Comparison of Mean Shift Algorithms and Evaluation of Their Stability

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ABSTRACT

Mean Shift is an universal and robust segmentation algorithm used also for image segmentation. Implementation corresponding to definition is slow for real-time image processing, thus some faster variants were proposed. Speed and quality of the segmentation can be influenced by the variant of the algorithm as well as by setting its parameters. Modification of a parameter causes change of number of segments and their shape as well. By using segmentation evaluation algorithm, we analyze and present these changes for original and modified Mean Shift algorithms. Influence of noise is also studied.

Keywords

Mean Shift, segmentation stability, Segmentation Difference.

1. INTRODUCTION

Mean Shift is a segmentation method for point data originally. By representing color channels of an image as other dimensions, we could use Mean Shift for segmentation of images [Com02a]. The main disadvantage lies in slow computation. Therefore, some variants of original Mean Shift algorithm were proposed.

We analyze original and modified algorithms by using evaluation method called Segmentation Difference [Sru10a]. Unlike other methods for evaluation of segmentations, this can evaluate refinement of a segmentation separately from the shape of common objects. By changing parameters of a segmentation algorithm, resulting segmentations should differ in refinement, not in the shape of borders of segments.

Similar evaluation was recently presented [Kaf08a]. By using a simple evaluation method, they were restricted to comparison of segmentations created by different algorithms but with the same parameters. We are able to analyze influence of different algorithms as well as different parameters.

2. MEAN SHIFT ALGORITHMS

Original Mean Shift

Segmentation by Mean Shift is based on density of points only. For each point, path of the steepest density increase for the point is found. End of each path is located in some local density maximum (called attractor). All pixels having the same attractor are put to common segment. The path is computed iteratively:

$$x^{(i+1)}=\frac{\sum_j k\left(\left\|\frac{x^{(i)}-x_j}{h}\right\|\right)\cdot x_j}{\sum_j k\left(\left\|\frac{x^{(i)}-x_j}{h}\right\|\right)},$$

where $x^{(i)}$ is location on the path in iteration i, x_j is a location of a data point and $k(y)$ is a weighting function denoted as a kernel, h is a vector and the division is point-wise. Typically, the kernel is non-zero only on interval <0,1> and vector h determines the size of the influence of the kernel in each dimension separately. In further comparisons, we will denote this original Mean Shift as OMS.

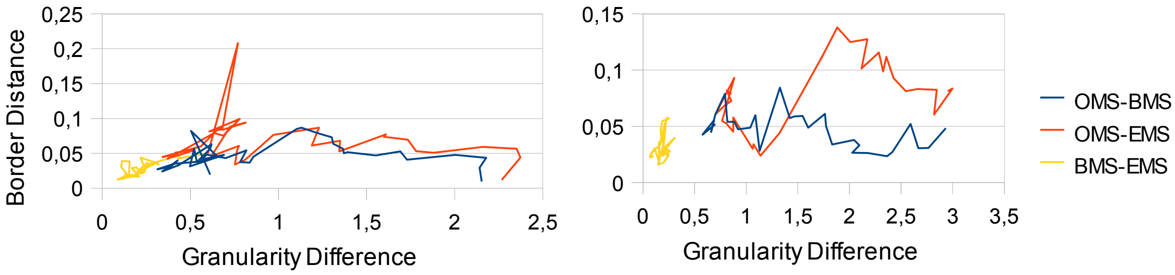


Figure 2. Analysis of segmentations with different spatial (left) and color (right) kernel sizes. Point on each curve represents comparison of two different algorithms with the same parameters. Size of spatial kernel size was set from 0 to 40. Size of color kernel size was set from 0 to 1.

