Applying Particle Swarm Intelligence for Feature Selection of Spectral Imagery

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Abstract

Feature selection is necessary to reduce the dimensionality of spectral image data. Particle swarm optimization was originally developed to search only continuous spaces and, although many applications on discrete spaces had been proposed, it could not tackle the problem of feature selection directly. We developed a formulation utilizing two particles swarms in order to optimize a desired performance criterion and the number of selected features, simultaneously. Candidate feature sets were evaluated on a regression problem modeled using neural networks, which were trained to construct models of chemical concentration of glucose in soybeans. We present experimental results utilizing real-world spectral image data to attest the viability of the method. The particle swarms approach presented superior performance for linear modeling of chemical contents when compared to a conventional feature extraction method.

1. Introduction

Spectral imaging devices capable of acquiring several hundreds of spectral images from the visible to the infrared region of the spectrum are commonly referred to as hyperspectral sensors. Nonetheless, neighboring spectral bands are usually highly redundant [11]. In real-world applications, the typical scenario of few data samples in a high-dimensional feature space causes what was termed by Bellman [2] as the curse of dimensionality, referring to the exponential increase in complexity of high-dimensional spaces with the increase in the number of measurements. To avoid the curse of dimensionality, algorithms for feature extraction/selection have been proposed to reduce the amount of data and, at the same time, keep the relevant information necessary to image interpretation or classification [6].

Particle swarm optimization (PSO) is an evolutionary computation technique that has been developed due to research on bird flock simulation by Kennedy and Eberhart [8]. The PSO algorithm is able to solve most optimization problems, or problems that can be converted to optimization problems. PSO's main attractiveness is its simplicity and velocity, allied with robustness. The application of PSO to process hyperspectral data is appealing due to the capability to visualize the location of particles' positions in the search space. Since each spectral dimension corresponds to one band wavelength, the location of the particles' positions may be useful to identify interesting characteristics of the physical process associated with the induction algorithm.

Different approaches for feature selection using PSO have been reported [5, 10]. Nevertheless, the search is commonly limited to a pre-defined number of features, which can be difficult to determine a priori for many problems. In addition, the question of how to define the target functions to be optimized may be highly dependent on the problem at hand.

In this paper, we present a method for spectral band selection based on PSO. A method using two particle swarms and an aggregated function is proposed to solve a two-criterion optimization problem. We developed a method to select optimal spectral bands from hyperspectral data applied on a regression problem in the remote sensing field. Neural networks were implemented to learn models of glucose content in soybeans. Experiments were carried out using real-world hyperspectral datasets from soybean fields.

2. Feature Selection Algorithm

Feature selection is a subtype of feature extraction where the dimensionality reduction is achieved by selecting bands rather than transforming the data [9]. Feature selection methods are advantageous when the user needs to make decisions based on meaningful features of the original data, or if he or she wants to exclude non-necessary data components to reduce the cost and labor of data acquisition. Thus, feature selection is highly suitable to hyperspectral imagery analysis, in which the data is intrinsically related to physi-

cal wavelengths, and not all spectral bands are always necessary for a certain application.

Assume that the hyperspectral imagery data matrix I is composed of n spectral images $I(\lambda)$, $(\lambda = 1, \ldots, n)$, at each wavelength band λ acquired by the sensor. The aim of feature selection is to find a set of m bands, where $m < n$, to minimize the evaluation criterion.

Feature selection can be implemented as an optimization procedure of search for the optimal feature set that better satisfy a desired measure. We propose a method, as shown in Fig. 1, utilizing two swarms of particles to optimize simultaneously the number of selected features and the error of the model. Each candidate feature set is evaluated by observing its performance on a regression problem. The induction algorithm is a neural network utilized to construct regression models.

2.1. Particle Swarm Optimization

The PSO algorithm performs optimization in continuous, multidimensional search spaces. PSO starts with a population of random particles, from where the name "particle swarm" is derived. Each particle in PSO is associated with a velocity. Particles' velocities are adjusted according to the historical behavior of each particle and its neighbors while they fly through the search space. Therefore, the particles have a tendency to fly towards the better and better search area over the search process course.

