Estimation of Relative Exposure Levels For Cellular Phone Users Using A Neural Network

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The wide and growing use of cellular phones has raised questions about the possible health risks associated with radio frequency (RF) electromagnetic fields. It would be helpful for epidemiologists as well as cellular phone users to obtain the relative exposure levels, because the RF exposure level is very difficult to accurately measure and quantify for all individuals. In this study, a neural network model was developed to estimate relative exposure levels on a scale of 0–10 and thus rank the individual risk of exposure using available information. We used parameters such as usage time per day, total usage period, hands-free usage, extension of antenna, specific absorption rate (SAR) of the cellular phone, and flip or folder type, which are related to RF exposure. Using the relative exposure levels obtained from this model, epidemiologists can divide the subjects into exposed and nonexposed groups in a study investigating the relationship between exposure level and brain cancer in the future, provided that more knowledge between the cellular phone usage pattern and the exposure is available.

INTRODUCTION

According to an announcement in July, 2003 from the Korea Ministry of Information and Communication, there were more than 33 million cellular phone users out of a population of 47 million [www.mic.go.kr]. As the population of cellular phone use has been rapidly growing, questions about possible harmful effects of RF (radio frequency) are constantly being raised and many studies in epidemiology, biology, and dosimetry are being done internationally.

Epidemiology is important in determining whether RF is hazardous or not. However, it is difficult to execute such studies due to few cases of tumors being associated with RF exposure, the existence of a latent period, and the ambiguity of direct relations. Moreover, it is difficult to maintain long-term studies on thousands of subjects, requiring immense expenditure, continuous data collection, and accurate estimation of RF exposure on the human body. Nevertheless, long-term epidemiological studies based on wide and diverse samples are necessary to determine the association between the health risk and RF exposure from cellular phones. Therefore, many studies are in progress all over the world [Chou et al., 1995; Bit-Babik et al., 2003; Cook et al., 2003; Hossman and Hermann, 2003; Warren et al., 2003; Ahlbom et al., 2004; Kundi et al., 2004]. As a result, many studies have been published on the relationship between brain tumors and cellular phone usage. However, more research is needed to establish any long-term detrimental effects of cellular phone usage.

Previous research has asserted that cellular phone use is related to brain tumors [Hardell et al., 2000], and the governments of several developed countries have guided teenagers to refrain from using cellular phones for extended periods of time. It would be very useful for epidemiologists to access exposure levels of study subjects. This is a really difficult task and a method for estimating individual exposure level has been lacking. A new approach is being suggested to estimate the relative exposure level of each cellular phone user pattern in this study. This approach utilizes easily...
accessible information provided by users and is based on published results.

Exact measurements of SAR in vivo, which has a direct effect on the user in relation to the output level of the cellular phone, are almost impossible. It seems inappropriate to conclude that RF exposure from cellular phones causes brain tumors, as previous studies indicated [Muscat et al., 2000; Erman et al., 2001; Inskip et al., 2001; Kane, 2001; Park, 2001; Trichopoulos and Adami, 2001; Auvinen et al., 2002; Muscat et al., 2002; Mild et al., 2003; Christensen et al., 2004; Lonn et al., 2005]. But a relatively high risk could be associated with high RF exposure levels. One study has reported tumors in the temporal and occipital areas in relation to the side in which the cellular phone was used [Hardell et al., 2000]. Hocking [1998] and Chia et al. [2000] have reported the prevalence of headache symptoms in connection to the usage of cellular phones. Nevertheless, many studies could not conclude that using cellular phones has any effect on brain tumors due to the lack of clinical data and the difficulty in accurately assessing exposure levels with the current technology.

In order to estimate an individual’s exposure level, the following parameters were considered; average usage time per day (hour), total period of usage (year), specific absorption rate (SAR) of the specific cellular phone (W/kg), hands-free usage (y/n), antenna extraction (y/n), and the type of cellular phone (flip or folder). The first two parameters were appropriately weighted assuming the RF exposure level would be proportional to the parameter values because we do not know a quantitative relationship between those values and RF exposure. The others were objectively weighted based on the literatures. Utilizing such weights, the ultimate goal of this study was to make a mapping function using a neural network in order to provide both cellular phone users and epidemiologists with an indirect estimation of relative exposure level (0–10).

