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An Unsupervised Image Clustering Method Based on EEMD Image Histogram

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Abstract. *This paper presents a novel unsupervised image clustering approach based on the image histogram, which is processed by the empirical mode decomposition (EMD). The proposed algorithm exploits an intermediate step derived from the empirical mode decomposition, which can decompose any nonlinear and non-stationary data into a number of intrinsic mode functions (IMFs). The IMFs of the image histogram have interesting characteristics and provide a novel workspace that is utilized in order to automatically detect the different clusters into the image under examination. The proposed method was applied to several real and synthetic images and the obtained results show good image clustering robustness.*
Keywords: Clustering, unsupervised clustering, empirical mode decomposition, ensemble empirical mode decomposition, intrinsic mode functions, segmentation.

1. Introduction.

Clustering problem has been addressed in many contexts and in many disciplines and this is the main reason for its extensive appeal and usefulness as a primary step in many applications. Clustering participates in pattern recognition, spatial data analysis, image processing, image classification in world wide web and large image databases, image segmentation, document retrieval, data mining and generally in data analysis [4, 6, 10, 12, 13, 21, 22, 24, 29, 30, 31, 32, 38, 41, 43]. However, clustering is a difficult problem due to many assumptions, different contexts and the variety of input data.

In the last few decades, there has been a growing interest in developing effective and fast methods for detecting the different clusters into an input image. Clustering in image processing and computer vision is a procedure for identifying groups of similar image primitives, such as image pixels, local features, segments, objects or even complete images. The general goal in image clustering is to classify the different image objects or patterns in such a way that samples of the same cluster are more similar to one another than samples belonging to different clusters.

There are two main types of image clustering algorithms, the supervised and the unsupervised methods. In the supervised image clustering algorithms, the researchers incorporate a priori knowledge, such as the number of image clusters. The main restriction in supervised image clustering is that human intervention is required. On the other hand, unsupervised methods aims at providing the correct number of image clusters without any a priori information. So far, various systems of supervised and unsupervised image clustering have been presented in the literature. These systems can be broadly divided into three main categories:

- hierarchical approaches,
- partitioning approaches,
- overlapping approaches.

In spite of the type of the algorithm adopted to perform clustering, the goal is always the same, i.e., the maximization of homogeneity within each cluster and the minimization of heterogeneity between different clusters. Additional information about the aforementioned clustering categories can be found in the excellent review publications that have appeared in the literature [4, 10, 12, 13, 31, 41].

Hierarchical image clustering methods build a cluster hierarchy which allows exploring the input data on different levels of granularity. Hierarchical image clustering methods are separated into agglomerative and divisive methods. An agglomerative clustering algorithm starts with clusters composed by one image pixel and recursively merges two or more appropriate image clusters. On the other hand, a divisive clustering algorithm starts with one cluster composed by all the image pixels and recursively splits the most appropriate clusters. The recursively procedure, in both categories, is based on a well defined criterion, e.g. the number of image clusters. Hierarchical clustering methods are used by many researchers to perform image clustering [1, 5, 16, 19, 20].

Hierarchical image clustering methods separate gradually the input image into clusters while partitioning image clustering algorithms learn directly the image clusters. Partitioning image clustering algorithms construct various partitions of the input data and then evaluate them by some criterion. The basic idea of partitioning image clustering is to select a number of instances to represent the image clusters and all the remaining instances are assigned to their closer center based on appropriate selected attributes. The main difficulty in this category, is to find a distance measure that can efficiently classify the input data into different clusters. The most famous partitioning clustering method is the k-means algorithm [23], but many other approaches have been also introduced [9, 14, 27, 28, 34].

The aforementioned traditional clustering methods classify each point of the data set just to one cluster. As a consequence, the results are often very crisp, i.e., in image clustering each pixel of the image belongs just to one cluster. However, in many real situations, issues such as limited spatial resolution, poor contrast, overlapping intensities, noise and intensity inhomogeneities reduce the effectiveness of hard (crisp) clustering methods. Hence, a new category of image clustering approaches has been appeared: overlapping approaches. Overlapping algorithms produce data partitions that can be soft, i.e., objects can belong to one or more clusters [7, 33]. Fuzzy set theory [44] extends this notion to associate each pattern with every cluster using a membership function. Fuzzy clustering, as a soft segmentation method, has been widely studied and successfully applied in image clustering and segmentation [2, 15, 17, 18, 26, 36, 37, 42].

