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Identification of Surimi Gel Strength Classes using
Backpropagation Neural Network and Principal Component Analysis

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Abstract: This study proposes two practically and efficiently supervised and unsupervised classifications for surimi gel strength patterns. An supervised learning method, backpropagation neural network with three layers of 17-34-4 neurons for each later, is used. An unsupervised classification method consists of the data dimensionality reduction step via the PCA algorithm and classification step using correlation coefficient similarity measure. In the similarity measure step, each surimi gel strength pattern is compared with the surimi eigen-gel patterns, produced by the PCA step. In this study, we consider a datum pattern as a datum dimension. The training data sets (12 patterns or 12 data dimensions) of surimi gel strength are collected from 4 experiments having different fixed setting temperature at 35, 40, 45, and 50°C, respectively. Testing data sets (48 patterns) are including original training set and their added Gaussian noise with 1, 3 and 5 points, respectively. From the experiments, two proposed methods can classify all testing data sets into its proper class.

Key words: Backpropagation neural network, principal component analysis, surimi eigen-gel patterns, backprogpagation neural network

INTRODUCTION

Surimi is a concentrate of the myofibrillar proteins, primarily myosin and actin, of fish muscle, that is mechanically deboned, water-washed fish meat. In order to manufacture surimi-based products, the raw or frozen surimi is ground with salt and other ingredients and then passed through thermal processing to set the shape and develop the texture (Lanier and Lee, 1992). During the thermal process, myofibrillar protein is induced to form the actomyosin gel, mainly derived from the myosin portions, which gives the unique elastic textural properties of the products (Hall and Ahmad, 1997). Surimi is very well-known in food processing topics. Applications or surimi based products are Crap-analog or Kani-kamabogo, Kamaboko, Chikuwa, Satsumage, fish sausage and Shell fish-analog, etc. (Lanier and Lee, 1992).

Generally, surimi gel is formed following two heating-steps, a preheating process below 50°C (setting step) prior to cooking at 80 or 90°C to produce an opaque, highly elastic and strengthened gel (Lanier and Lee, 1992). The setting period is an important step in surimi gel development. This is because the setting at low temperature prior to heating at a higher temperature allows slow ordering of the protein molecule resulting in good gelation, fine structure and great elasticity (Hermansson, 1978; Lanier and Lee, 1992). Different temperatures in the setting step result in different conformation of the proteins leading to different structure and strength of the final gel (Hossain *et al.*, 2001).

The qualities of surimi gel, notably gel strength and structure, can be affected during gelation by various physical conditions such as high pressure, heating temperature and heating period during setting. In this study, we emphasize on only surimi gel strength patterns which obtained from various setting temperatures and times. From the preliminary experiments, it can be observed that all patterns of surimi gel strength have similar shape. The final gel strengths increased to the maximum value and then decreased to the plateau in all setting temperatures. It is difficult to determine classes of each surimi gel strength. In order to determine their proper classes, both supervised and unsupervised classification learning methods are applied to identify the qualities of surimi gel pattern.

MATERIALS AND METHODS

The experiments were conducted in Reading, UK during 2003-2004 and in Thailand during 2005-2006.
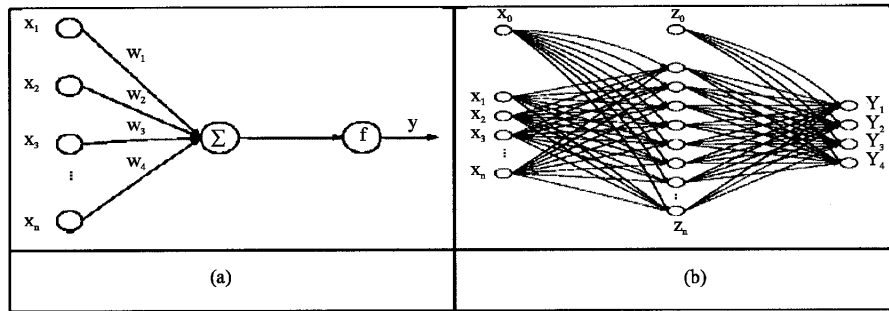
Fig. 1: (a) Perceptron neural network and (b) Backpropagation neural network used in the study

Materials: Cod (*Gadus morhua*) fillets were purchased from Frosts Fish LTD, Reading, UK. The fillets were skinned, rinsed with clean water, blended in a Lab Micronizer (Waring Commercial), washed by the ratio of water: minced fish at 3:1 (v/w). Then, the minced fish was dewatered by a basket centrifuge, then mixed with 6% sugar and 0.2% tetrasodium pyrophosphate and stored in a freezer at-18°C as a frozen surimi sample.

