Trabalho de Implementação 2

Discipline: CMP197 - Introdução à Visão Computacional

Professor:

- Cláudio Jung

Authors:

- Lucas Nedel Kirsten, 230262
- Diego Severo Jardim, 319862

Importing the necessary libraries

In [1]:
```
from time import time
import numpy as np

import matplotlib.pyplot as plt
from skimage.io import imread

from utils.block_matching import compute_ssd, compute_aggregation
from utils.plot_utils import plot_images
```

Setting global parameters

In [2]:
```
max_disp_steps = 50  # maximum disparity to consider

window_sizes = [1, 3, 5, 7, 11]
ssd_window_sizes = [1, 3, 5, 7, 11]

penalties = [10, 100, 1000]

# teddy image path
teddy_left_img_path  = "../data/teddy/im2.png"
teddy_right_img_path = "../data/teddy/im6.png"

cones_left_img_path  = "../data/cones/im2.png"
cones_right_img_path = "../data/cones/im6.png"

# open images
teddy_left  = imread(teddy_left_img_path)
teddy_right = imread(teddy_right_img_path)

cones_left  = imread(cones_left_img_path)
cones_right = imread(cones_right_img_path)

images = [(teddy_left, teddy_right), (cones_left,cones_right)]
```

Task 1

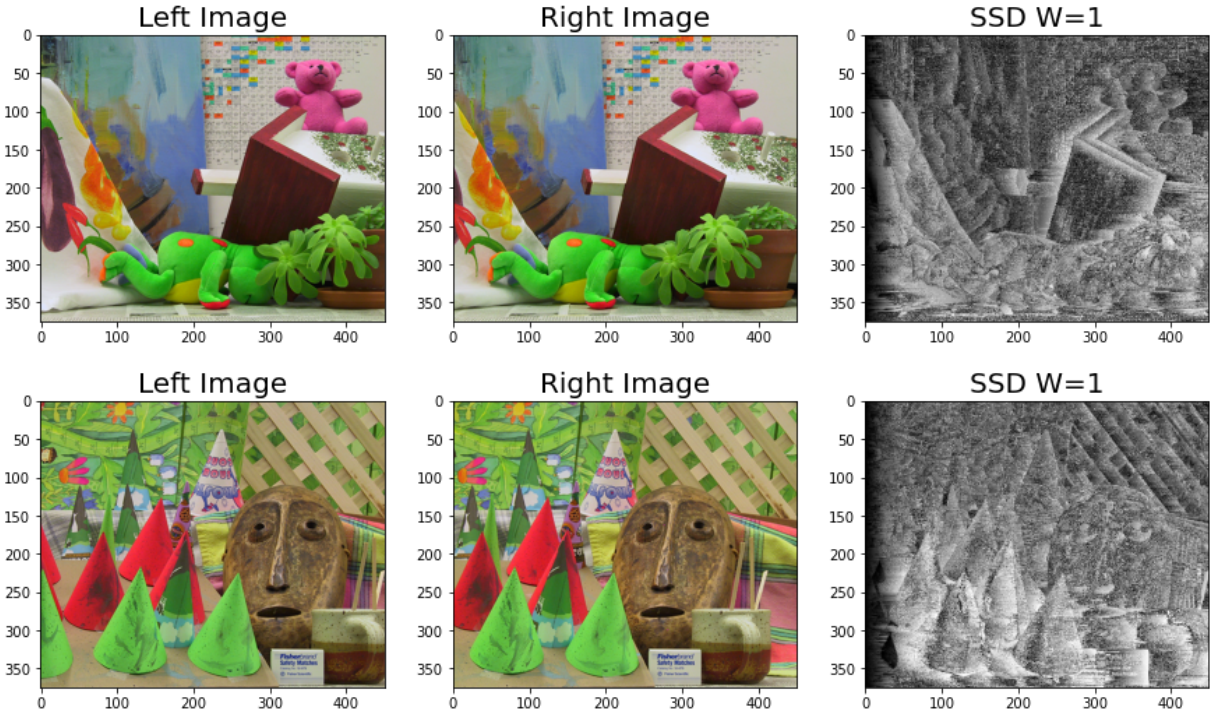
Task 1A

Computing Block Matching using SSD

In [3]:
```
# define window size
window_size = 1
```

In [4]:
```
for (left_img, right_img) in images:
    init = time()
    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=window_size,
                         apply_dist=False)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    print(f'SSD time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
                disp_map1_title=f"SSD W={window_size}")
```

```
SSD time: 0.56 s
SSD time: 0.51 s
```



Task 1B

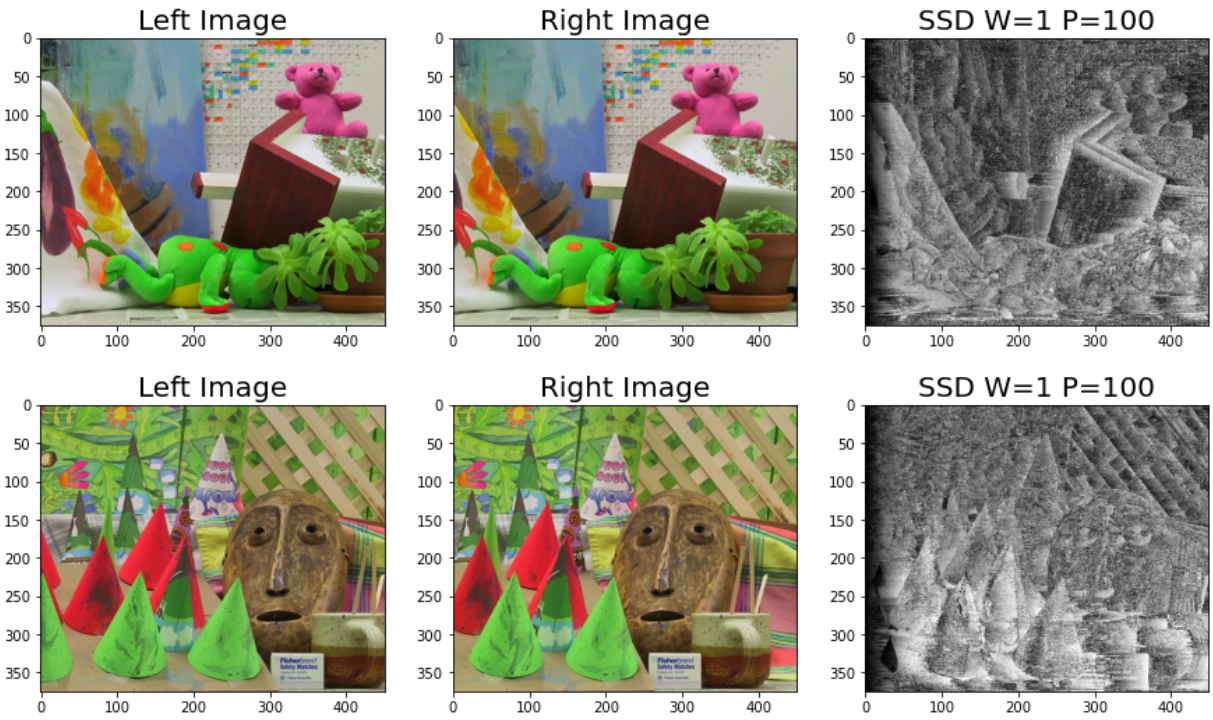
Computing Block Matching using SSD + Penalty value

In [5]:
```
# define window size and penalty
window_size = 1
penalty = 100
```

In [6]:
```
for (left_img, right_img) in images:
    init = time()
    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=window_size,
                         apply_dist=True,
```

```
                                penalty=penalty)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    print(f'SSD time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
                disp_map1_title=f"SSD W={window_size} P={penalty}")
```

```
SSD time: 0.48 s
SSD time: 0.48 s
```



Looping over windows and penalties

(Be aware: this can take awhile and consume a lot of memory!)

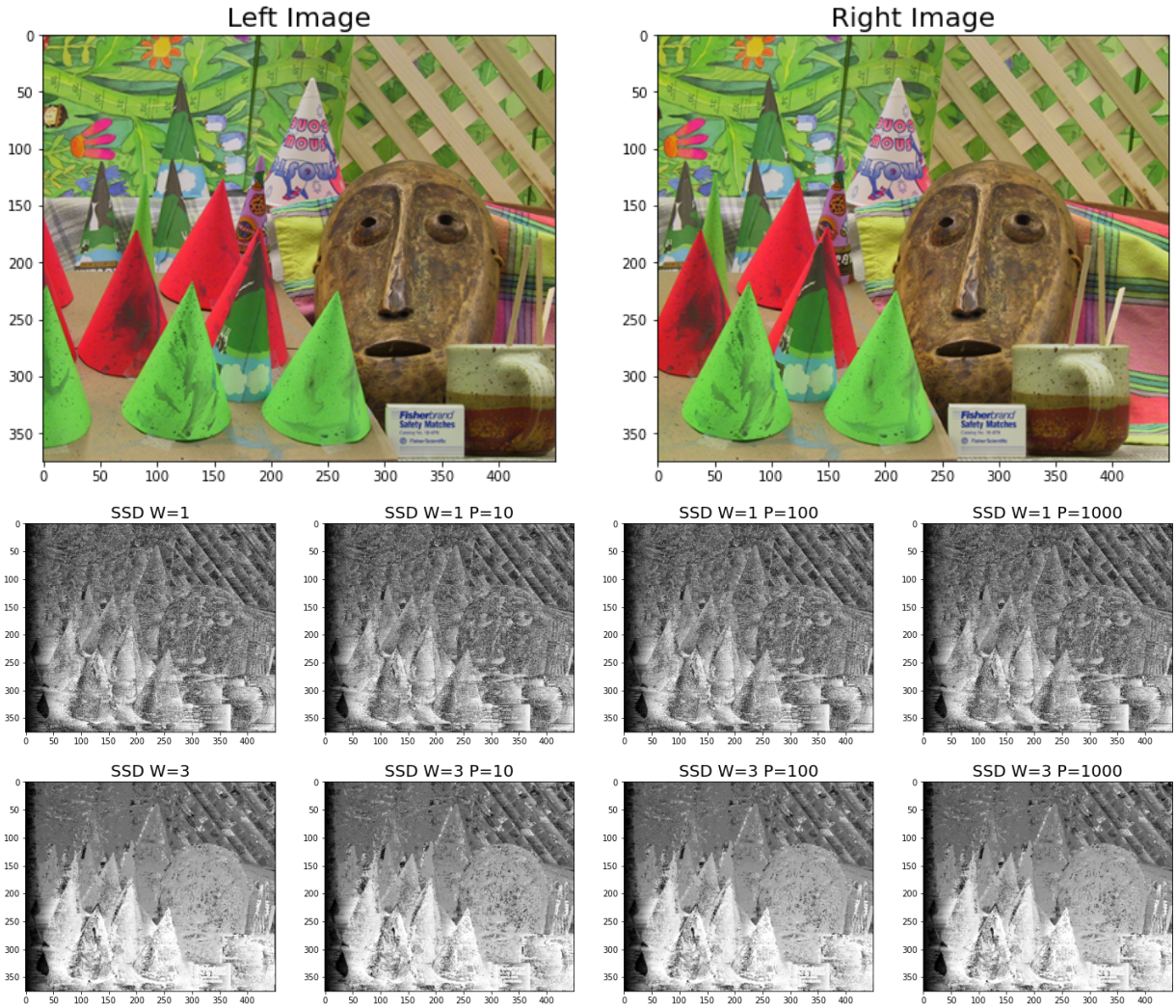
In [7]:

