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Visibility of noise texture changes in CT images

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ABSTRACT

Noise texture in CT images, commonly characterized by using the noise power spectrum (NPS), is mainly dictated by the shape of the reconstruction kernel. The peak frequency of the NPS (f_{peak}) is often used as a one-parameter metric for characterizing noise texture. However, if the downslope of the NPS beyond the f_{peak} influences noise texture visibly, then f_{peak} is insufficient as a single descriptor. Therefore, we investigated the human-detectable differences in NPSs having different f_{peak} and/or downslope parameters.

NPSs were estimated using various reconstruction kernels on a commercial CT scanner. To quantify NPS downslope, half of a Gaussian function was fit through the NPS portion that lies beyond f_{peak}. The σ of this Gaussian was used as the downslope descriptor of the NPS. A two alternative forced choice observer study was performed to determine the just-noticeable-differences (JND) in f_{peak} only, σ only, and both simultaneously. Visibility thresholds for these changes were determined and an elliptical limiting detectability boundary was determined.

The JND threshold ellipse is centered on the reference values and has a major and minor radius of 0.47 lp/cm and 0.12 lp/cm, respectively. The major radius makes an angle of 143° with the x-axis. A change in only f_{peak} of 0.2 lp/cm is below the detection threshold. This number changes if the apodization part of the NPS changes simultaneously.

In conclusion, both the peak frequency and the apodization section of the NPS influence the detectability of changes in image noise texture.

Keywords**:** Noise texture, noise power spectrum, CT, Image perception

1. INTRODUCTION

The noise texture in CT images is mainly dictated by the shape of the reconstruction kernel and can be quantified by the noise power spectrum (NPS). The NPS of CT images reflects a ramp that dominates the lower spatial frequencies, and an apodization dominating the higher spatial frequencies[1]. Currently, it is common for the peak frequency (f_{peak}) to be used as a one-parameter descriptor of the NPS[2,3]. Since the first section of the NPS, up to the f_{peak}, is generally monotonically increasing, f_{peak} can be assumed to sufficiently describe this portion of the NPS. However, the shape of the downslope of the NPS, past f_{peak}, can vary considerably, independent of the value of f_{peak}. Therefore, if the shape and extent of the NPS downslope have a significant influence on the perception of noise texture, then f_{peak} is not a sufficient descriptor of it. Furthermore, using newly developed, deep-learning based, reconstruction algorithms, it seems possible to decouple resolution and noise texture from each other to a larger extent than in current reconstruction algorithms. This may allow for additional manipulation of the noise texture during reconstruction, which could be of interest since noise texture influences detectability of lesions. Therefore, as a first step before such noise texture optimization can take place, it would be of interest to know what changes in noise texture are perceptible by a human observer. Therefore, the purpose of this study was to investigate the just-noticeable differences (JNDs) in noise texture, as described by the shape of the downslope and the f_{peak} of the NPS. In addition, for this, a method to more completely parameterize the NPS was developed.

2. METHODS

An observer study was performed to investigate the JNDs of noise texture in CT images. For this, during the study image patches with various noise textures, created in real time from a possibly large number of NPS were needed. Therefore, a

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method was first needed to generate a continuous distribution of NPSs at will, in order to be able to apply these to image patches of white noise. To be able to generate this distribution, a parametrized model of the NPS was developed that sufficiently describes the NPS of real CT images, based on the f_{peak} and a downslope descriptor.

2.1 NPS parameterization

An empirical model was created based on the concept that the NPS in a CT image reflects a ramp that dominates the lower spatial frequencies, and an apodization dominating the higher spatial frequencies. Both of these components are determined by the convolution kernel applied prior to reconstruction[1]. To represent this mathematically, we defined the NPS as a multiplication of a linear function and a Gaussian:

$$NPS(f) = a \cdot f \cdot e^{-\frac{(f-\alpha)^2}{2\beta^2}} \tag{1}$$

where f is the spatial frequency and a determines the amplitude of the peak frequency. The fit parameters α and β determine the peak frequency and the roll-off of the function. The peak frequency can be derived from (1) by:

$$f_{peak} = \frac{\alpha+\sqrt{\alpha^2+4\beta^2}}{2} \tag{2}$$

We tested the applicability of this fit using the NPS resulting from the scan of a 320 mm water phantom acquired on a multi-detector CT (Aquilion One PRISM Edition, Canon Medical Systems Corporation, Otawara, Japan) for eight different kernels. The kernels used were cardiac and abdomen kernels of the hybrid iterative reconstruction (Hybrid-IR) (FC11-FC15, FC17-FC19, AIDR 3D, Canon Medical Systems Corporation, Otawara, Japan)

