Studying the Effect of Camera Noise in Laser Speckle Contrast Imaging

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***Abstract*—In this project, we are focusing on the quality of a technique called Laser Speckle Contrast Imaging (LSCI), which is a rapidly developing method to do blood flow imaging and has different applications in brain, retina and skin imaging. Noise in images, which typically arises from the camera, is a key factor that limits LSCI quality. In this project we study the impact of different kinds of noise in LSCI. We develop two models, a speckle model to calculate different speckle dynamics, and a noise model used to create different kinds of noise. We show that averaging images does not compensate for noise. We show that noise has a different impact on different tissue types, highlighting the importance of understanding the noise in the camera when doing LSCI experiments.**

I. Introduction

In the healthcare industry and research, blood flow imaging is widely used. It helps to diagnose and treat some of the most common causes of death worldwide, such as heart attack, cancer and dementia, by providing visualization of blood flow. Techniques based on Laser speckle contrast have become a vital technique as they allow high spatial and temporal resolution blood flow to be visualized without injecting contrast agents [1].

LSCI is based on the theory that a spontaneous interference pattern called speckle pattern arises from the back-scattered light from an object that is illuminated with coherent laser light. Movement of particles within the object causes fluctuations in this speckle pattern, resulting in speckle images being blurred. If the fluctuations are caused, for instance, by the movement of red blood cells, this blurring can be related to blood flow [2].

A speckle image can be composed of both static and dynamic speckles. Static speckles are speckles that do not alter over time, whereas dynamic speckles shift over time. Dynamic speckles provide information about the motion of the particle within the object [2]. The dynamics of the speckle pattern can be visualized by calculating the contrast of the image, which is defined as the ratio of the standard deviation to the mean intensity

$$K = \frac{\sigma}{< I >} \tag{1}$$

where K is the contrast, σ refer to the standard deviation and I is the mean intensity [1].

In this project we use both global contrast, which is calculated for the whole image, and local contrast which gives pixel by pixel results for the contrast, for a chosen neighborhood around each pixel, from the contrast we can calculate the blood flow index, which is a relative measure of flow speed. It is defined as [3]

$$BFI = \frac{1}{K^2} \tag{2}$$

For LSCI, the experimental setup is very basic. The object being examined, which is imaged by a digital camera, is illuminated by laser light. The image is recorded by custom software and processed [2]. LSCI has several limitations, LSCI is not quantitative, resulting in very limited inter-patient comparability, correction of movements artifacts (unwanted tissue movement, a patient who can not stay still), the most important is noise that arise from the camera.

In this project we are developing a computational model for speckle simulation, we will introduce different kinds of noise in our modeled data to study the effect of noise on LSCI and how to minimize the impact of noise.

In the following sections a description of the methods applied in the study is given. After that, the obtained results are discussed and analysed. Lastly, final conclusions about the research are given.

II. Methods

In this section the methods used to model the speckle pattern and noise are described in detail. After that, the implementation of the models and generation of experiment data is described.

A. Speckle model

First, a volume was formed with randomly distributed particles to represent the vessel. Second, we define the sensor and the location of the pixels and for each pixel, the electric field of light scattered by a particle can be described as [4]

$$E = \frac{exp(ikr - ikct)}{r} \tag{3}$$

where i is imaginary unit, r is the distance from particle to pixel, c is the speed of light and k is a wave-number $(2\pi/\lambda)$, wavelength λ = 0.785 µm. The model implements each particle as a light source instead of modeling a light source being scattered by each particle, this was done to simplify the calculations [4].

