# Myocardial Twist from X-ray Angiography

## Can we Observe Left Ventricular Twist in Rotational Coronary Angiography?

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**Abstract.** We present preliminary evidence that left ventricular twist can be observed and thus estimated from rotational coronary angiography. Our method is based on an ellipsoidal parametric model initially developed for functional analysis of cardiac tagged MRI. First, we fit the model to 3D coronary artery centerlines reconstructed from rotational angiography and then use 3D/2D registration to optimize for the functional parameters driving the model. On two clinical acquisitions, we show that our method is able to recover cardiac motion indicated by an average reduction in reprojection error of 28.1±3.0 %. Analysis of the functional progression of the functional parameters over time reveals radial and longitudinal contraction, and left ventricular twist. We believe that these results are exciting and encourage improvement of the proposed method in future work.

## 1 Introduction

X-ray angiography using C-arm cone-beam systems is the clinical gold standard imaging modality for diagnostic assessment and interventional guidance of coronary artery disease [1]. Recently, rotational angiography has received considerable attention. In this imaging protocol, the X-ray source rotates around the patient on a circular source trajectory acquiring images with high spatial and temporal resolution while contrast agent is administered to selectively contrast the coronary arteries. These acquisitions allow for 3D and 3D+t reconstruction of the vascular tree that are associated with increased diagnostic value [1, 2]. In contrast to static 3D reconstructions, dynamic 3D+t models further offer the possibility to recover functional parameters of the myocardium [3, 4], as the coronary arteries are directly attached to the outer wall of the heart muscle [5]. One potentially exciting application is the estimation of left ventricular twist from rotational angiography, a functional parameter that has so far not be considered in X-ray-based imaging due to the uniformity of the myocardial tissue in the X-ray spectrum [4]. In order to derive functional heart parameters from rotational angiography, surface models can be fitted to the imaging data. Until now, bicubic hermite splines [6] and superquadrics [7] have been used, however, in virtually all models functional parameters, such as longitudinal contraction of ventricular twist, have to be derived rather than being integral part of the model representation. On the contrary, Park et al. [8] proposed a left ventricular (LV) heart model for the functional analysis of cardiac tagged MRI. The left ventricle is modeled as a deformable ellipse and otherwise global ellipsoid parameters are replaced by parameter functions that vary over both the apical-basal axis and time to express shape and deformations, respectively. Moreover, these regional parameters are directly related to functional parameters of the heart [8]. Based on our previous work that described fitting a static parameter ellipsoid to a 3D coronary artery model [9], we present preliminary evidence that LV twist can be recovered from rotational coronary angiography. Our method estimates parameter functions of the LV model over time via 3D/2D registration of the parametric model to the rotational angiography sequence to recover physiologically meaningful parameters of the left ventricle.

## 2 Material & methods

In the following, the formulation of the parametric ellipsoid model is introduced. We then briefly review prior work on fitting a static model to 3D coronary artery centerlines. Finally, our contribution is the dynamic fitting process over the cardiac cycle in a 3D/2D registration approach. The section is concluded by an overview of test data and evaluation methods.

### 2.1 Parametric ellipsoid model

Park et al. modeled the left ventricle as a parameter function ellipsoid (PFE) cut off at $u = \frac{\pi}{4}$ [8]. $f_{\mathbf{t},\mathbf{a}_x,\mathbf{a}_y,\mathbf{a}_z,\mathbf{e}_x,\mathbf{e}_y}(u,v)$

$$= \underbrace{\begin{pmatrix} \cos\tau(u) & -\sin\tau(u) & 0 \\ \sin\tau(u) & \cos\tau(u) & 0 \\ 0 & 0 & 1 \end{pmatrix}}_{\text{twisting}} \underbrace{\begin{pmatrix} a_x(u)\cos u \cos v \\ a_y(u)\cos u \sin v \\ a_z(u)\sin u \end{pmatrix}}_{\text{ellipsoid and scaling}} + \underbrace{\begin{pmatrix} e_x(u) \\ e_y(u) \\ 0 \end{pmatrix}}_{\text{axis offset}}$$

with $u \in [\frac{-\pi}{2}; \frac{\pi}{4}]$ and $v \in [-\pi; \pi]$. The ellipsoid parameters are described in terms of functions $\tau(u)$, $a_x(u)$, $a_y(u)$, $a_z(u)$, $e_x(u)$, $e_y(u)$: $[u_{\min}; u_{\max}] \rightarrow \mathbb{R}$ along the apical-basal $u$-axis, which coincides with the $z$-axis in the PFE's reference system. Changes in $a_x(u)$ and $a_y(u)$ ($a_z(u)$) lead to contraction and elongation across (along) the apical-basal axis. $e_x(u)$ and $e_y(u)$ describe bent shape of the left ventricle by an offset from the principal axis. Lastly, the twist $\tau(u)$ rotates the model around the long axis. The impact of the different parameters is illustrated in Fig. 1.

