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Automatic Target Detection Using Wavelet Transform

S. Arivazhagan

Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi 626 005, India
Email: s_arivu@yahoo.com

L. Ganesan

Department of Computer Science and Engineering, Government College of Engineering, Tirunelveli 627 007, India
Email: drlgtnly@yahoo.com

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Automatic target recognition (ATR) involves processing images for detecting, classifying, and tracking targets embedded in a background scene. This paper presents an algorithm for detecting a specified set of target objects embedded in visual images for an ATR application. The developed algorithm employs a novel technique for automatically detecting man-made and non-man-made single, two, and multitargets from nontarget objects, located within a cluttered environment by evaluating nonoverlapping image blocks, where block-by-block comparison of wavelet cooccurrence feature is done. The results of the proposed algorithm are found to be satisfactory.

Keywords and phrases: discrete wavelet transform, target detection, texture, wavelet cooccurrence features.

1. INTRODUCTION

The last three decades have seen rapid development in electronic automation, though mechanical automation was there for the past 200 years. Computer vision researchers have for many years attempted to model the basic components of the human visual system to capture our visual abilities. The steps required for successful implementation of an automatic target recognition (ATR) task involves automatic detection, classification, and tracking of a target located in an image scene.

The wavelet transform is a multiresolution technique, which can be implemented as a pyramid or tree structure and is similar to subband decomposition. The discrete wavelet transform (DWT) has properties that make it an ideal transform for the processing of images encountered in target recognition applications, including rapid processing, a natural ability to adapt to changing local image statistics, efficient representation of abrupt changes and precise position information, ability to adapt to high background noise and uncertainty about target properties, and a relative independence to target-to-sensor distance.

In this paper, target detection is achieved by calculating cooccurrence matrix features from detail subbands of discrete wavelet transformed, nonoverlapping but adjacent subblocks of different sizes, depending upon the target image. From these calculations, the subblock with the maximum of combined wavelet cooccurrence feature values (WCFs) is identified as a seed window. Then, by applying a region growing algorithm, the subblock or regions are grouped into a larger block or region based on some predefined criteria. Then, the target is identified by a bounded rectangle. The proposed algorithm is applied on both man-made and non-man made single-, two-, and multitarget images.

This paper is organized as follows. In Section 2, the detailed literature survey about the texture analysis and target detection are given. In Section 3, the theory of DWT and wavelet filter bank for image decomposition are presented. A brief discussion about gray-level cooccurrence matrix is given in Section 4. The target detection system is explained in Section 5. In Section 6, experimental results for various target images are discussed in detail. Finally, concluding remarks are given in Section 7.

2. BACKGROUND

2.1. *Texture analysis*

The success of most computer vision problems depends on how effectively the texture is quantitatively represented. Regardless of whether the application is target detection, object recognition, texture segmentation, or edge detection, one must be able to recognize and label homogeneous texture regions within an image and differentiate between distinct regions [1]. Thus, texture analysis is one of the most important techniques used in the analysis and interpretation of images, consisting of repetition or quasirepetition of some fundamental image elements [2].

Analysis of textures requires the identification of proper attributes or features that differentiate the textures in the image for segmentation, classification, and recognition. The features are assumed to be uniform within the regions containing the same textures. Initially, texture analysis was based on the first-order or second-order statistics of textures [3, 4, 5, 6, 7, 8]. Then, Gaussian Markov random field (GMRF) and Gibbs random field models were proposed to characterize textures [9, 10, 11, 12, 13, 14]. An adaptive anisotropic parameter estimation in a weak membrane model which uses the MRF and an adaptive pattern recognition system for scene segmentation are proposed in [15, 16]. Later, local linear transformations were used to compute texture features [17, 18]. Then, a texture spectrum technique was proposed for texture analysis [19]. The above traditional statistical approaches to texture analysis, such as cooccurrence matrices, second-order statistics, GMRF, local linear transforms, and texture spectrum, are restricted to the analysis of spatial interactions over relatively small neighborhoods on a single scale. As a consequence, their performance is best for the analysis of microtextures only [20].

More recently, methods based on multiresolution or multichannel analysis, such as Gabor filters and wavelet transform, have received a lot of attention [20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30]. But, the outputs of Gabor filter banks are not mutually orthogonal, which may result in a significant correlation between texture features. Finally, these transformations are usually not reversible, which limits their applicability for texture synthesis. Most of these problems can be avoided if one uses the wavelet transform, which provides a precise and unifying framework for the analysis and characterization of a signal at different scales [20]. Another advantage of wavelet transform over Gabor filters is that the lowpass and highpass filters used in the wavelet transform remain the same between two consecutive scales while the Gabor approach requires filters of different parameters [23]. In other words, Gabor filters require proper tuning of filter parameters at different scales. Later, Kaplan proposed extended fractal analysis for texture classification and segmentation and Wang and Liu proposed multiresolution MRF (MRMRF) parameters for texture classification [31, 32]. Wavelet statistical features (WSF) and WCF were proposed and effectively used for texture characterization and classification [33].

