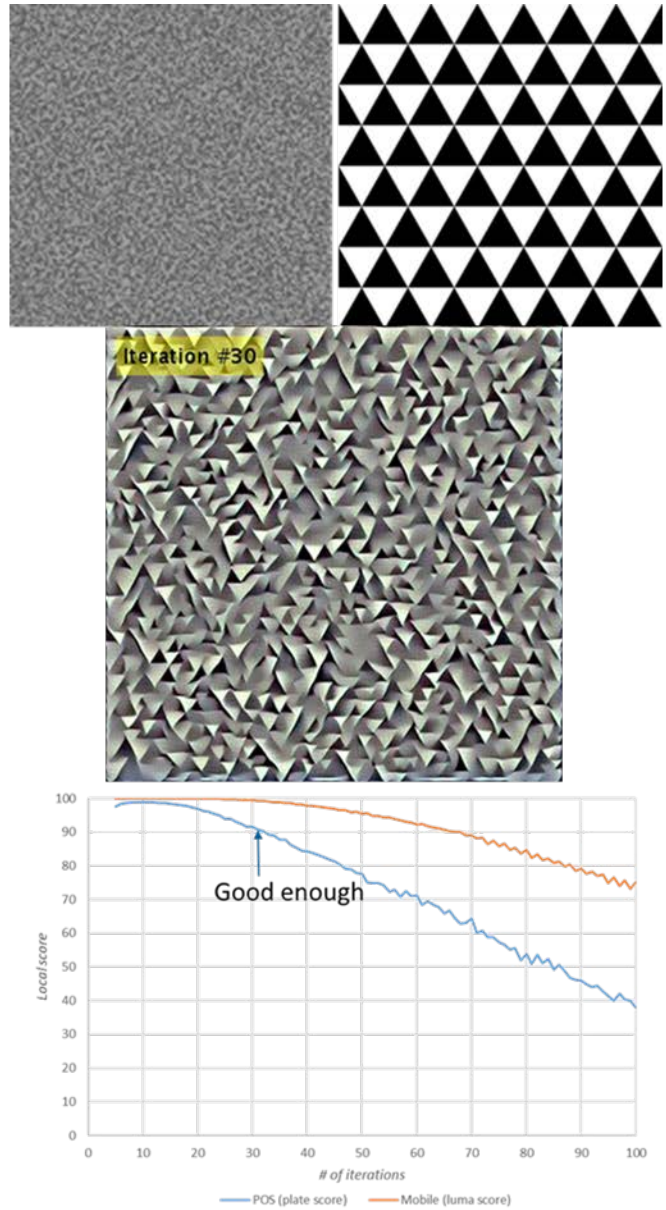

Figure 12 Style transfer SRA based on deep learning using the VGG16 neural network [8]. At the top left image is the content image, the top right is the style image, the middle image is the embedded signal carrying pattern obtained using style transfer after 30 iterations. The bottom image shows the average detection rates (POS and Mobile) for each iteration of the style transfer up to 100 iterations. The mixed image used to seed the first iteration is an AWGN noise-like image. As the number of iterations increase, the mixed image begins to resemble the style image more and more, but the signal quality also degrades after peaking around 10 iterations as shown in the bottom plot. The mixed image after 30 iterations has a good tradeoff between visual quality and detection rate. The number of iterations varies depending on the style image, so the automated process helps us narrow the search space.

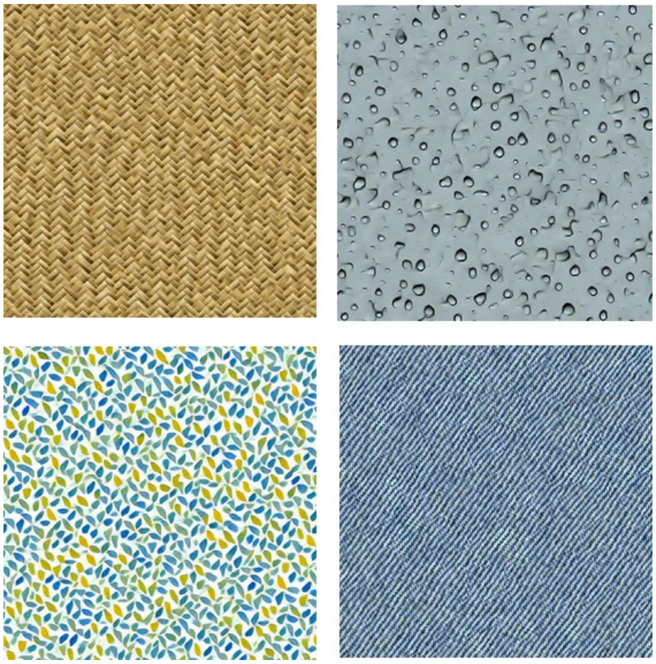

Figure 13 Sample SRA embeds obtained using the fast style transfer algorithm [9]. Clockwise from the top left, the styles applied are 'basket weave', 'raindrops', 'denim' and 'leaves'. In this case, the network is pre-trained for each style image, and is then applied to any content image.

