SGN-34006 - 3D and Virtual Reality Project Assignment

Dense disparity estimation via local stereo matching

Project overview

Implement the local color-weighted disparity estimation algorithm and evaluate its performance on a set of stereo image pairs. **The project is completed alone,** i.e. it is not a group assignment. Sharing of code is not allowed.

Demo scripts showing the results of most of the steps are provided. You should use the demo m-files as a skeleton for your implementation and start replacing the provided functions (p-files) with ones you write yourself (see folder 'Function templates').

The algorithm includes the following steps:

1. Cost function calculation *(mandatory)*
2. Cost aggregation based on three methods (*mandatory*)
    a. Box filtering
    b. Gaussian filtering
    c. Local color-weighted filtering (guided filter)
3. 'Winner-takes-all' disparity estimation *(mandatory)*
4. Detection of occlusions *(1p)*
5. Computation of confidence values for disparity estimates *(1p)*
6. Post-filtering to tackle occlusions and bad pixels *(1p)*
7. Implementation of bilateral filter based aggregation *(1p)*

Steps marked as mandatory should be completed in order to pass the exercise (grade 1). Each additional point will be directly added to the grade. The tasks should be implemented in numerical order since 6 depends on 4 and 5, and 7 is the most challenging one. Grade 5 requires all steps to be completed. **List clearly, which steps you have completed** with a table like below**.**

Step	**Completed**
Steps 1, 2, 3	X
Step 4	X
Step 5	X
Step 6	
Step 7	

Your implementation should produce equivalent (not necessary identical) output to the demo files.

Deliverables

- A report: a pdf with all of the figures generated by the demo scripts using your implementation of the functions. If there are problems with some tasks, please make a note of it in the report and describe the issue. Tasks marked as completed without any additional remarks are expected to work. Implementations generating obviously wrong results (empty images, noise, heavy artifacts etc.) will not be given a second chance after the evaluation, whereas documented problems are
- Your own implementation of the requested functions for tasks which you mark as completed. The demo script has to run without errors on a standard Matlab 2017a installation with all toolboxes available, as found in the IT classes at TUT.

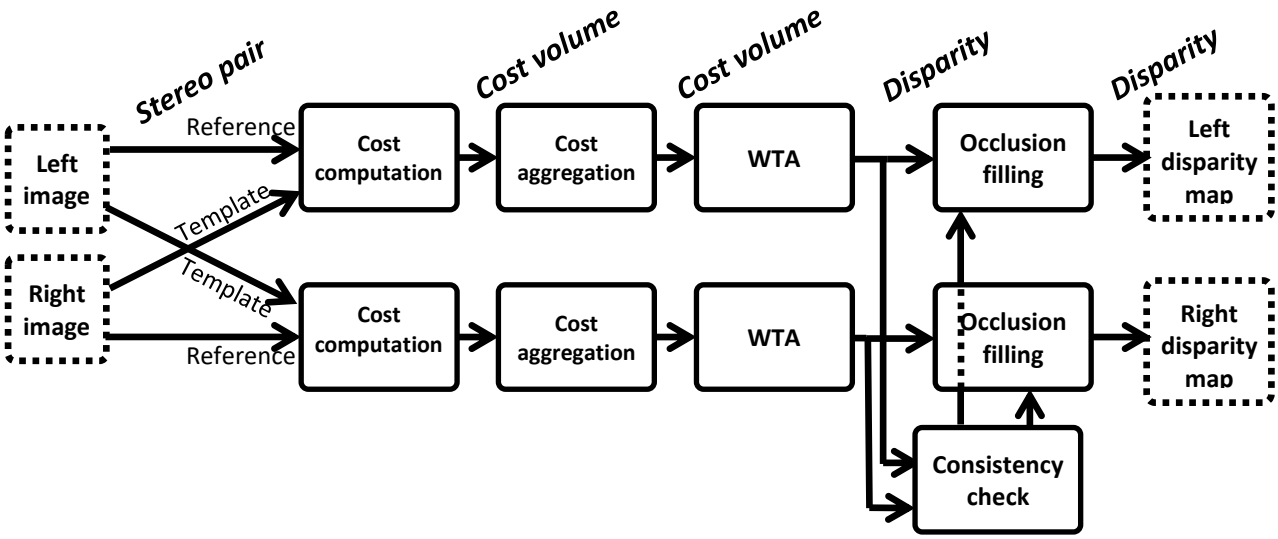


Figure 1. Illustration of the stereo matching pipeline

Test data and the quality metric

Start with a rectified image stereo pair taken from the Middlebury stereo vision site http://vision.middlebury.edu/stereo/ (included in the Moodle files). Use views 2 and 6 as they have the corresponding ground truth disparity maps provided.

