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Real-Time Identification of Media in a Laboratory-Scaled Penetrating Process

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***Abstract*—**In this paper, a neural network technique is applied to real-time classifying media while a projectile is penetrating through them. A laboratory-scaled penetrating setup was built for the experiment. Features used as the network inputs were extracted from the acceleration of penetrator. 6000 set of features from a single penetration with known media and status were used to train the neural network. The trained system was tested on 30 different penetration experiments. The system produced an accuracy of 100% on the training data set. And, their precision could be 99% for the test data from 30 tests.

***Keywords*—**back-propagation, identification, neural network, penetration.

I. Introduction

MODERN defensive military fortification is mostly below ground or reinforced and often multi-layered. In order to enable weapons to detonate at a desired point inside buried or reinforced structures, knowing the depth of the weapon into the structure or counting layers that the weapon has passed is critical.

The process of knowing the depth or counting layers while the weapon is penetrating media relates to an effective algorithm of classifying penetrating signals. Min et al. [1] proposed a real-time decision making process by selecting proper thresholds of penetrating signals and their features. In order to set aside a particular class from all other classes, a lot of thresholding rules were created. This also means a lot of experiments are needed, which will increase the cost. It is therefore our objective to study on another algorithm.

Neural networks have long been applied to a variety of classification tasks [2]. One of their advantages is that they can adjust themselves to the data without any explicit specification of functional or distributional form for the underlying model [3]. So, using the neural network technique can be a better alternative in media identification during penetrating.

In this paper, a neural network based classifier system is applied in an attempt to real time identify media during penetrating. The strategy includes extracting features from the acceleration signals of the penetrator as the network inputs, using a set of experimental features to train the network, and using the well-trained network to test 30 set of experimental features. The results of testing are discussed at the end of the paper.

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II. Features extraction

The response of materials to impulsive loading involves a variety of disciplines including theoretical and applied mechanics, material behavior, and dynamics. The experimental setup (,which will be discussed in section 4-1) we built to verify the identifying system is a four-meter-tall mechanism with the penetrator free falling from the top or launched by a spring-driven accelerator. Therefore, the striking velocities of penetrator we were dealing with are less than 50 m/s. According to Zukas [4], it belongs to a problem of primarily elastic effect which may be related to the structural dynamics and the overall deformation of the structure. So we first used Boxcar averaging technique [5], [6] to make the acceleration of penetrator less volatile and more obvious. Before doing that, we also introduced a software filter by calculating the mean of some values from the sampled data to eliminate noise. The number of the values, which was defined as the window size (ws), was chosen by roughly judging its effectiveness on noise elimination. In order to assess the effectiveness of different window sizes, we implemented the Discrete Fourier Transformation [7]. The experiment was conducted with a penetrator free falling from the top of a 4-meter-tall experimental setup to the ground with no medium in between, in which the sampling rate was 100 kHz. Fig. 1 shows a result with worse effectiveness on noise elimination, in which the window size is 50. Fig. 2 shows a better effectiveness on noise elimination, in which the window size is 200. Although we have roughly got a relation between the window size and the effectiveness that the bigger window size can yield a better effectiveness, increasing the window size would lower the performance such as the processing time. Therefore, we picked 200 as the window size throughout this work.

The filtered acceleration can be written as

$$W[i] = \sum_{j=0}^{ws-1} S[ws \times i + j] / ws \tag{1}$$

where $S[k]$ denotes every signal collected, and, *i*, *j* and *k* are integers.

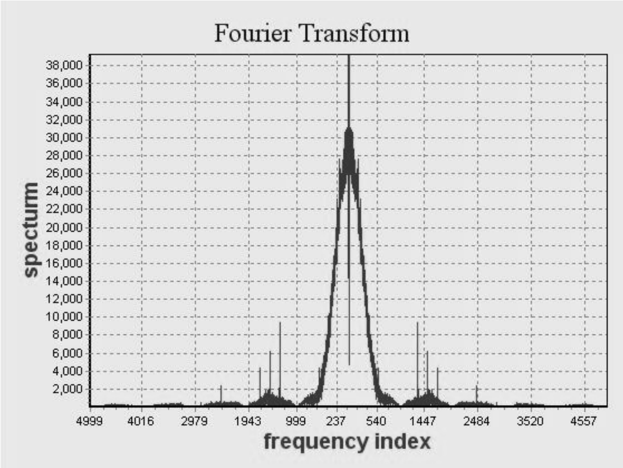

Fig. 1 Discrete Fourier Transform of the filtered acceleration with the window size of 50