Gel preparation: The frozen surimi was thawed at 4°C until the temperature of surimi reached 0°C and then, mixed with 2.5% salt by using a Lab Micronizer (Waring Commercial). The sol obtained was stuffed into stainless-steel cylinders of 2.5 cm inner diameter and 2.5 cm length. Surimi gels were prepared by heat setting at 35, 40, 45 and 50°C for 0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60, 120, 180, 240 and 300 min in a water bath (Grant Y28, type VFP). Then, the gels were cooked at 90°C for 20 min and cooled in ice water. The obtained surimi gels were stored at 4°C for 24 h before analysed.

Gel strength analysis: The gel strengths of surimi gels were tested by using a TA-XT2 Texture Analyser (Stable Micro Systems Ltd., Surrey, UK). All the cooked gels were compressed to 15 mm at the speed of 1.1 mm sec^{-1} using a cylindrical shaped probe of 2.5 cm in diameter. Then, the changes in applied force were recorded. The gel strength was obtained from the peak force multiplied by the compression distance at the peak.

Proposed classification methods: The objective of the study is to classify each surimi gel strength pattern into a proper class. We propose both supervised and unsupervised learning methods to identify the class or quality of surimi gel patterns.

Supervised learning is the backpropagation neural network. And unsupervised learning is the Principal component analysis and comparing the results by the correlation coefficient similarity method.

Backpropagation neural network: Artificial neural network or neural network is a parallel processing mechanism which similar to human brain learning system. There are both supervised, unsupervised and reinforcement learning systems (Haykin, 1999). The first and simple neural network structure is called the Perceptron neural network. Perceptron consists of input neurons, connection weight, adding function, activation function and output as illustrated in Fig. 1a.

where $[x_1, x_2, \ldots, x_n]^T$ are the input vectors, $[w_1, w_2, \ldots, w_n]^T$ are the connection weights, β is a bias, $f()$ is an activation function and y is an output. y can be written as follows:

$$net = \sum \left(x_1 w_1 + x_2 w_2 + \cdots + x_n w_n \right) + \beta \qquad (1)$$

$$y = f(net) \qquad (2)$$

The backpropagation neural network (Haykin, 1999) with three layers, input-hidden-output, is used. The neurons in each layer are 17-34-4 for input-hidden-output layer, respectively. Neural network learning algorithm starts with the random weight w_{hi} and w_{jh}. The input vectors $[x_1, x_2, \ldots, x_{17}]^T$ are fed to the hidden layer Z using the weight w_{hi}. Then hidden vectors $[z_1, z_2, \ldots, z_{34}]^T$ are fed again by the weight w_{jh} in order to produce the output vectors $[y_1, \ldots, y_4]^T$. Backpropagation network structure is shown in Fig. 1b. Let t be a desired target. The objective function is a Summed Squared Error (SSE) as follows:

$$E = \frac{1}{2} \sum \left(y - t \right)^2 \qquad (3)$$

And the activation function is a Sigmoidal function as follows:

