Nonrigid Registration Using Free-Form Deformations: Application to Breast MR Images

Presentation by:
Razvan Valentin Marinescu (Lead presentation)
Benedetta Biffi (Contributions)
Emma Hill (Limitations)

Aims & Motivation

- Application of image registration for MR mammography

- Authors proposed an algorithm for non-rigid registration that combines:
  a. The advantages of voxel-based similarity measures
  b. Nonrigid transformation model of the breast

- Limitations of previous registration methods:
  a. Breast motion is assumed to be rigid
  b. Cannot deal with non-uniform intensity change
  c. Limited to small degrees of freedom

Methodology

- The goal of image registration is to find a function that relates two images:

$$T(x,y,z) = T_{global}(x,y,z) + T_{local}(x,y,z)$$

- Global motion is modelled with an affine transformation:

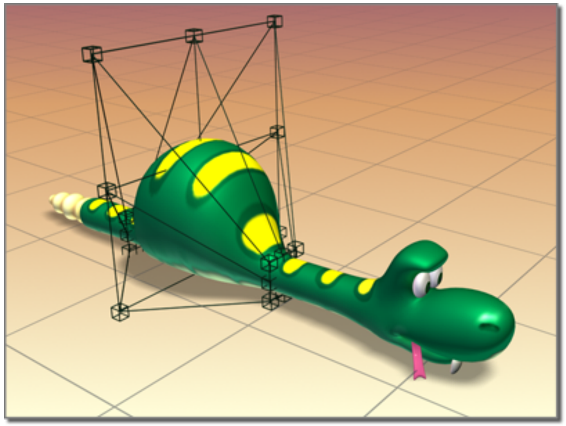
$$T_{global}(x,y,z) = \begin{pmatrix} \theta_{11} & \theta_{12} & \theta_{13} \\ \theta_{21} & \theta_{22} & \theta_{23} \\ \theta_{31} & \theta_{32} & \theta_{33} \end{pmatrix} \begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} \theta_{14} \\ \theta_{24} \\ \theta_{34} \end{pmatrix}$$

Methodology - local motion

- Modelled using an free-form deformation model based on B-splines:

$$T_{local}(x,y,z) = \sum_{l=0}^{3}\sum_{m=0}^{3}\sum_{n=0}^{3} B_l(u)B_m(v)B_n(w)\phi_{i+l,j+m,k+n}$$

$$B_0(u) = (1-u)^3/6$$
$$B_1(u) = (3u^3 - 6u^2 + 4)/6$$
$$B_2(u) = (-3u^3 + 3u^2 + 3u + 1)/6$$
$$B_3(u) = u^3/6$$



- The resolution of the control mesh is increased until the desired level is achieved:

$$T_{local}(x,y,z) = \sum_{l=1}^{L} T_{local}^{l}(x,y,z)$$

Methodology - optimisation framework

- To constrain the transformation to be smooth a penalty term is applied:

$$C_{smooth} = \frac{1}{V}\int_0^X \int_0^Y \int_0^Z \left[\left(\frac{\partial^2 T}{\partial x^2}\right)^2 + \left(\frac{\partial^2 T}{\partial y^2}\right)^2 + \left(\frac{\partial^2 T}{\partial z^2}\right)^2 + 2\left(\frac{\partial^2 T}{\partial xy}\right)^2 + 2\left(\frac{\partial^2 T}{\partial xz}\right)^2 + 2\left(\frac{\partial^2 T}{\partial yz}\right)^2 \right] dx\, dy\, dz$$

- Normalised mutual information is used as a similarity criterion between images:

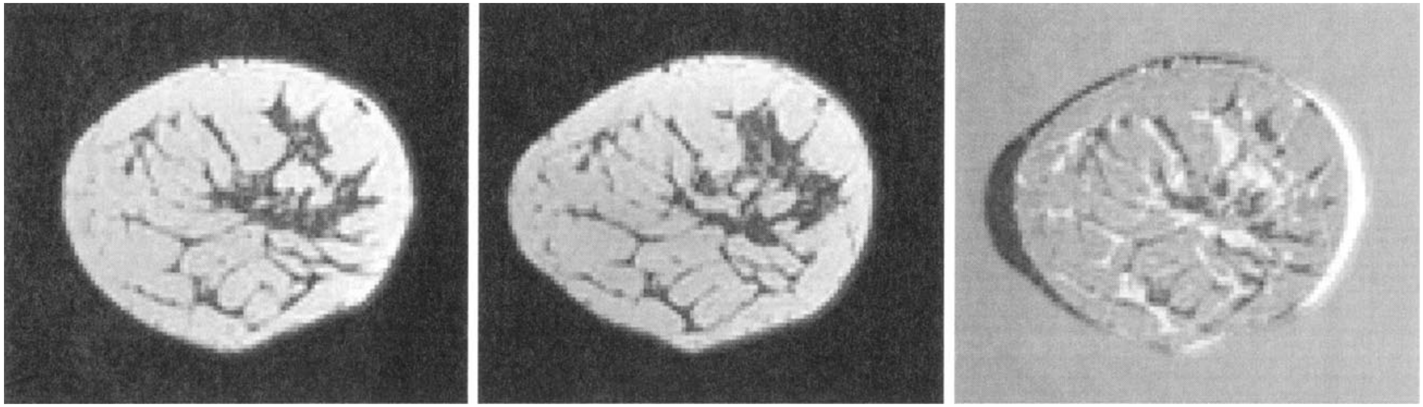
$$C_{similarity}(A, B) = \frac{H(A) + H(B)}{H(A, B)}$$

