Hierarchical manifold learning for the interpretation of multi-level data -Application to cardiac imaging

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Goal: Manifold learning aims at representing high-dimensional data with a much lower amount of dimensions. This is particularly relevant to analyze the image content within a specific database: indeed, the images and/or the patterns they contain can reasonably be considered to lie on a non-linear manifold; besides, manifold learning estimates a low-dimensional latent space which facilitates population study. However, in medical imaging, physicians may use several imaging modalities to diagnose patients, which is particularly challenging for manifold learning as these data can be of heterogeneous types and appropriate fusion schemes are required. A few multimodal manifold learning techniques can be used to integrate these multiple data sources, such as multiple kernel learning [1] or similarity network fusion [2]. Nonetheless, these methods fuse all the data at the same time, and do not use prior knowledge on the relative importance or priority of the different types of data.

Method: Clinicians often integrate data in a hierarchical way, to guide their interpretations from simple to more complex data. Inspired by this, our objective is to demonstrate the relevance of an unsupervised hierarchical manifold learning scheme to integrate image content based on simpler but more robust information (parent level) and therefore better exploit the richness of more complex image information (child level). We adapted the hierarchical manifold learning framework proposed in Bhatia et al.[3], initially proposed to represent images at multiple scales. In our problem, we exploited the method for the hierarchical integration of two different types of imaging data, as shown in Fig.1.

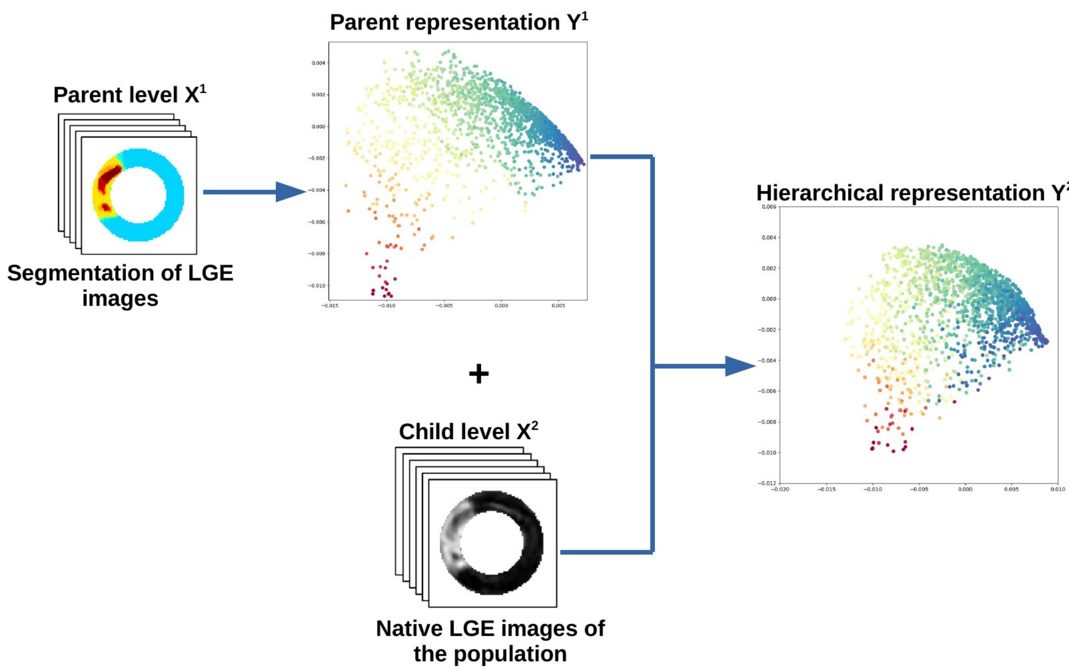

Figure 1: Illustration of the hierarchical integration of LGE images and their segmentation.