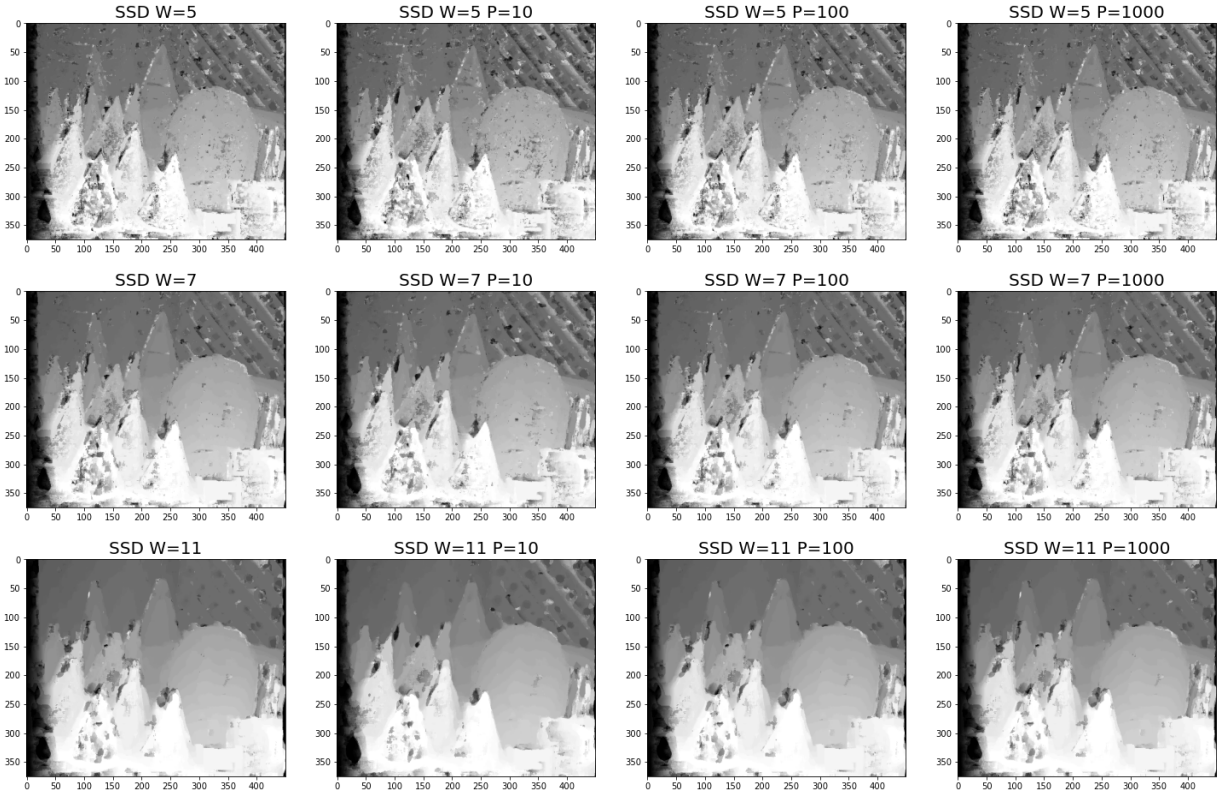
```
# define if to use teddy or cones images
left_image  = cones_left
right_image = cones_right
```

In [8]:

```
init = time()

fig = plt.figure(figsize=(15, 15))
ax1 = fig.add_subplot(1, 2, 1)
ax1.set_title("Left Image", size=20)
ax1.imshow(left_img)
ax2 = fig.add_subplot(1, 2, 2)
ax2.set_title("Right Image", size=20)
ax2.imshow(right_img)
plt.show()

cols = len(penalties)+1
for window_size in window_sizes:
    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=window_size,
                         apply_dist=False)
```

```
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    plt.figure(figsize=(25, 10))
    plt.subplot(1,cols,1)
    plt.title(f"SSD W={window_size}", size=20)
    plt.imshow(min_cost, cmap='gray')

    for i,penalty in enumerate(penalties):
        costs0_pen = compute_ssd(left_image=left_img,
                                 right_image=right_img,
                                 disparities=max_disp_steps,
                                 window_size=window_size,
                                 apply_dist=True,
                                 penalty=penalty)
        min_cost_pen = np.mean(np.argmin(costs0_pen, axis=-1), axis=-1)


        plt.subplot(1,cols,i+2)
        plt.title(f"SSD W={window_size} P={penalty}", size=20)
        plt.imshow(min_cost_pen, cmap='gray')

        del costs0_pen, min_cost_pen

    plt.show()

    del costs0, min_cost

print(f'Elapsed time: {(time() - init):.2f} s')
```






```
Elapsed time: 133.03 s
```

Comments

Considering only a pixel as reference (neighborhood of 1x1) there is a big room for ambiguity pixels on the block matching calculation. Analyzing the outcomes from tasks 1A and 1B, we can visualize this problem. Because of the ambiguity of pixels between both stereo images, the disparity map obtained ends up to be very noisy.

When we apply the match windows approach we get better results. So, as we can see in the previous images plots, as we increase the window sizes until a certain neighborhood size we get smoother disparity maps with fewer noise. However, as the window size increases we end up losing fine details, such as object boundaries.

Lastly, regarding the robust distance metric (i.e., the penalty value) which we applied in the SSD calculation of the Task 1B, we can conclude (by testing different penalty values) that it seems to be difficult to define the right setup for it (i.e., the best values of window size and penalty value to be used in order to get the best result). As we increase the penalty value, we get fewer matching mistakes (black pixels in the previous images) on the disparity maps comparing the plots with smaller penalty values or even without penalty; but, on the other hand, we also end up losing fine details, such as object boundaries.

Task 2

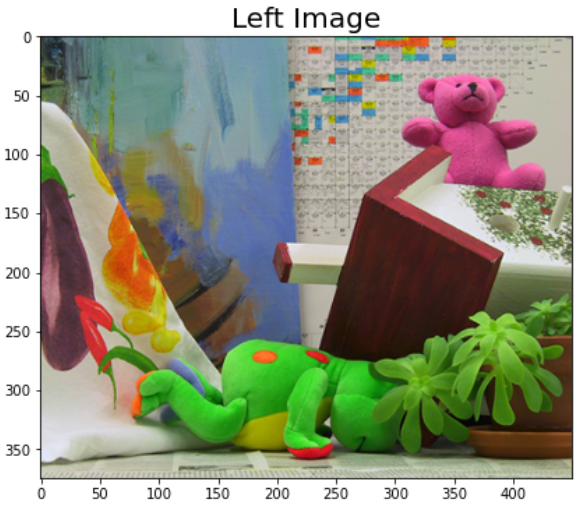
Task 2A

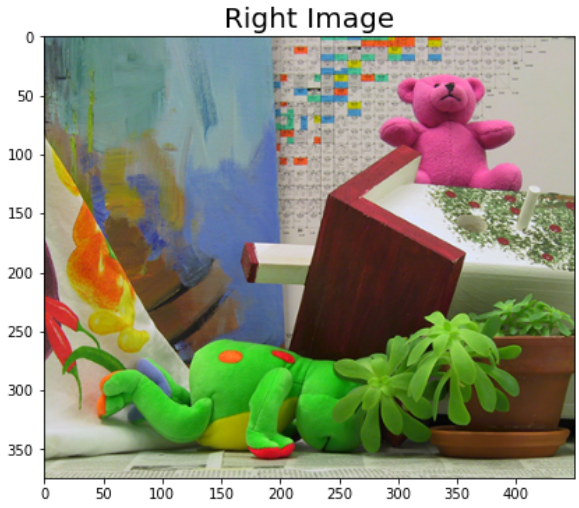
Computing Block Matching using SSD + Mean Aggregation

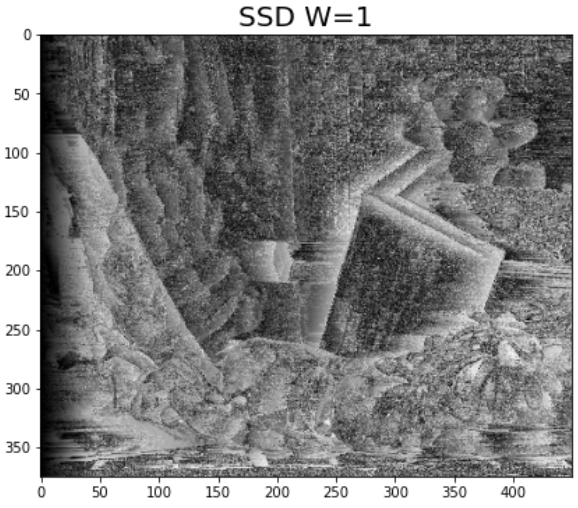
In [9]:
```
# define windows values
ssd_window = 1 # for the vanilla ssd
agg_window = 7 # for the aggregation
```

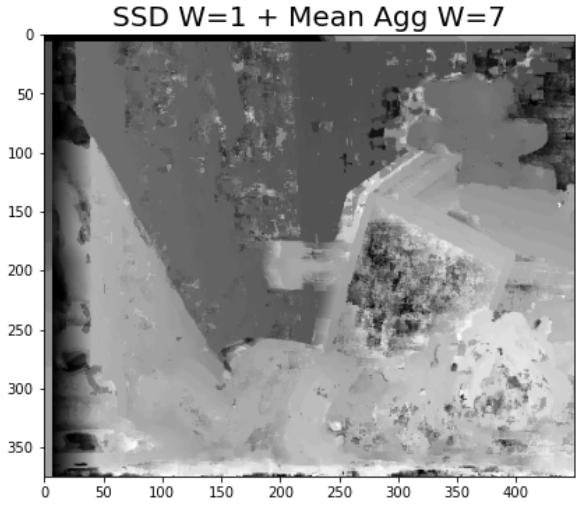
In [10]:
```
for left_img,right_img in images:
    init = time()

    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=ssd_window,
                         apply_dist=False)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    mean_agg = compute_aggregation(costs0=costs0, window_size=agg_window, moc
    min_cost_mean_agg = np.mean(np.argmin(mean_agg, axis=-1), axis=-1)

    print(f'Mean Aggregation time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
                disp_map2=min_cost_mean_agg,
                disp_map1_title=f"SSD W={ssd_window}",
                disp_map2_title=f"SSD W={ssd_window} + Mean Agg W={agg_windov
```

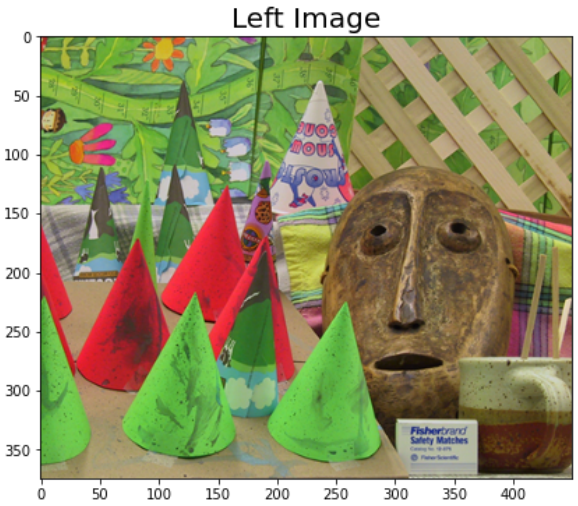
```
Mean Aggregation time: 2.73 s
Mean Aggregation time: 2.46 s
```

