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Discovering High-level Parameters for Visualization Design

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Abstract

In most graphics and visualization applications, the effects of the mapping parameters on the output domain are multidimensional, non-linear and discontinuous. The complexity of such mapping often makes it difficult for a user to manually explore and manipulate the design parameter space to produce the desired output. Computer assistance is therefore useful in setting the mapping parameter values to generate desired outputs. Existing systems rely on exploring the entire input parameter space, which can be time and resource-intensive, particularly if the number of input parameters is large. We introduce a new approach to handling a large number of mapping parameters more efficiently. The basis for our approach is the identification of a small and effective set of high-level parameters that can be associated directly with the characteristics of the outputs. Users will have a better understanding of this small set of high-level parameters and can easily modify their values interactively to produce the desired outputs. We demonstrate this technique in manipulating mapping parameters for a non-photorealistic volume rendering application.

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications

1. Introduction

Setting parameter values manually to generate a desired output is difficult and tedious for many rendering, modeling and motion-control processes. Common parameter-setting problems include light selection and placement for image rendering, opacity and color transfer function specification for volume rendering, motion control for articulated-figure animation, expression synthesis of three-dimensional human faces, and automatic modeling of human bodies. Such graphics and visualization applications involve finding good parameters to control the mapping to the output domain. These mapping functions are often multidimensional, discontinuous and non-linear. Thus, manually setting the input parameters to produce the desired output is difficult.

Our research simplifies the process of setting parameters to obtain the desired output. We propose a new approach that addresses the problem of managing a large number of mapping parameters by introducing a small and effective set of new high-level parameters. These parameters are chosen so that they represent most of the characteristics of the output. The user can control these high-level parameters interactively to generate output images with desired characteristics. We use decision trees to learn the correspondence between the high-level parameters and the low-level parameters from data gathered in a user survey. We then partition the low-level space using the learned decision trees to produce images that have the desired high-level parameter values. We demonstrate the effectiveness of our method by applying it to the selection of parameters for expressive volume rendering using volume illustration.

2. Application

A key objective of graphical illustration is to provide useful information about the object rather than photo-realistic accuracy. Volume illustration [RE01] is an approach that uses a set of non-photo realistic (NPR) techniques for the visualization of volume models. The approach uses flexible and parameterized enhancement techniques to increase the expressiveness of the images rendered. Enhancement techniques include boundary enhancement, silhouette enhancement, distance color blending, feature halos, and tone shading. These techniques are controlled by dozens of parameters. For simplicity, we restrict ourselves to these five enhancement techniques and 25 of the parameters that control them. Table 1 list these techniques and the corresponding parameters. Boundary enhancement emphasizes the boundaries between data regions by increasing the opacity of voxels with high gradient magnitude. Silhouette enhance-

Technique	Input Param	Description
Boundary	k_{gc}	Contribution of non-boundary regions.
	k_{gs}	Scale of gradient enhancement.
	k_{ge}	Tightness of enhancement fall-off.
Silhouette	k_{sc}	Contribution of non-silhouette regions.
	k_{ss}	Scaling in silhouette regions.
	k_{se}	Enhancement fall-off.
Distance Color Blending	k_{ds}	Amount of color blending.
	k_{de}	Rate of color blending.
	c_b	Background color in RGB.
Feature Halos	k_{hpe}	Threshold for neighbor's gradient.
	k_{hse}	Tightness of halos in view plane.
	h_s	Halo size.
	o_{he}	Scaling of halo on opacity.
	c_{he}	Scaling of halo on color.
Tone Shading	k_{ta}	Amount of ambient light.
	I_a	Intensity of ambient light.
	k_{td}	Amount of directed light.
	c_w	Warm color in RGB.
	c_c	Cool color in RGB.

Table 1: *Mapping parameters associated with selected enhancement techniques in the volume illustration application.*

ment further enhances transition regions in which the gradient direction is orthogonal to the view direction. Distance color blending fades out distant regions by making them darker and more blue. Feature halos strengthen depth relationships by giving foreground features visibility-impeding halos. Tone shading strengthens shape cues by using warm tones on features facing the light source and cool tones on features facing away.

