An Empirical Method for Threshold Selection

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Abstract

The performance of a number of image processing methods depends on the output quality of a thresholding process. Typical thresholding methods are based on partitioning pixels in an image into two clusters. In this paper, a new thresholding method is presented. The main contribution of the proposed approach is the application of the empirical mode decomposition (EMD) on detecting an optimal threshold for an input image. The EMD algorithm can decompose any nonlinear and non-stationary data into a number of intrinsic mode functions (IMFs). When the image is decomposed by empirical mode decomposition (EMD), the intermediate IMFs of the image histogram have very good characteristics on image thresholding. The experimental results are provided to show the effectiveness of the proposed threshold selection method.

Keywords: Threshold selection, clustering, empirical mode decomposition, ensemble empirical mode decomposition, intrinsic mode.

1 Introduction

Image thresholding is one of the main and most important tasks in image analysis and computer vision. Thresholding principle is based on distinguishing an object (foreground) from the background in order to be extracted useful information from the image. Thresholding is a procedure similar to clustering, which assigns a pixel to one class whether its gray value is greater than a predefined threshold or not.

In the computer vision literature, various methods have been proposed for image thresholding [17, 21]. However, the design of a robust and an efficient thresholding algorithm is far from being a simple process, due to the existence of images depicting complex scenes at low resolution, uneven illumination, scale changes, etc.

Thresholding techniques could be categorized in six groups [21] according to information being exploited. These categories are:

- Shape-based methods, which analyze the shape of the histogram of the image (i.e., the peaks, valleys and curvature) [5, 15, 20]. Methods belong to this category achieve, thresholding based on the shape properties of the histogram. Each method uses different forms of properties. The distance from the convex hull of the histogram is investigated in [15, 16], while the histogram is forced into a smoothed two-peaked representation via autoregressive modeling in [5]. Other algorithms search explicitly for peaks and valleys, or implicitly for overlapping peaks via curvature analysis [20].

- Clustering-based methods, which label the gray-level samples as background or foreground (object), or alternatively they model them as a mixture of two Gaussians [11, 12, 13, 15, 20, 27]. In this category, the gray-level data undergoes a clustering analysis, with the number of clusters being always equal to two. Some algorithms search for the midpoint of the peaks, since the two clusters correspond to the two lobes of a histogram [27]. Other methods are based on the fitting of the mixture of Gaussians [3]. Mean-square clustering is used in [13], while fuzzy clustering ideas have been adapted in [9].
- Entropy-based methods, which use the entropy of the foreground and the background regions, the cross-entropy between the original and the binarized image etc. [10, 18, 29]. These algorithms exploit the entropy of the distribution of the gray levels in an image. The maximum information transfer is considered to be the maximization of the entropy of the thresholded image [10, 18]. Other methods minimize the cross-entropy between the initial gray-level image and the output binary image, in order to preserve the image information.
- Attribute-based methods, which seek a measure between the gray-level and the binarized images, such as fuzzy shape similarity, edge coincidence, etc. [6, 7, 14]. These algorithms evaluate the threshold value by using attributes quality or similarity measures between the initial gray-level image and the output binary image. Some methods exploit the form of edge matching [6], shape compactness, gray level moments, connectivity, texture or stability of segments objects [14]. In the same category, other algorithms evaluate directly the resemblance of the initial gray level image to the binary image, using fuzzy measures [7] or resemblance of the cumulative probability distributions.
- Spatial methods, which exploit higher-order probability distribution and/or correlation between the image pixels [1, 2]. The algorithms in this category utilize not only the gray level distribution, but also the dependency of pixels in a neighborhood, for example, the probabilities, correlation functions, cooccurrence probabilities, local linear dependence models of image pixels, 2-D entropy etc.
- Local methods, which adapt the threshold value on each image pixel to the local image characteristics [19, 23, 28]. Algorithms belonging in this class, calculate a threshold at each image pixel, which depends on some local statistics such as range, variance [19], contrast [23] or surface-fitting parameters of the pixel neighborhoods [28].

