A Population-based Automatic Clustering Algorithm for Image Segmentation

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ABSTRACT

Clustering is one of the prominent approaches for image segmentation. Conventional algorithms such as k-means, while extensively used for image segmentation, suffer from problems such as sensitivity to initialisation and getting stuck in local optima. To overcome these, population-based metaheuristic algorithms can be employed. This paper proposes a novel clustering algorithm for image segmentation based on the human mental search (HMS) algorithm, a powerful population-based algorithm to tackle optimisation problems. One of the advantages of our proposed algorithm is that it does not require any information about the number of clusters. To verify the effectiveness of our proposed algorithm, we present a set of experiments based on objective function evaluation and image segmentation criteria to show that our proposed algorithm outperforms existing approaches.

CCS CONCEPTS

• **Computing methodologies → Bio-inspired approaches**.

KEYWORDS

Image segmentation, automatic clustering, optimisation, population-based algorithms, human mental search.

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1 INTRODUCTION

Image segmentation can be formulated as a clustering problem [4] in which each pixel corresponds to a pattern and image regions are indicated by clusters. Conventional clustering algorithms such as k-means have been extensively employed for image segmentation tasks [9, 14], but unfortunately suffer from drawbacks such as getting stuck in local optima and sensitivity to initialisation.

Population-based metaheuristic algorithms such as genetic algorithms (GAs) [36], particle swarm optimisation (PSO) [30] and differential evolution (DE) [31] can be used to alleviate these problems. In general, these approaches commence with a set of randomly generated candidate solutions, which are then subsequently improved based on operators that typically incorporate an element of randomness while allowing information to be shared among candidate solutions.

In recent years, population-based algorithms have been widely used for clustering-based image segmentation. [29] proposes a combination of GA and k-means for image segmentation, while fuzzy c-means (FCM) is combined with a GA in [1] for segmentation of satellite images. Other metaheuristics employed include, among others, PSO [23, 24, 37], DE [11, 34], artificial bee colony (ABC) [27], self-organizing migrating algorithm (SOMA) [22], and human mental search (HMS) [17].

However, one of the drawbacks of the above methods is that the number of clusters must be known in advance, while often and in particular for images, the number of clusters is generally unknown. Automatic clustering, i.e. automatically identifying the number of clusters, in imaging-based applications has become an area of intense research [3, 26]. [3] proposes an automatic clustering algorithm for image segmentation that uses an encoding strategy based on an array of length $k_{max} + k_{max} \times d$ where the first k_{max} elements contain floating-point numbers indicating active or inactive clusters, and d is the number of features used in the clustering process. In [35], a similar encoding strategy is employed for an automatic clustering algorithm based on harmony search (HS).

Human mental search (HMS) [15, 19] is a recent population-based metaheuristic algorithm inspired by the exploration strategies of on-line auctions and has been shown to yield competitive performance for imaging applications such as image thresholding [16], colour quantisation [18, 21] and clustering-based image segmentation [17, 20]. HMS is based on three main operators, mental search, grouping, and movement. Mental search explores the vicinity of each candidate solution based on a Levy flight distribution, grouping determines a promising region using a clustering

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algorithm, while during movement, candidate solutions shift towards promising regions.

This paper proposes an automatic clustering-based image segmentation algorithm based on HMS. Our approach is capable of finding both the correct number of clusters and the optimal cluster centres simultaneously. Experimental results confirm our method to work well on a benchmark set of images and to outperform other automatic clustering algorithms.

The remainder of the paper is organised as follows. Section 2 describes the HMS optimisation algorithm, while our proposed automatic clustering algorithm is introduced in Section 3. Experimental results are provided in Section 4, and Section 5 concludes the paper.

2 HUMAN MENTAL SEARCH

Human mental search (HMS) [15, 19] is a recently introduced population-based optimisation algorithm inspired by the exploration strategies in an on-line auction. Similar to other population-based algorithms, HMS starts with a set of randomly generated candidate solutions (called bids in HMS). HMS employs three operators to direct the candidate solutions towards the global optimum, mental search, grouping, and movement towards a promising region.

