UNVEILING INTRINSIC SIMILARITY
Application to Temporal Analysis of ECG

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Abstract: The representation of data in some visual form is one of the first steps in a data-mining process in order to gain some insight about its structure. We propose to explore well known visualization and unsupervised learning techniques, namely clustering, to improve the understanding about the data and to enhance possible relations or intrinsic similarity between patterns. Specifically, Clustering Ensemble Methods are exploited separately and combined to provide a clearer visualization of data organization. The presented methodology is used to improve the understanding of ECG signal acquired during Human Computer Interaction (HCI).

1 INTRODUCTION

Critical to the understanding of data is the ability to provide its pictorial or visual representation. This process is particularly relevant for analyzing large volumes of complex data (e.g. multidimensional) that are available from a variety of sources. The human visual system has an enormous capacity for receiving and interpreting data efficiently (Treinish and Goettsche, 1989).

There are many numerical and statistical techniques that can be used to analyze structural information from multidimensional data. Discovery and understanding of the structure in the data has many applications in science and business. Examples of structure include clusters, regular patterns, outliers, distance relations, proximity/similarity of data points, etc... (Post et al., 2003).

The underlying tool for most of the pattern recognition methods is a distance function, or more generally a similarity or dissimilarity measure. In the literature there are many proposed similarity/dissimilarity measures (see (Fred, 2002) and the references therein). Moreover each clustering algorithm induces a similarity measure between data points, according to the underlying clustering criteria (Fred and Jain, 2006). The representation of such similarities is the focus of this paper.

Multidimensional scaling (MDS) techniques enable the representation of multidimensional data (embedded in an *n*-dimensional space) in lower dimensional spaces such that the structural properties of the data are preserved. Given a dissimilarity (or similarity) pairwise matrix (containing pairwise information), MDS techniques represent the objects in a low-dimensional space, preserving all pairwise, symmetric dissimilarities between data objects (Pekalska and Duin, 2003).

Data clustering and Unsupervised learning is used in many disciplines and contexts, as an exploratory data analysis (EDA) tool. Ensemble methods, namely the evidence accumulation clustering (EAC) technique (Fred and Jain, 2005), represent state of the art in data clustering methods, and a way of learning the pairwise similarity between the data in order to proper partitioning the data points (Fred and Jain, 2006).

In this paper we present a methodology based on data Clustering techniques, aiming at improving the understanding about the data, enhancing its intrinsic structure. We apply this methodology to electrophysiological data, namely ECG, provided under the scope of a HCI study.

The paper is organized as follows: in section 2 we briefly present the MDS techniques; in section 3

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we formalize the clustering problem and present several methods to enhance the intrinsic data structure: in subsection 3.1 using the dissimilarity matrix; and in subsection 3.2 mapping the associations in a new similarity measure using the evidence accumulation clustering method. Finally, in section 4, this methodology is presented in the analysis of ECG data. Throughout the paper we present illustrative examples.

2 MULTIDIMENSIONAL SCALING

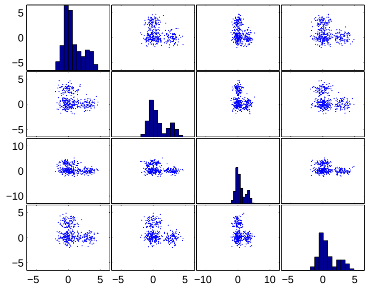
Multidimensional scaling (MDS) in wide sense refers to any technique that produces a geometric representation of data, on a low dimensional space, usually Euclidean, where quantitative or qualitative relationships in data are made to correspond with geometric relationships in the geometric representation (Cox and Cox, 1994) (de Leeuw, 2000). Data objects judged to be similar to one another result in points being close to each other in this geometric representation (Pekalska and Duin, 2003). For more technical details about MDS techniques consult Cox and Cox (Cox and Cox, 1994) or Pekalska and Duin (Pekalska and Duin, 2003).

