2D/3D-Registration of Cerebral DSA Data

Clemens M. Hentschke, Klaus D. Tönnies

Department of Simulation and Graphics, University of Magdeburg
cmh@isg.cs.uni-magdeburg.de

Abstract. We present a method to automatically register cerebral 2D digital subtraction angiography sequences (2D-DSA) to 3D rotational X-ray angiography (3D-RA) volumes. The application is the validation of blood flow simulations for aneurysm treatment. We compute projection images of 3D-RA data sets and compare them to the 2D-DSA images. A three-step strategy is presented to calculate the registration where no user interaction is needed. We tested the accuracy of our method on studies of five patients by manually setting fiducial markers and measured a root mean square projection error of 1.78 mm ± 0.45 mm.

1 Introduction

Simulation methods have recently been proposed to support treatment of intracranial aneurysms [1]. Patient-specific simulation of blood flow provides information about the effect of inserted implants such as stents to the blood flow.

Currently, no imaging modality exists that includes spatial and time-resolved blood flow information with high resolution. Time-dependent 2D-DSA displays the blood flow in a projection image. Static 3D-RA volumes incorporate the morphology of vessels. By fusing both modalities, blood flow and spatial information are available. We describe a method to achieve such a 2D/3D-registration.

Although 2D/3D-registration methods exist for quite some time (e.g. [2]), they require appropriate initialization for being successful. Such interaction is not acceptable for use in practice. Hence, our goal is to provide a fully automatic registration algorithm. The lack of user interaction should not affect the precision of our method with regard to similar approaches like [3] and [4].

The main challenges are to cope with the low information content in angiographies and the fact that acquisition geometry is known only approximately.

2D/3D-registration requires a projection of the 3D volume to the 2D image. X-ray based modalities like X-ray fluoroscopy were successfully registered to CT data sets [2]. An intensity-based approach was published that registers 2D-DSA to magnetic resonance angiography volumes [3] and later extended to register also 3D-RA volumes [4]. Recently, a feature-based deformable 2D/3D-registration for vascular models was presented [5].

The disadvantage in many algorithms is the need for user interaction. Several approaches rely on setting an initial position of the 2D image with respect to the 3D volume. In case of feature-based methods, a segmentation is commonly needed. Our registration requires neither a preprocessing step, nor user intervention. Also, in contrast to other algorithms only the approximate projection geometry has to be known.

2 Material and Methods

We achieve automatic registration by an iterative scheme that finds subsets of correct registration parameters in three steps. We will first describe the registration parameters before we continue with a description of the process.

The first input data set consists of a sequence of n 2D-DSA images that shows the blood propagation. The second input modality is a static 3D-RA volume. We assume that there are no major changes in the cerebral vessel system and a known orientation of both data sets.

The image intensities in both modalities correlate with the measured contrast agent (CA). As a 3D-RA data set shows the distribution of CA in the whole cerebral vessel system, we simulate this behavior by integrating the intensity values in the 2D-DSA sequences over time. The result is denoted as a 2D-MAX image. A projection is computed by raycasting through the 3D volume.

We use the maximum intensity projection (MIP) technique to produce 2D projection images and employ two transfer functions to visualize different vessel aspects. The first function aims to simulate a 2D-MAX image by visualizing large and medium vessels predominantly (MIP_1, Fig. 1(a)). The second function is used for displaying also small vessels and potential noise (MIP_2, Fig. 1(b)).

Registration requires to find intrinsic and extrinsic parameters. Intrinsic parameters can be assumed to be known as they can be estimated from image properties and meta information [4]. Extrinsic parameters describe the rigid transformation parameters and a projection with respect to a world coordinate system. Six extrinsic parameters $(\phi, \theta, t_x, t_y, s, \alpha)$ have to be found. ϕ and θ are the projection parameters (Fig. 1(c)). t_x and t_y are the 2D translation parameters, s and α are the 2D scaling and the in-plane rotation, respectively.