The high-level parameters we have identified are sketchiness, realism, contrast, detail, smoothness and flatness. These high-level parameters represent characteristics of an images that an end user might wish to manipulate directly in order to improve the rendered images. There are intuitive relationships between certain low-level parameters and high-level parameters. The boundary parameter k_{gc} and the silhouette parameter k_{sc} are likely to be negatively correlated with sketchiness, since higher k_{gc} and k_{sc} values decrease the gradient and silhouette enhancement respectively, producing less sketchy images. The boundary parameter k_{gs} and the silhouette parameter k_{ss} are likely to correlate positively with sketchiness, since higher values of these low-level parameters increase the gradient and silhouette enhancement. The boundary parameter k_{ge} and the silhouette parameter k_{se} control the sharpness of the sketch lines, so intuitively they should correlate with the high-level detail parameter. The distance color blending and halo parameters bring out the 3D structure of the volumes, so we would expect them to be correlated with the high-level flatness parameter. High values of these low-level parameters can enhance the perception of depth in the images, making them less flat.

These intuitions, however, are not quantifiable, and may not in fact correspond to the way that users understand the high-level parameters. Therefore, we performed a user survey to record users' correspondences between high-level and low-level parameters, and used a machine learning approach to construct a mapping from high-level to low-level parameters, enabling users to directly manipulate the high-level parameters of the rendered images.

3. Related Work

Several researchers have developed methods to explore the parameter space of applications such as selection and placement of light in image rendering, generating opacity and color transfer functions for volume rendering, generating models for the synthesis of 3D faces, automatic modeling of human bodies, and motion control for particle-system and articulated-figure animation. Interactive evolution, inverse design and design galleries are methodologies for computer-assisted parameter setting. In interactive evolution [HHKP96, HAE99, KFL91, Sim91, KKH02], the computer uses a set of possible parameter settings and provides the user with output alternatives to select from. After the selection, the user provides guidelines for the computer to further generate more alternatives. Thus the user acts as an objective-function oracle and helps to refine the exploration process. A more automated methodology is inverse design [BV99, LGC94, NM93, SMT03], in which the user provides a mathematically stated objective function, and the computer finds the parameter settings that optimize this function. This approach depends on the user being able to identify the qualities that make the output desirable. The third methodology, Design Galleries [MAB*97], automatically generates an exhaustive set of output alternatives, each being perceptually different. These alternatives are then organized in a "gallery," which has a hierarchical structure. This allows the user to easily select the desired output without having to provide any guidelines or objective functions. All three approaches emphasize generating interesting samples of the parameter space, rather than parameterizing the space in a more intuitive and useful manner.

4. Approach

Our approach provides a simple and convenient interface for the user to generate desired images in terms of their high-level parameters. A *forward mapping* is provided from the

high-level parameters to the low-level parameters so that the user can generate images by modifying the values of the high-level parameters. In order to generate the forward mapping, a reverse mapping (from the low-level parameters to the high-level parameters) is also required. The system provides a user-friendly interface consisting of buttons that increase or decrease each high-level value. Starting from a default image, the user increases or decreases each high-level value until the desired image is generated.

4.1. Reverse Mapping: Low-level Parameters to High-level Parameters

The reverse mapping maps from the low-level parameters to high-level parameters, identifying the high-level value at each coordinate position in the low-level space. A reverse mapping is generated in three steps: first, a user survey defines the relationship between low- and high-level parameters; second, decision trees are constructed using the data from the user survey; and third, the low-level space is partitioned into bins of constant high-level parameter value.

4.1.1. User Survey

Using knowledge about the relationship between the low-level parameters and the high-level values and by trial and error, we determined 20 unique combinations of low-level values to generate a set of images such that at least four images represent each value (between zero and four) of each high-level parameter. We then selected another 20 perceptually different images from a set of 100 randomly generated images. In all, we used a total of 40 unique combinations of low-level values to generate images. A total of 160 such images were generated using four different volume datasets: abdomen, foot, fuel, and tomato.

Eight subjects participated in the user survey. Four of them had experience in volume illustration; the others did not have any visualization experience. Each subject was shown all images. The images of each dataset were shown as a group, but the order of the datasets was randomized, as was the order of the groups. For each image, the subject was asked to estimate the value for each of the high-level parameters, on a scale from 1 to 4.

