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Robust Huber similarity measure for image registration in the presence of spatially-varying intensity distortion

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ABSTRACT

Similarity measure is an important part of image registration. The main challenge of similarity measure is lack of robustness to different distortions. A well-known distortion is spatially-varying intensity distortion. Its main characteristic is correlation among pixels. Most traditional intensity based similarity measures (e.g., SSD, MI) assume stationary image and pixel to pixel independence. Hence, these similarity measures are not robust against spatially-varying intensity distortion. Here, we suppose that non-stationary intensity distortion has a sparse representation in transform domain, i.e. its distribution has high peak at origin and a long tail. We use two viewpoints of Maximum Likelihood (ML) and Robust M-estimator. First, using the ML view, we propose robust Huber similarity measure (RHSM) in spatial transform domain as a new similarity measure in a mono-modal setting. In fact, RHSM is a combination of ℓ_2 and ℓ_1 norms. To demonstrate robustness of the proposed similarity measure, image registration is treated as a nonlinear regression problem. In this view, covariance matrix of estimated parameters is obtained based on the one-step M-estimator. Then with minimizing Fisher information function, robust similarity measure of RHSM is introduced. This measure produces accurate registration results on both artificial as well as real-world problems that we have examined.

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1. Introduction

Image registration is the process of spatially aligning one image to another under different scenarios, such as time, subject, and imaging modality. This process has different applications in many areas, e.g., remote sensing [1], computer assisted surgery [2], medical image analysis and processing [3] and computer vision [4].

Because of the importance of image registration, many methods have been proposed for this purpose. These methods are categorized into feature-based and

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edges, geometric shape and contour, image skeleton, or feature points such as landmark [5–8], Gabor filter [9], alpha stable filter [10] or intensity histogram [11] can be used as features. The accuracy of this class of methods is dependent upon the accuracy of feature extraction. In the famous class of intensity based method, the similarities between the intensities of two images are directly utilized. In fact, in this class, the intensities are

intensity-based methods. Feature-based approaches are based on alignment between the features or land-

marks in the two images for registration. Gradient,

the simplest features which can be used. These methods are consisted of three main parts: a similarity measure, a geometric transform (rigid or non-rigid), and an optimization technique. Since the goal of image registration is spatial alignment of images and the simplest feature has little information about geometry of the image, hence, similarity measure has the crucial role in the accuracy of this method, especially in the presence of noise, outlier, bias field distortion, and spatially-varying intensity distortion.

Quantification of matching between two images is expressed using similarity measure. The images are considered to be correctly aligned when the similarity measure is maximal (minimal). In the common similarity measures, for example, sum of squared differences (SSD), correlation coefficient (CC), correlation ratio (CR) [12], and mutual information (MI) [13,14], the assumption of pixel to pixel independence and their stationary is used without consideration of the intensities spatial dependencies. In [15], maximum a posteriori (MAP) perspective shows these similarity measures by considering pixel to pixel independence. Hence, registration by these similarity measures may fail in the presence of an intensity distortion with pixel to pixel dependence such as spatially-varying intensity distortion. For example, brain magnetic resonance images (MRI) may often be corrupted by slow varying intensity bias fields [16]; or visual band images can have illumination nonhomogeneity and reflectance artifacts [17] and illumination variations in geometric images [18].

Similarity measure has a major role and a challenging task when images are corrupted by spatially-varying intensity distortion or non-stationary intensity distortion. The traditional similarity measures do not consider the spatial dependency of the intensities. The random shuffling of pixels in the two images will not change the value of these similarities. Three categories of registration methods are proposed for robustness against this model distortion: simultaneous intensity correction and registration, modelling higher order pixel interdependencies, and employment of the local similarity estimation.

In the first category, the non-stationary intensity distortion is corrected before doing any image registration. Computational complexity and time consuming are the problems of these approaches. The works of researchers [19–21] fall into this category. However, the well-known similarity measure of Residual Complexity (RC) [22,23] which has minimal complexity belongs to this category. In this approach, image registration and non-stationary intensity distortion correction are simultaneously done. RC produces accurate registration results.

In the second category, the non-stationary intensity distortion is modelled using complicated probabilistic models [24–26]. Markov random fields (MRF) and MAP-MRF are two used models in this category.

In the last category, the basis of the approach is the simple idea of constant spatially-varying intensity distortion within a small neighbourhood around each pixel. So, local similarity measures can be useful for defining robust similarity measure such as MI, CR and CC that are invariant to adding a constant to intensities. For instance, [16] introduced Regional Mutual Information (RMI) which is a linear weighted sum of local evaluations of MI. Loeckx et al. [27] proposed the conditional MI (cMI) as a new similarity measure for non-rigid image registration. In fact, in their method the expected value of the MI is used for a given spatial distributions. Locally evaluated MI in

combination with standard global MI was proposed as a similarity measure [28]. A global entropic framework based on Tsallis entropy was used for non-rigid image registration [29]. An important point to note is that these similarities have numerous local minima of the objective function, and the size of local region is also a problem.

To define robust estimator, the topic of robust statistic is one of important tools in signal and image processing. M-estimators are one of the classes in this topic [30,31]. For example in the application of pattern recognition, to define robust classifier in the presence of outlier data, a modified support vector machine based on M-estimator was proposed [32]. In [33], robust fractal image coding based on Huber norm is proposed in the presence of outlier. In [34], M-estimator was used to define robust correlation coefficient in the presence of occlusion for the application of template matching and rigid registration. In this paper we use M-estimator view to illustrate the robustness of the proposed similarity measure.

In this paper, we introduce a new similarity measure that is based on ML. Our main idea is that spatially-varying intensity distortion has a sparse representation in spatial transform domain. In fact, we assume that energy of the distortion is compacted into a few coefficients of spatial transform representation and these coefficients are also independent. In other words, problem of pixel to pixel dependence of distortion is converted to the coefficient to coefficient independence that can be used by the ML approach. It is important to note that by considering a sparse representation, spatially-varying intensity distortion has a role of outlier data. Hence, traditional measures like SSD are not robust against outliers. Therefore, robust similarity measures are needed. In this paper, we first propose robust Huber similarity measure (RHSM) based on ML. RHSM is a combination of SSD and ℓ_1 norm. Then, we show that this similarity measure is robust in M-estimator view. In fact, here, image registration is considered as a non-linear regression problem. With this perspective, it is shown that the estimated parameters of geometric transform have a distribution that is asymptotically Gaussian.

The rest of the paper is organized as follows. Section 2 illustrates our main idea. In Section 3, new similarity measure is introduced based on MAP view. Section 4 considers image registration as a non-linear regression problem and states robustness of our similarity measure. Section 5 provides experimental results on a medical imaging data set that demonstrate the effectiveness of our method and compares its performance to those of RC, MI, and SSD approaches. Finally, in Section 6, we conclude and point out possible future work direction.

2. Main idea

Our goal is a feature based approach that is prudent to non-stationary intensity distortion. Hence the following mathematical model of mono-modal image registration is considered:

$$R = F(T) + S + \eta \tag{1}$$

where *F* and *R* are moving and fixed images, η is a zero mean white Gaussian noise, *S* is a non-stationary distortion such as

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