Data Driven Surrogate Signal Extraction for Dynamic PET Using Selective PCA

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***Abstract*—Respiratory motion correction is beneficial in PET. Methods of motion correction include gated reconstruction, where the acquisition is binned, based on a respiratory trace. To acquire these respiratory traces, an external device, like the Real Time Position Management System, or a data driven method, such as PCA, can be used. Data driven methods have the advantage that they are non-invasive, and can be performed post-acquisition. However, data driven methods have the disadvantage that they are adversely affected by the tracer kinetics of a dynamic acquisition. This work seeks to evaluate several adaptions of the PCA method, through which it can be used with dynamic data. The methods explored in this work include, using a moving window (similar to the KRG method of Schleyer et al. (PMB 2014)), extrapolation of the principal component from later time points to earlier time points, as well as a method to select and combine multiple respiratory components. The respiratory traces acquired, were evaluated on 21 patients, by calculating their correlation with a Real Time Position Management System surrogate signal. The results indicate that all methods produce better surrogate signals than when applying static PCA to dynamic data. Extrapolating a late principal component, produced more promising results than using a moving window, and selecting and combining components held benefits for all methods.**

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I. INTRODUCTION

RESPIRATORY motion reduces image resolution by introducing blurring and mis-alignment artefacts [1]. Methods of Motion Correction (MC) include gated reconstruction; bin the acquisition based on a Surrogate Signal (SS). This SS is a respiratory trace which reflects the position of the patient in the respiratory cycle over time [2], [3]. Methods to determine the SS include those which use an external device, for instance, the Real Time Position Management (RPM) [4]. A disadvantage of such methods are that they require the use of additional equipment, and a change to clinical practice. Thus, data driven methods to extract the SS have become an alternative for static PET data. However, current data driven methods are adversely affected by the radiotracer kinetics of a dynamic PET acquisition; where the tracer is injected after the beginning of the scan. As an example, methods that use dimensionality reduction (such as PCA [5], [6]) are hampered by the fact that at the start of the scan, rapid redistribution of the radiotracer causes more variance in the data, than the respiratory motion.

Previously, work was performed to extend Spectral Analysis Method (SAM) to be robust to radiotracer kinetics. This work proposed the use of Short-time Fourier transform (STFT), to generate masks for SAM. This

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was called Kinetic Respiratory Gating (KRG) [7]. STFT operates by splitting the data into time windows, and doing a Fast Fourier Transform on them independently. This could be approximated by windowing the data first, and then performing SAM.

The aim of this work is to propose several adaptions of the PCA method, through which it can be used with dynamic PET data, and compare their performance with a method based on KRG. The methods explored in this work include; the use of a moving window, re-use of the Principal Components (PCs) from a later time point to estimate the SS from earlier time points, and the automatic selection and combination of multiple PCs.

II. METHODS

A. Data Acquisition

Data was acquired from a research study with patients suffering from idiopathic pulmonary fibrosis. 21 dynamic 18F-FDG PET acquisitions, with a Field of View covering the upper lung and heart, were acquired on a GE Discovery 710 [8], [9]. SSs were acquired in parallel using the RPM.

B. Data Preparation

Time-of-Flight (TOF) data were unlisted into low spatial resolution sinograms, each with a time frame duration of $500\,\mathrm{ms}$, using the GE PetToolbox, resulting in sinograms with dimensions $95 \times 16 \times 47 \times 11$ (radial positions$\times$angles$\times$transaxial plane$\times$TOF).

Data was pre-processed, first by applying a Freeman-Tukey transformation [10], before then applying a Yeo-Johnson power transformation [11]. This is in order to attempt to transform the Poisson distributed data to be more Gaussian-like. The resultant sinograms are further spatially downsampled.

PCA was applied to the TOF data [12].

C. Moving Window

The data is split into a series of windows, where each subsequent window overlaps with the previous by half its length. The size of each window is predetermined and was selected experimentally. For this method PCA is applied independently on each window, and the results are averaged together, after sign correction. As the sign of the signal from each window is arbitrary, the overlapping allows for a common sign to be found, by comparing the correlation coefficient of neighbouring windows. If SAM is used here rather than PCA, then the method approximates KRG [7].

In Fig. 1, the Moving Window size optimisation for the PCA method can be seen.

