

A New Method for Fuzzy Agent-based Color Clustering

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ABSTRACT: Fuzzy objective function-based clustering methods are proved to be fast tools for classification and segmentation purposes. Unfortunately, most of the available fuzzy clustering methods are using the spherical or ellipsoidal measures, which have been proved to result in spurious clusters, when working with color data. Also, the local minima is an unsolved problem in this field. In this paper, a cylindrical fuzzy clustering agent for color fields is proposed. Embedding a few such agents in a cooperating set, it is shown that the set converges very quickly. To avoid the probable trapping in local minima and non-perceptual results, a new cluster validity measure is proposed. The proposed clustering method for color images uses the results of the competition between different cooperative sets. Using various experimental results, the repeatability of the proposed method and the quality of its results are shown. **Keyword:** Fuzzy Clustering, Color Image Processing, Agent-Based Processing.

1 Introduction

As a non-hierarchical clustering method, fuzzy clustering, has proved to be efficient in clustering a set of given vectors into a few homogenous groups [1]. In conventional clustering methods, samples are either accepted or rejected to be assigned to each class, while the fuzzy clustering methods, incorporate the membership concept into the clustering results. The fuzzy clustering is becoming more popular because it can produce the crisp results when needed. Also, fuzzy clustering is less prone to falling into local optima than the crisp clustering algorithms, but not completely safe [2].

The idea of fuzzy clustering came from the *Hard C-Means* (HCM) method proposed by *Ruspini* (1969) [3]. *Dunn* (1973) [4] generalized the minimum-variance clustering procedure into a Fuzzy *ISODATA* clustering technique. *Bezdek* (1981) [5] generalized *Dunn*'s approach to obtain an infinite family of algorithms which is called the *Fuzzy C-Means* (FCM), by introducing the concept of fuzziness (m). An extension to the FCM is the *Gustafson-Kessel* (GK) method [6], which uses the covariance matrix of data to capture ellipsoidal properties of the clusters. The novel idea of the GK method is using the *Mahalanobis* distance. After that, the *Gath-Geva* method (GG) used the same distance [7]. Other contributions in this field, include the *fuzzy c-varieties* (FCV) [8] and the *fuzzy c-elliptotypes* (FEC) [8]. In 1993, *Krishnapuram* and *Keller* proposed the *probabilistic fuzzy C-means* (PCM) clustering method [9], which although adds more noise robustness to the FCM, but uses the same definition of Euclidean distance between the points and the clusters.

Any clustering method is based on the membership values, computed in terms of a distance function [10]. Although, the

color clustering is an inherently ambiguous task, (because of the edge blurring [2]), but the importance of choosing a proper distance function is overlooked in the color image processing literature. For example, many researchers have used the *Euclidean* distance-based homogeneity criteria in the color domain with no explicit proof of its performance (see [11] as an example). It is proved that the *linear partial reconstruction error* (LPRE) method, results in a proper likelihood measure for processing natural color images [12]. In this methodology, the likelihood of the vector \vec{c} to the cluster r is defined as,

$$e_r(\vec{c}) = \|\vec{v}^T(\vec{c} - \vec{\eta})\vec{v} - (\vec{c} - \vec{\eta})\|^2, \quad (1)$$

where \vec{v} shows the direction of the first principal component, $\vec{\eta}$ is the expectation, and $\|\vec{x}\|$ denotes the L_2 norm [12]. The comparison of the LPRE with the conventional Euclidean and Mahalanobis distances, has proved its superiority, (both in terms of likelihood measurement and homogeneity decision) [13]. In fact, The Euclidean and the Mahalanobis distances are leading to spurious likelihood and homogeneity decisions in color fields [13]. Thus, the FCM, the HCM, and the PCM (which are based on the Euclidean distance measurement), are theoretically inappropriate for color clustering. The same happens for the GK, GG, and FEC methods, (which use the Mahalanobis distance). One of the main drawbacks of the fuzzy clustering methods is the probability of local minima trapping. In this paper, we use a cooperative-competitive agent-based platform to find the best color clusters in natural color images.

