# Feature Extraction of Hyperspectral Data for under Spilled Blood Visualization Using Particle Swarm Optimization

S. T. Monteiro[1*], K. Uto[1], Y. Kosugi[1], N. Kobayashi[2], E. Watanabe[2], K. Kameyama[3]
[1]Department of Mechano-Micro Engineering, Tokyo Institute of Technology, Japan
[2]Department of Surgical Neurology, Jichi Medical School Hospital, Japan
[3]Tsukuba Advanced Research Alliance, University of Tsukuba, Japan
*monteiro@pms.titech.ac.jp

*Abstract*—**In this paper, an intraoperative application of a particle swarm optimization based feature extraction algorithm for hyperspectral imagery data visualization is proposed. The objective of the algorithm is to extract the features that generate the best visualization of an area covered by blood. The proposed method uses a binary version of a particle swarm optimizer to select a subset of band wavelengths in the near-infrared region, in which the optical absorption characteristics of blood allows some visual information to be extracted. A linear image transformation is subsequently applied to the selected features. Two transformation equations were tested, for the selection of three and four bands. The transformed image was then evaluated using four different fitness criteria: entropy, Euclidean distance, contrast and correlation. We present experimental results using human blood and an artificial background to validate the method and assess the fitness functions. The entropy better evaluated the amount of visual information under the layer of blood. The four-bands transformation produced higher fitness values and better visualization. The enhanced images of the extracted features revealed good visualizations under the layer of spilled blood.**

*Keywords*— **Biomedical imaging, feature extraction, hyperspectral imagery, particle swarm optimization**

## I. INTRODUCTION

The hindering effect of blood spilled over a scene during a surgery is a problem that requires time-consuming efforts by the surgeon to keep the area clean of blood. We had successfully demonstrated the possibility of exploring a spectral interval of less blood optical absorbance in the near-infrared region of the spectrum to generate visualizations under the layer of blood [1]. The final goal is to obtain a visualization of blood-covered areas that cannot be seen in the visible region.

Hyperspectral imaging systems are able to acquire several hundreds of spectral information from the visible to the infrared region. Nevertheless, neighbouring image bands are usually highly redundant. To avoid the curse of dimensionality that affects these kinds of data sets, feature extraction algorithms have been proposed to reduce the amount of data and at the same time keep the relevant information necessary to image interpretation or classification. In the remote sensing field, several approaches of feature extraction of hyperspectral data have been developed but mainly aimed at improving or preserving classification accuracy [2].

Particle swarm optimization (PSO) is a very promising evolutionary computation technique that had been developed recently for solving nonlinear optimization problems [3]. PSO's main attractiveness is its simplicity and velocity allied with robustness. PSO has similar capabilities as genetic algorithms but has the advantage of simpler implementation and reduced bookkeeping. Typically, PSO is able to solve most optimization problems, or problems that can be converted to optimization problems. PSO has been successfully applied to feature selection for quantitative structure-activity relationship correlation [4]. Nonetheless, the problem to define the target function to be optimized is highly dependant on the application at hand.

In this paper, we present a new approach for feature extraction of hyperspectral data based on PSO. The goal of our method is to extract optimal bands of hyperspectral imagery data that better represents the information under a layer of blood in order to produce a better visualization of the covered area. We present experimental results with real data sets of hyperspectral images acquired in the medical field. We investigate two types of data transformation applied to four different information content metrics.

## II. METHODS

### A. Feature Extraction

Feature extraction methods transform the original feature bands to new feature space. Feature selection is a subtype of feature extraction where the dimensionality reduction is achieved by selecting bands rather than transforming the data. Feature selection can be implemented as an optimization procedure of search for an optimal subset of bands that better satisfy a desired measure. We propose to combine a feature selection algorithm with an image data transformation and use appropriate fitness evaluation functions. Our method has three phases, as presented in Fig. 1. Firstly, the optimization algorithm selects a determined number of features (band wavelengths). Then, the selected features are transformed using an image combination equation. The transformed image is then evaluated. The process is repeated until convergence (stopping criterion is same fitness value repeated over a long period).

