Wavelet-Based Medical Image Registration for Retrieval Applications

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Abstract

In this paper, a novel, fully automatic, multiscale wavelet-based image registration technique is proposed for image retrieval applications. We present a fast 2-D rigid registration scheme for retrieval applications. Here, the use of multiscale wavelet representation with mutual information (MI) is expected to facilitate matching of important anatomical structures at multiple resolutions. We propose to use a dyadic grid in the parameter search space for efficient computation in the multiscale domain. The proposed approach has several novel aspects including the use of MI in multiscale wavelet domain and variable bin sizes for each level of decomposition. The technique is also tested under varying noise levels. The results show high efficacy of the proposed approach.

1 Introduction

One of the most exciting and fastest growing research area in the field of medical domain is image retrieval with particular interest in content-based image retrieval (CBIR). The notion of image retrieval is to find similar images from a large image database with the help of some key attributes associated with the images or features inherently contained in the images. There are few medical CBIR systems reported in the literature, such as ASSERT [16], CBIR2 [19], IRMA [7], I-BROWSE [18] and Pathfinder [20].

In the medical domain, the goal of image retrieval is to provide diagnostic support by displaying relevant past cases, along with proven pathologies as ground truth [17]. Moreover, medical image retrieval may also be useful as a training tool for medical students and residents, follow-up studies, and for research purposes. Registration is another important technique in the area of medical image analysis. Generally, it is needed for combining information from multiple imaging modalities, monitoring changes, image guided surgery or compare individuals anatomies to standard atlas.

Majority of literatures discuss medical image retrieval and registration separately with various techniques and methodologies for a variety of image modalities. Recently, it has been realized that both retrieval and registration techniques in medical domain share some common image processing steps and require to be integrated in a larger system to complement each other [15]. In this paper, 2-D rigid registration (translation and rotation) is preferred for fast and robust image retrieval applications due to the following reasons:

- Medical images are multimodal and heterogeneous with temporal properties. Hence multimodal image registration is an integral part of any medical image retrieval application.
- Another important property of medical images is the higher dimensionality, such as 3-D or 4-D [15]. However, the 3-D or 4-D biomedical images are often organized and visualized as collections of 2-D slices. Hence 2-D registration is a basic common denominator for image retrieval applications in medical domain.
- The size of the medical images at higher dimensions (3-D and 4-D) is also a bottleneck on the speed and computational requirements for registration. Image retrieval applications involve large number of images to be processed. This factor also supports 2-D registration as opposed to higher dimensions.
- Image retrieval applications demand in favor of fast, robust and fully automatic registration techniques. Given the current state-of-the-art technology, rigid registration techniques appear to be more suitable as deformable registration generally require some form of manual intervention [15].
• Deformable registration could easily fail in the presence of tumor or artifacts [6].

Image registration, particularly in multi-modal setting, is a difficult problem. Mutual information (MI) based techniques have been quite successful in the area of medical image registration [11, 14]. On the other hand, multiresolution and wavelet based approaches tend to be more robust [13, 8, 12, 21]. Recently, wavelet based image retrieval has been advocated for medical applications [15]. In [13], multiresolution representation of the image was used for registration. Currently, there are several multiresolution based registration techniques in the literature. In [8], Gabor Filters were employed for multiresolution decomposition. In [12], remote sensing data was registered using HL and LH coefficient of the wavelet representation. In [21], low-pass Haar wavelet coefficients along with MI and SAD (sum of absolute difference) were used for registration. Kullback-Leibler distance in multiresolution setting was employed in [4] where pre-aligned training images were used.

In the multi-modal scenario image structure is more important than absolute gray levels. It has been shown that sometime global count of MI can be misleading due to the absence of spatial information. Computation of a similarity index based on MI with spatial information is shown to be promising [11, 1]. Magnetic Resonance (MR) field inhomogeneity is a well know problem in MR images. Literature on medical image registration do not generally discuss about this problem because normally, the same scanner acquires images being registered. However, this assumption doesn’t hold good in a general image retrieval scenario. Due to these issues we propose to use Multiscale wavelets with MI for robust and automatic image registration.

The proposed work differs significantly in several ways from the previous ones. First, identification of 2-D rigid registration (as opposed to 3-D deformable registration required in clinical applications) as a good candidate for image retrieval applications in medical domain. Second, MI in multiscale wavelet domain is employed to achieve fully automatic image registration. Third, this scheme doesn’t inherit the problem of local maxima caused (in MI profile) by subsampling of the data at higher scales (as discussed in [14, 13]). Fourth, we have suggested using variable bin sizes (at multiple scales) to speed-up the computation. We have achieved good results without using partial volume (PV) interpolation and training data.