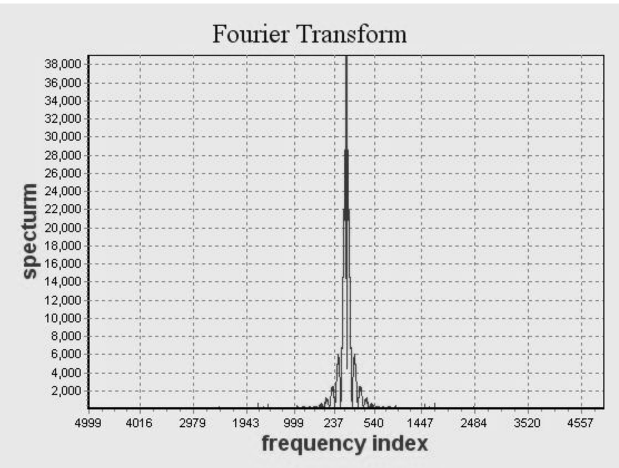

Fig. 2 Discrete Fourier Transform of the filtered acceleration with the window size of 200

The four features used in this work are extracted based on the filtered acceleration and are described as follows. Feature 1 is defined to represent the effect of the acceleration of the projectile, in which the four-point-span moving average technique is used, as

$$F1[i] = \{ \sum_{j=0}^{3} W[i-j] \}/4 \quad , i \geq 3 \tag{2}$$

where $F1[0] = W[0]$, $F1[1] = \{ W[0] + W[1] \}/2$ and $F1[2] = \{ W[0] + W[1] + W[2] \}/3$.

Feature 2 adopts the two-point-span moving average for higher resolution, which is written as

$$F2[i] = \{ \sum_{j=0}^{1} W[i-j] \}/2 \quad , i \geq 1 \tag{3}$$

where $F2[0] = W[0]$.

In order to include the destructive effect of motion, we use the average changes of filtered acceleration as

$$A[i] = W[i] - W[i-1] \tag{4}$$

The trend of the average changes of filtered acceleration by using the four-point-span moving average is defined as Feature 3, as

$$F3[i] = \{ \sum_{j=0}^{3} A[i-j] \}/4 \quad , i \geq 3 \tag{5}$$

where $F3[0] = A[0]$, $F3[1] = \{ A[0] + A[1] \}/2$ and $F3[2] = \{ A[0] + A[1] + A[2] \}/3$. Feature 4 is defined to consider the effect of second order change of filtered acceleration, as

$$F4[i] = \left\{ \sum_{j=0}^{3} A[i-j] - A[i-j-1] \right\}/4 \quad , i \geq 4 \tag{6}$$

where $F4[0] = A[0]$, $F4[1] = \{ A[0] + (A[1] - A[0]) \}/2$, $F4[2] = \{ A[0] + (A[1] - A[0]) + (A[2] - A[1]) \}/3$, and $F4[3] = \{ A[0] + (A[1] - A[0]) + (A[2] - A[1]) + (A[3] - A[2]) \}/4$.

III. The Neural Network Structure

A feed forward back-propagation neural network was used for medium identification. The structure of the neural network, as shown in Fig. 3, is organized into three layers: input, hidden, and output. The input layer contains 4 nodes representing the 4 features mentioned in section II. One hidden layer of sigmoidal neuron with 5 nodes is fully connected to all input units and the nodes in the output layer. In this work, we constructed a two-layered setup for the experiments. In addition, statuses of penetrator during penetrating including resting, accelerating, in the void and grounding (hitting the sand in the bottom) were also considered. Therefore, the output layer has 6 output nodes representing 2 different media and 4 statuses which are denoted by digital codes from 0 to 5.

In order to train the neural network, we performed a penetration experiment to acquire the acceleration of the penetrator. 6000 set of features were extracted from the filtered acceleration data, which were used as the neural inputs. The outputs were then manually assigned to derive the weights and the thresholds of the neural network. Weights and thresholds of connections between the input and hidden units and between the hidden units and output units were modified by the error function.

$$E = \left(\frac{1}{2}\right) \sum_{j=1}^{Ncycle} (T_j - Y_j) \tag{7}$$

where *Ncycle* denotes the learning cycle, T_j is the neural

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network output of the jth neuron and Y_j is the desired output of the jth neuron. This process was repeated until the error function fell below a predefined tolerance level or the maximum number of iterations is achieved. The well-trained thresholds and weights in the network were then used to predict the statuses and media during the test period.

