

Non-Rigid Multimodal Image Registration Based on Local Variability Measures and Optical Flow

I. Reducindo, E. Arce-Santana, D.U. Campos-Delgado and F. Vigueras-Gomez

Abstract—In this paper, we present a novel methodology for multimodal non-rigid medical image registration. The proposed approach is based on combining an optical flow technique with a pixel intensity transformation by using a local variability measure, such as statistical variance or Shannon entropy. The methodology is basically composed by three steps: first, we approximate the global deformation using a rigid registration based on a global optimization technique, called particle filtering; second, we transform both target and source images into a new intensity space where they can be compared; and third, we obtain the optical flow between them by using the Horn and Shuck algorithm in an iterative scales-space framework. After these steps, the non-rigid registration is made up by adding the resulting vector fields, computed by the rigid registration, and the optical flow. The proposed algorithm was tested using a synthetic intensity mapping and non-rigid deformation of MRI images. Preliminary results show that the methodology seems to be a good alternative for non-rigid multimodal registration, obtaining an average error of less than two pixels in the estimation of the deformation vector field.

Index Terms—Non-rigid image registration, multimodal images, optimization.

I. INTRODUCTION

Image Registration is a very important task in image processing, which can be classified into two types: rigid and non-rigid (elastic). In the literature, there are a lot of previous proposals to solve the rigid problem [1], which basically minimizes a cost function that depends on a small set of parameters of a rigid transformation (affine or perspective [2]). The goal of these methods is to obtain a set of parameters describing the geometric transformation between target and source images by optimizing a similarity metric (e.g. Mutual Information) [3], using for this purpose algorithms like gradient descent [4], or more recent approaches based on global optimization techniques such as particle filtering (PF) [5] or genetic algorithms [6]. On the other hand, the non-rigid or elastic registration is a more complex and involved problem, especially for multimodal images, however it has a greater number of applications in medical imaging [7]. In the literature, the most common method to solve the elastic registration problem is by means of splines, where a family of functions are used to approximate complex deformations by seeking their best parameters by optimizing a similarity metric [8]. The problem of these methods is their complexity, besides the high computational cost. A most

recent proposal to solve the non-rigid registration problem is based on an iterative optical flow (OF) framework in order to find the deformation vector field, after conducting an initial rigid registration using the PF [9]; this method has shown promising results in [10] and [11]. Nonetheless, the problem of this algorithm is its restriction to unimodal images or the necessity of an injective intensity transference function between the target and source images, which is not the case in multimodal registration. Thus in this work, we proposed a new methodology where the problem of multimodal registration could be solved by mapping images into an space where their intensities can be compared, and next to apply an iterative OF as in [9] using scale space [12]. The paper focuses on the application to tomography or MRI brain images.

The paper is organized as follows: in the first section, we introduce and explain the basic ideas for the proposed methodology. Second, we review the rigid registration based on PF, and the non-rigid registration based on OF, in subsection II-A and II-B, respectively; details of the proposed algorithm are described in subsection II-C. In section III, we show and discuss the preliminary (quantitative and qualitative) results. Finally, in section IV, some conclusions are drawn about this work, as well as, future research line.

II. PROBLEM STATEMENT

The non-rigid registration can be seen as finding the vector field V such that it can align a source image I_S with a target one I_T . This idea can be mathematically written as follows:

$$I_T(r) = F(I_S(r+V(r))), \quad (1)$$

where $F(\cdot)$ represents an intensity mapping, and r are the pixels coordinates in an image or volume. According to this equation, if the registration is unimodal the mapping F is the identity and the problem can be seen as to find the OF registering both images. However, to simplify the OF computation, it is convenient to restrict the search to small displacements between the correspondent pixels. For this reason, before estimating the OF, we obtain first a rigid approximation to align initially the images based on the PF [5].

A. Rigid registration based on the PF

The basic idea of the parametric registration based on PF is to estimate the parameter vector of a geometrical transformation (affine or perspective) by an stochastic search over an optimization surface (cost function) using a set of N test points called particles $(\theta_1, \dots, \theta_N)$, and their associated

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weights W_j $j = 1, \dots, N$ given by a *likelihood* function $P(z|\theta_j)$ for a measurement z between the images:

$$W_j = \frac{1}{\sigma_\eta \sqrt{2\pi}} \exp \left\{ -\frac{(2 - \text{NMI}\{I_T(r), I_S(T(r|\theta_j))\})^2}{2\sigma_\eta^2} \right\}. \quad (2)$$

where σ_η^2 is the variance of the measurement noise, $T(\cdot)$ is a parametric transformation depending on the parameters vector θ , and $\text{NMI}(I_1, I_2)$ denotes the normalized mutual information function [13] between images I_1 and I_2 used as similarity metric between the images; this metric offers a better performance for this method as it is reported in [14]. Particle weights W_j are used to approximate a posteriori probability distribution function (PDF) of unknown parameters $P(\theta_j|z)$, and then used to estimate the parameters vector of the transformation [15]. Next, a brief description of the algorithm is presented: given a set of particles and their associated weights at iteration $k-1$, $\{\theta_j^{k-1}, W_j^{k-1}\}_{j=1}^N$, the iterative algorithm for parametric registration can be summarized in the following steps:

1. Resample the particles: eliminate the particles that have small weights and concentrate with particles with large contributions $\tilde{\theta}_j^{k-1}$.
2. Obtain a new particle set by using a random-walk search: $\theta_j^k = \tilde{\theta}_j^{k-1} + v^{k-1}$, where v^{k-1} is a Normal noise samples vector with mean zero and covariance matrix Σ_{k-1} .
3. For each new particle θ_j^k , compute its weight according to (2) and normalized it by the overall sum.
4. Reduce the covariance matrix Σ_k of the noise components v^k , with the aim of gradually reducing the variability in the random search.

\Rightarrow Steps 1 to 4 are iteratively performed until a convergence criterion is satisfied [10],[16].

5. Finally, the estimated parameters $\hat{\theta}^k$ at the k -th instant can be computed by some statistical measure of the reconstructed PDF, for example the mean:

$$\hat{\theta}^k = E[\theta^k|z^k] \approx \sum_{j=1}^N W_j^k \theta_j^k. \quad (3)$$

For more details of the implementations of this technique, the reader is referred to [5], [10], [14], [15],[16].

B. Non-rigid registration based on OF

Once achieved the initial rigid registration using the PF, the displacements of the pixels between the target and source images are expected to be small, and if the images are unimodal, then we can find these displacements by using an OF technique. In order to find the OF, we employed a well-known algorithm proposed by Horn and Schunck [17], in which it is necessary to minimize the following energy function (continuous domain):

$$\varepsilon^2 = \int \int (\varepsilon_b^2 + \alpha \varepsilon_c^2) dx dy, \quad (4)$$

where ε_b is the sum of the error in the intensity changes between the target and source images, ε_c is the smoothness measurement of the velocity flow, α is a regularization

term to control the flow speed, and x and y the cartesian coordinates. For more implementation details of the Horn-Schunck algorithm, see [17].

Now, according to [9], an iterative process may be carried out in order to estimate a parametric registration and optical flow, accumulating the vector field obtained at each iteration until a convergence condition is achieved. In the case of multimodal registration, the algorithm proposed in [9] approximates the intensity transference function between images using a joint histogram, but this approach is feasible only if the mapping of intensities between the images is injective; however, in the present work, we propose an extension to this previous algorithm in order to overcome this limitation that includes a scale space implementation to iterate only the OF, and an intensity transformation by using local variability measures.

C. Proposed algorithm for multimodal non-rigid registration

The key idea of the proposed algorithm is an intensity transformation into a space where the pixels could be compared in both images despite their multimodal characteristic. Our suggestion is to use metrics that do not depend on the gray level of the pixels, but on the intensity variability around neighbor elements, for example the Shannon entropy [18] or the statistical variance. Thus, the- proposed methodology for non-rigid multimodal registration is composed for the next steps:

1. **Rigid registration.** Find the parameters $\hat{\theta}$ of a perspective transformation T that aligns I_S with I_T using the parametric registration based on particle filtering, and obtain $I_R(r) = I_S(T(r|\hat{\theta}))$, and the error vector field for the rigid deformation $V_R(r) = r - T(r|\hat{\theta})$.
2. **Local variability mapping.** Compute for each pixel in both images (I_R and I_T) the local variability, $\tilde{I}_T(r) = LV(I_T(r))$ and $\tilde{I}_R(r) = LV(I_R(r))$, using equation (5) if it is decided to use the entropy or equation (6) for the variance.

$$LV_1(I(r)) = \sum_{i \in N_r} p(I(i)) \log_2(p(I(i))), \quad (5)$$

$$LV_2(I(r)) = \sum_{i \in N_r} p(I(i)) (\mu - I(i))^2, \quad (6)$$

where N_r represents a set of pixels of a window centered in the pixel r and size $n \times n$, $p(\cdot)$ is the probability of intensities $I(r)$ inside the window N_r , and μ is the expected value of the intensities, $\mu = \sum_{i \in N_r} p(I(i)) I(i)$.

3. **Equalization.** After the mapping, the intensities of the images (\tilde{I}_T , \tilde{I}_R) have small values and are concentrated in a very short dynamic range. For this reason, it is necessary to scale the intensities into a range from 0 to 255, and to apply a histogram equalization [2].
4. **Scale space** . In order to achieve more complex deformations, the OF is applied over a scale space [12], since it allows to find large displacements in coarse scales. Thus, given the equalized images \tilde{I}_T and \tilde{I}_R of size $2^K \times 2^K$ and a sub-scale m :
 - a) Set an initial value for the OF at the scale m , $V_0^m = 0$.

