

Computer vision
Assignment 3 – Stereo Vision

Names

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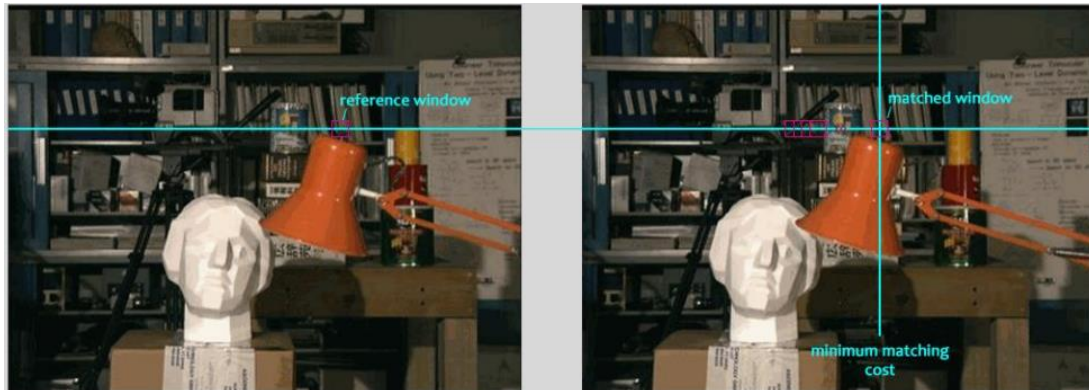
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First part : block matching

In this method we find the disparity in the images by matching every pixel in the left image to a certain pixel in the right image.

- First, we define a reference window in the left image, then we slide a similar window across the epipolar line in the right image and compare the contents with the reference window using a certain metric. This process is repeated for every pixel in each scanline.



- We compare the results of window sizes 1 (pixel to pixel comparison), 5, and 9.

```
def block_matching(img1, img2, window_size, metric):  
  
    height, width = img1.shape  
    disparity_map = np.zeros((height, width), np.uint8)  
    half_window = window_size // 2  
  
    # Loop through every pixel in the left image  
    for y in range(half_window, height - half_window):  
        for x in range(half_window, width - half_window):  
  
            # Get the current window  
            window = img1[y - half_window: y + half_window + 1, x - half_window: x + half_window + 1]  
            # Define the minimum SSD and best disparity  
            min_metric = 255 * window_size * window_size  
            # min_metric = 1000000000000  
            best_disparity = 0  
  
            # compare with each window from the right image  
            for xRight in range(half_window, width - half_window):  
                # Get the current window from the right image  
                current_window = img2[y - half_window: y + half_window + 1, xRight - half_window: xRight + half_window + 1]  
                # Calculate the SSD / SAD  
                m = metric(window, current_window)  
                # if the SSD / SAD is smaller than the minimum metric update the minimum metric and the best disparity  
                if m < min_metric:  
                    min_metric = m  
                    best_disparity = np.abs(x - xRight)  
  
            # Update the disparity map  
            disparity_map[y, x] = best_disparity  
  
    return disparity_map
```

- We use 2 metrics to estimate matching cost:
 - Sum of Absolute Differences (SAD) Computed by calculating the absolute difference of the reference window and matching window's pixels element by element then adding them up.
 - Sum of Squared Differences (SSD) Computed by calculating the squared difference of the reference window and matching window's pixels element by element then adding them up.

Cons of using this method

1. This method is taking so long as it goes $O(\text{ROWS} * \text{COLUMNS}) * O(\text{COLUMNS})$
2. We can reduce the complexity by having a limit on the disparity so we can limit the number of comparisons for each window.

Second part : Dynamic Programming

- This method uses a dynamic programming algorithm to calculate the minimum cost for matching a whole row in the images.

For every pixel in the image there are 3 possible conditions:

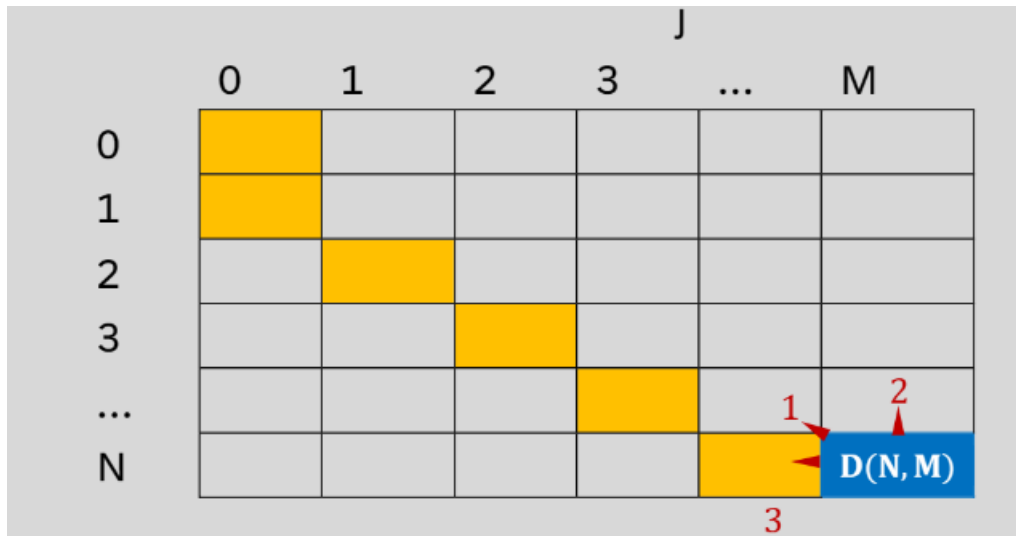
- The pixel is visible in the left and right images (it is matched).
- The pixel is visible in the left image but occluded in the right image.
- The pixel is visible in the right image but occluded in the left image.

$$d_{ij} = \frac{(I_l(i) - I_r(j))^2}{\sigma^2}$$

where σ is some measure of pixel noise. The cost of skipping a pixel (in either scanline) is given by a constant c_0 . For the experiments here we will use $\sigma = 2$ and $c_0 = 1$. Given these costs, we can compute the optimal (minimal cost) alignment of two scanlines recursively as follows:

1. $D(1, 1) = d_{11}$
2. $D(i, j) = \min(D(i - 1, j - 1) + d_{ij}, D(i - 1, j) + c_0, D(i, j - 1) + c_0)$

- After D is fully computed, the total cost of matching two scanlines can be found in the element $D(N, M)$.
- We now perform a backwards pass from $D(N, M)$ along the optimal path (minimum cost) to get the optimal alignment for the 2 images and calculate the disparity of each pixel in the corresponding pixel maps.



Starting at $(i, j) = (N, N)$

we choose the minimum value of D from $(i-1, j-1)$, $(i-1, j)$, $(i, j-1)$.

- Selecting $(i-1, j)$ corresponds to skipping a pixel in I_l , so the left disparity map of i is zero.
- Selecting $(i, j-1)$ corresponds to skipping a pixel in I_r , and the right disparity map of j is zero.
- Selecting $(i-1, j-1)$ matches pixels (i, j) , and therefore both disparity maps at this position are set to the absolute difference between i and j .

Sample output