The basic PSO algorithm [13] can be described mathematically by the following equations:

$$v_{id}^{t+1} = w v_{id}^{t} + c_1 r_1^t (p_{id}^t - x_{id}^t) + c_2 r_2^t (p_{gd}^t - x_{gd}^t) \quad (1)$$

and

$$x_{id}^{t+1} = x_{id}^t + v_{id}^{t+1} \ , \quad (2)$$

where c_1 and c_2 are positive constants, called learning rates; r_1 and r_2 are random functions in the range $[0, 1]$; w is an inertia weight; $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ represents the position of the i^{th} particle in a problem space with D dimensions; $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$ represents the rate of change of position (velocity); $P_i = (p_{i1}, p_{i2}, \ldots, p_{iD})$ represents the best previous position of the swarm; the index g indicates the best particle among all the particles in the population; and t indicates the iteration number. If the sum of the factors in the right side of Eq. (1) exceeds a specified constant value, particles' velocities on each dimension are clamped to a maximum velocity $V_{\max}$.

The first swarm of particles in our method is a "continuous" PSO configured to search for the optimal number of features being selected. The search space of this particle swarm is limited by the number of dimensions of the original dataset. In the case of hyperspectral imagery data, it corresponds to the maximum number of spectral bands available.

2.2. Binary PSO

To perform the selection of feature sets, the PSO concept needs to be extended in order to deal with binary data. We utilize a binary scheme for feature selection in which each feature is represented by one bit of the particle [1]. If the feature is selected its value is set to 1, if it is not used, it is set to 0.

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

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

where α is the selection pressure, which controls the probability of selecting highly fit or less fit features.

The second particle swarm in our method is a "binary" PSO, as described above. Its particles are encoded in n bits, according to the number of dimensions of the dataset.

The feature selection process is carried out in cycles called epochs. In our method, each epoch consists of two phases. Firstly, the continuous particle swarm is evolved, letting the particles update their positions. Then, the second swarm is evolved, each step selecting up to the number of features defined by the particles of the first swarm. The second swarm may be updated several times at each epoch, for the different positions of the first swarm. However, if two or more particles of the fist swarm are in the same position, only the first occurrence will result in the evolution of the second swarm.

2.3. Evaluation Function

By simply minimizing the error rate of the induction algorithm, it cannot be expected that the feature selection algorithm will also minimize the number of selected features. We want to search for the smallest feature set that satisfies a desired level of performance of the induction algorithm. For this purpose, the feature selection must be treated as a constrained optimization problem, in which the search is constrained by the size of the feature set and by the specified satisfactory error rate [14].

However, even the binary version of PSO cannot handle this kind of problem directly. We developed a formulation in order to provide control on the balance between the two constraints, necessary when dealing with hyperspectral datasets on regression problems. Otherwise, very small feature sets may be preferred by the algorithm in detriment of possible better performing feature sets with more features.

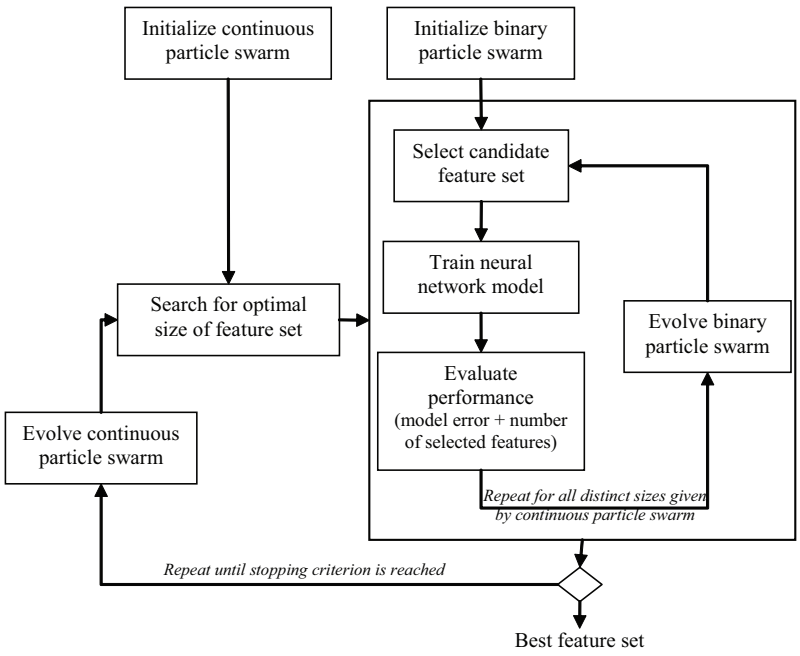


Figure 1. Diagram of the algorithm for feature selection of spectral imagery based on two particle swarms.

