Laboration 2:
ASUS Xtion Pro: Calibration, noise characterization and filtering

Sensors and Sensing

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1 Introduction: Structured light cameras

Structured light cameras are a low-cost option for depth measuring in three dimensional space. The cameras project a known light pattern to a scene and record the reflection of that light pattern. This recorded data is then used for triangulation.

For this lab, the ASUS Xtion Pro sensor was used as a structured light camera.

2 Task and implementation

The task at hand was to set up and calibrating the sensor, as well as to characterize the noise in the depth measurement and to set up filtering routines.

2.1 Basic setup

To set up the camera, the package `openni2` for ros-indigo was used. When launching the node `openni2.launch`, it publishes a wide range of topics from the camera.

For this laboration, only the topics which publish a viewable image were of interest. This included two main topics:

- `/camera/rgb/`
  This topic publishes data from the RGB camera on the ASUS Xtion Pro. The topic `/camera/rgb/raw` shows the unprocessed RGB image like a regular camera. A sample image from this topic is shown in figure 1.
- `/camera/depth/`
  This topic publishes the depth data as a 2D-array of float variables containing the depth values in meters. A sample image from this topic is shown in figure 2.
- `/camera/depth_registered`
  This topic combines the RGB and the depth image into a coloured point cloud. A visualization of this topic through the tool `rviz` is shown in figure 3.

Figure 1: Output image of `/camera/rgb/raw`

Figure 2: Output image of `/camera/depth/`

Figure 3: Screenshot of the vizualized pointcloud of `/camera/depth_registered`

2.2 Basic ROS node

After the basic setup, a ROS node template was used as a base to process the images and point clouds published. The received images are shown in figure 4 and figure 5.

2.3 Color camera calibration

Figure 4: Save of the RGB image

Figure 5: Save of the depth point cloud

2.4 Noise characterization

In this part we cropped small windows of varying sizes in the center of the depth image. Then the camera was placed in several known distances from a wall and the average and standard deviation of the depth values in the cropped images were recorded.

The mean error of 10 seconds of measurement in relation to the distance is shown in figure 6. The variances are shown in figure 7.

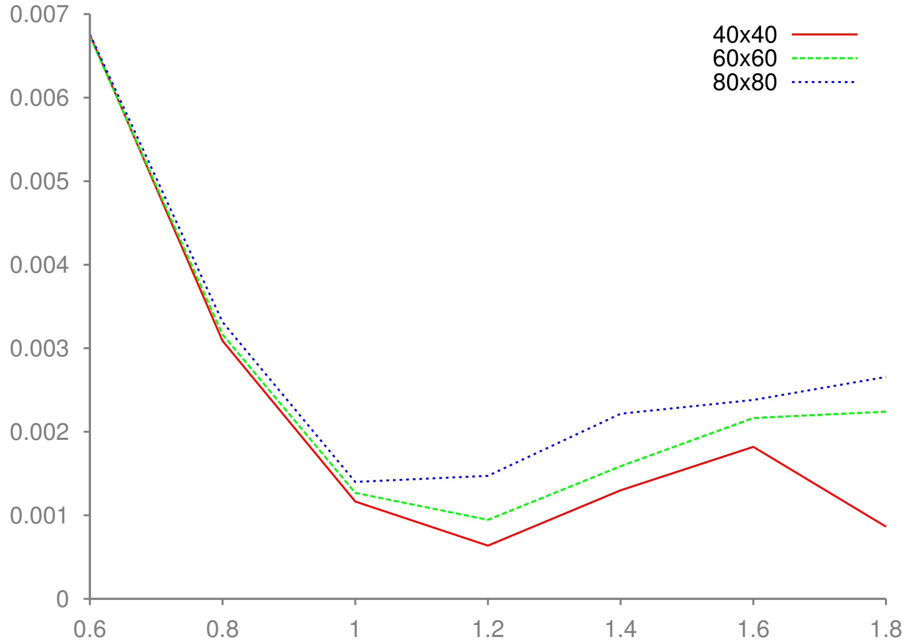


Figure 6: Mean absolute error of the mean depth in relation to the ground truth distance

Analysing the mean error (fig. 6), one can see that the error values diverge with the error size and the distance to the wall. The high error values under 1 meter are expected to be caused by errors in the ground truth measurement, since the measuring tools at hand weren't optimal. The variance values also increase with the ground truth distance.

