Feature coincidence trees for registration of ultrasound breast images

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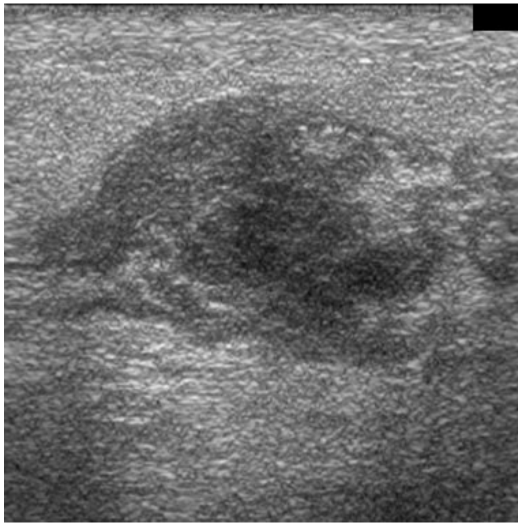
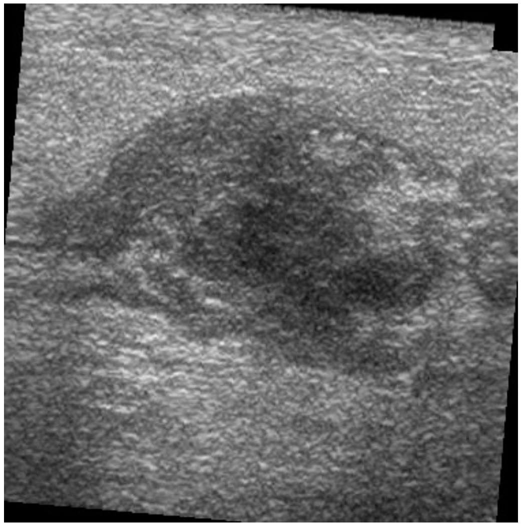
Outline

1. Breast Imaging and Registration Background
2. α-MI Criterion
3. Higher Order Feature Selection
4. Experimental results



(a) Image X_0



(b) Image X_i

Figure 1: A multidate 3D breast-registration example

Background

Some statistics (US)

- One out of nine women will contract breast cancer in their lifetimes
- Breast cancer is second leading cause of cancer death among women
- Diagnostic ultrasound (UL) is cheap/available screening modality
- 65% of malignant breast lesions are missed by community practitioners

What measures are needed to improve detection?

- Routine screening exams: Serial UL studies
- Volumetric imaging to discriminate low contrast lesions from benign microcalcifications and cysts
- Requirement: **Fast and accurate volumetric image registration**

MI Registration of Gray Levels (Viola&Wells:ICCV95)

- X: a $N \times N$ UL image (lexicographically ordered)
- $X(k)$: image gray level at pixel location k
- X_0 and X_1: primary and secondary images to be registered

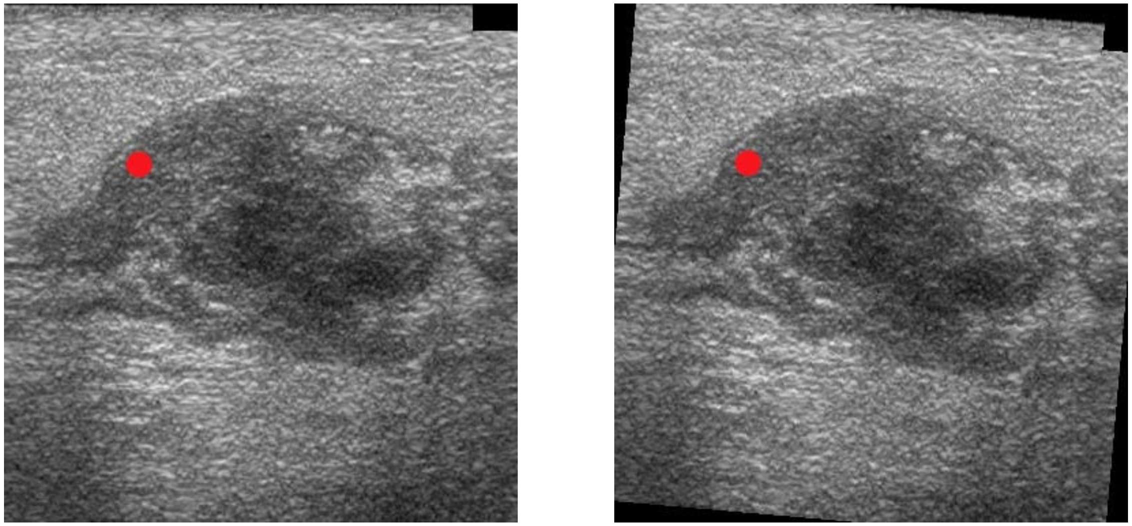
Hypothesis: $\{(X_0(k), X_i(k)\}_{k=1}^{N^2}$ are i.i.d. r.v.'s with j.p.d.f

$$f_{0,i}(x_0, x_1), \quad x_0, x_1 \in \{0, 1, \ldots, 255\}$$

Mutual Information (MI) criterion: $\mathrm{T} = \mathrm{argmax}_{\mathrm{T}_i} \hat{\mathrm{MI}}$

where $\hat{\mathrm{MI}}$ is an estimate of

$$\mathrm{MI}(f_{0,i}) = \int \int f_{0,i}(x_0, x_1) \ln f_{0,i}(x_0, x_1) / (f_0(x_0) f_i(x_1)) dx_1 dx_0. \qquad (1)$$



