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Optimization of an Adaptive SPECT System with the Scanning Linear Estimator

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Abstract

A method for optimization of an adaptive Single Photon Emission Computed Tomography (SPECT) system is presented. Adaptive imaging systems can quickly change their hardware configuration in response to data being generated in order to improve image quality for a specific task. In this work we simulate an adaptive SPECT system and propose a method for finding the adaptation that maximizes the performance on a signal estimation task. To start with, a simulated object model containing a spherical signal is imaged with a scout configuration. A Markov-Chain Monte Carlo (MCMC) technique utilizes the scout data to generate an ensemble of possible objects consistent with the scout data. This object ensemble is imaged by numerous simulated hardware configurations and for each system estimates of signal activity, size and location are calculated via the Scanning Linear Estimator (SLE). A figure of merit, based on a Modified Dice Index (MDI), quantifies the performance of each imaging configuration and it allows for optimization of the adaptive SPECT. This figure of merit is calculated by multiplying two terms: the first term uses the definition of the Dice similarity index to determine the percent of overlap between the actual and the estimated spherical signal, the second term utilizes an exponential function that measures the squared error for the activity estimate. The MDI combines the error in estimates of activity, size, and location, in one convenient metric and it allows for simultaneous optimization of the SPECT system with respect to all the estimated signal parameters. The results of our optimizations indicate that the adaptive system performs better than a non-adaptive one in conditions where the diagnostic scan has a low photon count — on the order of thousand photons per projection. In a statistical study, we optimized the SPECT system for one hundred unique objects and demonstrated that the average MDI on an estimation task is 0.84 for the adaptive system and 0.65 for the non-adaptive system.

Index Terms

Adaptive single photon emission computed tomography (SPECT); task based assessment of image quality; simulation study; system optimization

I. Introduction

Adaptive spect systems can rapidly alter their data-acquisition configuration in response to data being generated and therefore are capable of improving image quality with respect to detection or estimation tasks [1]. The usefulness of adaptive SPECT has been explored by a number of prototypes e.g. [2][3][4]. Finding the optimum configuration using a task based

measure of image quality requires an optimization strategy. Few such optimization methods have been proposed to automate the adaptation problem.

For a detection task the ideal observer sets an upper limit on task performance. Using this observer, the performance of each imaging configuration can be assessed by the Area Under Curve (AUC) of the Receiver Operating Curve (ROC) [5]. One approach to adaptation is to calculate the ideal-observer test statistic by using a Markov-Chain Monte Carlo (MCMC) technique [5][6]. Since calculation of the ideal observer requires complete knowledge of image statistics, this method can be applied to a stochastic object model that is fully described by a set of parameters. This method is computationally time consuming, making it impractical for optimization of adaptive systems with numerous imaging configurations. For an estimation task, the posterior mean estimator sets a lower limit for the ensemble mean squared error and is thus often thought of as an ideal estimator. However, the posterior mean estimator also requires time consuming MCMC techniques and is therefore not very useful for adaptive imaging.

Even though adaptive systems can be altered continuously during acquisition, Barrett [7] proposed a one-step adaptation method. A scout image is acquired and some information about the object is derived from it and used to generate a simulated ensemble of objects consistent with the scout data. Imaging configurations are evaluated based on the performance of the ideal linear (Hotelling) observer for a detection task, or the the ideal linear (Wiener) estimator for an estimation task, on the ensemble of simulated objects. Van Holen [4] calculated a surrogate figure of merit to select object parameter instances that have a higher probability based on the collected scout image. This information is then used to generate an object ensemble for the optimization step. Whitaker [8] showed that the Wiener estimator can estimate the activity or size of a signal but is unable to find its location. She showed that the Scanning Linear Estimator (SLE) derived as a special case of maximum a posteriori (MAP) estimation, performs well for activity, size and location.

