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Color Image Segmentation of Seed Images Based on Self-Organizing Maps (SOM) Neural Network

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Abstract. This paper presents a threshold color image segmentation methodology based on Self-Organizing Maps (SOM) Neural Network. The objective of segmentation methodology is to determine the minimum number of color features in six seed lines ("nh1", "nh2", "nh3", "nh4", "nh5" y "nh6") of seed castor (Ricinus comunnis L.) images for future seed characterization. Seed castor lines are characterized for pigmentation regions that not allow an optimum segmentation process. In some cases, seed pigmentation regions are similar to background make difficult their segmentation characterization. Methodology proposes to segment the seed image in a SOM-based idea in an increasing way until to some of SOM neuron not have allocated none of the image pixels. Several experiments were carried out with others two standard test images ("House" and "Girl") and results are presented both visual and numerical way.

Keywords. Image segmentation, neural network, self-organizing maps.

1 Introduction

Image segmentation is the process of image partition into homogeneous regions (sets or pixels) that share certain visual characteristics [1, 2]. The objective of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze [3]. Generally image segmentation depends on threshold dependent criteria [4].Otsu method is a classical technique frequently applied to image segmentation [5]. More recently, in field of image segmentation, researchers have extensively worked over this fundamental problem and applied various algorithms/methods. One of these algorithms is Artificial Neural Networks (ANN) [6]. The interest on ANNs has been on the rise due to them being inspired on the nervous

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(a) nh1


(b) nh2


(c) nh3


(d) nh4


(e) nh5


(f) nh6


(g) house


(h) girl

Fig. 1. Images analyzed

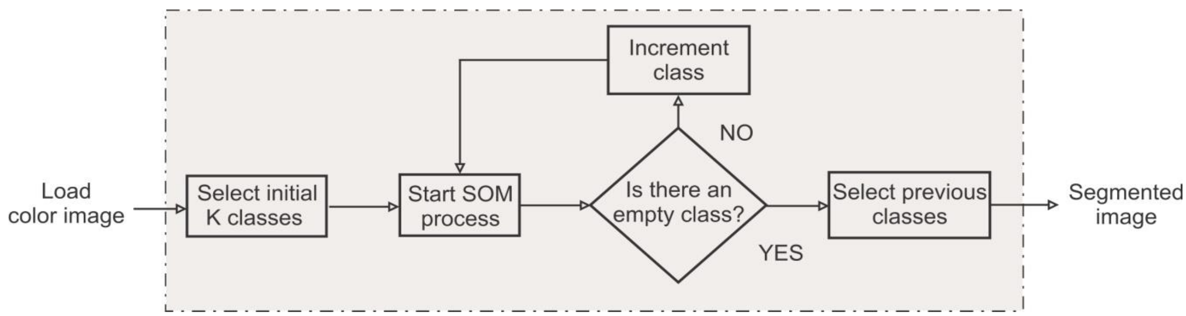

Fig. 2. SOM methodology

Table 1. SOM network parameters

Parameters	Values
Number of iterations	100
Number of experiments	100
Number of segments	15
Initial segment	2
input data	$480 x 640 x 3$
SOM network structure	[1 1 3]
Distance type	Euclidean

system, their usefulness for solving pattern recognition problems and their parallel architectures [7].

ANN can change their responses according to the environmental conditions and learn from experience [8]. It has been seen that ANN is a good approach to analyze images and segment different objects present in a given image [4]. ANN has been used for image segmentation based on its supervised and unsupervised methods [9].

