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Design and Validation of an Adaptive SPECT System: AdaptiSPECT

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Abstract

In order to obtain optimal image quality with respect to a particular task, adaptive imaging systems automatically change their acquisition parameters in response to preliminary data being recorded from the object under study. Currently, the adaptive aspect in Single Photon Emission Computed Tomography (SPECT) is limited to a manual collimator interchange and the choice of detector rotation radius. Furthermore, there is often no optimization of any kind with respect to a certain task. There is thus a need for more versatile SPECT systems that autonomously optimize their acquisition geometry for every task and every patient. Here we describe a pinhole SPECT imager, AdaptiSPECT, which is being developed at the Center for Gamma Ray Imaging (CGRI) to enable adaptive SPECT imaging in a pre-clinical context. Furthermore, ideas for an autonomous adaptation procedure are discussed and some preliminary results are reported upon.

Index Terms

SPECT; adaptive imaging

I. Introduction

In order to obtain optimal image quality with respect to a particular task, adaptive imaging systems automatically change their hardware configurations and acquisition parameters in response to preliminary data or scout data being recorded from the object under

investigation. Single-Photon Emission Computed Tomography (SPECT) systems are useful for a wide variety of tasks, ranging from simple tumor detection tasks to more complicated estimation tasks. Since it is impractical to have a separate system available for each task, an adaptive SPECT system should be able to adapt itself to the task being performed and to the particular subject being imaged. Even if the system would be defined by the task, the ensemble of possible objects under investigation can be very large. In the exemplary case of a dedicated brain scanner optimized for the estimation of perfusion defect volume, object size, size of the brain, location of the perfusion defect and lesion shape are just a number of parameters that contribute to the large object variability. Adaptive SPECT narrows down the object ensemble by using information extracted from the scout scan and, based on that information, optimizes its geometry for the patient under study.

Adaptive formulations for the Hotelling and Wiener observers have previously been documented by Barrett [1] and different scout-data-based adaptation rules have been described. The practical feasibility and usefulness of Adaptive SPECT has been demonstrated with a recently developed prototype, implementing an adaptive pinhole SPECT system [2], [3], which used heuristic adaptation rules.

Section II describes the features of a pinhole-based pre-clinical adaptive SPECT system, AdaptiSPECT, being developed at the Center for Gamma Ray Imaging (CGRI) and illustrate the system's versatility by calculation of system characteristics of some representative system configurations. Intuitively, such a pinhole system would be able to autonomously: i) trade spatial resolution when a larger field of view (FOV) is required ii) adjust the amount of overlap in projections as a response to the sparseness of the tracer distribution, thereby optimizing system sensitivity.

In section III, we describe early investigations for autonomous adaptation in an estimation task. The idea is to calculate the probability for a fixed set of parameters θ to be estimated, such as activity, size or location of a lesion. We will demonstrate that we can calculate a surrogate figure of merit that tells us how much information the scout scan contains about the underlying parameters θ . The higher the information in the scout data (extracted from the surrogate figure of merit), the better we can narrow down our initial ensemble of θ .

II. Design of AdaptiSPECT

A. System Description

The AdaptiSPECT design is an upgrade to our existing FastSPECT II system [4], [5] and, as a result, is subject to constraints imposed by working within the design of the existing system. These constraints include physical limits on the size of the imaging aperture, the range of motion for the gamma cameras, and to some extent the imaging geometry. The system consists of 16 cameras, arranged in two rings of 8 cameras offset with a 22.5 degree angle with respect to each other. The 16 cameras are stationary with respect to rotation around the object, but contrary to the FastSPECT II design, cameras can now move individually and continuously in the radial direction (Fig. 1(a)). This allows for continuous and camera-specific variation of detector distance d from the camera central axis ranging from 320 mm to 165 mm, thereby trading resolution for an enhanced field of view (FOV).