The type of movement of the particles must be taken into account before visualizing the intensity image, Brownian

(a) 1 particle (b) 2 particles (c) 1000 particles (d) summed speckle pattern

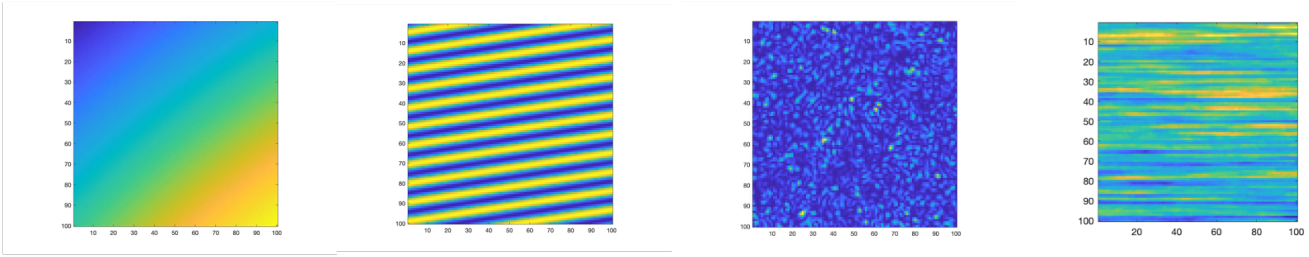

Fig. 1: Speckle pattern with different numbers of particles, (Fig1a) a speckle pattern with one particle, (Fig1b) a speckle pattern with two particles (Fig1c), a full speckle pattern with 1000 particles, (Fig1d) summed image of 5000 speckle images.

motion for small vessels and ordered motion for larger vessels [5]

$$I = E * \overline{E} \tag{4}$$

Equation 4 was used to display the Intensity, in order to provide a full speckle pattern image. Fig. 1 demonstrate how the speckle interference changes with the number of particles. The number of particles for the experiments was set to 1000.

Using the speckle model, a data-set is created for different types of tissues (large vessel, medium vessel and parenchyma). The auto-correlation function $g_2(\tau)$ was used when creating each data-set, to ensure the desired motion type was modeled [5]. An auto-correlation is a correlation of the signal with itself at different time lags. The autocorrelation of the data was calculated as:

$$g_2(\tau) = \frac{< I(t)I(t+\tau) >}{< I(t)^2 >} \tag{5}$$

From [5] we know that the auto-correlation function of dynamic light scattering can be related to the electric field correlation $g_1(\tau)$, by the Siegert relation [5]

$$g_2(\tau) = 1 + \beta \mid g_1(\tau) \mid^2 + C \tag{6}$$

Where τ is the time lag, β represents the properties of the source coherence and C is an offset representing the noise, $g_1(\tau)$ is defined by

$$g_1(\tau) = exp(-(\frac{\tau}{\tau_c})^n) \tag{7}$$

where τ_c is the correlation time constant and n varies depending on the type of motion [5]
For each type of tissue, equation 5 was used to calculate $g_2(\tau)$. This was then fit to equation 6 to get the correlation time, τ_c. The displacement of the particles was adjusted by trial and error until the desired correlation time was reached. The datasets created were: Large vessel - ordered motion, τ_c = 20 µms, Mid-sized vessel – ordered motion τ_c =80 µms and Parenchyma – brownian motion τ_c = 500 µms [4]. For each tissue type, data was created with three different speckle to pixel size ratios. The speckle to pixel size ratios used was 1, 2 and 4.

B. Noise model

We modeled three types of noise that arise from the sensor: Shot noise (salt and pepper), Fixed pattern noise and Pixel cross-talk) [3]. Pixel cross-talk is actually a camera artifact, but we will refer to it as a type of noise in this report.
We were given a noise data-set recorded by a camera in a dark room to investigate the noise characteristics. The shot noise was found to have an exponential distribution. The fixed pattern noise was found to have a Gaussian distribution. According to [3] pixel cross-talk can be modelled as a convolution with a $7x7$ Gaussian Kernel with a standard deviation of 0.5 pixels.

