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A simple approach for gamut boundary description using radial basis function network

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Abstract

Accurately describing the gamut of a color device is the basis for gamut mapping, device color characterization and device gamut volume prediction. There are many ways to describe gamut boundary in the past and the methods can be used in combination with each other for the more accurate and effective gamut boundary description. However, it is difficult to find a commonly used method after introducing the way of color space segmentation. In this paper, we reorganize the existing gamut boundary description techniques according to purpose and method. We also propose a new simple approach of predicting gamut boundary. This new approach uses a machine learning based Radial Basis Function Network(RBFN) that can simplify the gamut boundary description process. This simple method can directly predict the desired gamut boundary description.

Introduction

Every color device has a color range that can be reproduced for each device. We call it gamut and it is important to describe the gamut accurately. Gamut boundary description is the basic step for device color management. The description of gamut boundary is used to characterize device color and to reproduce colors between devices using a gamut mapping algorithm. And accurate prediction of the gamut is a means of verifying the color gamut performance of a color device. So, we need a standardized or generalized technique for an equivalent gamut comparison between devices.

There are many ways to describe gamut boundary in the past, and These methods can be used in combination with each other to provide accurate and effective gamut boundary description algorithms. However, it is difficult to find a commonly used method after introducing the color space segmentation method. [1]

In this paper, we configure the conventional gamut boundary description methods according to purpose and method. We also propose a new approach of predicting gamut boundary to simplify color gamut boundary methods. The proposed method can replace methods of various steps with one simple method. This approach uses the machine learning based RBFN. This method can directly predict the gamut boundary at the desired location. This makes the gamut boundary description algorithm conceptually easier and simplifies the process.

Conventional Method

We analyzed various existing gamut boundary description techniques according to purpose and method. These techniques can be configured as shown in [Figure 1]. And these are all a way for gamut boundary description, but they can be subdivided according to purpose. So, it is divide into three steps as follows:

- Define target
- Predict gamut boundary
- Triangulation.

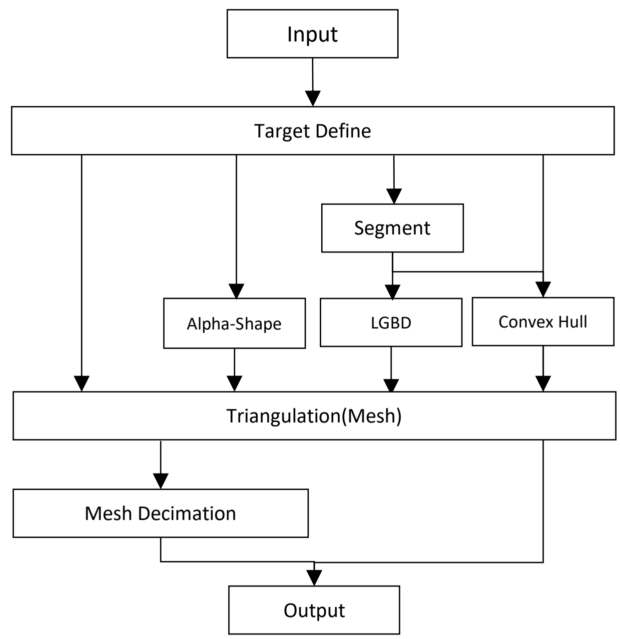


Figure 1. Configuration of various gamut boundary descriptions.

Define target

The first step is to define target. This step configures and defines a data set to make the gamut boundary description more accurate and efficient. The accuracy of existing methods of calculating gamut boundaries can be improved by use of an enlarged gamut boundary training set to derive the gamut boundary descriptor. [2] Here, a test image for defining media gamut boundaries is presented. Defining the test target not only improves the accuracy of the gamut boundary description, but also helps the algorithm to describe the gamut boundary work efficiently. Additionally, there are things to consider when using media boundary target. Due to the characteristic of the color device, the boundary target does not always mean the gamut surface. For example, If the printer is unstable, the boundaries of the boundary target color may be reduced due to over-saturation characteristics of the device. So, when we make media boundary target, we need to adjust the target according to the characteristics of the printer. Alternatively, we can maintain the convexity so that the gamut boundary does not decrease when predicting the gamut boundary.