The diverging error values and increasing variances can be explained by the geometric characteristics of the measurement (see fig.8).

Figure 8 shows a 2D schematic view of the measurement. The camera records the depth values of an area around a maximum value of θ. The depth value at C doesn't contain the actually desired distance to the wall d, but rather

$$h = \frac{d}{\cos \theta}.$$

As the distance to the wall d increases, so does the absolute error between h and d. Increasing the observed window size additionally increases θ, which has a similar effect.

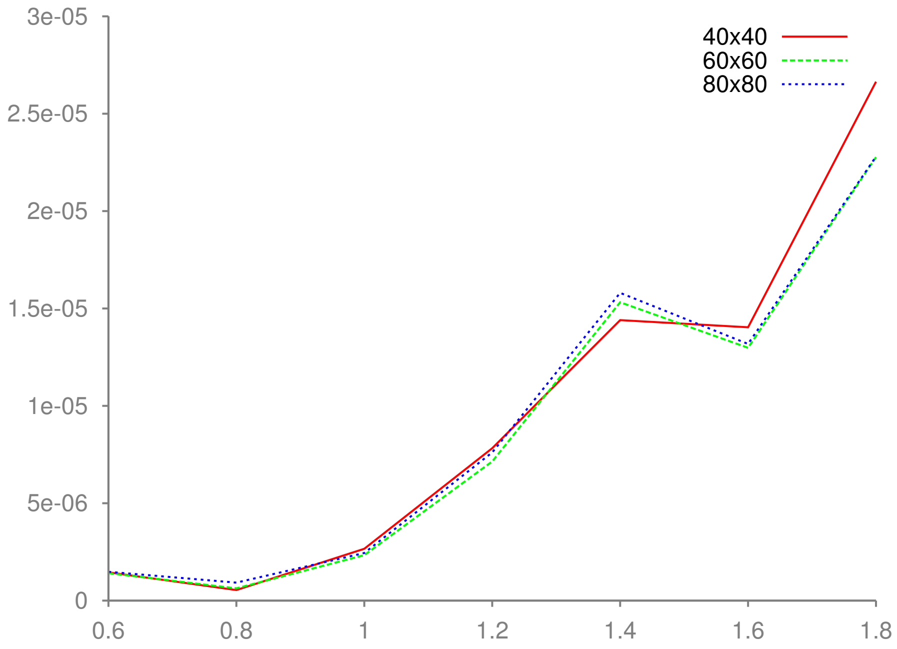


Figure 7: Mean of the variance of the depth in relation to the ground truth distance

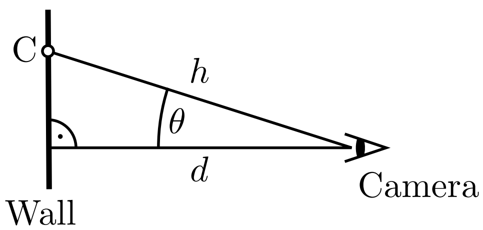


Figure 8: Schematic of the distance measurement

2.5 Noise filtering

In this part we applied several filters to the depth images in order to remove the noise from the measurement data. These filters are:

- Gaussian blur
- Median filter
- Bilateral filter
- Median over several image samples
- Average over several image samples

The effect on the image data after the application of the filters will be discussed in the following.

