A Multilayer Perceptron Neural Network Based Model for Predicting Subjective Health Symptoms in People Living in the Vicinity of Mobile Phone Base Stations

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Abstract

Advances in modern technologies such as telecommunication, have widely expanded the applications of wireless systems. Therefore, humans are continuously exposed to electromagnetic fields (EMFs) produced by widely used devices such as mobile and cordless phones and Wi-Fi routers. According to WHO, electromagnetic hypersensitivity (EHS) is the medical term for variety of non-specific symptoms which afflicted subjects attribute to exposure to different sources of EMF. About 25% of the general population report different levels of environmental intolerance to factors such as EMFs and studies performed in Europe shows that about 75% of general practitioners had visited patients complaining of EHS. In this paper, multilayer perceptron neural network (MLPNN) based models are proposed to predict the subjective health symptoms in inhabitants living in the vicinity of mobile phone base stations. The classifier uses several parameters such as demographic data, environmental exposure to mobile phone station, and health condition of an individual as input to estimate subjective health symptoms. Out of 699 data sets recorded from 363 men and 336 women via questionnaire, 70% was used for training, 15% for validation and the remaining 15% for testing the developed system. The performance of the developed system (sensitivity and specificity) in predicting the subjective health symptoms are as follows: headache (72%, 91%), fatigue (8%, 98%), sleep disturbance (97%, 93%), dizziness (65%, 85%), vertigo (65%, 84%). These promising results suggest that using this system might be useful as a means for predicting the health symptoms in people living in the vicinity of mobile phone base stations which ultimately enhances the quality of life of these individuals through providing appropriate medical and introducing effective methods for

reducing the effect of these exposures.

Keywords: Mobile Phone Base Stations, Electromagnetic Hypersensitivity (EHS), Artificial Neural Network, Radiofrequency (RF).

1. Introduction

The past few decades have witnessed an exponential advance in modern technologies such as telecommunication and the applications of wireless systems. More than ever, now humans are continuously exposed to electromagnetic fields (EMFs) produced by different sources ranging from wireless baby watch to Wi-Fi routers, mobile and cordless phones. The rapid growth of wireless technology has raised global concerns about how exposure to EMF may affect human health (Abdel-Rassoul et al., 2007; Berg-Beckhoff et al., 2009; Bortkiewicz et al., 2012; Gomes, Al Zayadi, & Guzman, 2011; Hutter, Moshammer, Wallner, & Kundi, 2006; Loughran et al., 2016; Safian et al., 2016; Schoeni, Roser, Bürgi, & Röösli, 2016; Shen et al., 2016; Son et al., 2016). According to world health organization (WHO), electromagnetic hypersensitivity (EHS) is the medical term for a variety of non-specific symptoms, which afflicted individuals attribute to exposure to EMF. It has been reported that about 25% of the general population report different levels of environmental intolerance to factors such as EMFs (Nordin & Nordin, 2016). Furthermore, studies performed in Europe shows that about 75% of general practitioners had visited patients complaining of EHS (Slottje et al., 2016). Although the underlying mechanisms are not fully understood, now we know that the health symptoms linked to exposure to EMF are real and cause functional impairment.

Over the past several years, several studies have been conducted to investigate the health risks of electromagnetic fields (Abdel-Rassoul et al., 2007; Ahlbom et al., 2001; Berg-Beckhoff et al., 2009; Bortkiewicz et al., 2012; Brain et al., 2003; Elliott et al., 2013; Feychting & Ahlbom, 1993, 1995; García, Sisternas, & Hoyos, 2008; Gomes et al., 2011; Habash, Brodsky, Leiss, Krewski, & Repacholi, 2003; Hutter et al., 2006; Johansen, 2004; Maslanyj et al., 2007; Meo et al., 2015; S. M. J. Mortazavi et al., 2012; S. M. J. Mortazavi, 2013; S. M. J. Mortazavi, Ahmadi, & Shariati, 2007; S.M.J Mortazavi et al., 2013). At the non-ionizing department of Ionizing and Non-ionizing Radiation Protection Research Center (INIRPRC) at Shiraz University of Medical Sciences, we also have conducted experiments on the health effects of exposure to different sources of electromagnetic fields such as cellular phones (S. Mortavazi et al., 2009; S. M. J. Mortazavi et al., 2008, 2012, 2014, 2007; S.M.J. Mortazavi, Taeb, & Dehghan, 2013; S.M.J Mortazavi et al., 2013), mobile base stations (S. A. Mortazavi, Mortazavi, & Mortazavi, 2016; S. M. J. Mortazavi, 2013), mobile phone jammers (S.M.J. Mortazavi et al., 2013) and laptop computers (S.M.J Mortazavi et al., 2010). Regarding the challenging issue of electromagnetic hypersensitivity, we have previously shown that when the self-reported hypersensitive participants were asked to report their perception about the real and sham exposures, only 25% could discriminate the real exposure/sham exposure phases (this simply could be due to chance). Furthermore, when all of the these hypersensitive participants were connected to intensive care unit (ICU) monitors and the alterations in their heart rate, respiration, and blood pressure during real and sham exposure phases were recorded, no statistically significant changes between the means of these parameters were detected in real/sham exposures. At that time (this dates back to 2011) we concluded that psychological factors are possibly involved

