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A digital instrument simulator to optimize the development of a hyperspectral imaging system for neurosurgery

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ABSTRACT

In recent years, hyperspectral imaging (HSI) has demonstrated its capacity to non-invasively differentiate tumors from healthy tissues and identify cancerous regions during neurosurgery. Indeed, the spectral information contained in the HS images allows to identify more chromophores, refining the information provided by the imaging system, and allowing to identify the unique signature of each tissue types more accurately. Our HyperProbe project aims at developing a novel HSI system optimized for neurosurgery. As part of this project, we are developing a digital instrument simulator (DIS), based on Monte-Carlo (MC) simulations of the light propagation in tissues, in order to optimize both the hardware and data processing pipeline of our novel instrument. This framework allows us (1) to test the effect on the accuracy of the measurement of several hardware parameters, like the numerical aperture or sensitivity of the detector; (2) to be used as numerical phantoms to test various data processing algorithms; and (3) to generate generic data to develop and train machine learning (ML) algorithms. To do so, our framework is based on a 2-step method. Firstly, MC simulations are run to produce an ideal dataset of the photon transport in tissue. Then, the raw output parameters of the simulations, such as the exit positions and directions of the photons, are processed to take into account the physical parameters of an instrument in order to produce realistic images and test various scenarios. We present here the initial development of this DIS.

Keywords: Hyperspectral imaging, neuronavigation, surgical imaging, tissue optics, cancer imaging, Monte-Carlo, light propagation, simulations.

1. INTRODUCTION

Hyperspectral imaging (HSI) is a promising technology that has demonstrated its usefulness in medical applications[1]. This technology is an extension of traditional 2D imaging, as it adds a spectral dimension to the recording. Indeed, HSI primarily utilizes very narrow and adjacent spectral bands over a continuous spectral range to reconstruct the spectrum of each pixel in the image. To do so, multiple acquisition strategies can be employed, like (1) spectral scanning modes, where the 2D image is acquired at each wavelength separately, (2) spatial scanning modes, where all the wavelength are acquired simultaneously for a small portion of the image, and (3) snapshot modes that can acquire both the spatial and spectral dimension simultaneously. The interested reader can find more details about HSI in recent reviews[1,2].

In order to improve this technology, two main avenues can be explored. The first one consist in refining the hardware used to produce the hypercube (i.e., spectral images) and the second one consist in refining the data processing scheme used to processes the hypercube. Regarding the hardware, HSI relies on key elements both from the source and detector side. We can cite the key parameters of the source as being its spectral power and numerical aperture, the latter being dictated mainly by the coupling optics used. For the detection side, the key parameters are dictated by the optical system (OS) and detector used. The OS will encompass all the element to focus the light from the tissues to the detector, usually a CCD sensor.

In the recent year, simulation tools have arisen in order to model the entire instrument[3]. This possibility can help to refine systems' developement by testing various components or strategies without having to implements them physically, thus

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reducing their cost. These tools can also provide synthetic datasets in order to try novel data processing pipelines. Indeed, the current trend is to move towards artificial intelligence (AI) methods, including machine learning (ML) and deep learning (DL)[4]. These methods are becoming a tool of choice for HIS as it provided a good framework to process large multidimensional datasets to overcome the well-known *curse of dimensionality*[5].

We are currently focusing on HIS imaging for application in brain surgery. Indeed, in this context, HIS can be used in order to non-invasively differentiate tumors from healthy tissues and identify cancerous regions[6] or functional areas[7]. Our HyperProbe project[8] aims at developing a novel HSI system optimized for neurosurgery. To do so, we will build a novel HSI system and produce novel ML algorithms in order to take the most out of the vast amount of data produced. The interested reader can refer to the proceeding EB102-52 by Giannoni *et al.* for more information about the project. As part of this project, we are developing a digital instrument simulator (DIS), based on Monte-Carlo (MC) simulations of the light propagation in tissues, in order to optimize both the hardware and data processing pipeline of our novel instrument. This framework will allow us (1) to test the effect on the accuracy of the measurement of several hardware parameters like the numerical aperture or sensitivity of the detector, or the wavelength selected and (2) to be used as numerical phantoms to test various data processing algorithms and (3) to generate generic data to train ML algorithms. In this work, we will present the basic principles of our DIS, together with a quick example of a parameter that can be modeled with it.

2. INSTRUMENT SIMULATOR FRAMEWORK

The DIS is based on a 2-stage approach depicted in figure 1. The first step is to simulate the propagation of the light through tissue. This is done using a MC approach, which will be describe in section 2.1. The second step takes the raw output of the MC simulations and incorporates the real instrument parameters in order to produce realistic images. This step will be described in section 2.2.

