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Prediction of burn healing time using artificial neural networks and reflectance spectrometer

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Abstract

Background: Burn depth assessment is important as early excision and grafting is the treatment of choice for deep dermal burn. Inaccurate assessment causes prolonged hospital stay, increased medical expenses and morbidity. Based on reflected burn spectra, we have developed an artificial neural network to predict the burn healing time.
Purpose: Our study is to develop a non-invasive objective method to predict burn-healing time.
Methods and materials: Burns less than 20% TBSA was included. Burn spectra taken on the third postburn day using reflectance spectrometer were analyzed by an artificial neural network system.
Results: Forty-one spectra were collected. With the newly developed method, the predictive accuracy of burns healed in less than 14 days was 96%, and that in more than 14 days was 75%.
Conclusions: Using reflectance spectrometer, we have developed an artificial neural network to determine the burn healing time with 86% overall predictive accuracy.

Keywords: Burn healing time; Artificial neural network; Reflectance spectrometer

1. Introduction

With the widespread practice of early excision and grafting, the accuracy of burn depth assessment has become increasingly important. Evaluation of skin burn depth based on appearance and sensory function is the method most commonly used, but studies have shown that this is often unreliable. Burns that appear to be set to heal spontaneously within 14 days at the time of onset may convert to a full thickness burn in 3–10 days, making diagnosis difficult and the choice of treatment complicated.

Various non-invasive methods, such as thermography [1], laser Doppler [2–8], differential reflectance photometry [9–13], ultrasound [14–16] and optical coherence tomography [17] have been developed to assess the depth of burn injuries. However, their clinical use remains limited due to problems with methodology and accuracy. Based on the premise that reflectance intensity of different optical wavelength ranges represents different degrees of burn, Heimbach et al. used the Burn Depth Indicator method to predict the depth of burn by recording the ratios of red/green, red/infrared, and green/infrared light reflected from the burn wound. In 2000, Leonardi et al. employed near infrared spectroscopy to assess burn injuries. Hsiao et al. also have shown that the degree of burn depth can be estimated online by using the ratio of red and green spectral peaks reflected from the burn wound [18]. However, clinical application of using several specific light frequency ranges to assess burn depth has not gained widespread clinical acceptance. The reason may be due to the fact that the details of the frequency ranges may be different for different degrees of burns, even though their averages remain almost the same. Besides, other frequency ranges may also contribute and contain information about burn depth.

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The purpose of this study is to develop a non-invasive objective system for the prediction of burn healing time, based on optical information contained in reflected spectra from visible to near-infrared ranges. We first employed the reflectance spectrometer and computer notebook to setup a spectra acquisition system. As the acquired reflected spectra contains abundant amounts of information, artificial neural networks [19–21] are good pattern-recognition engines and robust classifiers that are used for spectra analysis, picking up specific optical information that signals the difference between burns that heal in less than 14 days and that heal in more than 14 days.

2. Methods

2.1. System

A portable reflective spectrophotometer (SD-2000, Ocean Optics Inc., USA) with a Y-bundle fiber of 600 μm diameter is used for spectral measurement on burn patients. To minimize ambient effect, a dc-regulated light source (AIS-UV-2D, Ocean Optics Inc., USA) is used to provide a stable measurement condition. The schematic diagram of the portable spectral system is shown as Fig. 1. The reflected light is collected by a fiber tip, which was placed near the skin surface with optimal peak intensity from the reading of the spectrophotometer. The recorded spectra are then saved into an individual database for off-line analysis. Both ratio calculation of identified peaks, e.g. red/green, and Artificial Neural Network (ANN) are implemented for comparative purposes. Based on the modular concept of this system, it can be easily integrated and/or modified for clinical applications.

2.2. Subjects

Between August 1, 1997 to January 31, 1999, 47 wounds in 39 patients with less than 20% TBSA burns were studied using a reflectance spectrometer. Data collected from 41 wounds were used to train a neural network for healing predictions. Six wounds in four patients were excluded from the study because their natural course of healing was interrupted by surgical manipulations ($n = 4$), wound infections ($n = 1$), or incomplete follow-up ($n = 1$). Among the 41 wounds, 28 were scalds, 5 were grease contact burns and 8 were flame. Twelve wounds healed spontaneously or were grafted after 14 days, while 29 healed in less than 14 days. The age ranged from 6 to 79 years, and the mean was 26. There were 19 females and 16 males with male to female ratio 1.2:1.