A performance evaluation function is introduced to accommodate the two constraints, assessing the evolution of the two particle swarms. It can be expressed by the following equation

$$\mathrm{PEF}(x) = k * l(x) + f(e(x)) \,, \tag{4}$$

where x is the candidate feature set selected by the binary particle swarm; l is the cost associated with the size of the feature set, measured by the number of selected features scaled by a constant factor k; and $f(e)$ is a penalty function for the error $e(x)$ of the induction algorithm.

The penalty function defines a region of feasibility of possible solutions in the error space. It can be expressed as

$$f(e(x)) = \frac{\exp((e(x) - u)/s) - 1}{\exp(1) - 1} \,, \tag{5}$$

where u is a feasibility threshold, and s is a small scaling constant.

A feature set is considered feasible if the error in the model output is below the feasibility threshold. For other feature sets presenting higher error, the value of the penalty function grows rapidly.

2.4. Artificial Neural Networks

We implemented artificial neural networks as the induction algorithm to provide linear models of the regression problem. The linear model was obtained using a single-layer perceptron network [3]. The output of the linear network is calculated as $y = f(x) = Wx + b$, where x is the input vector; y is the output vector; W is the weight vector; and the parameter b is the bias. The number of neurons in the input layer is proportional to the number of features of the reduced dataset. The linear networks were trained using the least means squares algorithm [15].

3. Experiments

3.1. Spectral Image Dataset

To attest the validity of the proposed method in real-world datasets, experiments were conducted with spectral image data from soybean fields. The experimental data was obtained using a hyperspectral sensor, coupled with CCD camera and computer controller. The sensor acquires data in two dimensions, one containing spatial information and, the other, spectral information. In the spatial plane, the hyperspectral camera produces 484 pixels per line. The spectral range comprises the visible to the near-infrared, from 400 nm to 1000 nm, each band interleaved by approximately 5 nm, thus producing 121 spectral bands.

The hyperspectral data was acquired in middle summer on a sunny day, around noontime. The data sample consisted of 13 different varieties of green vegetable soybeans

cultivated in an experimental field. In addition, to provide target data for the supervised training of the neural networks, freeze-dried samples from the soybean fields were analyzed in the laboratory using liquid chromatography. The neural networks were trained to model the chemical concentration of glucose in soybeans; the purpose is to predict the sweetness of the soybean crops non-invasively [12].

3.2. Results

The parameters of the particle swarms, shown in Table 1, were chosen through experimentation. To define the constants of the penalty function Eq. (5), the error rate of the induction algorithm must be taken into account. The feasibility threshold u must be a value at least slightly greater than the minimum error expected by the best feature set. After preliminary experiments, u was defined as $u = 0.17$. The scaling factor was $s = 5\%$.

The determination of the constant k, in the performance evaluation function Eq. (4), must consider the dimensionality of the problem and the desired performance. If $k = 0$, the PEF value would be equivalent of that of the penalty function alone. When $k = 1$, the PEF value would give a very heavy punishment for acquiring the spectral bands. A more reasonable search space for the hyperspectral dataset problem was obtained by using $k = 0.05$.

To account for the stochastic nature of the PSO algorithm, the experiments were performed over 20 independent runs for each algorithm, every time initializing the swarms with a different random seed. The performance of the best performing particle swarms is presented in Fig. 2, along with the averages of all 20 runs. Note that the best particle swarms finished the training at epoch 41; the last value was repeated in the plot for comparison purposes with the overall average. The final particles' positions, assigned to the correspondent spectral band wavelengths, of the 20 runs of the algorithm are shown in Fig. 3.

In practice, however, only the best performing feature set selected by the particle swarms is retained, i.e., the feature set presenting the lowest error and highest correlation on the regression problem. In order to verify the accuracy of the method, a linear regression analysis was performed between the best feature set modeled by the neural networks and the ground reference measurements obtained by laboratory analysis. Figure 4 shows the resulting analysis for the best prediction of glucose content using a reduced feature set modeled by the neural network.

3.3. Comparison with Principal Components Analysis

Principal components analysis (PCA) is a widely used technique to reduce the dimension of hyperspectral datasets.