in electromagnetic hypersensitivity (S. M. J. Mortazavi et al., 2011). It is worth noting that this conclusion was flawed due to the limitations we had in our previous studies and when we obtained sufficient data, we realized that EHS was not linked to psychological issues. Later we introduced a novel multi-phase method for effective screening of the patients diagnosed with electromagnetic hypersensitivity(Khademi, Mortazavi, Haghani, & Mortazavi, 2014; Mortazavi, Khademi, Motamedifar, Haghani, & Mortazavi, 2014) .

Artificial neural networks (ANNs) are gaining a great deal of interest in pattern recognition and data analysis mainly because of their flexibility and ability to adapt complicated problems. In fact, the configuration of ANNs is developed through training by cyclical processing of the training samples. In addition, recent advances in computer and software technology have led to the development of toolboxes and simulator software that make designing and developing an appropriate network relatively simple. In recent years, there has been an explosion of interest in the application of ANNs in health systems, biomedicine, and biomedical engineering. This rapid rise has led to the development of several algorithms for biomedical signal processing (Kamali, Boostani, & Parsaei, 2014; Parsaei, Nezhad, Stashuk, & Hamilton-Wright, 2009; Parsaei, Nezhad, Stashuk, & Hamilton-Wright, 2010; Parsaei & Stashuk, 2013, 2011; Rasheed, 2007; Thompson, Picton, & Jones, 1996; Xu, Xiao, & Chi, 2001), medical image processing (Amiri, Movahedi, Kazemi, & Parsaei, 2017; Bezdek, Hall, & Clarke, 1993; Daniel J Withey, 2008), clinical decision support systems (Graupe, Liu, & Moschytz, 1988; Güler & Koçer, 2005) and medical data analysis. In this paper, a system based on multilayer perceptron neural network (MLPNN) is presented for predicting subjective health symptoms in people living near mobile phone base stations. The characteristics of this method, its objectives and how it was developed and evaluated, are presented in detail in this paper.

1. Methodology

The presented method is to predict the subjective health symptoms in individuals living near mobile-base stations. More specifically, the main objective was to determine if these individuals may have health symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations. As with other pattern recognition system, the developing process consists of three main steps: data collection, data preprocessing, feature extraction, and classification. Following is a detailed description of these steps.

1.1. Data collection

Data were collected through a questionnaire-based conducted on 699 individuals (363 men, 336 women) living in the vicinity of cellular phone base stations, in Shiraz, Fars, Iran. Trained interviewers interviewed participants selected by a random sampling method at a multistage program. The first step was the selection of some mobile phone base-stations out of a few hundred stations existing in Shiraz. For this purpose, we randomly selected 20% of the stations in each district of Shiraz (Shiraz was divided into 11 districts). In the second step, houses located at distances <1000m were selected. Then houses were divided into 4 different categories based on their distance from the nearest station (less than 100m, 100-300 m, 300-600 m and 600-1000 m). The rationale for selecting these distances was the findings of our previous study which revealed that living at a distance of < 300 m to base station can lead to symptoms such as tiredness headache, sleep disturbance, discomfort, irritability, depression, loss of memory, dizziness, and altered libido. In this study, people living at distances greater than 600m were considered as the control group to prevent any selection bias due to potential differences in socio-economic and lifestyle factors. All participants signed an informed consent before answering the questionnaires prepared for this study. In total, 363 men (32 $\pm$13years) and 336 females (32 $\pm$12years) were examined.

1.2. Data Preprocessing

In this step, the objective was to find the outliers and remove them from further analysis. This step was completed by finding inconsistent data via using graphical method such as scatterplots and box plots. Inconsistent data were those which one of the recorded parameters was unacceptable (e.g., the daily cellphone use >24 hour).

Moreover, to reduce the dimensionally of the feature space (number of input parameters), we used sequential forward selection (SFS) technique (Duda, Hart, & Stork, 2000). The SFS algorithms are a family of dimension reduction/feature selection methods that are used to select a subset of features that is most relevant to the problem. The SFS algorithms start with an empty set and then add one feature at the time based on the classifier accuracy until either the classifier accuracy is saturated or a feature subset of the desired size is reached. The objective of using the SFS algorithm in this work was to reduce the computational complexity of the system and the generalization error of the system by removing irrelevant features.

