# Welcome



Apr 26, 01 16:44 <b>splninterp.c</b>	Page 1/7	Apr 26, 01 16:44 <b>splninterp.c</b> Page 2/7
/* Interpolation of a volume described by B-spline coefficients at arbitrary points. Jan Kybic, 1999		return 0 ; }
\$Id: splninterp.c,v 1.1.1.1.2.6 2001/04/26 14:44:47 cvsuser Exp \$ */		
<pre>#ifdef BIGSPLINES #include *BGsplines.h* #include <math.h> #endif</math.h></pre>		<pre>extern int spinterp /* Takes an input matrix of size nxi*nyi*nzi, containing B-spline coefficients of degree 'degree'. Samples the resulting function at mcc*nyc*nzc points given by coord, each point described by ndc coordinates. Uses mirror boundary conditions. Everything should be allocated in advance.</pre>
<pre>extern int mfoldmirroronbound(int k,int n) /* having a signal 0n-1, fold k using mirror on boundary conditions,     i.e. k=n-1 gives n-1, k=n gives n-2, k=-1 gives 1 etc. */ { int m;     if (nc=1) return 0;     m=2*(n-1);     k=(k&lt;0) ? k%m+m : k%m;</pre>		<pre>z the index which changes slowest. C convention is applied for indexing, i.e. the first element of 'input' is assumed to correspond to point (0,0,0). If coord gives multidimensional coordinates, they are laid consecutively, i.e., as the fastest changing (sub)index - even faster than x. */</pre>
return k>=n ? m-k : k ; }		<pre>double *input,</pre>
<pre>extern double mfolddmirroronbound(double k,int n) /* having a signal 0n-1, fold k using mirror on boundary conditions,     i.e. k=n-1 gives n-1, k=n gives n-2, k=-1 gives 1 etc. */     int m, q:     int m, q:     int m, therefore a signal of the signal a signa</pre>		<pre>int nxi, int nyi, int nzi, /* input size */ int nxc, int nyc, int nzc, /* output size */ int ndc, /* coordinate range dimensionality */ int degree, /* 0 - Haar, 1 - Linear etc. */ int dflag, /* 0 - value, 1,4,16 - first derivative with respect to x,y,z ; 2,8,32 - second der. */ int bcond</pre>
<pre>settern int mfoldmirroroffbound(int k,int n) /* having a signal 0n-1, fold k using mirror off boundary conditions,     i.e. k=n-1 gives n-1, k=n gives n-1, k=-1 gives 0 etc. */     if (n&lt;-1) return 0;     m=2n;     k=k&lt;0) ?, k%m+m : k%m;     return k&gt;=n ? m-1-k : k; }</pre>		<pre>{     int ix, iy, iz, ofs, jx, jy, jz, kz, lx, ly, lz;     double (*eveplnx)(double);</pre>
<pre>settern double mfolddmirroroffbound(double k,int n) /* having a signal 0n-1, fold k using mirror off boundary conditions,     i.e.ken-1 gives n-1, k=n gives n-1, k=-1 gives 0 etc. */ { int m,q;     m=2*n;     gefloor(k/m) ; k-=q*m;     return k&gt;n-1 ? m-1-k : k ; }</pre>		<pre>switch(bcond) {     case MirrofOfBounds:         mfold=mfoldmirroroffbound ;         mfold=mfoldmirroroffbound ;         break:     case MirrofOnBounds:         mfold=mfoldmirroronbound ;         mfold=mfoldmirroronbound ;         break:     case It:::     case It::::     case It::::::::::::::::::::::::::::::::::::</pre>
<pre>extern int evalbspln(double *x,double *y, int n, int degree) /* Evaluates B-spline of degree 'degree' at n-points x[0],,x[n-1] */ /* results are put into y[0],,y[n-1] */ { int i,supp ;     double (*evsplnx)(double) ;</pre>	*/	<pre>myErrMsg("Unsupported boundary conditions.") ; return 1 ; } // mexPrintf("splninterp called with nxi=%d nvi=%d nzi=%d nxc=%d nzc=% </pre>
<pre>return 1 ; } for (i=0;i<n;i++) ;<="" pre="" y[i]="(*evsplnx)(x[i])"></n;i++)></pre>		<pre>d ndc=%d degree=%d\n", nxi, nyi, nzi, nxc, nyc, nzc, ndc, degree); if (choosespln(degree,&amp;evsplnx,Ksupp,dflag &amp; 3) choosespln(degree,&amp;evsplnx,NULL,(dflag &amp; 12)&gt;&gt;2) choosespln(degree,&amp;evsplnz,NULL,(dflag &amp; 48)&gt;&gt;4)) {</pre>
Tuesday July 17, 2001	splni	interp.c 1/4

