Works on Automatic Segmentation of Magnetic Resonance Images of the Human Brain

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- Future work
  - Early diagnostic of neurodegenerative diseases

Personal introduction

(June, 2005) Engineer in computer science (5-year degree) in the University of the Basque Country.

- Master Thesis title: "**Magnetic Resonance Imaging Illumination Correction**".

(since september,2005- up to now) PhD student

- University of the Basque Country (UPV/EHU)
- Campus of Donostia-San Sebastián
- Computer science college
- Dept. of Computer Science and Artificial Intelligence (CCIA)
- Group of Computational Intelligence

Grants

Contracts funded by research projects of the IC group:

- (01/05/2005-31/01/2006) “Implementation of illumination correction algorithms”.
- (01/02/2006-31/12/2006) “Image Segmentation robust to illumination effects”.
- (24/01/2007- 01/11/2007) “Diagnostic of Multiple Sclerosis by MRI analysis”.

(15/11/2007-28/02/2010) UPV/EHU’s pre-doctoral grant.

My research interest

- Two research lines which are closely related
  - MRI Intensity Inhomogeneity (IIH) correction
  - MR image analysis for early diagnostic of neurodegenerative diseases
    - Multiple Sclerosis
    - Alzheimer’s disease

IC Group

Facultad de Informática de San Sebastián,

Paseo Manuel de Lardizabal 1, CP/20018

Dpto. CCIA

Computational Intelligence Group
(Grupo de Inteligencia Computacional)
(www.ehu.es/ccwintco)

Update on research lines of the Computational Intelligence Group

1. **Neuroimage processing**: MRI image segmentation for early diagnosis of neurodegenerative diseases such as Alzheimer. Works on segmentation and image registration.
2. **Multi robot systems**: design of control and perception for multi-robot systems. Current project on the design of autonomous hoses for highly unstructured environments such as shipyards.
3. **Swarm computing**: application to graph colouring problem.
4. **Hyperspectral image processing**: emphasis on spectral unmixing analysis of the images, with unsupervised endmember extraction from the images.
5. **Synchronization of chaotic systems with applications to encrypted communication**.
6. **Augmented Reality** (with Vicomtech): embedding information and simulated reality into life video for training and tourist applications.
7. **Colour image processing**: chromatic normalization for improved image segmentation and analysis.
8. **Lattice Computing**: non linear algorithms based on lattice operators inf and sup.
9. **Tabletop** (with Innovae Vision): table like interactive surfaces for multimedia information points.

Neuroimage processing. Collaborations and funded projects

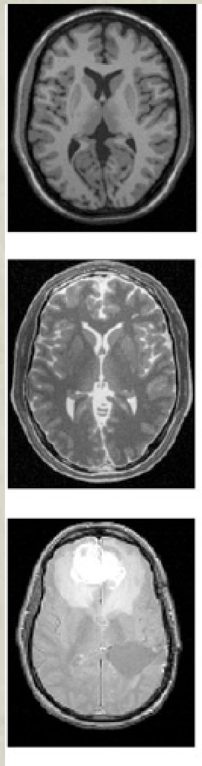
- ***(2000) "Magnetic resonance imaging using hyperpolarized helium gas as a tool for the diagnosis of selected respiratory diseases"***
  - Leader researcher: Manuel Cortijo (Universidad Complutense de Madrid).
  - Funding organization: European commission (2-years project).
- ***(2006) "Contributions to the diagnosis of Multiple Sclerosis by the Magnetic Resonance image analysis"***
  - Leader researcher: Elsa Fernández.
  - External collaborator: J. Ruiz-Martínez M.D. (Department of Neurology, Hospital de Mendaro).
  - Funding organization: Diputación Foral de Guipúzcoa. (1-year project).
- ***(2007) "Detection of prodomal Alzheimer's disease via pattern classification of MRI"***
  - Leader researcher: Maite García-Sebastián.
  - Funding organization: Diputación Foral de Guipúzcoa. (1-year project).
- ***(2007) "Development of MR imaging analysis techniques for detection of prodomal Alzheimer's disease under a friendly environment "***
  - Leader researcher: Maite García-Sebastián.
  - External collaborator: J. Villanúa M.D. (OSATEK Guipúzcoa. The main Magnetic Resonance service in the Basque Country).
  - Funding organization: Gobierno Vasco. (2-years project).
- ***Other collaborations***
  - Undergraduate student stays
    - ***(2008) Evaluation of skull-stripping algorithms on the OASIS database.***
      - Charlotte Rosak (Institut supérieur des Bio-science (ISBS), Université Paris XII).
      - Jean Luc Lor (Institut supérieur des Bio-science (ISBS), Université Paris XII).