The high-level values given by the subjects were averaged for each image. The average standard deviation of the ratings given by the non-expert subjects, by the expert subjects, and by all subjects were calculated for each of the 160 images. Average standard deviations for all subjects were in the range 0.82 (Contrast) to 1.03 (Sketchiness and Smoothness). More homogeneous groups displayed smaller average standard deviations: 0.49 (Contrast) to 0.56 (Flatness) for non-experts and 0.53 (Contrast) to 0.81 (Flatness) for experts. The correlation between the two groups was reasonably high, ranging from 0.37 (Flatness) to 0.70 (Detail), where 0.0 indicates no correlation and 1.0 a perfect positive correlation.

4.1.2. Decision Trees

A decision tree was generated for each high-level parameter from the user survey data. A decision tree [RN03] takes as input an object or situation described by a set of properties and outputs a decision. In this approach, a decision tree is used to classify the high-level parameter values; it outputs a high-level value for any set of low-level parameter values. We generate the decision trees using the C4.5 algorithm because of its support for continuous attributes [Qui96].

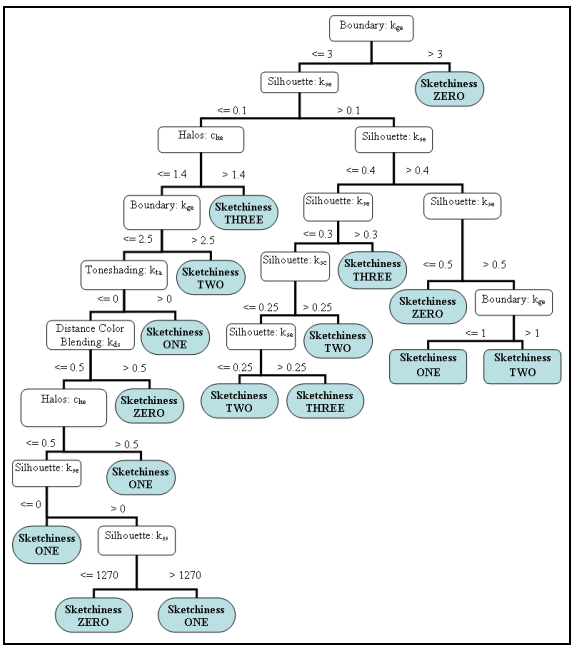

Figure 1: *Decision tree for the sketchiness parameter. The leaf nodes indicate sketchiness values; internal nodes correspond to the low-level parameters.*

One of the learned decision trees is shown in Figure 1, which clearly shows the dependence of the sketchiness value on the boundary and silhouette parameters. High values of k_{gs}, k_{ge}, k_{ss} and k_{se} produce a high sketchiness value, because they emphasize the fine outline structure of the volume.

Classification in the decision trees operates from top to bottom, based on the values of each internal node (low-level parameter). Starting from the root node, a decision is made at each level of the tree whether to move to the left child or the right child of the tree until a leaf node is reached. The value of the leaf node is returned; this value gives the high-level value for that set of low-level values.

The generated decision trees seem to match the intuitive relationships between the low- and high-level parameters. High contrast is related to high illumination levels, large boundary and silhouette enhancements, and large depth cue enhancements. Flatness is inversely related to the values of

parameters controlling distance color blending, halos, and tone shading. Detail is influenced by most of the low-level parameters, while sketchness and smoothness are related primarily to the boundary and silhouette parameters.

4.1.3. Reverse Mapping using Bins

The decision trees are next used to create bins that define the reverse mapping. A *bin* for a low-level space of P dimensions is a hyper-polygonal shape with $2P$ faces, where each pair of opposite faces relate to a low-level parameter. One bin is created for each leaf node of a decision tree, consisting of a minimum and maximum value for each low-level parameter. Each bin also has an associated high-level parameter value, corresponding to the value of that leaf node in the decision tree. For any set of low-level values, the bin in which it is located is identified by checking whether each of the low-level values is between the minimum and maximum limits of that bin for that low-level parameter. The partitions of low-level space can be different for each high-level parameter. The process of generating the reverse mapping by conducting the user survey, generating the decision trees, and partitioning the low-level space into bins is done offline as a preprocessing step. This makes the actual exploration of the parameter space—that is, the forward mapping—faster and more efficient.

