Eurographics Workshop on Visual Computing for Biology and Medicine (2021)
K. Nieselt and T. Schultz (Editors)

Short Paper

Strategies for Generating Multi-Time Frame Localization of Cardiac MRI

S. Sabokrohiyeh[1], K. Ang[1] and F. Samavati[1]

[1]University of Calgary, Canada

Abstract

4D Flow MRI is a recent promising technology that is able to capture blood flow information within the heart chambers over a cardiac cycle. To accurately study the flow inside the chambers, there is a need for a high quality anatomical reference which can be provided by another scan known as 3D cine MRI (short-axis 3D (multiple 2D slices) cine SSFP). To take advantage of both scans, data fusion can be done using an intensity-based registration. To reduce the impact of noise on the registration result and the chance of misalignment between the organs, defining a region of interest (localization) should be done prior to the registration. Localizing a dataset – especially a time-varying dataset – can be a daunting task since the localization should be provided for all time frames. We design and evaluate different strategies for extending single time frame localization to time varying data in order to register the 4D Flow MRI and 3D cine MRI over the cardiac cycle.

CCS Concepts

• ***Applied computing*** $\rightarrow$ ***Life and medical sciences;***

1. Introduction

Heart disease is one of the main causes of death worldwide. Magnetic resonance imaging (MRI) is improving rapidly to assist cardiologists in gaining some prior knowledge about the structure and function of the heart, which is helpful in treatment and early diagnosis of heart disease. Cardiac MRI (3D cine MRI) can capture high quality anatomical information, which has helped a lot in treatment and diagnosis of heart disease that depends on the anatomy of the heart. However, cardiac disorders that require studying the flow behaviour cannot be identified by studying the anatomy alone. 4D Flow MRI is a recent powerful technology that is able to capture the flow within the heart chambers. Taking advantage of both of these MRI technologies together can ease the process of identification and treatment of cardiac disorders for clinicians.

3D cine MRI and 4D Flow MRI datasets may be captured in different orientations and some misalignment will exist due to patient movement during the scans. Therefore, to fuse these two time-varying datasets we need to transform them to the same coordinate system and align the corresponding regions over the cardiac cycle. The process of aligning two datasets is called registration. Registration of cardiac images is a challenging task due to the complexity of cardiac anatomy and its dynamic nature.

Since the heart has a complex anatomical structure, registration of cardiac images is a challenging task. Moreover, there are some structures surrounding the heart which are visible in the images and affect the result of the registration. The noise and the unwanted parts will significantly influence the registration result. Therefore, trying to register the data without excluding the unwanted parts may result in a wrong registration. Because of this, localization of the images (i.e. defining a region of interest that we want to register) is a vital step prior to registration.

In this paper, to register both time-varying datasets (i.e. 3D Cine MRI and 4D Flow MRI), we extend the single time frame localization (which can be provided by any segmentation technique, cropping box or even sketch-based masks introduced in [SAES19]) to each time frame to obtain a multi time frame localization. To do this, we introduce, analyze and evaluate different registration scenarios for fusing the 3D cine MRI and 4D Flow MRI datasets. Each scenario includes choosing a localization scheme and registration of a single corresponding time frame, then choosing a time varying extension strategy to provide the registration for the complete cardiac cycle. We analyse five different time-varying strategies: copy-paste, repeat, hybrid, non-rigid registration and non-rigid hybrid and we compare them using execution time, interaction time and accuracy. The non-rigid strategy is heavy in execution time and the repeat strategy is heavy in interaction time. However, they both have better accuracy compared to the copy-paste, hybrid and non-rigid hybrid strategies, which might not work in cases where the patient moves during the scans.

Section 2 covers background information about 4D Flow MRI, registration, and localization. In Section 3 we describe the methodology by explaining our five strategies. Section 4 covers the eval-

DOI: 10.2312/vcbm.20211342

uation of our scenarios and some comparison between the results, and Section 5 is presents a conclusion and future work.

2. Background and Related Work

4D Flow MRI is primarily used to capture flow dynamics, although magnitude images which provide the anatomical structure of the heart are also constructed. However, due to the narrow intensity range of these magnitude images, even expert clinicians have difficulty delineating the heart structure visually [DBB*15]. There is always a need to study the flow within the chambers of the heart with respect to the anatomical information, but high quality anatomical information cannot be provided by the 4D Flow MRI data itself [vdGG16]. One solution to this problem can be fusing the flow information with another dataset that can provide the anatomical information.

