Detecting motion from the data

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Motion effect

Patient motion during data acquisition leads to blurring in the reconstructed images, leading to:

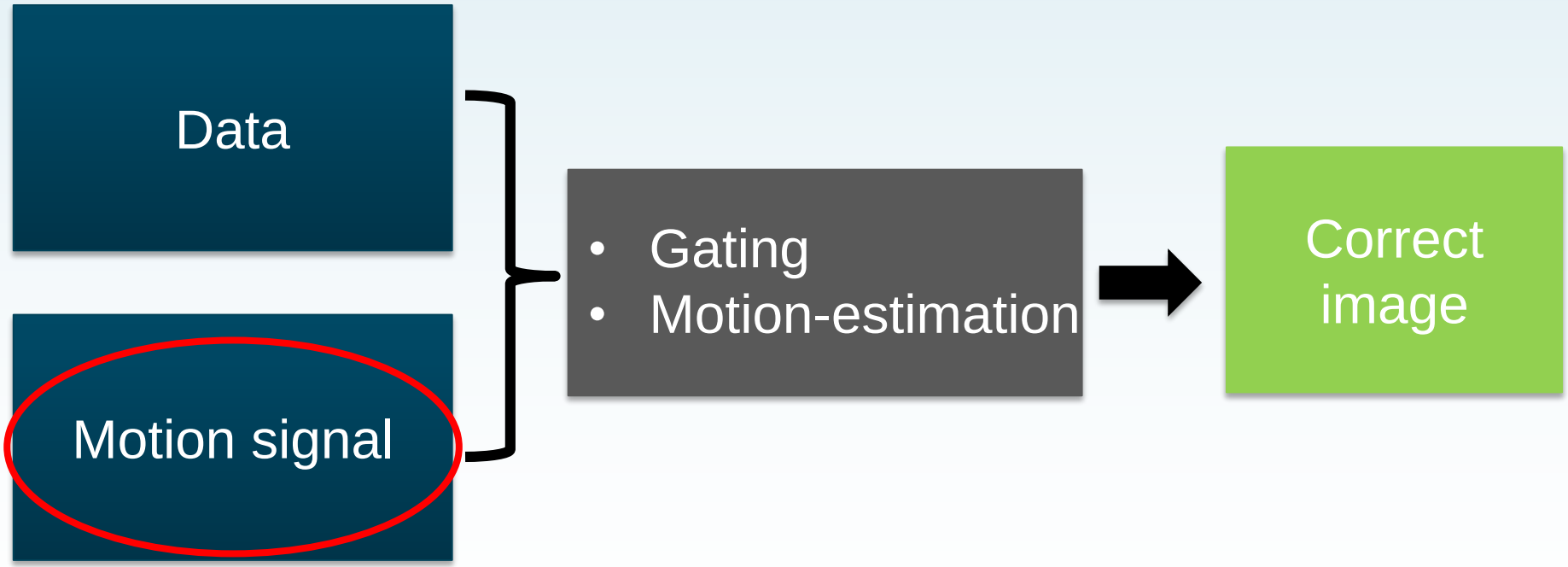
- overestimation of lesion size and volume;
- underestimation of lesion uptake;
- potential attenuation correction artifacts due to mismatch between images.

These artifacts have the potential to:

- lead to misidentification of lesions, affecting the correct diagnosis of diseases;
- provide inappropriate planning of target volumes for radiotherapy;
- impair staging of disease;
- lower the quantitative accuracy of the imaging modality.

Motion correction

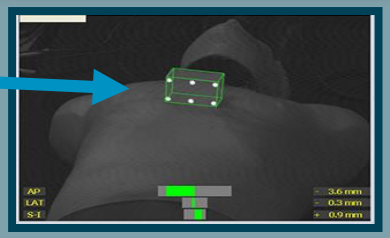
Motion needs to be detected, in order to correct for it.