2 Proposed Method

2.1 Corporative Agents

As shown in Figure 1, the proposed agent contains two characteristic vectors of $\vec{\eta}$ and \vec{v} . While $\vec{\eta}$ controls the expectation vector of the agent, \vec{v} shows its direction and it always satisfies $\|\vec{v}\| = 1$. For a given data cloud, $X = \{\vec{x}_i | i = 1, \dots, n\}$, each agent searches for a cylindrical structure and fits itself into it. In this manner, each agent goes towards minimizing the objective function defined as,

$$J_a = \sum_{i=1}^n p_i^m \Psi(a, \vec{x}_i), \quad (2)$$

where m is the fuzziness factor, p_i denotes the fuzzy likelihood of \vec{x}_i to the agents vicinity, and $\Psi(a, \vec{x}_i)$ shows the distance from the agent to the vector \vec{x}_i . The agent a sees the a color vector \vec{x} , at the distance computed as,

$$\Psi(a, \vec{x}) = \|\vec{x} - \vec{\eta}_a - \vec{v}_a^T(\vec{x} - \vec{\eta}_a)\vec{v}_a\|^2. \quad (3)$$

Note that $\Psi(a, \vec{x})$ measures the residue of \vec{x} , when it is estimated by its project on the 1-D space described as,

$$\Omega_a = \{\vec{\eta}_a + \lambda \vec{v}_a | \lambda \in \mathbb{R}\}. \quad (4)$$

It is proved that the best choice for the agent, $a_i = [\vec{\eta}_i, \vec{v}_i]$, is the new point $[\vec{\eta}_i^*, \vec{v}_i^*]$, where $\vec{\eta}_i^*$ and \vec{v}_i^* are the fuzzy expectation and first fuzzy principal direction of the fuzzy set defined as [14],

$$\tilde{X} = \{(\vec{x}_i; p_i) | \vec{x}_i \in X\}. \quad (5)$$

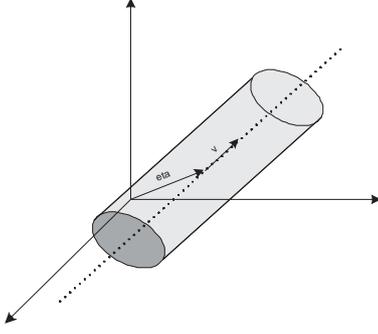


Figure 1: Proposed cylindrical agent.

A set of c agents incorporate into a cooperative set when they share their information regarding the distances to the data points. It is proved that, for a set of cooperative agents, $A = \{a_1, \dots, a_c\}$, defining the likelihood of the color vector \vec{x} to the i -th agents cluster as:

$$P_i^A(\vec{x}) = \frac{\Psi(a_i, \vec{x})^{-\frac{1}{m-1}}}{\sum_{k=1}^c \Psi(a_k, \vec{x})^{-\frac{1}{m-1}}}, \quad (6)$$

helps minimizing the objective function J_{a_i} faster[14]. Thus, the objective function for the agent a_i in the cooperative set A is defined as,

$$J_a^A = \sum_{j=1}^n P_i^A(\vec{x}_j)^m \Psi(a_i, \vec{x}_j). \quad (7)$$

A set of cooperative agents is considered as converged if at an iteration,

$$\max_i \|\vec{\eta}_{a_i}^* - \vec{\eta}_{a_i}\|_\infty < \varepsilon, \quad (8)$$

for a preselected value of ε .

2.2 Competition between Agent Sets

Considering a value of c , a cooperative set of agents, A , is produced, consisting c randomly initialized agents and the uniform random value of m in the interval $]1, 2]$. Note that in all stages all agents satisfy the normality of the direction vectors. Here, we propose two ranks for a converged set of cooperative agents. First, the final value of objective function for each agent is a descriptor of the result. Note that the summation of the c objective functions equals,

$$J = \sum_{j=1}^c \sum_{i=1}^n P_j^A(\vec{x}_i)^m \Psi(a_j, \vec{x}_i). \quad (9)$$

Figure 2 shows results of three converged cooperative sets on the image shown in Figure 4-(a) with $c = 2$, $m = 1.07$, and $\varepsilon = 5$. Note the local minima shown in Figure 2-(c) and the corresponding high value of J . Figure 3 shows that the low value of J is not a proof for perceptual validity of the clustering results, as among the cases shown in Figure 3, Figure 3-(c) has got the lowest J , but it is not preferred to Figure 3-(a). To solve this ambiguity we propose to use the cluster spread histograms. consider the set of cooperative agents, A , and the data cloud, X . We call $\vec{x}_i \in X$ belongs to the territory of $a_j \in A$, if,