**MATERIALS AND METHODS**

**Factors Influencing Exposure Level**

In this study, we considered exposure level based on usage preferences and the types of cellular phones. These factors were considered to quantitatively estimate the relative RF exposure level from 0 to 10. Easily accessible information from the users (average usage time per day, total period of usage, hands-free usage, and antenna usage), the cellular phone type, and SAR of the specific model of the cellular phone were chosen as the input parameters of the neural network model.

The parameters for the cellular phone usage preferences, the cellular phone model, and the previous study results on each parameter are as follow(s): (1) Average usage time per day and (2) total period of usage: These parameters influence the amount of exposure and are thus the most important factors in the epidemiological study. We needed a data set for training the neural network to make nonlinear mapping function, but could not get one from previous literature and research. Therefore, we assumed RF exposure level to be proportional to SAR. In this study, linear weights with the median values have been given to the usage time, the period, and SAR of the cellular phone. For example, the weight for the usage time < 1.5 was given as 0.63 (1.25/2); (3) Hands-free usage: This condition significantly reduces the exposure level by 1/10 [www.cancer.gov]; (4) Antenna extraction: According to the Motorola researchers, if the antenna of the flip type cellular phone is pulled out, half of the SAR is produced compared to the case when the antenna is not pulled out [Kim, 1997]; (5) SAR of phone: This parameter indicates the amount of absorbed voltage per unit of mass while a living body is exposed to RF. The RF exposure level is closely dependent on the SAR of each cellular phone [Choi et al., 1992]. Only CDMA phones were considered. The SAR values were obtained from the manufacturers of the models; (6) The cellular phone type: While maintaining a typical posture in using the cellular phone, the folder type has a 40% lower level of SAR than the flip type due to the increased distance between the antenna and the head [Jung and Lee, 2002].

**Neural Network Model**

The model used in this study is the multilayer perception model as shown in Figure 1. This feed-forward
neural network model has more than one hidden layer between the input and output layer, without direct connections between each layer. The input nodes \((L = 6)\) consist of the six parameters mentioned above. The hidden layer has been trained to achieve stable convergence, and the output node \((N = 1)\) present the relative exposure level from 0 to 10. The exposure level was obtained by the interparameter weights, which were determined by the neural network as shown in Equation 1. In the other words, we obtained the nonlinear mapping function using the neural network. However, since the exposure levels heavily depend on the weights shown in Table 1, we need to update the weights in Table 1 whenever the new research results are available

\[
\text{Level of exposure} = f(W \times p + b)
\]  

(1)

\(W\), weight obtained by neural network training; \(p\), input (factors influencing the SAR exposure, \(1 \sim 6\)); \(b\), input bias.

Before executing the neural network training, the expected output of the previously chosen input was defined. An exposure level of 10 was determined when all the parameters were at the highest level of exposure. For example, an exposure level of 10 is twice much exposed than a level of 5, but this does not mean that incident probability of cancer is twice. Table 1 shows the weight of each factor used for the neural network training. The weights of the factors such as hands-free, phone type, and antenna were determined based on the published literature [www.cancer.gov; Choi et al., 1992; Kim, 1997].

Considering every possible case for each factor, 800 cases were possible in this study \((5 \times 5 \times 2 \times 4 \times 2)\). The training set was established by combining all the possible cases. The six parameters of Table 2 were used as input layers of the neural network and the sigmoid function was used for decision function. The nonlinear decision function was chosen to determine the exposure level from 0 to 10 for the output layer.

Table 2 shows some of the data from 800 cases that were used in training the neural network. The exposure levels in Table 2 were calculated by multiplying the corresponding weight of each factor in Table 1 by 10. These values were used in the training process of the neural network. For example, the exposure level of the first case in Table 2 becomes 10 because all the weights of the factors are 1.0 (from Table 1) and are multiplied by 10. Each factor and its weight can be easily modified in the developed software in order to update new study results, and the new interfactor weights will be determined after going through the training of the neural network again.

