A compact and accurate set of basis functions for model-based reconstructions

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Abstract: Model-based perfusion reconstruction (MBPR) by using a weighting sum of basis functions, is used to describe the dynamic contrast agent distribution by superposition of incorporated prior knowledge. It handles temporal under-sampling in measurements acquired with a slowly rotating X-ray-based imaging system, in our case a C-arm based computed tomography (CT). However, here challenging issue arises that the computing complexity increases proportional to the number of prior knowledge elements. Thus, the aim of this study is to analyze clinical data and elaborate basis functions, that maps various patients with a small orthonormal basis set (ONB).

This work is based on five reconstructed clinical perfusion CT data sets. For each patient, regions of interest were manually figured out in order to enhance the content. Therefore, bones and catheters have to be removed out of the data, to prevent a falsification of the curves by them. The principal component analysis (PCA) to compress the relevant information of perfusion and create an ONB was used. In order to achieve an ONB which also optimal maps unknown patients, the cross validation method was used, i.e. the datasets of four patients were utilized for the estimation of the ONB, while the remaining patient was used for evaluation. Finally, the ONB gets evaluated by the mean-absolute-percentage-error (MAPE) of MBPR. A compact ONB with three basis functions that maps all five patients without a significant deviation of the approximated curves and the original ones is obtained. Especially, regions with high blood supply can be reconstructed very accurately and a reduction of noise is qualitatively visible in the image. An optimum ONB for the MBPR requires that the curves can be modeled as exactly as possible with a few basis elements. The use of only a few elements also leads to short computing times. In this work a good approximation of the curves with three basis elements is received. This results in an improved MBPR that in turn can lead to a higher precision of stroke diagnostics and treatments by using C-Arm CT.

Keywords: C-arm CT, model-based reconstruction, perfusion imaging

1 Introduction

The most common type of stroke is the ischemic that is caused by an inadequate blood supply of the brain. A precise and fast diagnostic is necessary for a successful stroke therapy. Caused by transports between the radiology, where the 4D perfusion imaging proceeds, and the angiography up to two hours can be lost. 4D-C arm CT supported treatment of strokes directly in surgery would enhance the success [5]. In other words, it would avoid transports between the radiology, where the 4D perfusion imaging proceeds, and the angiography [6]. The issues are addressed to the temporal undersampling of the acquired projections due to the long rotation duration and the slow detector read-out rate of a C-arm system (in comparison to the standard CT). Hence, model-based approaches has to be applied in order to handle enable 4D C-Arm CT.

Beside various approaches, e.g. see Wagner et al. [11] or Manhart et al. [10], aims is to support model-based methods that are estimating the distribution of contrast agent by a superposition of prior knowledge in form of an orthonormal set of basis functions. Motivated by works presented by Neukirchen et al. [6, 7], Neukirchen [8], Serowy et al. [9] and Bannasch et al.[3] that i. a. showed that appropriate prior knowledge is essential for an accurate MBPR with a low computational complexity, this work is focused on generating a compact and accurate set of basis functions for model-based reconstructions.

2 Material and Methods

The framework is based on reconstructed clinical perfusion CT data sets. The reason for using the clinical CT perfusion data for elaborating of basis functions is given by the rotational speed of ∼ 1000 frames per seconds (fps). The data

1 This procedure is also known as the one stop shops [4] and is one project of the Forschungscampus STIMUALTE. It follows the guideline: time is brain.

2 Actually, distributions of a gamma-variate, see [12] function as prior knowledge represents the gold standard for a analytical basis set.
Tab. 1: clinical CT patient data

<table>
<thead>
<tr>
<th>patient</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>duration of acquisition in sec.</td>
<td>50.9</td>
<td>48.0</td>
<td>48.0</td>
<td>48.0</td>
<td>48.0</td>
</tr>
<tr>
<td>number of temporal samples</td>
<td>34</td>
<td>28</td>
<td>28</td>
<td>28</td>
<td>28</td>
</tr>
</tbody>
</table>

can be interpreted as simultaneous acquired projections and an arbitrary algorithms, e.g. the filtered backprojection i.e. explained in Buzug [1] or Dössel and Buzug [2], can be used for reconstruction. However, 4D reconstructions are only limited by exposure and represent the gold standart of CT perfusion imaging. The sampling rate of 5 different perfusion data sets are shown in table 1.

