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Prediction of relationships between hydrostatic coefficients and processing parameters of porous PZT ceramics by radial basis function

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ABSTRACT

The high hydrostatic coefficients of porous piezoelectric materials provide the reduced acoustic impedance for the effective coupling with water medium as well as biological tissues. The hydrostatic strain coefficient (d_h), voltage coefficients (g_h) and longitudinal piezoelectric coefficient (d_{33}) of porous piezoelectric materials has a strong dependence on processing parameters such as porosity parameter, polymer percentage, density and poling voltage. In this work, a nonparametric regression has been carried out to figure out the nonlinear relationships between the hydrostatic coefficients and its processing parameters. The nonparametric regression has been carried out by artificial neural network. The Network architecture utilized is radial basis function (RBF) which is combined with Fuzzy Clustering Method (FCM) to identify the hidden node numbers and widths. The porosity parameter was calculated from scanning electron micrographs of the porous piezoelectric materials using conventional image processing techniques. The results of the artificial neural network were evaluated against experimental data.

1. Introduction

Over the last few decades the interests in piezoceramic materials are becoming active center of materials science research due to its wide applications in sensors, actuators and transducers. The various processing [1,2] and doping techniques [3] are used to produce different grades of piezoelectric materials to satisfy the desired requirements. Recently the porous piezoelectric materials [4] are one of the successful outcomes of the processing techniques, which provide high hydrostatic coefficients than conventional piezoelectric materials. These materials are widely used for acoustic transducers, medical imaging, sonar and non-destructive evaluation. The hydrostatic strain coefficient, d_h ($\sim d_{33} + 2d_{31}$), which defines the actuating capability of the piezoceramic material, is related to the piezoelectric charge coefficients, both in the polarization (d_{33}) and transverse (d_{31}) directions. The significance of the piezoceramic research is to obtain porous piezoelectric materials with high hydrostatic coefficients. So its correlation with processing parameters such as porosity parameter, poling voltage, density and the percentage of polymer needs to be revealed.

Artificial neural networks (ANNs) are networks of simple processing elements (called 'neurons') operating on their local data and communicating with other elements. The design of ANNs was motivated by the structure of a real brain, but the processing elements and the architectures used in ANN have gone beyond their biological inspiration. In principle, neural network has the power of a universal approximator, i.e. it can realize an arbitrary mapping of one vector space onto another vector space [5,6]. The advantage of neural networks is to use the unknown hidden information for evaluating the relationship between the data. It has found wide acceptance in the ceramic science, especially for the estimation of pore volume fraction of Al_2O_3/SiC ceramic cake [7] and to analyze the electrical properties of PZT [8,9] and $BaTiO_3$ [10].

In our study, artificial neural network is utilized to reveal the hidden relationship between the hydrostatic coefficients of porous piezoelectric materials and its processing parameters.

2. Artificial neural network

2.1. Overview

The methodology of artificial neural network has found wide implementation in the fields like materials science, mathematics

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and image processing. There are many types of neural networks with similar basic principles. The neuron in the network is used to receive input signals, to process them and to send output signal. Each neuron is connected at least with one neuron, and the connection is evaluated by a real number, called the weight coefficient, that reflects the degree of importance of the given connection in the neural network. Process of 'capturing' the unknown information is called 'learning of neural network' or 'training of neural network'. In mathematical formalism, learn means to adjust the weight coefficients in such a way that some conditions are fulfilled. The neural network that knows the desired output for the given input and adjusting its weight coefficients in order that calculated and desired outputs are as close as possible are called as supervised neural networks (e.g. Radial Basis Function Network).

2.2. Radial Basis Function Network

An RBF neural network [11] can be considered as a special three-layered network. The structure of an RBF neural network is shown in Fig. 1, which is similar to that of a traditional three layer feed forward neural network. The input layer of the network is a set of m units, which accept the elements of an m dimensional input feature vector. The input nodes pass the input values to the internal n hidden units nodes that formulate the hidden layer. The nonlinear responses of the hidden nodes are weighted in order to calculate the final outputs of network in the third (output) layer. A typical hidden node in an RBF network is characterized by its center, which is a vector with dimension equal to the number of inputs to the node. In this structure, the hidden units are named RBF units.