- The cost function that needs to be optimised is:

$$C(\Theta, \Phi) = -C_{similarity}(I(t_0), T(I(t))) + \lambda C_{smooth}(T)$$

Results - volunteer data

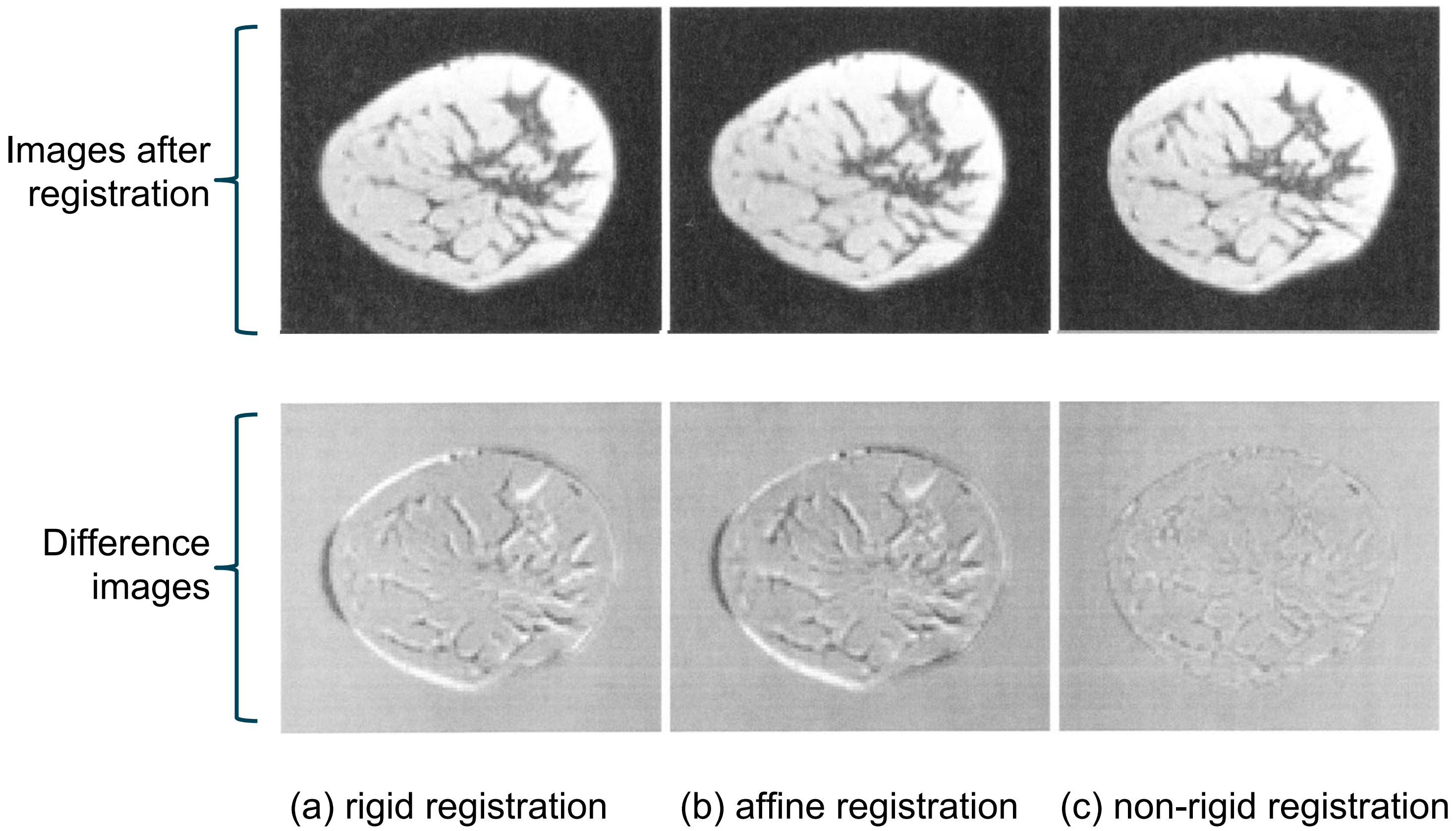
- Fig 2. mis-registration caused by motion of volunteer



(a) before motion (b) after motion (c) After subtracting (b) from (a)

Results - volunteer data

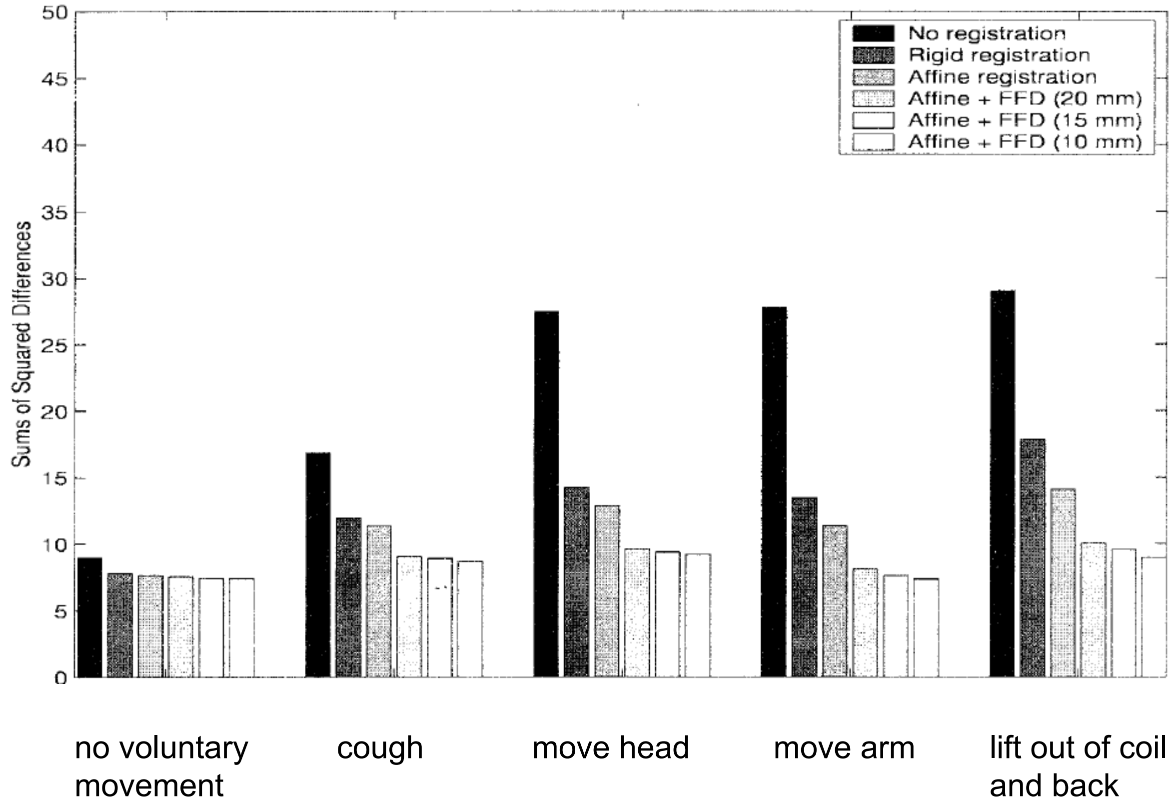
- Fig 3. Comparison of different registration techniques