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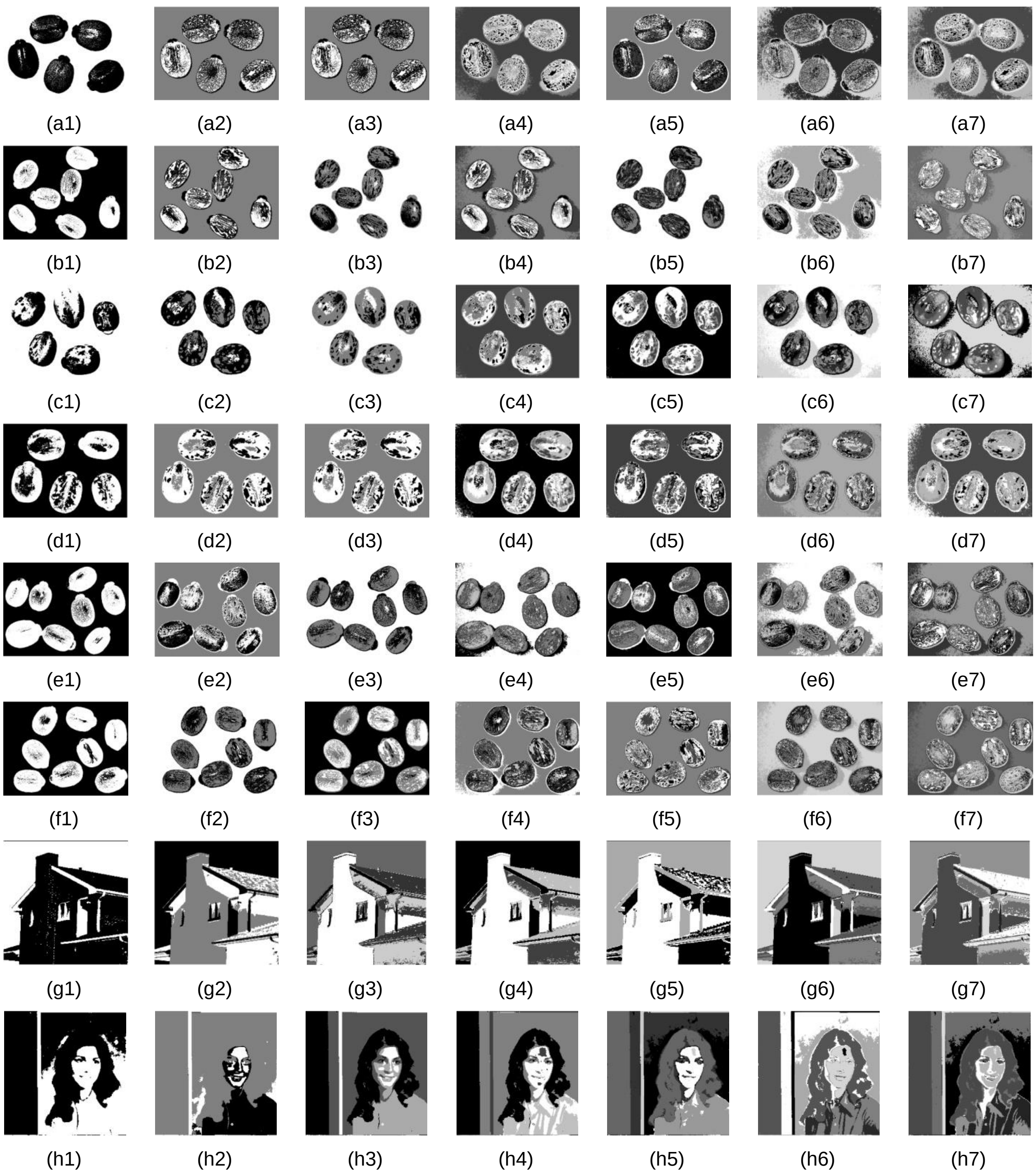

Fig. 3. Segmented images with 2, 3, 4, 5, 6, 7 and 8 thresholds

Table 2. Threshold values for nh1

Image	k	Threshold
nh1	*2*	0.7094, 0.0107
	3	0.5073, 0.0245, 0.8879
	4	0.9871, 0.0302, 0.6800, 0.3846
	5	0.0485, 0.4599, 0.7178, 1.0067, 0.1252
	6	**0.0558, 0.0615, 0.7763, 0.5769, 0.3562, 1.0309**
	7	0.0615, 0.5769, 1.0309, 0.3562, 0.3918, 0.0558, 0.7763
	8	0.0650, 0.7711, 0.2774, 0.4784, 0.0394, 0.6562, 0.8269, 1.0499
	9	0.6466, 0.8655, 0.0615, 0.3562, 0.5769, 0.6962, 0.7763, 0.0558, 1.0309
	10	0.5769, 0.7763, 0.3562, 0.6321, 0.5926, 0.0615, 0.7449, 0.0558, 1.0309, 0.6815

Table 3. Threshold values for nh2

Image	k	Threshold
nh2	2	0.7448, 0.0335
	3	0.5122, 0.9119, 0.04517
	4	**0.6520, 0.9630, 0.3255, 0.0517**
	5	0.3255, 0.7013, 0.9630, 0.0517, 0.6520
	6	0.4358, 0.0517, 0.9630, 0.3255, 0.7820, 0.6520
	7	0.6280, 0.0748, 0.4157, 0.9766, 0.6078, 0.6916, 0.062275245
	8	0.2162, 1.0155, 0.0173, 0.6388, 0.4414, 0.8243, 0.0861, 0.7758
	9	0.5609, 0.0320, 0.3165, 0.5397, 0.5599, 0.9988, 0.0814, 0.7676, 0.6882
	10	0.6439, 0.8243, 0.6995, 0.6388, 0.0861, 0.2771, 0.4414, 1.0155, 0.2162, 0.0173

In the segmentation of color images, unsupervised learning is preferred to supervised learning because the latter requires a set of training samples, which may not always be available [6, 10]. The Self-Organizing Maps (SOM), a widely used image segmentation algorithm [2], is a type of unsupervised ANN [11].