Li and Meng proposed a SPECT system with adaptive angular sampling [9]. The relative importance of each sampling angle is based on the covariance matrix of reconstructed images and it requires calculation of a Fisher Information Matrix (FIM) for each imaging configuration. The optimization is based on a gradient search method which could converge to a local minima. To reduce the size of the FIM and facilitate its inversion, the non-uniform object-space pixelation (NUOP) [10] method is utilized. Pato uses contrast-to-noise ratio as a figure of merit for system evaluation [11]. In this method, image quality is evaluated based on an FIM calculation; to avoid inverting a large FIM, local shift invariance is assumed. Another approach for reducing the dimensionality of the FIM is to subsample the matrix [12]. FIM methods require performing reconstructions from many noise realizations. This is a time consuming process; to speed up the computation analytical approximations are used and assumptions such as linear shift invariance are made which are not always necessarily valid [13].

In this paper we utilize the task based assessment of image quality for the optimization of an adaptive SPECT system [14][15]. Our task is to obtain estimates of signal activity, size, and location for an object imaged by various imaging configurations. Even though SLE was

derived to minimize Ensemble Mean Square Error (EMSE) [8], there are no analytic expressions for an aggregate figure of merit required for more complicated tasks that involve estimating multiple parameters [16]. To mitigate this problem, we propose using the Modified Dice Index (MDI) defined in Eq. (15) as a figure of merit for evaluating system performance. The Modified Dice Index is based on the Dice similarity index which has been successfully applied to clinical imaging tasks [17][18]. This figure of merit combines the error in estimates of activity, size, and location, in one convenient metric and it allows for simultaneous optimization of the SPECT system with respect to all the estimated signal parameters.

There are several advantages to our method. Instead of using a surrogate figure of merit [19] we utilize MDI, which is directly related to the estimation task. Some published works apply task based measures of image quality to optimization [20]. First they compute image reconstructions from projection data, then they use that information to estimate the parameters of interest. We avoid computing an image reconstruction, as this step prolongs the optimization process and introduces additional artifacts in the results [21]. Instead, we apply the raw projection data in the SLE estimation rule of Eq. (10). Our method is faster than the MCMC optimization technique in reference [5]. We make use of MCMC to generate a posterior ensemble from the scout data; however, a parallel implementation of SLE runs much faster than the posterior mean estimator. One disadvantage of our method is that we are optimizing over a discrete set of system configurations while the optimal system may not be in this set. Another drawback to our method is that it requires expensive computational resources, such as Graphical Processing Units (GPUs) with sufficient memories, and processing speeds that are detailed in section 3C.

II. Methods

We follow a two step optimization method. First we acquire a scout image which serves as the starting point for selecting an ensemble of objects consistent with the scout data. Second, we image members of the object ensemble with a given system configuration and use the images to estimate the signal parameters listed in Eq. (1). The estimates are used to calculate a figure of merit for each object in the ensemble according to Eq. (14). The performance of the imaging configuration is found by computing the average MDI_j for the ensemble per Eq. (15). This process is repeated for every imaging configuration; the one that yields the maximum MDI_j is optimal. The diagram shown in Fig. 1 illustrates the steps taken in the optimization process.

A. Markov-Chain Monte Carlo

To acquire the scout data we specify an imaging configuration for the scout system and denote its system operator as H_{scout} . The object f is made out of a background and a signal. The background b is the MOBY phantom [22] shown in Fig. 3. The activity of the organs in the phantom are specified by the vector $[a_1 \dots a_K]$. The signal, s , is a sphere with a parameter vector θ which includes the activity a , radius R and location of the signal r , hence $\theta = (a, R, r)$. For convenience we condense the list of all the object parameters, including the background and signal, in a vector σ .

$$\sigma = [\alpha_1, \dots, \alpha_K, a, R, r] \quad (1)$$

The simulated object is,

$$f(\sigma) = b(\alpha) + s(\theta). \quad (2)$$

For a discrete object made of N voxels, the object can be expressed as $N \times 1$ vector.

$$f(\sigma)_{N \times 1} = \sum_{j=1}^K ([O_1 \dots O_K] * \text{Diag}([\alpha_1 \dots \alpha_K]))_{ij} + s(a, R, r) \quad (3)$$