C. Experiment data

The speckle model was used to generate 5000 frames, with a difference of $1\mu s$ between frames. The frames where summed and averaged, to generate a single image frame, simulating a camera with an exposure time of 5 ms (see fig. 1d). Having $1\mu s$ between frames is assumed to be short enough to correctly estimate a continuous measurement. The noise model was used to generate 100 noise images, which individually was added to the summed speckle image. This was done to get a better understanding of the mean influence of the noise on the contrast. When adding the noise to the speckle image, first the speckle image is convolved with the Gaussian kernel to apply the pixel cross-talk, then the shot noise and fixed pattern noise was added on on top of that image.

III. Results

We want to investigate how the contrast changes as we change the mean intensity of the image, and what is the effect of changing the shot noise means on the contrast.
The results obtained will be divided into three parts. Firstly, results obtained from adding only shot noise are commented. Then results from adding shot noise and pixel cross-talk with lower mean contrast. Lastly, the final results given by adding all 3 types of noises.
Fig. 2 displays an average of 100 images for 3 vessels with a mean contrast of Parenchyma of 0.2, indicating a change in the mean intensity of the image against the normalized mean local contrast. The yellow line is the true contrast, the red line is the noise-free model, the blue line is shot noise with mean

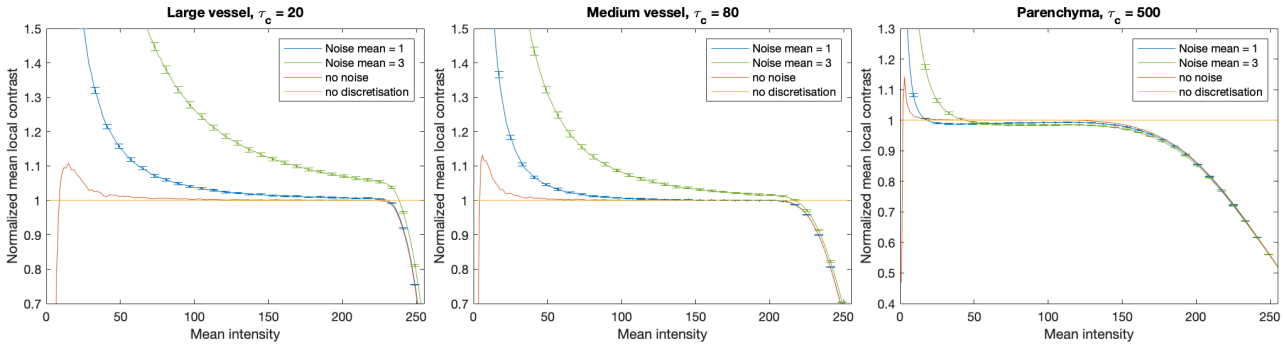

Fig. 2: Mean intensity compared to normalized mean local contrast for 3 types of vessels, with mean parenchyma contrast 0.2. Noise type: Only shotnoise.

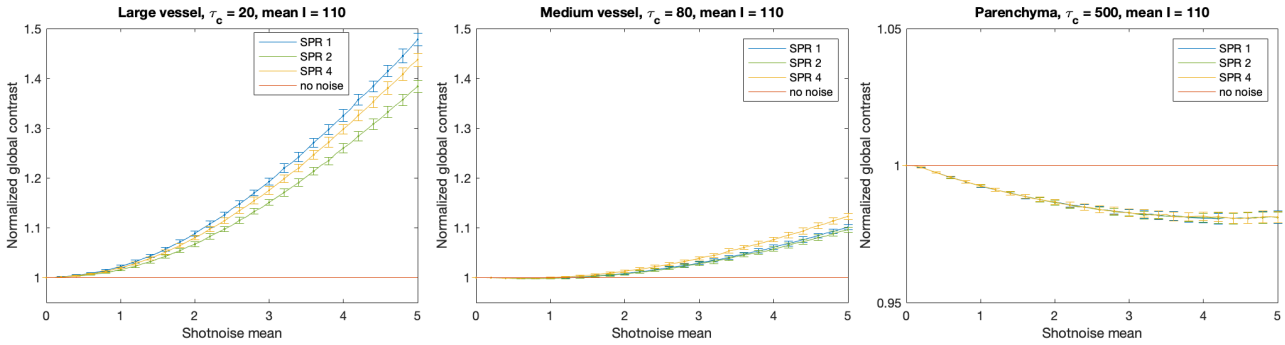

Fig. 3: Shotnoise mean compared to normalized global contrast for 3 types of vessels with different speckle to pixel size ratio. Mean paranchyma contrast 0.2. Noise type: Only shotnoise.