Brain MRI

- MR images
- MRI processing general pipeline
  – IIH artefact

Magnetic Resonance Imaging (MRI)

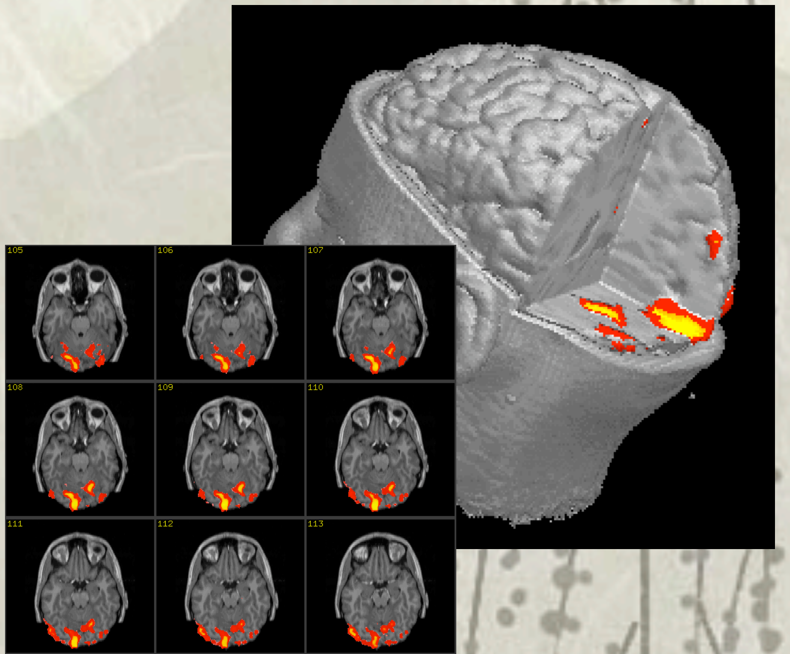
MRI is a non ionizing medical imaging technique commonly used to visualize the structure and function of the body. It belongs to the radiology clinical techniques.



<u>Structural MRI</u>

- Three dimensional (3-D)
- High soft tissue contrast
- High spatial resolution
- Structural images: T1, T2, PD
- Possibly multi-spectral
- Image artefacts
  - Intensity Inhomogeneity (IIH)
  - Motion artefact
  - Partial volume artefact
  - …

Magnetic Resonance Imaging (MRI)



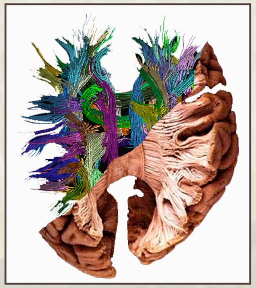
<u>Functional MRI</u>

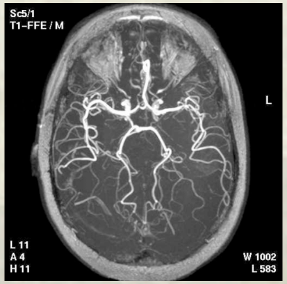
- Three dimensional (3-D) temporal
- Lower spatial resolution
- Functional images: T2*
- It measures the haemodynamic related to:
  - Neural activity in the brain
  - Spinal cord

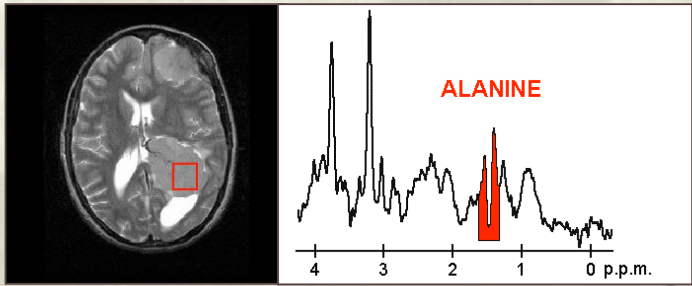
Blood-oxygen-level dependent (BOLD)

fMRI is a method of observing which areas of the brain are active at any given time.

