

Mimicking Hand-Drawn Pencil Lines

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Abstract

In applications such as architecture, early design sketches often mislead the target audience [SSRL96]. Approximate human-drawn sketches are typically accepted as a better way of demonstrating fundamental design concepts. To this end we have designed an algorithm that creates lines that perceptually resemble human-drawn lines. Our algorithm works directly with input point data and physically based mathematical model of human arm movement. Further, the algorithm does not rely on a database of human drawn lines, nor does it require any input other than the end points of the lines to generate a line of arbitrary length. The algorithm will generate any number of aesthetically pleasing and natural looking lines, where each one is unique. The algorithm was designed by conducting various user studies on human line sketches, and analyzing the lines to produce basic heuristics. We found that an observational analysis of human lines made a bigger impact on the algorithm than a statistical analysis. A further study has shown that the algorithm produces lines that are perceptually indistinguishable from straight hand-drawn pencil lines.

Categories and Subject Descriptors (according to ACM CCS): I.3.m [Computer Graphics]: Miscellaneous— non-photorealistic rendering, natural media simulation, pencil rendering, dynamic optimization yielding voluntary arm movement trajectory, image processing.

1. Introduction

Non-photorealistic Rendering (NPR) can convey information more effectively by omitting extraneous detail (abstraction), by focusing the viewer's attention on relevant features (emphasis), and by clarifying, simplifying, and disambiguating shape. In fact, a distinguishing feature of NPR is the concept of controlling and displaying detail in an image to enhance communication. The control of image detail is often combined with stylization to evoke the perception of complexity in an image without its explicit representation. NPR imagery allows the:

- communication of uncertainty—precisely rendered computer graphics imply an exactness and perfection that may overstate the fidelity of a simulation or representation; and
- communication of abstract ideas—simple line drawings such as diagrams used in textbooks can communicate abstract ideas in ways that a photograph cannot.

While there is no precise metric to differentiate between hand-drawn and computer-generated line drawings (some attempts have been made for specific techniques [MIA*08]),

humans can typically distinguish with ease the difference by a shear glance. For pencil lines this may be due to changes in grey levels, a variation not proportional to the path, or a change in the path orientation. Such variations make it difficult to produce aesthetically pleasing, natural looking results that mimic human-drawn lines.

Our method is based upon observation and statistical analysis of hand-drawn lines in conjunction with a model of human arm movement to create unique lines—given only a start and an end point without the use of a large sample line database. In addition, our method does not require the setting of user-determined parameters (patterns of deformation, pressure, density, etc.). The only parameter users are required to select through the system interface is one of eight commonly used pencil types. Our method then formulates and reproduces a curvature and texture that conforms and mimics real human-drawn pencil lines.

The goal of this research is to capture the essence of a single stroke, drawn by humans as straight pencil lines of arbitrary length, and encode it into an algorithm. In turn, an ap-

plication may use this algorithm to produce lines that resemble human-drawn lines (e. g., [Bre65]). Ideally, such an algorithm would reproduce the details carried by a human-drawn pencil line, without the need of storage libraries or user input to specify line attributes (as is the case, e. g., with [SB00]). Since the lines do not have set widths, colors, or particular textures, our proposed method will approximately reproduce the pencil details within the stroke it follows. In addition, such a line should not have repeated sections so that each line is unique.

We divide our algorithm for generating a human-like pencil lines into two parts: (a) synthesizing the path that corresponds to human arm movement and (b) synthesizing the pencil texture applied along the path, inspired by the textures produced by real pencils. Based on this general approach, our algorithm:

- produces high quality simulations of hand-drawn lines;
- easily incorporates into existing applications;
- produces lines of arbitrary length;
- does not require a library of sample lines (only a grey level dynamic range array and a co-occurrence matrix); and
- creates unique lines for every set of input point pairs.

Our contribution is a high quality pencil media line reproduction agent for creating aesthetically pleasing lines that mimic human-drawn lines. For this purpose, we use methods of image synthesis and a model of human arm movement for its replication. Our method avoids computationally expensive techniques and large storage space while continuously producing new, unique lines.

2. Previous Work

Our work draws from research on interactive non-photorealistic rendering (NPR) methods that approximate artistic hand-drawn images or paintings. In particular, we draw from NPR approaches for generating human line drawings and the simulation of graphite pencil texture, texture synthesis, and literature on the trajectory of human arm movement while drawing.

