Chicken embryo development detection using Self-Organizing Maps and K-mean Clustering

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***Abstract*—This paper presents a set of procedures for detecting the primary embryo development of chicken eggs using Self-Organizing Mapping (SOM) technique and K-means clustering algorithm. Our strategy consists of preprocessing of an acquired color image with color space transformation, grouping the data by Self-Organizing Mapping technique and predicting the embryo development by K-means clustering method. In our experiment, the results show that our method is more efficient. Processing with this algorithm can indicate the period of chicken embryo in on hatching. By the accuracy of the algorithm depends on the adjustment the optimum number of iterative learning. For experiment the learning rate using the example of number 4 eggs, found that the optimum learning rate to be in the range of 0.1 to 0.5. And efficiency the optimum number of iterative learning to be in the range of 250 to 300 rounds.**

***Keywords*—Self-Organizing Map, K-mean Clustering, Learning Rate, Chicken Embryos**

I. Introduction

Poultry breeding is one of the important businesses in Thailand. Manufacturers can export fresh chicken products and make high profit to Thailand economics annually. High effective manufacturing becomes the requirement of the breeding process. Especially, hatching of eggs is an important process to get the high number of chicks by using the incubator. During this hatching period, the detection of embryo development is useful to classify which one fertile or non-fertile. It allows hatcheries to remove some non-developed eggs out the incubator in order to save the space, handle costs and protect the infection from exploder eggs. In the past, domestic chicken farmers normally detect the embryo development of the incubating eggs manually. Low expertise, intensive labor results being sensitive to emotional factors are the defect of the manual process. It has seriously limited the improvement of the production efficiency and the product quality. To solve this problem, the paper presented computer vision technique to automatically detect the embryo development of the incubating eggs.

Therefore, the computer has a role in the functioning of these instead of humans and for detecting the embryo development of chicken eggs. The researchers have invented a variety of image processing method to check the abundance of detecting the embryo development of chicken eggs through the infrared image processing technique in real time [1], and inspected by photography for positioning the detecting the embryo development of chicken eggs by spectrum [2-3]. The threshold value is used to adjust as optimal discontinuous brightness which is black-and-white image analysis of detecting the embryo [4]. The study and related researches found that the checking the embryo in the egg inefficiency in monitoring the fertilized of chicken embryo.

The objective of this paper is to develop an algorithm of chicken embryo development detection using Self-Organizing Mapping (SOM) technique and K-mean clustering algorithm. The embryo variation is daily detected along the period 18 days of incubation in the experiment. This paper is organized as follows: Section II shortly explains the composition parts of chicken embryo development detection algorithm.

II. Algorithm of Embryo Development Detection

In vision pattern of the egg, there are many algorithm to observe the chicken embryo in a dark room with candling. Egg will be detected for finding living embryo by observing a dark spot. At the longer development period, the blood vessels will more obviously appear that we can observe their random pattern by vision, for example in Fig. 1. However, in this case, we need to use the computer vision program to detect and specify automatically what the period of embryo development. This algorithm shown in Fig. 2 includes the principle parts: embryo image acquisition, data preprocessing, and data prediction using artificial intelligence method. In the metrology, we kept the embryo image samples day by day within 18 days of the incubation and used them as the prototype embryo development of each day.