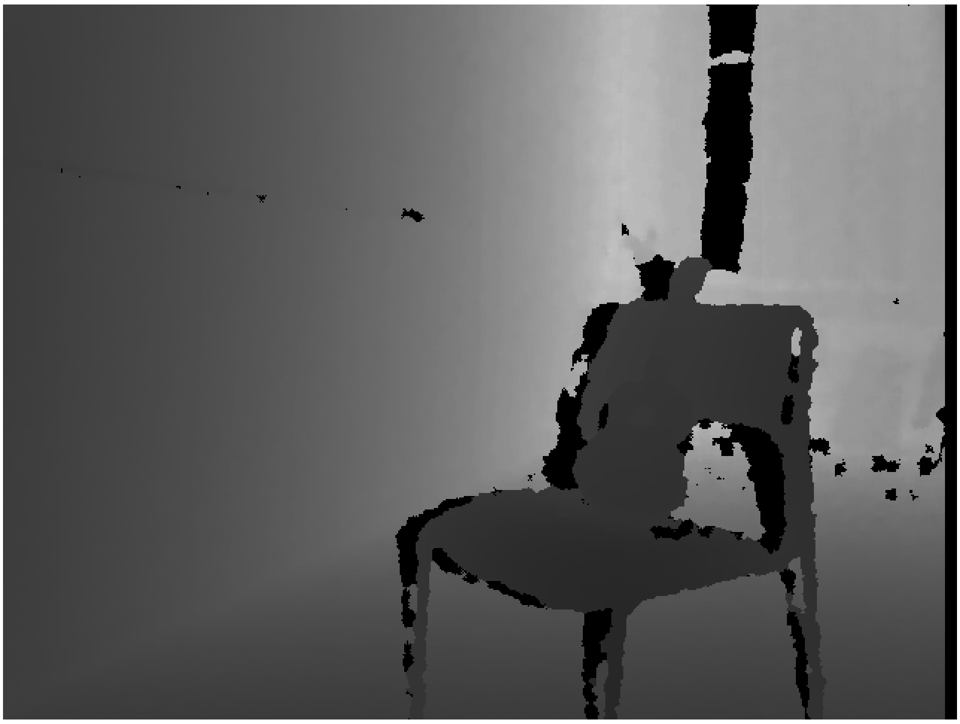


Figure 9: Original depth image

2.5.1 Filter effects

Gaussian blur The gaussian blur filter (fig. 10) blurs the contours of the observed objects. Additionally, the pixels with `NaN` values reproduce and strongly disturb the algorithm. This can be explained as every kernel containing a `NaN` value gives every pixel in the whole kernel a `NaN` value. This also explains the “blocky” artifacts in areas which originally contained small `NaN` speckles.

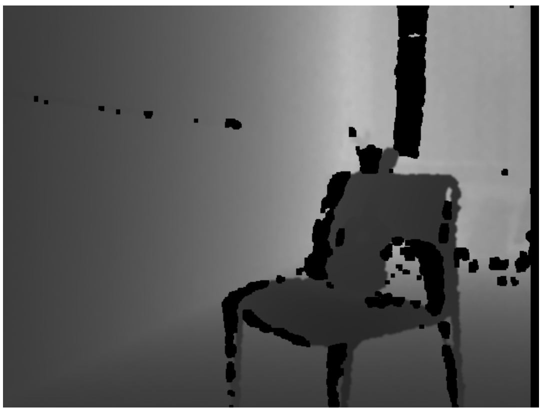


Figure 10: Gaussian blur

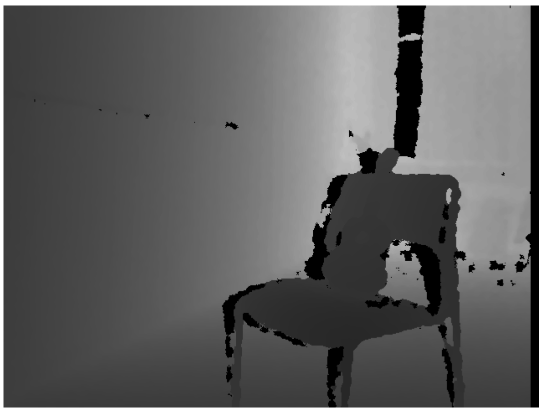


Figure 11: Median filter

Median filter The median filter (fig. 12) doesn’t show a big difference to the original image.