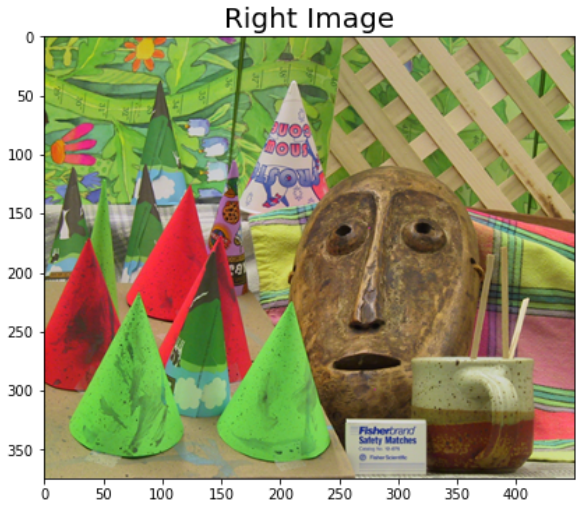


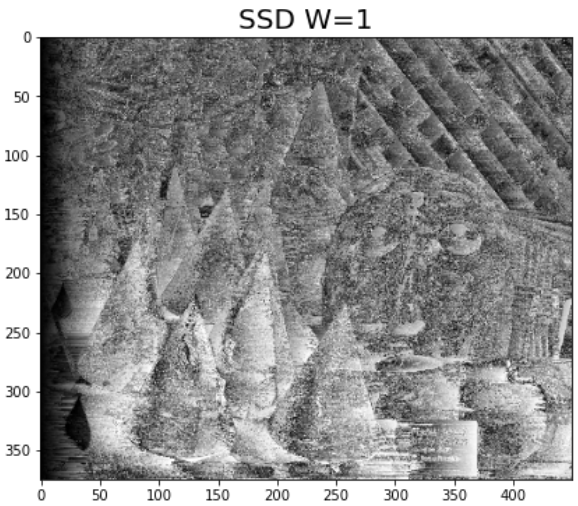


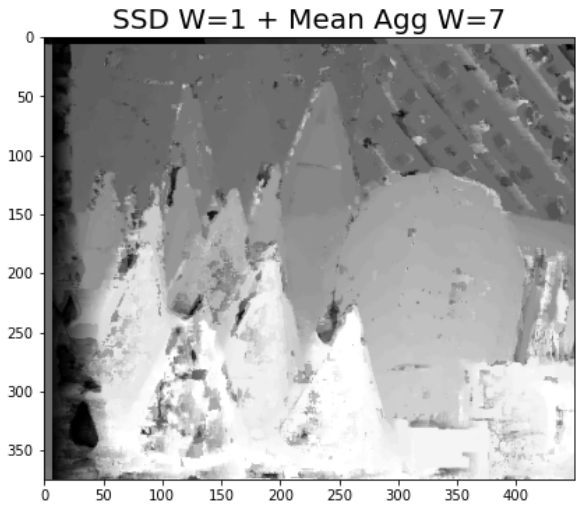












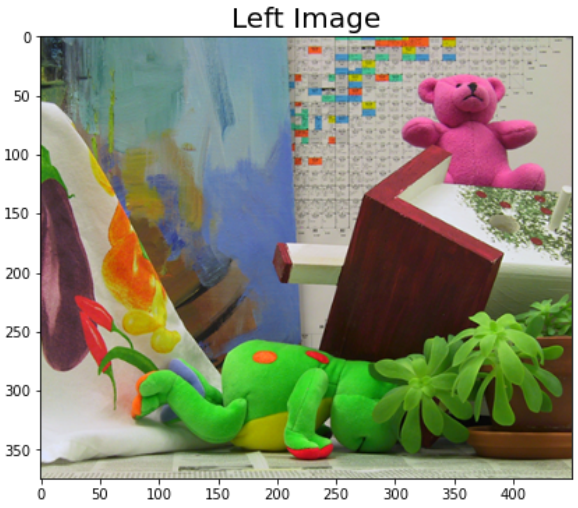
Computing Block Matching using SSD + Penalty value + Mean Aggregation

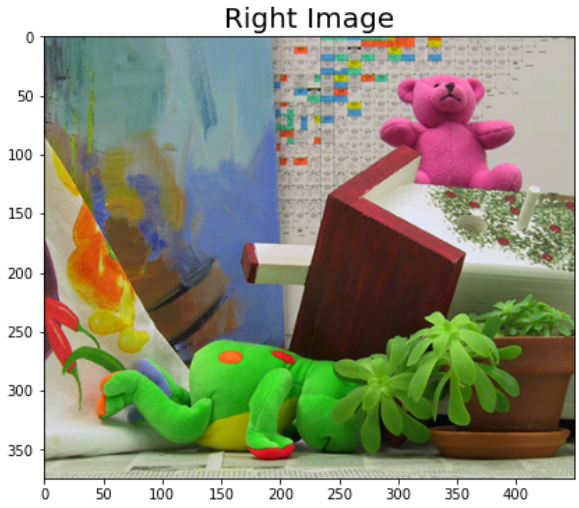
In [11]:
```
# define values
ssd_window = 1 # window size for the vanilla ssd
agg_window = 7 # window size for the aggregation
penalty = 100  # penalty value
```

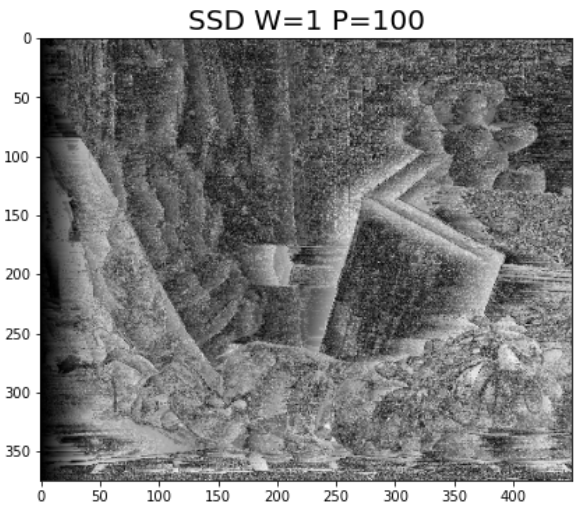
In [12]:
```
for left_img,right_img in images:
    init = time()

    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=ssd_window,
                         apply_dist=True,
                         penalty=penalty)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    mean_agg = compute_aggregation(costs0=costs0, window_size=agg_window, moc
    min_cost_mean_agg = np.mean(np.argmin(mean_agg, axis=-1), axis=-1)

    print(f'Mean Aggregation time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
```

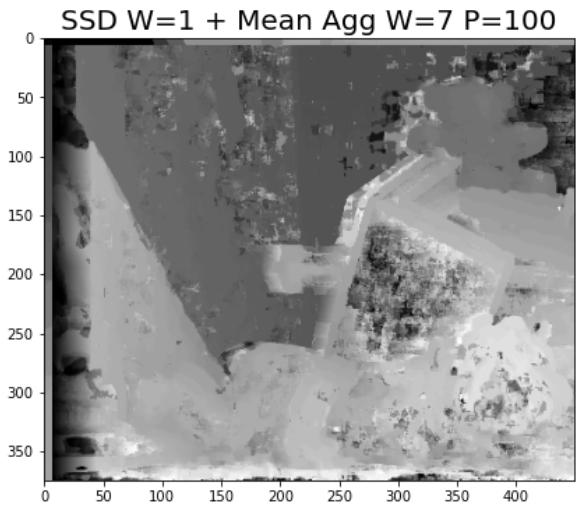
```
                disp_map2=min_cost_mean_agg,
                disp_map1_title=f"SSD W={ssd_window} P={penalty}",
                disp_map2_title=f"SSD W={ssd_window} + Mean Agg W={agg_windo
```

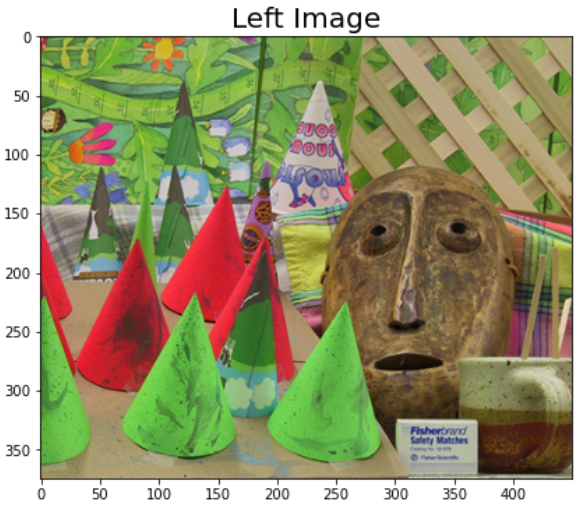
```
Mean Aggregation time: 2.57 s
Mean Aggregation time: 2.65 s
```

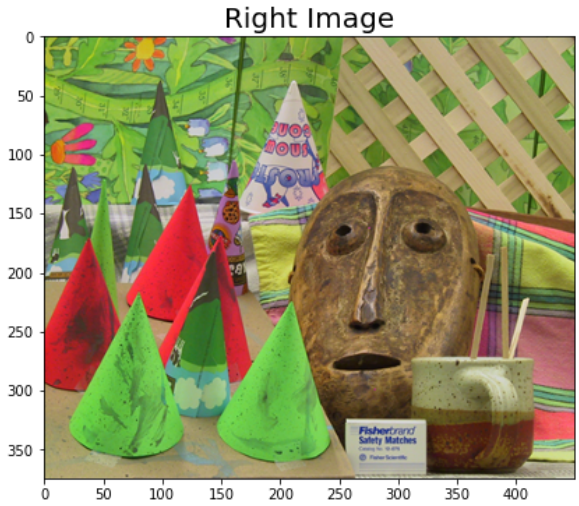


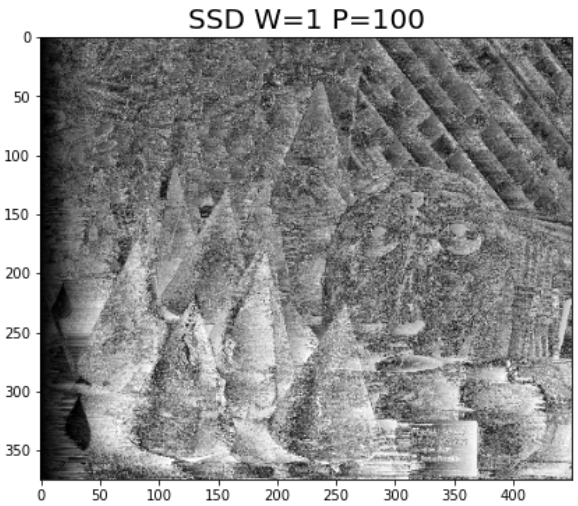


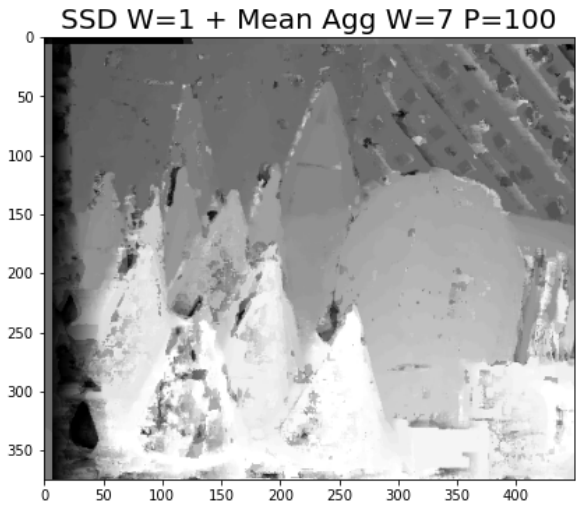












Task 2B

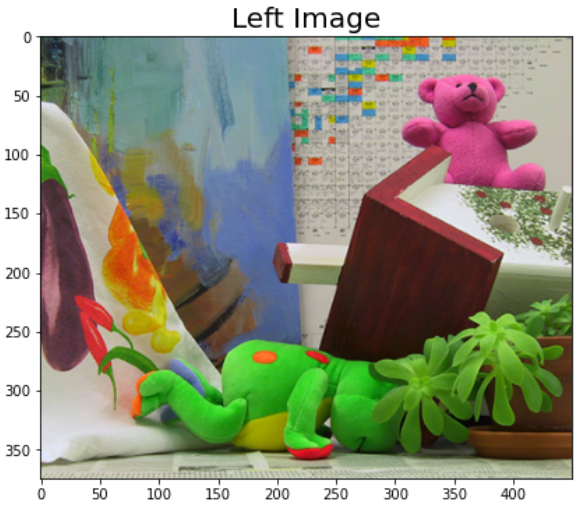
Computing Block Matching using SSD + Median Aggregation

