COLOR IMAGE SEGMENTATION BY GRAVITATIONAL CLUSTERING IN COLOR SPACE USING NEIGHBOR-RELATIONSHIP

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Abstract: In this paper, we propose a color image segmentation method based on gravitational clustering using neighbor relations in the spatial domain and distance information in RGB space among pixels. Most clustering-based segmentation algorithms use only color space distances after pixels are mapped from the spatial domain to color space, ignoring their neighbor relations; but we use both information. We use gravitational clustering, which imitates the Law of Gravity, and the gravitational force is applied only to neighboring clusters. The results show that the proposed method is effective in finding exact boundaries of regions.

1 INTRODUCTION

Image segmentation involves partitioning an image into meaningful regions, where “meaningful region” is usually based on pixels of similar colors. Segmentation methods can be classified into two categories: image space approaches and measurement space approaches.

The image space approach segments an image in its (x,y) coordinate space; it includes split/merge algorithms and region growing algorithms(Zhu, 1995). The measurement space approach first transforms an image into a measurement space such as a histogram or color space, then segments the image by finding clusters in that space(Cannon, 1986)(Lim, 1990). The color space histogram method has several drawbacks: first, it loses the spatial information of pixels; second, a large amount of memory is required for a three-dimensional (color) histogram; third, clustering algorithms such as K-means or fuzzy C-means are affected by initial centers and/or require the number of clusters as input; fourth, each cluster needs to be remapped to the spatial domain, and a region labeling process is required to separate regions which are not adjacent to each other, but belong to the same class just because they have similar colors.

In this paper, the first and fourth drawbacks are overcome by incorporating neighbor relations in the clustering process, while the second and third are overcome by the gravitational clustering algorithm. That is, we keep neighbor relations in the measurement space; we need only as much memory as the data and do not need memory to store a three-dimensional color histogram; the centers and number of clusters are automatically determined in gravitational clustering; and we don’t need the region labeling process since non-adjacent regions are not classified into the same region even though they have similar color as we use neighbor relations in the clustering process.

The organization of this paper is as follows: section 2 introduces gravitational clustering, section 3 presents the proposed algorithm which incorporates neighbor relations in the clustering process for segmentation, section 4 contains experimental results, and section 5 concludes the paper.

2 THE GRAVITATIONAL CLUSTERING STRUCTURE OF A SCRIPT

The gravitational clustering algorithm is modeled after the gravitational force field of nature, and it is used for clustering n-dimensional data, as originally proposed by Wright (Wright, 1977). The method belongs to agglomerative clustering methods(Forsyth, 2002). It considers each datum as

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a particle with unit mass initially. Let each particle attract each other by gravitational force; sufficiently close particles are merged together to form a bigger particle with mass equal to the sum of the merged particles, and the location is determined by the mass center of the merged particles. This method has the advantage of finding clusters automatically without giving the number of clusters as in some clustering algorithms such as the K-means algorithm. However, when the process of moving and merging is continued for a sufficiently long time, all the particles will be merged to form a single cluster; hence, we should have some provisions to prevent this. This problem is discussed in section 3.2.2.

The movement of particles is governed by Newton's gravity equations; however, we propose some variations here that make the algorithm work well in practice for clustering.

2.1 Physical models

As in Nature, the particles move due to their accelerations caused by the force of gravity. Let
$N(t)$ represent particles at time t,
$s_i(t)$ represent the position of particle i at time t,
$m_i(t)$ represent the mass of particle i at time t,
$v_i(t)$ represent the velocity of particle i at time t,
$a_i(t)$ represent the acceleration of particle i at time t,
then

$$s_i(t) = s_i(t-\Delta t) + v_i(t)\Delta t + \frac{1}{2}a_i(t)\Delta t^2 \quad (1)$$

$$v_i(t) = \int_0^t a_i(r)dr \quad (2)$$

$$a_i(t) = \sum_{j\in N(t), j\neq i=0} G\frac{m_i(t)m_j(t)}{m_i(t)}\frac{1}{\left|s_j(t)-s_i(t)\right|^2}\frac{s_j(t)-s_i(t)}{\left|s_j(t)-s_i(t)\right|}\Delta t^2 \quad (3)$$

where G is (gravitational constant). Here, Δt is taken to be 1.