Data fusion, known as image registration, has been widely used to register images from different modalities for different organs (e.g., there are many works about registering functional and anatomical images of brain MRIs [MA13]). Despite this, there are some challenges that make cardiac image registration more complex than brain image registration. This complexity stems from the beating and deformation over time, complicated thorax structure, fewer accurate anatomical landmarks and lower resolution images compared to brain images [MCS*02]. There are several different works that used image registration to fuse brain and cardiac datasets from different modalities such as computed tomography (CT), magnetic resonance (MR), X-ray and functional MR (fMR) [MA13, PCS*89, vHV*04, MCS*02, SWWFD05].

There are several studies that acquired manual segmentation as a localization mask prior to registration [EvdGC*17, KWvdP*18, GCS*18]. Providing a manual segmentation for all time frames is very expensive and time-consuming. In another recent work [GBF*18] on registering 4D Flow MRI to breath hold cine MRI, a box was used as a localization mask around the heart. Sketch-based techniques [CSSM06, CSSJ05] can be used for localization. In [SAES19] they introduced sketch-based techniques which reduced the manual interaction for providing the localization and resulted in more accurate registration results than the cropping box used in [Här16]. However, they provide only one localization and used it for all time frames.

3. Methodology

To extend localization which is done for a single time frame on 3D Cine MRI to the rest of the time frames, we came up with five strategies categorized below:

- Copy-paste: Copy the single time frame localization mask for the rest of the time frames without changing it.
- Repeat: Redo the localization independently for each time frame.
- Hybrid: Do the localization for critical time frames and copy it for in-between time frames.
- Non-rigid registration: Deform the single time frame localization mask to estimate the localization mask for other time frames using non-rigid registration.
- Non-rigid hybrid: Deform the single time frame localization mask to estimate the localization mask at critical time frames and copy it for in-between time frames.

The advantages and disadvantages of each of these strategies is discussed below.

3.1. Copy-paste

In order to register all time frames of a cardiac cycle (i.e. approximately 30 time frames), localization masks for all time frames must be determined. In this strategy, we use the localization provided for one time frame for the rest of the time frames. The localization mask can be provided on the diastolic time frame (the time frame that the heart reaches its maximum size), as this ensures the best chance of containing the region of interest (ROI) in the remaining time frames. Providing localization for the rest of the time frames with this strategy is easy. However, if the patient moves during the scan, the ROI might not be contained within this localization mask, which can affect the result of the registration.

3.2. Repeat

In this strategy, the single time localization technique is repeated for all of time frames. If we use manual segmentation as our localization mask for the first time frame (15 contours for a single time frame), we would simply repeat the manual segmentation for the remaining time frames. This requires manually segmenting 30 time frames (i.e., providing 450 contours). This strategy provides us with more precise localizations, which will result in more accurate registration and less registration time, but with a very high user interaction time. Alternatively, if we create the mask using a single sketch or three sketches for localization [SAES19], we can reduce the user interaction to some extent. However, it still requires some level of interaction for every time frame.

3.3. Hybrid

Instead of repeating the localization for every time frame, which can be tedious and time consuming, one can repeat the localization only for some critical time frames. By critical time frames, we mean the time frames in which the heart has a lot of deformation (See Fig. 1).

This strategy is inspired by key frame animation in computer graphics where a character or model is only manually animated in key poses, which show the overall motion of the character, and the in-between frames are generated automatically by some type of interpolation [DAC*03]. In the hybrid technique (using the left ventricle as the ROI) we choose two critical time frames and provide the localization for those, and then copy and paste the localization for the time frames in between. Observing the segmentations of the data shows that the left ventricle is large at the first time frame t_1 and the size reduces from time frame t_7 to t_{15} where there is a lot of change in the size of the left ventricle. Time frame sixteen could also be a critical time frame, but in practice we found that simply reusing the first time frame gave sufficient results, due to the left ventricle being large in both of these frames. Therefore, as a specific case of the hybrid strategy, we use t_1 and t_7 as the critical time

