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Hybrid Bat-BP: A New Intelligent tool for Diagnosing Noise-Induced Hearing Loss (NIHL) in Malaysian Industrial Workers

Nazri Mohd. Nawi[1, a], M. Z. Rehman[1,b], M. I .Ghazali[2,c], M. N. Yahya[2,d], Abdullah Khan[1,e]

[1]Faculty of Computer Science and Information Technology (FSKTM), Universiti Tun Hussein Onn Malaysia (UTHM), 86400, Parit Raja, Batu Pahat, Johor, Malaysia.

[1]Faculty of Mechanical and Manufacturing Engineering (FKMP), Universiti Tun Hussein Onn Malaysia (UTHM), 86400, Parit Raja, Batu Pahat, Johor, Malaysia.

[a]nazri@uthm.edu.my, [b]zrehman862060@gmail.com, [c]imran@uthm.edu.my, [d]musli@uthm.edu.my, [e]hi100010@siswa.uthm.edu.my

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Abstract. Noise-Induced Hearing Loss (NIHL) has become a major health threat to the Malaysian industrial workers in the recent era due to exposure to high frequency noise produced by the heavy machines. Recently, many studies have been conducted to diagnose the NIHL in industrial workers but unfortunately they neglected some factors that can play a major role in speeding-up NIHL. In this paper, a new Hybrid Bat-BP algorithm which is based on the trio combination of BAT based metaheuristic optimization, back-propagation neural network, and fuzzy logic is proposed to diagnose NIHL in Malaysian industrial workers. The proposed Hybrid Bat-BP will use heat, body mass index (BMI), diabetes, and smoking along with the century old audiometric variables (i.e. age, frequency, and duration of exposure) to better predict NIHL in Malaysian workers. The results obtained through Hybrid Bat-BP will be able to help us identify and reduce the NIHL rate in the workers with high accuracy.

Introduction

With the advent of Modern Industrial era in Malaysia, noise is becoming a common part of our life. It is tolerant to an extent at some sound pressure levels (SPL) but it becomes intolerable as the exposure to noise is prolonged or SPL is increased. Noise is experienced mostly by blue-collared employees in the manufacturing, packaging and power plants industries, where the noise usually exceeds the permissible limits of 85 decibels exposure as set by the Factories and Machinery Act 1989 [1-2]. One of the major occupational health problems that an Industrial worker faces today due to noise is Noise-Induced Hearing Loss (NIHL). Noise-Induced Hearing Loss (NIHL) usually occurs due to continuous exposure to the noise levels of 90 plus decibels emitting from the heavy machines. NIHL in early stages is curable but in later stages it becomes permanent and left the person handicapped for the rest of his life [3-5]. Recently, a number of studies have been carried-out to find the significant factors involved in causing NIHL in industrial workers. The recent improvements in the technology especially in Neural Networks has paved a way for researchers to predict various harmful effects of noise on humans such as human work efficiency in noisy environment, noise induced sleep disturbance, speech interference in noisy environment, noise induced annoyance [6-12].

In an early study carried on NIHL [13], three variables such as age, work duration and noise exposure were selected and Levenberg-Marquardt (LM) model was used for hearing impairment prediction in industrial workers. Later in another study, on tympanic membrane perforation, three factors were identified that directly affect human workers (i.e. noise level, frequency and duration of exposure). It also negated the fact that age; an important factor in permanent hearing loss in older people can play the same effect on the young people [6]. More recently, NIHL in workers is predicted using age, work-duration, and noise exposure as the main factors using Gradient Descent with Adaptive Momentum (GDAM) algorithm. GDAM showed promising prediction results for both ears. It achieved 99 percent accuracy with a Mean Squared Error (MSE) for Left Hearing Loss (LHL) and Right Hearing Loss (RHL) to be 2.18×10^{-3} and 2.30×10^{-3} respectively [4]. All of these studies on NIHL are in full-agreement that noise levels in excess of 85 decibels can cause permanent hearing loss but still some factors that can be helpful in finding harmful effects of NIHL in human hearing are neglected. Also, the input parameters that have been used in the previous studies have neglected human factors indicated in the latest medical studies. In 2005, Ferrite [14] indicated that the distinct ototoxic substances in the chemical composition of mainstream smoke may synergistically speed-up the NIHL. In 2007, Sakuta [15] found body mass index (BMI) and diabetes accelerating NIHL in the middle aged group. Similarly, a multivariate analysis showed that heat is directly associated with NIHL out of the other factors like alcohol drinking, organic solvent, heavy metal, and dust [16-17].