2.2 The Markov model

Velocity is accumulated acceleration as given in equation (2). However, we may use a different model though it differs from nature. In this model, the velocity is reset at each time so as not to accumulate acceleration; thus, the position $s_i(t)$ depends only on current position and acceleration, not on past information. This model is therefore a Markov model. It can be obtained by removing the velocity component from the physical model, so that the movements of particles are determined only by acceleration due to gravity, regardless of past velocity. The position of particle *i* at time *t* is given by the following equation.

$$s_i(t) = s_i(t-\Delta t) + \frac{1}{2}G\sum_{j\in N(t), j\neq i=0} m_j(t)\frac{s_j(t)-s_i(t)}{\left|s_j(t)-s_i(t)\right|^3}\Delta t^2 \quad (4)$$

The Markov model generally produces better results in clustering since the movements of particles are not affected by past history. This model is used in this paper.

3 THE PROPOSED SEGMENTATION METHOD

This section explains segmentation using gravitational clustering in color space taking neighbor relationship into account. The segmentation proceeds as in figure 1.

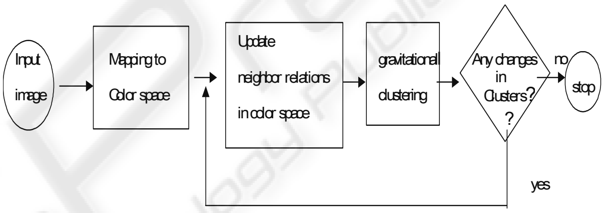


Figure 1: The configuration of segmentation process

3.1 Mapping an image into the color space

This section explains the mapping of pixels in an image into color space. A pixel of (R, G, B) image can be considered as a 5-tuple (r,g,b,x,y). Most measurement space techniques uses only the distances in (R, G, B) color space ignoring (x,y). However, we use both (r,g,b) and (x,y) in the clustering. As the two sources of information are of different units, we should treat them differently: (r,g,b) is used to compute distance as in other algorithms, and location information (x,y) is incorporated in neighbor relations along which the clustering process is performed. Figure 2 shows that a pixel P at (P_x, P_y) with (R,G,B) value (P_R, P_G, P_B) is mapped to P' at (P_R, P_G, P_B) in (R,G,B) space. Most measurement space algorithms use only (P_R, P_G, P_B) in (R,G,B) space and ignore spatial information (P_x, P_y).Figure 3(a) shows an image region of 3 × 3 pixels connected by 4-neighbor relationship in the spatial domain. Figure 3(b) conceptually shows how those pixels map to color space with their neighbor relations kept as lines. In the clustering stage, we apply gravitational force only among neighboring pixels . That is, even if two pixels may be close to each other in color space, they would not attract each other unless they are spatial neighbors.

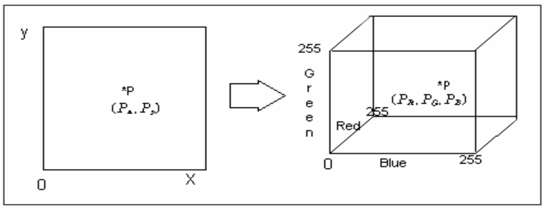
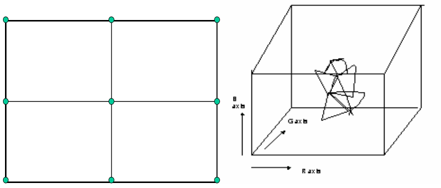


Figure 2: Mapping of a pixel



(a) 3×3 pixels in special domain connected by 4-neighbor
(b) specially neiboring pixels in color space

Figure 3: Pixels in spatial domain and in color space

3.2 Gravitational clustering utilizing neighbour relations

As stated above, those pixels close to each other in color space are clustered only if they are connected by neighbor relations, not like other measurement space algorithms such as (Yung, 1998). The algorithm is as follows:

Step 1. Let each pixel be a particle.
Initialize parameters such as merging distance ε .
Step 2. Update neighbor relations altered by merged particles
(Initially 8-neighbor).
Step 3. Compute gravitational force among neighbors, move particles in color space according to the gravitational force attraction.
Step 4. If the distance to a neighbor is less than ε , merge it with the neighbor.
Step 5. If there is no more merge or movement of particles, then stop.
Otherwise, go to step 2.

