Signal Classification and Pattern Detection based on Non-Linear Mixture Processing

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Abstract

A framework based on non-linear mixture processing (NLMP) proposed by the Signal Processing Group of the Institute of Telecommunications and Multimedia Applications of the Polytechnic University of Valencia is presented. This approach can be applied to complex problems involving multivariate densities for detection, classification, filtering and prediction. An implementation of the NLMP structure for classification based on mixtures of independent component analyzers is included. The versatility of this implementation to solve problems in diverse real applications is demonstrated with the following applications: Quality control using impact-echo testing; Diagnosis of the consolidation status in historic building restoration; Archaeological ceramic classification; Segmentation and object similarity in image processing; and Detection of learning styles in learning web activities.

Keywords: non-linear mixture processing, ICA mixtures, ICA, material quality classification, non-destructive testing.

1. Introduction

Classical statistical signal processing relies on exploiting second-order information. Spectral analysis and linear adaptive filtering are probably the most representative examples. From the perspective of optimality (optimum detection and estimation), second-order statistics are sufficient statistics when Gaussianity holds, but lead to suboptimum solutions when dealing with general probability density models. A natural evolution of statistical signal processing, in connection with the progressive increasing in computational power, was exploiting higher-order information. Then, high-order spectral analysis and nonlinear adaptive filtering received the attention of many researchers in this field.

Clearly inside this framework of evolution from second to higher-order information is the transition from principal component analysis (PCA) to independent component analysis (ICA) [1]-[3]. Briefly, PCA is a technique for linearly transforming a vector of correlated components in a vector of variance-ordered uncorrelated components; meanwhile ICA linearly transforms a vector of statistically dependent components in unordered independent components. ICA, can also be considered a natural evolution of prewhitening linear transformation (like PCA but no variance ordering is being produced). When Gaussianity holds both ICA and prewhitening get equivalent transformations, and infinite solutions may exist, as any rotation of the prewhitened vector keeps the uncorrelation among the vector components. However, when non-Gaussianity appears, ICA produces a different transformation, that can be unique if appropriate constraints are introduced into the design. That is the reason why ICA became as popular as a technique for blind source separation when at maximum one source is Gaussian.

Most interesting is recognizing that ICA implicitly assumes a model for multivariate probability density functions (PDF's). The multivariate PDF of the transformed vector will be the product of the (one-dimensional) marginal PDF's of its components. Dealing with one-dimensional PDF's makes tractable different complex problems involving multivariate PDF's [4]. This perspective suggests that ICA can be an interesting tool to be considered inside areas of intensive data analysis. Actually, dealing with estimates of PDF's, or defining optimality criteria involving PDF's (like entropy, mutual information, Kullback-Liebler distances,...) can be considered the last generation in statistical signal processing approaches: a natural evolution from second and higher-order statistics to data distribution information [5]. Some authors have termed these later approaches as non-linear information processing [6]. It is relevant recognizing the fact that non-linear information processing establishes a bridge between statistical signal processing and computational and artificial intelligence sciences. That is why many people from signal processing are increasingly involved in areas like data mining, machine learning or clustering, and many researchers from computational sciences are working in new data intensive signal and image processing applications.

Recently, the Independent Component Analysis Mixture Model (ICAMM) was introduced as an extension of ICA [7][8]. ICAMM is a kind of nonlinear ICA technique that extends the linear ICA method by learning multiple ICA models and weighting them in a probabilistic manner [7]. Thus, ICAMM has emerged as a flexible approach to model arbitrary data densities using mixtures of multiple ICA models with non-Gaussian distributions for the independent components (i.e., relaxing the restriction of modelling every component by a multivariate Gaussian probability density function).

In the next sections, we present a summary of a non-linear mixture processing approach developed by the Signal Processing Group of the Polytechnic University of Valencia. This approach has been applied in solving detection, classification, filtering, and prediction problems. In this paper, only applications on signal classification and pattern recognition are included [9].

2. From non-Gaussian mixture models to the non-linear mixture processor structure

A non-Gaussian mixture model assumes that the space of observations can be decomposed in K classes. Every class is characterized by a non-Gaussian PDF. More specifically, it is assumed that every class satisfies an ICA model: vectors x_k corresponding to a given class C_k $k = 1 \ldots K$ are the result of applying a linear transformation A_k to a (source) vector S_k, whose elements are independent random variables, plus a bias or centroid vector b_k , i.e. $x_k = A_k s_k + b_k$ $k=1 \ldots K$.

The underlying multivariate PDF will be the mixture

$$p(\mathbf{x}) = \sum_{k=1}^{K} p(\mathbf{x}/C_k) = \sum_{k=1}^{K} \left|\det \mathbf{A}_k^{-1}\right| p(\mathbf{s}_k) \tag{1}$$

where

$$\mathbf{s}_k = \mathbf{A}_k^{-1}(\mathbf{x} - \mathbf{b}_k) \tag{2}$$

We have assumed that all the classes are equally probable *a priori* to ease the equations. Equations (1) and (2) lead naturally to the proposed non-linear mixture processor (NLMP) structure showed in Fig. 1. Basically NLMP has K processing channels. Every channel is a linear processor implementing the last equation (recovering of the source vectors), followed by a non-linear processor $g(s_k)$. This later will be the same in classification, filtering or prediction, but will be different in the detection configuration. As we will see, estimation of $p(s_k)$ will be required to compute $g(s_k)$ in all the cases. This later point illustrates the fact that complex multivariate PDF estimation generally required in nonlinear information processing is simplified to the estimation of marginal one-dimensional PDF's, corresponding to the independent elements of vectors s_k $k=1 \ldots K$. Every kind of problem will also have a different post-processing of the NLMP outputs.

NLMP may be considered an extension of different structures previously proposed in the statistical signal processing literature. Thus, for example, multiple channel structures are very usual in signal processing as a way for finding projections of a signal into its subspace components. Filter banks structures are the most typical examples of this kind. In this sense we can say that NLMP makes a "statistical" decomposition of the observation vector x, i.e., it finds the class-membership through $p(s_k)$, or, similarly, it decomposes $p(x)$ into its non-Gaussian components.

From a different perspective NLMP may be considered a multichannel extension of the classical nonlinear Wiener filter [10]: a FIR filer followed by a zero-memory nonlinear function. A linear-plus-nonlinear processing scheme is also present in every neuron of a neural network [11].

