# Session 3A1a Automatic Classification of Spectral Signatures and Scattering Patterns

A New Approach to Polarimetric SAR Image Classification	
J. Yang (Tsinghua University, China); T. Xiong (Tsinghua University, China); YN. Peng (Tsinghua	
University, China);	698
Soft Computing and Neural Adaptive Techniques for High Accuracy Data Classification	
E. Binaghi (Universitàdegli Studi dell'Insubria, Italy); I. Gallo (Universitàdegli Studi dell'Insubria, Italy);	699
A Method to Solve an Acoustic Scattering Problem Involving Smart Obstacles	
F. Zirilli (Universitádi Roma La Sapienza, Italy);	700
A Neural Adaptive Algorithm for Feature Selection and Classification of Hyperspectral Data	
I. Gallo (Universitàdegli Studi dell'Insubria, Italy);	701
Classification of Single Particle Optical Scattering Patterns	
G. F. Crosta (Universitàdegli Studi Milano - Bicocca, Italy);	702
Feature Extraction by Fractional Order Differentiation	
G. F. Crosta (Universitàdegli Studi Milano - Bicocca, Italy);	703

### A New Approach to Polarimetric SAR Image Classification

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In this paper, a Generalized Optimization of Polarimetric Contrast Enhancement (GOPCE) is employed for supervised polarimetric synthetic aperture radar (SAR) image classification. The GOPCE introduced by the authors [1] is the extension of Optimization of Polarimetric Contrast Enhancement (OPCE), and it includes three optimal coefficients associated with the Cloude entropy and two special similarity parameters [2] in addition to the optimal polarization states. For classification, we first classify a polarimetric SAR image into several sets:  $C_1, C_2, \ldots C_m$  and the mixed sets  $C_{1,2}, C_{2,3}, \ldots C_{m-1,m}$  by some parameter (e.g., span), based on the polarimetric SAR data of the training areas. Then a mixed set is divided into two classes by using the GOPCE for several times. For comparison, we also use the Maximum Likelihood (ML) classifier, based on the complex Wishart distribution [4]. The classification results of a NASA/JPL AIRSAR L-band image over San Francisco by two approaches are listed in Table 1 and Table 2, respectively, demonstrating the effectiveness of the GOPCE based classifier.

GOPCE	Sea area	Quasi-natural surface	Woods area	Urban area
Sea area	96.89%	3.11%	0%	0%
Quasi-natural surface	0.75%	$\mathbf{98.43\%}$	0.82%	0%
Woods area	0%	4.56%	$\boldsymbol{95.41\%}$	0.03%
Urban area	0	0	9.00%	91.00%

Table 1: Classification results by the proposed method.

Table 2: Classification results by the Maximum Likelihood classifier.

ML	Sea area	Quasi-natural surface	Woods area	Urban area
Sea area	98.30%	1.57%	0.05%	0.08%
Quasi-natural surface	0.35%	96.74%	2.21%	0.7%
Woods area	0%	5.6%	92.17%	2.24%
Urban area	0%	6.84%	2.8%	90.36%

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## Soft Computing and Neural Adaptive Techniques for High Accuracy Data Classification

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In this present work we intend to survey the recent salient experiences and main results obtained by our group in the field of Soft Computing and Neural Learning for Pattern Recognition.

To document our first significant research activity, we present a supervised classification model integrating fuzzy reasoning and Dempster-Shafer propagation of evidence; the model is built on top of connectionist techniques to address classification tasks in which vagueness and ambiguity coexist. The salient aspect of the approach is the integration within a neuro-fuzzy system of knowledge structures and inferences for evidential reasoning based on Dempster-Shafer theory. In this context the learning task can be formulated as the search for the most adequate "ingredients" of the fuzzy and Dempster-Shafer frameworks such as the fuzzy aggregation operators, for fusing data from different sources and focal elements, and basic probability assignments, describing the contributions of evidence in the inference scheme. The new neural model allows us to establish a complete correspondence between connectionist elements and fuzzy and Dempster-Shafer ingredients, ensuring both a high level of interpretability and high performance in classification.

A second salient experimental work developed by our group concerns contextual classification of remote sensing images. Many cases of remote sensing classification present complicated patterns that cannot be identified on the basis of spectral data alone, but require contextual methods which base class discrimination on the spatial relationships between the individual pixel and local and global configurations of neighboring pixels. However, the use of contextual classification is still limited by critical issues, such as complexity and problem dependency. We present a contextual classification strategy for object recognition in remote sensing images in an attempt to solve recognition tasks operatively. The salient characteristics of the strategy are the definition of a multiresolution feature extraction procedure exploiting human perception and the use of soft neural classification based on the Multi-Layer Perceptron model. Three experiments were conducted to evaluate the performance of the method-ology, one in an easily controlled domain using synthetic images, the other two in real domains involving built-up pattern recognition in panchromatic aerial photographs and high resolution satellite images.

The last work presented is representative of recent research interest focusing on 3D image analysis. In particular the work investigates the potential of neural adaptive learning to solve the correspondence problem within a two-frame adaptive area match-ing approach. A novel method is proposed based on the use of the Zero Mean Normalized Cross Correlation Coefficient integrated within a neural network model which uses a least-mean-square delta rule for training.

