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The Optimization Method by Using the Transformation of Two Variable Dependent Experiment Results into Image Data and Its Usability in the Food Engineering Applications

Selahaddin Batuhan AKBEN[1], Selin KALKAN[2*], Demet ÇANGA[3]

[1] The University of Osmaniye Korkut Ata, Bahçe Vocational School, Department of Computer Technologies, Osmaniye/Turkey
[2] The University of Giresun, Faculty of Engineering, Department of Food Engineering, Giresun/Turkey
[3]The University of Osmaniye Korkut Ata, Bahçe Vocational School, Department of Food Processing, Osmaniye/Turkey

*Corresponding Author: selin.kalkan@giresun.edu.tr

Abstract

In this study, it is aimed to determine the variable values which should be selected to produce the optimal experiment results in the field of Food Engineering by using image processing methods. In the study, the matrix of experiment results dependent on two variable values is transformed into the gray-scale image matrix, then the cells with the darkest color values (cells with black color is the least-valued) in the image matrix were identified. Finally, the variable limits (coordinate limits) of the black color cells have been determined. Determined limits were considered to be variable limits which will produce the optimal result of the experiment. The method proposed in the study has been tested in an exemplary experiment in which the antimicrobial effect of the *Lactobacillus casei* Shirota against the *Staphylococcus aureus* is determined by *in-vitro*. According to the obtained findings, it was confirmed that the proposed method can be used to determine the optimum variable limits in similar Food Engineering analyzes. Also which of the image processing methods would be useful in such optimizations were proposed.

Keywords: Antimicrobial effect, Image processing, Optimization, Two variable dependent analysis

INTRODUCTION

The Optimization is used in Food Engineering processes to analyze and determine the interactions of independent variables with each other and their effects on the target in order to produce the optimal results. The optimal result called as target function is the experimental result value desired to maximize or minimize with increasing or decreasing the independent variables according to predetermined criteria. In Food Engineering, response surface methodology that uses simple empirical models derived from trial sets is the most frequently used optimization methods. For example, in the analyses of hazelnut roasting processes, production of β-carotene and pulluan with using fermentation methods, protein recovery by using foam separation methods, determination of tarhana viscosity, determination of enzymatic browning of apple juice, inactivation of *Listeria innocua* etc., there are many successful results were offered to literature by using response surface methodology (Saklar et. al., 2001; Goksungur et al., 2004; Ibanoglu& Ainsworth, 2004; Ürküt et al., 2007; Aksay&Mazza, 2007; Buzrul, 2008).

Therefore, it can be said that the response surface methodology widely used in other engineering fields seems very useful in Food Engineering.

However, recently the new optimization methods through the help of computer softwares, mathematical and statistical methods, machine learning and data mining methods, etc. have been developed and are rapidly integrated into many engineering applications while Food Engineering has still lack of these developments.

The reason of this lack is the integration of newly developed optimization methods of Food Engineering are hard as compared to other engineering disciplines because food ingredients simulation and modeling is not easy due to the complexity of the physicochemical characterization. Also, it can be said that the response surface methodology is an only one and unique optimization technique used in the field of food science and technology because of this complexity problem for now. However, the response surface method has some problems of polynomial grade selection, experience requirement for initial trials, etc. (Koç&Kaymak-Ertekin, 2010).

So, the integration of optimization methods to Food Engineering is an important necessity to increase method varieties and to overcome disadvantages of old current methods. For example, the image processing techniques can be suggested as a solution because the image processing applications have begun to be used recently in food industry and effective agriculture (Kılıç et al., 2006; Samtaş&Gülesin, 2012; Sofu et al., 2013). Some researchers have performed the determination of the dimensional properties of the selected food samples, the classification of the samples in quality and color, the analysis of the gel image and the examination of the microscope images of the proteins etc. by using image processing technique. However, to analyze the experimental results by converting it into image data has not yet been attempted.In fact, all images consist of image values in the cells of an image matrix. Therefore, image processing techniques can be applied to all data including experimental results.