A survey of thresholding methods can be found in the excellent review publication that has appeared in the literature [21]. Four well-known thresholding methods will be reviewed in this paper: (i) Otsu's thresholding method [13], (ii) Huang and Wang's fuzzy entropy measure-based thresholding method [7], (iii) Kittler's thresholding algorithm [11], and (iv) Kwon's thresholding method [12].

Otsu [13] has suggested a thresholding method that minimizes the weighted sum of within-class variances of the foreground and background pixels $J_T = \left[P_1 P_2 (m_1 - m_2)^2\right] / (\sigma_1^2 + \sigma_2^2)$, in order to establish an optimum threshold T. P_1 and P_2 are the number of pixels belonging to the two classes, i.e. the foreground and background, m_1 and m_2 are the average gray level of each class and σ_1^2 and σ_2^2 are their variances. Recall of the minimization of within-class variances is tantamount to the maximization of between-class scatter. This method gives satisfactory results when the number of pixels in each class are close to each other.

Huang and Wang [7] have developed a fuzzy entropy-based thresholding method, which utilizes the histogram image pixels, thus it is not necessary to deal with each pixel individually. This method creates an index of fuzziness by measuring the distance between the gray-level image and its binary version. The image I is represented as the array $\mu_f(I)$, where $0 \leq \mu_f(I) \leq 1$ represents the fuzzy measure of belonging to the foreground. Given the fuzzy membership value for each image pixel, an index of fuzziness for the whole image can be obtained via the Shannon entropy, which is used as a cost function. The optimum threshold is calculated by minimizing the index of fuzziness defined in terms of class (foreground and background) medians or means and membership functions $J_T = -\frac{1}{ln2}\sum_{z=0}^{255}[\mu_f(g)ln(\mu_f(g)) + (1-\mu_f(g))ln(1-\mu_f(g))]$.

Kittler and Illingworth [11] assume that the image can be characterized by a mixture distributions of foreground and background pixels and addresses a minimum error Gaussian density-fitting problem $J_T = P_1 log(\sigma_1) + P_2 log(\sigma_2) - P_1 log(P_1) - P_2 log(P_2)$. P_1 and P_2 are the number of pixels belonging to the two classes (foreground and background), and σ_1 and σ_2 are the standard deviations of each class.

Kwon [12] has recently developed a clustering-based algorithm, addressing the minimization of an intra-class and inter-class similarity problem $J_T = [P^2(\sigma_1^2+\sigma_2^2)+1/2((m_1-m)+(m_2-m))]/(m_1-m_2)^2$. P is the total number of image pixels, m_1 and m_2 are the average gray level value of each class (foreground and background) and σ_1 and σ_2 are their standard deviations.

This paper presents a novel, fast and robust image thresholding method. The method is based on the decomposition of the histogram of the image by the *Empirical Mode Decomposition* (EMD) [8] to its *Intrinsic Mode Functions* (IMFs). More specific, the decomposition is performed by the *Ensemble Empirical Mode Decomposition* (EEMD) [25], which provides noise resistance and assistance to data analysis. The properties of the desired IMFs [8, 25] will be shown that provide an efficient threshold for the image under examination.

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 thresholding 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 determine the image threshold, will be briefly reviewed. More details regarding the decomposition process, its properties and all the adopted assumptions are presented in [8, 25].

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 [8], 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 [8].