The Markov model discussed in section 2.1 is used in step 3. The resulting particles are clusters, and pixels in each cluster belong to a segment.

3.2.1 The merging distance ε

The ε can be determined in many ways; we considered the distance histogram which accumulates distances between a pixel and its neighbors in color space. Pixels in a segment have similar color value, making a high peak near distance zero in the histogram. The first valley of the histogram where the histogram value starts increasing after the decrease from the high peak near zero distance can be a candidate for the ε value. However, if ε is too small, the image may be over-segmented. Thus, we selected the first valley beyond a distance of 10 from the zero peak that is empirically obtained. In most cases, a value of 16 produced good results. As clustering proceeds, those neighboring clusters having similar colors are merged, and their centers are replaced by the center of mass. Thus, the inter-cluster distances get bigger, while intra-cluster distances get smaller. If ε is large, the color error given in equation (5) of section 4 becomes large as the center value does not represent the pixel values in the segment accurately, but it will produce a small number of segments. If a small ε is used, the image may be over-segmented even if the error gets smaller.

3.2.2 Extent of gravitation effect

If the process of gravitational clustering is continued, all the particles will be merged to form a single cluster eventually. We need some provision to prevent this and find optimal clusters. Various methods taken by others are reviewed first.

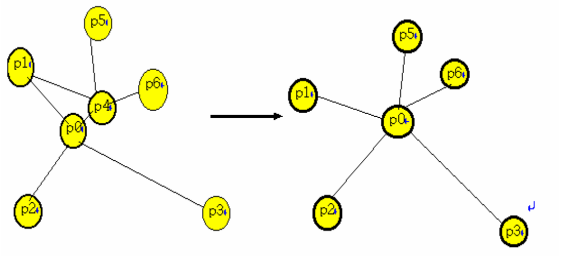
Wright(Wright, 1977) applied the gravitational force to all the data at all times. The clustering process was actually continued until all the particles were merged, and the time was measured between every merge event and the next. The best clustering is considered to be the clustered state just before the longest time elapse until anothermerge event occurs. This method has the disadvantage of long computing time since the process must be continued until all the particles are merged.

Yung and Lai(Yung, 1998) took a different approach. They restricted the extent of gravitational force; they called it “force effective field (FEF)”, conceptually similar to the neighbor function of the SOFM neural net(Kohonen, 1997). They decreased the extent of FEF as the iteration proceeded.

Another possible method is to let the data space expand like the Universe and find the equilibrium state of contraction and expansion.

The approach taken in this paper is to restrict the merge distance such that particles are merged only when they are within a certain distance, and the gravitational force is applied only to ‘neighboring’ particles in the spatial domain..

Figure 4 shows how the neighbor relation is updated after a merge event. In the figure, p0….p6 are particles (clusters) in the color space. The lines represent neighbor relations and their lengths represent the distances. Consider p0 for example. The gravitational forces on p0 by p1,p2,p3 and p4 are computed; if p0 and p4 are merged together, new neighbors of p0 are p1,p2,p3 and p5,p6 which were neighbors of p4 previously, as shown in figure 4(b). In the next iteration, p0 would be affected by these new neighbors. As two particles p0 and p4 are merged, their mass becomes 2. Heavier particles will exert stronger gravitational force than lighter ones, and they will attract lighter ones toward them. This effect is equivalent to finding the center of mass for those pixels that belong to the cluster. As the iteration continues, the number of particles will be reduced by merging.



