TIME-WEIGHTED EVALUATION OF IMAGE SEGMENTATION WITH A GENETIC ALGORITHM

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Abstract: The performance of a segmentation algorithm can be evaluated by systematic comparison with hand-segmented ground-truth images. When evaluation extends over an algorithm's parameter space, then the search for satisfactory settings has a considerable cost in time. This paper considers applying a genetic algorithm (GA) to avoid an exhaustive search. To further reduce evaluation time and subsequent image batch-processing times, this paper introduces a time factor into the GA cost function. This procedure while preserving the GA solution, selection of parameters to minimize the fit to hand-segmented images, also improves interpretation and parameter selection.

1 INTRODUCTION

Contrasting image segmentation to recognition tasks such as the use of handwriting, and face databases, the authors of (Martin et al., 2001) remark "Typically [in segmentation] researchers will show their results on a few images and point out why the results 'look good". Part of the problem may be the logistics of quantitative evaluation in performing a large number of evaluations, as an exhaustive search with multiple parameter settings is an onerous task and may require use of a cluster computer. Alternatively, we have used a genetic algorithm (GA) (Goldberg, 1989) search module in our evaluation environment to decrease the processing time for the search as a whole.

The GA acts to optimize the selection of parameters. The contribution of this paper is adding the time taken to complete the segmentation for each parameter set as a factor in the GA cost function. The rationale behind this addition is that the quality of the segmentation results is not the only value one would like to improve, as there is also a need to balance the quality with the segmentation processing time. Adding this time factor gave some insight into the significance of some of the algorithm parameters not only in respect to the processing time performance but also to the quality of the segmentation performance. For instance, while experimenting without using the time factor, the GA module will randomly vary certain parameters that actually do not affect the overall quality of the segmentation, once optimization of the significant parameters for the algorithm has taken place.

2 ADDING TIME AS A FACTOR

The mean-shift algorithm (Comaniciu and Meer, 2002) makes a convenient example, especially as the authors have made EDISON code available at http://www.caip.rutgers.edu/riul/research/robust.html, for which we are grateful. The Berkeley database (Martin et al., 2001) encourages users to download benchmarking code as well as 200 training images and a further 100 test images of size 240×160 pixels. Fig 1a is a test image from the Berkeley database, Fig 1b is an example hand-segmentation also included in the database. Fig. 1c shows the result of varying the mean-shift parameters. Higher values of `radiusR` results in less regions, while higher values of `radiusS` effectively results in more computation but smoother region boundaries.

Adding processing time to the cost function can take place in various ways such as through an additive or multiplicative factor. Using a multiplicative factor provides a trade-off between segmentation evaluation and computational time, and, therefore, after initial investigations, the cost function was modified in this way. It was decided that including a time factor as an exponential weighting gave too much emphasis to achieving low processing times. The time that the GA itself took for processing was not included, as this time was negligible and certainly less than 5% of any

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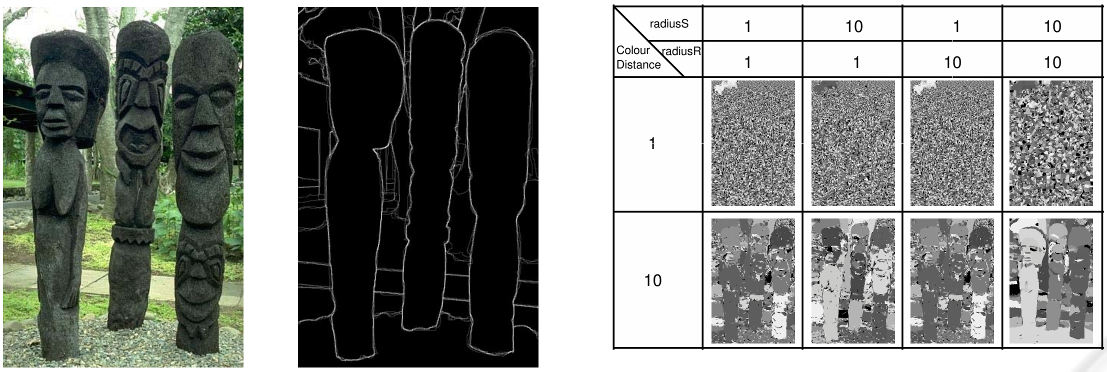

a b c

Figure 1: (a) Example image (Easter island statues) from the Berkeley segmentation database (b) human hand-segmentation (c) variation of segmentations with parameter settings.

segmentation processing time.

