

# Model-based Catheter Shape Reconstruction for Interventional MRI

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## Introduction

The use of real-time MRI for guidance of intravascular interventions is a rapidly developing research field given its superior soft-tissue contrast and the lack of hazardous radiation [1]. In order to visualize the entire length of such a catheter, a three dimensional (3D) image of a complete volume covering the catheter is necessary. Conventional MR imaging methods result in prohibitively long measurement times hampering 3D imaging in real-time. This may be addressed by applying sparse signal sampling theorems [2] to 3D MR imaging of catheter shapes [3]. Despite progress in this direction, undersampling factors remain limited to reconstruct images at sufficient quality for performing 3D curve fit of the catheter shape. Recently, a reconstruction method was proposed to determine parameters of perfusion model directly from undersampled  $k$ -space data [4].

In the present work a model-based reconstruction technique is proposed to determine the parameters of a 3D catheter shape model from undersampling  $k$ -space data taking into account the limited degrees of freedom. For this, a parameterized model of a catheter is fitted to the acquired  $k$ -space data by minimizing the  $l_2$ -norm. Using computer simulations and phantom data it is demonstrated that the catheter shape can be reconstructed from highly undersampled data indicating the potential of the method for 3D real-time imaging of catheter devices.

## Materials and Methods

### Theory

Registration of two objects refers to optimizing a similarity function between the target object  $y_t$  and the transformed source object  $x_t$  at time point  $t$ , e.g. by minimising the  $l_2$ -norm of the difference signal  $\|y_t - x_t\|_2 \rightarrow \min$ . Parseval's theorem states that the  $l_2$ -norm in both domains is identical which means that the optimization problem can be solved in the  $k$ -space taking the acquired MR signal  $d_t$  at time point  $t$  as target signal. In order to perform a least-squares fit, the representation of the source object in the  $k$ -space has to be modelled (Fig. 1).

To this end, a parametric model of the catheter shape is transformed from the image domain to  $k$ -space and then registered to the acquired data. Thereby the number of independent degrees of freedom to be solved for in reconstruction is reduced. The problem of fitting a parameterized curve in 3D to MR data can be written as

$$\|\mathbf{WFI}(c(\mathbf{p}_t)) - d_t\|_2 \rightarrow \min_{\mathbf{p}_t}$$

where  $\mathbf{p}_t$  is a parameter vector describing the curve  $c$  at time point  $t$ ,  $\mathbf{I}$  is the image model of the given curve,  $\mathbf{F}$  is the Fourier transform operator and  $\mathbf{W}$  contains the sampling pattern (Fig. 1).

### Experiment

A phantom experiment was carried out to assess the proposed technique. Data were acquired on a 3T MR scanner (Achieva, Philips Healthcare, Best, The Netherlands) using a standard head coil to achieve a homogeneous sensitivity profile. A tubing of 14 cm length (inner  $\varnothing$  2.5 mm) was filled with Gd-DPTA-doped water to decrease T1 relaxation time. The tube was placed in open space to mimic selective fluorine imaging of a catheter [5]. For data acquisition, a 3D balanced SSFP sequence (field-of-view  $200 \times 100 \times 100 \text{ mm}^3$ , spatial resolution  $1 \times 1 \times 1 \text{ mm}^3$ , TR/TE/flip  $2.8/1.36/45^\circ$ ) was acquired and equidistant undersampling of phase encodes was performed retrospectively. The shape of the catheter in the acquired position was modelled with 12 parameter using Catmull-Rom splines with four nodes equidistantly distributed along the curve. The catheter shape was dislocated from the correct position by bending the last node away from its optimal position, hence modelling a catheter with a bending head (Fig. 2a) and the evolution of the cost function assessed for full sampling, 80- and 140-fold undersampling resulting in acquisition of 7840, 87 and 56 profiles, respectively.