RESULTS

Figure 2 shows the error convergence of 300 trainings using the developed neural network. The convergence is affected by the number of hidden layers

### TABLE 1. Weight of Each Parameter Used to Estimate RF Exposure Level

<table>
<thead>
<tr>
<th>Usage/day (hour)</th>
<th>Usage period (year)</th>
<th>Hands-free</th>
<th>Antenna extrac.</th>
<th>SAR (W/kg)</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>2≤</td>
<td>1</td>
<td>1</td>
<td>No</td>
<td>1.6</td>
<td>Flip</td>
</tr>
<tr>
<td>&lt;2.0</td>
<td>0.88</td>
<td>&lt;7</td>
<td>Yes</td>
<td>0.5</td>
<td>&lt;1.6</td>
</tr>
<tr>
<td>&lt;1.5</td>
<td>0.63</td>
<td>&lt;5</td>
<td>0.57</td>
<td>Yes</td>
<td>0.1</td>
</tr>
<tr>
<td>&lt;1.0</td>
<td>0.38</td>
<td>&lt;3</td>
<td>0.29</td>
<td>Yes</td>
<td>0.5</td>
</tr>
<tr>
<td>&lt;0.5</td>
<td>0.13</td>
<td>&lt;1</td>
<td>0.07</td>
<td>Yes</td>
<td>0.0</td>
</tr>
</tbody>
</table>

### TABLE 2. Example of Training Data for the Neural Network

<table>
<thead>
<tr>
<th>Usage/day (hour)</th>
<th>Usage period (year)</th>
<th>Hands-free</th>
<th>Antenna extraction</th>
<th>SAR (W/kg)</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.0</td>
<td>7</td>
<td>No</td>
<td>No</td>
<td>1.6</td>
<td>Flip</td>
</tr>
<tr>
<td>2.0</td>
<td>7</td>
<td>No</td>
<td>No</td>
<td>1.4</td>
<td>Flip</td>
</tr>
<tr>
<td>2.0</td>
<td>5</td>
<td>No</td>
<td>No</td>
<td>1.4</td>
<td>Flip</td>
</tr>
<tr>
<td>1.0</td>
<td>5</td>
<td>No</td>
<td>No</td>
<td>1.6</td>
<td>Flip</td>
</tr>
<tr>
<td>1.0</td>
<td>5</td>
<td>No</td>
<td>No</td>
<td>1.6</td>
<td>Folder</td>
</tr>
<tr>
<td>0.5</td>
<td>5</td>
<td>No</td>
<td>Yes</td>
<td>1.0</td>
<td>Folder</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>No</td>
<td>Yes</td>
<td>1.0</td>
<td>Folder</td>
</tr>
<tr>
<td>0.5</td>
<td>1</td>
<td>Yes</td>
<td>Yes</td>
<td>1.0</td>
<td>Folder</td>
</tr>
</tbody>
</table>
and nodes, but there have been no optimal solution [Vemuri, 1992]. The number of the hidden layers and nodes used in our model were 1 and 6, respectively. Implementation of the neural network was accomplished by the Levenberg–Marquardt algorithm, which has the fastest training speed using MATLAB 7.0. After the 300th training, errors converge to 0. The time required for the 300th training was 6.7 seconds using a Pentium 4 processor (3.0 GHz, 512 Mb).

Figure 3 shows an example of running the proposed neural network model for the worst input condition. The worst input condition, comprised of factors with maximal weights of 1, was expected to result in exposure level of 10.0. The exposure level of 10.0 was obtained as shown in Figure 3.

Table 3 shows exposure levels determined by the neural network using untrained random inputs. The exposure level with the worst input condition resulted in the maximum of 10.0 for the first row. For the second row, the usage period was reduced to 6 years from 10 years with the remaining factors unchanged, resulting in an exposure level of 9.5. For the third row, usage per day decreased to 1.6 from 2.0 h, resulting in an exposure level of 8.2 and so on. Using the developed neural network, an exposure level can be obtained for any input condition for the six factors.

