Principal Component Analysis of the 3He ADC

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Introduction

Comparison of hyperpolarized ^{3}He MRI images of the lungs is often based on the analysis of the average ADC (Apparent Diffusion Coefficient) value for the entire lung, since registration of images between subjects is problematic. This method immediately loses any spatial heterogeneity which is clearly apparent in the images.

A change in mean ADC *may* reflect the main difference between the images, but there may be other features that are of interest, which this method fails to highlight. Here we present a novel way of analysing the distribution of ADC to assess changes in the lung that simple analyses may miss.

Materials

1.5T whole body system (Eclipse, Philips Medical Systems, max grad. strength 27 mTm^{-1}, rise time to max 370 μs). Flexible twin saddle quadrature ^{3}He T-R coil used (IGC Medical Advances).

^{3}He gas polarized on site to 30% by optical pumping with rubidium spin exchange apparatus (Amersham Health).

In-vivo imaging was performed at *full inspiration* following breath-hold of a 300ml ^{3}He/800 ml N_2 mixture from a Tedlar bag.

Age matched groups of
- **twelve healthy non-smokers,**
- **five healthy smokers,**
- **six patients with moderate COPD**

were studied with approval from the local Research Ethics Committee.

Methods

MR sequence : interleaved low flip angle gradient echo acquisition with reference scan (*b=0*) followed by a diffusion-weighted acquisition (*b=1.6 scm^{-2}* – bipolar trapezoids - strength 19.5 mTm^{-1}, duration 460 μs & 500μs ramp time –***direction in-slice***).

Phase encoding : *centric* - 112 views, flip angle 7°, 11 **coronal** slices, 15 mm slice thickness & 5 mm gap, FOV=42 cm, TE=2.5 ms, TR=6.7 ms, 128 samples, BW ±16kHz.

Spirometry was performed on all subjects. Diffusion imaging was performed following hyperpolarized 3-Helium gas inhalation to produce regional ADC maps, which were assessed in random order by an observer who was blinded to all the patient data. Figure 1 displays example ADC images of a healthy volunteer.

Data processing

Raw data processed with Matlab® code (Natick, MA, USA). The trachea and bronchi were deliberately segmented out of the analysis.

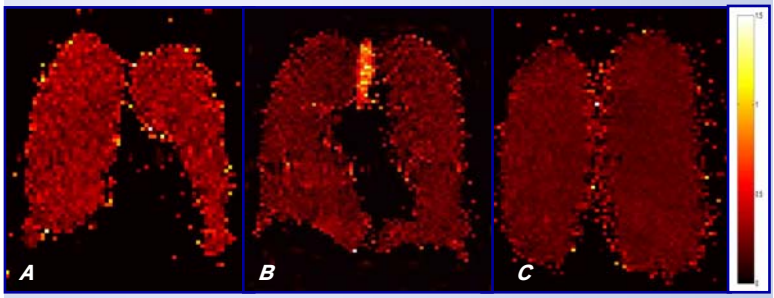


Figure 1: ***Coronal ADC images of a healthy volunteer. A is an anterior slice, which is 2 slices anterior to the tracheal slice, (B). C is an ADC image from a slice that is 2 slices posterior to the tracheal slice***

Statistical Analyses

The statistical analysis is based on the frequency distributions of all voxel values of ADC from the specified ROI from each of the nine images for one subject. Exploratory analyses are based on the histograms and kernel density estimates (KDE) of the distributions of ADC and Figure 2 compares the KDEs for a healthy subject and a subject with diseased lungs. There are clear differences in the mean, spread and possibly skewness between the two distributions.