$$\forall k \neq j, P_k^A(\vec{x}_i) < P_j^A(\vec{x}_i). \quad (10)$$

Assume showing the territory of a_i by X_{a_i} . The projection set of a is defined as,

$$h_a = \{\vec{v}_a^T(\vec{x} - \vec{\eta}_a) | \vec{x} \in X_a\}. \quad (11)$$

The histogram of h_a shows the spread of the cluster corresponding to the agent a around its axis. To gain noise robustness and to make the histogram of h_a comparable for different agents, we propose to remove the minimum and the maximum vicinity of the data out of h_a . It is empirically observed that estimating the *probability density function*(pdf) with the histogram and removing values of x , satisfying $f(x) \leq 0.02$ or $f(x) \geq 0.98$ is a fast method for increasing the noise robustness of the proposed method. Here, $f(x)$ denotes the estimated pdf. The histogram of the resulting data which is computed in 100 bins shows a highly non-smooth shape. Thus, an averaging kernel of size 5 is applied on the histogram for τ times and the result is normalized to have area of one. Cutting the result with the average line, the number of segments are counted for each cluster. We call the average number of segments in a cooperative set as the integrity shown as i . Using the two measures of J and i , different cooperative sets can compete. We propose rejecting the sets with high values of i and then selecting the least J in the remainder. Note that using this method in Figure 2 the winner is Figure 2-(a) and in Figure 3 the winner is Figure 3-(a), as desired by human observers.

2.3 The Clustering Method

Consider the given color image I in RGB color space and the corresponding 3-D histogram H . Assume selecting the number of the cooperating sets n , and their sizes, c . We propose to down-sample the given image for the sake of increasing the performance of the agents. For practical reasons, we used a horizontal down-sampling of 20 : 1. In each cooperating set, all the agents and the value of m are randomized as described in Section 2.1. The best values of ε and τ are empirically proved to be 5 and 10, respectively. Also, it is observed that setting $n = 10c$ is sufficient. Each set works on the image independently and the resulting values of J and i are stored. Among those sets with the smallest value of i , the one with the smallest value of J is considered as the winner. The territories of the agents in the winner set are the clusters. the segmentation result is produced by indexing pixels due to their belonging to the agents territories. In this paper we used 50 sets of cooperative agents in all tests.

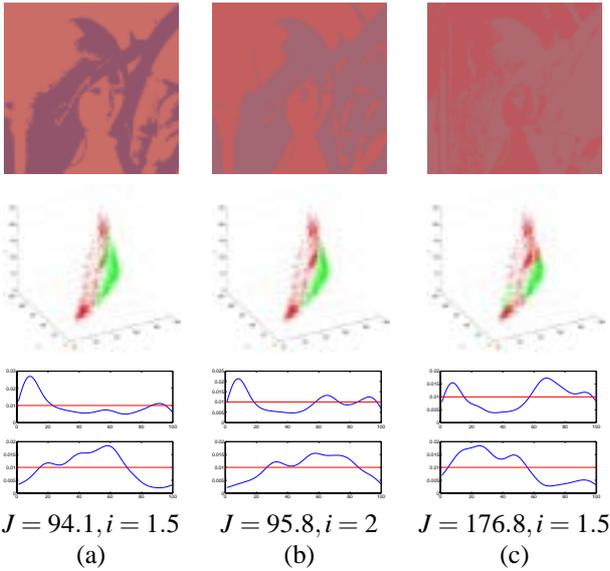


Figure 2: Three converged cooperative sets results for the image shown in Figure 4–(b) with $c = 2$, $m = 1.07$, and $\epsilon = 5$. Top: The corresponding segments. Middle: The clusters. Bottom: The cluster spread histograms.

3 Experimental Results

The tests are performed on a PIV 2.6GHz personal computer with 256MB of RAM. The database is a large digital image archive, containing professional photographs [15] and standard images. All samples are medium sized 512×512 high-quality JPEG images in RGB format. Figure 4 shows some of the test images.