2.1. Human Line Drawings

Characteristics of lines in sketched and hand-drawn images have been studied closely in the field of NPR. Many algorithms captured style characteristics and applied multiple parameters (such as length, width, pressure, etc.). Previous methods [HL94, SSSS98, SS02] used style parameters and distorted a textured predefined piecewise polynomial curve or polygon path to create a stylized line. Other approaches reproduced and synthesized similar styles from examples lines [JEGPO02, KMM*02, FTP03, FS94, SD04, Bru06].

Our method differs from example-based methods in that we

do not require example lines to generate unique paths and textures. For each pencil type there exists two pieces of information in the algorithm, a dynamic range, and a co-occurrence matrix. We simply require vector endpoints to produce lines. Our aim is not to generate varying style from a single given style as seen in example-based methods, but to develop an algorithm that generates lines that vary in path orientation and texture synthesis mimicking observed real human movement and graphite pencil deposits noticed from straight line drawings on paper.

Our work is inspired by methods that simulated pencils as a medium, specifically the work by Sousa and Buchanan [SB99, SB00], who contributed a low-level simulation of graphite pencils on a paper medium. They designed a system to simulate graphite pencil on paper using microscopic observations [SB99]. Their work focused on generating fill strokes, using it for hatching purposes to reproduce artistic drawings. Our method differs because our lines are not restricted to short strokes and can vary greatly in length with no repeating segments. We also base our work on interactive pen-and-ink illustration by Salisbury et al. [SABS94], who described a level-of-detail system that interactively produces multiples of strokes to avoid tediously placing them manually. Our algorithm for drawing lines could easily be incorporated into the above approaches, adding the benefit of a model of human arm movement and a simple perceptual simulation model for graphite pencils without the requirement of a library of lines to copy, paste, and reshape.

2.2. Texture Synthesis

We were also influenced by a texture synthesis method based upon sequential synthesis [GM85] that preserves the second order statistics of the natural texture into the newly synthesized texture. Gagalowicz and Ma [GM85] also provided experimental evidence that the visual system is only sensitive to second-order spatial averages of a given texture field. More recent texture synthesis research renames second order statistics (spatial averages) using the term co-occurrence (CC) models or grey level co-occurrence (GLC) models [CRT01]. We use the GLC model, which is defined as the proportion of second order probability statistics of grey levels pairs that differ by a delta in the texture.

Applying co-occurrence matrices to synthesize texture have been shown to be extremely efficient in creating artificial textures that are hard to discriminate from in real textures [JB87]; the amount of data necessary to achieve the synthesis is very small and the texture can be generated easily to fit all kinds of surface shapes and sizes. Using this method allows us to control the second-order spatial averages of a given texture, since the synthesis is achieved directly from them without the computation of higher order statistics [GM85]. Also, texture similarity techniques using GLC probability distribution have shown to have high correlation with human percep-

tion of textures (the images appear to be visually similar to the original natural images).

Copeland et al. [CRT01] used a texture similarity metric based on the texture field of a model texture. The multi-resolution version of their algorithm, “Spin Flip”, showed satisfactory performance and resulted in pleasing outputs.

Zalesny and Gool [ZG01] introduced a similar texture synthesis method based on simulation of image intensity statistics. They collect the first order statistics (an intensity histogram), then extract the co-occurrence matrix (CCM) using cliques, i.e. pair of points (a head and a tail). Zalesny and Gool apply an additional criteria for classifying groups of cliques, using the CCM to store the distribution of intensity differences between the heads and tails pixels for a given orientation. We found this latter criteria was not necessary for our approach. Our CCM is calculated by summing all the joint probabilities of intensities for a given pixel neighborhood into their relative position in the CCM.

2.3. Dynamic Optimization of Human Arm Movement

In order to produce a good simulation of a human drawn lines we have also examined studies of the coordination of voluntary human arm movements. Human motor production has been analyzed, modeled and documented for well over a century [Woo99, Ber67, Ada71, Sch75]. Over the past few decades, theories of the functions of the Central Nervous System (CNS) with respect to human arm movement lead to the hypothesis of various mathematical models [FH85, UKS89, BMIG91, MAJ91, KG92, CVGB97].

