629. A proposal for visually handicapped students to use electrical control laboratory

H. Selcuk NOGAY[1], Tahir Cetin AKINCI[2]
[1]Kirklareli University, Technical Education Faculty,
Department of Electrical Education, Kirklareli, Turkey
E-mail: *hidirselcuknogay@gmail.com*
[2]Kirklareli University, Faculty of Technology,
Department of Electrical & Electronics Engineering, Kirklareli, Turkey
E-mail: *cetinakinci@hotmail.com*

(Received 30 January 2010; accepted 15 May 2011)

Abstract: In this paper a technical solution is presented for blind or visually impaired students to acquire abilities of experimental work in laboratory conditions enabling them to participate in the experiments jointly with the healthy students. For this purpose a special apparatus has been designed, which possesses deciding and declaring properties to aid the visually impaired persons in the laboratory environment. An approach based on artificial neural network was implemented. Motor sounds generated during experiments were used for training the ANN model. The results demonstrate that the designed ANN model produces highly reliable estimates used in the operation of the apparatus.

Keywords: aiding apparatus, control laboratory, technical education, sightless students, experiments.

1. Introduction

Students with physical challenges are entitled to be presented with all the information that they need to be successful in their chosen fields. Certainly blindness does not preclude a person from being an innovative and successful engineer, mathematician or scientist. There are approximately 100,000 blind youth in the United States, but few of them fully participate in science instruction at their schools (National Federation of the Blind Jernigan Institute, 2006a). Blind students are increasingly integrated into regular classrooms, and are often the only blind person at their school. Without blind peers and blind adults who can serve as role models, students may not develop confidence in their ability to participate in science or become advocates for their needs as non-visual learners. This situation is similar to Turkey. There are approximately 80,000 blind people in Turkey (T.U.I.K - Turkey Statistic Institute). The accommodations that must be made to support the learning of blind students are often viewed as too challenging and costly for schools. Thus, blind students are frequently left without critical classroom resources. For example, important graphical information, which is ubiquitous in science, is often not made available in alternate formats that are accessible to the blind. This problem is particularly severe in technical and engineering education because key concepts in the curriculum are often conveyed through visual representations and observations. Without adaptations for non-visual learners, these are typically not accessible to blind students [1,2].

There are many technological innovations to facilitate the lives of visually impaired individuals and to develop themselves in different areas. “Braille Embosser”, “Braille Translation Software”, “Closed Circuit Television”, “Large Print Printers”, “Optical Character Recognition”, “Refreshable Braille Display”, “Screen Magnification Software”, "Screen Reading Software" and "Text to Speech" are some of these technologies. Today, a visually impaired individual to receive training in any area of technical education is impossible even to imagine. Visually impaired individuals usually prefer to study the social areas. With the development of sound or touch-sensitive devices for the visually impaired students receive technical training, even if some of the obstacles can be reduced somewhat.

Attending visually handicapped students to occupational and technical education processes is unavoidable necessity to contribute production in industry. When technological developments and necessity of qualified personnel are considered, occupational and technical education is indispensable part of all training processes. In this study, a method is proposed for visually handicapped students to adapt to control laboratory condition. For this aim, an apparatus that will aid students and running by using laboratory experiment’s sounds (motor sounds) was designed. A neural network model which uses sonic data had been designed. Also, the determination mechanism had been tested by the ANN model. The control laboratory is located at the Marmara University, Technical Education Faculty in Turkey [3,4].

2. Principle of the Proposed Approach

In Fig. 1, a part of the control laboratory is illustrated. There are six experimental boards in the control laboratory as indicated in Fig. 2. It was considered that different experiments could be carried out on each experimental set. When visually impaired students come to laboratory, they at first must get information about the current situation in the laboratory. It is important for visually impaired students to recognize which experiments are conducted at the laboratory in order to adapt to laboratory conditions at that time. For this aim, an apparatus is proposed which evaluates the current situation of the laboratory when needed and providing the collected information to the students. Apparatus output is generated by sensing the sounds associated with ongoing laboratory experiments. Six induction motors that have different power and size were used for experiments. Labels of induction motors are given by Table 1. As it is indicated in Fig 2, the aiding apparatus that registers sounds of experiments (i.e. motor sounds) is placed out of the door. The sound recorder is placed on the desk for proving the system accuracy by ANN. The apparatus can be placed anywhere in the laboratory. For example, a switch can be placed on the left of the laboratory door (outside the laboratory). When visually handicapped students turn on the apparatus switch, it provides information about the current condition and running experiments in the laboratory.