(a) Image X_1 (b) Image X_0

Figure 2: Single Pixel Coincidences

Joint Feature Histogram Scatterplots

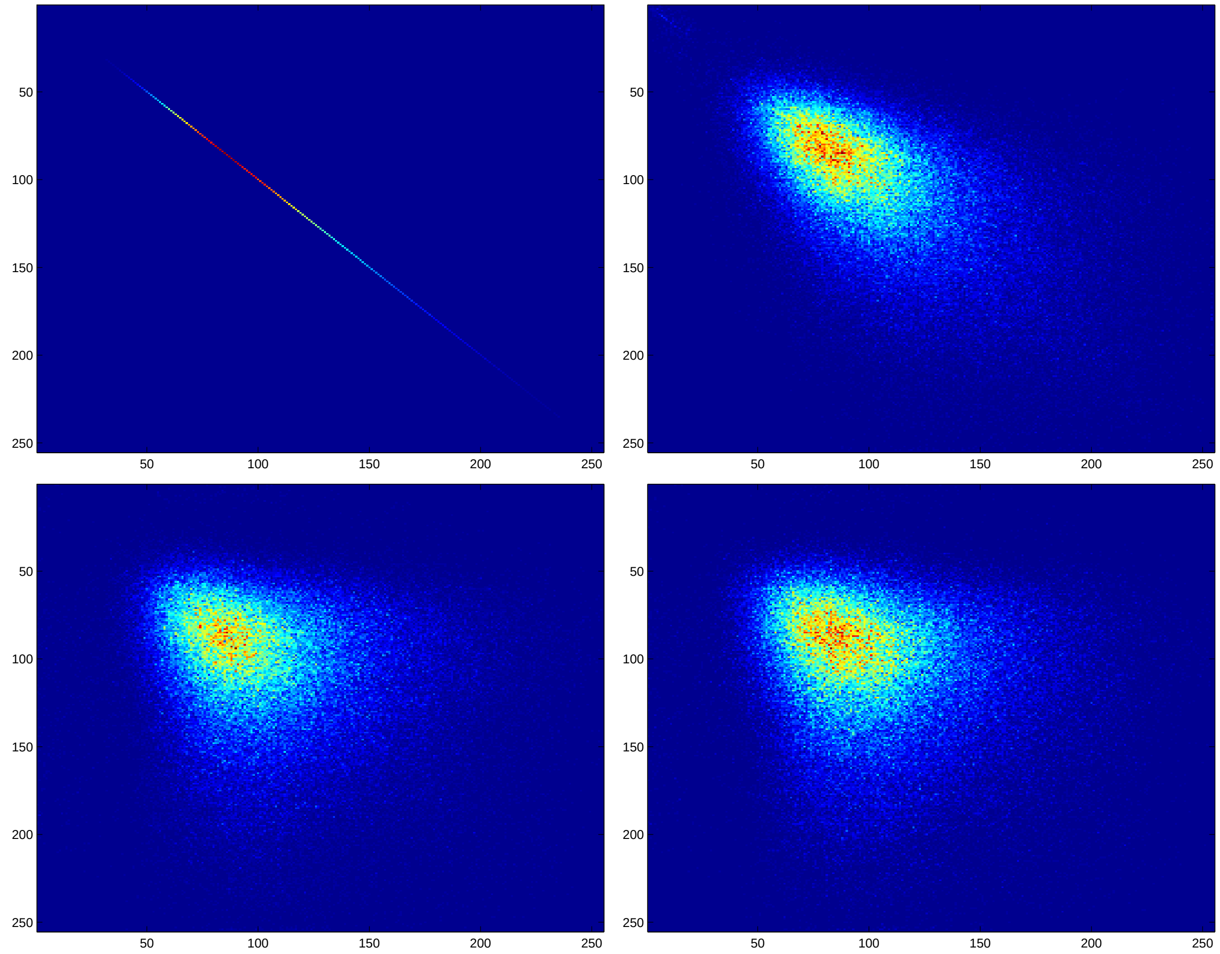


Figure 3: MI Scatterplots. 1st Col: target=reference slice. 2nd Col: target = reference+1 slice.