Figure 6 shows the values of J and dx in consecutive iterations and Figure 5 illustrates the corresponding clusters and segmentation results. Here, the clustering method is performed on the image shown in Figure 4–(a) and the parameters are set as $\epsilon = 1$, $c = 2$, and $m = 1.05$. As shown in Figure 5, after the first iteration, the desired result is almost reached. Also, note the decline of J by factor of about 19 in the first iteration while at the fifth iteration the the value of J does not change significantly. In this example, setting $\epsilon = 5$, does not disturb the performance of the method, while it enhances the algorithm’s speed (20%). Figure 7 and Figure 8 show the results for the image shown in Figure 4–(g) with the parameters set as $\epsilon = 5$, $c = 3$, and $m = 1.05$. In this case J is almost divided by a factor of 12 in the first iteration, while it remains almost stationary in the fifth iteration. In the same manner, setting $\epsilon = 5$ does not result in spurious results here. The same results has been observed in other sample images. In the forthcoming parts of this paper, the ϵ is always set equal to 5.

Figure 9 shows the results of the proposed method applied on the image shown in figure 4–(d) in three different races. Here, c is selected equal to 4. The detailed results are listed in Table 1. Note that although the values of m and J are different in different races, but the final result and the integrity are the same. As seen in this test, and also observed in others, the value of i is more distinguishing than the value of J . This test along with other observations on other sample images shows

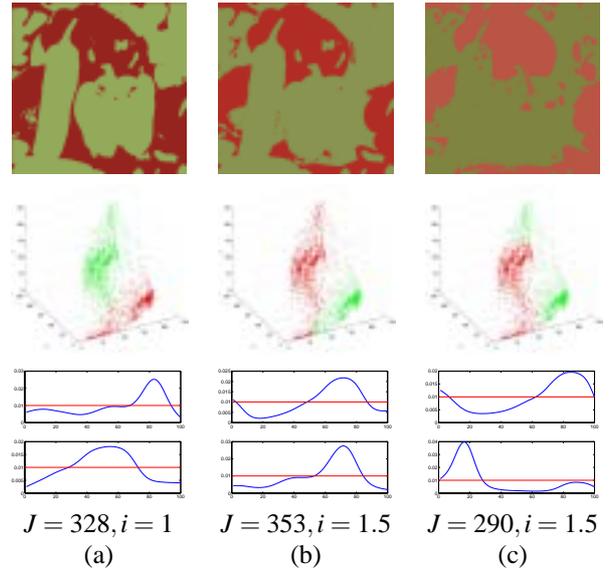


Figure 3: Three converged cooperative sets results for the image shown in Figure 4–(a) with $c = 2$, $m = 1.07$, and $\epsilon = 5$. Top: The corresponding segments. Middle: The clusters. Bottom: The cluster spread histograms.

the high repeatability of the proposed method.

Table 1: Results of three different races on the image shown in Figure 4–(d). [t: Elapsed Time, J: Objective Function Value. i: Integrity.]

m	$t(s)$	J	i
1.14	200	41.7	1.25
1.61	220	32.5	1.25
1.81	200	31.0	1.25

Figure 10 shows the results of the proposed clustering method performed on the image shown in Figure 4–(e) with different values of c . Detailed results are listed in Table 2. Note that altering c controls the resolution of the clustering, while in all cases the result is perceptually valid. Also, note that the elapsed time of the method depends quadratically on c and that the value of J drops when c increases, and thus its is not comparable for sets of cooperative agents with different sizes. The same happens for the value of i .

Table 2: Results of the proposed clustering method performed on the image show in Figure 4–(e) with different values of c . [t: Elapsed Time, J: Objective Function Value. i: Integrity. c: Cluster Count.]

m	$t(s)$	J	i	c
1.86	76	521	1	2
1.21	140	262	1	3
1.81	170	97	1.25	4
1.32	250	64	1.2	5
1.65	340	56	1.17	6

Figure 11 shows the results of the proposed clustering method applied on the images shown in Figure 4 using 50

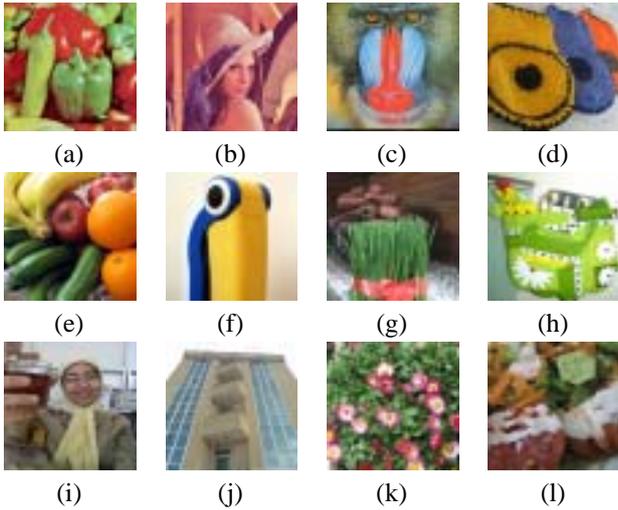


Figure 4: Some of the test images, (a)–(c) Standard images, (d)–(l) Adopted from [15].