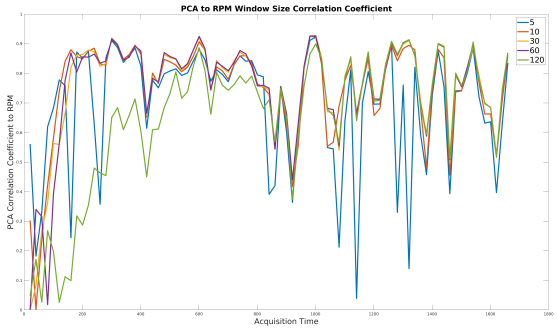

Fig. 1. A plot showing the Moving Window size optimisation for the PCA method. For different fixed window sizes, the correlation of the extracted signal to the RPM is shown for the windows sliding over the whole acquisition (taken for the first acquisition of patient one). Note that $0.5\,\mathrm{s}$ time frames were used.

D. Late Time Point

A PC from a late time point is taken, and used with early time point data. The cutoff between early and later time points was determined experimentally; by varying the cutoff point and observing the impact on the correlation coefficient, between the output and RPM signal for the first $120\,\mathrm{s}$ (between $20\,\mathrm{s}$ and $140\,\mathrm{s}$).

E. Select and Combine

Here a "respiratory score" is used to order and combine multiple PCs to maximise this score.

1) Selecting PCs: We used two methods for scoring:

In the first, Power Spectral Density (PSD) are calculated, and frequency windows representing the content of information related to radiotracer kinetics, respiratory motion, and noise are defined. The contribution within each window is determined for each PC, by finding the maximum magnitude within the windows. Ratios are then calculated between the respiratory and the kinetic windows, and the respiratory and the noise windows and a score determined by the product of these two values.

In the second, a Neural Network (NN) was used for scoring. The NN is a pre-trained model, designed to accept a signal as input, and return a score between 0.0 and 1.0, where the greater the value the more respiratory-like the signal. The NN was originally trained on a similar set of training data, where the scores were predetermined by clinicians [13].

2) Combining PCs: PCs are first sorted according to the score. The sorted PCs are iterated over and both summed and subtracted with a weighting (the score), and a new score is found for both resulting signals. If one of the signals increases the score, it becomes the new best PC, and goes forward to the next iteration. PCs are

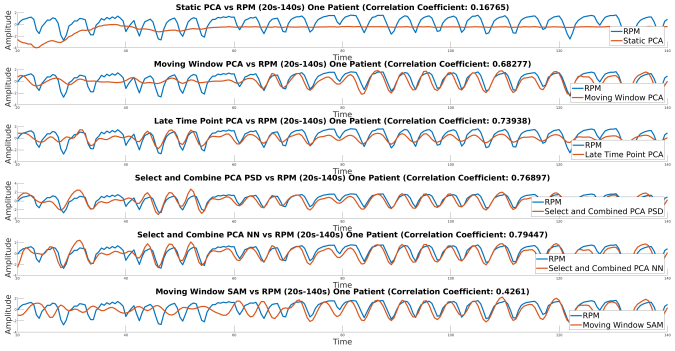

Fig. 2. A plot showing for each method its output compared to the RPM for the first 120 s (between 20 s and 140 s) (taken for the first acquisition of patient one).

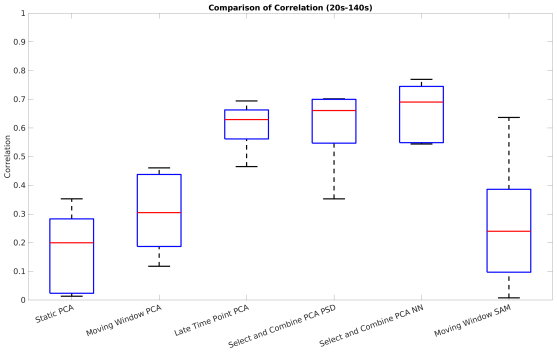

Fig. 3. A box plot showing for each method its correlation coefficient, to the RPM, for the entire acquisition (taken for seven acquisitions).

both summed and subtracted to handle the arbitrary sign problem.

A similar method of combining signals was developed in [2]. However, the scoring method used there (standard deviation) is not directly related to respiration. In addition, [2] combined signals from voxels where our methods uses PCs.

F. Evaluation

For evaluation of the results, the correlation coefficient of each SS between each method and the RPM, for all acquisitions, has been calculated. The correlation coefficient has been calculated for both the first 120 s, and also the entire acquisition.

III. RESULTS

From Fig. 2 and Fig. 5 it can be observed that the Static PCA method has failed, as expected. Both Moving Window methods extract a signal at later time points only. The Late Time Point, Select and Combine PSD, and Select and Combine NN methods all appear to be able to extract a usable signal, down to 20 s after the start of the scan.