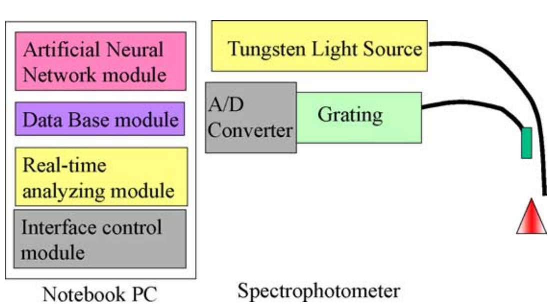

Fig. 1. Schematic diagram of the portable spectral system for burn wound assessment, which consists of a Tungsten light source, a Y-bundle fiber, a spectrometer and the software modules for system operation. In the artificial neural network module, the Radial Basis Function network is used for the advanced spectroscopic analysis. Data base module handles both spatial and temporal patient-related information (spectra and qualitative description). The real-time analyzing module uses ratio of specific peaks of spectra as an index for comparisons. Interface control module sets the commands for data acquisition and peripheral devices.

2.3. Procedures

Reflected burn spectra were taken on the third or fourth postburn day, after the wounds were cleaned and debrided, before the new dressing was applied. Patients were hemodynamically stable, and no wounds had cellulitis or other signs of infection. Standard sedative and analgesic medications were given before the readings were taken. The selection of burn sites was based on: (1) anatomical region easy to recognize for long-term follow-up, such as the dorsum of the hand; (2) indeterminate burn depth.

During measurement, readings were taken at room temperature with patient core temperatures under 38 °C. The spectrometer probe was held about 1 cm from the wounds. Three measurements were taken on each selected wound. The wounds were observed until they healed spontaneously or were grafted. Pictures were taken for documentation.

Wounds were said to have healed spontaneously, when no dressings were needed or a layer of new epithelium could be identified.

2.4. Data analysis

The collected spectra were fed into the computer for data analysis. A Radial Basis Function (RBF) neural network was trained and used to predict the healing time. Background noises were found at peaks of 410, 440 and 545 nm, which were then filtered out by smoothing algorithm. The data were then normalized using ‘‘area norm’’ as shown in the following equation [18]:

$$\hat{X}_i = \frac{X_i}{\sum_{i=1}^{n} X_i} \quad (1)$$

n is total number of sampled wavelength.

A RBF neural network typically has three layers of neurons, which are named as input layer, hidden layer and output layer as shown in Fig. 2. The input layer has a finite number of nodes, which is equal to the number of the sampled wavelength. The normalized spectra data, $\hat{X}_i$, are denoted as the input value of input node, i. The output layer consists of nodes with their output value representing the categories of recognized burn spectral pattern. In our case, we used two output nodes in the output layer to distinguish between those spectra that healed in less than 14 days and

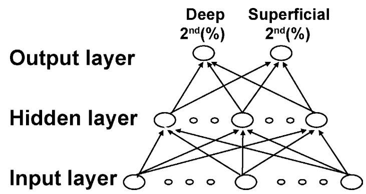

Fig. 2. Schematic diagram of a typical three-layered ANN architecture. Such a network will map the distinguished input spectra to the categories of deep (10) or superficial (01) second deep burn by using a two-bit binary coding format. Each individual input nodes on the input layer receive digitized spectral data with or without normalization. The number of hidden nodes can be optimally determined by cross-validation method and generally correspond to the principal components or factors of the input spectra. The output layer consists of necessary number of nodes for classification. The weighted summation of connection weight and input value of each of the nodes will be subjected to a linear or non-linear transfer function to determine the output value. After the initial learning phase, the connection weight matrixes between input/hidden and hidden/output layers will be used to calculate measured spectra to predict the burn wound state.

that longer than 14 days. The output value of each node in the output layer will range from 1 to 0, which can be viewed as a probability index for clinical evaluation. The hidden layer normally has the same number of nodes as in the input layer. Their state of activity is determined by the weighted summation of all connected input nodes and corresponding connection weights. Due to its inaccessibility to either input or output layer, it was named the hidden layer. The output activity of each individual neuron is governed by a transfer function, e.g. linear or sigmodal function, of its weighted summation input. The difference between actual outputs and expected output provides an error signal for weight update, e.g. an iterative learning process for the training phase. One can then use a trained network with reasonable error index for prediction of untrained spectra by the actual output.

In order to test the performance of this burn depth determination system, the CV method is adopted to calculate the burn spectrum predictive accuracy. The CV method is a general and widely used algorithm for validation of the performance of a multivariate spectra analysis [19]. A full CV procedure requires splitting samples into N groups with each group consisting of only one sample. One of the N samples is kept apart for training purposes, and the remaining groups are used for calibration. Hence, the system trains on all but one of the samples, estimates the burn healing time in that sample, then rotates the test sample back into the general pool and repeats the cycle until all samples have served as an unknown on that subject. In this CV method, this system can be used to evaluate the performance for the burn healing time of spectrum analysis in each unknown sample.