Every NLMP channel is an independent component analyzer followed by a non-linear processor

3. Non-linear mixture processor design

Before considering NLMP inside the framework of every selected application, let us devote a little time to the design of the structure. Usually from a set of observation vectors are allowed to be learned the parameters A_k, B_k and the PDF's $p(s_k)$ $k=1 \ldots K$. The Signal Processing Group-UPV [20] [12] and other authors [7][8],[13]-[16] have been working in some learning algorithms of ICA mixtures. Basically, these algorithms try to maximize the likelihood of the unknowns given the set of observed vectors, assuming some parametric or non-parametric models for $p(s_k)$. Semi-supervision (part of the learning set is unlabelled) and hierarchy (grouping or separation of classes to establish the appropriate number K) have being already considered [17]. However, from the perspective of NLMP, there is a design problem still deserving much attention: the adaptive learning in nonstationary environments. Nonstationarity is present in many applications, so it is a significant area of research. We want to face problems like how a new element (labelled or unlabelled) incoming into the learning set should modify the NLMP parameters. In a similar manner we will study a dynamic definition of the number of channels (classes), by performing adaptive hierarchy analysis, among other complex problems. In essence, solving these problems will give a more (nonlinear) signal processing perspective to the classical machine learning point of view.

4. ICA mixture algorithm for signal classification

We developed a NLMP configuration for classification called Mixca (Mixture of Component Analyzers) [18]-[20]. For this case, we are interest

Mixca includes pdf' nonparametric estimation, semisupervision, dependency correction

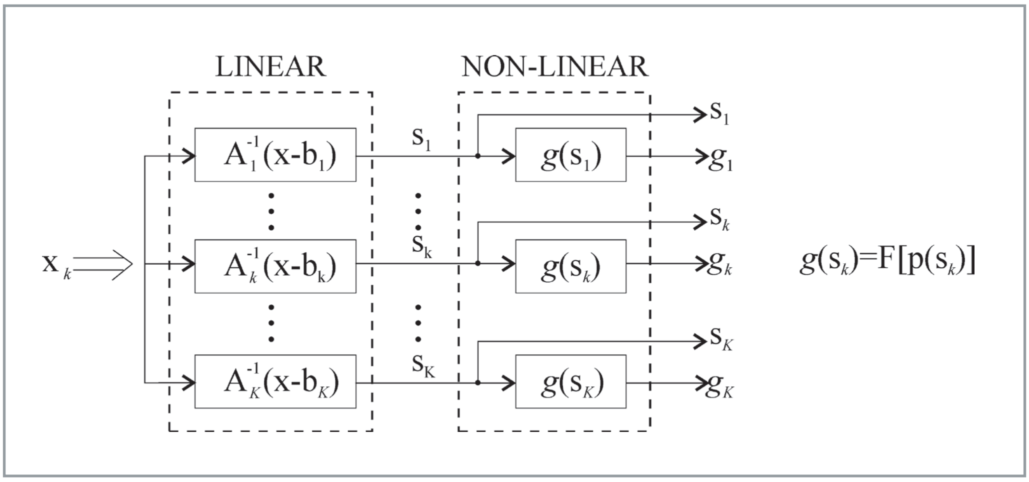


Figure 1. *Non-linear Mixture Processor structure (NLMP)*

in computing

$$p(C_k/\mathbf{x})=\frac{p(\mathbf{x}/C_k)}{P(\mathbf{x})}P(C_k)\propto\left|\det\mathbf{A}_k^{-1}\right|p(\mathbf{s}_k) \quad (3)$$

thus, we select $g(\mathbf{s}_k)=\left|\det\mathbf{A}_k^{-1}\right|p(\mathbf{s}_k)$ and the maximum of the outputs corresponding to the K channels indicates the selected class.

The Mixca algorithm employs a non-parametric estimation of the source PDF's. This is the most general way of approaching this problem since no particular parametric models are needed. Imposing independence $p\left(\mathbf{s}_k^{(n)}\right)=p\left(s_{k1}^{(n)}\right)p\left(s_{k2}^{(n)}\right)\ldots p\left(s_{kM}^{(n)}\right)$, we have to estimate the marginals $p\left(s_{km}^{(n)}\right)$ $m=1\ldots M,\ k=1\ldots K$. This can be done by means of

$$p\left(s_{km}^{(n)}\right)=a\cdot\sum_{n'\neq n}e^{-\frac{1}{2}\left(\frac{s_{km}^{(n)}-s_{km}^{(n')}}{h}\right)^2} \quad m=1\ldots M \quad k=1\ldots K \quad (4)$$

where a is a normalization constant and h is a constant that defines the degree of smoothing of the estimated PDF [21].

Semi-supervision is included using the known $p\left(C_k/\mathbf{x}^{(n)},\mathbf{A}_k^{-1},\mathbf{b}_k\right)$ for the k-n pairs where there is prior knowledge. In addition, the method allows the incorporation of any ICA algorithm into the learning of the ICA mixture model.

The non-linear part of the algorithm is implemented by an estimation of residual dependencies after training for correction of the posterior probability of every class to the testing observation vector. Thus, the estimation of the source PDF is improved applying post-convergence correction using a multidimensional density estimator such as,

$$p(\mathbf{s}_k)=a_0\cdot\sum_{n=1}^{N}e^{-\frac{1}{2}\left(\frac{\left[\mathbf{s}_k-\mathbf{s}_k^{(n)}(I)\right]^T\left[\mathbf{s}_k-\mathbf{s}_k^{(n)}(I)\right]}{h_0^2}\right)} \quad (5)$$

where I is the iteration number at the end of the parameter learning stage of the classifier.

5. Applications

This section includes the following applications of the algorithm of Section 4: Quality control using impact-echo testing; Diagnosis of consolidation status in historic building restoration; Archaeological ceramic classification; Segmentation and object similarity in image processing; and Detection of learning styles in learning web activities.

5.1 Quality control using impact-echo testing
This application consists of discriminating patterns for material quality control from homogeneous and defective materials inspected by impact-echo. The problem is modelled as an independent component analysis (ICA) mixture, representing a class of defective or homogeneous material by an ICA model whose parameters are learned from the impact-echo signal spectrum. The material conditions were: homogeneous, one-defect (hole or crack), and multiple-defects. The impact-echo signals can be considered as a convolutive mixture of the input signal and the defect signals inside the material, as shown in Fig. 2. (a material with 11 internal focuses due to point flaws that build a crack-shape-like defect that is oriented in the plane xy).