As input for these techniques it is required a measure of similarity (or dissimilarity - inversely related to similarity) between objects in the high-dimensional space. Consider δ_{ij} a measure of dissimilarity (usually called *disparity*) between the data objects i and j, and d_{ij} the estimated geometric distance in the low dimensional space used to represent data objects i and j. The *raw stress*, is the most elementary MDS loss function, which quantitatively characterizes a given geometric configuration for the data representation:

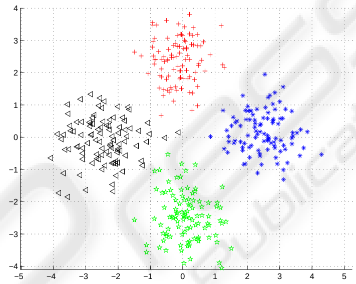
$$S^{raw}(X) = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} (\delta_{ij} - d_{ij})^2 \qquad (1)$$

An iterative optimization process can be used to find a geometric configuration that minimizes the loss function presented above (or other given in the literature).

Consider as an illustrative example of the MDS technique a 2-dimensional representation of a set of 4-dimensional gaussian data (R^4), with identical covariance matrices ($\Sigma = 0.5 I_4$), and centered, respectively in $\mu_1 = [3,0,0,0]$, $\mu_2 = [0,3,0,0]$, $\mu_3 = [0,0,3,0]$ and $\mu_4 = [0,0,0,3]$. Figure 1(a) represents the matrix plot of the multidimensional data (that is: the i-th row and j-th column of this matrix is a plot of X_i variable versus X_j variable; the main diagonal represents the histograms of each variable). Figure 1(b) presents the



(a) Matrix Plot



(b) MDS

Figure 1: Multidimensional data representation. Projections in 2-D dimensional spaces. MDS configuration.

obtained configuration in the 2-D euclidean space, using as optimization criteria the Kruskal's normalized stress1 criterion (equation above). For better understanding of the obtained representation, different colors and shapes where used to represent each of the different gaussians. In the next section we will briefly review the methods that unsupervisely group data objects.

3 CLUSTERING

The goal of clustering is to enhance the interpretability of the data by organizing data in meaningful groups (or clusters) such that the patterns in a cluster are more similar to each other than patterns in different clusters (Jain and Dubes, 1988), (Pekalska and Duin, 2003). Each clustering algorithm visualizes data in a different way, inducing different similarity measures between data points according to the underlying clustering criteria (Fred and Jain, 2006).

There are a number of problems with clustering methods. The most important one is that there are

Clustering is a difficult problem, hundreds different techniques have been proposed in the literature, yet no single algorithm is able to identify all sorts of cluster shapes and structures that are encountered in practice.

A recent trend in clustering, that constitutes the state-of-the art in the area, are the clustering combination techniques (also called ensemble methods). They attempt to find a robust data partitioning by combining different partitions produced by a single or multiple clustering algorithms. Several combination methods have been proposed (Fred, 2001; Strehl and Ghosh, 2002; Fred and Jain, 2002; Topchy et al., 2004) to obtain the combined solution.

3.1 Dissimilarity Matrix

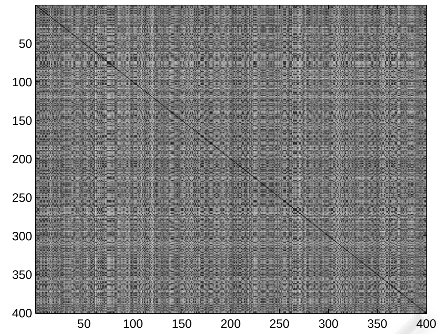
There is some work in visual approaches for assessing cluster tendency (Bezdek and Hathaway, 2002) based directly on visualizing the dissimilarity matrix obtained from the data. In (Bezdek and Hathaway, 2002) Bezdek and *al.* presented an algorithm - the visual assessment of cluster tendency (VAT) - which reorders the dissimilarity data so that possible clusters can be enhanced.

The images in Figure 2 are intensity image, where the intensity or gray level of the pixel (i,j) depend on the value of δ_{ij}, the dissimilarity between sample i and j. The value 0 corresponds to pure black; and the pure white represent the maximum dissimilarity. They were obtained with Euclidean distance for the gaussian data set presented previously. The figure 2(a) represents the obtained dissimilarity images when the samples are randomly positioned, and the figure 2(b) when the samples are re-organized so that the samples that are close together are as near as possible (as described in VAT (Bezdek and Hathaway, 2002)). By analyzing this dissimilarity image we identify dark rectangular areas, characteristic of items that are close together and that could constitute a cluster.