3. Results

Burn spectra from different burn depths were shown as Fig. 3 using Labview user interface computer program. The program includes method of normalization for different spectra and method of spectral characteristic analysis and overlaying of different measurements from reflective spectra in the visible or near infrared region.

The predictive accuracy PA (%) is calculated and used as a performance result of CV method. The calculated equation is

$$\mathrm{PA}\,(\%) = \frac{N_{\mathrm{AP}}\,(\text{accurate prediction})}{N_{\mathrm{Total}}\,(\text{total number})} \times 100\% \qquad (2)$$

Based on the Eq. (2), the CV results show that the PA (%) in burns healed in less than 14 days was 96%, PA (%) in burns

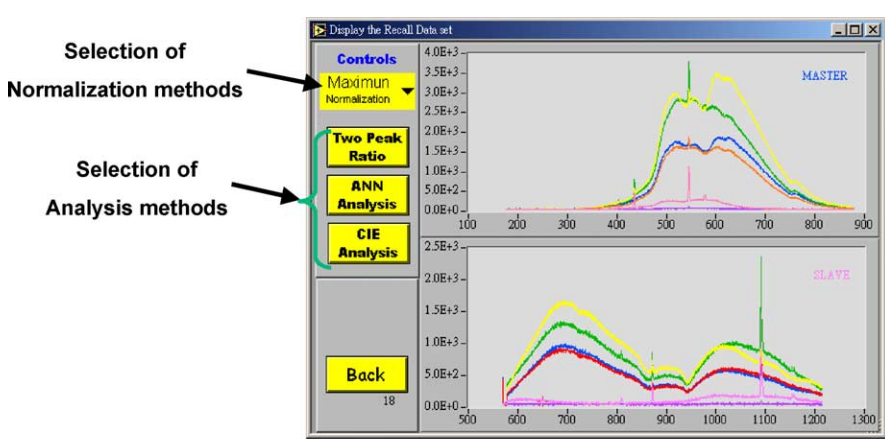

Fig. 3. The user-interface of analysis module. In this diagram, both visible range (Master channel) and near infrared range (Slave channel) of reflectance spectra can be overlaid displayed for direct visualization of the differences between burn wounds. While the visible range of spectra contains the hemoglobin information of blood circulation and color appearance, the near infrared ones might have high correlations with water contents of the wounded areas. The methods of normalization (maximum or euclidean norm) can be chosen to enhance the details of spectra. Quantitative index can be calculated by using different rationales. Ratio of two peaks (e.g red/green) can provide real-time index for quick functional evaluation of the burn wounds. CIE analysis provides the quantitative reflectance color index for evaluation and description. The ANN analysis helps to predict the outcomes of burn wounds based on the learned examples of typical spectra.

Table 1
Results of spectroscopic diagnosis using the RBF in CV analysis

Spectroscopic diagnosis	Observed wound healing time	
	No. of cases healed (>14 days)	No. of cases healed (≤14 days)
No. of cases healed (>14 days)	9	1
No. of cases healed (≤ 14 days)	3	28
Total number	12	29

The sensitivity and specificity are 75 and 97%, respectively. The averaged accuracy is 86%.

healed in more than 14 days was 75%, and the average PA (%) was 90%. Table 1 shows the RBF results.

4. Discussion

ANNs are mathematical models that simulate some of the biological properties of nervous systems. This information processing system is composed of a large number of highly interconnected processing elements that are analogous to neurons and are tied together with weighted connections that are analogous to synapses. ANNs can learn through training or exposure to a set of input/output data, as well as clustering of input data by self-organizing. They are able to store knowledge and solve problems that are too complex for conventional technologies. Recent studies have shown that they can provide useful aids to assist physicians in the diagnosis of many diseases. Clinical applications include predictions of the length of hospital stay in burns [22], diagnosis of myocardial infarction [23], in prediction of survival of burn patients [24], breast cancer diagnosis [25], predictions of healing times and risk factors for venous leg ulcers [26], diagnosis of interstitial lung disease on chest radiographs [27], etc. Chen et al. have used artificial neural network and near infrared spectroscopy to predict the drug content and the hardness of intact tablets [28].

Since ANNs are good at pattern recognition, they can be used to classify multivariate spectra. Different degrees of burn injuries may have different reflected spectra pattern. There is an abundance of information contained in the reflected burn spectrum from visible to near-infrared ranges. Some may be significant, while some may not. The process of burn depth classification based on reflected burn spectra is too complex for conventional methods. Thus, in this study, we extended the clinical application of ANNs to the prediction of burn healing time using the reflectance spectrometer.

