SPATIAL NORMALIZATION OF BRAIN IMAGES WITH FOCAL LESIONS USING COST FUNCTION MASKING

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IMA204

OUR TEAM

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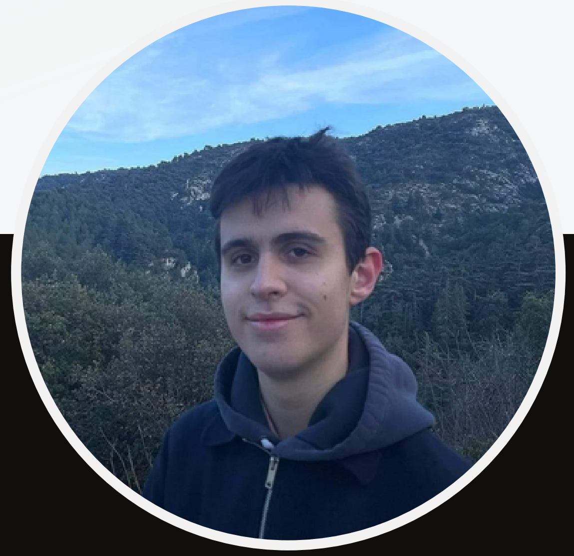

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CONTENT

INTRODUCTION

THE IMPORTANCE OF SPATIAL NORMALIZATION

Benefits

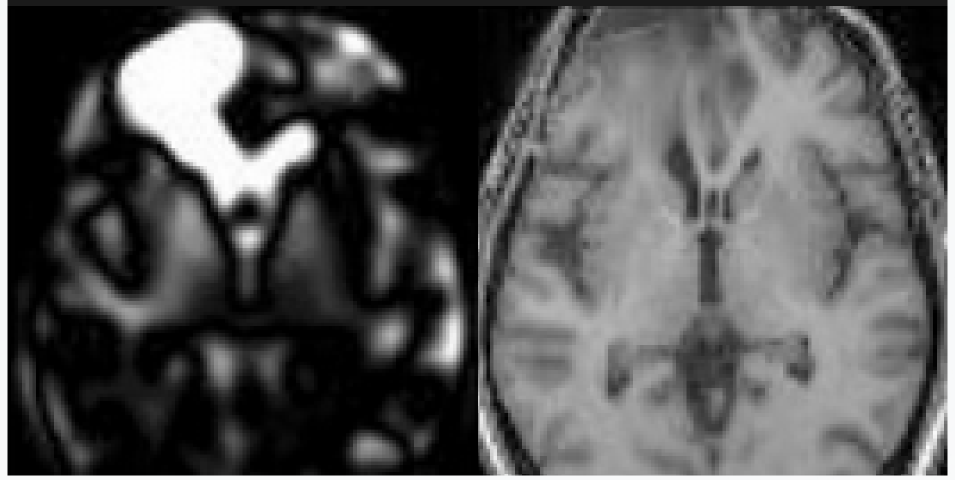
When studying focal brain lesions, it is important to be able to compare our MRI to a **standardized template** for multiple reasons :

- It facilitates the reader's **comprehension**
- Sets of data are **homogenized**
- Researchers can **overlap** the normalized images

- Cost function normalization (earliest algorithms) leads to **deformation** caused by the intensity of the lesion
- Affine-only transformations are **not optimal**

- For the moment, there is **no standardized procedure** for normalization
- There is **no metric** to define the success of the operation

Problematics



THEORY

The research paper heavily focuses on the methodology found in the SPM99 algorithm, which seeks to **optimize** a set of parameters **p** that will minimize our cost function, which is the **sum of squared differences**

$$\begin{bmatrix} d_1(\mathbf{p}+\mathbf{t}) \\ d_2(\mathbf{p}+\mathbf{t}) \\ \vdots \end{bmatrix} = \begin{bmatrix} d_1(\mathbf{p}) \\ d_2(\mathbf{p}) \\ \vdots \end{bmatrix} + \begin{bmatrix} \frac{\partial d_1(\mathbf{p})}{\partial p_1} & \frac{\partial d_1(\mathbf{p})}{\partial p_2} & \cdots \\ \frac{\partial d_2(\mathbf{p})}{\partial p_1} & \frac{\partial d_2(\mathbf{p})}{\partial p_2} & \cdots \\ \vdots & \vdots & \ddots \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ \vdots \end{bmatrix},$$