### B. Binary PSO

The basic PSO algorithm starts with a population of random particles, from where the name "particle swarm" is derived [5]. Each particle in PSO is associated with a velocity. Particles' velocities are adjusted according to the historical behaviour of each particle and its neighbours while they fly through the search space. Therefore, the particles

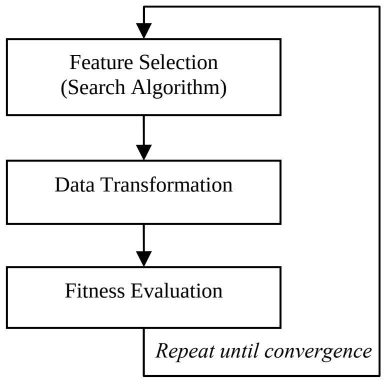


Fig. 1. Diagram for Hyperspectral Imagery Data Feature Extraction Algorithm.

have a tendency to fly towards the better and better search area over the search process course.

The PSO algorithm is described as follows:

$$v_{id} = w \cdot v_{id} + c_1 rand()(p_{id} - x_{id}) + c_2 Rand()(p_{gd} - x_{id}) \tag{1}$$

$$x_{id} = x_{id} + v_{id} , \tag{2}$$

where $c_1$ and $c_2$ are positive constants called learning rates, *rand()* and *Rand()* are two random functions in the range [0, 1], and $w$ is a inertia weight. The symbol $g$ represents the index of the best particle among all the particles in the population. $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ represents the $i^{th}$ particle and $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ represents the best previous position of the $i^{th}$ particle. $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ represents the rate of the position change (velocity) for particle $i$. In (1), if the sum of the factors in the right side exceeds a specified constant value, particles' velocities on each dimension is then clamped to a maximum velocity $V_{\max}$.

To realize the feature selection, the PSO concept needs to be extended in order to deal with binary data. The feature selection search utilizes a binary scheme where each feature is represented by one bit of the particle. If the feature is selected its value is set to 1, if it is not used, it is set to 0.

The subset of features are determined using a roulette wheel selection. At each spin of the roulette, the wheel's marker will point to the selected feature. The roulette is played until the desired number of features is reached. Each feature is assigned with a probability $p_{id}$ proportional to the real value calculated in (2), limited to the interval [0, 1], according to the equation:

$$p_{id} = \frac{x_{id}{}^{\alpha}}{\sum_{d=1}^{n} x_{id}{}^{\alpha}} , \tag{3}$$

where $\alpha$ is the selection pressure, controlling the probability of selecting highly fit or less fit features.

At each generation of particles, the selected bands are linearly combined and its fitness assessed using a target function. This will determine the best global and local particles for the next generation.

### C. Image Data Transformation

We propose two types of linear combination of selected bands. The first is a simple linear combination of three band wavelengths in which all bands have the same weight in the formation of the final image. The output intensity $q$, for each pixel *(i, j)* of $k$ selected images $\lambda_k$ , is calculated as

$$q_{ij} = \tfrac{1}{3}\lambda_1 + \tfrac{1}{3}\lambda_2 + \tfrac{1}{3}\lambda_3 . \tag{4}$$

The second method uses an empirical transformation in which different weights are assigned for the selected bands, derived from the results of [6], aiming to enhancing the visualization under the blood. The transformation is expressed, using the same symbols described above, by the following equation:

$$q_{ij} = -0.4\lambda_1 + 1.2\lambda_2 - 0.6\lambda_3 + 0.8\lambda_4 . \tag{5}$$

### D. Fitness Metrics

We assessed four different metrics in order to provide a quantitative measure of the extracted band's information content. During the search procedure, the criteria are maximized.

*1) Information Entropy:* The entropy estimates the amount of information in the image [7]. The information entropy measure $S$, of an image $\lambda$ is defined as

$$S(\lambda) = -\sum_{k=1}^{m} p(I_k) \ln p(I_k) , \tag{6}$$

where $p$ is the probability distribution function of the image's intensity value $I(\lambda)$ estimated via histogram for each bin $k$, and $m$ is the number of bins used.

*2) Euclidean Distance:* The Euclidean distance measures the resemblance of pairs of points in a feature space [8]. The distance $d$ between two points $x_1$ and $x_2$ can be defined as

$$d(x_1, x_2) = \sqrt{\sum_{i=1}^{n} (x_1 - x_2)^2} , \tag{7}$$

where the points are measured on $n$ axes or features.