In this study, the original data matrix consisting of the experimental results was transformed into the image matrix and the limits of the independent variables which will produce optimal results by using image processing techniques are determined. Then the offered method was tested on a sample experiment related with antimicrobial effect of *L. casei* Shirota against *S. aureus* by *in-vitro*. As a result of the test, a new optimization method which can be used in the field of Food Engineering was proposed.

MATERIAL and METHOD

Material

A sample experiment was used to test the proposed method. In the sample experiment, antimicrobial effect of *Lactobacillus casei* Shirota which is one of the probiotic lactic acid bacteria exhibiting antimicrobial activity against *Staphylococcus aureus,* which is an important food pathogen was measured in terms of time and concentration variables by *in-vitro*. In the experiment, *S. aureus* was grown on Nutrient Broth (Merck) medium at 37 °C for 18-24 h, with a concentration of 10^5-10^6 / mL. *L. casei* Shirota was incubated for 24 h at 30 °C on MRS Broth (Merck) medium and with a concentration of 10^6 / mL. For determination of antimicrobial activity, 50, 100, 150 and 200 µL of *L. casei* Shirota was added onto *S. aureus* which in liquid medium (Nutrient Broth, Merck).

Samples which added *L. casei* Shirota were incubated at 37 °C and *S. aureus* colonies were counted after incubation for 0, 4, 8, 12, 24, 36, 48, 60 and 72 hours at Baird-Parker Agar (Merck) medium. In addition, the analysis was made in 3 replications for each time value. As

a result, the 27×4 dimensional original data matrix was created. In this original data matrix the lowest microorganism value is the optimal result (output) measured by analyses and the variable values (inputs) that will produce this optimal output are the optimal input values. The original data matrix is shown in Table 1. Matrix cell values are the antimicrobial effect of *L. casei* Shirota against *S. aureus* as microorganism concentrations. *S. aureus* concentration unit was given as log cob/mL.

Table 1. The experimental results matrix (original matrix) used to test the proposed method

	Concentration of *Lactobacillus casei* Shirota (log cob/µL)			
Time(hours)	**25**	**50**	**100**	**150**
0	6.32	6.25	6.17	6.02
0	6.28	6.18	6.02	5.96
0	6.31	6.22	6.13	5.88
4	5.87	5.86	5.67	5.60
4	5.80	5.92	5.53	5.47
4	5.63	5.42	5.58	5.63
8	6.21	6.15	6.05	6.00
8	6.32	6.23	6.12	6.02
8	6.12	6.08	5.95	5.96
12	6.88	6.85	6.81	6.79
12	6.75	6.89	6.75	6.66
12	6.96	6.79	6.88	6.89
24	7.92	7.90	7.80	7.74
24	7.89	7.74	7.75	7.68
24	7.96	7.98	7.91	7.82
36	7.65	7.54	7.12	7.08
36	7.58	7.65	7.08	7.11
36	7.63	7.49	7.22	7.09
48	7.72	7.43	7.31	7.15
48	7.63	7.56	7.22	7.08
48	7.8	7.37	7.45	7.19
60	7.81	7.62	7.25	7.21
60	7.88	7.58	7.36	7.36
60	7.75	7.70	7.14	7.07
72	7.58	7.83	7.47	7.37
72	7.45	7.93	7.56	7.24
72	7.69	7.69	7.33	7.49

Transforming data to image

The gray scale image is a matrix containing 256 color values from 0 to 255 in each cell (pixel). As these values increased the resulting color tone will change from black to white (0 means black, 255 means white and between 0-255 means gray tones). If the image is colored, there are three matrices containing the red, green and blue instead of gray tones.

The image depends on the colors that are created by superimposing (joining) these three matrices. The name of the 3D matrix formed by combining 3 matrices is the RGB matrix. Although color images are useful for visual analysis, grayscale images are more useful for analysis (Russ, 2016). The grayscale image sample and its matrix can be shown in Figure 1.