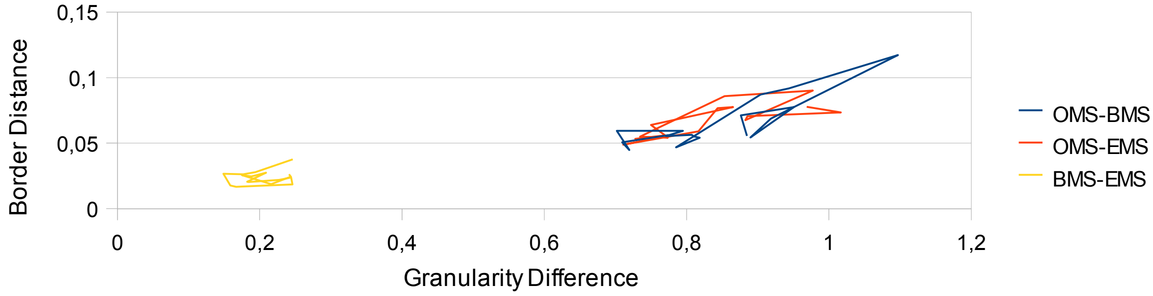
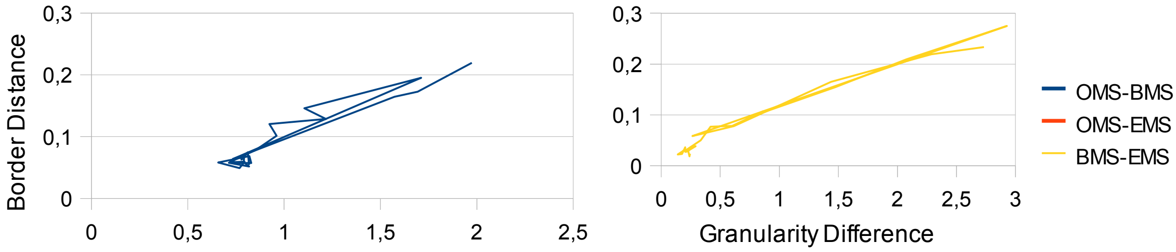


Figure 3. Analysis of segmentations with different kernel shapes. Exponents were set from 0.2 to 10.



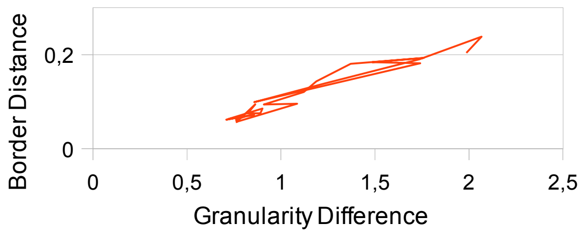


Figure 4. Analysis of segmentations with different Gaussian noise level. Point on each curve represents comparison of two different algorithms with the level of applied Gaussian noise. Variance of noise was set from 0 to 0.098.

Blurring Mean Shift

Mean Shift variant called Blurring Mean Shift (BMS) was presented in [Car00a, Car06a]. BMS formula is given by

$$x^{(i+1)} = \frac{\sum_j k\left(\left\|\frac{x^{(i)} - x_j^{(i)}}{h}\right\|\right) \cdot x_j^{(i)}}{\sum_j k\left(\left\|\frac{x^{(i)} - x_j^{(i)}}{h}\right\|\right)},$$

where the term $x_j^{(i)}$ represents point from the previous iteration.

Evolving Mean Shift

In 2009 whole new idea of Mean Shift segmentation was developed [Zha09a] called Evolving Mean Shift (EMS). It is an energy minimization method. EMS computes mean shift vectors for all pixels in an image. Then EMS searches for the longest mean shift vector and proceeds the shift of the corresponding pixel. Therefore, the energy is maximally decreased. This is repeated until the energy decreases to some level. Energy of a data set can be written as

