

MANIFOLD LEARNING FOR PATIENT POSITION DETECTION IN MRI

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ABSTRACT

Magnetic resonance imaging is performed without ionizing radiation, however, the applied radio frequency power leads to heating, which is dependent on the body part being imaged. Determining the patient position in the scanner allows to better monitor the absorbed power and therefore optimize the image acquisition. Low-resolution images, acquired during the initial placement of the patient in the scanner, are exploited for detecting the patient position. We use Laplacian eigenmaps, a manifold learning technique, to learn the low-dimensional manifold embedded in the high-dimensional image space. Our experiments clearly show that the presumption of the slices lying on a low dimensional manifold is justified and that the proposed integration of neighborhood slices and image normalization improves the method. We obtain very good classification results with a nearest neighbor classifier operating on the low-dimensional embedding.

Index Terms— Manifold Learning, Classification, MRI

1. INTRODUCTION

Current magnetic resonance (MR) scanners allow the acquisition of high resolution images. However, this comes with a higher dose of radio frequency (RF) power applied to the patient. This leads to heating in the body and has to be monitored by measuring the specific absorption rate (SAR). The limits for the maximal SAR depend on the patient position inside the scanner. If the position is not known, the lowest SAR limit along the body, which is in the neck area, is to be set to the global limit [1]. Determining the patient position within the MR scanner enables to impose an SAR model, adaptive to the body region, and consequently, to exploit the maximal image resolution.

In our previous work [1], we proposed to use the novel "move during scan" imaging protocol to determine the patient position. This enables the acquisition of low-resolution images during the initial positioning of the patient in the scanner. This has the advantage that the workflow does not have to be altered, ensuring its seamless integration and practicability. During the acquisition, the bed moves with a relatively high but constant speed, leading to low-resolution slices, having a

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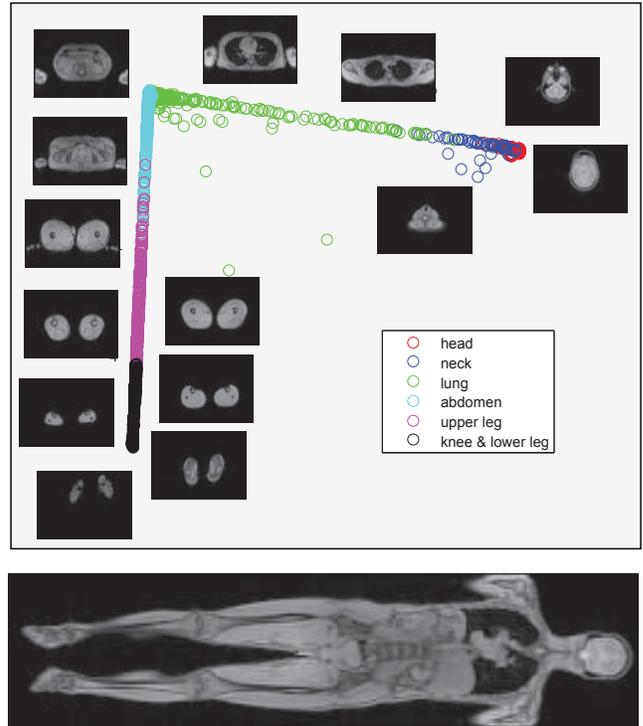


Fig. 1. Low dimensional embedding of manifold using Laplacian eigenmaps (w/ Nbh, w/ normalization) with ground truth labeling. Below, coronal plane of move during scan volume.

resolution of 64×64 pixels, and a slice spacing of 7.5 mm to 15 mm (see Figure 1 for examples and a coronal view).