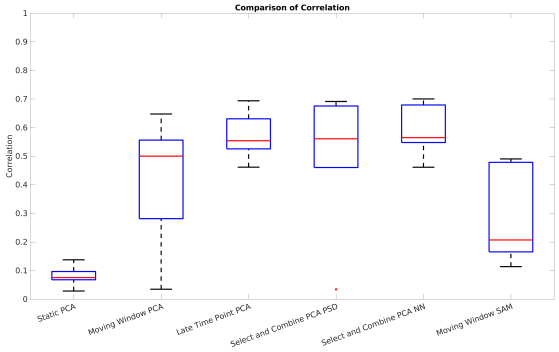

Fig. 4. A box plot showing for each method its correlation coefficient, to the RPM, for the first 120 s (between 20 s and 140 s) (taken for seven acquisitions).

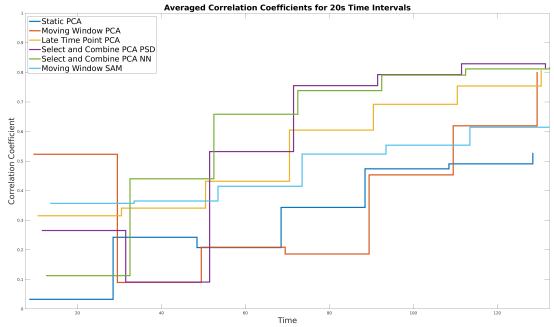

Fig. 5. A plot showing for each method its correlation coefficient, to the RPM, for the first 120 s (between 10 s and 130 s, in 20 s windows, taken as a mean for all data).

In Fig. 3 and Fig. 4, the improvement of the Late Time Point, Select and Combine PSD, and Select and Combine NN methods is most apparent, with high correlation coefficients for both the early time point, as well as for all data. The Select and Combine methods show marginally higher correlation coefficients than the Late Time Point method, and the NN shows slightly higher correlation coefficients than the PSD.

In Fig. 6 it can be observed the Static PCA method returns a PC which closely resembles the input data, leading to the conclusion that variation from a number of sources is included. It appears from a visual inspection that the least confounding variation and noise is included in the Select and Combine with NN method.

IV. DISCUSSION AND CONCLUSIONS

Results from the comparison to the RPM indicate, the Late Time Point and both Select and Combine methods are more robust and afford higher quality signals than both Moving Window methods. The results also indicate, both Select and Combine methods can give a higher correlation coefficient earlier than the Late Time Point method. The

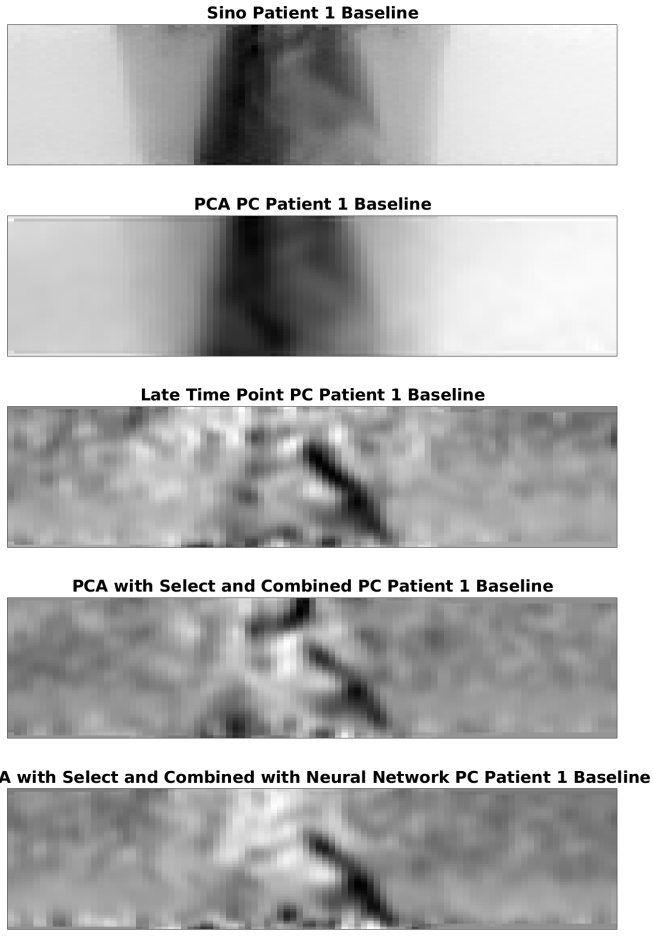

Fig. 6. A plot showing the PC used to generate the output signal (taken for the first acquisition of patient one).

NN shows slightly higher correlation coefficient than the PSD.

In the future, research will focus on further development of the method, including, optimisation of the NN scoring method. In the next stage, these methods will be applied to the task of implementing advanced respiratory Motion Correction on dynamic PET data.

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