Use the percentage of bad pixels as a quality metric to compare your estimation result with the ground true disparity. Bad pixels are defined here as pixels whose disparity value differ from the ground truth by more than 1 in either direction.

Cost Calculation

Calculate a 3D volume of per-pixel differences of the input images

$$C(x, y, d) = |L(x, y) - R(x - d, y)|$$

In order to reduce the effect of outliers on matching quality, the individual cost values in the 3D cost matrices should be capped, so they do not reach values over e.g. 150 (in case of L1 cost metric).

Cost Aggregation

Cost volume aggregation is per-slice filtering of the Cost Volume to make it more consistent within the disparity dimension. Performing this operation on the cost volume is equivalent to block matching (like done e.g. in motion estimation). The filter window size should be a parameter in your implementation.

$$C_{agg}(x,y,d) = \sum_{u,v \in \Omega(x,y)} C(x,y,d)W(u,v),$$

where $\Omega(x,y)$ is the windowed neighborhood of (x,y) and $W(u,v)$ the weighting function inside the window. In block matching, the weights are constant over the whole window, while in the Gaussian case they follow the normal distribution. In the case of color weighted filtering, the weights are computed from the associated color image. Hint: *help imfilter, guidedfilter*

Bilateral filtering for aggregation (task 6)

This approach is also called cross-bilateral filtering. In addition to considering the spatial distance when computing the contribution of a pixel to the filtering result (e.g. Gaussian filter), the difference in intensity is also taken into account.

Spatial proximity (Euclidian distance) between pixels *p* and *q* in coordinate space *(u,v)*:

$$\Delta g_{pq} = \sqrt{(u_p - u_q)^2 + (v_p - v_q)^2}$$

Color similarity between pixels *p* and *q*:

$$\Delta c_{pq} = \sqrt{(L_p - L_q)^2 + (a_p - a_q)^2 + (b_p - b_q)^2}$$

Weights:

$$\mathrm{W(p,q)} = \exp\left(\frac{-\Delta c_{pq}^2}{\gamma_c}\right)\exp\left(\frac{-\Delta g_{pq}^2}{\gamma_g}\right)$$

A suitable starting point for the values of γ_c and γ_g is for instance 10 (assuming the image intensities are [0,255]). It is a good idea to test your filtering function on a regular 2D image to see if it works properly and how the selection of those parameters affects the outcome. E.g. applying it on the image `I=imnoise(imread('cameraman.tif'))` should suppress some of the added noise, but not blur the edges of the image too much.

Cross-bilateral filtering

The process of applying a cross-bilateral filter is similar to the previously described case, but it involves using two sets of input data: the image to be filtered (or in this case, slice of cost volume) and the reference image. The weights $\mathrm{W}(\mathrm{p},\mathrm{q})$ are computed solely based on the reference image. They are then applied to the target of the filtering. Hint: this filter involves complex processing. Make sure your filter works correctly before you start testing the effect of the filter size. Running it with different windows size to complete 2c may take hours to process.

Disparity by WTA

The disparity *D* can be estimated from the cost volume *C* using the "Winner-takes-all" approach,

$$D(x,y) = \underset{d}{\operatorname{argmin}}\, C(x,y,d).$$

For sub-pixel level estimation, it would be possible to fit a quadratic function to the cost vector along the d-dimension (not required).

Comparison of different aggregation approaches

Compare 3 different aggregation methods for different window sizes in terms of the BAD metric

- Square window (block matching)
- Gaussian window (only considering spatial proximity)
- Adaptive weights (guided filter)

The resulting graph should be something similar to Fig 2.