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-1 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

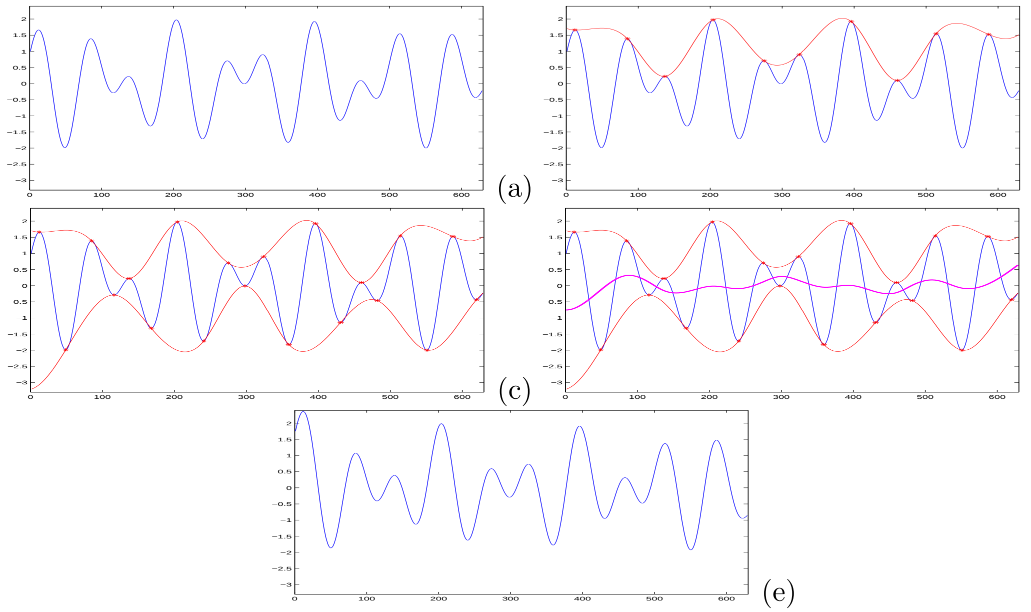


Figure 1. *The very first step of the sifting process.* ***(a)*** *is the input data,* ***(b)*** *identifies local maxima and plots the upper envelope,* ***(c)*** *identifies local minima and plots the lower envelope,* ***(d)*** *plots the the mean of the upper and lower envelope, and* ***(e)*** *the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

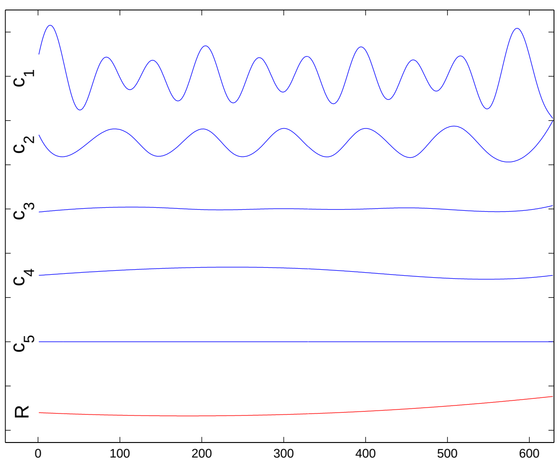


Figure 2. *The intrinsic mode functions (IMFs) of the input data displayed in Figure 1(a).*

average of the two (upper and lower) envelopes, and Figure 1(e) illustrates the residue signal, 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.* [4] and Wu and Huang [24] have shown that, when the data consists of white noise, the EMD behaves as a dyadic filter bank: 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 of IMFs of a data set is close to log_2N, 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_2N. 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 [8]. 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 [26].

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 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) [26]. 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 $c_j(t) = \lim_{N\to\infty} \frac{1}{N}\sum_{k=1}^{N} c_{jk}(t)$ 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 Threshold Selection Based-On EEMD

In this Section, the image threshold selection method is introduced. This method is fully automated and is based on the IMFs extracted by the EEMD algorithm applied on the histogram of the image under examination.

