

VISION: GC Dispar

Lucrezia Tosato

1 Goal

Given two rectified images:

- Compute a disparity map using a graph cut. See course on graph cuts for details.
- Display the resulting disparity map.
- Compare with the region-growing algorithm: precision, smoothness and computation time.

2 Impact of the parameters

2.1 Patch size

As the patch size increases results tend to be less noisy as small differences between the two image have less weight in the correlation computation.

Increasing it too much on the other hand will yield a result with less details (fig. 1).

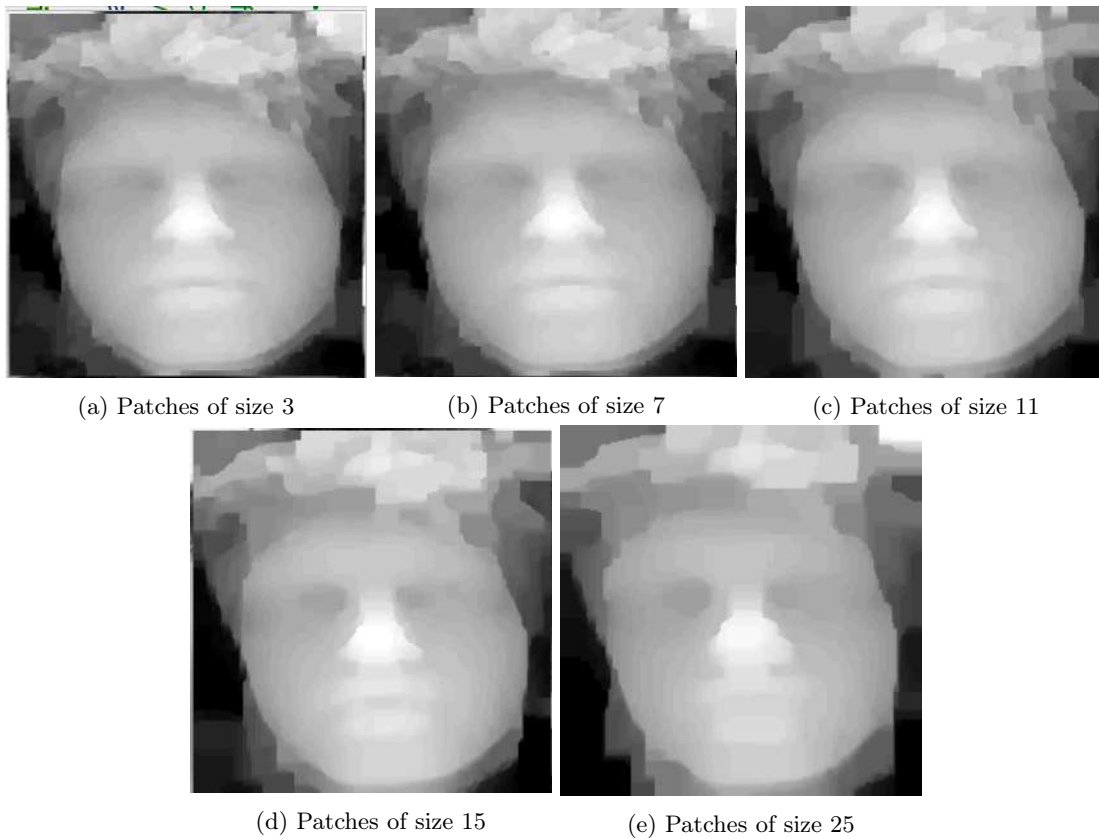


Figure 1: Disparity map obtained for the provided images with different patches and $\lambda = 2$.

2.2 Influence of λ

Small value of λ will yield a noisy result as having lot of changes in disparity between neighbor pixels won't be penalized enough (fig. 2), setting $\lambda = 0$ there is no interaction between neighbor pixel! On the other hand if λ is too large the optimal cut will have few disparity values.