Our hierarchy consists of two levels. The parent level corresponds to the segmented lesions (infarct and microvascular obstruction / MVO), considered as an image with categorical pixel values. The child level corresponds to the raw grayscale images, whose range was normalized between 0 and 1. The hierarchical manifold learning aims at minimizing:

$$\underset{\mathbf{Y}^2}{\arg\min} \ (1-\mu)\sum_i \sum_j \|\mathbf{y}_i^2 - \mathbf{y}_j^2\|^2 W_{ij}^2 + \mu \sum_i \|\mathbf{y}_i^2 - \mathbf{y}_i^1\|^2$$

where $\mathbf{Y}^2$ is the latent space associated to the child level, $\mathbf{Y}^1$ is the latent space of the parent level of the hierarchy, $\mathbf{W}^2$ the affinity matrix encoding inter-subject relationships for the second level of the hierarchy, and $\mu \in [0,1]$ a weighting parameter. The first term of the equation corresponds to the embedding performed by the diffusion maps algorithm [4] for the child level of the hierarchy. The second term quantifies the distance between the hierarchical embedding $\mathbf{Y}^2$ and the embedding of the first level $\mathbf{Y}^1$**.** As demonstrated in [3], this problem has an analytic solution which allows fast computations of the child embedding from the parent embedding:

$$\mathbf{Y}^2 = (\mu\mathbf{I} + 2(1-\mu)\mathbf{L}^2)^{-1}\mu\mathbf{Y}^\mathbf{1}$$

where **I** stands for the identity matrix, and $\mathbf{L}^2$ stands for the graph Laplacian of $\mathbf{X}^2$.

Results: We illustrate this approach on the study of a population of 123 acute myocardial infarction patients, from the MIMI study [5], totalling 1711 2D slices. The clinical objective is to better characterize ischemia-reperfusion mechanisms and determine whether image appearance can be of added value over simple descriptors of the lesions and their segmentations. The 1711 LGE MR image slices are of size 80x80 pixels, and the myocardium has been aligned on a single geometrical reference, as described in [6]. Our hierarchical scheme provides a balanced contribution between the segmented images and the raw image content, as visible in Fig.2.

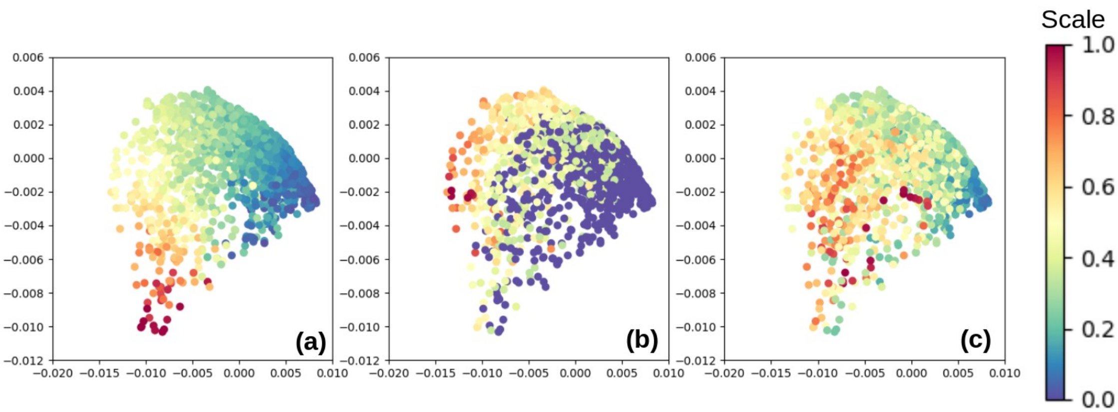

Figure 2 :Resulting latent spaces for μ = 0.47 (balanced energy) with different color scales to better appreciate the balance between the child and parent levels of the hierarchy: colored according to the amount of infarct (a), MVO in the myocardium (b), or the mean value of grayscale image intensity (c)

This hierarchical latent space roughly preserves the global structure of the parent level, but carries information about the imaging appearance. A way of seeing this is to look at the few closest neighbors of some key points. We observed that the close neighborhoods of such individuals were more coherent concerning the similarity of imaging content patterns, while still being close regarding the segmented images.

Conclusion: Our results show the relevance of the proposed unsupervized hierarchical manifold learning framework for the hierarchical representation of multiple data descriptors. This framework can be used to better understand the underlying structure of the dataset, as illustrated here for the characterization of lesion patterns in LGE images. It can also be used for dimensionality reduction purposes, as preprocessing for a classification algorithm for example. As briefly illustrated, this allowed us to guide the integration of raw LGE image content from the more reliable segmented images, while being robust to usual grayscale image exploitation difficulties due for example to image artifats or specific MVO patterns. The exploitation of this space will help us in the comprehension of ischemia-reperfusion patterns in the context of acute myocardial infarction.

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