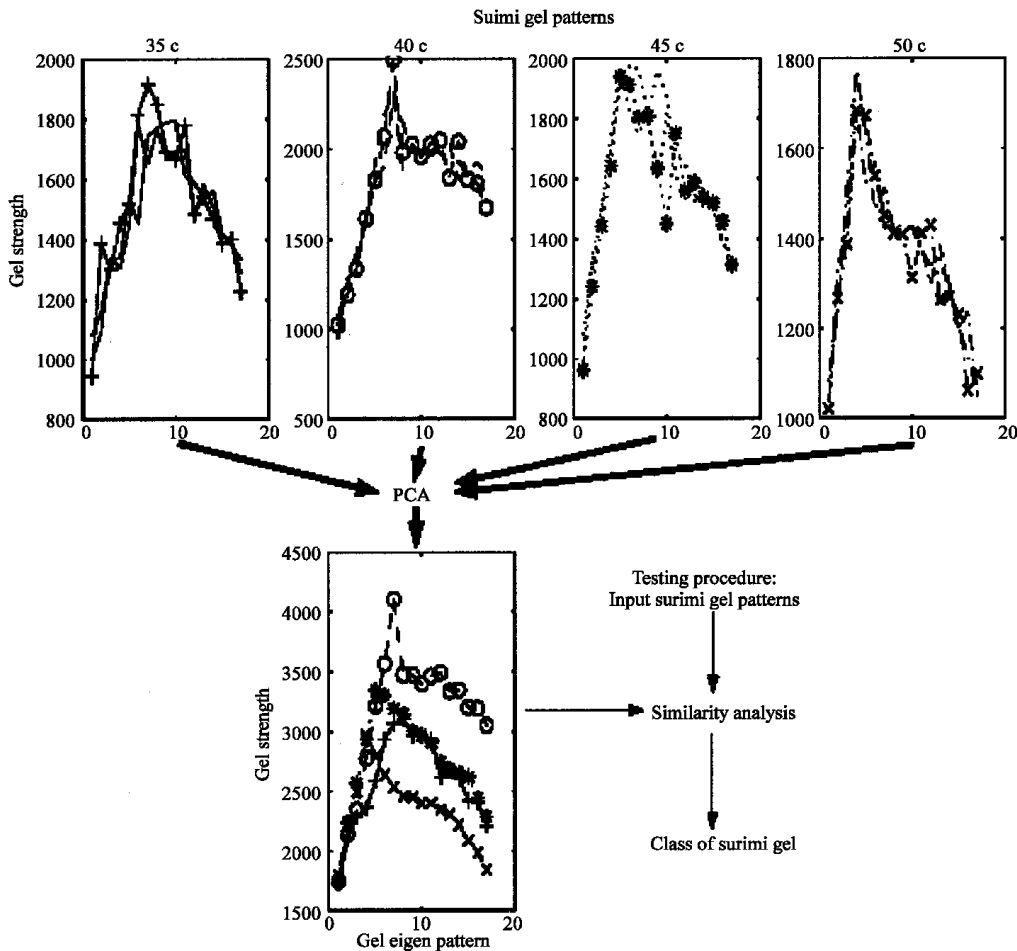$$f\left(net \right) = \frac{1}{1 + e^{-net}} \qquad (4)$$

Fig. 2: System structures for surimi Gel Eigen Pattern identification

Principal component analysis to surimi gel pattern: The second method for classifying each surimi gel strength is the principal component analysis and the similarity measure method. An identifiable system consists of two main parts, the construction of surimi gel eigen-patterns and similarity analysis. First, the PCA method is used for searching an eigen-pattern by returning the principal direction for each class of surimi gel quality. Second, correlation coefficient similarity method between the eigen gel pattern and surimi gel strength pattern is used for classifying a class of them. A structure chart of the overall system is illustrated in Fig. 2.

Constructing principal direction or eigen-pattern Chinnasarn *et al.* (2005) presented constructing procedures are composed of two main steps, surimi gel strength matrix formation and computing an eigen-pattern. First, the surimi gel strength matrix formation step, input data for modeling surimi gel eigen-patterns are surimi gel strength from 3 replications. Then from the previous conditions, three input vectors of surimi gel strength

were obtained for each setting temperature. And they are formed as a row major matrix with a dimension of 3 by 17.

Second, computing an eigen-pattern step, the principal component analysis can be carried out. The calculation of surimi gel eigen-pattern is given by the solution to the following step (Duda *et al.*, 2001):

1. Compute the mean for each row $mean_i$
2. Generate the zero-mean matrix Mz for each row i,
$$Mz_{ij} = M_{ij}\text{-}mean_i \qquad (5)$$
   where $1 \le i \le 17$.
3. Compute the covariance matrix Cov for Mz,
$$Cov(Mz) = E[(Mz)(Mz)^T] \qquad (6)$$
   where E[.] is an expectation value and $(Mz)^T$ is a transpose matrix of Mz. Then the dimensions of Cov(Mz) are 3 by 3.
4. Compute an eigenvalue, d and eigenvector, v, for the covariance matrix Cov.
5. Project M onto new axis by eigen-vector *v*,
$$P = v^T M \qquad (7)$$

where v^T is a transpose matrix of v.

Similarity measure: The main objective of the classification problem is to find a natural grouping in a set of data (Duda *et al.*, 2001). In other words, we want to say that the samples in class c_i are more like one another than like samples in other class c_j, where i ≠ j.