The objective of patient position detection is to classify these slices according to different regions of the body such as head, abdomen, and lower leg. In [1], principal component analysis (PCA) is used to reduce the dimensionality before the classification is performed. PCA [2] and also the independent component analysis (ICA) [3] find a set of basis images, and represent an input image as linear combination of those. However, the representation of images as a linear combination of those basis images may require many of those for an accurate representation, and further, the internal structure may not be easy to identify by analyzing the weighing parameters. Having data that lies on a low-dimensional manifold

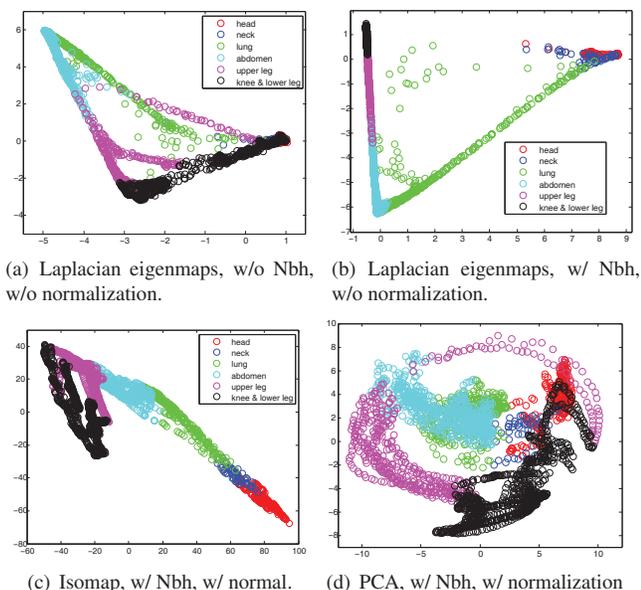


Fig. 2. Low dimensional embeddings. Data labeling with ground truth segmentation.

living in a high-dimensional space, more appropriate methods were proposed that respect this structure [4, 5]. In this article, we evaluate those methods for patient position detection, focusing on Laplacian eigenmaps [5], with exemplary low-dimensional embeddings shown in Figures 1 and 2. Additionally, we investigate if the MR slices lie on a manifold with intrinsic low dimensionality. In order to achieve good classification results, we adapt manifold learning methods by integrating the consideration of neighboring slices and a preceding normalization. The classification is performed with a nearest neighbor classifier.

2. BACKGROUND

The task of dimensionality reduction is to find the underlying structure in a large set of points embedded in a high dimensional space. The advantages of a successful dimensionality reduction are: First, it assists the classification because a direct classification in high-dimensional space does not respect the manifold structure whereas the classification on the low-dimensional embedding does. And second, the lower-dimensional embedding enables to visualize the manifold and, therefore, indicates whether a classification seems feasible.

Manifold learning for dimensionality reduction has recently gained much attention to assist image processing tasks such as segmentation [6], registration [7, 8], tracking [9], recognition [10], and computational anatomy [11]. Common techniques for manifold learning are Isomap [4], local linear embedding [12], and Laplacian eigenmaps [5]. The applications vary by using either the intensity image as input or

Table 1. Results of classification for Laplacian eigenmaps with neighborhood and image normalization. The overall correct classification rate is 94.0%.

	Recognized Class Labels in %					
	Head	Neck	Lung	Abd.	U. Leg	L. Leg
Head	95.0	5.0	0.0	0.0	0.0	0.0
Neck	25.9	69.0	5.2	0.0	0.0	0.0
Lung	0.0	0.9	92.0	6.9	0.3	0.0
Abd.	0.0	0.0	2.0	97.2	0.8	0.0
U. Leg	0.0	0.0	0.0	2.1	84.5	13.5
L. Leg	0.0	0.0	0.0	0.0	1.6	98.4

calculating coordinate transformations, for instance diffeomorphic warps [13, 11, 8], between the images, which subsequently serve as input. The calculation of the deformation field makes sense, if all images to be analyzed show similar objects *e.g.* brain images. In our application, we need to deal with images from all body parts, for which it would not be possible to register one to the other. We therefore directly perform the dimensionality reduction on the original images. The suggestion that the MR slices lie on a low-dimensional manifold in the ambient space seems to be justified because variations between neighboring slices are smooth, and further, slices from the same body position but different patients are similar.

3. METHOD

In this section we describe the details of the proposed manifold learning approach. Throughout, we consider one dimension of the ambient space for each image pixel. Considering k points $\mathbf{x}_1, \dots, \mathbf{x}_k$ in \mathbb{R}^N lying on a manifold, we want to find a set of corresponding points $\mathbf{y}_1, \dots, \mathbf{y}_k$ in the low-dimensional space \mathbb{R}^n ($n \ll N$).