The most significant change deals with the creation of a pinhole aperture which now consists of 3 rings of pinholes with different diameter g , respectively, at distance $f = 25.4$ mm, 50.8 mm, and 76.2 mm from the central axis (Fig. 1(b)). Recent developments in fabrication methods described in [6] have enabled us to pursue a wider range of aperture geometries than previously available through traditional machining practices. These fabrication methods have also allowed for the creation of novel pinhole geometries, such as the lofted hole, which tapers from a rectangular to a circular profile (Fig. 1(c)). This geometry offers improved penetration characteristics. The choice of pinhole diameter is such that approximately equal sensitivity is maintained over the 3 different pinhole rings.

We designed a special shuttered pinhole design, also enabled by the novel fabrication processes in [6], on the two outer pinhole rings that allows us to switch instantly from a one-pinhole configuration to a five-pinhole (quincunx) configuration (per camera) thus increasing sensitivity at the cost of increased multiplexing, and dependent on the tasks being performed [7]. Fig. 1(b) also shows the shutter mechanism (for the central pinhole ring only). Platinum blocks can be rotated to either block or open up the outer 4 pinholes for imaging. This can be done individually for all 16 pinhole groups. The tradeoff between sensitivity and multiplexing by switching between single and quincunx hole patterns also leads to an interesting tradeoff between data ambiguity and axial and transaxial sampling.

In Fig. 2(d), a tungsten-polymer cast (still in its mold) of the high magnification section of the aperture is shown. Rapid prototyping is used for designing the molds. This allows for a large flexibility in designing the aperture geometry.

All components of the imager, except for the cameras, have been delivered to CGRI and are currently being assembled.

B. System characteristics

In order to demonstrate the versatility of the AdaptiSPECT scanner, nine representative configurations were chosen for further study. The most important characteristics of each configuration can be found in Table I. The system matrix, H , of each individual system was calculated using ray tracing and stored using a sparse-matrix representation. Pinhole diameters were modeled by tracing 456 rays through each pinhole while sensitivity, S , was calculated using

$$S = \frac{g^2}{16d^2} \cos \alpha, \quad (1)$$

where α is the ray incidence angle, g the pinhole diameter and d the pinhole distance to the center of the FOV. Geometric resolution R was calculated over the entire FOV using

$$R = \sqrt{\left(g \frac{d}{d-f}\right)^2 + R_i^2}, \quad (2)$$

with the intrinsic resolution $R_i = 2.5$ mm. FOV was calculated as an adequately sampled region seen by 12 pinholes or more. Results for the FOV size, and the sensitivity and resolution in the center of the FOV can be found in Table I. In summary, magnification ranges from $2\times$ to $12\times$, resolution from $550\ \mu\text{m}$ to $3\ \text{mm}$, and sensitivity from 3×10^{-4} to 13×10^{-4} . The FOV ranges from $10\ \text{mm}$ to $90\ \text{mm}$ in the transaxial direction and from $10\ \text{mm}$ to $45\ \text{mm}$ in the axial direction for a single bed position. By scanning the subject in different axial bed positions we can extend the axial FOV. To illustrate the versatility of the AdaptiSPECT system, Fig. 2, Fig. 3, and Fig. 4, respectively, show transaxial sensitivity maps, resolution maps, and number of pinholes seen by the object in three representative system configurations.

III. Autonomous adaptation

Here, we report on initial results for autonomous adaptation in an estimation task. First, adaptive imaging will be generally described and notations will be introduced according to [1]. Next, the idea for autonomous adaptation will be sketched and the onset for the adaptation procedure will be validated with simulations.

A. Adaptive imaging

Most current SPECT procedures are performed with a fixed geometry. Imaging of an object, $\mathbf{f}$, with a fixed system, described by system matrix H , results in measured data $\mathbf{g}$:

$$\mathbf{g} = H\mathbf{f} + \mathbf{n}, \quad (3)$$

where $\mathbf{n}$ represents the measurement noise. Based on a scout scan, $\mathbf{g}_s$, or - more generally - based on the data collected up to a certain time point during the scan (Fig. 5), an adaptive imaging system should autonomously reconfigure its acquisition parameters in order to optimally perform a given task:

$$\mathbf{g} = H(\mathbf{g}_s)\mathbf{f} + \mathbf{n} \quad (4)$$

In a general estimation task, we are interested in estimating a set of parameters θ from the data $\mathbf{g}$.