The aim of mental search is to explore the vicinity of a bid based on a Levy flight distribution. Sequences generated by a Levy flight include some small steps and sudden big jumps, and it thus can enhance both exploration and exploitation. The mental search operator generates bids as

$$NS = bid + S, \tag{1}$$

with S calculated as

$$S = (2 - NFE(2/NFE_{\max}))0.01 \frac{u}{v^{1/\beta}}(x^i - x^*), \tag{2}$$

where NFE is the number of objective function evaluations so far , $NFE_{\max}$ is the maximum number of function evaluations, x^i is the current bid, and x^* is the best bid found so far, while u and v are two random numbers calculated as

$$u \sim N(0, \sigma_u^2), \quad v \sim N(0, \sigma_v^2), \tag{3}$$

with

$$\sigma_u = \left\{ \frac{\Gamma(1+\beta)\sin(\frac{\pi\beta}{2})}{\Gamma[(\frac{1+\beta}{2})]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta}, \quad \sigma_v = 1, \tag{4}$$

where Γ is a standard gamma function.

Grouping in HMS clusters the current population using a clustering algorithm (k-means in standard HMS). Then, the average objective function value for each cluster is calculated and the cluster with the minimum value (in a minimisation problem) selected as the winner cluster.

Finally, in the movement operator, other bids approach the best bid in the winner cluster based on

$$^{t+1}bid_n = {}^{t}bid_n + C(r \times {}^{t}winner_n - {}^{t}bid_n), \tag{5}$$

where $^{t+1}bid_n$ is the n-th bid element at iteration $t+1$, $^{t}winner_n$ is the n-th element of the best bid in the winner group, t shows the current iteration, C is a constant number, and r is a random number between 0 and 1 drawn from the normal distribution.

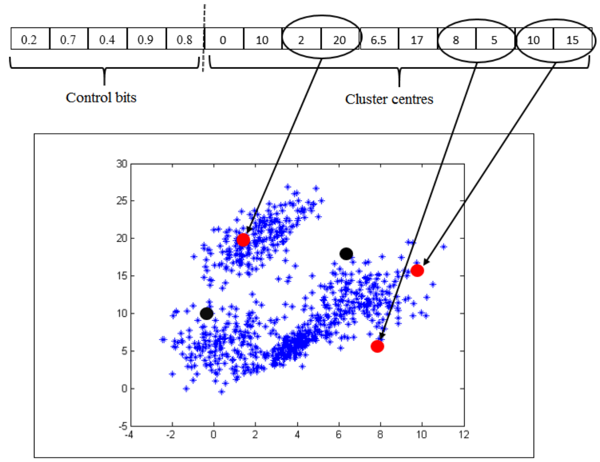

Figure 1: An example bid. For 3 of the 5 clusters the control bit is greater than 0.5 making them active clusters (red circles) while the other two are inactive (black circles).

3 AUTOMATIC CLUSTERING USING HMS

The goal of automatic clustering for image segmentation is to find both cluster centres and the correct number of clusters at the same time. In this paper, we propose a novel automatic clustering-based image segmentation approach using the HMS algorithm. Since HMS is a population-based metaheuristic algorithm, two issues need to be considered to adapt it for automatic clustering-based image segmentation, namely encoding strategy and objective function. The encoding strategy defines the structure of each bid, while the objective function expresses its quality for the task. In the following, we first explain the components of our algorithm and then summarise the whole approach.

3.1 Bid structure

In our approach, each bid is of length $k_{max} + k_{max} \times d$. The first k_{max} elements are control "bits" that indicate active ($>$ 0.5) or inactive ($\leq$ 0.5) clusters, while the remaining elements define the clusters by their centres with d the length to define one cluster centre. k_{max} defines the maximum number of clusters. Figure 1 shows an example bid for $k_{max} = 5$ with 3 active clusters.

3.2 Objective function

As objective function we use a clustering indicator, in particular the Davies-Bouldin (DB) index [5]. Here, the scatter within the i-th cluster is calculated as

$$S_i = \frac{1}{n_i} \sum_{x_j \in c_i} d(x_j, m_i), \tag{6}$$

where n_i is the number of patterns of the i-th cluster c_i, and $d(x_j, m_i)$ is the Euclidean distance between x_j and its cluster centre m_i. The between-cluster separation is computed as

$$R_{ij} = \frac{S_i + S_j}{d(m_i, m_j)}, i \neq j, \tag{7}$$

and the DB index is then defined as

$$DB = \frac{1}{K}\sum_{k=1}^{K} R_k, \tag{8}$$

where $R_k = \max_{j=1,2,\ldots,K} R_{ij}$ and $i = 1, 2, \ldots, K$.