4.2. Forward Mapping: High-level Parameters to Low-level Parameters

The forward mapping maps from high-level parameters to low-level parameters. Since the output image can only be rendered from the low-level values, we need to use the forward mapping to identify the low-level parameter values that correspond to a requested change in a high-level parameter. The initial image displayed corresponds to a known coordinate position in the low-level space. When the user changes any high-level value, the forward mapping is used to find the new coordinate position that best reflects the desired change in the high-level value.

The output of the forward mapping change is represented as a direction vector in the low-level space and a step size in that direction. The *direction vector* is a vector in the low-level space from the current coordinate position towards the new coordinate position that corresponds to the change in the high-level value desired by the user. There can be more than one such direction vector; an ideal direction vector will produce the correct change in the high-level value under consideration without affecting the other high-level values. The *step size* is the distance to move along the direction vector in order to obtain the new coordinate position. The ideal step size is the distance that will only bring the desired change in the high-level value under consideration without affecting the other high-level values. For example, in Figure 2, in order to decrease the sketchiness value from one to zero, we need

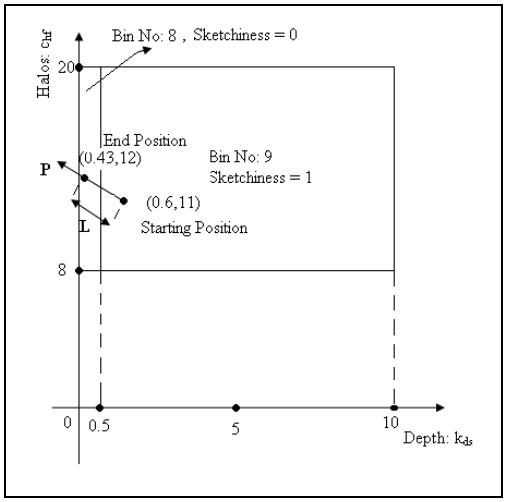

Figure 2: *P is the direction vector; L is the step size that is required to change the sketchiness value from one to zero.*

to move to the end position from the start position, along the direction vector P with step size L.

4.2.1. Calculating the Direction Vector

After partitioning into bins, the low-level space becomes a discrete space. The low-level direction corresponding to a high-level value change is identified in this discrete low-level space. The method first identifies the bin that corresponds to the current position in the low-level space. It then considers all of its neighbor bins to find the one that would best produce the desired change in the high-level value. Neighbor bins are those bins that share their low-level boundaries with the bin that corresponds to the current position. The best neighbor bin is the one that produces the largest change in the high-level value, relative to the current bin while having the least effect on the the other high-level parameter values. After determining the best neighbor bin, the direction vector is calculated as the vector from the current position to the center of the best neighbor bin.

4.2.2. Calculating the Step Size

After the direction vector is selected, the step size is calculated Simply moving the coordinate position to the center of the best neighbor bin might have the undesirable side effect of changing other high-level parameter values. On the other hand, moving the coordinate position by a small constant step size might produce effects on the image too small to be discerned. In our approach, the initial step size is half the distance between the current position and the center of the best neighbor bin, divided by the change in the high-level value. This step size is reasonable: it will limit the change in other high-level values and at the same time should produce

a noticeable change in the high-level value under consideration.

Our method also checks to be sure that the step size does not cause the new coordinate position to be in the wrong bin. For example, in Figure 3, the user tries to increase the sketchiness value. The direction vector *P* is calculated first, then the step size *L* is calculated using the heuristic described above. The resulting coordinate position belongs to a bin that has a sketchiness value less than that of the original one. To avoid this problem, our method shifts the new coordinate position again by half of the current step size. The new coordinate position is shifted until the position belongs to a bin that corresponds to the desired change in the high-level value. In Figure 3, the new coordinate position is shifted until it belongs to the bin whose sketchiness value is three.