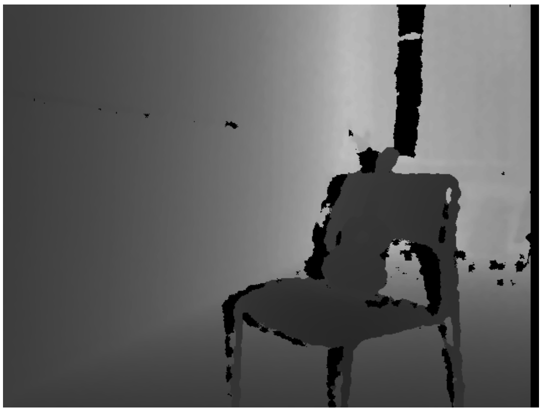


Figure 12: Median filter

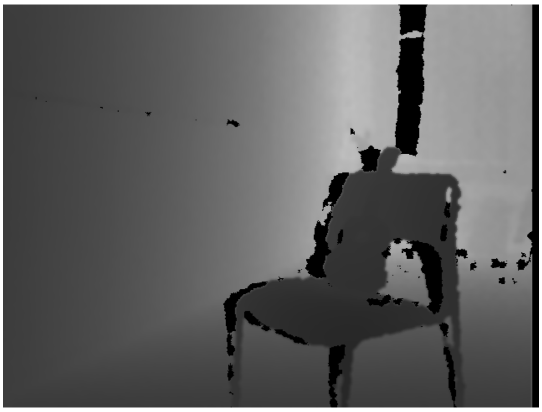


Figure 13: Bilateral filter

Bilateral filter The bilateral filter (fig. 14) blurs the contours of the objects. Otherwise, no remarkable differences to the original image are discernible.

In order for this filter not to produce very artifact-prone images, the `NaN`-values had to be adjusted. We chose to replace the `NaN`-values with entries of depth 0.

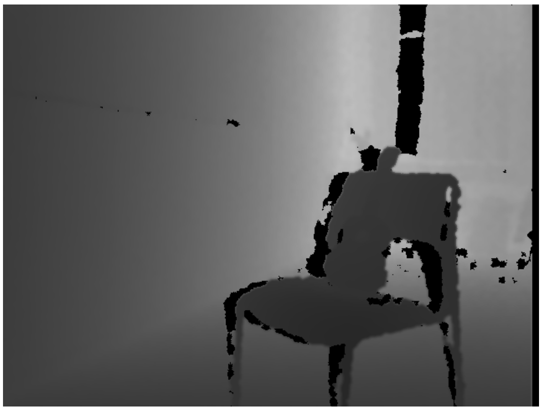


Figure 14: Bilateral filter

Figure 15: Moving median image

Median over several image samples The moving median image (fig. 15) leaves the contours visible and removes smaller spots with `NaN` values.

Mean over several image samples The moving mean image (fig. 16) blurs the contours of the objects (although not as strongly as previous contour blurring algorithms). It also removes small speckles of `NaN` values.

Figure 16: Moving mean image

2.5.2 Filters and distance error

In this part, the effects of the used filters is analyzed on the distance windows recorded in subsection 2.4.

All of the filters show only little change on the absolute error values. The variance values differ on the other hand, while roughly keeping the general form of the curves.

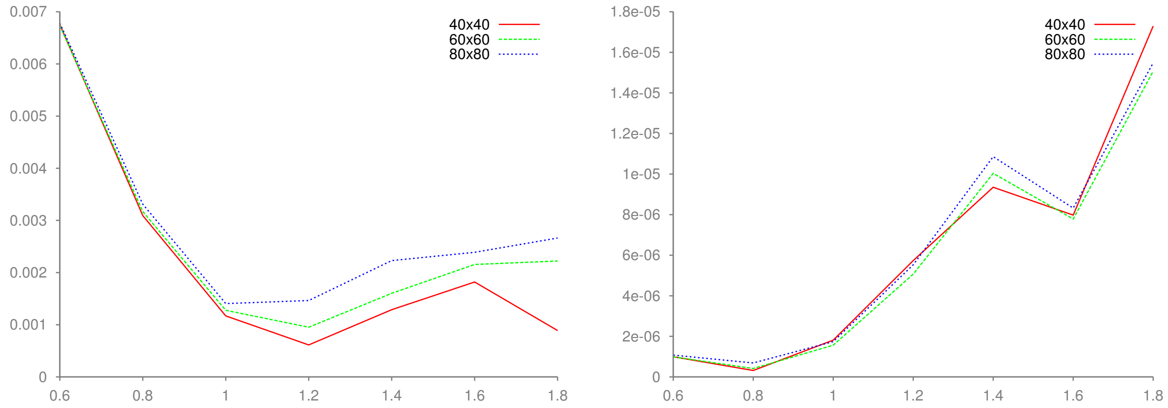
Gaussian filter The gaussian filter (fig. 17) decreases the variance values by a factor of roughly 0.66.

Median filter The median filter (fig. 18) decreases the variance values by a factor of roughly 0.8.