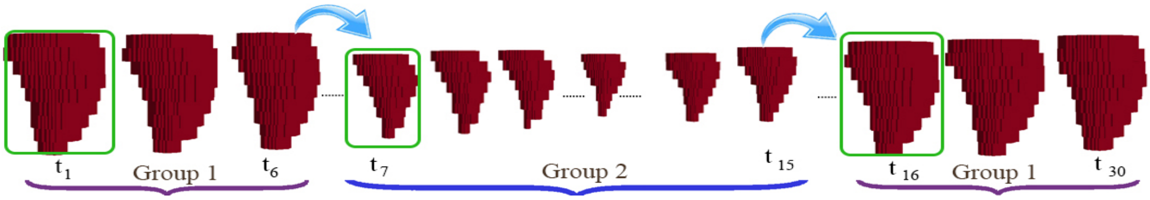

Figure 1: *Critical time frames where there is a big change in the size of the left ventricle and dividing the data to two groups characterized by the size of the left ventricle. Using the hybrid strategy, one time frame from each is localized and used for the others in the group.*

frames to repeat the localizations, reducing the number of critical time frames to two (See Group1 and Group2 in Fig. 1).

We have one localization for the bigger-sized left ventricles (Group 1) and one for the smaller-sized left ventricles (Group 2)). We choose t_1 for group1 and t_7 for group2 as they have the biggest left ventricle size among their groups. Therefore, the possibility of containing the ROI within these localization masks is higher.

As an example, we employed manual segmentation as our localization mask for our two critical time frames, which required contouring fifteen slices for each time frame (30 contours in total). Using this technique reduces user interaction, but has lower accuracy compared to the repeat strategy.

3.4. Non-rigid Registration

Another alternative for providing efficient localization, instead of using substantial manual effort to provide the localizations, is to use one localization and deform it to fit the rest of the data. This deformation can be carried out using a non-rigid registration using technique using Normalized Mutual Information (NMI) as a similarity metric [LVSOMR02]. The single time frame localization must be provided on the 3D cine MRI data rather than the 4D Flow MRI, as a dataset with clearly visible heart features and edges is needed for the non-rigid registration.

For example, if we have the left ventricle manual segmentation, by using non-rigid registration we can deform it to fit the left ventricle in different time frames of the 3D cine MRI (Fig. 2). The input masks deforms iteratively to fit the ground truth. After providing the deformed localization mask for all of the 3D cine time frames, we can use them as localization masks for rigidly registering (using only rotation and translation) the corresponding 3D cine MRI time frames to the 4D Flow MRI time frames.

This strategy reduces the user interaction time and results in high quality registration, but it has high execution time (42 minutes and 25 seconds) compared to the repeat strategy (12 minutes and 8 seconds).

3.5. Non-rigid Hybrid

To address the high execution time of the non-rigid registration strategy and also to reduce the user interaction required in the hybrid strategy, we developed another strategy which we call the non-rigid hybrid strategy. As in the hybrid strategy, we provide localization masks for critical time frames and use those same localizations for in-between time frames; however, to obtain the localization masks for the critical time frames we use non-rigid registration. By using non-rigid registration to deform the localization for only a few critical time frames instead of all of the time frames.

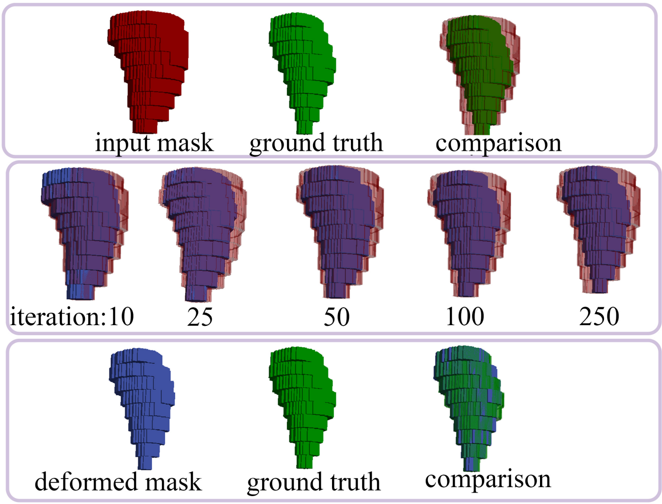

Figure 2: *The iterative process of deforming the input localization in order to get the deformed mask, which matches the ground truth.*

As an example, if we use a manual segmentation as our localization mask, we first provide the localization for the first time frame. We need to also provide another localization for time frame t_7 (which is a critical time frame), but instead of repeating the localization scheme for this time frame, we obtain the localization by deforming the first localization mask using non-rigid registration.