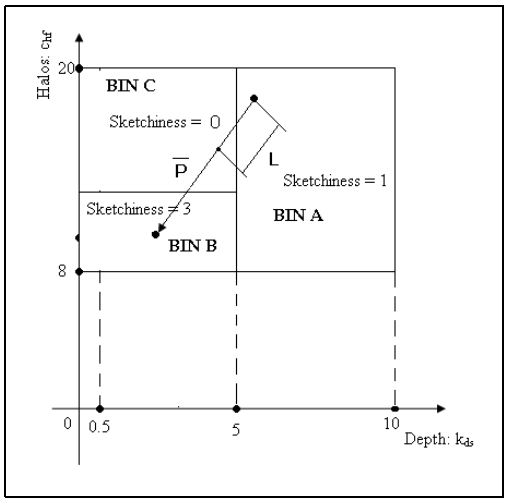

Figure 3: *An example where the new coordinate position can belong to a wrong bin.*

5. Results

The user interface displays of an initial source image for reference and allows the user to change the high-level values in order to obtain the desired target image. At each step, the user can change one high-level value and render an image. The image rendered at each step is used as a reference to select the next high-level parameter.

Figure 4 shows the effect of modifying the value of the smoothness parameter on the tomato dataset. Figure 4(a) has the highest smoothness value; Figure 4(f) has the lowest smoothness value; and the smoothness value decreases from Figure 4(a) to Figure 4(f). One can observe the body of the tomato, which becomes sketchier and less smooth. There is a subtle difference in the smoothness value between Figure 4(e) and Figure 4(f). Modifying any high-level value can affect some of the other high-level values. One can observe

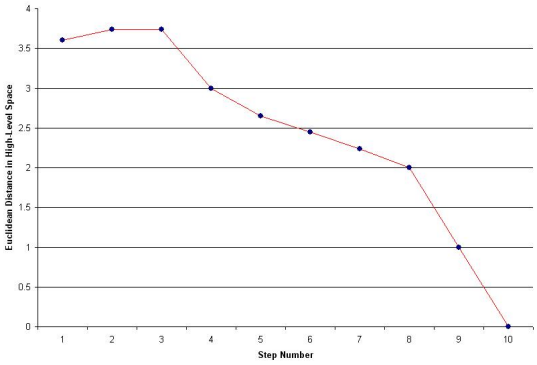

Figure 6: *Graph showing the Euclidean distance between the images generated (at each step) and the target image in the high-level space. Steps 1 to 10 correspond to the images in Figures 5 (a) to (l).*

that the Figure 4(f) is sketchier than Figure 4(a), producing an increase in the sketchiness value. One can also observe the inner structure of tomato more clearly as smoothness is decreased, producing an increase in the detail value.

In order to increase the smoothness of the images generated, the values of ten low-level parameters must be changed (namely, the boundary enhancement, silhouette enhancement and the toneshading enhancement parameters). Using our approach, the user can simply modify the value of one high-level parameter—smoothness—to obtain the desired results. There are two advantages to our approach. First, it provides a small set of high-level parameters for the user to modify in order to generate the desired output. Second, it defines the high-level parameters in such a way that the user easily understands the relationship between the parameters and the characteristics of the output.

We performed a number of exercises where the goal was to get from an initial image to a target image using the high-level parameter controls. We conducted five such trials where only the boundary and silhouette enhancements were applied to both the source and the target image. In these trials, other low-level parameters had a value of zero. Four of the five trials produced successful results: the final image was visually identical to the target image. An average of 11 steps was required to obtain the target image in these four trials. One such trial is shown in Figure 5. It shows the steps followed to obtain the target image (Figure 5 (b)) starting from the source image (Figure 5 (a)) for the tomato dataset. Figure 5 (c) was generated after increasing the sketchiness value of the source image. A further increase in the sketchiness value produced Figure 5 (d). After nine steps, Figure 5 (k) was generated, which is nearly identical to the target image. The nine steps included increasing the sketchiness value twice, increasing the detail value three times, and then decreasing the smoothness value four times.