This report has been organized as follows. In section II a brief overview of the multiscale wavelet decomposition is provided. In section III, mutual information (MI) in wavelet decomposition is discussed. In section IV, registration algorithm for maximization of MI at dyadic scales is provided. Section V provides the details about the fuzzy step control. Section VI discusses the results with 2-D images under rigid transformation. This report concludes with the future directions in section VII.

2 Multiscale Edge Representation and Decomposition

Multiscale edge representation of the signal [9, 10] provides characterization of signal singularity, namely, Lipschitz exponents. This representation is efficiently computed at dyadic scales using separable low-pass and high-pass filters. In order to compute the decompositions at coarse scale, filters are upscaled instead of subsampling the image itself. Hence, this scheme doesn’t inherit the problem of local maxima caused by subsampling of the data at higher scales (as discussed in [14, 13]). In [10] it has been shown that a close approximation of original signal can be reconstructed from its wavelet transform modulus maxima. In [5] this representation is used for image registration using edge correlation as matching criterion.

In this section introduces the multiscale edge detection and representaion through dyadic wavelet transform. The same notations (as in the original work [10]) is used here for obvious reasons. In two dimensions, a multiscale edge detection can be formalized through a wavelet transform defined with respect to two wavelets $\varphi_1^1(x, y) = \frac{1}{\sqrt{2^j}} \varphi^1 \left( \frac{x}{2^j}, \frac{y}{2^j} \right)$ and $\varphi_2^1(x, y) = \frac{1}{\sqrt{2^j}} \varphi^2 \left( \frac{x}{2^j}, \frac{y}{2^j} \right)$. The wavelet transform of an image $f(x, y) \in L^2(R^2)$ at the scale has two components defined by, $W_2^1 f(x, y) = f \ast \varphi_1^1(x, y)$ and $W_2^1 f(x, y) = f \ast \varphi_2^1(x, y)$. The 2-D dyadic wavelet transform of $f(x, y)$ as the set of functions $W f = \{W_2^1 f(x, y), W_2^2 f(x, y)\}_{j \in Z}$.

The magnitude of this wavelet decomposition is given as,

$$M_2 f(x, y) = \sqrt{|W_2^1 f(x, y)|^2 + |W_2^2 f(x, y)|^2} \quad (1)$$

It has been shown that if $\varphi_1^1(x, y)$ and $\varphi_2^1(x, y)$ are quadratic spline functions (derivative of a cubic spline function) then the wavelet transform can be implemented efficiently using very simple separable filters [10]. The figure 1 shows a sample image and figure 2, shows its multiscale wavelet decompositions ($W_2^1 f(x, y)$, $W_2^2 f(x, y)$ and $M_2 f(x, y)$ column wise) at scales It can be observed from figure 2 that fine details are available at lower scales while coarse details are observed at higher levels. It can also be seen that this decomposition is invariant under various transformations of the object (viz. translation, rotation and scaling etc).
is related to Shannons entropy as,
\[ H(A, B) = H(A) + H(B) - H(A, B) \]  
where \( H(A) = -\sum_a P_A(a) \log P_A(a) \) and \( H(A, B) = -\sum_{a,b} P_{A,B}(a,b) \log P_{A,B}(a,b) \).

In practice, MI is computed from normalized joint histogram of the two images being registered [14]. The joint histogram is computed using 64 bins at each scale. It should be noted that using less number of bins also makes the computation of MI faster.

4 Multiscale Registration Technique

Now we describe the registration technique using MI in multiscale edge representation. Our approach is similar to [12], where, approximate search for maximum correlation is done at coarse scale and refinement is done at finer scales. However, this approach is different than the previous techniques in two respects. First, we have proposed dyadic search space (consisting of both rotation and translation) for each scale and second, we have proposed to compute MI using variable bin sizes for joint histogram to fully exploit the multiscale decomposition.

Let \( \Delta_D \) and \( \Delta_R \) be the resolution in translation and rotation for the finest scale. Then for the level \( j \) we set resolution for translation \( S^j_D = 2^{-j-1} \Delta_D \) and \( S^j_R = 2^{-j} \Delta_R \) for rotation. If \( N_B \) is the number of bins to be used at finest scale then we set number of bins at level \( j \) as \( S^j_B = N_B/2^j \).