Table 1. Label values of experimental motors

Motor Number	P (Kw)	F (Hz)	I (A)	n (rpm)	Cosø	U (V)
1 (3 ~)	7.5	50	15	3000	0.81	380
2 (3 ~)	3	50	7.1	1420	0.80	380
3 (1 ~)	0.15	50/60	1.33	---	---	220
4 (3 ~)	3	50	7.1	1420	0.80	380
5 (3 ~)	0.3	50	0.9	1410	0.80	380
6 (3 ~)	0.37	50	0.9	1410	0.80	380

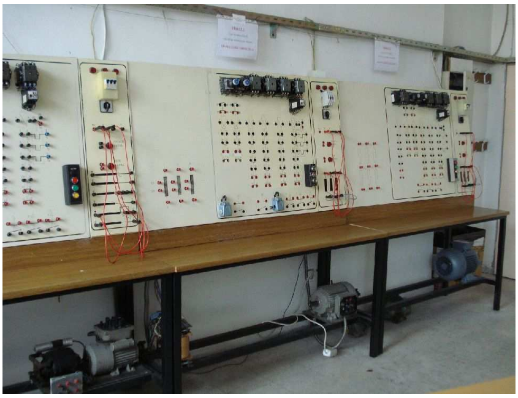

Fig. 1. Photo of a part of control laboratory

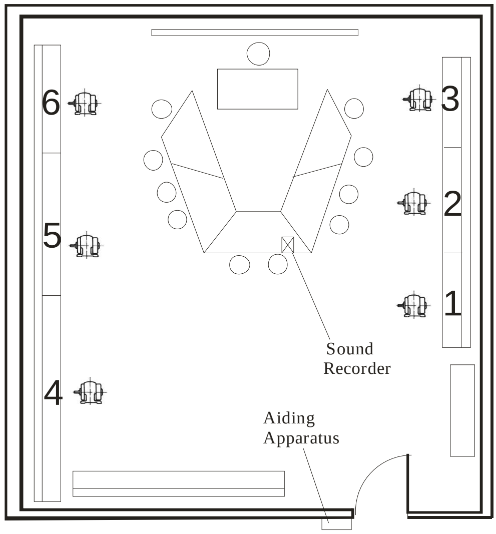

Fig. 2. Plan of the control laboratory

3. Artificial Neural Network (ANN)

Artificial neural networks are parallel and distributed data processing structures developed with inspiration from the human brain, connected to each other with weighting connections and consisting of processing components each having a memory of its own. In other words, artificial neural networks are computer programs that imitate the neural networks. ANNs are self-learning mechanism that does not require conventional abilities from a programmer.

There are multitudes of different types of ANN models. Some of the more popular of them include the multilayer perceptron, which is generally trained with the back propagation algorithm. Back propagation is a training method for multilayer feed forward networks. Such a network including three layers of perceptrons was designed as neural network structure in Fig. 3. The back propagation algorithm (Rumelhart and McClelland, 1986) is used in layered feed-forward ANNs. This means that the artificial neurons are organized in layers, and send their signals "forward", and then the errors are propagated backwards. The network receives inputs by neurons in the input layer, and the output of the network is given by the neurons on an output layer. There may be one or more intermediate hidden layers. The back propagation algorithm uses supervised learning, which means that we provide the algorithm with examples of the inputs and outputs we want the network to compute, and then the error (difference between actual and expected results) is calculated. The idea of the back propagation algorithm is to reduce this error, until the ANN learns the training data. By the algorithmic approach known as Levenberg-Marquardt back propagation algorithm, the error is decreased repeatedly. In the supervisory training, the actual output of ANN is compared with the desired output. The training set consists of presenting input and output data to the network. The network adjusts the weighting coefficients, which usually begin with random set, so that the next iteration will produce a closer match between the desired and the actual output. The training method tries to minimize the current errors for all processing elements. This global error reduction is created over time by continuously modifying the weighting coefficients until the ANN reaches the user defined performance level. This level signifies that the network has achieved the desired statistical accuracy for a given sequence of inputs. When no further training is necessary, the weighting coefficients are frozen for the application. After a supervisory network performs well on the training data, then it is important to determine what it can do with data it has not encountered before. If a system does not provide reasonable outputs for this test set, the training period is not over. Indeed, this testing is critical to insure that the network has not simply memorized a given set of data, but has learned the general patterns involved within an application. There are many types of devices and methods used by impaired or blind persons to navigate in the real environment [5-11]. Most of the studies on the visually impaired people focused on facilitation of their daily life. However, there is no study in the literature to facilitate the work of the visually impaired people in a laboratory environment.