Printed by Jan Kybic

#### Programming

#### Mathematics

$$B(\mathbf{f}, \mathbf{g}) = \int_{\mathbb{R}^{2m}} \mathbf{f}^{T}(\mathbf{x}) \mathsf{V}(\mathbf{x}, \mathbf{y}) \mathbf{g}(\mathbf{y}) \mathrm{d}\mathbf{x} \mathrm{d}\mathbf{y}$$

$$B(\mathbf{f},\mathbf{g}) = \frac{1}{(2\pi)^m} \int_{\mathbb{R}^m} \hat{\mathbf{f}}^T(\boldsymbol{\omega}) \, \hat{\mathbf{U}}(\boldsymbol{\omega}) \, \hat{\mathbf{g}}^*(\boldsymbol{\omega}) \, \mathrm{d}\boldsymbol{\omega}$$

**Lemma 0** A function  $\mathbf{f}_{out}$  from F satisfying  $\langle \mathsf{H}, \mathbf{f}_{out} \rangle = \mathbf{s}$  solves the variational problem  $\mathcal{P}$ , if and only if there is a real vector  $\boldsymbol{\lambda}$  such that for all  $\mathbf{g} \in F$ 

$$B(\mathbf{f}_{out},\mathbf{g}) = \boldsymbol{\lambda}^T \langle \mathsf{H},\mathbf{g} \rangle$$

$$D^{M}f = \begin{bmatrix} \frac{\partial^{M}f}{\partial x_{1}^{M}}, \dots, \frac{\partial^{M}f}{\partial x_{k_{1}} \dots \partial x_{k_{M}}}, \dots, \frac{\partial^{M}f}{\partial x_{m}^{M}} \end{bmatrix} \quad \mathbf{E}\begin{bmatrix} \frac{\partial^{\alpha}}{\partial t^{\alpha}}B_{H}(t)\frac{\partial^{\alpha}}{\partial s^{\alpha}}B_{H}(s) \end{bmatrix} = -\frac{\partial^{\alpha}}{\partial t^{\alpha}}\frac{\partial^{\alpha}}{\partial s^{\alpha}}|t-s|^{2H} = \rho(t-s)$$

$$\underbrace{\begin{bmatrix} \mathbf{A} & \mathbf{Q}_{1} \\ \mathbf{Q}_{2} & \mathbf{0} \end{bmatrix}}_{\mathbf{B}}\begin{bmatrix} \mathbf{\lambda} \\ \mathbf{a} \end{bmatrix} = \begin{bmatrix} \mathbf{s} \\ \mathbf{0} \end{bmatrix} \qquad \qquad \frac{\partial E}{\partial c_{\mathbf{j},m}} = \sum_{\mathbf{i}\in I_{b}}\frac{\partial e_{\mathbf{i}}}{\partial f_{w}(\mathbf{i})}\frac{\partial f_{t}^{c}(\mathbf{x})}{\partial x_{m}}\Big|_{\mathbf{x}=\mathbf{g}(\mathbf{i})}\beta_{n_{m}}(\mathbf{i}/\mathbf{h}-\mathbf{j})$$

Programming

#### Mathematics

Papers

#### Unwarping of Unidirectionally Distorted **EPI** Images

Jan Kybic<sup>†</sup>, Philippe Thévenaz, Arto Nirkko and Michael Unser

far, this aspect has been too often neglected. In this paper, we suggest a new approach using an algo-rithm specifically developed for the automatic registration orrect MRI images. We model the deformation field with splines, which gives us a lot of flexibility while comprising the affine transform as a special case. The registration cri-terion is least-squares. Interestingly, the complexity of its evaluation does not depend on the resolution of the control evaluation does not adjend on the resolution of the cohron lish high approximation order. The short support of aplines leads to a fast algorithm. A multiresolution approach yields robustness and additional speed-up. The algorithm was tested on real as well as synthetic data, and the results were compared with a manual method.

data, and the results were compared with a manual method. A wavelet-based Sobolev-type random deformation genera-tor was developed for testing purposes. A blind test indi-cates that the proposed automatic method is faster, more reliable, and more precise than the manual one.