3.1. Pre-Processing

Precedent to applying the dimensionality reduction, we normalize the intensity values in the images. Inhomogeneities and imaging artifacts lead to variation in the intensity values making the normalization necessary. Further, we integrated neighborhood information to make each slice also dependent on its locally neighboring slices. The idea is similar to the consideration of neighborhood information in many image processing tasks by looking not only at single pixel intensities but the local context, to make the processing more robust. In our case, we create a new data point \mathbf{x}'_i by concatenating it with exactly those neighbors of distance m away

$$\mathbf{x}'_i = [\mathbf{x}_{i-m}, \mathbf{x}_i, \mathbf{x}_{i+m}]. \quad (1)$$

The concatenation leads to input slices with three times higher dimensionality. In order to avoid the dimensionality growth,

Table 2. Results of classification for Laplacian eigenmaps w/o neighborhood but w/ image normalization. The overall correct classification rate is 92.6%.

	Recognized Class Labels in %					
	Head	Neck	Lung	Abd.	U. Leg	L. Leg
Head	95.7	2.8	0.0	0.0	0.0	1.4
Neck	60.3	34.5	5.2	0.0	0.0	0.0
Lung	0.3	0.3	91.7	6.6	0.9	0.3
Abd.	0.0	0.0	2.7	96.4	1.0	0.0
U. Leg	0.0	0.0	1.8	1.8	83.8	12.6
L. Leg	0.0	0.0	0.0	0.0	3.3	96.7

we downsample the data points \mathbf{x}_i' by the factor 3, so that the input dimensionality remains N .

3.2. Laplacian Eigenmaps

Laplacian eigenmaps [5] build upon the construction of a graph, which respects the neighborhood information of the data set. Subsequently, the graph Laplacian is applied to calculate a low-dimensional representation of the data that preserves the local neighborhood information in an optimal way. Laplacian eigenmaps are well founded on mathematical concepts (Laplace Beltrami operator) and computationally efficient.

We construct a graph with a node for each point \mathbf{x}_i and with edges connecting neighboring nodes. The neighborhood can be defined with an ϵ -neighborhood around each point, so \mathbf{x}_j is in the ϵ -neighborhood of \mathbf{x}_i if $\|\mathbf{x}_i - \mathbf{x}_j\|^2 < \epsilon$, with $\|\cdot\|$ the Euclidean norm. Although this is geometrically motivated, a disadvantage is the selection of the parameter ϵ . In our implementation, we search instead for the l nearest neighbors and add edges between them in the adjacency graph. Further, heat kernel-based weights are assigned to the edges with $w_{ij} = e^{-\|\mathbf{x}_i - \mathbf{x}_j\|^2 / (2 \cdot \sigma^2)}$ and σ^2 the variance [5].

The similarity measure is important for finding nearest neighbors and assigning edge weights, where the calculation of the Euclidean norm between the points is equivalent to calculating the the sum of squared differences (SSD). A vast number of similarity measures are proposed in the context of medical image registration. For our application, we utilize SSD, however, it is similar to calculate SSD on the normalized images and the correlation coefficient on the original ones.

Once the neighborhood graph is constructed, the eigenvectors of the graph Laplacian provide the embedding map. In our implementation we choose to consider the 40 nearest neighbors, so $l = 40$ and, further, dimension $n = 2$ as intrinsic manifold dimensionality with $N = 64 \times 64$ the dimensionality of the ambient space. In our experiments, we found out that $n = 1$ is not sufficient for correctly distinguishing the classes and the good results for $n = 2$ make a further increase

Table 3. Results of classification for Laplacian eigenmaps w/o neighborhood and w/o image normalization. The overall correct classification rate is 90.0%.

	Recognized Class Labels in %					
	Head	Neck	Lung	Abd.	U. Leg	L. Leg
Head	90.1	2.6	0.0	0.0	0.0	7.4
Neck	62.1	6.9	5.2	0.0	6.9	19.0
Lung	0.0	0.0	92.6	4.6	1.7	1.1
Abd.	0.0	0.0	2.7	96.5	0.8	0.0
U. Leg	0.0	0.0	6.4	2.1	86.1	5.5
L. Leg	7.2	0.2	0.0	0.0	3.0	89.6

superfluous.