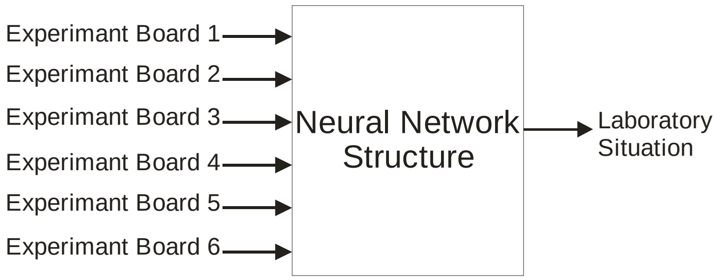

Fig. 3. Neural Network Structure

In order to use the ANN simulator for any application, first the number of neurons in the layers, type of activation function (purelin, tansig, logsig), the number of patterns, and the training rate must be chosen [12].

4. ANN Design Process

ANN designing involves five steps: collection of input data, normalizing the data, selecting the ANN architecture, training the network, and validation-testing the network. In the training step, six input variables: experiments and output variable: situation of the laboratory [13].

4.1. Collection of the Input and Output Data

All of the motor sounds during the different experiments in the laboratory were recorded by sound recorder. It was considered that, the output of ANN or aiding apparatus is laboratory situation. For this aim, data sets needed to develop the ANN model were generated by conducting experiments in the laboratory. In Fig. 10, numbers in bold correspond to running motors, experiment number and, at the same time, experiment board numbers. The aim of this study is to test the applicability of the system using ANN model trained by these data sets. A plausible estimation of the ANN model will be an affirmative hint about the applicability of the proposed approach. The main point is to record sound data simultaneously in order to ensure maximum accuracy and reliability of the data set. As indicated in Fig. 2, sound is recorded by the sound recorder placed on the desk in the middle of the laboratory. During experiments, first, all of the motors were operated simultaneously and different experiments were performed on each laboratory board. Then, separate experiments were performed on each board. Regarding the laboratory conditions, experiments were conducted by considering one laboratory including one motor to six motor and their sound data were recorded. 277 data sets were used for the ANN: 167 of them were used for training the ANN model, 55 data sets were used for validation tasks and the 55 sets were used for testing the ANN model as illustrated in Table 2 [14].

4.2. Normalizing the Data

Normalization of data is a process of scaling the numbers in a data set to improve the accuracy of the subsequent numeric computations and is an important stage for training of the ANN. Normalization also helps in shaping the activation function. For this purpose [+1, -1] normalization function was used.

4.3. Selection of the ANN Architecture

The number of layers and the number of processing elements per layer are important decisions for selecting the ANN architecture. Choosing these parameters to a feed forward back propagation topology is the art of the ANN designer. There is no quantifiable, best answer to the layout of the network for any particular application. There are only general rules picked up over time and followed by most researchers and engineers applying this architecture to their problems. The first rule states that if the complexity in the relationship between the input data and the desired output increases, then the number of the processing elements in the hidden layer should also increase. The second rule says that if the process being modeled is separable into multiple stages, then additional hidden layer(s) may be required. The result of the tests has demonstrated that the optimal number of neurons in the first layer can be chosen as 20 also, the activation function was chosen as a hyperbolic tangent sigmoid function for all of the layers [15, 16].

