

UNSUPERVISED STATISTICAL SKETCHING FOR NON-PHOTOREALISTIC RENDERING MODELS

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ABSTRACT

This paper 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 by Destrempe et al. for contour detection. A global prior deformation model for each pencil stroke is also considered. In this Bayesian framework, the placement of each stroke is viewed as the search of the Maximum A Posteriori estimation of the posterior distribution of its deformations. We use a stochastic optimization algorithm in order to find these optimal deformations. This yields an unsupervised method to create realistic hand-drawn pencil drawings. Combined with an example-based local rendering model, used to transfer the textural tone value of a given depiction style, the proposed scheme allows to simulate automatic synthesis of various artistic illustration styles[†].

1. 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 techniques which can transform an image into a specific artistic styles (or more precisely that *suggest* an artistic style) such as ink painting, charcoal drawing, engraving, etc., or, more generally, in a style other than realism (see [1] for an 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 clarify or simplify shapes and to focus the viewer's attention on relevant features. In addition, this depiction style allows to efficiently convey a great deal of information with very few pencil strokes.

There are many commercial softwares [2, 3] or previous works [4, 5, 6] which propose (widely) supervised systems in which the user has to place each individual stroke manually and in which the system control over the tone, the smudging and amount of details or systems that use a 3D polygonal mesh information [7]. None considered an unsupervised system for pencil stroke placement allowing to create automatic realistic hand-drawn pencil drawing directly from a 2D grey-scale real image. Let us add that the methods proposed by the computer graphics community are generally

[†] cf. [http : www.iro.umontreal.ca/~mignotte/ICIP03/](http://www.iro.umontreal.ca/~mignotte/ICIP03/) for additional and color Non-Photorealistic Rendering results.

specifically tailored to a particular rendering style and/or are purely deterministic algorithmic techniques (excepted [8, 9]) and not statistical.

The main contribution of this paper is to provide a Bayesian formulation for the sketch rendering problem. This model exploits a recent likelihood model based on the statistical distribution of the gradient vector field introduced in [10] and a global prior deformation model for each pencil stroke. This global Bayesian sketch rendering model can also be efficiently combined with the non-parametric (and example-based) Bayesian local rendering model proposed in [11]. This example-based rendering model can also be used to transfer the tonal adjustment or the texture of a given artistic (rendering) depiction style. Combination of these two techniques allows to create various artistic illustration styles.

This paper is organized as follows. In Sections 2 and 3 we present the prior and likelihood models of our Bayesian sketch rendering method. Sections 4 and 5 describe the localization and rendering procedures of a pencil stroke. Finally, obtained results of our freehand sketching method are presented and combined with the sample-based rendering model proposed in [11].

2. PRIOR MODEL & DISTRIBUTION

2.1. Prior Model

In our model, a pencil stroke is represented by a template, i.e., a set of τ labeled points $\gamma = (x_1, y_1, \dots, x_\tau, y_\tau)$ equally sampled, which approximate the outline of a straight line (see Fig. 1). A cubic B-spline shape representation involving these τ control points is then defined. In order to take into account the variability of the pencil stroke deformations, we introduce on this template, a set of admissible global non-affine and affine deformations.

Non-Affine Deformations

This deformation model was first proposed by Jain *et al.* [12] for the localization of shapes. In this approach, the template image is considered to be mapped to the unit square $S = [0, 1]^2$. The deformation is then represented by a displacement function denoted $\mathcal{D}(x, y)$. The mapping $(x, y) \mapsto (x, y) + \mathcal{D}(x, y)$ is thus a deformation of S , a smooth mapping of the unit square onto itself. The space of such displacement functions is spanned by the following orthogonal bases,

$$\begin{aligned} e_{m,n}^x(x, y) &= \left(2 \sin(\pi n x) \cos(\pi m y), 0 \right), \\ e_{m,n}^y(x, y) &= \left(0, 2 \cos(\pi n x) \sin(\pi m y) \right), \end{aligned}$$

for $m, n = 1, 2, \dots$. Low values of m and/or n correspond to lower frequency components of the deformation in the x and y directions, respectively. The displacement function is then chosen as follows,

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

where $\lambda_{m,n} = \pi^2(n^2 + m^2)$ are the normalizing constants. The parameter vectors ξ are the projections of the displacement function on the orthogonal basis previously defined. In order to allow a sufficiently wide range of possible deformations, while keeping the number of parameters reasonable, we use $M = N = 2$. Fig. 1 illustrates the series of deformations of an initial template using higher order terms and different values of M and N . We can notice that these deformations can efficiently express the inherent variability of a pencil stroke and that the deformation becomes more complex as higher frequency components are added to the displacement function \mathcal{D} .