According to these CNS theories, arm movements are produced in either one of two ways:

- Natural movements maintain a constant ratio of angular velocities of joints to bring reduction in control complexity and constrain the degrees of freedom.
- Hand trajectories are in extra-corporal space, joint rotations and additional non-physical parameters are tailored to produce the desired or intended hand movements.

Plamondon’s model [Pla95] describes a synergy of agonist and antagonist neuromuscular systems involved in the production of arm movements. He developed his theory by modeling the impulse responses to neuromuscular activities; His system produces a close proximity bell-shaped velocity profile to represent an entire point-to-point movement.

The *minimum jerk model* introduced by Flash and Hogan [FH85] formulated an objective function to solve a dynamic optimization problem for measuring the performance of any possible movement as the square of the jerk (defined as the change rate in acceleration) of the hand position integrated over an entire movement from start to end positions. Flash and Hogan [FH85] showed that the unique trajectory of planar, multi-joint arm movements that yields the best perfor-

mance was in agreement with experimental data. Their analysis was based solely on the kinematics of movement and independent from the dynamics of the musculoskeletal system as in the work done by Plamondon [Pla95]. We adopt the Flash and Hogan model because the model represents human arm trajectory in a planar field, similar to the movement of a human hand guided pencil across a piece of paper.

3. Algorithm

There are two parts to this work. The first constructs an algorithm to generate a realistic path. The second synthesizes a suitable texture to mimic a human line using a specific pencil. Our technique analyzes both the path and the stroke texture.

3.1. The Path

One of the hardest parts of replicating a human line drawing is creating the natural variation in the path of the line. We construct a path that conforms to a human arm trajectory using the method described by Flash and Hogan [FH85]. This method provides “the smoothest motion to bring the hand from an initial position to the final position in a given time” [FH85]. Our goal is to simulate a hand-drawn line only given two points. The Flash and Hogan model produces trajectories that (1) are invariant under translation and rotation and (2) whose shape does not change with amplitude or duration of the movement. All of these characteristics are based on observations of low frequency movements of human subjects. No high frequency movements were observed or implemented in the Flash and Hogan model. Our work adopts the same assumptions.

The Flash and Hogan mathematical model leads to a fast and interactive line path algorithm by providing a realistic overall velocity and acceleration profile and trajectory.

Our lines are defined by Equation 1, a fifth order polynomial:

$$\begin{aligned} x(t) &= x_0 + (x_0 - x_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \\ y(t) &= y_0 + (y_0 - y_f)(15\tau^4 - 6\tau^5 - 10\tau^3) \end{aligned} \quad (1)$$

where,

$$\tau = \frac{t}{t_f}, t \in [0, 2]$$

in which x_0, y_0 are the initial hand position coordinates at time increment t , and x_f, y_f are the final hand positions at $t = t_f$. The value of t varies from $[0, 2]$ the from start position t_0 to end position t_{final} . We found empirically that $t_{final} = 2$ provides satisfactory results, regardless of line length.

Line orientation is not present in the mathematical model, but we conducted user studies that indicate the disparity of the line orientation was not noticed by participants and did not effect the classification of real versus computer-generated drawings.

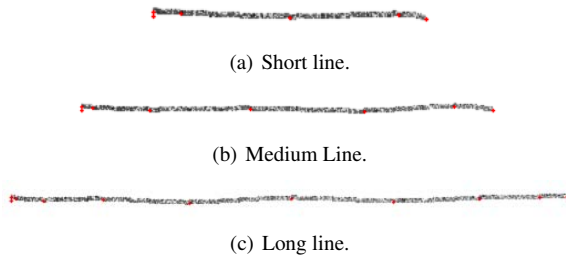


Figure 1: Generated lines and control point positions for varying lengths. For (a) $\Delta t = 0.5$, for (b) $\Delta t = 0.3$ and for (c) $\Delta t = 0.2$. The red dots represent the control point.

The points resulting from the polynomial of Equation 1 provide control points for a Catmull-Rom interpolating spline [SAG*05]. The number of points (defined by the time step, Δt) depend on the length of the line. Experimental evidence [FH85] shows that short hand drawn lines are perceptually closer to straight lines and longer lines have more variation. We conducted experiments to find reasonable values for Δt and provide the results in Table 1. Figure 1 shows the positions of the control points for three lines of varying length using each of the prescribed values for Δt .