Each column in the matrix $[O_1 \dots O_K]$ is a binary vector of an organ; there are K organs in the volume of interest. We multiply this matrix with the diagonal matrix of α to adjust the activity of each organ. The columns of the background matrix are then summed up and the signal vector is added to the resulting background vector. For a camera with M pixels the system matrix has dimensions $M \times N$ and a single projection of the scout data is an $M \times 1$ vector as shown in Eq 4. The tomographic scout data vector is obtained by rotating the object and acquiring an image for each rotation. The images for all the projections are then reshaped into a single column to make up the scout data vector.

$$gs(\sigma)_{M \times 1} = H_{\text{scout}} f(\sigma)_{N \times 1} + n \quad (4)$$

In Eq. (4) n is a zero-mean random vector that accounts for Poisson noise. The noise model for this imaging system can be expressed as the following:

$$\text{pr}(gs|b, s) = \prod_{m=1}^M \exp[-(b_m + s_m)] \frac{(b_m + s_m)^{gs_m}}{gs_m!} \quad (5)$$

To generate an ensemble of objects from the scout data, we adopt the MCMC method proposed by Kupinski et al. [5]. We draw a sample parameter vector $\tilde{\sigma}$ from a proposal density $q(\tilde{\sigma}|\sigma^{(i)})$ and calculate the acceptance probability γ for the proposed parameter vector by the following rule:

$$\gamma = \min \left[1, \frac{\text{pr}(\tilde{\sigma}|gs) q(\sigma^{(i)}|\tilde{\sigma})}{\text{pr}(\sigma^{(i)}|gs) q(\tilde{\sigma}|\sigma^{(i)})} \right] \quad (6)$$

Since we do not have the posterior distribution $\text{pr}(\tilde{\sigma}|gs)$, we use Baye's rule

$$\text{pr}(\sigma|\text{gs}) = \frac{\text{pr}(\text{gs}|b(\alpha), s(\theta))\text{pr}(\sigma)}{\int d\theta' d\alpha' \text{pr}(\text{gs}|b(\alpha'), s(\theta'))\text{pr}(\sigma')} \quad (7)$$

to rewrite Eq. (6) as:

$$\gamma = \min \left[1, \frac{\text{pr}(\text{gs}|\tilde{\sigma})\text{pr}(\tilde{\sigma})q(\tilde{\sigma}|\sigma^{(i)})}{\text{pr}(\text{gs}|\sigma^{(i)})\text{pr}(\sigma^{(i)})q(\sigma^{(i)}|\tilde{\sigma})} \right] \quad (8)$$

In Eq. (8) $\text{pr}(\text{gs}|\tilde{\sigma})$ is the noise model from Eq. (5), $\text{pr}(\tilde{\sigma})$ is the prior and $q(\tilde{\sigma}|\sigma^{(i)})$ is the proposal density. In these equations the variable $\sigma^{(i)}$ is the previous parameter vector in the Markov Chain. Once we calculate the acceptance ratio, then we generate a uniform random number between 0 and 1. If the acceptance probability is larger than the random number and it does not violate any of the physical restrictions of the object, $\tilde{\sigma}$ is accepted and added to the Markov Chain; otherwise another sample vector is drawn and the process is repeated. The Markov Chain obtained with this method consists of a sequence of unique object parameter vectors shown in Eq. (9) where each link in the chain is denoted by a superscript. The chain is run until we reach a predefined maximum number I of parameter vectors.

$$[\sigma^{(1)}, \sigma^{(2)}, \dots, \sigma^{(I)}] \quad (9)$$

B. Scanning Linear Estimator

Barrett has shown [23] that among all possible estimators the posterior mean minimizes EMSE. In estimation task EMSE, which is the mean square error between the estimate and the true value of a parameter, is a quadratic cost function. The estimation rule for SLE was derived as a special case of maximum a posteriori (MAP) estimation for a Gaussian likelihood [8]. The scanning action of the estimator refers to seeking a solution that maximizes a metric that is linear in the data. The SLE performs well when estimating the activity, size, and location of a signal [24]. For the case in which the search variable θ has a uniform probability distribution function, the estimation rule for SLE is shown in Eq. (10).

$$\hat{\theta}(g_j(\sigma^{(i)})) = \underset{\theta}{\text{argmax}} \left\{ H_j s(\theta)^t K_{g|\theta}^{-1} (g_j(\sigma^{(i)}) - H_j \bar{b} - \frac{1}{2} H_j s(\theta)) \right\} \quad (10)$$