Seeing all these human factors effecting the human workers directly, this study will use heat, BMI, diabetes, and smoking along with the century old audiometric variables (i.e. age, frequency, and duration of exposure) to better predict NIHL in Malaysian workers. And for the sake of Precision, this study propose the use of a new Hybrid Bat-BP algorithm which is based on the trio combination of BAT based metaheuristic optimization [18], back-propagation neural network[19], and fuzzy logic[20] is proposed to diagnose NIHL in Malaysian industrial. The Hybrid Bat-BP algorithm is expected to predict with lesser MSE and a higher accuracy.

The rest of the paper is organized as follows: Section II describes the Bat Algorithm [18], Section III, introduces the proposed Bat-BP [21] algorithm. NIHL Inference System using Hybrid Bat-BP is discussed in Section-IV and finally the paper is concluded in the Section-V.

The Bat Algorithm

Bat is a metaheuristic optimization algorithm developed by Xin-She Yang in 2010 [18]. Bat algorithm is based on the echolocation behavior of microbats with varying pulse rates of emission and loudness. Yang [18] has idealized the following rules to model Bat algorithm;

1) All bats use echolocation to sense distance, and they also "know" the difference between food/prey and back-ground barriers in some magical way.
2) A bat fly randomly with velocity (v_i) at position (x_i) with a fixed frequency ($f$min), varying wavelength λ and loudness A_0 to search for prey. They can automatically adjust the wavelength (or frequency) of their emitted pulses and adjust the rate of pulse emission $r \in [0,1]$, depending on the proximity of their target.
3) Although the loudness can vary in many ways, Yang [18] assume that the loudness varies from a large (positive) A_0 to a minimum constant value A_{min}.

First, the initial position x_i, velocity v_i and frequency f_i are initialized for each bat b_i. For each time step t, the movement of the virtual bats is given by updating their velocity and position using Equations 2 and 3, as follows:

$$f_i = f_{min} + (f_{max} + f_{min})\beta \quad (1)$$

$$v_i^t = v_i^{t-1} + (x_i^t + x_*)f_i \quad (2)$$

$$x_i^t = x_i^{t-1} + v_i^t \quad (3)$$

Where β denotes a randomly generated number within the interval [0,1]. Recall that x_i^tdenotes the value of decision variable j for bat i at time step t. The result of f_i in Equation 1 is used to control the pace and range of the movement of the bats. The variable x^* represents the current global best location (solution) which is located after comparing all the solutions among all the n bats. In order to improve the variability of the possible solutions, Yang [18] has employed random walks. Primarily, one solution is selected among the current best solutions for local search and then the random walk is applied in order to generate a new solution for each bat;

$$x_{new} = x_{old} + \epsilon A^t \tag{4}$$

Where, A^t stands for the average loudness of all the bats at time t, and $\epsilon \in [-1,1]$ is a random number. For each iteration of the algorithm, the loudness A_i and the emission pulse rate r_i are updated, as follows:

$$A_i^{t+1} = \propto A_i^t \tag{5}$$

$$r_i^{t+1} = r_i^0[1 - exp(-\gamma t)] \tag{6}$$

Where α and γ are constants. At the first step of the algorithm, the emission rate, r_i^0 and the loudness, A_i^0 are often randomly chosen. Generally, $A_i^0 \epsilon [1,2]$ and $r_i^0 \epsilon [0,1]$[12].

The Proposed BAT-BP Algorithm

In the proposed BAT-BP algorithm [21], each position represents a possible solution (i.e., the weight space and the corresponding biases for BPNN optimization in this paper). The weight optimization problem and the position of a food source represent the quality of the solution. In the first epoch, the best weights and biases are initialized with BAT and then those weights are passed on to the BPNN. The weights in BPNN are calculated and compared in the reverse cycle. In the next cycle BAT will again update the weights with the best possible solution and BAT will continue searching the best weights until the last cycle/epoch of the network is reached or either the MSE is achieved.