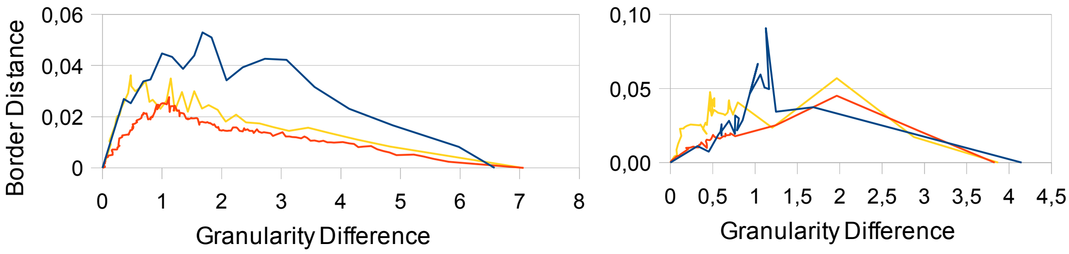


Figure 5. Analysis of stability of methods according to spatial kernel size. Smaller kernels than in reference segmentation are on the left graph, larger kernels are on the right graph. Size of spatial kernel size was set from 20 to 0 (using steps of size 0.1) and from 20 to 40 (steps 0.5).

$$E_{x_i} = \sum_{j \neq i} \left(E_{x_i x_j} + E_{x_j x_i} \right),$$

$$E_{x_i x_j} = k\left(\left\| \frac{x_i - x_j}{h} \right\| \right).$$

3. COMPARISON

All segmentations are created using gray-scale image of Lena with resolution 256 x 256 pixels. Each point on a curve in figures 2-4 represents comparison of two segmentations with the same parameters by Segmentation Difference. Each graph covers influence of change of a single parameter, while the other parameters are preserved.

Reference elements of vector h corresponding to spatial dimensions are set to 20, elements of color space are 0.125. An image is internally represented in the range <0,1>. Stopping conditions are 200 iterations or minimal change of position 0.001. Reference kernel is Epanechnikov kernel:

$$k(y) = 1 - y^2.$$

Kernel size

Kernel function is non-zero only on interval <0,1> but we change an area of influence of the kernel by setting of elements of the vector h, which will be denoted naturally but inexactly as a kernel size.

Figure 2 represents comparisons for different spatial kernel sizes as well as for different color kernel sizes. Similar segmentations are placed near to 0. Evidently, BMS and EMS are very similar in this test.

Kernel shape

Kernel is, typically, a decreasing function. We are not able to compare all decreasing functions, thus we analyze kernel types defined as follows

$$k(y) = 1 - y^z, z \in \langle 0, \infty \rangle.$$

One extreme case where *k(y)=1* is called uniform kernel. By setting z to 1 and 2 gives us another widely used triangular and Epanechnikov kernel respectively. We used exponents from 0.2 to 10. Analysis of influence of the kernel shape on the resulting segmentation can be seen in the figure 3.

Influence of Noise

Our approach consists of adding Gaussian noise with variance from 0 to 0.098 to the reference image (fig. 1) and measuring differences between all three variants of Mean Shift (see figure 4).

4. ANALYSIS OF STABILITY

Segmentation algorithm is, typically, influenced by its parameters. By changing parameters, we could expect change in number of segments, not change of shape or position of segments. Such preservation of shape and position will be called stability of a segmentation algorithm.

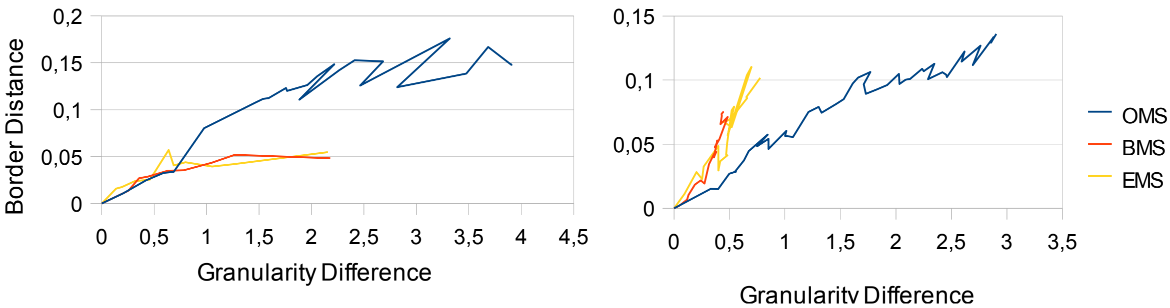


Figure 6. Analysis of stability of methods according to color kernel size. Smaller kernels than in reference segmentation are on the left, larger kernels are on the right. Size of color kernel was set from 0 to 1.