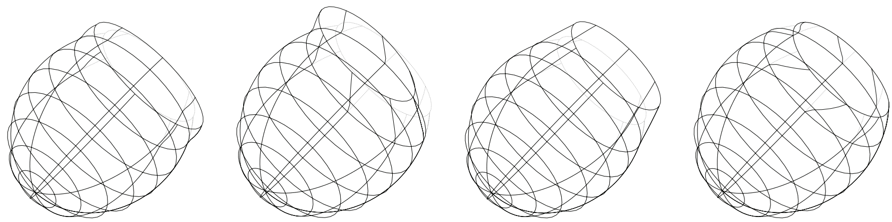
### 2.2 Centerline reconstruction and static model fitting

Coronary artery centerlines are segmented in all 2D fluoroscopy images and then reconstructed in 3D at an end-diastolic heart phase using a symbolic reconstruction algorithm based on the epipolar geometry [2]. Fitting the static parametric model to the 3D centerlines at end-diastole is a two step process, the details of which are provided in [9]. Put concisely, we first estimate the long axis of the LV using projection domain annotations of the user (apex and mid-basal points in two images) and, using this data to initialize the principle axis, fit a regular ellipsoid to the centerline points. Second, we replace the global parameters by parameter functions and refine the initial fit in a coarse-to-fine scheme. In this stage, the twist is set to zero. Once converged (Fig. 2), we associate each centerline point with its closest point on the model for further optimization.

### 2.3 Estimating a dynamic model

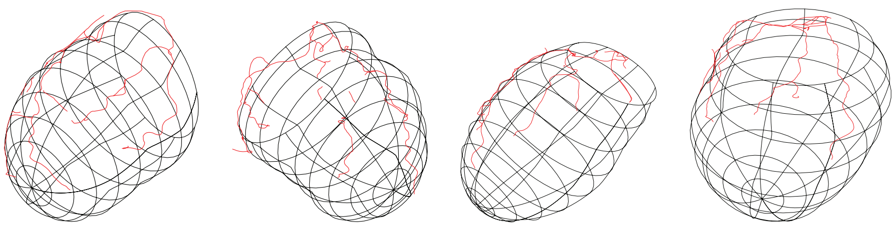
The static parameter function map retried in Sec. 2.2 is extended by a temporal dimension and initialized using the static result. Each projection image is associated with a normalized cardiac time $[0, 1[$, such that the dynamics can be recovered via 3D/2D registration. We seek to optimize

$$\underset{\mathbf{T}_x,\mathbf{A}_x,\mathbf{A}_y,\mathbf{A}_z\mathbf{E}_x,\mathbf{E}_y}{\arg\min} \sum_{\mathbf{u}}^{U} \sum_{i}^{I} \Gamma_i(proj(f_{\mathbf{T}_x,\mathbf{A}_x,\mathbf{A}_y,\mathbf{A}_z\mathbf{E}_x,\mathbf{E}_y}(\mathbf{u}, t_i), \mathbf{P}_i)) \tag{1}$$



(a) $a_x(u)$ and $a_y(u)$ (b) $e_x(u)$ and $e_y(u)$ (c) $a_z(u)$ (d) $\tau(u)$

**Fig. 1.** Effects of changed parameters of the parameter function ellipsoid at the basis.



(a) (b) (c) (d)

**Fig. 2.** Static PFE fitting result for P1 (a,b) and P2 (c,d) in two views each.

**Table 1.** Average reprojection error over all projections for the static (Sec. 2.2) and dynamic model (Sec. 2.3).

| | P1 [mm] | P2 [mm] |
|---|---|---|
| Static | 2.67 | 2.67 |
| Dynamic | 2.12 | 2.05 |

where $I$ is the number of projection images, $U$ is the set of centerline points on the PFE, and $\Gamma_i$ is the distance transform of the 2D centerline used to read out the reprojection error in view $i$. Further, uppercase letters $\mathbf{T}, \mathbf{A}, \mathbf{E}$ denote the dynamic versions of the parameter maps introduced in Sec. 2.1, and $proj((u), \mathbf{P}_i)$ describes the projective mapping of a 3D point $\mathbf{u}$ to 2D image coordinates of image $i$ using the projection matrix $\mathbf{P}_i$. Eq. 1 is optimized in a coarse-to-fine scheme using a line-search algorithm.

### 2.4 Data and experiments

We evaluate the proposed method on two clinical rotational angiography acquisitions referred to as P1 and P2, respectively. The data was acquired on a Siemens Artis Zee (Siemens Healthcare GmbH, Forchheim) and consists of 133 projections over 5 seconds. Coronary arteries centerlines were segmented and reconstructed, and the static model fitted as described in Sec. 2.2. We then adapt the dynamic model to the 2D projections by optimizing Eq. 1. On the finest resolution, 5 time steps are defined and parameters are interpolated in between. Finally, we state the average reprojection error before and after 3D/2D registration to quantify the effectiveness of motion compensation and plot the parameter functions over time to review whether LV twist could be retrieved.

