Feature extraction with regularized siamese networks for outlier detection: application to lesion screening in medical imaging

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Introduction

Medical application context

Design a Computer Aided Diagnostic (CAD) system for lesion screening in brain MR images

$\Downarrow$

Assist clinicians in fast lesion detection in routine exams

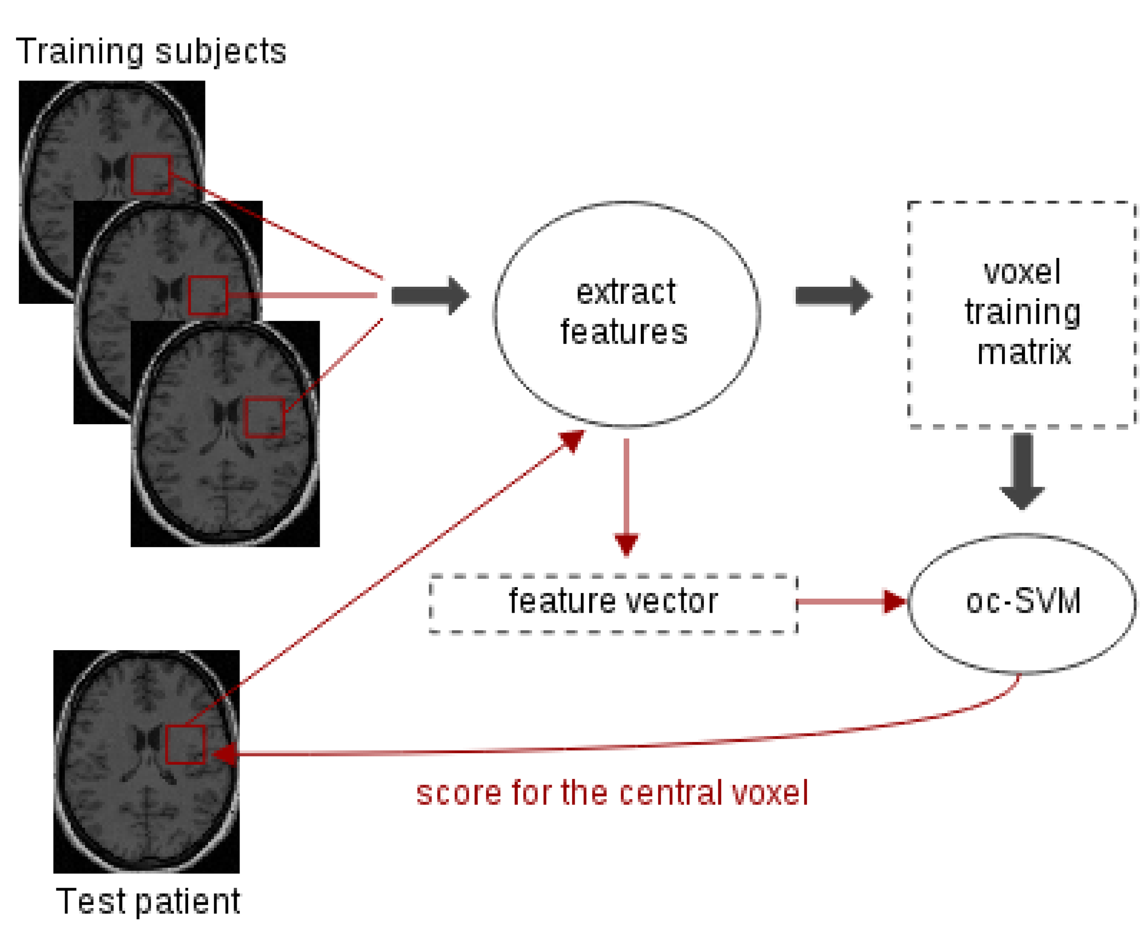
Specifics

- No annotated pathological data $\Longrightarrow$ voxel-level outlier detection problem
- Relatively small data set (around 100 training subjects)

Objective

Design an *automatic feature extraction method* to be used in outlier detection problem at voxel level

CAD pipeline description



- **Data**

  Training set: 96 T1-weighted MR images of healthy subjects obtained with 2 different acquisition protocols (29 versus 67)

  Test set: 9 patients with confirmed epileptogenic lesions

  All images are registered to a common template
- **Feature extraction**

  For each voxel v, gather its feature vector of dimension 32 by using a patch centered at the voxel as input to the proposed feature extraction method (see the blue block)
- **Voxel-level oc-SVM**

  For each voxel v, extract the feature vectors from all the healthy subjects and train a oc-SVM [2] model with rbf kernel ($\mathbf{x_i}$ is the feature vector of subject i) as in [3]:

$$\min_{\mathbf{w},\rho,\xi_i} \frac{1}{2}||\mathbf{w}||^2 + \frac{1}{\nu n}\sum_{i=1}^{n}\xi_i - \rho$$
$$\text{subject to } \mathbf{w}\cdot\phi(\mathbf{x_i}) \geq \rho - \xi_{\mathrm{i}}, \qquad \xi_{\mathrm{i}} \geq 0, \mathrm{i} \in [1, \mathrm{n}]$$