The SOM features are very useful in data analysis and data visualization, which makes it an important tool in image segmentation [8]. It has two major characteristics, (i) it produces a low dimensional representation of the input space (ii) it groups together similar samples [9].

These two characteristics of SOM help us in segmenting the regions of the image that has similar features, and it reduces the number of colors required to represent an image [6]. SOM studies each input component and then classifies the input into the corresponding class (color). The basic Self-Organizing Maps (SOM) [18]. Neural Network consists of the input layer and the output layer, which is fully connected with the input layer

Table 4. Threshold values for nh3

Image	k	Threshold
	2	0.4880, 0.0282
	3	0.7061, 0.0282, 0.4880
	4	0.0535, 0.8358, 0.2451 0.4779
nh3	5	0.2451, 0.6461, 0.4779, 0.0535, 0.8358
	6	0.0816, 0.4042, 0.2550, 0.0666, 0.8955, 0.6269
	7	0.0378, 0.0745, 0.9051, 0.3133, 0.1916, 0.4514, 0.6544
	8	0.8955, 0.2578, 0.2550, 0.0666, 0.6193, 0.4042, 0.0816, 0.6269
	9	0.8831, 0.3496, 0.5751, 0.1742, 0.3383, 0.2214, 0.4695, 0.5935, 0.0585
	10	0.6269, 0.7603, 0.0666, 0.2550, 0.0816, 0.8955, 0.4042, 0.4145, 0.6443, 0.5123

Table 5. Threshold values for nh4

Image	k	Threshold
	2	0.4880
	3	0.3085, 0.0489, 0.7488
	4	0.8358, 0.0535, 0.2451, 0.4779
	5	0.8358, 0.2451, 0.0535, 0.7457, 0.4779
nh4	6	0.5935, 0.0585, 0.6122, 0.3496, 0.8831, 0.1742
	7	0.8003, 0.4779, 0.2451, 0.0535, 0.7836, 0.8358, 0.7471
	8	0.0666, 0.2550, 0.6164, 0.8955, 0.4042, 0.0816, 0.6269, 0.6292
	9	0.0816, 0.3702, 0.2373, 0.8955, 0.0666, 0.2550, 0.5246, 0.6269, 0.4042
	10	0.2564, 0.0931, 0.3911, 0.5456, 0.0316, 0.3814, 0.1168, 0.9272, 0.6386, 0.7235

by the adjusted weights (prototype vectors). The number of units in the input layer corresponds to the dimension of the data. The number of units in the output layer is the number of reference vectors in the data space (image).

In SOM, the high-dimensional input vectors are projected in a nonlinear way to a low-dimensional map (usually a two-dimensional space), and SOM can perform this transformation adaptively in a topologically ordered fashion. Therefore, the neurons are placed at the nodes of a two-dimensional lattice.

Every neuron of the map is represented by an n-dimensional weight vector (prototype vector), θ=[θ_1,…,θ_n], where θ denotes the dimension of the input vectors. The prototype vectors together form a codebook. The units (neurons) of the map are connected to adjacent ones by a neighborhood relation, which indicates the topology of the map. SOM can adjust the weight vectors of adjacent units in the competitive layer by competitive learning.

In the training (learning) phase, the SOM forms an elastic net that folds onto the "cloud" formed by

Table 6. Threshold values for nh5

Image	k	Threshold
nh5	2	0.0139, 0.6460
	3	0.0303, 0.4406, 0.7890
	4	0.8998, 0.6184, 0.3353, 0.0358
	5	0.4150, 0.1156, 0.0524, 0.9199, 0.6546
	6	**0.9199, 0.4150, 0.1156, 0.6546, 0.0524, 0.3140**
	7	0.6993, 0.9412, 0.3079, 0.3874, 0.5131, 0.0621, 0.0537
	8	0.7561, 0.6022, 0.0302, 0.0681, 0.4355, 0.9657, 0.2448, 0.7089
	9	0.6470, 0.3557, 0.0715, 0.0167, 0.9787, 0.1820, 0.7907, 0.5056, 0.4119
	10	0.6022, 0.0681, 0.9657, 0.2448, 0.4355, 0.3187, 0.6133, 0.0302, 0.2601, 0.7561