Keywords—image registration, splines, geometrical distor-tion, unwarping

#### I. INTRODUCTION

A EPI features

Echo planar imaging (EPI) [1] is a fast magnetic resonance imaging (MRI) technique permitting an acquisition of a two-dimensional slice using a single excitation, which leads to very short scan times. It is used mainly for functional imaging (fMRI), the in vivo non-invasive study of the temporal, spatial and behavioral dependencies of brain activations. The basis of fMRI lies in the fact that deoxyhemoglobin (the hemoglobin without a bound oxygen molecule) is paramagnetic. Neural activation in the cerebral cortex leads to an increase of blood flow, hence to a decrease of deoxyhemoglobin concentration.<sup>1</sup> This results in a measurable alteration of the magnetic field and in a consequent increase of signal intensity in the appropriately weighted MRI images (blood oxygen-level dependent, BOLD). It is therefore difficult to compensate for the unwanted magnetic field inhomogeneities induced mainly by the spatially varying magnetic susceptibility of the subject [2]. In contrast to conventional MRI, where the number

<sup>†</sup> indicate corresponding author. Jan Kybic Philippe Théreaux, and Michael Unser new with Biomolical Insigning Comp. DMT/ROA, Swiss Federal Institute of Technology Lausanne CH-0105 Lausanne EPFL, Switzerland, email: Jan,Kybic6BepLch. Arto Nirkko is with Inselspital, Bern, Switzerland <sup>1</sup> This effect prevails over the increase of oxygen consumption.

Abstract— Echo-planar imaging (EPI) is a fast nuclear magnetic field inhomogenetics induced mainly by the sub-ject's presence cause significant geometrical distortion, pre-dominantly along the phase-encoding direction, which must be undone to allow for meaningful further processing. So neous magnetic field will manifest itself mainly as a geometrical distortion of the 2D slice image along the direction of this gradient. This effect is clearly visible in Figure 1 Since the stronger gradient is less affected, the distortion is essentially unidirectional. Letting g be the unknown warping (deformation) function, we have

#### $f^o(q(x, y), y) \simeq f^u(x, y)$ (1)

where  $f^o$  is the observed EPI image and  $f^u$  is the hypothetical ideal undistorted EPI image. We can consider each slice separately, as the shift in the z axis due to patient's movement is insignificant because his head is at tached. Should there be such a displacement, it can by readily corrected by existing algorithms [3].

#### B. The reasons to unwarp

The amplitude of the deformation g can be as large as 3-5 mm [4] (confirmed by our own observations), which typically amounts to several pixels. In some cases, as in Figure 1, specifically intended to illustrate EPI distortion, the deformation can be even more pronounced. Moreover g can vary significantly from slice to slice and from acquisition to acquisition. For localization applications like stereotactic surgery, this inaccuracy is much larger than the required limit of 1 mm and therefore EPI cannot currently be used to this end. It also severely hinders the performance of the statistical processing of sets of fMRI images used to obtain activation information. Since the task-induced signal changes represent typically only 5-10% of the mean signal intensity in fMRI [1,5], they will not stand out clearly unless the perturbations caused by the deformation g are undone.

#### Existing distortion correction techniques

One approach consists in changing the acquisition procedure [2, 4, 6]. However, this is often not practical due to technical or organizational limitations, for example lack of support or approval. Furthermore, while the alternative acquisition sequences reduce the distortion, the distortion is never removed completely, and the methods usually sacrifice either sensitivity or acquisition speed.

The second group of methods uses a two-step procedure [4,7]. First, a field map or a deformation map is

- Programming
- Mathematics
- Papers
- Conferences



#### Elastic Image Registration using Parametric Deformation Models

Jan Kybic

#### **Overview**

- Registration and its applications
- Manual registration
  - Interpolation
  - Variational reconstruction
- Splines
- Automatic registration
  - Algorithm
  - Semi-automatic registration
  - Applications
- Conclusions
- Party

#### **Overview**

- Registration and its applications
- Manual registration
  - Interpolation
  - Variational reconstruction
- Splines
- Automatic registration
  - Algorithm
  - Semi-automatic registration
  - Applications
- Conclusions
- Party

#### What did we do?

#### **Overview**

- Registration and its applications
- Manual registration
  - Interpolation
  - Variational reconstruction —
- Splines
- Automatic registration
  - Algorithm —
  - Semi-automatic registration —
  - Applications —
- Conclusions
- Party

#### What did we do?

## What is image registration?

## Find corresponding points





American Tux

## Find corresponding points



## Find corresponding points



#### American Tux

#### Tux bordelais

### **Correspondence function**



Reference image

Test image

#### **Correspondence function**



Reference image

Test image

$$\mathbf{\hat{g}} \left( [x \ y]^T \right) = [x' \ y']^T$$













#### 0 % deformation



#### 25 % deformation



#### 50 % deformation



#### 75 % deformation



#### 100 % deformation

## **Image registration**



## **Image registration**



### Is registration useful?

### Is registration useful?

Yes!

## (Biomedical) applications

- ... of image registration
- Comparing images
  - Different times
  - Different methods
  - Different subjects
- Analyzing sequences
  - Motion estimation
  - Segmentation

Qualitative and quantitative information.

## Image alignment



## Image alignment



## **Registration types**

- Manual
- Automatic
- Semi-automatic

### **Manual registration**





#### Landmark identification

### **Manual registration**





- Landmark identification
- Landmark interpolation
## What is interpolation?