Table 1. Parameters of the particle swarms.

Parameter	Value
Population size continuous swarm	20
Population size binary swarm	40
Learning rate $c_1 = c_2$	2
Maximum particle velocity $V_{\max}$	4
Maximum number of epochs	200
Maximum epochs with constant error	30
Initial inertia w_i	0.9
Final inertia w_f	0.2
Epoch of final inertia	190
Selection pressure α [a]	1

[a] Utilized by the roulette wheel scheme to turn the second swarm into binary.

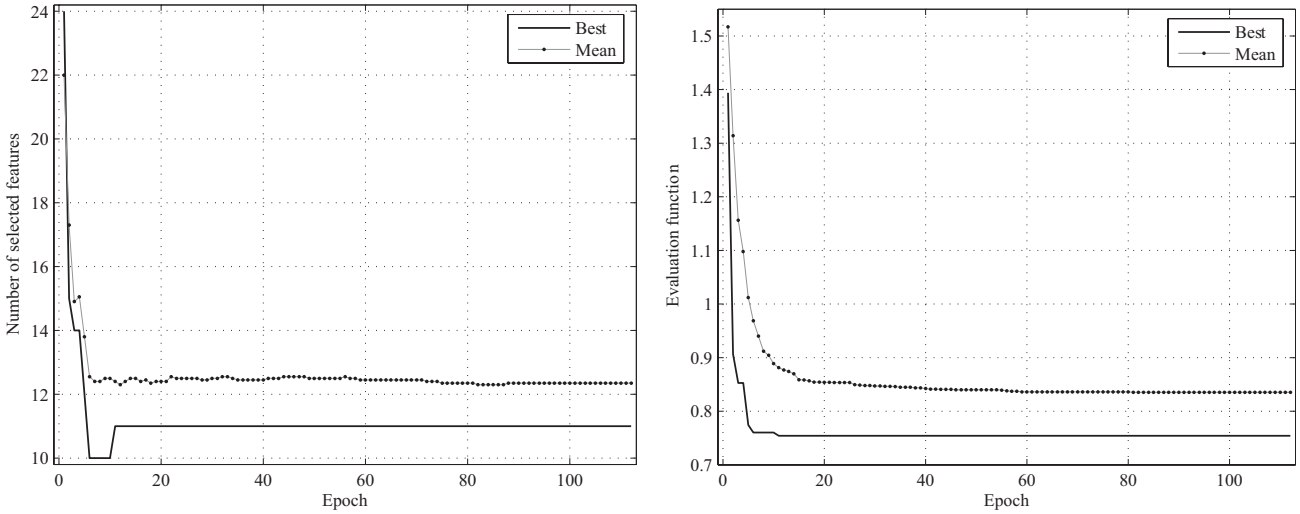
The PCA algorithm identifies and extracts interesting features by retaining only those components that account for a greater part of the variation in the dataset [7]. The principal components were ordered according to the magnitude of their variance. We set the variance threshold to 99.98%, retaining 11 principal components, same number of features obtained by the particle swarms.

In order to more comprehensibly compare the results between the different methods, the correlation coefficient was calculated as $\mathrm{R}(y) = C(y^o, y^t) \Big/ \sqrt{C(y^o, y^o) \cdot C(y^t, y^t)}$, where C is the covariance matrix, and o and t indicate the neural network output and the test dataset measurement, respectively. A summary of the results comparing the proposed method, the best feature set selected by the particle swarms, and the PCA is presented in Table 2.

Table 2. Comparison of particle swarms feature selection (PSO-FS) and PCA, applied to model glucose content in soybean crops from hyperspectral data using neural networks.

Algorithm	PEF[a]	MSE[b]	R[c]
PSO-FS	0.7542	0.0311	0.6187
PCA		0.0401	0.4524

[a] Performance evaluation function
[b] Mean squared error
[c] Pearson's correlation coefficient



(a) Number of selected features optimized by the first swarm

(b) Performance evaluation function minimized by both swarms

Figure 2. Learning curves showing the mean of all particle swarms over 20 runs and the performance of the best particle swarm.

4. Conclusions

This paper proposes a feature selection method based on two particle swarms, a continuous and a binary, to search not only for the optimal feature set, but also for the optimal number of features, at the same time. Furthermore, the applicability of the method to extract information from hyperspectral imagery data was demonstrated. The method was successfully validated with experiments utilizing real-world datasets of soybean fields applied to a regression problem, Fig. 4.

