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A robust image registration method based on total variation regularization under complex illumination changes

Khadijeh Aghajani [a,*], *Mohammad T. Manzuri* [a], *Rohollah Yousefpour* [b]

[a] *Department of Computer Engineering, Sharif University of Technology, Tehran, Iran*

[b] *Department of Mathematical and Computer Sciences, University of Mazandaran, Babolsar, Iran*

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ABSTRACT

Background and objective: Image registration is one of the fundamental and essential tasks for medical imaging and remote sensing applications. One of the most common challenges in this area is the presence of complex spatially varying intensity distortion in the images. The widely used similarity metrics, such as MI (Mutual Information), CC (Correlation Coefficient), SSD (Sum of Square Difference), SAD (Sum of Absolute Difference) and CR (Correlation Ratio), are not robust against this kind of distortion because stationarity assumption and the pixel-wise independence cannot be obeyed and captured by these metrics.
Methods: In this paper, we propose a new intensity-based method for simultaneous image registration and intensity correction. We assume that the registered moving image can be reconstructed by the reference image through a linear function that consists of multiplicative and additive coefficients. We also assume that the illumination changes in the images are spatially smooth in each region, so we use weighted Total Variation as a regularization term to estimate the aforesaid multiplicative and additive coefficients. Using weighted Total Variation leads to reduce the smoothness-effect on the coefficients across the edges and causes low level segmentation on the coefficients. For minimizing the reconstruction error, as a dissimilarity term, we use $l_1$norm which is more robust against illumination change and non-Gaussian noises than the l_2 norm. Primal-Dual method is used for solving the optimization problem.
Results: The proposed method is applied to simulated as well as real-world data consisting of clinically 4-D Computed Tomography, retina, Digital Subtraction Angiography (DSA), and iris image pairs. Then, the comparisons are made to MI, CC, SSD, SAD and RC qualitatively and sometimes quantitatively.
Conclusions: The experiment results are demonstrating that the proposed method produces more accurate registration results than conventional methods.

* *Corresponding author.* Department of Computer Engineering, Sharif University of Technology, Tehran, Iran. Fax: +981132535104.
E-mail address: agajani@ce.sharif.edu (K. Aghajani).

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1. Introduction

Image registration is the process of aligning two or more images of the same scene which may be taken at different times, from different viewpoints or by different sensors. Lots of novel approaches have been developed for this purpose. They can be classified into two categories: feature-based and area-based methods [1–4]. The feature-based approaches consist of 3 steps: (1) extracting features from each image, (2) finding the correspondences between the extracted features using a similarity metric, and (3) estimating the transform parameters according to the locations of the corresponding points. Some examples of the most common features that are used at the feature extraction phase are the salient points (extracted by Harris [4,5] or SIFT [6,7]), lines [1], contours [8], geometric shapes, Gabor filter [9] and alpha stable filter [10], etc.

In the area-based approaches, the transfer function's parameters are estimated directly based on the intensity of the overlapping points of the two images. They can be estimated by maximizing (minimizing) a similarity (dissimilarity) function defined on all overlapping points. The estimation can generally be done as follows:

$$T^* = \arg\max_{T} Sim(R, FOT) \tag{1}$$

Here F is the floating image; R is the reference image and T is the geometric transfer function which makes F and R to be aligned. *Sim* is regarded as a value that measures the similarity between the two images. It has to be noted that Eq. (1) is an ill-posed problem, so in order to turn it into a well-posed one we need to apply a regularization term on T in the energy function.

Depending on the relationship between the intensities of the corresponding points in the two images, different similarity metrics, such as SSD, SAD, MI and CC, have been offered. Two fundamental assumptions in obtaining these metrics are pixel-wise independence and stationarity [11,12]. It is clear that any analogous shuffling of the pixels of the two images does not constitute these metrics changes. In other words, there is no spatial information in the aforesaid metrics. The above similarity metrics are applicable in case there is no outlier or spatially varying intensity distortion in images. On the contrary, such similarity metrics tend to fail when registering the images which are corrupted by non-stationary intensity distortion. To deal with this challenge, a number of methods have recently been proposed to increase the registration accuracy. These methods can be classified in five categories.

The first group consists of methods in which conventional similarity metrics such as MI or CC are used locally [13–15]. The main idea behind such methods is that a spatially slow varying intensity distortion can be considered constant within a small pixel neighborhood. Compared to their global implementation, local similarity metrics enjoy a better performance; however they are more sensitive to outliers and they also need more time and space for computation.

In the second category, complicated probabilistic models are adopted to construct higher order pixel interdependencies. In [16], Markov Gibbs Random Field is used to model the visual appearance of the images. Second image is registered by maximizing its probability under the learned appearance model. In [17], a Markov Random Field-based method which uses saliency and gradient information is proposed to register DCE (Dynamic Contrast Enhanced)/MR (Magnetic Resonance) images of the heart. The performances of aforesaid methods depend on the initialization of the learned parameters.

The third group consists of methods based on the structural image representation. These methods are proposed for multimodal image registration problems, but they can be used in intensity-distorted monomodal cases, too. In these methods, a value (values) is (are) assigned to each pixel dependent on the local structure and not on the intensities used to encode them. Then, for registration, a simpler similarity metric such as SSD is used to measure the similarity of the two structural images. The Entropy images, the Laplacian images [18], MIND [19] and LPCR [20] are some of the examples that belong to this group.

The fourth group comprised the methods, the first step of which is to estimate the intensity distortion and illumination change compensation, and the second step is to register the images after enhancement [21,22]. The repetition of these two steps is done in an iterative fashion until the convergence occurred. The drawback of these methods seems to be the sequential perspective it adopts toward obtaining two mutually dependent components in one optimization problem.

The fifth group consists of the approaches that perform registration and intensity correction simultaneously. The difference between this group and the fourth one is that it acts simultaneously rather than sequentially. In [11], a similarity metric called Residual Complexity has been introduced and is used to register the images in the presence of slowly spatially varying intensity distortion. At first, they analytically solve the intensity correction field and eliminate it from the objective function. The final obtained objective function depends on the level of the coding complexity of the residual image in the Discrete Cosine Transform (DCT) domain. In [23] and [24], some modifications on RC method were made in order to improve the registration performance. In [25] and [26], the distortion field is supposed to be in the form of additive and in the form of multiplicative coefficients, respectively. To estimate the coefficients, in both methods, Total Variation is used as a regularization term on the assumed distortion field.

In [27], a model based on illumination correction has been proposed, which can handle the arbitrary shaped regions of local intensity variations. For each region, an additive (offset) and a multiplicative coefficients (gain) are considered to compensate the illumination changes. The drawback of their approach is that it is required to know the number of the regions.

In [28] a locally linear reconstruction base similarity metric has been proposed. The main idea behind LLR is the assumption that in each local region the registered moving image can be reconstructed by a linear synthetic model consisting of multiplicative and additive correction fields. It is also supposed that the coefficients are similar to each other in a small local region (3*3 local patches).

In this paper, we propose an efficient numerical method for simultaneous intensity correction and registration. We assume that the registered moving image can be reconstructed by the reference image through a linear function consists of multi-