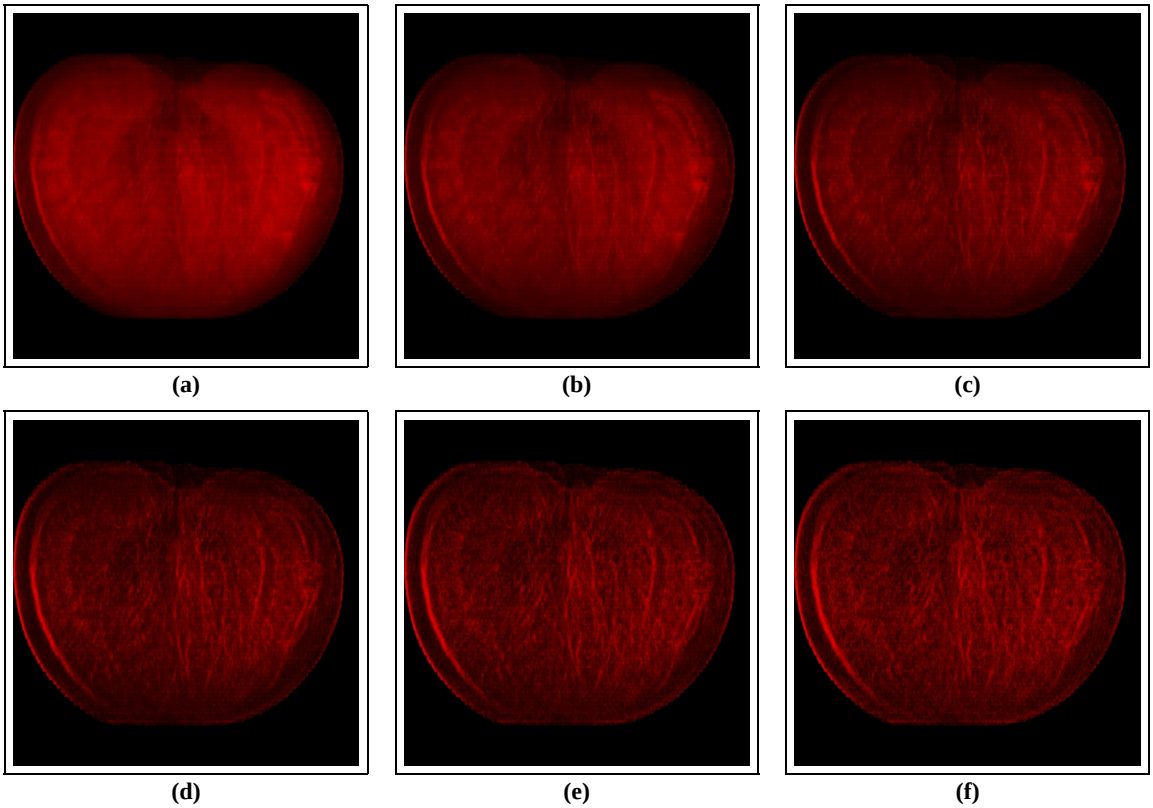

Figure 4: *Images generated by modifying the smoothness value of the tomato. The value of smoothness decreases from (a) to (f).*

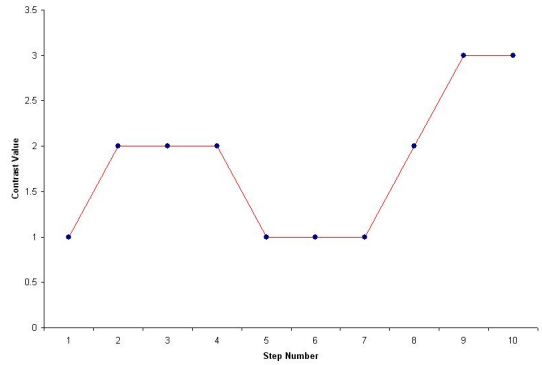

Figure 7: *Graph showing change in the contrast value at each step. Step number 1 to 10 correspond to the images Figure 5 (a) to (l).*

Figure 6 shows the Euclidean distance of the images generated at each step from the target image in the high-level parameter space. Step one corresponds to the source image. We can observe that there is a slight increase in the distance for the first two steps and then it monotonically decreases to the goal of having a zero distance.

Figure 7 shows the change in the contrast value at each step of the second trial. The source image (step one) had a contrast value of 1; the contrast value of the target image was 3. Therefore, an increase in the contrast value was desired. However, change in other high-level values can also affect the contrast value, as in Figure 7, where the contrast value increases initially but then decreases when other high-level values are changed. The contrast value increases again to 3 in step 9.