The estimate of the signal parameter vector, $\hat{\theta}(g)$, is equal to the parameter vector that maximizes the quantity enclosed in the curly braces. An optimization routine is required to search for and find the optimum parameter vector. For a parameter vector in the search space of the optimization the signal $s(\theta)$ is constructed and imaged by an imaging configuration with system operator H_j . Each parameter vector in the MCMC ensemble is utilized to create an object which is imaged by system H_j to yield the data vector shown in Eq. (11).

$$g_j(\sigma^{(i)}) = H_j f(\sigma^{(i)}) + n \quad (11)$$

The covariance matrix $K_{g|\theta}$ in Eq. (10) is the sum of noise, background and signal covariances. However, following the slowly varying signal assumption in reference [8] the signal covariance term is ignored. The noise covariance is a diagonal matrix of the image data averaged over all possible backgrounds and noise. $\bar{K}_{\bar{g}}^{\text{bkgnd}}$ is the background covariance calculated by using the background ensemble from the scout data and the MCMC simulation.

$$K_{g|\theta} \approx \bar{K}_n + \bar{K}_{\bar{g}}^{\text{bkgnd}} \approx \text{Diag}(\bar{g}) + \bar{K}_{\bar{g}}^{\text{bkgnd}} \quad (12)$$

In Eq. (10) the vector $\bar{b}$ is the average of the background ensemble.

$$\bar{b} = \langle b(\alpha) \rangle_i \quad (13)$$

The SLE provides an estimate for the activity, radius and location of the spherical signal. Using the radius and the location estimates we can calculate the volume occupied by the estimated signal $V(\hat{R}^{(i)}, \hat{r}^{(i)})$. In a clinical subject, we cannot know what the true signal is. However, because we have a well-defined model for the object and the signal, we can utilize the scout data to simulate an object ensemble. Each member of the ensemble is fully described by a fixed number of background and signal parameters that are listed in a vector shown in Eq. (1). We consider the signal parameters in this vector as the actual signal and use that information to calculate $V(R^{(i)}, r^{(i)})$, which is the volume occupied by the actual signal. Using these volumes we can compute the Dice index, which is a percentage of overlap between these two volumes. The MDI expressed in Eq. (14) is the Dice index multiplied by an exponential factor that takes into account the percent of error in the activity estimate $\hat{a}$.

$$\text{MDI}_j^{(i)} = \frac{2 \left(V(\hat{R}^{(i)}, \hat{r}^{(i)}) \cap V(R^{(i)}, r^{(i)}) \right)}{V(\hat{R}^{(i)}, \hat{r}^{(i)}) + V(R^{(i)}, r^{(i)})} \times \exp \left[- \left(\frac{\hat{a}^{(i)} - a^{(i)}}{a^{(i)}} \right)^2 \right] \quad (14)$$

For each object in the ensemble we calculate the $\text{MDI}_j^{(i)}$ using Eq. (14) and take the average over the ensemble, MDI_j , as a figure of merit for the performance of the imaging configuration H_j .

$$\text{MDI}_j = \langle \text{MDI}_j^{(i)} \rangle_i \quad (15)$$

The maximum value of MDI_j is 1, which corresponds to the estimated parameters being exactly equal to the actual parameters. The minimum value of MDI_j is 0, which indicates there is no volume overlap between the true and estimated signal. In this paper we are using this figure of merit for signal estimation, however, it could also be used with a threshold to detect signals.

III. Simulations

This optimization study is entirely based on simulations. The tomographic imaging system is modeled with a Monte Carlo SPECT system simulator [25]. The object is a mouse phantom (MOBY) in which organ shapes are modeled with non-uniform rational B-spline (NURBS) surfaces based on high-resolution 3-D magnetic resonance microscopy data [22]. In the previous section we discussed the use of MCMC to generate object ensembles and SLE to optimize system performance. Both of these methods are implemented via numerical simulations discussed in this section.