**DISCUSSION AND CONCLUSIONS**

FDA (Food and Drug Administration), CTIA (Cellular Telecommunications Industry Association) and many other organizations have continuously studied the effects of cellular phones on the human body. Since digital cellular phones have been widely used in recent years, any conclusion can only be considered after sufficient long-term study results have accumulated. In addition, even if RF electromagnetic fields generated by cellular phones prove to have some harmful effects on the human body, it is impossible to prevent people from using cellular phones. Hence, further studies to reduce RF exposure or to investigate

<table>
<thead>
<tr>
<th>Usage/day (hour)</th>
<th>Usage period (year)</th>
<th>Hands-free</th>
<th>Antenna extraction</th>
<th>SAR (W/kg)</th>
<th>Type</th>
<th>Exposure level</th>
</tr>
</thead>
<tbody>
<tr>
<td>2.0</td>
<td>10</td>
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<td>No</td>
<td>2.0</td>
<td>Flip</td>
<td>10.0</td>
</tr>
<tr>
<td>2.0</td>
<td>6</td>
<td>No</td>
<td>No</td>
<td>2.0</td>
<td>Flip</td>
<td>9.5</td>
</tr>
<tr>
<td>1.6</td>
<td>6</td>
<td>No</td>
<td>No</td>
<td>2.0</td>
<td>Flip</td>
<td>8.2</td>
</tr>
<tr>
<td>1.6</td>
<td>6</td>
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<td>No</td>
<td>1.3</td>
<td>Flip</td>
<td>7.1</td>
</tr>
<tr>
<td>1.6</td>
<td>6</td>
<td>No</td>
<td>No</td>
<td>1.3</td>
<td>Folder</td>
<td>4.3</td>
</tr>
<tr>
<td>0.8</td>
<td>4</td>
<td>No</td>
<td>No</td>
<td>1.3</td>
<td>Folder</td>
<td>0.9</td>
</tr>
<tr>
<td>0.1</td>
<td>0.5</td>
<td>Yes</td>
<td>Yes</td>
<td>1.0</td>
<td>Folder</td>
<td>0.0</td>
</tr>
</tbody>
</table>
the effects of RF exposure on the human body should be continued. Under these circumstances, this study aimed to propose a new method to estimate quantitative and relative RF exposure levels using a neural network model.

The following factors were considered but discarded at the beginning of this study: distance between the cellular phone and the head, orientation slope of the phone, urban/rural, ages, sex, and symptom/no symptom, etc. Although the first two factors have scientific basis on exposure level, these were dropped because most people have the same usage pattern. The other four remaining factors were also dropped because of the insufficient scientific basis or difficulty in assigning them appropriate weights.

This neural network model is nonlinear because the weights of the parameters were used for the training and then the weights between the levels of the parameters were determined by the neural network. Therefore, the weights in Table 1 should be updated more scientifically, based on future research, to accurately estimate RF exposure level. In addition, the exposure levels supplied to train the neural network should be updated based on the future research in order to produce more accurate exposure levels.

The significance of this study is not to provide cellular phone users or epidemiologists with relative exposure levels but to propose a new method to estimate exposure levels using a neural network. However, with more scientific relationships revealed between the parameter values and the exposure levels, the neural network model developed in this study can be very useful in providing epidemiologists with exposure assessment and thus exposed and nonexposed grouping useful in providing epidemiologists with exposure levels. In addition, the weights of the parameters were used for the training and then the weights between the levels of the parameters were determined by the neural network. Therefore, the weights in Table 1 should be updated more scientifically, based on future research, to accurately estimate RF exposure level. In addition, the exposure levels supplied to train the neural network should be updated based on the future research in order to produce more accurate exposure levels.

The references of this study are not to provide cellular phone users or epidemiologists with relative exposure levels but to propose a new method to estimate exposure levels using a neural network. However, with more scientific relationships revealed between the parameter values and the exposure levels, the neural network model developed in this study can be very useful in providing epidemiologists with exposure assessment and thus exposed and nonexposed grouping for studies investigating the relationship between exposure levels by cellular phones and brain tumors in the future.

REFERENCES