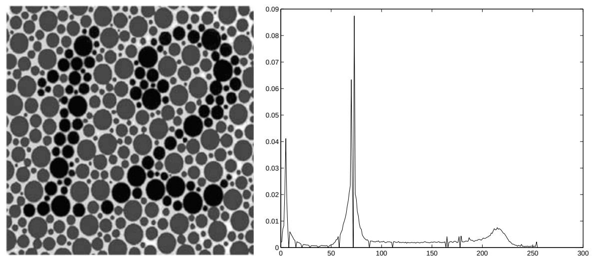


Figure 3. *An image for color blindness test and its probability mass function.*

The histogram $h(k)$ is computed for an input image I with $k = 0 \ldots G$ and G being the maximum luminance value in the image I, typically equal to 255 when 8-bit quantization is assumed. Then, the probability mass function (PMF) of the image histogram is defined as the normalized histogram by the total pixel number:

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

where N is the total number of image pixels. An example of an image and its normalized histogram is depicted in Figure 3. Also, the cumulative normalized histogram (probability mass function) is given by:

$$P(k) = \sum_{i=0}^{k} p(i). \tag{4}$$

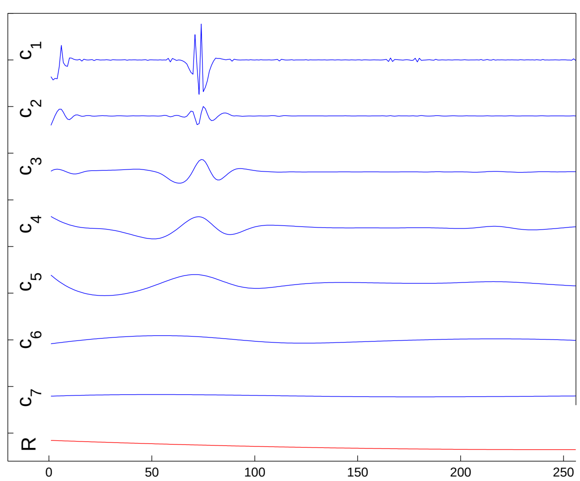


Figure 4. *The IMFs of the histogram for the image depicted in Figure 3 with a noise of amplitude 0.2 and 1000 trials are performed.*

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 find an efficient threshold 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 a noise of amplitude 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 $log_2(256) = 8$.

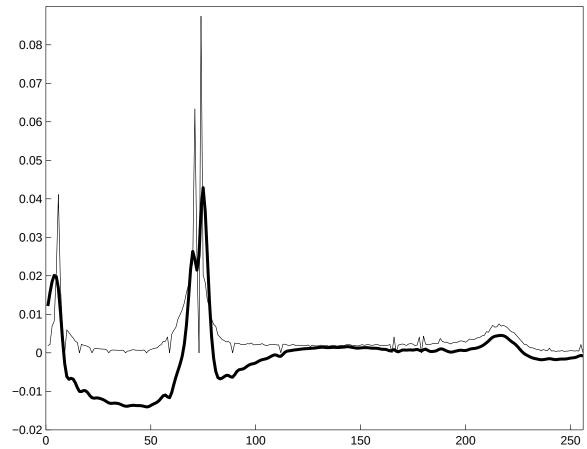


Figure 5. *The histogram of the image shown in Figure 3 (thin line) and the summation of the c_2 to c_5 IMFs (fat line).*

One can easily see in Figure 4 that the first IMF c_1 mainly carries the histogram "noise", irregularities and the sharp details of the histogram, while IMFs c_6, c_7 and the residue R mostly describe the trend of the histogram. On the other hand, IMFs c_2 to c_5 describe the initial histogram with simple and uniform pulses. This is the main reason that the proposed method is focused on c_2 to c_5 IMFs. Let us define the summation c_m of these IMFs as follows:

$$c_m = \sum_{i=2}^{5} c_i. \tag{5}$$

Figure 5 depicts the summation c_m (fat line) in contrast to the initial histogram (thin line). One can notice that this summation c_m describes the main part of the histogram leaving out all its meaningless details.

The minimum of summation c_m is given by:

$$T^* = \arg\left\{\min_{0\leq T\leq G} c_m(T)\right\}, \tag{6}$$

where T^* is the desired image threshold. Since the summation c_m provides a better, more clear and uniform formation of the image histogram, its minimum can be considered as an optimal threshold for the input image and its efficiency will be experimentally shown in the next Section.