Recently, we proposed an ICA model applied to multichannel non-destructive impact-echo testing. This model considered the transfer functions between the impact location and point defects spread in a material bulk as "sources" for blind source separation. It was validated with finite element simulations and lab experiments finding its suitability for classification and detection of flaws [22]-[28]. In order to extend the analysis of defective materials by impact-echo to classifications related with the size, orientation and kind of defects, several levels of classification with different detail in the knowledge of the defects were approached applying different classifiers, such as LDA (Linear Discriminant Analysis), kNN (k-Nearest Neighbors), and MLP (Multi-Layer Perceptron) [29]-[33].

In [34][35], we formulated a mixture ICA model taking into account the resonance phenomenon involved in the impact-echo method. This model extended to defects with different shapes, such as cracks or holes, and formulated the quality condition determination of homogeneous and defective materials as an ICA mixture problem. The following was demonstrated,

$$R^{(k)} = H^{(k)} \cdot s^{(k)} + b^{(k)} \; k = 1 \ldots K \tag{6}$$

where
$R^{(k)}$: compressed spectra of the multichannel impact-echo setup for the defective material class k

$H^{(k)}$: mixture matrix for the defective material class

$s^{(k)}$: compressed spectra from the focuses f_j, $j=0 \ldots F$, for the defective material class k, being f_0 the impact excitation

Fig. 3 shows the estimated mixing matrixes (represented in grey scale) and sources with their corresponding kurtosis values for four classes of materials corresponding to real experiments on specimens of aluminium alloy series 2000. The quality of the materials were: homogeneous, one defect –hole, one-defect –crack, and multiple defects. The differences in the estimated mixing matrixes among the classes clearly show the suitability of the ICAMM model for classifying different kinds of defective materials inspected by impact-echo. The estimated sources represent linear combinations of the spectrum elements produced by the defects that activate different resonant modes of the material. In this level of classification, the pattern of the defects was detected independently of their orientation and dimension. These patterns are related to the number of point flaws that build the defects and the spatial relationship between the flaws. In defective materials, the propagated waves have to surround the defects and their energy decreases, and multiple reflections and diffraction with the defect borders are produced. The patterns of the displacement waveforms are affected by the shape of the defects [36] building a kind of signature of the defect. This signature is distinguishable in the parameters estimated by Mixca since the mixing matrix is different for every class and there are particular densities of the sources that are recovered only for a specific class. Classification results obtained by Mixca using non-parametric source density estimation overcome the results obtained by LDA, kNN, and MLP.

5.2 Diagnosis of the consolidation status in historic building restoration

We have researched in techniques based on ultrasonic testing for the conservation and restoration of heritage buildings and materials. The signal processing of these techniques are based on time-frequency techniques [38][39], higher order statistics [37], and ICA [40]. In this latter application, we used the Mixca algorithm configured to estimate the parameters for only one ICA. The application consists of determining consolidated and non-consolidated zones in a wall of a dome during its process of restoration. The material diagnosis was made by ultrasounds using pulse-echo technique. The injected ultrasonic pulse is recovered, buried in backscattering grain noise plus sinusoidal phenomena; this latter is analyzed by ICA. The mixture matrix is used to extract useful information concerning to resonance phenomenon of multiple reflections of the ultrasonic pulse at non consolidated zones [40].

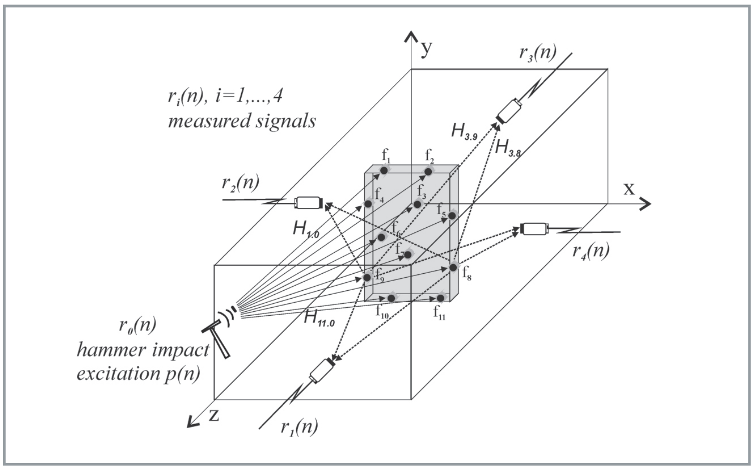


Figure 2. *Wave propagation scheme proposed for an inspection by impact-echo using 4 sensors. The path between the point flaws and the sensors is depicted only for a few focuses.*

The recorded signals are modelled as the superposition of the backscattered signal plus sinusoidal phenomena. This latter sinusoidal contribution should be determined to know if it is due to useful information on the material structure, such as material resonances, or interferences due to the instrumentation during measurement. ICA statement of the problem is:

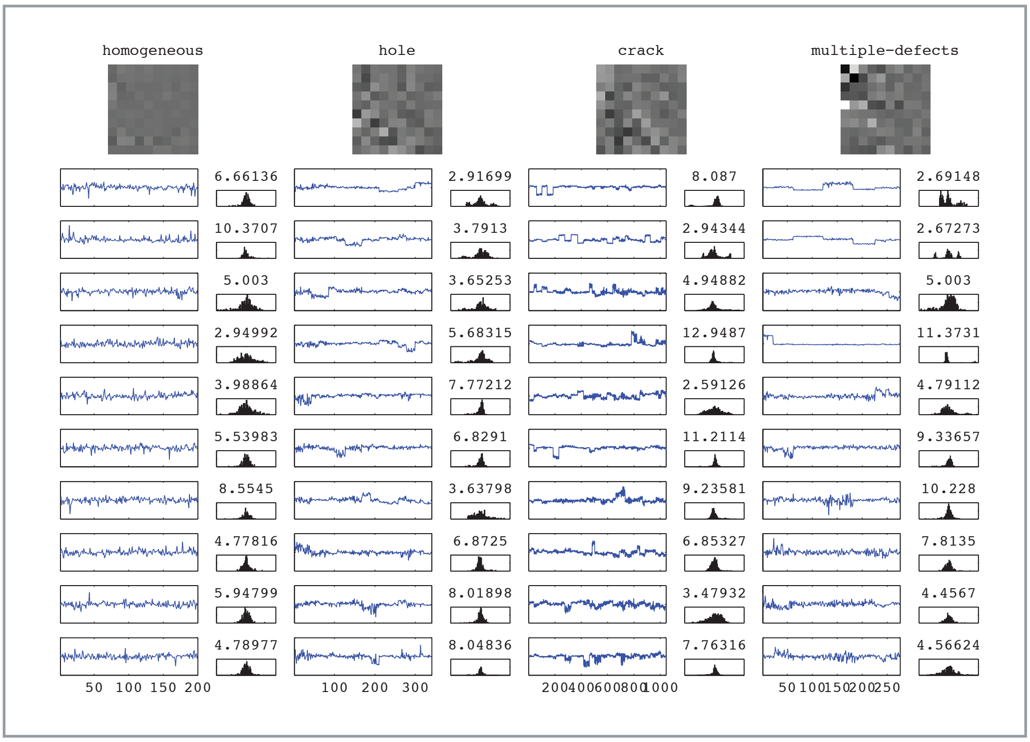
$$x_l(t) = s_l(t) + \sum_{i=1}^{N-1} \alpha_{il} e^{j(\omega_i t + \theta_{il})} \qquad l = 1 \ldots L \tag{7}$$