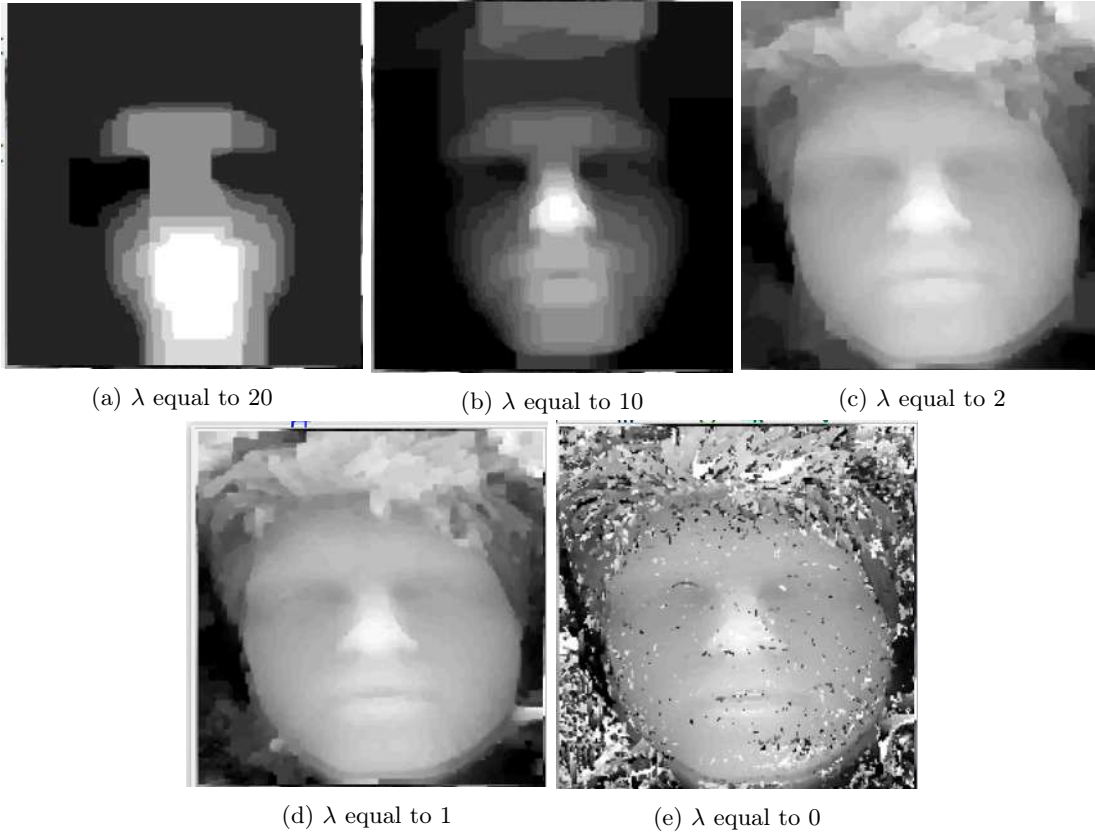


Figure 2: Disparity map obtained for the provided images with different λ and patches = 3.



Figure 3: Pair of images used as input.

3 Results

Some results obtained:

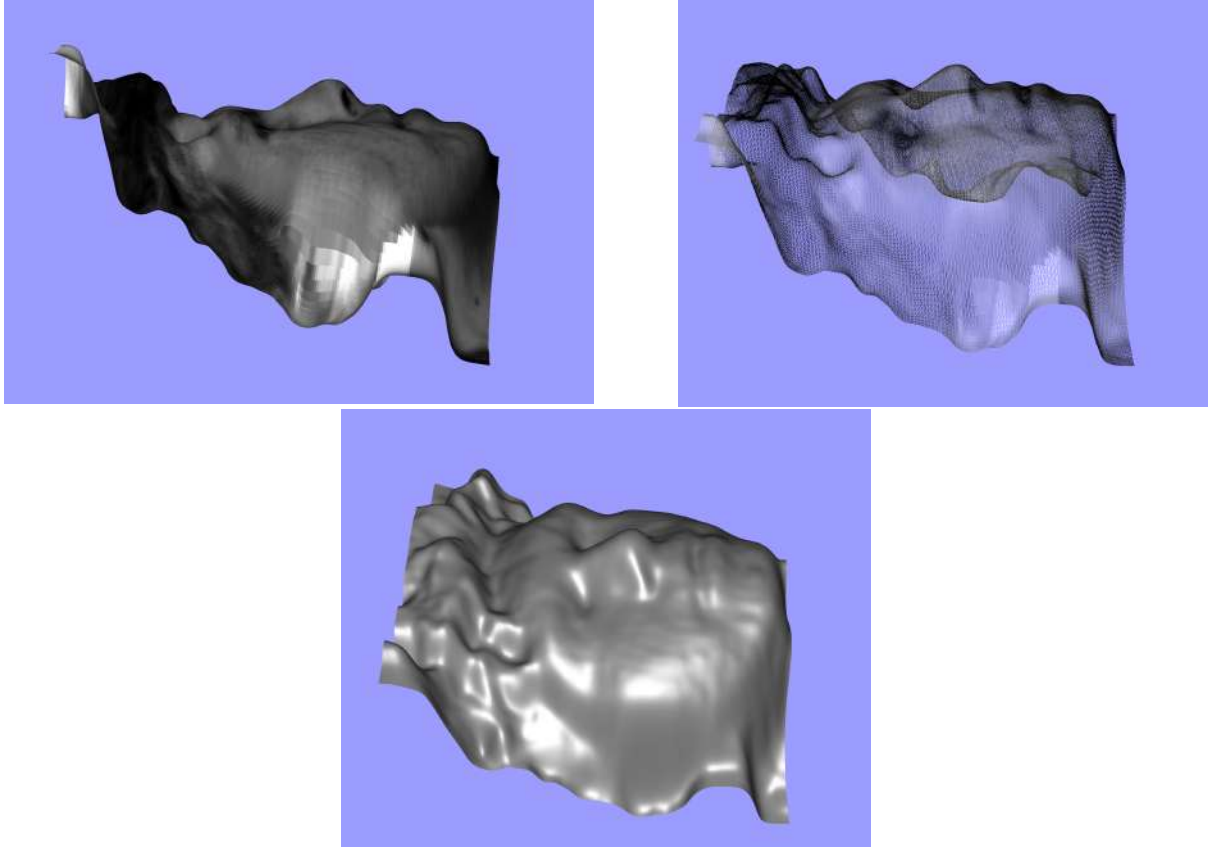


Figure 4: Side images $\lambda = 2$, patches=3

4 Comparison with the region-growing method

The graph-cut method takes half the time required by the region-growing one (26 seconds versus 55 seconds when using a zoom of 2 for the graph cut method and no cache of the average of patches in the region-growing method).

