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Development of Ultrasonic Test Equipment for Investigating the Morphology of Barrier Materials

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Abstract

Recently, LG chemical corporation developed new material called HYPERIER, which has an excellent barrier characteristic. It has many layers which are made of nano-composite within LDPE(Low-Density Poly Ethylene). In order to guarantee the quality of the final product from the production line, a certain test equipment is required to investigate the existence of layers inside the HYPERIER. In this work, ultrasonic sensor based test equipment for investigating the existence of inner layers is proposed. However, it is a tedious job for human operators to check the existence by just looking at the resounding waveform from ultrasonic sensor. Therefore, to enhance the performance of the ultrasonic test equipment, wavelet and PCA(Principle Componet Analysis) schemes are introduced into neural network scheme which is used for classification. To verify the feasibility of the proposed scheme, some experiments are executed.

Key Words : Barrier characteristic, Wavelet, PCA, Ultrasonic sensor

1. Introduction

The use of plastics in the packaging industry has received enormous attention because plastics are lightweight, cheap, disposable and have design flexibility. However, polymer materials are not inherently impermeable to gases such as oxygen, carbon dioxide, water vapour and organic materials. Therefore, in order to render them as good packaging materials, they must typically be engineered at a molecular level to inhibit the permeation of these gases through the walls of the container[1]. Recently, LG chemical company developed the high performance barrier material called HYPERIER which has nano-composite multi-layers. It is imperative to check the existence of these layers in order to guarantee its full performance. So far, optical cross- sectioning method which takes a lot of time and money has been adopted to investigate the internal morphology of the HYPERIER. Therefore, a new test methodology should be developed for efficiency.

With the arrival of ultrasonic methods, many applicators such as investigation of internal morphology of the materials has switched to UT(Ultrasonic Testing)[2]. UT uses high frequency sound energy to conduct examinations and make measurements. The sound energy is introduced and propagates through the materials in the form of waves. When there is a discontinuity in the wave path, part of the energy will be reflected back from the discontinuous surface. The reflected wave signal is transformed into electrical signal by the transducer. From the signal, information about the reflector location, size, orientation and other features can be effectively gained[3].

Recently, wavelet transform has emerged as a powerful tool for signal processing and data compression. It has good localization in both frequency and time domains. Especially, in the field of data compression, the performance of the wavelet transform comes from its ability in concentrating a large portion of total signal energy in a few coefficients. These coefficients can also be used to reconstruct the original signal without losing significant information[4-5].

PCA(Principle Component Analysis) has been proposed for optimal information preserving transformation. It is a general purpose feature extraction algorithm producing features that retain the maximum possible amount of information from the original data set, for a given degree of data compression. Therefore, reduction of dimensionality by PCA has been shown to facilitate many types of multivariate analysis, including data validation and fault detection[6-7].

Recently, artificial neural networks are effectively applied to quality control fields. Role of the neural network is to distinguish normal and abnormal state based on the training and continuous measurement from the product. Among various neural networks, ANFIS(Adaptive Neuro-Fuzzy Inference System) proposed by J.R. Jang can also be utilized in this field[8-9]. ANFIS is functionally equivalent to fuzzy inference systems which can be trained with data sets. Generally, in oder to get a better result of quality control based on ANFIS, some feature extraction from the training data set should be done.

In this work, a new UT system for HYPERIER is proposed. The purpose of the proposed system is to efficiently check the existence of multi-layers inside of the test material. The proposed system consists of two part. One is hardware which includes pulser/receiver, transducer, A/D converter and

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PC. The other is classification algorithm which utilizes wavelet, PCA and ANFIS. The role of the classification algorithm is to determine the quality of the test material. In section 2, a brief description on the principle of ultrasonic test is given. In section 3, the proposed UT system is explained. In section 4, the feasibility of the proposed scheme is verified by executing experiments and finally, test results are discussed.