3.3. Classification

The dimensionality reduction significantly facilitates the classification and simple classifiers, such as k -nearest neighbors (KNN), can be applied for performing the classification in the low-dimensional space. Following the comparison of supervised learning algorithms [14], random forests and decision trees outperform KNN, and therefore could lead to further little improvements of the classification results.

4. EXPERIMENTS

We evaluate the manifold learning embedding on 13 whole-body data sets, consisting of acquisition from male and female patients. Further, some acquisitions were done with a pillow below the legs and the position of the arms varies. A manual labeling of the data sets was done under supervision of a medical expert, assigning each slice one of the 6 classes: head, neck, lung, abdomen, upper leg, and lower leg. We perform the dimensionality reduction with Laplacian eigenmaps, Isomap, and PCA, see Figures 1 and 2. PCA is used to compare to our previous work [1] and illustrate the advantages of the non-linear embedding methods. We further evaluate the influence of image normalization and the integration of the neighboring slices.

Next to graphs of the 2D dimensional embedding of the data, we also present classification results with KNN. To quantify the performance we perform a cross-validation with a leave-one-out strategy. In Tables 1 to 5, we show the results of the study of the selected approaches. Each row indicates the percentage of a slice being assigned to one of the 6 classes. Looking at Table 1, for instance, head slices are assigned with 95% to the head class and with 5% to the neck class.

We obtain the highest overall correct classification rate of 94.0% with Laplacian eigenmaps in combination with the normalization of the images and neighborhood integration. In Table 1, it can be seen that especially the classification of the head and lower leg slices works to a very high accuracy,

Table 4. Results of classification for Isomap w/ neighborhood and w/ image normalization. The overall correct classification rate is 90.1%.

	Recognized Class Labels in %					
	Head	Neck	Lung	Abd.	U. Leg	L. Leg
Head	93.3	6.7	0.0	0.0	0.0	0.0
Neck	29.3	60.3	10.3	0.0	0.0	0.0
Lung	0.0	1.1	92.6	6.3	0.0	0.0
Abd.	0.0	0.0	7.7	89.3	2.9	0.0
U. Leg	0.0	0.0	0.0	3.7	86.3	10.0
L. Leg	0.0	0.0	0.0	0.0	7.4	92.6

which is important to determine if the patient moves in head or feet first. Remarkable is that in the case of wrong classifications, labels from neighboring classes are assigned, so that, for example, no head slice wrongly got detected as abdomen or leg. This does not hold for the classification without normalization or neighborhood. For Isomap, the classification accuracy is lower, however, also there the wrong assignments are limited to neighboring classes. The results for PCA show the lowest classification performance.

The low correct classification results for the neck are due to a significantly lower number of slices for training, where even for the medical expert, it is difficult to uniquely assign the transition from head to neck and neck to shoulders.

5. CONCLUSION

We proposed the application of manifold learning techniques for patient position detection. Our results clearly indicate that the image slices lie on a low-dimensional manifold embedded in the high-dimensional image space. We propose to apply Laplacian eigenmaps for the manifold learning and achieved superior results in comparison to Isomap. Moreover, the proposed adaption of the method to the specific scenario by the consideration of neighboring slices and image normalization lead to a further improvement of recognition rates. For the evaluation, we perform a classification with KNN and subsequent cross-validation, and obtain very good results.

6. REFERENCES

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Table 5. Results of classification for PCA w/ neighborhood and w/ image normalization. The overall correct classification rate is 80.0%.

	Recognized Class Labels in %					
	Head	Neck	Lung	Abd.	U. Leg	L. Leg
Head	82.0	7.0	0.7	0.0	0.0	10.3
Neck	31.0	25.9	3.4	13.8	0.0	25.9
Lung	0.0	0.3	56.9	42.0	0.0	0.9
Abd.	0.0	0.0	16.1	82.0	1.8	0.0
U. Leg	4.6	0.0	0.0	4.8	82.9	7.8
L. Leg	7.9	0.1	0.5	0.0	2.4	89.1

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