Based on a scout scan, $\mathbf{g}_s$, the system has to be reconfigured according to $H(\mathbf{g}_s)$ in order to optimally estimate θ from $\mathbf{g}$.

B. How can we use information in the scout data to guide adaptation?

The idea is to calculate the probability $\text{pr}(\theta)$ for each instance of an ensemble of parameters. Each instance is described by a vector, θ , of parameters to be estimated (e.g. θ can represent activity, size, or location of a lesion, or a combination of these). Before any scan has started, and without any prior information on θ , all values of $\text{pr}(\theta)$ will be assumed equal and the probability distribution will thus be uniform over a limited pre-defined range. After observing some scout data $\mathbf{g}_s$, we can consider the posterior probability conditioned on $\mathbf{g}_s$, $\text{pr}(\theta|\mathbf{g}_s)$. If the probability distribution on θ given the scout data $\text{pr}(\theta|\mathbf{g}_s)$ is now concentrated

around certain values, we can choose only these θ with highest probability to create a new ensemble of θ .

Let's assume Gaussian likelihood for the scout data $\mathbf{g}_s$:

$$\text{pr}(\mathbf{g}_s|\theta) \approx \frac{1}{\sqrt{(2\pi)^M \det(\mathbf{K}_{\mathbf{g}_s|\theta})}} \times \exp \left[-\frac{1}{2}(\mathbf{g}_s - \bar{\mathbf{g}}(\theta))^t \mathbf{K}_{\mathbf{g}_s|\theta}^{-1} (\mathbf{g}_s - \bar{\mathbf{g}}(\theta)) \right] \quad (5)$$

where $\mathbf{g}_s$ represents the scout data, and $\bar{\mathbf{g}}(\theta)$ is the data, averaged over both measurement noise and background variability. In [1], it was proposed to use a smooth reconstruction of $\mathbf{g}_s$ as the mean data vector. By simply adding the candidate θ to this smoothed reconstruction and feeding it through the system matrix, we construct $\bar{\mathbf{g}}(\theta)$ from the scout data:

$$\bar{\mathbf{g}}(\theta) = H_s(\mathbf{R}\{g_s\} + \mathbf{f}_l(\theta)), \quad (6)$$

where the operator $\mathbf{R}\{\cdot\}$ represents a reconstruction operation, to be detailed in the next paragraph, $\mathbf{f}_l(\theta)$ is the candidate lesion image specified by θ and H_s is the system matrix of the scout imaging procedure.

In equation (5), $\mathbf{K}_{\mathbf{g}_s|\theta}$ is the covariance on the measured data, conditional on θ , which means we would have to reevaluate the covariance not only over measurement noise, but also at every possible candidate θ . However, under a weak-signal assumptions $\mathbf{K}_{\mathbf{g}|\theta}$ becomes $\mathbf{K}_{\mathbf{g}}$. If initially, before the scout, we assume a uniform probability for θ , the posterior becomes:

$$\text{pr}(\theta|\mathbf{g}_s) \approx \frac{\exp \left[-\frac{1}{2}(\mathbf{g}_s - \bar{\mathbf{g}}(\theta))^t \mathbf{K}_{\mathbf{g}}^{-1} (\mathbf{g}_s - \bar{\mathbf{g}}(\theta)) \right]}{\sum_n \exp \left[-\frac{1}{2}(\mathbf{g}_s - \bar{\mathbf{g}}(\theta_n))^t \mathbf{K}_{\mathbf{g}}^{-1} (\mathbf{g}_s - \bar{\mathbf{g}}(\theta_n)) \right]} \quad (7)$$