The next two metrics are texture features calculated from the grey level coocurrence matrix [9], which represents the relative frequency of occurrence of two pixels with grey levels $i$ and $j$ in an image, in the neighborhood of two pixels separated by a distance $d$ in a given direction $\theta$. Given the total number of grey levels $Ng$, the matrix is expressed as a symmetrical matrix whose values are calculated as

$$p(i,j) = \frac{P(i,j)}{\sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} P(i,j)} . \tag{8}$$

*3) Contrast:* The contrast texture is a measure of the spatial frequency of grey levels in the neighborhood, expressed by

$$C = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} (i-j)^2 \, p(i,j) \,. \qquad (9)$$

*4) Correlation:* The correlation texture measures how linear dependent are the grey levels in the neighborhood, can be calculated as

$$C = \sum_{i=0}^{Ng-1} \sum_{j=0}^{Ng-1} \frac{(i-\mu_i)(j-\mu_j)\, p(i,j)}{\sigma_i \sigma_j} \,, \qquad (10)$$

where $\sigma$ is the standard deviation and $\mu$ is the mean.

## III. Results

### A. Hyperspectral Imagery Data Acquisition

The hyperspectral data is acquired using an ImSpector N17 imaging spectrograph. The sensor scans the scene in two dimensions, one containing the spatial line information and other the spectral information. The data set comprises 160 bands in the near infrared region of the spectrum, with wavelengths ranging from 900 to 1700 nm, interleaved by 5 nm interval between bands. The hyperspectral data acquired by this kind of sensor is composed by spatial and spectral information that is usually described as a data cube. Fig. 2 presents the data cube with a sample visualization of the band 1100 nm of a scene of blood-water solution, with approximately 3mm of thickness, put in a Petri dish with a calendar sheet as background.

### B. Feature Extraction

The algorithms were implemented using Mathworks' Matlab software and tested on a Pentium 4, 1.8 GHz, with 1GB of RAM. The results presented in this section are the average of 10 runs of each algorithm. The stopping criterion was 30 epochs without change on the fitness value, meaning convergence reached or stuck in local maxima. Redundant processing was avoided by maintaining a lookup table with previously calculated fitness of selected feature combinations.

In all experiments, some of the binary PSO parameters are the same. The chosen values are not intended to be optimal but only to provide a reasonable compromise between exploration and convergence of the algorithm. The learning rate is $c_1 = c_2 = 1$. The inertia is $w = 0.9$. The selection pressure is $\alpha = 0.5$; this value is set to a value less than 1 to promote exploration.

In the Euclidean distance calculation, two areas under the layer of blood were pre-selected to serve as criteria, one corresponding to a white-paper area, and, the other one, an area containing the black-printed number. A median filter was then applied to the pixel values and the Euclidean distance was calculated with the resulting values.

In the calculation of the grey level coocurrence matrix, the distance and angles are $d = 2$ and $\theta = (45°, 135°, -135°, -45°)$. The contrast and correlation results are the mean values of the calculated directions.

*1) Three Features:* In this case, the population size of the binary PSO was 50. Table I summarizes the results of the experiments for the selection of three features. Fig. 3 presents the resulting images for each fitness function. The visualization was obtained by contrast stretching of the image's liner combination of the three selected wavelengths.

*2) Four Features:* In this case, we increased the population size of the binary PSO to 80, to improve the exploration and reduce probability of being stuck in local maxima. Table II summarizes the results of the experiments

TABLE I
THREE FEATURES EXTRACTION

| Function | Features [a] | Fitness [b] (Hits) | Time [c] (Epochs) |
|---|---|---|---|
| *Entropy* | 1270, 1275, 1280 | 3.5930 (10) | 58 (46) |
| *Euclidean* | 1260, 1265, 1285 | 0.03588 (8) | 46 (44) |
| *Contrast* | 1265, 1270, 1275 | 0.17089 (10) | 119 (47) |
| *Correlation* | 1255, 1260, 1265 | 0.55656 (7) | 99 (47) |

[a] Selected band wavelengths, in nanometers.
[b] Maximum fitness value reached over 10 runs; and number of times this result was obtained.
[c] Average computation time until stopping criterion reached, in seconds; and number of epochs until convergence.

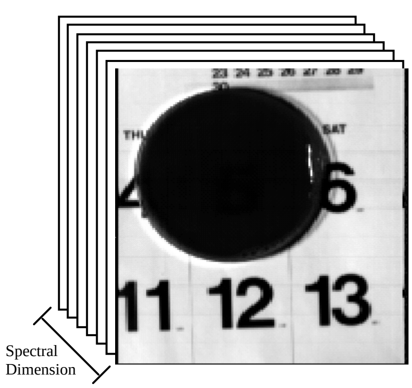


Fig. 2. Hyperspectral image data cube with visualization of the band wavelength 1100 nm.