(a) before merge (b)after merge

Figure 4: Updating neighbor relations

3.3 Image Segmentation

Those algorithms that just find clusters in the color space without considering neighbor relations need a region labeling process after clustering to find individual segments, since those clusters contain pixels of similar color regardless of their location. In contrast, our algorithm does not need region labeling, since each cluster contains only neighboring pixels of similar color. Even though pixels may have similar color in RGB space, they do not belong to a cluster unless they are neighbors to others. Thus, a cluster corresponds to a separate region in our algorithm.

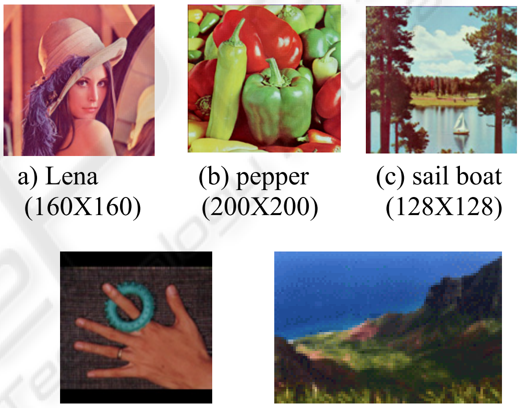
4 EXPERIMENTAL RESULTS

True-color images were used as input to the segmentation algorithm. The 8-neighbor relation was used in the clustering. Experiments were performed to compare the effect of the distance parameter ε and the effect of taking neighbor relations into account. The algorithm was then compared with segmentation by the K-means clustering algorithm. The following criterion (Liu, 1994) is used to measure the performance of segmentation algorithms,

$$F(I) = \sqrt{R} \times \sum_{i=1}^{R} \frac{e_i^{\ 2}}{\sqrt{A_i}} \qquad (5)$$

where R is the number of regions, A_i is the number of pixels in i-th region, e_i is color error of i-th region defined as $e_i = \sum_{(x,y)\in R_i} \left\| p_{x,y} - p'_{x,y} \right\|$. $p_{x,y}$ is the original color value (r,g,b) of pixel at (x,y), and $p'_{x,y}$ is the color value of the segment to which the pixel at (x,y) belongs. The $\sqrt{R}$ factor imposes a penalty for too many regions, and the $\frac{e_i^2}{\sqrt{A_i}}$ term imposes a penalty for small regions or regions for which the color difference error is large.

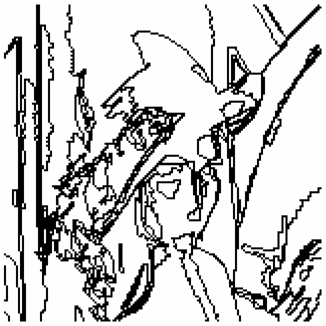
A smaller F value means better segmentation. We normalized F with respect to image size.



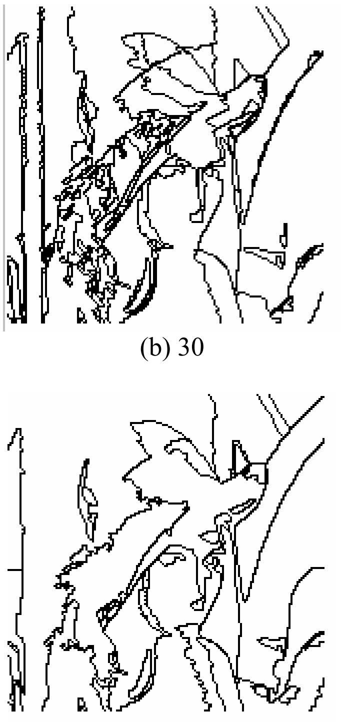
a) Lena (160X160) (b) pepper (200X200) (c) sail boat (128X128)

(d) hand (128×128) (e) valley (96×64)