Table 7. Threshold values for nh6

Image	k	Threshold
nh6	2	0.0139, 0.6843
	3	0.4667, 0.0369, 0.8460
	4	0.0456, 0.3392, 0.9411, 0.6384
	5	**0.3392, 0.9411, 0.6384, 0.0456, 0.5783**
	6	0.9618, 0.0643, 0.4346, 0.6843, 0.1285, 0.2820
	7	0.8028, 1.0090, 0.2650, 0.6366, 0.0389, 0.4627, 0.0782
	8	0.7395, 0.7321, 0.0748, 0.0570, 0.3165, 0.9817, 0.5323, 0.7126
	9	0.8361, 0.5286, 0.1972, 0.3731, 1.0212, 0.0820, 0.6787, 0.0208, 0.4602
	10	0.6366, 0.0782, 1.0090, 0.0389, 0.4627, 0.3143, 0.6641, 0.2650, 0.2441, 0.8028

the input data. Similar input vectors should be mapped close together on the nearby neurons, and group them into clusters.

SOM is an unsupervised classification which is used to cluster a data set based on statistics only, and can be trained by an unsupervised learning algorithm in which the network learns to form its own classifications of training data without external help.

The SOM is trained iteratively. Recently, many researchers have explored the alone Self-Organizing Maps (SOM) Neural Network capabilities in image segmentation and proposed several models for object shape recovery [12], to deal with images containing regions characterized by intensity in homogeneity [13] or to segment a Landsat image [14].

In addition, many researchers have explored the SOM capabilities combined with other techniques for brain image segmentation [15] or to identify the water region from LANDSAT satellite image [16]. However, the choice of image segmentation technique depends on the problem being considered [17]. In this paper, a threshold color image segmentation methodology based on SOM Neural Network is presented.

Table 8. Threshold values for house image

Image	k	Threshold
house	2	0.3874, 0.1353
	3	0.2391, 0.1449, 0.5375
	4	0.5373, 0.6698, 0.1449, 0.2390
	5	0.2256, 0.6698, 0.3969, 0.6142, 0.1446
	6	0.1465, 0.2955, 0.6698, 0.6135, 0.3953, 0.2286
	7	0.6698, 0.1464, 0.6831, 0.3953, 0.2286, 0.2955, 0.6135
	8	0.1519, 0.3807, 0.5352, 0.7102, 0.6698, 0.2987, 0.1968, 0.2344
	9	0.2987, 0.6698, 0.5352, 0.2344, 0.7226, 0.7102, 0.1968, 0.1519, 0.3807
	10	0.2352, 0.5357, 0.3817, 0.7105, 0.2041, 0.4775, 0.3134, 0.6698, 0.0560, 0.1560

Table 9. Threshold values for girl image

Image	k	Threshold
Girl	2	0.6607, 0.1493,
	3	0.6517, 0.8824, 0.1787,
	4	0.3765, 0.6689, 0.9197, 0.1064
	5	0.3742, 0.1061, 0.9535, 0.6948, 0.6526
	6	0.4653, 0.1110, 0.6756, 0.6907, 0.9750, 0.2918
	7	0.2929, 0.1103, 0.6045, 0.6814, 0.4655, 0.9762, 0.7102
	8	0.2914, 0.5080, 0.6230, 0.7242, 0.9832, 0.7136, 0.1104, 0.4673
	9	0.3484, 0.5294, 0.2988, 0.7303, 0.9845, 0.7193, 0.6613, 0.1101, 0.4719
	10	0.7200, 0.3057, 0.4389, 0.9848, 0.1835, 0.5326, 0.4761, 0.7318, 0.6696, 0.0673

In this paper, a threshold color image segmentation methodology based on SOM Neural Network is presented.

The objective of the segmentation methodology is to identify and separate the seed castor (Ricinus comunnis L) to determine the minimum number of color features.

The remainder of this paper is organized as follows. In Section 2, the images analyzed in our experiments and methodology are presented. In Section 3, we show the experimental results obtained by the proposed methodology. Finally, Section 4 contains the conclusions of this research.

2 Material and Methods

2.1 Material

In this paper, the color image segmentation methodology segments seed *castor ricinus* images ("nh1", "nh2", "nh3", "nh4", "nh5" y "nh6") and two standard test images ("House" and "Girl").