Predict Gamut Boundary

The second step is to predict the gamut boundary descriptor from the defined color data set. In General, color space segmentation method is used to describe a gamut boundary description. The well-known Segment Maxima method divides the color space into spherical segments. And gamut boundary descriptors are obtained using the maximum radius in each segment. [3] This approach is similar to sampling the input data in each segment, it can reduce the complexity of the algorithm and provide efficient approach when gamut boundary predicting. In this method, many segments can be used to increase the accuracy of the prediction. but, this increases the number of empty segments and requires complex interpolation algorithms. Also, because it uses a spherical segmentation method, it requires more color data sets in the dark and light areas. The uniform segment visualization method improves this problem by equally dividing the color space using the triangle tessellation technique. [4] This technique uses a triangle-based segment to suggest a more uniform segment compared to the existing segment maxima. On the contrary, there is also a method of estimating a partially non-uniform gamut boundary descriptor. [5] However, the latter two methods can improve the accuracy of gamut boundary description but increase the complexity of the algorithm.

Another commonly used technique to predict gamut boundary description is convex hull. it creates smallest convex set containing a set of points. However, this method is difficult to predict the concave color gamut boundary that can be caused by the characteristics of the printer system. To solve this problem, modified convex hull is proposed. [6] This method uses the nonlinear gamma function to transform the concave part of the color space convexly and apply a convex hull method. In this case, it is important to use proper gamma to correctly predict the gamut boundary. In addition, a Quick hull method has been proposed to reduce the computational complexity of the convex hull and increase the speed. [7]

And alpha shape is also widely used as a way of predicting gamut boundary description. [8] Using this method, we can accurately represent the concave and convex shape ambiguities of the gamut boundary using an alpha hull (a circle with a radius of alpha). This method describes gamut boundary using a parameter called alpha to recognize concave and convex. If Alpha is 0, it is the same as the input sample. If it is infinity, it is the same as convex hull. And the resulting point or polygon is a subset of the Delaunay Triangle. Also, it can use a Voronoi tessellation technique, which is radial growth in seeds as a way to reduce the computational complexity of the alpha-shape. [9] However, this technique can be less accurate because the final shape of the gamut boundary description can be a polygon rather than a triangle.

Convex hull and Alpha-Shape can predict the concave and convex gamut boundary well, but its accuracy is affected by parameter gamma and alpha and depends on actual device characteristics.

Triangulation

Triangulation or mesh technology that use a set of points to create tessellated triangles is a common way of constructing gamut boundaries. In general, a triangulation or mesh is used as the final form of the gamut boundary description. Because the triangular tessellation is the best way to approximate the sphere shape. Also, triangulation is commonly used for gamut mapping.

Triangulation is started with Delaunay triangulation in mathematics and computational geometry. There are also techniques optimized for gamut boundary description. One way is to simplify the triangles by knowing pairs of device colors and measurement colors. It transports the CMY triangulation into CIELAB space by simply replacing the CMY vertices of the triangulation by their measured CIELAB counterparts. [10] And for gamut mapping algorithm, there is a way to create a triangle so that the gamut boundary description is convex called FTM (Face Triangulation Method). The FTM checks the intersections of all four triangles of all quads on all faces of the RGB cube with the given line and chooses the one that is farthest from the L axis. This is the most favourable choice for gamut mapping. [11]

If the segment is a pre-process for gamut boundary description, mesh decimation can be considered as post-process. Both processes are techniques that reduce complexity by reducing sample based on accuracy. Mesh decimation is a technique to reduce the number of triangles after triangulation. This method utilizes all input points to construct the initial surface. Then, a mesh decimation algorithm is used to reduce the complexity of the generated surface. [12] And it uses Quadric Error Metrics to remove edge between each vertex. [13] It decimates the condition that the cost(error) between each vertex is minimized and consequently gamut boundary description can be approximated accurately. In addition, such a decimation method can contribute not only to reducing the complexity of the gamut boundary technique but also to improve the accuracy of the gamut boundary prediction by eliminating errors that may occur due to the characteristics of the printer system.