4. Results and Evaluation

To evaluate our strategies, we compared the results of registration using four different masks. The masks used for the registrations were (1) manually delineated segmentation (ground truth) of the left ventricle, (2) three-sketch localization, (3) single-sketch mask around the whole heart [SAES19], and (4) a bounding box around the heart. The two datasets used comprise 30 pairs of volumes, which were registered using each localization mask. Run time was based on the elastix toolbox implementation [KS15]. Although this is not necessarily the most efficient implementation, we used it as a comparative metric. The accuracy is quantified using two different metrics: Dice coefficient (DICE) and Hausdorff Distance (HD), as discussed in [TH17, SAES19]. We compare the execution time, accuracy and user interaction time for time varying registration using different localization schemes. Fig. 3 shows that the total time for the registration of all time frames using different strategies is almost the same, except for the non-rigid registration strategy, which has a high execution time compared to the others. The execution time (registration time) using the repeat strategy is slightly less than the copy-paste, hybrid and non-rigid hybrid strategies.

Fig. 4 and Fig. 5 depict the comparison of the DICE and Hausdorff Distance (HD), which indicate the accuracy of the registration. These two metrics are calculated between the two ground truth segmentations: one from the 4D Flow MRI and the other from the 3D cine MRI after registration. Comparing the results, the repeat strategy has higher DICE and lower HD (which means higher accuracy) for manual segmentation and three sketch localization than the copy-paste, hybrid and non-rigid hybrid strategies. The hybrid, non-rigid hybrid and copy-paste strategies are almost the same. Non-rigid registration works as well as the repeat strategy for the manual segmentation and three sketch localization. However, non-rigid registration and non-rigid hybrid strategies generate large inaccuracies in the case of single sketch localization. The reason for this could be the existence of parts other than the left ventricle visible in the mask; these affect the result of the non-rigid registration, which means that we did not get correct localizations after our non-rigid registration using the single sketch localization.

Fig. 6 depicts the comparison between different strategies for relative interaction time needed to provide the time-varying localizations. The repeat strategy has a high interaction time as the localization is done for every single time frame. The lowest interaction time is for copy-paste, non-rigid registration and non-rigid hybrid strategies. Copy-paste, non-rigid registration and non-rigid hybrid strategies have the same interaction time because only the first localization needs to be done by the user. The hybrid strategy needs more interaction time than the copy-paste, non-rigid registration and non-rigid hybrid as it requires providing more than one localization manually. However, it is still much faster than the repeat strategy.

