Fuzzy Partition and Correlation for Image Segmentation with Differential Evolution

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Abstract—**Thresholding-based techniques have been widely used in image segmentation. The selection of appropriate threshold is a very significant issue for image thresholding. In this paper, a new image histogram thresholding method based on fuzzy partition and maximum correlation criterion is presented. In the proposed approach, the regions, i.e. object and background, are considered ambiguous in nature, and hence the regions are transformed into fuzzy domain with membership functions. Then, the fuzzy correlations about regions are constructed and the optimal threshold is determined by searching an optimal parameter combination of the membership functions such that the correlation of the fuzzy partitions is maximized. Since the exhaustive search for all fuzzy parameter combinations is too costly, the differential evolution algorithm is introduced into fuzzy correlation image segmentation to solve this optimal problem adaptively. Experimental results on general images and infrared images demonstrate the effectiveness of the proposed method.**

Index Terms—**image thresholding, fuzzy partition, maximum correlation criterion, differential evolution algorithm**

I. Introduction

IMAGE segmentation is an important low-level preprocessing step for many computer vision problems. The purpose of this step is that objects and background are separated into nonoverlapping sets [1], [2]. Usually, this segmentation process is based on the image gray-level histogram, namely image histogram thresholding [3]. In that case, the aim is to find a critical value or threshold. Through this threshold, applied to the whole image, pixels whose gray levels exceed this critical value are assigned to one set and the rest to the other. In recent decades, many thresholding methods have been proposed [4]–[23]. In 1979, Otsu proposed a method that maximizes the separability of the resultant classes in gray levels utilizing a between-class variance function [4]. The Otsu method is one of the most famous thresholding approaches for image segmentation. Entropy model is also one of the most popular techniques in thresholding [5]–[10]. The Kapur method is developed based on the maximization of the class entropies [6]. Inspired by the idea of chaos and fractal theory, Yen et al. [12] presented a novel criterion for image thresholding, i.e. maximum correlation criterion. Computational analyses and simulation results indicate the high effectiveness of the maximum correlation criterion for image thresholding [12].

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There are some fuzziness factors in nature on image processing such as information loss while mapping 3-D objects into 2-D images, ambiguity and vagueness in some definitions (such as edges, boundaries, regions, and textures), ambiguity and vagueness in interpreting low-level image processing results [13]–[15]. Fuzzy sets theory is finding extensive applications to describe the vague concepts in the modern mathematical framework. For example, in pattern classification problem, instead of the conventional deterministic assignment of a sample to a class, fuzzy partitioning strategies provide soft description of the classes, where each of the sample points is assigned a membership in each of the classes. Image thresholding can be regarded as a classic pixels classification problem. To tackle the fuzzy characteristics exists in images, several fuzzy thresholding methods have been proposed for image segmentation, such as fuzzy partition entropy method [14]–[18].

In this paper, we present a new thresholding method utilizing the maximum correlation criterion based on the probability partition, fuzzy partition and differential evolution (DE) [24] algorithm. The image is divided into two parts: object and background in the proposed method, and the Z-function and S-function are adopted as the membership functions of background and object. Since the exhaustive search for all fuzzy parameter combinations of member functions is too costly, we introduced DE algorithm into fuzzy image segmentation to solve this optimal problem adaptively.

The paper is organized as follows. In Section 2, the maximum correlation criterion is reviewed and the fuzzy correlation criterion is proposed based on probability analysis, fuzzy partition and correlation theory. In Section 3, the basic principle of DE is described and the specific method of DE applied in fuzzy correlation image segmentation is proposed. More experiments are discussed in Section 4 to demonstrate the effectiveness and usefulness of the proposed approach. Finally, the conclusions are drawn in Section 5.

II. Fuzzy partition and maximum correlation for image segmentation

In this section, we give brief descriptions about the correlation and fuzzy partition approach for image segmentation.

A. Maximum correlation criterion

Let $I = [f(x,y)]_{M\times N}$ be an L-level digital image, $f(x,y) \in G$, $G = \{0,1,2,\cdots,L-1\}$ is the set of gray levels. Let h_i be the frequency of gray level i and $p_i = h_i/(M\times N)$ be the probability of occurrence of gray level i. Hence, a distribution $\{p_i|i \in G\}$ can be obtained. Suppose t is an assumed threshold, t partitions the image into two regions, namely, the object O and the background B. We assume gray values in $[t+1,\cdots,L-1]$ constitute the object region, while those in $[0, \cdots, t]$ constitute the background. If $\sum_{i=0}^{t} p_i$ is larger than zero and smaller than one, then two distributions can be derived from distribution $\{p_i | i \in G\}$ after normalization.

$$\begin{aligned} B &= \left\{ \frac{p_0}{P(t)}, \frac{p_1}{P(t)}, \cdots, \frac{p_t}{P(t)} \right\} \\ O &= \left\{ \frac{p_{t+1}}{1-P(t)}, \frac{p_{t+2}}{1-P(t)}, \cdots, \frac{p_{L-1}}{1-P(t)} \right\} \end{aligned} \tag{1}$$

Where $P(t) = \sum_{i=0}^{t} p_i$ is the total probability up to the tth gray level. In the maximum correlation criterion, the basic idea is to choose the threshold such that the total amount of correlation provided by the object and background is maximized. The total amount of correlation provided by distributions B and O is [12]

$$\begin{aligned} TC(t) &= C_B(t) + C_O(t) \\ &= -\ln \sum_{i=0}^{t} \left(\frac{p_i}{P(t)} \right)^2 - \ln \sum_{i=t+1}^{L-1} \left(\frac{p_i}{1-P(t)} \right)^2 \end{aligned} \tag{2}$$

In order to obtain the maximal correlation contributed by the object and background in the image I, $TC(t)$ must be maximized. The maximum correlation criterion [12] it to determine the threshold t^* such that

$$TC(t^*) = \arg \max_{t \in G} [TC(t)] \tag{3}$$

B. Fuzzy partition

The concept of fuzzy partitioning can be extended for digital image thresholding by visualizing the object and background regions as fuzzy sets, O and B, with each of the pixels showing a partial membership in each of the regions according to its gray value, i.e. $\mu_O(g) \in [0, 1]$, $\mu_B(g) \in [0, 1]$. With this sort of a partition, regions are no more guaranteed to be mutually exclusive; in other words, there may not exist a crisp boundary between regions.