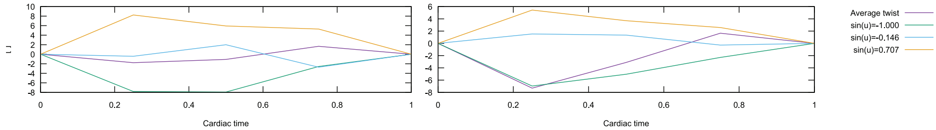
## 3 Results

We state the average reprojection error for P1 and P2 in Tab. 1. We observe a reduction in reprojection error when the proposed dynamic model was used, however, the errors are still well above the lower bound. This bound was obtained by computing the reprojection error with respect to the images used for reconstructing the 3D centerlines only and is 1.13 mm and 1.01 mm for P1 and P2, respectively. Additionally, we show the temporal progression of the parameter functions at the base, mid-ventricle, and at the apex in Fig. 3. From Fig. 3(a), we observe LV twist in opposite directions and base and apex, respectively, which is in agreement with the expected behavior [4].

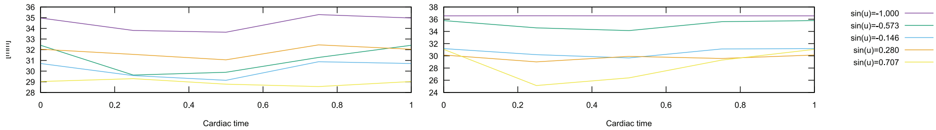
## 4 Discussion & conclusion

Both datasets show changes in the twist parameter w.r.t. the apex ($\sin u = -1$) compared to the base ($\sin u = 0.707$). Regarding long axis offset $e_x, e_y$, results are very noisy especially around the apex. Overall, the fitting process appears to be unable to fully recover the heart motion, which can be attributed to several factors. Very sparse sampling of coronary arteries at the apex does not allow for robust estimation of all functional parameters in that region. Further, erroneous segmentation have a two-fold effect on the results. First, it leads to discontinuities in the reconstructed artery tree of the reference phase, further affecting the sparsity problem. Second, wrongly segmented pixels in the other views can severely increase the reprojection error in the dynamic case.

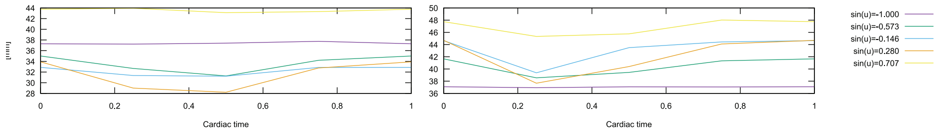
In conclusion, we presented preliminary indication that LV twist can be estimated from rotational coronary angiography. We used an ellipsoidal parametric model initially developed for cardiac tagged MRI to estimate the LV surface based on coronary artery centerlines. We then recovered the parameters of



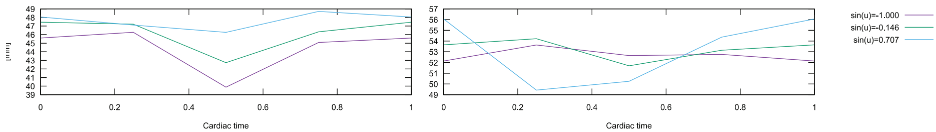

(a) $\tau(u,t)$



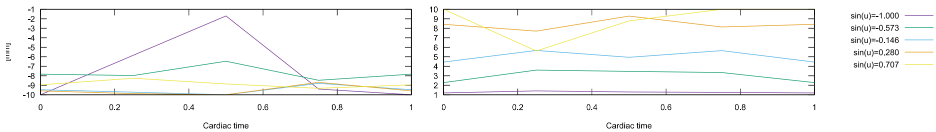

(b) $a_x(u,t)$



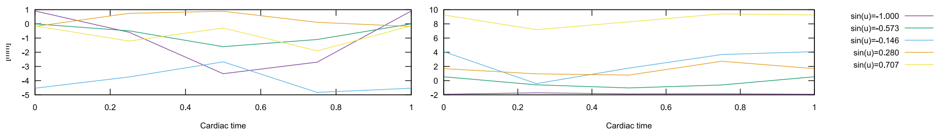

(c) $a_y(u,t)$




(d) $a_z(u,t)$




(e) $e_x(u,t)$




(f) $e_y(u,t)$

**Fig. 3.** Temporal progression of the functional parameters for P1 and P2 in the left and right column, respectively.

a dynamic model using 3D/2D registration to the projections. The proposed approach was able to compensate for cardiac motion and retrieves functional parameters, such as LV twist. While improvements to the method are necessary to draw more resilient conclusions, we believe that the results encourage future work.

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