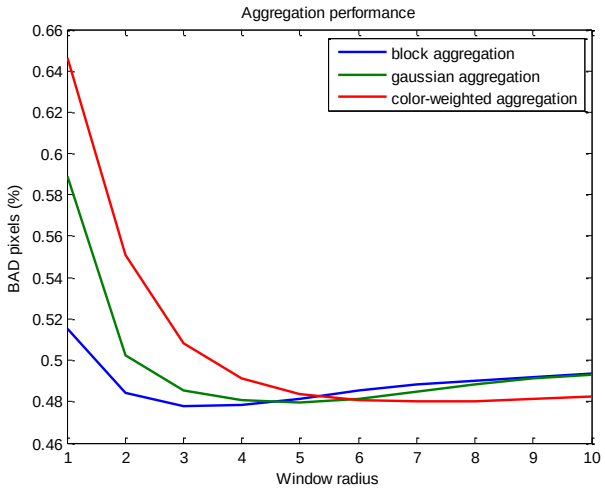


Figure 2. Example of a graph comparing different aggregation methods

Outlier detection

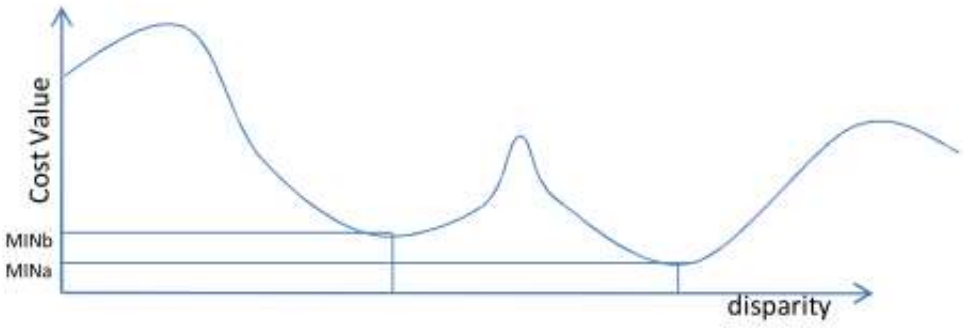
Disparity maps suffer from outliers caused by incorrect matches and occluded areas. Post processing should be applied to mitigate such errors. Outliers in the estimated disparity maps can be detected by performing a left-to-right correspondence check. The disparity estimation process should provide you two disparity maps, one corresponding to the point of view of each of the views. These maps should be consistent – the same point should have the same disparity in both images. A reasonable allowable difference is +-1. Fortunately, the disparity value itself tells where the corresponding point should be found in the other image. By taking a disparity value *d* from the left image, subtracting it from its x-coordinate and comparing it to the position in the right image, it is possible to check if both estimates agree on the point's value. If not, the pixel is marked as inconsistent.

Hint: you can test your implementation by running the consistency check on the ground truth disparity maps. The result should be more or less the same as the occlusion maps given in the source data.

Confidence map

All of the estimates given by disparity estimation are not as reliable as the others. This behavior is examined with a confidence map. Each value of the map gives a numerical estimate on how trustworthy the disparity estimate for the corresponding point is. One way of measuring this is to compute the *peak ratio*, which quantifies how "sharp" the minimum of the cost function found by WTA is.

$$PR = \frac{|MinB - MinA|}{MinB}$$



The peak ratio can then be combined with the information from the occlusion detection, so that occluded pixels have zero confidence. For determining which pixels should be filled in in the next stage, a reasonable threshold value for the confidence has to be determined. Any pixels with confidence less than that will be replaced by the filling step. Hint: *help findpeaks,* though you can expect it to be quite slow to run. If a peak ratio can't be computed (only one minimum or no minima), make sure to assign a confidence value which makes sense.

Outlier filling

A possible filling method is for instance rank order filling, where an occluded pixel is filled in with the e.g. median or minimum value of their neighborhood. Other occluded pixels in the neighborhood

shouldn’t naturally be considered when computing the median/min. It is a relatively simple method, but the disadvantage is that it doesn’t follow real object boundaries and thus might cause objects to “leak” into their surroundings. This approach is implemented in this project. Hint: *help nlfilter, help nanmedian.* You will likely have to repeat the filtering process iteratively until the middle sections of the image are filled out and no changes are happening. You can ignore the blank areas on the edges.