Bilateral filter The bilateral filter (fig. 19) decreases the variance values by a factor of roughly 0.5

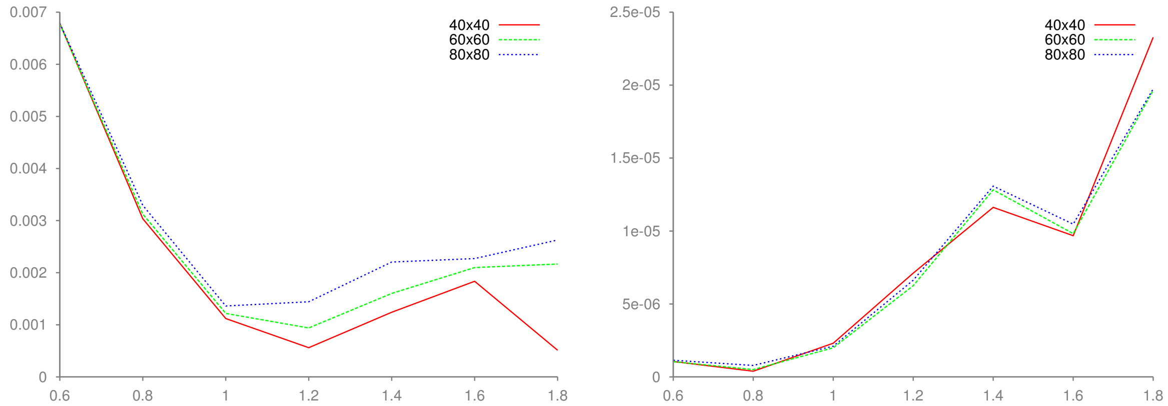
Mean over several image samples The running median (fig. 20) image shows only little change on the variance curve.

Median over several image samples The running mean image (fig. 21) decreases the variance values by a factor of roughly 0.8.