Other MRI images

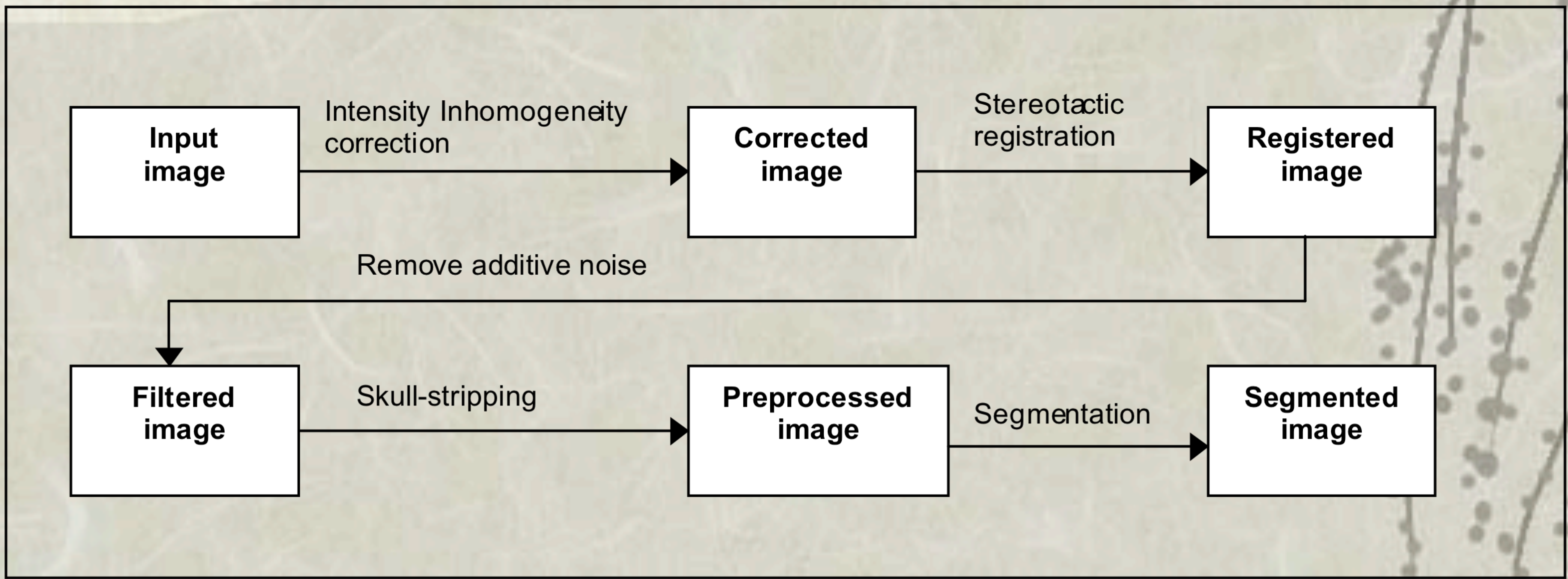






- Diffusion MRI (DTI)
  - It is to map the tracts in the grey matter.
- Magnetic resonance angiography (MRA)
  - It is used to detect the blood vessels
- Magnetic resonance spectroscopy (MRS)
  - Gives biochemical information about the tissues in a non-invasive way.

sMRI processing general pipeline



IIH artefact

- Intensity inhomogeneity , intensity nonuniformity, shading or bias field.
- It appears in images obtained by different imaging modalities
  - Microscopy
  - Computer tomography
  - Ultrasound
  - Magnetic resonance imaging (*****)

IIH artefact

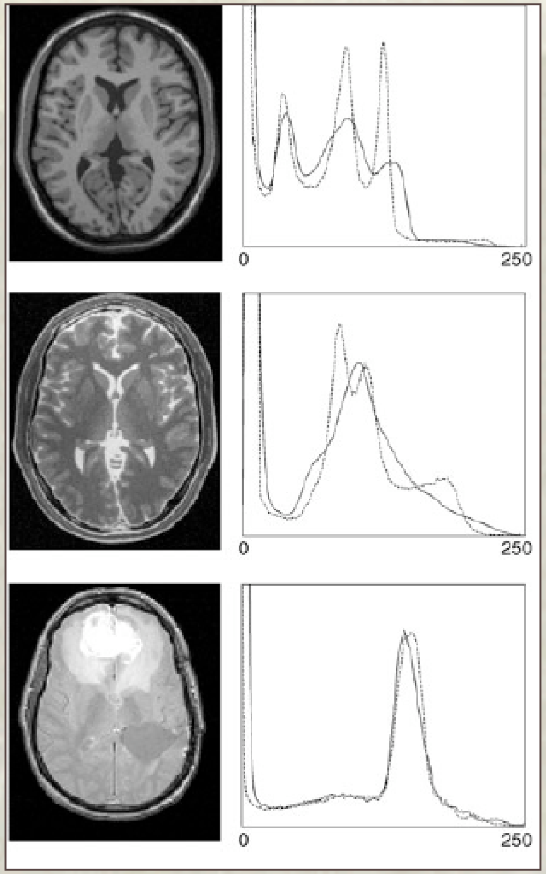
- IIH is due to the spatial inhomogeneity in the excitatory Radio Frequency signal and other effects.
- The Intensity Inhomogeneity field is usually assumed to be smooth.
- the ideal properties of an IIH correction algorithm:
  - Can correct all the different MRI modalities.
  - It can be applied to other anatomical structures without major modifications.

Effect of IIH on the image histogram

T1

T2

PD



Review of work done up to date

- Assumed image model
- Parametric versus non parametric approaches
- Our parametric proposal (PABIC inspired)
- Our non-parametric proposal (SOM inspired)*

Image formation model

$$y_i = \beta_i \cdot x_i + \eta_i,$$

Where:

- $\mathbf{y} = (y_i; i \in I)$; $i \in I \subset \mathbb{N}^2$ is the observed image,
- β_i is the multiplicative inhomogeneity field,
- x_i is the clean signal
- η_i is the additive noise term

The image logarithm if we discard the additive noise term

$$\log y_i = \log \beta_i + \log x_i.$$

Parametric versus non-parametric algorithms

- There are two kinds of IIH correction algorithms:
  - Parametric: parametric model for the IIH field.
  - Non-parametric: non-parametric estimation of the IIH at each voxel.
    - Most Bayesian image processing approaches
    - Fuzzy clustering

GradClassLeg

- Parametric algorithm
- Gradient descent of the classification error in images corrected by products of Legendre polynomials.
- In this approach we work with the original image. We do not perform the logarithm transformation.

