Biomedical Signal Processing and Control 45 (2018) 325–338

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

A-RANSAC: Adaptive random sample consensus method in multimodal retinal image registration

Zahra Hossein-Nejad [a], Mehdi Nasri [b,*]

[a] Department of Electrical Engineering, Sirjan branch, Islamic Azad University, Sirjan, Iran
[b] Young researchers and elite club, Khomeinishahr branch, Islamic Azad University, Khomeinishahr, Iran

ARTICLE INFO

Article history:
Received 23 December 2017
Received in revised form 13 May 2018
Accepted 6 June 2018

Keywords:
Angiographic imaging
Image registration
Retinal images
SIFT
RANSAC

ABSTRACT

In this paper, an adaptive Random Sample Consensus (A-RANSAC) method is proposed for multimodal retinal image registration. In this method, the features of two various images from images taken with different modalities such as FA (Fluorescein angiography) and RF (Red free) are extracted using a modified version of Scale Invariant Feature Transform method (SIFT) called SAR-SIFT which is originally used for Synthetic Aperture Radar images. Then, the matching performance between these images is enhanced using the proposed A-RANSAC. In the A-RANSAC method, the threshold value is chosen so that the Root Mean Square Error (RMSE) and the number of removed matches are optimized simultaneously. The efficiency of the proposed method has been investigated in other modes such as high resolution and low-quality retinal image registration in addition to multimodal registration. The simulation results on several retinal image datasets show that the proposed method improves the precision matching by 9.89% and rate of success by 25% on the average compared to the SAR-SIFT method.

1. Introduction

Fluorescein angiographic (FA) is done to diagnose retinal problems and diseases related to it such as diabetic retinopathy, and age-related macular degeneration [1,2]. FA is taken using Scanning Laser Ophthalmoscope (SLO) that, one or two images before injection of sodium fluorescein dye and a few images at regular intervals after the injection [3,4]. Normally, fluorescein does not leak from retinal vessels (including late venous and arteriovenous) and remains in the vessel space. If blood vessel walls are abnormal, this dye may leak into the retina. In this case, vessels obstruction, damage to the lower layers of the retina, or appearance of new blood vessels with abnormal growth underneath may emerge. To identify and assess the progression of the disease, it is necessary to perform image registration between different phases (arterial phase, arteriovenous phase, venous phase, late venous phase, and recirculation phase) of FA, which ultimately can help ophthalmologists to diagnose and provide better treatment planning [5,6].

Image registration is a key component in automatic image analysis and this process has an important role in medical images including retina. Retinal image registration is the process of finding geometric transformations between two or more images of the retina, taken at different times, different viewpoints or by different sensors [7,8]. For various reasons, due to reduction of the retina images' quality, a general approach is not applicable to these images. However, registration methods of retina images in general can be divided into area-based and feature-based [9–11].

Area-based registration methods directly use gray (intensity) surface distribution of images in the windows with the same dimensions. For this purpose, use similarity metric, geometric transformation parameters between images are determined. Common similarity metrics for retinal angiography images include mutual information (MI) [12,13], entropy correlation coefficient (ECC) [14,15], and phase correlation [16]. Performance of MI, when there are changes in the texture of the retinal image and changes in scale, is not suitable [17,18]. When there is high translation and content changes between images, phase-based methods do not have a good performance [19]. Thus, overall it can be concluded that area-based methods face different challenges. One of these challenges is that when illumination changes between the images are high, overlapping areas in the images are low [7,20]. In this case, when changes in the texture and content are high, this category of methods has unsuitable performance. In addition, the run-time of area-based methods is high, as they use entire content of the image [21]. In references [22,23], comparisons have been conducted between registration methods showing that feature-based methods have better performance for retina images registration.

Feature-based registration methods detect salient features of images and then calculate matching and parameters of transforma-

* Corresponding author.
E-mail addresses: hoseinnejad.zahra@yahoo.com (Z. Hossein-Nejad), nasri_me@iaukhsh.ac.ir (M. Nasri).

https://doi.org/10.1016/j.bspc.2018.06.002
1746-8094/

tion [24]. Anatomical features such as vessels bifurcations [25,26], optic disc [27], fovea [28] are common features, and Harris [29], SIFT [30], and Speed Up Robust Feature (SURF) [31] are mostly used detectors in feature based retinal image registration. Anatomical features such as vessels bifurcation are invariant to changes in intensity, scale and rotation, but detection of these features in unhealthy images of the retina and low quality images is difficult [17,32,18]. Corners and keypoints of SIFT are easily detected in low quality images. In reference [32], Harris-Partial Intensity Invariant Feature Descriptor (Harris-PIIFD) method is used for matching multimodal images.[1] In this method, the corners are uniformly distributed as features in the images of the retina and the performance is good on low quality images, but not good against image scale. In reference [20], SURF algorithm that is invariant to the change of scale is used to improve angiography retinal images. In Reference [33] edge-driven dual-bootstrap-iterative closest point (ED-DB-ICP) using SIFT keypoints and edges for registration red-free (RF), and FA images are used. The algorithm is suitable for registration of multimodal retinal images with nonlinear intensity changes, but this algorithm is not suitable for some multimodal images of retina with scale changes and for low quality images. In another work [21], Uniform Robust Scale Invariant Feature Transform-PIIFD (URSIFT-PIIFD) is suggested where keypoints are uniformly distributed by the URSIFT algorithm [34]. This procedure is suitable for retinal image registration with scale changes, but does not have a good performance when the images have very low quality or there are content changes between them. In another paper [8] the SIFT algorithm and spherical model is used to register retinal images. This method is suitable for performing super resolution. In reference [35], structure based region detector is used for high resolution retinal fundus image registration. This region detector is suitable against rotation changes, small scale changes and intensity and content changes, but this method does not have a good performance for multimodal retinal image registration. In reference [36], the blood vessels are extracted from the retinal image using segmentation techniques, and then the SIFT algorithm is used for features detection on the retina blood vessels. This method is suitable for both normal and pathological retinal images, but this method has a high computational complexity.