THE OPTIMIZATION PROBLEM

Our problem is minimized when

$$\mathbf{At} \simeq \mathbf{b},$$

So we proceed iteratively with

$$\mathbf{t} = (\mathbf{A}^T\mathbf{A})^{-1}\mathbf{A}^T\mathbf{b}.$$

$$\mathbf{p}^{(n+1)} = \mathbf{p}^{(n)} + \mathbf{t}$$

THE ALGORITHM

- Smoothed using 8-mm isotropic Gaussian filter
- Optimisation weighed using Bayesian approach
- Use of a masking image delimiting the brain area

SETTINGS

LESION AREA MASKING

We create a **mask** of the **lesion area**

$$A = \begin{bmatrix} -\frac{\partial d_1(p)}{\partial p_1} w_1 & -\frac{\partial d_1(p)}{\partial p_2} w_1 & \cdots \\ -\frac{\partial d_2(p)}{\partial p_1} w_2 & -\frac{\partial d_2(p)}{\partial p_2} w_2 & \cdots \\ . & . & . \end{bmatrix}$$

We add **weights** to our A matrix in order for the cost function to not take into account the **lesion area** and everything outside the brain

We obtain the following **cost function**

METHODOLOGY

PRIMARY CONCERNS ⚠

01

USER-DEFINED ABNORMAL SIGNAL POSITIONS

02

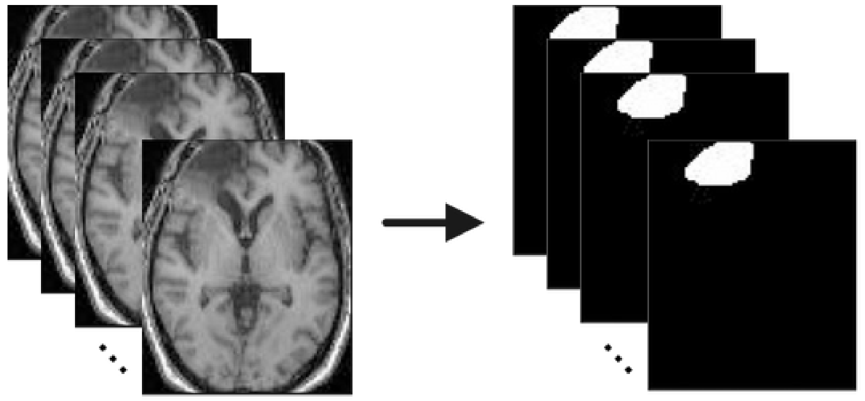
COST FUNCTION MASK EXPANSION

03

COMPARISON BETWEEN COST FUNCTION MASKING AND THE STANDARD NORMALIZATION

DATABASE

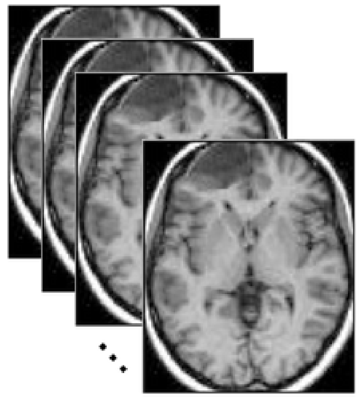
- **10** TI MRI images with varied **lesions**
- **4** sets of binary **masks** of lesion definitions
- Statistical Parametric Mapping (**SPM99**)
    - **Template**: derived from the average of healthy MRI images
    - Thresholded template brain mask (**TTBM**) to exclude areas outside of the brain
- **10 simulated** lesion images: **10** T1-weighted MRI scans of **healthy** brains + mask (set 1)
    - Scale factor: ratio between the masked means from the healthy and from the abnormal brain