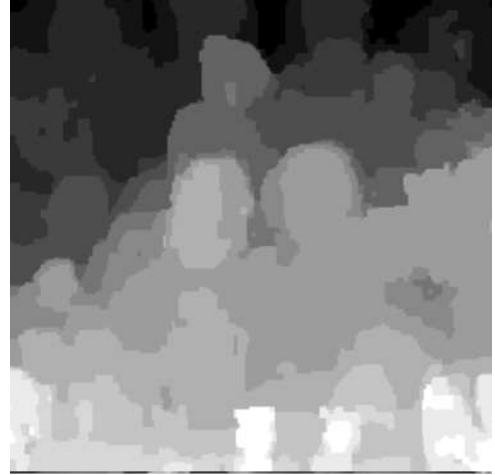
To obtain good results it is necessary to modify the parameters, which are set to optimise the method with the first image ("face00R.png" and "face01R.png") but, applied to the image used last week, do not give good results,(fig 3). We can indeed verify that there is a hint of depth but it's very little visible and not comparable with the real one.

By modifying the parameters we can obtain better results, although even if I understand that all these parameters are specific to the data that are handled and that the crucial ones are d_{min} and d_{max} that are evaluated based on min and max disparity of SIFT correspondences. I am not sure that the result obtained is actually the best one, since i think that in the reality the depth between the different dools was more accentuated.

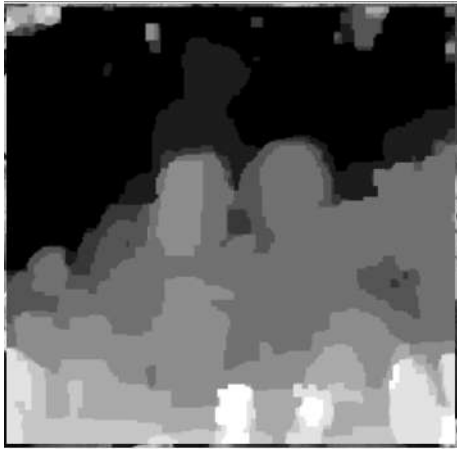
In any case, certainly the graph-cut method yield result that are less noisy thanks to a global regularization (fig. 5).



(a) Region-Growing method



(b) Graph-cut method changing some parameters



(c) Graph-cut method with initial parameters



(d) 3D result with initial parameters

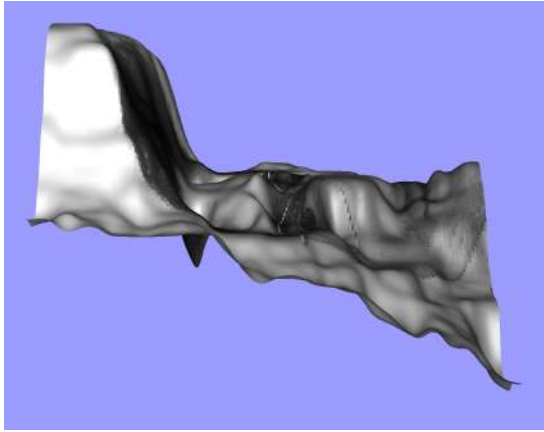
Figure 5: Results
Input images are shown in fig. 3.

5 Added Notes

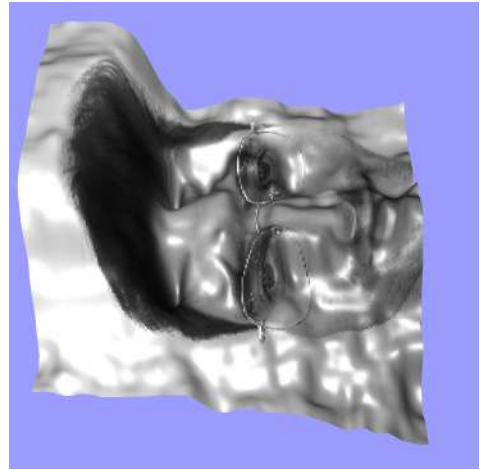
I have also tried to use the algorithm with picture of a friend, the result seems to be very alterate, although in some places the results are consistent(the nose and the mouth). As mentioned above, I know it depends on the parameters d_{min} and d_{max} . All the images used can be find in the folder: the main two with the name:

- main ones: face00R.png and face01R.png
- the one about the dools: img31.png and img21.png
- the one of my friend: img3.png and img2.png

All of them are commented in the code.



(a)



(b)