A. System Modeling

The adaptive SPECT system studied in this paper is shown in Fig. 2. There are eight imaging units at fixed 45° angles surrounding the object. Each imaging unit is made of a single pinhole aperture, placed at a fixed distance from the object, and a camera mounted on a translation stage. The translation stages are controlled by a single controller which moves the cameras in the radial direction. Hence magnification is adjusted by moving all the cameras toward or away from the pinhole apertures simultaneously. All of the pinholes on a given octagonal cylinder have the same size. However, the size of the pinholes can be adjusted by replacing the octagonal cylinder with one that contains the appropriate pinhole size. The system specifications are listed in table I. Once the pinhole size and magnification are selected, a system operator H_j is calculated for the imaging configuration; this operator is applied to all eight tomographic imaging units.

We compute the system operator H_j with the SPECT simulator tool developed by Li and Furenlid [25]. This SPECT simulator traces gamma rays from the source through the aperture to the interaction positions inside the scintillation crystal. This is followed by a Monte Carlo calculation which simulates the visible photon transport process inside the detector. The modeled physical processes include absorption, attenuation and Compton scattering of gamma rays by the aperture. The model also accounts for light photon processes inside the scintillation crystal, such as reflection, refraction and absorption.

To compute a system operator H_j for a given pinhole size and magnification, the object space is divided into a grid of 32^3 voxels. A point source is placed at each grid location and the SPECT simulator traces one million rays from the point source to the detector. The output of the simulator is a list of positions of photons incident on the detector. The detector is binned into 150^2 pixels and the number of photons incident on each pixel is counted. A Gaussian function is fitted to the image of the point source on the detector and its amplitude, mean, and covariance are stored in the computer. Storing the Gaussian parameters reduces the required memory and allows for interpolation of H_j matrix for intermediate magnification

and pinhole configurations [26]. The sensitivity of the average imaging system in table I is on the order of 10 cps/MBq.

B. Phantom

It is possible to simulate cardiac and respiratory motions in the MOBY phantom, and this will result in a dynamic object made of multiple frames. For a dynamic object, SLE is applied to all of the frames simultaneously, and the data vector in Eq. (11) contains the projections of all of the frames. Here we assume that the object is at rest and therefore only one object frame is generated. An example of such an object is shown in Fig. 3.

The MOBY object is contained in a support region of 32^3 voxels. The object voxel size is 0.5 mm in each dimension, and the support region is a cube with a side length of 16 mm. In the axial direction, the starting and ending slices are selected such that liver, lung, stomach, pancreas, kidneys, spleen, rib, and part of the spine are in the field of view. We simulate and store a binary matrix for each organ separately. For example, we set the activity of the liver to one, while the activities of all other organs are set to zero and generate a binary representation of the liver. This allows us to easily adjust the activity of organs in the volume of interest without the need to initialize and simulate the entire phantom each time. The object can then be imaged by a particular configuration in the adaptive SPECT system. Figure 4 shows eight projections of the kidneys imaged by an imaging configuration with a pinhole size of 1 mm and a magnification of 5.

C. Optimization

The activity parameters of the object imaged by the scout system are samples drawn from the experimental biodistributions measured for various organs and the tumor. We ran the Markov Chain for one thousand iterations, discarded the first 500 samples due to burn-in [5], and of the remaining accepted samples randomly selected one hundred objects for the ensemble. The acceptance rate is mostly determined by the variance of the proposal distribution and the noise in the scout image.

The smaller the amount of variance and noise, the higher the acceptance rate becomes. Since a low acceptance rate requires running the chain for many iterations, it is not efficient. A high rate leads to insignificant changes in the object and produces ensemble members that are too similar to the original object. Our aim was to reach an acceptance rate of 50%. To reach our target we conducted several simulation experiments and chose a variance of 0.2 for the Gaussian proposal density, as well as an exposure time of one thousand seconds for the scout image.

The use of the SLE for estimating signal parameters was discussed in the previous section. The estimation rule in Eq. (10) requires an optimization method for estimating the parameter vector θ . The parameters that we are estimating are activity, radius and location of a spherical signal. Radius and location are determined in terms of pixel numbers and are inherently discrete values. Activity can be continuous, but it is restricted to a discrete number to take advantage of a combinatorial optimization method.

