REGISTRATION OF ULTRASOUND IMAGES USING AN INFORMATION-THEORETIC FEATURE DETECTOR

Zhe Wang

New Jersey Institute of Technology
Department of Electrical and Computer Engineering
Newark, NJ 07102

Greg Slabaugh, Gozde Unal, Tong Fang

Siemens Corporate Research
Intelligent Vision and Reasoning Department
Princeton, NJ 08540

ABSTRACT

In this paper, we present a new method for ultrasound image registration. For each image to be registered, our method first applies an ultrasound-specific information-theoretic feature detector, which is based on statistical modeling of speckle and provides a feature image that robustly delineates important edges in the image. These feature images are then registered using differential equations, the solution of which provides a locally optimal transformation that brings the images into alignment. We describe our method and present experimental results demonstrating its effectiveness, particularly for low contrast, speckled images. Furthermore, we compare our method to standard gradient-based techniques, which we show are more susceptible to misregistration.

Index Terms— Image registration, information theory, biomedical image processing

1. INTRODUCTION

Image registration is fundamental problem in medical imaging and has numerous clinical applications, including disease detection, analysis, and treatment. The images may be taken at different times, from different viewpoints, from different sensors, etc., and the goal is to recover the geometric transformation that brings the images into alignment.

There has been much literature devoted to the general problem of image registration and several good surveys [1, 2] and books [3, 4, 5] exist on the subject. A recent trend in the literature is the use of information theory to statistically model or compare images/image regions as well as differential equations [6, 7] to solve for the registration parameters. We adopt such an approach in this paper. In addition, we note that recently there has been a renewed interest in gradient-based registration techniques [8], which are simple to implement and have numerous advantages over mutual-information based methods.

While generic image registration methods can be used to align ultrasound images, better results are attainable when one incorporates domain-specific knowledge into the registration algorithm. Ultrasound images are corrupted by speckle, which is an interference process resulting from random backscattering in a resolution cell of the ultrasound beam. Speckle appears as a spatially correlated noise pattern, and its intensity distribution is well-known to be non-Gaussian. Indeed, fully formed speckle is known to have a Rayleigh distribution in the envelope detected image and Fisher-Tippett (doubly exponential) distribution in the log-compressed image [9].

For a fixed position of scatterers relative to the ultrasound beam, speckle is deterministic. Therefore, for small displacements, the speckle is correlated in one image to the next, and this fact has been used in speckle tracking methods [10]. However, if the displacement is larger, or images are taken of the same region from different scans, from different transducers, etc., the correlation of the speckle will no longer exist. In such cases, registration algorithms that are based on comparing images on a pixel-to-pixel basis will have difficulty, since two corresponding pixels from the same anatomic structure can have very different intensity levels due to intensity variations of the speckle. Instead of comparing *samples* of Fisher-Tippett distributions from one image to another, it would be preferable to compare estimates coming from the *distributions* instead. This is the method we take in our approach.

While papers on ultrasound registration appear in the literature [11], many of these papers use generic registration algorithms. However, ultrasound-specific registration algorithms that have appeared in the literature include [12, 13], which are based on probability distributions that come from theoretical speckle models. The similarity metrics used in these papers rely on pixel-to-pixel intensity comparisons, which, for reasons given above, may not be desirable in many applications, given then randomness of speckle noise. Unlike such previous work, our method is distribution-based, improving robustness to the noise.

In our previous work [14], we introduced analytic expressions for the J-divergence of Rayleigh and Fisher-Tippett distributed variables for comparing regions in an ultrasound image in the context of feature (edge) detection. It was shown that this feature detector is more robust to speckle than other, more common edge detection methods like the derivative of

Gaussian filter or the Canny edge detector. In this paper, we use these feature detected images for registration. For each image to be registered, we first apply our information-theoretic feature detector to the image, producing a feature map that is robust to noise but still captures the significant edges in the image. We then register these feature maps using a sum of squared differences (SSD) similarity metric, which is used to guide differential equations that update the registration.