A novel unsupervised image clustering algorithm is presented in this paper. The proposed algorithm provides efficiently the number of the different image clusters and the image clusters. The proposed technique exploits an intermediate step of the Empirical Mode Decomposition (EMD) applied to the image histogram, in order to classify the image pixels in appropriate clusters. More specifically, the Ensemble Empirical Mode Decomposition (EEMD), which provides noise resistance and assistance to data analysis, decomposes the image histogram into a number of Intrinsic Mode Functions (IMFs). The local minima of the IMFs summation provides the desired number of image clusters and a combination of them is used as a criterion for image clustering.

The remainder of the paper is organized as follows. The *Empirical Mode Decomposition* (EMD) with its ensemble mode (EEMD) is presented in Section 2. In Section 3, the image clustering method is introduced. Experimental results are shown in Section 4 and conclusions are drawn in Section 5.

2. **Empirical Mode Decomposition (EMD).**

In this Section, the empirical mode decomposition (EMD) and the derived intrinsic mode functions (IMFs), which are used in order to perform image clustering, will be briefly reviewed. More details regarding the decomposition process, its properties and all the adopted assumptions are presented in [11, 40].

The basic idea embodied in the EMD analysis is the decomposition of any complicated data set into a finite and often small number of intrinsic mode functions, which have different frequencies, one superimposed on the other. The main characteristic of the EMD, in contrast to almost all previous decomposition approaches, is that EMD works directly in temporal space, rather than in the frequency space. The EMD method, as Huang *et al.* pointed out [11], is direct intuitive and adaptive with an *a-posteriori* defined basis based on and derived from the data and therefore, highly efficient. Since the decomposition of the input signal is based on the local characteristic time scale of the data, the EMD is applicable to nonlinear and non-stationary process.

The IMFs obtained by the decomposition method, constitutes an adaptive basis, which satisfies the majority of properties for a decomposition method, i.e., the convergence, completeness, orthogonality and uniqueness. Moreover, EMD algorithm copes with stationarity (or the lack of it) by ignoring the concept and embracing non-stationarity as a practical reality [11].

The possibly non-linear signal, which may exhibit varying amplitude and local frequency modulation, is linearly decomposed by EMD into a finite number of (zero mean) frequency and amplitude modulated signals. The remainder signal, called as a residual function, exhibits a single extremum and is a monotonic trend or is simply a constant.

In the EMD algorithm, the data $x(t)$ is decomposed in terms of IMFs c_i, as follows:

$$x(t) = \sum_{i=1}^{N} c_i + r_N, \tag{1}$$

where r_N is the residue of data $x(t)$, after N number of IMFs are extracted. IMFs are simple oscillatory functions with varying amplitude and frequency, and hence have the following basic properties:

- Throughout the whole length of a single IMF, the number of extrema and the number of zero-crossings must either be equal or differ at most by one (although these numbers could differ significantly for the original data set).
- At any data location, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

In practice, the EMD is implemented through a "sifting process" that uses only local extrema. From any data r_{i-1}, the procedure is as follows:

1. Identify all the local extrema (the combination of both maxima and minima), connect all these local maxima (minima) with a cubic spline as the upper (lower) envelope, and calculate the local mean m_i of the two envelopes.
2. Obtain the first component $h = r_{i-1} - m_i$ by taking the difference between the data and the local mean of the two envelopes.
3. Treat h as the data and repeat steps 1 and 2 as many times as required until the envelopes are symmetric with respect to zero mean under certain criteria.

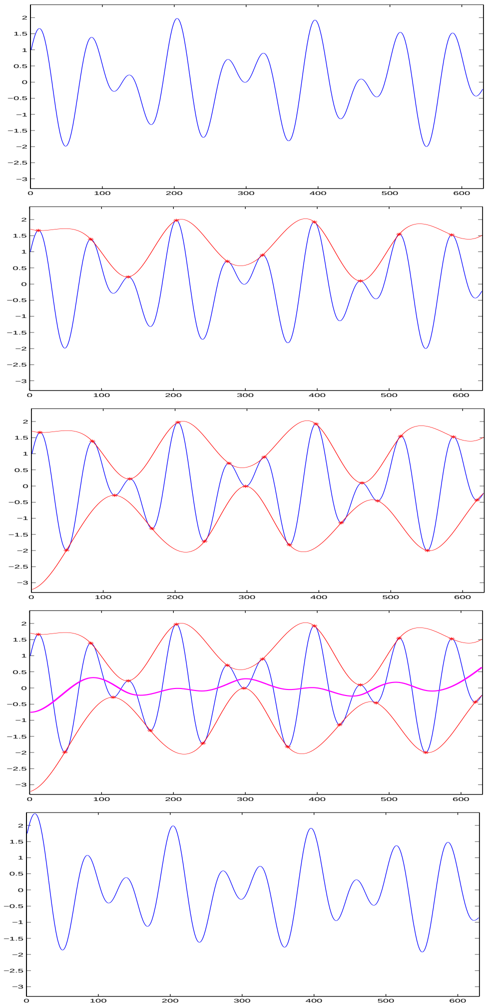
The final h is designated as c_i. The procedure can be repeatedly applied to all subsequent r_i, and the result is