2.2. Target detection

Kubota et al. proposed a vision system with real-time feature extractor and relaxation network using a multiresolution technique [34]. An algorithm for boundary detection using edge dipole and edge field is presented in [35]. An adaptive pixel-based data fusion is proposed for boundary detection [36]. Huntsberger and Jawerth proposed wavelet-based techniques for automatic target detection and recognition and for acoustic and nonacoustic antisubmarine warfare [37, 38]. Espinal et al. proposed wavelet-based fractal dimension for ATR [1]. Chernoff bounds was proposed for ATR from compressed data [39]. Regularized complex DWT (CDWT) optical flow algorithm was used for moving target detection in infrared imagery [40]. Then, Tian and Qi used spectral analysis statistics and wavelet coefficient characterization (SSWCC) for target detection and classification [41]. Later, Renyi's information and wavelets were used for target detection [42]. Howard et al. proposed directed principal component analysis followed by clustering for real-time intelligent target detection [43]. Then, a preattentive selection mechanism based on the architecture of the primate visual system was implemented for target detection in cluttered natural scenes [44]. Kubota et al. proposed edge-based probabilistic relaxation for subpixel contour extraction, a useful subtechnique for target detection [45].

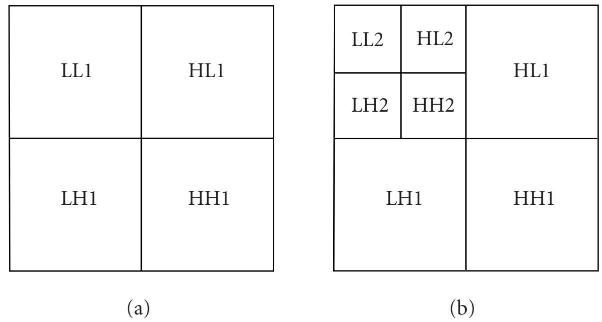


Figure 1: Image decomposition. (a) One level. (b) Two levels.

Although there have been previous efforts involved in texture analysis and target detection, limitations still exist in their applicability in detecting man-made and non-man-made, two and multitargets. Our approach effectively exploits the cooccurrence features, derived from detail subbands of discrete wavelet transformed images for the detection of man-made and non-man-made two and more targets, in both cluttered and noncluttered environments.

3. DISCRETE WAVELET TRANSFORM

Wavelets are functions generated from one single function ψ by dilations and translations. The basic idea of the wavelet transform is to represent any arbitrary function as a superposition of wavelets. Any such superposition decomposes the given function into different scale levels where each level is further decomposed with a resolution adapted to that level [46].

The DWT is identical to a hierarchical subband system where the subbands are logarithmically spaced in frequency and represent octave-band decomposition. By applying DWT, the image is actually divided, that is, decomposed into four subbands and critically subsampled as shown in Figure 1a. These four subbands arise from separable applications of vertical and horizontal filters as shown in Figure 2.

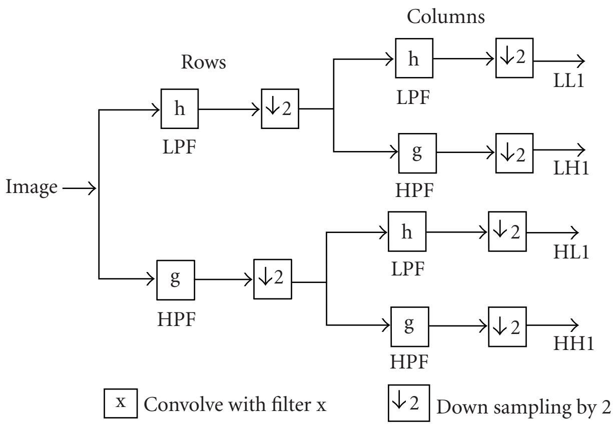


FIGURE 2: Wavelet filter bank for one-level image decomposition.

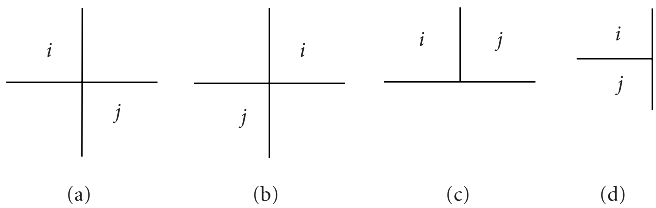


FIGURE 3: Cooccurrence matrix-orientations. (a) $d = (1, 1) - 135^\circ$. (b) $d = (1, -1) - 45^\circ$. (c) $d = (0, 1) - 0^\circ$. (d) $d = (1, 0) - 90^\circ$.

The filters h and g shown in Figure 2 are one-dimensional lowpass filter (LPF) and highpass filter (HPF), respectively. Thus, decomposition provides subbands corresponding to different resolution levels and orientations. These subbands labeled LH1, HL1, and HH1 represent the finest scale wavelet coefficients, that is, detail images, while the subband LL1 corresponds to coarse-level coefficients, that is, approximation image. To obtain the next coarse level of wavelet coefficients, the subband LL1 alone is further decomposed and critically sampled using a similar filter bank shown in Figure 2. This results in a two-level wavelet decomposition as shown in Figure 1b. Similarly, to obtain further decomposition, LL2 will be used. This process continues until some final scale is reached.