Algorithm 1

(1) Set parameters
(2) Define the initial classe k
(3) **While** $Experiments_{max} < 100$
(4) **While** $Segments_{max} < 15$
(5) **While** $iterations_{max} < 15$
(6) Initialize each weight of node in SOM
$0 < w < 1$
(7) Choose a random vector
(8) Find the BMU
(9) Calculate the Euclidean distance $D = \sqrt{\sum_{i=0}^{i=n}(v_i - w_i)^2}$
(10) Calculate the radius of the neighborhood around the BMU
(11) Update the nodes in the neighborhood of the BMU

$$w_j(t+1) = w_j(t) + \eta(t)(i_1 - w_{j(t)})$$

(12) Increase k and repeat from step 3 while $Segments_{max} < 15$
(13) Increase experiment and repeat from step 3 while $Experiments_{max} < 100$
(14) **End While**
(15) **End While**
(16) **End While**

Table 12. Number of pixels for nh3

Image	k	Pixels
	2	92202, 214998
	3	0, 214998, 92202
	4	**183744, 20857, 68696, 33903**
	5	68696, 0, 33903, 183744, 20857
nh4	6	45898, 30645, 48015, 150529, 14643, 17470
	7	60430, 125333, 13610, 36943, 34467, 21128, 15289
	8	14643, 0, 48015, 150529, 0, 30645, 45898, 17470
	9	15901, 47748, 0, 48821, 0, 0, 0, 20317, 174413
	10	17470, 0, 150529, 48015, 45898, 14643, 30645, 0, 0, 0

The seed collections were supplied by the National Research Institute for Forestry, Agriculture and Livestock (in Spanish: Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias, INIFAP) of Mexico at the Bajío.

Standard images were obtained from University of Southern California[1] in miscellaneous section.

[1] *http://sipi.usc.edu/database/*

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Table 10. Number of pixels for nh1

Image	k	Pixels
	2	110379, 196821
	3	66741, 186472, 53987
	4	31517, 181754, 52558, 41371
	5	154248, 42405, 46203, 27939, 36405
nh1	6	61733, 122073, 34516, 36715, 28638, 23525
	7	122073, 36715, 23525, 28638, 0, 61733, 34516
	8	112609, 0, 19370, 29452, 67752, 32049, 25753, 20215
	9	0, 0, 122073, 28638, 36715, 0, 34516, 61733, 23525
	10	36715, 34516, 28638, 0, 0, 122073, 0, 61733, 23525, 0

Table 11. Number of pixels for nh2

Image	k	Pixels
	2	92446, 214754
	3	52716, 48633, 205851
	4	**42199, 36775, 28987, 199239**
	5	28987, 0, 36775, 199239, 42199
nh3	6	0, 199239, 36775, 28987, 0, 42199
	7	0, 149567, 29761, 33816, 0, 37512, 56544
	8	15026, 24621, 80228, 26821, 21833, 21589, 117082, 0
	9	29018, 71738, 20754, 0, 0, 28633, 130041, 27016, 0
	10	0, 21589, 0, 26821, 117082, 0, 21833, 24621, 15026, 80228

Seed images were acquired under standard conditions using a microtouch (Dinolite digital microscope) over a white background at 29 cm.

Images were stored in the Joint Photographic Experts Group (JPG) format (480 x 640 pixels color image).

Figure 1 shows a representative set of the six castor lines analyzed. Standard images have a TIFF format with dimensions of 256x256 color image and 96 ppp.

Figure 1a shows the image for nh1, 1b for nh2, 1c for nh3, 1d for nh4, 1e for nh5 and 1f for nh6.

2.2 Methodology

With the objective of determining the minimum number of color features in six seed lines (nh1, nh2, nh3, nh4, nh5 and nh6) of castor (*Ricinus comunnis* L.) for future seed characterization process, a color image segmentation methodology is presented. Figure 2 illustrates the segmentation methodology.