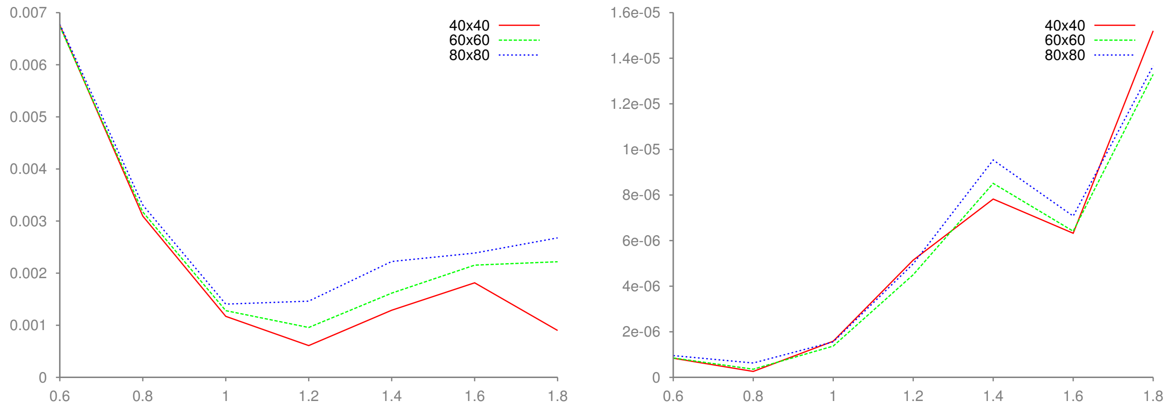
(a) Absolute Error (b) Variance

Figure 17: Gaussian filter on distance measurement



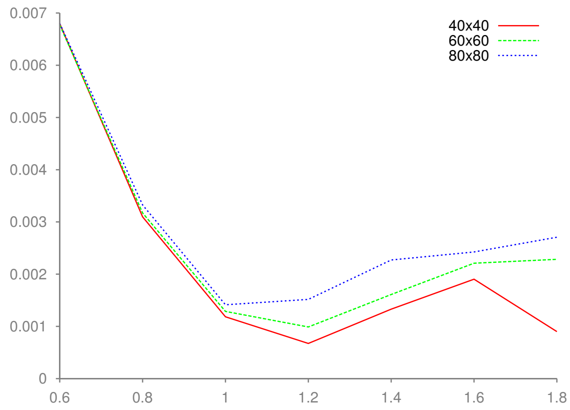
(a) Absolute Error (b) Variance

Figure 18: Median filter on distance measurement

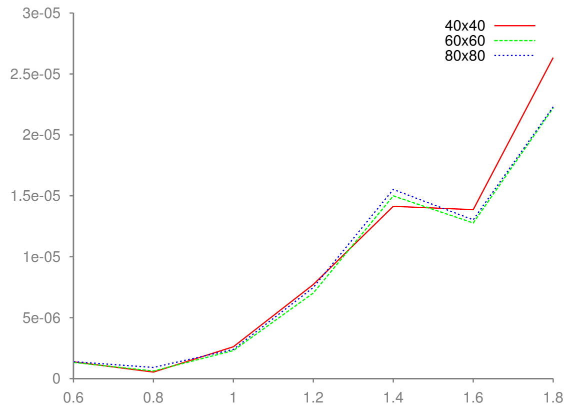


(a) Absolute Error (b) Variance

Figure 19: Bilateral filter on distance measurement

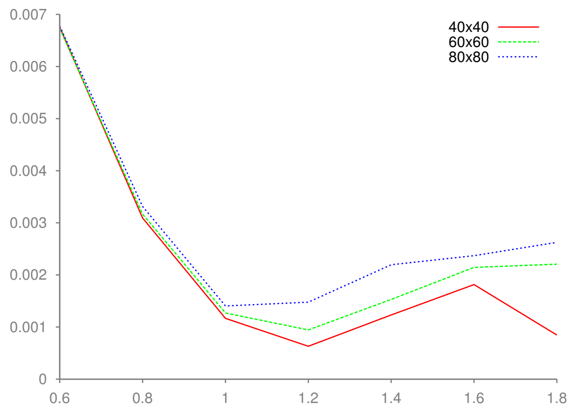


(a) Absolute Error

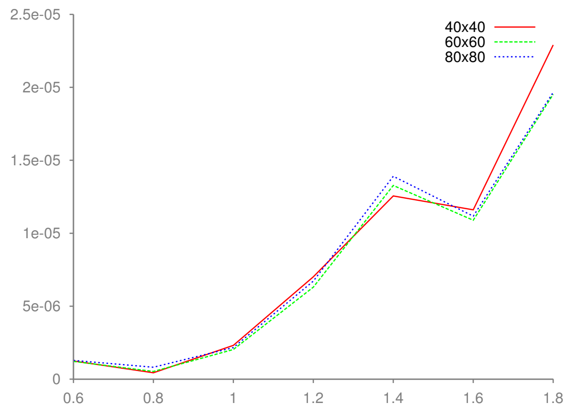


(b) Variance

Figure 20: Running median of the distance measurement



(a) Absolute Error



(b) Variance

Figure 21: Running mean of the distance measurement

2.5.3 Salt-and-pepper removal properties

The depth images didn't suffer from noise clearly visible to the eye. In order to test the noise cancelling properties of the filters, artificial salt-and-pepper noise was added to the image file. This was achieved by changing random pixels in the image to black or white in each received depth-image.