## Results

Fig. 2a shows the centerline of the parameterized catheter model (black) with a bent head in relation to the actual acquired position (volume rendered, gray). Fig. 2b shows the  $l_2$ -norm for angulations around  $x$ - ( $\alpha$ ) and  $y$ -direction ( $\beta$ ), respectively. For all orientations and undersampling factors, the cost function shows a single global minimum which reflects the robustness of recovering the catheter from fully and highly undersampled data.

## Discussion and Conclusion

The simulations and phantom experiments prove the feasibility of model based reconstruction for 3D catheter shape recovery from sparse MRI data. It was shown that a model of the catheter curve can be fitted to acquired complex data in  $k$ -space with undersampling factors up to 140. Setting bounds for the search space based on length- and displacement-constraints may help to promote termination of the least-squares solver in the global minimum. Further experiments are warranted to test the framework on actual catheter data obtained with fluorine imaging and optimized sampling schemes.

[1] Razavi et al., Lancet 2003 1877-82

[2] Lustig et al., MRM 2007 1182-95

[3] Schirra et al., MRM 2009, 341-7

[4] Awate et al., Proc. IEEE EMBS 2006, 936-41

[5] Kozerke et al., MRM 2004, 693-7

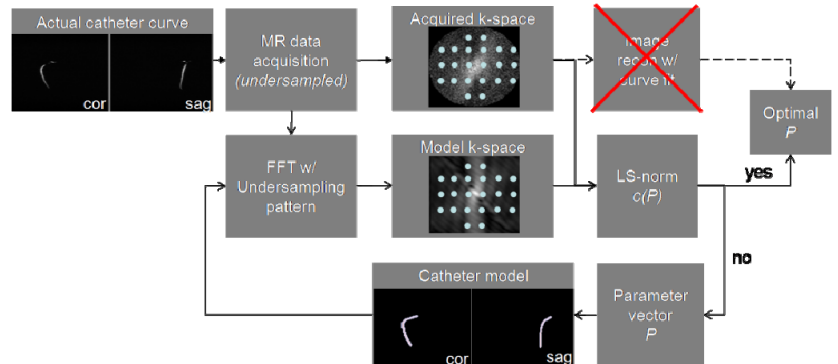


Fig. 1: Catheter modeling and fitting scheme where a parametric catheter model is fitted in  $k$ -space. From a set of parameters  $\mathbf{p}_t$  at time point  $t$  a parameterized curve and a binary image of the catheter model is calculated. Subsequently, its  $k$ -space representation is derived and its similarity to the acquired  $k$ -space data measured using the  $l_2$ -norm.

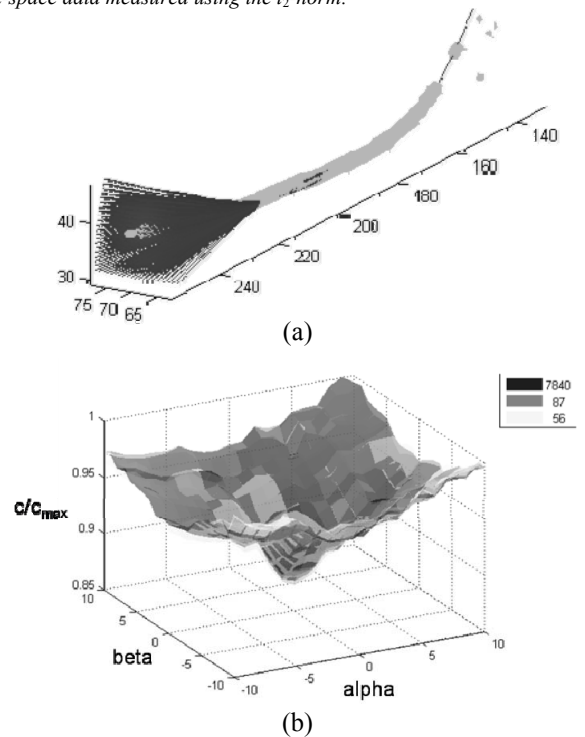


Fig. 2: Fitting parameterized model to acquired complex data. The distal node was bent from its optimal position (a) and the  $l_2$ -norm calculated for angulations around the  $x$ - and  $y$ -axis (b).