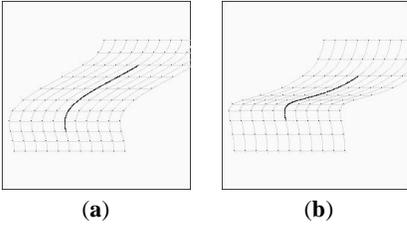


FIG. 1 – Global non-affine deformations, (a) $\xi_{1,2}^x = -4, \xi_{2,2}^x = -1, \xi_{1,0}^y = 4$. (b) by adding $\xi_{2,2}^y = -4$.

Affine Deformations

Finally, we introduce a set of admissible linear and rigid deformations on γ . These deformations involve translation (τ_x, τ_y) , scaling s , and rotation ψ applied point-wise to the template.

Let now γ_θ be a deformed version of the original prototype γ_0 according to the aforementioned deformations with parameter vector θ . A global configuration of the deformable template is thus described by four parameters corresponding to affine transformations, and four global non affine deformation parameters (due to the symmetry of the non-deformed original template associated to the pencil stroke), i.e., $(\xi_{1,2}^x, \xi_{2,2}^x, \xi_{1,0}^y, \xi_{2,1}^y)$. The prototype template along with the set of aforementioned deformations θ constitute our global prior model of a pencil stroke.

2.2. Prior Distribution

Let Θ be the random variable corresponding to the vector of (affine and non-affine) deformations. As proposed by Jain *et al.* [12], we model the distribution of Θ by,

$$P_\Theta(\theta) \propto \mathcal{U}(\tau_x, \tau_y, s, \psi) \exp\left(-\rho \underbrace{\sum_{\xi_i \in \xi} ((\xi_i^x)^2 + (\xi_i^y)^2)}_{U_p(\xi)}\right).$$

where \mathcal{U} designates the uniform distribution and where the parameter ρ allows to control the “rigidity” of the pencil stroke. ξ , the set of possible deformation parameter, allows to control the complexity of the used admissible deformations.

Let us add that the Bayesian sketch model we propose is also suitable for an example-based deformation model of pencil stroke

from a sample of pencil strokes extracted from a real freehand sketch drawing. This can be done in a training step by using a Probabilistic Principal Component Analysis or a mixture of PPCA [13] allowing to learn the principal non-linear deformations (and the prior distribution associated to these deformations) of the stroke shape preferentially used by the artist of a freehand drawing. Nevertheless, reliable detection of individual strokes in a freehand drawing, necessary to constitute the learning set, is not an easy task and can only be done with supervision.

3. LIKELIHOOD MODEL & 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. Already applied for the unsupervised detection of contours [10] and the localization of complex shape [14], this model can define, with a true statistical meaning, the likelihood of a deformation θ (or equivalently a pencil stroke template γ_θ with deformation parameters θ) by the following Gibbs distribution,

$$P_{Y/\Theta}(y/\theta) = \frac{1}{Z_y} \exp(-U_l(\theta, y, \gamma)),$$

where Y represents the field of observation, i.e., the set of random variable couples associated to the gradient vector (norm and angle) of each pixel of the input image. Z_y is a normalizing constant depending on the observable data y only and γ designates the parameter vector of this likelihood distribution, estimated in a Maximum Likelihood (ML) sense in a preliminary training step (see [10] for more details).

4. STROKE LOCALIZATION

We deduce from above and from Bayesian inference the posterior distribution of a deformed pencil stroke given the observable data,

$$\begin{aligned} P_{\Theta/Y}(\theta/y) &\propto P_{Y/\Theta}(y/\theta) P_\Theta(\theta), \\ &= \exp\left(-\left(U_l(\theta, y, \gamma) + \rho U_p(\xi)\right)\right), \\ &= \exp(-U(\theta, y, \gamma)). \end{aligned}$$

Where U_l is the likelihood energy term and U_p the prior energy term. We view the localization of a pencil stroke in a sketch drawing as finding its deformation θ that maximizes the posterior distribution $P_{\Theta/Y}(\theta/y)$ or equivalently as the search of the *Maximum A Posteriori* estimation of θ , $\hat{\theta}_{\text{MAP}} \in \arg \min_\theta U(\theta, y, \gamma)$.

The search of $\hat{\theta}_{\text{MAP}}$ is equivalent to the minimization of U . Our assumption is that an optimal solution for the energy function U corresponds to a good location, orientation, scale and non-affine deformation of a pencil stroke.

The objective function $U(\theta, y, \gamma)$ to be minimized is complex with several local *extrema* over the deformation parameter space. In order to solve it efficiently, we resort to the (evolutionary) stochastic optimization algorithm described in [15]. In order to speed up the convergence rate, we proceed in the following manner,

Initialization Step

First, we use a Canny edge detector [16] to estimate the edge map of the input image. We exploit one edge point of this Canny edge detection out of x ($x = 3$ in our application) edge points as a set of potential location (τ_x, τ_y) of a pencil stroke.