$$\begin{array}{lcl} x(t) - c_1 & = & r_1 \\ r_1 - c_2 & = & r_2 \\ & \cdots & \\ r_{N-1} - c_N & = & r_N. \end{array} \tag{2}$$

The decomposition process finally stops when the residue, r_N, becomes a monotonic function or a function with only one extremum from which no more IMF can be extracted. By summing up equation (2), one can derive the basic decomposition equation (1). That is, a signal $x(t)$ is decomposed to N IMFs (c_i) and a residual r_N signal.

The very first step of the sifting process is depicted in Figure 1. Figure 1(a) depicts the original input data, while Figures 1(b) and 1(c) show the extrema (maxima and minima) of the data with their corresponding (upper and lower) envelopes. Figure 1(d) depicts the average of the two (upper and lower) envelopes, and Figure 1(e) illustrates the residue signal, that is the difference between the original data and the mean envelope. This procedure is repeated, as mentioned above, and all the IMFs are extracted from the original input signal. An example of the EMD algorithm and the extracted IMFs for the input data shown in Figure 1(a), is presented in Figure 2.

Based on this simple description of EMD, Flandrin *et al.* [8] and Wu and Huang [39] have shown that, when the data consists of white noise, the EMD behaves as a dyadic filter bank:



(a) (b) (c) (d) (e)

Figure 1. *The very first step of the sifting process.* ***(a)*** *is the input data,* ***(b)*** *identifies local maxima and plots the upper envelope,* ***(c)*** *identifies local minima and plots the lower envelope,* ***(d)*** *plots the mean of the upper and lower envelope, and* ***(e)*** *the residue, the difference between the input data and the mean of the envelopes.*

the Fourier spectra of various IMFs collapse to a single shape along the axis of logarithm of the period or the frequency. Then the total number (N+1) of IMFs of a data set is close to $log_2 N'$, with N' being the number of total data points. On the other hand, when the data is not pure noise, some scales could be missing, and as a consequence, the total number of the IMFs might be fewer than $log_2 N'$. Additionally, the intermittency of signals in certain scale would also cause mode mixing.

One of the major drawbacks of EMD is mode mixing. Mode mixing is defined as a single IMF either consisting of signals with widely disparate scales or consisting of a signal with a similar scale residing in different IMF components. Mode mixing is a consequence of signal intermittency. The intermittency could not only cause serious aliasing in the time-frequency distribution but could also make the individual IMF lose its physical meaning [11]. Another side effect of mode mixing is the lack of physical uniqueness. Supposing that two observations of the same oscillation are made simultaneously, one contains a low level of random noise and the other does not. The EMD decompositions for the corresponding two records are significantly different [40].

However, since the cause of the problem is due to mode mixing, one expects that the decomposition would be reliable if the mode mixing problem is alleviated or eliminated. To achieve

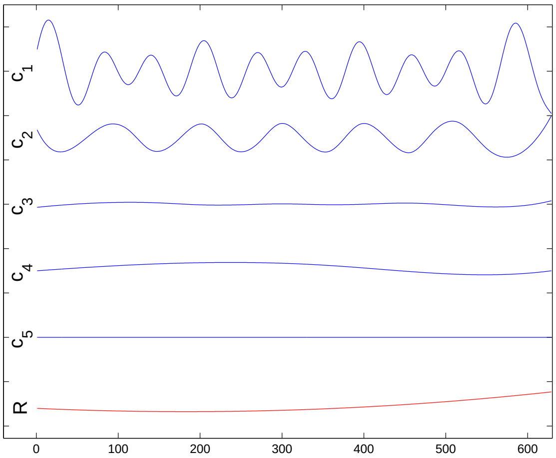


FIGURE 2. *The intrinsic mode functions (IMFs) of the input data displayed in Figure 1(a).*

the latter goal, i.e., to overcome the scale mixing problem, a new noise-assisted data analysis method was proposed, named as the ensemble EMD (EEMD) [40]. The EEMD defines the true IMF components as the mean of an ensemble of trials, each one consisting of the signal with white noise of finite amplitude.