The values or transformed coefficients in approximation and detail images (subband images) are the essential features, which are as useful for texture discrimination and segmentation. Since textures, either micro or macro, have nonuniform gray-level variations, they are statistically characterized by the values in the DWT transformed subband images or the features derived from these subband images or their combinations. In other words, the features derived from these approximation and detail subband images uniquely characterize a texture. The features obtained from these DWT transformed images are shown here as useful for target detection and are discussed in the Section 5.

4. GRAY-LEVEL COOCCURRENCE MATRIX

The cooccurrence method of texture description is based on the repeated occurrence of some gray-level configuration in the texture and this configuration varies rapidly with distance in fine textures and slowly in coarse textures [3]. Consider the part of textured image to be analyzed is of size $M \times N$. In the cooccurrence matrix, an occurrence of some gray-level configuration is described by a matrix of relative frequencies $C_{\theta,d}(i, j)$ describing how frequently two pixels with gray levels i, j appear in the window separated by a displacement vector d in direction θ. For example, if the displacement vector is specified as $(1, 1)$, it has the interpretation of one pixel below and one pixel to the right, in the direction of 45° as shown in Figure 3a and if it is specified as $(1, -1)$, it has the interpretation of one pixel below and one pixel to the left, in the direction of 135° as shown in Figure 3b. Similarly, the displacement vector $(0, 1)$ has the interpretation of zero pixel below and one pixel to the right, that is, in the direction of 0° as shown in Figure 3c and the displacement vector $(1, 0)$ has the interpretation of one pixel below and zero pixel to the left, that is, in the direction of 90° as shown in Figure 3d.

These cooccurrence matrices are symmetric if defined as given below. However, an asymmetric definition may be used, where matrix values are also dependent on the direction of cooccurrence. Nonnormalized frequencies of

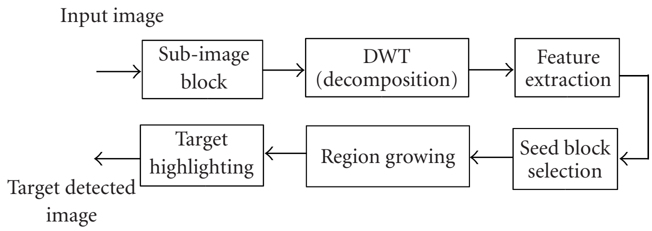


FIGURE 4: Target detection system.

cooccurrence as functions of angle and distance can be represented as

$$\begin{aligned}
C_{0^\circ,d}(i,j) &= \big|\{[(k,l),(m,n)] \in D : k-m=0,\\
&\qquad |l-n|=d,\ f(k,l)=i,\ f(m,n)=j\}\big|,\\
C_{45^\circ,d}(i,j) &= \big|\{[(k,l),(m,n)] \in D : (k-m=d,\ l-n=-d)\\
&\qquad \text{OR } (k-m=-d,\ l-n=d),\ f(k,l)=i,\\
&\qquad f(m,n)=j\}\big|,\\
C_{90^\circ,d}(i,j) &= \big|\{[(k,l),(m,n)] \in D : |k-m|=d,\ l-n=0,\\
&\qquad f(k,l)=i,\ f(m,n)=j\}\big|,\\
C_{135^\circ,d}(i,j) &= \big|\{[(k,l),(m,n)] \in D : (k-m=d,\ l-n=d)\\
&\qquad \text{OR } (k-m=-d,\ l-n=-d),\ f(k,l)=i,\\
&\qquad f(m,n)=j\}\big|,
\end{aligned} \tag{1}$$

where $|\{\cdots\}|$ refers to set cardinality and $D = (M\times N)\times(M\times N)$.

The gray-level cooccurrence matrix $C(i,j)$ can be obtained by counting all pairs of pixels having gray levels i and j, separated by a given displacement vector d in the given direction.

5. TARGET DETECTION SYSTEM

The steps involved in the target detection process is shown in Figure 4.

Here, the input images of size $N\times N$ are considered. The target detection is carried out by considering nonoverlapping sub-images (i.e., blocks) of different sizes, depending upon the target images. Each distinct sub-image block, taken from the top-left corner of the original image, is decomposed using one- or two-level DWT and wavelet cooccurrence matrices (C) are derived for $\theta = 135^\circ$ and $d=(1,1)$ (i.e., one pixel below and one pixel to the right) for detail subbands (i.e., LH1, HL1, HH1, LH2, HL2, and HH2). Here, it is important to note that the required level of DWT decomposition depends on the window size used, that is, for larger window size, the image can be decomposed into more levels of DWT, while for smaller window size, a smaller level of DWT decomposition is used. In turn, the window size depends on the size of the target and the image.

