Towards a Surgical Tool Using Hyperspectral Imagery as Visual Aid

Sildomar T. Monteiro[1], Kuniaki Uto[1], Yukio Kosugi[1], Eiju Watanabe[2]

[1] Department of Mechano-Micro Engineering, Interdisciplinary Graduate School of Science and Engineering, Tokyo Institute of Technology, 4259 Nagatsuda, Midori-ku, Yokohama 226-8502, Japan
{monteiro, uto, kosugi}@pms.titech.ac.jp
[2] Department of Surgical Neurology, Jichi Medical School Hospital, 3,311-1 Yakushiji, Minamikawachi, Kawachi-gun, Tochigi 329-0498, Japan
eiju-ind@umin.ac.jp

Abstract. This paper presents a new application to exploit the capabilities of hyperspectral imagery as a visual supporting tool during surgeries. In order to enhance the visualization of regions affected with spilt blood, a hyperspectral imaging technique has been developed. We propose a neural network approach to nonlinearly combine the wavelengths of the spectrum in order to reduce the effect of spilt blood in an image and produce a clearer image of the concealed area. Preliminary experimental results guinea pigs are presented to validate the method. A sketch of a four-band multi-spectral camera, tuned in wavelengths identified using the learning algorithm, is also presented.

1 Introduction

During a brain surgery, the presence of blood spilt on the surface of the tissue becomes a problem that needs to be tackled properly. It would be very helpful if we can provide the surgeon with a clearer image of the area being treated. An innovative technology has to be introduced to overcome difficulties confronted by conventional image approaches.

In the field of remote sensing, imaging spectrometers have been developed to remotely measure and analyse the electromagnetic radiation of materials, at each wavelength and over a broad spectral band [1]. Hyperspectral sensors, as they are usually referred, can sample the reflective portion of the visible region (0.4-0.7 µm) through the near infrared (about 2.4 µm) in hundreds of narrow contiguous bands about 10 nm wide. Spectrographic analyses have also been applied to medical support, mainly focusing on non-invasive monitoring or pathology detection [2].

We propose a new medical application, by processing and combining images from different wavelengths of the spectrum, we envision the possibility of revealing images under the split blood that could not be seeing with the naked eyes. However, it may be difficult or even impossible to determine *a priori* which bands should be emphasized over others. This problem poses as a potential target for the flexibility and facility of artificial neural networks (ANN). The mathematical intractability and nonlinearity that characterizes hyperspectral remote sensing features adds up to the notion that ANNs can provide better results than traditional spectral analysis techniques.

2 Neural Network

An ANN was designed to extract the relevant information directly from the available spectral channels. The ANN is a common multilayer perceptron feedforward network trained by the backpropagation algorithm with momentum [3].

The ANN architecture is shown in Fig. 1 and needs 150 inputs, the number of available channels of our hyperspectral sensor, and 128 neurons in its output layer that produces a grey scale image as output. The hidden layer comprises 10 neurons, number chosen by rules of thumb. As pre-processing steps, each pixel provided by the sensor as raw data was corrected to its reflectance value and normalized to fall in the range [-1,1].

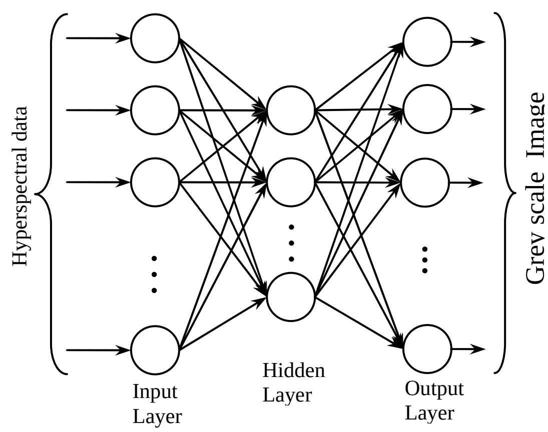

Fig. 1. ANN architecture for the hyperspectral image processing. A multi-layer perceptron network with 150 input channels, corresponding to each wavelength, and one hidden layer

3 Experimental Results

Experiments were performed using a guinea pig and its blood. The blood was diluted in saline water with nearly 50% of proportion. Then a specifically built acrylic box with 0.3 mm thickness top and bottom lids, providing a transparency of approximately 95%, and 3 mm of height was filled with the rats' blood. The data was acquired by scanning the test sample with a near infrared hyperspectral line sensor in the range from 900 to 1700 nm.

Two sets of experiments are presented. First, we utilized a printed-paper with the letters "*Jichi Medical School*" written in black, as shown in Fig. 2.