❖ Energy function

$$\beta_i(\boldsymbol{p}) = \sum_{j=0}^{m} \sum_{k=0}^{m-j} \sum_{l=0}^{m-k-j} p_{jkl} P_j(i_x) P_k(i_y) P_l(i_z),$$

$$e(\boldsymbol{p}, \Gamma) = \sum_{i \in I} \left(\frac{y_i}{\hat{\beta}_i(\boldsymbol{p})} - \mu_{x_i} \right)^2,$$

- Convexity of the energy function

$$\frac{\partial^2 e(\boldsymbol{p},\Gamma)}{\partial^2 p_{jkl}} = \sum_{i\in I} \hat{\mu}_{\hat{x}_i} \frac{y_i (P_j(i_x)P_k(i_y)P_l(i_z))^2}{\hat{\beta}_i^3(\boldsymbol{p})}, \tag{24}$$

$$\frac{\partial^2 e(\boldsymbol{p},\Gamma)}{\partial p_{jkl}\partial p_{mno}} = \sum_{i\in I} \frac{\hat{\mu}_{\hat{x}_i} y_i P_j(i_x)P_k(i_y)P_l(i_z)P_m(i_x)P_n(i_y)P_o(i_z)}{\hat{\beta}_i^3(\boldsymbol{p})}. \tag{25}$$

Energy minimization

- Gradient descent

gradient descent on the inhomogeneity field parameters

$$\boldsymbol{p}_{t+1} = \boldsymbol{p}_t + \alpha_t^p \nabla_{\boldsymbol{p}} e(\boldsymbol{p}, \Gamma),$$

gradient descent on the class intensity means

$$\Gamma_{t+1} = \Gamma_t + \alpha_t^{\Gamma} \boldsymbol{\nabla}_{\boldsymbol{\Gamma}} e(\boldsymbol{p}, \Gamma).$$

$$\nabla_{\boldsymbol{p}} e(\boldsymbol{p}, \Gamma) = \left\{ \frac{\partial}{\partial p_{jkl}} e(\boldsymbol{p}, \Gamma) \right\},$$

$$\frac{\partial}{\partial p_{jkl}} e(\boldsymbol{p}, \Gamma) = \sum_{i \in I} \left(\frac{y_i}{\hat{\beta}_i(\boldsymbol{p})} - \hat{\mu}_{\hat{x}_i} \right) \frac{-y_i P_j(i_x) P_k(i_y) P_l(i_z)}{\hat{\beta}_i^2(\boldsymbol{p})},$$

$$\nabla_{\boldsymbol{\Gamma}} e(\boldsymbol{p}, \Gamma) = \left\{ \frac{\partial}{\partial \mu_\omega} e(\boldsymbol{p}, \Gamma) \right\}$$

$$\frac{\partial}{\partial \mu_\omega} e(\boldsymbol{p}, I) = \sum_{i \in I | \hat{x}_i = \omega} -\frac{1}{2} \left(\frac{y_i}{\widehat{\beta}_i(\boldsymbol{p})} - \widehat{\mu}_\omega \right).$$

- We assume that the inhomogeneity field model is a linear combination of 3D products of Legendre polynomials

$$\beta_i(\boldsymbol{p}) = \sum_{j=0}^{m} \sum_{k=0}^{m-j} \sum_{l=0}^{m-k-j} p_{jkl} P_j(i_x) P_k(i_y) P_l(i_z),$$

$$\boldsymbol{p} = \{p_{jkl}\}$$

$$n = (m+1)\,\frac{m+2}{2}\,\frac{m+3}{3}.$$

Evaluation procedures & measures

IIH correction

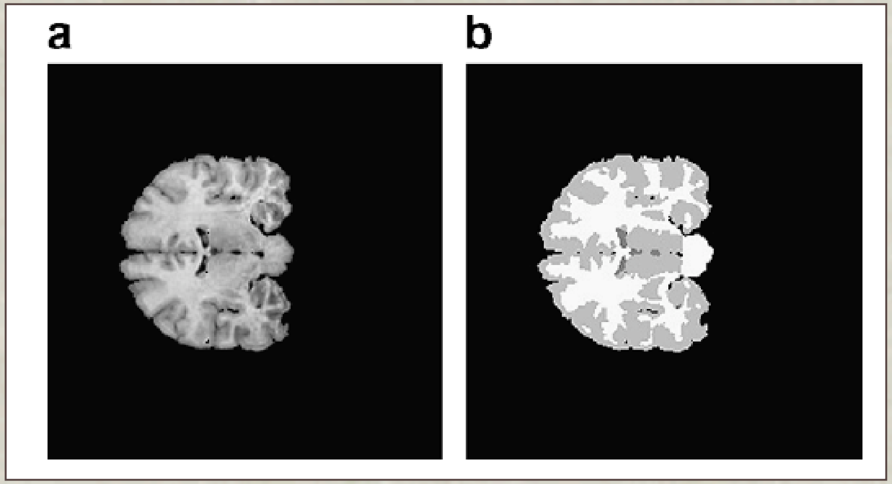
- Evaluation Strategies
  - Qualitative (Visual inspection)
    - Spatial domain
      - Intensity and inhomogeneity profiles
      - Original and corrected images
      - Phase diagrams
      - Manualy selected reference points
      - Homogeneous regions of support
      - Volume surface rendering
      - Probability maps
      - Isointensity lines
      - Segmentation results by tissue delineation
    - Statistical visualization
      - Inhomogeneity field histograms
      - Scatter plots
      - Profile of mean slice intesity
  - Quantitative (objective measures)
    - Inhomogeneity field
      - Root mean square error (rms)
      - Mean square error (MSE)
      - Correlation coefficient (CC)
    - Intensity variation
      - Coefficient of variation (CV)
      - Coefficient of joint variation (CJV)
    - Segmentation
      - Misclassification ratio (MCR)
      - Jaccard similarity Tanimoto coefficient
      - Dice coefficient
      - Accurate segmentation ratio (ASR)
      - Segmentation accuracy (SA)
      - False positive,True positive,True negative False negative Sensitivity,Specificity
      - False negative fraction (FNF)
      - Measurement of the change of tumor volume
      - Structural Similarity Index (SSIM-INDEX)
      - Difference Ratio Metric