- b) Scale the images to size $2^{K-m} \times 2^{K-m}$.
- c) Estimate the optical flow between \tilde{I}_T^m and \tilde{I}_R^m , and set $t = 0$.
 - i) Obtain an auxiliary image $I_A = \tilde{I}_R^m(r + V_t^m(r))$.
 - ii) Increment $t = t + 1$.
 - iii) Compute the OF V_t^m between \tilde{I}_T^m and I_A using Horn-Schunck.
 - iv) Accumulate the displacements $V_t^m = V_t^m + V_{t-1}^m$.
 - v) If $\sum_r |V_t^m(r) - V_{t-1}^m(r)| < \epsilon$, go to d) else return to i).
- d) Set the next scale $m = m - 1$.
- e) If $m \geq 0$, propagate displacements to the next scale $V_0^m(r) = 2B(V^{m-1}(r))$ and go to (b), else $V_E(r) = V^0(r)$ and continue with step 5. Here $B(\cdot)$ is an interpolation function (e.g. bilinear form).

5. **Compute non-rigid registration.** Finally, we can obtain the vector field of the non-rigid deformation adding the vector fields obtained in steps 1 to 4, $V(r) = V_R(r) + V_E(r)$; we can also obtain the elastic registered image $I_E(r) = I_S(r + V(r))$.

The window size used to compute the local variability was 7×7 pixels for the entropy and 13×13 for the variance, these values were obtained after an evaluation of the method with respect to the window size, however the optimal window size can differ depending on the target and source images. Another important parameter is the convergence threshold ϵ in step 4.c.v, which depends on the image size, but it is easy to define it based on the desired resolution in the OF.

III. PRELIMINARY RESULTS AND DISCUSSION

To test the algorithm, we started with a real non-rigid MRI registration problem, as shown in Fig. 1, where the images size is 256×256 pixels. We can visually evaluate that the proposed method achieved a good non-rigid registration in general terms. We can see in Fig. 1.(e) the results obtained when we used the entropy in (5) as a variability measure; notice that the registration errors occur mainly at the edges of the skull. In the case of the variance in (6), Fig. 1.(g), we can observe that the errors are mainly in the gray matter. We infer that the errors in the skull edges are because the entropy estimation is affected by the black background which cover a large part of the window (N_r) when it is centered on those edges. On the other hand, this effect is not presented with the variance since it defines better the edges due to the contrast with the background. The opposite occurs with the gray matter, where there is not much contrast, but there exists more texture. These differences give us some guidelines to work in a multidimensional OF combining the information of the two variability measures, as future research line.

In order to obtain a numerical validation that give us more information about performance of the proposed algorithm, we first simulated a multimodal image using a polynomial of degree 5 as intensity mapping, and then generated an elastic deformation combining a cylindric and an affine deformation. The vector field of the non-rigid transform is computed and

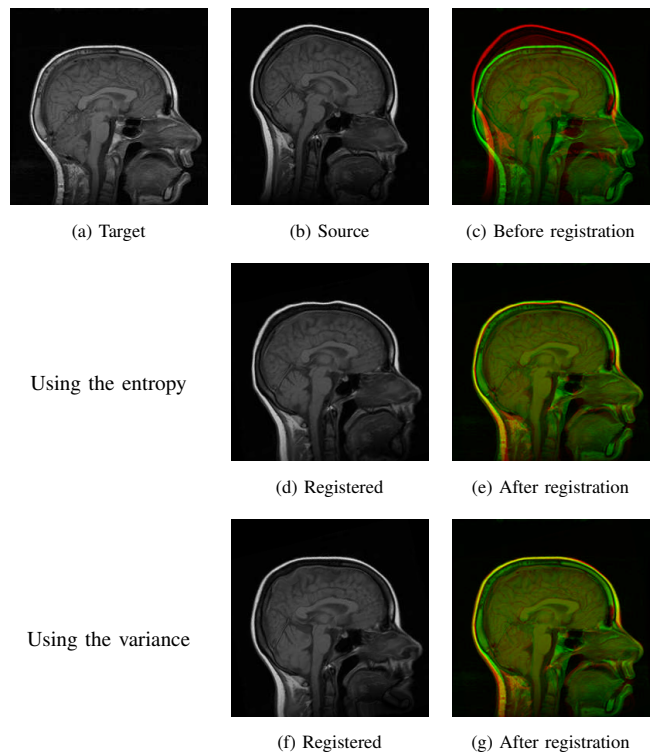


Fig. 1. Real non-rigid registration. (a) Target image, (b) Source image, (c) Overlapped images before of registration, (d) Source registered using the entropy, (e) Overlapped images after non-rigid registration using the entropy, (f) Source registered using the variance, (g) Overlapped images after non-rigid registration using the variance. In the third column the target image is shown in green and the registered image is shown in red.

