Automatic Extraction of quasi-Synchronous Views from Rotational Angiographic Sequence without ECG-Data

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Abstract. In this contribution we present an automatic method to extract quasi-synchronous views from a sequence of monoplane rotational coronary angiograms. Based on [1] we build the image of horizontal integrals, which contains information about the vertical motion of the coronary tree. The maxima of this motion correspond to end-distole states. We extract a curve of vertical motion and perform a spectral analysis to extract local maxima. We perform a spatial analysis to detect irregularities in the cardiac cycle, in order to extract just the regular views. Finally we present experiments on several angiographic sequences and compare the results to available electrocardiogram (ECG-) signal.

1 Introduction

3D centerline reconstruction of coronary vessels from rotational angiography sequences mostly involves ECG-data to detect synchronous views [2, 3]. Of interest are the end-diastolic states, since the heart has the minimal motion in this state. Several problems arise with the usage of ECG data: Firstly, the assignment of heart states from the ECG-signal is not an easy task and can be unprecise. Secondly, examined patients can have coronary diseases therefore the ECG-data is misleading. Thirdly, the next generation of C-arms does not offer the triggering with this signal. Finally there is a delay between the electrical state observed in the ECG-signal and the mechanical state observed in the angiograms [1]. Therefore, there is a need to develop methods for automatic extraction of *mechanically* synchronous views directly from the image sequence.

Based on the idea of Blondel[1], synchronous views can be extracted from a rotational monoplane angiographic sequence by analyzing the curve of vertical motion (CVM). Each image is preprocessed to enhance only the vessels. The *horizontal integrals* are then computed: For each row the sum over all columns is calculated. This integration marginalizes the horizontal motion and captures the vertical one. All these vectors (for each frame) are concatenated to get an image of horizontal integrals. The end-diastolic views are the maxima of the motion observed. To extract them a reference frame should be specified and the distances between the horizontal integrals of the reference image and the rest of the sequence are computed to get a one-dimensional CVM. Synchronous views are determined by computing the periode using the auto-correlation function of the curve. This method assumes a preprocessing, which completely eliminates the background and just preserves the vessels. It also assumes a certain regularity in the cardiac cycle and depends on the chosen reference image. In this contribution we present a new method, which try to overcome these limitations.

2 Method

We preprocess a whole sequence with an operator that enhances the vessels and reduces the background[4]. Scales that enhance especially big vessels are used. Those are mostly located at the beginning of the coronary tree and are bound in their motion. We build the image of horizontal integrals as described in[1]. The CVM is approximated by the *curve of maxima* along each column (red curve). Figure 1 visualizes these steps.

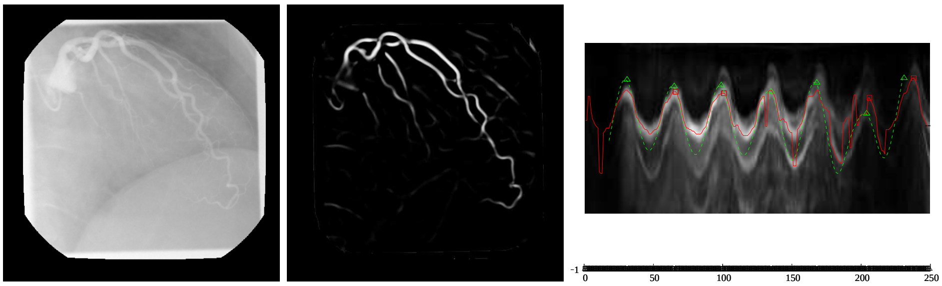

Fig. 1. From left to right: original image. Preprocessed image. The image of horizontal integrals.

Spectral Smoothing: The CVM is denoted by a set of points $v = v_0, \cdots, v_{N-1}$ of length N, the number of frames in the sequence used to compute the image of horizontal integrals. This is a finite discrete signal, which is mostly corrupted by noise and irregularities. Performing a Fourier transform would only deliver useful information if the signal is periodic or regular. Computing the power spectral density requires stationarity of the signal. Those are in most sequences not available. So we propose to perform a local spectral analysis using the short time Fourier transform (STFT). We aim to transform the signal v into a smoother one, having similar developing and preserving the maxima. The (finite) STFT can identify not only the frequency content of a signal, but also how that content evolves over time:

$$\mathrm{FSTFT}(n,k) = \sum_{\tau=0}^{T-1} v_\tau \gamma^*_{\tau-n} \exp\left(-j\frac{2\pi}{T}k\tau\right), \quad k = 0, \cdots, T-1, \tag{1}$$