Since division by zero may occur when calculating the objective function, we first check whether the number of members of a cluster is at least 2 and re-initialise the bid if this is not the case.

3.3 The algorithm

Algorithm 1 summarises the workings of our algorithm in pseudo code.

4 EXPERIMENTAL RESULTS

We benchmark our algorithm on six commonly used images, Lenna, Airplane, House, Peppers, MRI, and Caspian Sea, and five benchmark images from the Berkeley segmentation database [12], 12003, 42049, 181079, 18054, and 385028, all shown in Figure 2. All images are greyscale images and the cluster centres are thus pixel intensity values. We compare our proposed method with a number of other population-based algorithms including automatic GA-based clustering, automatic DE-based clustering [3], automatic PSO-based clustering [25], automatic HS-based clustering [10], and automatic ABC-based clustering [26]. Each algorithm is run 50 times on each image, while in the following we report the averages over these 50 runs. A maximum number of 10,000 objective function evaluations is used as stopping criterion for all runs. Other employed parameters are given in Table 1.

First, we compare the algorithms visually, taking image 385028 as a representative example. Figure 3 shows both the manual segmentations provided in the Berkeley dataset, as well as the results of the various clustering algorithms. As can be seen, the best segmentation is achieved by our HMS approach.

Turning to objective measures, Table 2 lists the DB index results for all images and algorithms. For each image, we also provide a ranking of the algorithms which we then average over all images to arrive at an overall ranking. As we notice, our proposed algorithm is ranked top for 7 of the 11 images and second for the other 4. Over the whole dataset, this leads to the best overall rank, clearly outperforming all other algorithms. In addition, we also confirm that there is a statistical difference between the performance of our HMS method and the other evaluated algorithms. The employed Wilcoxon signed rank test [6] confirms that our proposed approach is indeed statistically superior to all other methods.

In addition, we compare our algorithm to conventional clustering algorithms, namely k-means and fuzzy c-means (FCM). Since these require the number of clusters to be defined, we set it to the (rounded) number of clusters obtained by the population-based algorithm that gives the best result for this image. The results are shown in Table 3 and as we can see from there, our proposed method clearly outperforms k-means and FCM.

Last but not least, we evaluate our algorithm in terms of image segmentation quality based on three commonly used measures, namely the Borsotti criterion (BOR) [2], variance of information (VOI) [13], and the probabilistic rand index (PRI) [28]. The BOR results are given in Table 4, while Table 5 and 6 show the VOI

Algorithm 1 HMS-based automatic clustering for image segmentation

// L: lower bound; U: upper bound; M_l and M_h: minimum and maximum number of mental processes; N_{pop}: number of bids; K: number of clusters; $iter$: current iteration; NFE_{max}: maximum number of function evaluations

X = initialise population of N_{pop} bids
Calculate objective function values (OFVs) of bids using Eq. (8)
x^* = find the best bid in the initial population
for i from 1 to N_{pop} **do**
    β_i = random number between L and U
end for
$NFE = N_{pop}$
$iter = 0$
while $NFE <= NFE_{max}$ **do**
    $iter = iter + 1$
    // Mental Search
    for i from 1 to N_{pop} **do**
        q_i = random integer number between M_l and M_h
    end for
    for i from 1 to N_{pop} **do**
        for j from 1 to q_i **do**
            $s = (2 - NFE(2/NFE_{max}))0.01\frac{u}{v^{1/\beta_i}}(x^i - x^*)$
            $NS_j = x^i + s$
        end for
        t = find NS with lowest OFV
        if $cost(t) < cost(x^i)$ **then**
            $x^i = t$
        end if
        $NFE = NFE + q_i$
    end for
    // Grouping
    Cluster N_{pop} bids into K clusters
    Calculate mean OFV of each cluster
    Select cluster with lowest mean OFV as winner cluster
    $winner$ = select the best bid in the winner cluster
    // Move bids towards best strategy
    for i from 1 to N_{pop} **do**
        for n from 1 to N_{var} **do**
            $x_n^i = x_n^i + C(r \times winner_n - x_n^i)$
        end for
    end for
    Calculate OFVs of new bids using Eq. (8)
    $NFE = NFE + N_{pop}$
    for i from 1 to N_{pop} **do**
        β_i = random number between L and U
    end for
    x^+ = find best bid in current bids
    if $cost(x^+) < cost(x^*)$ **then**
        $x^* = x^+$
    end if
end while