The techniques described above are used either directly or indirectly to predict the gamut boundary. However, it is not easy to choose a technique that predicts precise gamut boundaries. For example, it has been suggested that using uniform segment visualization with a modified convex hull can improve gamut boundary description accuracy. [3] Likewise, we can increase the accuracy of the gamut boundary description using one or a combination of these techniques. However, depending on the circumstances, finding the best approach may not be easy.

Proposed Method

The objective of proposed method is to simplify complex color gamut boundary description. There are many techniques to predict color gamut boundary as show in [Figure 1]. The proposed method is to use a machine learning based technique called RBFN (Radial Basis Function Network), which can replace various techniques described above with a single method as show in [Figure 2]. This makes it easy and simple to describe the gamut boundary.

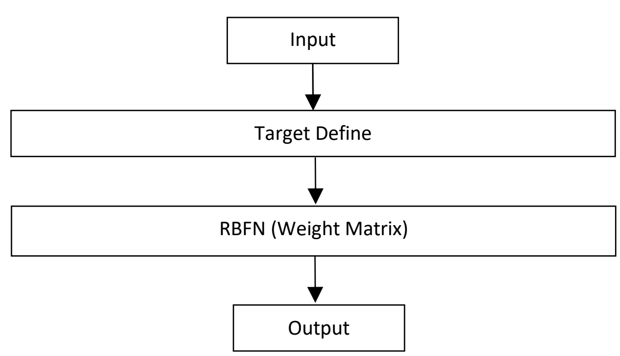


Figure 2. Proposed Method using RBFN.

Radial Basis Function Network

RBFN is a simple neural network consisting of three layers for mathematical modeling. Activation function of the hidden layer uses a radial basis function, and the output is a linear combination of the radial basis functions of the input and neuron parameters as shown in [Figure 3].

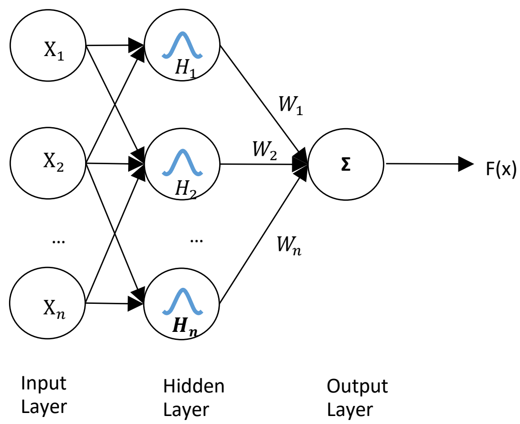


Figure 3. Radial Basis Function Network

The following is a linear model for a function F(x): [14]

$$F(x) = \sum_{i=1}^{n} W_i * H_i(X) \tag{1}$$

Some example of radial basis functions: [15]

- The gaussian:

$$\mathrm{H(X)} = \mathrm{xp}(-\varepsilon r^2) \tag{2}$$

- The multiquadratic:

$$\mathrm{H(X)} = \sqrt{(1 + (\varepsilon r)^2)} \tag{3}$$

- The inversemultiquadraic:

$$\mathrm{H(X)} = \frac{1}{\sqrt{(1+(\varepsilon r)^2)}} \tag{4}$$

- Polyharmonic spline:

$$\mathrm{H(X)} = r^k \log r, \mathrm{k} \in \{2, 4, 6\ldots\} \tag{5}$$

Where r is the length of a vector and ε is some scaling factor. Also, when k = 2 for RBF interpolation using polyharmonic splines, it is also called a thin plate spline. [15]

Although RBFN has a simple structure, it is used in various technical fields such as color characterization, image deformation, 2D interpolation and surface reconstruction. Here, A remarkable technical field is the surface reconstruction. Using this technology, we can create variable surfaces smoothly from a given surface data and recover incomplete parts. [16] Reconstructing the 3D surface using RBFN is the same approach as predicting the gamut boundary. So, we decide to describe the gamut boundary description using RBFN.

Gamut boundary description using Radial Basis Function Network

The proposed method consists of two simple steps for prediction of gamut boundary as shown in [Figure 4]. The first step is to calculated weight for predicting of gamut boundary. The second step is to predict gamut boundary using the weight. Measurement data is used as a training set to obtain the RBFN weight. And W(weight) having color gamut boundary information of the color device is formed in a matrix form.