2. METHOD

Our method has two major steps: first, using a feature detection method, we compute an edge map for each image to be registered. Next, we register the edge maps using differential equations.

2.1. Feature detection

Our feature detector is fully described in [14]; however, for completeness we briefly review it here.

The feature detector we employ is based on a statistical comparison of regions in an ultrasound image. As mentioned above, fully formed speckle in the log-compressed image (also called the *display* image) can be modeled using a Fisher-Tippett (FT) distribution. The FT distribution has the form

$$p(I(x,y)) = 2e^{\left(2I(x,y)-\ln 2\sigma^2 - e^{2I(x,y)-\ln 2\sigma^2}\right)}, \qquad (1)$$

where σ^2 denotes the Fisher-Tippett parameter of the reflectivity samples. Note that this distribution is fully described by this one parameter.

Given a region Ω inside an ultrasound image, we can statistically estimate the FT distribution using the maximum likelihood estimator, $\sigma^2 = \frac{1}{2}\frac{\int_\Omega e^{2I(x,y)}dxdy}{\int_\Omega dxdy}$, where $\int_\Omega dxdy$ is the area inside the region.

Our feature detector is based on information-theoretic comparison of two regions in an ultrasound image. That is, given two FT distributions coming from different regions in the image, one parameterized by σ_1 and other parameterized by σ_2, we compute the J-divergence, or symmetrized Kullback-Liebler distance, as a measure of how “different” the distributions are. The J-divergence of two Fisher-Tippett distributed variables was derived in [14] as

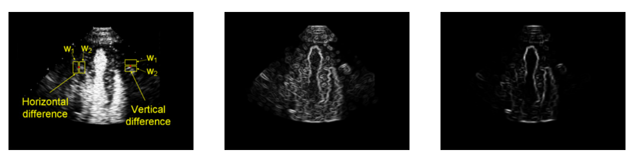
$$\begin{aligned} J \;=\;& \frac{1}{2}e^{-\frac{1}{2\sigma_1^2}}\left(-\ln 2\sigma_1^2 + \ln 2\sigma_2^2 - 1\right. \\ & \left. -\frac{1}{2\sigma_1^2} + \frac{\sigma_1^2}{\sigma_2^2} + \frac{1}{2\sigma_2^2}\right) \\ & +\frac{1}{2}e^{-\frac{1}{2\sigma_2^2}}\left(-\ln 2\sigma_2^2 + \ln 2\sigma_1^2 - 1\right. \\ & \left. -\frac{1}{2\sigma_2^2} + \frac{\sigma_2^2}{\sigma_1^2} + \frac{1}{2\sigma_1^2}\right) \qquad (2) \end{aligned}$$

Our feature detector forms sliding windows, which are placed on either side of a pixel, as shown for two windows w_1 and w_2 in Figure 1 (a). Given the set of pixels in w_1, we determine a FT parameter σ_1^2 (using the estimator give above), and likewise, we estimate σ_2^2 in w_2. Then, we compute J-divergence between these two distributions using Equation (2) as a measure of how different the regions are. When the windows are placed to the left and to the right of the pixel, this gives a horizontal distance map $J_x(x,y)$ that is functionally similar to the gradient operator in the x direction, except that the values are non-negative. This can be repeated in the y direction. Then, we define a feature map $F(x,y)$ as

$$F(x,y) = \sqrt{J_x(x,y)^2 + J_y(x,y)^2}. \qquad (3)$$

Figure 1 (c) shows an example of a cardiac ultrasound image and its feature map $F(x,y)$. Note that this feature detector is much less distracted by the speckle compared to the gradient estimator shown in (b), yet still detects the important edges in the image. The robustness of the feature detector comes from two sources: first, it compares distributions to distributions, rather than pixels to pixels, and second, it is based on integrals of the image and not derivatives. Taking derivatives of noisy data is often undesirable in image processing, as doing so emphasizes the noise.

