



Introduction

In the past few years, there has been a great deal of research works in creating artistic styles by computer. This field of research is known as Non-Photorealistic Rendering (NPR). These methods refer to any image processing technique which can transform (or more precisely *suggest*) an image into a specific artistic style such as ink painting, charcoal drawing, engraving, etc., or in a style other than realism [1] for a excellent review of existing NPR techniques).

Among them, freehand sketch style remains especially appealing as artistic depiction style. It can be used for illustrative purposes or artistic effects, but this representation style is also interesting due to its appealing ability to abstract away detail, to simplify shapes and to focus the viewer's attention on relevant features.

This work investigates the use of the Bayesian inference for devising an unsupervised sketch rendering procedure. As likelihood model of this inference, we exploit the recent statistical model of the gradient vector field distribution proposed in [2] and a global prior deformation model for each pencil stroke. The placement of each stroke is then viewed as the search of the (MAP) Maximum A Posteriori estimation of its deformations. This yields an unsupervised method to create realistic hand-sketched pencil drawings. Combined with an example-based local rendering model [3] the proposed scheme allows to simulate automatic synthesis of various artistic illustration styles.

Prior Distribution

A pencil stroke is represented by a set of points $\gamma = \{x_i, y_i, \dots, x_n, y_n\}$ equally sampled, mapped to the unit square $S = [0, 1]^2$, and on which we introduce a set of,

Non-Affine Deformations

Represented by a displacement function $\mathcal{D}(x, y)$ [4]. The mapping $(x, y) \mapsto (x, y) + \mathcal{D}(x, y)$ constitutes our non-affine deformation model.

$$\mathcal{D}(x, y) = \sum_{m=1}^M \sum_{n=1}^N \lambda_{m,n} \xi_{m,n}^x(x, y) + \xi_{m,n}^y(x, y)$$

The parameter vectors ξ are the projections of the displacement function on the following orthogonal basis,

$$\xi_{m,n}^x(x, y) = (2 \sin(\pi n x) \cos(\pi m y), 0)$$

$$\xi_{m,n}^y(x, y) = (0, 2 \cos(\pi n x) \sin(\pi m y))$$



Non-affine deformations, with $\xi_{1,1}^x = -4\xi_{1,1}^y = 4$ and by adding $\xi_{1,2}^x = -4$

Affine Deformations

We also introduce a set of admissible linear deformations on γ involving translation (τ_x, τ_y) , scaling s , and rotation ψ .

Let γ_0 be a deformed version of the original prototype γ_0 according to the deformations with parameter vector θ (4 affine transformation parameters + 1 global non affine deformation parameters $\{\xi_1^x, \xi_1^y, \xi_2^x, \xi_2^y\}$). The prototype template along with the set of aforementioned deformations θ constitute our global prior model of a pencil stroke.

Prior Distribution

Let Θ be the random variable corresponding to the vector of (affine and non-affine) deformations. We model the distribution of Θ by,

$$P_{\Theta}(\theta) \propto \mathcal{L}(\tau_x, \tau_y, s, \psi) \exp\left(-\sum_{i=1}^4 \frac{(\xi_i^x)^2 + (\xi_i^y)^2}{\tau_{\Theta}(i)}\right)$$

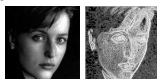
where ρ allows to control the "rigidity" of the pencil stroke and ξ is related to the complexity of the admissible deformations.

Likelihood Distribution

We base the likelihood of deformations of a given (candidate) pencil stroke on the statistical distribution of the gradient vector field (norm and angle) of the gray levels [2, 5]. This model can define, with a true statistical meaning, the likelihood of a deformation θ (or equivalently a pencil stroke template γ_0 with deformation parameters θ) by the following Gibbs distribution,

$$P_{\gamma|\Theta}(y|\theta) = \frac{1}{Z_{\theta}} \exp(-U(\theta, y, \gamma))$$

where γ represents the set of random variable couples associated to the gradient vector (norm and angle) of each pixel of the input image.



Real picture & Likelihood map for the statistical distribution of the gradient norm

Stroke localization

We view the localization of a pencil stroke in a sketch drawing as finding its deformation θ that maximizes the distribution,

$$P_{\Theta|\gamma}(\theta|\gamma) \propto P_{\gamma|\Theta}(y|\theta) P_{\Theta}(\theta) \\ = \exp\left(-\frac{(U(\theta, y, \gamma) + \rho U_{\Theta}(\theta))}{C|\theta|_{\Theta}}\right)$$

or equivalently as the search of θ that minimizes $U(\theta, y, \gamma)$. We use the stochastic optimization algorithm E/S described in [6] to minimize U and the following strategy,

Sketch Rendering Procedure

Input image to be sketched
Size of I
Gibbs energy field
Deformation parameters of a stroke (τ_x, τ_y) : location
 s : scale factor
 ψ : orientation, $\psi[s]$: gradient angle at s
 $\xi_{m,n}$: non-linear deformations
Size of the sliding window

1. Initialization

Set of potential location \leftarrow Canny on I
 $k \leftarrow 0$

2. Pencil Stroke Placement

For each $N_x \times N_y$ non-overlapping sliding window W over I do

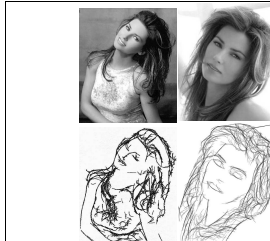
For each potential location s with coordinate (τ_x, τ_y) within W do

$\theta \leftarrow$ E/S minimization of $U(\theta)$ with:

$$\frac{N_I}{13} \leq s \leq \frac{N_I}{3} \\ \psi(\tau_x, \tau_y) = \frac{\pi}{2} \leq \psi \leq \psi(\tau_x, \tau_y) + \frac{\pi}{2} \\ -\infty \leq \xi_{m,n} \leq 5, \quad \forall m, n.$$

$\theta_k \leftarrow \arg \min_{\theta} U(\theta)$

Draw γ with parameter θ_k
 $k \leftarrow k + 1$



Sketch Rendering

In order to simulate automatic synthesis of illustration style, we use an example-based local rendering model [3] to transfer the textural tone value of a given depiction style,

Multiscale Rendering Procedure

y Input image (to be rendered)
 z Image to be synthesized
 x Input sample
 z^0, \dots, z^L A pyramid of synthesized images
 β Rendering weighting factor

Initialization:

- Stretch histogram of y according to the one of x
- Initialize z^0, \dots, z^L with a random noise
- $G_x \leftarrow$ Build Gaussian Pyramid from y
- $G_z \leftarrow$ Build Gaussian Pyramid from x
- Stretch the histogram of z^L according to the one of x^L $\forall i \in [0, \dots, L]$

— iterations $\leftarrow 0$

While (iterations < ITERMAY) do

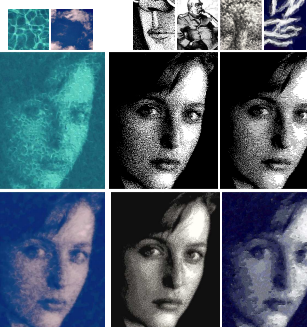
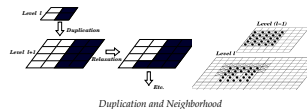
ForEach level l , from lower to higher resolution of G_z do

- ICM optimization [7] with ANN search [8] on

$$U^l(x, y, z) = \sum_{i \in [0, \dots, L]} \min \{D(N(x_p), N(y_l)) + \beta D(N(x_p), N(z_l))\}$$

- Duplication

$G_x \leftarrow$ Build Gaussian Pyramid from z^0
iterations \leftarrow iterations + 1



References

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