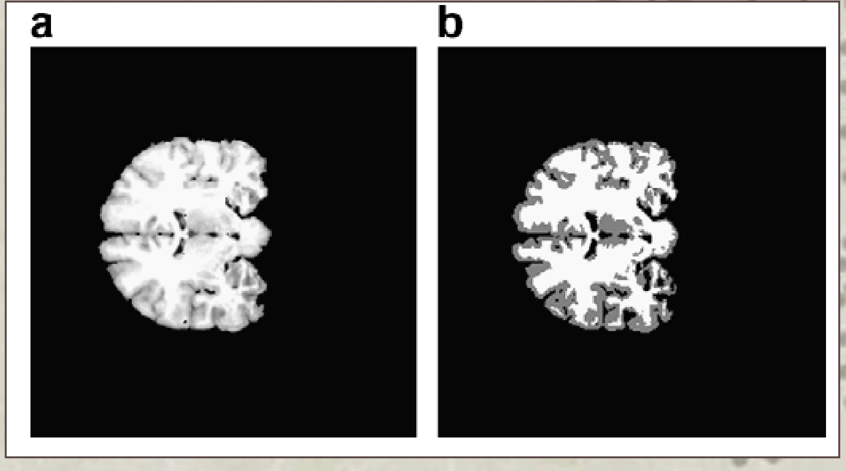
Some results

$$T(\omega) = \frac{|\{x_i = \omega \wedge \hat{x}_i = \omega; i \in I\}|}{|\{x_i = \omega \vee \hat{x}_i = \omega; i \in I\}|},$$

Table 1
Average overlap between manual segmentation and the algorithms tested in this paper

Algorithm	GM	WM
Wells	0.564	0.567
BMAP	0.558	0.562
BFCM	0.630	0.709
GradClassLeg	0.745	0.732
Siyal and Yu (2005)	0.750	0.724