The ensemble EMD (EEMD) algorithm could be summarized as follows:

1. add a white noise series $w(t)$ to the original input data $x_i(t) = x(t) + w_i(t)$,
2. decompose the data with added white noise into IMFs $c_{jk}(t)$,
3. repeat steps 1 and 2 but with different white noise series each time, and
4. obtain the (ensemble) means of corresponding IMFs $c_j(t) = \lim_{L\to\infty} \frac{1}{L}\sum_{k=1}^{L} c_{jk}(t)$ of the decomposition as the final result.

The critical concepts advanced in EEMD are based on the following observations:

- A collection of white noise cancels each other out in a time-space ensemble mean. Therefore, only the true components of the input data can survive and persist in the final ensemble mean.
- Finite, not infinitesimal, amplitude white noise is necessary to force the ensemble to exhaust all possible solutions.
- The physically meaningful result of the EMD is not from the data without noise, but it is designated to be the ensemble mean of a large number of EMD trials of the input data with the added noise.

The mode mixing is largely eliminated using EEMD, and the consistency of the decompositions of slightly different pairs of data is greatly improved. Indeed, EEMD represents a major improvement over the original EMD. Furthermore, since the level of the added noise is not of critical importance and of finite amplitude, EEMD can be used without any significant intervention. Thus, it provides a truly adaptive data analysis method. The EMD, with the ensemble approach (EEMD), has become a more mature tool for nonlinear and non-stationary time series (and other one dimensional data) analysis.

3. **Image Clustering Based-On EEMD.** In this Section, the proposed image clustering method is introduced. This method is based on the IMFs extracted by the EEMD algorithm applied on the histogram of the image under examination. The proposed method belongs to the unsupervised image clustering algorithms, thus, it is assumed that the number of the image clusters is unknown and expected to be determined by the proposed algorithm.

The histogram $h(k)$ is computed for an input image I with $k = 0 \dots G$ and G being the maximum luminance value in the image I, typically equal to 255 when 8-bit quantization is

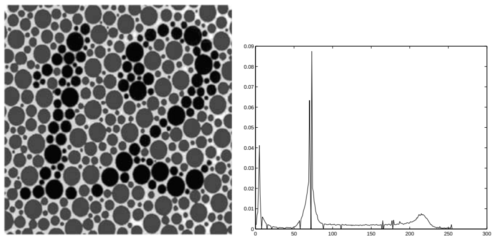


FIGURE 3. *An 8-bit image for color blindness test and its probability mass function.*

assumed. Then, the probability mass function (PMF) of the image histogram is defined as the normalized histogram by the total pixel number:

$$p(k) = \frac{h(k)}{M}, \tag{3}$$

where M is the total number of image pixels. An example of an 8-bit image and its normalized histogram is depicted in Figure 3.

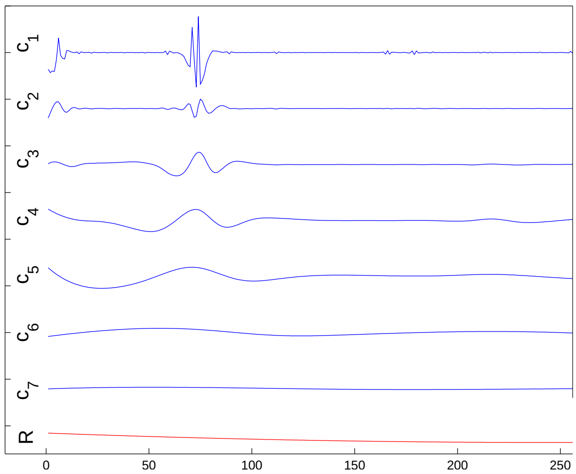


FIGURE 4. *The IMFs of the histogram for the image depicted in Figure 3 with a Gaussian noise of variance 0.2 and 1000 trials are performed.*

The normalized histogram $p(k)$ of an image could provide very useful information when it is properly analyzed. In the proposed method, the EEMD algorithm has been selected in order to analyze the histogram into its IMFs, in order to detect the different image clusters, as well as, the number of clusters for the image under examination. The IMFs of the histogram of the image shown in Figure 3, are presented in Figure 4. The IMFs are produced using the EEMD algorithm with Gaussian noise of zero mean, variance equal to 0.2 and 1000 trials are performed. The number of the extracted IMFs (including the residue function) for a 8-bit quantized image is $log_2(256) = 8$.