where L is the number of measurements, $x_l(t)$ is the received signal from the material at the position l of the B-Scan, $s_l(t)$is the backscattering signal that depends on the material microstructure, and $\alpha_{il} e^{j\omega_i t + \theta_{il})}$ $i=1 \ldots N-1, l=1 \ldots L$ (are the sinusoidal sources to be analyzed.

B-Scans diagrams were used to visualize consolidated and non consolidated material zones to check the quality of restoration in the wall.

B-Scan is a 2D representation of a signal set. The evolution in time windows of a parameter such

Estimated sources represent spectral linear combinations from the material defects.

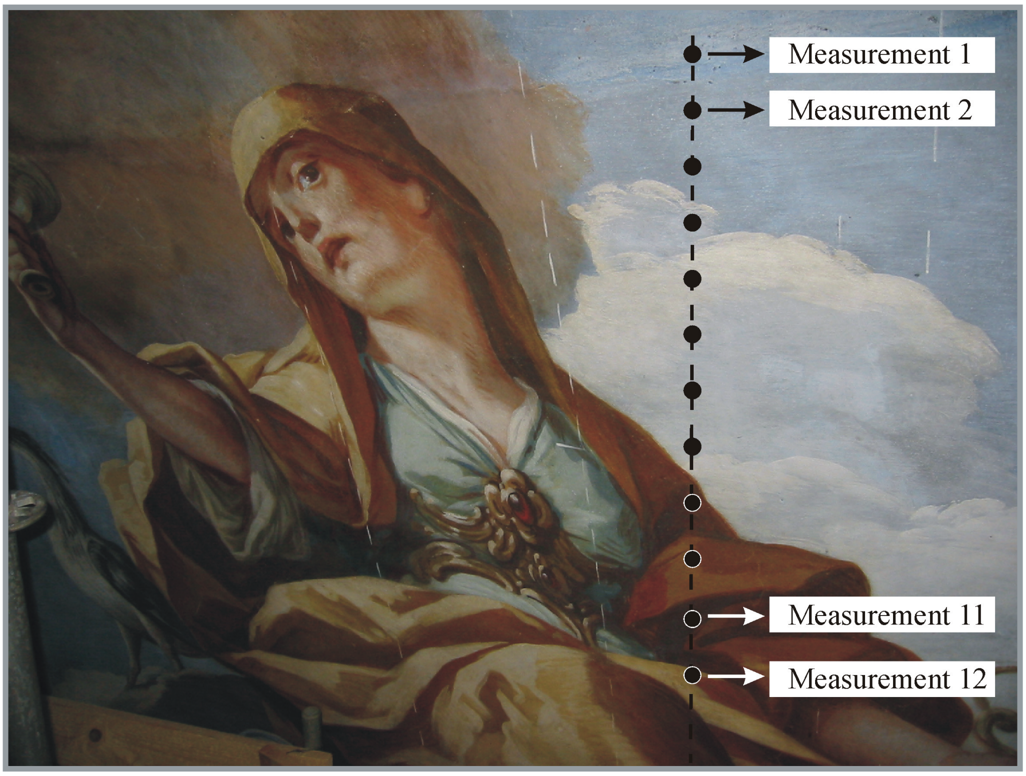


■ **Figure 3.** *Mixing matrixes and sources estimated for four different kinds of defective materials tested in impact-echo experiments. The kurtosis values are displayed for the source densities*

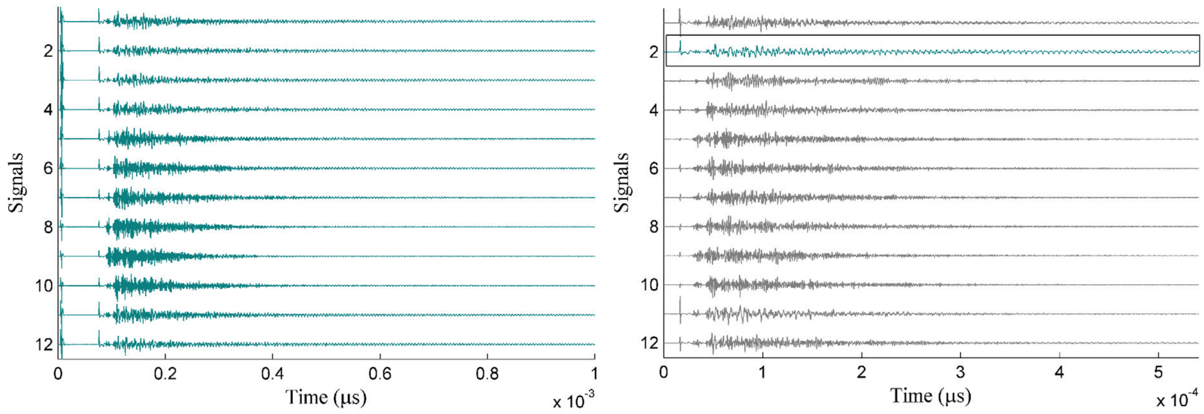
as power or spectrum was calculated for each one of the signals. Then all of the calculated information was put together in a representation of the measurement point versus the signal parameter evolution. Fig. 4 shows different points of a B-Scan measured by ultrasound at the dome.

Fig. 5 shows the recorded signals and the recovered sources by ICA; the processed number of samples was from 600 to 6000.

Fig. 6a and Fig. 6b show two power's B-Scans obtained from the mixture matrix corresponding to $\mathbf{x}=\sum_{l=1}^{12}\mathbf{a}_l s_l,\ s_l=0\ (l=2)$



■ **Figure 4.** Ultrasound inspection at the cupola



(a) Recorded signals (b) Recovered sources

Figure 5. *Recorded signals and recovered sources (the sinusoidal "interference" is highlighted)*

and $\mathbf{x} = \sum_{l=1}^{12} \mathbf{a}_l s_l,\ s_l = 0\ (l \neq 2)$ respectively.