Our results have shown that the combined use of ANNs and the reflectance spectrometer has an overall accuracy of 86% in the prediction of burn healing time. Although it is better than the direct visual examination that has an accuracy of 50–75% [2,8], this system is less accurate than laser Doppler flowmetry. Studies have shown that the predictive accuracy of burn healing using laser Doppler flowmetry is more than 90% [2,9]. However, it does not mean that laser Doppler flowmetry is much more superior to ANNs and reflectance spectrometer system as a screening tool for personnel unfamiliar with burn depth assessment. This is because laser Doppler flowmetry has a much higher cost and takes a longer measuring time than ANNs and reflectance spectrometer system. Moreover, the former is much more sensitive to motion than the latter.

There are several factors influencing the reflected burn spectra. These include the background light and light source, tissue constituent of a burned skin, surface exudates and the applied antibacterial cream. The background light, the intensity of the light from the testing probe and the distance of the probe from the burn surface may have negative influences on the reflected spectra. These negative influences, however, can be reduced to a minimum by keeping the testing probe 2 mm from the wound and using a constant light power source. It is not necessary to perform the test in the dark in order to cutoff the background light as we found that consistent results may be attained by spectra normalization. In addition, visible regions rather than NIR regions were used in ANNs processing as the former contain more features than latter.

Antibacterial creams, such as silver sulfadiazine and surface exudates may affect the spectral value, as more light is being absorbed during measurements. Thus, wounds should be cleaned thoroughly before measurement.

It is believed that superficial dermal burn may convert to deep dermal burn or full thickness burn a few days after burn. This always makes the burn depth determination at the early burn stage difficult. Burn with depth that is difficult to determine at the early stage of burn may be considered as indeterminate burn. Our previous burn depth study has shown that the accuracy to predict burn that heals in 14 days and that after 14 days on postburn day 3 in experienced burn doctors is about 70%, with 54% sensitivity and 40% specificity. The predictive accuracy is much less in inexperienced doctors. Although 3 weeks has been traditionally used as a cutoff point for graft determination in a burn, physician predictive accuracy on postburn day 3 in determining burns that heal in less than 3 weeks and that after 3 weeks has not been well studied.

Some may argue that it is inappropriate to choose 14 days as the cutoff point in our study. Our reasons of using 14 days as the cutoff point are: first, patients with burns heal after 14 days have a higher risk of developing hypertrophic scar than that less than 14 days, especially in oriental people. Second, it is impractical to use 21 days as the cutoff point in our clinical burn depth study because wounds that were determined to need grafts could still be operated on in less than 3 weeks. Any grafting or debridement before 3 weeks from the injury would definitely affect the results of the study, and it is impractical to have all studied patients be observed for 3 weeks without any surgical interventions even when grafting is essential. Finally, the predictive accuracy of experienced physicians in the determination of burn that heals in 14 days and that after 14 days is far from satisfactory.

It may be true that the study should compare the predictive accuracy of the devices in burn depth determination to that of trained physicians. However, before making comparison with trained physicians, a neural network needs to be trained for reflected burn spectra analysis and its accuracy in burn healing time prediction needs to be determined. As the predictive accuracy of the devices would be trained to its maximum with larger sampling groups, comparison study with trained physicians may not be justified at the early stage of the study.

The determination of the sample site is frequently questioned in burn depth study. In this study, burns were screened by visual examination before selection of sample sites. In the beginning of the neural network training, very superficial burns presenting as homogenous pink moist burns or full thickness burn with leathery dry white appearance were chosen due to their distinct reflected burn spectra differences. As the network has acquired the ability to recognize distinct reflected burn spectra, truly indeterminate burn was then selected for further training in the mid and late stage of the study.

As in most burn depth devices, the main disadvantage of the reflectance spectrometer is that it gives a 1 mm spot measurement. Spot measurement is always an inadequate representation of the burn, especially in a large burn, and when the burn depth is not uniform. However, a screening test by visual examination followed by device measurement on the questionable area may solve the problems.

It is unclear how many samples per burn taken are considered as adequate. The reason for taking three samples per burn in our study is to feed more optical data into the neural network for training. Clinically, it may be true that one measurement on an indeterminate burn is enough for a well-trained neural network.

5. Conclusion

We have developed a non-invasive portable system of neural networks and reflectance spectrometer to predict burn-healing time. The overall predictive accuracy is 86%. The system is good enough to be used as a screening tool for personnel unfamiliar with burn depth assessment, especially in an emergency room, and its efficacy can be improved further with larger sample sizes.

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