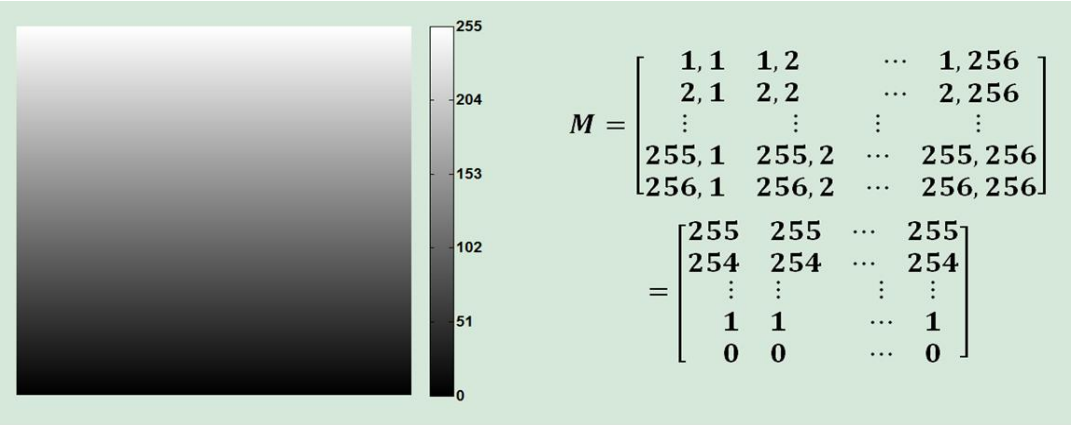

Figure 1. A grayscale, 256 x 256 resolution (256 x 256 pixels) sample image and its matrix

In this study, the method proposed as transforming experiment result matrix (original data matrix) into image matrix. Transformation of data matrix to image matrix can be done by equalizing (normalizing) the cell values to between 0 and 255 (Burger&Burge, 2016). Digital image processing: an algorithmic introduction using Java. Springer. Matrix normalization method for image creation is shown in Equation 1.

$$\mathbf{M} = \left\| \left(\mathrm{D} - \mathrm{D}_{\min} \right) \times 255 \right) / \left(\mathrm{D}_{\max} - \mathrm{D}_{\min} \right) \| \qquad (1)$$

In Equation 1, D is the data matrix, $\mathrm{D}_{\min}$ is the minimum value of D, $\mathrm{D}_{\max}$ is the maximum value of D and M is the image matrix.

Increasing Image Resolution

The larger the size of an image matrix (the higher the resolution) means the better its visual analysis. At the same time, the greater resolution means the more precisely the coordinates of the optimum variable values of the data matrix can be determined. There are two ways to increase the image resolution. The first is the addition of new cells around each cell in the image matrix. In this first method, the values of cells to be newly created, are calculated by the averages of the values in neighboring cells. However, since artificial colors are added with this method, the image will be a bit different from the original and the resolution will also deteriorate (Lau & Lin, 2016). The second method is to increase the size of the original data matrix. This is can be done by a polynomial model that produces output values corresponding to the variable values. Namely, the larger data matrix can be obtained by calculating the output values (experiment result values) corresponding to the unused variables in the model polynomial. As a result, the size of the image matrix will be larger and the resolution will be higher. In this study, the polynomial model was constructed using the Vandermonde matrix.

Reason of this method use is the product of the Vandermonde matrix with the polynomial coefficients is the outputs (Experiment result values) corresponding to the variable inputs (Cordova et al., 2016). Using the Vandermonde matrix the polynomial coefficients and model polynomials can be determined as follows.