4.4. Training the Network

ANN simulator has been trained through the 100 epochs. The training process has been stopped when the error has become stable. Variation of the total absolute error through the epochs is shown in Fig. 7 [17].

4.5. Testing the Network

In the test, an unknown input pattern has been presented to the ANN, and the output has been calculated. Linear regression between the ANN output and the target is performed. Regression coefficients determined as a result of ANN learning and testing procedures indicate that target and ANN output values are closely related each other. The regression analyses are presented in Figs. 4-6 with respect to the learning step. The coefficients reveal that target and ANN output values are tightly interrelated [18, 19].

5. Conclusion

In this study we presented the pre-design work of a device that may help blind or visually impaired students in the laboratory environment to gain the ability of the experimental work. In the proposed application the sounds are employed in order the visually impaired students would be able to determine themselves which machines are running and which experiments are carried out at that moment in the electrical control laboratory. For this purpose the artificial neural network method was adopted. Motor sounds from different experimental setups are used as inputs to the designed ANN model. Status of the laboratory is specified as the output of the ANN model. Test schedule was implemented in order to obtain data sets used in this study. Status of the laboratory is numbered for the output of the data set. The results have demonstrated that the prediction error obtained by the ANN model is acceptable, thus the ANN model is able to deliver sufficiently reliable estimate of the current laboratory situation based on the generated motor sounds. The results have also pointed out that the ANN can accommodate other data prediction efforts easily and successfully.

Table 2. ANN results

	Indices	Performance	Regression
Train	1x167	0.00000067288	0.99999
Validation	1x55	0.00041775	0.99643
Test	1x55	0.00026395	0.99729