The search range at next fine scale \( j \) is only \([X_{D,1}^{j+1} - S^j_D, X_{D,1}^{j+1} + S^j_D]\) for translation and \([X_{R,1}^{j+1} - S^j_R, X_{R,1}^{j+1} + S^j_R]\) for rotation. Where \( X_{D,1}^{j+1} \) and \( X_{R,1}^{j+1} \) is search results (translation and rotation) from previous scale. In the following we describe two search techniques for image registration.

4.1 Full Search at Coarse Scale (FSCS)

Here we propose to do full search at the coarse scale. MI is computed by translating and rotation by the amount in the search grid points. In the following we describe the algorithm.

1. Initialization: \( \Delta_D, \Delta_R \) and \( N_B \).
2. Compute \( M_{2,j} f(x,y) \) for both reference image \( f_R(x,y) \) and floating image \( f_F(x,y) \) at each scale \( j = 1 \ldots J \).
3. For each scale \( j = J \ldots 1 \),
   - Compute: \( S^j_D, S^j_R \) and \( S^j_B \).
   - If \( j = J \),

Figure 1. A sample image

Figure 2. \( W^j_{1,2}, f(x,y) \) and \( M_{2,j}, f(x,y) \) (column wise) of the image in Fig. 1, with \( j = 1 \) to 5 levels (top to bottom).
– Compute MI using $S^j_B$ bins, for points in the entire search space with step sizes $S^j_D$ and $S^j_R$.
– Find $X^j_D + 1$ and $X^j_r + 1$, corresponding to the maximum MI.

• Else,
– Compute MI using $S^j_B$ bins, in the search space $[X^j_D - S^j_D, X^j_D + S^j_D]$ and $[X^j_R - S^j_R, X^j_R + S^j_R]$ with step sizes $S^j_D$ and $S^j_R$.
– Find $X^j_D + 1$ and $X^j_r + 1$, corresponding to the maximum MI.
• End if,

4. End For,

5. Latest values of $X^j_D + 1$ and $X^j_r + 1$ are the final result.

It can be seen that full search at coarse scale is less efficient particularly when scale change and shear is also incorporated the search space. However, this technique has the advantage of being implemented in parallel because MI at a point can be computed independently from other search points.

4.2 Neighborhood Search at Coarse Scale (NSCS)

In order to do efficient search, we implement a neighborhood search scheme at coarse level. The overall algorithm is same as in FSCS except step-3, where at $j = J$ we compute MI's at a given point and around its $3 \times 3 \times 3$ (x-displacement, y-displacement and rotation) neighborhood. After each neighborhood computation, movement is done on the search point which has maximum MI. This step is repeated until MI at point is higher than its neighbors. Starting point of the search can be done anywhere however, we chose to start at [0,0,0], assuming that the floating image is very close to the reference image.

5 Results and Discussions

The test images were obtained from BrainWeb [2], simulated MRI database at MNI, Montreal, Canada. The complete scheme was implemented in MATLAB. The multi-scale decomposition was done at 5 levels ($J = 5$). Initial parameters were setup as $\Delta_D = 1$ pixel (both x, y directions), $\Delta_R = 0.5$ degrees and $N_B = 256$. Global search space is $[-32, 32]$ pixels both x and y directions. And rotation varies as $[-48, 48]$ degrees. Hence an exhaustive search would require $65 \times 65 \times 193 = 815425$ iterations. The FSCS search scheme took 433 $(325 + 4 \times 27)$ iterations, a
gain of \(\approx 1800\) times! NSCS took varying number of iterations depending upon the problem. Normally, it varies from 189 to 216 iterations, with an upper bound of FSCS. The multi-modal registration under noisy conditions are shown figures 3.

In practice, the ranges and setup parameters can be obtained from the knowledge of the problem domain. It is should be noted here that the accuracy in the present scheme does not match with the requirements of registration in a clinical setting. The intended application of this scheme is image retrieval for which the results are very encouraging.

6 Conclusions

In this paper, we have presented 2D, rigid, registration scheme for image retrieval applications. We have presented a robust and efficient multimodal image registration technique for image retrieval applications using MI in multi-scale wavelet decomposition. We attempted to fully exploit the multiscale decomposition by suggesting appropriate step and bin sizes. We have not used any refinement techniques (such as PV interpolation) to see the limits of the proposed approach. Nevertheless, we provided parallel and neighborhood search methods for efficient implementation. The results demonstrate the high efficacy of the approach under noisy environment.

References