$$\text{Contrast} = \sum_{i,j=1}^{N} (i-j)^2 C(i,j), \tag{2}$$

$$\text{Cluster shade} = \sum_{i,j=1}^{N} \left(i-M_x+j-M_y\right)^3 C(i,j), \tag{3}$$

$$\text{Cluster prominence} = \sum_{i,j=1}^{N} \left(i-M_x+j-M_y\right)^4 C(i,j), \tag{4}$$

where

$$M_x = \sum_{i,j=1}^{N} iC(i,j), \qquad M_y = \sum_{i,j=1}^{N} jC(i,j). \tag{5}$$

Then, from these cooccurrence matrices (C), significant WCFs such as contrast, cluster shade, and cluster prominence are computed using the formulae given in (2) to (4). These feature values are subjected to either linear or logarithmic normalization, depending on their dynamic ranges. The contrast features have moderate values and hence they are subjected to linear normalization, while cluster shade and cluster prominence are subjected to logarithmic normalization, since they have very large dynamic range of values. Selecting the seed block often can be based on the nature of the problem. When a priori information is not available, the procedure is to compute at every pixel or subregion the same set of properties that ultimately will be used for the selection of seed and also for the growing process. In our implementation, the sub-image block, with the maximum of combined normalized feature values of contrast, cluster shade, and cluster prominence (S_{high}) is identified as *seed block or seed window*. The concept of wavelet and cooccurrence features show that the feature values are high for a window that is surely a part of the target.

Region growing is a region-based segmentation process in which subregions are grown into larger regions based on predefined criteria such as threshold and adjacency.

Input: Target image of size $N \times N$
Output: Target detected image
(1) *Read the target image.*
(2) *Obtain* 32×32 *or* 16×16 *sub-image blocks, starting from the top-left corner.*
(3) *Decompose sub-image blocks using 2D-DWT.*
(4) *Derive cooccurrence matrices for detail subbands of DWT decomposed sub-image blocks.*
(5) *Calculate WCFs, such as contrast, cluster shade, and cluster prominence, from cooccurrence matrices.*
(6) *Repeat Steps 2 to 5 for all sub-image blocks.*
(7) *Sort the sum of feature values of all windows in ascending order and choose the window, having the maximum combined feature values* (S_{high}) *as the seed window.*
(8) *Obtain the threshold, that is, the average of feature sums of the first* n% *windows.*
(9) *Apply the region growing algorithm using the mean distance method by merging windows based on the threshold and adjacency.*
(10) *Highlight the target by a bounded rectangle.*

Algorithm 1

In our implementation, the region growing algorithm is based on mean distance method. In this method, the first step is to sort the feature values of all the windows, that is, sub-image blocks in ascending order so that the window whose value is the largest would be the seed window. The threshold is determined by finding the average (A) of the first n% of the windows, which are adaptively chosen depending upon the target image. Now, the feature values of all the 8-adjacent blocks are compared with the average value, A, and the S_{high} value. The window whose value is closer to S_{high} value will be merged with the seed window. This process is repeated for all 8 adjacent blocks. If no window is merged from the 8 adjacent blocks, then the algorithm terminates. If at least one window is merged from the 8 adjacent blocks, then the above procedure will be repeated with the 16 adjacencies and so on. At the end, a rectangle, bounding all the merged windows, is drawn to highlight the target detected. The target detection algorithm is given as in Algorithm 1.