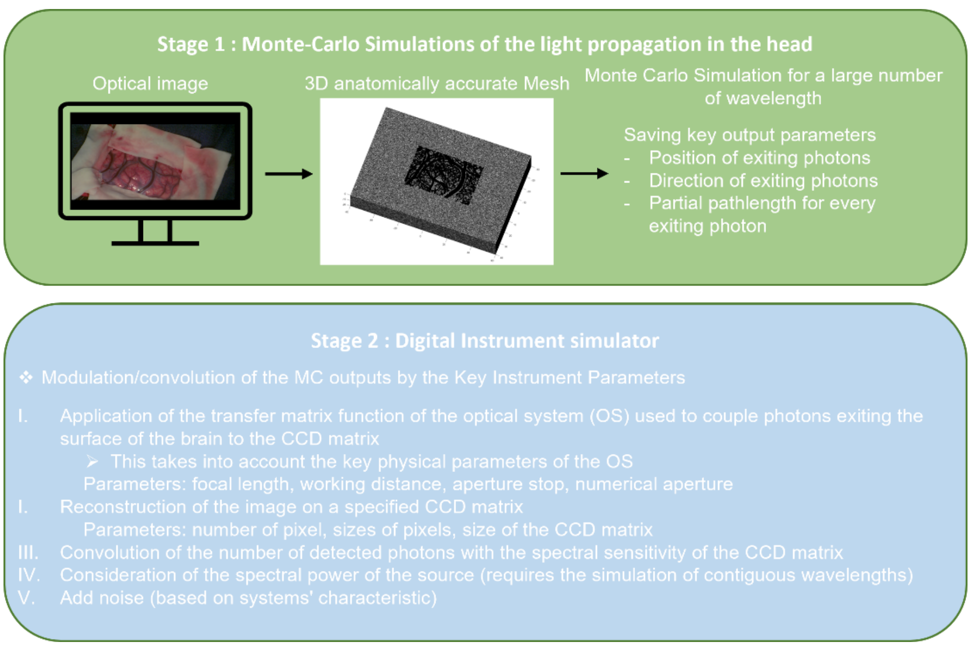

Figure 1. Summary of the main steps to design the digital instrument simulator (DIS).

2.1 Stage 1 – Monte Carlo simulations

This first steps uses the same core approach as we previously used in a work looking at an HSI system build to image the exposed cortex of rodents[9,10]. Here, we use the well know Mesh-based Monte Carlo (mmc) tool[11,12] to simulate the propagation of the light in the tissues. The mmc tool relies on 3D-mesh, which allows to generate complex medium. The first step to run the simulation is thus to produce a 3D-mesh. In order to produce the most realistic mesh, we start by segmenting an intraoperative RGB image in order to extract the vasculature. This segmentation is performed with a thresholding operation. On the intraoperative RGB image, the vascular network appears darker than the gray matter due to the high absorption of hemoglobin. In order to operate a binary segmentation mask of the vascular network and the gray matter an adaptive threshold is used. This thresholding method is weakly impacted by the disparity of illumination and aims to detect structure with a desired size within the image. Here the desired size is the diameter of the blood vessels. An example of RGB intraoperative image is presented in figure 2. In this image, the diameters were estimated for small and large vessels. Average diameters for small and large vessels were 0.26mm and 2.04mm respectively, with a standard deviation of 0,12mm and 0,63mm. The threshold was computed with a Gaussian kernel of 5.0mm (63 pixels) in order to preserve the blood vessel structures.

After this segmentation, the image is cropped and rotated (figure 2.c) and the 3D-mesh is generated (figure 2.d). A block of tissue is then added to the mesh of the vasculature. Finally, a planar source located above the tissue is also meshed, resulting in a final mesh similar to the one presented in figure 3.a. All the meshing steps are done using the iso2mesh tool[13]. Finally, the elements of the mesh are assigned their optical properties (absorption coefficient μ_a, scattering coefficient μ_s, anisotropy g, and refractive index n), based on their tissue type (for more details, see reference 9). Once the domain has been defined (i.e., both geometry and optical properties), the final step is to place a single large detector on top of the medium in order to detect the reflected photons and run the simulation.

Multiple parameters can be saved for each simulation but the one that we considered are the exit position and direction of each detected photon (to be used by the DIS, see next section), together with their partial pathlength (to study the light propagation in tissues). It worth noting that that these parameters are not affected by the absorption and that these simulations are thus called white MC[14]. The advantage of this approach is that the absorption can then be considered *a posteriori*, by using the beer-lambert law. Thus, when changing the absorption parameters of the mesh (i.e., to simulate a brain activation for example), the simulation doesn't need to be run again, speeding up the processing.

