Effective Image Clustering using Self-Organizing Migrating Algorithm

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ABSTRACT

Image segmentation is an important task in computer vision. Clustering is a common image segmentation approach which divides an image into homogeneous regions, but conventional clustering algorithms such as k-means have a tendency of getting stuck in local optima. In this paper, we propose a novel clustering algorithm based on the Self-Organizing Migrating Algorithm (SOMA). In particular, we adopt SOMA Team To Team Adaptive (SOMA T3A), a recent variant of SOMA, to image clustering. Experimental results on a set of benchmark images show excellent image clustering performance, also in comparison to other state-of-the-art metaheuristics.

CCS CONCEPTS

• **Theory of computation → Evolutionary algorithms**; **Bio-inspired optimization**; • **Computing methodologies → Image segmentation**; **Image processing**;

KEYWORDS

Image clustering, image segmentation, optimisation, SOMA.

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1 INTRODUCTION

Image segmentation is a crucial task in image processing and machine vision applications. Clustering is a commonly adopted approach to perform segmentation, while conventional clustering algorithms such as k-means suffer from dependence on initialisation conditions and a tendency to get trapped in local optima.

Population-based metaheuristic algorithms such as genetic algorithms (GAs) provide a powerful alternative to address these issues. Population-based metaheuristic algorithms that have been used for clustering-based image segmentation include particle swarm optimization (PSO) [11] [8], differential evolution (DE) [1, 6], artificial bee colony (ABC) [9] and harmony search (HS) [13].

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Input : D: dimensionality; $NFC_{\max}$: maximum number of function evaluations, N_P: population size
Output : x^*: the best solution

generate (uniform randomly) initial population ;
evaluate fitness for each candidate solution ;
$NFE = N_P$;
while $NFE < NFE_{\max}$ **do**
  select m individuals randomly from current population;
  migrants M = select the n best of these m individuals;
  select k individuals randomly from current population;
  leader L = select best of these k individuals;
  $PRT = 0.05 + 0.9\frac{NFE}{NFE_{\max}}$;
  $Step = 0.15 - 0.08\frac{NFE}{NFE_{\max}}$;
  for $i = 1$ **to** *number of migrants* **do**
    if *migrant is not leader* **then**
      migrant moves to leader as $M_i^{new} = M_i + t(L - M_i)PRT$, with t (jumping step) from 0 by $Step$ to path length;
      calculate fitness for new position of migrant;
      $NFE = NFE + 1$;
      update the better position of migrant;
    end
  end
end
x^* = best candidate solution;

Algorithm 1: Pseudo-code of SOMA T3A algorithm.

2 IMAGE CLUSTERING USING SOMA T3A

The Self-organizing Migrating Algorithm (SOMA) [2, 15] is a population-based metaheuristic that has been shown to yield competitive performance for various optimisation problems.

SOMA Team To Team Adaptive (SOMA T3A) [3] is a recent variant of SOMA, with improved optimisation performance as indicated e.g. by its third rank among 34 competitors in the CEC 2019 100-digit challenge [10]. SOMA T3A comprises three main steps, organisation, migration, and update. Algorithm 1 provides an overview of the algorithm in terms of pseudo-code.

In this paper, we propose a novel image segmentation based on the concept of clustering and SOMA T3A. To this end, we use SOMA T3A to find the optimal cluster centres for image clustering with the cluster centres encoded as real-valued vector and bounded by the minimum and maximum image values. Our fitness function