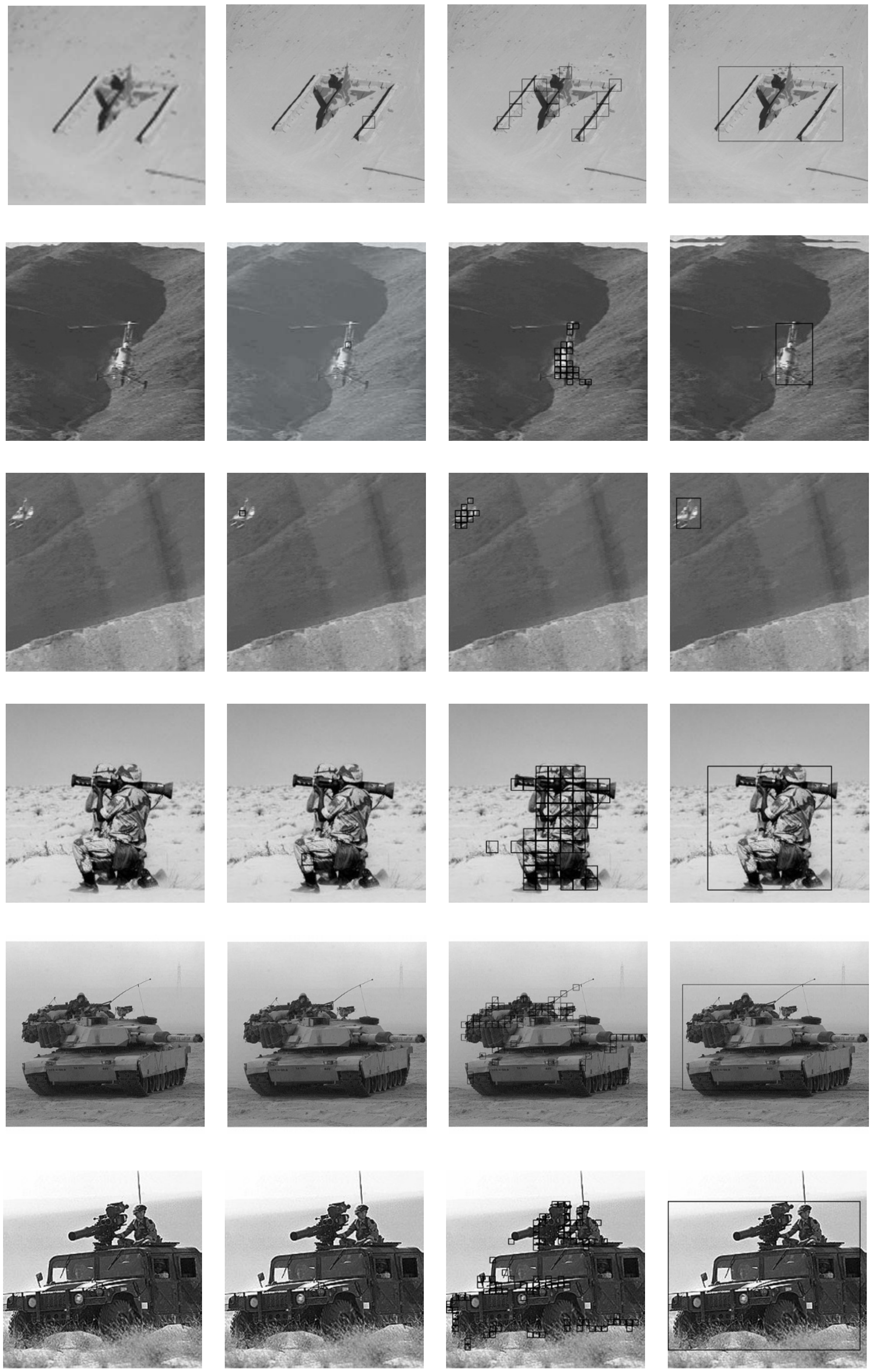
6. EXPERIMENTAL RESULTS AND DISCUSSION

The target detection algorithm discussed in the previous section is applied on twelve different man-made single-target images of sizes either 512×512 or 256×256, three non-man-made or natural single-target images, a man-made two-target fused image, two non-man-made two-target images (i.e., images with two birds), and a non-man-made multitarget image (i.e., image with animals). These images are chosen in such a way that some images are with a clear natural background while other images are in cluttered environment. Also, the images of different sizes are chosen to prove the effectiveness of the proposed target detection algorithm. Though the number of levels of DWT decomposition depends on the window size used, all the target images are subjected to two levels of wavelet decomposition using Daubechies fourth-order filter. For the region growing process, the mean distance method provides better results compared with the Euclidean distance method. The target detection results obtained for the first twelve man-made single-target images are shown in Figures 5 and 6, where column (a) shows original images, while columns (b), (c), and (d) show images with seed window, images after region growing process, and target detected images, respectively. From the figures, it is observed that for all the twelve images, the proposed algorithm results in a better detection process.

The target detection results obtained for the three numbers of non-man-made single-target images are shown in Figure 7. The results of the man-made two-target image, fused from infrared and visible light images using the method given in [47], are shown in Figure 8. In the results of the two-target images, the first image of the second row shows the image after suppressing the first detected target. The results of non-man-made two-target images, each having two birds, are shown in Figures 9 and 10. Finally, the target detection results of the multitarget image having animals are shown in Figure 11, where the first images of the second, third, and fourth rows show the image after suppressing the first, second, and third detected targets, respectively. From the results shown in Figures 5–11, it is observed that the seed window selected is normally the farthest from the center of the man-made object, while for non-man-made (or) natural objects, the seed window is mostly at the center of the object. Further, the results obtained for both man-made and non-man-made