10 $\qquad$ $10 \cdot (3+1)$

$$sl_i = \begin{cases} ra_i \cdot s & \text{if } rld_i = 1 \\ n_i & \text{otherwise} \end{cases}$$

Simulated lesion



10

$$RMS_{a,b} = \sqrt{\sum_{i=1}^{N} (d_i^{a,b})^2 / N}$$

$$d_i^{a,b} = \sqrt{(x_i^a - x_i^b)^2 + (y_i^a - y_i^b)^2 + (z_i^a - z_i^b)^2}$$

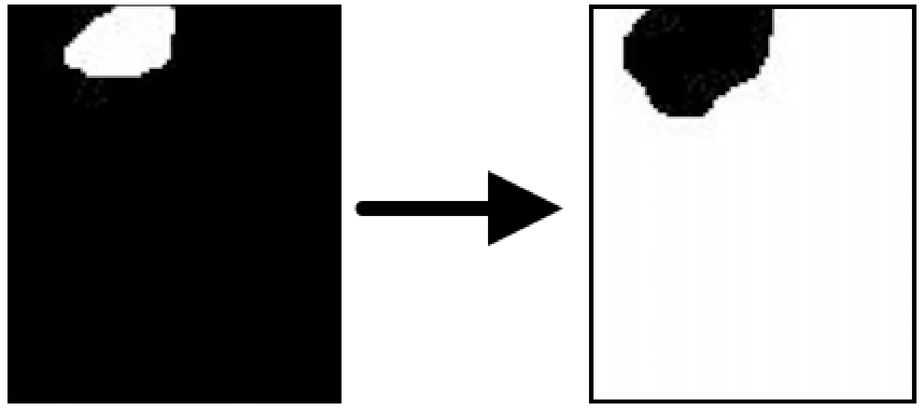
Deformation field

LESION AREA EXPANSION

- **Processed normalization masks**: **smoothed** lesion definitions (sets 2..4) with a Gaussian filter of 8 mm; then, **inverted** and **thresholded** the resulting images
  - Comparison (RMS) between normalizations:
    - **Simulated lesions**: Affine normalization, affine and nonlinear normalization, and affine and nonlinear normalization with cost function masking
    - **Standard** of normalization of the original image

$$pnm_i = \begin{cases} 1 & \text{if } sld_i \leq t \\ 0 & \text{otherwise} \end{cases}$$

Processed normalization mask



threshold (%)	Expansion (mm)
25	2.3
10	4.3
5	5.5
1	7.7
0.1	9.6
0.001	10.1
0.0001	10.2

QUALITATIVE ASSESSMENT

- Normalizations:
  - affine plus non linear with **processed masks** with threshold of 0.1%;
  - **affine** only.
- Success: normalized images are similar to each other and to the template image
  - Similarity **between normalized images**: weighted mean
    - Scale factor: image's masked mean
  - Similarity of the **images to the template**: scaled difference and variance image

$$y_{ij}^m = \begin{cases} y_{ij}/s_j & \text{if } nld_{ij} = 0 \\ 0 & \text{otherwise} \end{cases}$$