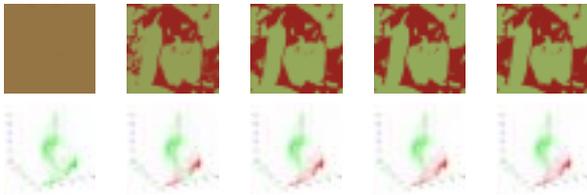


Figure 5: Consecutive iterations of one set of cooperating agents working on the image shown in Figure 4–(a). Top: the segmentation results. Bottom: clusters.

agents sets. The detailed results are shown in Table 3. note that for c clusters, the value of $i \leq 1 + \frac{1}{c}$ means that, at least $c - 1$ agents have reached to single clusters, while at most one has experienced a split cluster. This event have a meaningful description; all of the agents except only one have found the real clusters, and the remainder's territory includes the residual points (the background). Investigating Table 3 shows that this is the case for all samples, except for the image shown in Figure 4–(i), in which two agents out of seven have failed, while the final clustering results are satisfactory. Also, note that the value of J for different images, even with the same value of c , are not comparable. This means that no general threshold on J can be defined. Also, note that the range of the values of m almost fills the entire $[1^+, 2]$ interval, meaning that the initial selection of the range for m can not be limited.

4 Conclusions

A new cooperative–competitive agent–based method for color clustering is proposed. The method relies on a few parameters for most of which, default values are proposed. The only user–dependant parameter is the number of clusters, and it is proved that selecting different values of cluster number does not affect the performance of the proposed method. New measure for color cluster fidelity is proposed and its usefulness and distinguishing power is proved experimentally. In the proposed method, sets containing the clustering agents compete,

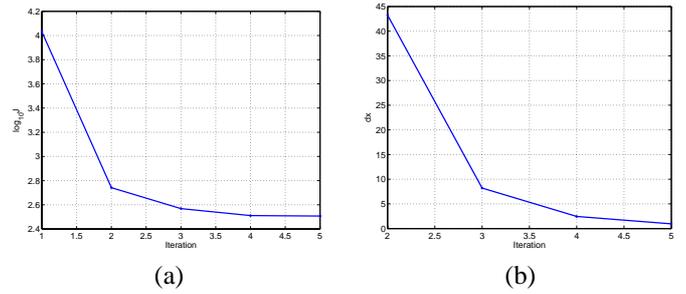


Figure 6: Results of the proposed clustering method for the image shown in Figure 4–(a). (a) Decline of $\log_{10} J$ in consecutive iterations. (b) dx values corresponding to each iteration.

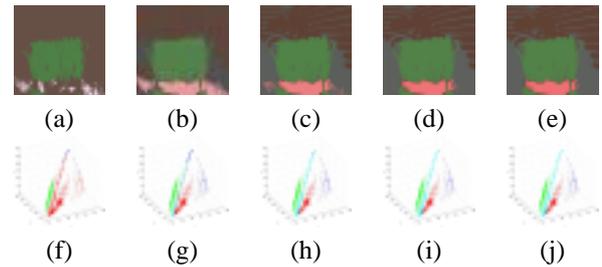


Figure 7: Consecutive iterations of one set of cooperating agents working on the image shown in Figure 4–(g). Top: the segmentation results. Bottom: clusters.

while among a set, agents cooperate by sharing local data. the proposed method is proved to be repeatable, while it often survives from the local minima. The efficiency of the proposed clustering method is shown in various tests.

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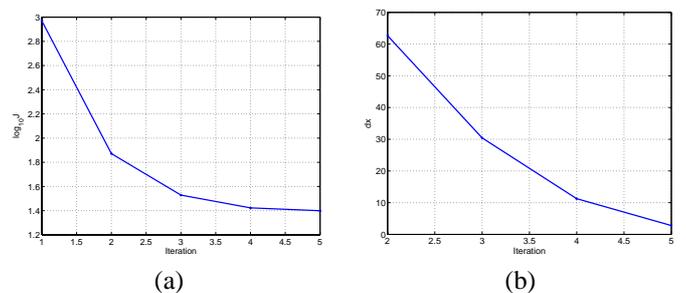


Figure 8: Consecutive iterations of one set of cooperating agents working on the image shown in Figure 4–(g). Top: the segmentation results. Bottom: clusters.