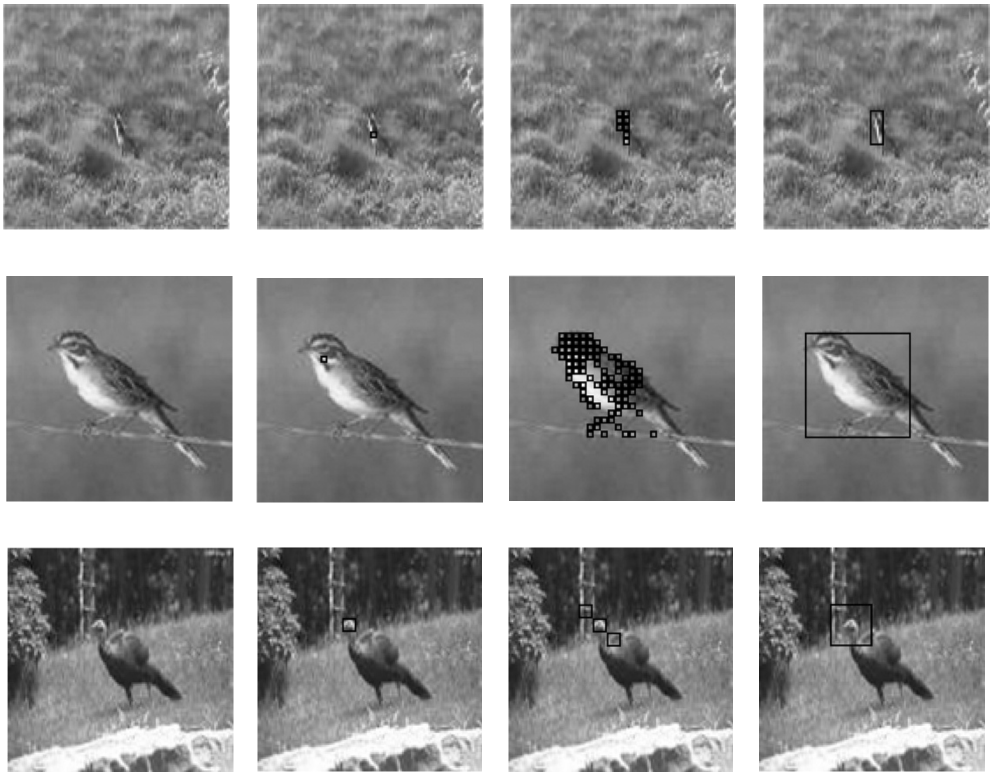
(a) (b) (c) (d)

Figure 5: Man-made single-target detection results (columnwise). (a) Original images. (b) Images with seed window. (c) Images after region growing. (d) Target detected images.



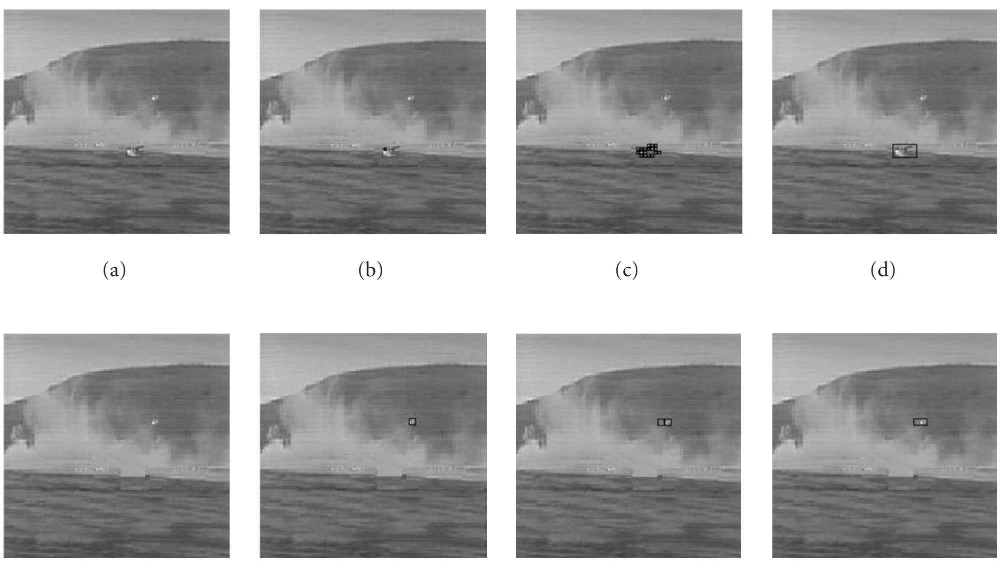
(a) (b) (c) (d)

Figure 6: Man-made single-target detection results (columnwise). (a) Original images. (b) Images with seed window. (c) Images after region growing. (d) Target detected images.



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

Figure 7: Non-man-made single-target detection results (columnwise). (a) Original images. (b) Images with seed window. (c) Images after region growing. (d) Target detected images.



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

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

Figure 8: Man-made two-target detection results. (a) Original image fused from IR and visible images. (b)–(d) Results of the first target. (e) Image after suppressing the first detected target. (f)–(h) Results of the second target.