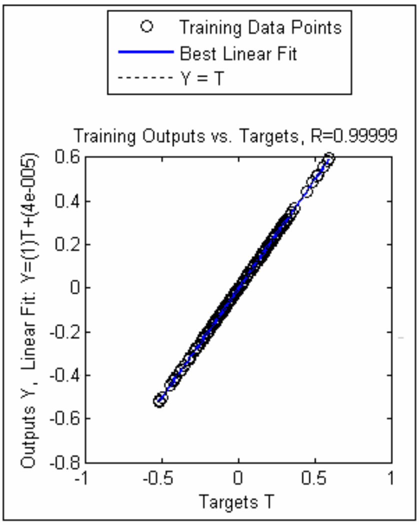

Fig. 4. Linear regression results between ANN training results and target

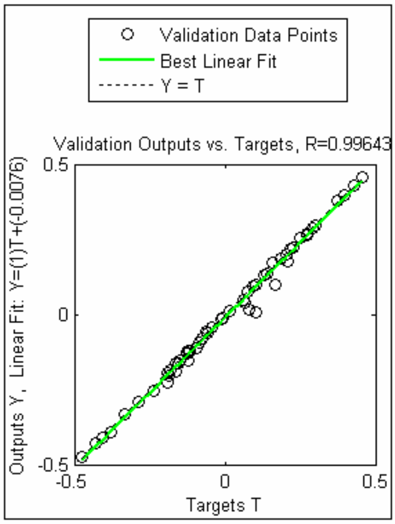

Fig. 5. Linear regression results between ANN validation results and target

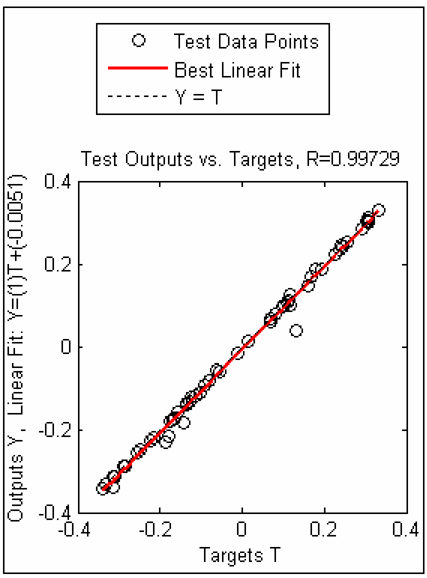

Fig. 6. Linear regression results between ANN test results and target

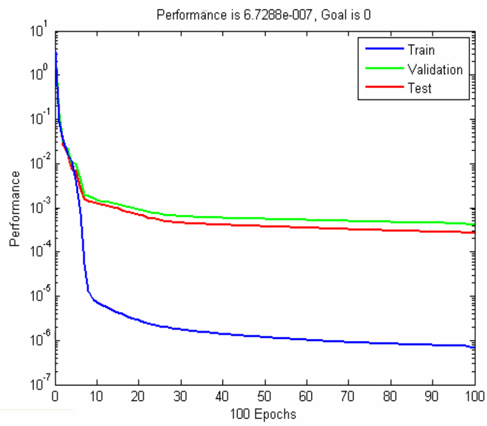

Fig. 7. Variation of the total absolute error through the Epochs

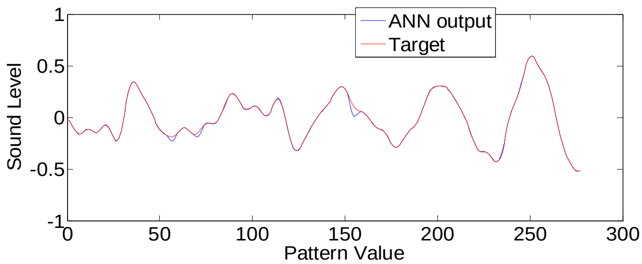

Fig. 8. Variation of the ANN data together with the target data

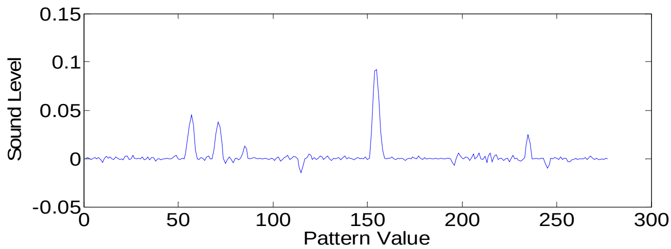

Fig. 9. Variation of the ANN error

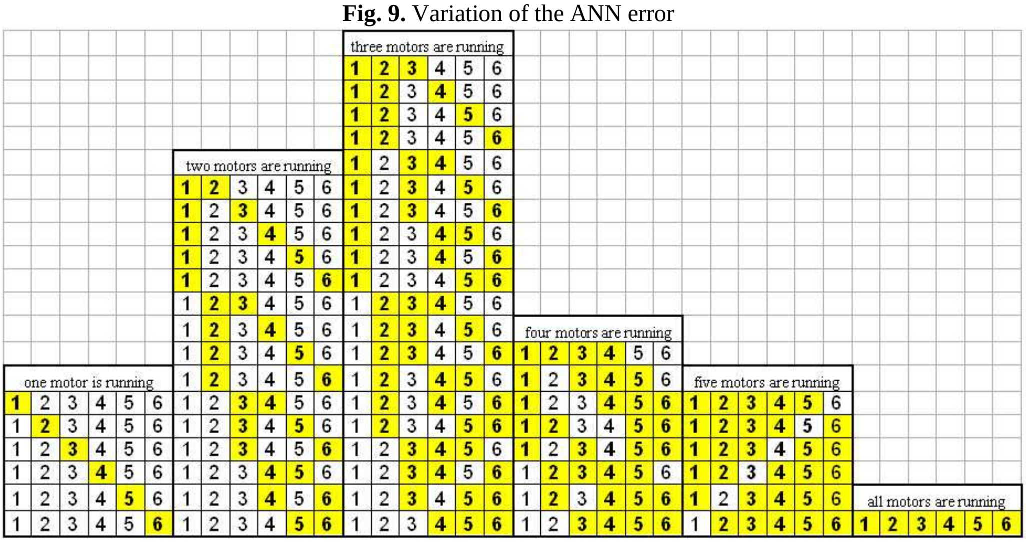

Fig. 10. Experiments chart for obtaining data set

References

[1] **L. Bogges.** A Fast Inexpensive Means of Creating Tactile "Drawings" of Graphs and Networks for Blind Students, 29'h ASEE/IEEE Frontiers in Education Conference, November 10 - 13,1999 San Juan, Puerto Rico, 1999.