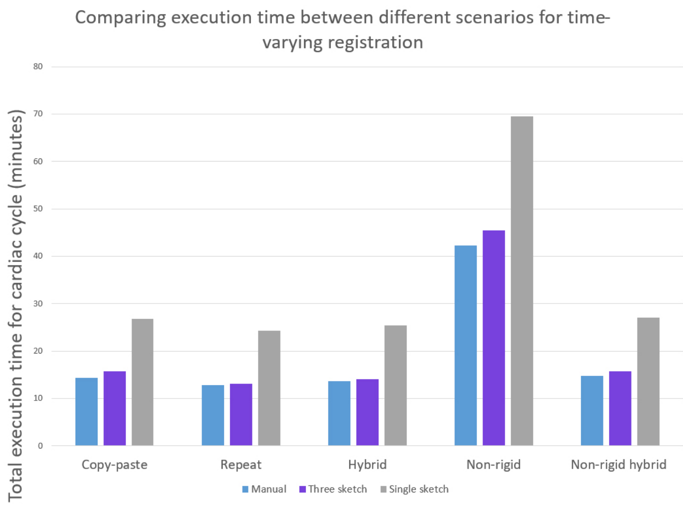

Figure 3: *Comparison of execution time.*

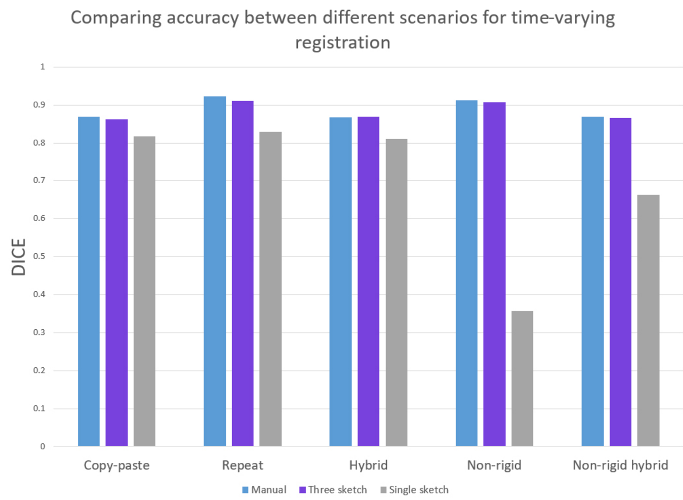

Figure 4: *Comparison of DICE.*

5. Conclusion and Future Work

The main goal of this work is to register the 4D Flow MRI and 3D cine MRI via multi time frame localization. To do this we used five different strategie. We did the registration with existing localizations such as manual segmentation, bounding box and sketch-based localizations. We also compared them based on execution time, interaction time and accuracy. Each strategy has its pros and cons and a strategy can be chosen based on the user's need. However, non-rigid registration is able to provide high accuracy and low interaction time which are the two most important features for the medical community. The execution time is highly dependant on the algorithm used for the registration and this can be improved by using higher computation power and GPU implementations.

As future work, for doing the non-rigid registration we used cubic B-spline basis functions; however, other basis functions such as partition of unity parametrics (PUPs) [RS11] and other deformation techniques, such as cage deformation [NS13], can be used instead to see how they perform for cardiac image registration. Moreover, our method could be extended to other medical datasets beyond cardiac images to reduce the impact of noise on the registration result.

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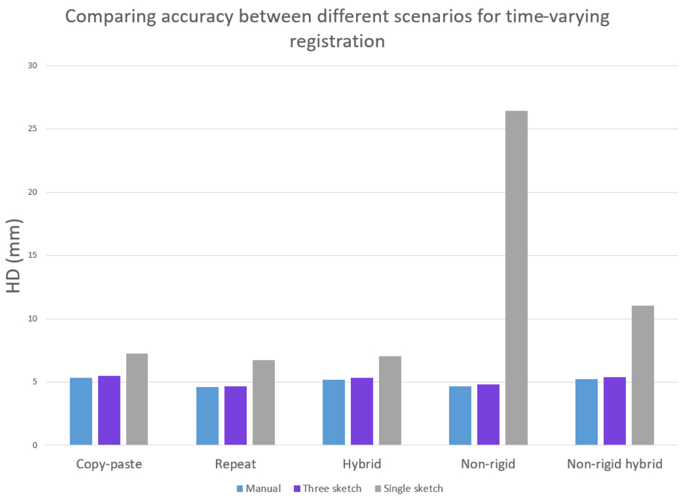

Figure 5: *Comparison of Hausdorff distance.*

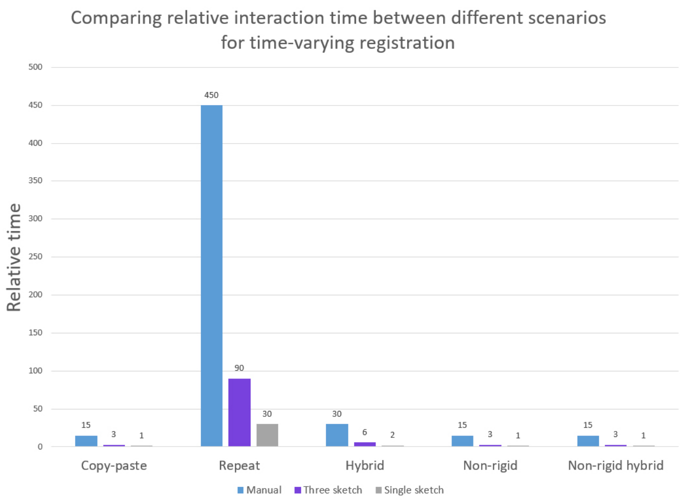

Figure 6: *Comparison of interaction time for providing the localization masks.*

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