MEASUREMENTS OF TURBULENT WALL HEAT TRANSFER USING TEMPERATURE SENSITIVE PAINT WITH IMAGE DENOISING BY A MACHINE LEARNING METHOD

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ABSTRACT

In order to improve the performance and reliability of heat transfer equipment such as heat exchangers, it is important to understand turbulent heat transport phenomena. Despite the fact that turbulent heat transfer is unsteady and non-uniform, few experiments have focused on the spatio-temporal characteristics of turbulent heat transfer because of the difficulties in measuring it. Since most of earlier experiments are limited to time-resolved point measurement or time-averaged field measurement, the characteristics of turbulent heat transfer are still not well known especially for complex flows, to which DNS is difficult to apply. Recently, Nakamura and Yamada (2013) investigated the spatio-temporal variation of heat transfer in a turbulent boundary layer using a thin-film heater and high-speed infrared thermography. Their unsteady measurements captured thermal streak structure caused by turbulence structure near the wall.

In this study, application of temperature sensitive paint (TSP) to the spatio-temporal measurement of wall temperature was attempted in a turbulent channel flow to develop a new temperature measurement technique. In order to improve the frequency response to the fluctuating heat transfer by near-wall turbulence, thin-film heater was employed as a bottom wall with a thermal insulation layer. A thin TSP layer was coated on the film heater to optically measure fluctuating wall temperature distribution. The noise in the TSP images of fluctuating wall temperature was drastically reduced by a deep-learning based denoising technique, to which a noise-extraction technique proposed by the authors was applied.

INTRODUCTION

Since most of the flow in industrial equipment is turbulent, the associated heat transfer becomes unsteady, varying in time and space. Therefore, it is important to develop experimental methods to measure the unsteady wall temperature and heat flux distribution to evaluate the heat transfer coefficient. A method using a titanium foil heater and an infrared camera was demonstrated by Nakamura and Yamada (2013) to measure the variation of heat transfer coefficient due to turbulence, but in general it requires a careful consideration to the window material and the shooting angle in order to obtain highly accurate measurement. In order to avoid the weaknesses of an infrared camera, temperature sensitive paint (TSP) made of Ru(phen)$_3$ is applied in this study to measure the temperature fluctuation on the thin metal-film heater. Since the emission wavelength band of Ru(phen)$_3$ is in the visible light range, transparent acrylic walls and a high-speed CMOS camera can be applied. This enables us to obtain high-resolution images of instantaneous temperature distribution at relatively low cost. However, due to the small temperature sensitivity of TSP, the noise in the captured image is relatively large when measuring the slightly fluctuating wall temperature. To improve the spatio-temporal resolution of wall temperature fluctuation measurement using TSPs, it is important to reduce the noise in the captured images.

Recently, Lehtinen et al. (2018) have developed a machine learning technique called Noise2Noise (N2N) to remove noise from images. It was achieved by a deep learning technique using a type of CNN called U-Net (Ronneberger et al., 2015). Unlike conventional machine-learning denoising methods that use "supervised learning," in which noise-containing images are paired with noise-free images, Noise2Noise is superior in that it does not use noise-free images “directly” as training dataset. However, it still “indirectly” requires noise-free images to generate noisy image pairs as the training dataset. Therefore, it is usually considered difficult to apply the method to non-stationary phenomena where it is difficult to obtain noise-free images with long exposures.

Therefore, in this study, a noise-reduced image was generated by applying FFT and a low-pass filter to the noise-containing time-series images of the wall surface temperature acquired by TSP. Then, the noise-reduced images were considered as an approximation of the "noise-free images" to produce noisy image pairs for the training of the N2N network. By this method, the noise images specific to the current experimental setup can be extracted by subtracting the noise-reduced images from the raw images. Noisy image pairs as a training dataset are then produced by adding the randomly-selected noise pair to the noise-reduced images.