Correlation Coefficient Analysis, ρ. The correlation coefficient ρ between two random variable x and y can be described as:

$$\rho(x,y) = \frac{\text{cov}(x,y)}{\sqrt{\text{var}(x)\,\text{var}(y)}} \qquad (8)$$

where cov(x, y) is the covariance between two random variables and var(.) is the variance of a random variable. Correlation coefficient values are within [-1,…, 1]. If x and y are completely correlated, ρ(x, y) is 1 or-1. If they are absolutely uncorrelated, ρ(x, y) is 0.

RESULTS

Some simulations have been made on surimi Gel Strength patterns, which contain 17 data points for each pattern. Testing sets (12 data) include the original training set and their added Gaussian noise with 1, 3 and 5 points, respectively. Then, in total, the testing sets have 48 patterns. Graphical representation of all testing sets are illustrated in Fig. 3a-d, respectively. It can be seen that it is very difficult to identify a class for input pattern by hand. How can we do that?

Backpropagation neural network: In the learning step, we set $\epsilon \leq 0.00001$. The learning is terminated after 35 epochs. Table 1(a-d) display the probability of each surimi gel strength pattern to be each expected class. Probability values from Table 1a-d confirm that all testing set patterns can be classified into a proper class even they have some noises. For example from Table 1d, degree of similarity between testing pattern 1 to expected class 1,
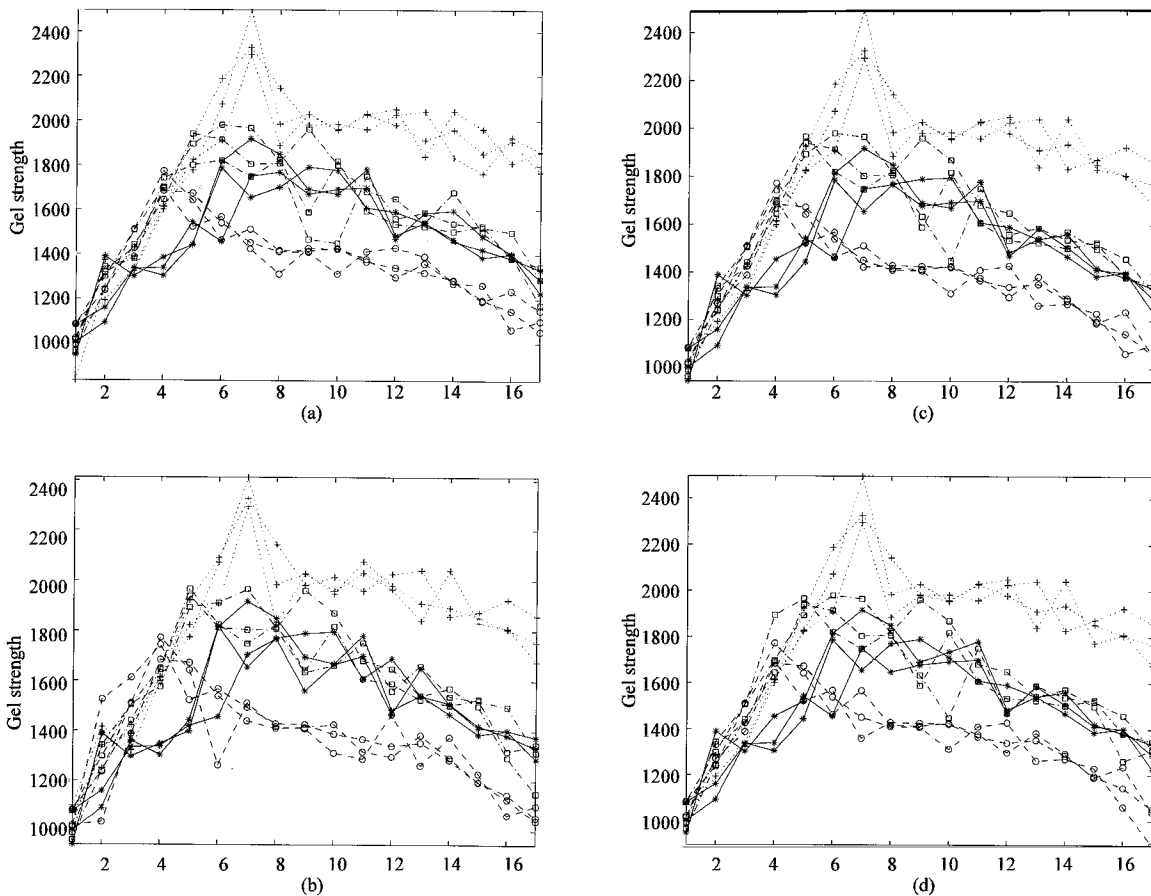

