Evaluation of time-series registration methods in dynamic area telethermometry for breast cancer detection

EVALUATION OF TIME-SERIES REGISTRATION METHODS IN DYNAMIC AREA TELETHERMOMETRY FOR BREAST CANCER DETECTION

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Automated motion reduction in 3D dynamic infrared imaging is on demand in many applications. Few methods for registering time-series dynamic infrared frames have been proposed. Almost all such methods are feature based algorithms requiring manual intervention. We apply different automated registration methods based on spatial displacement to 11 datasets of Breast Dynamic Infrared Imaging (DIRI) and evaluate the results in terms of both the image similarity and anatomical consistency of the transformation. The aim is to optimize the registration strategy for breast DIRI in order to improve the spectral analysis of temperature modulation; thus facilitating the acquisition procedure in a Dynamic Area Telethermometry framework. The results show that symmetric diffeomorphic demons registration outperforms both warped frames similarity and smoothness of deformation fields; hence proving effective for time-series dynamic infrared registration.

Introduction

Dynamic Area Telethermometry (DAT) can be useful in detecting breast cancer. The basic assumption is that normal tissues show temperature modulation that is different from cancerous tissue [1]. The surface temperature modulation caused by cancer, depends on specific aspects such as angiogenesis, local deoxygenation, and production of nitric monoxide [1]. Such physiological temperature modulation occurs at some specific frequencies [1]; hence, the spectral analysis of the time variations of the local temperature could allow for spotting cancerous lesions.
During a DAT examination, several frames of the patients' breasts are acquired. Prior to spectral analysis, the patient movement must be eliminated and the sequential frames must be registered. The movements disarrange the time-temperature series of each pixel, thus originating thermal artifacts that might be interpreted as a false positive.

Very few methods were proposed for automated dynamic infrared images registrations, all were concentrated on manual feature-based motion reduction [2],[3]. In a previous work from our team [3], a marker-based registration was applied on breast dynamic thermograms. However, there were some drawbacks (e.g. difficulty in manually placing the markers as well as deciding the optimal number of markers, additional prior marker detection algorithms, limitation on choosing types of registration parameters).
The purpose of this paper is to perform different types of linear/non-linear intensity based registration methods (implemented in ITK [4]) on the healthy subjects, in order to improve the accuracy of the spectral analysis of temperature modulation. This should ease the patient acquisition procedure in a DAT framework with respect to the marker-based method.
To evaluate the performance of each registration method, we exploited breast boundary overlap along with Normalized Mutual Information (NMI), likewise final deformation field (DF) is demonstrated for visualizing misalignment errors.

Materials and Methods

In time-series registration method, different frames inside a 3D thermogram are aligned, where the first frame is chosen as fixed and all the rest sequential frames as the moving image, while applying optimal parameters.
In breast thermal images, intensities directly correspond to temperature, hence the similarity metrics must minimize the geometric displacement of the pixels, instead of the pixel intensities, otherwise leads to losing information.
Prior to experiments, the breast regions are segmented, using a semi-automated algorithm developed by N. Scales et al [5], while unsharp masking is applied to negate the noise and oversmoothness of interpolation.

Intensity based DAT registration methods

First, affine registration (L1) with the Mattes Mutual Information is applied as similarity metric. The registration parameters are listed in Table.1.
Evaluating the linear registration is significant, since in many applications the sequences are not aligned in phase and single level linear registration could be satisfactory. Therefore choosing a suitable linear registration, satisfies evaluation criteria even prior to a deformable registration and reduces the complexity.
Next, two different non-linear registrations are applied: Parametric multi-level/multi-resolution Bspline method (NL1) [6] and non-parametric diffeomorphic demons (NL2) [7]. In a multi-level/multi-resolution registration, the non-linear characterized Bspline registration is followed by the linear registration to roughly align the frames, while the non-linear registration is divided to coarse and fine resolution with respect to number of bspline grid points. Cost functions and registration parameters for each method are presented in Table 1, 2.
In the non-parametric demons, by using gradient symmetric forces, the DF is obtained and it is warped onto the moving image, by minimizing the following energy functional:

$$E(s,c)=\frac{1}{\delta_i^2}Sim(F,M^\circ c)+\frac{1}{\delta_x^2}dist(s,c)^2+\frac{1}{\delta_T^2}Reg(s)$$

$Sim(F,M^\circ c)$represents geometric pixel disparity metric of fixed and moving image, $dist(s,c)^2$ considers a correspondence error between transformation c and deformation field s as Gaussian noise, hence, a Gaussian smooth kernel is applied on DF as a regularizer along with smoothness degree of deformation $Reg(s)$ leading to well-posed framework as well as a smoother vector field. δ_i^2, δ_x^2, δ_T^2 maintain the trade-off between the three terms in the cost function. In the demons algorithm, pixels representing the same homologous point on an object have the same intensity on both the fixed and moving images, hence well suited for the time-series thermogram registration. Significant parameters are listed in Table 2.