and PRI results, respectively. Since the latter two require a ground truth segmentation, results are provided only for the images of

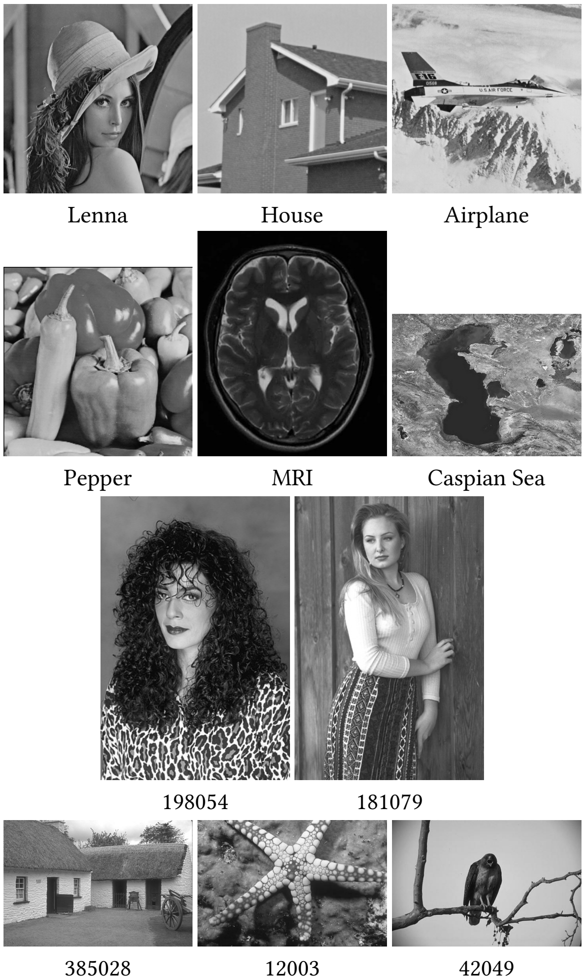

Figure 2: Test images.

the Berkeley segmentation dataset. As we can observe from the obtained results, our proposed algorithm also outperforms the other techniques based on these criteria and is thus shown to yield the best segmentation results.

Table 1: Parameter settings for all algorithms.

algorithm	parameter	value
GA [33]	crossover probability	0.8
	mutation probability	1/chromosome length
DE [31]	scaling factor	0.5
	crossover probability	0.1
PSO [32]	cognitive constant	2
	social constant	2
	inertia constant	1 to 0
ABC [8]	limit	$n_e \times$ dimensionality
HS [7]	harmony memory considering rate	0.9
	pitch adjusting rate	0.1
HMS	number of clusters in bid grouping	5
	C	1

Table 2: DB index results for all imaged and algorithms. R indicates the ranking of the algorithms for each image.

