

Scalable high performance Image Registration framework by unsupervised deep feature representation learning.

Presented By -

Vijay Deshpande (201761003)

August 3, 2018

Table of contents

1.Introduction

2.Classification

3.Recent Trends

4.Conclusion

Introduction

- ▶ Intensity based registration won't provide point to point correspondence. Handcrafted features are ad-hoc. Conventional method requires expert knowledge of the modality. PCA , ICA unable to preserve the highly non-linear relationships when projected to low- dimensional space. Deep learning is promising because 1. Unsupervised learning 2. Hierarchical deep architecture. 3. Completely data driven . We are using convolutional stacked autoencoder and compare the results with state of the art registration methods. Evaluation is on 1.5 tesla MR brain images (ADNI and LONI) dataset. It also gives better results on 7.0 tesla MR brain Images.

Method

- ▶ Overall idea is to transform high dimensional input space to small set of coefficients. Training data size $X_{L \times M}$
- ▶ **Naive Methods for intrinsic Feature representations :**
 $f : R^L \rightarrow R^K$ where $K < L$. Limitation of using this approach is number of centroids grows as the input dimension grows. PCA is also one method here the steps are 1.
 Calculate the mean by $\hat{x} = \frac{1}{M} \sum_{m=1}^M x_m$ 2. Compute the eigenvectors $E = [e_j]_{j=1, \dots, L}$ for covariance matrix $\frac{1}{M-1} \bar{X} \bar{X}^T$, where $\bar{X} = [x_m - \hat{x}]_{m=1, \dots, M}$ and E are sorted in descending order of eigenvalues and then determine the first Q largest eigen values. Each training data can be reconstructed as $x_m = \hat{x} + E_q b$ where E_q contains the first q largest eigen vectors of E and $b = E_q^T (x - \hat{x})$

- ▶ In the testing stage given the new testing the data x_{new} , it's low dimensional feature representation is given by
$$b_{new} = E_q^T(x_{new} - \hat{x})$$
- ▶ PCA is orthogonal linear transform and hence not applicable for highly Non- Gaussian Distribution. So we need some method to infer intrinsic feature representaion.

- ▶ **Learning Intrinsic feature representation by Unsupervised Deep learning**
- ▶ **Introduction to Autoencoder**