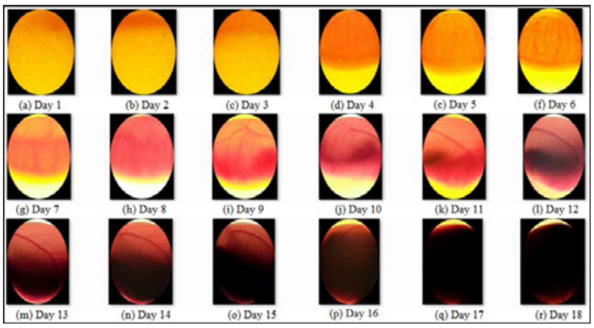

Fig. 1. The sample of chicken embryo development within 18 days

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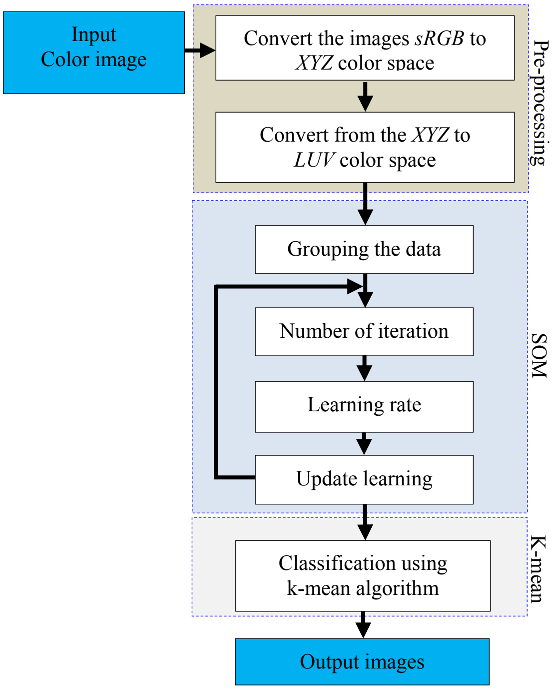


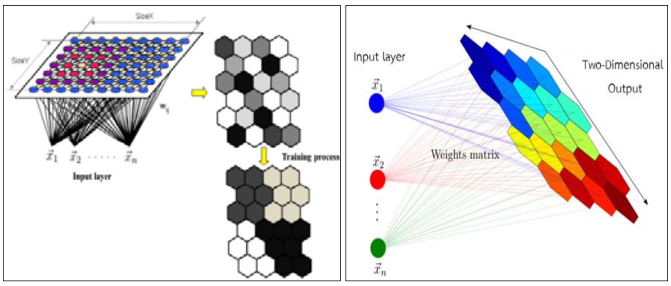
Fig. 2. Algorithm of embryo development detection.

A. Color Space transformation

After the part of embryo image acquisition, this image is in the requirement of the concordance between the human eye consideration and the computer program calculation of the development of the eggs that occur during hatching. Therefore the image signal is from digital camera images in the RGB color space. We should be converted into a color space corresponding to the human eye. It repeat can convert RGB color space to CIE-XYZ and CIE-LUV.

B. Self-Organizing Mapping (SOM) technique

Procedures for detecting the primary embryo development of chicken eggs is used Self-Organizing Mapping (SOM) technique [5]. The process will with the data to searching the value of the weight of all available which data by the number of groups that the artificial neural network is shown in Fig. 3.



(a) Basic structure of SOM. (b) The visualization of similarity.

Fig. 3. Structure of self-organizing map (SOM) [6].

The following are the steps of SOM algorithm:

Step 1 : Initialization - each node's weights.

Step 2 : Sampling - Random vector from training data and present it to the SOM.

Step 3 : Matching – Calculate the distance d_{ij} between the input vector and the weights W_{ij} of each node. When the neural are weighing is near value to W_{ij} will is called the neural that the best matching unit (BMU). From the equation as follows:

$$d_{ij} = \sum(x(t)-w_{ij}(t)) \qquad (1)$$

Step 4 : Updating - The adjusting of neuron W_{ij} is BUM. And adjust the learning rate of neural $\eta(t)$, to the neural that this new approach data nearby more. From the equation as follows:

$$W_{ij}(t+1) = W_{ij}(t)+\eta(t)h_{kj}(t)\left[X(t)-W_{ij}(t)\right] \qquad (2)$$

Where, t is the number of iteration

x(t) is the random vector from the Input data. Import processing each time.

$\eta(t)$ is the learning rate.

$h_{kj}(t)$ is the adjusting of neuron a neighborhood more like the BMU.

Step 5 : Continuation - keep returning to step 2 until the feature map stops changing

After completion of a learning process of the SOM algorithm. The researchers have been using K-mean clustering in groupings of nodes in the diagram SOM which was used to detecting the chicken embryo.