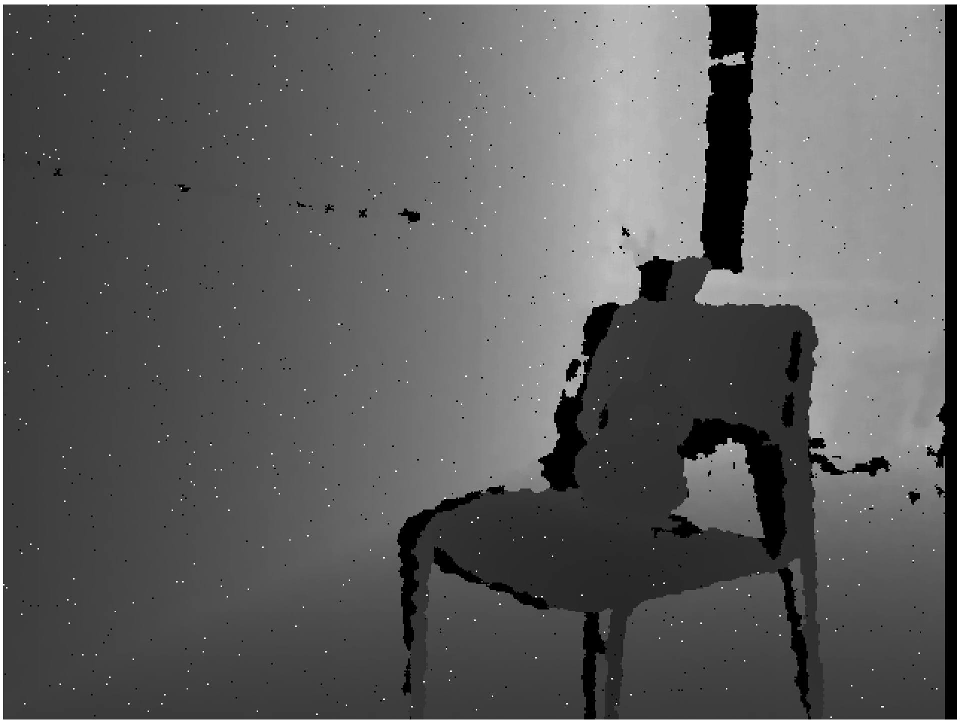


Figure 22: Original depth image with salt and pepper

Gaussian blur The gaussian blur (fig. 23) doesn't filter out the salt and pepper appropriately. It rather spreads the noisy data, negatively influencing the surrounding, proper data.

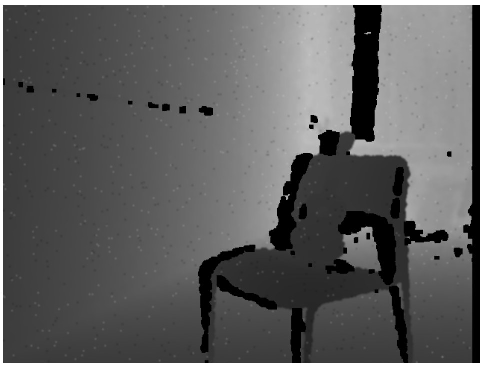


Figure 23: Gaussian blur with salt and pepper

Figure 24: Median filter with salt and pepper

Median filter The median filter (fig. 24) removes the salt and pepper speckles reliably.

Bilateral filter The bilateral filter (fig. 25) decreases the influence of the salt and pepper speckles in the image, although they are still visible.

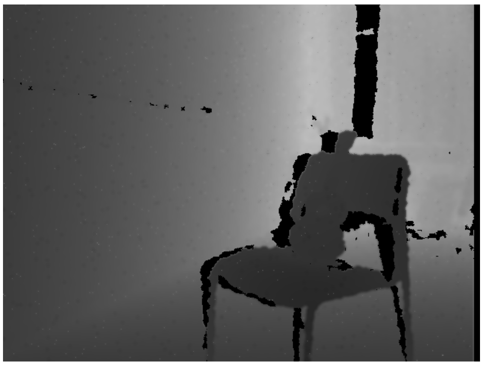


Figure 25: Bilateral filter with salt and pepper

Figure 26: Moving median image with salt and pepper

Median over several image samples The bilateral filter (fig. 26) removes the salt and pepper speckles reliably.

Average over several image samples The bilateral filter (fig. 27) accumulates the salt and pepper speckles of all recorded images. Although the speckles overall are more dull, their amount increased, still showing a considerable amount of noise.

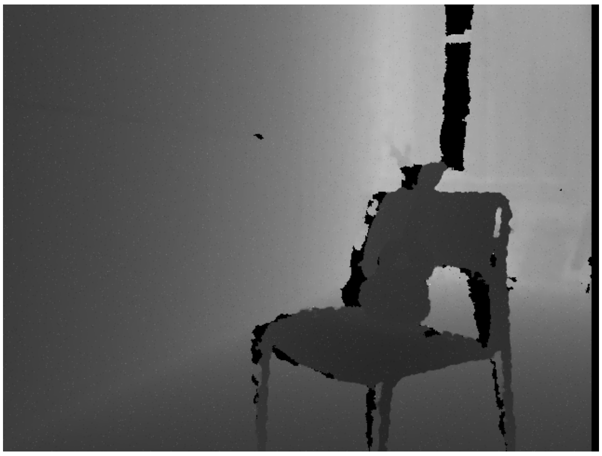


Figure 27: Moving mean image with salt and pepper