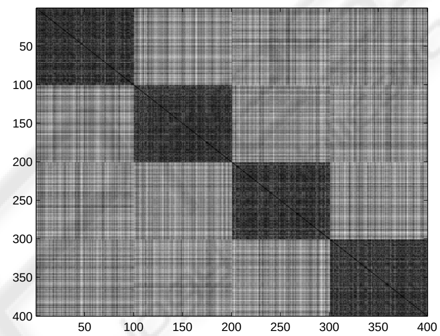
3.2 Evidence Accumulation Clustering

The Evidence Accumulation Clustering (EAC), proposed by Fred and Jain in (Fred, 2001) (Fred and Jain, 2005), is one of the clustering combinations techniques proposed in the literature. This method combines different visions over the data set, obtained by different algorithms or a single algorithm with different initializations, aiming to find the intrinsic similarity of the data. The different partitions obtained by the clustering algorithms, are called the *clustering ensemble*.

The EAC is based on the mapping of the relationships between pairs of patterns into a $n \times n$ co-association matrix, $\mathcal{C}$. This matrix accumulates the



(a) Dissimilarity Matrix



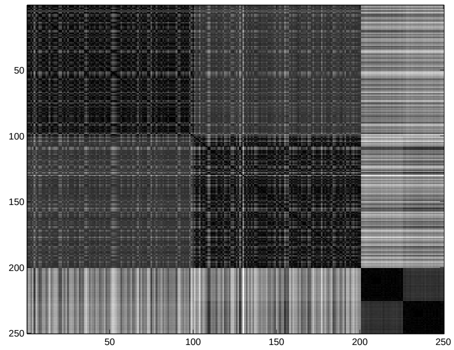
(b) VAT

Figure 2: Dissimilarity Images.

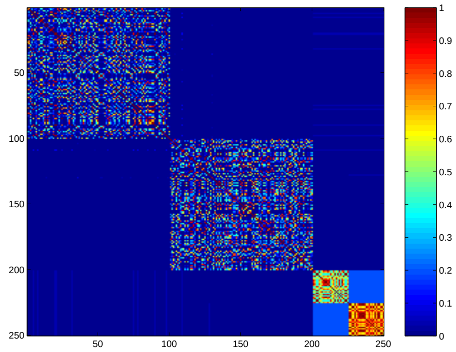
co-occurrence of pairs of samples in the same cluster over the N clusterings of the clustering ensemble $\mathbb{P}$ according to the equation:

$$\mathcal{C}(i,j) = \frac{n_{ij}}{N}, i,j \in 1,..,N \qquad (2)$$

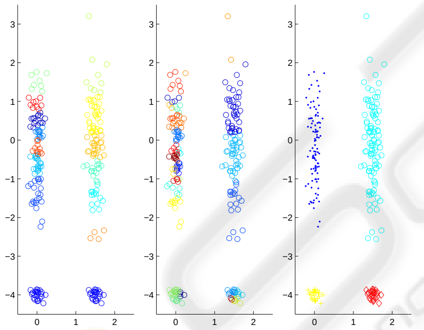
where n_{ij} represents the number of times a given sample pair (i,j) has co-occurred in a cluster over the N clusterings. Assuming that patterns belonging to a ”natural” cluster are very likely to be co-located in the same cluster in different clusters of the partitions of the clustering ensemble, the co-occurrences of pairs of patterns summarizes the inter-pattern structure perceived from these clusterings. Each co-occurrence of a pair of samples in the same cluster are taken as a vote for the association of those samples. For that reason this method is also known as majority voting combination scheme. In order to recover the natural clusters, and to emphasize the neighborhood relationships, in (Fred, 2001), the Single-link hierarchical algorithm (Jain and Dubes, 1988) is applied on the new feature space represented by the co-association matrix, yielding the combined data partition P^*. Other algorithms may be applied in this final step (Fred and Jain, 2005).



(a) Dissimilarity Matrix.



