Opacity Quantification In Cardiac Angiogram Sequences

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Abstract. The level of perfusion is routinely analyzed from the level of opacity in cardiac X-ray angiograms. We propose an image enhancement method for angiogram sequences by motion compensation and background subtraction. Moreover, we extract a time-series describing the opacification in a given region-of-interest to enable opacity quantification. The effect of background subtraction on opacity curve extraction and angiogram enhancement is tested as well as the performance of region tracking based on non-rigid alignment. The tests are performed with clinical data.

1 Introduction

We analyze a cardiac X-ray angiogram sequence to quantify microvascular injuries resulting from myocardial infarction. The aim is to develop a simple to use semi-automatic or fully automatic method to accomplish objective measurement of perfusion, as opposed to currently used observer-dependent visual inspection.

Cardiac angiogram sequences have four different phases [1] which are: *inflow* when the dye enters the arteries, *complete state* when the arteries are fully opacified, *washout* when the dye leaves the arteries and *venuous phase* when it enters the veins. An example of an input image can be seen in Figure 2 (left). For our algorithm we need at least the first three phases to be present in the data. During the inflow or the complete state phases the opacity of microvasculature increases, and depending on how much and how long the opacity persists we can determine the level of perfusion for small vessels and thus also the level of damage. In this work we present a method to extract curves describing the time course of the opacification.

2 Methods

The proposed method is based on image registration to compensate heart motion. Registration is followed by background estimation, search for matching cardiac cycle frames, region-of-interest (ROI) tracking and the quantification itself.

2.1 Registration

For movement compensation, we use a non-rigid image registration method where deformation is represented as a B-spline transform [2,4,5]. Multi-resolution is used in both image and transformation space to improve speed and robustness, specifically Gaussian pyramids and B-spline pyramid. The alignment error is measured using a SSD-criterium which is optimized using a L-BFGS optimizer. Non-rigid registration is initialized by translational alignment which compensates the table shifts, if present.

2.2 Background subtraction

After registration, we estimate the background as the mean intensity image over all frames in the aligned sequence:

$$B(\vec{x}, j) = \sum_{k=0}^{n} I(T_{j,k}(\vec{x}), k)$$

where $I(\vec{x}, k)$ is the k-th frame and $T_{j,k}$ is the deformation between frames j and k, found in the preceding step. Subtracting the background removes static objects and emphasizes opacity changes, see Figure 2 (right), similar to digital subtraction angiography (DSA).

$$I'(\vec{x}, j) = B(\vec{x}, j) - I(\vec{x}, j)$$

where $I'(\vec{x}, j)$ is the inverted image after background subtraction.

2.3 Matching frames

Unfortunately, the registration yields alignments with varying quality. We therefore propose to take only frames which are well aligned with the current frame to get better results. A chance for a good alignment is bigger for frames pertaining to the same phase of the heart beat (systole, diastole) as the current frame – we call such frames *matching frames*. We use the fact that the heart tissue is periodically stretched and compressed which shows as different intensity levels. For each frame we search for a set of matching frames, one in each heart beat. Heart rate is estimated from the periodicity of the image mean intensity $r(j)$ in time:

$$r(j) = \int I(\vec{x}, j) d\vec{x}$$

More specifically, we estimate the heart beat frequency f as the most prominent frequency after applying a high-pass filter H using Fourier transformation (Figure 1):

$$\hat{f} = \arg\max_f R(f)H(f) \text{ where } R(f) = \mathrm{FFT}_t(r)$$

Alternatively, we could obtain f from simultaneous ECG. However, in our case ECG data is not available.