A fuzzy thresholded description of an image can be characterized by two membership functions μ_O and μ_B in such a way that they reflect the nature of object and background gray distribution event after thresholding. The description reflects the compatibility measure of each of the pixel/gray value in object and background regions.

C. Fuzzy correlation for image thresholding

In the proposed fuzzy maximum correlation approach, the thresholding is used to classify pixels to object group and background group. With this aim, two fuzzy sets, object O and background B be considered, whose membership functions are defined in this paper as below

$$\mu_B(g) = \begin{cases} 1, & g \le a \\ 1 - \dfrac{(g-a)^2}{(c-a)(b-a)}, & a < g \le b \\ \dfrac{(g-c)^2}{(c-a)(c-b)}, & b < g \le c \\ 0, & g > c \end{cases} \tag{4}$$

$$\mu_O(g) = \begin{cases} 0, & g \le a \\ \dfrac{(g-a)^2}{(c-a)(b-a)}, & a < g \le b \\ 1 - \dfrac{(g-c)^2}{(c-a)(c-b)}, & b < g \le c \\ 1, & g > c \end{cases} \tag{5}$$

Where $0 \le a < b < c \le L-1$, $g \in G$ is the independent variable, a, b, and c are parameters determining the shape of the above two membership functions as shown in Figure 1. Obviously, $\mu_B(g) = 1 - \mu_O(g)$. Hence, $\mu_B(g)$ and $\mu_O(g)$ is fuzzy 2-partition of the image. The probabilities of the two fuzzy events object O and background B are defined as

$$P_B = \sum_{g=0}^{L-1} \mu_B(g) p_g \tag{6}$$

$$P_O = \sum_{g=0}^{L-1} \mu_O(g) p_g \tag{7}$$

According to maximum correlation criterion [12] for image thresholding, in the proposed approach we define the amount of fuzzy correlation provided by fuzzy events object and background as follows

$$FC_B = -\ln \sum_{g=0}^{L-1} \left(\frac{\mu_B(g) p_g}{P_B} \right) \tag{8}$$

$$FC_O = -\ln \sum_{g=0}^{L-1} \left(\frac{\mu_O(g) p_g}{P_O} \right) \tag{9}$$

The total amount of fuzzy correlation is defined as

$$FC(a, b, c) = FC_B + FC_O \tag{10}$$

Since different combination of (a, b, c) corresponds to different fuzzy 2-partition, so, the fuzzy correlation varies along with three parameters a, b, and c. We can find an optimal combination of (a, b, c) such that the fuzzy correlation $FC(a, b, c)$ has maximum value, i.e.

$$(a^*, b^*, c^*) = \arg \max [FC(a, b, c)] \tag{11}$$

Then, the optimal threshold t^* for image segmentation can be computed as

$$\mu_B(t) = \mu_O(t) \tag{12}$$

As shown in Figure 1, threshold t^* is the point of intersection of μ_B and μ_O. According to Eqs. (4) and (5), the solution can be computed as

$$t^* = \begin{cases} a^* + \sqrt{\dfrac{(c^*-a^*)(b^*-a^*)}{2}}, & (a^*+c^*)/2 \le b^* \le c^* \\ c^* - \sqrt{\dfrac{(c^*-a^*)(c^*-b^*)}{2}}, & a^* \le b^* \le (a^*+c^*)/2 \end{cases} \tag{13}$$

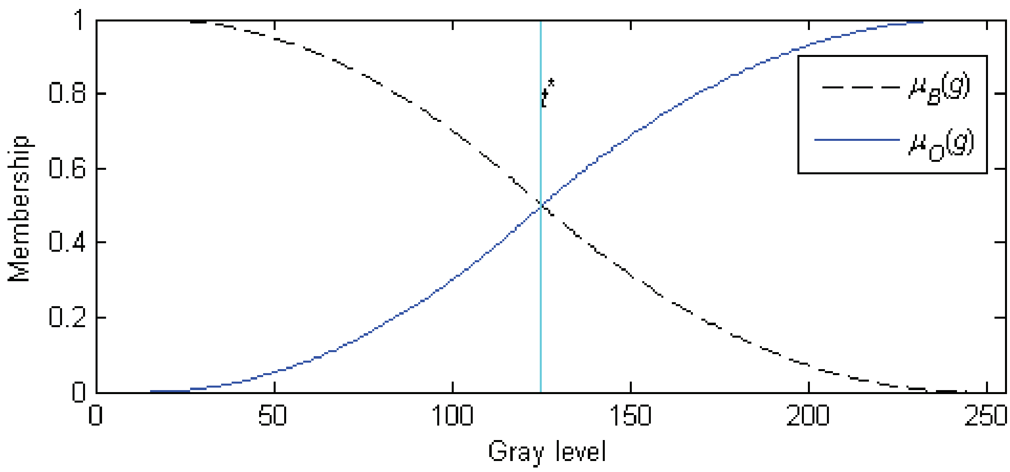


Fig. 1: The plot of membership function with $(a, b, c) = (15, 120, 245)$ and the optimal threshold t^*

III. Fuzzy partition and maximum correlation for image segmentation

From above description, we can see that it is not an easy work for finding the optimal fuzzy membership function parameters combination of (a, b, c). Since a, b, and c may take values from $\{0, 1, \cdots, L-1\}$, the search space of parameters combination (a, b, c) is close to L^3. Such procedure is characterized by high computation cost. In this section, we propose a DE algorithm to find the optimal combination of (a, b, c).