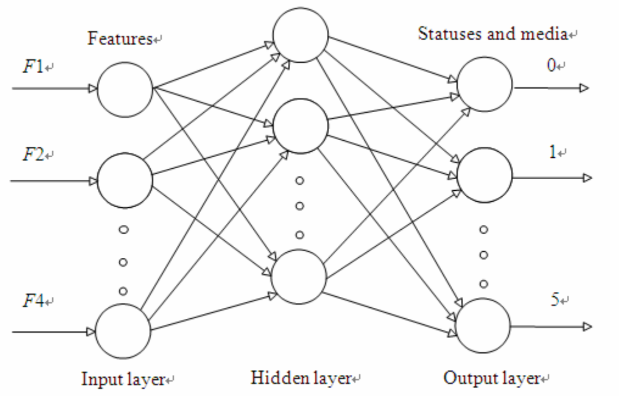


Fig. 3 The Back-propagation neural network architecture for medium identification

IV. Experimental Design and Results

A. Apparatus

Fig. 4 shows a schematic diagram of the laboratory-scaled penetration apparatus. It contains an accelerator on the top in order to create various initial velocities. Two different media are mounted in the midway for testing. The materials of the media used in this work were the extruded expanded polystyrene (XEPS) and the molded expanded polystyrene (MEPS) foam boards. The specification of the penetration apparatus is shown in Table I. The penetrator (also shown in Fig. 5) is equipped with a SEIKA B1 accelerometer to measure the deceleration of the penetrator. The signals measured are then sampled by an analog-to-digital converter (ADLINK PCI-9118DG) at a rate of 100 kHz. Further works of feature extraction and identification are implemented by using C programming language in an IBM compatible personal computer.

TABLE I
THE SPECIFICATION OF PENETRATION APPARATUS

Item	Name	Length (cm)
1	Penetration apparatus	400
2	Penetrator	10
3	Distance from the initial position of the penetrator to XPES	200
4	Distance between XPES and MPES	80

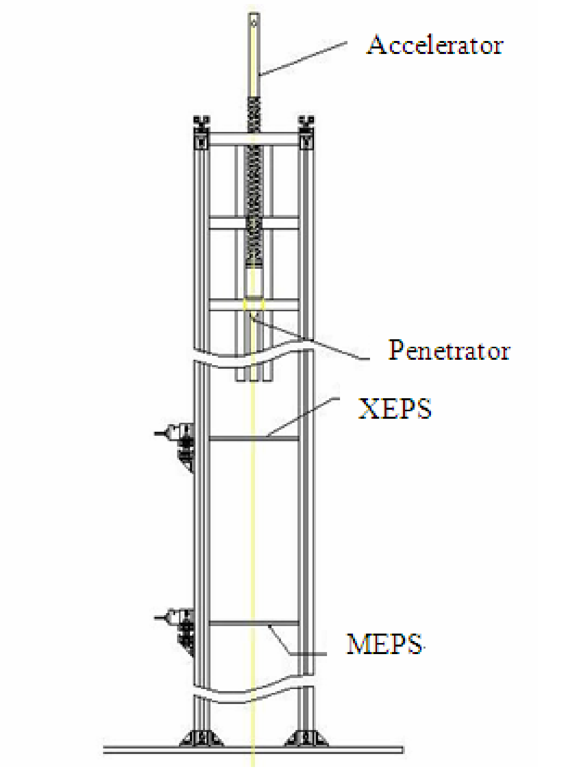
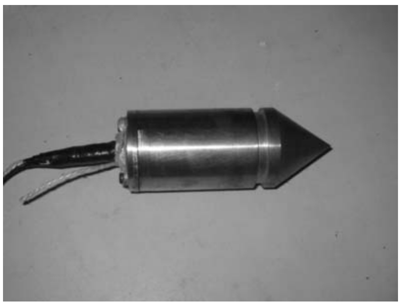


Fig. 4 The Schematic diagram of the laboratory-scaled penetration apparatus



,Fig. 5 The penetrator

B. Experiments

Free-fall experiments were first preformed. Fig. 6 shows one set of acceleration data with the sampling time of 10 micro seconds during the whole process. Fig. 7 shows the identified result, in which six targets including resting, void, XEPS, MEPS, grounding, and accelerating are represented by digital numbers from 0 to 5 respectively. In order to investigate the influence of the initial velocity of penetrator on the identification, we preformed tests with the penetrator being accelerated at the initial position. The corresponding acceleration history is shown in Fig. 8. Fig. 9 shows the identified outputs of the proposed neural network.