Results - volunteer data

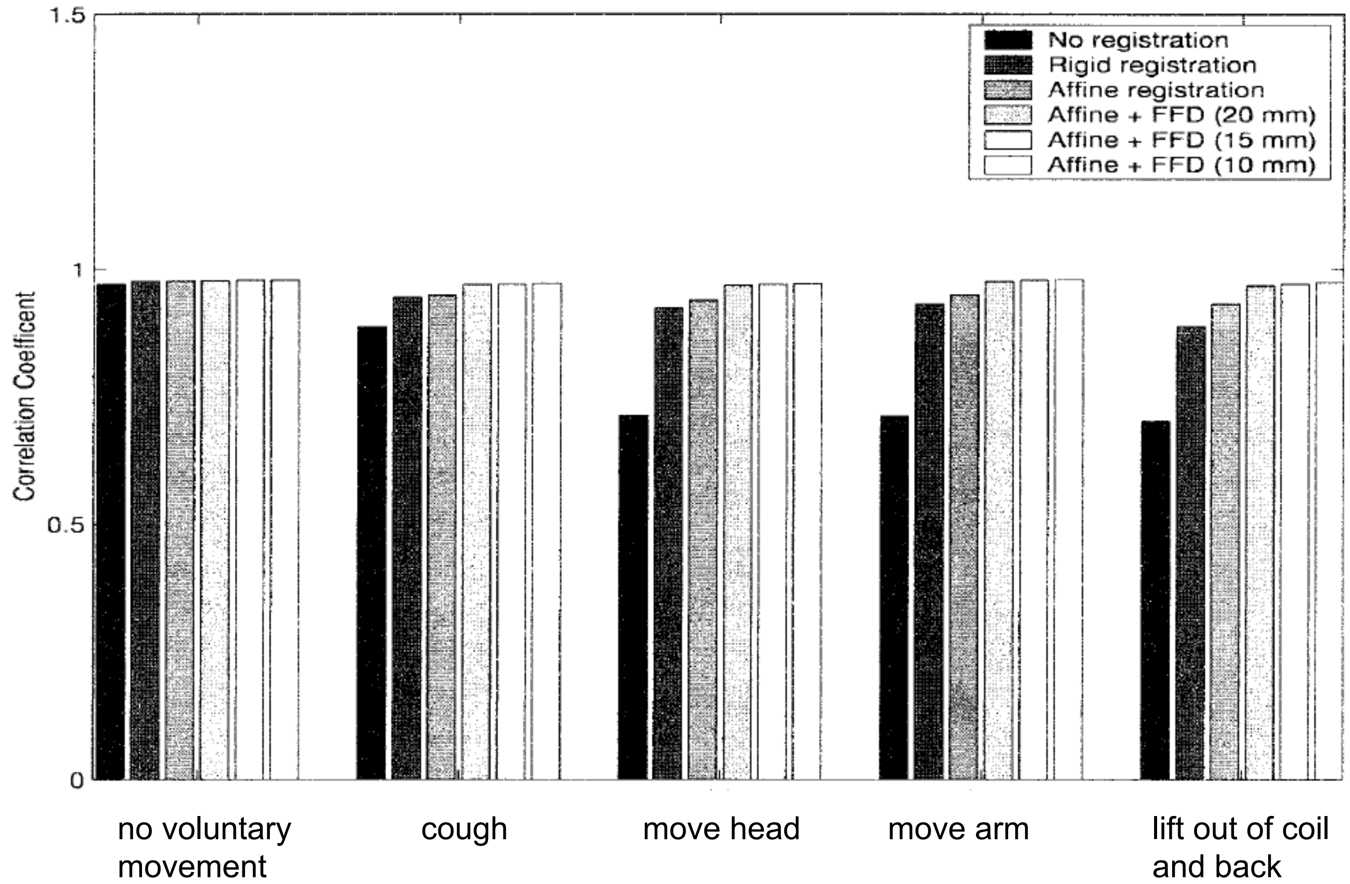
Fig 4. Registration error - sum of squared differences

- Affine+FFD registration performs best
- performance increases with FFD resolution