We apply this feature detector to each image to be registered. This transforms the image into a feature image that contains the important edges needed for registration while simultaneously mitigating false responses due to the speckle. These feature-detected images are then passed to the registration algorithm, described next.



(a) (b) (c)

Fig. 1. Feature detection in a cardiac ultrasound image. Image (a), gradient (b), and J-divergence feature map (c) computed on the display image using the Fisher-Tippett method. Please see the digital version of the images for maximal quality.

2.2. Registration

Let $T(x,y)$ be the transformation between the two feature detected images, F_1 and and F_2. Our objective is to estimate the parameters of the transformation so that the feature images become aligned. To accomplish this, we minimize an energy functional based on the sum of square differences between the two feature maps,

$$E(T(x,y)) = \int [F_1(x,y) - F_2(T(x,y))]^2 \, dxdy, \qquad (4)$$

where the transformation is applied to the second image. We note that $T(x,y)$ can include rigid, affine, projective, or non-rigid transformations; in this paper we consider rigid transforms. Starting with an initial guess, we can iteratively update the transformation using differential equations based on a Gauss-Newton optimization [15] to minimize the energy functional in Equation 4. Upon convergence, the transformation will be a local optimum of the energy.

3. EXPERIMENTAL RESULTS

We begin with some experiments with synthetically generated data, designed to study the registration performance as the image contrast is diminished. The images and their feature detection results are shown in Figure 2. For comparison, we also produce results using a standard edge map formed using a difference of Gaussian filter, which provides a smoothed implementation of the gradient. Notice that the Fisher-Tippett feature detector robustly identifies the important features without many false detections due to speckle. In these experiments, the ground truth registration parameters are $(5,5)$ for the translation and 5° for the rotation. The registration error is denoted as the squared error of the estimated parameter compared to the ground truth value, and plotted in Figure 3. Notice that the registration error of the gradient-based edge maps (blue solid curves) quickly increases as the contrast is diminished, while the registration of the proposed method (red dashed curves) is significantly lower.

We examined the effectiveness of the proposed scheme for large regions extracted from abdominal ultrasound images (which is more challenging that registering the full images), depicted in Figures 4 and 5. While ground truth is not available, we do compute difference images and the sum of squared differences (SSD) between the original and registered images. Notice that the difference images for the Fisher-Tippett technique, image (j) in Figures 4 and 5, is significantly lower than those of the gradient method, shown in (k) of the two figures. Quantitatively, the SSD decreased by 51.4% and 56.3% for the proposed method; while with gradient-based method, the SSD was decreased only by 0% and 21.2%.

4. CONCLUSIONS

In this paper, we presented an ultrasound image registration method based on matching edge maps generated by a statistical feature detector based on theoretical distributions of fully formed speckle in an ultrasound image. We presented the details of our method, and demonstrated its ability to accurately register ultrasound images, even for low contrast, speckled data, and showed how this method is more robust to noise than standard gradient-based methods.

For future work, we are interested in fully validating the method by testing it with more data. However, the preliminary results presented in the paper indicate the proposed method has much promise in robust registration of ultrasound data.

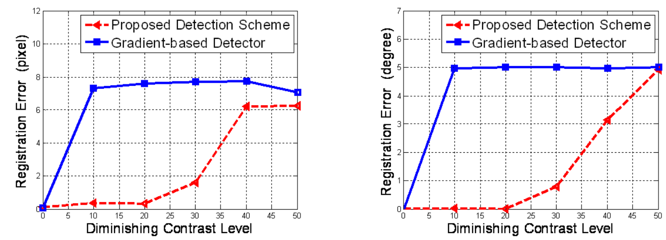


Fig. 3. Registration error as a function of diminishing contrast. We show both the translational error (left) and rotational error (right) for the feature images generated by the gradient (blue) and Fisher-Tippett (red) detectors.