Assume that $\mathrm{x}_{\mathrm{n,m}}$ is the m^{th} value of n^{th} input variable and y_{n} is the output value corresponding to input variable $\mathrm{x}_{\mathrm{n,m}}$. In this case the relation between the input variable $\mathrm{x}_{\mathrm{n,m}}$ and output value y_{n} is as in Equation 2. So, the polynomial model is Equation 2.

$$c_{n,m}{x_{n,m}}^{n} + \cdots + c_{2,m}{x_{n,m}}^{2} + c_{1,m}{x_{n,m}}^{1} + c_{0,m}{x_{n,m}}^{0} = y_{n,m} \quad (2)$$

The c_n values in Equation 2 are polynomial coefficients can be calculated as in equation 3.

$$\begin{bmatrix} {x_{0,m}}^{0} & {x_{0,m}}^{1} & {x_{0,m}}^{2} & \cdots & {x_{0,m}}^{n} \\ {x_{1,m}}^{0} & {x_{1,m}}^{1} & {x_{1,m}}^{2} & \cdots & {x_{1,m}}^{n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ {x_{n,m}}^{0} & {x_{n,m}}^{1} & {x_{n,m}}^{2} & \cdots & {x_{n,m}}^{n} \end{bmatrix} \begin{bmatrix} c_{0,m} \\ c_{1,m} \\ \vdots \\ c_{n,m} \end{bmatrix} = \begin{bmatrix} y_{0,m} \\ y_{1,m} \\ \vdots \\ y_{n,m} \end{bmatrix} \quad (3)$$

Since there are two variables in this study, the m value in Equation 2 and Equation 3 was assigned as first "1" then "2". Thus, polynomials were created as $y_{n,m} = y_{n,1}$and $y_{n,m} = y_{n,2}$.Since $y_{n,1} = y_{n,2}$ for the same n value, the polynomial with two variables was also calculated as $P_{a,b} = \frac{y_{a,1}+y_{b,2}}{2}$ for $a = \{1,2,\dots,n\}$ and $b = \{1,2,\dots,n\}$. However, note that the other methods can be used to create polynomial models instead of providing method based on vandermonde matrix.

RESULTS and DISCUSSIONS

In an experiment, the smallest or largest value of the resulting value from the input variable is the optimum result value. Therefore, the minimum (black color with a value of 0) or maximum (White color with a value of 0) values are the optimums of outputs in the image matrix. In the image matrix, the row and column coordinates of these values are the variable values that will produce the optimal result also. The sample data matrix used in the study is the data matrix created to measure the antimicrobial effects of *L. casei* Shirota that is a probiotic lactic acid bacterium on *S. aureus*. The input variables of this matrix are time and *L. casei* Shirota concentration. The original data matrix is 27×4 dimensional and is modeled as 721×1521 dimensional by using polynomials. Thus, the dimension (resolution) of the image matrix was increased also. The visual result (image) of transforming the data matrix obtained by the polynomial model into the image matrix by normalization method is as shown in Figure 2.