The segmentation methodology starts setting the maximum number of experiments, the maximum number of SOM number of image seg-

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Table 13. Number of pixels for nh4

Image	k	Pixels
	2	92202, 214998
	3	86138, 190111, 30951
	4	**20857, 183744, 68696, 33903**
	5	20857, 68696, 183744, 0, 33903
nh4	6	20317, 174413, 0, 47748, 15901, 48821
	7	0, 33903, 68696, 183744, 0, 20857, 0
	8	150529, 48015, 0, 14643, 30645, 45898, 17470, 0
	9	45898, 0, 0, 14643, 150529, 48015, 0, 17470, 30645
	10	40945, 76719, 0, 14631, 93790, 28612, 30031, 11300, 0, 11172

Table 14. Number of pixels for nh5

Image	k	Pixels
	2	194533, 112667
	3	182467, 61433, 63300
	4	34477, 54508, 40916, 177299
	5	39811, 38828, 149676, 30357, 48528
nh5	6	30357, 39811, 38828, 48528, 149676, 0
	7	39248, 25968, 27228, 0, 34573, 127122, 53061
	8	28106, 32354, 63442, 112677, 27925, 21281, 21415, 0
	9	29829, 21627, 104333, 66858, 18806, 17685, 22571, 25491, 0
	10	32354, 112677, 21281, 21415, 27925, 0, 0, 63442, 0, 28106

Table 15. Number of pixels for nh6

Image	k	Pixels
	2	192089, 115111
	3	68612, 179389, 59199
	4	173430, 41514, 33298, 58958
	5	41514, 33298, 58958, 173430, 0
nh6	6	28729, 151350, 42334, 50448, 34339, 0
	7	25948, 19641, 21849, 35358, 51665, 30488, 122251
	8	0, 39925, 130406, 46485, 27527, 24677, 38180, 0
	9	21098, 28197, 16239, 22428, 17430, 112211, 31975, 57622, 0
	10	35358, 122251, 19641, 51665, 30488, 0, 0, 21849, 0, 25948

Table 16. Number of pixels for house image

Image	k	Pixels
house	2	38913, 26623
	3	24342, 25596, 15598
	4	15361, 256, 25596, 24323
	5	20830, 256, 10032, 8740, 25678
	6	23417, 2490, 256, 8750, 10073, 20550
	7	256, 23414, 3, 10073, 20550, 2490, 8750
	8	21858, 7201, 7733, 3136, 256, 2435, 3097, 19820
	9	2435, 256, 7733, 19820, 0, 3136, 3097, 21858, 7201
	10	19765, 7708, 7195, 3124, 3009, 6, 2188, 256, 1166, 21119

Table 17. Number of pixels for girl image

Image	k	Pixels
girl	2	22850, 42686
	3	12314, 6594, 46628
	4	25917, 11401, 4679, 23539
	5	25588, 23395, 3580, 6300, 6673
	6	10147, 22813, 9199, 3949, 3171, 16257
	7	16102, 22648, 4096, 3717, 9966, 3145, 5862
	8	15782, 2167, 4050, 2923, 3006, 5446, 22674, 9488
	9	1919, 2115, 15824, 2758, 2962, 4467, 4386, 22209, 8896
	10	4334, 16099, 1778, 2958, 7597, 2088, 8424, 2732, 4146, 15380

ments. Then segmentation process segments the image in an increasing way. If the SOM process finds an empty class, the process selects the previous SOM network and ends. On the other hand, the process increments one neuron and another SOM network is created.

The number of neurons in SOM is increased until one of them is empty. When SOM process finds an empty class, it is considered that selected network represents the minimum number of segments in image. The main steps of the SOM methodology are described in algorithm 1.

In the first step, segmentation process selects an initial number of k classes. In second step, SOM method segments the image into the k selected classes. If the SOM process found an empty class, the processes end and selects the previous SOM network to represents the segmented image.

On the other hand, the SOM process increments one class and another SOM network is created with an additional neuron to segment the image. The number of neurons in SOM is increased until one of them is empty.

3 Experimental Results

This section presents the obtained results. Six seed lines ("nh1", "nh2", "nh3", "nh4", "nh5" and "nh6") of seed castor (*Ricinus comunnis* L.) are used for conducting experiments. Two standard test images ("House" and "Girl") obtained from University of Southern California in Miscellaneous section were also used for testing. According to section 2B, table 1 shows the implemented SOM network parameters.

3.1 Image Segmentation Results

This section shows the results obtained by different network structures for each seed image. Figure 3 shows the image segmentation results by the applied methodology. From top to bottom, they are "nh1", "nh2", "nh3", "nh4", "nh5" and "nh6" seed images and "House" and "Girl" standard images. The first column to the seven columns show, respectively, the corresponding images of segmentation results with two to eight thresholds obtained by the methodology.

For nh1 seed image, the figure with the minimum number of segments is 3(a5), for nh2 is 3(b3), for nh3 is 3(c3), for nh4 is 3(d4), for nh5 is 3(e5), for nh6 is 3(f4).

