TOWARDS APPLYING HYPERSPECTRAL IMAGERY AS AN INTRAOPERATIVE VISUAL AID TOOL

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ABSTRACT

During a surgery, the inevitable presence of blood covering the surgical field demands efforts to keep the area as clean as possible. A new hyperspectral data processing method is being developed to deliver clearer images to the surgeon. The analysis of optical absorption properties of the blood and water indicates that, between the visible and near infrared spectral regions, some valuable information under the blood laver may be obtained using a spectral imaging system. We propose a neural network approach to provide a nonlinear combination of spectral band reflectance in order to reveal images that could not be seeing with unprocessed images. This paper describes the implementation of single-layer and multi-layer perceptron architectures to perform the hyperspectral data processing. We present experimental results attesting the viability of the proposed method. We demonstrate that hyperspectral imagery can be exploited as visual aid for surgical guidance.

KEY WORDS

Hyperspectral imagery, neural networks, blood, surgical guidance, image manipulation, medical imaging.

1. Introduction

Visual inspection is the most important guide to the microsurgery. Blood covering the surgical field is the largest obstacle to a proper surgical manipulation. It is no exaggeration to say that successful surgery comes from blood-less operating field. The surgeon devotes a lot of time to keep the surgical field clean of blood. If we can see through the blood layer, surgical time might decrease and the result would be better.

Spectroscopy concerns with the measurement and analysis of the electromagnetic radiation reflected or emitted by materials at several wavelengths [1]. Imaging spectrometers have been developed to sample the reflectance spectrum extending from the visible region (λ = 400–700 nm) through the near infrared (λ = 0.7–1.3 µm) to the mid infrared (λ = 1.3–3 µm) in numerous narrow contiguous bands about 10 nm wide. The class of image spectroscopy sensors that is able to acquire hundreds of

bands of information remotely for spectral signature analysis are usually referred as hyperspectral sensors [2]. Advances in sensor equipment technology have led to applications in many different areas.

In the biomedical field, optical spectrometers have been used for pathology sample analysis [3], live cell microscopy [4], non-invasive blood and other fluids analysis [5]. In the field of remote sensing, many algorithms have been developed to extract scene information from spectral images [6], mainly aimed at pixels classification [7], material presence estimation[8], target detection [9] and change detection [10].

Recent works have presented different methodologies to deal with objectives that can be related to ours. W.-C. Lin, et al., proposed a method in [11] to reduce the effect of superficial blood contamination for in vivo tissue diagnosis. The direct ratio of fluorescence and diffuse reflectance was employed as the differential criteria for tissue discrimination. They demonstrated that this ratio, instead of solely the fluorescence spectrum, is less affected by superficial blood contamination for optical spectroscopy, in the range $\lambda = 300-600$ nm. Notwithstanding sharing a similar purpose, we rely only on the spectral reflectance information and from a different wavelength range, generating an enhanced image of the area, instead of a classification index. Another related research was presented by S. Oka and Y. Takefuji in [12]. They presented an image-clustering algorithm based in a self-organizing neural network to produce a RGB image that emphasizes features in satellite hyperspectral images. Their goal is also closely related to ours, to reveal new images that could not be seen in unprocessed images. The difference here lies in the fact that we have a target area to be enhanced, the blood affected area.

In this paper, we present a new medical field application of a hyperspectral imaging spectrograph in the near infrared region. By processing and combining spectral reflectance information from various wavelengths of the spectrum, we envision the possibility of revealing images under the blood that could not be seeing with the naked eye. However, it may be difficult or even impossible to determine *a priori* which bands should be emphasized over others. We propose an artificial neural network (ANN) approach to provide a nonlinear combination of pixel data from different wavelengths in order to reduce the effect of blood spilled over the scene, producing a clearer image of the submerged area. ANNs have been successfully applied to a wide range of applications in remote sensing, medical data analysis and image processing [13].

In section 2, we present the theoretical basis of our research. Section 3 presents a brief description of the methods employed for hyperspectral data acquisition and processing. The design of the ANN architectures is described. Section 4 presents experimental results of the ANNs implemented, along with an empirical performance analysis. Finally, the conclusions and future works are discussed in section 5.