Automatic registration is carried out in three steps with 2D-MAX image and projection image as input. Each step focuses on a subset of registration

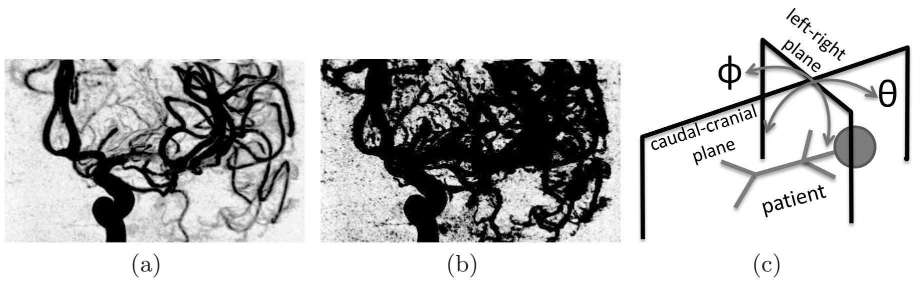


Fig. 1. Example of a projection image created with MIP_1 (a) and MIP_2 (b); scheme of the projection parameters ϕ and θ that define the position of the C-arm (c).

parameters. We apply a regular step gradient descent and use the normalized cross correlation (NCC) as similarity measure [3]. Preliminary experiments have shown that all parameters are within a certain range. t_x and t_y are constrained by the image size. s is in the range of [1.0, 1.4], ϕ and θ are in the range of $[-20°, +20°]$ from their given values, α is assumed to have a value of about 0°. Initial values for s, ϕ and θ are taken from image meta information.

The first step initializes the registration in terms of roughly superimposing 2D-MAX and projection image. The second step finds the correct scaling factor and the third step optimizes the projection parameters. The step-wise process was chosen to apply a coarse-to-fine approach.

In the first step, only t_x and t_y are regarded. All other parameters are set to their approximate values. t_x and t_y are initialized with either 1 or 5 different positions: $p_t(1) = \{c\}$, $p_t(5) = \{c, c + p_{x,y}, c + p_{-x,y}, c + p_{x,-y}, c + p_{-x,-y}\}$. c denotes the image center, $c + p_{x,y}$ indicates a point translated towards the corner of the image. MIP_2 is used in this step as it is more robust against initial translations. The maximal NCC value of p_t is regarded as the best translation. The output of the first step is the determination of $t_{\mathrm{x,\ init}}$ and $t_{\mathrm{y,\ init}}$.

In the second step, t_x and t_y, s and α are optimized. $t_{\mathrm{x,\ init}}$ and $t_{\mathrm{y,\ init}}$ are used for all initializations, α is set to 0. This time, s is varied for different initializations in the assumed range. MIP_1 is used in this step to simulate a 2D-MAX image.

In step 3, ϕ and θ are optimized. Approximate initial values of both parameters are known, t_x and t_y, s and α values are given by the result of the last step. MIP_1 is used as projection technique. In each iteration, ϕ and θ are altered by a value of $\pm\Delta = 5°$ and the other parameters are optimized like in step 2. The optimization process ends if no more improvement in terms of the NCC is measured. All six transformation parameters are determined.

We tested our algorithm on 10 dual-plane 2D-DSA images and 5 corresponding 3D-RA volumes from 5 different patients of the cerebral vasculature. All patients had one or more aneurysms. In one case, the 2D-DSA image was acquired before treatment of the aneurysm, the 3D-RA volume afterwards. The 2D-DSA had a resolution of $[720^2, 2048^2]$ pixels with $[20, 30]$ time frames and a pixel spacing of $[0.08, 0.29]$ mm. The 3D-RA images had a resolution of $[256^2, 512^2]$ pixels with $[149, 444]$ spatial frames and a pixel spacing of $[0.16, 0.53]$ mm.

In our first experiment, we aim to measure the robustness to find the correct initial translation in step 1. The first step is crucial for the whole registration. Starting with manually determined translation parameters as input, we gradually increase the distance of t_x and t_y and measure the capture range by using p_t with either 1 or 5 initialization points and by using MIP_1 or MIP_2. We consider registration step 1 as successful, if the Euclidean distance between computed result and manual estimation of t_x and t_y is lower than 10 mm. This distance is sufficient as initialization for the next step. The capture range is defined as the greatest distance that corresponds to an average success rate of ≥ 75 %.

The second experiment evaluates the precision of our method by using reference markers. Markers were set at salient image features (bifurcations,

Table 1. Average success rate of step 1 with regard to the number of initialization points (# i) and the used MIP for different distances from the correct position.