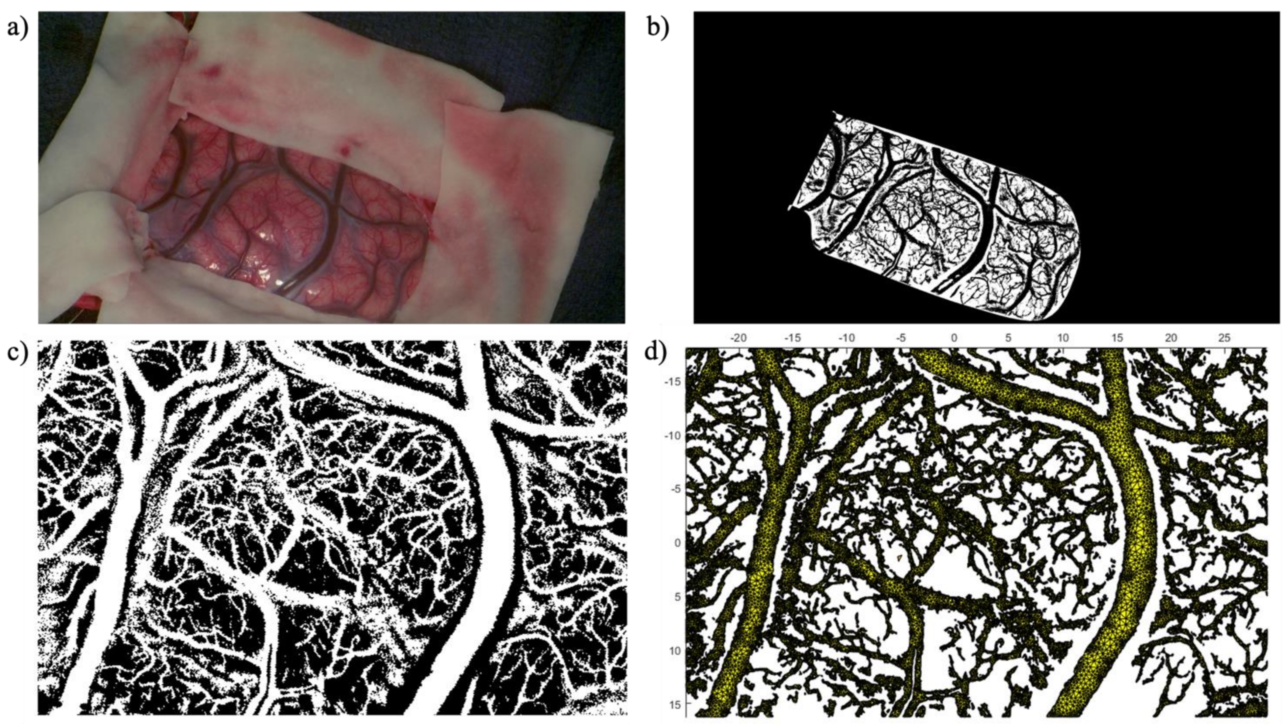

Figure 2. Illustration of the segmentation and meshing of brain blood vessels. a) Initial RGB intraoperative image. b) Segmented image, using the segmentation methods describes in section 2.1. c) cropped and rotated segmented image used to do the meshing. d) Final 3D-mesh of the brain vasculature.

2.2 Stage 2 – Digital instrument simulator (DIS)

The second part of the simulator consist of generating realistic data that considers the physical parameters of an optical system (OS). This type of approach has already been introduced previously. We can cite for example the work of Sudakou *et al*.[15]. In this paper, time domain functional near infrared spectroscopy (TD-fNIRS) measurement were simulated using a MC approach and the responsivity of the detectors of a particular system was introduced to simulate realistic data acquired by this system. The authors showed that the consideration of the responsivity of the detectors was shifting the optimal wavelengths to use for their application, highlighting the importance of taking into account the physical limits of the instrument in simulations. We want to take a similar approach here and consider all the key parameters of both the source and detection scheme, to generate a complete digital instrument simulator (DIS).

To do so, the first step is to calculate the position of each photon exiting the tissue onto the detector (for example a CCD camera). This is done by taking the initial exit photon position and direction and applying the transfer matrix of the OS[16] that couples the light to the detector, and which considers all its key elements (i.e., focal length, working distance, size of the optics, numerical aperture). This allows us to reject all the photons that would not be detected by the system. Then the photons are sorted in a matrix according to the principal characteristics of the CCD matrix (i.e., number and sized of pixels, and size of the matrix). Finally, the number of photons detected is adjusted according to the spectral responsivity of the detector. These steps generate an image that would be comparable to a noise free detection for a single wavelength. The final steps are to consider the spectral characteristics of the source and to add realistic noise. To do so, it is worth mentioning that the simulation has to be repeated for a large number of wavelengths in order to be able to take into account the characteristics of a real source. Indeed, the output spectra of a real single wavelength light source won't be a Dirac delta function and will have a spectral broadening. Thus, in order to take this into account, the results of multiple simulation at various contiguous wavelength are convoluted with the spectral power distribution of the source and then integrated to produce a realistic result. Once this data is produced, the final step is to add realistic noise to the data (i.e., dark noise, read-out noise of the camera, etc.).