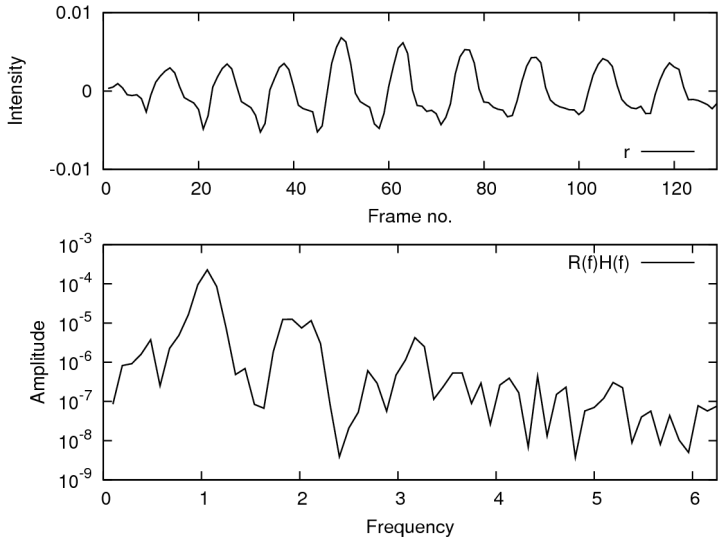

Figure 1. Heart rate estimation from the image mean intensity.

2.4 Opacity curve

The opacity changes are evaluated inside the ROI $\Omega(j)$ which is drawn by user in one frame or along one heart beat. Thanks to known inter-frame deformations T we can track the ROIs throughout the sequence.

$$\Omega(j) = T_{k,j}(\Omega(k))$$

Warped ROIs can be further adjusted by the user. We have observed that it is better to use a ROI from a matching frame than from an arbitrary frame.

As the last step, an *opacity curve* (Figure 3) describing the evolution in time of the mean opacity in the ROI is extracted as follows:

$$q(j) = \int_{x \in \Omega(j)} I(\vec{x}, j) d\vec{x} \Big/ \int_{x \in \Omega(j)} d\vec{x}$$

Instead of the mean, a high percentile (90%) of intensities inside the ROI can be used, as opacity values lie in the upper part of the histogram.

3 Results

The proposed method was validated using sequences obtained from patients at the hospital Na Bulovce, Prague, Czech Republic. Selected sequences are 8 bit 480x480 pixels, containing 75-100 frames, 12.5 frames per second, produced by a single-plane X-ray angiographic machine Philips Integris H. In the first experiment, tracked ROIs were compared to manually defined ROIs. When initialized in a single frame the mean overlap between automatic and manual ROIs was 59±6%, significant improvement to 84±7% can be achieved when initializing along a complete heart beat. Alignment of two frames takes 10-40s depending on desired accuracy and actual deformation.