We conducted a pilot study in which the participants were seated upright in front of a horizontal table with no constraints. Each participant drew a number of pencil lines between different orientation pairs of points.

To introduce a variation across the line, we include a deviation parameter based on observations of how humans draw lines. The data we collected showed considerably more variation from the centre line that wasn't accounted for with the variation of trajectories assumed by Equation 1.

To represent this variation, we introduce a deviational parameter we call *squiggle* as an extension to the Flash and Hogan model. The additional term is necessary to provide sufficient variation in the line paths based on our observations of human drawn drawings. Experiments were conducted to validate this choice, Section 5 provides details on the experiments we conducted. We define *squiggle* as a variable, D , for controlling the deviation normal to the Catmull-Rom spline at each of the lines control points also similar to methods used by Strothotte et al. [SS02]. The magnitude of the *squiggle* parameter controls the magnitude of random displacements applied to the Catmull-Rom spline controls points and therefore strongly influences the appearance of the path.

The deviational value is applied approximately normal to the Catmull-Rom spline at each of its control points. The variable D varies randomly in order to provide variation along the path; we empirically found a range [-5,+5] worked for our lines regardless of length and produces independent displacement values for each control point.

approx. Line Length in pixels	Time step Δt
[0, 200]	0.5
(200, 400]	0.3
> 400	0.2

Table 1: Empirical Values for the time step Δt .

3.2. The Texture

For each pencil type, we conduct a one time analysis of example lines in order to create a statistical profile, encoded in a histogram and CCM. Our algorithm creates the line texture after the natural-appearing path is created by initializing the stroke with random values, applying a bell-shaped fall-off of intensities from beginning to end of the stroke, applying the CCM for the pencil type, and then applying a Gaussian filter.

First, we obtain texture for simulating hand drawn lines by scanning and analyzing the statistical properties of example lines drawn by human participants using a wide range of pencils of the following types: 2H, H, HB, F, B, 3B, 6B, 8B (examples are shown in Table 2) on plain, 100% recycled, white paper. The following steps are taken to correctly capture the textural properties of the model texture:

- First, we determine the range of grey levels for pixels along the approximate centre of the pencil line (non-repeating Catmull-Rom control points) and record the histogram for the range $[min_{mid}, max_{mid}]$.
- Next, we determine the histogram of the grey levels for the line image, assuming that white pixels surround each line segment; since very few white pixels appear inside the line image, we do not consider white in the histogram. The histogram records intensities in the range $[min_{range}, max_{range}]$.
- Finally, we compute the co-occurrence matrix for the line image.

To determine the co-occurrence matrix (CCM), each image scan is rotated so that the line is approximately vertical. The co-occurrence matrix is updated by examining each pixel (p, q) with value $i \in [0, 255]$ and it's immediate neighbor in the positive y -direction, $(p, q + 1)$ with value $j \in [0, 255]$. The values (i, j) are indices to increment the appropriate cell of the co-occurrence matrix C defined over an $n \times m$ image I , parameterized by an offset $(\Delta x, \Delta y)$ as in Equation 2:

$$C(i, j) = \sum_{p=1}^n \sum_{q=1}^m \begin{cases} 1 & \text{if } I(p, q) = i \text{ and} \\ & I(p + \Delta x, q + \Delta y) = j \\ 0 & \text{otherwise} \end{cases} \quad (2)$$

We use the dynamic range and the co-occurrence of a target pencil texture to synthesize new the texture. We formulate a grey value distribution technique according to statistical observations that indicate, for most pencil lines, the distribution of grey pixel values starts at a dark value in the middle

of the line and falls off according to the bell-shaped curve in the direction normal to the line, see Figure 2.