Figure 5: Images used in the experiments



(a) 20



(b) 30

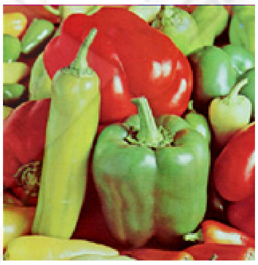
(c) 40

Figure 6: Variations on ε

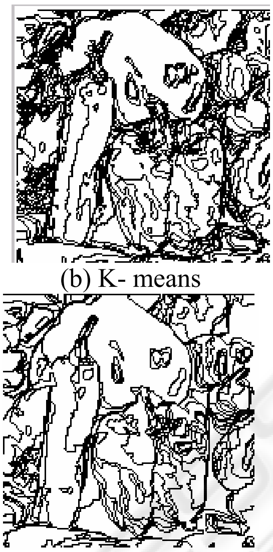
Figure 6 shows the results of varying ε. As expected, a large value of ε produces a small number of regions, while a small value of ε generates more regions. Thus, the value of ε can be used for controlling the degree of details in segmentation.

Table 1: The number of regions (R) and evaluation (F) of results in figure.

ε	20	30	40
R	165	97	50
F	333	369	610



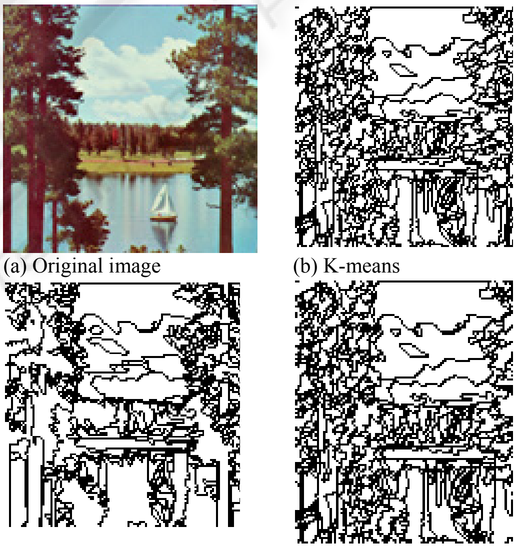
(a) Original image



(b) K- means

(c) Proposed method

Figure 7: Comparison of K-means and our method for the image in figure 5(b)



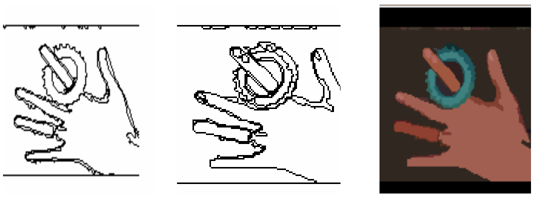
(a) Original image

(b) K-means

(c)Gravitational clustering with neighbor relations

(d) gravitational clustering without neighbor relations

Figure 8: The K-means and gravitational clustering algorithms with and without using neighbor relations for the image in figure 5(c)



(a) K-means

(b) Proposed method

(c) Result in (b) painted with cluster center values

Figure 9: Another comparison of K-means and our method

As we can see in the figure 7 and 8, the result of the K-means method is not as good as our method for images where the K (the number of color clusters) is not easily given. In figure 9(c), each region is painted with the center value of each cluster. It shows that the upper part of the finger with the smaller ring is separated from the other part of the hand. This shows a characteristic of the proposed algorithm, which separates regions that are not adjacent even though their colors are similar. One part of the finger is painted darker because fewer pixels than the other part of the hand are contained in the cluster and that part is more affected by shadows . The K-means method in figure 9(a) does not separate fingernails which may be important in further image computations, and does not separate darker protrusions on the larger ring. We compared the gravitational clustering segmentation with and without neighbor relations. By computing gravitational force and allowing mergers for only neighboring particles, the amount of computation is greatly reduced and the speed is order of magnitude faster compared to the algorithm without incorporating the neighbor relations(Yung, 1998). Proposed method also produced better segmentation results in quality.

5 CONCLUSION

In this paper, a new segmentation algorithm is proposed, which uses gravitational clustering in the color space and incorporates neighbor relations. The method produces better results compared to the K-means method. As the clustering is performed along the neighbor relations, pixels having similar colors are not clustered unless they are adjacent. Hence there is less need of a region labeling process. Incorporation of neighbor relations also reduces the computation time. As both the distance in the color space and neighbor relations in the spatial domain are used, it can be considered a hybrid of measurement space and image space algorithms.

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