A. Description of differential evolution

Differential evolution is an evolutionary computation algorithm developed by Storn and Price which solves real valued problems based on the principles of natural evolution [24]. It is a heuristic optimization method which can be used to optimize nonlinear and non-dfferentiable continuous space functions. It has been extended to handle mixed integer discrete continuous optimization problem also [23]–[26]. DE uses a population P of size n that evolves over t generations to reach the optimal solution. Each individual X_i is a vector that contains as many parameters as the problem decision variables D.

$$P^t = \left[X_1^t, X_2^t, \cdots, X_n^t\right] \tag{14}$$

$$X_i^t = \left[X_{i,1}^t, X_{i,2}^t, \cdots, X_{i,D}^t\right], i = 1, 2, \cdots, n \tag{15}$$

The population size n is an algorithm control parameter selected by the user which remains constant throughout the optimization process. The optimization process in DE is carried out using the three basic operations: Mutation, Crossover and Selection. The algorithm starts by creating an initial population of n vectors. Random values are assigned to each decision parameter in every vector as follows.

$$X_{i,j}^0 = X_j^L + r \cdot \left(X_j^U - X_j^L\right) \tag{16}$$

Where $i = 1, 2, \cdots, n$ and $j = 1, 2, \cdots, D$; X_j^L and X_j^U are the lower and upper bounds of the jth decision parameter; and r is a uniformly distributed random number within $[0, 1]$ generated for each value of j. $X_{i,j}^0$ is the jth parameter of the ith individual of the initial population. The main steps of the DE algorithm are shown in Figure 2.

Initialization
Evaluation
Repeat
  Mutation
  Crossover
  Evaluation
  Selection
Until (termination criteria are met)

Fig. 2: Illustration of the main steps of the DE algorithm

In DE algorithm, the mutation operator creates mutant vectors D_i by perturbing a randomly selected vector X_a with the difference of two other randomly selected vectors X_b and X_c.

$$D_i = X_a + F \cdot (X_a - X_c), i = 1, 2, \cdots, n \tag{17}$$

Where X_a, X_b, and X_c are randomly chosen vectors among the n population, and $a \neq b \neq c \neq i$. The scaling constant F is an algorithm control parameter used to adjust the perturbation size in the mutation operator and to improve algorithm convergence.

The crossover operation generates trail vectors T_i by mixing the parameters of the mutant vectors D_i with the target vector X_i according to a selected probability distribution.

$$T_{i,j} = \begin{cases} D_{i,j}, if((rn \leq CR) or (j = d)) \\ X_{i,j}, otherwise \end{cases} \tag{18}$$

Where $i = 1, 2, \cdots, n$ and $j = 1, 2, \cdots, D$; d is a randomly chosen index from $\{1, 2, \cdots, D\}$ that guarantees that the trail vector gets at least one parameter from the mutant vector; rn is a uniformly distributed random number within $[0, 1]$ generated for each value of j. The crossover constant CR is an algorithm parameter that controls the diversity of the population and aids the algorithm to escape from local minima. $X_{i,j}$, $D_{i,j}$ and $T_{i,j}$ are the jth parameter of the ith target vector, mutant vector and trail vector at current generation, respectively.

The selection operation forms the population by choosing between the trail vectors and their predecessors (target vectors) those individuals that present a better fitness or are more optimal according to Eq. (19).

$$X_i^{t+1} = \begin{cases} T_i, if(f(T_i) > f(X_i^t)) \\ X_i^t, otherwise \end{cases} \quad (19)$$

This process is repeated for several generations allowing individuals to improve their fitness as they explore the solution space in search of optimal values.

DE has three essential control parameters: the scaling factor F, the crossover constant CR and the population size n. The scaling factor is a value in the range $[0, 2]$ that controls the amount of perturbation in the mutation process. The crossover constant is a value in the range $[0, 1]$ that controls the diversity of the population. The population size determines the number of individuals in the population and provides the algorithm enough diversity to search the solution space.

B. DE implementation for image segmentation

While applying DE to solve the parameters optimization problem of fuzzy membership function, each vector in the DE population represents a candidate solution of the given problem. Considering the optimal problem mentioned above, the individuals in the population are constructed and the population search strategy is proposed. We choose 3 as the dimension of the search space, i.e. $D = 3$ and each individual in the population is three-dimensional vector of real numbers. The fuzzy correlation function (10) is the given fitness function. The procedure is described as follows.

Step 1. Initialize n individuals in population according Eq. (16), where X_j^L and X_j^U are the minimum and maximum gray level of the given image, respectively.

Step 2. Evaluate the fitness of each individual in the population using the fuzzy correlation function (10).

Step 3. Carry out the mutation, crossover, evaluation and selection operators for each individual in the population. In order to obtain better convergence, the scaling factor F and the crossover constant CR are set as follows

$$F = 0.5 \times (1 + rand(0, 1)) \quad (20)$$

$$CR = CR_{min} + (CR_{max} - CR_{min}) \cdot (It_{max} - It)/It \quad (21)$$

Where rand(0,1) denotes a uniform random number with range $[0, 1]$; CR_{max} and CR_{min} denote the maximum and minimum of cross probability CR, they can be assigned value in the step of initialization; It_{max} and It denote the biggest iteration number that be allowed and the current iteration number of the DE algorithm, respectively.

Step 4. Repeat Step 3 until termination criteria are met.

IV. Experimental results and analysis

For evaluation the performance of the proposed approach, we have applied the proposed method to a variety of images and compared the performance with that of some existing methods. The thresholding methods proposed in references [16], [17] and [18] are based on fuzzy set which claimed the satisfactory performance in image segmentation. Therefore, we compared the performance of the proposed algorithm with that of the method in references [16], [17] and [18]. For the sake of convenience, we call these methods in references [16], [17] and [18] Benabdelkader method, Tao method and Tang method, respectively. In addition, we compared the performance of the proposed method with that of some classical image thresholding methods, i.e. Otsu method [4], Pun entropy method [5], Kapur entropy method [6], and Yen correlation method [12].

