HYBRID FEATURE-BASED LOG-DEMONS REGISTRATION FOR TUMOUR TRACKING IN 2-D LIVER ULTRASOUND IMAGES

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ABSTRACT

Traditional intensity-based registration methods are often insufficient for tumour tracking in time-series ultrasound, where the low signal-to-noise ratio significantly degrades the quality of the output images, and topological changes may occur as the anatomical structures slide in and out of the focus plane. To overcome these issues, we propose a hybrid feature-based Log-Demons registration method. The novelty of our approach lies in estimating a hybrid update deformation field from demons forces that carry voxel-based local information and regional spatial correspondences yielded by a block-matching scheme within the diffeomorphic Log-Demons framework. Instead of relying on intensities alone to drive the registration, we use multichannel Log-Demons, with channels representing features like intensity, local phase and phase congruency. Results on clinical data show that our method successfully registers various patient-specific cases, where the tumours are of variable visibility, and in the presence of shadows and topological changes.

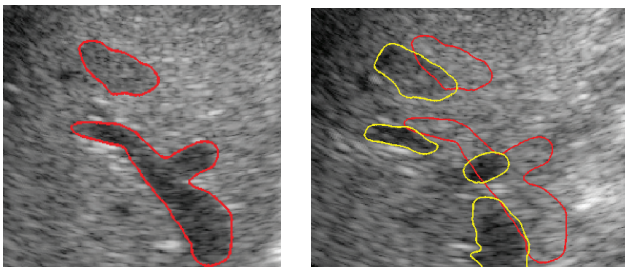
***Index Terms*—** Diffeomorphic, Log-Demons, block-matching, ultrasound, tracking

1. INTRODUCTION

While ultrasound (US) imaging is affordable, fast and offers good support for real-time tumour tracking and monitoring, exploiting such images is often difficult. In particular, registration methods for tumour tracking in 2-D liver US need to tackle both imaging-related and patient-specific challenges.

The imaging-related issues stem from US image acquisition. For instance, the low signal-to-noise ratio and the inherent noisy speckle significantly degrade the quality of the output images. The patient-specific challenges are linked to the location of the liver tumours. The liver is partially covered by the rib cage, which means that transcostal acquisition has a limited field of view and is likely to depict shadows produced by the bones. As a consequence, those structures in proximity to the bones often exhibit variations in intensity contrast across frames. Finally, since the liver moves due to breathing, topological changes may occur as the anatomical structures slide in and out of the focus plane. These issues are noticeable, for example, in the two US frames in Fig.1. The tumour (top) exhibits changes in intensity contrast as it moves towards the shadowed region to the left, whereas the appearance of the vessel (middle-bottom) is different in the two images.

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Target Source

Fig. 1. Two US frames with overlaid segmented structures.

Traditional intensity-based registration methods are usually unable to handle such complex issues. Existing techniques that attempt to deal with these problems either build a more sophisticated similarity measure which takes into account the US physics and noise model (e.g. CD_{2bis} [1]), or rely on identified anatomical landmarks [2] and image features [3] rather than intensities alone.

In this paper we propose a new hybrid feature-based registration technique for tumour tracking in time-series 2-D liver US. Our aim is to apply this method in a targeted drug-delivery project, where accuracy is a key requirement. Our method extends the diffeomorphic Log-Demons registration technique [4] to take into account regional spatial correspondences supplied by a block-matching scheme. Its novelty lies in estimating hybrid update deformation fields from demons forces that carry voxel-based local information and region-based spatial correspondences.

Fig.2 shows the limitation of the original Log-Demons technique, illustrated for the application at hand. Source (a) and target (b) represent two US frames that display a black shadow on top, a tumour as darker circle (a) and oval (b), and another larger and brighter structure. Log-Demons inappropriately pushes the tumour towards the shadow in (c), using the estimated deformation field (d). In this case, it is unable to register the tumour using voxel-based information only.