The object ensemble obtained from the scout data gives some information about the range of discrete values that each parameter can hold. Using this information we can construct all the possible parameter vector combinations, evaluate the linear metric in Eq. (10), and identify the parameter vector that maximizes the linear metric. This computation is well suited for multi-threading and takes about 30 – 40 seconds to run on a Tesla K40m GPU card.

To perform a system optimization and find the imaging configuration with the highest MDI_j , we simulate a discrete set of system matrices. The pinhole size and magnification range listed in table I are each divided into nine linearly spaced values. The combination of imaging configurations based on these sets yields a total of 81 H matrices. Four of the system operators are simulated by the method described in section 3A, and all of the intermediate ones are calculated by an interpolation method [26]. Each system operator is applied in the SLE Eq. (10) and the corresponding estimate is used to calculate the MDI in Eq. (14). The system optimization task was executed in parallel on eight Tesla K40m GPU cards, and it took 40 – 60 minutes to complete.

IV. Results and Discussion

The main motivation for performing adaptive imaging is to determine an imaging configuration that extracts the most useful information regarding the signal in a particular object under study. In other words, the optimum system depends on the object characteristics, noise and the preliminary information derived from the scout data. Here we present some examples that illustrate the effects of the aforementioned factors on the system optimization outcomes.

A. Adaptation based on object variability

To show the effect of object variability, two object samples were selected. The parameters for these objects are listed in table II. Both objects were imaged by a scout system with a pinhole diameter of 0.5 mm, a magnification of 1.5, and an exposure time of one thousand seconds. The optimization method described in section 3C was applied to these objects. The exposure time for every imaging configuration in the optimization routine was set to one second. The activities are samples drawn from the measured bio-distribution data reported in [27] and are expressed in units of the percent injected dose per gram of the body weight of the mouse (% dose/g). The radius of the signal and its location are reported in units of millimeters. The origin of the coordinate system is located at a corner of the cube that supports the object; the location distances in x, y and z directions are measured from that origin.

Each time we run the optimization for a specific object, the MCMC routine generates a slightly different object ensemble. The Markov Chain must progress through hundreds of thousands of iterations to adequately sample the posterior distribution. Due to time and GPU memory constraints, we only run the chain for one thousand iterations and randomly select one hundred objects for the ensemble. The limited number of samples from the posterior distribution and the variability in the imaging system's noise realization leads to variance in the optimization results. Therefore, it is important to repeat the optimization multiple times to observe the changes in variance. As we increased the number of the optimization trials,

we realized that by the fifth trial, the average variance started to stabilize to within 10% of the maximum-minimum range of the plot. Therefore, we concluded that the minimum requirement for the number of optimization trials is five times.

The error bar plot for the optimization of object 1 is shown in Fig. 5. The x-axis and y-axis indicate the pinhole size and the magnification for each configuration; the surface connecting the MDI data points is interpolated. The contour plot shown in Fig. 6 is the projection of the mean MDI values on a plane. For object 1, a maximum MDI of 0.645 ± 0.04 is obtained by using a pinhole diameter of 1 mm and a magnification of 3.25. A minimum MDI of 0.279 ± 0.04 occurs when imaging with a pinhole diameter of 0.5 mm and a magnification of 8.5. In Fig. 6 we can identify a region with high MDI values, which indicate that a number of imaging configurations can serve as the optimum. Given that the range of MDI in this plot is 0.366 and the average variance is 0.04, the difference between the best and worst performing configurations is statistically significant, therefore the optimization is useful. The error bar and contour plot for the optimization of object 2 are shown in figures 7 and 8 respectively. The contour plot illustrates that the region of high MDI values has shifted towards larger pinhole sizes and magnifications. Studies of the SLE have shown that the nuisance parameters, such as the background parameters affect the estimates of the signal and are accounted for in the estimation rule in Eq. (10). The difference in object characteristics results in the unique MDI plots for objects 1 and 2. For the second object, a maximum MDI of 0.749 ± 0.05 is achieved for imaging configuration with a pinhole diameter of 1.375 mm and a magnification of 5. A system with pinhole diameter of 0.5 mm and a magnification of 8.5 yields the minimum MDI of 0.419 ± 0.05 . The range of MDI is 0.33 and the average variance is 0.05. Given the range and variance of MDI values in this case, the optimization helps with selecting an optimum system. It is interesting to note that both tested objects have signals that are 1.5 mm in radius and resulted in a pinhole size larger than 1 mm for the optimal imaging configuration. This outcome agrees with the aperture optimization results reported by Myers et al. [28]. In that study, it was found that for an object with a stochastic background, the optimum aperture size matches the signal size. We expect smaller signals to be resolved by smaller pinhole sizes, and we are conducting a more detailed study to test this hypothesis.