Although there are many improvements in SIFT for multimodal retinal image registration, there are still challenges in registration. These medical images include SIFT keypoints mostly detected in homogeneous areas. Gradient values in homogeneous areas under different reflectivity conditions are various. In angiographic images there are multiplicative and additive noises [54]. Some multiplicative noise in these images makes the Gaussian scale space (GSS) used in the SIFT of most edges and fine details in the image, such as capillaries and small blood vessels in the retina, be eliminated, which eventually has a significant impact on features detection. The SIFT descriptor is not suitable in the presence of multiplicative noise because it uses different method to calculate the gradient. In addition, due to the complex nature of medical images including images of retina, a large number of mismatches are created in the algorithm that ultimately lead to interference in the process of multimodal retinal image registration. A great deal of research has been done to remove mismatches, the examples of which include Multi-Attribute-Driven Regularized Mixture Model (MAD-RMM) [37], Graph Transformation Matching (GTM) [38] and RANdom Sample Consensus (RANSAC) [39].

RANSAC is a robust estimation method introduced by Fischler [39]. To eliminate mismatches, this algorithm is robust and stable against noise. But, one of its disadvantages is that the threshold value is considered empirically. Selection of the appropriate threshold value in RANSAC is a critical problem. If a small value is chosen, the rate of true matches diminishes; and in the case of big value selection, we face the increased rate of mismatches. It puts a drastic impact on the registration process outcome and finally the diagnosis of retinal diseases and retinal image analysis face problems and become impaired. In reference [36] RANSAC is used to remove incorrect matches in registration retinal images. The disadvantage of this method is that the threshold value in this algorithm is empirically chosen, in which elimination of mismatches is very effective. Reference [40] proposed an adaptive method for determining threshold value in RANSAC algorithm. This method is very efficient in determination of the threshold value in this algorithm compared to experimental methods, but one of the disadvantages of this method is that it cannot remove all the mismatches and keeps maximum number of correct matches. Since in registration of retinal images, as well as removing all mismatches, it is necessary to preserve maximum number of correct matches. In medical images registration, including retinal images, it is necessary to eliminate all mismatches because of a mismatch will lead to incorrect registration in these images, and ultimately interferes with the diagnosis of the disease. On the other hand, lots of keypoints are not detected in the medical images [41], so it is necessary to maintain all the correct matches to improve the registration accuracy. Eliminating mismatches and keeping the correct matches depend on the threshold value in RANSAC algorithm. For example, if a low threshold value is selected, besides eliminating mismatches, a large number of correct matches are also deleted. If a high threshold value is selected, in addition to maintaining correct matches, a large number of mismatches are nor removed either. In general, reduction in one of them leads to reduction in another. Thus, obtaining the optimal threshold can play a very important role in images registration. It is necessary to propose a method with optimal threshold value in RANSAC algorithm.

In this paper, a new method is proposed for multimodal retinal image registration. In this proposed method To increase the performance of SIFT and compatibility with the complex nature of medical images especially images of retina, the SAR-SIFT feature extraction algorithm used previously in SAR image registration [42] is utilized in retinal image registration by applying necessary changes. For identifying keypoints, calculating the gradient value and creating descriptors, the Laplacian of Gaussian (LOG) scale space, ratio method, and circular window are used in this algorithm in order to reduce the effect of multiplicative noise. To remove mismatches, the proposed improved RANSAC algorithm is used, where for determining the appropriate threshold value a multi-objective problem is considered, and the purpose herein is to minimize the removal of matching and proper root-mean-square errors (RMSE) simultaneously. The combination of these two methods and their application in retinal images make the process of image registration and diagnosing the disease be done well.

The organization of the paper is as follows. In Section II, methods are described and in Section III, the simulation results are reviewed. Finally, Section IV concludes the paper.

2. The proposed framework

In this paper, we concentrate on the feature-based registration method for multimodal retina images. According to Fig. 1, the proposed method is composed of four main steps, feature extraction

[1] Images taken with different sensors or different modalities (e.g. RF and FA) are multimodal, whilst images taken by the same senor at different times (e.g. fundus camera) are mono-modal. The aim of multimodal registration is to integrate the information obtained from different source streams to gain more complex and detailed scene representation (like diagnosing disease). The aim of mono-modal registration is to evaluate changes in scene which appeared between the consecutive image acquisition (like disease progression).