We note that, unlike the recent geometrically constrained Log-Demons [5] that relies on a distance measure from point sets to jointly register T1 MRI and brain fiber bundles, here we adopt a block-matching approach, in similar spirit to [6]. However, our technique differs substantially from that in [6]. While Lu et al. [6] use block-matching to find corresponding salient points in MR and then use these pairs of landmarks in the Log-Demons framework, here we completely integrate the block-matching scheme into the Log-Demons framework to update the regional spatial correspondences at each iteration. Moreover, instead of relying on point landmarks as in [6], we establish the correspondences based on multiple image

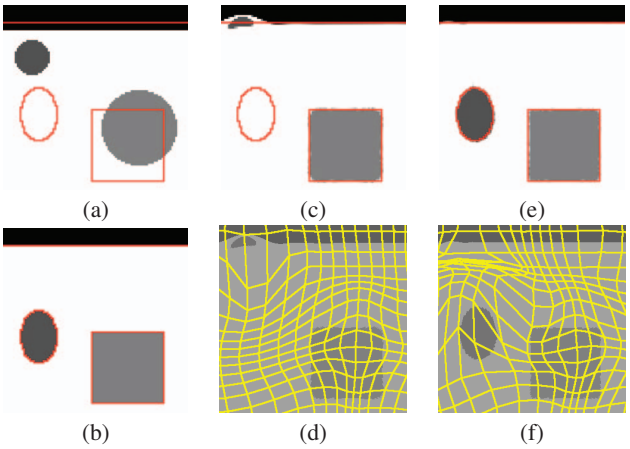


Fig. 2. A synthetic example: (a)-(b) source and target with overlaid target contours; deformed source and corresponding deformation fields with (c)-(d) Log-Demons and (e)-(f) BMLD.

features extracted from the ultrasound data. Lastly, we apply our technique to tumour tracking in US images which poses different challenges, compared to the registration of diffusion weighted MRI in [6].

We address the inadequacy of using intensity alone to drive the registration of US images, by considering two additional image features: local phase (LP) and phase congruency (PC). LP is a qualitative descriptor of the structural features present in the images, and PC measures the features' significance. Both measures are contrast invariant, which makes them particularly suitable for our application. For instance, such phase-based descriptors proved to perform well in cardiac US registration [7] as well as in multimodal cases [8].

Section 2 details the components of our method. Then, Section 3 presents the results on clinical data. Finally, Section 4 concludes the paper with an emphasis of our contribution.

2. METHOD

Our method builds upon the diffeomorphic Log-Demons technique [4]. The Log-Demons method derives from the seminal work of Thirion [9] and estimates a deformation field s, parameterized by a stationary velocity field u, that best aligns a source image I_S with a target one, I_T.

A fundamental component, specific to the family of Demons-derived registration techniques, is the correspondence field c added in the optimization of the energy functional:

$$E(s,c) = \frac{1}{\lambda_i^2} Sim(I_T, I_S \circ c) + \frac{1}{\lambda_x^2} dist(s,c)^2 + \frac{1}{\lambda_d^2} Reg(s) \quad (1)$$

c ensures the demons are well-posed and informs upon the image matching quality regardless of the regularity of s. Sim is the similarity between the deformed source and target, with the sum of squared differences (SSD) a common choice. $dist$ is the L_2-norm of the two deformations and ensures that c stays close to s. The final term is a regularizer that smoothes the transformation. The λ parameters control the influence of image noise (λ_i), the spatial uncertainty (λ_x) and the amount of regularization (λ_d), respectively. A thorough discussion on the selection of these parameters is presented in [10]. c is obtained by composing s with an update field, δu, defined as:

$$\delta u(x) = -\frac{I_T - I_S \circ s}{\|\nabla (I_S \circ s)\|^2 + (\lambda_i/\lambda_x)^2} \nabla (I_S \circ s) \quad (2)$$

2.1. Block-Matching Log-Demons (BMLD)

In the energy functional (1), c carries only image-based information, yielded by voxel-wise similarity of the input images. To deal with more complex issues (e.g. shadow effect, poor US image quality) that the locally image-driven Log-Demons would be unable to handle adequately, we add two components to the framework above: (1) we consider three image features (intensity (I), LP and PC) instead of intensity only, in a multichannel Log-Demons implementation; (2) we introduce an additional sparse displacement field, δu^{BM}, obtained with a block-matching scheme (Sec. 2.3). The algorithm below presents the steps of our method:

Algorithm 1 BMLD

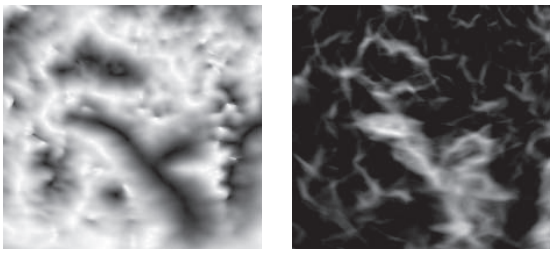
Require: deformation $s = exp(u)$
Require: correspondence $c = exp(u_c)$
Require: update field $exp(\delta u)$
1: $u = Id$
2: **repeat**
3: estimate δu^i using (2) on each image feature f_S^i, f_T^i
4: estimate δu^{BM} using block-matching (Sec. 2.3)
5: $\delta u = w \cdot K_1 \star (\sum_i \delta u^i) + (1-w) \cdot K_2 \star (\delta u^{BM})$
6: estimate u_c such that $exp(u_c) \approx exp(\delta u) \circ exp(u)$
7: $u \leftarrow K_3 \star u_c$
8: **until** convergence

The method follows the steps involved in the optimization of the energy (1). In classic Log-Demons, this is performed by alternating two minimization steps. First s is fixed and c is estimated by minimizing the first and second term in (1). Then, c is fixed and s is estimated by minimizing the second and third term. Steps 3, 6 and 7 in Alg.1 are the same as in the original Log-Demons. u and u_c are the parameterizations of s and c, and we use the Baker-Campbell-Hausdorff (BCH) approximation to estimate u_c in step 6 (see [4] for details). In step 3 we compute demons forces using the voxel-based estimation (2) on each image feature. Then, in step 4 we estimate the region-based demons forces using the block-matching scheme on the three features (Sec. 2.3). K_1 and K_2 are Gaussian kernels convolved with these demons forces (fluid-like regularization) and K_3 is a Gaussian kernel that ensures a diffusion-like regularization of the estimated field. We estimate the hybrid update deformation field in step 5, from the voxel-based update of each image feature δu^i and the spatial correspondences δu^{BM}.

The weighting w can vary during the optimization to give more importance to one demons force or another. In practice, more weighting should be given to δu^{BM} in the beginning of the optimization, to ensure a good initial alignment (e.g. $w = 0$). Then, w can increase to rely more on the local voxel-based information.

2.2. Image Features

Our technique can be used with any number and type of image-driven features. LP and PC were selected owing to their robustness to noise, and for offering good structural localization. We estimate LP with the monogenic signal [11], which has two components. An even one, I_e, is obtained by band-passing the input image with a filter, here the log-Gabor filter. The odd component is the result of the



(a) (b)

Fig. 3. Image features obtained from the Target image in Fig. 1: (a) local phase (LP), and (b) phase congruency (PC).

convolution of I_e with two anti-symmetric filters $(h_1 \star I_e, h_2 \star I_e)$, commonly the Riesz transforms [11]. The LP at point x is then defined as:

$$\phi(x) = atan(\frac{I_e}{\sqrt{(h_1 \star I_e)^2 + (h_2 \star I_e)^2}}) \quad (3)$$

PC is interlinked with the LP in that it uses the phase information in its construction. We compute it using the PC_2 definition in [12]:

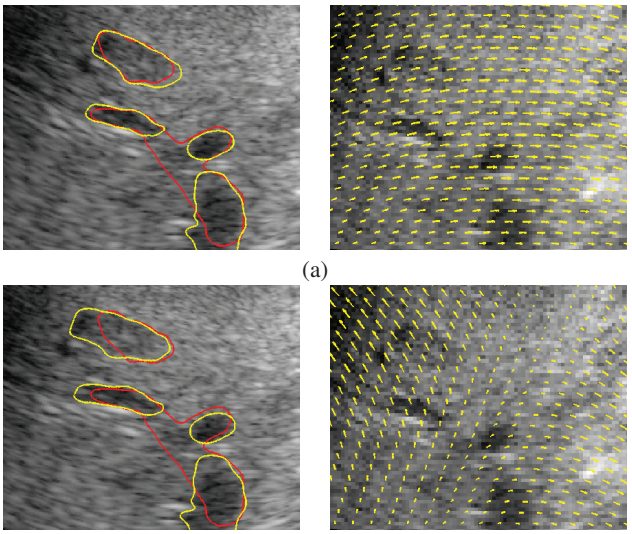
$$PC_2(x) = \frac{\sum_n W(x) \lfloor A_n(x) \Delta\Phi_n(x) - T \rfloor}{\sum_n A_n(x) + \epsilon} \quad (4)$$