We also used our system for five trials (going from source to target image) where all the enhancement techniques were applied. These trials were somewhat less successful, due to unintended color changes. An average of 19 steps was required to obtain an image that was most similar to the target image. When the user was given a separate control to set the color values, an average of only 13 steps was required to obtain the target image.

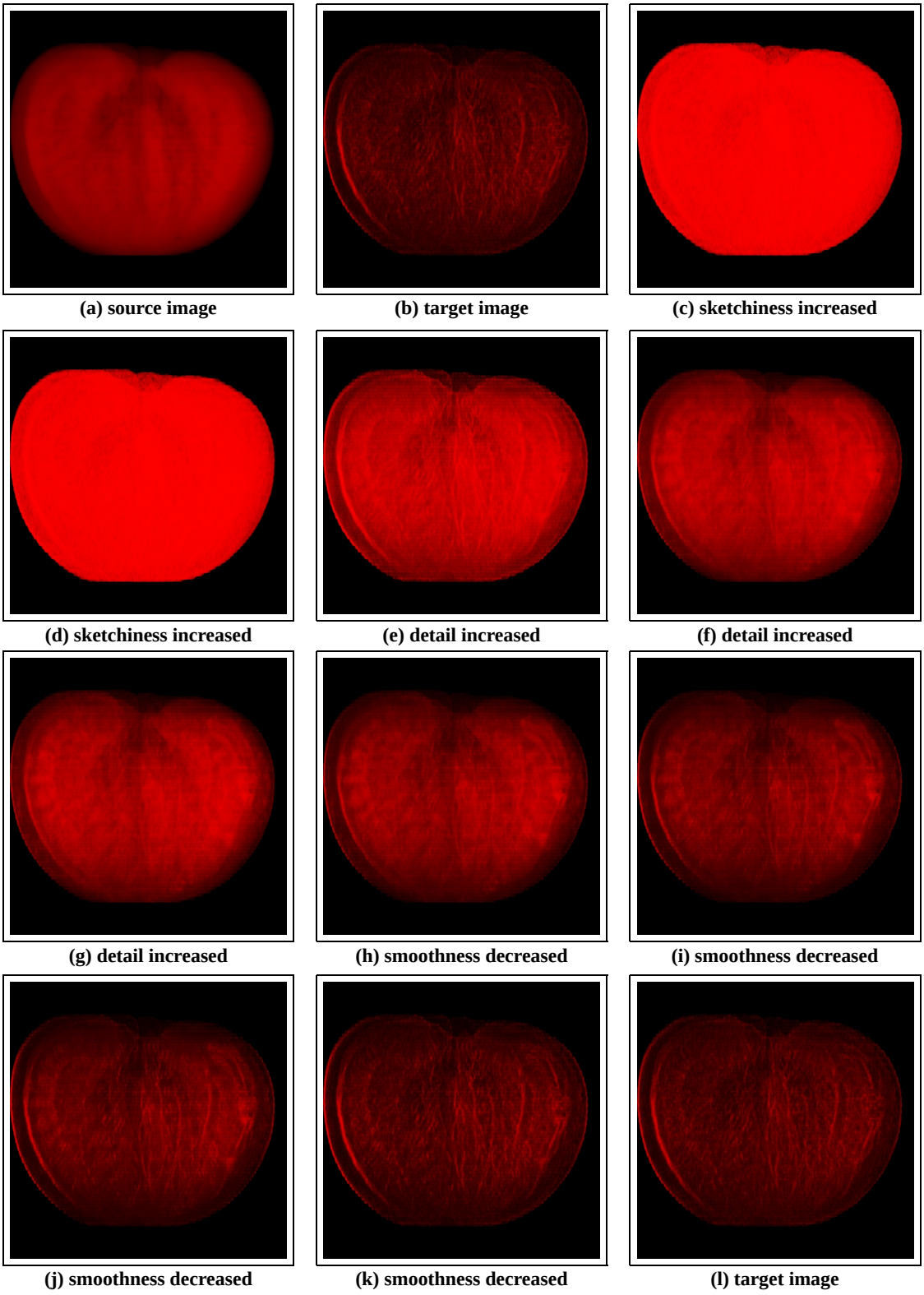

Figure 5: *Using our system to generate the target image starting from the source image (a).*

6. Future Work

The high-level parameters identified are continuous parameters; therefore, using regression trees instead of decision trees may be helpful. In the present approach, when the bin corresponding to the current position in the low-level space has no neighbors with greater high-level values, the system halts as soon as the user tries to increase the high-level value. Even if the low-level space has bins with greater high-level values, the system considers only the neighbors who share their boundaries with the current bin. As a result, the system cannot always identify a new position in the low-level space that corresponds to the desired change in the high-level value. We plan to extend our approach to consider a larger neighborhood.