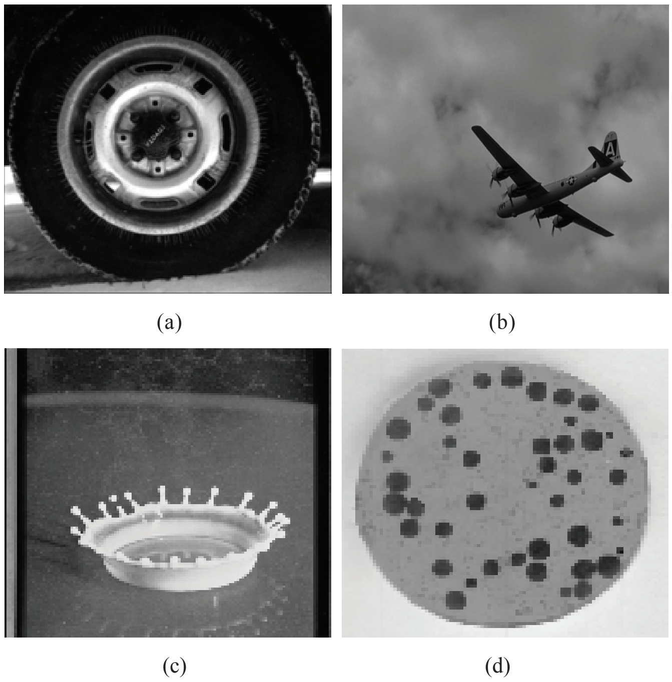


Fig. 3: The test images. Original image of (a) tire, (b) plane, (c) milkdrop and (d) shot1

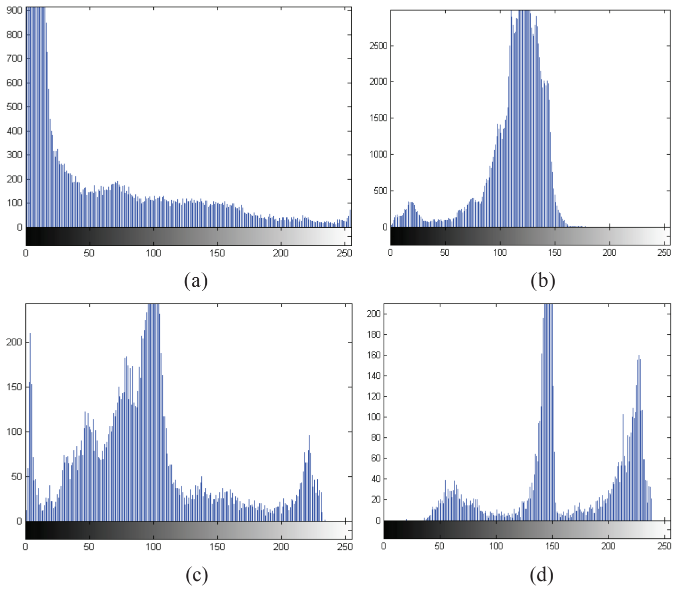


Fig. 4: The histograms of test images. (a) tire, (b) plane, (c) milkdrop and (d) shot1

The all algorithms were coded in Matlab version 7 and run on an Intel 2.66 GHz Pentium4 CPU, 2.00 GB RAM personal computer, under Microsoft Windows XP pro Operating System. In our experiments the population size of the proposed DE algorithm is set to 30, the number of maximum iteration It_{max}, the maximum cross probability CR_{max} and the minimum cross probability CR_{min} are set to 100, 0.9 and 0.1, respectively.

Firstly, four real-world images with different shapes of gray levels histogram distribution are applied to test the segmentation performance of different thresholding methods. The four images are 'tire' image, 'plane' image, 'milkdrop' image and 'shot1' image and their sizes are 232×205, 481×321, 128×128 and 94×93, respectively. The original images of the test images are shown in Figure 3 and their corresponding gray levels histograms are shown in Figure 4.

The threshold values obtained with the different thresholding methods on test images are shown in Table 1 and the corresponding thresholded result by these threshold values for test images are shown in Figures 5-8.

From Figures 5-8, it can be seen that the best segmented results can be obtained by the proposed method while there are some defectives exist in the results by the other methods. For 'tire' image, the results obtained by Yen method and Tao method are over-segmentation while keeping the under-segmentation error in the results obtained by Pun method, Benabdelkader method and Tang method. For 'tire' image, these five methods can not distinguish the object and background well. For 'plane' image, the object is separated from background very well by the Tao method and the proposed method while a lot of background noise exist in the results obtained by other six methods, especially in the results obtained by Pun method, Benabdelkader method and Tang method. For 'milkdrop' image, there are same flaws exist in the results by Pun method, Benabdelkader method and Tang method as that of in 'plane' image. For Otsu method, Kapur method and Yen method, there is much noise in the results by these three methods while for the Tao method, the over-segmentation error appears again in the segmented results. For 'shot1' image, the mentioned above flaws exist in the results by Otsu method, Pun method, Benabdelkader method, Tao method and Tang method appear again while for the other three methods, the object separated from background well.

Because the effects of fuzzy correlation image segmentation depend on the selected threshold, it is essential to compare the threshold selected by the DE method with the threshold selected by the exhaustive search method. Comparison of results and time of the DE method and the exhaustive search for test images is shown in Table 2. Since DE is a stochastic global optimization algorithm, we repeated experiments to test the search stability of the DE method. Results and time of the DE method shown in Table 2 are the average results of 20 independent and repeated experiments. As can be seen from Table 2, the DE method can give the similar optimal fuzzy parameter combination and threshold as that of the exhaustive search. In contrast, the search time of the DE method is very less than that of the exhaustive search. For example, the DE method and the exhaustive search obtain the similar optimal fuzzy parameter combination $(0.0, 0.9, 255.0)$ and threshold 75.0 for 'tire' image, but the search time of the DE method is approximately one thousandth of that of the exhaustive search. Therefore, it can be concluded that the DE method can greatly improve the efficiency of the proposed image segmentation method. From the search results of all the experimental images, we can conclude that the DE method has good adaptability in selecting the optimal fuzzy parameter combination and threshold when applied to different kinds of real-world images.