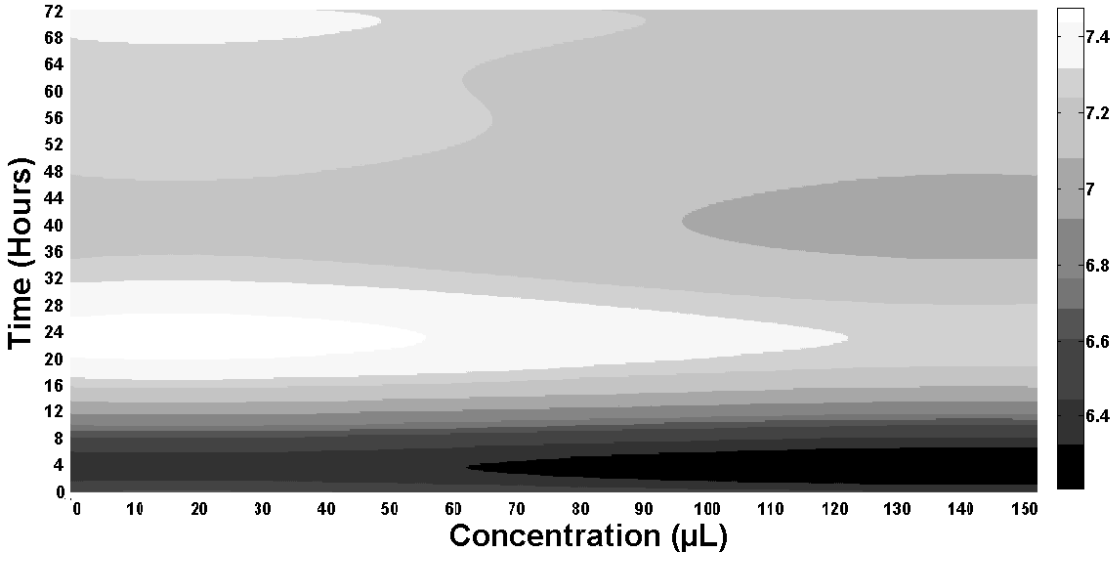

Figure 2. Image resulting from transforming of the original data matrix to image matrix

In Figure 2, the black colors are the cells with the lowest concentration of microorganism (The cells with optimum output values). If Figure 2 is analyzed visually it can be observed that the time variable that will produce the optimal outputs (optimal experimental results) are within 2-6 hours. According to the same visual analysis the input variable related with concentration to produce the optimal output is about within 60-150 µL range. However, although the human eye can distinguish up to 256 tones per color the non-adjacent contrast colors cannot be distinguished for more than 16 tones. In other words, the dark gray tones similar to darkest black color in the same region at Figure 2 may be thought to be the same tones as the darkest black color. Therefore, visual analysis of images can be deceptive and quantitative analysis of the image matrix will be more accurate. If the black cell coordinates of image matrix are calculated as in Equation 4 variable coordinates that will produce the

$$\boldsymbol{Find}\ D_x\ and\ \ D_y\ If\ D < 1 \tag{4}$$

optimal results can be determined precisely.

This method in Equation 4 is actually a low pass filtering for the image. According to result of filtering the value ranges of the input variables that will produce the optimal outputs are within 3.3-3.9 hours for the time and 131-149 µL for the concentration. The image obtained according to Equation 4 is also as shown in Figure 3. This is the filtered image of the region where the optimal outputs will be obtained (image of only the darkest black color cells).

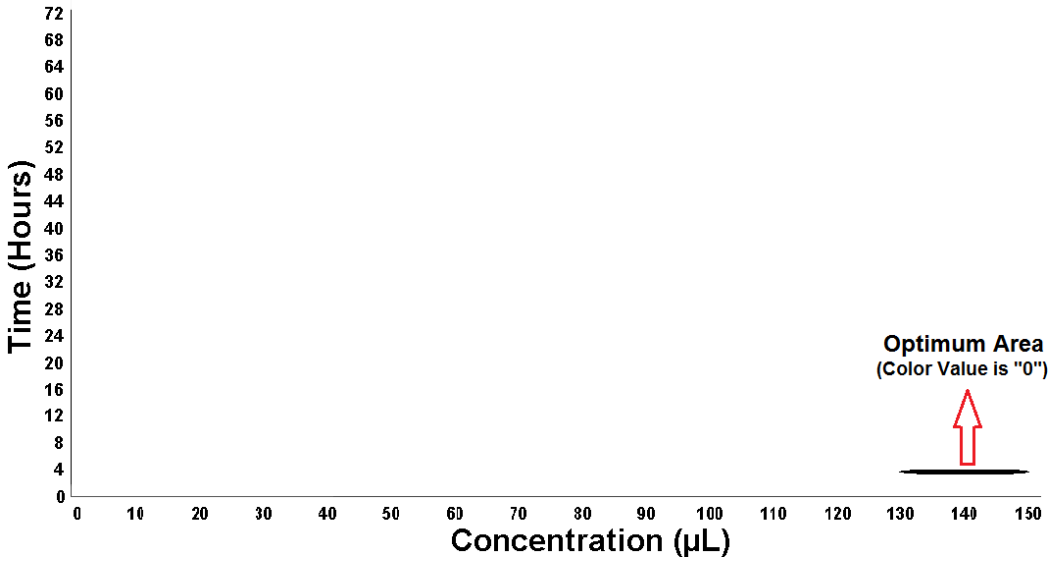

Figure 3. The Image of the region where optimum output is obtained by image filtering

By visually inspecting the image in Figure 3, the limits for optimum values of input variables can be more clearly determined. Thus, by applying low pass filtering for the image the limits of the input variable values which will produce optimum output can be observed more clearly. Image enlargement is another image processing technique can also be used for a clearer visual analysis. The image obtained by the image enlargement technique is as shown in Figure 4.