EXPERIMENTAL METHOD

Temperature sensitive paint (TSP) is a polymer-based paint that utilizes thermal quenching (Chen et al., 2020). Since the luminescence intensity depends on the temperature of the paint, the temperature distribution on the surface of an object coated with TSP can be measured by capturing the luminescence intensity with a CMOS digital camera. The relationship between luminescence intensity I and absolute temperature T can be given in the Arrhenius form as follows (Liu and Sullivan, 2005):

$$\ln\frac{I(T)}{I_{ref}(T_{ref})} = \frac{E_{nr}}{R}\left(\frac{1}{T} - \frac{1}{T_{ref}}\right) \tag{1}$$

where E_{nr} is the activation energy for non-radiative process, R is the universal gas constant, and I_{ref} is the luminescence intensity at a reference temperature T_{ref}. From Eq. (1), it can be seen that the logarithm of the luminescence intensity ratio is proportional to the reciprocal of the temperature. In practice, temperature is obtained from the luminescence intensity ratio using Eq. (2), which is a generalized form of Eq. (1) (Chen et al., 2020).

$$\frac{I}{I_{ref}} = \sum_{n=0}^{N} A_n\left(\frac{T}{T_{ref}}\right)^n \tag{2}$$

Figure 1 shows a schematic of the experimental setup to obtain a calibration curve, which gives a relation between TSP temperature and luminescence intensity. In the calibration experiments, a test piece coated with TSP was placed on the Peltier-type temperature controller in a darkroom. The surface temperature of the test piece was measured with a thermocouple. A power LED with an emission wavelength of 405 nm was used as the excitation light source. A 300-450 nm band-pass filter was attached to the power LED to remove excess light. Fluorescence intensity images of TSP at selected temperature in the range of 35 to 70 °C were captured by a high-speed camera (MEMRECAM Q1v) equipped with a long-pass filter (> 550 nm), which was also used in the following wind tunnel experiments. One hundred images were taken at each temperature both for light-off background images and light-on images. The fluorescence intensity I and I_{ref} at 35 °C in Eq. (2) was obtained by averaging the 100 light-on images and subtracting the background images at each temperature. Figure 2 shows a calibration curve obtained in the form of N = 2 in Eq. (2).

In the experiment, the temperature sensitivity S_T is defined by the following equation according to Egami, et al. (2014).

$$S_T = -\left(\frac{dI(T)}{dT}\right)\frac{1}{I(T)}\times 100\ \ [\%/^{\circ}\mathrm{C}] \tag{3}$$

The temperature level of the heater surface in the wind tunnel test was 60 to 70 °C, and the temperature sensitivity of TSP in this temperature range was 2.5 to 2.9 %/°C. This corresponds to a change of 52 to 53 counts/°C in the camera signal (luminescence intensity) in our experimental conditions. The error of measured temperature due to the shot noise of our high-speed camera was estimated to $\pm$1.1 °C, which is calculated from a mean standard deviation of the fluctuating signal counts within a temperature range (60 to 70 °C) measured in the calibration process. This indicates that noise reduction is required to capture the detail of small temperature fluctuation less than $\pm$1 °C.

The experiments were performed at the air central velocity of U_c = 1.0, 2.0, 5.0 and 10.0 m/s in a wind tunnel with a rectangular cross-section of 80 mm in width and 20 mm in height; the total channel length is 1800 mm. Corresponding Reynolds number based on the channel height are 1250, 2500, 6250 and 12500, respectively. Figure 3 shows an experimental setup, including the side and cross-sectional views of the test section. The bottom wall of the test section is an isothermal wall, of which temperature is controlled by hot water circulation. A thin-film heater (5 μm thick titanium film) is installed in a section of the isothermal wall. The heater is set above an insulation air layer of 1 mm in depth, which was created by machining the bottom wall. The insulation between the heater and the bottom wall was maintained by adjusting the mean temperature of the heater close to that of the isothermal wall. The titanium-film electric heater was spray-coated with TSP to measure the surface temperature. A high-speed camera (MEMRECAM Q1v) was used to acquire the luminescence of TSP. The frame rate, exposure time and spatial resolution were 1000 frames per second, 997 μs and 134 μm/pixel, respectively. To obtain mean temperature distribution, 1024 images were taken at each experimental condition.

DENOISING TECHNIQUE

In this paper, we focus on the fluctuating temperature of thin film heater due to the convective heat transfer by wall turbulence. The wall temperature fluctuation T' is defined by Eq. (4), where T_w is an instantaneous temperature on the heater and $\overline{T}_w$ is the time-averaged value at each pixel.

$$T' = T_w - \overline{T}_w \tag{4}$$

Figure 4 shows typical temperature fluctuation fields obtained by TSP measurements for (a) U_c = 5.0 and (b) U_c = 10 m/s. It is confirmed that thermal streak structures relevant to the near-wall turbulence are observed. However, detailed structure of the thermal streaks cannot be clearly observed due to the small magnitude of temperature fluctuation, which are comparable to the error levels of TSP measurements mentioned above.