One can easily see in Figure 4 that the first IMFs (c_1 for an 8-bit image) mainly carries the histogram "noise", irregularities and the sharp details of the histogram, while the last IMFs (c_6, c_7 and the residue R for an 8-bit image) mostly describe the trend of the histogram. On the other hand, the intermediate IMFs (c_2 to c_5 for an 8-bit image) describe the initial histogram with simple and uniform pulses. This is the main reason that the proposed method is focused on c_a to c_b intermediate IMFs, where a and b define the range of IMFs under consideration. Let us define the summation $c_{a,b}$ of these IMFs as follows:

$$c_{a,b} = \sum_{i=a}^{b} c_i. \tag{4}$$

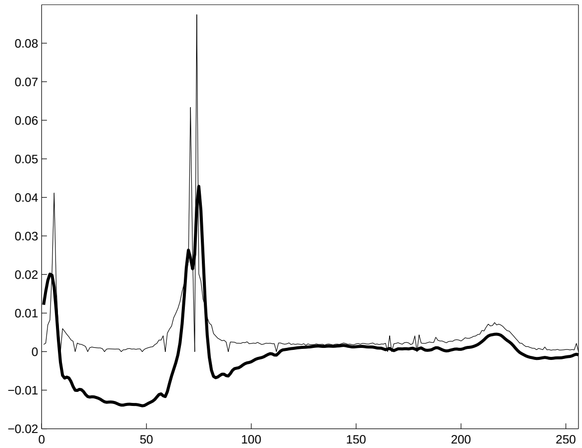


Figure 5. *The normalized histogram of the image shown in Figure 3 (thin line) and the summation of the* c_2 *to* c_5 *IMFs (fat line).*

Figure 5 depicts the summation $c_{a,b}$ (fat line) in contrast to the initial histogram (thin line) for the 8-bit image shown in Figure 3. One can notice that the summation $c_{a,b}$ describes the main part of the histogram leaving out all its meaningless details. Those details, most of the times, lead the histogram clustering, as well as, other algorithms based on histograms to wrong results and conclusions.

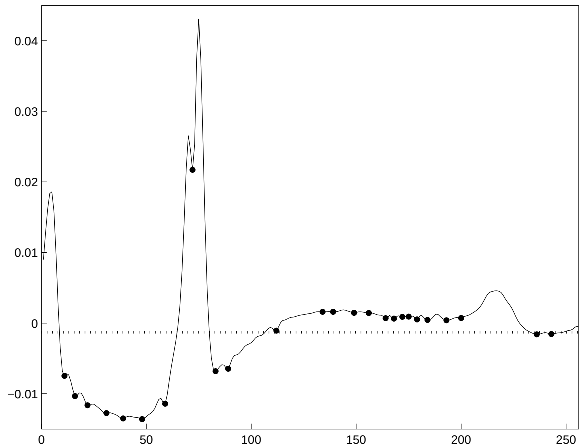


Figure 6. *The produced vector* $c_{a,b}$ *(Figure 5), the local minima (dots) and the threshold produced by the proposed algorithm (dotted line).*

The next step of the proposed algorithm is the determination of all local minima of the produced vector $c_{a,b}$:

$$C^* = \{\min_{0 \le T \le G} c_{a,b}(T)\}. \tag{5}$$

Figure 6 depicts the local minima (fat dots) of the vector $c_{a,b}$ of the image histogram shown in Figure 3. All those local minima could express image clusters, but most of them are very close to each other and some of them lie too high to be a cluster. Thus, the proposed algorithm truncate those local minima to the important ones, i.e., to those that could express an image cluster. This truncation procedure is consisted by two steps. The first truncation step is the removal of the local minima (candidate clusters) that are very high. Thus, a threshold is determined for that purpose, which could be dynamically calculated by the average of the values of the local minima:

$$thr = \frac{1}{2N_{C^*}} \sum_{c_i^* \in C^*} c_i^*, \tag{6}$$

where the c_i^* denotes a local minimum belonging to the vector C^* carrying all local minima and N_{C^*} is the number of local minima belonging to C^*. An example of that threshold is shown in Figure 6 with a dotted line.