2. Theoretical Background

The optical properties of absorption and transmission of materials are controlled by the electronic, vibrational, and rotational characteristics of the constituent molecules. Basically, the percentage of light transmitted through a medium can be described by Beer-Lambert's law as

$$A = \exp(-\mu_a(\lambda)l) \tag{1}$$

where A is the absorbance, μ_a is the absorption coefficient, dependent on the wavelength λ , and l is the optical path length. The optical absorption properties of tissue in the ultraviolet, visible and near infrared regions are dominated by the absorptions of proteins, DNA, melanin, haemoglobin and water, and have been analysed by Vogel and Venugopalan in [14]. In the case of the blood, haemoglobin and water are the basic components and main chromophores. While haemoglobin dominates the absorption properties in the visible spectrum, as the wavelength value increases, water becomes the principal responsible for absorption. The optical absorption curve of haemoglobin and water in the spectrum is shown in figure 1, based on data gathered by Prahl in [15] and [16].



Figure 1. Optical absorption curves of water and haemoglobin (Hb and HbO₂) in the range $\lambda = 250-2500$ nm

Our method derives from the assumption that there exists a "window", between the visible and near-infrared regions, where the optical absorption of haemoglobin and water would permit to obtain some valuable information under the layer of blood, with the constraint that the layer is thin enough or the light source is powerful enough. Our preliminary practical experiments pointed that this gap would fall approximately in the range $\lambda = 1100-1300$ nm, as can be verified by the spectral reflectance curve of blood-water in figure 6, (c). An absorption curve for whole blood diluted in isotonic saline with a trough in nearly the same spectral region was presented by J.F. Black, et al., in [15].

The blood-water solution presents a nonlinear optical absorption curve and its precise absorbance value at a given wavelength is inherently dependent on the layer thickness and on the haemoglobin concentration. We ponder that the determination of the interesting wavelengths and the data combination to get the image under the blood layer is a nontrivial problem that may require a nonlinear solution.

3. Methodology

The problem of how to find a combination of wavelength data acquired by a hyperspectral sensor that enhances features hidden under a liquid substance poses as a potential target for the flexibility of ANNs. ANNs are computational tools that were developed imitating some functions of the human brain, based on biological concepts borrowed by the artificial intelligence community. ANNs provide a general and practical method for approximating complex nonlinear functions from examples [20].

The mathematical intractability and nonlinearity that characterizes hyperspectral remote sensing features adds up to the notion that ANNs usually provide better results than traditional spectral analysis techniques, besides lacking a comprehensive theoretical explanation relating its problem solving capability and the intricate problem at hand [18].

3.1. Hyperspectral Data Acquisition

We utilized an imaging spectrograph called ImSpector N17, with a range $\lambda = 900-1700$ nm interleaved by 5 nm of distance, producing 161 wavelength bands. It uses a prism-grating-prism dispersive element and transmission optics, which creates a straight optical path that can be combined with a normal CCD camera and lenses [19]. The sensor scans the scene in two dimensions, one containing the spatial line information and other the spectral information. Thus, there is the necessity of moving the object, or the camera, to form the other spatial dimension and produce the three-dimensional data cube.

The experimental data acquisition setup is shown in figure 2. It consists of a light source (halogen lamp) a

computer-controlled table, and the hyperspectral line sensor.



Figure 2. Experimental hyperspectral imaging setup

To calibrate the hyperspectral imaging system, two auxiliary data were acquired in the moment of the experiments: the radiance of a reference white board placed in the scene and the dark current, measured by keeping the camera shutter closed. The raw data was then corrected to reflectance using the following equation:

$$I_{ref} = \frac{I_{raw} - I_{dark}}{I_{white} - I_{dark}}$$
(2)

where I_{ref} is the calculated reflectance value, I_{raw} is the raw data radiance value of a given pixel, and I_{dark} and I_{white} are, respectively, the dark current and the white board radiance, acquired for each line and spectral band of the sensor.

3.2. Neural Network Architectures

At first, a single-layer perceptron was implemented [23], as shown in figure 3.