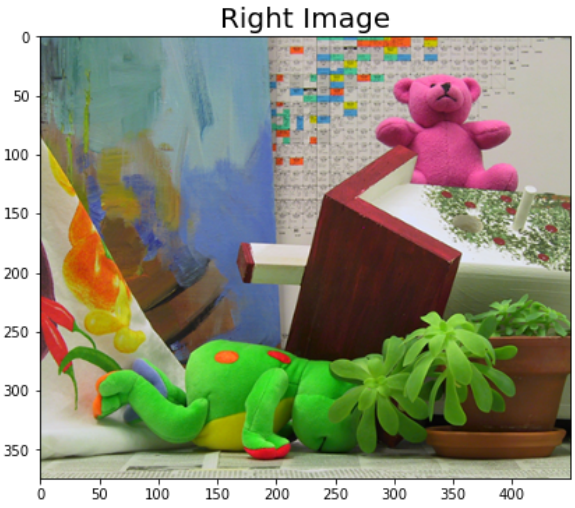
In [13]:
```
# define values
ssd_window = 1 # window size for the vanilla ssd
agg_window = 7 # window size for the aggregation
```

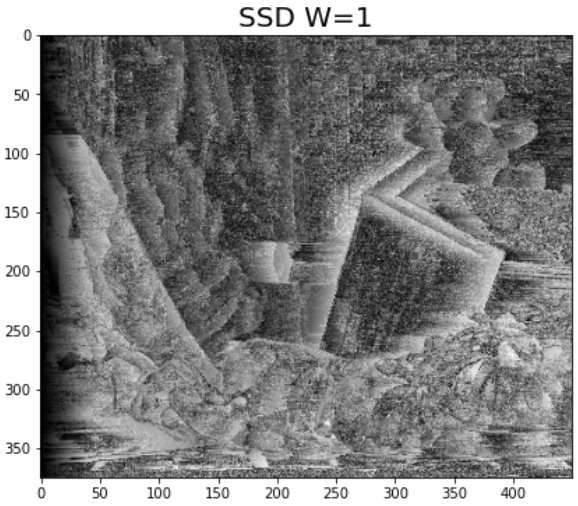
In [14]:
```
for left_img,right_img in images:
    init = time()

    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=ssd_window,
                         apply_dist=False)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    median_agg = compute_aggregation(costs0=costs0, window_size=agg_window, m
    min_cost_median_agg = np.mean(np.argmin(median_agg, axis=-1), axis=-1)

    print(f'Median Aggregation time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
```

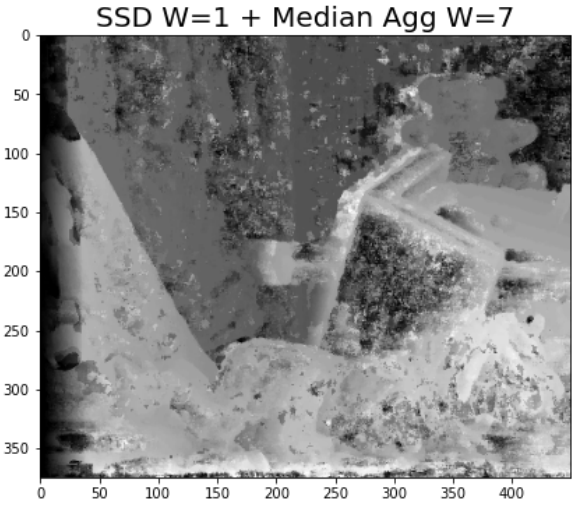
```
                disp_map2=min_cost_median_agg,
                disp_map1_title=f"SSD W={ssd_window}",
                disp_map2_title=f"SSD W={ssd_window} + Median Agg W={agg_winc
```

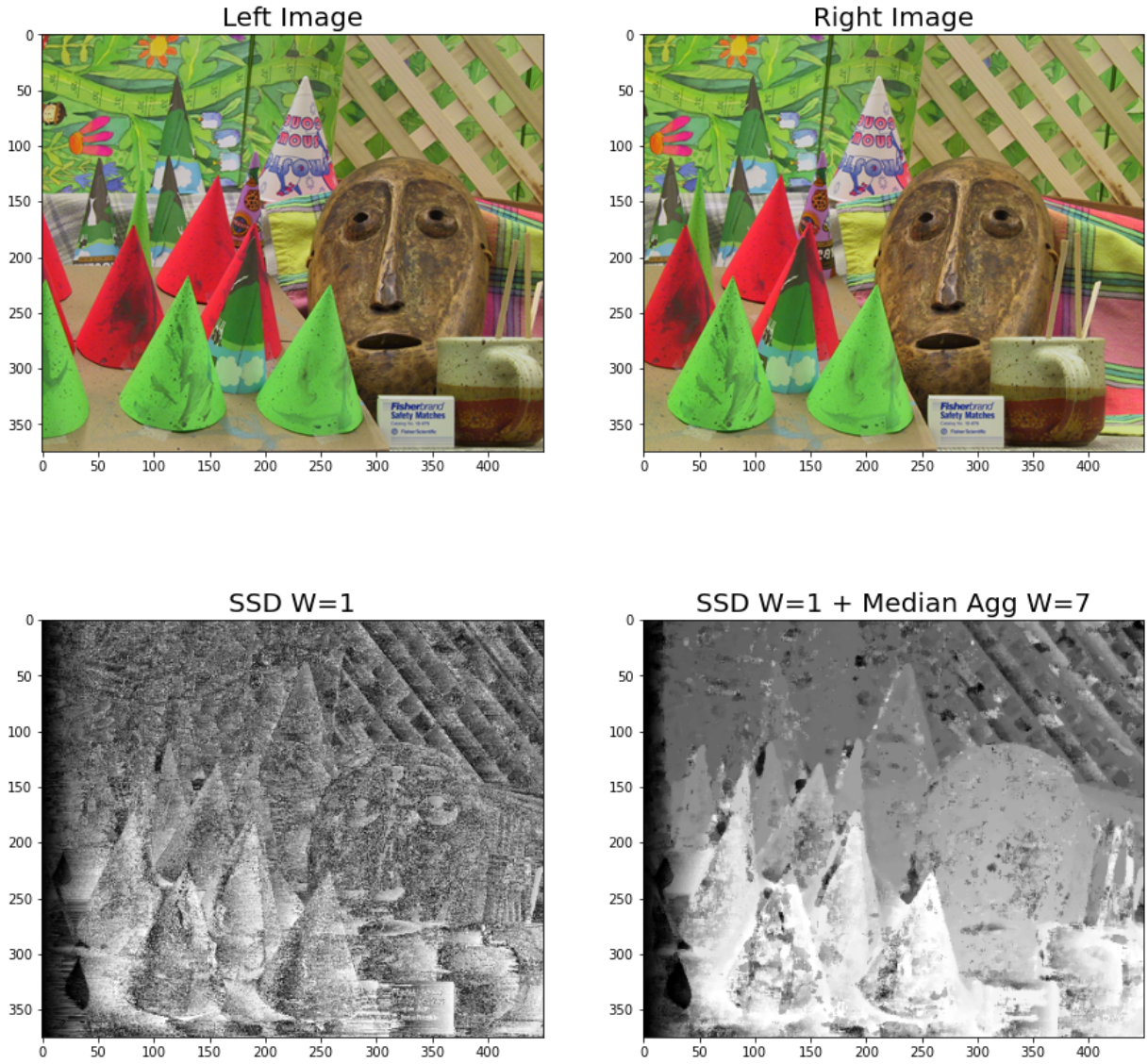
```
Median Aggregation time: 21.94 s
Median Aggregation time: 23.26 s
```











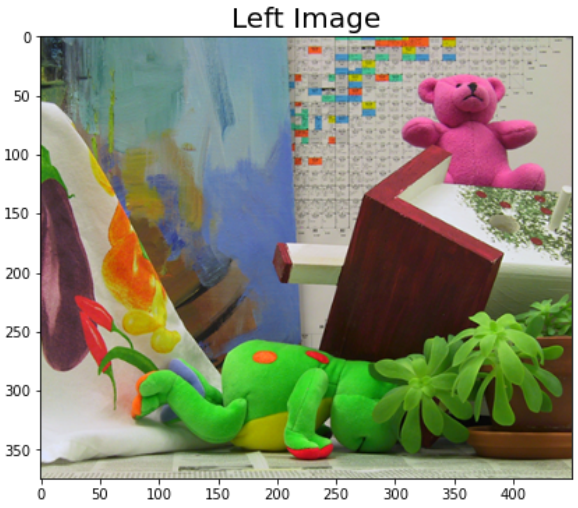
Computing Block Matching using SSD + Penalty value + Median Aggregation

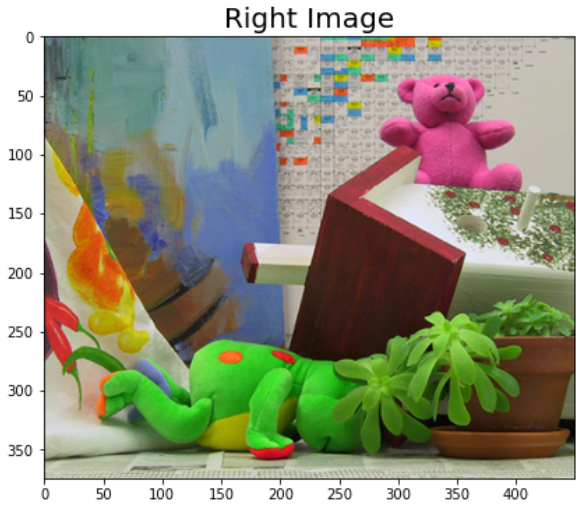
In [15]:
```
# define values
ssd_window = 1 # window size for the vanilla ssd
agg_window = 7 # window size for the aggregation
penalty = 100  # penalty value
```

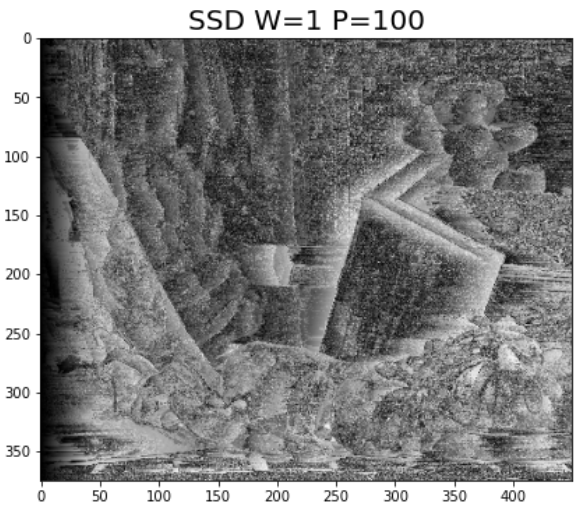
In [16]:
```
for left_img,right_img in images:
    init = time()

    costs0 = compute_ssd(left_image=left_img,
                         right_image=right_img,
                         disparities=max_disp_steps,
                         window_size=ssd_window,
                         apply_dist=True,
                         penalty=penalty)
    min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)

    median_agg = compute_aggregation(costs0=costs0, window_size=agg_window, m
    min_cost_median_agg = np.mean(np.argmin(median_agg, axis=-1), axis=-1)

    print(f'Median Aggregation time: {(time() - init):.2f} s')

    plot_images(imageL=left_img,
                imageR=right_img,
                disp_map1=min_cost,
```