Two experiments were conducted for evaluating the neural model proposed. The first aimed to produce dense disparity maps based on the analysis of standard test images. The second experiment, conducted in the biomedical field, aimed to model 3D surfaces from a varied set of SEM (Scanning Electron Microscope) stereoscopic image pairs.

# A Method to Solve an Acoustic Scattering Problem Involving Smart Obstacles

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In the context of time harmonic acoustic scattering we formulate an Inverse problem involving smart obstacles and we propose a method to solve it. A smart obstacle is an obstacle that when hit by an incoming acoustic wave tries to pursue a given goal circulating a suitable pressure current on its boundary. A pressure current is a quantity whose physical dimension is pressure divided by time.

The goals pursued by the smart obstacles that we have considered are the following ones: to be undetectable or to appear with a shape and/or acoustic boundary impedance different from its actual ones eventually in a location in space different from the actual location. We fix our attention on obstacles that pursue the goal of being masked that is obstacles that try to appear with a shape and an acoustic boundary impedance different from their actual ones. As a special case of masked obstacles we consider the case of furtive obstacles, that is obstacles that try to be undetectable.

We consider the following time harmonic inverse scattering problem: from the knowledge of several far fields generated by the smart obstacle when hit by known time harmonic waves, the knowledge of the goal pursued by the smart obstacle and of its acoustic boundary impedance reconstruct the boundary of the obstacle.

A method to solve this inverse problem that generalizes the so called HERGLOTZ function method used in inverse obstacle scattering is proposed. This method is based on the definition of two HERGLOTZ functions, one for the acoustic field scattered by the smart obstacle and one associated to the pressure current through an auxiliary variable. Under some hypotheses the HERGLOTZ functions are determined from the knowledge of the far fields. The knowledge of the HERGLOTZ functions makes possible the reconstruction of the boundary of the smart obstacle using ad hoc equations. Two numerical experiments that validate the method proposed are presented.

The website http://www.econ.univpm.it/recchioni contains a general overview of the work on scattering done in the past years.

# A Neural Adaptive Algorithm for Feature Selection and Classification of Hyperspectral Data

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Recent applications of Pattern Recognition and in particular of Image Analysis and Classification deal with high dimensionality data. In this context, the use of automated classification procedures is still limited by the lack of robust methods able to cope with the intrinsic complexity of high dimensionality and the consequent Hughes phenomenon, implying that the required number of labelled training samples for supervised classification increases as a function of dimensionality. The problem can be addressed in two complementary ways: identify a classification model less sensitive to the Hughes phenomenon and/or reduce the dimensionality of data and redundancies by applying feature selection strategies. Neural networks seems to be very good candidates for simultaneous feature selection and classification. In view of these considerations, I designed an experimental study to investigate the robustness of a non conventional classification model when dealing with high dimensionality data.

In particular this work presents a supervised adaptive classification model built on the top of Multi-Layer Perceptron, able to integrate in a unified framework feature selection and classification stages.

The feature selection task is inserted within the training process and the evaluation of feature saliency is accomplished directly by the back-propagation learning algorithm that adaptively modifies special bell functions in shape and position in order to minimize training error. This mechanism of feature selection avoids trial and error procedures which imply several training stages.

The model includes a method to determine whether a hidden unit should be removed or maintained. This pruning mechanism is fundamental for training speed up and in many cases leads to a hidden layer with only the minimum number of neurons i.e., two. An important aspect of this method is that it avoids to retrain the network after removal of a neuron and relative synapses, because the neuron was excluded by the learning procedure.

The adaptive model is conceived as a composition of full connected neural networks, each of them devoted to selecting the best set of feature for discriminating one class from the others.

Performances were evaluated within a Remote Sensing study aimed to classify MIVIS hyperspectral data. Inside the classification problem, a comparison analysis was conducted with Support Vector Machine and conventional statistical and neural techniques. The adaptive neural classifier performed a selection of the most relevant features and showed a robust behaviour operating under minimal training and noisy situations.

Moreover, experimental results on standard datasets confirm that this feature selection strategy achieves a competitive behaviour with respect to the other methods considered.

### **Classification of Single Particle Optical Scattering Patterns**

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Some experimental methods such as TAOS [1] are capable of collecting the light scattered by single airborne particles in the micrometer size range when the latter are illuminated by a triggered laser source (wavelength = 532 nm). Data consist of intensity patterns (Fig. 1) collected in a suitable solid angle at a high rate (>100 patterns per second).



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Typical scattering pattern (a07b03b) produced by an aerosol particle from skid braking tests on a car racing track. Aerosol was collected by an 8-stage impactor device, re-suspended in water and injected into the TAOS apparatus.