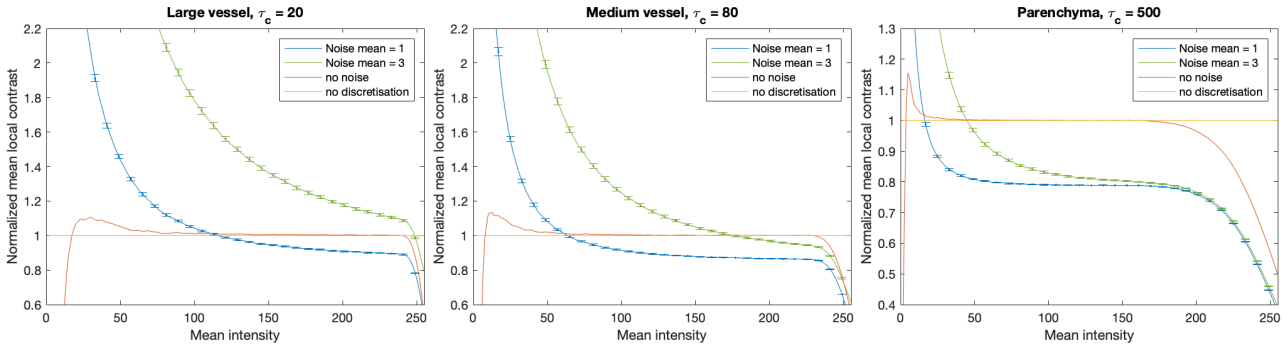

Fig. 4: Mean intensity compared to normalized mean local contrast for 3 types of vessels with mean parenchyma contrast 0.1. Noise type: shotnoise and pixel cross-talk.

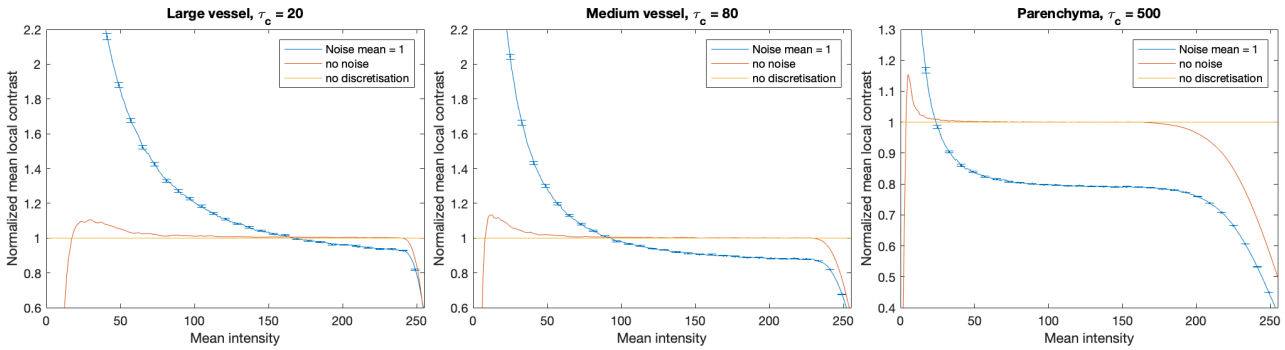

Fig. 5: Mean intensity compared to normalized mean local contrast for 3 types of vessels with mean parenchyma contrast 0.1. Noise type: shotnoise, pixel cross-talk and fixed pattern noise with mean 3.5