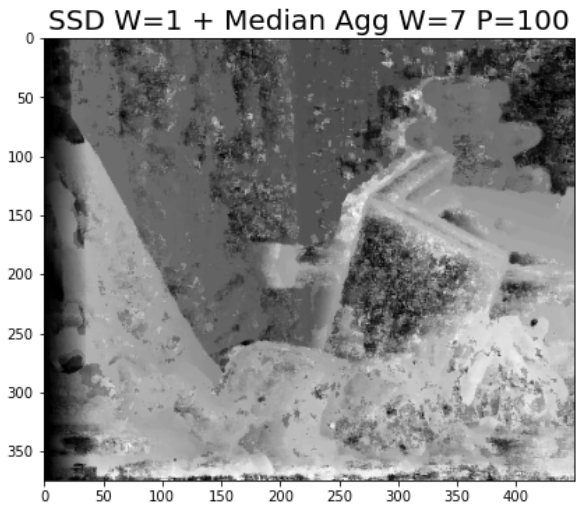
```
                disp_map2=min_cost_median_agg,
                disp_map1_title=f"SSD W={ssd_window} P={penalty}",
                disp_map2_title=f"SSD W={ssd_window} + Median Agg W={agg_winc
```

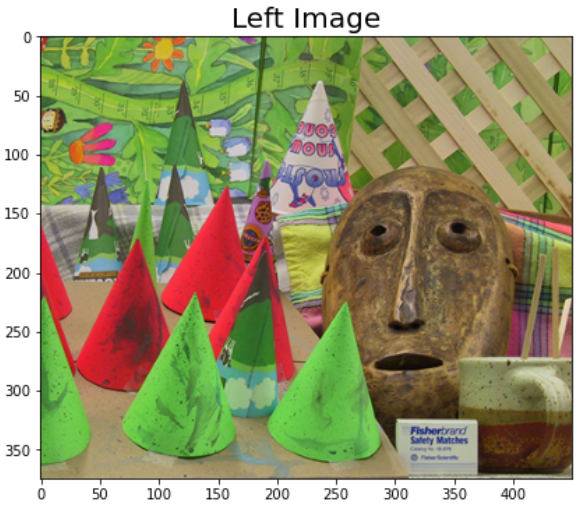
```
Median Aggregation time: 23.64 s
Median Aggregation time: 23.78 s
```

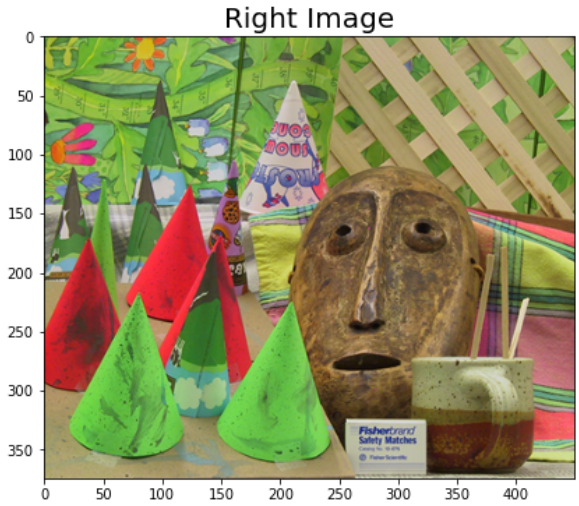


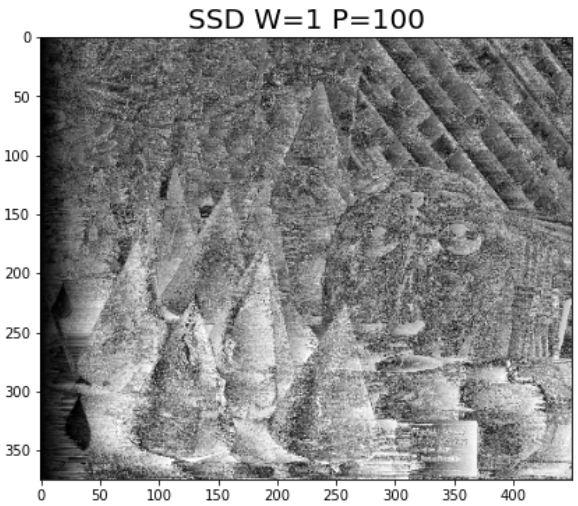


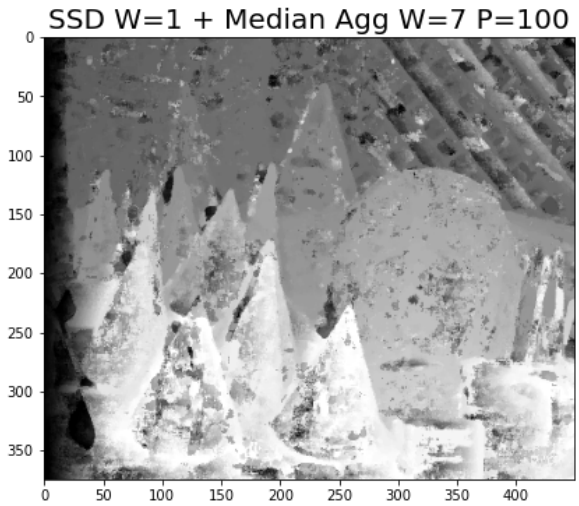












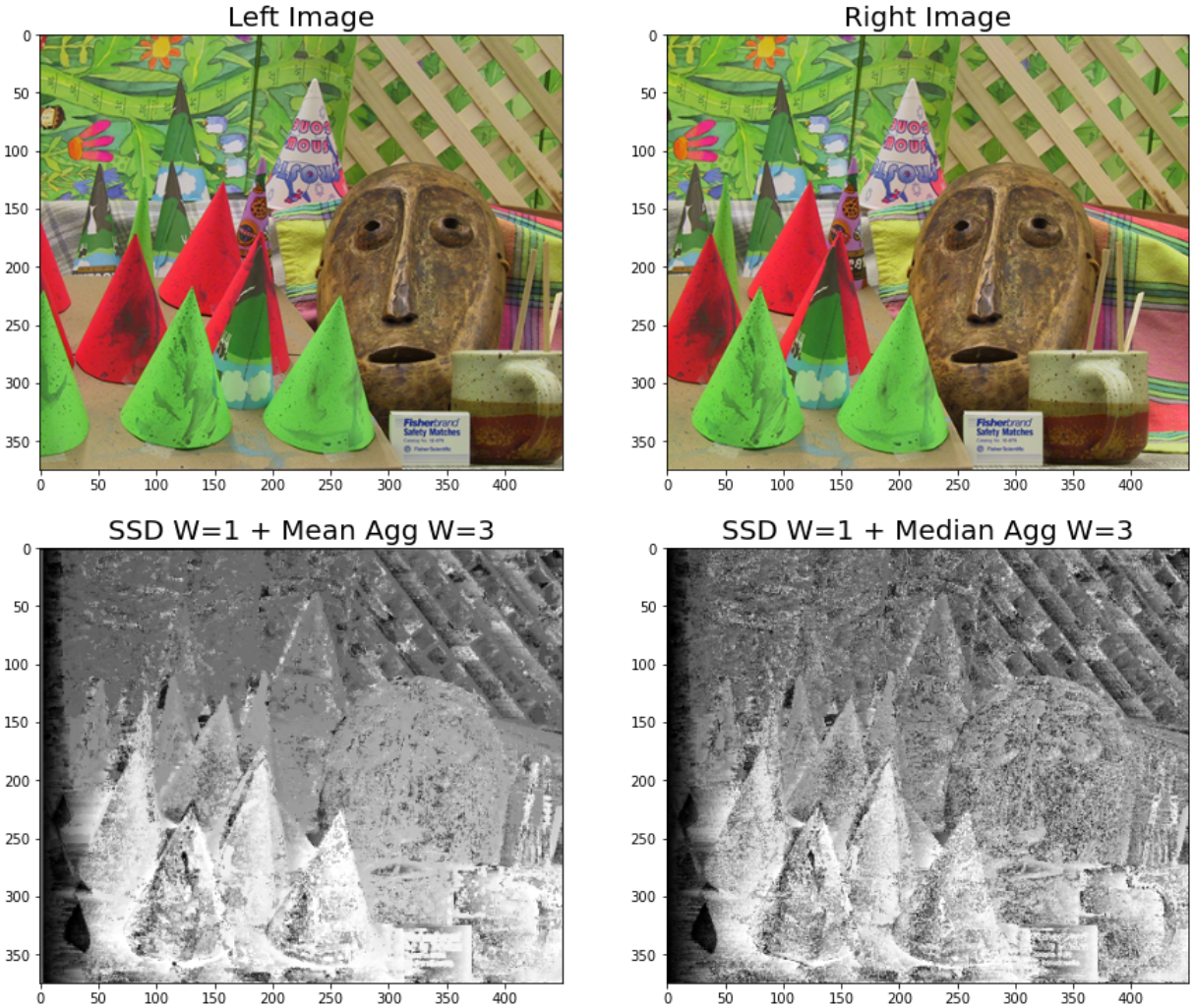
Looping over windows for aggregation

(Be aware: this can take awhile and consume a lot of memory!)

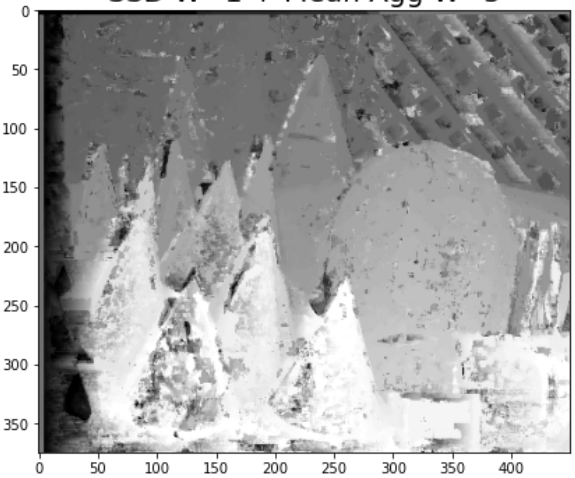
In [17]:
```
# setup values to be used
ssd_window = 1 # window size for the vanilla ssd

# define penalty parameters (if to use)
apply_dist = False # if to use penalty
penalty = 100      # penalty value
```

In [18]:
```
init = time()

fig = plt.figure(figsize=(15, 10))
ax1 = fig.add_subplot(1, 2, 1)
ax1.set_title("Left Image", size=20)
ax1.imshow(left_img)
ax2 = fig.add_subplot(1, 2, 2)
ax2.set_title("Right Image", size=20)
ax2.imshow(right_img)
plt.show()

for ssd_window in ssd_window_sizes:
    for window_size in window_sizes[1:]:
        costs0 = compute_ssd(left_image=left_img,
```