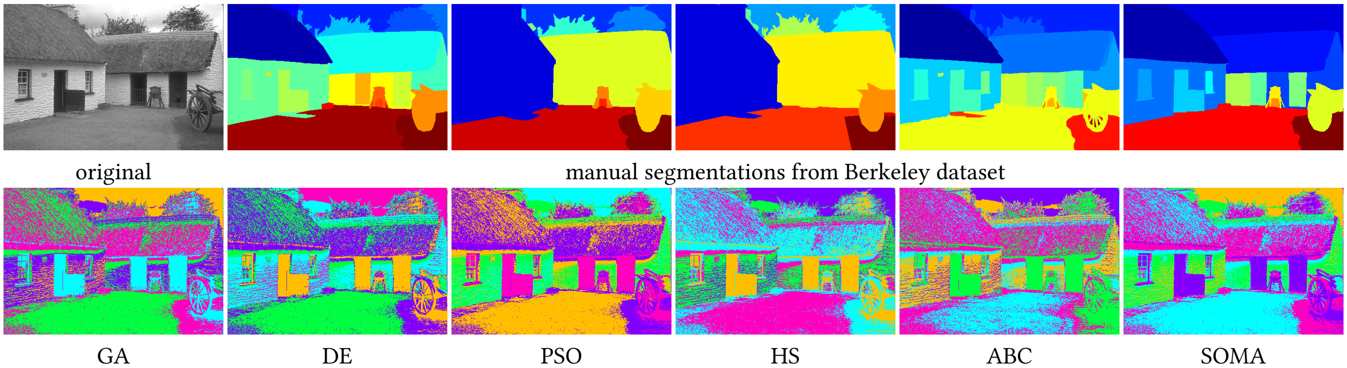

Figure 1: Image clustering results for *385028* image.

is based on the mean squared error (MSE) defined as

$$MSE = \frac{\sum_{j=1}^{K} \sum_{P_i \in C_j} d(P_i, C_j)}{n}, \tag{1}$$

where $d(P_i, c_j)$ is the Euclidean distance between pixel P_i and its cluster centre C_j, and n is the number of pixels.

3 EXPERIMENTAL RESULTS

For our experiments, we select 5 popular test images, *Lenna*, *House*, *Airplane*, *Peppers*, and *MRI*, as well as five images from the Berkeley segmentation dataset [7], *12003*, *42049*, *181079*, *198054*, and *385028*.

We compare our proposed algorithm with GA [14], DE [12], PSO [11], HS [4], and ABC [5]. The population size and number of function evaluations for all algorithms are set to 50 and 6000, respectively, while the number of clusters is $k = 5$. For SOMA, we set $m = 10$, $n = 5$, and $k = 10$, and we use default values for the parameters of the other algorithms. Each algorithm is run 25 times on each image and we report the average over these 25 runs.

As evaluation measure, we use the widely adopted peak signal-to-noise-ratio (PSNR) defined as

$$PSNR = 10 \log_{10} \frac{255^2}{MSE} \tag{2}$$

Table 1 gives the obtained results for all algorithms and all images. As we can see from there, SOMA yields the best result for every single image, while in several cases other algorithms are tied for the best result. Overall, SOMA gives the best image clustering results.

To further illustrate the obtained results, Figure 1 gives, as an example, the image clustering outcomes for image *305028*.

Table 1: Results of all algorithms on all images [dB].

image	GA	DE	PSO	HS	ABC	SOMA
Lenna	**28.18**	27.98	**28.18**	27.88	27.60	**28.18**
Airplane	28.86	28.73	**28.88**	28.68	28.38	**28.88**
House	29.27	29.13	28.94	29.13	28.85	**29.33**
Peppers	27.11	26.95	**27.12**	26.73	26.73	**27.12**
MRI	30.92	30.75	**30.93**	30.65	30.44	**30.93**
42049	29.79	29.62	29.80	29.52	29.31	**29.82**
12003	26.69	26.60	**26.73**	26.51	26.35	**26.73**
181079	**26.12**	25.91	**26.12**	25.87	25.49	**26.12**
198054	**26.76**	26.58	**26.76**	26.55	26.43	**26.76**
385028	26.21	26.02	26.22	25.98	25.87	**26.24**

4 CONCLUSIONS

In this paper, we have used the Self-Organizing Migrating Algorithm, in particular its recent Team To Team Adaptive (SOMA T3A) variant, for the challenging task of image clustering and have shown it to yield very satisfactory results outperforming other metaheuristics and thus SOMA to be an interesting candidate for optimisation problems in image processing.

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