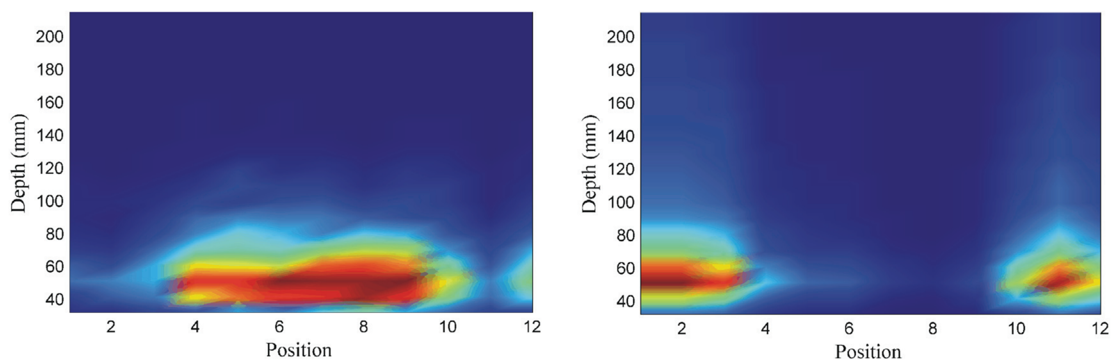
The first B-Scan represents the sinusoidal phenomenon depicting the non consolidated zone. Thus this phenomenon can be associated with the shape of the material non consolidated zone. The second B-Scan is the complementary information concerning to the consolidated zone. The diagrams obtained from ICA information depict more precisely the two different zones of the material than the one obtained by non-stationary analysis. Thus, the use of ICA as preprocessor allows the power signal B-Scans of the wall to be enhanced; and thus, a better insight into the underlying physical phenomena was obtained.

5.3 Archaeological ceramic classification

This application introduces the ICA mixture models in ultrasonic non-destructive testing of materials, particularly in classifying archaeological pottery sherds from different ages [41]-[44]. The analyzed archaeological pottery pieces come from three deposits at the East Spain: Requena, Lliria, and Enguera. A total of 480 pieces were available from the Bronze Age, Iberian, Roman, and Middle Age periods that were measured by ultrasonic testing in through transmission mode (using two transducers: one emitter and one receiver) [45]. From the recorded signals the following features were extracted: total signal attenuation, propagation velocity, principal frequency, principal frequency amplitude, principal frequency attenuation, signal power, attenuation curve initial value, centroid frequency, time-reversibility, third order autocovariance, and instantaneous centroid frequency.

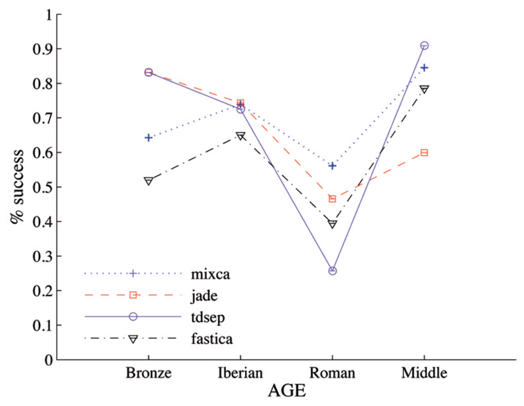
The signal features were preprocessed with PCA. An iterative process of classifying with a variable number of components was applied, using LDA and kNN as classifiers to determine the best number of PCA components [9]. The selected components were used as input for the Mixca procedure using: non-parametric ICA, JADE, TDSEP, and fastICA [18],[46]-[48] to compute the increments of the model parameters and several semi-supervision ratios were tested [17] (semi-supervision ratio is the proportion between labelled and unlabelled data in training stage). Results up to 100 Montecarlo trials of the classifications were obtained.

The averaged classification accuracy of the ICA

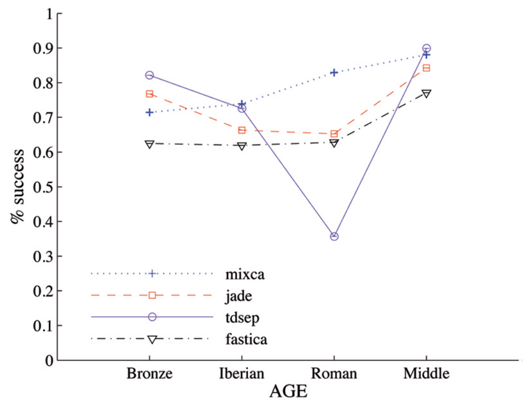


(a) B-Scan from sinusoidal components (b) B-Scan from backscattered components

Figure 6. *Power B-Scan after ICA preprocessing*



■ **Figure 7.** *Results for 0.5 supervision ratio*



■ **Figure 8.** *Results for 0.7 supervision ratio*

mixture classifications using different ICA algorithms for estimating the increments of the model parameters and two different supervision ratios are shown in Fig. 7 and Fig. 8. We had a total of 480*0.75=360 original samples for training. 3 replicates adding spherical Gaussian noise to the original samples were estimated to obtain a total of 1440 samples for training. Then for a supervision ratio of 0.7, we had 1008 labelled and 430 unlabelled samples for training stage. The best performance in classification for the ICA mixture algorithm was obtained using the non-parametric Mixca. For 0.5-supervision ratio average results of percentage of success were: Mixca=71%, JADE=65%, TDSEP=65.5%, and fastICA=60.4%. Mixca results with this little supervision in training are comparable with the best results of LDA with quadratic distance (72.7%). For a supervision ratio of 0.7 the results are much better for Mixca(80.42%) and for JADE(72.3%) are comparables with LDA-quadratic distance; results for TDSEP(67.8%) and fastICA(66.7%) become better than LDA- linear and Mahalanobis distances and kNN.