Local Optimization

For each $N_w \times N_w$ non-overlapping sliding window over the input image, we select one pencil stroke in the following manner,

1. For each potential location (τ_x, τ_y) within this window and defined in the initialization step, we use the optimization algorithm described in [15] in order to minimize the Gibbs field U on a restricted domain defined by,

$$\begin{aligned} \frac{N_i}{13} &\leq s \leq \frac{N_i}{3}, \\ \psi(\tau_x, \tau_y) - \frac{\pi}{4} &\leq \psi \leq \psi(\tau_x, \tau_y) + \frac{\pi}{4}, \\ -5 &\leq \xi_{m,n} \leq 5, \quad \forall m, n \end{aligned}$$

where $N_i \times N_i$ is the size of the input image and $\psi(\tau_x, \tau_y)$ designates the gradient orientation at (τ_x, τ_y) .

2. We keep the configuration of the pencil stroke that is the most likely i.e., the deformation of the pencil stroke associated to the lowest Gibbs energy.

5. PENCIL STROKE & SKETCH RENDERING

The first enhancement we propose is to render each pencil stroke with variable width and pressure. In our model, the stroke thickness and pressure first depends on the considered depiction style and is also considered to be linearly inversely proportional to the Gibbs energy (i.e., a less probable stroke is drawn with a low thickness and pressure and inversely).

The second enhancement is to simulate a given texture for the stroke (e.g., charcoal, sanguine, graphite pencil, etc.). In our application, the texture of a stroke is rendered by the non-parametric (and example-based) local rendering model proposed in [11]. This example-based model can also be used to transfer the tonal adjustment (or the texture created by the smudging effect in regions where there is no detected contours and thus no pencil stroke placement) of a given artistic rendering depiction style.

6. EXPERIMENTAL RESULTS

The prototype template of a pencil stroke is a B-spline connected 12-points model. The gradient vector field probability map and its parameters are given by [10]. For the Canny edge detector, the lower and upper thresholds are given by the estimation technique proposed in [16]. This estimation relies on a single threshold determining the percentage of edges to be found. This last threshold and the size of the non-overlapping sliding window N_w determine the number of strokes of the sketch drawing. The weighting factor ρ penalizing the prior term U_p with respect to the likelihood term U_l is set to 0.1. The Diameter of the exploration graph of the E/S algorithm are set equal to $D = 32$ and the size of the population is $n = 20$. These two control parameters are classically used and are independent of the energy function to be minimized [15]. We consider 1000 iterations of the E/S optimization procedure for each local optimization procedure. In total, the procedure takes 20 minutes for a sketch drawing on a 1.2 GHz PC workstation running Linux.

Several examples of sketch drawing results are shown in Figs. 2. In these examples we use the local rendering model proposed in [11] to simulate a charcoal texture for each pencil stroke. Several examples of sketch rendering results, combined with an example-based local rendering model, used to transfer the textural

tone value of a given depiction style, are also shown in Fig. 3 and Figs. 4. The proposed scheme allows to simulate automatic synthesis of various artistic illustration styles such as the charcoal, sanguine and graphite pencil style ([†] see [http : www.iro.umontreal.ca /~mignotte/ICIP03/](http://www.iro.umontreal.ca/~mignotte/ICIP03/) for additional and color rendering results).



FIG. 2 – (a) Real picture, (b) Examples of sketch drawing with a pencil stroke simulating the graphite (top) and charcoal style (middle and bottom)[†].

7. CONCLUSION

In this paper, we have presented a statistical method for the free-hand sketch rendering problem. This model is based on a likelihood model of the gradient vector field distribution and a simple parametric prior deformation model for each pencil stroke. The model we propose is also suitable for an example-based deformation model of pencil stroke by a Probabilistic Principal Component Analysis or a mixture of PPCA [13]. This method would allow to learn the principal non-linear deformations (and the prior distribution associated to these deformations) of the stroke shapes preferentially used by an artist in a given freehand drawing. The global Bayesian parametric sketch rendering model we propose can also be efficiently combined with the local Bayesian non parametric rendering model proposed in [11] in order to enhance the sketch drawing by simulating the textural tone value or the smudging process of a given artistic rendering depiction style. These two complementary schemes allow to simulate automatic synthesis of various artistic illustration styles.



FIG. 3 – Example of sketch drawing combined with an example-based local rendering model. From top to bottom, real drawing sample used to train the local rendering model ([11]) with the black ink style, sketch drawing with the textural tone value generated by this local rendering model[†].

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[†] cf. <http://www.iro.umontreal.ca/~mignotte/ICIP03/> for additional and color Non-Photorealistic Rendering results.



FIG. 4 – Examples of sketch drawing combined with an example-based local rendering model. From top to bottom and left to right, real drawing sample used to train the local rendering model ([11]) with respectively the graphite pencil, sanguine and charcoal style, sketch drawing with the textural tone value generated by each local rendering model with the above-mentioned style[†].