7. Conclusions

We provided a convenient interface to allow users to modify the high-level values. Our system allows the users to directly manipulate the high-level characteristics of the image in order to generate a desired image. The best feature of our system is its ease of use. As shown in our results, the images generated at each step (where a change in one high-level value is considered a step) were predictable. It was also easy to determine the next high-level parameter whose value should be changed to progress towards the desired image. Thus any user who can associate the meaning of the high-level parameters with the characteristics of the image can use our system to easily progress from a source image (provided as an initial reference) to the desired target image (some vision).

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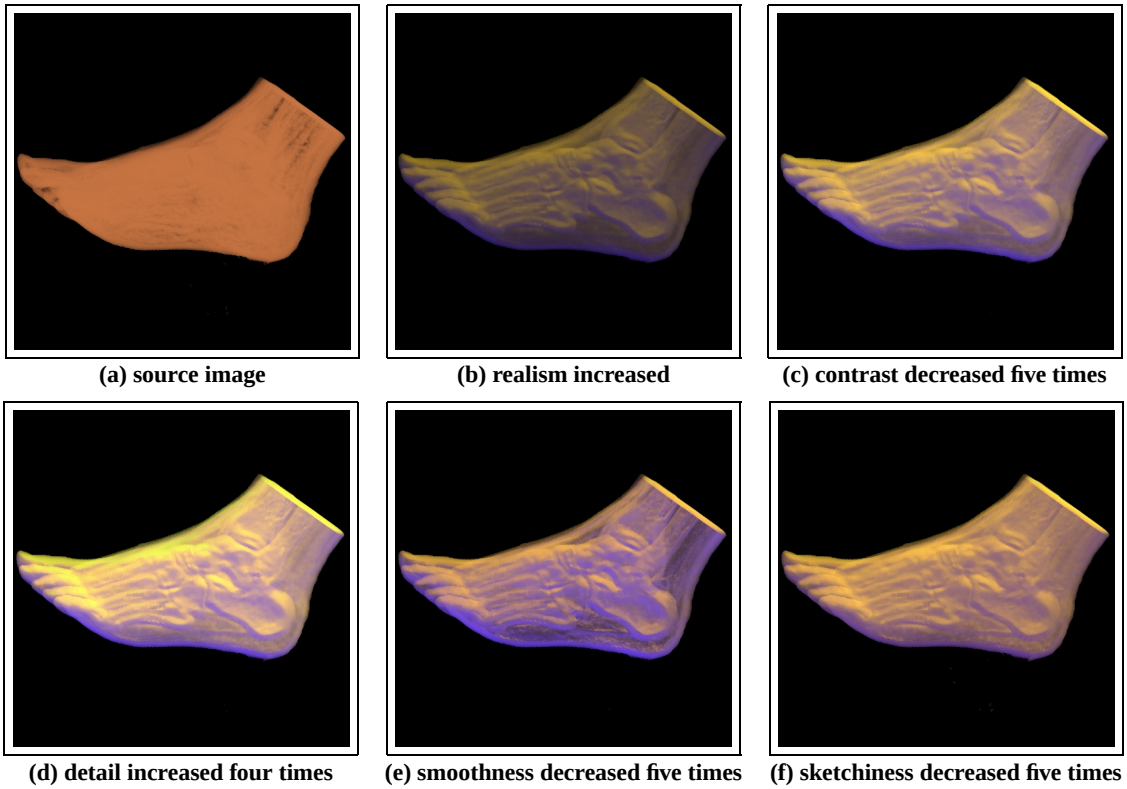

(a) source image **(b) realism increased** **(c) contrast decreased five times**

(d) detail increased four times **(e) smoothness decreased five times** **(f) sketchiness decreased five times**

Figure 8: *Images generated by changing different high-level values of the foot dataset.*