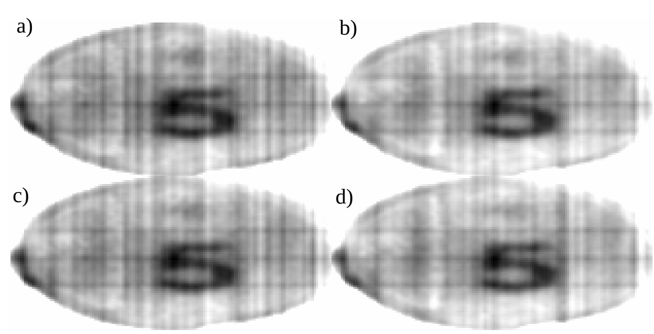


Fig. 3. Blood area visualization of the transformation of three selected bands. a) Entropy; b) Euclidean distance; c) Contrast; and, d) Correlation.

for the selection of four features. Fig. 4 presents the visualization after contrast stretching of the linearly combined image of the four selected wavelengths.

## IV. Discussion

The three-features selection process tends to choose groups of bands in the neighborhood of the band wavelength 1270nm, for each given fitness function. This spectral region is exactly the region where the blood-water solution presents less optical absorbance. Still, the selected bands are too spectrally close and, thus, highly correlated.

Using a more elaborated transformation, the four-features selection process was able to sample wavelengths that are more distinct. The result is a more rational use of the available spectral information, and an increase in the maximum fitness value for all functions.

To a human observer, there is little visual distinction between the transformed outputs. Indeed, the band wavelengths selected, in order, by the different fitness functions are spectrally close among then, thus the combined image visualization being very similar.

The information entropy function outperformed the other metrics as discriminating criterion for feature selection. Entropy presented a performance more stable and robust between different runs of the experiments, allowing the selection of the optimum set of features more times than the others criteria.

The Euclidean distance closely followed the entropy performance. Its output visualization is slightly clearer than the others' output, notably for the four bands transformation case. Nevertheless, in our proposed approach, it has the disadvantage of requiring a previous knowledge of the image's content to be calculated.

TABLE II
FOUR FEATURES EXTRACTION

| Function | Features [a] | Fitness [b] (Hits) | Time [c] (Epochs) |
|---|---|---|---|
| *Entropy* | 1000, 1130, 1155, 1285 | 4.2567 (9) | 193 (60) |
| *Euclidean* | 1050, 1120, 1160, 1260 | 0.05939 (8) | 190 (59) |
| *Contrast* | 1110, 1135, 1185, 1240 | 0.25328 (2) | 291 (55) |
| *Correlation* | 1080, 1125, 1235, 1250 | 0.80915 (2) | 258 (50) |

[a] Selected band wavelengths, in nanometers.
[b] Maximum fitness value reached over 10 runs; and number of times this result was obtained.
[c] Average computation time until stopping criterion reached, in seconds; and number of epochs until convergence.

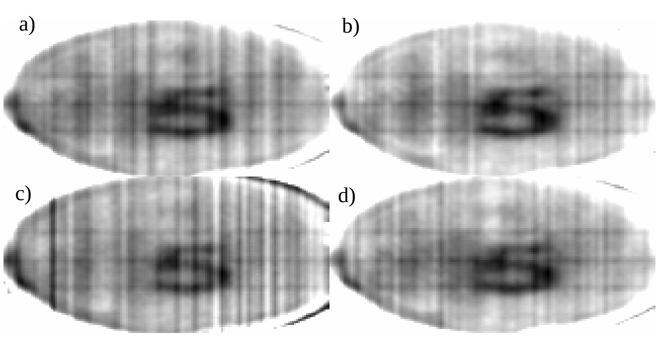


Fig. 4. Blood area visualization of the transformation of four selected bands. a) Entropy; b) Euclidean distance; c) Contrast; and, d) Correlation.

## V. Conclusion

The binary PSO demonstrated to be efficient on the search for the optimum set of bands. The image output generated by the combination of selected features produced a good visualization of the calendar's number covered by blood. The main benefit of the feature extraction procedure is the obvious reduction in the time required for subsequent image processing, owing to the reduction in the amount of data. The proposed method of feature extraction using PSO has the advantage of fast implementation and requires reasonable processing time.

The information entropy provided the most robust overall assessment. Nevertheless, all four fitness function assessed proved capable of evaluating the amount of information available under the layer of blood.

The image transformation equation has a great impact on the determination of the output visualization. The next step in this research will be to design new experiments in order to optimize not only the selected band wavelengths but also the transformation equation coefficients.

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