For house standard image, figure 3(g8) shows the minimum number of segments. In the case of the Girl image, the process not found a minimum number of segments to represent the image. In all process, the experiments were extended to 15 segments. Figures 3(h1) to 3(h7) show the process for eight segments.

For seed images, something important to emphasize is the segmentation of their shadows that allow the measure of their dimensions. However, as we show in the background of figures 3(a6) or 3(b4), with the number of k threshold increasing, some segments of the image are distortional.

3.2 Accuracy Evaluation

A numerical representation of the best results obtained by the methodology are shown in tables II, III, IV, V, VI, VII for the seed lines. For House and Girl standard images, tables VIII and IX show the number of pixels segmented for the threshold values. In all tables, the best segmentation results are emphasized in boldface.

It can be found that for nh1 the algorithm obtain the minimum representation when k=6, for nh2 when k=4, for nh3 when k=4, for nh4 K=5, for nh5 when K=6 and for nh6 when k=5. For standard House image, table VIII shows the minimum representation when k=8. As mentioned previously, in case of the Girl image, the SOM process not found a minimum number of segments to represent the image until 15 segments.

3.3 Stability Evaluation

For stability evaluation, tables X, XI, XII, XIII, XIV and XV show the segmented pixels for each seed line. The best results are emphasized in boldface.

For nh1, due to in the K=7 segmentation result the algorithm obtain an empty neuron, the methodology select the value of k=6. This value is also obtained when k=9 and K=10. For nh2, the selected value was K=4. This value is also obtained when K=6. For nh3 the selected value was K=4. For nh4 was K=4, this value is also obtained when K=6. For nh5 was K=5 and for nh6 was K=4. Tables XVI and XVII show the segmented pixels for standard images.

3.4 Convergence Evaluation

In order to evaluate the convergence of the obtained results, figure 4 and table XVIII show a summary of the number of pixels that bellow to each threshold in 100 experiments.

3.5 Computational Time Evaluation

Tables XIX and XX show the computational elapsed and the standard deviation obtained in the 100 times. However, it is necessary to calculate the mean value μ and standard deviation std to show the stability.

Table 18. Average of segmented in 100 times that the algorithm ran

Classes	**Seed images**						**Standard images**	
k	**nh1**	**nh2**	**nh3**	**nh4**	**nh5**	**nh6**	**house**	**girl**
2	2	2	2	2	2	2	2	2
3	3	3	3	3	3	3	3	3
4	4	4	4	4	4	3	4	4
5	5	4	5	4	5	4	5	5
6	6	5	5	5	5	5	6	6
7	6	6	6	6	5	4	7	7
8	7	6	6	6	6	6	8	8
9	8	7	6	7	6	7	8	9
10	8	7	7	6	7	7	9	10

Table 19. Mean computational time

Classes	**Seed images**						**Standard images**	
k	nh1	nh2	nh3	nh4	nh5	nh6	house	girl
2	113.7242	114.772	140.3726	145.9877	188.16861	185.8431	42.8439	40.628
3	116.7574	117.8129	140.8579	145.8736	190.5456	188.5461	43.4832	41.1045
4	119.1461	120.152	141.9788	147.4625	193.7347	190.681	43.6677	41.489
5	121.19	122.2104	143.6273	148.7781	196.6336	193.1109	44.3868	42.0343
6	123.2374	124.1324	145.1459	150.4769	198.7607	194.8986	44.6526	42.4431
7	125.1423	126.2949	148.33	152.4804	201.3035	197.3598	45.2181	42.965
8	127.1337	128.317	148.6636	154.1318	203.5051	199.7161	45.705	43.4335
9	129.2232	130.2506	150.0953	155.2709	204.9444	201.814	46.2501	43.9008
10	131.1884	132.1837	151.3128	156.9613	206.9461	204.4079	46.5627	44.37

The mean value and standard deviation are defined as:

$$\mu = \frac{\sum_{i=1}^{n_e} CC_i}{n_e}, \qquad std = \sqrt{\frac{\sum_{i=1}^{n_r} (CC_i - \mu)^2}{n_e}},$$

where n_e is the number of times the algorithm ran and CC is the value of the computational cost each time.

The mean computational time and standard deviations are obtained in one hundred experiments.

4 Conclusions

This paper presents a color image segmentation methodology based on Self-Organizing Maps (SOM) Neural Network.

It is allowed to segment appropriately the seed pigmentation classes in a single class and to determine the minimum number of color features in six seed lines.