Label	Trans.	Sim.	Opt.	Lvl./ Res.
L1	Affine	[a]MMI	[b]GD	-
NL1	Bspline	MMI	[c]LBFGS	Multi/ Multi
NL2	Demon	[d]GMS	Iterative	Single /Multi

Table 1. Linear and deformable registrations. [a]Mattes Mutual Information, [b]Gradient Descent, [c]Low-memory conjugate gradient descent. [d]Geometric-Mean Squared Error.

Label	Iteration number	Max step length	Bspline grid points	Reg. Time (min)
L1	200	0.1	-	45
NL1	[a][20, 50]	10	[b](15,30)	15
NL2	40	-	-	15

Table 2. Registration parameters. Registrations are performed with Intel Core 2Duo 2.27 GHz CPU, 3GB RAM. [a][linear level, non-linear level], [b](coarse stage, fine stage).

DAT Registration evaluation methods

As a DAT specific evaluation, "*symmetric alignment of breast boundaries assessment*" of every frame is implemented. Next, image difference residual is calculated via NMI for all the sequentially warped thermograms.

Finally, a qualitative evaluation of DF is performed to analyze how physically logic the transformation is computed.

Categories of breast infrared subjects

The infrared image sequences were acquired with an AIM256Q camera for 10s and the frame rate of 50 frames/s; hence, each sequence consisted of 476 thermal images of 256 × 256 pixels, down quantized to 14 bits. The field of view was 38×38cm, element spacing of approximately 1.5x1.5mm. To perform repeatability evaluation, we acquired 4 subjects, each arbitrary acquired several times. Subject1 was acquired 4 times, subject2 only once, subject3 and subject4 each three times, hence we totally have 11 dynamic breast cases for the experiments.

Results and Discussion

Inter-subject case-independent results
We applied each registration method to all the subjects and evaluate the performance, based on the evaluation metrics provided. For each method, distribution of errors with respect to all cases is presented in Fig.1(a).
Intra-subject case-dependent approach
We evaluated the registration result of each method with respect to cases within each subject. Therefore we assessed the within-subject distribution of the errors for each method. Fig.1(b) shows statistical distribution errors of NMI for all the method on only Subject1.
Repeatability evaluation approach
Base on breast boundary overlap error, we evaluate how well the dynamic frames of each case are aligned. Hence, distribution of the errors belonging to all the methods performed on each individual case is assessed, helping to know which case has the least movement and better recovery inside a subject. Fig.1(c) shows the errors distributed on each case.