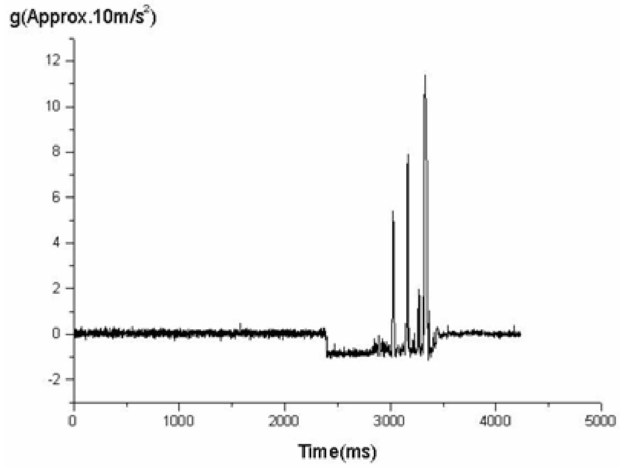


Fig. 6 An acceleration history (free-fall)

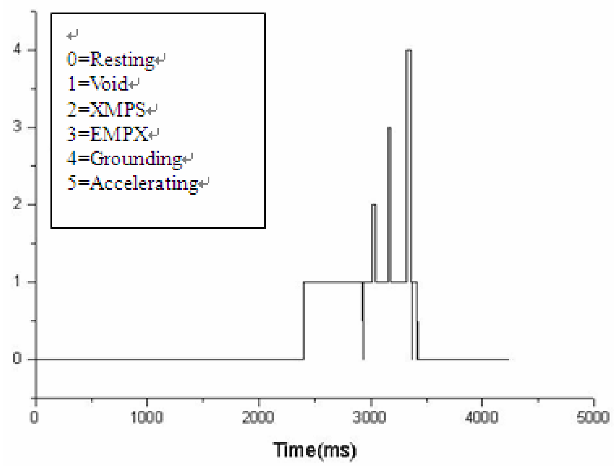


Fig. 7 An identified result (free-fall)

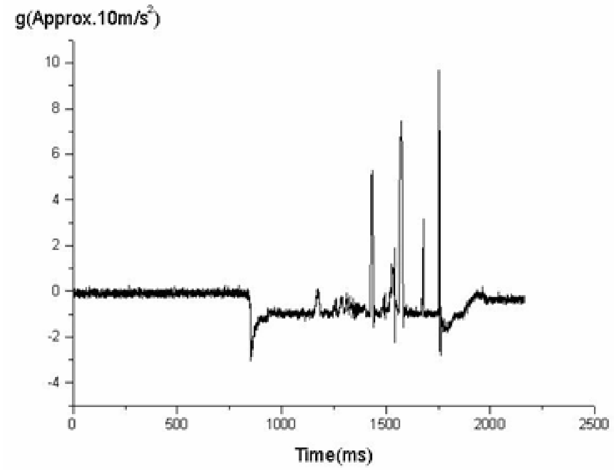


Fig. 8 An acceleration history (accelerated)

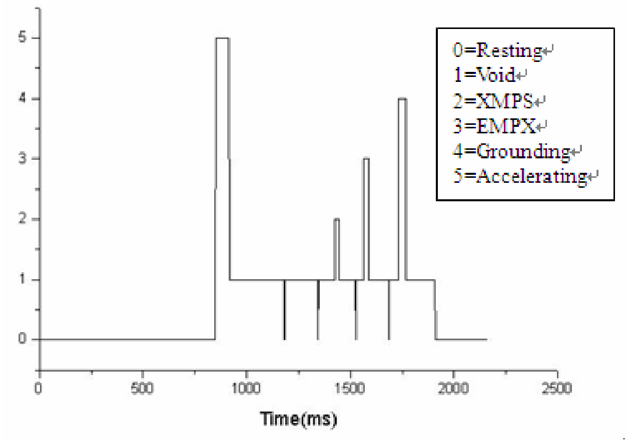


Fig. 9 An identified result (accelerated)

As we can see in both results in Fig. 7 and Fig. 9, there exist some errors. The average identification rate of a single test can be calculated with

$$IR = \frac{\text{Number of windows - Number of errors}}{\text{Number of windows}} \times 100\% \quad (8)$$

A mean value of 99% from 30 penetrating experiments was achieved. However, the overall identification rate for 30 tests was only 16.6%, according to (9).

$$OIR = \frac{\text{Number of tests - Number of failed test}}{\text{Number of tests}} \times 100\%, \quad (9)$$

in which the failed test denotes one single test containing any error. The reasons for the low *OIR* is quite complex, because variables like feature selection and the window size determination definitely contribute to some of them. Table II shows the influence of the window size to the error function.

TABLE II
VALUES OF ERROR FUNCTION VERSUS DIFFERENT WINDOW SIZES

Window size	Value of error function
50	0.0487
100	0.0199
150	0.0171
200	0.0094

V. CONCLUSIONS

In this work, we used the BP neural network for real-time identifying different media and statuses in a laboratory-scaled penetration process. It's declared that 99% of average identification rate of a single test and 16% of overall identification rate from 30 tests was achieved. But, in order to get a better performance, to discard irrelevant features and optimize the window size are suggested to be the further study.

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