Once the realistic data set has been produced, one can test various combination of wavelength or data algorithm pipeline to optimize the accuracy of the measurements.

3. EXAMPLE OF SIMULATED INSTRUMENT PARAMETER: THE NUMERICAL APERTURE

In this section, we will present an example of the use of our DIS on a specific parameter. Indeed, this simulator can be used to model the entire hardware, but one of the benefits of numerical approaches is to be able to isolate one parameter to study its effect independently. Here we report a quick study of the effect of the numerical aperture on the number of detected photons. To do so, we have used the raw output of one of the simulations presented in reference 9, with a mesh presented in figure 3.a. By knowing the directions of every exiting photon comprised in the aperture of the system, we can select the photons that are not exceeding the maximum angle of the NA of the system, and can be detected. For example, by taking an arbitrary OS using a lens with a F-number of 1.7 (half-angle 17.11°), we see that only 8.1% of the total number of exiting photons can be collected by the system. An illustration of the exiting photons together with their angular distribution is presented in figure 3.b and c.

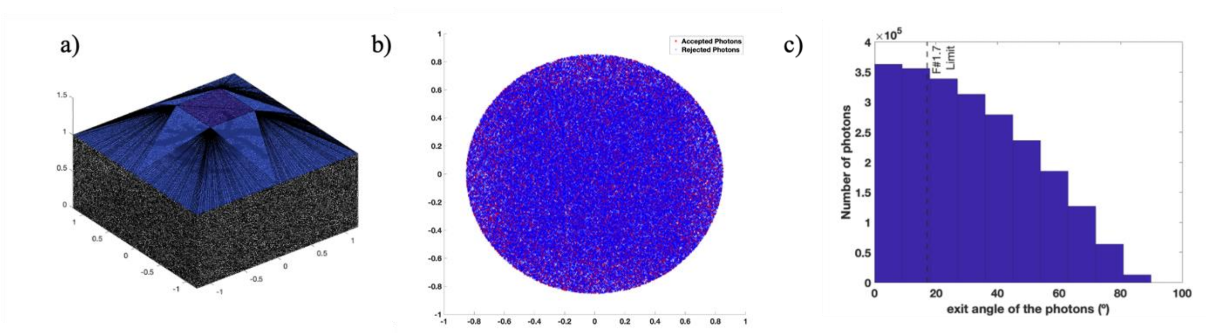

Figure 3. a) Illustration of the 3D-Mesh used for this simulation, comprising the source, the air and the brain tissues. More information can be found in reference 9. b) Example of an image of the exiting photons passing though the aperture of the OS. The red dots represent the photons able to be detected by the system (here F#1.7). c). Histogram of the angular distribution of the exiting photons passing through the aperture of the system. The limit angle of the F#1.7 is also marked.

This quick example shows how we can use our DIS to study a specific parameter. This could be used to optimize the development of our system in order to maximize its light harvesting by looking at the benefits of using OS with various NA. It can notably help us to gain time in the development by quantifying the potential gain of using different optics and focusing on the most significant parameters. For example, using an OS with a F#1.4 would collect 4% more light compared to the F#1.7. This information can be used in combination with other system's parameter in order to decide if such improvement would be significant for the data quality of our images, and thus whether or not it should be implemented physically.

4. CONCLUSIONS AND PERSPECTIVES

We have reported here the initial development of an optical DIS designed to optimize the development of a novel HIS system for brain surgery. This simulator is based on MC simulations of the light propagation of the photons in tissues in order to model as realistically as possible the photon trajectories in tissues. Then the raw outputs of the MC simulation are convoluted with the key instrument parameters in order to produce realistic images.

This approach will allow us to optimize the design of our new HIS system. Indeed, we are currently modeling our initial system with this instrument simulator and comparing it with well-defined phantom measurements. This will allow us to validate the accuracy of our numerical tool before using it to optimize key parameters of the optical system, like the number of wavelengths used, without the need to physical implement all the solutions. Moreover, this tool will be used in combination to phantom validation in order to select the most appropriate data processing pipeline. Once the ultimate characteristic of the system will have been reached, this simulator will be able to be used in order to generate large amount of synthetic data to help the training of ML algorithms.

Finally, it worth mentioning that this DIS is versatile and not restricted to exposed cortex situations. Indeed, the 2-step approach enables to model any kind of geometries and OS, providing that the main characteristics of each element are known. Thus, systems based on fiber coupling, like traditional fNIRS instruments, can also be modeled with this tool. We think that this capacity should be helpful for the entire community and help to its adoption.

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