Fig. 2. Visualization image of wavelength 1100nm, printed-paper and blood layer with 3mm

For this scene, the training set consisted of the half-upper part of the letters *m*, *e* and *d*, as highlighted by the rectangle in Fig. 3a. The image in Fig. 3c is the test set image obtained by generalization of the neural network. A comparison of the processing of the same area using a traditional method of contrast enhancement is presented in Fig. 3b, by manipulating the wavelength 1100nm, that presents the best simple visualization under the blood. Some distortion due to the acrylic box and some reflex of the top lid can be observed. When processed by the neural network, the letters under the blood appear much more clearly.

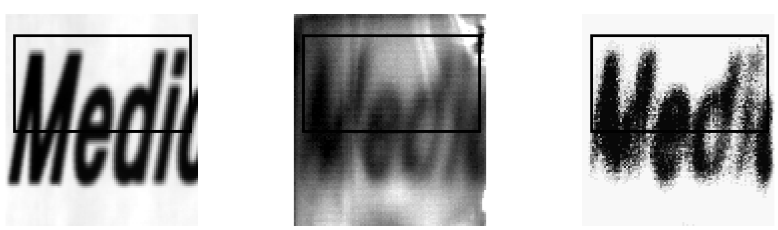

Fig. 3. Printed-paper experiment results. (a) Training set from image without blood. (b) Contrast stretched image of wavelength 1100nm. (c) Neural network output image

Second, the experiment using the guinea pig itself is shown in Fig. 4.

Fig. 4. Visualization image of wavelength 1100nm, guinea pig opened abdomen with viscera shown, covered with a blood layer of 3mm thickness

The training set consisted of the lower part of the area covered with blood, as highlighted by the rectangle in Fig. 5a. As in the printed-paper case, a comparison with a traditional image processing technique is presented in Fig. 5b. Finally, the output of the neural network is presented in Fig. 5c.

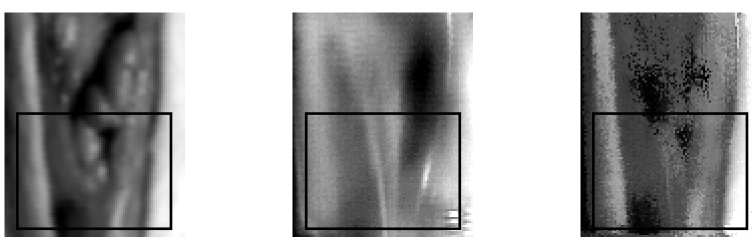

Fig. 5. Guinea pig experiment results. (a) Training set from image without blood. (b) Contrast stretched image of wavelength 1100nm. (c) Neural network output image

This case was harder for the neural network to be trained. Still, it is noticeable that at least the fur and the abdominal cavity can be more clearly distinguished after the neural network processing.

4 Discussion

A plot of the spectral reflectance curve of two distinct regions under the blood, of Fig. 2, and the calculated difference between those measures, is presented in Fig. 6. The difference curve presents highest values in the range from 1000 to 1300nm, but the processing of these wavelengths using traditional methods of linear combination and contrast stretching did not produced good visualizations.

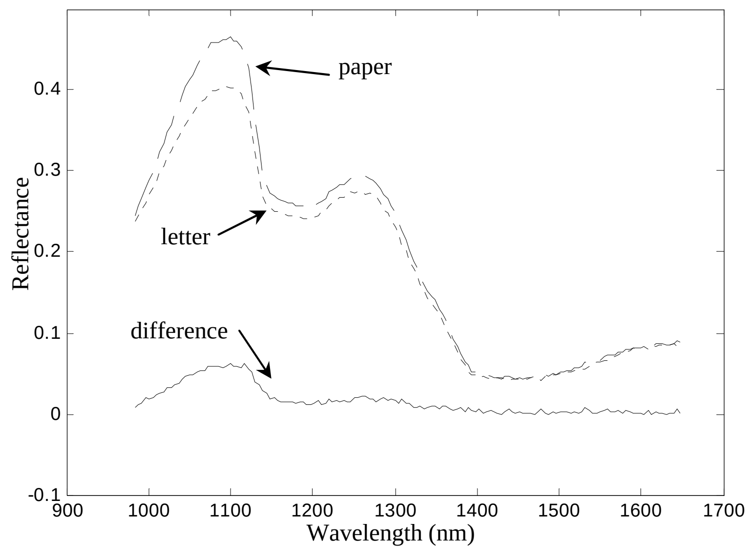

Fig. 6. Spectral reflectance curve of two regions under the blood layer

The assumption of our method is that, in the near infrared spectral region, exists a window of wavelengths where blood-water solution presents lower optical absorbance, which may be used to extract valuable information under the layer of blood. Indeed, by using a neural network approach, we can automatically combine these wavelengths producing a clearer image.