where the phase deviation $\Delta\Phi_n(x) = (cos(\phi_n(x) - \overline{\phi}(x)) - |sin(\phi_n(x) - \overline{\phi}(x))|)$, mean phase $\overline{\phi}(x)$ and the local energy $A_n(x) = \sqrt{(I_{ne})^2 + (h_1 \star I_{ne})^2 + (h_2 \star I_{ne})^2}$ correspond to the band-passed images with log-Gabor filters of scale n. $W(x)$ is a weighting factor for frequency spread and T is a noise estimator. $\lfloor \rfloor$ operator in (4) implies that only positive values are considered. Fig. 3 shows the LP (a) and PC (b) corresponding to the target image in Fig. 1.

2.3. Block-Matching

This technique aims at determining local spatial matches between input images. For this, we divide the deformed source image into a set of regular blocks. Then, for each such block b_S, we search for the block b_T in I_T, that is most similar to b_S. Once the best match is found, we define a displacement vector between the centres of the two blocks $u^{BM}(b_S, b_T)$. The set of all these vectors forms a displacement field δu^{BM} (step 4 in Alg.1) that carries information about the spatial correspondences in regions of the two input images. We measure the similarity of two blocks with the L_2 norm of the selected features: $Sim^{BM} = \|F_{b_S} - F_{b_T}\|^2$, where $F_{b_S} = \{f^i_{b_S}\}$ and $F_{b_T} = \{f^i_{b_T}\}$, $i = \{I, LP, PC\}$ denote the feature vectors of the source and target blocks, respectively.

We note that this block-matching scheme may generate outliers. To reduce their occurrence, we restrict the search for candidate blocks b_T to a small spatial neighbourhood around each b_S. Here, a typical block-size is $[9 \times 9]$ within a $[11 \times 11]$ neighbourhood. Moreover, we only take into account blocks that contain relevant geometric information, such as boundaries or structures. A simple variance thresholding over each feature block helps us discard those homogeneous regions likely to yield poor matches. The eventual outliers are then handled adequately by smoothing δu^{BM} with the Gaussian kernel K_2 in step 5.



(a)

(b)

Fig. 4. Registration results and corresponding deformation fields using (a) Block-Matching Log-Demons (BMLD) (b) Multichannel Log-Demons (MCLD). Contours correspond to target (red) and deformed source (yellow).

3. RESULTS

Unlike the original Log-Demons, our Block-Matching Log-Demons (BMLD) technique is able to adequately register all three structures in our synthetic example in Fig. 2 (e), using the estimated deformation field (f).

We applied our technique to 8 $2D+t$ US scans from 5 patients, comprising between 22-71 frames per dataset. Each scan was acquired with a linear probe kept fixed while recording the tumour movement under free or shallow breathing. The data was obtained from patients with recurrent tumours, who had ablation treatments prior to scanning. Tracking is particularly difficult in these cases because the recurrent tumour is surrounded by scarred tissue, and parts of the new growth may be overshadowed by calcifications or ribs. Therefore, the proposed registration method needs to handle variability in tumour size, texture and location.

