Non-Invasive Optical Imaging Techniques for Burn-Injured Tissue Detection for Debridement Surgery

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Abstract

Burn debridement is a challenging technique that requires significant skill to identify regions requiring excision and appropriate excision depth. A signal processing technique to develop an intraoperative burn surgery assist device (DeepView™ Wound Imaging System, Spectral MD, Dallas, TX) is presented. The viable wound bed, which must be exposed to allow for skin grafting, is distinguished from other types of tissues. The input metrics are based on three main sets of features: photoplethysmography (PPG) features, which identify pulsatile blood flow in the skin’s microcirculation; real image (RI) features, taken from a black-and-white photograph of the injury; and multispectral imaging (MSI) features, which collects the tissue reflectance spectrum of the light. Tissue classification is performed using quadratic discriminant analysis (QDA). This tool is being developed in order to assist surgeons by providing a quantitative assessment of burn-injured tissue. The system has been tested on sample wounds from pigs (Fig. 3). The results of this testing are reported.

Relevance & State of the Art

Spectral MD™’s technology uses a non-invasive modality to assess the health of burns. Clinical research to date has provided images for physicians to research the healing processes before their impact is fully discernable at the skin’s surface. The ultimate goal is to discover new information that can reduce patient stays, recovery times, and provider costs.

DeepView™ Imaging System Background

The DeepView™ imaging system is a portable device, becoming a suitable alternative to imaging studies that require patients to travel to different buildings for assessment. The system is formed by a computer that processes in real-time data provided by a camera [2]. Figure 2 shows different uses of the system.

Classifier

Quadratic Discriminant Analysis (QDA) [3] is a popular classification algorithm for machine learning applications. A set of features per pixel is required. They are calculated based on the output of the DeepView™ imaging process in combination with the real image and the multispectral images. In order to generate supervised learning training data, a burn specialist analyzed the injury sites and decided the status of each area of tissue. This data was used to separate the image data into classes corresponding with each tissue type. We have six tissue classes in total: healthy, excised, hyperemia, blood burned, and shallow burned. Figure 4 shows an example in 2D of the separation in regions for 4 classes. For the classification, we are given a set of features of an unknown class, denoted by a vector \( x \).

\[
\delta_k(x) = -\frac{1}{2} \log |\Sigma_k| - \frac{1}{2} (x - \mu_k)^T \Sigma_k^{-1} (x - \mu_k) + \log(p_k) \tag{1}
\]

The classification criterion is then that the unknown belongs to the class that has the maximum \( \delta_k \) shown by equation (2).

\[
G(x) = \arg \max_k \delta_k(x) \tag{2}
\]

Figure 3. Simplified diagram of the DeepView™ algorithm.

Figure 4. Example of the performance of the QDA for separating 4 classes. Continuous non-linear lines indicates the boundary regions. QDA separates the classes more accurately than linear discriminations.

Results

We have trained and tested our system on a series of DeepView™ system results for injury sites on pigs. The data we have pertains to two pigs, each with six injury sites. Each site was captured twice at each of the following stages: pre-injury, post-injury, first excision, second excision and third excision, giving 120 total cases for training and testing. Figure 5 shows sample results of our classification, performing cross-validation, comparing with the original Ground Truths (GTs). We have incorporated some pre-processing algorithms to increase the accuracy of the classifier. A post-processing methodology based on the mode of a small neighborhood helps to reduce small misclassifications and to increase the total accuracy of the global performance.

Conclusions

1. Definition of new features to help improve the classification efficiency.
2. Further testing with a larger sample size of pigs and ultimately switch to data from human samples.
3. Investigation of further pre-processing and feature calculation to compensate for varying lighting conditions from case to case.
4. Post processing algorithms to establish confidences on each classified pixel.

Future Work

1. Development of new features to improve the classification efficiency.
2. Testing with a larger sample size of pigs and ultimately switch to data from human samples.
3. Investigation of further pre-processing and feature calculation to compensate for varying lighting conditions from case to case.
4. Post processing algorithms to establish confidences on each classified pixel.

References