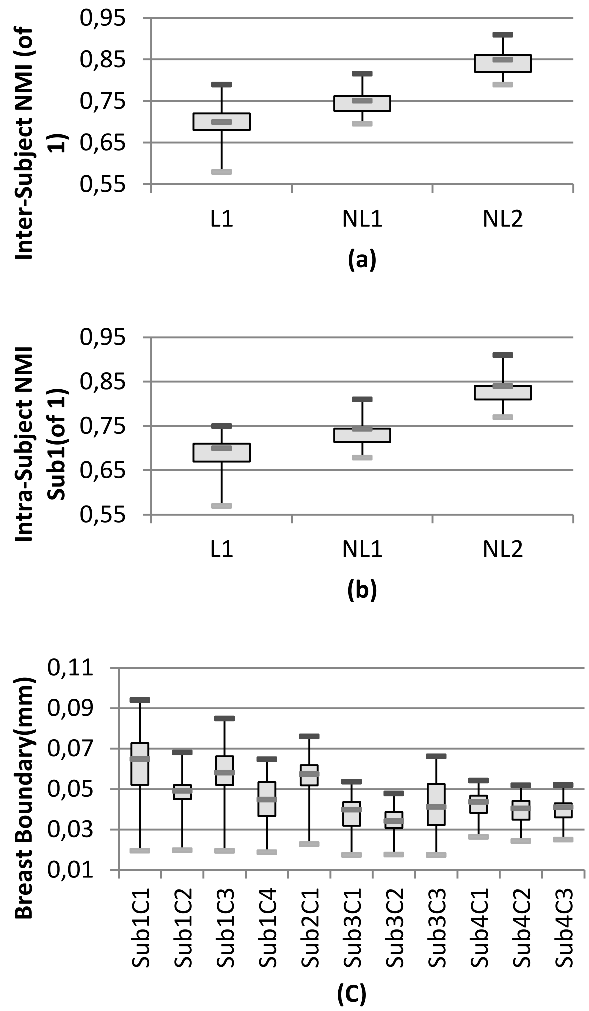

Fig.1. (a)Distribution of NMI error performed for each method as inter-subject evaluation. (Larger better) (b)NMI distribution as intra-subject evaluation for only Subject1.
(c)Repeatability evaluation of every subject by breast boundary overlaps error criteria. (Smaller better)

By referring to the results, for both inter-subject and intra-subject evaluation, Demons registration yielded both higher NMI and smaller breast boundary overlap error quantitatively (Fig.1). Fig.1(c) shows that there is some variation in subject1, with Case4 being relatively easy to register and Case1 the most difficult. In order to qualitatively evaluate the methods, Fig.2 illustrates the sequential final DF obtained for subject1-case1 overlaid on the warped frames. DF in the demons method is the smoothest comparing to other methods, due to the fact that considering the temperature in a point at a given time, total derivative of temperature with respect to time is proportional to velocity of skin portion [3].

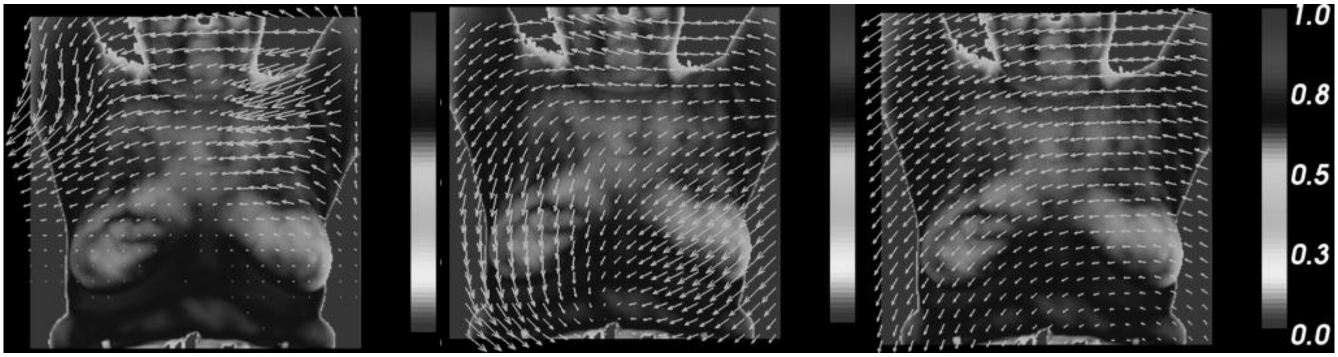

Fig. 2. DF overlaid on warped images belonging to current frame of subject1-case1, in order to show the smoothness of final DF yielded for each method.

Demons method, calculates the 2D velocity in the image, approximating image motion from sequential time-ordered images, which also guarantees the similarity of warped frames. Demons, assumes motion displacement but no intensity error, and uses Gaussian kernel to smooth the deformation field after each iteration, therefore, the corresponding points have the same intensity. The main criteria are dependent upon the local geometric variations of the images as well as the registration parameters.

Finally, we compare the different methods. Table 3 presents average error for both NMI and breast boundary alignment, assigned for each method with respect to inter/intra subject evaluation for all the subjects. As concluded, demons algorithm shows better warped frames alignments.

Label	Intra-Subject		Inter-Subject	
	Avg NMI Error	Avg Breast Boundary	Avg NMI Error	Avg Breast Boundary
L1	0,68	0,13	0,69	0,14
NL1	0,75	0,043	0,75	0,044
NL2	**0,85**	**0,0013**	**0,84**	**0,0011**

Table 3. Method comparison. Average errors of each method with respect to evaluation metrics in terms of inter/intra subject variability.

Conclusion

Respiratory motion can be a significant effect when applying breast infrared thermography. We implemented time-series registration techniques in ITK, validating the methods by inter/intra repeatability evaluation approaches. Based on the results, demons registration due to homologous symmetric forces enforcing the pixel geometric disparities to be shortened on all the frames, excelled in terms of both frame similarity and smooth DF, comparing to other methods. Obtaining optimal DAT registration parameters is considered as a future work.

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