To reduce the noise levels of the temperature fluctuation fields, a low-pass filter with a cut-off frequency of 50 Hz was first applied to the time-series of measured data. Figure 5 shows the results of the temperature fluctuation fields corresponding to the images in Fig. 4. It is confirmed that the low-pass filtered temperature fluctuation fields gives better spatial resolution to the thermal streak structures. Finer thermal streak structures have appeared and the contour maps seem to be more smoothly distributed, as confirmed by the increase in the white area between the positive (red) and negative (blue) thermal streaks. However, an undesirable level of noise still remains, which could hinder detailed analysis, such as an inverse analysis of the heat transfer coefficient considering the heat capacity of the metallic foil heater.

To further reduce the noise level, noise reduction by machine learning (ML) seems to be a promising approach. In this study, we applied a ML-based noise reduction method called Noise2Noise (N2N) proposed by Lehtinen, et al., 2018. The N2N uses a type of CNN called U-Net (Ronneberger et al., 2015) to learn a denoising network to remove noises from images. In the author's view, the N2N learning requires a large number of noisy image pairs, each of that differs only in their noise components; the one is a noise-free image A with a noise B added, and the other one is a noise-free image A with a noise C added. Then, a network is trained to generate an output noisy image (= A + C) from an input noisy image (= A + B). After training the network on a large number of such noisy image pairs, the "averaged" network obtained will eventually be able to output an "averaged" image that is intermediate between an input image with noise B' and an "unknown" image with noise C' corresponding to the other one of the image pair. This is similar to the principle that an average of a large number of noisy images yields a noise-free averaged image. As a result, the output image by N2N are expected to be an image that contains greatly reduced noise.

The weakness of Noise2Noise is that it requires image pairs that differ only in their noise components to train the network. This requires a noise-free image A. However, it is generally difficult to obtain such a clean image, except for stationary phenomena in which a noise-free image can be obtained by long exposures. In addition, it is expected that in order for the noise reduction by N2N to be effective, it is necessary to add noises specific to the experimental conditions and methods of the measurement to learn the network.

To overcome these difficulties, the authors devised a method to generate a noise-free image (or more precisely, an image with as little noise as possible) using FFT and a low-pass filter. That is, after applying the FFT to each pixel in the time direction, we remove the frequency components above 50 Hz to obtain an image with significantly reduced noise, which we consider to be the noise-free image A. Next, the noise component B, which is unique to this experiment, is extracted by subtracting the image A from the original image.

Figure 6 shows a schematic of our method for noise-extraction from the noisy raw images and the following procedure to obtain training data set of N2N. To prepare data for training, 500 time-series images were prepared. Based on these images, 500 noise images and 500 noise-free images were created, respectively. For the generation of network training data, 96 noise-free images A, which were selected at regular time intervals from 500 images, were used. The input and output image pairs required for the training were generated by adding two noise images (noise image B and noise image C), which were randomly selected from the 500 images, to the noiseless image A. Except for the method of adding a noise to a clean image, the code and learning conditions basically follows the original N2N code available on GitHub (https://github.com/NVlabs/noise2noise).

RESULTS AND DISCUSSION

Figure 7 (a) shows the noisy raw data of instantaneous temperature fluctuations at U_c = 5.0 m/s. Thermal streaks related to the near-wall turbulence can be recognized, but quantitative evaluation is difficult due to the large noise. Figure 7 (b) shows the result of applying a trained denoising network using N2N. It can be seen that the noise is greatly reduced and the thermal streaks specific to the turbulent field can be clearly observed. To see the effect of N2N denoising network trained with extracted noise specific to the current experiments, Fig. 8 shows a comparison of power spectrums of wall temperature fluctuation between raw data and four denoised data, which are processed from the raw images by a low-pass filter (cut-off frequency: 50 Hz), median filter, Gaussian filter, and the Noise2Noise network with a proposed noise-extraction technique. It is confirmed that N2N network can reduce the noise more effectively than Gaussian and median filters over the whole frequency range. The most interesting point is that the noise reduction by N2N also removes noise below 50 Hz, which is significantly different from the noise reduction by a low-pass filter, which is completely ineffective for noise below 50 Hz. It is interesting to note that even though the noise used for N2N training contains only frequency components above 50 Hz, noise reduction was effective even for noise below 50 Hz.

SUMMARY

Spatio-temporal measurement of the wall temperature distribution in a turbulent channel flow was attempted to develop a new temperature measurement technique using TSP for turbulent heat transfer phenomena. Noise in TSP images was drastically reduced by the N2N denoising network with a proposed noise extraction technique. As a result, the transient behavior of the thermal streak structure, which is relevant to near-wall turbulence, is clearly captured.