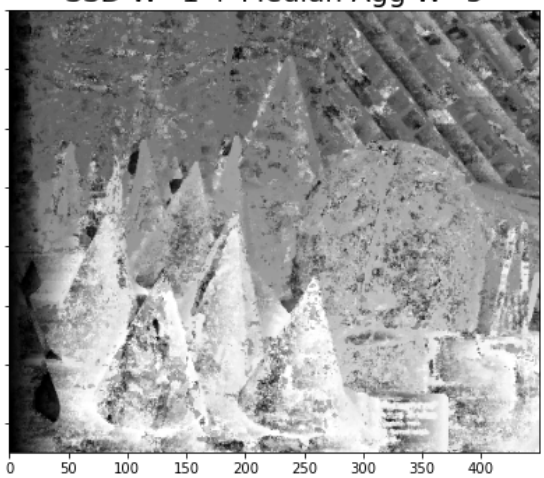
```
                                right_image=right_img,
                                disparities=max_disp_steps,
                                window_size=ssd_window,
                                apply_dist=apply_dist,
                                penalty=penalty)
            min_cost = np.mean(np.argmin(costs0, axis=-1), axis=-1)
            mean_agg = compute_aggregation(costs0=costs0, window_size=window_size
            min_cost_mean_agg = np.mean(np.argmin(mean_agg, axis=-1), axis=-1)

            median_agg = compute_aggregation(costs0=costs0, window_size=window_si
            min_cost_median_agg = np.mean(np.argmin(median_agg, axis=-1), axis=-1

            fig = plt.figure(figsize=(15, 10))
            ax1 = fig.add_subplot(1, 2, 1)
            ax1.set_title(f"SSD W={ssd_window} + Mean Agg W={window_size}", size=
            ax1.imshow(min_cost_mean_agg, cmap='gray')
            ax3 = fig.add_subplot(1, 2, 2)
            ax3.set_title(f"SSD W={ssd_window} + Median Agg W={window_size}", siz
            ax3.imshow(min_cost_median_agg, cmap='gray')
            plt.show()

            del costs0, min_cost, mean_agg, min_cost_mean_agg
            del median_agg, min_cost_median_agg

print(f'Elapsed time: {(time() - init):.2f} s')
```