Table 1 contains the confusion matrix obtained by Mixca with 0.7 supervision ratio. The category Roman is not very difficult to classify but it is often assigned to pieces of Bronze and Iberian ages. Middle age pieces are 11% confused with Iberian pieces. Thus Roman and Middle age pieces cause misclassification of Bronze and Iberian pieces. The good average percentage of success obtained (80.42%) indicates good matching of the 6D component space projected from the calculated features to an ICA mixture model. Some of the pieces were treated by consolidation products for conservation, but it did not seem to

	Bronze	Iberian	Roman	Middle age
Bronze	71	0	21	7
Iberian	0	74	15	11
Roman	0	7	83	1
Middle age	0	2	1	88

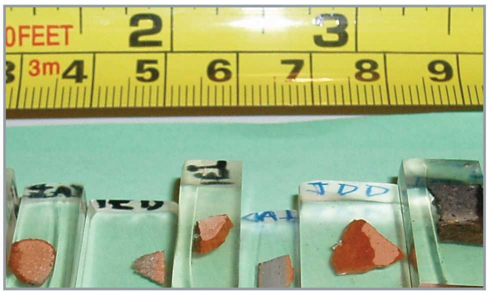
■ **Table 1.** *Confusion matrix by Mixca with 0.7 supervision ratio. Values are in percentages*

affect their classification on archaeological age. In addition, there was knowledge about correlation of the ceramic age with material porosity: Bronze and Iberian (high porosity), Middle age (medium porosity), and Roman (low porosity). Thus the correct classification of the sherds indicates that ultrasonic signal features could measure changes in physical properties, as porosity, of the archaeological ceramics. Complementing the measures with ultrasounds, have been carried out a diversity of morphological and physiochemical characterization by means of conventional instrumental techniques in order to be contrasted with the above mentioned. 25 representative pieces were selected for chemical and physical analyses.

Those pieces were observed, photographed and analyzed by means of optical microscope, scanning electron microscope (SEM) and X-ray diffraction techniques. As well physical analysis for the evaluation of density and open porosity parameters were applied on the selected pieces. Some of the test tubes prepared for SEM are shown in Fig. 9.

Data provided by these analytical studies show that there are clear differences at a morphological level between the different groups of processed fragments. So, ceramic corresponding to the Bronze age exhibits a dark brown tone with quite a lot of porosity and the presence of a lot of dark tone ferrous-composition spots associated with magnetite as well as reddish ferrous iron oxide nucleus.

The Iberian ceramic coming from Enguera has a variable tonality, between orange and black. It can be found abundant ferrous iron oxide nucleus (III) as well as more isolated dark magnetite spots. It is an iron-rich ceramic (up to 7.45% of Fe2O3), with a noticeable content in calcium (up to 6.30% of CaO). In relation with the physical properties we can said that the real densities were around 2.4 g/cm3 and the bulk density and the porosity were around 1.8 g/ cm3 and 22%, respectively.



■ **Figure 9.** *Results for 0.7 supervision ratio*

The fragments of Roman ceramic coming from Lliria have variable characteristics depending on the typology (sigillata, common or amphora). In all cases, they are orange tone mush, small size porosity as well as low level of degreaser, rising in quantity from the sigillata typology to the amphora, with content in Fe2O3 of 5.71, 6.36 and 9.24% respectively, and content in CaO of 0.67, 2.92 and 1.29% respectively. The real densities are very similar, between 2.4 and 2.7 g/cm3, and the bulk densities and porosity are around 2.1, 1.75 and 1.8 g/ cm3, and 42, 28 and 31% respectively. It is worth noting the high value of porosity showed by the fragments of sigillata, which is associated with pores of small to very small size and very connected, which allows big water absorption once the varnish layer is removed. Finally, the Middle age ceramic shows a bright orange to brown colour that remarks that are ferrous mush. It can be seen quite red ferrous iron oxide nucleus of small to very small size as well as dark tone magnetite spots. Also it can be seen white tone limy masses, associated to a high content in CaO (around 8%). In relation with the physical properties of density and porosity, it is worth mentioning real density values ranging in 2.0-2.38 g/ cm3, bulk density of 1.68-1.88 g/ cm3 and porosity of 10.0-25.7%.

Results from chemical and physical analyses from a sample of the pieces showed differences among porosities and properties of pieces from different ages. Those results seem to be correlated with the extracted ultrasound parameters.

5.4 Segmentation and object similarity in image processing

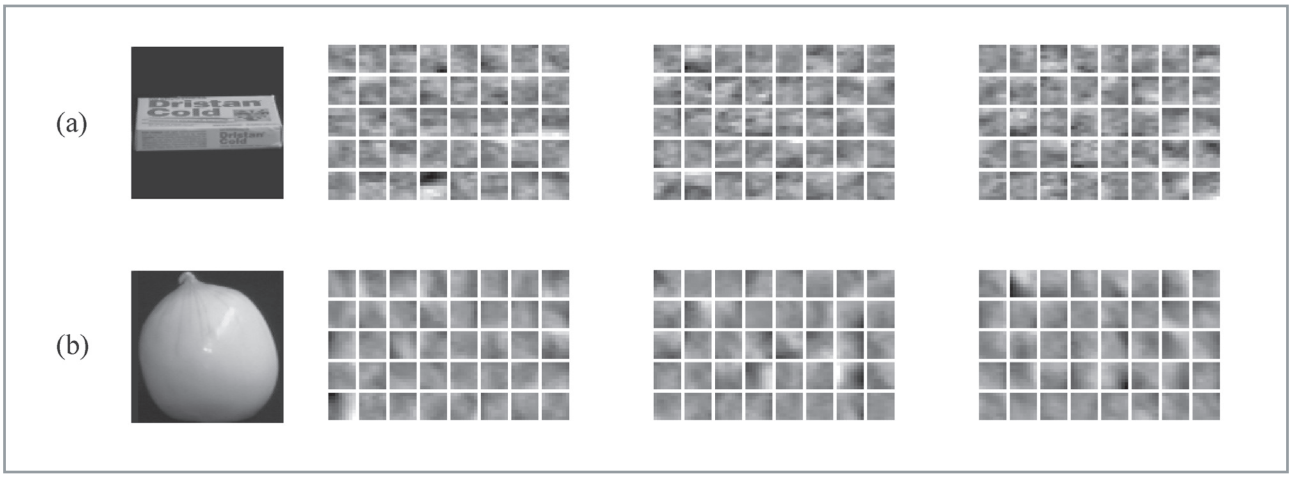
In this application, we provided a new algorithm to process the parameters of ICA mixtures in order to obtain hierarchical structures from the basis function level to higher levels of clustering [12][49]. Particularly the algorithm was applied to image analysis obtaining promising results in discerning object similarity and suitable levels of hierarchies by processing image patches. This kind of feedforward process would suggest some relation with abstraction. The algorithm is agglomerative and uses the symmetric Kullback-Leibler distance [5] to select the grouping of the clusters at each level.

5.4.1 Object similarity

For the hierarchical classification of object images, the COIL-100 database was used [50]. This database consists of different views of objects over a dark background. The method applied to preprocess the images was the following [1]: the images were converted to greyscale, and grouped in different views in order to obtain several images to train up to three classes per object; from each image, patches of 8 by 8 pixels were randomly taken to estimate the basis function previous a whitening process, with a reduction to 40 components. A total of 1000 patches for object were extracted. It is well known that local edge detectors can be extracted from natural scenes by ICA algorithms [51].