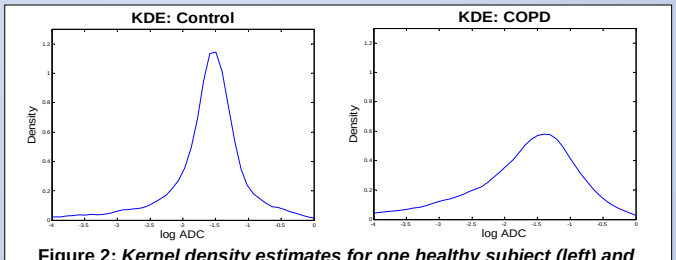


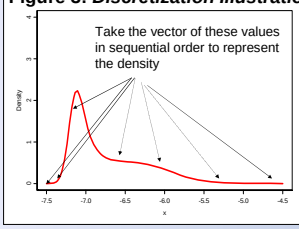
Figure 2: ***Kernel density estimates for one healthy subject (left) and one subject with COPD (right)***

The main analysis is ***functional principal component analysis (FPCA)***, a multivariate technique aiming to locate the principal sources of variation between the distributions by principal component analysis of the discretized distributions. The resulting principal components (PC) are used to construct an exemplary set of distributions providing the distinct types of variation.

Method: The first step is to summarize the functions in a small number of parameters and this is achieved by discretization, which is explained in Figure 3. Each distribution can now be represented by a vector of 100 values enabling standard principal component analysis of the data.

The results however, need to be interpreted in terms of density functions. This method is based on ideas from Ramsay and Silverman (1997). The first few principal components account for most of the variation of the data and will therefore be the most interesting. Later principal components explain decreasing amounts of variation and can be regarded as 'noise' and so discarded.

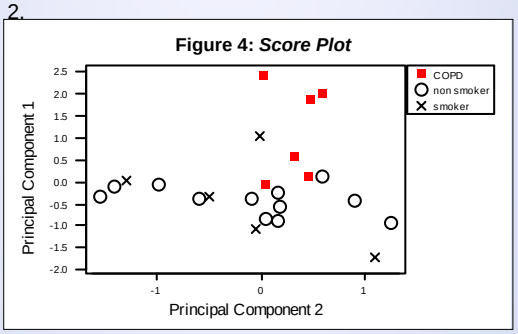
Figure 3: ***Discretization Illustration***



Results

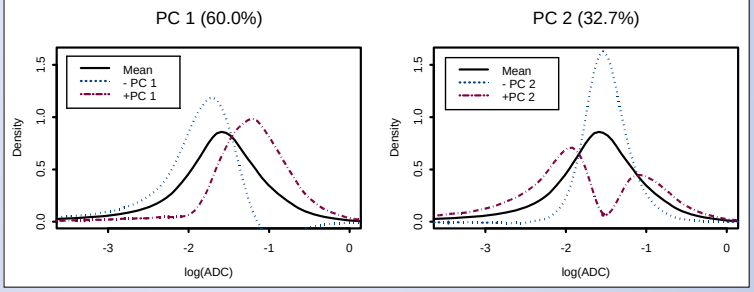
Figure 4 displays the score plot of the first two PCs from FPCA. This indicates some discrimination between healthy and diseased lungs on PC 1, where patients with COPD tend to have higher values. The functional principal components (Figure 5) indicate that the main source of variation (PC 1) is due to the mean and spread. High values on PC 1 reflect diffuse distributions with a larger mean value0. This corresponds to the KDE of a COPD patient in Figure 2.

Figure 4: ***Score Plot***



The second component reflects the difference between a bimodal and unimodal distribution and accounts for over 30% of the total variation. This raises new questions and provides additional insight for further investigations.

Figure 5: ***Functional Principal Components One and Two***



Discussion

Application of FPCA to ^{3}He ADC colour maps of the lungs is an entirely novel, more sophisticated method of analysing these types of images. The technique is not only detecting the obvious change in mean ADC but differences in spread and modality too. Although their biological importance is unknown to date, they may be linked to the vast amounts of spatial heterogeneity seen in each image.

This method is also being applied to similar images from other areas of MRI, where we need to assess heterogeneous voxel values on an ROI basis with promising results.

References:

[1] Fichele, S., et al. (2004). *J Magn Reson Imaging*, 20(2):331-335.

[2] Ramsey, J., & Silverman, B. (1997). *Functional Data Analysis*. Springer-Verlag, London.

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