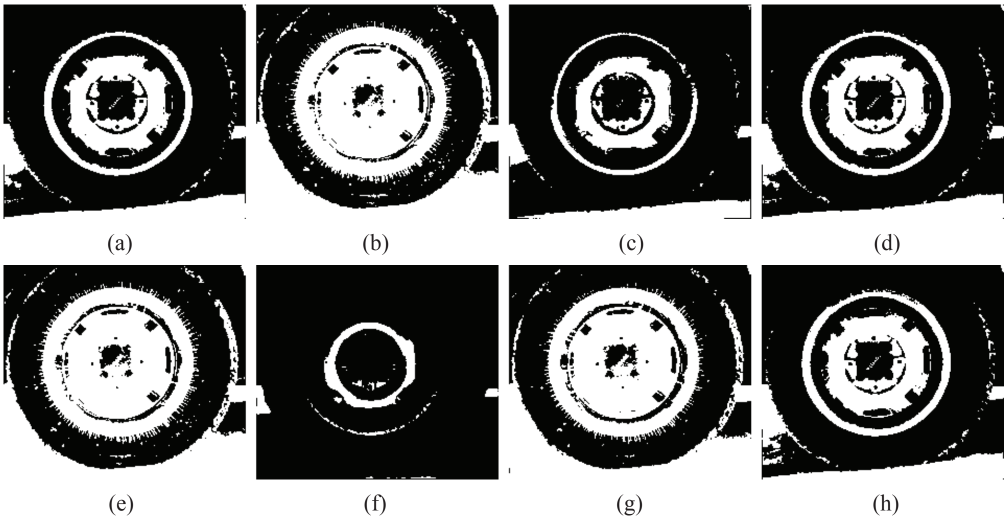
Time efficiency is an important index for different algorithms on image segmentation. So the experiments of CPU time cost of all methods for obtaining the optimal threshold value on every test image were also conducted in this paper. The results are reported in Table 3. The Otsu, Pun, Kapur et al., and Yen et al. methods are implemented by exhaustive search in this paper. The fast recursive algorithm was used in Benabdelkader et al. method and Tang et al. method. The ant colony optimization algorithm was used in Tao et al. method. These three methods are implemented according to their original paper in our experiment. From Table 3, it can be seen that the exhaustive search algorithm used in Otsu, Pun, Kapur et al., and Yen et al. methods cost less CPU time than other methods because the time complexity of these methods is $O(L)$, where L is number of gray levels of image. The time complexity of other methods is larger than $O(L)$. Therefore, although some optimization algorithms or recursive algorithms are used in these methods, it still cost much CPU time than other methods. However, compared the proposed method with its exhaustive search version, it can be seen from Table 2, the time cost of the proposed method is less than that of the exhaustive search. For example, the search time of the proposed method is approximately one thousandth of that of the exhaustive search for test images. From Table 3, we can see that the cost time of the proposed method is also less than that of Tang et al. method.

Infrared target detection is widely application in many fields [17], [21], [27], [28], such as video surveillance [29], [30]. At the last experiment, for further testing the performance of the proposed method, we applied the proposed method to infrared human image segmentation. Figure 9 shows two infrared human images and their gray levels histograms. For convenience, we call these two infrared images 'IR1' and 'IR2'. Figures 10 and 11 show the segmented results by 8 different methods referenced in this paper.

From Figures 10 and 11, it can be seen that the human targets are separated from background well by the proposed method while the results obtained by the other methods are not ideal. For 'IR1' image, the thresholds obtained by Otsu method, Pun method, Benabdelkader method and Tang method are 67, 76, 76 and 68, respectively. When 'IR1' image is segmented by these thresholds, the object can not be distinguished from background. For Tao method, from our experiments, it usually will appear over-segmentation error sometimes while for Kapur method and Yen method their segmentation is deficient at the some time. For example, the flaws of these methods appear in the segmented results of 'IR2' image.

V. Conclusions

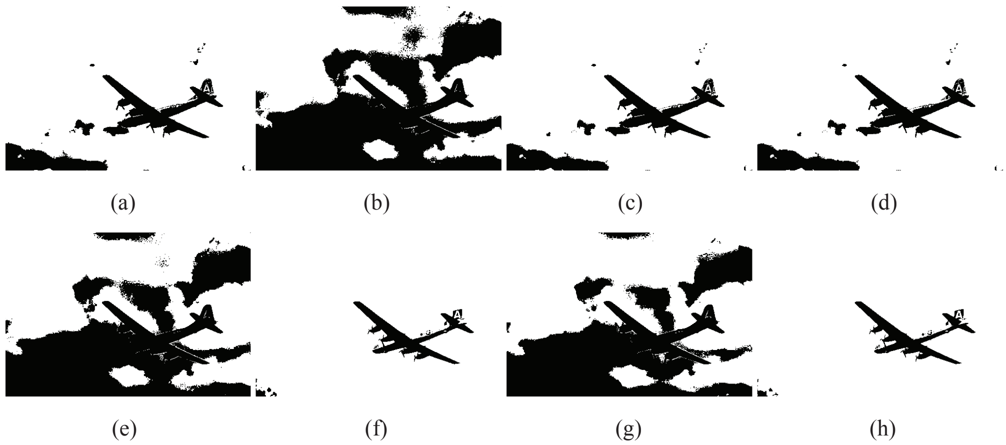
In this paper, a new image thresholding method is presented based on fuzzy partition and correlation theory. At the same time the DE algorithm is introduced into fuzzy correlation image segmentation to find the best fuzzy parameter combination of membership function and threshold adaptively. Some real-world images and infrared human images are selected as the experimental data and the proposed method obtains satisfactory results in the segmentation experiments. The DE method can obtain the similar optimal fuzzy parameter combination and threshold as that of the exhaustive search while its search time is very less than that



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

(e) (f) (g) (h)

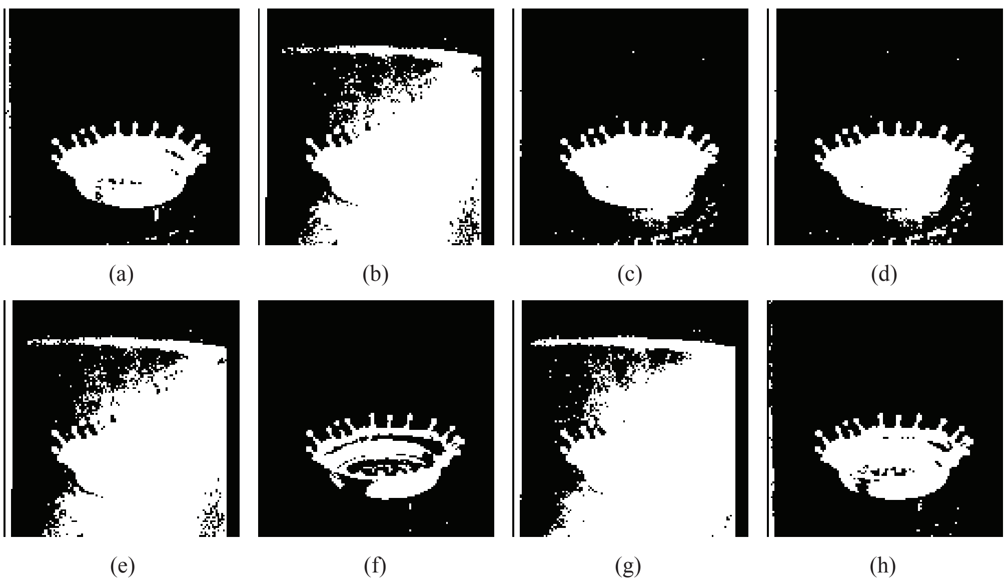
Fig. 5: Segmented results of tire image by (a) Otsu method, (b) Pun method, (c) Kapur method, (d) Yen method, (e) Benabdelkader method, (f) Tao method, (g) Tang method and (h) The proposed method