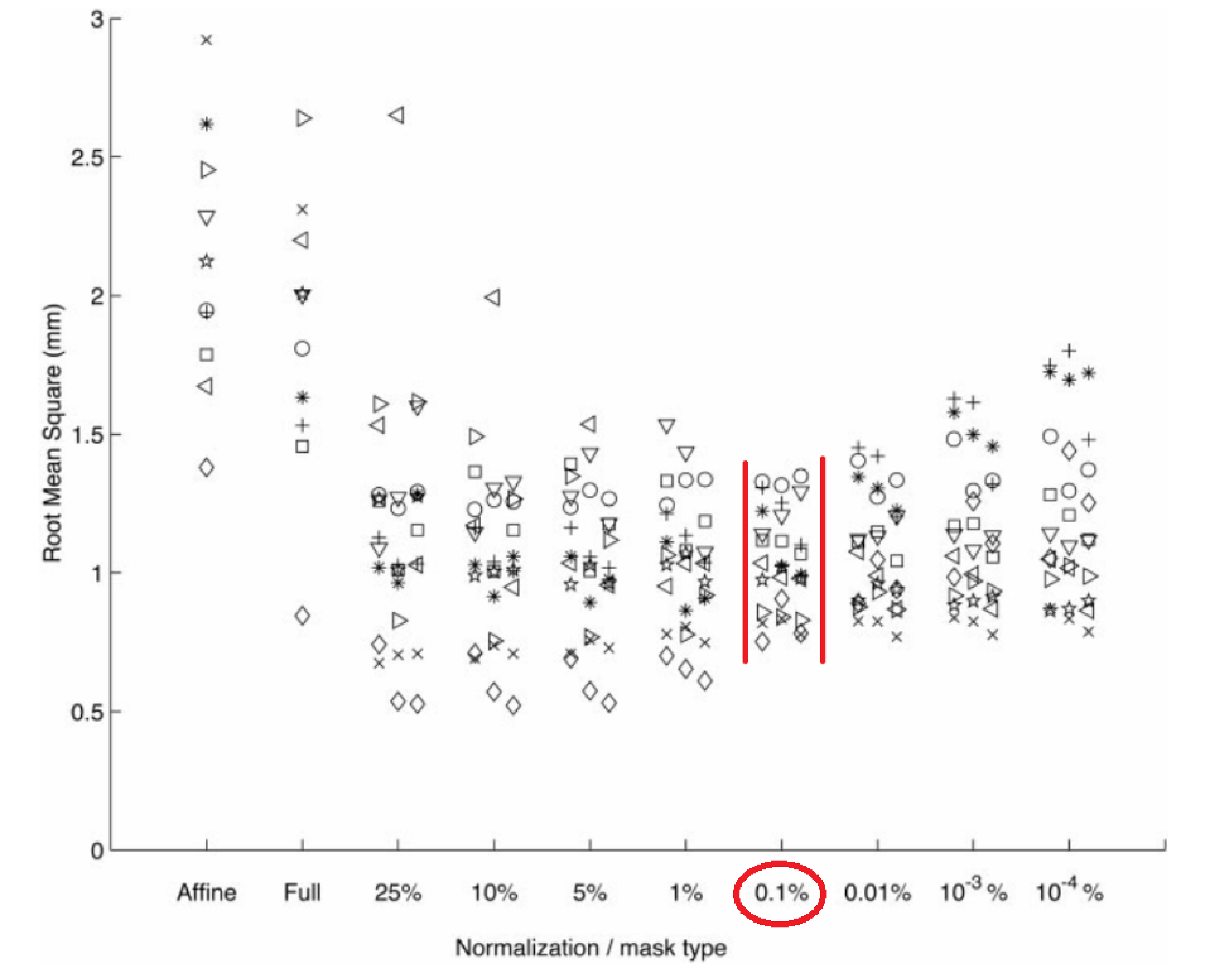
$$mn_i = \begin{cases} \sum_{j=1}^{10} y_{ij}^m / n_i^m & \text{if } n_i^m > 5 \\ 0 & \text{otherwise} \end{cases}$$

$$d_{ij}^m = \begin{cases} y_{ij}/s_j - t_i/s_t & \text{if } nld_{ij} = 0 \\ 0 & \text{otherwise} \end{cases}$$

$$v = \begin{cases} \sum_{j=1}^{10} (d_{ij}^m)^2 / (n_i^m - 1) & \text{if } n_i^m > 5 \\ 0 & \text{otherwise} \end{cases}$$

RESULTS

ADVANTAGES



Result 1

The scatter of values across images, i.e., the variability in the effectiveness of normalization across different images/lesions, is significantly reduced.