1 and the green line is shot noise with mean 3.
Due to discretisation we see some variations in the contrast, since pixel values in an 8 bit image are integers between 0 and 255. At higher intensities we start to get saturation of the pixel values because it can not go above 255, resulting in lower mean contrast. This effect is more evident for the parenchyma where the saturation starts at mean intensity values of around 130. We see that the combined effect of shot noise and discretisation has a larger influence on contrast at lower mean intensity values.
The shot noise versus the normalized global contrast is shown in Fig. 3 and the three curves are 3 different speckle to pixel size ratio (SPR), blue is SPR of 1, green is SPR of 2 and yellow is SPR of 4. Global contrast was used to accurately understand the influence of noise on different SPR values.
We see that increasing the shot noise mean, increases the global contrast, we also see that each vessel type responds differently to the change in shot noise mean. It has a larger influence in the large vessel and a smaller influence in the mid-size vessel and in the parenchyma increasing shotnoise decreases the contrast value. There is not a big difference between different SPR values.
Fig. 4 corresponds to the same plot as Fig. 2 however we add pixel cross-talk to the model and decrease mean contrast of parenchyma to 0.1. For large and midsized vessels pixel cross-talk reduces the contrast and the shotnoise increases the contrast. This results in contrast being higher than the true contrast value for smaller mean intensities, and lower than true contrast for larger mean intensities. In the parenchyma both shot noise and pixel cross-talk reduce the contrast, so the two add up to a larger decrease in contrast compared to the true contrast value.
Fig. 5 is an expression of the typical experimental setup used by many for Laser Speckle Contrast Imaging, where they have a mean contrast of parenchyma of 0.1, a shot-noise of mean 1, fixed pattern noise and pixel cross-talk [4].
The lower mean parenchyma contrast increases the effect of the noise. For large and midsized vessels, Shot noise and fixed pattern noise increase the contrast, and pixel cross-talk reduces the contrast. The combined effect results in a contrast that varies a lot from low to high mean intensities.
In the appendix additional plots are presented to show the effect of adding pixel crosstalk or changing the mean parenchyma contrast individually. Appendix A shows the shot noise mean compared to global contrast plots. Appendix B shows the mean intensity compared to mean local contrast plots.

IV. Discussion

According to [4], one of the common methods of minimizing the effect of noise is by averaging multiple images. All our results show that averaging has no effect in removing the influence of noise in LSCI.
Looking at fig. 2, 4 and 5 it can be seen that capturing images with a low mean intensity will result in images highly influenced by noise and discretisation. Choosing a high mean intensity will be influenced by discretisation seen as saturation, especially in the parenchyma. From this we can make a recommendation of using a mean intensity in the range of 100-120 to reduce these effects.
Fig. 3 shows there is not a big difference in the influence of the noise when using different speckle to pixel size ratios, but it seems that using a speckle to pixel size ratio of around 2 generally gives the best results (see also appendix A).
In fig. 4 and 5 it can be seen that pixel cross-talk has a large influence on the contrast. Looking at parenchyma in fig. 2 and 3 it can be seen that shot noise alone only changes the contrast a few percent, whereas pixel cross-talk lowers the contrast to around 80 percent of the true value. Understanding the amount of pixel cross-talk present in the specific camera setup will have a big influence on how the results obtained should be evaluated.
The main point we see in the results is the large difference in the effects of noise in different vessels. The BFI is either over or underestimated depending on the type of noise present in the camera setup and the speed of the blood flow in the vessel being imaged. This fact that the noise is not a constant means that when doing LSCI it is difficult to compare the different vessel types to each other. For instance in fig. 4, if we have a mean intensity value of 90, depending on the type of vessel, it will give us a contrast of 1.1 for large vessel, 0.9 for a mid-size vessel and 0.8 for parenchyma. Meaning that the BFI will be around 83%, 123% or 160% of the true BFI, depending on the type of vessel, or rather the speed of the blood flow in the vessel being imaged. When LSCI is used to do studies on the effect of occluding a vessel on the blood flow in a region of the brain, then before occlusion the BFI may be underestimated, and following the occlusion the BFI may be overestimated. The result of the experiment will be a smaller change in BFI than what actually occurs. This means that understanding the type and amount of noise in the camera setup is important to make a conclusion in that kind of study.
According to [4] many studies with LSCI is done with a camera setup similar to what is seen in fig. 5 they take a mean intensity of 50 which results in a contrast of 1.7 for large vessel, 1.3 for mid size vessel and 0.8 for parenchyma, meaning a BFI of 34%, 60% and 156% of the true BFI. This should highlight the poor nature of that setup. At such a low mean intensity, even small differences in the speed of blood flow in the vessel will result in very different BFI values.