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

(e) (f) (g) (h)

Fig. 6: Segmented results of plane image by (a) Otsu method, (b) Pun method, (c) Kapur method, (d) Yen method, (e) Benabdelkader method, (f) Tao method, (g) Tang method and (h) The proposed method



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

(e) (f) (g) (h)

Fig. 7: Segmented results of milkdrop image by (a) Otsu method, (b) Pun method, (c) Kapur method, (d) Yen method, (e) Benabdelkader method, (f) Tao method, (g) Tang method and (h) The proposed method

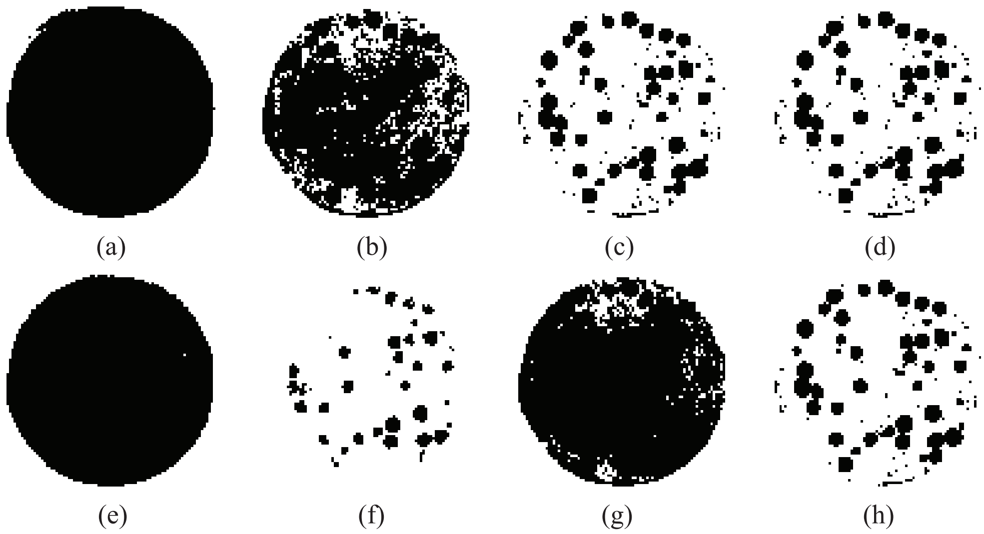


Fig. 8: Segmented results of shot1 image by (a) Otsu method, (b) Pun method, (c) Kapur method, (d) Yen method, (e) Benabdelkader method, (f) Tao method, (g) Tang method and (h) The proposed method

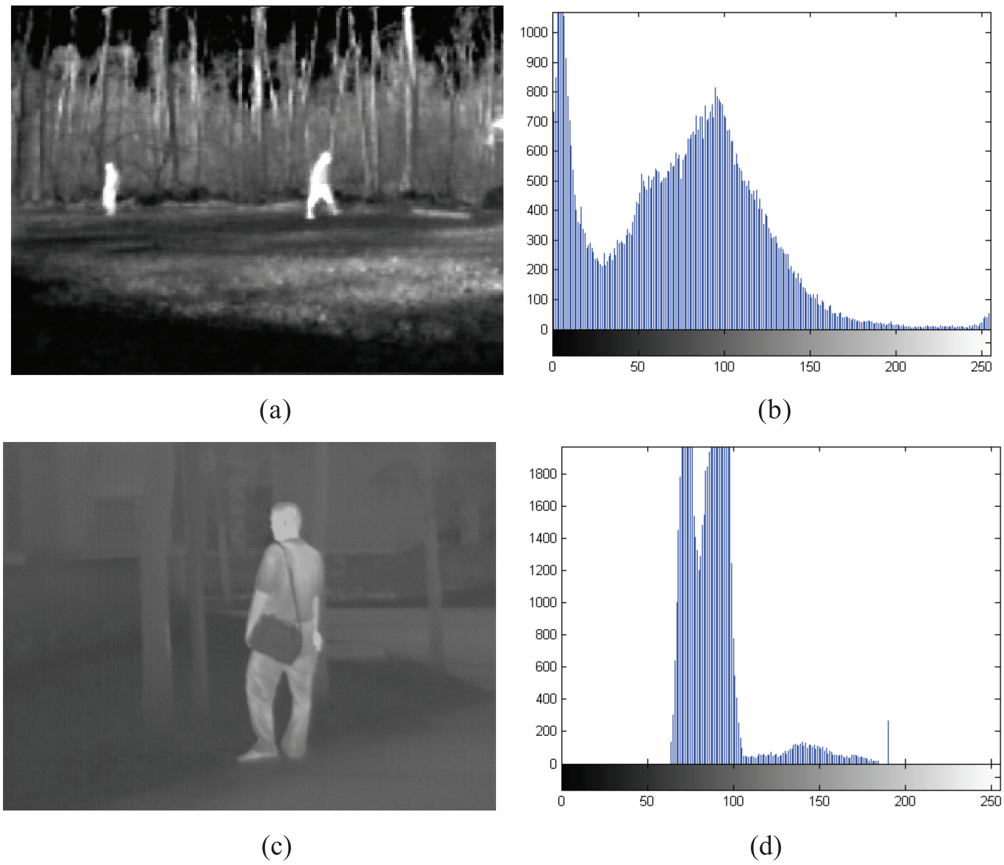


Fig. 9: Original infrared human images and their histogram. (a) IR1, (b) Histogram of IR1, (c) IR2 and (d) Histogram of IR2.