2. Principle of ultrasonic test

An ultrasonic vibration is sent into the coating by the probe(transducer) with the assistance of couplant applied to the surface. This vibration travels through the coating until a material with different mechanical properties(different coating layer) is encountered. The vibration is partially reflected at this surface (interface) and propagates back to the transducer. Meanwhile, a portion of the transmitted vibration continues to travel beyond that surface and also experiences further reflections at any material interfaces that are encountered as in Fig. 1.

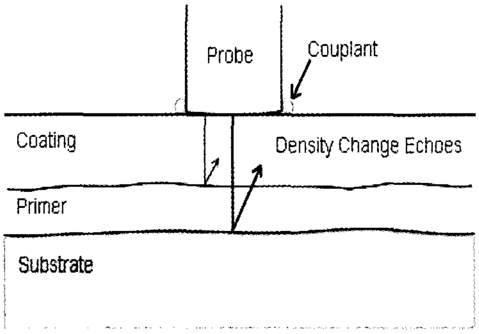


Fig. 1. Ultrasonic vibrations reflecting off coating interface

Since a potentially large number of echoes could occur, careful measurement is required to make a correct guess about the internal structure of the test material. For example, if a number of layers in a multi-layer application should be known, it can be easily carried out simply by counting the number of loudest echoes as in Fig. 2.

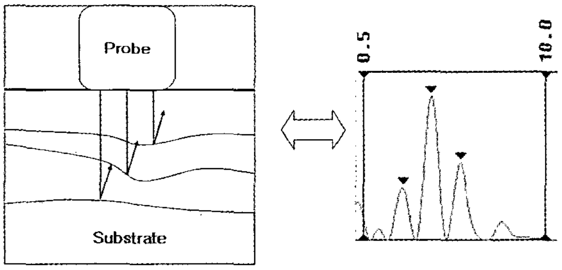


Fig. 2. Measurement of the individual layers in a multi-layered material

3. Proposed UT system for HYPERIER

3.1 Hardware and ultrasonic waveform

The proposed UT system for HYPERIER consists of several functional units as in fig. 3.

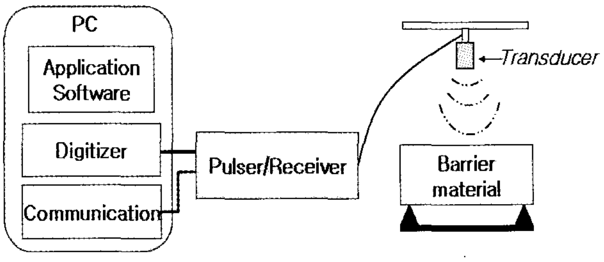
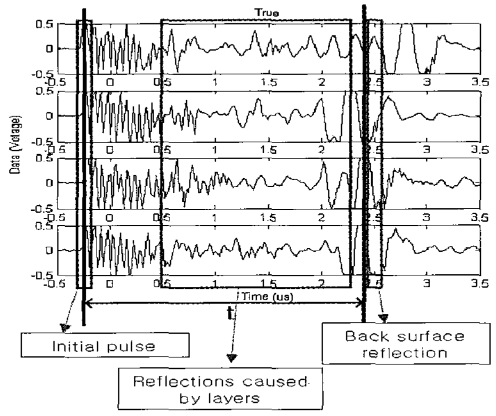