V. Conclusions

Over the past decade, LSCI has emerged as a very effective technique for visualizing flow changes, with excellent spatial and temporal resolution. The image noises that arise from the camera are one of the several limitations of LSCI.
In this project we showed that averaging does not compensate for noise. Based on our experiments we can recommend a mean intensity in the range of 100-120 and a speckle to pixel size ratio of around 2. We show that different kinds of noise,

influence different tissue types in different ways. Noise does not always increase or decrease contrast, it depends on the dynamics of the tissue being imaged.

We can conclude that when doing experiments with LSCI one must have a knowledge of the type of vessels that is being imaged, the type and strength of noise present, the speckle to pixel size ratio and the mean intensity for that specific experimental setup.

For future work it would be interesting to replicate the experiments from this project with real images and real noise data.

REFERENCES

[1] D. A. Boas and A. K. Dunn, "Laser speckle contrast imaging in biomedical optics," *Journal of Biomedical Optics*, vol. 15, no. 1, 2010.

[2] G. M. v. D. Wido Heeman, Wiendelt Steenbergen and E. C. Boerma, "Clinical applications of laser speckle contrast imaging: a review," *Journal of Biomedical Optics*, vol. 24, no. 8, 2019.

[3] S. E. E. Dmitry D. Postnov, Xiaojun Cheng and D. A. Boas, "Choosing a laser for laser speckle contrast imaging," 2019.

[4] "Private consultation with Dmitry D. Postnov," 2020.

[5] S. E. E. K. K. Dmitry D. Postnov, Jianbo Tang and D. A. Boas, "Dynamic light scattering imaging."

APPENDIX

APPENDIX A
SHOTNOISE V GLOBAL CONTRAST

Fig. 6 shows the reduction of contrast when adding pixel cross-talk. Fig. 7 shows the effect just changing the mean of parenchyma to 0.1. It can be seen that the effect of shot noise is increased. Fig. 8 shows the effect of both changing the mean contrast of parenchyma to be 0.1 and adding pixel cross-talk. This results in contrast being reduced for low shot noise means but at higher shot noise mean, the increased effect caused by the lower parenchyma contrast increases the global contrast.