Range of UL breast Image Types

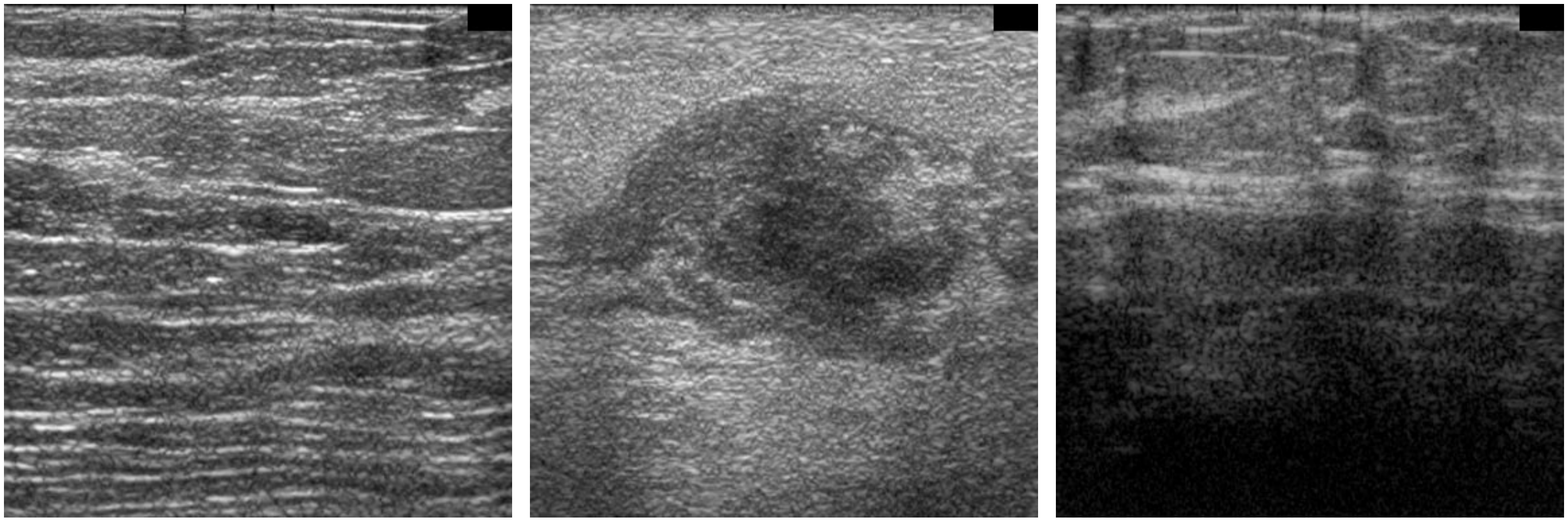


Figure 4: Three ultrasound breast scans. From top to bottom are: case 151, case 142 and case 162.

Limitations of Gray Level MI Registration Methods

Difficulties:

1. Gray levels are uninformative features for UL images
2. MI criterion is sub-optimal for classifying correct deformation T

Our approach:

1. Generalize gray levels to a more stable and pertinent feature set
2. Use inductive learning techniques for feature selection
3. Use new α-MI criterion in place of MI criterion

α-MI Registration of Coincident Features

- X: a $N \times N$ UL image (lexicographically ordered)
- $Z = Z(X)$: a general image feature vector in a P-dimensional feature space

Let $\{Z_0(k)\}_{k=1}^K$ and $\{Z_i(k)\}_{k=1}^K$ be features extracted from X_0 and X_i at K identical spatial locations

α-MI coincident-feature criterion

$$\mathrm{T} = \mathrm{argmax}_{\mathrm{T}_i} \hat{\mathrm{MI}}_\alpha$$

where $\hat{\mathrm{MI}}_\alpha$ is an estimate of

$$\mathrm{MI}_\alpha(f_{0,i}) = \frac{1}{\alpha - 1} \log \int \int f_{0,i}^\alpha(z_0, z_1) f_0^{1-\alpha}(z_0) f_i^{1-\alpha}(z_1) dz_1 dz_0. \qquad (2)$$

Why α-MI?

Special cases:

- α-MI vs. Shannon MI

$$\lim_{\alpha\to 1} \mathrm{MI}_\alpha(f_{0,i}) = \int\int f_{0,i} \ln f_{0,i}/(f_0 f_i) dz_1 dz_0.$$

- α-MI vs. Hellinger Mutual Affinity

$$\mathrm{MI}_{\frac{1}{2}}(f_{0,i}) \quad = \quad -\ln\left(\int\int \sqrt{f_{0,i} f_0 f_i}\, dz_0 dz_1\right)^2$$

- α-MI vs. Batthacharyya-Hellinger information

$$\int\int \left(\sqrt{f_{0,i}} - \sqrt{f_0 f_i}\right)^2 dz_0 dz_1 = 2\left(1 - \exp\{-\mathrm{MI}_{\frac{1}{2}}(f_{0,i})\}\right)$$

α-MI and Decision Theoretic Error Exponents

$$
\begin{aligned}
H_0 &: \quad Z_0(k), Z_i(k) \text{ independent} \\
H_1 &: \quad Z_0(k), Z_i(k) \text{ o.w.}
\end{aligned}
$$

Bayes probability of error

$$
P_e(n) \quad = \quad \beta(n)P(H_1) + \alpha(n)P(H_0)
$$

Chernoff bound

$$
\liminf_{n\to\infty} \frac{1}{n} \log P_e(n) = - \sup_{\alpha\in[0,1]} \left\{(1-\alpha)\mathrm{MI}_\alpha(f_{0,i})\right\}.
$$