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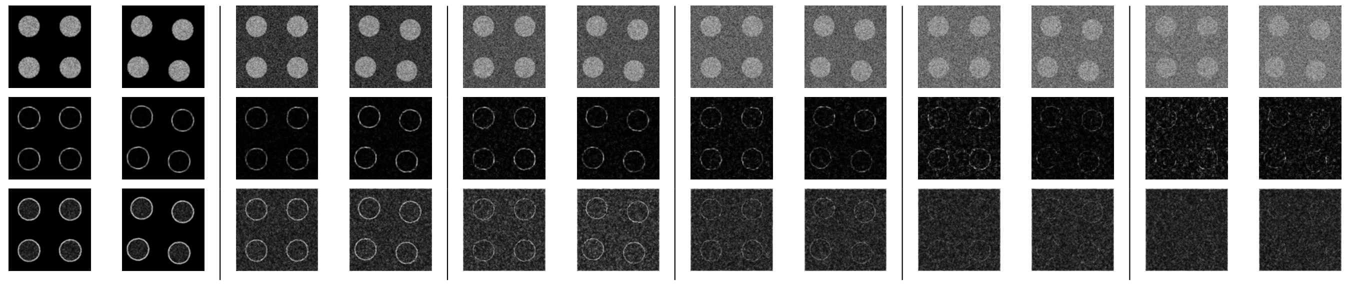

Fig. 2. Feature detection in synthetic ultrasound images. The top row shows the original synthetic ultrasound images with diminishing contrast. There are two images at each contrast level. The middle row shows the feature detection with Fisher-Tippett method, while the bottom row shows the feature detection with the difference of Gaussian filter. Notice the cleaner edge detection result of the Fisher-Tippett method, which has fewer false detections due to the speckle.

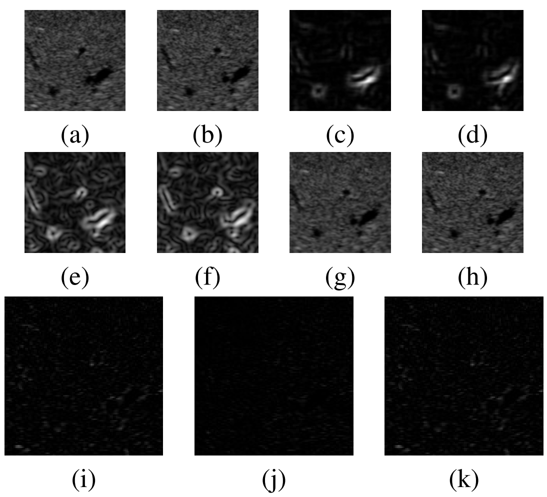

Fig. 4. Registration results of ultrasound images. Original (a)(b), feature detection with Fisher-Tippett (c)(d), gradient-based feature detection (e)(f), registered image with Fisher-Tippett and gradient detector (g)(h), original residue image (i), residue image with Fisher-Tippett detector (j), residue image with gradient detector (k).

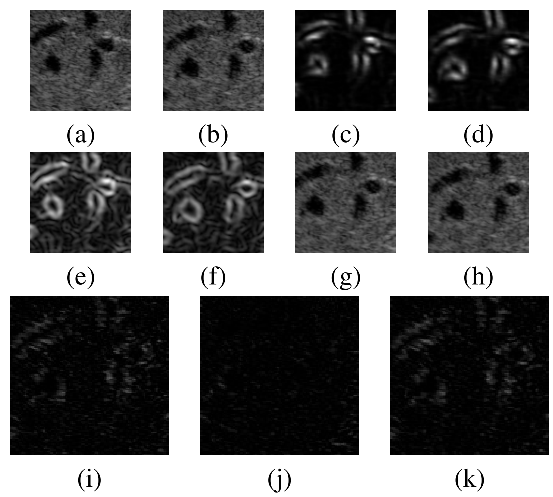

Fig. 5. Registration results of ultrasound images. Original (a)(b), feature detection with Fisher-Tippett (c)(d), gradient-based feature detection (e)(f), registered image with Fisher-Tippett and gradient detector (g)(h), original residue image (i), residue image with Fisher-Tippett detector (j), residue image with gradient detector (k).

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