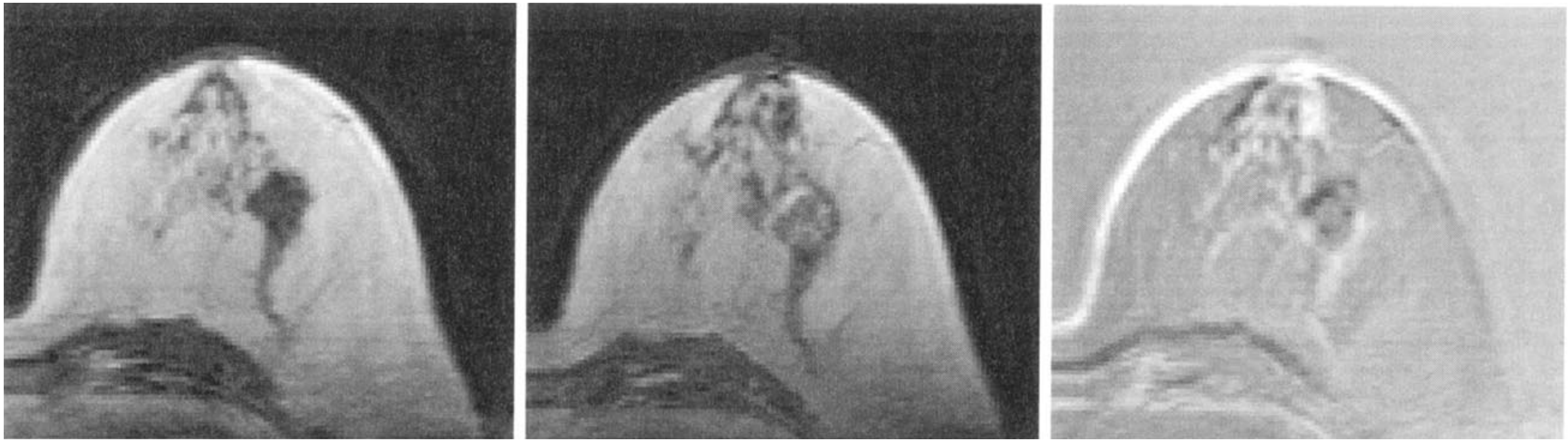
Results - volunteer data

Fig 5. Registration error - Correlation Coefficient



Results - patient study

Fig 6. Misregistration in contrast-enhanced patient study



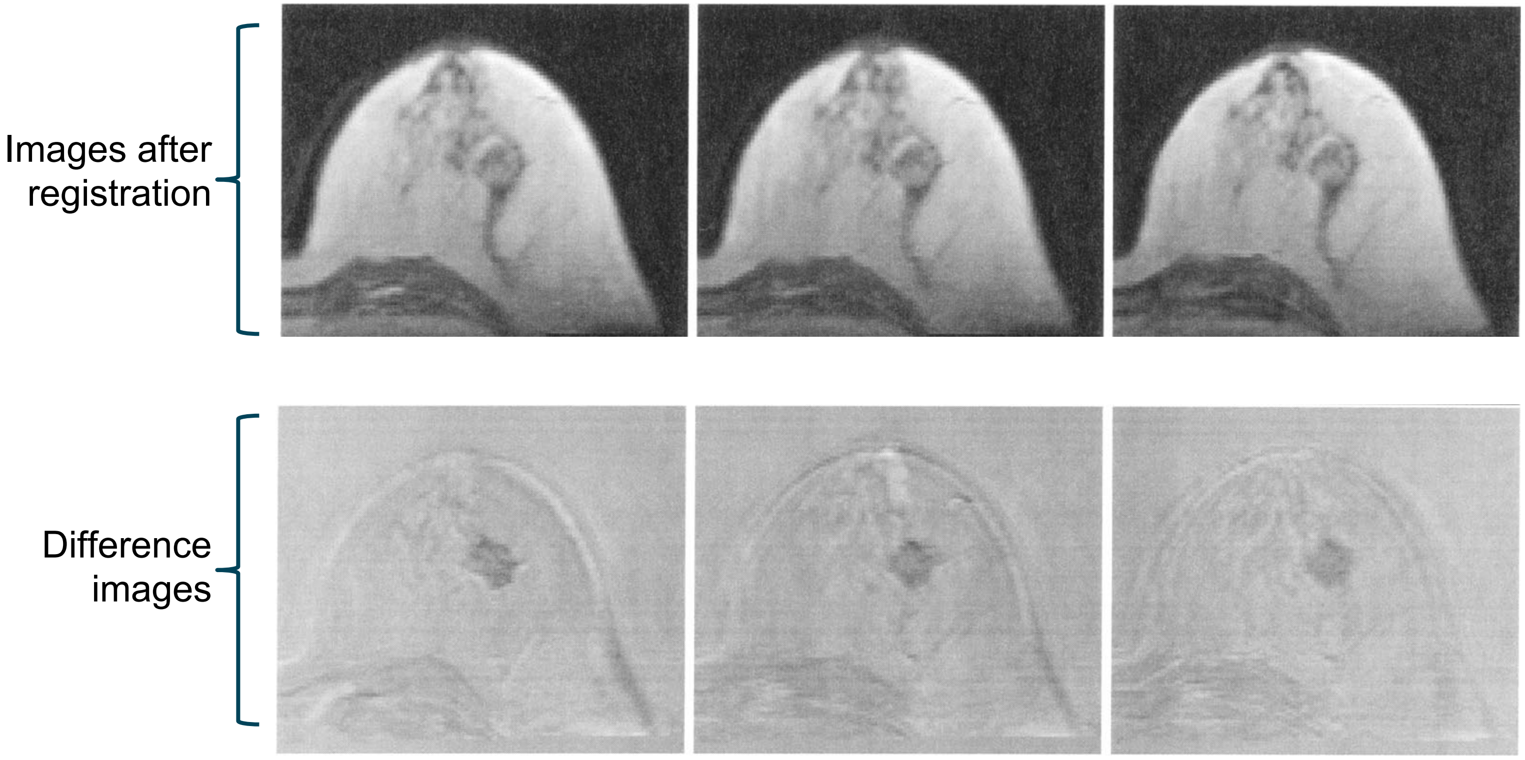
(a) before injection of contrast medium

(b) after injection of contrast medium

(c) after subtraction of (a) from (b) without registration

Results - patient study

Fig 7. Results of different transformations on the registration of pre- and post-contrast enhanced images