The proposed algorithm truncates all local minima (candidate clusters) that have a value larger than the produced threshold:

$$C^t = \{c_i^*\}, \quad \text{if } c_i^* < thr \text{ and } c_i^* \in C^*. \tag{7}$$

In Figure 6, the vector C^t is consists of all local minima (candidate clusters) which are less than the estimated threshold thr (dotted line).

The second and last truncation step of the proposed algorithm is the removal of the candidate image clusters which are consisted of a very small number of image pixels, i.e., less than 2% of the total number of image pixels. Thus, the proposed algorithm applies an iterative procedure that calculates the number of image pixels belonging to each candidate image cluster and prunes the cluster with the smallest number of image pixels and in the same time this number is below than a predefined threshold, usually a low rate of the total image pixels:

$$C = \{c_i^t\}, \quad \text{if } n_i^t < n_{thr} \text{ and } c_i^t \in C^t, \tag{8}$$

where the n_i^t denotes the number of image pixels belonging to the cluster configured from the c_i^t and c_{i+1}^t, and n_{thr} is the predefined threshold. The pruned candidate clusters are merged with their closest image clusters.

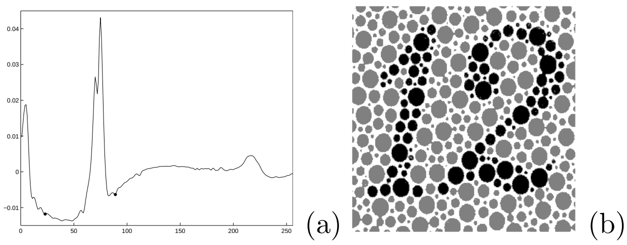


FIGURE 7. ***(a)****The final estimated clustering ranges (dots) and* ***(b)*** *the clustered image.*

Figure 7(a) presents the remained candidate clusters of the histogram examined in Figure 6, and Figure 7(b) illustrates the clustered image after applying the estimated cluster ranges.

The remaining vector C, not only defines the image clusters, but also determines the exact number of image clusters. The efficiency of the proposed method will be shown in the next Section.

Finally, the overall clustering algorithm is summarized in Figure 8.

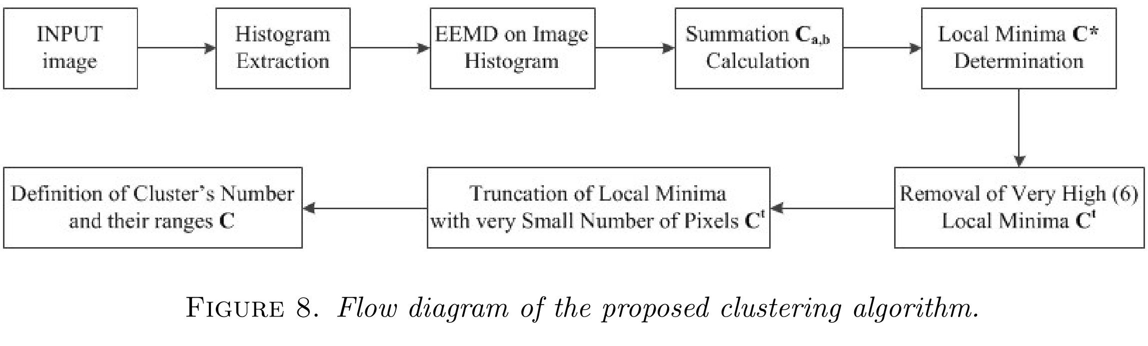


FIGURE 8. *Flow diagram of the proposed clustering algorithm.*

4. **Experimental Results.** In this Section, the performance of the proposed unsupervised image clustering method is examined by presenting numerical results using the introduced clustering approach on various synthetic and real images, with different types of histograms. The obtained results are compared with the corresponding results of a well-known unsupervised clustering method [3] applied to various images. In all the experiments, the EEMD image clustering

algorithm was used with Gaussian noise of zero mean and variance equal to 0.2 and 1000 trials are performed. Also, the IMFs range from $[a, b] = [2, 5]$, since in all the tested images was used 8-bit quantization.