The extent to which this new probability distribution is concentrated around certain values of θ can be investigated with the Shannon entropy, and the increase in information in $\text{pr}(\theta|\mathbf{g}_s)$ compared to the information in the prior $\text{pr}(\theta)$ can be investigated by calculating the Kulback-Leibler divergence, D_{KL} :

$$D_{\text{KL}}(\text{pr}(\theta|\mathbf{g}_s) \parallel \text{pr}(\theta)) = \sum_i \text{pr}(\theta_i|\mathbf{g}_s) \log \frac{\text{pr}(\theta_i|\mathbf{g}_s)}{\text{pr}(\theta_i)} \quad (8)$$

C. Simulations

A total of 100 MOBY mice [8] with Tc99m-MDP uptake were simulated in the scout configuration of the AdaptiSPECT scanner. The scout configuration selected here can be found in Table I under magnification 1.2 $\times$.

We used an identical background and created the 100 different scout datasets $\mathbf{g}_s(\theta_{\text{real}})$ by inserting 100 lesion of varying activity and size at a fixed location in the spine. The lesions were constructed with parameters $\theta = \{\mathbf{a}, \mathbf{s}\}$ where $\mathbf{a}$ is activity and $\mathbf{s}$ is size and with:

$$\mathbf{a} = [2.5; 3.0; 3.5; 4.0; 4.5; 5.0; 5.5; 6.0; 6.5; 7.0]$$

$$\mathbf{s} = [0.6; 0.8; 1.0; 1.2; 1.4; 1.56; 1.8; 2.0; 2.2; 2.4]$$

Next, we calculate the posterior distributions $\text{pr}(\theta_{\text{test}}|\mathbf{g}_s(\theta_{\text{real}}))$ for all 100 possible combinations of lesion parameters, θ_{test} , while fixing θ_{real} for the construction of $\mathbf{g}_s(\theta_{\text{real}})$ through:

$$\mathbf{g}_s(\theta_{\text{real}}) = H_s(\mathbf{f}_b + \mathbf{f}_l(\theta_{\text{real}})) + \mathbf{n}, \quad (9)$$

and by varying θ_{test} in equation (7) through the construction of a new instance for $\bar{\mathbf{g}}(\theta_{\text{test}})$:

$$\bar{\mathbf{g}}(\theta_{\text{test}}) = H_s(R\{\mathbf{g}_s(\theta_{\text{real}})\} + \mathbf{f}_l(\theta_{\text{test}})) \quad (10)$$

To investigate if the posterior is well-concentrated around the true θ_{real} , we calculate the normalized probability $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$ on the real underlying parameters θ_{real} :

$$\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s) = \frac{\text{pr}(\theta_{\text{real}}|\mathbf{g}_s)}{\max_{\theta} \text{pr}(\theta|\mathbf{g}_s)} \quad (11)$$

and investigate the correlation between D_{KL} and $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$

D. Operator $R\{\cdot\}$ = 200 MLEM iterations + 1 mm postsmoothing

We calculated Eq. 6 with $R\{\cdot\}$ = 200 MLEM iterations and Gaussian post-smoothing with FWHM=1 mm. In Fig. 6(a), the Kullback-Leibler divergence is plotted for all 100 possibilities of θ_{real} . Fig. 6(b) shows the normalized probability $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$ for all θ_{real} . In Fig. 6(c), we see a monotonic relation between D_{KL} and $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$. This indicates that D_{KL} is a good proxy for $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$. This is convenient since, in a clinical context we can calculate D_{KL} , while the true $\text{pr}_n(\theta_{\text{real}}|\mathbf{g}_s)$ can only be obtained in simulations. This results indicates that, the higher the divergence D_{KL} , the more information our scout scan contains on the real lesion parameters. Thus, the D_{KL} may be used as an indicator of how useful our scout data is to narrow down the ensemble of possible θ .