Figure 3. Single-layer perceptron network scheme

The output of the single-layer perceptron can be expressed as

$$y = g\left(\sum_{i=1}^{m} w_i x_i + b\right) \tag{3}$$

where w represents the synaptic weights of the perceptron, x are inputs applied to the perceptron and b is an external applied bias. The activation function g for the

output unit is a threshold function producing a binary output.

To learn acceptable weights and bias values of a network, a training rule procedure is defined. In supervised learning, training examples of desired network behaviour are provided to the learning rule. Perceptrons are trained in this way, starting with random weights and bias, then performing an iterative process of presenting the training example to the network and making corrections to the network based on the results. This process is repeated, until the misclassification is reduced to a target value. The perceptron training rule is described by the following equation

$$w_i = w_i + \eta(t - o)x_i \tag{4}$$

where w_i is weight associated with the input x_i , t is the target output, o is the actual perceptron output and η is the learning rate.

The other ANN architecture implemented was a multilayer perceptron feedforward network trained by the backpropagation algorithm with momentum, details of the training procedure for this architecture can be found in [21]. A diagram of this ANN architecture is shown in figure 4.



Figure 4. Multi-layer perceptron network scheme

As a pre and post-processing step, we propose to codify the image using a *discrete thermometer encoding*, as described by T. O. Jackson [22], due to the difficulty presented by the neural network in providing a good output generalization when dealing with continuous data such as the pixel image information. In the discrete thermometer encoding, the units are coded to respond over some interval of the input range [u, v]. It is a distributed scheme and a unit is always active if the input values is equal to, or greater than, its interval threshold. The thermometer code can be expressed in the following manner:

$$\begin{vmatrix} a_{1} \\ a_{2} \\ \vdots \\ a_{k} \end{vmatrix} = (+1)iff \begin{cases} x \ge u + \delta \\ x \ge u + 2\delta \\ \vdots \\ x \ge u + n\delta \end{cases}$$
(5)

where *n* is the number of nodes, a_n is the output activation of unit *n*, and δ is the interval size given by (v-u)/n+1.

The hyperspectral data processing by the ANN followed the steps shown in figure 5.



Figure 5. Block diagram of the hyperspectral data processing

First, we discard some bands that present excessive noise and then we manually select the spatial region of the data cube to be used as training (input and target) and test data. Second, each pixel's reflectance value is normalized to fall in the range [-1,1] and serve as input data. Third, the target data is codified using the discrete thermometer scheme. Forth, the ANN is trained until the mean squared error falls to zero or the maximum epoch is reached. The test set is then simulated with the trained ANN. Fifth, the output generated by the ANN needs to be decoded from the discrete thermometer scheme to a desired image format, like binary or 8 bits grey-scale.

Both ANN architectures need 151 input nodes, which is the number of useful channels of our hyperspectral sensor. For the multi-layer perceptron, we utilized rules of thumb to define the number of nodes in the hidden layer as 10.

To produce a binary output using the discrete thermometer encoding, we simply defined the number of nodes in the scheme n = 1. The result is a two level representation of the image, black or white values for each pixel. For this case, only one neuron in the output layer is sufficient.

To generate a grey-scale representation we defined the number of nodes n = 128, thus producing 128 halftone levels. This encoding requires 128 nodes in the output layer to be represented.

4. Experiments

The experiments were performed using the Hyperspectral line sensor to scan the near infrared spectra of a test sample. The hyperspectral data was processed off-line by the ANNs afterwards.

For our preliminary practical experiments, we analysed the spectral data of a solution of blood (70%) and saline water (30%), with approximately 3 mm of thickness, poured in an uncovered Petri dish. As background scene, we utilized a monthly calendar with big numbers. The typical data cube of the scene is presented in figure 6. The optical absorption of the bloodwater solution is very high, allowing reflectance variation in only a small spectral range, as can be observed in figure 6, (c).



