Local Compensation for Respiratory Motion in List-mode PET

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Abstract. In this work we present a method to estimate and compensate the local motion of a hot region in a PET list-mode acquisition directly on the measured LORs. The method is applicable for arbitrary motion patterns. Different shapes of the hot regions, different contrast ratios and different count statistics are examined. In a simulated anatomical data set the algorithm has recovered 98% of the true activity in a lung lesion with respiratory motion.

1. Introduction

Respiratory motion is a serious problem in clinical emission imaging. Motion artifacts from patient motion degrade image quality and hamper accurate quantification in many clinical applications of positron emission tomography (PET). The consequence is a reduced ability of detecting lesions and a worse quantification of uptake values, such as the standardized uptake value (SUV). Different techniques have been proposed to compensate for respiratory motion: either using respiratory gating information or sinogram based [1]. The first needs an additional signal (e.g. chest belt) and leads to degraded images after reconstruction due to reduced count statistics in the individual gated frames. New PET scanners allow the acquisition of the measurements in list-mode, where the coincidence events are chronologically stored in a list. The high temporal resolution intrinsic in list-mode data can be used to compensate for respiratory motion leading to better lesion detectability and better quantification of the SUV.

In this work we describe a new method to estimate the local motion of a hot region in a PET study with high temporal resolution. The method is described in detail in the second section of this article. The third section describes the application and results of simulated geometrical data sets. The section ends with an examination of a simulated anatomical data set. The results are discussed in the fourth section and finally in the last section a conclusion is drawn and an outlook on future investigations is presented.

2. Local Motion Compensation

The three main sources of motion artifacts in medical imaging are respiratory motion, cardiac motion and patient motion. The relevance of each type of motion clearly depends on the specific application. Cardiac motion and respiratory motion certainly pose no problem at all in brain imaging. Respiratory motion shows the biggest impact in lung imaging, and in cardiac imaging all three types of motion occur. There are different approaches to minimize motion in medical imaging. Patient motion can be reduced with positioning systems or by providing support for patient comfort. Instructions and audiovisual feedback that help the patient to breathe with a specific pattern are useful for respiratory gating. Cardiac imaging is especially difficult as both, respiratory and cardiac motion occur in combination.

Motion is complex and mostly too complicated to be described globally. There are large efforts made by many imaging companies to introduce technologies that acquire all kinds of information to help describing motion, e.g. breathing sensors, elastic belts, camera systems that visually track markers attached to the patient's body. All these devices complicate the workflow and do certainly not improve patient comfort. The ideal solution for motion would therefore be a correction method that works with the acquired PET data alone and requires no additional information at all. Even though this aim might be difficult to achieve for global motion, it appears feasible for local motion. Often, local structures of interest show no significant deformation. Compact tumors for example are relatively stiff objects without internal deformation during respiratory motion. This means that even if the overall movement and deformation of the lung are complex, the movement of a specific lesion or tumor in the lung is not.

Local motion compensation (LMC) is a method to select structures of interest and eliminate the motion in this selected region without changing the image globally. The LMC method can be separated into four steps:

1. VOI definition
2. Motion estimation
3. Data correction, and
4. Image reconstruction from the corrected data

Each step is described in the following.

VOI Definition. Our algorithm corrects motion locally, so it is necessary to define where in the image this correction should be applied. The easiest way to do this is to display a reconstructed (motion-blurred) PET image and let the clinician interactively define a volume of interest (VOI). It is important that the VOI contains the full trajectory of the object under consideration. Since nowadays PET/CT systems are common, the VOI can also be defined in the CT image. This sometimes is the case in PET/CT lung studies.

Motion Estimation. The acquired PET data is available in list-mode format, which means that for each coincidence the line of response (LOR) together with time information is available. We use this information to estimate the motion of the center of activity in the selected VOI over the course of time. This is done by generating intermediate VOI images for a number of short time frames. These small VOI images are generated with a simplified back projection algorithm. The simplification is that the exact overlap length of each LOR with each voxel is not calculated. Instead, voxel values inside the VOI are increased by 1 for each voxel that is intersected by the LOR. This simplified back projection is computationally very efficient as the number of required divisions and multiplications is minimal. The time for generating a sufficient number of intermediate VOI images is in the order of a few seconds.

