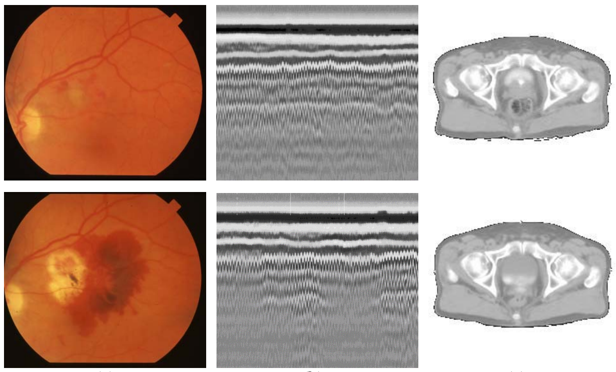
An Information-Theoretic Approach to Multimodal Subsurface Image Change Detection

Srinivas Andra (RPI), Dr. Richard J. Radke (RPI), Dr. Badri Roysam (RPI)

Objectives

The goal of this project is to develop robust and accurate change detection algorithms for multimodal subsurface images in the medical, underground, and underwater domains. Related CenSSIS applications are illustrated in Figure 1.



(a) (b) (c)

Figure 1: Examples of subsurface change detection problems. (a) Pathologies in the retina, (b) Deterioration of rebar underneath pavement, (c) Variable filling of the bladder and rectum in a CT image.

Technical Approach

Maes et al. and Wells et al. proposed an information-theoretic approach to multimodality image registration. We assume that two images I_1 and I_2 are related by a coordinate transformation T (e.g. rigid motion.) Then the transformation $\hat{T}$ that registers the images I_1 and I_2 is assumed to maximize the mutual information; that is:

$$\hat{T} = \arg\max_{T} \; h(p_1) + h(p_2) - h(p_{12})$$

where
- p_1 = sample distribution of I_1 pixel intensities
- p_2 = sample distribution of $T(I_2)$ pixel intensities
- p_{12} = sample joint distribution of $(I_1, T(I_2))$ pixel intensities
- $h(\cdot)$ = entropy of a distribution.

This approach has proven successful in the medical community for registering images, even when they are of different modalities. In particular, to compute the mutual information for a pair of gray-scale images, we need to compute the sample joint intensity distribution over the pixels z for which I_1 and $T(I_2)$ overlap:

$$p_{12}(i, j) = P(I_1(z) = i, T(I_2)(z) = j) \quad i, j = 0, \ldots, 255$$

Change detection is a well-studied problem that is often solved by processing the difference between two registered images. However, the problem is much more difficult when images to be compared have:

- Non-local variations in illumination
- Dissimilar orientations
- Different imaging modalities

In these cases, detecting changes by direct comparison of corresponding pixels is likely to yield an inaccurate result.

Our hypothesis is that changes can be detected in these difficult situations within the same information-theoretic framework that has been used for registration, by inspecting the joint intensity distribution. Typically, there is a large peak that corresponds to correctly-registered pixels, and several smaller peaks that may correspond to changes. Our ultimate goal is to develop an algorithm that (a) determines which changes are important for a given application and which are not, and (b) describes these changes in the context of the sample joint intensity distribution. We illustrate this idea with two examples.

Examples

A. CT slices of the male pelvis

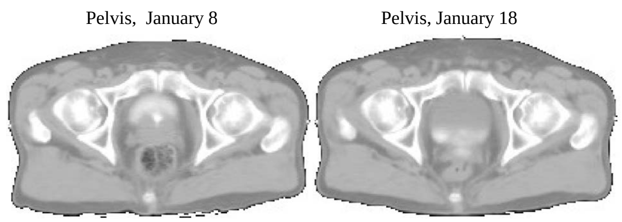
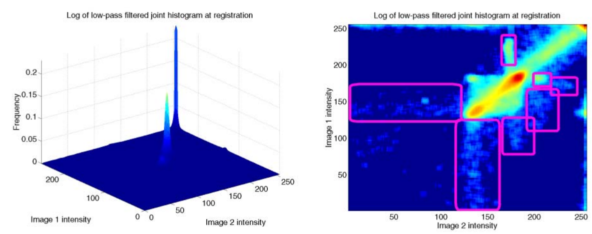


Figure 2: CT images of the male pelvis taken 10 days apart. The bladder and the rectum are filled differently on each day.



(a) (b)

Figure 3: (a) Three-dimensional and (b) pseudo-color visualizations of the joint histogram. The pink rectangles in (b) have been selected to surround smaller peaks that may correspond to changes in the image pair.