1.3. Classification

Classification, by definition, is the problem of assigning a label to a new pattern (sample), by using a set of data that their class labels are known (i.e., training data). An algorithm that implements classification is known as a classifier. In this work, artificial neural network-based systems have been used to predict the health status of a subject living in the vicinity of a mobile-base station. Specifically, the objective was to determine if these subjects may have health symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations.

In this work, we used a Multi-layer Perceptron Neural Network for classification purpose. MLPNN is a feed-forward multilayer network architecture composed of several layers of neurons, an input layer, an output layer and several hidden layers (Haykin, 2008). For most problems, a network with one hidden layer is used as it is shown that such a three –layer neural network can resolve complicated pattern recognition problems. An example of a three –layer neural network is shown in Figure 1.

Designing an MLPNN–based classifier includes two main steps: a) determining architecture and its parameters (number of layers and number of neurons in each layer); and b) training the network. The MLPNN used in this work consists of three layers: an input layer, a hidden layer, and an output layer. The input layer consists of 11 neurons which are equal to the number of features (parameters) used to represent living status of the subject under study. Specifically, the developed MLPNN model consists of 11 input nodes corresponding to: sex, age, daily mobile phone usage (min), mobile phone usage (month), cordless phone use (month), distance from mobile base station antennae (meter), duration of exposure to the antenna (hour), duration of residence in the present house (month), daily use of video display units (VDU) (min), living in the vicinity of a power line (yes/no), using other wireless devices (yes/no).

The output was the health status of the individuals. In this work we used one-versus-the other strategy in designing the classifier. Therefore, the MLPNN consisted of only one node. In total five MLPNN were designed so that each one predicting one symptom.

The number of neurons in the hidden layer was determined experimentally using cross-

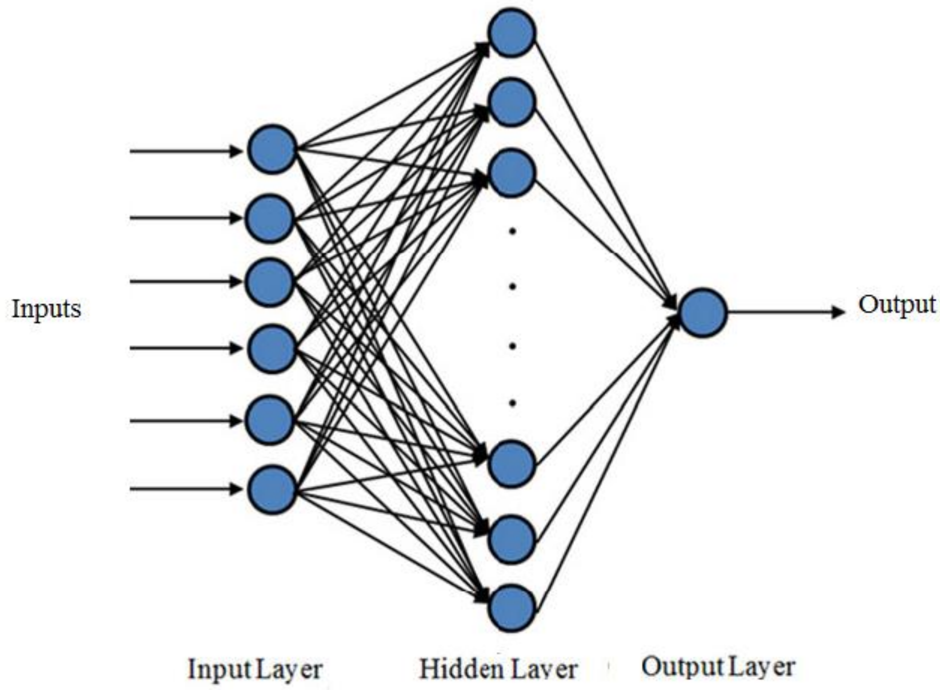

Figure 1: A three layer Perceptron Neural Network (Haykin, 2011)

validation, by setting different values for the number of neurons in the hidden layer (1 to 20), the network with the highest accuracy was chosen as the best system. Based on the obtained results, a hidden layer containing 10 neurons each including a sigmoid activation function provided the minimum testing error. For the output layer, two neurons were used. Training an MLPNN means estimating the value of the weights of the network using a learning algorithm such that the total error between the values estimated by the trained network and target value is minimized. Here, we used back propagation algorithm (Haykin, 2011), a widely used training algorithm, for this purpose. MATLAB software was used for all computations.

2. Results and Discussion

Considering the studied symptoms which served as the gold standard (ground truth), the performance of the developed MLPNN-based health condition prediction system was evaluated in terms of correctly predicting the type of symptom. Three performance indices were used for this purpose: sensitivity, specificity, and accuracy. These three indices are given by

$$Sensitivity = \frac{TP}{TP + FN} \times 100$$

$$Specificity = \frac{TN}{TN + FP} \times 100$$

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \times 100$$

where the parameters TP, TN, FP, and FN are defined as follows.