Gray Level α-MI Trajectories

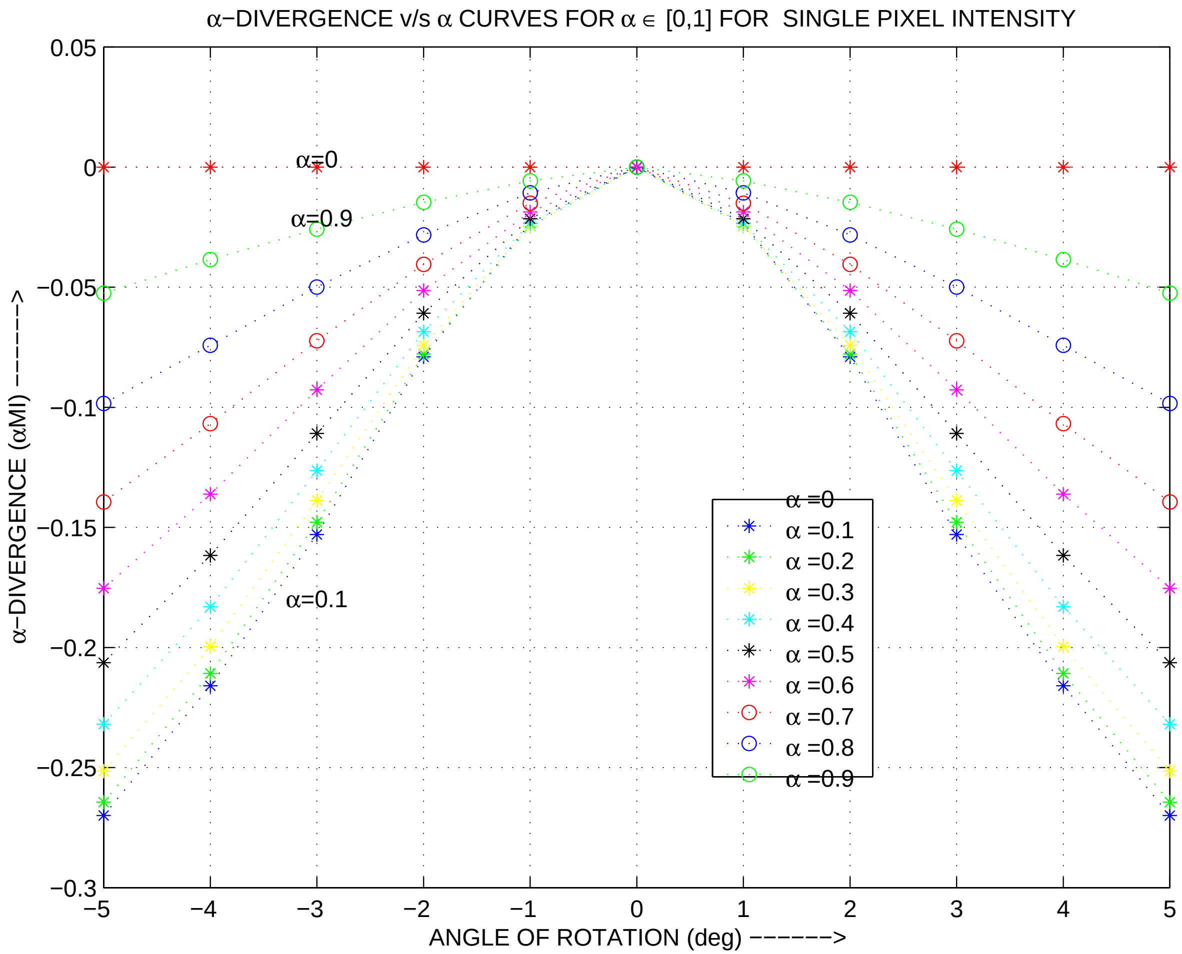


Figure 5: α-MI for ultra sound image registration

Peak Curvature of Gray Level α-MI

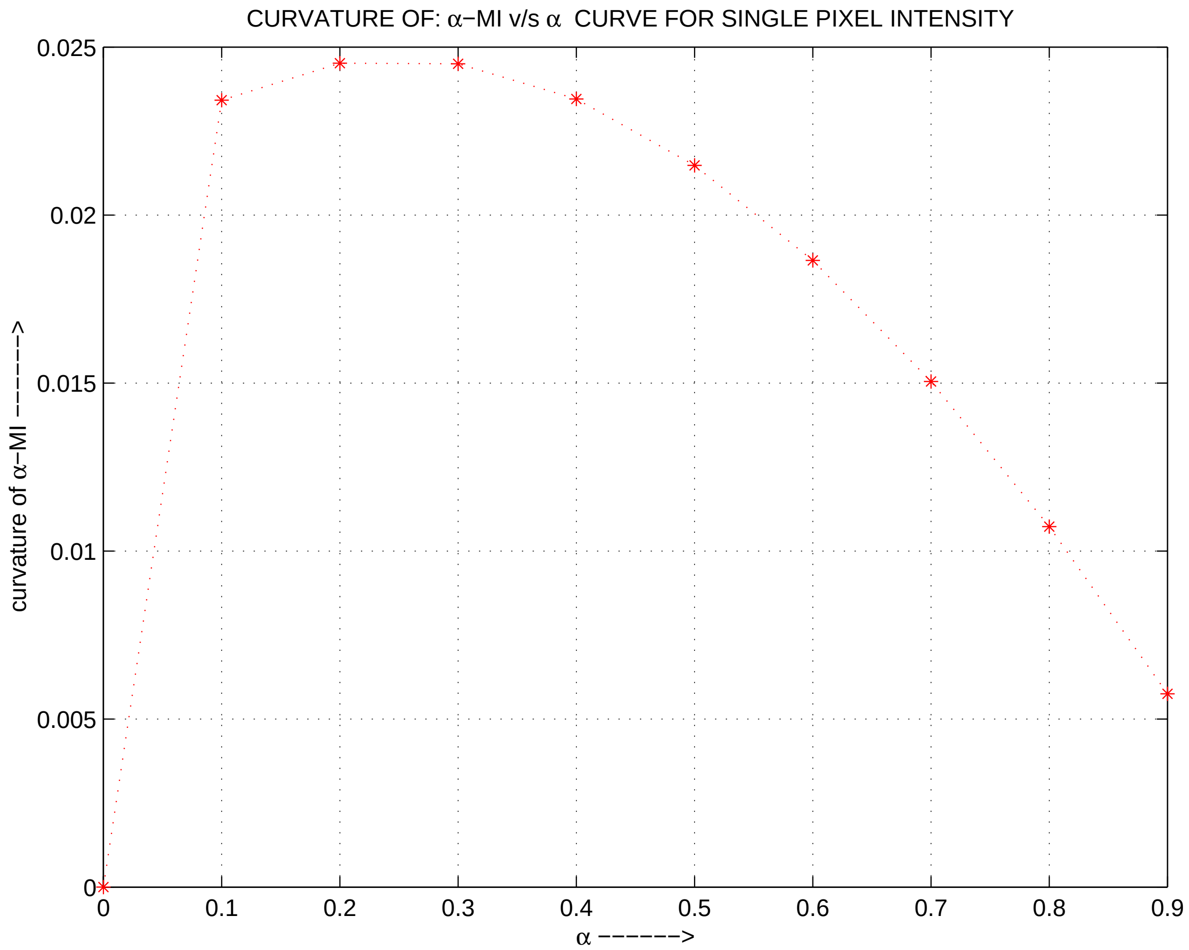
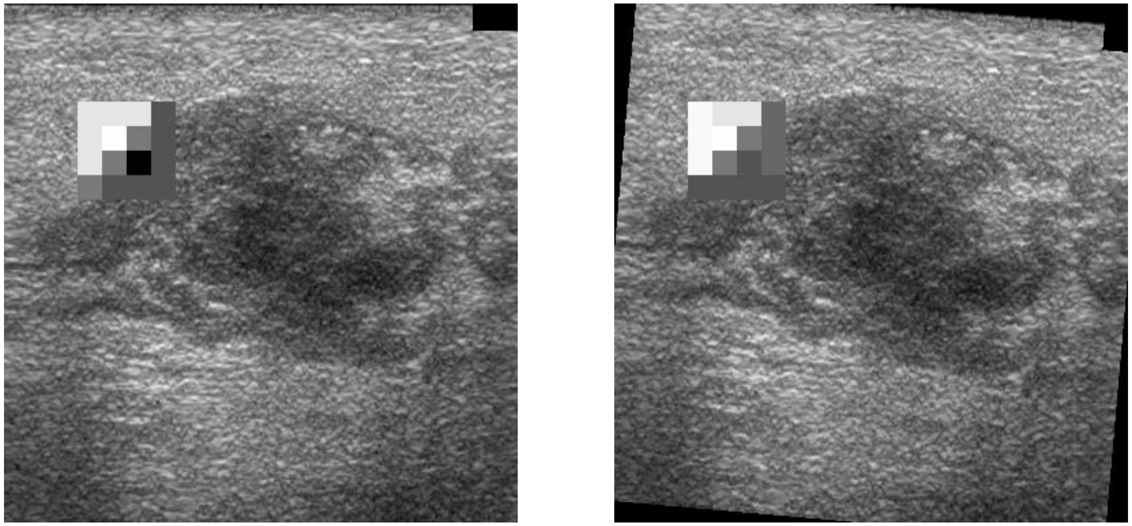


Figure 6: Curvature α-MI as function of alpha

Higher Order Features

1. Local tags
2. Spatial relations between local tags
3. Forests of randomized feature trees
4. Independent components analysis (ICA)