# i	MIP	10 mm	20 mm	30 mm	40 mm	50 mm	60 mm	70 mm	80 mm
1	1	100 %	56 %	46 %	52 %	29 %	25 %	31 %	31 %
1	2	96 %	77 %	69 %	48 %	42 %	38 %	38 %	38 %
5	1	100 %	94 %	88 %	75 %	81 %	81 %	69 %	56 %
5	2	100 %	81 %	88 %	100 %	75 %	75 %	69 %	56 %

Table 2. e_{RMS} of the registered test data sets. $P_1(2)$ refers to Patient 1 with angle 2.

measure	$P_1(1)$	$P_1(2)$	$P_2(1)$	$P_2(2)$	$P_3(1)$	$P_3(2)$	$P_4(1)$	$P_4(2)$	$P_5(1)$	$P_5(2)$
e_{RMS} [mm]	1.46	2.22	1.65	2.37	1.58	2.16	1.57	2.35	1.18	1.28

aneurysms) in the acquired image modalities by an expert. We employed a root mean square (RMS) projection error to sum the measured distances between corresponding markers: $e_{\mathrm{RMS}} = \sqrt{\frac{\sum_{i=1}^{N}(e_i)^2}{N}}$. e_i is the Euclidean distance between corresponding markers and $N = 20$ denotes the number of markers.

3 Results

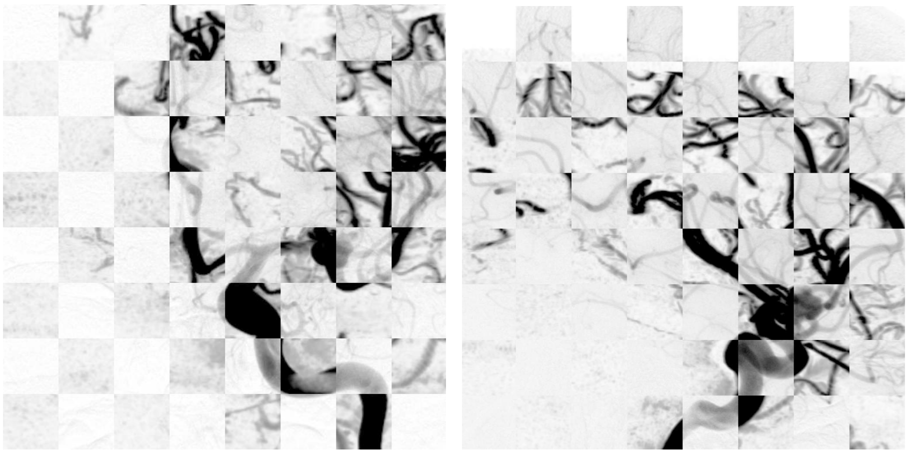
Table 1 summarizes the result of experiment 1. The robustness of step 1 is considerably higher using 5 initialization points than using 1 initialization point. Using a different MIP leads to a different robustness only in case of 1 initialization point. The actual distance in step 1 between starting point and correct determined $t_{\mathrm{x,\ init}}$ and $t_{\mathrm{y,\ init}}$ was always smaller than 70 mm in all our test data. The capture range using 5 initialization points is 60 mm in case of MIP_1 and MIP_2. The correct translation parameters could be determined in every case of our test data with 5 initialization points and the standard initialization.

Table 2 shows the result of experiment 2. e_{RMS} is between 1.0 mm and 2.5 mm with an average of 1.78 mm (standard deviation 0.45 mm). Fig. 2 visualizes two example results. The results for images with angle 2 are worse than for angle 1 because of the larger deviation from the initial parameters. We also tested the algorithm with a data set that violates one of our requirements, as an aneurysm treatment was done during image acquisition of 2D-DSA and 3D-RA. The algorithm also produced good results in this case.

4 Discussion

The proposed algorithm computes an automatic 2D/3D-registration. It was tested on a small number of samples. We measured a high robustness and a precision that is in the range of comparable approaches [3] and therefore achieved

Fig. 2. Two examples of registrations of $P_2(1)$ and $P_2(2)$, left and right, respectively. The projection and 2D-MAX image are arranged in a checkerboard pattern. Both images have a different intensity range. Additionally, due to the projection computation the vessel thickness is not always the same in both images. This leads to a challenging visual interpretation of the result images and also hampers the registration process.



our goal. By our three-step strategy we could eliminate the need for user interaction. The registration can be used for validation of simulation results.

Future work will include the extension of the registration algorithm for computing blood flow velocities in DSA data by backprojection.

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