In this work, the f_{peak} is used as descriptor for the upslope of the NPS. The downslope present at frequencies beyond the f_{peak} is approximated by fitting a half of a Gaussian function to the NPS for frequencies equal to or higher than f_{peak}:

$$g(f) = a' \cdot e^{-\frac{(f-f_{peak})^2}{2\sigma^2}} \qquad f \geq f_{peak} \tag{3}$$

Therefore, in this work, σ is used to describe the downslope of the NPS. So, two parameters, f_{peak} and σ, are used to fully describe the NPS. A graph explaining the various parameters and functions is shown in Figure 1.

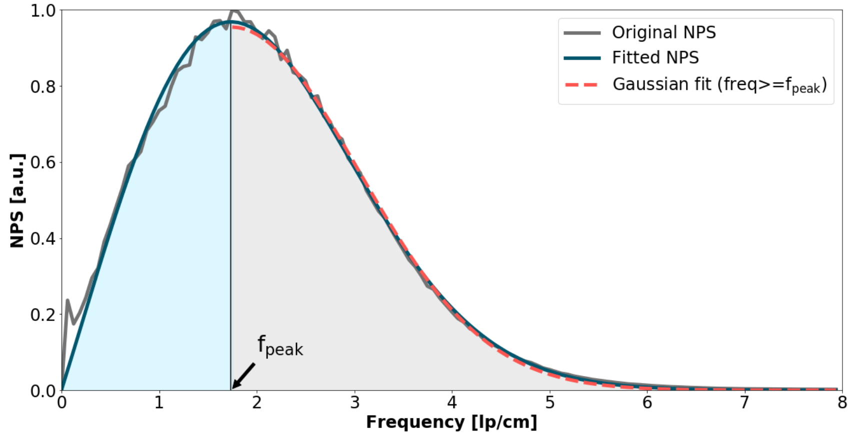


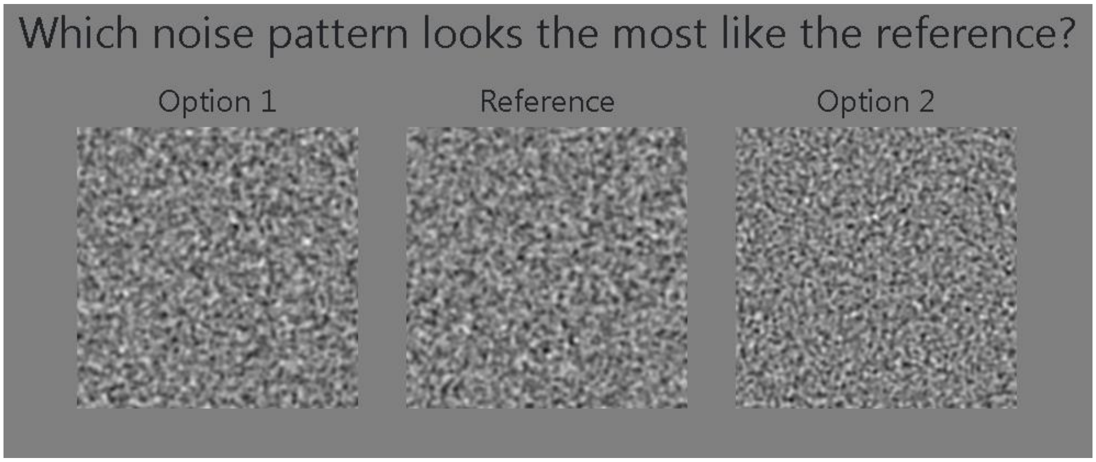
Figure 1. Example of NPS parameterization. The original NPS (grey) is fit (in dark blue). The peak frequency (f_{peak}) is used as the parameter to describe the first section of the NPS (light blue). The section beyond f_{peak} is fit with half a Gaussian (dashed red). The σ of the Gaussian is used as the parameter to describe the section of the NPS beyond f_{peak} (light grey).