Motion detection

External hardware

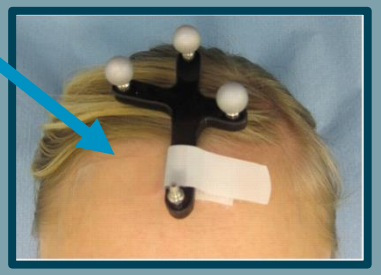
Tracker for RPM



Anzai belt

Respiration

Tracking markers for optical camera



Head motion

With Data-Driven (DD) methods: directly from the raw data

Raw data → **DD** → signal

- ✓ avoid use of external equipment
- ✓ advantage of patient and operator convenience
- ✓ potential increased fidelity to the internal movement

Image based Data-Driven methods

Respiratory motion:

•A ^{18}F-FDG point source is set on the patient's abdomen and its position used to track respiratory motion through the consecutive dynamic frames[1].

•A VOI is manually defined in a summed image around the lesion, the z-coordinate of the COM of the activity inside the VOI is used as a respiratory signal (**COM method**)[2].

Head motion:

•Short time frames are reconstructed and consequently aligned using registration software[3].

[1] A S Nehmeh et al., J Nucl Med, 44(10):1644–1648, 2003.
[2] R A Bundschuh et al., J Nucl Med, 48(5):758–763,2007.
[3] Y Picard and C J Thompson, IEEE Trans. Med. Imaging, 16 137-44

COM = Centre of Mass
VOI = Volume of Interest

Data-Driven methods on raw data

Respiratory motion:

•to extract the variation of the counts within regions subject to respiratory motion (Spectral Analysis Method, **SAM**)[1].

•to compute the centroids-of-distribution (**COD**)[2] of all radioactive events in the field-of-view using list-mode TOF-PET data.

Respiratory and head motion:

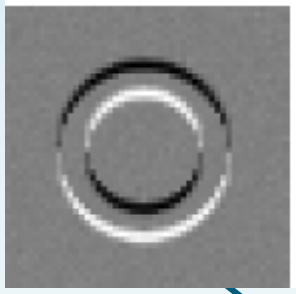
•to apply Dimensionality-Reduction methods (**PCA**[3,4]**, LE**[5]) to detect the biggest changes in the acquired data.

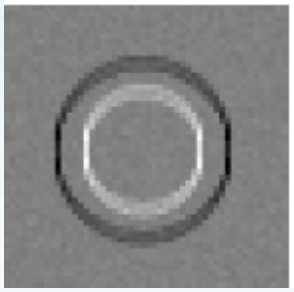
[1] P J Schleyer et al., Phys. Med. Biol., 54(7):1935-50, 2009.
[2] S Ren, et al., NSS/MIC IEEE, Conf. Record, pp. 1-5,
[3] K Thielemans et al., NSS/MIC IEEE, Conf. Record, pp. 3904–3910, 2011.
[4] K Thielemans et al., NSS/MIC IEEE, Conf Record, pp. 1-5, 2013.
[5] J C Sanders et al., NSS/MIC IEEE, Conf. Record, no.99, pp.1-1, 2016.