In a next step, the center of activity is determined for each intermediate VOI image. Here, it is important to note that coincidences from outside the VOI, which are associated with LORs that hit the selected VOI do also contribute to the intermediate images. This means, the locally constrained back projection described above has a considerable background from events outside the VOI. To minimize the impact of this background, only voxels with values above say 50% of the maximum VOI value are considered in the calculation of the center of activity. The results for all intermediate VOI images are combined to calculate the center of activity for the full time range of the acquisition. The difference to each of the centers of activity for the intermediate VOI images is also computed and stored in a vector array. This array is used to calculate an interpolated translation vector, see Figure 1.

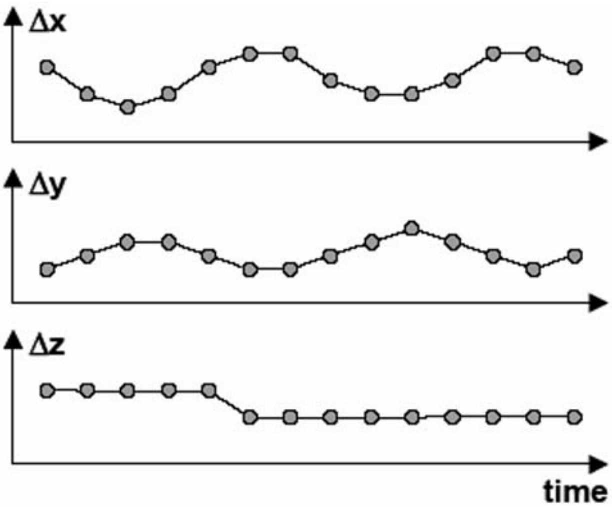

Fig. 1. The information about the position of the center of activity for each time bin and the overall center of activity for the full time range is used to calculate an interpolated translation vector.

Data Correction. Finally, shifting each LOR in the original dataset by the amount given by the translation vector generates a motion corrected list-mode dataset. This is done at the full timing resolution of the list-mode dataset, which is another advantage compared to gating where the data is still averaged or smeared over the duration of each time frame.

Image Reconstruction. The motion corrected list-mode dataset can be reconstructed with the same settings as in the initial motion-blurred reconstruction used for the VOI definition and can then be combined with the blurred image.

3. Application to Simulated Data Sets

The LMC implementation was evaluated and tested with different simulated datasets. The purpose was to test the validity of this approach for various imaging situations. The impact of three parameters was investigated:

- Shape of the object
- Different contrast levels
- Count statistics / image noise

Furthermore, LMC was tested with a realistic (anatomic) phantom to determine its impact on a typical clinical application, the SUV analysis of a lung lesion.
It shows that the algorithm works well for all tested types of shapes of the hot region. This is plausible since the shape of the object has no impact on the motion of the center of activity.

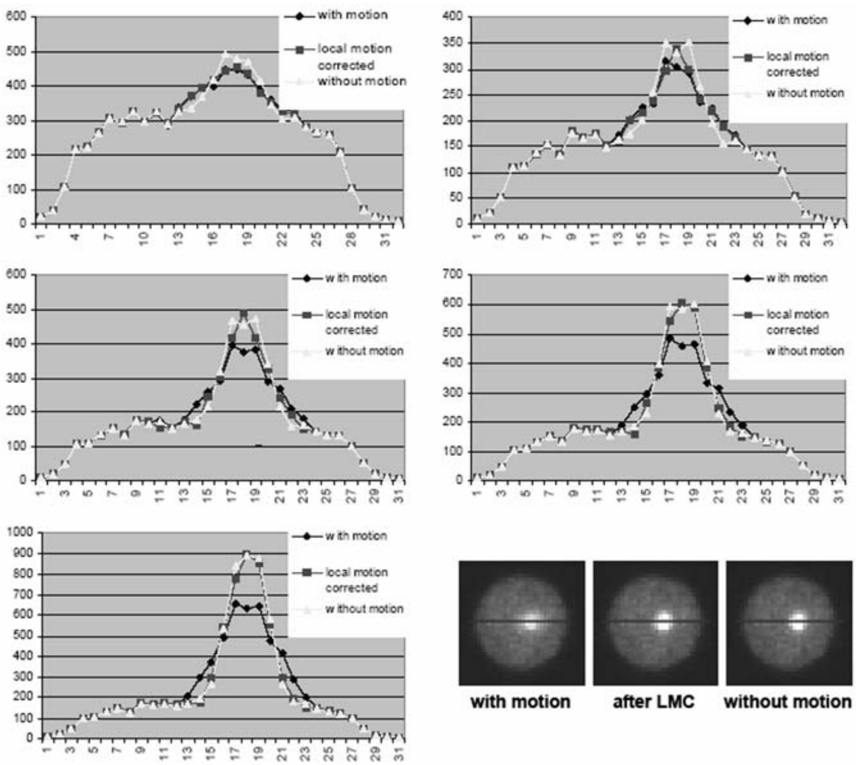

Fig. 2. A small moving sphere with background activity in different contrast rations is analyzed along a horizontal line in the direction of motion (bottom right) and compared to a non-moving sphere with the same activity.