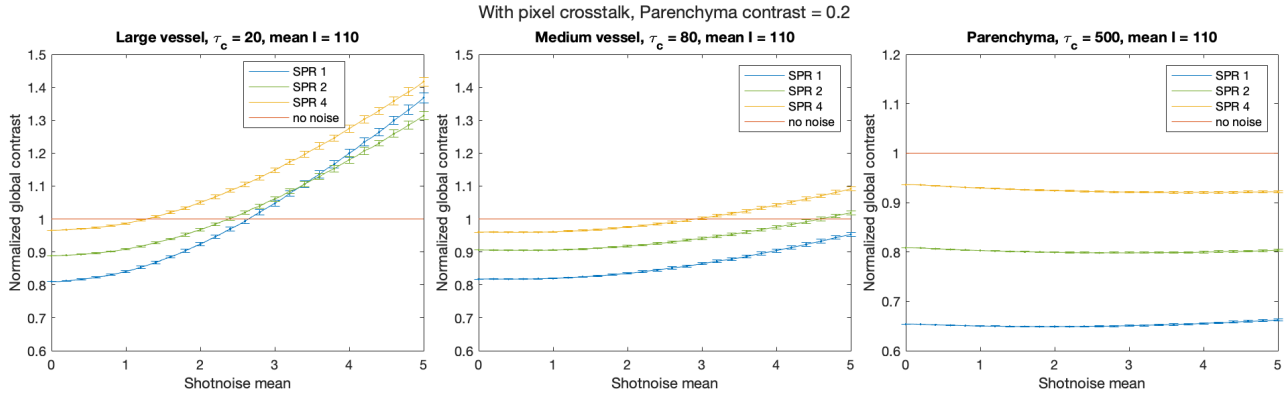

Fig. 6: Shotnoise mean compared to normalized global contrast for 3 types of vessels with different speckle to pixel size ratio. Mean parenchyma contrast 0.2. Noise type: shotnoise and pixel crosstalk.

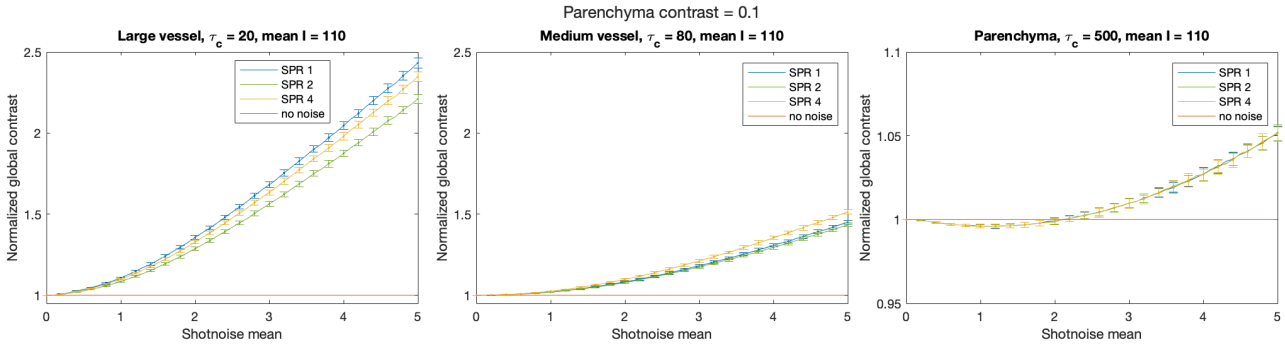

Fig. 7: Shotnoise mean compared to normalized global contrast for 3 types of vessels with different speckle to pixel size ratio. Mean parenchyma contrast 0.1. Noise type: Only shotnoise

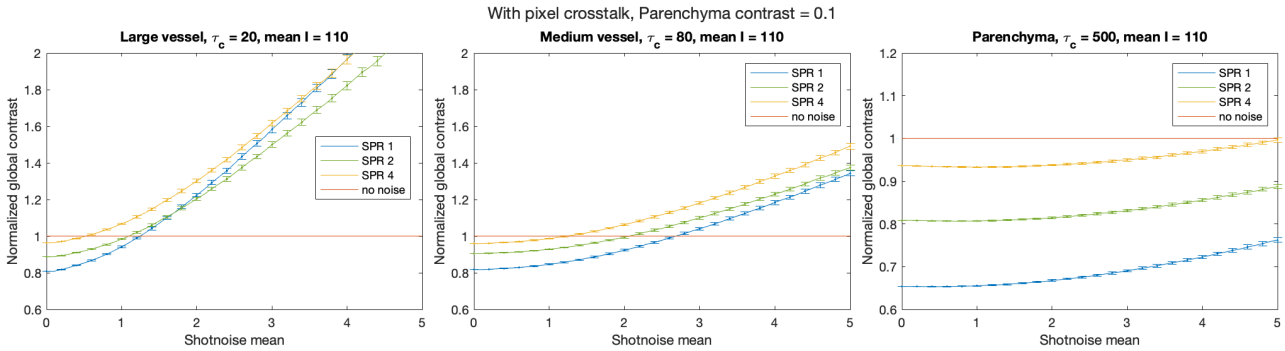

Fig. 8: Shotnoise mean compared to normalized global contrast for 3 types of vessels with different speckle to pixel size ratio. Mean parenchyma contrast 0.1. Noise type: shotnoise and pixel crosstalk.