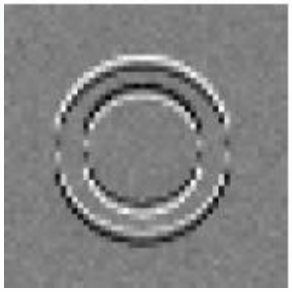
TAC= Time Activity Curve

PCA: simulation of beating heart with respiratory translation

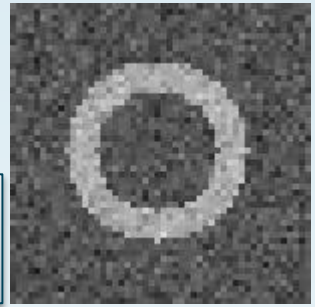
3 first Principal Components

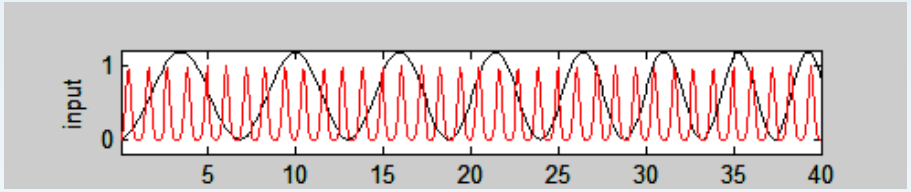




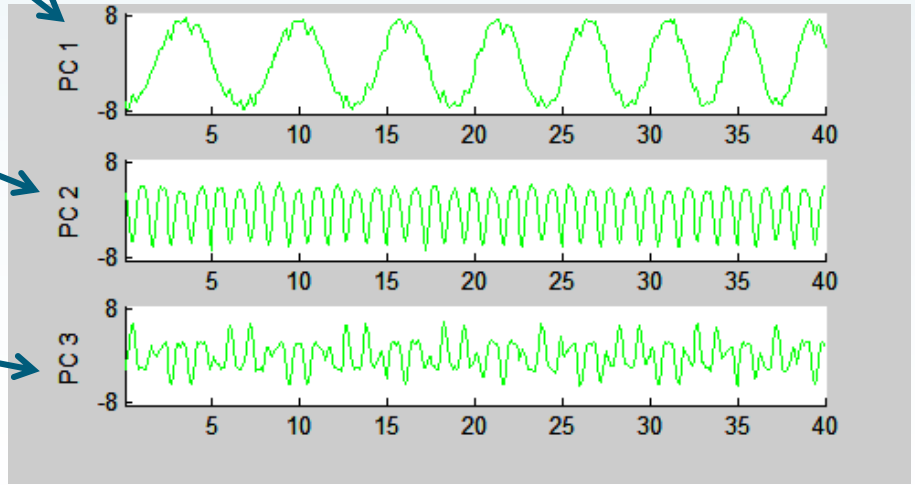


original movement
red: cardiac, **black: respiratory**





extracted gating signals

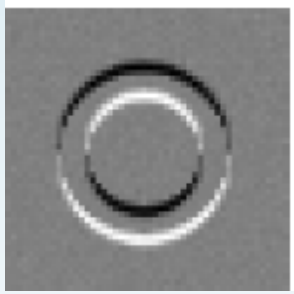


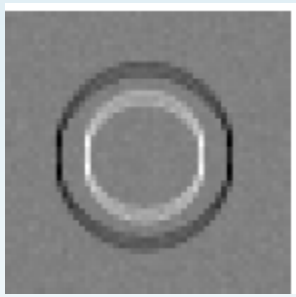
Thielemans et al
IEEE MIC 2011

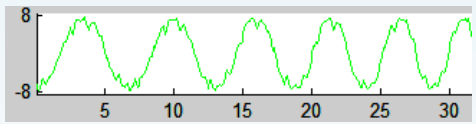
Visual explanation of PCs

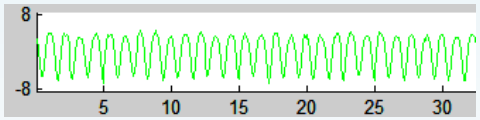
$$d_i \approx \bar{d} + \sum_{k=1}^{K} w_{ik}\, p_k$$

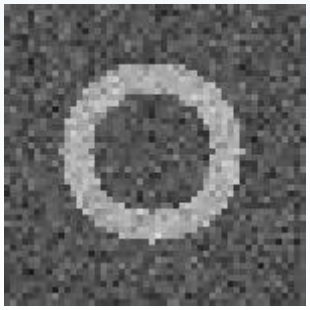
$$w_{ik} \approx (d_i - \bar{d}) \cdot p_k$$