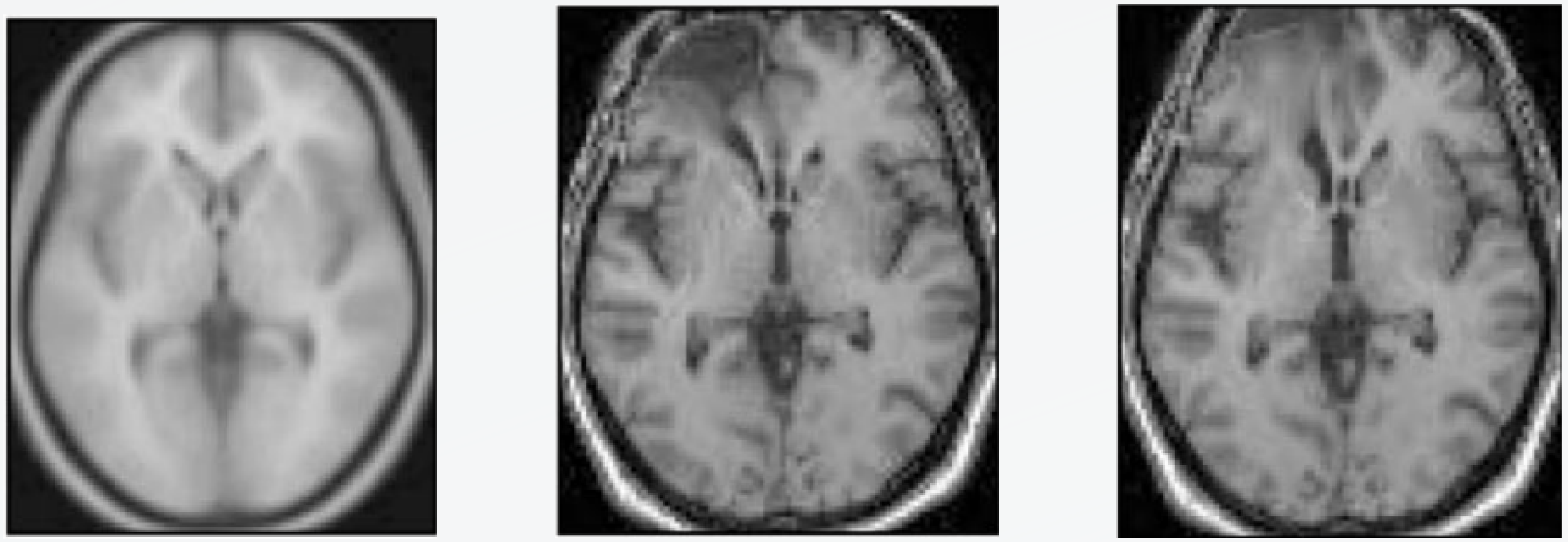
Result 2

The impact of lesion bias on the normalized image is reduced.

Criteria for choosing a threshold:

- low overall RMS values;
- narrow spread of values across images;
- minimal variation between masks from different observers.

ADVANTAGES



template

normalization using affine and nonlinear functions **with** cost function masking

standard normalization of A with nonlinear functions **without** cost function masking

Result 3

The ability to use nonlinear deformations without causing serious distortion in the damaged image.

CAVEATS

First

The method requires **some input from the user.**
Which requires approximately 30 minutes per scan.