B. Effect of noise on adaptation

The amount of noise in the image data is determined by the sensitivity of the imaging configuration and the exposure time. A noisy scout system will generate an object ensemble that is less likely to resemble the original object and, therefore, will not provide useful information for the subsequent optimization steps. Our preliminary studies indicate that a scout system with eight projection angles, collecting a million photons per projection, provides sufficient data for the rest of the optimization. The image in Fig. 9a illustrates such a scout scan; in contrast, the image in Fig. 9b only contains one thousand photons, which is not an adequate photon count for the optimization. The images in Fig. 9 are acquired with exposure times of: a) one thousand seconds, b) one second. Similarly, the amount of noise in an imaging configuration affects the signal estimate computed by SLE and the corresponding MDI for system performance.

To illustrate the effect of noise on optimization results, we start with object 1, whose attributes are listed in table II. The object is imaged by a scout system with a pinhole diameter of 0.5 mm, a magnification of 1.5, and an exposure time of one thousand seconds. The exposure time for every imaging configuration in the optimization routine was set to one hundred seconds, which is one hundred times longer than the exposure time in Fig. 5.

The resulting error bar and contour plots are shown in figures 10 and 11. Low noise improves the performance of all of the imaging configurations and yields very good estimates of the signal parameters. In this case a maximum MDI of 0.978 ± 0.03 is achieved for a pinhole diameter of 1 mm and a magnification of 4.125. A pinhole size of 1.5 mm and a magnification of 1.5 results in a minimum MDI of 0.843 ± 0.03 . At this noise level, the mean MDI range is 0.135 with an average variance of 0.03. Therefore, when the diagnostic scan has a high photon count, on the order of one hundred thousand photons per projection, all of the imaging configurations perform reasonably well and there is no need for an optimization.

The noise level in the scout system affects the optimization results. We select object 1 and perform the optimization detailed in section 4A with one small difference. This time, the exposure time for the scout system is set to one second, instead of the one thousand second exposure time in Fig 5. The small exposure time results in very noisy scout data. This significantly affects the variability in the object ensemble and consequently the variability in the system performance.

The optimization outcome for the system performance is shown in figures 12 and 13. A maximum MDI of 0.645 ± 0.1 is achieved for a configuration with a pinhole diameter of 1.125 mm and a magnification of 5. The minimum MDI is 0.512 ± 0.1 and occurs for a pinhole diameter of 0.5 mm and a magnification of 8.5. The MDI range of 0.133 with a mean variance of 0.1 indicates that our result is not sufficient for optimizing system performance. Therefore, when the scout scan has a low photon count, on the order of one thousand photons per projection, it may not be possible to extract any useful information about the object. In that case, the samples in the object ensemble will not resemble the original object and the estimates for the signal parameters will be highly variable.

C. Performance of adaptive versus non-adaptive systems

To compare the adaptive with a non-adaptive SPECT system, we generate one hundred objects with distinct parameter vectors and evaluate the system performance for each one. The optimization provides an MDI for every imaging configuration per object. In adaptive imaging we compute the average of the maximum MDI values, whereas in non-adaptive imaging we calculate the average of all MDI values. For the scout system, we select an exposure time of one thousand seconds, a pinhole size of 0.5 mm and a magnification of 1.5. All other imaging configurations are assigned an exposure time of one second. With these settings, the range and variance of the MDI are similar to the examples in section 4A. The factors that affect the MDI include: object variability, image noise, choice of the scout system, and the bias and variance of SLE. These factors affect our MDI values collectively. Our results indicate that the MDI for the adaptive system is 0.84 and for the non-adaptive

system is 0.65. These numbers indicate, that accounting for all sources of variability, adaptive imaging performs better than non-adaptive in this case.