image		GA	DE	PSO	HS	ABC	HMS
Lenna	DB	0.4408	0.4167	0.4245	0.4319	0.4302	0.4124
	R	6	2	3	5	4	1
Airplane	DB	0.4903	0.3495	0.3736	0.3758	0.3742	0.3544
	R	6	1	3	5	4	2
House	DB	0.4461	0.4002	0.4219	0.4106	0.4044	0.3916
	R	6	2	5	4	3	1
Pepper	DB	0.4314	0.4033	0.4053	0.4317	0.4220	0.3827
	R	5	2	3	6	4	1
MRI	DB	0.4212	0.3669	0.4080	0.4113	0.3781	0.3503
	R	6	2	4	5	3	1
Caspian Sea	DB	0.5555	0.4281	0.4321	0.4494	0.4429	0.4294
	R	6	1	3	5	4	2
198054	DB	0.4193	0.3636	0.3909	0.4022	0.3724	0.3554
	R	6	2	4	5	3	1
181079	DB	0.4401	0.4184	0.4335	0.4329	0.4299	0.4214
	R	6	1	5	4	3	2
385028	DB	0.4502	0.4197	0.4224	0.4419	0.4414	0.4181
	R	6	2	3	5	4	1
12003	DB	0.4535	0.4197	0.4241	0.3328	0.4273	0.4065
	R	6	3	4	1	5	2
42049	DB.	0.3440	0.3489	0.4075	0.3688	0.3634	0.3426
	R	2	3	6	5	4	1
average rank		4.46	1.91	3.91	4.55	3.73	1.36

5 CONCLUSIONS

In this paper, we have proposed a novel clustering algorithm for image segmentation based on the human mental search algorithm. One of the main characteristics of our approach is that it does not require the number of clusters in advance but determines it automatically. Our experimental results show our technique to yield good segmentation performance and to outperform both other metaheuristic and conventional clustering algorithms.

Table 3: Comparison, in terms of DB index, to conventional clustering-based image segmentation algorithms.

image	k-means	FCM	HMS
Lenna	0.5762	0.5705	0.4124
Airplane	0.4189	0.4297	0.3544
House	0.6279	0.5736	0.3916
Pepper	0.4985	0.4980	0.3827
MRI	0.4319	0.4455	0.3503
Caspian Sea	0.5181	0.5410	0.4294
42049	0.4395	0.4455	0.3554
12003	0.5202	0.5429	0.4214
181079	0.4726	0.4793	0.4181
198054	0.5784	0.5745	0.4065
385028	0.4280	0.4570	0.3426