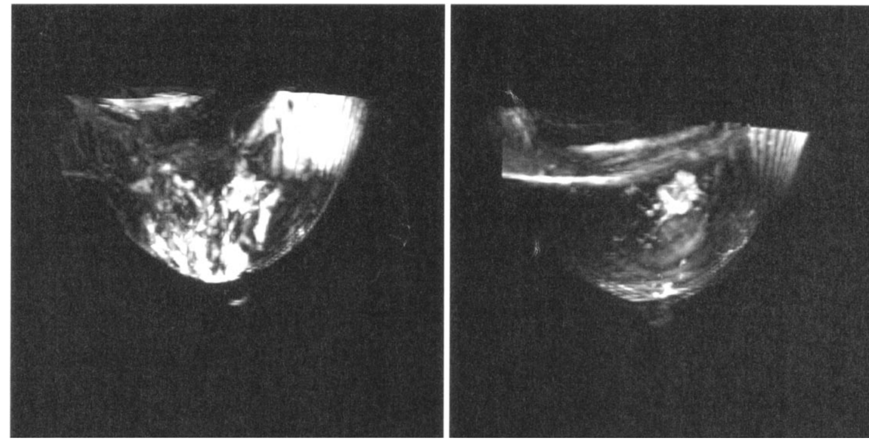


(a) rigid registration (b) affine registration (c) non-rigid registration

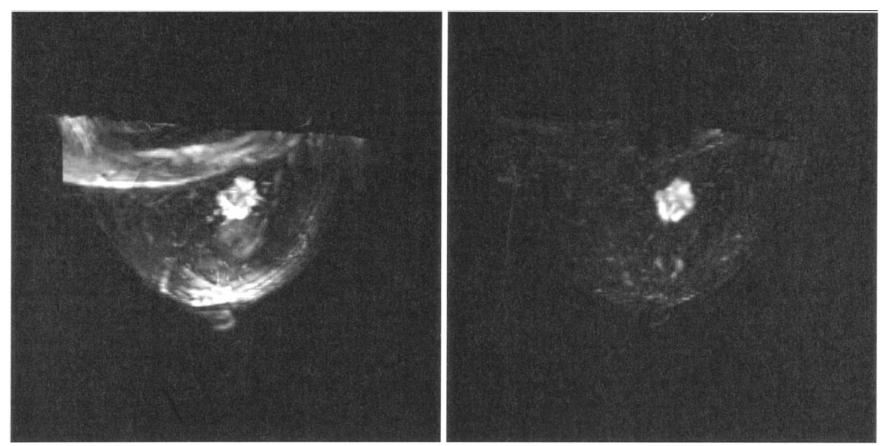
Results - patient study

- Fig 8. Maximum intensity projection (MIP) of the contrast-enhanced images

- Tumor is clearly visible with the non-rigid registration method



(a) Without registration (b) With rigid registration



(c) With affine registration (d) With non-rigid registration

Results - scores and ranking

- Comparison of average registration error of volunteer studies using SSD and CC scores:

Registration	SSD (mean)	SSD (variance)	CC
No registration	38.52	53.90	0.8978
Rigid	23.63	33.38	0.9604
Affine	21.38	29.84	0.9689
Affine + FFD ($20mm$)	14.35	23.43	0.9877
Affine + FFD ($15mm$)	13.28	20.91	0.9895
Affine + FFD ($10mm$)	12.53	19.25	0.9905

- Ranking of registration methods by radiologists (patient dataset):

Registration		Ranking		
A	B	$A < B$	$A = B$	$A > B$
Rigid	No registration	78%	22%	-
Affine	No registration	84%	16%	-
Affine + FFD	No registration	94%	6%	-
Affine	Rigid	13%	78%	9%
Affine + FFD	Rigid	94%	6%	-
Affine + FFD	Affine	94%	6%	-

Conclusion

- first efficient algorithm that can perform nonrigid multi-modal registration
- overcomes the limitations of the previous methods
- has subsequently been used even in other fields, such as:
  - PET-CT chest registration
  - neuroimaging
  - cardiac modelling

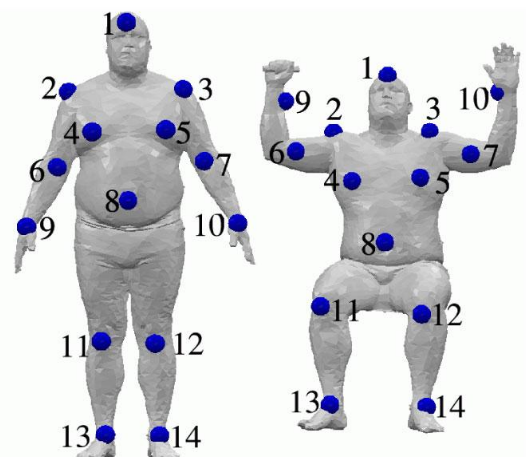
Contributions

Benedetta Biffi

Contributions

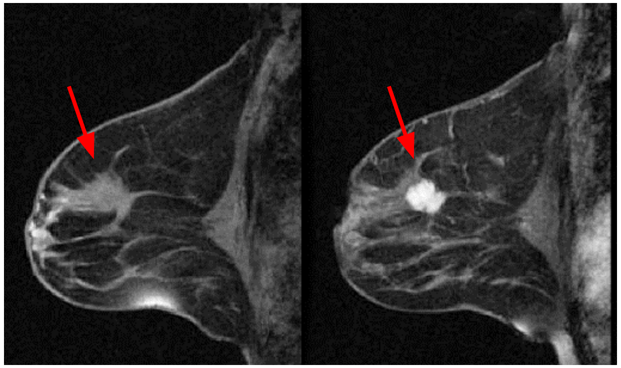
- First proposed **registration algorithm** able to take into account