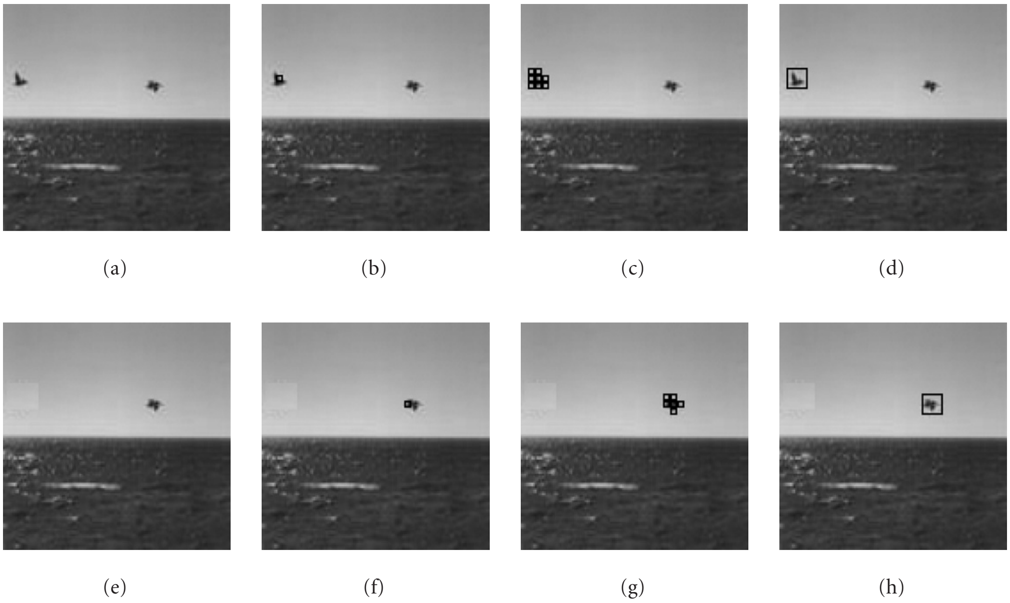


FIGURE 9: Non-man-made two-target detection results. (a) Original image having two birds. (b)–(d) Results of the first target. (e) Image after suppressing the first detected target. (f)–(h) Results of the second target.

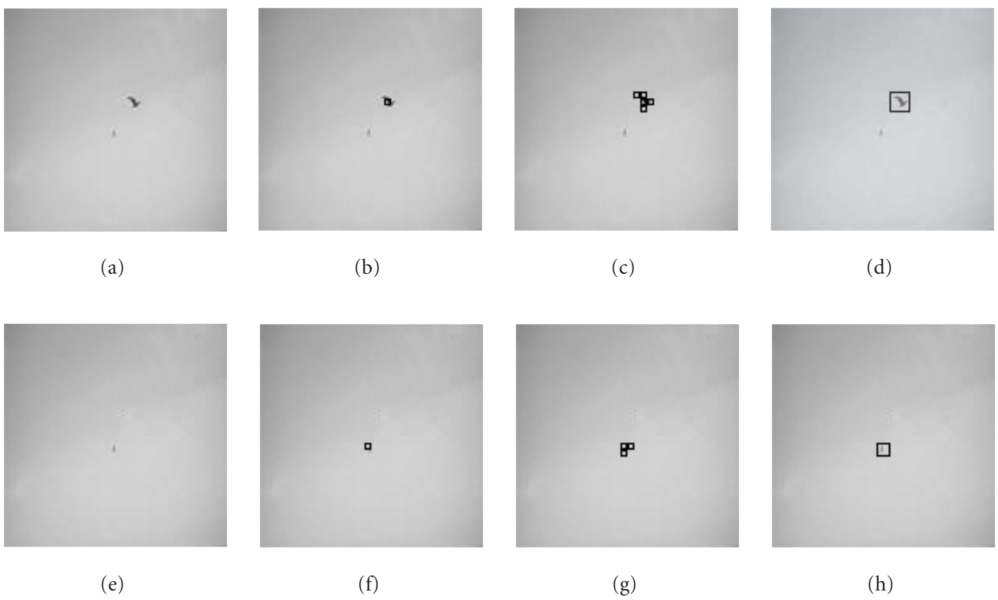


FIGURE 10: Non-man-made two-target detection results. (a) Original image having two birds. (b)–(d) Results of the first target. (e) Image after suppressing the first detected target. (f)–(h) Results of the second target.

single-, two- and multitarget images are found to be satisfactory.

7. CONCLUSION

Considering the role of technology in contemporary defense systems, automating of target detection is very important. The metric wavelet cooccurrence features used in our implementation proved to be very appropriate for that task. The proposed algorithm is found to be successful with the given set of man-made and non-man-made single-, two-, and multitarget images and the results are very convincing. This is useful for applications in defense, for finding the flaws in any objects based on its visual properties of the surfaces, and fault identification in fabrics which is currently under our active research.