#### **Find a function**



#### **Find a function**



#### **Find a function**



#### **Rank functions**



#### **Rank functions**



#### Variational reconstruction

# Find the **best** function satisfying the **constraints**.









reference



test



 $\int \|\nabla^{0.5} g(\mathbf{x})\|^2 \mathrm{d}\mathbf{x}$ 



 $\int \|\nabla^{0.9} g(\mathbf{x})\|^2 \mathrm{d}\mathbf{x}$ 



 $\int \|\nabla^{1.3}g(\mathbf{x})\|^2 \mathrm{d}\mathbf{x}$ 



 $\int \|\nabla^{2.5}g(\mathbf{x})\|^2 \mathrm{d}\mathbf{x}$ 

# **Tomographic reconstruction**



# **Tomographic reconstruction**





#### **Radon transform**



## **Tomographic experiments**

#### Phantom



# **Tomographic experiments**



8 angles (each  $22^{\circ}$ ), 32 samples per angle

# **Overview (2)**

- Registration and its applications
- Manual registration
  - Interpolation
  - Variational reconstruction
- Splines
- Automatic registration
  - Algorithm
  - Semi-automatic registration
  - Applications
- Conclusions
- Party

The splines

# What are splines, anyway?



# What are splines, anyway?

# The best functions in the world!

## (Uniform) splines

# (Uniform) splines



- - Continuous  $(n-1)^{\text{th}}$  derivative
  - (Uniform) knots

## **Uniform B-splines**

Haar $\beta_0$ linear $\beta_1$ quadratic $\beta_2$ cubic $\beta_3$ 



## **Uniform B-splines**

Haar $\beta_0$ linear $\beta_1$ quadratic $\beta_2$ cubic $\beta_3$ 





#### **Automatic registration**

#### How does it work?

# **Spline based warping**



- Approximation
  properties →
  precision
- Short support  $\rightarrow$  speed
- Scalability
- Representability of linear transforms

$$\mathbf{g}(\mathbf{x}) = \mathbf{x} + \sum_{\mathbf{i} \in \mathbb{Z}^2} \mathbf{c}(\mathbf{i}) \,\beta(\mathbf{x}/\mathbf{h} + \mathbf{d} - \mathbf{i})$$

# **Registration as minimization**



# **Registration as minimization**



# **Image warping (2)**



#### 0 % deformation

# **Image warping (2)**



#### 100 % deformation

# **Registration as minimization (2)**



#### **Evaluating the difference**










Elastic Image Registration using Parametric Deformation Models - p.34/45





Elastic Image Registration using Parametric Deformation Models - p.34/45

# **Registration as minimization (3)**



Elastic Image Registration using Parametric Deformation Models -p.35/45

#### Minimize criterion E with respect to parameters c.



## Find the lowest point

Elastic Image Registration using Parametric Deformation Models - p.36/45



## Frog search in the mist

Elastic Image Registration using Parametric Deformation Models - p.36/45



#### Next move

Elastic Image Registration using Parametric Deformation Models - p.36/45

## Acceleration

## It works. Now let's make it run fast.









# **Overview (3)**

- Registration and its applications
- Manual registration -
  - Interpolation
  - Variational reconstruction
- Splines
- Automatic registration
  - Algorithm
  - Semi-automatic registration —
  - Applications
- Conclusions
- Party



#### click here

#### EPI distortion



#### Before

(with Arto Nirkko)

Elastic Image Registration using Parametric Deformation Models – p.41/45

## EPI distortion



After

Elastic Image Registration using Parametric Deformation Models - p.41/45

- EPI distortion
- MRI atlas



Atlas

- EPI distortion
- MRI atlas



Aligned

Elastic Image Registration using Parametric Deformation Models - p.41/45

- EPI distortion
- MRI atlas
- CT alignment







Before

- EPI distortion
- MRI atlas
- CT alignment







After

- EPI distortion
- MRI atlas
- CT alignment
- SPECT atlas



(with University Hospital in Geneva)

Elastic Image Registration using Parametric Deformation Models -p.41/45

- EPI distortion
- MRI atlas
- CT alignment
- SPECT atlas
- Ultrasound



velocity (with María J. Ledesma-Carbayo)

## Conclusions

- Image registration is useful
- Our registration algorithm works
- Interpolation is interesting
- Variational is elegant
- Splines are great

# The End

Elastic Image Registration using Parametric Deformation Models – p.43/45

Díky! Merci! Thank you! Gracias! **Grazie!** Danke!

Elastic Image Registration using Parametric Deformation Models - p.44/45



#### Bâtiment de microtechnique, 4th floor

Elastic Image Registration using Parametric Deformation Models -p.45/45