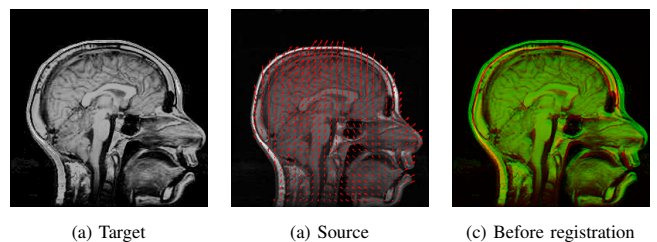


Fig. 2. Synthetic evaluation with MRI images. (a) Target image (artificially created from the source image), (b) Source image and non-rigid deformation vector field to created the target, (c) Overlapped images before registration, the source image in red and the target in green.

used as a Ground Truth in order to evaluate the proposed method; Fig. 2 shows the test images.

The non-rigid registration was carried out by using the proposed algorithm for the synthetic MRI images in Fig. 2; the results are shown in Fig. 3. These images show the registrations using the entropy (first row) and the variance (second row), images (a) and (b) correspond to the overlapped images, (b) and (e) are the errors in the estimation of the vector field, and the gray intensity errors in (c) and (f). According to this results, we can see that the use of the variance seems to offer better results that the entropy, but in general the errors are very similar for both variability metrics.

The values in Table I show the registration errors using three variants of the proposed algorithm: first, excluding

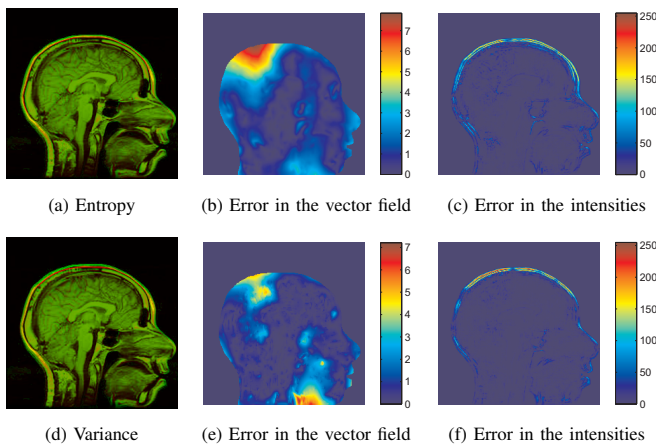


Fig. 3. Registration results with respect to the ground truth: (a) and (d) are the overlapped images after the registration, the target image is shown in green and the registered image is shown in red; (b) and (e) show the errors in the vector field; and (c) and (f) show the errors in the intensities.

steps 2 and 3 of the algorithm, and registering the target and source images in the unimodal case (without applying the intensity transformation); second, replacing step 4 by applying an optical flow without a scales-space framework; third, following all steps of the algorithm. For the second and third alternatives, the two variability measures were used. Notice that the challenge is to obtain similar errors to the unimodal implementation, but using the multimodal algorithm. Based on the data shown in Table I, the best results were obtained when we used the variance (as a measure) and a scales-space framework (its values are closer to those of the unimodal implementation). In this case, the mean error in the estimated vector field was very close to one pixel.

TABLE I. ERRORS IN THE ESTIMATED VECTOR FIELD AND IN THE INTENSITIES WITH RESPECT TO THE GROUND TRUTH AFTER THE NON-RIGID REGISTRATION.

Method	Vector field error		Intensities error	
	Mean	Std. Dev.	Mean	Std. Dev.
Unimodal	0.24	0.26	1.75	2.37
Without scales-space	Entropy 1.84	1.48	13.24	24.8
Using scales-space	Variance 1.69	1.97	9.38	13.7
Without scales-space	Entropy 1.46	1.56	11.50	22.36
Using scales-space	Variance 1.068	1.13	9.33	13.1

IV. CONCLUSIONS

After analysing the experiments and results of the proposed algorithm, we can appreciate that the method has a good qualitative performance for multimodal non-rigid registration, but in a quantitative evaluation the performance must be improved. However, according to these results, the algorithm, without modifications, may be considered as a good alternative for multimodal elastic registration.

For future work, modifications to the algorithm are necessary in order to increase its performance, and obtain errors similar to those obtained when the tone transfer function is known. One of these possible modifications is to apply a multidimensional optical flow by using simultaneously the two

variability measures in order to estimate the displacements. A more detailed evaluation is necessary for the algorithm, comparing it with other methods in the literature and using index errors for medical images registration. Finally, an implementation for volume registration will be also pursued.

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