Fig. 3. Proposed UT system for HYPERIER

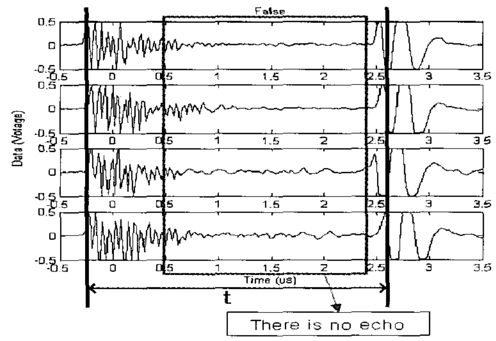
In fig. 3, pulser/receiver generates the high voltage pulse that is required by the ultrasonic transducer. Ultrasonic transducer is pulsed, sending out an ultrasonic wave. The subsequent echoes generate a voltage in the transducer, which is sent back to the pulser/receiver. The typical waveforms from the digitizer are shown in fig. 4. Fig. 4(a) shows resounding ultrasonic waveform for the qualified HYPERIER and Fig. 4(b) shows the waveform for a bad material. Initial pulse represents the ultrasonic wave coming from the pulser. Right after the trigger of initial pulse, the ultrasonic sensor acts as a receiver. the ultrasonic sensor continuously measures the resounding signal reflected from the layer inside of the material. From these resounding waveforms, the thickness of the test material can be easily calculated as follows.

$$D=(C \cdot t)/2 \qquad (1)$$

where, D and C represents the thickness of the material and the speed of ultrasonic which varies depending on the characteristics of the material. t represents the travelling time of ultrasonic.



(a)



(b)

Fig. 4 (a) the resounding ultrasonic waveform for the qualified barrier material (b) the resounding ultrasonic waveform for the bad material

If you see the waveform in fig. 4, there is a big difference between the qualified HYPERIER and bad one in their shape. However, it is a very tedious job for an operator to check visually whether the tested material has required layers or not. Therefore, it is required to extract certain features from the resounding waveform. Each of the waveforms should have a few features characteristic to that situation. Badly selected features probably lead to poor classification results even by using a best possible classifier.

3.2 Classification algorithm

In fig. 3, application software which plays a key role not only makes the user set up the test but also process/analyze the data from the digitizer. As mentioned earlier, it is a tedious job for an operator to check visually. For this, an intelligent classification algorithm which utilizes wavelet, PCA and ANFIS is proposed in this work. The structure of the proposed classification algorithm is shown in fig. 5.

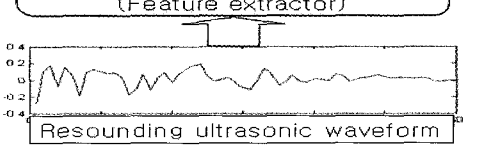


Fig. 5. Proposed classification algorithm

3.2.1 Wavelet for feature extraction

Wavelet transforms have recently emerged as powerful tools for a broad range of applications, such as data compression. It has good localization in both frequency and time domains, having fine frequency resolution and coarse time resolution and fine time resolution at lower frequency. The performance of a wavelet transform for data compression lies in its ability in concentrating a large percentage of total signal energy in a few coefficients. After the original signal is transformed into the wavelet coefficients, many coefficients are so small that these coefficients can be omitted without losing significant information. The multi-resolution signal analysis used in this work is briefly introduced.

Multi-resolution signal analysis decomposes a function into a smooth approximation of the original function and a set of detailed information at different resolutions. Formally, let $L^2(R)$ denote all functions with finite energy; the smooth approximation of a function $f \in L^2(R)$ at any resolution 2^i is a projection denoted as $A_{2^i}: L^2(R) \rightarrow V_{2^i}$, $V_{2^i} \in L^2(R)$, and the detail of f at any higher resolution 2^j is a projection of f onto a subspace O_{2^j} of $L^2(R)$ denoted as $P_{2^j}: L^2(R) \rightarrow O_{2^j}$, $j \geq i$. Consequently, the finest detailed information is contained in P_{2^j} with the highest resolution. For the discrete functions, it can be proven that there exist two families of functions:

$$\psi_{j,n} = 2^{-j/2}\psi(2^j t - n)_{n \in Z} \qquad (2)$$

$$\Phi_{j,n} = 2^{-j/2}\Phi(2^j t - n)_{n \in Z} \qquad (3)$$

which constitute the orthonormal basis of V_{2^j} and O_{2^j}, respectively. $\psi_{j,n}$ are called wavelets and $\Phi_{j,n}$ are the corresponding scaling functions.