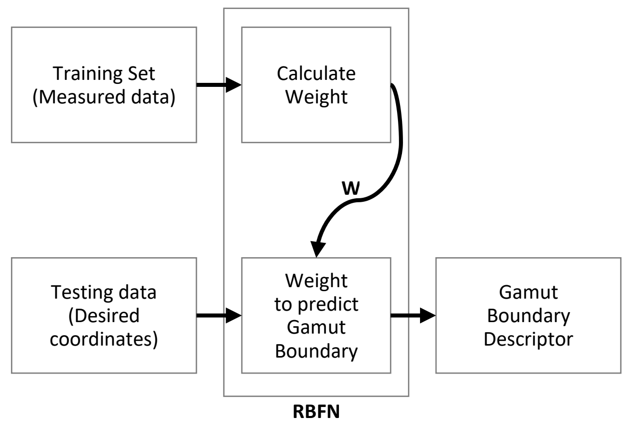


Figure 4. Gamut Boundary Description using RBFN

As with most machine-learning based methods, it is important to collect measured data corresponding to training sets in the proposed method. Therefore, the role of Target Define in [Figure 1] can become more important. We created a device model from the real measurement data and generated surface data from that model. So, we got 1558 surface data from 729 data samples in full color space as shown in [Figure 5]. And then, this data is used as training data for the gamut boundary description. Although There is an error between the measured color data and the generated data by the device model, but there is no problem verifying the proposed method.

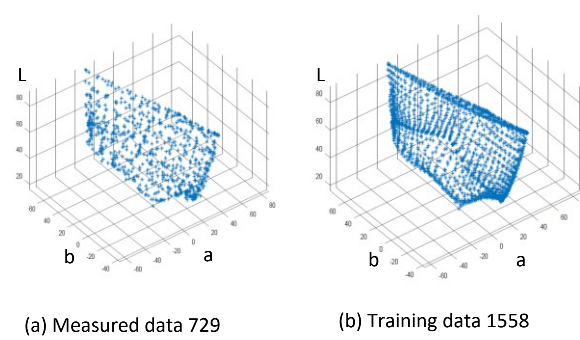


Figure5. Sample of training data

The RBFN structure is also simple as shown in [Figure 3]. The input layer and output layer are composed of α, θ, and γ used in the spherical segment to intuitively understand the behavior of RBFN. [1]. In a spherical coordinate system, α represents the angle of the horizontal direction and ranges from 0 to 360, and θ is the vertical angle, ranging from 0 to 180. γ is the radius of α and θ coordinates. Thus, the color gamut boundary data derived from the measured data data or modeling is converted into a spherical coordinate system, α and θ are the inputs of RBFN and γ is the output. As a result, weight(W) that can obtain the result γ corresponding to the desired coordinates α and θ is calculated. And W is the weight for the input to be the output. Here in, you can also use different configurations of input nodes and neurons, depending on how you use the encoding color space.

The W is defined by equation (6). H is referred to as design matrix and is the output of the RBFN, A^{-1} is the covariance matrix of the weights W, and the matrix Y is the output target. [17] And pseudoinverse method works by resolving the following general system of linear equations. [17]

$$W = A^{-1}H^{T}Y \tag{6}$$

$$Y = W * H \tag{7}$$

The calculated W contains the gamut boundary information in matrix form. By using the equation (7), it is possible to predict the gamut boundary by matrix-computing the input of the desired coordinates. Also, W can be used for gamut mapping algorithm between source device and destination device. As described above, the W_s (weigh of the source device) and W_d (weight of the destination device) of the source device and the destination device can be calculated respectively, and the gamut boundary required for the gamut mapping can be predicted directly using the same input coordinates α and θ as shown in [Figure 6]. And, W is also available for mesh decimation. In the same way as above, reduced vertex is obtained easily for mesh decimation by reconstructing of the input. Using the W containing gamut boundary information, you can easily and directly obtain the gamut boundary of the desired coordinates without additional interpolation method.