C. K-means Clustering Algorithm

This article presents the image segmentation using K-mean clustering algorithm. By K defining from data sets as initial clustering center of data sets and calculating the average of samples of each K clustering until clustering centers. If is not change [7].

In the K-means, it is defined the set as follows.

$$X = (x_1, x_2, x_3\ldots,x_n) \qquad (3)$$

Where, X is the initial data object sets.

$$dist = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \qquad (4)$$

The Euclidean distance of any two data, $x_i = (x_{i1}, x_{i2}, x_{i3}\ldots,x_{in})$ and $x_j = (x_{j1}, x_{j2}, x_{j3}\ldots,x_{jn})$ is calculated. The average of samples of each class as new K clustering centers, until clustering centers is not change.

III. Experimental Results and Discussions

The experimental detecting the embryo development of chicken eggs in each day with the algorithm is shown in Section II, by finding the accuracy of the algorithm with the experiment process of optimum learning rate coefficient. The is could indicate that the egg sample to be tested the development of the embryo on the day how much within 18 days. And egg samples used in image segmentation experiments that stored image information every day, in the same period until 18 days. There are a total of 18 images.

Then bring image into the process of recognition to image segmentation procedure K-mean clustering of images each days. The results of image segmentation is to the experiment efficiency of optimum the number of iterative learning in detecting the embryo development of chicken eggs in each day. The experimental results confirmed that the mean square error value (MSE). The formula for calculating MSE is as follows:

$$MSE = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}\left[i(x,y)-j(x,y)^2\right] \qquad (5)$$

Where, $i(x,y)$ is the pixel (x,y) of the original image.

$j(x,y)$ is the pixel (x,y) of the image enhanced.

$M \times N$ is the total number of pixels in the image

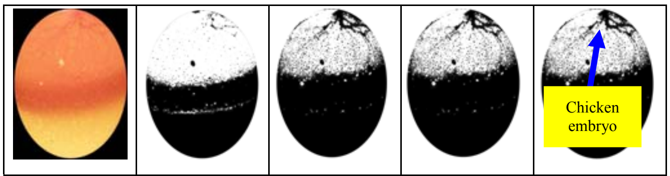
A lower value for MSE implies lesser error. The peak signal is to noise ratio (PSNR). The formula for PSNR is as follows:

$$PSNR = 10\log_{10}\frac{MAX_I^2}{MSE}\,[dB] \qquad (6)$$

Where, MAX_I is the maximum possible pixel value of the image.

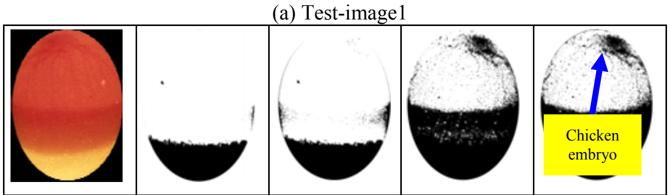
A. Experimental results of the Self-Organizing Maps (SOM)

The finding values of a accuracy of learning rate, are coefficients that represent the learning of the artificial neural networks. In this paper, the experiment values are in the range 0.001 to 0.5, which is the optimum value for learning in the defining. The artificial neural networks has been an weighted value change the most optimum value. The image is used in an experiment. There are a total of 4 images with different image formats.



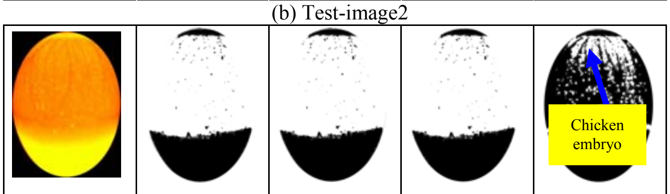
Original	$\eta(t)=0.001$ t=300	$\eta(t)=0.01$ t=300	$\eta(t)=0.1$ t=300	$\eta(t)=0.5$ t=300