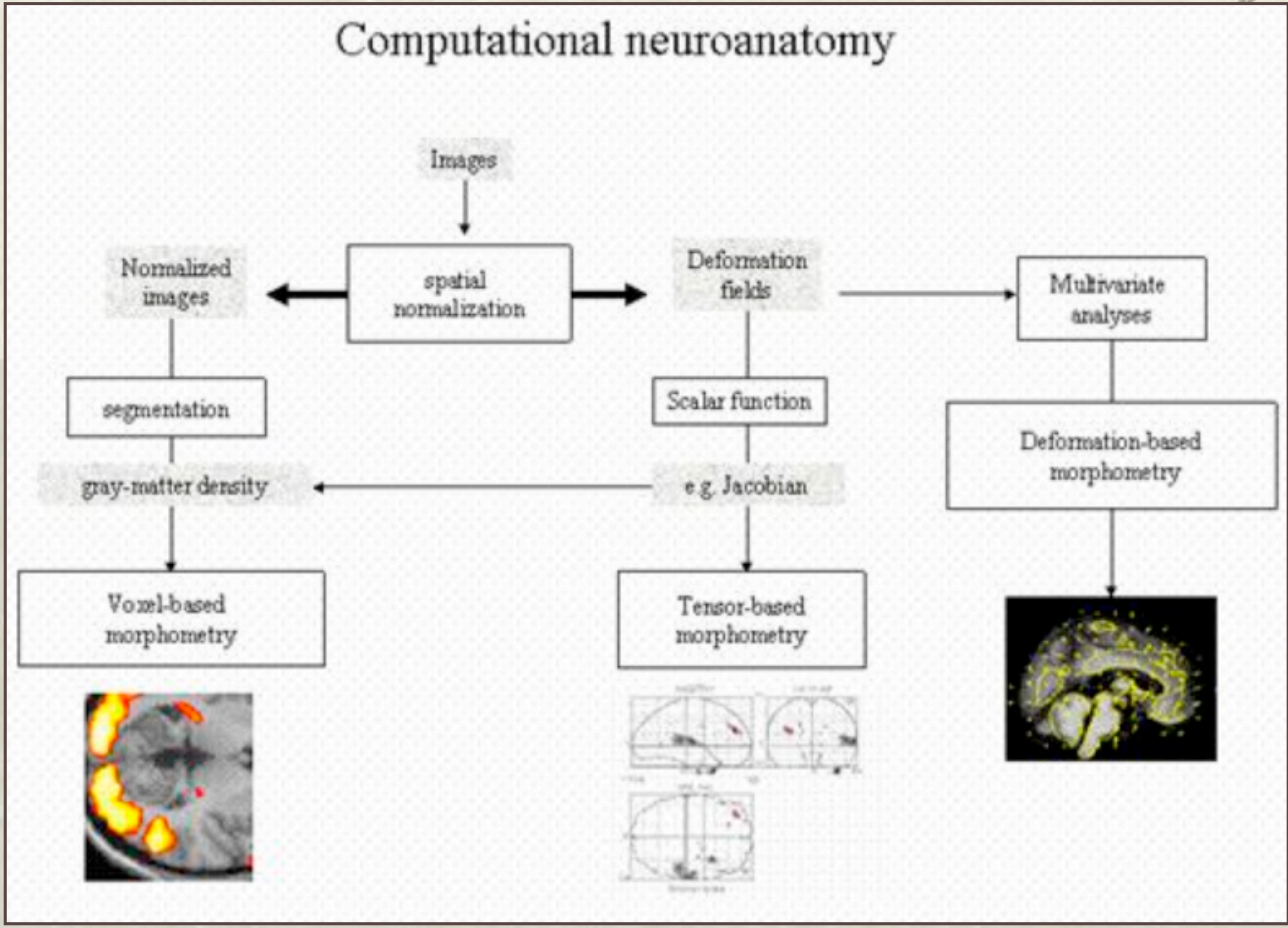


MRI image analysis for early diagnostic of neurodegenerative diseases

- State of the art: diverse approaches
  - – Brain mapping based on projections of the Brain cortex into a 2D plane
  - – morphometric analysis: voxel based, deformation based and tensor based
  - –fMRI
  - – Diffusion tensor image analysis
  - – Classification based image processing

Morphometry

- It is very useful to detect structural differences between groups of subjects.
  - Based on the local brain tissue composition: VBM (Voxel Based Morphometry)
  - Based on the brain shape:
    - DBM (Deformation Based Morphometry)
    - TBM (Tensor Based Morphometry)


Computational neuroanatomy
Images
Normalized images
spatial normalization
Deformation fields
Multivariate analyses
segmentation
Scalar function
Deformation-based morphometry
gray-matter density
e.g. Jacobian
Voxel-based morphometry
Tensor-based morphometry

- Requirement
  - Images with a relative high resolution ($1mm^3$ o $1.5mm^3$, isotropic voxels).

VBM

- The fastest and easiest approach to detect brain differences in a group.
- This approach compares voxel by voxel the local concentrations of the brain tissues which will be analyzed.
- It is possible to perform comparisons within a group or between groups.
- It is very sensitive to registration errors.
- Brain images must not contain any tumour or lesion
  - (not applicable to Multiple Sclerosis).
- It is also very sensitive to the image quality and to the existence of image artefacts.