Using wavelets and scaling functions, the discrete detail signal and discrete approximation at resolution 2^j are respectively defined as:

$$(D_{2^j} f)_n = 2^{-j/2}\langle f(u), \psi_{j,n}\rangle \qquad (4)$$

$$(A^d_{2^j} f)_n = 2^{-j/2}\langle f(u), \Phi_{j,n}\rangle \qquad (5)$$

Instead of calculating the inner products in eq.(4),(5), a pyramidal algorithm is applied for the decomposition of the function, and the detailed process is shown in fig. 6.

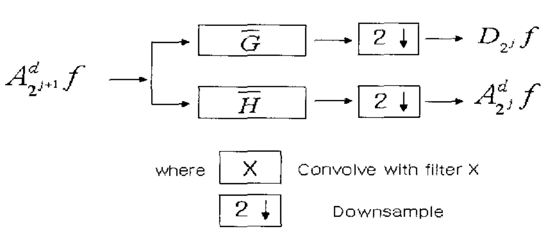


Fig. 6. Wavelet decomposition process

In this work, the wavelet's approximate coefficients derived from eq.(5) are used as a feature vector for each resounding ultrasonic waveform. Although there are many good alternatives for selecting the feature vectors, it's not sensible to use too many of them. If the dimension of these feature vector is big, it is difficult to directly use them as training data set for neural classifier. Generally, up to ten features is a resonable choice. Therefore, it is required to utilize a certain method for dimension reduction of feature vectors.

3.2.2 PCA for dimension reduction

PCA is a technique for mapping multidimensional data into lower dimension with minimal loss of information. Let **Y** represents a $n \times m$ data matrix (n=number of observations, m=number of variables). PCA is an optimal factorization of **Y** into two matrices, **T** called the scores matrix($n \times f$), and **P**, called the loading matrix($m \times f$), plus a matrix of residuals **E** ($n \times m$) as in eq.(6).

$$Y = T \cdot P^T + E \tag{6}$$

where f is the number of factors($f < m$). The condition of optimality on the factorization is that the Euclidean norm of the residual matrix, $\|E\|$, must be minimized for the given number of factors. To satisfy this criterion, it is known that the columns of **P** are the eigenvectors corresponding to the f largest eigenvalues of the covariance matrix of **Y** which can be expressed as in eq.(7).

$$cov(Y) = \frac{Y^T Y}{m-1} \tag{7}$$

It is useful to view PCA as a linear mapping of data from R^m to R^f. Taking $P^T P = I$ without loss of generality, the mapping has the following form:

$$\underline{T} = \underline{Y} \cdot P \tag{8}$$

where $\underline{Y}$ represents a row of **Y**, a single data vector, and $\underline{T}$ represents the corresponding row of **T**, or the coordinates of $\underline{Y}$ in the feature space. The loadings **P** are the coefficients for the linear transformation.

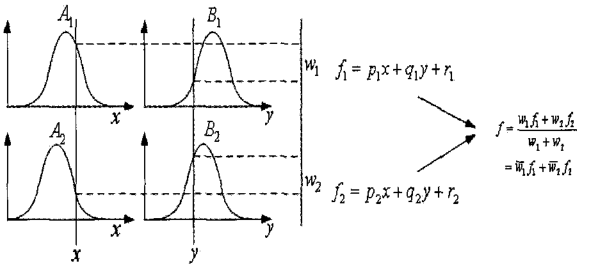
As mentioned in the previous section, wavelet coefficients can be extracted from the resounding ultrasonic waveform. These wavelet coefficients can be thought of as a feature vector for the corresponding waveform. If the dimension of the feature vector is so big, it is not easy to train neural classifier. Generally, it causes longer training time and lower recognition rate. Therefore, a certain dimension reduction of feature vector is required. By using eq.(8), a new feature vector with lower dimension can be easily obtained. These newly obtained feature vectors are used for training data for neural classifier.