For these experiments, the population size was set to 20 and the first 20 generations were run. The recombination rate was fixed at 0.6 and the mutation rate at 0.2. By observation, the GA module reaches an acceptable stable solution in much fewer generations when a comparatively large population size is employed. To see the start of the stabilization trend in the parameter search with the time factor, Fig. 2 shows the first three generations. The members of the population are plotted across the horizontal axis and the parameter values for a population member can be read off in the vertical direction. At the crossover point between the generations, the fittest parameter set is shown. It is clear from the parameter variation in the second and the third generations that the selection is already stabilizing. For example `RadiusS` tends to stabilize at value 2 and `RadiusR` at value 5. Therefore, employing a time factor arrives at similar results for the example image but may well increase the convergence speed as the values of less significant parameters are explored less.

Fig. 3 shows the application of the GA with and without a time factor in the cost function. The horizontal axis is annotated with the image numbers of 20 images from the Berkeley database. Consider the effect of the time factor on the value of the `radiusS` parameter: when the time factor is present, the value of this parameter is always equal or less than two. While without the presence of the time factor the same parameter value does not have a specific trend, and changes between different images in the test. The best explanation for this is that this parameter does not have a great significance for the quality of the segmentation. However, higher values of this parameter are computationally expensive. There is no similar trend for the `radiusS` parameter, and the time factor also does have any noticeable effect on the third `colorDistance` parameter.

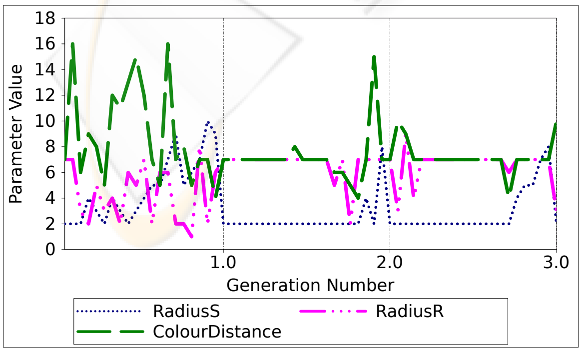

Figure 2: The first three generations of the meanshift GA evaluation.

Experiments with the Watershed algorithm (Vincent and Soille, 1991) also gave rise to a variety of results, depending on choice of parameters. Fig. 4 illustrates the optimal results found by the evaluation with and without the time factor. The main parameters used were firstly a watershed threshold parameter for the core watershed algorithm. This parameter is varied between 1 and 80. In our tests, a k-mean color quantization stage was also added as a pre-processing stage. The number k here refers to the number of colors that the image will be reduced to. The final parameter considered was the maximal number of iterations parameter for the k-mean algorithm. This is a parameter that controls how many iterations are carried out to search a pixel's neighbors for color similarity as part of the quantization process.

The first point to observe is that the threshold arrived at after application of the GA is always very high, higher than 60, and there is no difference in this between using the time factor or not using it. The reason for this is that higher thresholds tend to eliminate smaller details and segments that are not noticed by the human hand-segmenter and as such the evaluation

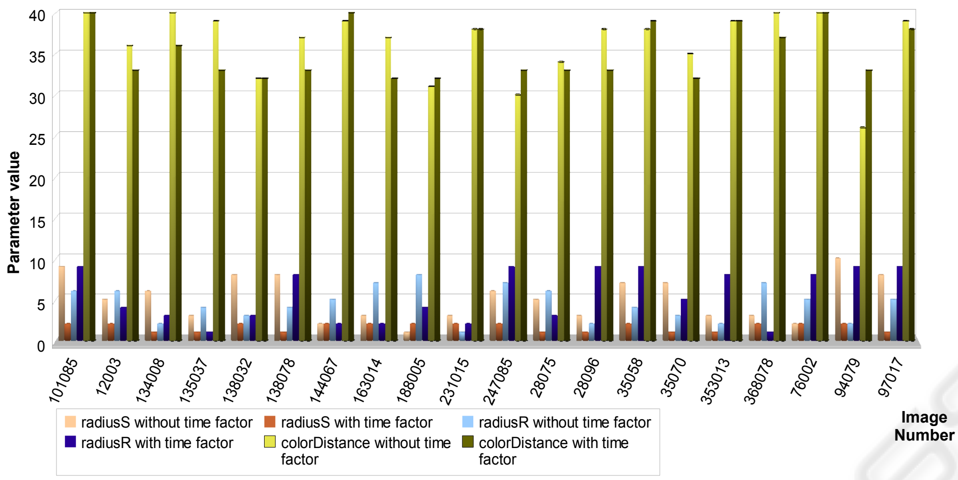

Figure 3: Meanshift segmentation evaluation for 20 images with and without a time factor.