[2] **B. Winchatz, M. A. Riccobono.** Advancing participation of blind students in Science, Technology, Engineering, and Math, Advances in Space Research, Elsevier, May, 2007.

[3] **R. Omar, Z. Mohammed.** Relationship between vision and reading performance among low vision students, Elsevier, International Congress Series (ICS) 1282- 679– 683, 2005

[4] **Y. Andreou, K. T. Kotsis.** The estimation of length, surface area, and volume by blind and sighted children, Elsevier, International Congress Series (ICS), 1282- 780–784-2005.

[5] **I. Ulrich, J. Borenstein.** The GuideCane - Applying Mobile Robot Technologies to Assist the Visually Impaired, IEEE Transactions on Systems, Man, and Cybernetics, Part A: Systems and Humans, Vol. 31, No. 2, pp. 131-136, 2001.

[6] **H. Shim, J. Lee, E. Lee.** A Study on the Sound-Imaging Algorithm of Obstacle Information for the Visually Impaired, The 2002 Intern. Technical Conf. On Circuits/Systems, Computers and Communications (ITC-CSCC), pp.29-31, 2002.

[7] **S. Shoval, I. Ulrich, J. Borenstein.** Robotics-based obstacle avoidance systems for the blind and visually impaired, IEEE Robotics and Automation Magazine, Vol. 10, No. 1, pp. 9-20, 2003.

[8] **V. Kulyukin, C. Gharpure, J. Nicholson, S. Pavithran.** RFID in Robot-Assisted Indoor Navigation for the Visually Impaired, IEEE/RSJ Intern. Conf. On Intelligent Robots and Systems, Sendai, Japan (IROS), pp. 353-357, 2004.

[9] **S. Namara, G. Lacey.** A robotic mobility aid for frail visually impaired people, Intern. Conf. On Rehabilitation Robotics (ICORR), pp. 129-132, Stanford, 1999.

[10] **Young-Jip Kim, Chong-Hui Kim, and Byung-Kook Kim.** Design Of Auditory Guidance System For The Blind With Signal Transformation From Stereo Ultrasonic To Binaural Sound, Proc. of the 32nd ISR (Intern. Symposium on Robotics), pp. 19-21, 2001.

[11] **A. Helal, S. Moore, B. Ramachandran-Drishti.** An Integrated Navigation System for Visually Impaired and Disabled, Intern. Symposium on Wearable Computers (ISWC), pp. 149-156, 2001.

[12] **G. E. Box., G. Jenkins.** Time Series Analysis, Forecasting and Control, Golden-Day, San Francisco, CA, 1970.

[13] **T. M. Hagan, H. B. Demuth, M. Beale.** Neural Network Design, PWS Publishing Company, 1996, 2-44.

[14] **B. K. Bose.** Modern Power Electronics and AC Drives, Prentice Hall PTR, USA, 2002, pp. 625-689.

[15] **C. Y. Lee, W. J. Lee, Y. N. Wang, J. C. Gu.** Effect of Voltage Harmonics on the Electrical and Mechanical Performance of a Three-Phase Induction Motor, Industrial and Commercial Power Systems Technical Conference, Atlanta, Canada, 1998, IEEE 88-94.

[16] **Y. Birbir, H. S. Nogay, S. Taskin.** Prediction of Current Harmonics in Induction Motors with Artificial Neural Network, International Aegean Conference on Electrical Machines and Power Electronics, (ACEMP'07), Electromotion' 07 Joint Conference, Bodrum, Turkey, September, 10 – 12, 2007

[17] **B. H. Ertan, M. Y. Uçtug.** Modern Electrical Drives, Springer - Verlag, New York, USA, 2000.

[18] **J. M. Ringrose, M. Negnevitsky.** Harmonic Source Monitoring in Power Systems Using State Estimation and Neural Networks, Elsevier, Australia, 1994.

[19] http://www.99main.com/~charlief/vi/adaptive.html.