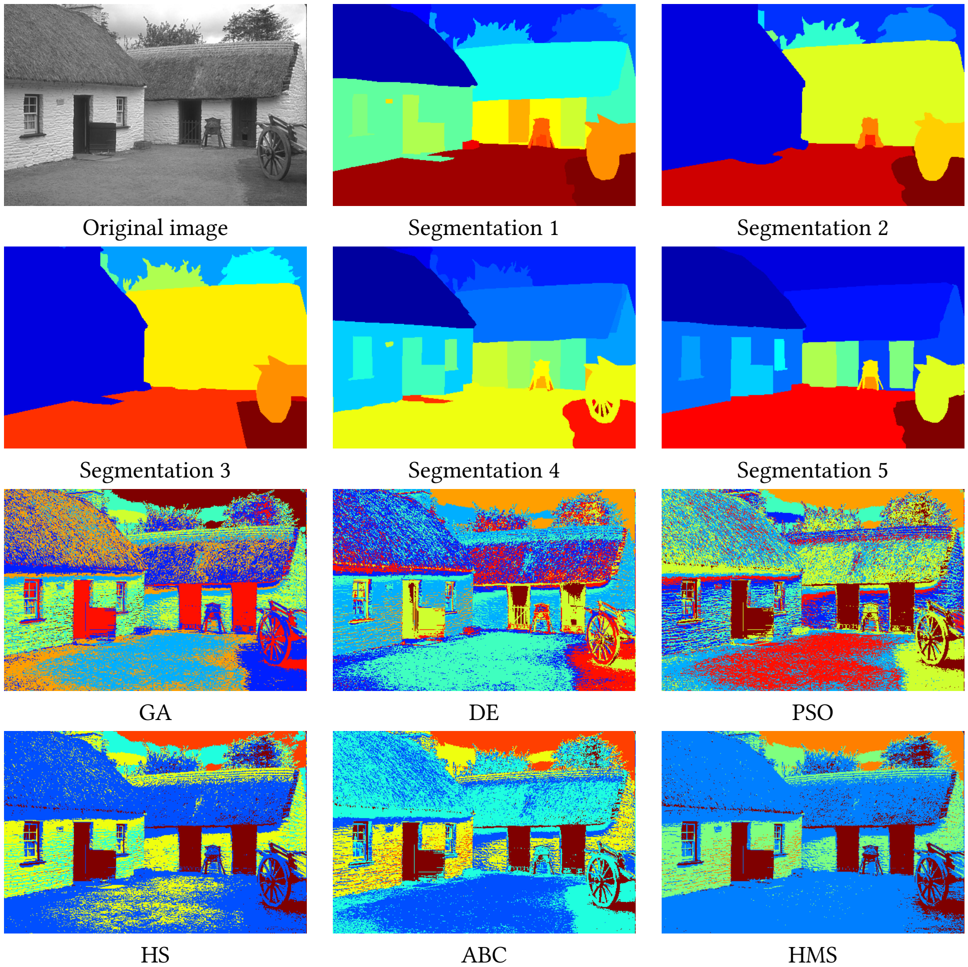

Figure 3: Segmented images for image 385028.

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Table 4: BOR results for all images and algorithms. A lower BOR indicates better segmentation performance.

image		GA	DE	PSO	HS	ABC	HMS
Lenna	DB	0.469	0.0424	0.0509	0.0448	0.0468	0.0452
	R	6	1	5	2	4	3
Airplane	DB	0.491	0.0474	0.0464	0.0374	0.0374	0.0372
	R	6	5	4	2.5	2.5	1
House	DB	0.325	0.0319	0.0267	0.0246	0.0314	0.0230
	R	6	5	3	2	4	1
Pepper	DB	0.598	0.0591	0.0593	0.0572	0.0591	0.0590
	R	6	3.5	5	1	3.5	2
MRI	DB	0.315	0.0308	0.0309	0.0257	0.0250	0.0243
		6	4	5	3	2	1
Caspian Sea	DB	0.477	0.0466	0.0450	0.0450	0.0440	0.0385
	R	6	5	3.5	3.5	2	1
198054	DB	0.463	0.0424	0.0349	0.0459	0.0429	0.0396
	R	6	3	1	5	4	2
181079	DB	0.811	0.0760	0.0781	0.0717	0.0825	0.0767
	R	6	2	4	1	5	3
385028	DB	0.572	0.0505	0.0501	0.0506	0.0551	0.0474
	R	6	3	2	4	5	1
12003	DB	0.688	0.0645	0.0607	0.0554	0.0658	0.0691
	R	6	3	2	1	4	5
42049	DB	0.588	0.0424	0.0429	0.0510	0.0567	0.0414
	R	6	2	3	4	5	1
average rank		6.00	3.32	3.41	2.64	2.82	1.91

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Table 5: VOI results for Berkeley images and all algorithms. A lower VOI indicates better segmentation performance.

image		GA	DE	PSO	HS	ABC	HMS
198054	DB	2.3765	2.3647	2.8795	2.3694	2.3638	2.3445
	R	5	3	6	4	2	1
181079	DB	3.3940	3.1828	4.0570	3.6325	3.1576	2.9794
	R	4	3	6	5	2	1
385028	DB	3.3663	3.1607	3.6942	2.9692	3.1533	3.0224
	R	5	4	6	1	3	2
12003	DB	2.2544	2.0401	2.5744	2.1271	2.0259	1.9915
	R	5	3	6	4	2	1
42049	DB	4.4215	3.7786	4.1039	3.6922	3.5437	3.6834
	R	6	4	5	3	1	2
average rank		5.00	3.40	5.80	3.40	2.00	1.40

Table 6: PRI results for Berkeley images and all algorithms. A higher PRI indicates better segmentation performance.

image		GA	DE	PSO	HS	ABC	HMS
198054	DB	0.5234	0.5375	0.5551	0.5294	0.5395	0.5476
	R	6	4	1	5	3	2
181079	DB	0.3166	0.5705	0.5527	0.5731	0.5589	0.5905
	R	6	3	5	2	4	1
385028	DB	0.3332	0.6375	0.6175	0.6277	0.6205	0.6486
	R	6	2	5	3	4	1
12003	DB	0.3186	0.7447	0.7355	0.7412	0.7375	0.7469
	R	6	2	5	3	4	1
42049	DB	0.2817	0.6985	0.6958	0.6426	0.6208	0.6715
	R	6	1	2	4	5	3
average rank		6.00	2.40	3.60	3.40	4.00	1.60

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