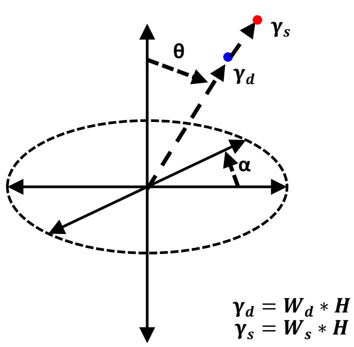


Figure 6. Example for Gamut mapping using W

Experimental Results

We performed experiments of gamut boundary prediction using RBFN in color laser printers. [Figure 7] is visualization result of training test. (a) is the Input data of color laser printer. This data is generated from A to B conversion in the device profile and used as training data for RBFN. (b) is result of the training. The four-basis function introduced in equation (2), (3), (4) and (5) were used for training. The graph is displayed differently from the conventional gamut graph. The x-axis is α, the Y-axis is θ, and the Z-axis is γ. It is better to see the whole data at a glance than an commonly used graph.

Visually, it can be confirmed that the training result closely approximates the input data. Due to the characteristics of the RBFN interpolation method, the region corresponding to the noise can be described robustly. However, we found that the edges of the gamut, the primary color and the secondary color, could be inaccurate and blurred. Especially, the training results of thin plate spline is superior.

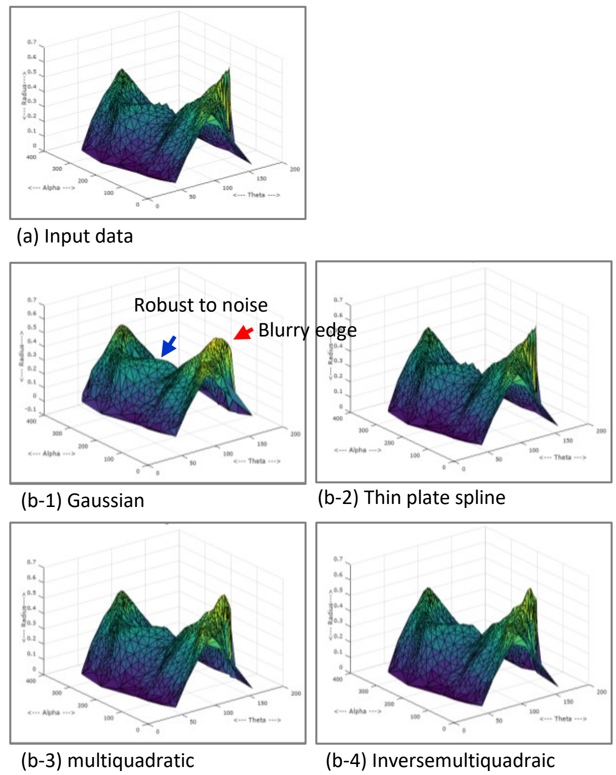
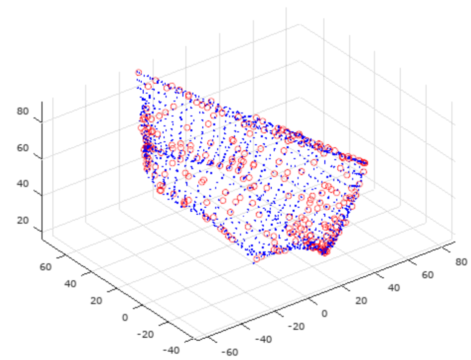
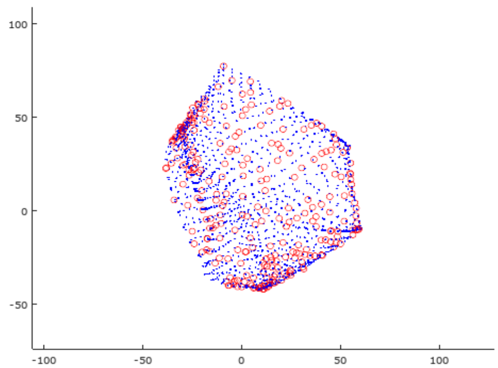


Figure 7. Visualization of training result

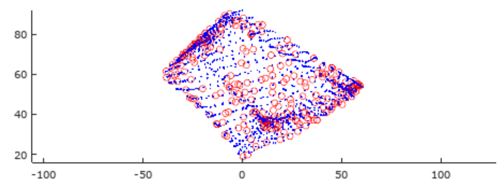
[Figure 8] is the test result of 1258 training data and 270 test data. Test data is selected randomly from a total set of 1558. And radial basis function is thin plate splines. It has the best performance of the four functions. The blue dot is the training data and the red circle is the test result. We can see that gamut boundary is visually well predicted.