TP : Number of subjects that correctly identified as with symptom.
TN: Number of subjects that correctly identified with no- symptom.
FP : Number of no- symptom individuals that are incorrectly identified with symptom.
FN: Number of people with symptom that incorrectly identified with no- symptom.

The classification performances of the developed system are summarized in Table 1. In estimating the performance of the developed MLPNN, out of 699 data sets recorded from 363 men and 336 women via questionnaire, 70% was used for training, 15% for validation and the remaining 15% for testing. In this Table, the performance indices only for testing data were reported.

As shown in Table 1, for most symptoms, the developed system could predict the subjective health symptoms with acceptable performance. However, the system was unable to predict fatigue status well. This may be due to many factors such as this point which fatigue can be caused by numerous factors other than exposure to EMF.

Table 1 Performance of the developed MLPNN-based system in predicting subjective health symptoms for people living near mobile phone base stations

Symptom	Sensitivity (%)	Specificity(%)	Accuracy(%)
Headache	71.8	90.9	83.8
Sleep disturbance	82.1	83.3	82.9
Dizziness	65.2	85.4	81.0
Vertigo	65.0	84.7	81.0
Fatigue	8.3	98.9	88.6

For all of the cases, the specificity of the system was higher than its sensitivity in predicting the subjective health symptoms. There are several reasons for this outcome. One possible reason is that the individuals with "No symptom" may answer the questions more correctly than the other subjects. In other words, the data for no symptom class are less noisy that the other class. The second reason is that the number of patterns in "no symptom" class is higher than that of the other class which causes the MLPNN adapts this class and learns the patterns related to this group better than the other classes.

In terms of designing the system, as mentioned above we used one-versus- the other strategy in designing the classifier, in which for predicting each of the discussed five symptoms (headache, sleep disturbance, dizziness, vertigo, fatigue) a single MLPNN was designed. For this five-class classification problem, a single MLPNN with 11 input nodes and 5 output nodes can be used to design the desired system. However, preliminary results showed that performance of this system is low and is not acceptable. In other words, we found that a single model did not work in predicting all of the studied symptoms. Hence, we used a separate model for each symptom.

The effect of the studied variables on each symptom considered in this work are different. Based on the results obtained by using sequential forward selection (SFS) technique (discussed in sub-section 1.2) , the most effective variable for headache symptom is “daily mobile phone usage”. There is an interaction between this variable and the two variables “duration of exposure to the antenna” and mobile phone usage (month). This results suggests that who “overuse” their cell phones as it is are better off not living near a base station. For sleep disturbance symptom, the three most effective features are “daily mobile phone usage”, “duration of exposure to the antenna” and “cordless phone use”. As we can see again overusing cell phones and cordless phones along with leaving near the BTS stations may cause sleep disturbance symptom. The same results are obtained for dizziness symptom. For the last studied symptom, the most important parameters are “Sex”and “duration of exposure to the antenna (hour)” are the most important variables.

The present study was prospective and not randomized; the objective was assessing the role of MLPNN-based models in predicting the health risks of exposure to EMF sources for an individual. We used relatively simple variables as inputs. Therefore, when the model is developed (i.e., the MLPNN is trained), similar variables would be needed to provide the required information (prediction). In terms of application, this model may help physicians and scientists reduce the health risks of electromagnetic fields via predicting the subjective health symptoms for people currently living or who would like to move to houses in the vicinity of mobile phone base stations. In other words, this MLPNN-based system can be used to investigate if a person is EHS or not and ultimately help us predict the health risks of living in the vicinity of mobile base stations. In terms of using this mode, it is easy and straight forward because many softwares such as MATLAB and R has neural network toolbox induced. So, the user who is interested to use the models presented in this work can collect his/her data, use the parameters discussed in this paper then put them in the toolbox.

3. Conclusions

Accurate prediction of the risk of subjective health symptoms in inhabitants living in the vicinity of mobile phone base stations can enhance the quality of their life through providing appropriate health care and suggesting effective methods for reducing the severity of these symptoms. In this paper, we proposed a MLPNN-based model for predicting the risk of several symptoms such as headache, fatigue, sleep disturbance, discomfort depression, loss of memory, dizziness, libido decrease, nervousness, and palpitations. Evaluation of the data collected in this survey that was conducted on 699 people living in the vicinity of cellular phone base stations, in Shiraz, Fars, Iran, reveals that the developed system can successfully predict the risk of subjective health symptoms (for most symptoms) with the sensitivities > 65% and specificities > 83%. We hope that the robustness and accuracy of the developed system will help scientists promote the applications of MLPNN and pattern recognition techniques in improving the health of the individuals living in the vicinity of mobile phone base stations.

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