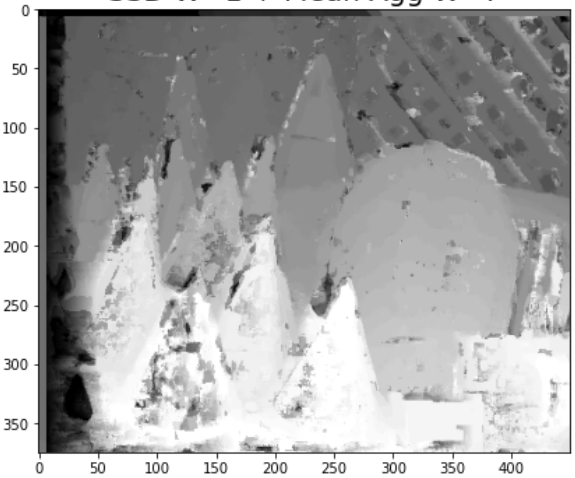
SSD W=1 + Mean Agg W=5



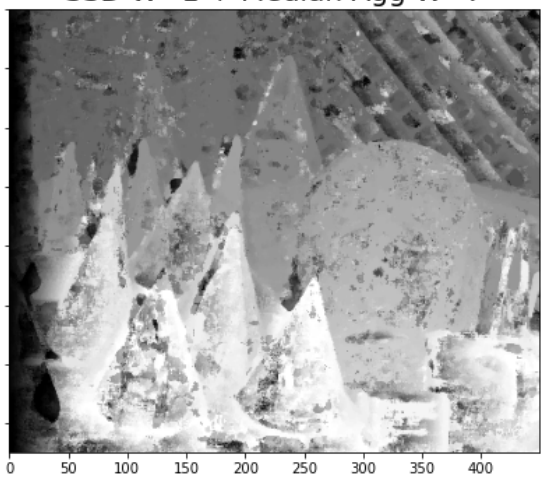
SSD W=1 + Median Agg W=5



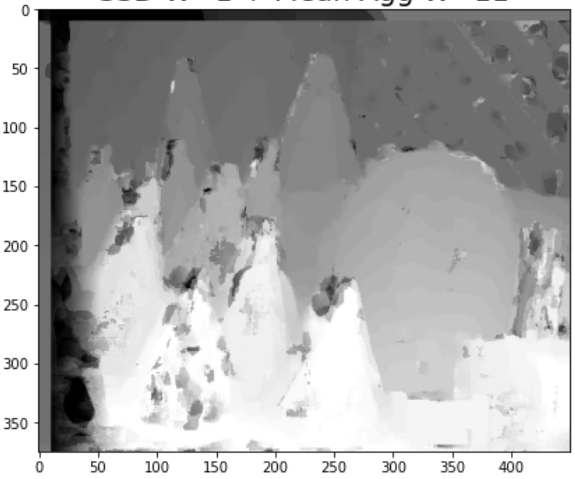
SSD W=1 + Mean Agg W=7



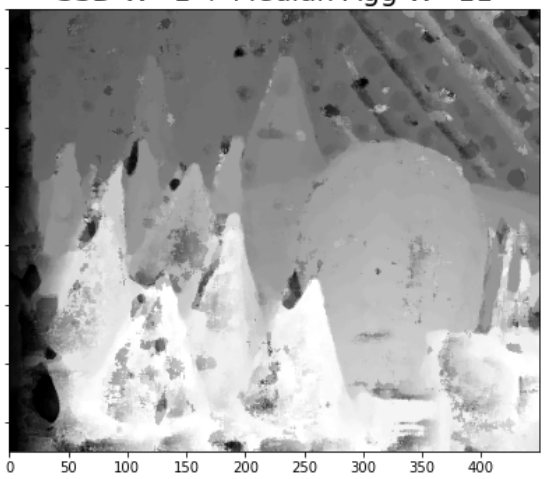
SSD W=1 + Median Agg W=7



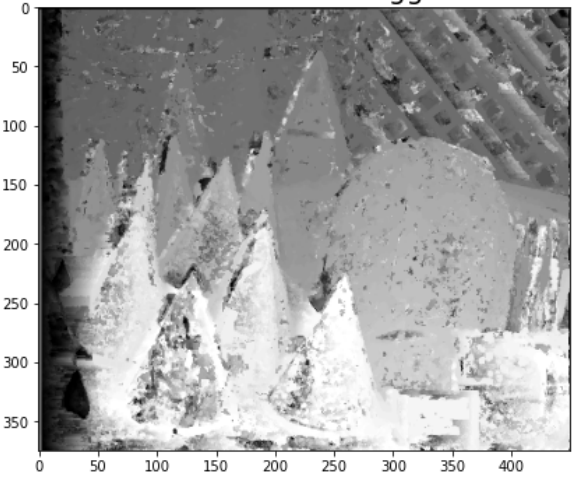
SSD W=1 + Mean Agg W=11



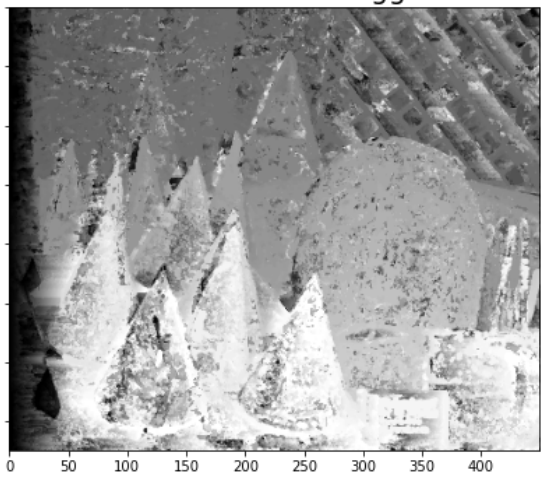
SSD W=1 + Median Agg W=11



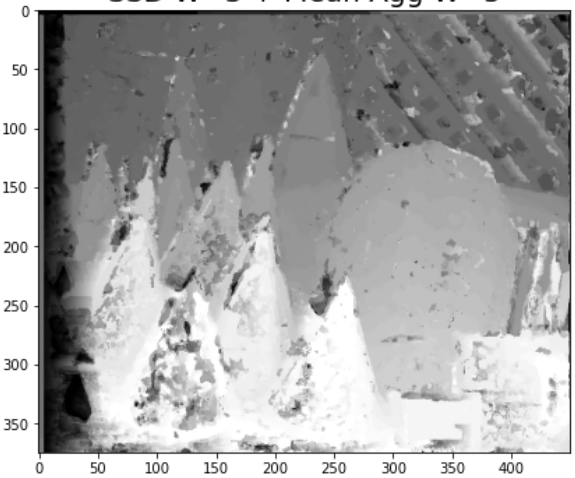
SSD W=3 + Mean Agg W=3



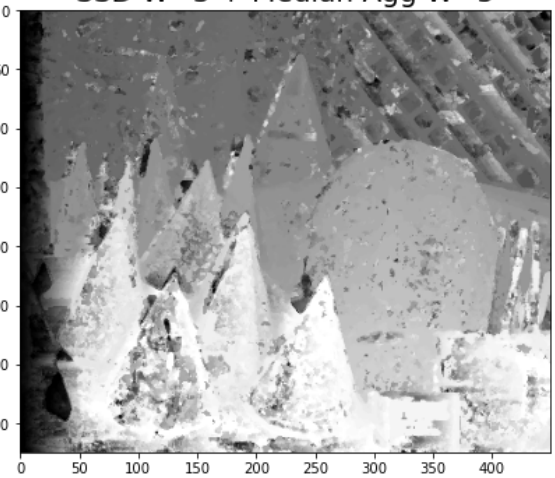
SSD W=3 + Median Agg W=3



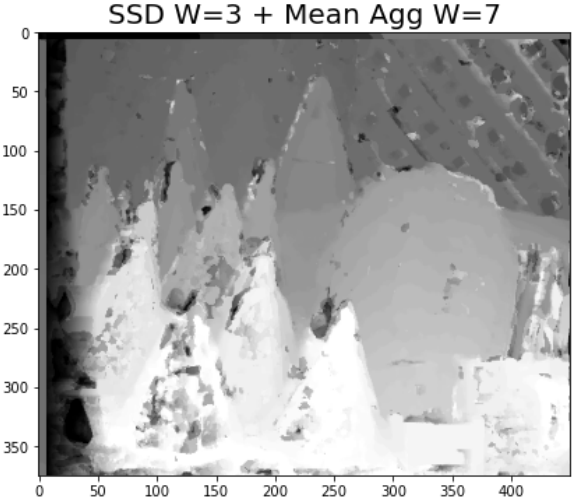
SSD W=3 + Mean Agg W=5



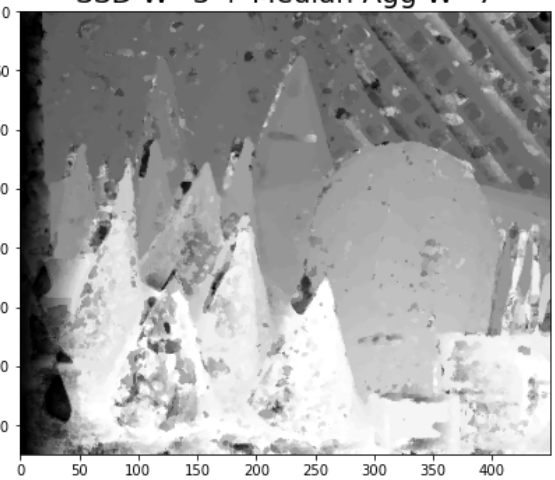
SSD W=3 + Median Agg W=5



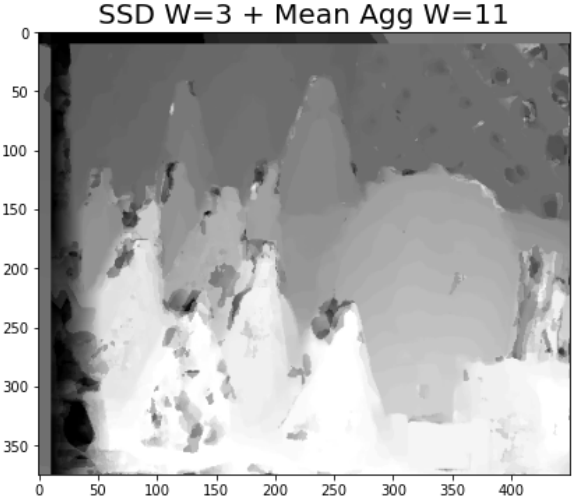
SSD W=3 + Mean Agg W=7



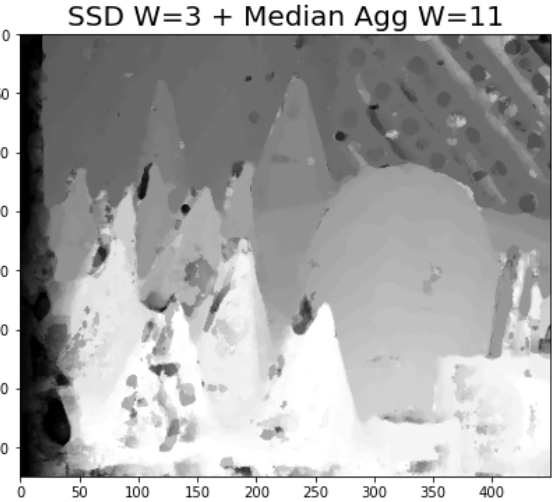
SSD W=3 + Median Agg W=7



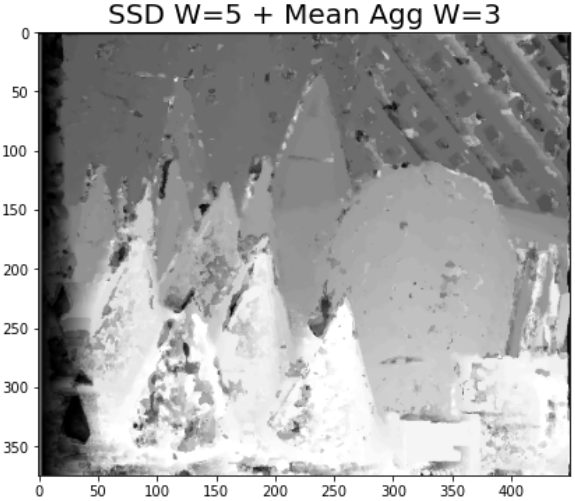
SSD W=3 + Mean Agg W=11



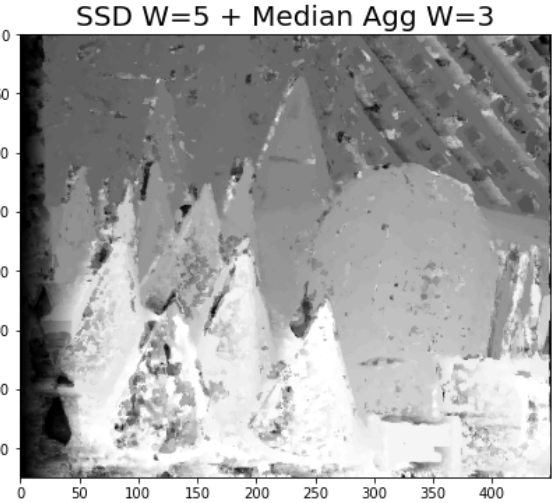
SSD W=3 + Median Agg W=11



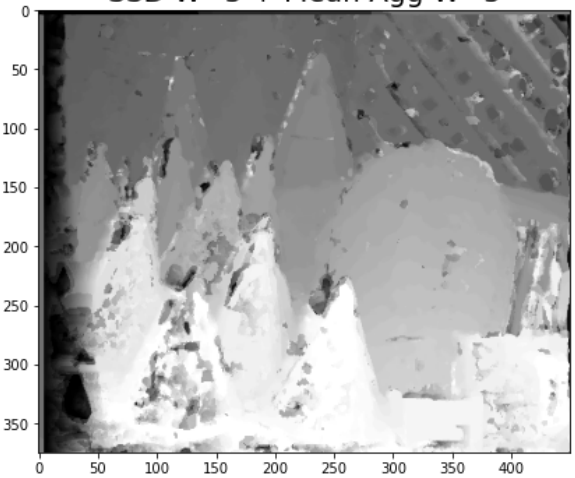
SSD W=5 + Mean Agg W=3



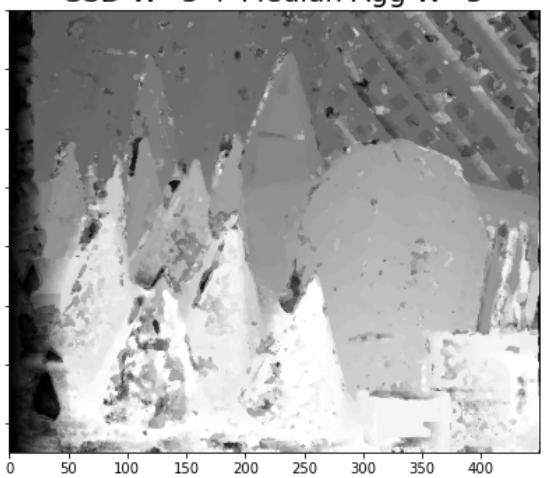
SSD W=5 + Median Agg W=3



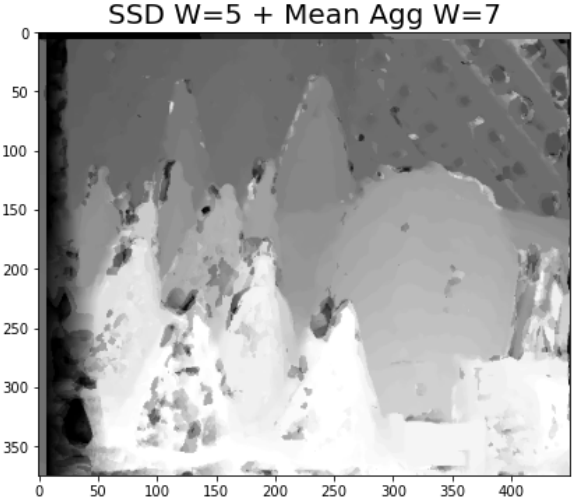
SSD W=5 + Mean Agg W=5



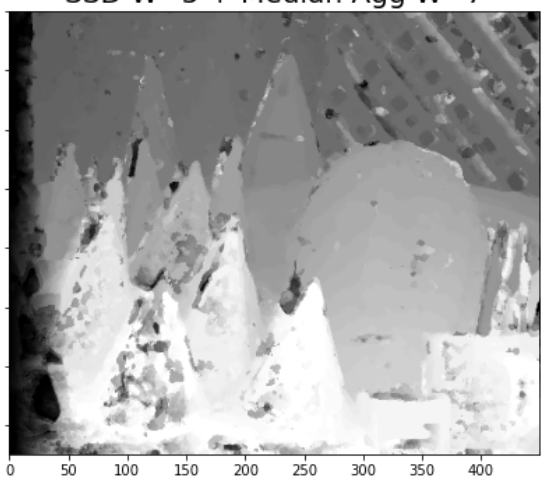
SSD W=5 + Median Agg W=5



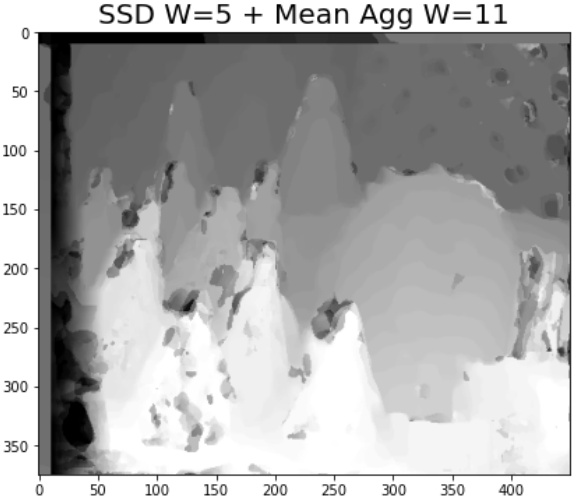
SSD W=5 + Mean Agg W=7



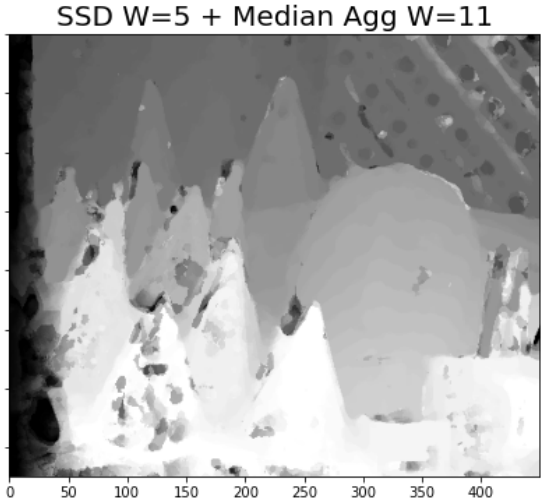
SSD W=5 + Median Agg W=7



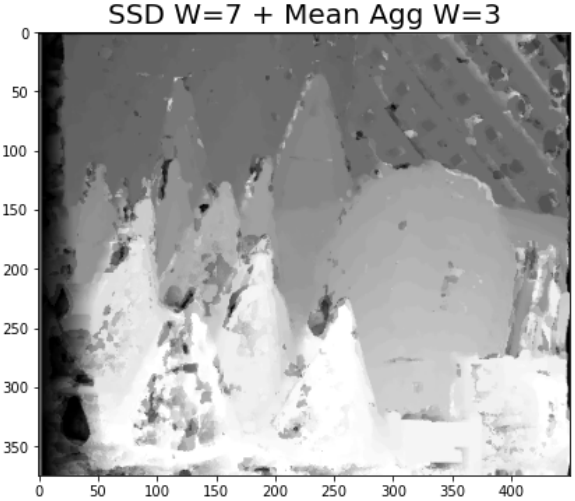
SSD W=5 + Mean Agg W=11



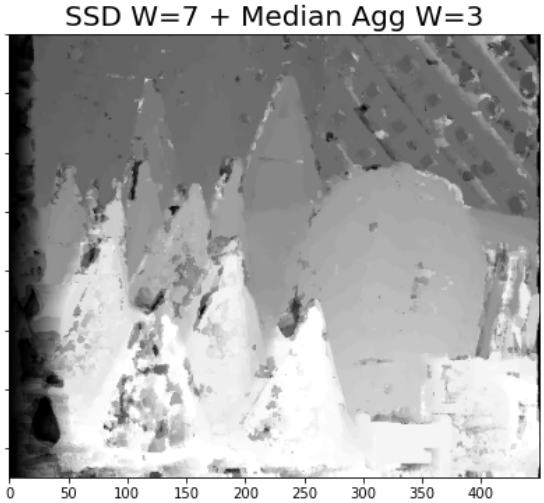
SSD W=5 + Median Agg W=11



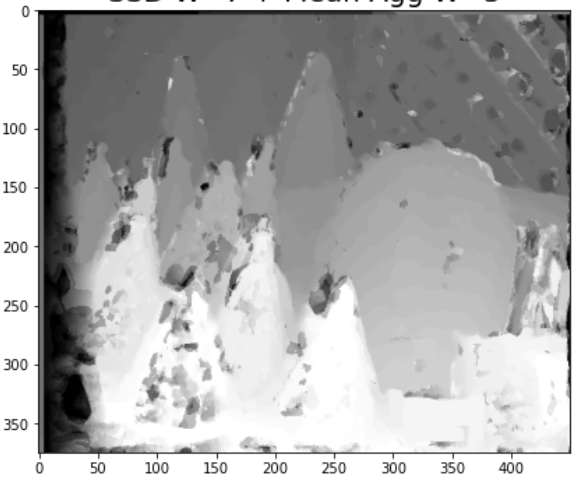
SSD W=7 + Mean Agg W=3



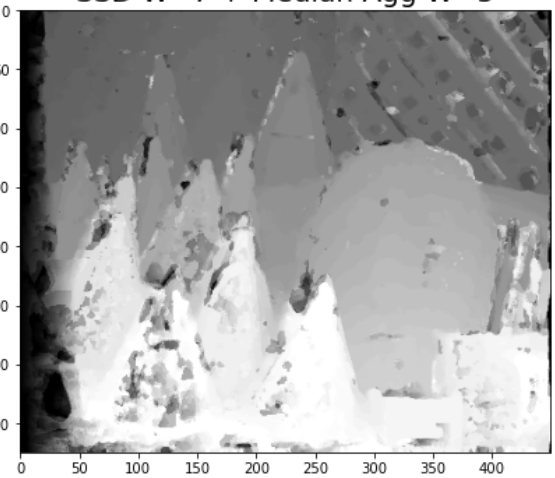
SSD W=7 + Median Agg W=3



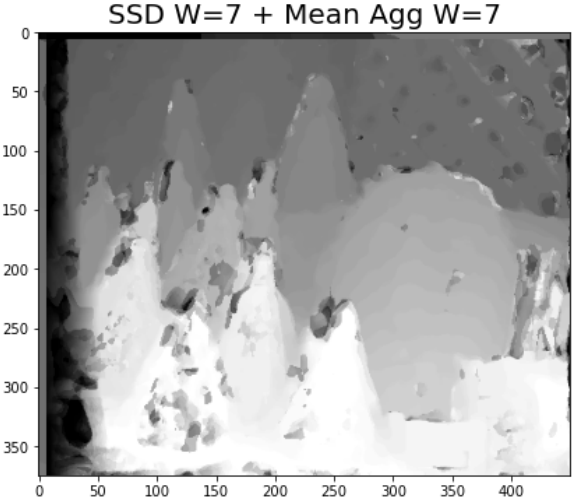
SSD W=7 + Mean Agg W=5



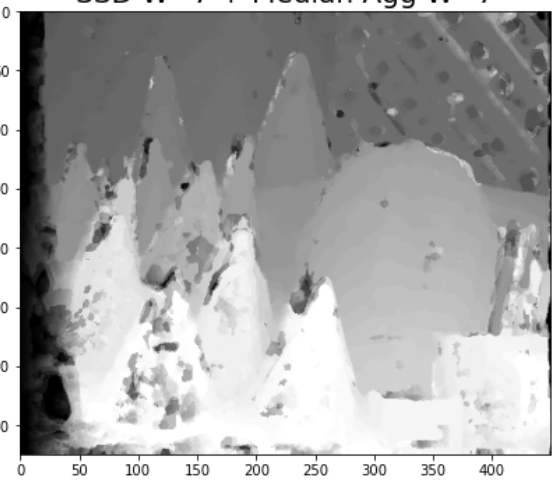
SSD W=7 + Median Agg W=5



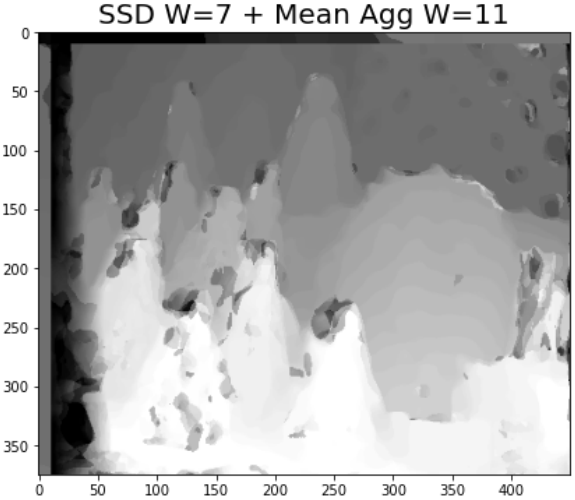
SSD W=7 + Mean Agg W=7