The basis functions of each class were then calculated with the ICA mixtures algorithm, considering supervision, and using the Laplacian prior to estimate the source PDF's. Fig. 10 shows the 40 basis functions of six classes corresponding to different views of two objects. The basis functions of Fig. 10a correspond to a box with a label inscribed whereas Fig. 10b corresponds to an apple. We can observe the similarity between the functions of each object and differences, for instance, the lower frequency in the pattern corresponding to a natural object versus the frequency in the pattern of a more artificial object.

A better insight into the underlying physical phenomena was obtained.



■ **Figure 10.** *Two groups of basis functions corresponding to two different objects. Basis functions at top are from a little box and basis functions at bottom are from an apple*

Hierarchy reveals meaningful bottom-up makeups merging natutal image zones.

The same data were used to measure the distance between classes estimating the symmetric Kullback-Leibler distance from the mixture matrices calculated previously. Distances reveal that basis functions allow the similarity (short distances) between classes corresponding to the same object (intra-object) to be found, whereas distances are much longer between classes of different objects (inter-object), see Table 2.

Additionally, various experiments in order to create a hierarchical classification of objects were performed. Thus, patches were sampled from a large number of objects, some of them very similar among themselves. A hierarchical representation was then created applying the agglomerative clustering algorithm.

Fig. 11 shows an example of classification of eight objects, with three main kinds of objects. The tree outlined by the dendrogram positively shows grouping of objects based on similarity content, and suitable similarities between 'families' of objects, e.g., cars were more alike with cans than with apples.

Object	box (a)	apple (b)
box (a)	1289	11490
apple (b)	11490	1381

Table 2. *Mean distances inter-object and intra-object of Fig. 10*

5.4.2 Natural images

The hierarchical algorithm was applied to natural images in order to obtain a bottom-up structure merging several zones of an image. Fig. 12 shows an image with 9 zones, some of them clearly different and others more or less similar each other. Dendrogram of Fig. 12 shows how the zones are merged from the patches. It shows two broad kinds of basis functions that correspond to the part of the image that mainly contains portions of sky, and those zones that correspond to patches where there is a predominant portion of stairs (high frequency). The dendrogram also shows the distances at which the clusters are merged; it can be used as a similarity measure of the zones of the image. The zones in the bottom part of the image are merged at low distances due to the high similarity in borders.

5.5 Detection of learning styles in learning web activities

This application consists of the detection of student learning styles in e-learning [52]-[54]. We used the Mixca algorithm configured to estimate one ICA. The application was carried out on data of graduate and undergraduate courses at the Universidad Politécnica Abierta (UPA) site. The UPA is a virtual campus at Universidad Politécnica de Valencia. The e-learning event activity at the campus web was analyzed to recognize patterns on learning styles of the students. Data from the use of the UPA web facilities included the following information about e-learning event activities: 1(course access), 2(agenda using), 3(news reading), 4(content consulting), 5(email exchange), 6(chats), 7(workgroup document), 8(exercise practice), 9(course achievement), and 10(forum participation). Date and time for each event also were available. Besides of the information on the web activity, the exercises achieved and grades obtained by the UPA's students were available. The data were collected from the virtual campus web in the period three years, totalizing 2'391,003 records.

A learning-style model classifies students according to where they fit in a number of scales corresponding to the ways in which they receive and process information. One of the most accepted learning style taxonomy for engineering students is the Felder's model [55], see Table 3 (one learning style is conformed by the combination of one feature in each dimension, for instance, intuitive-visual-deductive-active-global).

We applied ICA after reducing the data to 5 components by PCA, for grouping the events of the web activity in learning dimensions taking into account the Felder's framework [55]. PCA reduced 10 web event activities to 5 components. To solve the problem of detecting learning styles in e-learning, we assume that the underlying independent sources that generate the web log data are dimensions of the learning styles of the stu-

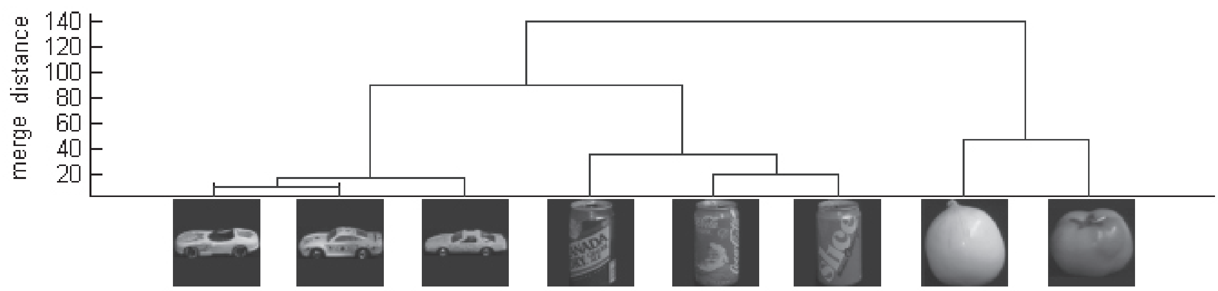


Fig. 11. *Hierarchical representation of object agglomerative clustering. Three kinds of object 'families' are obtained*

dents, and we observe x linear combinations of those styles through the use of the facilities at the virtual campus.

Then, s_i,($i=1,...,5$ *learning style dimension*) correspond to the "perception", "input", "organization", "processing", and "understanding" dimensions (see Table 3); and the mixture matrix A provides the relation between e-learning style dimensions and e-learning event activities, a_{ij},($i=1,...,5$ *learning style dimension*), ($j=1,...,10$ *e-learningactivity*).

Each source was associated with one learning dimension of Table 3, analyzing the weight of the web activities and considering the principal evaluation methodologies employed by teachers. For graduate courses with grades: dimension 1 was not detected and dimension 5 was detected twice. The methodologies assigned grades focusing on: achievement, individual student participation, or group work. The implicit teaching styles of the evaluation methodologies encourage specific learning styles of the students. The learning dimension 1 (sensory-intuitive) corresponding to "perception" was not detected in the ICA mixing matrix; it could be because the emphasis of educational strategies did not favour to highlight that dimension.