The contrast between the object of interest and the surrounding background has great impact on the applicability of LMC. Small contrast levels mean that the contribution increases for LORs hitting the VOI that do not originate from the actual object of interest. This hampers the accurate determination of the center of activity on small time scales. The results are shown in the Figure 2, where a small moving hot sphere with background activity in different contrast ratios has been analyzed in terms of line profiles. The location of the line profile is indicated in the right part of the bottom row.

We have found that LMC shows no or only a very small effect for contrast levels below 2 : 1 and that motion is correctly compensated when the contrast is above 3 : 1.

For the examination of the impact of noise the contrast level is fixed to 6 : 1 and list-mode data sets were generated and analyzed for different count statistics. We have found that even for very low count statistics (a total number of counts of 50000) LMC compensates motion artifacts correctly, which means that the algorithm is quite insensitive to image noise.

NCAT Phantom. A digital phantom was utilized to test LMC under more realistic conditions. The “4D NURBS-based Cardiac-Torso” (NCAT, [2]) phantom realistically models the effect of respiratory and cardiac motion on the skeletal structure and all organs of the torso. The phantom and the position of the lesion is shown in the left part of Figure 3. This analytical phantom was used to generate voxelized activity distributions and emission images for 50 gates of the full respiratory cycle. The 50 activity distributions were then fed into an event generator that produced a list-mode dataset for the full cycle with a specified number of events.

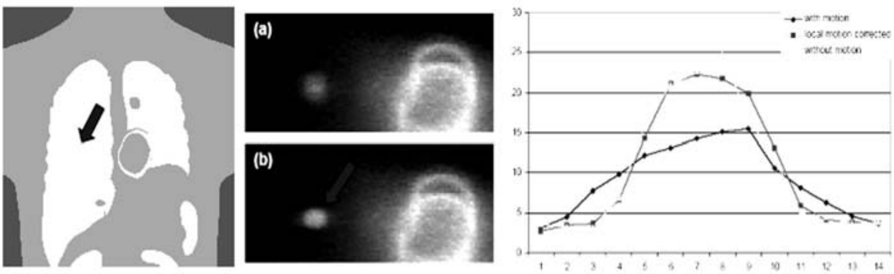

Fig. 3. The NCAT software phantom was used to simulate a realistic motion of a lung lesion (left). The middle part shows the lesion as it appears in sagital view (a) motion-blurred and (b) after application of LMC. The right part shows activity profiles along the main direction of movement with motion, after LMC and without motion.

It is obvious how good LMC reproduces the activity of the moving lesion. A region of interest (ROI) analysis shows that the true activity in the lesion is reproduced to 98%, while the uptake in the motion blurred case is only 72%.

4. Results

The geometrical phantoms were used to examine the impact of different physical settings such as different kinds of motion, different shapes of the lesion or different contrast ratios. The algorithm performs well in periodic and non-periodic motion and in arbitrary object shapes. Down to a contrast ratio of 2:1 (lesion vs. background) the algorithm yields a good match of motion-corrected and motion-free images.

With a view to clinical applications, the NCAT phantom was used to study the performance of the algorithm in improving quantification of a hot lesion near the diaphragm having realistic motion due to respiration. The analysis of the motion-corrected image is in 98% conformance with the theoretically expected value in terms of mean uptake of the lesion, while the motion blurred lesion only shows 72% of the true uptake.

5. Conclusions

We examined a local motion estimation and motion compensation algorithm for a PET acquisition in list-mode. The algorithm is based on estimating the center of gravity of a VOI with a high temporal resolution, and then correcting the corresponding LORs. The impact of different lesion shapes, contrast levels and count statistics has been considered. It shows that a contrast ratio of 2:1 (lesion : background) is sufficient, also in low count studies. The application and evaluation of LMC to real measurements, phantoms and clinical acquisitions is ongoing.

References

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