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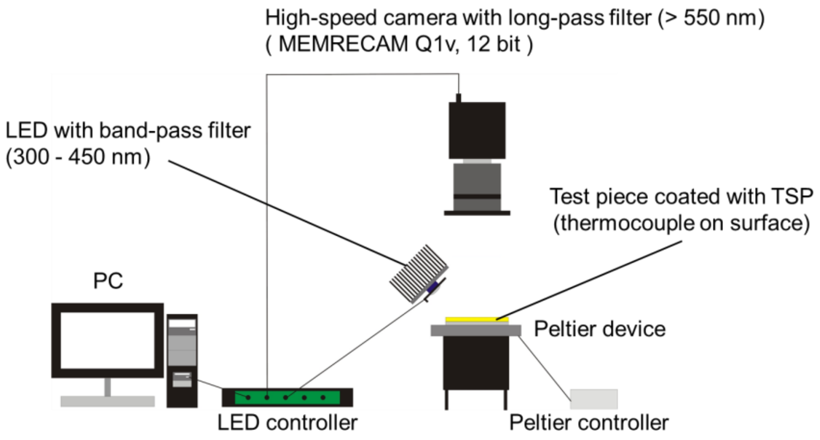


Figure 1. Experimental setup for the calibration of temperature measurement using temperature sensitive paint (TSP).

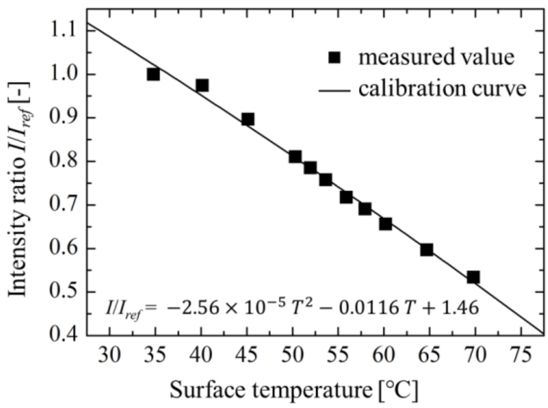


Figure 2. An obtained calibration curve of TSP (Ru-phen).

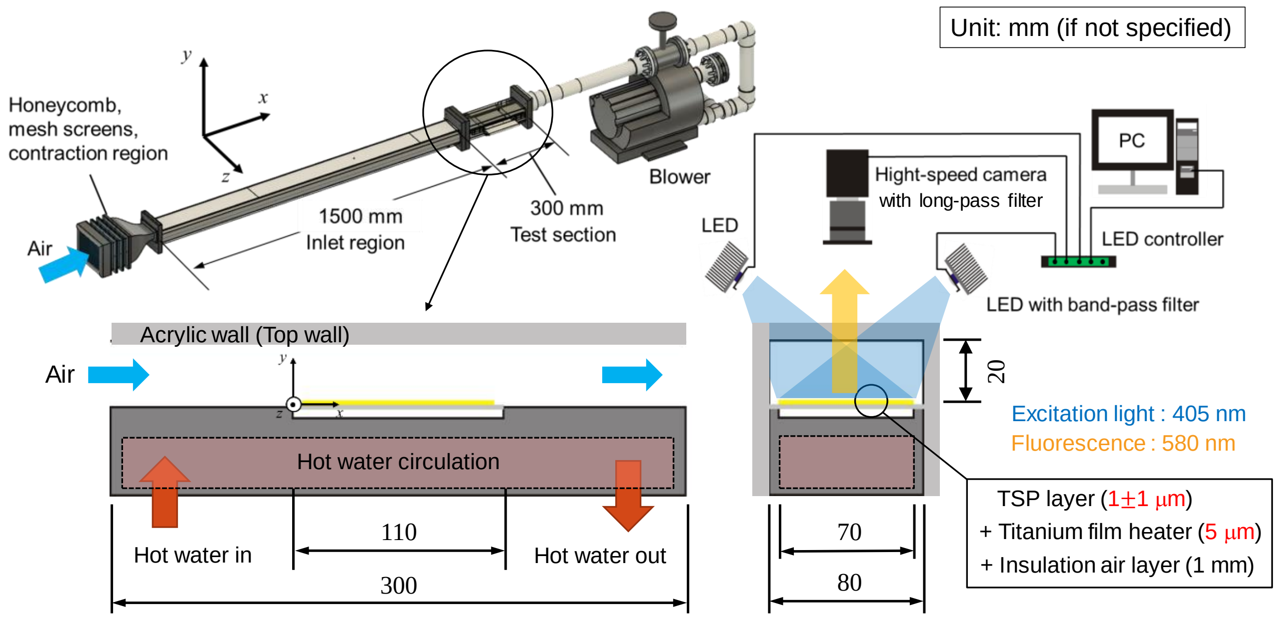
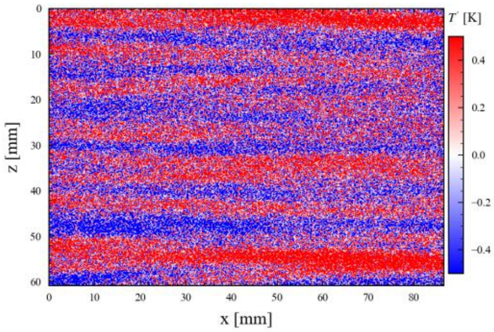
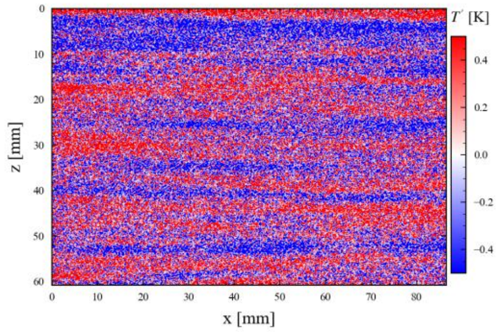