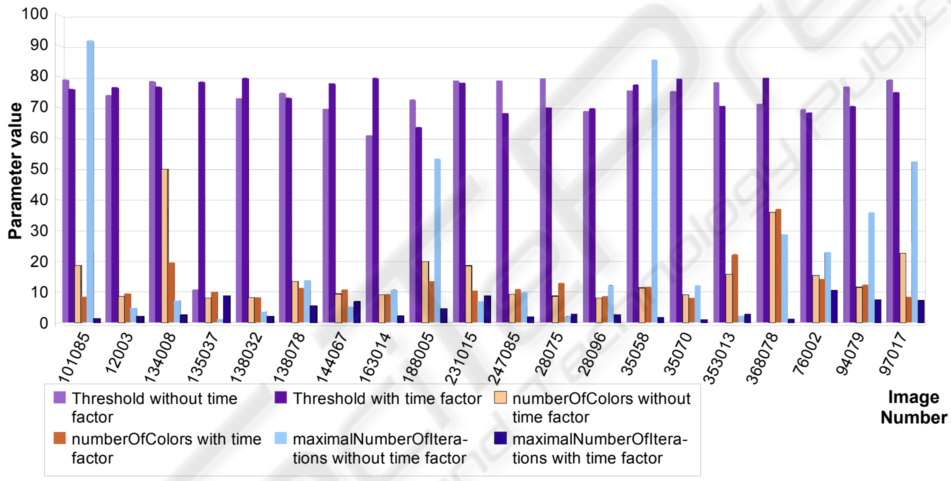

Figure 4: Watershed segmentation evaluation of 20 images with and without time factor showing parameters.

tends to prefer higher values for the threshold parameter. Another point to observe is that the evaluation tries to optimize the parameter set with lower values for the color quantization parameter, which means a more smoothing of the input images. Noting that the maximum value for k is 256, then 50 is a relatively low number and results in high quantization for natural images full of colors. However, there is no specific parameter value that is general for all the images. This can be attributed to the fact each image will have specific original color palettes and also that not all objects respond in the same way to color quantization.

The final observation is that the timing factor singles out the iteration parameter for 'extra' optimization. The time factor keeps this parameter's value as low as possible, not more than ten iteration for all the images. Evaluation without the time factor, gives no clear preference for high or low iteration values, which make one conclude that this parameter does not have much importance for segmentation accuracy. Evaluation without the time factor gave no preference for a parameter set with low computation time and as such did not consider low iteration values as an important target for optimization. Each image took about 20 minutes to evaluate when a time factor was not used and the evaluation time reduced to approximately half this value when this factor was included. Evaluation time was consistent with or without the time factor's inclusion.

The k-means algorithm, employed as an initial smoothing/color quantization process in the Watershed algorithm, can also be augmented by another smoothing stage that uses a k-nearest-neighbor algorithm to smooth out the image further. Again, the time factor was included in GA optimization. It was found that the threshold delta parameter had little effect on

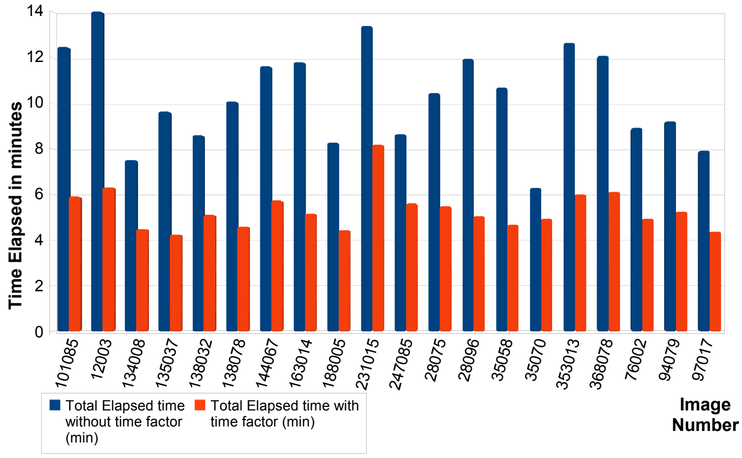

Figure 5: *K*-means segmentation evaluation timings of 20 images with and without time factor optimization.

the results. This parameter stops the processing iterations if the palette changes between the iteration is less than this value and in the implementation it was set to a range between 0.1 and 1.0. Again other parameters apart from the number of iterations were unaffected by the inclusion of the time factor. However, the evaluation time now decreased dramatically, as Fig. 5 illustrates.

3 CONCLUSIONS

Pixel-wise comparison between a segmented image and its ground-truth, herein using hand-segmented images, is dependent on choice of an algorithm's parameters. To arrive at a best-fit parameter configuration, in the face of a diversity of parameter-dependent results is a time-consuming task, yet seems necessary if quantitative evaluation is to become a standard procedure. Apart from the speed up over an exhaustive search, using a GA has highlighted the importance of parameter settings and the criticality of a particular parameter over another. The addition of a time factor into the GA cost function, does not just select for parameter settings that improve the throughput but also rationalizes the selection so that relatively unimportant parameters are not explored in too great detail.

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