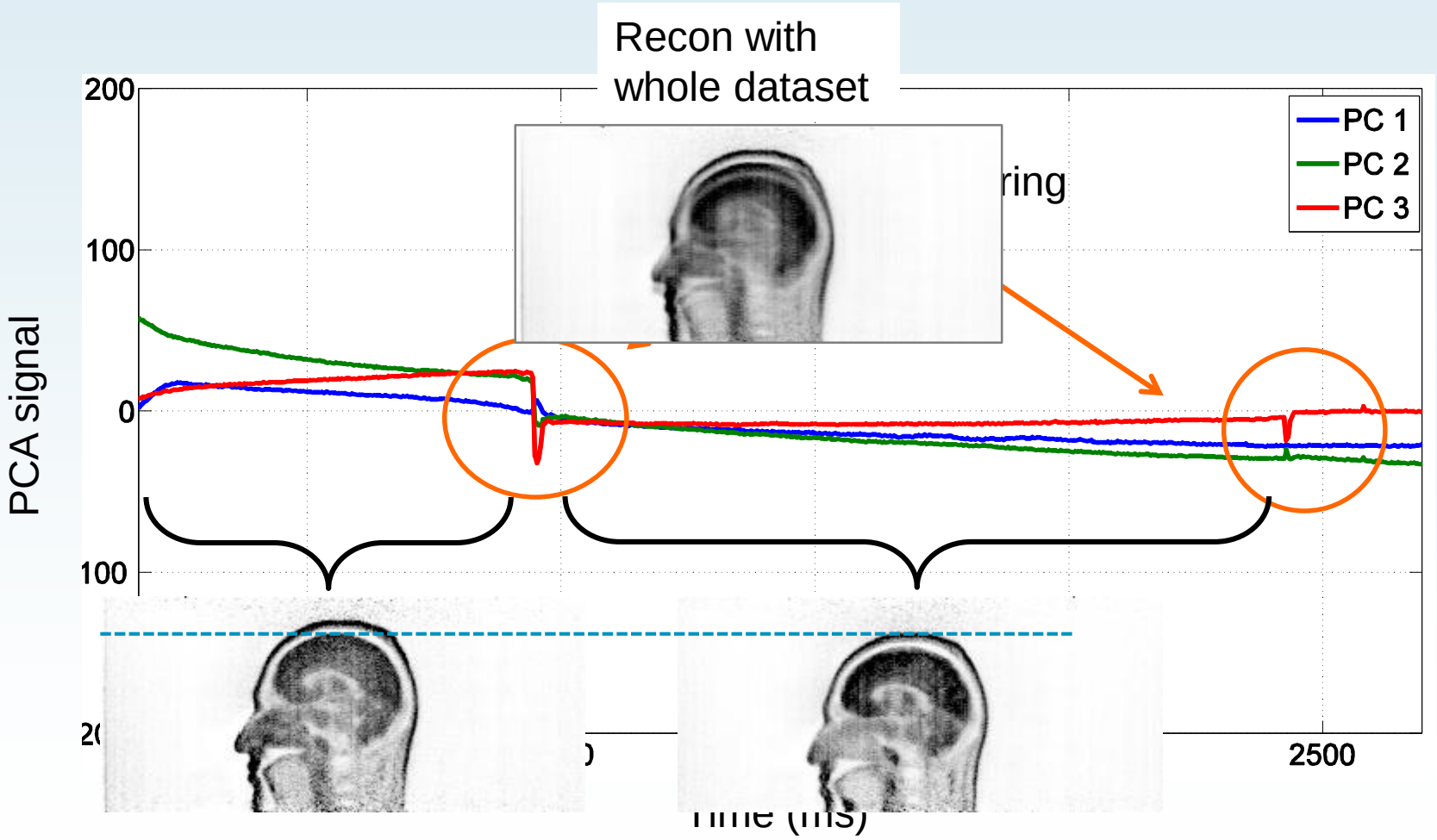


$\bar{d} + w_{i1}p_1$

$\bar{d} + w_{i2}p_2$

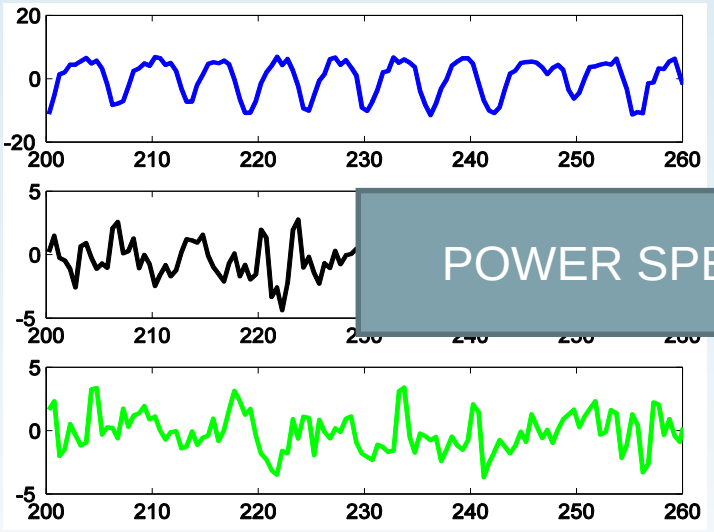
Head motion

PCA on PET raw data, head bed position → consider the first 3 PCs