2.2 NPS generation

Based on f_{peak} and the downslope descriptor σ, a continuous NPS distribution can be generated using equation 1, 2, and 3. For this, a procedure in *Python* was created using the *curve_fit* and *minimize_scalar* functions from the *scipy.optimize* package. These functions are used to find the most suitable values for α and β in equation 1, given a specific value for f_{peak} and σ using a non-linear least squares method for fitting.

2.3 Observer study

To investigate the detectability of changes in noise texture due to changes in the NPS, a two alternative forced choice (2-AFC) observer study was performed. Noise patches of 256x256 pixels were dynamically generated based on realizations of white noise colored by NPS with a specific f_{peak} and σ. During one trial of the 2-AFC study, the observer was shown three noise patches; one indicated as the reference and two alternative noise patterns. One of the alternative patterns was another noise realization with the same NPS as those of the reference, while the other had a different NPS. The noise patches were shown using a window level equal to the mean value of the noise patch, while the window width was ten times the standard deviation. The task for the observer was to select the alternative pattern that was most similar to the reference pattern (Figure 2). After the observer entered a decision, the correct pattern was highlighted for 1 s, and then the software continued to the next trial.



Which noise pattern looks the most like the reference?

Figure 2. Screenshot of a trial shown to the observer. The refence image and Option 1 (in this case) are different realizations of noise with the same NPS, Option 2 is a realization with a different NPS.

The reference NPS (using eq. (1)) was obtained from the image of a 320 mm diameter water phantom. The phantom was imaged on a Canon Aquilion One PRISM edition (Canon Medical Systems Corporation, Otawara, Japan) at the dose determined by the system when using abdominal settings. Reconstruction was performed using a Hybrid-IR method (AIDR 3D Enhanced, body kernel; FC18).

A staircase method was applied using starting values that resulted in what was deemed by one of the study investigators to be a clear visible difference between the two noise patterns[4]. The step size used was 15% of the distance between the reference values (for f_{peak} and σ) and the alternative values. The difference between the reference and alternative parameters was decreased by the step size after three correct responses and increased after one incorrect response. The procedure was stopped after twelve reversals and repeated six times. The values of the last eight reversals of the last five repetitions were used to calculate the geometrical mean of the parameter value. In this way, the geometrical mean should represent the 80% point on the psychometric curve[5]. The average parameter values from all five observers were calculated.

Eight directions in parameter changes were evaluated (Figure 3): change in f_{peak} only, change in σ only, and changes in both f_{peak} and σ in the diagonal directions (setting the slopes for these directions were based on the resulting thresholds from the single-parameter variation results). All directions were studied from both sides. An elliptical “limiting detectability boundary” was fit through the average limiting values from all directions.

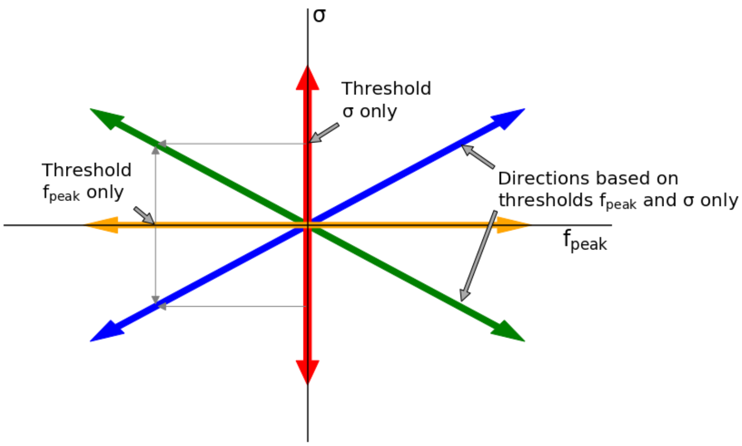


Figure 3. Directions in which the visibility was studied: f_{peak} only, σ only, and 2 diagonal directions. All directions were studied from both sides.

2.4 Results

All measured NPSs could be fit well using equation (1) ($R^2 > 0.99$).