where γ^*_n is the complex conjugate of a *window* function, having a short time duration, T represents some power of two containing the product of the signal and the window function which is zero-padded to the desired length T. Since we are dealing with a pseudo-sinusoidal noisy signal we propose to take the dominant periode of the signal as the width of the window $W = P_D$, where $P_D = \frac{N}{\lfloor k_{\max} \rfloor}$ and $k_{\max}$ is the index of frequency of highest amplitude among the Fourier coefficients of the Fourier transformed signal v. This choice has the advantage that we are able at some locations (at maxima) to recover a stationary signal with a complete single dominant periode of the original signal. Several typical window functions, that approximate the ideal but infinite Gaussian window, can be used. By applying a moderate one like the *Hann* window at position v_i

we smother the signal around v_i until vanishing at borders while preserving the value at v_i. At each position v_i the area under the square of the magnitude of this local product can be considered as a measure for the local variation at v_i. According to the Parseval's theorem [5] this area is equal to the area under the energy spectral density curve, that is $E(i) = \sum_{k=1}^{N} |\mathrm{FSTFT}(i,k)|^2$. We recover thus from the STFT-spectrogram a 1D-curve:*the curve of local energy* (CLE green in fig. 1). the CLE is smoother, more robust to noise and outliers and coincide with the original signal in the maxima.

Automatic Detection of Irregularities: This is a two-step approach. First the extrema of the input signal are extracted, by looking for points where the first order derivative vanishes. The first derivative disappears if its values are less or equal to the threshold $T_{\mathrm{d}eriv}$. The set of candidates is filtered to thin valleys of extrema and to through away points which are not consecutive minimum-maximum-minimum or maximum-minimum-maximum triplets. Second spatial features are computed and compared to decide for the regularity of the maxima. The ascending and descending double-amplitudes as well as the left and right half-periodes are computed for each triplet of extrema. Only extrema whose left and right values of periode and amplitude do not deviate a lot from the dominant periode and dominant amplitude are considered as regular. Four thresholds ($T_{\mathrm{A}low/up}$ for the amplitude, $T_{\mathrm{P}low/up}$ for the periode) have to be set to tune the sensitivity to this deviations.

3 Validation and Discussion

We applied the method on eight monoplane rotational angiographic sequences acquired using a Siemens AXIOM Artis system over an angular range of ca. $200°$. Four of them visualize the left coronary artery tree (LCT), the rest show the right tree (RCT). For all sequences the ECG-table was available as a relative percentage for each view of the cardiac cycle measured between two subsequent R peaks. We applied our method once on the CVM ($T_{\mathrm{d}eriv} = 0$) and once on the CLE ($T_{\mathrm{d}eriv} = 0.01$) setting $T = 256$, $T_{\mathrm{A}low} = T_{\mathrm{P}low} = 0.25$ and $T_{\mathrm{A}up} = T_{\mathrm{P}up} = 0.75$. The resulting curves are shown in fig. 2 and fig. 3. Due to the smoothing of the energy-curve, we additionalyy adjusted the extracted maxima by looking in the original signal within a window of 5 bothsides around the detected maxima.

We inspected the sequences visually and extracted manually end-Diastole views from the ECG-table. These are views which show the vessels completely filled before starting contraction. We chosed one reference image having this property and determined the views having nearest ECG-states to its state. These states are rarely the same due to the different frequencies of acquisition and heart beat. For each sequences we got six to seven ECG-states, which represent the ground truth.In order to quantitatively judge the method, we classifed the results to maxima that were detected and do correspond to an end-diastole state (F1). We tolerated hierby once one view and once two views of deviation. Maxima that were automatically detected but do not coorespond to end-diatole are false positive (F2). End-diatole views, which were not detected automatically represent the false negative (F3). Two sequences with RCT were not considered in the statistics, since signals were very corrupted. Table 1 summarizes the statistics for all sequences.