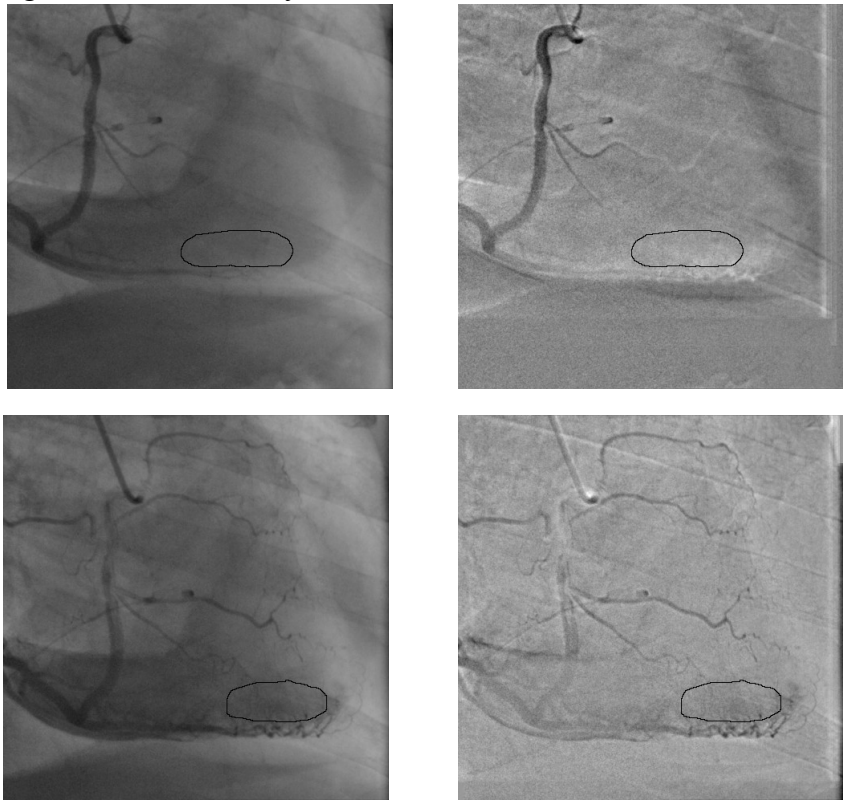

Figure 2. Inflow (top) and washout phase (bottom) angiographic frames with selected ROI. Unprocessed (left) and after background subtraction (right).

The second experiment (Figure 2) shows that background subtraction significantly improves readability of the images. Using only matching frames in background estimation gives better results as we exclude poorly aligned frames, and thus a sharper background is obtained. Also using less frames accelerates the algorithm. Similarly, while the opacity curves extracted without background subtraction are noisy, the opacity curves with background subtraction look more plausible (Figure 3). We can clearly observe how the dye enters and slowly exits the ROI. However, we have to be careful regarding opacity curve extraction. Background subtraction can introduce a bias towards lower opacity if we mistakenly include some opacity into the background. This bias depends on whether we use only the inflow phase matching frames for bacground subtraction (supposing good perfusion), or all matching frames (suitable for bad perfusion). With our data the differences are negligible.

We implemented an interactive tool containing the described method in C++ using the ITK toolkit [2]. Registration is computed offline to permit interactive exploration.

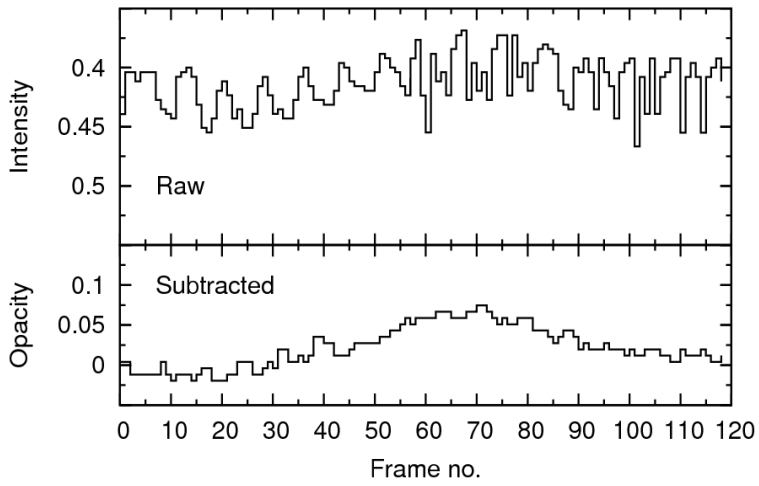

Figure 3. Opacity curve extracted from the original images (top) and after background subtraction (bottom).

4 Conclusions

We have proposed a method to enhance angiographic sequences by automatic alignment and background subtraction and to extract opacity curves for user-selected ROI. This should permit easier and faster semi-automatic perfusion classification. As far as we know, there are no other methods that deal with coronary opacity quantification. Since registration is essential to our approach, a better image registration technique less affected by auxiliary objects (catheter, electrode) and objects not important for our application (ribcage) would improve the results. Currently, we are developping an automatic method that uses described ROI opacity curve as a part of a toxicological model of perfusion to automatically assign TMP opacity level values [3]. Further details can be found in [6].

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