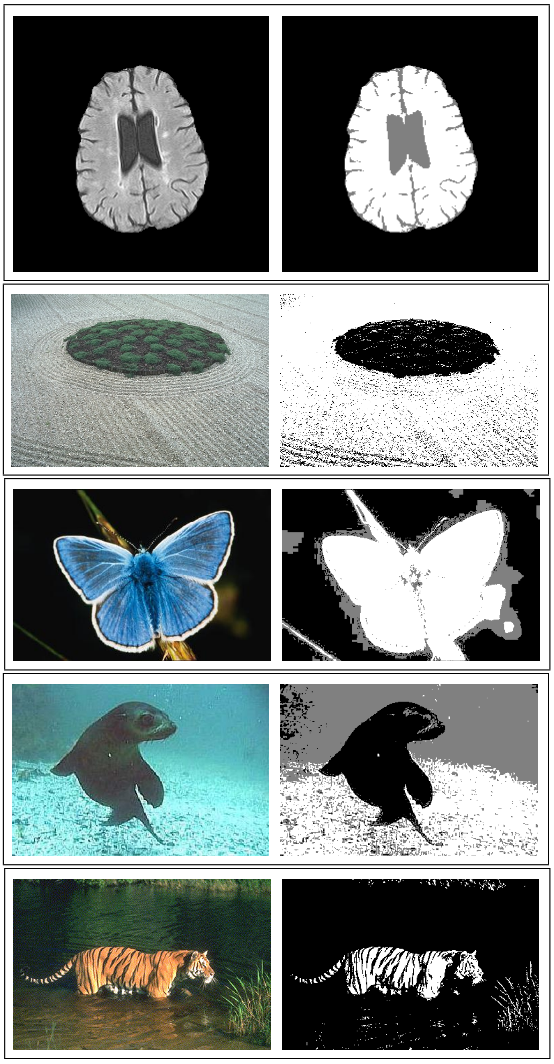


FIGURE 9. *Five images depicting real scenes (left column) and their corresponding image clusters produced by the proposed method (right column).*

Figure 9 presents five real images selected randomly from the Berkeley image segmentation database [25] and their corresponding image clusters obtained by the proposed approach. The left column in Figure 9 shows the initial images which depict real, complex scenes, while the right column shows the corresponding image clusters produced by the proposed algorithm. One can clearly see that the proposed method not only can provide the image clusters, but also can efficiently compute the number of image clusters.

In the next set of experiments, the proposed method was tested against a well known image clustering algorithm, the ISODATA [3] image clustering algorithm. In order to evaluate the two algorithms, ground truth data was extracted manually for the testing images. Figure 10 presents the image clusters extracted by the two afore mentioned methods for some of the testing images. The first column shows the initial images, the second columns depicts the ground truth data which was manually extracted in order to calculate the numerical results depicted in Table 1. The third column presents the image clusters produced by the proposed algorithm, while the final column shows the image clusters acquired by the ISODATA method [3]. One can easily see that the proposed image clustering algorithm provides better results than the other two algorithms.