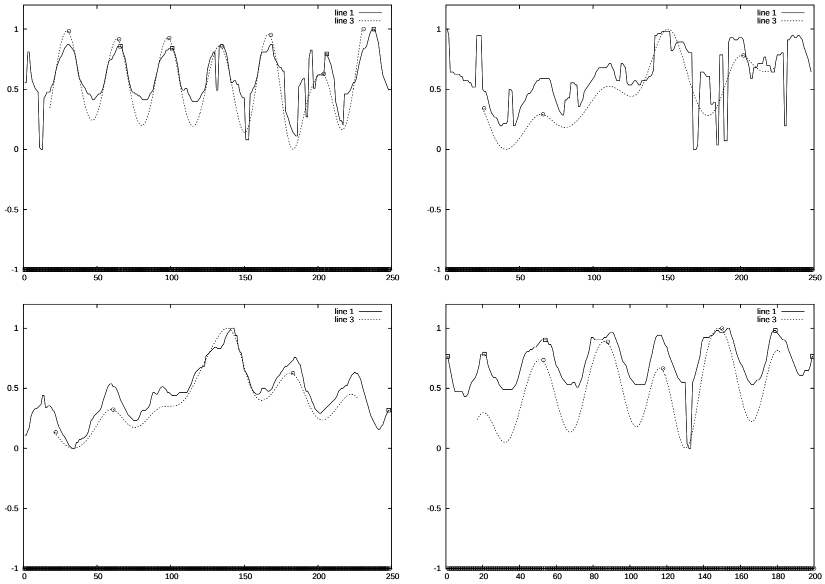

Fig. 2. Resulting maxima-CVM (continuousline) and CLE (dotted); automatically extracted maxima for seq. with LCT

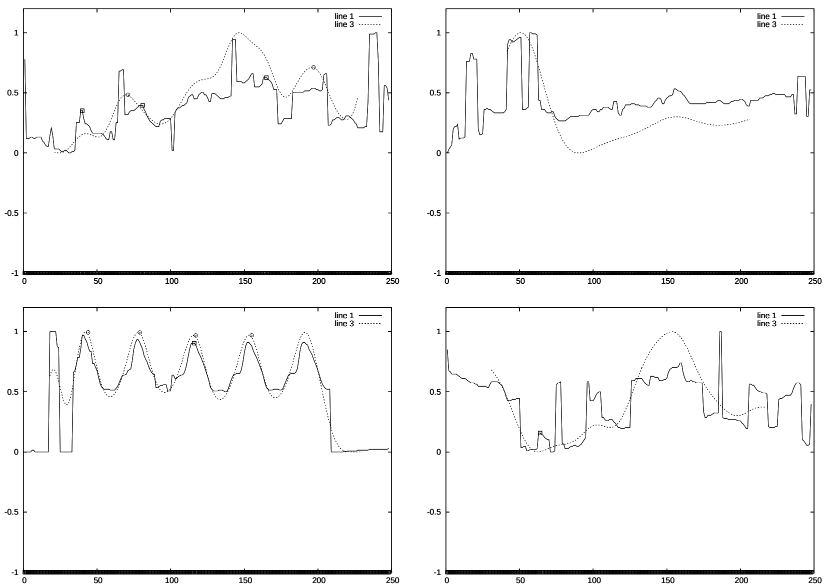

Fig. 3. Same caption as fig. 2 for seq. with RCT

		Four seq. with LCT (25 ECG-states)			Two seq. with RCT (13 ECG-states)		
	Tolerance	original	local enery	adjusted	maxima	local energy	adjusted
F1	1 view	20 %	36 %	48 %	23.08 %	15.38 %	30.77 %
	2 views	24 %	48 %	68 %	30.77 %	30.77 %	30.77 %
F2	1 view	12 %	36 %	24 %	7.69 %	30.77 %	15.38 %
	2 views	8 %	24 %	4 %	0 %	15.38 %	15.38 %
F3	1/2 views	68 %	28 %	28 %	69,23 %	53.85 %	53.85 %

Table 1. Evaluation of automatic extraction of quasi-synchronous states in all considered sequences

Discussion The curve of maxima is mostly very noisy and show many local maxima, valleys of maxima and discontinuities. The local energy transform operates like an overall smoothing, which -in several cases- avoids falling into local maxima. Most of time, more end-diastole states were correctly detected based on the local-energy curve (table 1, F1). Nevertheless the adjustment to the original signal revealed as advantageous, especially when allowing a deviation of two-views. Indeed up to 68% were then correctly detected ((table 1, F2). This tendency is better observed in sequences with LCT. Problems with the RCT can be explained by by the fact that the RCT moves rather horizontally, or their vertical motion overlap with C-arm rotation. Both cases hamper the detection of maxima. It has to be checked with an expert, whether this could be a pathological behavior. In general the more regular a signal is, the better is the automatic extraction. The detection of Irregularities sometimes discards states, which are at end-diastole according to the ECG-signal. This occur either at the beginning and the end of an energy curve (correspond to half of the window size of STFT), or where there is an irregularity in fact. We believe that discarding irregularities is eventhough advantageous for further processing.

Future work will concentrate on a better extraction of a starting curve, e.g by considering continuous maxima. Furthermore the deviation from the correct end-diastole state by one or two views has to be investigated wrt. 3D Model reconstruction.

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