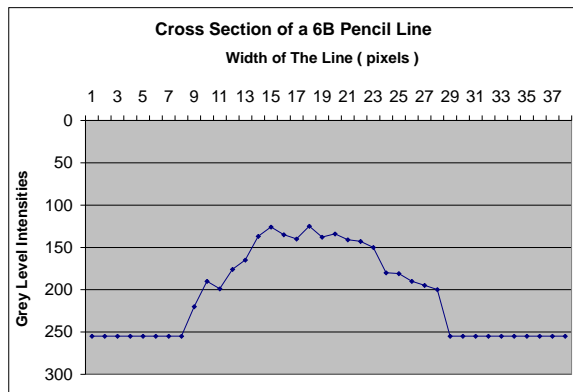


Figure 2: The approximately bell-shaped curve showing intensity values of cross sections of a lines drawn with a 6B pencil.

We first seed the line with initial random values (using the pre-selected pencil type) and then apply the co-occurrence matrix. According to the bell-shaped fall off we observed, we distribute the grey levels of the centre pixels of the generated spline, replicating the histogram in the range $[min_{mid}, max_{mid}]$. We determine an approximate direction normal to the line and the pixels along this direction to either side of the centre pixel are set to values randomly chosen in the range $[min_{range}, max_{mid}]$ and pixels further away are given a lighter intensity in the range $[max_{mid}, max_{range}]$, as illustrated in the texture sample of Figure 3.



Figure 3: Initial synthesized line texture and partial close-up view of the line texture. Placing the grey dynamic range values across the width and length of the path uniformly.

Next, we apply the CCM by comparing a 3x3 neighborhood of pixels. If the combination of pixel intensities does not exist in the CCM, each pixel's grey value is replaced with an existing neighboring value from the co-occurrence matrix. We repeat the co-occurrence process over the entire line multiple times until the amount of pixel changes reach a minimum, indicating how well the synthesized co-occurrence matrix represents the model CCM (see Figure 4).

Once complete, a single-pass Gaussian filter is applied to the generated lines to reduce tone differences and filter out aliasing effects (Figure 5).



Figure 4: Line and partial close-up view of the line texture after CCM step. The values of the pixels are analyzed and pairs of pixels are compared to their indices in the co-occurrence matrix and replaced with an appropriate value if their pair does not exist.



Figure 5: Final pencil line and close-up view of the line after a 3x3 single-pass Gaussian filter is applied.

4. Results

Our Human Line Algorithm (HLA) is implemented in C++ and runs on a 2.00 GHz Intel dual core processor workstation without any additional hardware optimization. We can interactively draw lines while the system synthesizes the new path and texture. All line drawing figures in this paper are drawn with our system when "generated by HLA" is indicated. Table 2 shows a comparison of hand-drawn lines with lines that were synthesized by our system.

The following is a pseudo-code description of the HLA algorithm, to enable easy application of the method:

- (1) Initialize the CCM and histogram to the User Selected Pencil type.
- (2) Read in Endpoints
- (3) If Endpoints == 2 then

- Find Control Points of the line between the two end points specified.
- Distribute random grey values across and along the line
- Use the CCM to replace random grey values along the line in 3x3 neighbourhood with existing co-located neighbour values in the CCM.
- Gaussian Blur the line.

5. Verification

In order to evaluate our technique, we designed a study using eighteen images; nine of which were scanned human made drawings, and the other nine were exact replications of the scanned images, made using our line algorithm. The aim of this study was to evaluate whether our generated lines would pass for real human drawn lines. Eleven participants participated in our study, all graduate and undergraduate students in the department of Computer Science at the University of













Line type	Real human line	"HLA"-generated lines
H		
HB		
B		
3B		
6B		
8B		

Table 2: Texture only line examples: comparison of hand-drawn lines with synthesized lines (squiggle, D parameter, set to zero).

Victoria. Each participant spent three seconds viewing each image and then selecting true if they thought the drawing was hand-made, false if they thought the drawing was computer generated. The timing was chosen empirically, such that participants had enough time to compare drawings without having too much time to over analyzing their decision.

Out of the 42% of mistakes made by all subjects, 69.5% of the decisions selected images to be of hand drawn type (when they were actually computer-generated) and 30.5% of the wrong choices selected images to be of computer-generated type (when they were actually real). A paired T-test showed a significant difference between computer-generated lines mistaken for real hand-drawn lines and the real hand drawn lines mistaken for computer-generated lines (paired $t(11) = 2.849, p < .05$). Our experimental results shows that the HLA generated line drawings were good enough to pass for hand-drawn lines.

