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Optimized Reconstruction of the Position of Interaction in High-Performances γ-Cameras

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Introduction

Targeted radionuclide therapy is one of the most widespread treatment modality for benign and malignant thyroid diseases. In order to maximize the therapeutic effects on the target tissues while minimizing the toxicity for organs-at-risk with adapted dose, individually defined for each patient taking account their own biokinetics, dedicated γ-imaging devices are required. They must be optimized for high energy γ-rays and high photon fluences and avalaible for repeated measurements at specific times before and after treatment administration. In order to overcome these shortcomings, our objective is to develop a portable high-resolution gamma camera specifically optimized for dose quantification at the patient's bedside during the treatment of thyroid diseases with ^{131}I. After a first prototype of gamma camera with a 5×5~cm^2 field of view (FoV) succesfully developed with very promising results~\cite{carlotta}, we are currently developing a fully operational clinical version of the mobile gamma camera with a 10×10~cm^2 FoV suited to the size of the thyroid, millimetric spatial performance and increased counting capabilities (200 kcps). Such spatial performances are obtained thanks to the use monolithic inorganic scintillators and pixelated photodetectors. It however requires efficient reconstruction methods of the position of interaction of the γ-rays in the medium. This is usually performed either by interpolation methods based on reference data or on a light distribution analytical model for each camera to be fit on the data. In both cases this requires strong computation, limiting its use for real time clinical applications. Neural networks propose an interesting alternative as they could provide both an efficient method for accurate reconstruction of γ-rays based on a reference dataset for training, prior its clinical use. The network can then be used at high frequency for real time imaging as the reconstruction for each γ-ray would be reduced to a simple tensor multiplication. We propose here a comparison of performances obtained with an interpolated fitting method and a neural network both based on experimental data for training and validation.

Material and Methods

The photodetection module of the mobile gamma camera is composed of a 10×10~cm^2 and 1 cm thick monolithic $CeBr_3$ scintillator with reflective optical coatings. It is optically coupled to a 4×4 Hamamatsu S13361-6050 arrays of 4×4 silicon photomultipliers (SiPMs). The pixels have an effective sensitive area of 6×6 mm^2 and a micro-cell size of 50×50 μm^2. The signals produced by the SiPMs are shaped and digitized by a commercial front-end electronics manufactured by the PETSys company. It is composed of four TOFPET 2B ASIC with 64 analog reading channels. The spatial performance were evaluated by using a ^{133}Ba source collimated by a tungsten collimator with a 0.5~m diameter hole. Thermal noise events (11 kcps for the operative bias and individual trigger threshold used) are completely suppressed by an internal hardware trigger (10ns coincidence window) which operates between two regions of the photodetector defined as a checkerboard where each square corresponds to a 4×4 SiPM array. The non uniformity of the photodetector light response was evaluated and corrected by irradiating the field of view with a pulsed LED source. The relative standard deviation of the light responses over the 256 pixels before and after correction are 12.8\% and 0.96\%, respectively. A scan of the whole FoV was performed with a 1~mm step, recording, for each position, about 2000 scintillation events. Half of these events were used as a reference dataset for training while the other half were used for performances evaluation. Additionally a flood-field uniformity acquisition was carried out with the same source, set at about 50~cm of the scintillator and with no collimator. Each scintillation event produce a light pulse within the monolithic scintillator that propagates – possibly after some reflections – to the SiPM array leading to a 16 × 16 frame. As the intensities in the pixels of the frame contains some information about the position of interaction of the incident gamma-ray, it is therefore possible to reconstruct the later *a posteriori* using dedicated algorithm. Two methods of reconstruction of the position of interaction limited in the (x, y) plane were tested: a least-square fitting method and a neural network. As the response function of each pixel of the camera is unknown, preventing the use of analytical models for fitting, the discrete light response functions of the pixels were determined by average the frames of the reference scan dataset. The other frames were then fit with standard least-square minimizing (Levenberg-Marquardt optimization) an objective function calculated, at each step, by bivariate spline interpolation. The neural network, on the other hand, were performed using Keras (Tensorflow) Python library, and using the *Deep Residual Convolution* architecture. A *Deep Residual Convolutional* block is composed of an input image, directed on one side through two classical convolutional layers, and on the other side through an identity shortcut. The output of these two branches are then summed and activated by a ReLU (Rectified Linear Unit) activation function. The network loss optimization is achieved thanks to the Adam algorithm. Our neural network uses two of these so called *Deep Residual Convolutional* blocks and is trained thanks to the aforementioned reference dataset, using the 256 pixels frames as input and the mechanical position of the source as output. For both reconstruction methods, the performances are evaluated, on the one hand by reconstruction of the second half of the scan dataset (not used for training), yielding a measurement of the spatial resolution by fit of a 2 dimensions gaussian on the reconstructed position of all the events for each scan position as well as a measurement of the bias by comparing the reconstructed position to the actual mechanical positions of the scan. On the other hand the uniformity of the spatial response was obtained by reconstruction of the positions of interaction of the flood-field data.

Results

The fit method yields a average intrinsic spatial resolution in the central FoV (75\% linear of the total FoV), of 1.33 ± 0.08~mm FWHM with a bias of 0.05 ± 0.03~mm and an integral and differential uniformity of respectively 10.19\% and 8.90\%. It however, strongly deteriorate towards the edges of the FoV, reaching an average spatial resolution of 9.13~mm FWHM with a bias of 0.52 ± 0.82~mm and an integral uniformity of 11.44\% and a differential uniformity of 18.17\%. On the other hand the intrinsic performances with neural network are better with a spatial resolution in the central FoV of 1.09 ± 0.06~mm FWHM but but with a bias of 0.09 ± 0.05~mm and an integral and differentials uniformity of respectively 4.95\% and 8.06\%, while less degrading near the edges with a spatial resolution of 6.74~mm FWHM and a bias of 0.42 ± 0.55~mm. It is however worse in terms of uniformity with 43.24\% and 34.32\% for the integral and the differential uniformity respectively.

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