In order to enhance the content of relevant information, a region of interest (ROI) is figured out for each patient. The arterial input as well as the central part of soft tissue are ROIs. In contrast to this white matter doesn’t matter for the elaboration of the basis functions. There is only less blood supply that causes an offset of the functions only. However, to prevent this and also a falsification of the functions by bones or catheters, a mask is used to remove them out of the data.

For compressing the relevant information of perfusion to a low dimensional ONB, the PCA was used. With the exception of the data of one patient, all provided clinical data are used to obtain an optimal ONB that maps all patients as accurately as possible. For optimizing the target ONB redundant dynamics are eliminated.

In addition, MBPR $\tilde{y}_i$ can be simulated by computing the inner product

$$\tilde{y}_i = \sum_j (\tilde{x}_i, \tilde{b}_j) \cdot \tilde{b}_j \quad (1)$$

of the basis functions $\tilde{b}_j$ and the primary data $\tilde{x}_i$.

The optimized set $\tilde{b}$ can be evaluated with the data set that was unexploited. The quantitative evaluation of the basis functions is done with the MAPE between the primary and the reconstructions.

3 Results

Figure 1 and 2 demonstrate the evolution of ONB starting with the first patient and ending with the fifth. An example for a rebuilt curve of contrast agent distribution is shown in 3. In addition to this ONB evolution, in figure 4 and 5 corresponding 4D CT images are illustrated for a selected temporal sample point. To visualize the difference between the images 4 and 5, a subtracted one is shown in the figure 6.

3 Further details are shown in [3].
4 Discussion

The comparison of the first 1 and the last 2 ONBs indicates that the inclusion of further data sets results in less noise or smoothed out the function elements. Hence, a regularization of the perfusion image is also effected to 5 by applying the ONB from 2. The exemplary curve in figure 3 and the subtracted image in 6 confirm this observation. A primary curve of contrast agent distribution as well as a reconstructed one, located in the superficial temporal artery, is shown. Both curves obtain the characteristic of a the AIF, whereby the reconstructed one obtains qualitatively less noise.

This kind denoising is caused by applying the PCA on an increasing number of data sets and elimination of redundancies. Thus, a high number of data sets will provide an analytical ONB, such that it is not necessary to use an additional regularization method in order to get an accurate perfusion image. This can be seen in 3, where the primary function as well as the reconstructed function of one voxel, located in the superficial temporal artery, is shown. Both functions have the characteristic of a the AIF, whereby the reconstructed one obtains qualitatively less noise. Furthermore, the curves in 3 show that the optimization progress has not yet been completed. There is still a mismatch of the time-to-peak parameter of the curves visible and a underestimation of the primary curve is also present. However, the MAPE decreases with an increasing number of used patient data, that can be seen in 7. Thus, further patient data has to be investigated in the further work, such that a smooth ONB that matches the relevant perfusion parameter, e. g. described in [13], is obtained in an optimal way.
5 Conclusion

Measurements received from slowly rotating X-ray-based imaging systems are temporal under-sampled. To deal with this problem MBPR is used to estimate the dynamics of contrast agent distribution by superposition of incorporated prior knowledge. To minimize the computing complexity the number of prior knowledge has to be kept low. Thus, the dimension of the target ONB has to be as small as possible. Based on clinical perfusion CT data, basis functions are computed. In order to increase the quality of the functions, regions of interest are figured out.

By an increasing number of patient data the noise can be eliminated by using i.a. the PCA and the MAPE. An ONB that maps all five patients without a significant deviation of the approximated curves and the original ones is obtained.

For further improvement of the ONB more perfusion data sets have to be investigated. Finally, they have to be applied to modern model-based reconstruction algorithms, like e.g. the time separation technique described in [3], and evaluated by means of perfusion parameters [13].

Acknowledgment: The authors thank Professor Dr. Thomas Henzler and the M²OLIE Forschungscampus for providing the CT data sets.

Author Statement

Research funding: The work of this paper is funded by the Federal Ministry of Education and Research within the Forschungscampus STIMULATE under grant number '13GW0095A'. Conflict of interest: Authors state no con-