APPENDIX B
MEAN INTENSITY V MEAN LOCAL CONTRAST

Fig. 9 shows the effect of just adding pixel crosstalk, reducing the local contrast. Fig. 10 shows the effect of just changing the mean parenchyma contrast to be 0.1. It shows that lower mean parenchyma contrast increases the effect of noise on local contrast.

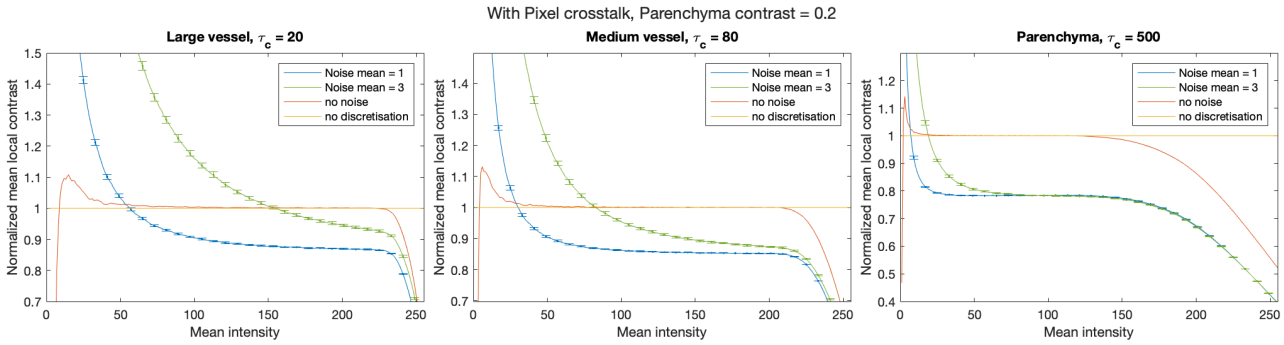

Fig. 9: Mean intensity compared to normalized mean local contrast for 3 types of vessels, with mean parenchyma contrast 0.2. Noise type: shotnoise and pixel crosstalk.

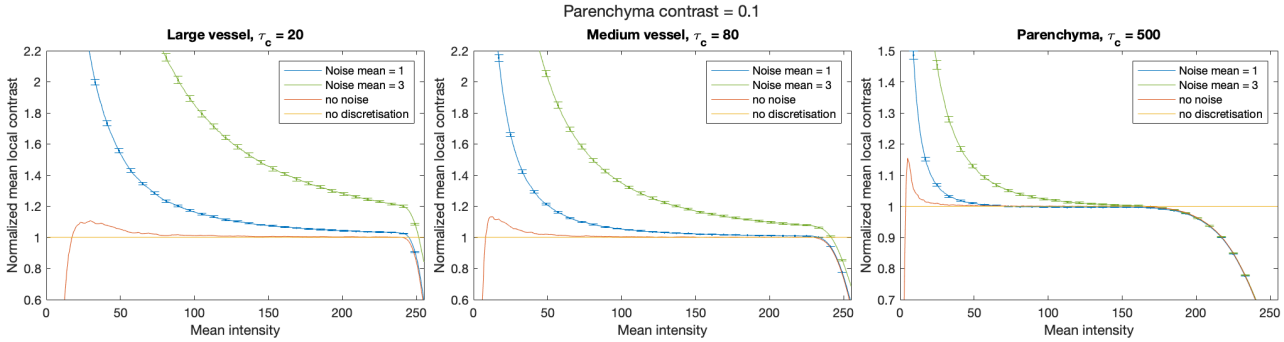

Fig. 10: Mean intensity compared to normalized mean local contrast for 3 types of vessels, with mean parenchyma contrast 0.1. Noise type: Only shotnoise.