Deformations



The correlated correspondence algorithm for unsupervised surface registration, NIPS 2004

Image intensity variations



PRE
No contrast

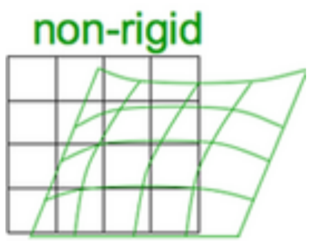
POST
Contrast enhanced

Breast magnetic resonance imaging, BCMJ, Vol. 47, No. 10, December 2005, page(s) 543-548

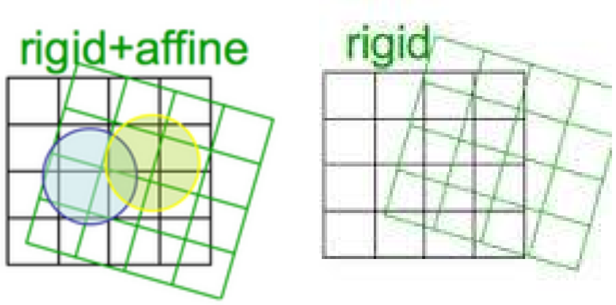
- Improving **breast cancer** diagnosis with **MRI**
  - Overcoming limitation of X-ray
  - 3D nature

Contributions - Methods

- Describes tissue motions with no “compromise”



vs

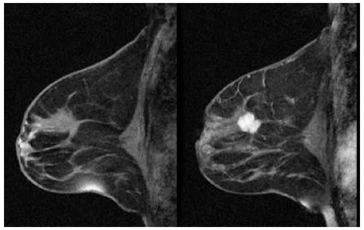


- Desirable properties of **FFD** with **B-splines**
  - Intrinsic smoothness of the transformation
  - B-spline are computationally efficient even for large number of control points
  - Versatility in modelling global or highly local deformation by varying the number of control points