IV. Discussion and conclusion

The goal of Adaptive SPECT is to image each subject under optimal conditions with respect to the imaging task. With the construction of the AdaptiSPECT system, this goal is accomplished in a pre-clinical setting. Here, a number of representative configurations have been described, but it is important to notice that AdaptiSPECT is not limited to these configurations. Some detectors can be chosen to operate in quincunx mode while others can operate in single pinhole mode. The results show that a range of resolutions from 0.55 to 3 mm can be achieved while maintaining constant sensitivity. Transaxial FOV can vary from 10 to 90 mm and, at the expense of multiplexing, sensitivity can be boosted by a factor of up to 4.86.

One method for incorporating the scout data to narrow the posterior ensemble and the justification of the approach has been described. We demonstrated here that we can calculate a figure of merit (the Kullback-Leibler divergence) that tells us how much information the

scout scan contains about the underlying parameters θ . The higher the information in the scout data (extracted from the figure of merit), the better we can narrow down our initial ensemble of θ . With the calculation of D_{KL} , we can predict whether the set of θ considered and their probabilities is strongly correlated with the true parameters θ_{real} . If so, when D_{KL} is large, we can use the most likely θ (e.g. top 25%) to create a representative new ensemble, and we can calculate the outcome for all systems listed in Table I and marginalize over the new parameter ensemble. The system configuration with best predicted observer outcome, averaged over the narrowed ensemble, will be chosen for the diagnostic scan. In the case D_{KL} is low, we conclude that we have to change our scout strategy for this particular subject. This will be the subject of future research.

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Fig. 1.

The Adaptive SPECT design. In (a) the gantry is shown with the radially translatable cameras (in red) and the axially translatable aperture (in center). In (b) the aperture is shown with the pinhole selection system in detail. In (c), a lofted pinhole insert is shown while (d) shows a tungsten cast of part of the aperture.

Fig. 2. Sensitivity maps. Transaxial slice through the center of the field of view of (a) the 2.2x, (b) the 3.0x and (c) the 8.5x magnification configurations of Table I

Fig. 3.

Resolution maps. Transaxial slice through the center of the field of view of (a) the 2.2x, (b) the 3.0x and (c) the 8.5x magnification configurations of Table I. The black areas, corresponding to resolution 0 are not seen by any pinholes in the system.

Fig. 4. Number of pinholes maps. Transaxial slice through the center of the field of view of (a) the 2.2x, (b) the 3.0x and (c) the 8.5x magnification configurations of Table I

Fig. 5.

General flow in an adaptive imaging system: after a short scanning time, the scout data $\mathbf{g}_s$ is used to possibly find a better system configuration. If scanning another short time period with this new configuration can further increase task performance, the system is reconfigured, the scout data $\mathbf{g}_s$ updated and a scan is performed over a new time period t . This procedure can be iterated until observer performance reaches an asymptotic limit and does not significantly increase anymore.

Fig. 6.

In (a), the Kullback-Leibler divergence is plotted for all 100 θ_{real} , (b) shows the normalized probability $pr_n(\theta_{real}|\mathbf{g}_s)$ and (c) shows the correlation between both.

TABLE I

Properties of some representative configurations

Magnification	1.2	2.2	3.2	1.7	3.0	4.2	5.5	8.5	11.5
pinhole distance (mm)	76.2	76.2	76.2	50.8	50.8	50.8	25.4	25.4	25.4
detector distance (mm)	165.1	241.3	317.5	165.1	241.3	317.5	165.1	241.3	317.5
pinhole diameter (mm)	1.5	1.5	1.5	1.0	1.0	1.0	0.5	0.5	0.5
Resolution (mm)	3.48	2.47	1.95	2.40	1.82	1.60	0.746	0.632	0.585
Sensitivity (1 pinhole per camera) ($\times 10^{-6}$)	341	326	331	341	326	343	341	326	331
transaxial FOV (mm)	90.0	52.5	37.5	48.0	30.0	24.0	20.0	13.5	10.5
axial FOV (mm)	40.5	45.0	25.5	24.0	30.0	13.5	7.50	10.5	9.00
5-pinhole sensitivity gain	3.75	4.86	4.02	3.76	3.76	4.86	N/A	N/A	N/A