Common $\nu = 0.03$, individual rbf kernel parameter adjusting per voxel

CAD output is the thresholded map of the oc-SVM scores per test patient

References

[1] S. Chopra et al. *CVPR*, 2005

[2] B. Schölkopf et al. *Neural computation*, 2001

[3] M. El Azami et al. *PloS one 11.9*, 2016

Feature extraction with regularised siamese networks

- **Definition: similar patches**

  Patches $(\mathbf{x_i}, \mathbf{x_j})$ are similar if they are centered at the same voxel v
- **Strategy**

  Randomly extract similar patches from different training subjects

  Feed into a regularized siamese neural network [1]
- **Architecture**

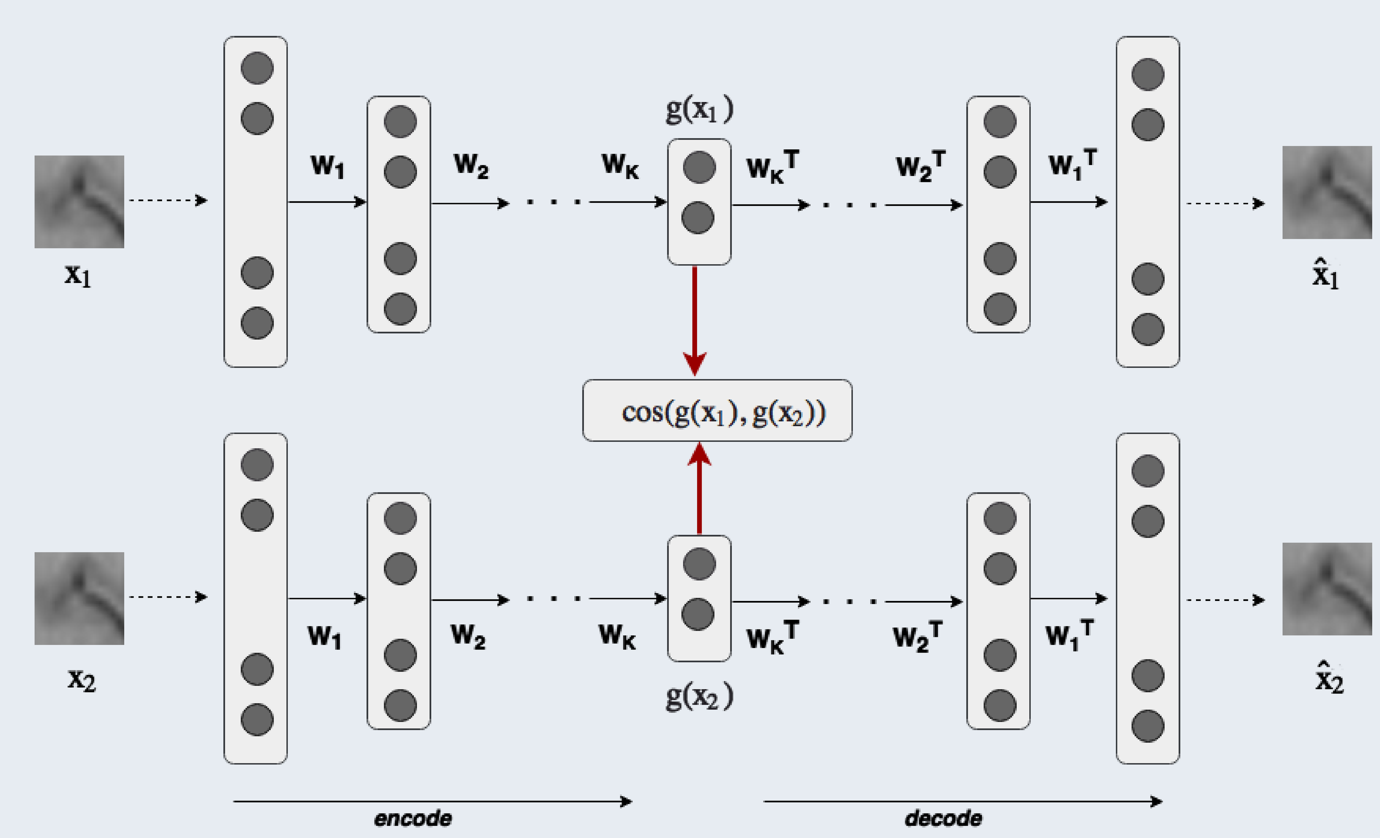
  Our regularized siamese neural network (rSNN) is composed of two identical stacked denoising autoencoder (sDA) subnetworks with l hidden layers
- **Loss function**

  In rSNN the proposed loss function for a single input pair $(\mathbf{x_1}, \mathbf{x_2})$ is:

$$L(\mathbf{x_1}, \mathbf{x_2}; \Theta) = \alpha \overbrace{\underbrace{\sum_{t=1}^{2} ||\mathbf{x_t} - \hat{\mathbf{x}}_\mathbf{t}||_2^2}_{\text{reconstruction error}}}^{\text{regularizer}} - \overbrace{(1-\alpha)cos(g(\mathbf{x_1}), g(\mathbf{x_2}))}^{\text{'close' representations for similar patches}}$$

- **Feature vector**

  Given an input patch $\mathbf{x}$, the middle-layer representation in the subnetworks $g(\mathbf{x})$ yields its feature vector



Results

Table 1: Test results for 9 patients with confirmed lesions reporting true positive/false positive clusters. Our rSNN features are compared to the handcrafted features in [3] and those obtained with stacked denoising autoencoder(sDA).