V. Conclusion

In this paper we present a method for optimizing an adaptive SPECT system and provide a few examples to illustrate the factors that affect the optimization and the requirements for the scout and diagnostic scans. We obtain some preliminary information about the object via the scout data. The MCMC can generate an ensemble of objects consistent with the scout data, if the photon count in the scout image is in the range of one hundred thousand to one million photons per projection. Conversely, for a scout image that contains a fewer photon count, the objects in the ensemble are not in agreement with the data and the subsequent calculations for the figure of merit are not reliable.

The simulated object ensemble also provides information regarding the range of possible activities, radii, and locations for the signal which helps constrain the parameter search range during the optimization. This information, in addition to the application of parallel processing techniques, allows us to calculate a figure of merit that quantifies the performance of a single imaging configuration in about 30 seconds. The optimization plots in this paper each contain 81 imaging configurations and take on of average 40 minutes to compute.

Our results indicate that the optimal imaging configuration depends on the object characteristics. We experimented with two unique objects and found that the optimum pinhole size and magnification is different in each case. We then extended this study to include one hundred unique objects and found that the average figure of merit, on a signal estimation task, is 0.84 for the adaptive system and 0.65 for the non-adaptive system.

Through our experiments we also learned that an adaptive system performs better than a non-adaptive system in conditions where: a) a scout image with a high photon count (on the order of one million photons per projection) is available, b) a diagnostic scan with a fast acquisition time one second in our example) is required for a dynamic study. Adaptive imaging and the optimization method we propose are suitable for dynamic studies in which the distribution of the radiotracer in the tissue is evolving continuously and short acquisition times are preferred. However, the importance of the optimization diminishes for a study that is not time-critical. If the study permits for a diagnostic scan with a long acquisition time (on the order of ten seconds), non-adaptive imaging is a feasible option.

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Fig. 1.

Diagram illustrates simulation steps in the optimization process.

Fig. 2.
Diagram of the adaptive SPECT system model studied in this paper.

Fig. 3.
Sample object which consists of multiple organs of the MOBY phantom and a spherical signal.

Fig. 4.
Eight projections of the kidneys imaged by the adaptive SPECT system in Fig. 2.

Fig. 5.
Optimization results for the adaptive SPECT system illustrating the mean and variance of MDI for object 1.

Fig. 6.
Contour plot of the mean MDI in Fig. 5.

Fig. 7.
Optimization results for the adaptive SPECT system illustrating the mean and variance of MDI for object 2.

Fig. 8.
Contour plot of the mean MDI in Fig. 7.

Fig. 9.

The object imaged in these projections contains eight organs of the MOBY phantom and a spherical signal enclosed in the box. The images are acquired from the the same projection angle and the exposure times were set to: a) one thousand seconds, b) one second.

Fig. 10.

Optimization results illustrating the mean and variance of MDI for a diagnostic scan with a high photon count.

Fig. 11.
Contour plot of the mean MDI in Fig.10.

Fig. 12.
Optimization results illustrating the mean and variance of MDI for a scout scan with a low photon count.

Fig. 13.
Contour plot of the mean MDI in Fig. 12.

TABLE I

Geometry parameter values for the imaging configurations.

System parameter	value(s)
Object-pinhole distance (mm)	25
Pinhole-detector distance (mm)	37.5 – 212.5
Pinhole diameter (mm)	0.5 – 1.5
Magnification	1.5 – 8.5

TABLE II

Parameter values used to simulate objects 1 and 2

Parameter	object 1	object 2
Liver activity (% dose/g)	2.1	1.9
Lung activity (% dose/g)	2.3	2.3
Stomach activity (% dose/g)	1.9	1.9
Pancreas activity (% dose/g)	2.0	1.9
Kidney activity (% dose/g)	1.9	2.2
Spleen activity (% dose/g)	2.6	2.8
Rib activity (% dose/g)	0.7	0.5
Spine activity (% dose/g)	0.7	0.9
Signal activity (% dose/g)	2.5	2.9
Signal radius (mm)	1.5	1.5
Signal (x,y,z) location (mm)	(6, 3, 11)	(4, 3.5, 9)