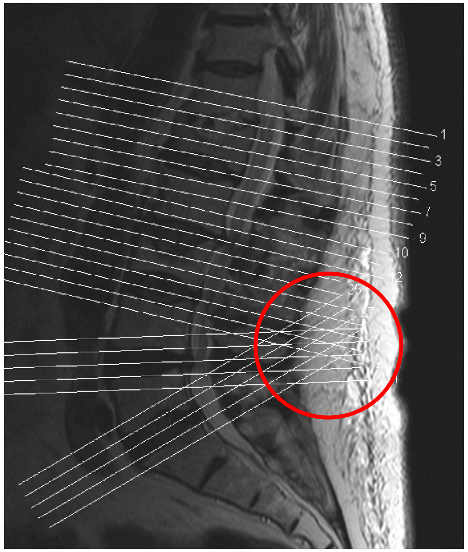
Contributions - Methods

- Adoption of **Normalized Mutual Information**

Intensity variations accounted

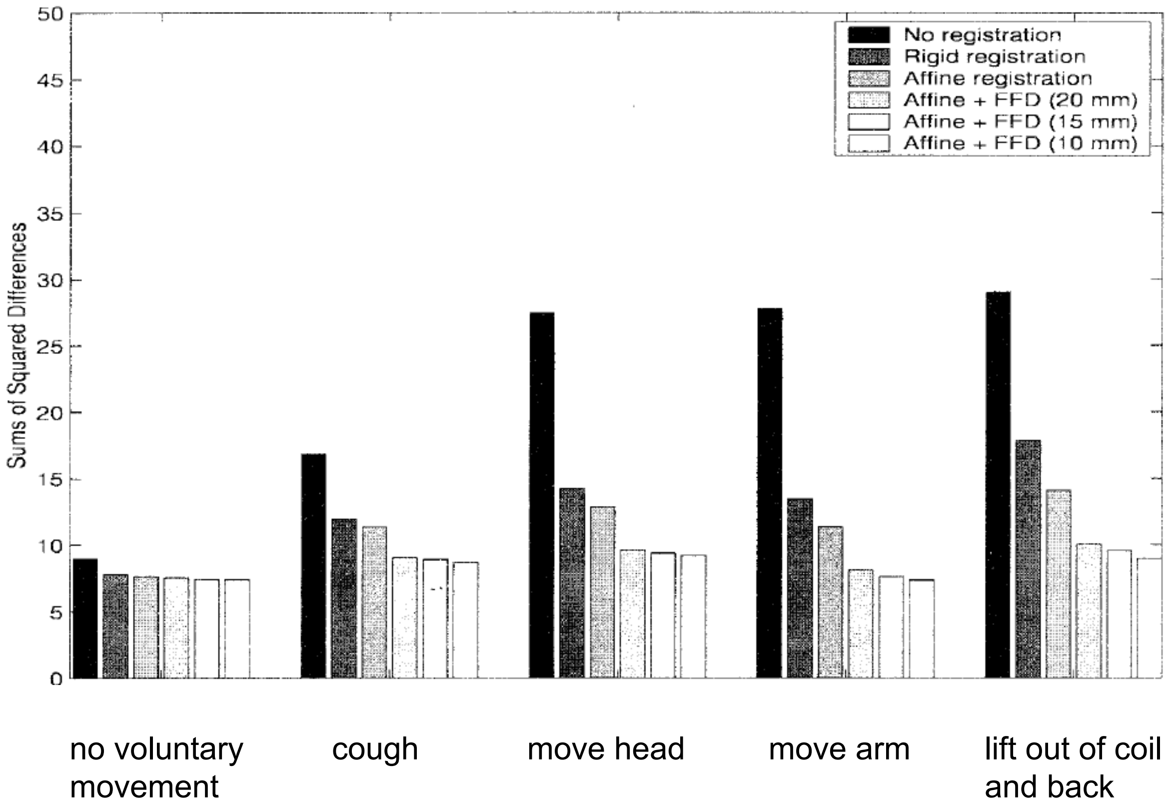


Independence from image overlap



Contributions - Results

- Volunteer data application
  - “Validation” with SSD and CC



Contributions - Results

- Patient data application
  - “Validation” with blind test on radiologists

Registration		Ranking		
A	B	$A < B$	$A = B$	$A > B$
Rigid	No registration	78%	22%	-
Affine	No registration	84%	16%	-
Affine + FFD	No registration	94%	6%	-
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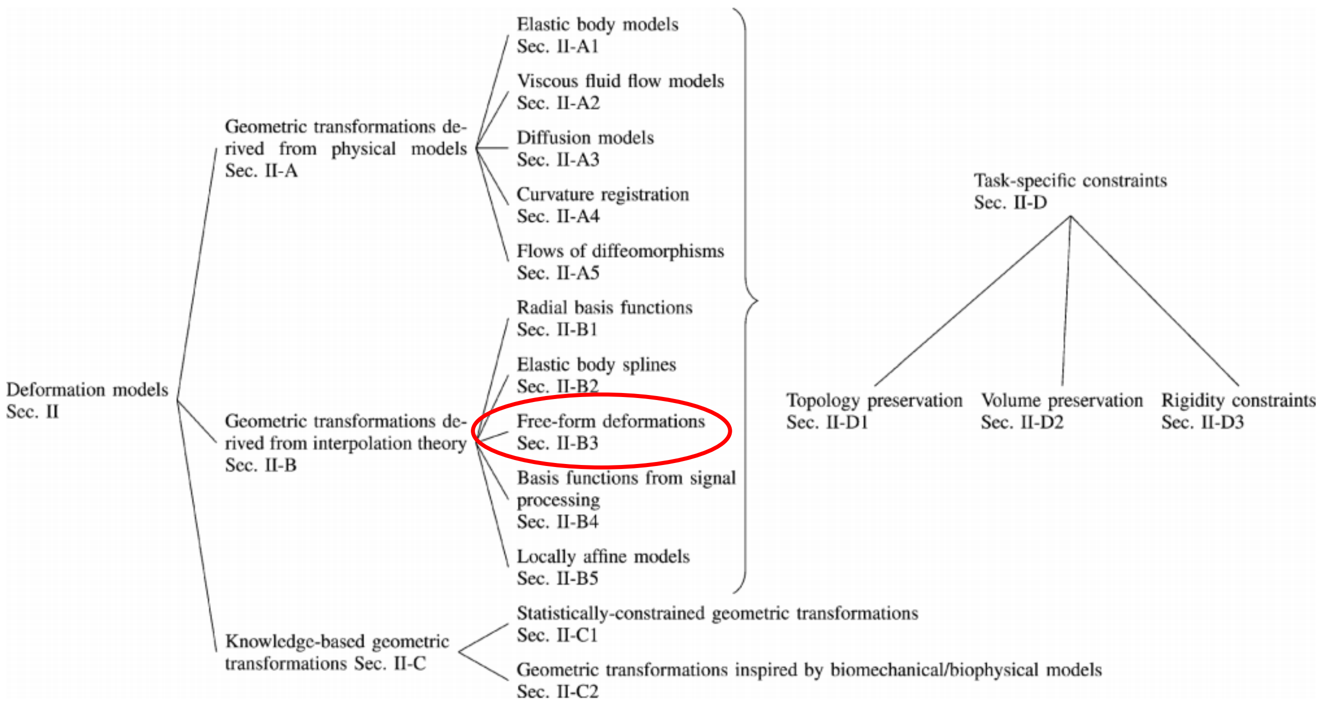
Affine + FFD	Rigid	94%	6%	-
Affine + FFD	Affine	94%	6%	-

Contributions - Conclusions

- **Fully automated** registration
- Significant **reduction of motion artefacts**
- Reasonable **computational time** for clinical applications
- Avoid the **unnecessary complications** of physics-based deformation models

Contributions - Conclusions

- **Great impact!** (3297 citations)
  - Often cited at first when analysing FFD methods for image registration
  - Broad **application** in medical imaging (orthopaedic, brain, cardiac...)



Mutual-Information-Based Registration of Medical Images: a Survey, IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 22, NO. 8, AUGUST 2003

Limitations

Emma Hill

Limitations

- This is not a physics-based model
- The paper has an empirical approach- minimal explanation for choice of λ and mesh resolution in experiments

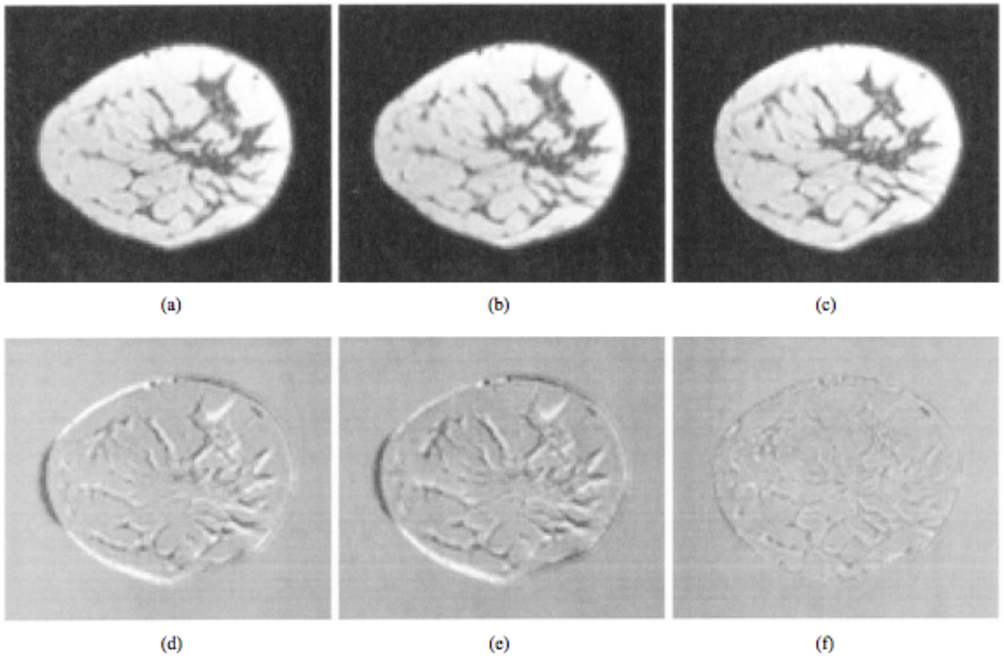


Fig. 3. Example of different transformations on the registration for the volunteer study in Fig. 2: after (a) rigid, (b) affine, and (c) nonrigid registration. The corresponding difference images are shown in (d)–(f).