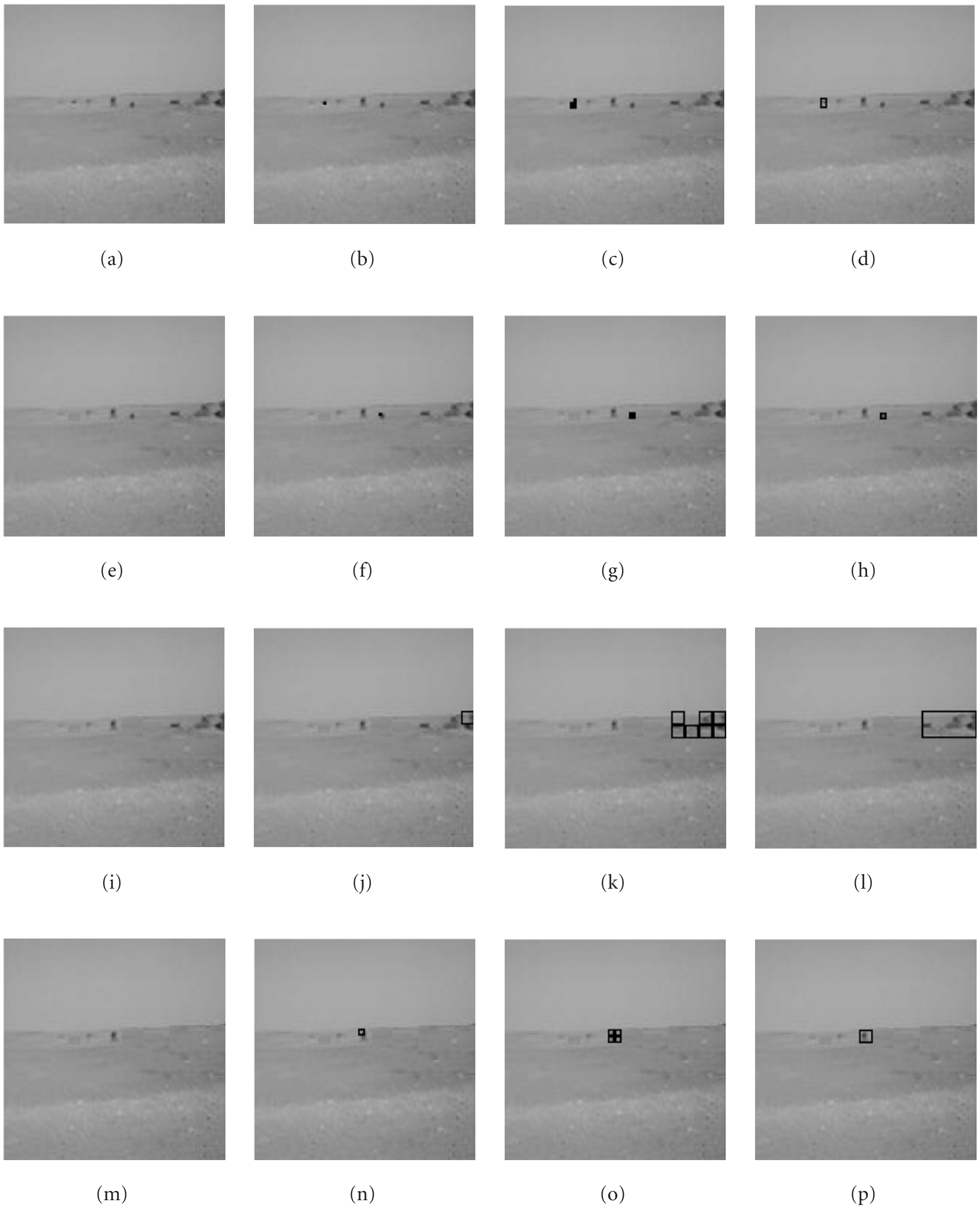


Figure 11: Non-man-made multitarget detection results. (a) Original image having more animals. (b)–(d) Results of the first target. (e) Image after suppressing the first detected target. (f)–(h) Results of the second target. (i) Image after suppressing the second detected target. (j)–(l) Results of the third target. (m) Image after suppressing the third detected target. (n)–(p) Results of the fourth target.

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S. Arivazhagan was born in 1965, in Sivakasi, Tamil Nadu. He received his B.E. degree in electronics and communication engineering from Alagappa Chettiar College of Engineering and Technology, Karaikudi, in 1986, and his M.E. degree in applied electronics from College of Engineering, Guindy, Anna University, Chennai, in 1992. He has submitted his Ph.D. thesis in the area of texture image analysis using wavelet transform to Manonmaniam Sundaranar University, Tirunelveli. Presently, he is working as an Associate Professor in the Department of Electronics and Communication Engineering, Mepco Schlenk Engineering College, Sivakasi. He has eighteen years of teaching and research experience. He has been awarded the Young Scientist Fellowship by Tamil Nadu State Council for Science and Technology in the year 1999. His areas of interest include image processing and computer communication. He has published/presented 31 technical papers in the international/national journals and conferences. He has also coauthored a book entitled *Digital Circuits and Design*. He is the Principal Investigator of a Research and Development Project sanctioned by Defense Research and Development Laboratory (DRDL), Hyderabad, and Indian Space Research Organization (ISRO), Trivandrum. He is a Life Member in the Indian Society for Technical Education (ISTE) and Institute of Electronics and Telecommunication Engineers (IETE).

L. Ganesan born in Ettayapuram (southmost part of India) in 1961. He received his B.E. degree from Thiagarajar College of Engineering, Madurai Kamaraj University Madurai, and obtained his M.E. degree from Government College of Technology, Bharathiar University Coimbatore. He completed his Ph.D. in Indian Institute of Technology, Kharagpur, West Bengal. He started his career as an Associate Lecturer in Government College of Engineering, Tirunelveli, in 1983. He is presently working as a Head of the Department of Computer Science and Engineering, Government College of Engineering, Tirunelveli. He is a Life Member of the Indian Society for Technical Education (ISTE). He has been doing continuous research and guiding 12 research scholars in the disciplines of computer vision, image processing, texture analysis, character recognition, and so forth. He has published 27 technical papers in reputed international journals and presented 85 technical papers in international/national conferences. He has authored a book titled *Information Theory and Coding*.