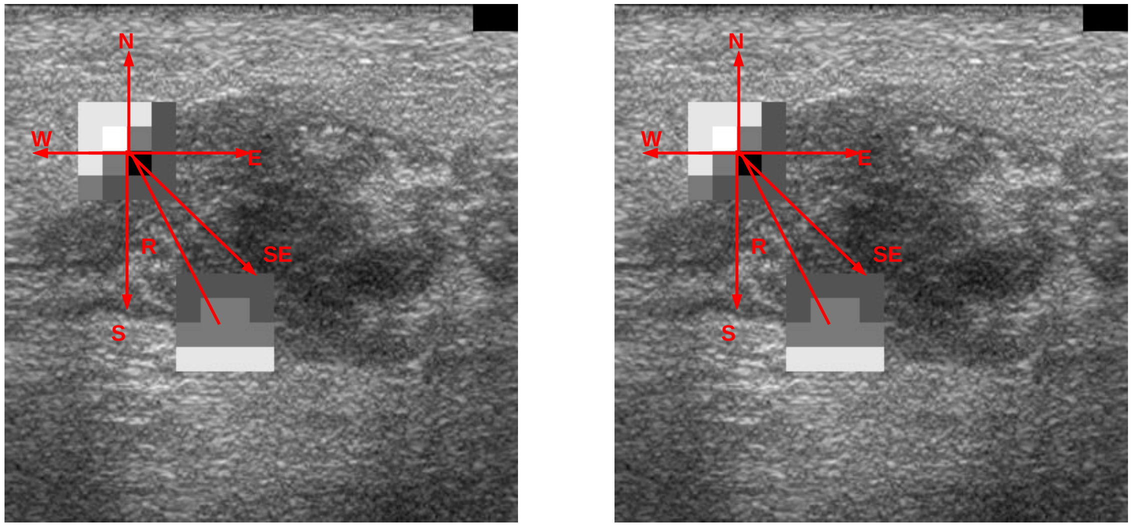
Local Tags



(a) Image X_0 (b) Image X_i

Figure 7: Local Tag Coincidences

Spatial Relations Between Local Tags



(a) Image X_0 (b) Image X_i

Figure 8: Spatial Relation Coincidences

Feature Coincidence Tree of Local Tags

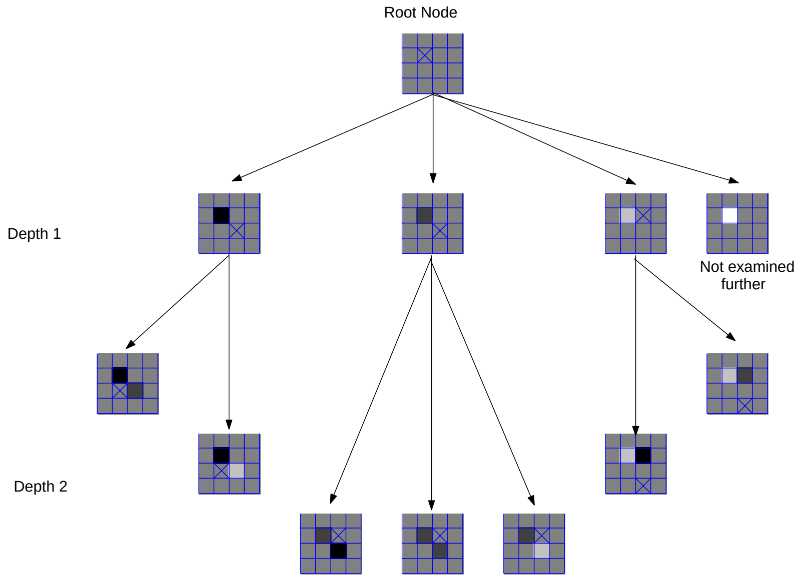


Figure 9: *Part of feature tree data structure.*

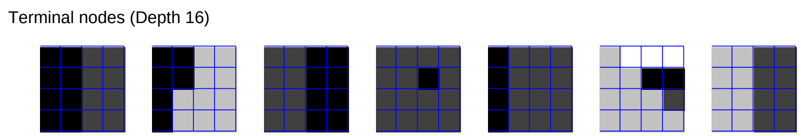


Figure 10: *Leaves of feature tree data structure.*

Forests of Randomized Feature Trees

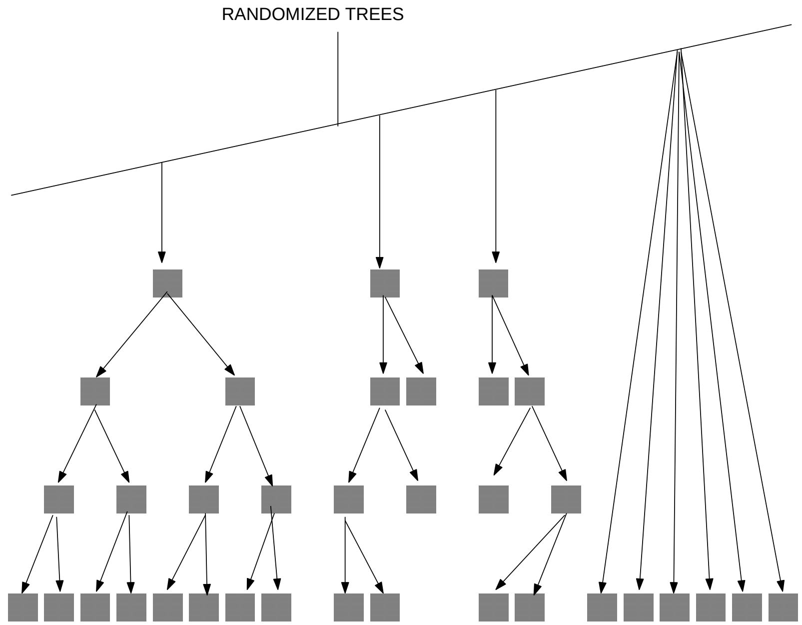


Figure 11: *Forest of randomized trees*

Registration criterion:

$$\mathrm{T} = \mathrm{argmax}_{\mathrm{T}_i} \sum_{t=1}^{\#\,trees} \hat{\mathrm{MI}}_{\alpha}(t)$$

ICA Features

Decomposition of $M \times M$ tag images $Y(k)$ acquired at $k = 1, \ldots, K$ spatial locations

$$Y(k) = \sum_{p=1}^{P} a_{kp} S_p$$

- $\{S_k\}_{k=1}^{P}$: statistically independent components
- a_{kp}: projection coefficients of tag $Y(k)$ onto component S_p
- $\{S_k\}_{k=1}^{P}$ and P: selected via MLE and MDL
- Feature vector for coincidence processing:

$$Z(k) = [a_{1k}, \ldots, a_{Pk}]^T$$

ICA Basis for Breast 141

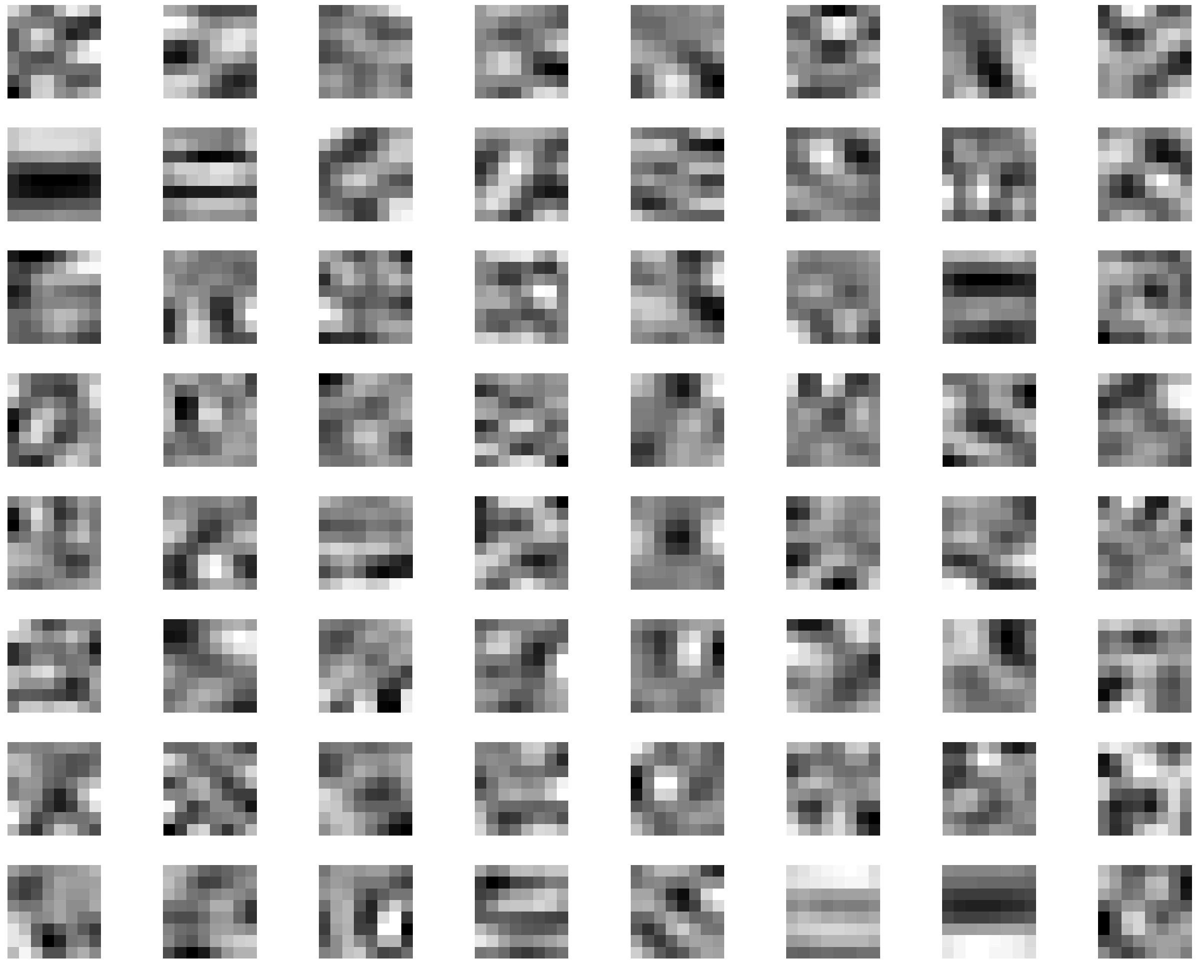


Figure 12: *Estimated ICA basis set for ultrasound breast image database*

Simple Example

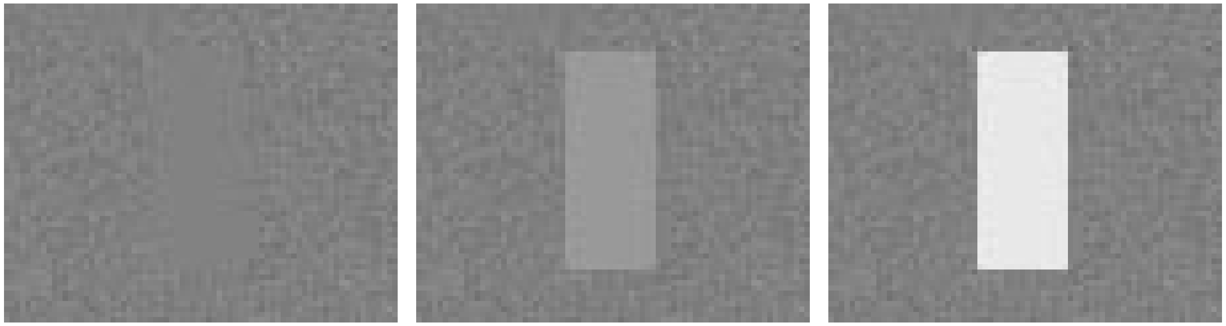


Figure 13: Bar images with contrast 1.02, 1.07 and 1.78. Background is low variance white Gaussian while bar is uniform intensity.

Single Pixel vs Feature Tag

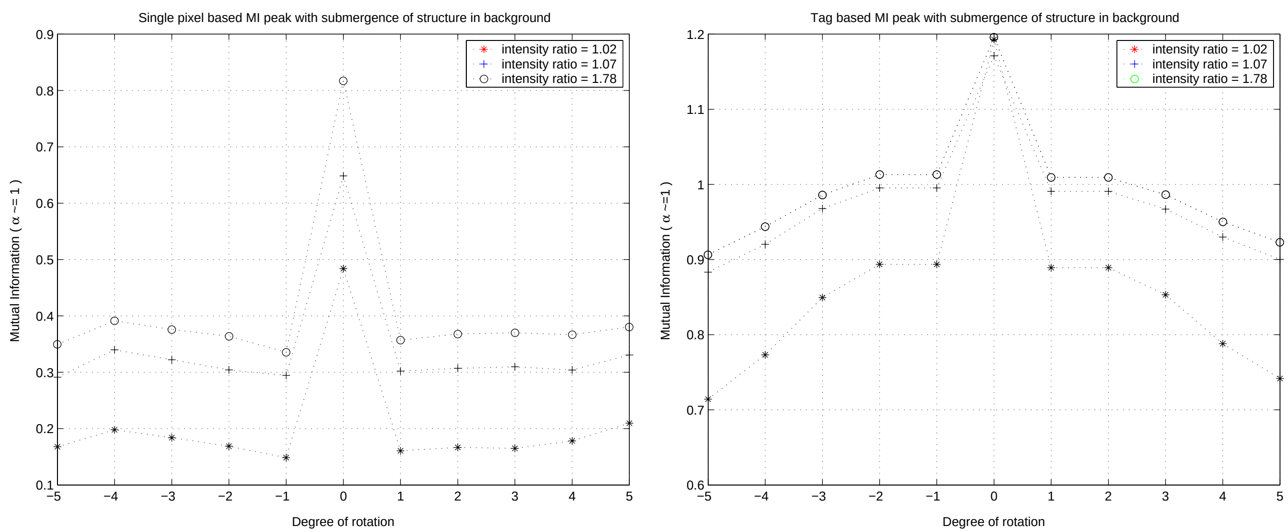


Figure 14: Upper curves are single pixel based MI trajectories while lower curves are 4×4 tag based MI trajectories for bar images.

UL Registration Comparisons

	151	142	162	151/8	151/16	151/32
pixel	0.3/0.9	0.6/0.3	0.6/0.3			
tag	0.5/3.6	0.5/3.8	0.4/1.4			
spatial-tag	0.99/14.6	0.99/8.4	0.6/8.3			
ICA				0.7/4.1	0.7/3.9	0.99/7.7

Table 1: Numerator =optimal values of α and Denominator = maximum resolution of mutual α-information for registering various images (Cases 151, 142, 162) using various features (pixel, tag, spatial-tag, ICA). 151/8, 151/16, 151/32 correspond to ICA algorithm with 8, 16 and 32 basis elements run on case 151.

Conclusions

1. Inclusion of better higher order features
2. Implementation of better registration criterion
3. Open issues:
   (a) How best to estimate α-MI?
   (b) How to determine best α empirically?
   (c) What are best 3D features for coarse registration vs. fine registration?