The pseudo code of the proposed Bat-BP algorithm is shown in the Figure 1:

Step 1: *BAT initializes and passes the best weights to BPNN*
Step 2: *Load the training data*
Step 3: ***While*** *MSE < Stopping Criteria*
Step 4: *Initialize all BAT Population*
Step 5: *Bat Population finds the best weight in Equation 2 and pass it on to the network, the weights,* w_{ij} *and biases,* b_i, *in BPNN are then adjusted using the following formulae;*

$$w_{ij}(k+1) = w_{ij}k + \mu \partial_j y_i$$
$$b_i(k+1) = b_i k + \mu \partial_j$$

Step 6: *Feed forward neural network runs using the weights initialized with BAT*
Step 7: *Calculate the backward error*
Step 8: *Bat keeps on calculating the best possible weight at each epoch until the network is converged.*
End While

Fig. 1 Pseudo code of the proposed Bat-BP algorithm

Hybrid Bat-BP Inference System for NIHL

The Hybrid Bat-BP Neuro-Fuzzy Inference system will be using Bat-BP [21] algorithm combined with Fuzzy logic [20] as its backbone for finding out hearing loss in industrial Workers. The data variables will be consisting of age, frequency, duration of exposure, heat, BMI, diabetes, and smoking. The user will input the NIHL data in the Bat-BP Neuro-Fuzzy inference system. The Neuro-fuzzy Inference system will consist of a fuzzification module, an inference engine, Bat-BP

[21] algorithm and a defuzzification module. The fuzzification module will pre-processes the input values submitted to the Inference system. The values are then passed on to the Bat-BP algorithm for training and testing and to generate the NIHL prediction results. The inference engine will use the results of the Bat-BP and accesses the fuzzy rules in the fuzzy rule base to infer what output values to produce for NIHL. The final output of the NIHL will be provided by the defuzzification module. The simple block diagram of the Hybrid Bat-BP NIHL Inference System can be seen in the Figure 2;

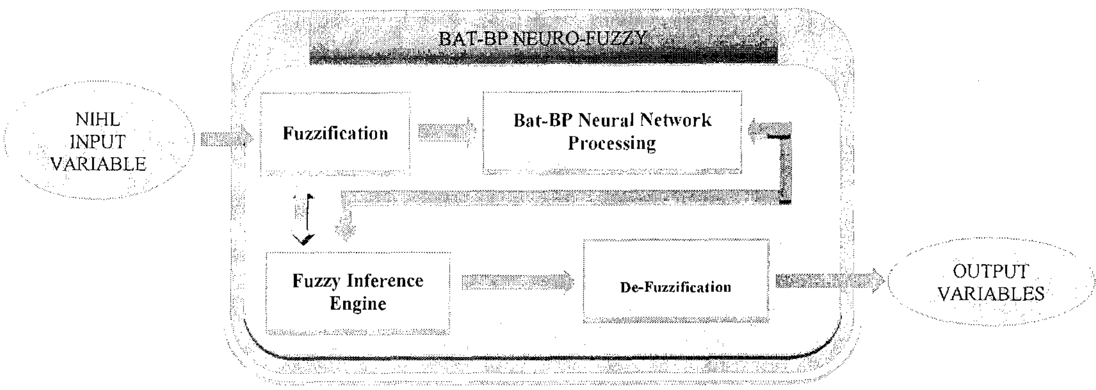

Fig. 3 Hybrid Bat-BP NIHL Inference System

Conclusions

In recent years, noise pollution has emerged as a major cause of several occupational health diseases in Malaysia. One of the disease identified in the workers and associated with the noise pollution is Noise-Induced Hearing Loss (NIHL). As compared to the developed nations, emerging economies still not consider noise as a threat to the health of a blue collared employee. Recently, many studies have been conducted to diagnose the NIHL in industrial workers but unfortunately they neglected some factors that can play a major role in speeding-up NIHL. In this paper, a new Hybrid Bat-BP algorithm which is based on the trio combination of BAT based metaheuristic optimization, back-propagation neural network, and fuzzy logic is proposed to diagnose NIHL in Malaysian industrial workers. The proposed Hybrid Bat-BP will use heat, body mass index (BMI), diabetes, and smoking along with the other old audiometric variables (i.e. age, frequency, and duration of exposure) to better predict NIHL in Malaysian workers. The results obtained through Hybrid Bat-BP will be able to help us identify and reduce the NIHL rate in the workers with high accuracy. The study outcomes will also help legislators (i.e.; Department of Occupation Safety and health, Malaysia- DOSH) to strengthen law enforcement inside the industries in order to ensure safe environment for the workers. The results based on the NIHL prediction will be published in the next writing.

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