(a) Test-image1



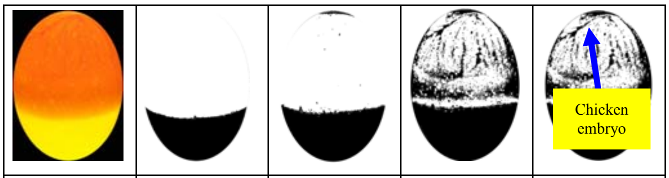
Original	$\eta(t)=0.001$ t=300	$\eta(t)=0.01$ t=300	$\eta(t)=0.1$ t=300	$\eta(t)=0.5$ t=300

(b) Test-image2



Original	$\eta(t)=0.001$ t=300	$\eta(t)=0.01$ t=300	$\eta(t)=0.1$ t=300	$\eta(t)=0.5$ t=300

(c) Test-image3



Original	$\eta(t)=0.001$ t=300	$\eta(t)=0.01$ t=300	$\eta(t)=0.1$ t=300	$\eta(t)=0.5$ t=300

(d) Test-image4

Fig. 4. The optimum learning rate

From the Fig. 4, it show that the experimental to find learning rate coefficients of optimum. It found that range of optimum learning rate to be in the 0.1 to 0.5.

B. Experimental results of the K-mean clustering

In the clustering analysis procedure, a clustering the number of K=10, the number of iterative learning, t=300, and learning rate coefficient value, $\eta(t)=0.5$ are define. The parameters are used in the experiment. Images used in experiments to detecting embryo development of chicken eggs is shown in Fig. 1 and the results are shown in Fig. 5.

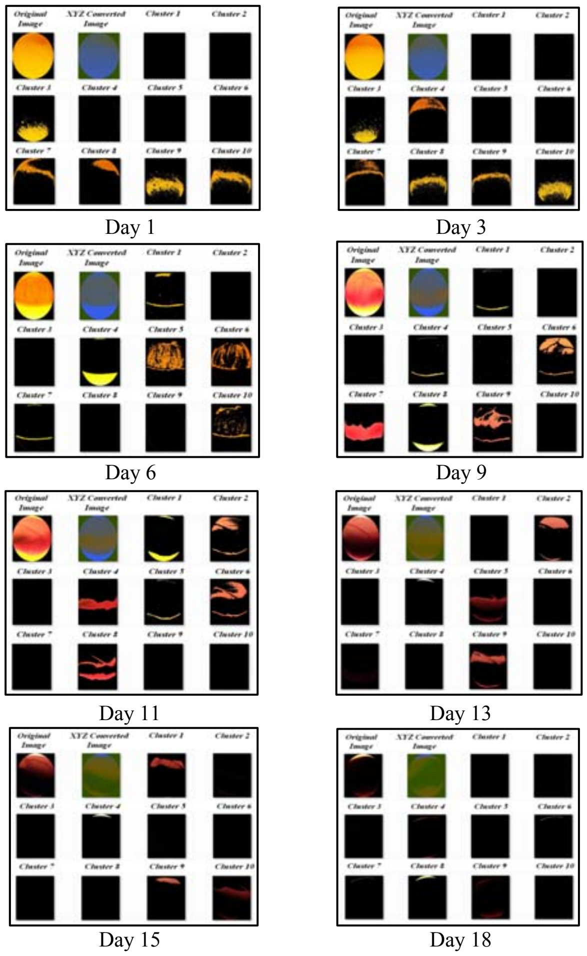


Fig. 5. Results of K-mean clustering

From the Fig. 5, the results of K-means clustering for detecting the embryo development of chicken eggs within 18 days is shown in the Fig.5. It found that during the period 1 to 13 days, the image segmentation in each group different colors. But during the period of 14 to 18 days, the image segmentation in each color group decreased, thus clustering results are the mostly in similar color groups.

C. Experimental results of the number of iteration

Experimental efficiency of the number of iterative learning, the process for the experiment as shown in Table I. By comparison the MSE value and PSNR value, in each the number of iterative learning, image is used in the experiments were the result of K-mean clustering as shown in Fig. 5. By the selecting clusters methods have lowest MSE value and a high PSNR value of each period within 18 days to compare values the range optimum the number of iterative learning. The results are shown in Table I.