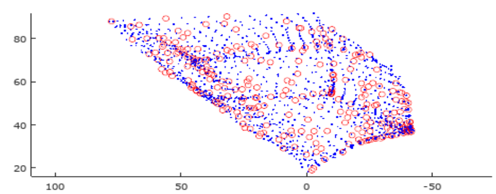
(a) Overall Result



(b) Result of a-b plane



(c) Result of L-C plane (270)



(d) Result of L-C plane (180)

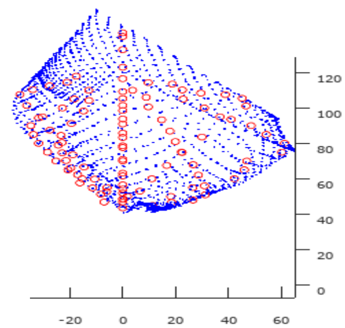
Figure 8. Test result of thin plate spline function

The following table is an error in training and testing. The error is deltaE76. All the result of the four basic functions are less than 3. Thin plate spline is the best result and Gaussian is the lowest performance.

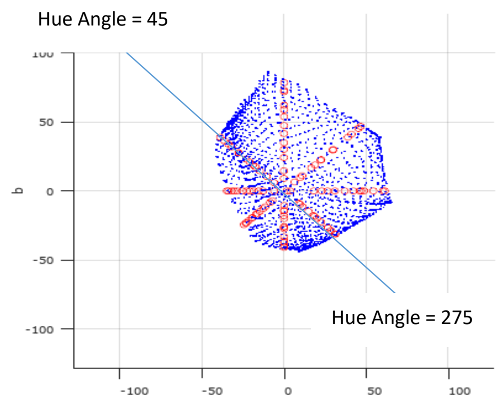
Table 1. Training and test error

DE76	Training	Test
Gaussian	2.84	2.86
Thin Plate Spline	0.0002	0.41
Multiquadratic	1.44	1.75
Inverse Multi-Quadratic	1.23	1.85

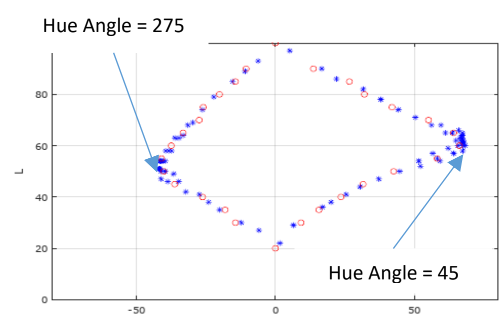
The following is the result of finding the gamut boundary description using testing data as desired coordinates. We experimented to predict gamut boundary description for a given hue and brightness. The given hue angle is 0, 45, 90, 135, 180, 225, 270 and 315. And The given lightness is increased 0 to 100 in 5-step size. As shown in [Figure 9], Gamut boundary description is well predicted at the given coordinates compared to the real measured data. This result shows that the gamut boundary description of the desired coordinates can be well predicted using RBFN. (a) is the overall prediction result for the testing data. (b) is the result of the ab-plane of CIE-Lab coordinates. we can see that the gamut boundary descriptor is well predicted for a given hue. And (c) is the gamut boundary prediction result according to brightness in the same hue plane (45 to 275). Likewise, gamut boundary is well predicted for given brightness.



(a) Overall Result



(b) Result of a-b plane



(c) Result of L-C plane

Figure 9. Result of desired test data

Conclusion

We have presented a simple approach to predict gamut boundary using machine learning based RBFN. The result show that RBFN can predict gamut boundary well at the desired coordinates. This method does not segment the color space or use the geometric techniques. It also does not require interpolation or triangulation using vertex and face array. Therefore, our method can conceptually make it easier to describe gamut boundary and simplifies the process. In addition, this approach can be used for triangulation or gamut mapping because it can directly predict the gamut boundary description at the desired location.

Furthermore

Because RBFN has characteristics of the approximation, we should find alternative way to accurately predict the edges of the gamut, such as the primary and secondary color. And we will apply it directly to triangulation or gamut mapping algorithm to demonstrate the usefulness of this method.

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