4 Experimental Results

In this Section, the performance of the proposed method is examined by presenting numerical results using the introduced thresholding approach on various synthetic and real images, with different types of histogram. The obtained results are compared with the corresponding results of four well-known thresholding methods [7, 11, 12, 13]. In all the experiments, the EEMD algorithm was used with a noise of amplitude equal to 0.2 and 1000 trials are performed.

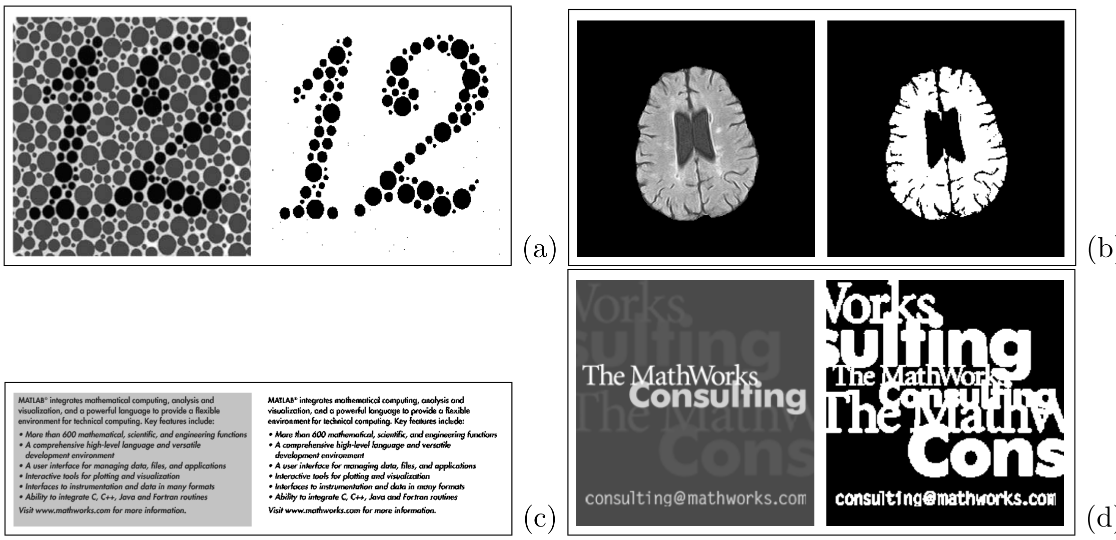


Figure 6. *Various images (left column) and their corresponding thresholded images produced by the proposed method (right column).*

Table 1. Threshold values determined by five threshold selection methods with the corresponding area difference measure results.

Method	Color blindness (Fig. 6(a))	MRI image (Fig. 6(b))	Doc. image 1 (Fig. 6(c))	Doc. image 2 (Fig. 6(d))
Proposed	0.006 (46)	0.006 (135)	0.017 (126)	0.136 (75)
Kittler's [11]	0.738 (179)	0.834 (193)	0.998 (195)	0.136 (75)
Otsu's [13]	0.615 (136)	0.100 (86)	0.091 (45)	0.781 (140)
Huang's [7]	0.711 (169)	0.230 (1)	0.085 (170)	0.760 (122)
Kwon's [12]	0.577 (110)	0.228 (48)	0.063 (152)	0.730 (101)

Figure 6 presents various real and synthetic images and their corresponding thresholded images obtained by the proposed approach. The left column shows the initial images, while the right column depicts the corresponding thresholded images produced by the proposed algorithm. One can clearly see that the proposed method can efficiently threshold the images under examination. Table 1 confirms the results in terms of the well known