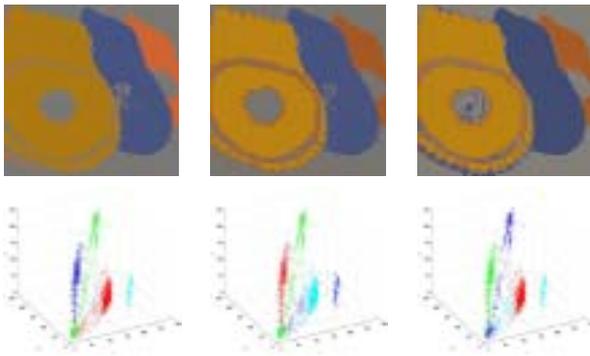


Figure 9: Results of three different races on the image shown in Figure 4-(d).

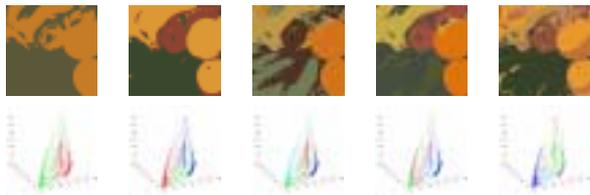


Figure 10: Results of the proposed clustering method performed on the image show in Figure 4-(e) with different values of c .

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Table 3: Results of the proposed clustering method performed on the images shown in Figure 4. [m: Fuzziness. t: Elapsed Time, J: Objective Function Value. i: Integrity.]

Image	m	$t(s)$	J	i	c
4-(a)	1.71	28	308	1	2
4-(b)	1.1	200	17	1	5
4-(c)	1.09	160	110	1.25	4
4-(d)	1.81	200	31	1.25	4
4-(e)	1.32	250	64	1.2	5
4-(f)	1.26	140	59	1.33	3
4-(g)	1.34	250	16	1	5
4-(h)	1.81	140	96	1.33	3
4-(i)	1.3	300	7	1.29	7
4-(j)	1.35	150	16	1.25	4
4-(k)	1.83	180	56	1.25	4
4-(l)	1.79	200	29	1	4

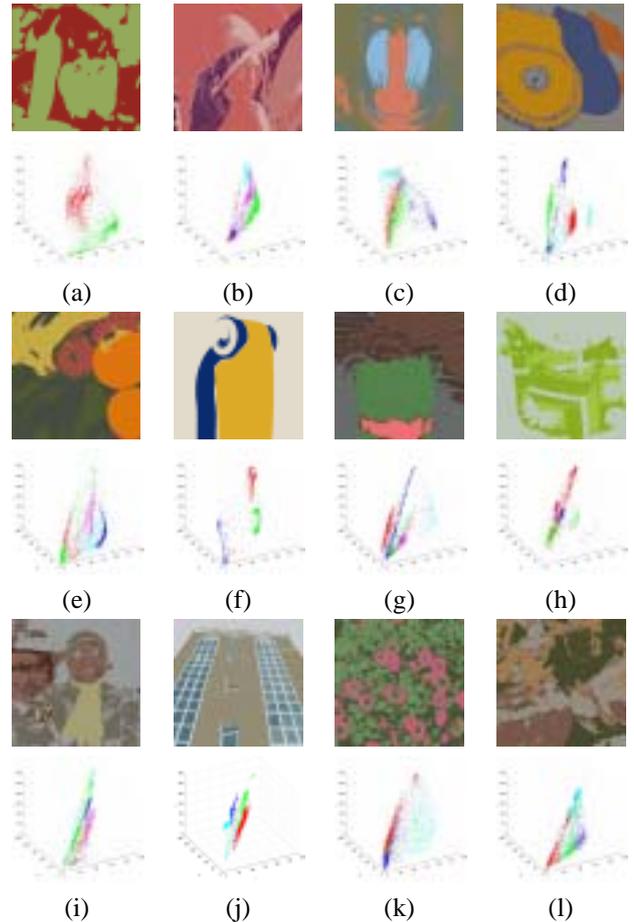


Figure 11: Results of the proposed clustering method performed on the images shown in Figure 4.

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