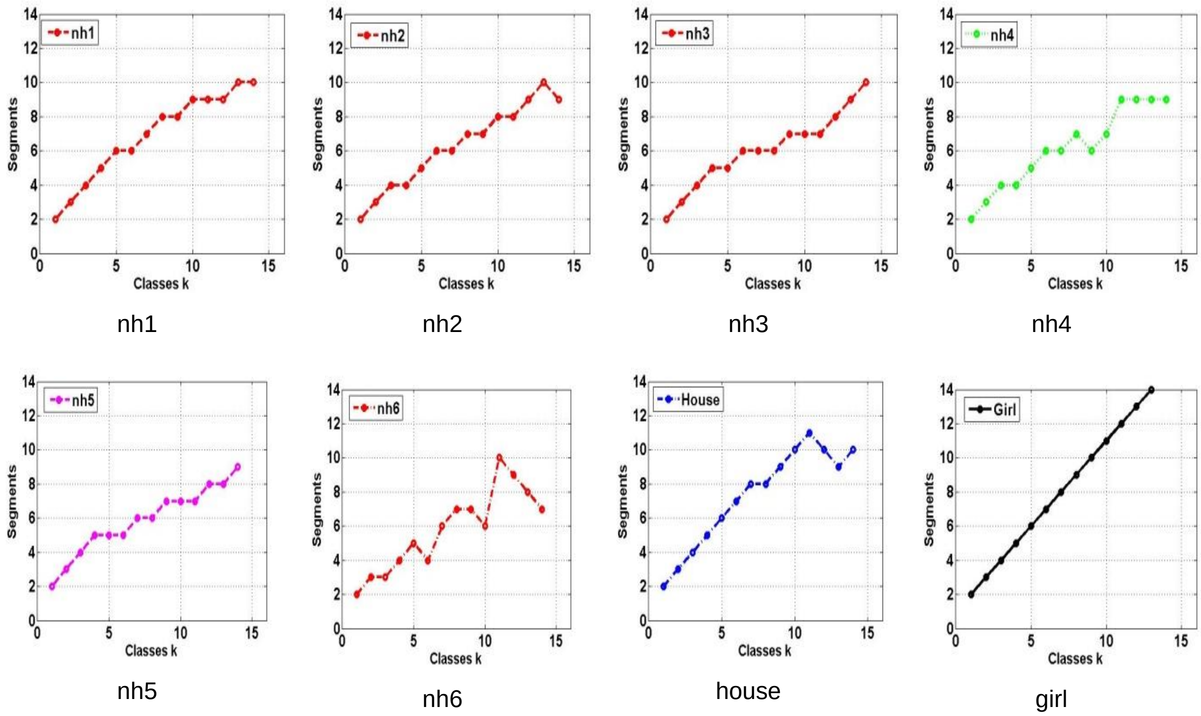

Fig. 4. Convergence evaluation

Table 20. Standard deviation

Classes k	Seed images						Standard images	
	nh1	**nh2**	**nh3**	**nh4**	**nh5**	**nh6**	**house**	**girl**
2	0.896	0.4084	6.8002	4.9806	4.4234	3.8527	1.8314	0.745
3	1.0676	0.796	1.788	2.3848	3.6912	3.6427	1.9452	0.7385
4	1.0749	0.84	1.7173	2.4315	3.6417	3.8458	1.7145	0.7796
5	1.0945	0.8289	1.706	2.514	4.5955	3.3241	1.9423	0.7931
6	1.0218	0.8095	1.7175	2.6821	4.5862	3.4614	1.8394	0.7851
7	1.0548	0.8956	2.0696	2.3397	4.8879	3.5614	1.9652	0.7659
8	1.0497	0.8323	1.2983	2.5473	6.0568	3.8525	1.9262	0.7947
9	1.0197	0.8196	1.5655	2.609	5.1599	4.6414	1.7972	0.8162
10	1.3205	0.7588	1.5776	2.9448	4.4379	4.3454	1.792	0.7431

Something important to distinguish in the segmentation process were the seed shadows detected perfectly.

Proposed methodology, segments seed castor ricinus images ("nh1", "nh2", "nh3", "nh4", "nh5" y "nh6") and two standard test images. The seed images were supplied by the National Research Institute for Forestry, Agriculture and Livestock (in Spanish: Instituto Nacional de Investigaciones Forestales, Agrícolas y Pecuarias, INIFAP) of Mexico at the Bajío. We Standard images were conclude that the proposed methodology is a good option because it obtained from University of Southern California. Results were presented both visual and numerical way.

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