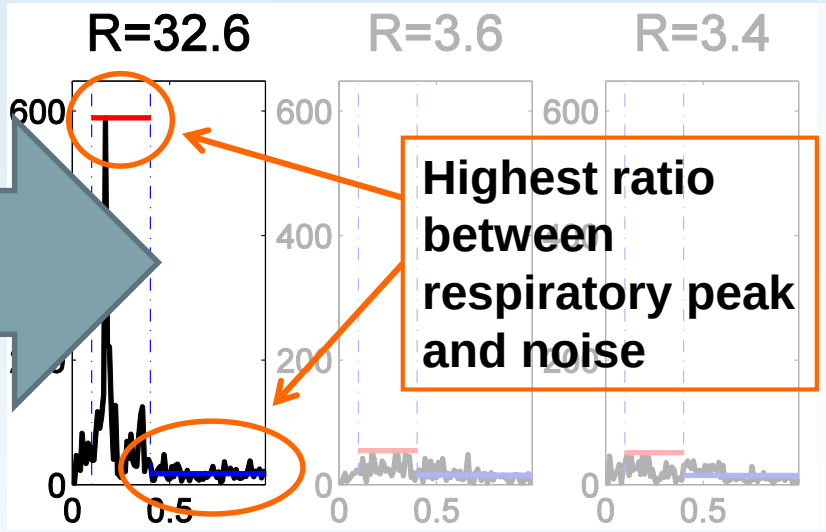


Respiratory motion

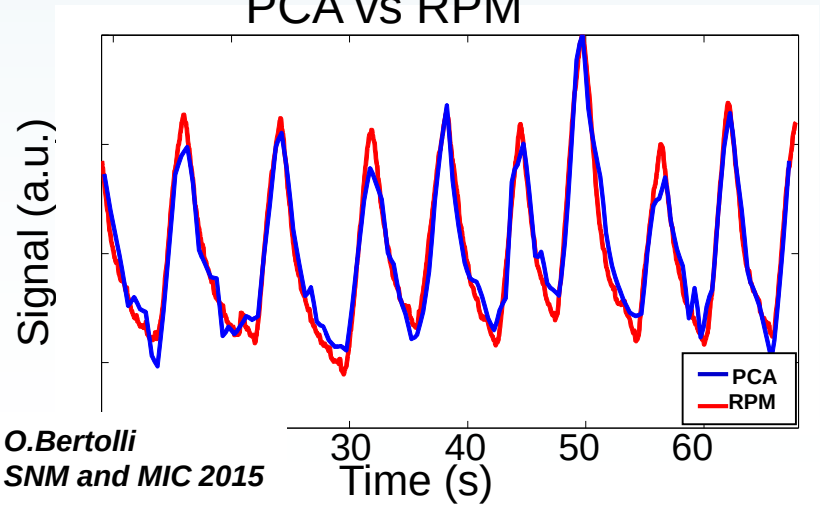
PCA on PET raw data, chest bed position → consider the first 3 PCs