The particle swarms were implemented in conjunction with neural networks to model the sweetness in soybean crops, a non-trivial problem. The particle swarms were able to optimize the combined criteria efficiently. In spite of the limited size of the particle swarms' populations, the proposed algorithm was capable of fast convergence towards the optimal region of the search space, Fig. 2. The particle swarms outperformed the PCA in our experiments.

We developed a performance evaluation function adapting the PSO algorithm to search for the optimal feature set while constrained by two criteria, the error rate of the induction algorithm and the size of the feature set. The performance evaluation function punishes feature sets with high dimensionality. This function may produce excessive punishment, particularly on real-world hyperspectral imagery data, causing the selection of small feature sets presenting undue error. Thus, in order to determine a better compromise between the number of selected features and the induction algorithm's error rate, a constant factor k in Eq. (4) was introduced.

The particle swarms also possess the advantage of permitting the visualization of the selected features in contrast with their spectral locations, providing an appealing analysis tool for the field of remote sensing. The linear models tended to induce the selection of feature sets in which most of the selected features lied in the range between 700 and 900 nm, Fig. 3, adjacent to the region known as "red-edge," which is reportedly important for vegetation processes [4]. We propose the method not only for dimensionality reduction, but also as a valuable tool for the spectral analysis of remotely sensed hyperspectral imagery.

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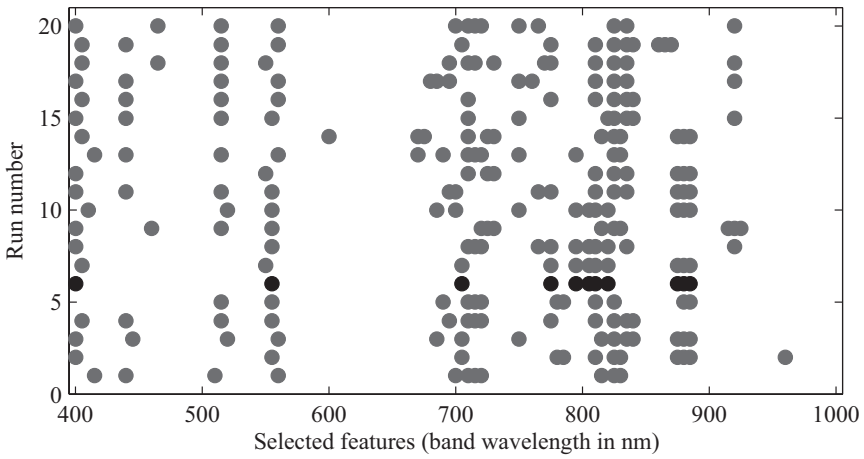

Figure 3. Spectral location of the feature sets selected by the particle swarms over 20 runs. The best performing feature set is indicated in dark black.

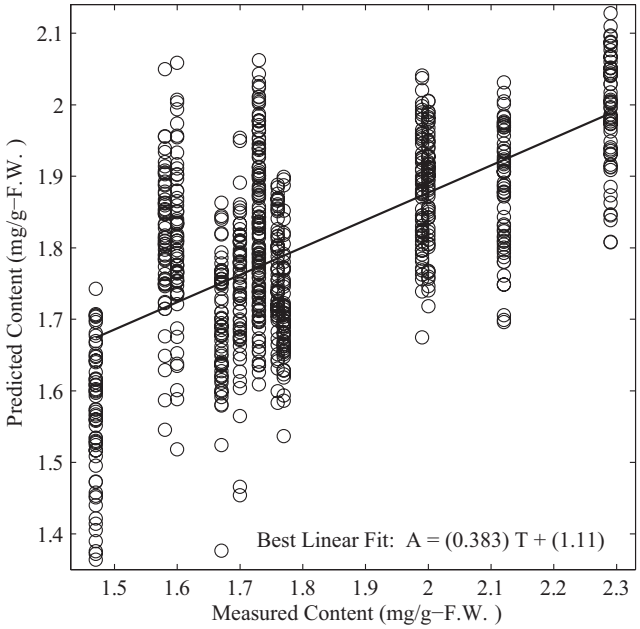

Figure 4. Linear regression analysis between the ground reference measurements and the predictions given by the best feature set.

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