TABLE I: Threshold values obtained with the different thresholding methods on test images

Image	Otsu	Pun	Kapur	Yen	Benabdelkader	Tao	Tang	Proposed
tire	84	20	110	83	21	180	25	75
plane	85	120	84	84	119	48	117	46
milkdrop	130	92	114	114	91	166	87	139
Shot1	174	147	131	131	164	68	149	128

TABLE II: Comparison of results and time of the DE method and the exhaustive search

Image	DE method			Exhaustive search		
	(a, b, c)	Threshold	Times(s)	(a, b, c)	Threshold	Times(s)
tire	(0.0, 0.9, 255.0)	75.0	0.2873	(0, 1, 255)	75.0	253.8
plane	(0.0, 0.1, 157.8)	46.2	0.2361	(0, 1, 157)	46.3	186.7
milkdrop	(1.0, 165.3, 233.9)	139.3	0.2437	(1, 165, 234)	139.2	215.2
Shot1	(117.5, 118.7, 154.2)	128.7	0.2795	(118, 119, 154)	128.9	193.7

TABLE III: Comparison of CPU time of the different methods (second)

Image	Otsu	Pun	Kapur	Yen	Benabdelkader	Tao	Tang	Proposed
tire	0.0543	0.0517	0.0607	0.0496	0.0873	0.2791	2.3105	0.2873
plane	0.0419	0.0435	0.0431	0.0458	0.0791	0.2404	2.4307	0.2361
milkdrop	0.0426	0.0397	0.0409	0.0379	0.0765	0.2456	2.0172	0.2437
Shot1	0.0413	0.0462	0.0508	0.0437	0.0698	0.2798	1.9762	0.2795

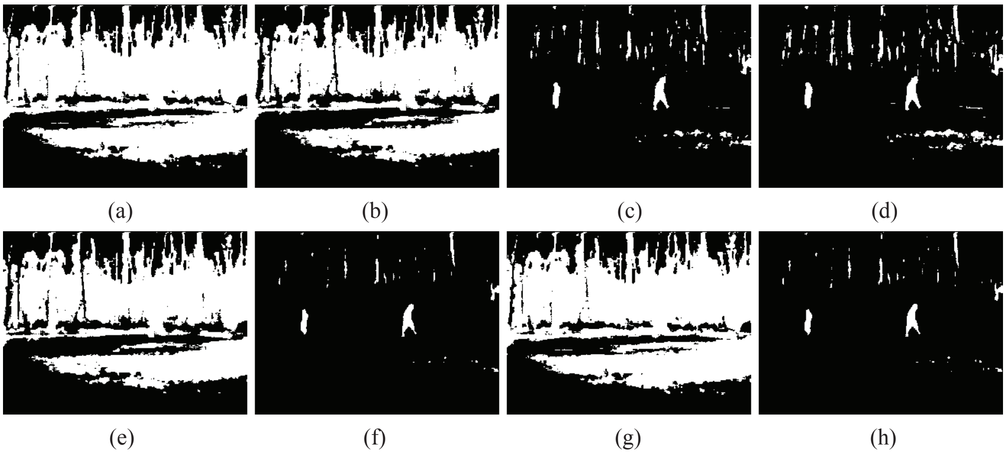


Fig. 10: Segmented results of IR1 image by (a) Otsu method $(t^* = 67)$, (b) Pun method $(t^* = 76)$, (c) Kapur method $(t^* = 154)$, (d) Yen method $(t^* = 145)$, (e) Benabdelkader method $(t^* = 76)$, (f) Tao method $(t^* = 179)$, (g) Tang method $(t^* = 68)$ and (h) The proposed method $(t^* = 180)$

of the exhaustive search. And the DE method has good search stability in the repeated experiments. Therefore, the proposed method is an efficient image segmentation method and can be applied to many fields, such as automatic target recognition, etc.

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REFERENCES

[1] N. Pal and S. Pal, "A review on image segmentation techniques," *Pattern Recognition*, vol. 26, no. 9, pp. 1277–1294, 1993.

[2] L. Zhang and Q. Ji, "Image segmentation with a unified graphical model," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. vol. 32, no. 8, pp. 1406–1425, 2010.

[3] M. Sezgin and B. Sankur, "Survey over image thresholding techniques and quantitative performance evaluation," *Journal of Electronic Imaging*, vol. 13, no. 1, pp. 146–165, 2004.

[4] N. Otsu, "A threshold selection method from gray-level histograms," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 9, no. 1, pp. 62–66, 1979.

[5] T. Pun, "A new method for grey-level picture thresholding using the entropy of the histogram," *Signal Processing*, vol. 2, no. 3, pp. 223–237, 1980.

[6] J. Kapur, P. Sahoo and A. Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," *Computer Vision, Graphics, and Image Processing*, vol. 29, no. 3, pp. 273–285, 1985.

[7] C. Li and C. Lee, "Minimum cross-entropy thresholding," *Pattern Recognition*, vol. 26, no. 4, pp. 617–625, 1993.

[8] C. Li and P. Tam, "An iterative algorithm for minimum cross-entropy thresholding," *Pattern Recognition Letters*, vol. 19, no. 8, pp. 771–776, 1998.

[9] M. Portes de Albuquerque, I. Esquef, A. Gesualdi Mello and M. Portes de Albuquerque, "Image thresholding using Tsallis entropy," *Pattern Recognition Letters*, vol. 25, no. 9, pp. 1059–1065, 2004.

[10] F. Nie, C. Gao, Y. Guo and M. Gan, "Two-dimensional minimum local cross-entropy thresholding based on co-occurrence matrix," *Computers & Electrical Engineering*, vol. 37, no. 5, pp. 757–767, 2011.

[11] N. Razmjooy, B. Mousavi, M. Khalilpour and H. Hosseini, "Automatic selection and fusion of color spaces for image thresholding," *Signal, Image and Video Processing*, doi:10.1007/s11760-012-0303-7, 2013.