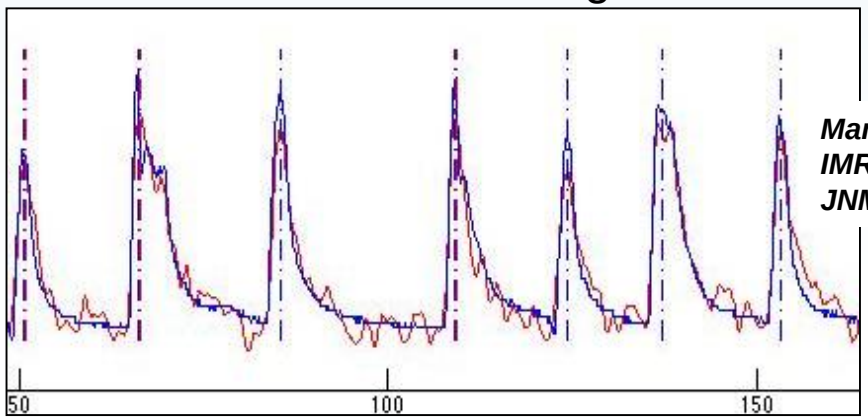
POWER SPECTRUM



PCA vs RPM



PCA vs MR navigator

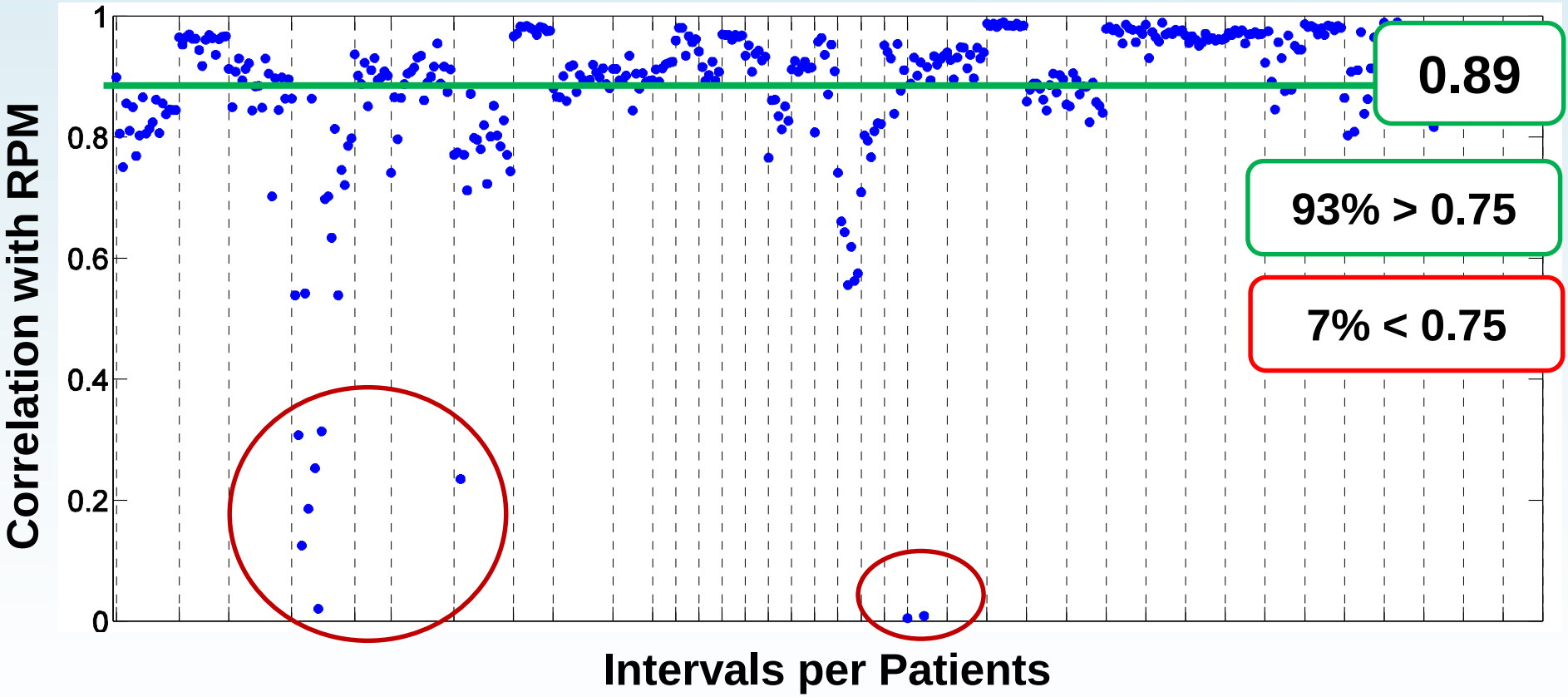


Manber et al, IMRSM 2014, JNM 2015

O.Bertolli SNM and MIC 2015

Quality of PCA signal

Clinical evaluation on 37 lung cancer patients, FDG PET, chest bed position.

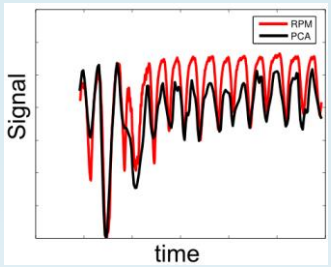


Several time intervals of different duration used per patient (50 to 360 seconds)
Each box is 1 patient.