The results in Table I, show that the efficiency comparison the number of iterative learning. It found that in the range 50 to 200 rounds, the high MSE value and the low PSNR value is in the range 250 to 300 rounds. The lowest MSE value and the high PSNR value. Therefore it concluded that in the range 250 to 300 rounds, that are deemed as range optimum the number of iterative learning of artificial neural network.

TABLE I. The result of MSE values and PSNR values & number of iteration

Time intervals	**Number of iteration**											
	t = 50		***t =100***		***t = 150***		***t = 200***		***t = 250***		***t = 300***	
	MSE	***PSNR (dB)***	***MSE***	***PSNR (dB)***	***MSE***	***PSNR (dB)***	***MSE***	***PSNR (dB)***	***MSE***	***PSNR (dB)***	***MSE***	***PSNR (dB)***
Day 1	181.954	25.56	175.311	25.72	171.867	25.81	171.857	25.81	**165.681**	**25.97**	**165.681**	**25.97**
Day 2	188.797	25.40	176.555	25.69	176.555	25.69	176.555	25.69	**175.828**	**25.71**	**169.167**	**25.88**
Day 3	184.077	25.51	182.042	25.56	175.014	25.73	174.825	25.73	**174.825**	**25.73**	**172.385**	**25.79**
Day 4	166.575	25.94	154.325	26.28	154.268	26.28	154.268	26.28	**154.268**	**26.28**	**153.723**	**26.29**
Day 5	171.467	25.82	166.964	25.93	166.964	25.93	166.794	25.94	**160.661**	**26.10**	**160.519**	**26.10**
Day 6	163.065	26.04	162.466	26.05	162.466	26.05	162.466	26.05	**162.466**	**26.05**	**162.430**	**26.05**
Day 7	171.755	25.81	144.515	26.56	144.515	26.56	144.515	26.56	**144.255**	**26.57**	**142.587**	**26.62**
Day 8	172.890	25.78	137.936	26.76	137.271	26.78	137.266	26.78	**133.345**	**26.91**	**129.497**	**27.04**
Day 9	161.468	26.08	135.198	26.85	135.198	26.85	135.189	26.85	**135.044**	**26.86**	**133.359**	**26.91**
Day 10	171.620	25.81	168.327	25.90	168.327	25.90	168.148	25.90	**168.142**	**25.91**	**166.064**	**25.96**
Day 11	185.082	25.49	174.538	25.74	168.253	25.90	162.245	26.06	**162.241**	**26.06**	**161.166**	**26.09**
Day 12	158.199	26.17	153.769	26.29	153.225	26.31	147.827	26.46	**147.396**	**26.47**	**128.831**	**27.06**
Day 13	150.268	26.39	135.477	26.84	135.153	26.85	130.249	27.01	**130.199**	**27.01**	**129.204**	**27.05**
Day 14	117.721	27.45	106.243	27.90	100.030	28.16	98.150	28.24	**98.150**	**28.24**	**98.144**	**28.24**
Day 15	83.944	28.92	74.197	29.46	73.507	29.50	73.463	29.50	**73.463**	**29.50**	**73.463**	**29.50**
Day 16	93.247	28.46	42.559	31.87	42.555	31.87	42.555	31.87	**32.226**	**33.08**	**31.769**	**33.14**
Day 17	18.453	35.50	17.378	35.76	15.679	36.21	15.657	36.21	**13.997**	**36.70**	**13.997**	**36.70**
Day 18	18.852	35.41	18.268	35.54	18.268	35.54	14.994	36.40	**13.519**	**36.85**	**13.364**	**36.90**

IV. CONCLUSION

This paper presents a set of procedures for detecting the primary embryo development of chicken eggs. The experiments were conducted of algorithm as shown in Fig. 2, the results detecting embryonic development of chicken eggs are shown in Fig. 4. The experiment results of learning rate coefficient of all 4 images found that a range of optimum learning rate in the 0.1 to 0.5. and efficiency comparing the number of iterative learning. It found that range of optimum learning rate in the 250 to 300 rounds which have the lowest MSE value and the high PSNR value that are deemed as range optimum the number of iterative learning.

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