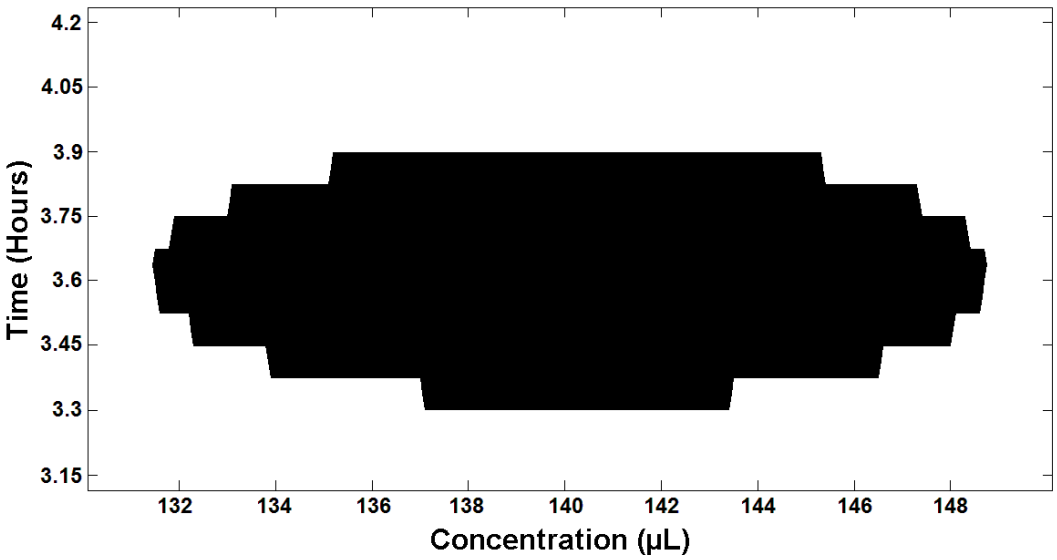

Figure 4. Enlarged image of the zone that will produce optimal output

Determined according to results from figure the value ranges of the input variables that will produce the optimal outputs are within 3.3-3.9 hours for the time and 131-149 µL for the concentration. So, the findings in equation 4 can also be visually observed.

In some cases, although the same input variable values are used, different output values can be generated due to many factors. In such cases it may be more accurate to determine the broader range for the optimized output. The suggested method is also suitable for such cases. Because instead of filtering only the minimum values of the image, the first 2 or 3 values closest to minimum can be also filtered. That is, by changing the threshold coefficient of the low-pass filter, a larger optimum region can be determined. If the optimum output is the maximum value resulting from the experiment then the highest values of the image can be selected by using high pass filter.

It is possible to determine the lowest output value in the original data matrix and identify the corresponding input variable values. However, it is not possible to determine the optimal output range. This is because the optimal output values can only be determined by visually or using data mining techniques. If so, the proposed method can be said to be more advantageous than the determination of the optimal output in the raw data matrix.

CONCLUSION

In this study, a new method proposed for the determination of the range of input variable values that should be used in order to produce optimal output. The proposed method is to create the modeled data matrix by using model related to input and output interaction of the experiment then transform the data matrix into the image matrix. By using this proposed method, it is possible to determine the ranges of variable values which should be used for the optimal experiment result to be produced. In food engineering applications, it is possible to determine the optimal independent variable values by means of some methods in the literature. However, these methods in the literature are not sensitive to the optimum output value which can vary with various factors. The proposed method is sensitive to change as it is in data mining methods. So, it is also possible to develop the method.

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