Figure 4 shows the threshold values for each observer, the average thresholds, and an ellipse fitted through the average thresholds. The center of the ellipse is (1.86, 1.30) lp/cm, in accordance with the reference values, and with a major and minor radius of 0.46 lp/cm and 0.12 lp/cm, respectively. The major radius makes an angle of 143° with the x-axis. Based on the elliptical boundary, a change of 0.2 lp/cm in peak frequency is below the detection threshold. This number changes if the apodization part (σ) of the NPS changes simultaneously.

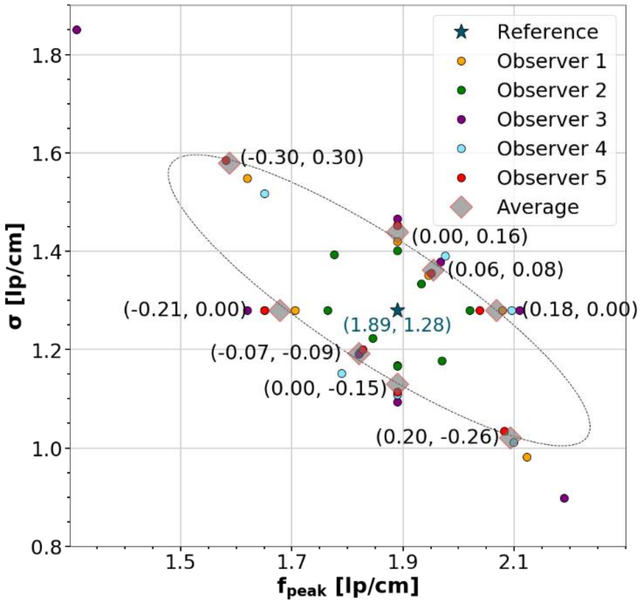


Figure 4. Results from the observer study. the reference values for f_{peak} and σ are shown, as well as the limiting values of these parameters for the eight directions that were investigated. The numbers at the average values are the differences of the parameter values to those of the reference (Δf_{peak}, $\Delta\sigma$). An elliptical "limiting detectability boundary" was fit through the average limiting values.
Note: some observer results coincide and therefore some observer symbols overlap and are not visible.

3. DISCUSSION

The NPS can be fitted well using equation 1 and parametrized using equations 2 and 3. In addition, describing the NPS only by f_{peak} is insufficient, since the apodization part of the NPS influences the perception of the noise texture substantially.

Since noise texture influences the detectability of lesions, and new CT reconstruction methods can more easily change noise texture with less influence on the resolution, it is of interest to determine what effect noise texture changes have on detectability. As a first step, we investigated what changes in noise texture in CT images are visible for a human observer. We hypothesize that changes within the JND boundaries don't affect the detectability. However, depending on the direction of the change in noise texture on the f_{peak}-σ plane, the inter-observer variability can be quite large. Especially in the direction of the major axis of the detectability ellipse, the variability seems to be larger than in other directions. In this direction the f_{peak} and σ work in opposite frequency-content directions. In other words, it is more difficult for some observers to detect changes in noise texture when f_{peak} is decreasing, and thus making the overall NPS content move to lower frequencies, while σ increases and therefore it is moving NPS content to higher frequencies, and vice-versa.

This study has a number of limitations. First, the fitting of equation 1 to the real NPSs was only performed on the kernels of one manufacturer and only on kernels used for imaging of two body parts. We anticipate that the equation can also be fitted well on other CT-related NPSs, but this needs to be verified. Second, for the observer study, we only used one reference NPS, and only five observers. For more thorough research, more reference NPSs, sampling the clinically-observed NPS range, should be performed, potentially using more observers. Finally, this study was performed by applying an NPS onto patches of Gaussian noise. However, it is known that especially model-based iterative reconstruction and potentially also deep-learning based reconstruction can result in non-gaussian noise distributions[6].

4. CONCLUSIONS

In conclusion, describing the NPS using f_{peak} alone is insufficient as changes in the apodization part, that are not reflected in f_{peak}, influence noise texture perception significantly. Furthermore, the NPSs resulting from the created reconstructions can be approximated well using equation 1 and parameterized using equations 2 and 3. both the peak frequency and the apodization section of the NPS influence the detectability of changes in image noise texture.

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