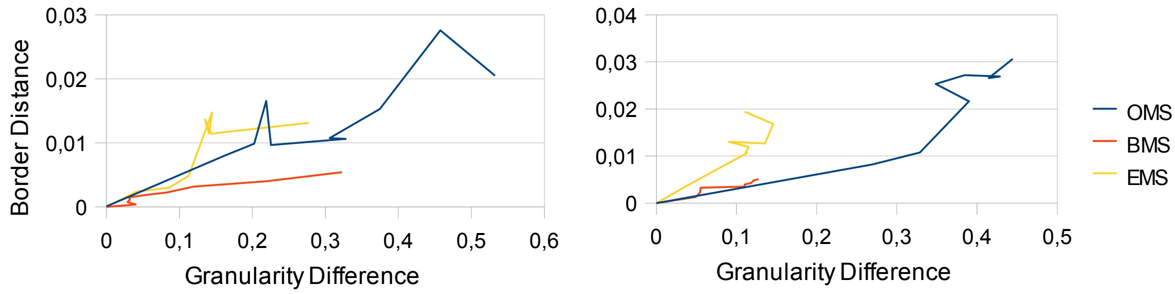


Figure 7. Analysis of stability of methods according to shape of the kernel. Results with kernels with exponent from 2 to 0.2 are on the left, the rest from 2 to 10 is on the right.

Stable segmentation would have all points lying on the horizontal axis. First stability analysis graphs in figure 5 represent influence of spatial size of the kernel. Next couple of graphs in figure 6 analyze influence of the color kernel size. Influence of the kernel shape is presented in the figure 7. Last graphs in the figure 8 tries to analyze influence of the Gaussian noise on the resulting segmentation.

5. DISCUSSION

Figures 2 and 3 shows some similarity of BMS and EMS. In other words, their segmentations look nearly the same for various kernel shapes and sizes. But any influence of noise leads to different segmentations of these methods. Original Mean Shift segmentation algorithm is much more unstable when changing its parameters in comparison with BMS and EMS. That is evident from high results of Border Distance values. However, OMS is the most stable algorithm in the presence of a noise. According to these evaluations, we cannot easily select the best algorithm.

6. CONCLUSION

We implemented three variants of Mean Shift algorithm. We compared them to each other and tested their stability according to change of some of their parameters and change of variance of noise. None of them can be marked as the best one, still we found high correlation between BMS and EMS variants.

7. REFERENCES

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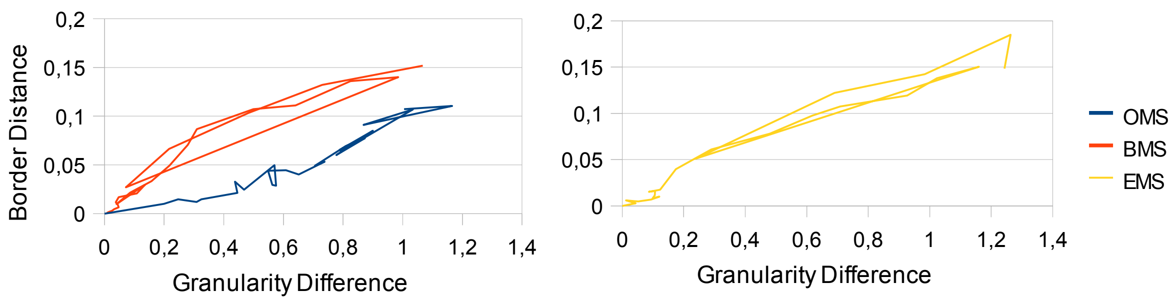

Figure 8. Analysis of stability of methods according to Gaussian noise level. Variance of noise was set from 0 to 0.098.