(b) Co-association matrix based on the ensemble.



(c) One of the partitions of the ensemble, k=14

(d) One of the partitions of the ensemble, k=28

(e) EAC combined partition.

Figure 3: Individual clusterings and combination results on the cigar data-set using a k-means ensemble.

Figure 3 presents a typical application of the EAC method on an artificial data set (cigar data-set). An ensemble of 25 partitions was produced using the k-means algorithm with random initialization and with k randomly chosen in the interval [10,30]. Examples of obtained partitions are illustrated in (c) and (d). The combination result is presented in (e). The *co-association* matrix (illustrated in (b)), corresponds to a new similarity between samples based on the information accumulated from the partitions in the clustering ensemble. In figure the axis represent the samples of the data set, organized such that samples belonging to the same cluster are displayed contiguous (as described in section 3.1). The color scheme in the figure ranges from red to blue, corresponding to a gradient in similarity. Pure Red corresponds to the highest similarity. It can be seen that, although individual data partitions are quite different, neighboring patterns occur in the same cluster in most of the partitions. As a result, the true structure of the clusters becomes more evident in the co-association matrix: notice the more clear separation between clusters (large blue zones) and more evident block diagonal structure in figure 3(b) as compared to the original dissimilarity matrix in figure 3(a).

In the described method each partition is given an equal weight in the combination process and all clusters in each partition contribute to the combined solution. Other approaches were taken, for example, weighting/selecting the partitions based on the quality of the overall partitions. More recently, instead of evaluating the overall performance of a clustering algorithm based on the final partition produced by it, in (Fred and Jain, 2006) it is assumed that each algorithm can have different levels of performance in different regions of the multidimensional space. It is proposed to learn pairwise similarity based on meaningful clusters, which can be identified based on cluster stability criteria. Thus only those clusters passing the stability test will contribute to the co-association matrix an to the learned similarity matrix yielding a more robust solution. Figure 4 presents this matrix for the same data set as above. We observe that the rectangular areas are perfectly defined clearly distinguishing the underlying clustering structure. When represented via MDS this matrix yields 4 separate points in the 2-dimensional space.

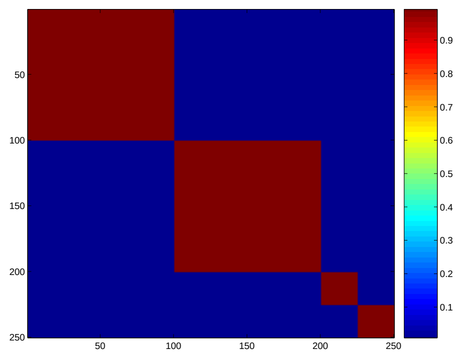


Figure 4: Learned co-association matrix.

4 ECG ANALYSIS

We applied the previous methodology to the analysis of ECG recordings, performed during the execution of a cognitive task using the computer, based on the work on (Silva et al., 2007). The ECG acquisition was part of a wider multi-modal physiological signal acquisition experiment aiming personal identification. The task consisted on a concentration task where two grids with 800 digits were presented, with the goal of identifying every pair of digits that added 10 and was designed for an average completion time of 10 minutes. A collection of 53 features were extracted from mean ECG waves for groups of 10 heart-beat waveforms (without overlapping): 45 amplitude values measured at sub-sampled points and 8 latency and amplitude features were also extracted (for more details see (Silva et al., 2007)).

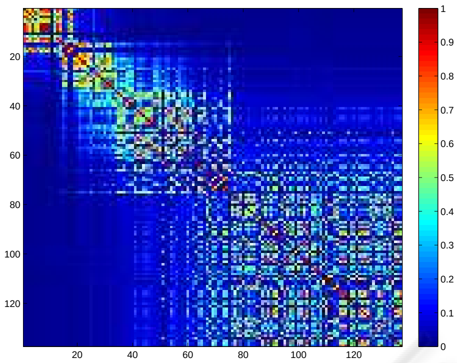
Instead of using the ECG features for personal identification, herein we study the data in a data-exploratory perspective, trying to find its underlying time evolution. The task was designed to induce stress in the subject (for more details see (Silva et al., 2007)) thus the ECG characteristics should vary over time. The aim of this preliminary analysis is access typical patterns of temporal evolution over the subjects based on the ECG extracted features.