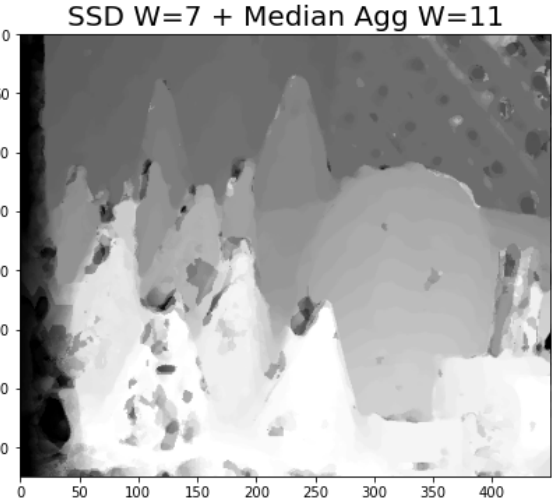
SSD W=7 + Median Agg W=7



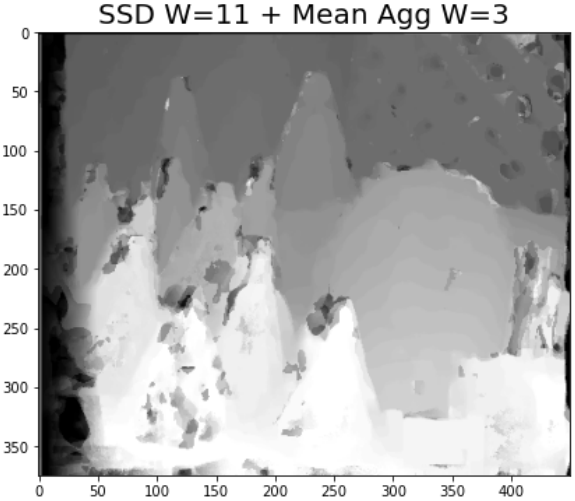
SSD W=7 + Mean Agg W=11



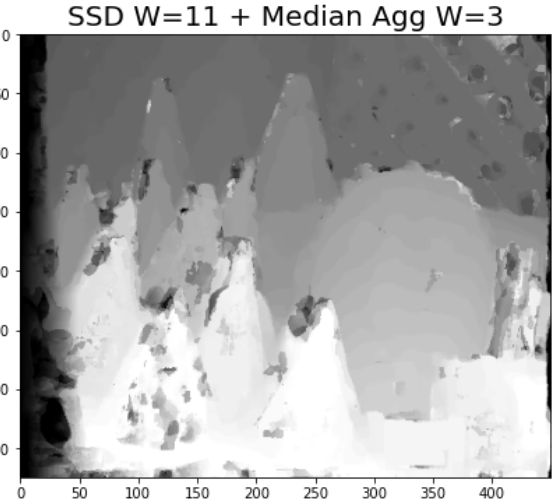
SSD W=7 + Median Agg W=11

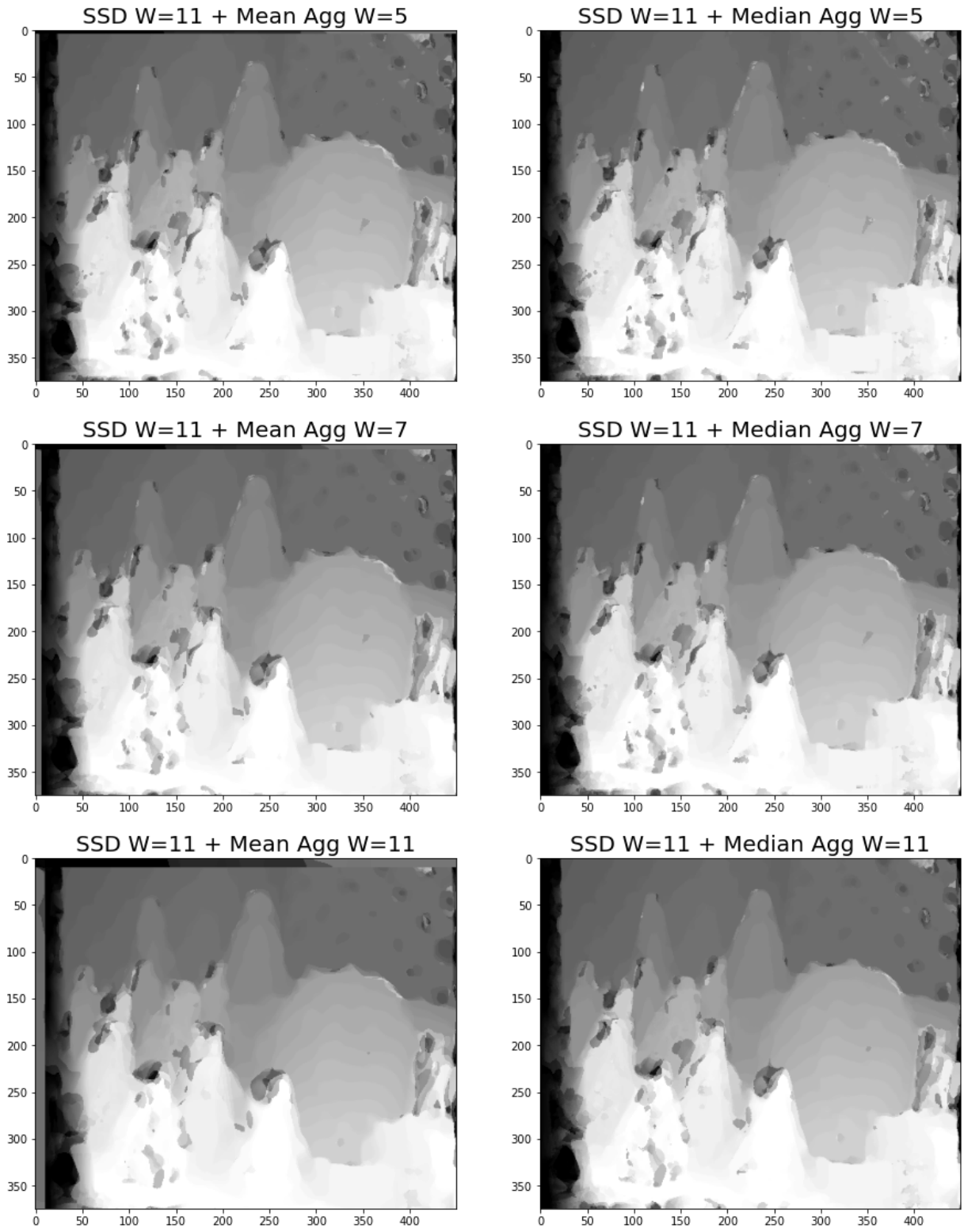


SSD W=11 + Mean Agg W=3



SSD W=11 + Median Agg W=3






```
Elapsed time: 537.43 s
```

Comments

Using the Mean and Median aggregation strategies, we notice an improvement on the disparity maps (regarding the ones from Task 1), because the visual results showed smoother and more detailed images. It seems to be a good strategy to first compute the disparity map using some strategy (e.g., SSD) with a smaller window size and then using an aggregation method to finetune it (i.e., remove noises), since it improves the computation speed and return better (smoother) results.

Comparing both the Mean and Median strategies against each other, we concluded that the results returned after applying the Mean filter are smoother than the Median approach.

However, the last one apparently preserves more on the fine details of the objects on the scene. Moreover, since the Mean strategy allows the usage of integral images, it seems to be a more suitable strategy for applications that require fast feedback (e.g., self-driving cars), since it can be computed in a very fast fashion and ends up using low computational resources.

We also tested different window sizes values, using odd numbers ranging from 1 to 11. Analyzing the visual outcomes presented on the previous plots, we concluded that the best results were obtained using window sizes and kernel sizes (for the Mean and Median filters) of 5x5 and 7x7 (i.e., intermediate window sizes). The window size of 11x11 also presented good results, but from this neighborhood size and beyond, the disparity maps start to lose details, such as object boundaries and textures.