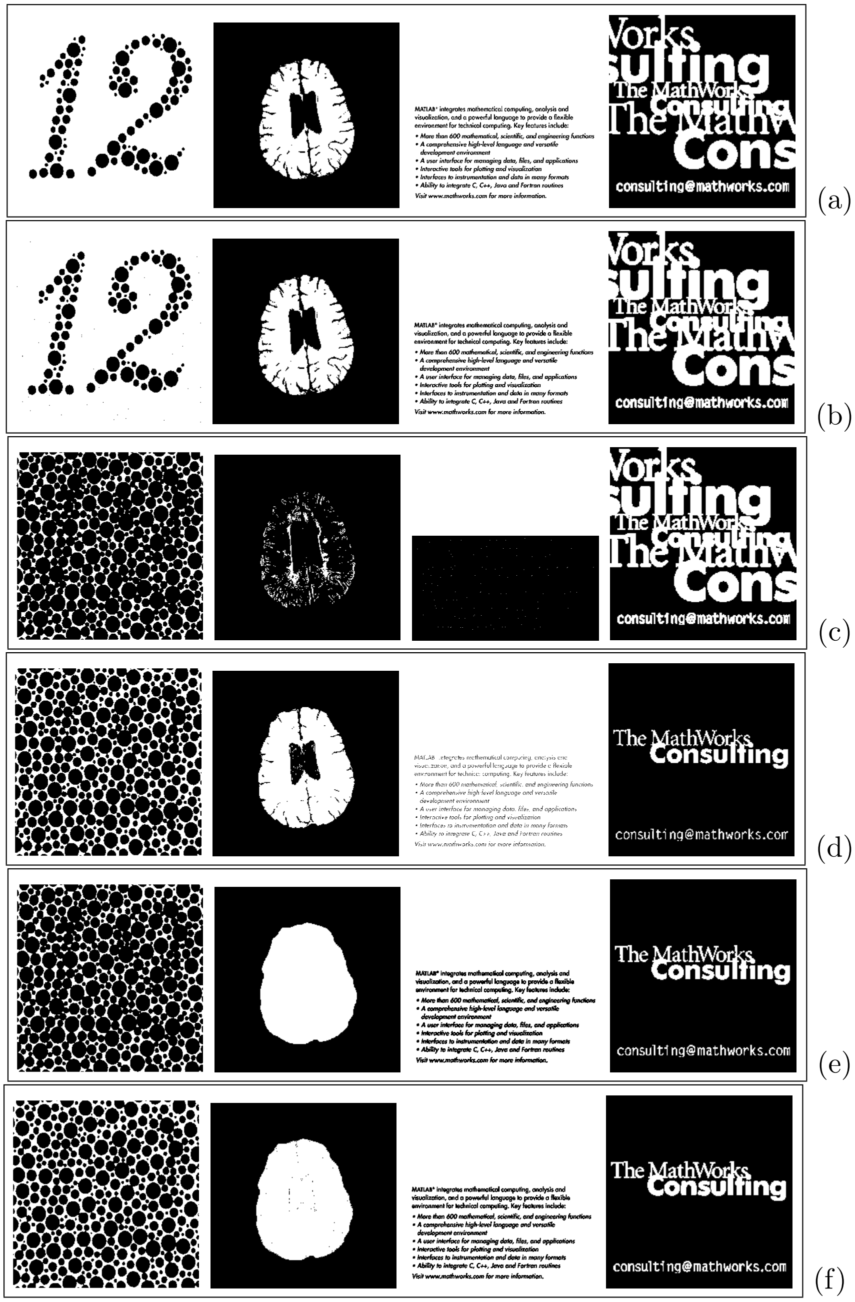
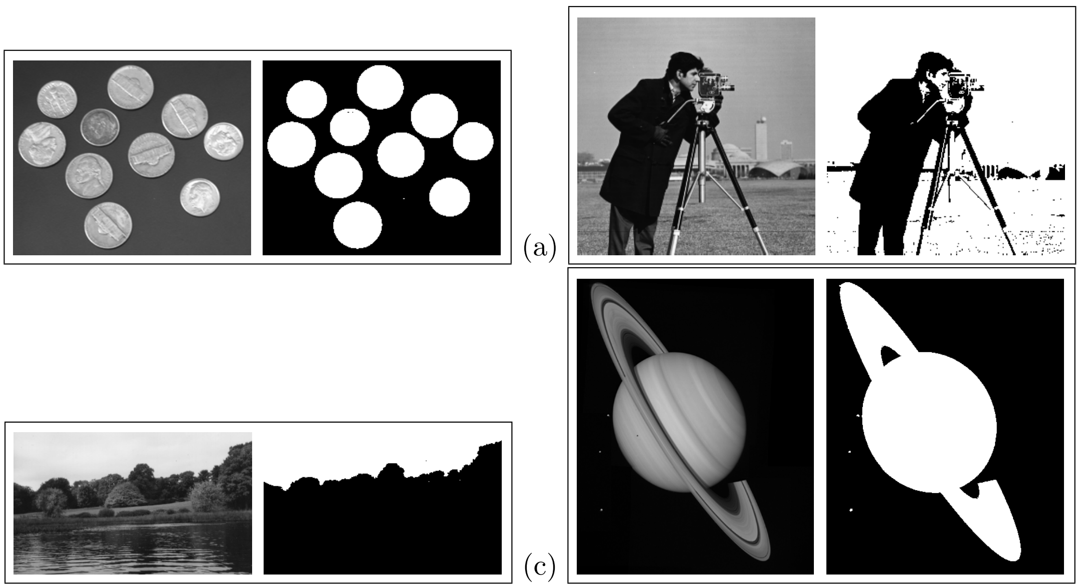