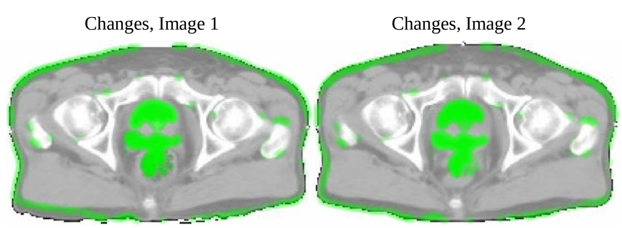


Figure 4: The image pixels that contribute to the selected regions in the joint histogram correspond to detected changes in the bladder and rectum. Change pixels around the exterior of the body correspond to slight image misregistration.

B. Fundus images of the retina

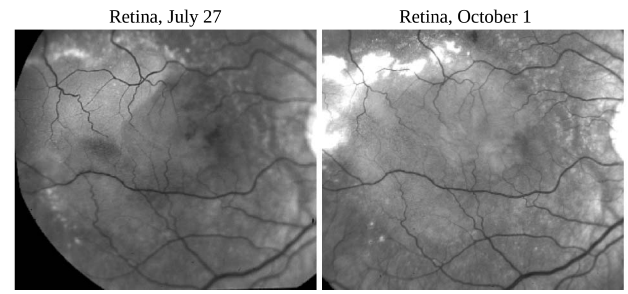
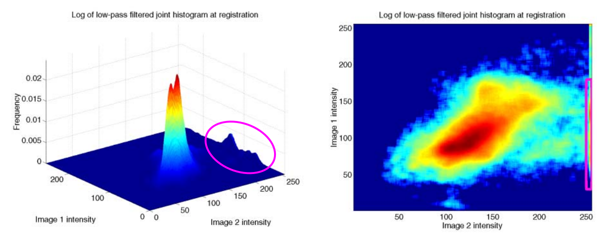


Figure 5: Fundus images of the retina taken 2 months apart. There is a clear pathology in the upper left-hand corner.



(a) (b)

Figure 6: (a) Three-dimensional and (b) pseudo-color visualizations of the joint histogram. The pink regions in (a) and (b) have been selected to surround smaller peaks that may correspond to changes in the image pair.

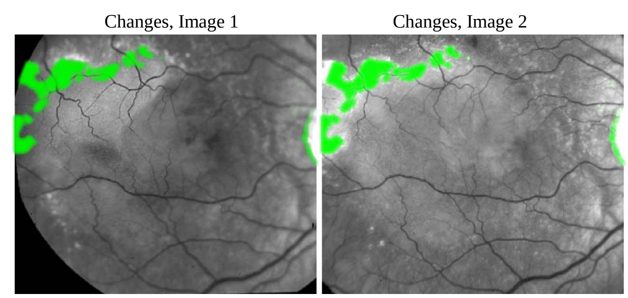


Figure 7: The image pixels that contribute to the selected regions in the joint histogram correspond to the pathology in the upper left-hand corner.

Status and Plans

These simple proof-of concept examples show that an information-theoretic approach may have promise in change detection. We plan to:

- Develop clustering algorithms in histogram space to detect and isolate candidate peaks/regions
- Develop morphological algorithms in image space to clean up detected change pixels.
- Integrate our change-detection algorithm in-line with a mutual-information based registration algorithm. In this way we will simultaneously determine which pixels should be used to estimate registration parameters, and which should be classified as changes.
- Test our algorithms on a wide variety of subsurface images and modalities
- Extend our results to incorporate non-rigid motion between images (see Xiaoli Tang's poster, R2-C(III).)

References

[1] F. Maes, A. Collignon, D. Vandermeulen, G. Marchal, P. Suetens. "Multimodality image registration by maximization of mutual information." IEEE transactions on Medical Imaging, vol. 16, no. 2, pp. 187-198, April 1997.

[2] W. M. Wells III, P. Viola, H. Atsumi, S. Nakajima and R. Kikinis. "Multi-modal volume registration by maximization of mutual information." Med. Image Anal., vol. 1, no. 1, pp. 35-51, Mar. 1996.

[3] E. Durucan and T. Ebrahimi. "Change Detection and Background Extraction by Linear Algebra." Proc. of the IEEE, vol. 89, no. 10, October 2001.

PI Contact Information

Richard J. Radke, Assistant Professor
Dept. of Electrical, Computer, and Systems Engineering
Rensselaer Polytechnic Institute
110 8th Street, Troy, NY, 12180
rjradke@ecse.rpi.edu