3.3.3 ANFIS for classification

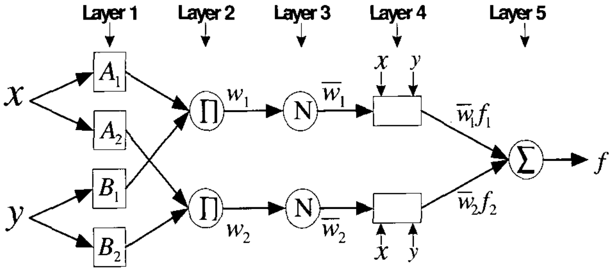
The architecture of ANFIS proposed by R. Jang is shown in fig. 7. Structurally, network configuration should be of feedforward type. Due to its minimal restrictions, its applications are immediate and immense in various areas.

ANFIS shown in fig. 7 can be considered the same as the following two fuzzy if-then rules of Takagi and Sugeno' type.

Rule 1: *If* x *is* A_1 *and* y *is* B_1, *then* $f_1 = p_1 x + q_1 y + r_1$
Rule 2: *If* x *is* A_2 *and* y *is* B_2, *then* $f_2 = p_2 x + q_2 y + r_2$



(a) Type-3 fuzzy reasoning



(b) Equivalent ANFIS

Fig. 7 Structure of ANFIS

There are five layers in ANFIS which function differently. Furthermore, each layer has its own parameters to be adjusted. The computation of these parameters (or their adjustment) is facilitated by a gradient vector, which provides a measure of how well the fuzzy inference system is modeling the input/output data for a given set of parameters. Once the gradient vector is obtained, any of several optimization routines could be applied in order to adjust the parameters so as to reduce some error measure. ANFIS uses either back propagation or a combination of least squares estimation and backpropagation for membership function parameter estimation. The ANFIS can be utilized as a neural classifier if it is trained with the input/output training data which are composed of feature vector obtained from PCA and its corresponding decision value.

4. Application of the proposed scheme to HYPERIER

Figure 8 shows the ultrasonic test equipment for this work. It consists of ultrasonic probe which acts in 15MHz, USB interfaced A/D converter, pulser/receiver and application program installed on notebook computer. The resounding ultrasonic signal obtained from A/D converter for the qualified barrier materials and bad materials were shown in fig. 4. As you can see in fig.4, there are many echoes right after the initial pulse. These echoes are caused by interaction between initial pulse and echoes from the surface of the test material. Therefore, this part of the waveform can be discarded for further process. Modified waveforms are shown in fig. 9.

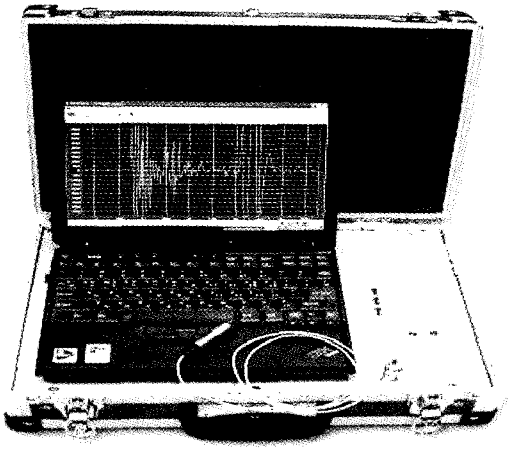
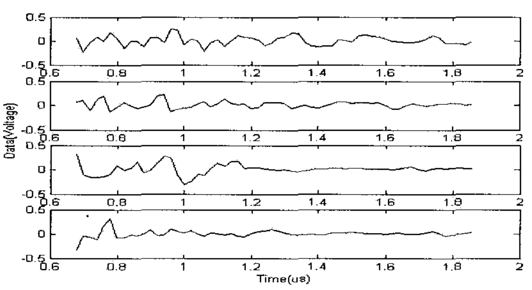
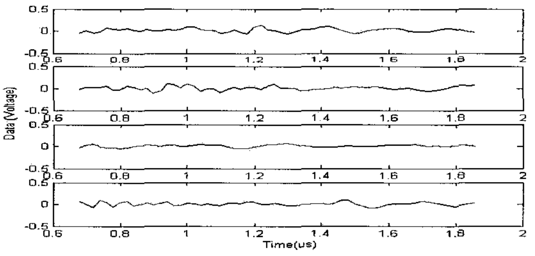