Voxel Based Morphometry

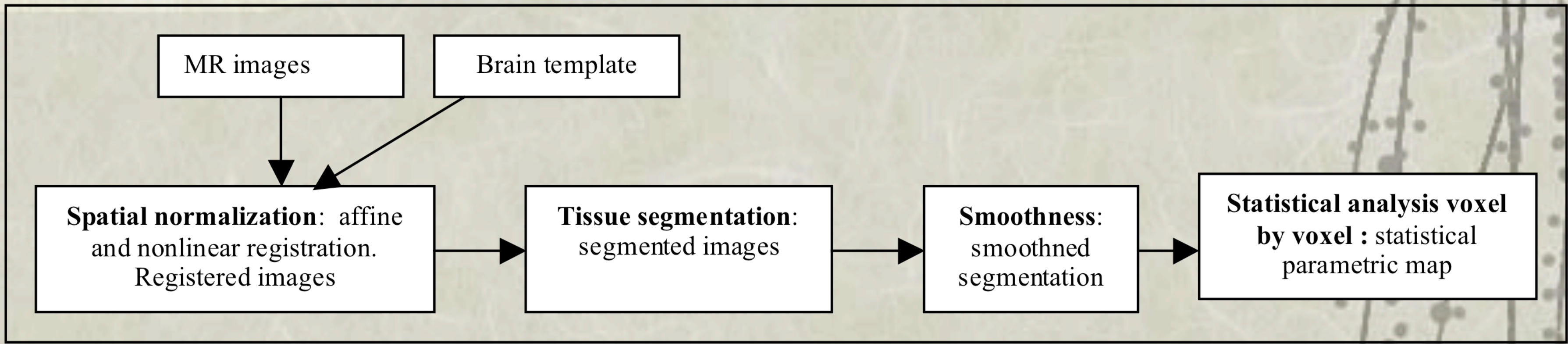
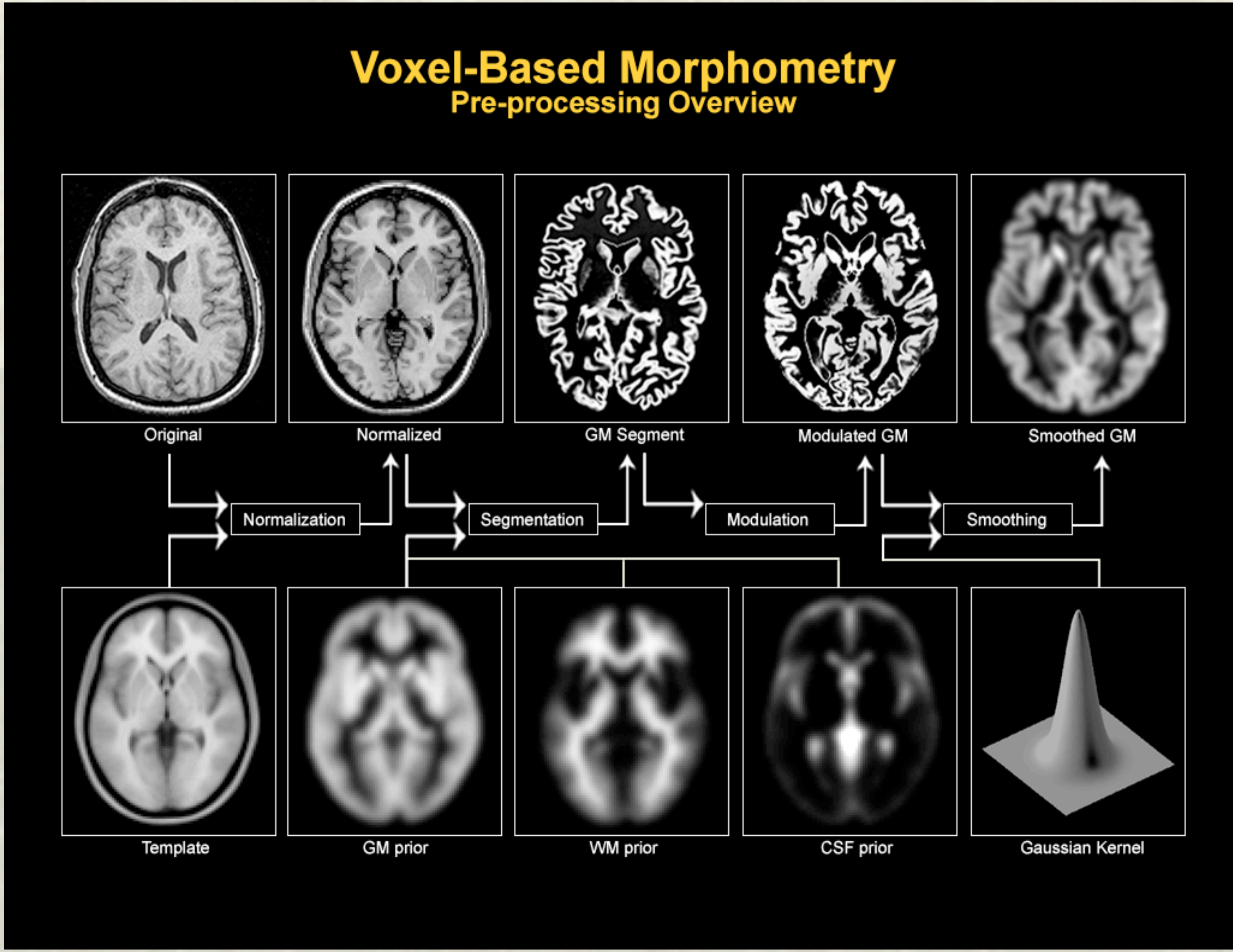


Figure 1.VBM Generic flowchart.


Voxel-Based Morphometry
Pre-processing Overview
Original
Normalized
GM Segment
Modulated GM
Smoothed GM
Normalization
Segmentation
Modulation
Smoothing
Template
GM prior
WM prior
CSF prior
Gaussian Kernel

Morphometric methods and the Alzheimer Disease

- Patients with Alzheimer's disease, MCI and controls
    - (VBM,DBM,TBM) grey matter atrophy in the temporal lobe and areas associated with the neocortex.
    - (DBM) Atrophy representative patterns in the temporal lobe, association neocortical areas, thalamus and the basal ganglia.
    - (DBM) Shape differences in brain ventricles.

Intended Work during my stay in Paisley

- We have tried two approaches for the image segmentation and we thought of applying a new computational paradigm.
- Study the state of the art of the AIS
- Evaluate the possibility to apply the AIS to MR image processing.
  - Propose an AIS for MR image segmentation
  - Compare it with other MRI segmentation approaches

Neuroimage processing research line publications

Journals

2008

Maite García-Sebastián, Carmen Hernandez, Alicia d'Anjou, "**Robustness of an Adaptive MRI Segmentation Algorithm Parametric Intensity Inhomogeneity Modeling**", Neurocomputing acepted for publication.