6. Applications

Our technique is suitable for several different domains. Our line generation incorporates easily into existing graphics programs that produce line end points, and are editable by artists or additional algorithms. Our technique only requires the selection of a pencil type and specification of the end points of each line. For example, Figure 6 show a Gosper's Flowsnake [Gar76] space filling curves rendered with human like lines using the B pencil setting. The synthesized lines are applied to each of the short individual line segments of each curve. The drawings could be improved by detecting co-linear segments and processing them as a longer line to better emulate a humans artist.

In Figure 7 hatching lines are generated and replaced with synthesized lines; in this way we can simulate the effect of filling a part of the plane with unique human-like lines.

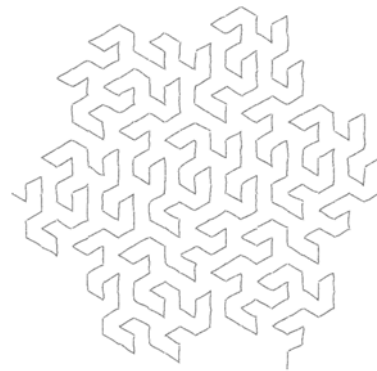


Figure 6: Flowsnake space filling curve using a B pencil generated by HLA.



Figure 7: Line hatching generated by HLA ($6B$ pencil).

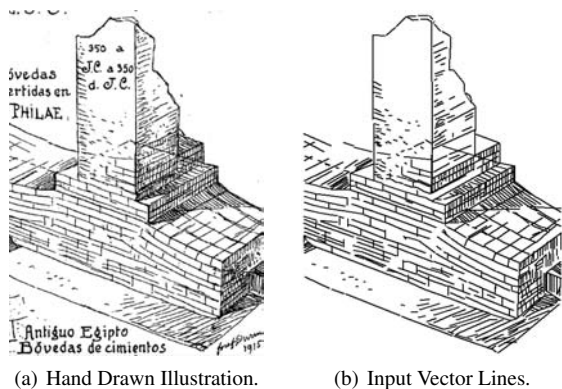
In Figure 8 a hand drawn illustration is used to extract vector lines, then used as input to the "HLA" algorithm resulting in part (c) of the figure. we note that our result is quite different than the artist's lines, but point out that our result in (c) has the appearance of being hand-drawn.

In Figure 9 an architectural model has been rendered using our lines. This example shows the variability of the line paths and provides the appearance of an hand-made image.

Finally, by capturing (e. g., through tablets) or tracing the lines drawn by artists we can apply the pencil style to those drawings as well.

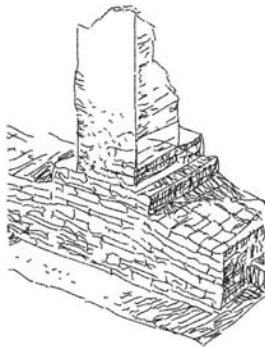
7. Conclusion and Future Work

The main contribution of this work is to provide a system that will serve as a high quality pencil line reproduction agent. Our system creates aesthetically pleasing human drawn pencil lines by using an image synthesis method and human arm movement replication model. The algorithm avoids computationally expensive techniques and large storage space. More investigation is needed to mimic the appearance of variable pressure along the lines. Choosing parameters that will make the lines appear to have more character will definitely increase the aesthetic property of the lines.



(a) Hand Drawn Illustration.

(b) Input Vector Lines.



(c) Result generated by HLA.

Figure 8: Our method takes as input lines specified only via their start and end points, such as the vector line drawing in (b), and produces a line drawing that mimics a real hand drawn graphite pencil drawing (a) by modeling human arm trajectory and a statistical model of graphite texture to produce unique, aesthetically pleasing and natural looking lines, without the need for databases of example strokes.

Similar approaches to the work documented here may work for drawing curved lines (Figure 10), but further investigation would be necessary to correctly mimic the resulting graphite textures on curved paths. Also more work can be done to mimic human hatching by conducting similar studies and observing the relationship between arm and wrist movement when producing shorter strokes. Figure 7 demonstrates our first attempt to consider hatching as an application, more experiments and analysis are needed to present accurate human hatching techniques.

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Figure 9: A barn generated by HLA (H pencil).



Figure 10: Example curve generated by HLA, using Flash and Hogan curve optimization methods, inspired by [FS94].

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