Nevertheless, if the blood and the region of interest are not in physical contact, due to optical limitations, it becomes more difficult to obtain valuable information, even in the wavelengths of greatest transparency of the blood-water solution. This factor may have affected the data acquisition in the guinea pig's experiment, where a small gap between the bottom of the acrylic box and the organs was observed.

In a real situation, during a surgery it is not practical to scan the image with a line sensor. To circumvent this problem, it is necessary to limit the number of wavelength bands in order to allow the design of a multi-spectral camera that acquires two-dimensional images at once. An analysis of the weights configuration learned by a perceptron network trained for the printed-paper case is shown in Fig. 7, following the scheme presented in [4]. The goal is to verify which wavelengths present larger impact on the formation of the image under the blood. An approximation using

Gaussian curves to represent four chosen bands to be optically filtered by a multi-spectral camera is shown over the weights configuration graphic.

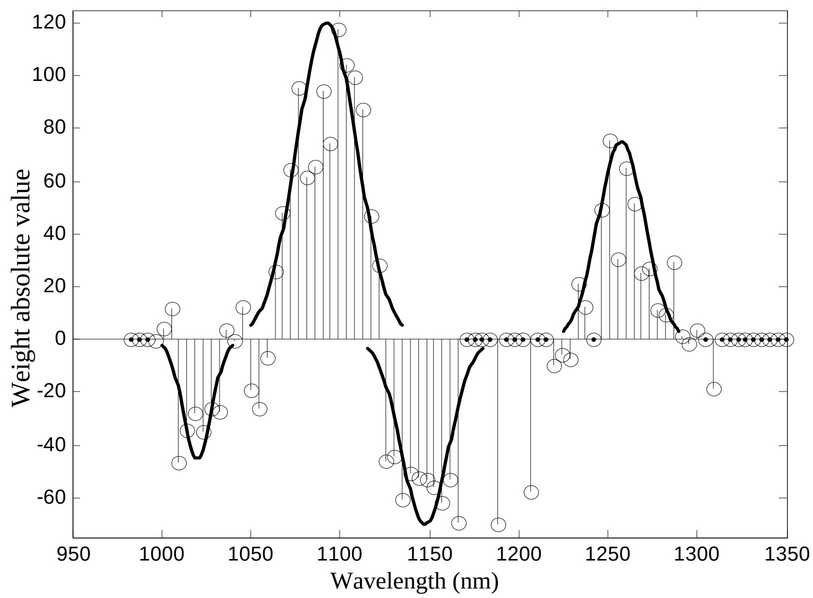

Fig. 7. Weights configuration of a single-layer perceptron trained network for the printed-image with blood case. In darker lines are Gaussian curves of band filters at chosen regions with higher weight values

A preliminary design of such a multi-spectral system is shown in Fig. 8. In this system, four CCDs are coupled to optical filters strategically placed and each filter is tuned in one of the chosen spectral regions.

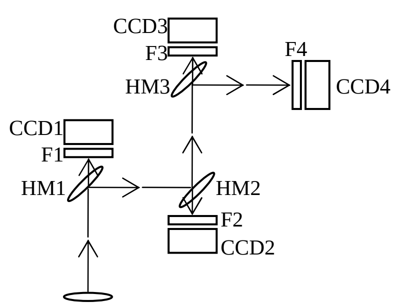

Fig. 8. Design of the four-band multi-spectral system. HMs are half mirrors, Fs are optical filters and CCDs are image acquisition devices

For each pixel (i, j) in the two-dimensional space, the output signal is defined as follows:

$$S_t(i, j) = \sum_{k=1}^{4} W_k S_k(i, j) \ , \qquad (1)$$

where, W_K is the weight value for each band, S_k is the signal acquired for each CCD and S_t is the signal representing the calculated total reflectance data acquired by the camera.

4 Conclusion

The ANN remarkably produced a good visualization of the image under the blood. The viability of utilizing imaging spectrometers to visualize images under the cloak of a blood-water solution was attested, with great potential for medical applications. The next step in this research will be to fine-tune the wavelength band range of the filters to be used in the designed multi-spectral camera.

References

1. Mather, P.M.: Computer Processing of Remotely-Sensed Images, An Introduction, John Wiley & Sons, Chichester (2004)
2. BoasD. A.: Diffuse Photon Probes of Structural and Dynamical Properties of Turbid Media: Theory and Biomedical Applications, PhD thesis, University of Pennsylvania, (1996)
3. Bishop, C. M.: Neural networks for pattern recognition, Oxford University Press, NY (1995)
4. Monteiro, S. T., Kosugi, Y., Uto, K., Watanabe, E.: Towards Applying hyperspectral Imagery as an Intraoperative Visual Aid Tool, Proc. 4th International Conference on Visualization, Imaging and Image Processing, Marbella, Spain (2004)