Second

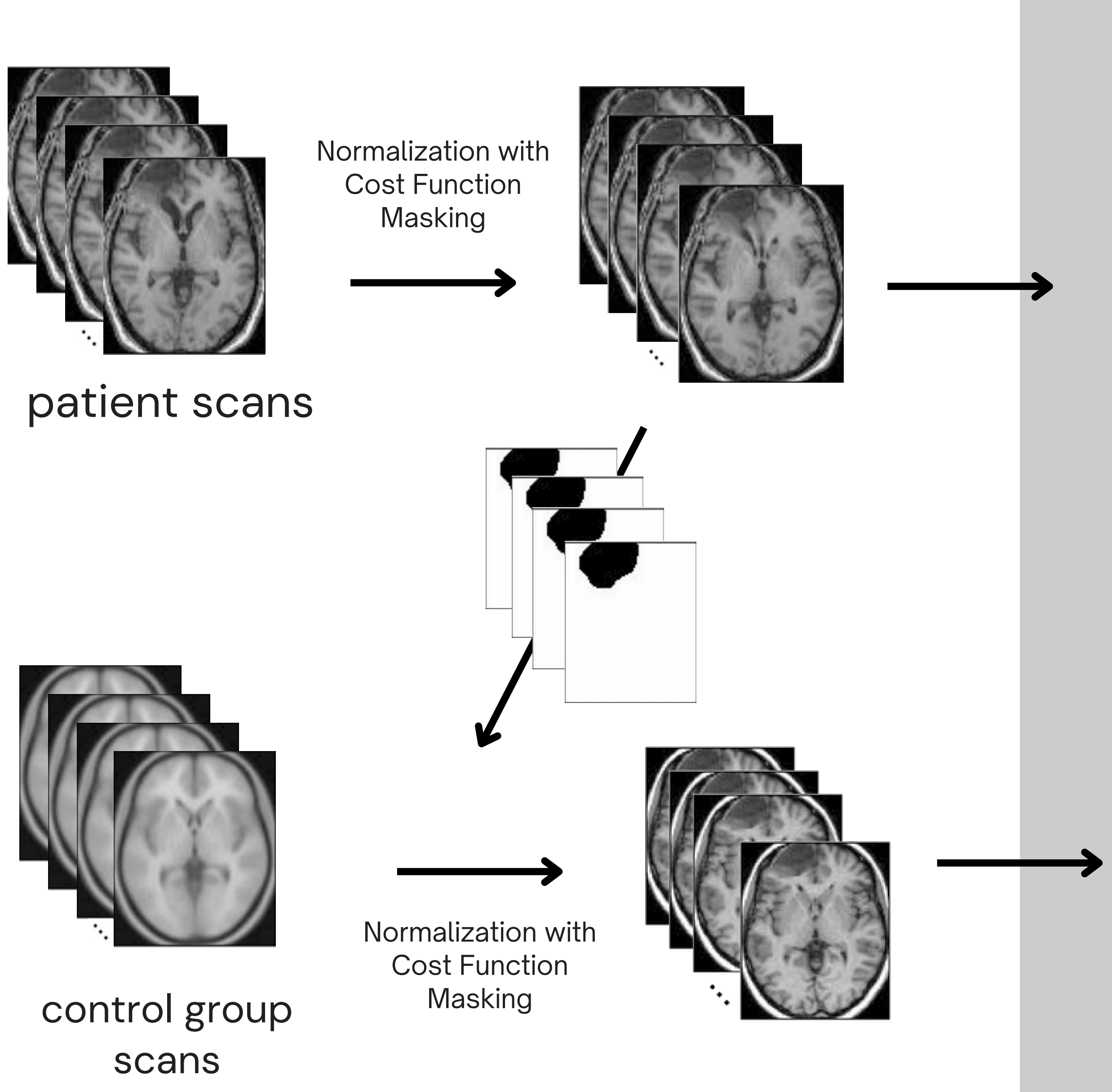
The masking technique does not work well when the lesion size is large relative to the brain volume.

It may be necessary to increase the weight for smooth nonlinear deformations (“nonlinear regularization in SPM99”).

In cases where a nonlinear match proves difficult to achieve, an affine-only match, with using a source mask to remove the effect of the lesion, may be necessary.

PRACTICAL VALUE

- **Problem:** reduced or mislocated average activation if patient scans were less successfully normalized than scans from controls or other patient groups.
- **A partial solution:** to reconcile the quality of normalization between patient and control groups is to pair the lesioned and control brains within a study, and use the masking cost function normalized lesion image for the patient to create a matching masking image for use on the unlesioned brain for the control.



INSIGHTS

OUR THOUGHTS

The article felt really **detailled** throughout the steps, particularly the **method** section, which really helped us understand the advantages and limits of this research

INSIGHT N°1

Provided the initial lesion segmenting algorithms, we felt like we would be able to implement this methodology in our works

INSIGHT N°2

The main limitation of this algorithm is that we still need to **manually input** some data to process the lesion area. Consequently, **automating** this process could be a very useful

INSIGHT N°3

THANK YOU FOR YOUR ATTENTION