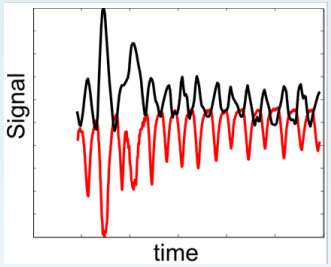
Arbitrary sign

$$d_i \approx \bar{d} + \sum_{k=1}^{K} w_{ik} p_k$$

The sign of weight and PC is arbitrary

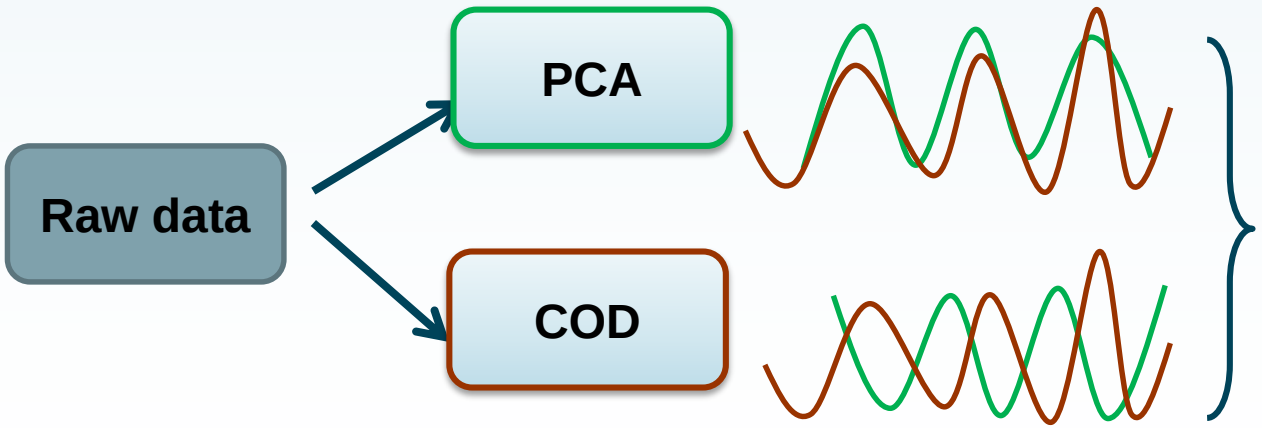


correct



opposite

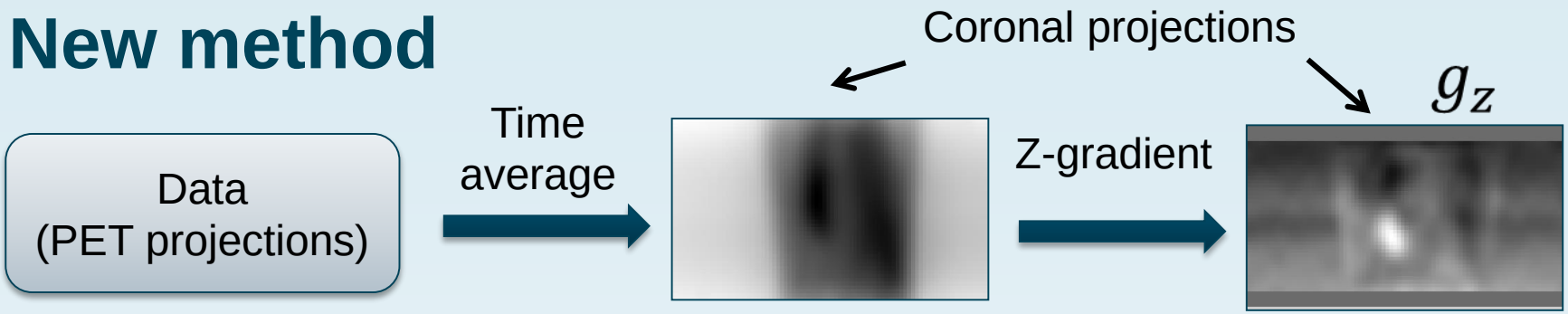
The sign can be fixed by comparing the PC signal to a signal that represents the correct direction of motion: e.g. the signal from another Data-Driven method like **COD**.



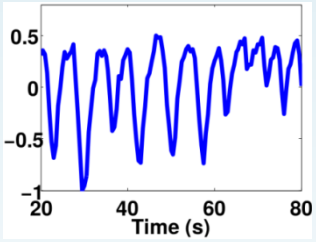
Compare and flip the sign

PCA signals are better than COD (more highly correlated to RPM)

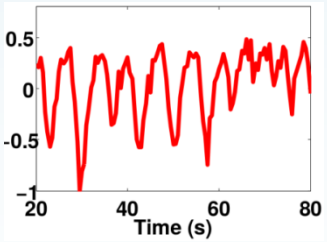
New method



PCA $w_{ik} \approx (d_i - \bar{d}) \cdot p_k$



New method: $r_i = (d_i - \bar{d}) \cdot \mathbf{g_z}$



Compare and flip the sign

We applied this method on 37 lung cancer patients datasets, subdividing the acquisitions in several time intervals (total of 431 intervals), and compared the resulting PCA signal to the RPM signal (external device currently used in practice):

Failure rate: 5.3 % (23 out of 431 evaluated intervals).
HIGHLY RELIABLE

Conclusions

Data-Driven methods:

- can provide information about the time in which motion occurred and, for respiratory motion specifically, are able to provide a signal representing the actual shape of the motion;

- do not require external devices, trained staff or extra acquisition time.

PCA:

- Has proven to be able to provide respiratory traces highly correlated to the external devices signals;

- does not require heavy computational efforts, it is fast and easy to implement and could be included in the clinical pipeline with little effort;

- the issue related to the arbitrary nature of the sign of the respiratory signals can be solved and the new method we presented has proven to be successful in the majority of the cases.

Acknowledgments

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