[12] J. Yen, F. Chang and S. Chang, "A new criterion for automatic

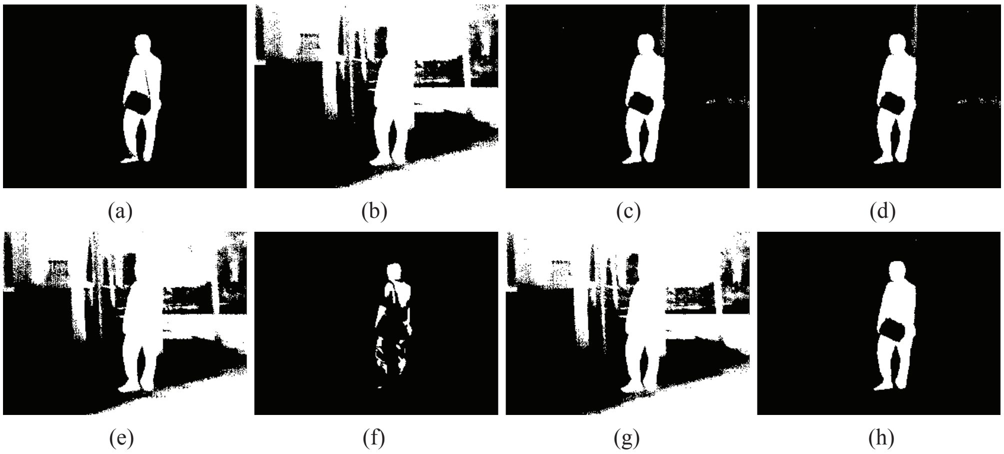

Fig. 11: Segmented results of IR2 image by (a) Otsu method ($t^* = 116$), (b) Pun method ($t^* = 87$), (c) Kapur method ($t^* = 103$), (d) Yen method ($t^* = 103$), (e) Benabdelkader method ($t^* = 89$), (f) Tao method ($t^* = 154$), (g) Tang method ($t^* = 87$) and (h) The proposed method ($t^* = 106$)

multilevel thresholding," *IEEE Transactions on Image Processing*, vol. 4, no. 3, pp. 370–378, 1995.

[13] O. Tobias and R. Seara, "Image segmentation by histogram thresholding using fuzzy sets," *IEEE Transactions on Image Processing*, vol. 11, no. 12, pp. 1457–1465, 2002.

[14] H. Cheng, J. Chen and J.Li, "Threshold selection based on fuzzy c-partition entropy approach," *Pattern Recognition*, vol. 31, no. 7, pp. 857–870, 1998.

[15] M. Zhao, A. Fu and H. Yan, "A technique of three-level thresholding based on probability partition and Fuzzy 3-partition," *IEEE Transactions on Fuzzy Systems*, vol. 9, no. 3, pp. 469–479, 2001.

[16] S. Benabdelkader and M. Boulemden, "Recursive algorithm based on fuzzy 2-partition entropy for 2-level image thresholding," *Pattern Recognition*, vol. 38, no. 8, pp. 1289–1294, 2005.

[17] W. Tao, H. Jin and L. Liu, "Object segmentation using ant colony optimization algorithm and fuzzy entropy," *Pattern Recognition Letters*, vol. vol. 28, no. 7, pp. 788–796, 2007.

[18] Y. Tang, W. Mu, Y. Zhang and X. Zhang, "A fast recursive algorithm based on fuzzy 2-partition entropy approach for threshold selection," *Neurocomputing*, vol. 74, no. 17, pp. 3072–3078, 2011.

[19] P. Sathya and R. Kayalvizhi, "Modified bacterial foraging algorithm based multilevel thresholding for image segmentation," *Engineering Applications of Artificial Intelligence*, vol. 24, no. 4, pp. 595–615, 2011.

[20] Z. Zahara, S. Fan and D. Tsai, "Optimal multi-thresholding using a hybrid optimization approach," *Pattern Recognition Letters*, vol. 26, no. 8, pp. 1082–1095, 2005.

[21] D. Feng, W. Wenkang, C. Liangzhou, D. Yong and Z. Zhenfu, "Infrared image segmentation with 2-D maximum entropy method based on particle swarm optimization (PSO)," *Pattern Recognition Letters*, vol. 26, no. 5, pp. 597–603, 2005.

[22] A. Nakib, H. Oulhadj and P. Siarry, "Image thresholding based on Pareto multiobjective optimization," *Engineering Applications of Artificial Intelligence*, vol. 23, no. 3, pp. 313–320, 2010.

[23] E. Cuevas, D. Zaldivar and M. Pérez-Cisneros, "A novel multi-threshold segmentation approach based on differential evolution optimization," *Expert Systems with Applications*, vol. 37, no. 7, pp. 5265–5271, 2010.

[24] R. Storn and K. Price, "Differential evolution C A simple and efficient heuristic for global optimization over continuous spaces," *Journal of Global Optimization*, vol. 11, no. 4, pp. 341–359, 1997.

[25] Y. Wang and J. Zhang, "Global optimization by an improved differential evolutionary algorithm," *Applied Mathematics and Computation*, vol. 188, no. 1, pp. 669–680, 2007.

[26] U. Maulik and I. Saha, "Automatic fuzzy clustering using modified differential evolution for image classification," *IEEE Transactions on Geoscience and Remote Sensing*, vol. 48, no. 9, pp. 3503–3510, 2010.

[27] J. Shaik and K. Iftekharuddin, "Detection and tracking of targets in infrared images using Bayesian techniques," *Optics & Laser Technology*, vol. 41, no. 6, pp. 832–842, 2009.

[28] J. Wang, D. Chen, H. Chen and J. Yang, "On pedestrian detection and tracking in infrared videos," *Pattern Recognition Letters*, vol. 33, no. 6, pp. 775-785, 2012.

[29] T. Zin, P. Tin, T. Toriu and H. Hama, "A novel probabilistic video analysis for stationary object detection in video surveillance systems," *IAENG International Journal of Computer Science*, vol. 39, no. 3, pp. 295-306, 2012.

[30] J. Ramírez-Quintana, M. Chacon-Murguia and J. Chacon-Hinojos, "Artificial neural image processing applications: a survey," *Engineering Letters*, vol. 20, no. 1, pp. 68-80, 2012.

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