Fig. 8. Ultrasonic test equipment



(a) waveform for qualified material



(b) Waveform for bad material

Fig. 9. Fitted waveforms for wavelet transform

To verify the feasibility of the proposed scheme, more than 80 different ultrasonic waveforms were obtained using UT system shown in fig. 8. The detailed procedure is as follows. First, respective fitted waveforms for wavelet transform should be obtained. Second, wavelet transform with decomposition level 2 is applied to these fitted waveforms. From the wavelet transform, 18 approximate coefficients are obtained. Third, to reduce the dimension of approximate coefficients, principle components are calculated using eq.(2),(3),(4). In this experiment, the number of largest eigenvalues of the covariance matrix is nine. Finally, reduced feature vectors obtained from PCA are used as training data for ANFIS nerual classifier.

The SSE(Sum Square Error) for ANFIS train is depicted in fig. 10. After training ANFIS, it was tested using training data. The output characteristic of ANFIS is shown in fig. 11.

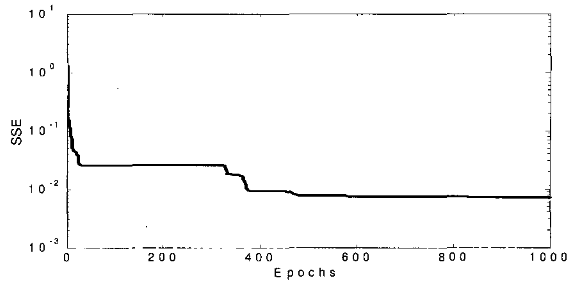


Fig. 10. SSE for training ANFIS

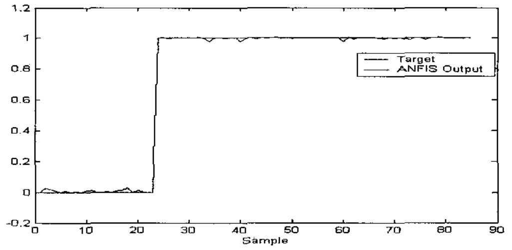


Fig.11. Output characteristic of trained ANFIS

To verify the performance of trained ANFIS, it was tested using 80 "never seen" waveforms. Fig. 12 shows the output characteristic of ANFIS for "never seen" waveforms.

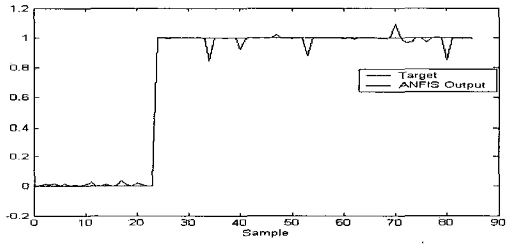


Fig.12. Output characteristic of ANFIS for "never seen" waveforms

In fig. 11, 12, the output value 1 represents qualified HYPERIER material and 0 represents the bad material. The experiments show that the proposed classification algorithm gave the desirable performance.

The various tests are performed changing the number of principle components. The ANFIS classification rate is given in Table I.

Table I. Classification rate depending on the number of principle components

number of principle components	Classification rate[%]
6	67.1
7	88.2
8	100

From the table 1, A choice of 8 principle components gave the best performance.

5. Conclusion

In this work, a new UT system for checking the existence of nano-composite multi-layers within the barrier material is proposed. The proposed UT system is utilizing the wavelet, PCA and ANFIS schemes. As it is known from the experimental results, the desirable classification results are obtained. Therefore, the proposed system can be effectively used for checking the existence of multi-layers in HYPERIER.

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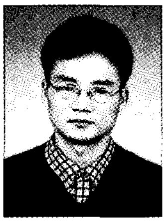

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