Feature type	*Pat. A*	*Pat. B*	*Pat. C*	*Pat. D*	*Pat. E*	*Pat. F*	*Pat. G*	*Pat. H*	*Pat. I*
Handcrafted	1/1	1/0	1/0	0/0	0/1	1/0	0/1	0/1	0/0
sDA	1/2	1/5	1/3	0/3	1/3	1/1	0/3	0/2	0/5
rSNN	2*/1	1/2	1/1	0/3	1/1	1/2	0/1	0/2	0/4

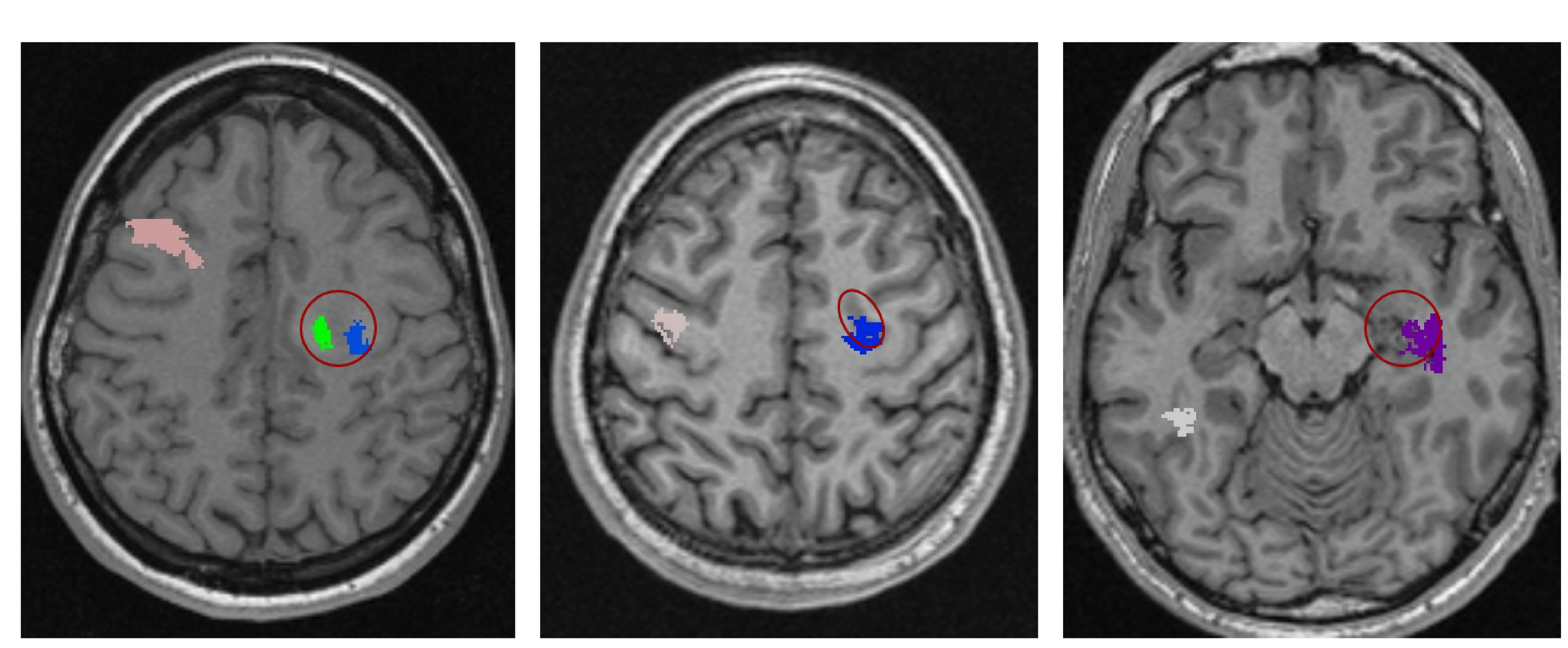


Figure 1: CAD output for patients A, C and E. Maximum intensity projections of clusters onto slices of interest are shown. Lesion location is highlighted in red circles.

Conclusion and future work

- Automatic feature extraction allows detecting voxel-level outliers in brain MR images and yields at least equivalent epilepsy lesion detection rate as epilepsy-specific handcrafted features.
- Slightly more false positive detections compared to the handcrafted features.
- Future work includes integrating other imaging modalities such as MR FLAIR images.