Fig. 3: (a) Original surimi gel patterns created by 35, 40, 45 and 50°C, (b) Original surimi gel added one point of Gaussign noise, (c) Original surimi gel added three points of Gaussign noise and (d) Original surimi gel added five points of Gaussign noise

Table 1: Probability of the surimi gel strength pattern using backpropagation neural network (a) original surimi gel patterns, (b) added 1 point of random gaussian noise, (c) added 3 points of random gaussian noise and (d) added 5 points of random gaussian noise

Testing pattern	Expected classes				Expected classes				Its actual class
	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 4	
1	0.9998	0.0000	0.0000	0.0000	0.9999	0.0000	0.0000	0.0000	1
2	0.9999	0.0013	0.0000	0.0000	0.9998	0.0015	0.0000	0.0000	1
3	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1
4	0.0000	0.9924	0.0008	0.0000	0.0000	0.9994	0.0008	0.0000	2
5	0.0001	0.9996	0.0000	0.0000	0.0001	0.9996	0.0000	0.0000	2
6	0.0000	0.9984	0.0001	0.0000	0.0000	0.9814	0.0029	0.0000	2
7	0.0000	0.0000	0.9995	0.0000	0.0000	0.0000	0.9998	0.0000	3
8	0.0000	0.0000	0.9999	0.0000	0.0000	0.0000	0.9999	0.0000	3
9	0.0000	0.0008	0.9990	0.0000	0.0000	0.0008	0.9990	0.0000	3
10	0.0000	0.0000	0.0002	0.9999	0.0000	0.0000	0.2592	0.9930	4
11	0.0000	0.0000	0.0005	1.0000	0.0000	0.0000	0.0011	1.0000	4
12	0.0002	0.0000	0.0000	10000	0.0000	0.0000	0.0248	1.0000	4
	(a)				(b)				
1	0.9989	0.0000	0.0000	0.0000	0.9957	0.0000	0.0000	0.0000	1
2	0.9643	0.0000	0.0000	0.0000	1.0000	0.0001	0.0000	0.0000	1
3	1.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1
4	0.0000	0.9992	0.0056	0.0000	0.0000	0.9960	0.0000	0.0000	2
5	0.0000	0.9997	0.0000	0.0000	0.0000	0.9996	0.0000	0.0000	2
6	0.0000	0.9984	0.0002	0.0000	0.0000	0.9988	0.0001	0.0000	2
7	0.0002	0.0074	0.9984	0.0000	0.0000	0.0000	0.9992	0.0000	3
8	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.9995	0.0000	3
9	0.0000	0.0005	0.9991	0.0000	0.0000	0.0005	0.9972	0.0000	3
10	0.0004	0.0000	0.0000	0.9995	0.0000	0.0000	0.0351	1.0000	4
11	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	1.0000	4
12	0.0002	0.0001	0.0001	0.9999	0.0000	0.0000	0.0027	1.0000	4
	(c)				(d)				

Table 2: Correlation coefficient (ρ) between (a) original surimi gel patterns, (b) added 1 point of random gaussian noise, (c) added 3 points of random gaussian noise and (d) added 5 points of random gaussian noise and the principal surimi gel eigen-patterns