A clinical expert manually segmented the visible tumours and, when possible, additional anatomical structures, like the vessel in Fig.1. We tested the proposed hybrid registration method using the features individually as well as combined in a multichannel fashion, and compared the results with the classic Log-Demons on the corresponding features input. For simplicity, we used here $w = 0.5$ and the same kernel for K_1 and K_2 to estimate the hybrid field. Fig.5 reports the mean and standard deviations of overlap in form of Dice coefficients of segmented structures for each dataset (1-8), and averaged across all scans (AVG). $IBMLD$, $LBMLD$ and $PBMLD$ are the results from our BMLD, with one feature only as input (I, LP and PC, respectively). Similarly, ILD, LLD and PLD are their counterparts obtained with the classic Log-Demons. LLD and PLD yield good overlap in average (AVG) of 90% and 88%, compared to 83% before registration. Intensity alone performs poorly in general and fails altogether in the registration of datasets $1, 6$ and 8. We attribute this failure to the presence of shadows and less visible tumours in these images. However, the addition of regional spatial correspondences is beneficial for instance in dataset 7, where we

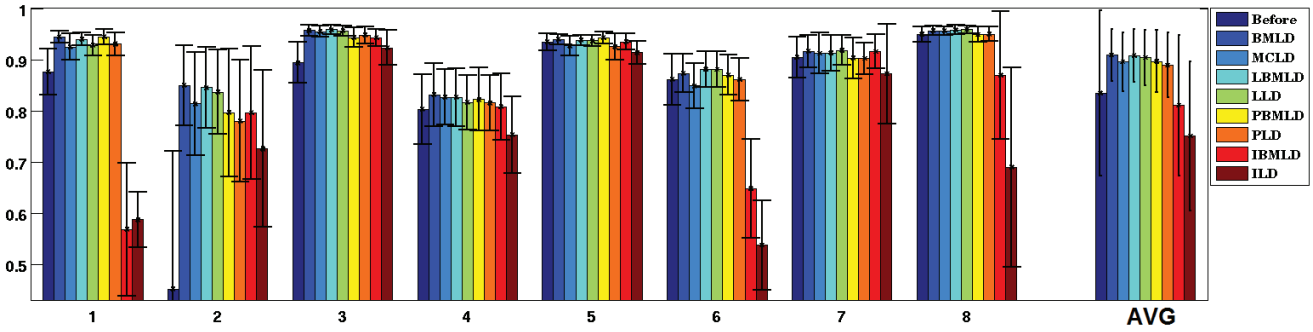


Fig. 5. Mean and standard deviations of Dice for different registration results from 8 datasets (see text for details).

obtain an overlap of 91% with $IBMLD$, as opposed to 87% with ILD (Dice before registration is 90%). Naturally, the high overlap of 94% for dataset 8 before registration indicates that little improvement can be made. Such high overlap prior registration observed for instance in datasets 5 and 8 is due to the small amount of movement of the tumour in these particular cases.

The results highlight that BMLD using the three features together yields in general superior results across all datasets, with a Dice coefficient of $90.8\% \pm 5$ as shown in Fig.5 (AVG). This improvement, albeit small, is important for our targeted drug-delivery to liver tumour application. The more accurate the alignment is, the more confident we are that the treatment will take place at the correct location. The most dramatic improvement was observed for dataset 2, from 45.1% before registration, to 81.3% using the three features in multichannel Log-Demons without spatial correspondences ($MCLD$), to 84.9% using BMLD.

A visual inspection of these registration results confirms that the tumours and the surrounding anatomical structures are adequately registered with our hybrid BMLD, in the presence of shadows and topological changes. Note for instance the overlay of the deformed source contour (yellow) onto the one extracted from the target image (red) before, Fig.1, and after registrations in Fig.4. BMLD with the combined three features registers the tumour accurately in Fig.4 (a). In contrast, the corresponding MCLD in (b) pushes the tumour towards the shadow on the left. The deformation fields estimated after one iteration in each of these two cases clearly show the tendency of Log-Demons in (b) to align the darker regions on the left rather than the tumours, as opposed to our hybrid technique that pushes the tumour to its correct location in (a).

4. CONCLUSIONS

In this work we presented a hybrid feature-based registration method for tumour tracking in 2-D liver US. Since a voxel-based registration approach would be unable to handle all problematic aspects of tumour tracking in liver US, we estimate a hybrid deformation field within the Log-Demons framework, that carries both voxel-wise information and block-matching spatial correspondences. The incorporation of three image features (image intensity, local phase and phase congruency) has helped to improve the accuracy and robustness of aligning structures in our proposed method. Our results show the superiority of our approach compared to the original Log-Demons. The implementation of our technique in the fast and efficient Log-Demons framework will be further developed for use in a real-time clinical application.

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