Figure 6. (a) Scene data cube with visualization of $\lambda = 1100$ nm. Spectral reflectance curve, in the range $\lambda = 900-1700$ nm, for: (b) the white paper and (c) the blood

4.1. Hyperspectral Image Processing Results

The hyperspectral data cube acquired was applied to both proposed ANNs architectures. In order to evaluate the results, we visually analysed and picked the single band presenting the clearest visualization of the blood-affected area, $\lambda = 1260$ nm. Then we processed the image with conventional techniques of contrast stretching and binary conversion using a threshold. The resulting images of a sample area, around the calendar's number 5 submerged in the blood, are presented in figures 7 and 8.



Figure 7. Comparison of binary images of a sample area after processing: (a) binary conversion using a threshold, image of $\lambda = 1260$ nm; (b) single-layer perceptron output; (c) multi-layer perceptron output



Figure 8. Comparison of grey-scale images: (a) contrast stretched image of $\lambda = 1260$ nm; (b) multi-layer perceptron output

The multi-layer perceptron notably generated the clearest visualization of the calendar's number under the blood. The single-layer perceptron was also able to learn a good visualization but the output presented more noise. The contrast stretching method and threshold binary transformation presented the less distinctive image.

4.2. Empirical Analysis of the ANN Performance

The long-term knowledge of an ANN is stored in the strength of the weighted connections between units. The simplicity of the output equation of the single-layer perceptron allows a verification of its weight vector and an empirical assessment of the problem of band combination, how the wavelengths are automatically weighed by the learning algorithm. The weights configuration of the single-layer perceptron trained is presented in a graphical format in figure 9. This graph shows that bands in the interval from band 41 ($\lambda = 1100$ nm) to 81 ($\lambda = 1300$ nm) really received higher weight values by the learning algorithm, confirming our initial assumption.



Figure 9. Single-layer perceptron weight values referred to each spectral band of the hyperspectral sensor, from band 1 ($\lambda = 900$ nm) to band 161 ($\lambda = 1700$ nm)

To follow the effective learning of the ANN we produced binary images processed by the multi-layer perceptron at several early epochs of the learning process, a montage with the resulting images is shown in figure 10. As weights are set randomly in the beginning, early images generated by the ANN are very noisy, but as the learning steps continue, output images become more and more definite. The stopping criterion to generate the images was 20% decay from the previous mean squared error value. The last image was obtained after the training algorithm had stopped completely.



Figure 10. Composite picture of sample images generated during the training process of the multi-layer perceptron. Training epochs are, from top left, respectively: 1, 67, 138, 214, 294, 383, 563 and 2000

5. Conclusion

Preliminary results in our investigation of combining wavelengths from the near infrared region to visualize images submerged in a blood layer are very promising. The ANN approach performed quite well in the above experimental assessment, attesting the viability of the proposed method. The ANNs proved able to learn how to combine the reflectance data from various spectral bands and generate a clearer image. The multi-layer perceptron presented the best performance and is the architecture of choice for further developments of the method. Still,the single-layer perceptron was also useful, providing a simple and comprehensible verification for the feasibility of the method.

The ANN main advantage is its ability to learn from example and generalize this result to other samples not presented to the ANN yet. Conventional image processing methods usually require an elaborate examination of the hyperspectral data to generate a single image. Nevertheless, ANN presents the difficulty of architecture design, typically a trial and error procedure, and has an intrinsic sensibility to the quality and diversity of the training data set.

The use of hyperspectral imagery to serve as a visual aid tool during surgical procedures demands an online and automatic method. The hyperspectral imaging spectrograph that we have been using represents a shortcoming of our method. Since it is necessary to linescan the image, its practical use is limited yet. Nonetheless, a medical application using a 10-band multispectral camera that acquires two-dimensional images at three frames per second was reported in [24]. Such a system could be tuned to the wavelengths of interest, and be utilized with an adapted version of our method.

We are continuing this research aiming at generating RGB pseudo-colour images and developing an unsupervised version of the method. Future experiments need to be performed to define the limit of thickness until which the blood layer can be seen through.

The results reported in this paper indicate the possibility of exploiting a spectral gap presented by the optical absorption property of a substance in order to generate an enhanced image of the subsurface area. The straightforward application is in the medical field, but extensions of the method to other substances can also be developed and applied to diverse fields such as arts, work of art analysis, and agriculture, remote crop assessment.

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