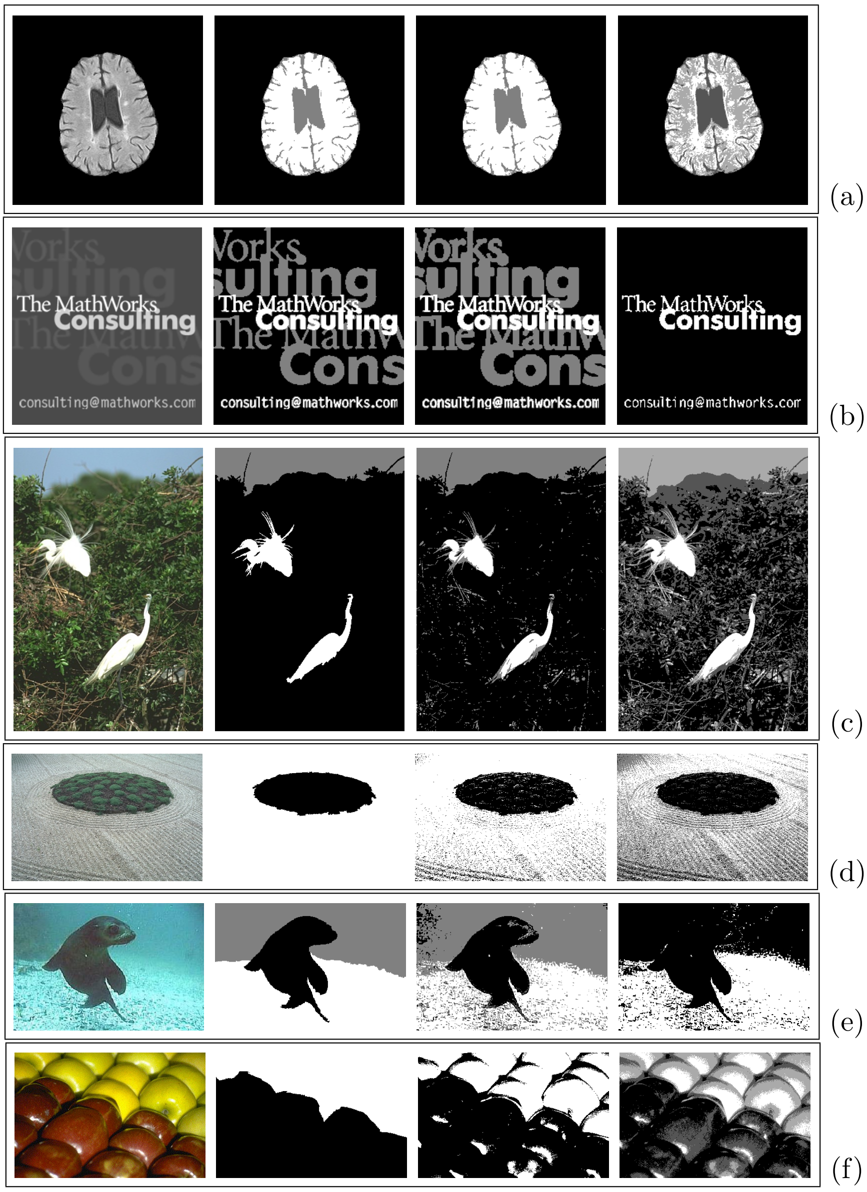


FIGURE 10. *Initial images (first column), image clusters: ground truth (second column), proposed method (third column) and ISODATA image clustering method* [3] *(last column).*

TABLE 1. Error comparison based on the Tanimoto/Jacard error for the proposed image clustering algorithm and the ISODATA method [3].

Tested Images	**Proposed**	**ISODATA** [3]
Fig. 10(a)	**0.0632**	0.1730
Fig. 10(b)	**0.0963**	0.2436
Fig. 10(c)	**0.0401**	0.5057
Fig. 10(d)	**0.0621**	0.4174
Fig. 10(e)	**0.1113**	0.4250
Fig. 10(f)	**0.1011**	0.4875
average values of tested images	**0.1178**	0.3757

This fact, is also confirmed by Table 1 which presents the well known Tanimoto/Jacard error

[35] measure $E(\cdot)$ defined as:

$$E(o,m) = 1 - \frac{\int_{I_o \bigcap I_m} dxdy}{\int_{I_o \bigcup I_m} dxdy}, \tag{9}$$

where I_m and I_o are the extracted and the desired segmented images respectively. In Table 1, the desired segmented images have been extracted manually and then, compared by equation (9) with the acquired segmented images produced by the proposed method and ISODATA clustering method [3]. The error for the proposed algorithm indicates very small values, which means that the acquired results are closer to the ground truth data. On the contrary, the ISODATA method produces lager error values, thus, the acquired image clusters differ from the ground truth data. Furthermore, the proposed algorithm estimates the number of image clusters more efficient (more reasonable) than the ISODATA method, which produces either overclustered images or images with a very small number of clusters. In this set of experiments, various images with real and synthetic scenes were used. All the images with real scenes are derived from Berkeley database [25]. The Berkeley database which contains image segmentation ground truth data from 30 different human subjects and can be easily used in order to identify the different image clusters in the testing image.

5. **Conclusion.** In this paper, a novel unsupervised image clustering method is introduced. The proposed approach exploits ensemble empirical mode decomposition (EEMD) to analyze the histogram of the image under examination. The EEMD algorithm can decompose any nonlinear and non-stationary data into a number of intrinsic mode functions (IMFs). The proposed algorithm uses only a number of the intermediate IMFs of the EEMD decomposition, which have interesting characteristics and provide a novel workspace that is utilized in order to automatically detect not only the different clusters, but also the number of clusters into the image under examination. The effectiveness of the proposed image clustering method is proved in the experimental results Section where the proposed image clustering algorithm is applied to various images with simple and complex scenes.

Furthermore, the extension of the proposed clustering algorithm to color image clustering is an open research topic, since there is no a systematic way to mixture color channels.

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