Testing pattern	Expected classes				Expected classes				Its actual class
	Class 1	Class 2	Class 3	Class 4	Class 1	Class 2	Class 3	Class 4	
1	0.9575	0.8661	0.7968	0.4129	0.9572	0.8421	0.8006	0.4142	1
2	0.9585	0.8258	0.8662	0.5848	0.9581	0.8261	0.8761	0.5949	1
3	0.9534	0.8567	0.7852	0.4321	0.9449	0.8334	0.7677	0.4182	1
4	0.8717	0.9805	0.7685	0.3218	0.8722	0.9806	0.7691	0.3227	2
5	0.8807	0.9896	0.7594	0.3489	0.8806	0.9898	0.7635	0.3531	2
6	0.8678	0.9864	0.7307	0.3105	0.8706	0.9857	0.7365	0.3229	2
7	0.7763	0.6666	0.9659	0.8288	0.7266	0.5869	0.9246	0.8297	3
8	0.8874	7663	0.9653	0.7679	0.8893	0.7673	0.9657	0.7679	3
9	0.7992	0.7661	0.9549	0.7524	0.7993	0.7670	0.9549	0.7524	3
10	0.5423	0.3323	0.8013	0.9819	0.5730	0.3794	0.8212	0.9741	4
11	0.4523	0.2820	0.7529	0.9717	0.4556	0.2649	0.7368	0.9578	4
12	0.4919	0.3613	0.8201	0.9713	0.4354	0.2792	0.7715	0.9652	4
	(a)				(b)				
1	0.9565	0.8656	0.8003	0.4076	0.9425	0.8575	0.7916	0.4205	1
2	0.9659	0.8174	0.8384	0.5187	0.9501	0.8440	0.7805	0.4328	1
3	0.9462	0.8789	0.7765	0.4154	0.9338	0.8443	0.7172	0.3690	1
4	0.8617	0.9751	0.7702	0.3253	0.8698	0.9777	0.7382	0.2794	2
5	0.8993	0.9875	0.7875	0.3741	0.9005	0.9853	0.7622	0.3499	2
6	0.8635	0.9848	0.6980	0.2759	0.8597	0.9826	0.7261	0.3158	2
7	0.6937	0.6066	0.9313	0.8130	0.8094	0.6932	0.9713	0.8010	3
8	0.8871	0.7564	0.9542	0.7791	0.8875	0.7346	0.9383	0.7427	3
9	0.8061	0.7788	0.9432	0.7446	0.8568	0.8045	0.9708	0.7488	3
10	0.5288	0.3145	0.7921	0.9635	0.3667	0.1332	0.6376	0.9196	4
11	0.4302	0.2484	0.7185	0.9584	0.3782	0.2118	0.6627	0.9181	4
12	0.4894	0.4065	0.8076	0.9281	0.5128	0.4503	0.8260	0.9138	4
	(c)				(d)				

class 2, class 3 and class 4 are 0.9957, 0.0000, 0.0000 and 0.0000, respectively. Then, it is classified to class 1 which is correct.

Principal component analysis: Table 2a-d display the degree of similarity between testing data sets and the principal direction of surimi gel strength using correlation coefficient analysis. Degree of similarity among them from Table 2a-d confirm that all testing set patterns can be classified into a proper class even they have some noises. For example from Table 2c, degree of similarity between testing pattern 3 to expected class 1, class 2, class 3 and class 4 are 0.9462, 0.8789, 0.7765 and 0.4154, respectively. Then it is classified to class 1 which is correct.

CONCLUSIONS

This study reports some applications of Back propagation neural network and PCA (Principal Component Analysis). Back propagation neural network is the supervised learning method. But PCA is an unsupervised classification method based on data information. Throughout the study, the identification of surimi gel patterns using Backpropagation neural network and eigen-pattern together with the correlation coefficient has been outlined. Good identification is obtained from the Backpropagation neural network but we need to know a class of each pattern in advance. On the other hand, the advantages of the PCA method developed in this study are as follows. (1) Each class or principal direction of surimi gel strengths is obtained by an unsupervised method, the PCA. Thus, for further identification of the surimi gel strength class, we can easily do this by passing surimi gel strength into the PCA. Then a new class of surimi gel strengths is created. In other words, the principal direction of surimi gel strengths is dynamic based on data characteristics. (2) It can be concluded that the correlation coefficient method gives an efficient result in the case where the testing patterns have very similar shape.

REFERENCES

Chinnasarn, K., S. Chinnasarn and D.L. Pyle, 2005. Surimi Gel Pattern Identification Using Eigen-pattern and Similarity Analysis. Proceeding of the 9th National Computer Science and Engineering Conference:, NCSEC2005, Bangkok, Thailand, pp: 153-160.

Duda, R.O., P.E. Hart and D.G. Stork, 2001. Pattern Classification, 2nd Edn., John Wiley and Sons, Inc.

Hall, G.M. and N.H. Ahmad, 1997. Surimi and Fish-mince Products. In Hall, G.M. (Ed.), Fish Processing Technology, London: Blackie Acadimic and Professional.

Haykin, S., 1999. Neural Network a Comprehensive Foundation, 2nd Edn., Prentice Hall.

Hermansson, A.M., 1978. Physico-chemical aspects of soy proteins structure formation. J. Texture Studies, 9: 33-58.

Hossain, M.I. *et al.* 2001. Contribution of the polymerization of protein by disulfide bonding to increased gel strength of walleye pollack surimi gel with preheating time. Fisheries Sci., 67: 710-717.

Lanier, T.C. and C.M. Lee, 1992. Surimi Technology. New York: Marcel Dekker.