Limitations

- They state the importance of balancing computing time and quality of data- but do not compare the method’s efficiency

- Assessment of accuracy could be improved

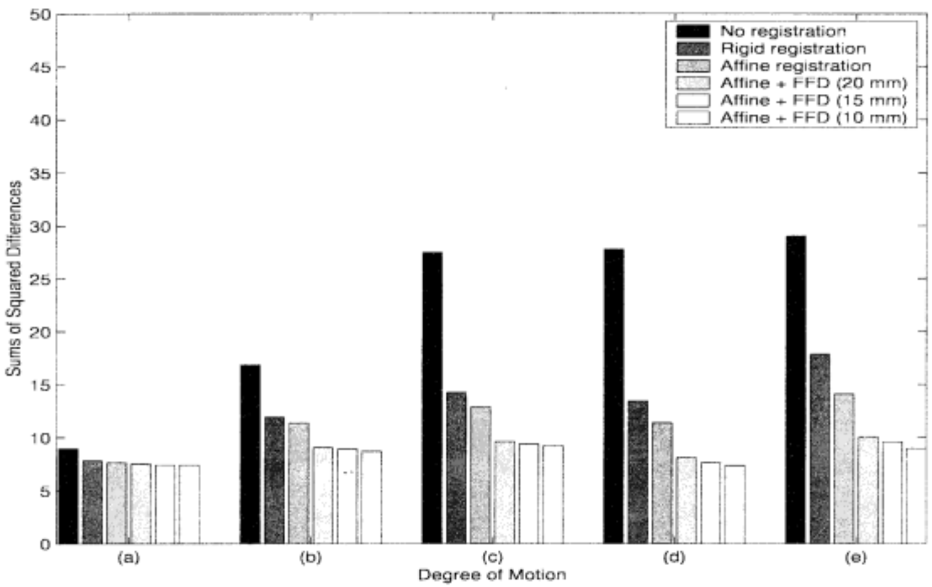


Fig. 4. Comparison of the registration error in terms of SSD for different degrees of volunteer motion. (a) No voluntary movement. (b) Cough. (c) Move head. (d) Move arm. (e) Lift out of coil and back.

Limitations

- The algorithm assumes smoothness of the deformation field and tries to find the transform that maximises mutual information. New information is suppressed.

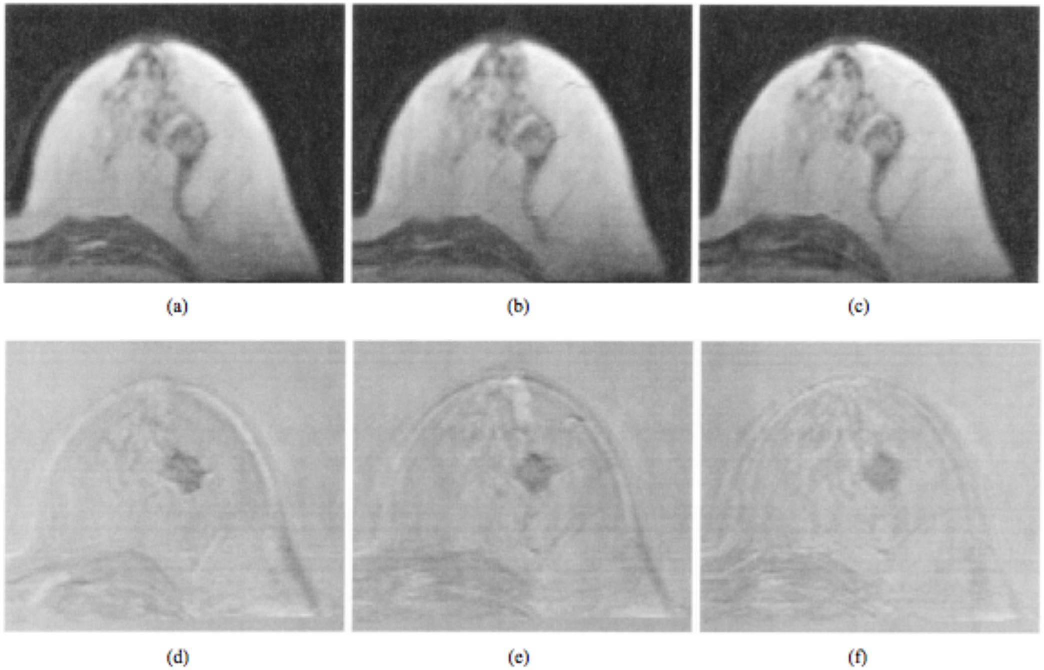


Fig. 7. Example of different transformations on the registration for the patient study in Fig. 6. (a) After rigid. (b) After affine. (c) After nonrigid registration. The corresponding difference images are shown in (d)–(f).

Limitations- a summary

- This is not a physics-based model
- There is a minimal explanation for choice of λ and mesh resolution in experiments
- The efficiency of the method is not given or compared
- The assessment of the method’s accuracy could be improved
- The algorithm may have a tendency to suppress/ contract the contrast-stained tumour