Figure 3. Experimental setup (top left) and a close-up of test section with TSP-coated metal film heater (bottom).

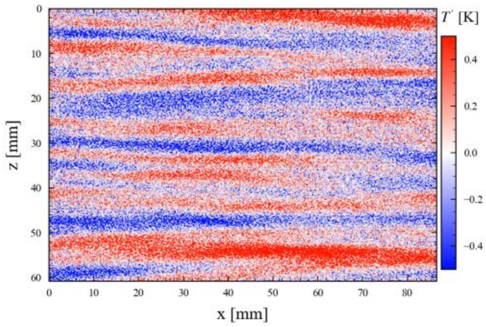


(a) U_c = 5.0 m/s, Re = 6250

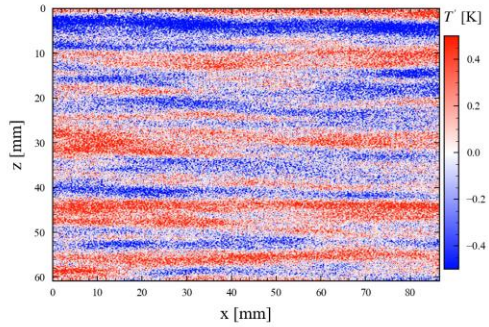


(b) U_c = 10.0 m/s, Re = 12500

Figure 4. Typical wall temperature fluctuation fields calculated from noisy raw TSP images.



(a) U_c = 5.0 m/s, Re = 6250



(b) U_c = 10.0 m/s, Re = 12500

Figure 5. Wall temperature fluctuation fields extracted by low-pass filtering (< 50 Hz) with pixel-by-pixel FFT in time direction.