For each subject, the temporal evolution of the ECG characteristics was performed as follows: each time window, represented by the 53 features, constitutes a sample; the application of clustering over these samples reveals groups of samples representing 'stable' phases of temporal behavior over the ECG. According to the previous ensemble methodology, we constructed a clustering ensembles of $N = 75$ K-means partitions with varying number of clusters, $k \in [2,30]$, applying the EAC approach and analyzed the induced similarity matrix.

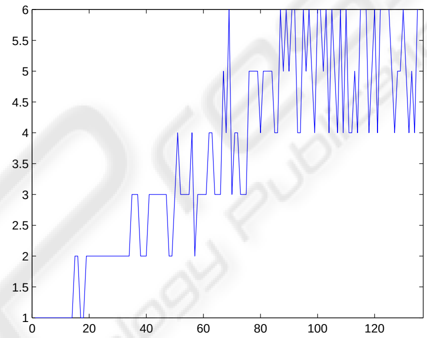
We applied this technique over the 26 subjects that performed the task. Figure 5 presents one example of the typical structures obtained in the analysis. Figure 5(a) represents the obtained co-association matrix. In this co-association matrix adjacent patterns (in rows and columns) represent time aligned samples (0 represents the beginning of the test) of the ECG recording. It is interesting to note its block diagonal structure revealing time relationships between the patterns. This structure is not so evident as in the previous toy example, but a similar diagonal pattern can be inferred.

Using the Ward's link and the life time criteria for choosing the number of clusters, 6 clusters are obtained. In figure 5(b) we present the temporal evolution of such clusters: x-axis correspond to the samples order by time; and the y-axis the discovered clusters $\{1,2,\ldots,6\}$. Analyzing this figure, we can perceive that over the time the changes in cluster are only between adjacent clusters: cluster 1 evolutes only to cluster 2; cluster 2, evolutes only between clusters 1 or 3, ..., cluster i evolutes only between $i-1$ and $i+1$. Note that this adjacent clusters are more similar that not adjacent ones. If we consider that each cluster represent a temporal behavior, this reveals a continual evolution of these behaviors, not observing drastic changes over time. These changes in the temporal behavior of the features could have been caused by the increasing stress levels induced by the test that was being resolved by the subjects.

Figure 6 presents the MDS representation of the data, based on the EAC induced similarity. The represented clusters (in different colors and shapes) are the same presented in figure 5(b). It is possible to note that samples of adjacent clusters are represented adjacently as previously discussed in the temporal evolution of clusters.



(a) Co-association Matrix based on the ensemble.



(b) Cluster Temporal-Evolution.

Figure 5: ECG Analysis based on induced similarity using the EAC algorithm over an ensemble of 75 k-means partions (with varying number of clusters).

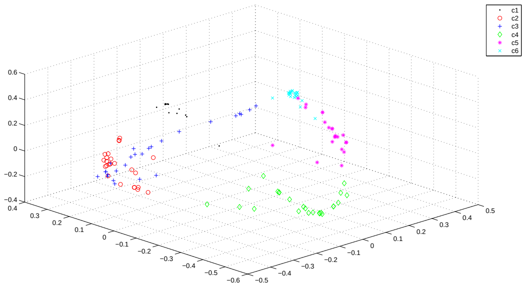


Figure 6: MDS representation of the data based on the EAC induced similarity. The clusters were obtained using the Ward's link and the life time criteria for choosing the number of clusters.

5 CONCLUSIONS

We presented a short overview of state of the art in data visualization and unsupervised learning techniques, to improve the understanding about the data.

Examples shown that the visualization either by dissimilarity matrix observation (using VAT), or co-association observation (obtained via EAC) or using Multidimensional Scalling (MDS), provide pictorial or alternative visual representations of multidimensional data important to gain insight about the data.

The preliminary analysis of the ECG signal demonstrates the potential of these visualization techniques in biosignal analysis. The results have shown typical patterns of time evolution of clusters which can be related with increasing stress levels.

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