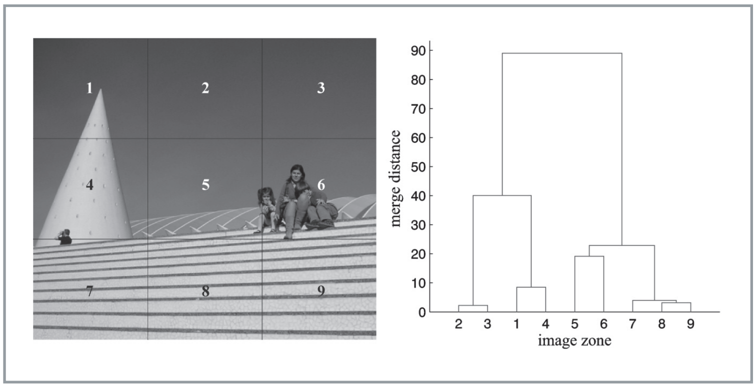
Table 4 shows the association found by ICA between learning styles and web activities (we have added a possible web activity combination for learning dimension 1). Note that some web activities are associated with more than one dimension; it has sense because a web activity could demand several capabilities of the students used in their learning process. Allowing that kind of relationship we can obtain more real and versatile descriptions of the student learning styles, besides of including all the dimensions of the learning framework.

Fig. 13 shows the sources 3, 4, and 5 (organization, processing, understanding) obtained for the graded graduate course dataset. Four labelled characterised zones in the learning style space are displayed: 1.) Represents the learning style more important in the population. The learning for the students in this zone emphasizes global understanding, active processing, and deductive logic (natural human teaching style), and high grades. 2.) This learning style is focused on inductive logic (natural human learning style), with sequential understanding, and relative active processing. Students within this style could have natural skills for virtual education. 3.) It is characterised by global understanding, deductive logic, and reflective processing. Students within this style would have higher abstraction skills that need of teaching. 4) Basically this cluster represents outliers with individual learning styles.

We can conclude that the dimension of understanding enables to project clearly the learning styles of the students, and its principal components are course achievement, content consulting, and use of agenda. This finding confirms the assumption that the more quickly way to change the learning style of the student is to change the assessment style, i.e., expected evaluation bias how the student learns [56].

We made a cluster validation procedure to determine the best quality of cluster configuration for data of Fig.13. It consisted of estimating the partition and partition entropy coefficients for different number of clusters [57]. The optimum number of clusters was 4 as shown in Fig. 13.

Results show learning style detection was possible only for courses with grades. The implicit teaching styles of the evaluation methodologies encourage specific learning styles of the students, i.e., the lack of assessment did not allow to detect student learning styles. Mixca using non-



■ **Figure 12.** *(Left) Image divided in nine zones. (Right) Hierarchical representation of the zones of the image based on basis functions similarity. Two broad groups of zones are shown.*

	Preferred Learning Style		Corresponding Teaching Style	
1	Sensory-Intuitive	Perception	Concrete-Abstract	Content
2	Visual-Auditory	Input	Visual-Verbal	Presentation
3	Inductive-Deductive	Organization	Inductive-Deductive	Organization
4	Active-Reflective	Processing	Active-Passive	Student Participation
5	Sequential-Global	Understanding	Sequential-Global	Perspective

■ **Table 3.** *Dimensions of learning and teaching styles (Felder's model)*

	Learning Style		Web event activity
1	Sensory-Intuitive	Perception	chats, forum participation, course access.
2	Visual-Auditory	Input	chats, forum participation, news reading, email exchange.
3	Inductive-Deductive	Organization	workgroup document, news reading, course achievement, content consulting .
4	Active-Reflective	Processing	email exchange, content consulting, workgroup document, exercise practice.
5	Sequential-Global	Understanding	course access, agenda using, content consulting, course achievement.

■ **Table 4.** *Association between learning styles and web activities*

NLMP builds a framework suitable for problems with complex data densities.

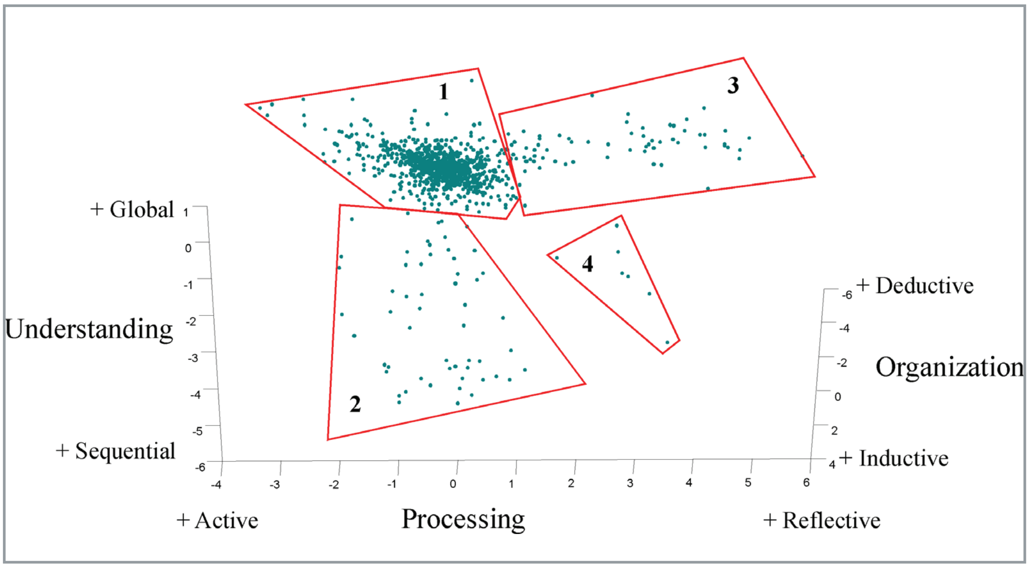


Figure 13. Three sources in a learning style space for graduate courses with grades.

parametric density estimation allow more suitable learning styles clusters were found than the learning styles found by Mixca using standard ICA algorithms.

6. Conclusions

The proposed NLMP structure builds a versatile and powerful framework that can be employed in many real problems involving complex data densities. We provided several applications in signal classification and pattern recognition processing different kinds of data, such as sonic and ultrasonic signals; images; and historic web log data. Thus, we demonstrated that the degrees of freedom afforded by mixtures of ICAs suggest that it is a good candidate for a broad range of problems.

The modelling of the data as mixtures of independent component analyzers contributes to obtain higher insights into the underlying physical phenomena of the applications since this modelling makes both source extraction and signal analysis simultaneously. This enables a more detailed explanation of the measured signals and of their source data generators that are behind the observed mixture. In any case, whether the complexity of the problem constraints a physical interpretation, the framework can be used as a general data mining technique.

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