There is no known theoretical method capable of determining the particle size, shape and complex refractive in dex from such incomplete data. As a consequence a heu ristic algorithm was developed, which relies on spectrum enhancement for feature extraction and on principal components (PC) analysis for classification. Spectrum en hancement of an image includes spatial differentiation, possibly of fractional order, followed by non-linear transformations aimed at separating structure from tex ture. PC analysis maps each input pattern into a point in the PC space. The classifier was trained with the aim of maximizing discrimination between suitable sets of TAOS patterns e.g., those labelled 1 and 2 in Fig. 2. New sets of patterns e.g., those from skid braking aerosol particles (labelled 4), were then submitted to the classifier. The result is also displayed by Fig. 2. From the PCs of a given pattern one can estimate how much the shape of the particle deviates from the spherical one.

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Figure 2: Classification of TAOS patterns from environmental aerosol particles: train on{1,2}→recognize{4}, 142.88432 <  $\varphi$  < 168.517815, 86.083414 <  $\vartheta$  < 93.948435, Exec = w05,  $\delta$  = 45deg, p = 2.2, d + 1 = 10, axis =  $u_1$ , 0 <= |u| <= 255, dim[{PC}] = 10.

### Feature Extraction by Fractional Order Differentiation

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The spectrum enhancement algorithm has been used for some time for separating structure from texture and extracting features from images (including optical scattering patterns) for automatic classification and recognition. The relevant definition and properties of spectrum enhancement and the relation of the latter to fractional differentiation are outlined below.

Let  $Q\Omega$  denote a square of sidelength L and  $\mathcal{T}$  the surface of the torus obtained by glueing the opposite sides of  $Q\Omega$  together. Assume the grayscale image is modeled by a function  $Qg[\mathbf{x}], \mathbf{x} \equiv \{x_1, x_2\} \in Q\Omega$ , which is continuous on  $\mathcal{T}$ . Next let  $Q\Omega$  be discretized by a square grid of steplength  $\ell$ . Let  $\mathbf{u} \equiv \{u_1, u_2\}$  be the spatial frequency vector. Then the discrete FOURIER transform  $G[\mathbf{u}]$  of Qg[.] is supported in the square  $0 \leq |u_1|,$  $|u_2| \leq u_{max} = L/2\ell - 1$  cycles/image. Let  $\mathbf{u}$  be represented in polar coordinates  $\mathbf{u} \equiv \{u, \theta\}$ . Denote by  $|G[\mathbf{u}]|^2$  the power spectral density. Let  $\Theta$  denote an arc symmetric with respect to either axis ( $\mathbf{u}_1$  or  $\mathbf{u}_2$ ) and let the normalized, arc-averaged spectral density profile be the function s[.] of  $u = |\mathbf{u}|$  defined in  $0 \leq u \leq u_{max}$ (cycles/image) according to

$$s[u] = \frac{1}{|\Theta|} \int_{\Theta} 10 \operatorname{Log}_{10} \left[ \frac{|G[u]|^2}{|G[0]|^2} \right] u \, d\theta, \tag{1}$$

where  $|\Theta|$  is the length of  $\Theta$  and obviously  $|G[0]|^2 \neq 0$  for any non-degenerate image. Let m[u] be a model spectral density such that

$$m^{(p)}[u] = 0, \quad 0 \le u \le 1; \quad m^{(p)}[u] = -10 \text{Log}_{10}[u^p], \quad u \ge 1 \quad \text{cycles/image},$$
 (2)

where p (>0) is the model exponent. Then, the  $m^{(p)}[.]$ -enhanced spectrum h[u] is defined by

$$h[u] = s[u] - m^{(p)}[u], \quad 1 \le u \le u_{\max}.$$
 (3)

Intuitively, the function  $h^{(p)}[.]$  represents deviations of s[.] from the model  $m^{(p)}[.]$ . The values of L,  $u_{max}$ ,  $|\Theta|$ , p are determined by the intended application.

Assume the image is not degenerate. Then the following properties can be shown to hold.

a) If p satisfies p/2 = N (>0), integer, then the tempered distribution  $H^{(p)}[\boldsymbol{u}]$  defined by

$$H^{(p)}[u] = |u|^{p} \frac{|G[u]|^{2}}{|a_{0,0}|^{2}} + \delta[u], \qquad (4)$$

has the following representation in terms of FOURIER transforms ( $\mathcal{F}$ ) of derivatives of Qg[.]:

$$H^{(p)}[u] = \frac{1}{|a_{0,0}|^2} \sum_{n=0}^{N} \binom{N}{n} \left| \mathcal{F} \left[ \frac{\partial^N Qg}{\partial^{(N-n)} x_1 \partial^n x_2} \right] \right|^2 + \delta[u].$$
(5)

b) If p/2 is not an integer, then fractional derivatives and anti-derivatives of Qg[.] of net order p/2 appear in the representation of  $H^{(p)}[\mathbf{u}]$  and the sum in Eq. (5) is replaced by a binomial series.

c) In either case, if all FOURIER coefficients satisfy  $|a_{l,m}|^2 \ge \varepsilon > 0$  the relation between  $H^{(p)}[.]$  of Eq. (4) and the enhanced spectrum  $h^{(p)}[.]$  of Eq. (3) is

$$h[u] = \frac{10}{|\Theta|} \int_{\Theta} \operatorname{Log}_{10} \left[ H[u] \right] u \, d\vartheta.$$
(6)