2007

Maite García-Sebastián, E.Fernandez, M. Graña and F.J. Torrealdea, ***"A parametric gradient descent MRI illumination correction algorithm"***, in Pattern Recognition Letters 28 (2007) 1657-1666.

2004

Elsa Fernandez, Manuel Graña, Jesús Ruiz-Cabello. "**On a Gradient Based Evolution Strategie For Parametric Illumination Correction**". Electronic Letters, 40(9):531-532.

2003

R. Perez de Alejo, J. Ruiz-Cabello, M. Cortijo, I. Rodriguez, I. Echave, J. Regadera, J. Arrazola, P. Avilés, P. Barreiro, D. Gargallo, M. Graña, "**Computer-Assisted Enhanced Volumetric Segmentation Magnetic Resonance Imaging Data Using a Mixture of Artificial Neural Networks**", Magnetic Resonance Imaging, 21:901-912.

2002

J. Ruiz-Cabello, M. Cortijo, I. Echave, M. Graña y otros, "**Monitoring actute inflammatory processes in the mouse muscle by MR imaging and spectroscopy: a comparision with pathological results**", NMR in Biomedicine, 15:204--214 .

2000

J. Ruiz-Cabello, I Rodriguez, P. Avilés, M. Graña, I. Echave, J. Regadera, D. Gargallo, M. Cortijo. "**Magnetic resonance imaging to monitor the biology of inflammation**", European Biopohysics Journal, 29(4-5) pp.363.

Book chapters

2008

Maite García-Sebastián, A. M. Savio, Manuel Graña, "***Comments on an Evolutionary Intensity Inhomogeneity Correction Algorithm***", WCCI 2008. Proceedings CEC 2004, pp.4147-4151. **ISBN 978-1-4244-1823-7**.

2007

Maite García-Sebastián, Manuel Graña, ***"SOM for intensity inhomogeneity correction in MRI",*** in *The 15th European Symposium on Artificial Neural Networks. Advances in Computational Intelligence and Learning*, ESANN 2007. **ISBN 2-930307-07-2**; pp. 109-114.

Maite García-Sebastián, Ana I. Gonzalez, and Manuel Graña, ***"Derivation of SOM-like rules for intensity inhomogeneity correction in MRI"*** in *Computational Intelligence an Bioinspired Systems*, IWANN 2007. Springer Verlag, Berlin.

2006

Ana I. González, Alicia D'Anjou, M. Teresa García-Sebastian, Manuel Graña, ***"SOM and Neural Gas as Graduated Nonconvexity Algorithms***", in *The 2006 International Conference on Computational Science and its Applications*, ICCSA 2006, part 3 . Springer Verlag, Berlin Heidelberg. M. Gavrilova et al.(Eds.): ICCSA 2006, LNCS 3982. **ISBN 3-540-34075-0**; pp. 1143-1152. **JCR(2005) 0.402.**

C.Hernández, J. Gallego, Maite García-Sebastián, Manuel Graña Romay, ***"On Clustering Performance Indices for Multispectral Images"*** in *Knowledge-Based Intelligent Information and Engineering Systems, 10 International Conf.*, KES 2006. Springer Verlag, Berlin Heidelberg. B. Gabrys, R. J. Howlett and L. C. Jain (Eds.): KES 2006, Part III, LNCS 4253. **ISBN 978-3-540-46542-3**; pp. 277-283. **JCR(2005) 0.402.**

2005

Maite García-Sebastián, E.Fernandez, M. Graña and F.J. Torrealdea, ***"A gradient descent MRI illumination correction algorithm",*** in *Computational Intelligence an Bioinspired Systems*, IWANN 2005. Springer Verlag, Berlin, LNCS 3512. **ISBN 3-540-26208-3**; vol. 3512, pp. 913-920. **JCR(2005) 0.402.**

Book chapters

2004

*E. Fernandez, M. Graña, J. Ruiz-Cabello.” **An Instantaneous Memetic Algorithm for Illumination Correction**”. IEEE Press, CEC2004. ISBN 0-7803-8516-0.*

2002

*M. Graña, I. Echave, J. Ruiz-Cabello, M. Cortijo. “**Segmentation of infected tissues in MRI based on VQBF filtering**”, ICSP'02; Yuan B., Tang X. (eds), pp 1540-1543. IEEE Press, ISBN. 0-7803-7488--6.*

2000

*M. Graña , I. Echave, J. Ruiz-Cabello. “**VQ based Bayesian image filtering**”, ICIP’2000. ISBN. 0-7803-6300-0.*

1999

*M. Graña, A.I. Gonzalez, I. Echave, Jesus Ruiz-Cabello. “**VQ based image filtering**”. M.I. Torres, A. Sanfeliu (eds) Pattern Recognition and Image Analysis SNRFAI’99, pp. 471-478*

*A.I. González, M. Graña, I. Echave, J. Ruiz-Cabello. “**Bayesian VQ Image Filtering design with fast adaptation Competitive Neural Networks**”, pp. 341-249. REF. REVISTA/LIBRO: Engineering Applications of Bio-inspiredArtificial Neural Networks J. Mira, J. V. Sanchez-Andres (eds). Springer-Verlag,ISBN. 3-540-66068-2.*

Thank you for your attention