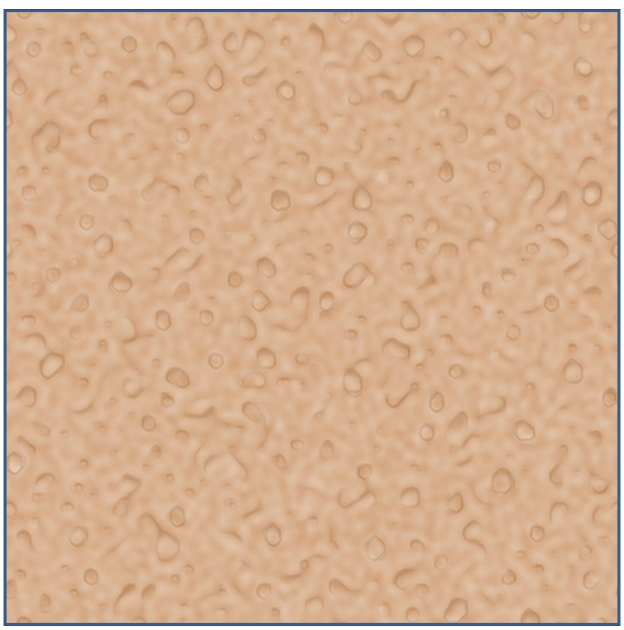

Figure 14 How the style transfer algorithm is embedding the signal: this figure shows an overlay of the 'raindrops' style transfer SRA sample (shown in previous figure) with the target embedded 'content' image. It is seen that the raindrops shapes closely follow the contours of the underlying content image, which ensures a high correlation with the watermark signal.

Figure 15 SRA generated using image stylization filters. The top left is the original unmarked image, the top right is a heavily watermarked version of the same image that we use as input to the stylization filters. We would never watermark an image this heavily in practice, because the watermark signal is clearly visible. The four images at the bottom show various image stylization filters applied to the watermarked image. The stylization weakens the watermark signal a bit, but it also hides the signal very well.

Image Stylization Filters

The third approach to generating SRA is based on regular signal processing algorithms. Commonly used image processing tools such as Adobe Illustrator and Gimp as well as specialized applications such as FotoSketcher [10], have a number of image stylization filters which apply an artistic stylization to any image, such as a pencil sketch, crayon, pen and ink or watercolor style, to name a few. To generate SRA, we simply start with a strongly watermarked image prior to applying the style filter. Though the stylization weakens the signal strength, the grading method allows us to select the style parameters to ensure adequate signal as well as high covertness from the stylization. Examples are shown in Figure 15.

Conclusion

We described a new application of watermarking of embedding the signal as an explicit pattern for artistic enhancement or as a neutral background pattern, which we call Signal Rich Art or SRA for short. We described a few ways of generating such signal carrying patterns, based on regular signal processing methods, as well as using more recent deep learning tools. SRA may be a viable solution for embedding monochrome or vector artwork, where traditional embedding approaches may not work. Another advantage is that SRA places the signal embedding earlier in the design workflow, instead of as a final enhancement applied to the artwork just before printing. These methods are already being tested in real world applications with partners of Digimarc.

The generation of signal carrying patterns is potentially a vast area of research with myriad possibilities. This paper gives a small sample as an introduction to the concept. The samples presented here also illustrate the versatility of the Digimarc watermark signal, since it requires zero changes to the detector algorithms to recover the watermark ID in all cases.

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Author Biography

Ajith Kamath received his BTech in Electrical Engineering from IIT Madras (2000) and PhD in Electrical Engineering from North Carolina State University (2005). He is currently working as an R&D Engineer at Digimarc Corporation since 2009. His work focuses on the development of embedding and detection algorithms, as well as novel applications of watermarking.

Harish Palani studies Electrical Engineering & Computer Science and Business Administration as part of the Management, Entrepreneurship, & Technology Program at the University of California, Berkeley. His research journey began years ago with Quakify, an independently-developed earthquake early warning solution which won second place at the Intel International Science & Engineering Fair (among other accolades). Most recently, he spent a summer on the R&D team at Digimarc, where he focused on signal rich art technologies.

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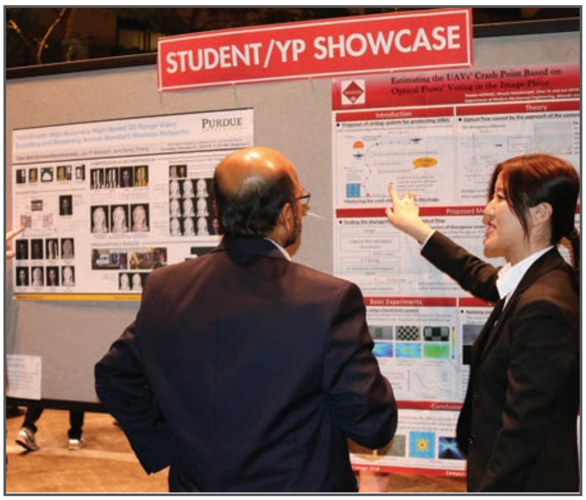

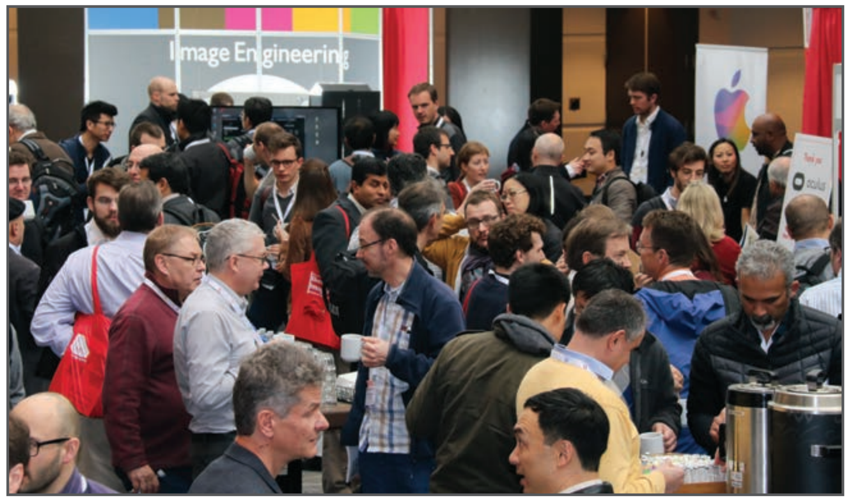

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