An RBF neural network can be considered as a mapping: $\Re^m \rightarrow \Re^o$. Let $I \in \Re^m$ be the input vector and $C_j \in \Re^m$ $(1 \leqslant j \leqslant n)$ be the node centers, which are prototype of input vectors. Then the activity $R_j(I)$ of the jth node is the Euclidean norm of the difference between the input vector $I(i_1, i_2, \ldots i_m)$ and the node center C_j and is given by:

$$R_j(I) = R_j(\|I - C_j\|), \quad j = 1, 2, \ldots n \tag{1}$$

The output function of the node is a radially symmetric function. A typical choice, which is also used in this work, is the Gaussian function:

$$R_j(I) = \exp\left(-\frac{(\|I - C_j\|)^2}{\sigma_j^2}\right) \tag{2}$$

where σ_j is the width of jth node. The kth output $Y_k(I)$ of an RBF network is

$$Y_k(I) = \sum_{j=0}^{n} R_j(I) \times w(k,j), \quad k = 1, 2, \ldots o \tag{3}$$

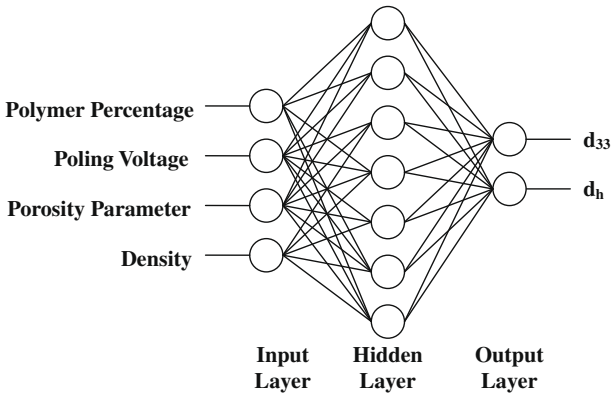

Fig. 1. Schematic of RBF neural network for porous PZT.

where $w(k,j)$ is the weight of jth receptive fields to the kth output.

2.3. Training

In the proposed training method, the calculation of the hidden node centers is based on the fuzzy means clustering algorithm, while the connection weights are obtained using linear regression (least square method). The fuzzy means clustering algorithm initially produces a fuzzy partition in the input space, by defining a number of triangular fuzzy sets on the domain of each input variable. The centers of these fuzzy sets produce a multidimensional grid on the input space. The knots of the grid constitute the set of candidates for becoming hidden node centers. The most appropriate knots are chosen by applying a rigorous selection algorithm and are used as centers in the produced RBF network model. The idea behind the selection algorithm is to place the centers in the multidimensional input space, so that there is a minimum distance between the center locations. At the same time the algorithm assures that for any input example in the training set there is at least one hidden node that is close enough according to a distance criterion. The above algorithm has a number of advantages compared to the standard k-means clustering technique, which is the most popular algorithm for selecting the centers of an RBF network.

3. Experimental procedures and neural computation

The porous PZT ceramics was prepared using $Pb_{0.98}La_{0.02}(Zr_{0.53}Ti_{0.47})_{0.975}Nb_{0.025}O_3$ as a base material, developed at our Center. The average particle size of the powder was 1.15 μm. The calcined PZT powder was mixed with 10, 30 and 50 vol% of PMMA polymer for 30 min using agate pestal mortar. The powder was added with binder and uniaxially pressed to get 22 mm circular disks. The disks were fired at 600 °C for 10 h. The specimens were then sintered at 1260 °C for 1 h. the densities of the sintered specimens were measured form first principle. The sintered specimens were poled by corona poling technique [12]. The micrographs of the sin-

Table 1
Experimental parameters given as input layer.

Sample no.	1	2	3	4	5
% of polymer	40	40	30	40	50
Density (g/cc)	4.8	4.72	5.04	4.70	3.8
Poling voltage (kV)	15	15	13	14	15
	6	7	8	9	10
% of polymer	50	20	20	30	30
Density (g/cc)	3.7	6.5	6.3	5.1	5.07
Poling voltage (kV)	15	15	14	13	15
	11	12	13	14	15
% of polymer	30	10	10	50	10
Density (g/cc)	5.2	6.8	6.7	3.6	6.73
Poling voltage (kV)	15	12	12	13	14

Table 2
Experimentally measured results of all the formulations.

Sample no.	1	2	3	4	5
d_h (pC/N)	29.1	31.5	27.6	21.7	45.4
d_{33} (pC/N)	110	122	109	96	102
	6	7	8	9	10
d_h (pC/N)	43.2	18.1	10.7	18.8	26.4
d_{33} (pC/N)	90	130	134	112	106
	11	12	13	14	15
d_h (pC/N)	23.9	9.7	11.1	40.3	13.2
d_{33} (pC/N)	115	138	140	85	160