Figure 7. *Thresholded images: **(a)** ground truth, **(b)** proposed method, **(c)** Kittler's method, **(d)** Otsu's method, **(e)** Huang's method and **(f)** Kwon's method.*

Tanimoto/Jaccard error [22] $E(\cdot)$ defined here as:

$$E(o,m) = 1 - \frac{\displaystyle\int_{I_o \cap I_m} dxdy}{\displaystyle\int_{I_o \cup I_m} dxdy}, \tag{7}$$

where I_m and I_o are the extracted and the desired thresholded images respectively. In Table 1, the desired thresholded images have been extracted manually and then, compared (7) with the acquired thresholded images produced by the proposed method and four well known thresholding methods [7, 11, 12, 13]. The errors of the proposed methods are small enough to enforce one to claim that they are insignificant. On the contrary, the other four methods produce larger errors, a fact that is also depicted in Figure 7. The thresholded images produced by the proposed algorithm are more efficient. In Table 1, is also shown, the thresholds produced by the corresponding algorithms (the value in the parenthesis).



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

Figure 8. *Various images (left column) and their corresponding thresholded images produced by the proposed method (right column).*

Figure 7 presents the thresholded images extracted by the proposed and the rest algorithms [7, 11, 12, 13]. Figure 7a shows the ground truth which manually extracted in order to calculate the numerical results depicted in Table 1. Figure 7b depicts the thresholded images produced by the proposed algorithm, while Figures 7c-7f show the thresholded images acquired by the Kittler's method [11] (Fig. 7c), Otsu's method [13] (Fig. 7d), Huang's method [7] (Fig. 7e) and Kwon's method [12] (Fig. 7f).

Finally, Figure 8 shows various images (left column) and their corresponding thresholded images acquired by the proposed method. All images in Figure 8 depict complex scenes, especially Figure 8(d). However, the proposed algorithm thresholds these images in a very reasonable way, a fact that is also proved in Figures 6 and 7 and in parallel provides better performance than the other four methods.

5 Conclusion

In this paper, a novel image thresholding 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 specific components, the intermediate IMFs of the EEMD decomposition, in order to evaluate an optimal image threshold. The effectiveness of the proposed threshold selection method is proved in the experimental results Section where the proposed thresholding algorithm is applied to various images with simple and complex scenes. The extension of the proposed method for multi-level thresholding and color images is an open problem and being studied.

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