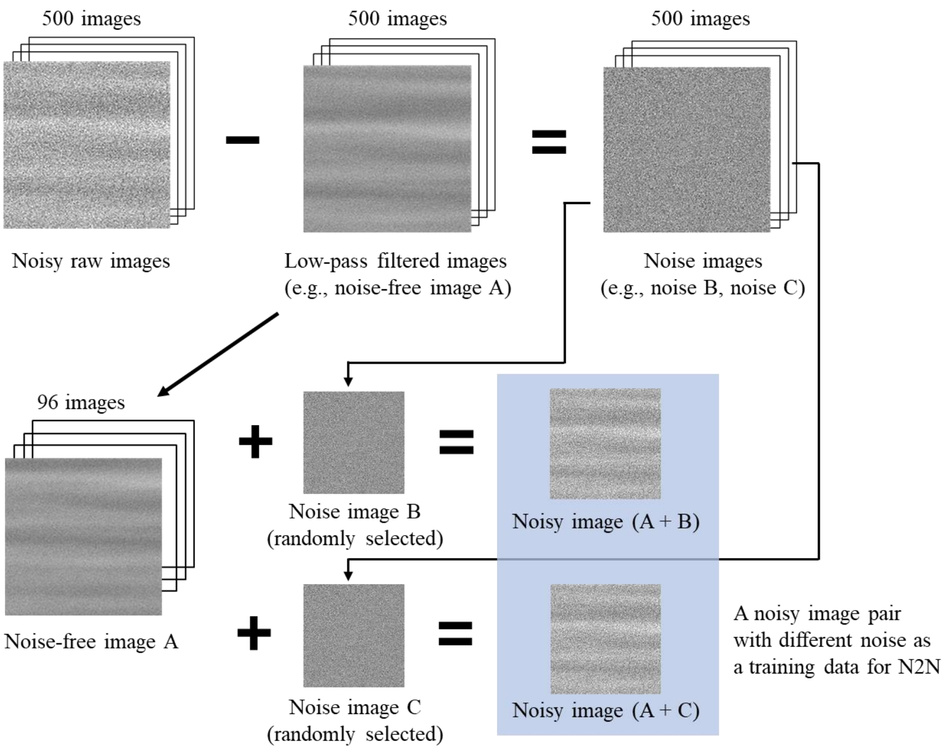


Figure 6. A schematic of our noise extraction technique and the following procedure to obtain noisy image pairs as inputs to N2N.

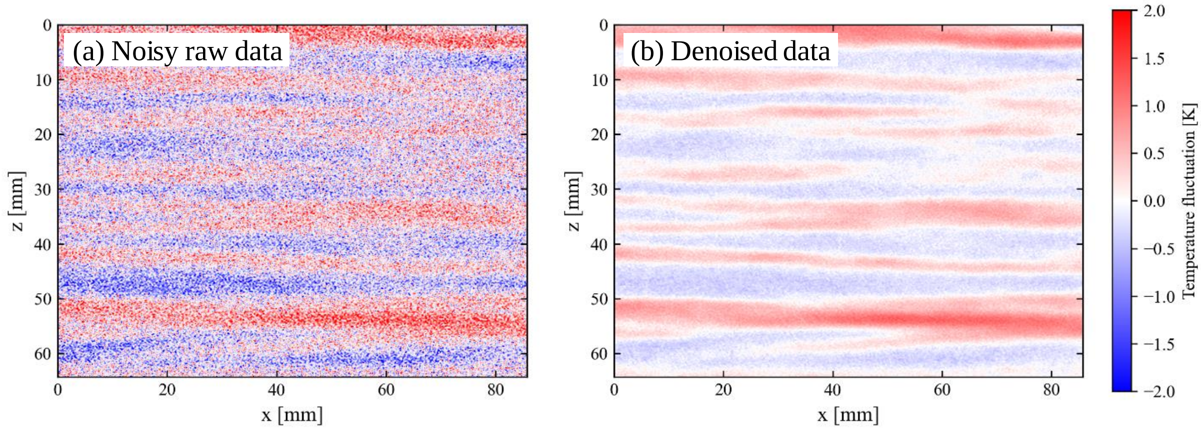


Figure 7. Wall temperature fluctuation on a TSP-coated thin-film heater; (a) noisy raw data and (b) denoised data.

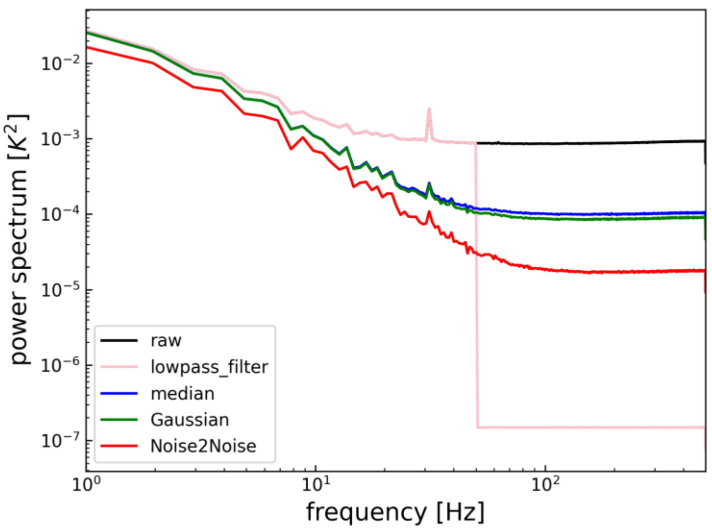


Figure 8. Comparison of power spectrums of wall temperature fluctuation between raw data and denoised data, which are processed by a low-pass filter (cut-off frequency: 50 Hz), median filter, Gaussian filter, and the Noise2Noise network with a proposed noise-extraction technique.