International Journal on
"Technical and Physical Problems of Engineering"
(IJTPE)
Published by International Organization of IOTPE

ISSN 2077-3528
IJTPE Journal
www.iotpe.com
ijtpe@iotpe.com

June 2015 | Issue 23 | Volume 7 | Number 2 | Pages 60-64

FINDING SPECIFIC TARGETS BASED ON FUZZY LOGIC USING ZERNIKE MOMENTS AND SUPPORT VECTOR MACHINE

E. Yakhti Fard [1] A. Amiri [2]

1. Department of Computer, Zanjan Branch, Islamic Azad University, Zanjan, Iran, e_yakhtifard_it@yahoo.com
2. Department of Computer Engineering, University of Zanjan, Zanjan, Iran, a_amiri@znu.ac.ir

Abstract- In this paper, it has been tried to employ suitable algorithms such as Zernike moments and support vector machine (SVM) to obtain the accurate detection of moving targets. In this method, we try to find some invariant features of targets in video frames. In the proposed algorithm, by using the invariant Zernike moments, which are applied on images, we extract features and by employing multiplex SVMs (ensemble of classifiers), we are able to increase the efficiency and decrease the error of tracking within sequence of images. Fuzzy logic is used to identify objects in video sequences.

Keywords: Zernike Moments, Support Vector Machine (SVM), Fuzzy Logic.

I. INTRODUCTION

One of the important issues concerned in these days is machine vision and image processing. Inside view of the image processing contexts, the detection of moving objects in a sequence of images is one of the challenging fields. In the field of detecting moving targets, the researchers have conducted some limitations such as obstruction and overlapping, fixed or movable camera which can be sensitive to rotation, scaling and translation in images. Different methods have been proposed in the field of image processing to detect and track moving targets. Translation, scaling and rotation are factors that they have influence on the performance of image processing systems. The algorithms must also be adjustable against changes during variations of light occurred in background and conditions. To do this, several methods have been proposed to increase the efficiency that influence on different factors within images. Every one of these methods discuss their advantages and disadvantages with their limitations. Hence, they are generally used to detect objects in a given sequence of images.

Zernike moments and support vector machines have been proposed to detect features especially in the field of medical image processing [1] and astrophysics [2]. Zernike moments for all interest of areas are computed as a feature vector. A support vector machine (SVM) is employed to classify data [1]. Both Zernike moments and SVM have been mixed to detect patterns of human eyes [3]. Some mixed algorithms calculating Zernike moments have been applied on images taken from war and natural scenes and then classified by SVM [4]. It has been accepted that Zernike moments can be used as a criterion to extract information of buildings appeared in satellite images to recognize them. Feature vector of each segment is computed by Zernike moments. Finally, SVM classifier used to assign a class label to each of the segments [5].

In the proposed approach, first, images are segmented. Then, by using Zernike moments (rotation, translation, and scale invariants moments), the features of targets and other regions are extracted from the image. By exploiting ensemble of SVMs, the algorithm can be able to recognize targets in a sequence of images and follows them in consecutive frames. By employing ensemble of SVM classifiers, the classification error dramatically decreases. Fuzzy logic approach is utilized to decrease errors during the identification process in video sequences.

II. ZERNIKE MOMENTS

Zernike introduced a set of complex polynomials which propose a complete orthogonal set over the interior of the unit circle ($x^2+y^2=1$) [6]. Let us to denote the set of these polynomials by $\{V_{nm}(x,y)\}$. The form of these polynomials is written by:

$$V_{nm}(x,y)=V_{nm}(\rho,\theta)=R_{nm}(\rho)e^{jm\theta} \quad (1)$$

where n and m are positive integer/zero and integer, respectively, with the constraint that $n-|m|$ is even and $|m|\le n$. Parameters ρ and θ are the length of vector from origin to (x,y) pixel and angle between vector ρ and x axis in counterclockwise direction, respectively [6,7].

$R_{nm}(\rho)$ Radial polynomial defined as:

$$R_{nm}(\rho)=\sum_{s=0}^{n-|m|/2}(-1)^s.\frac{(n-s)!}{s!((n+|m|)/2-s)!((n-|m|)/2-s)!}\rho^{n-2s} \quad (2)$$

note that $R_{n,-m}(\rho)=R_{nm}(\rho)$.

These polynomials are orthogonal [6] and satisfy:

$$\iint_{x^2+y^2\le 1}[V_{nm}(x,y)]^* V_{pq}(x,y)dxdy=\frac{\pi}{n+1}\delta_{np}\delta_{mq} \quad (2)$$

with

$$\delta_{ab} = \begin{cases} 1; & \text{if} \quad a = b \\ 0; & \text{if} \quad \text{otherwise} \end{cases} \tag{3}$$

Zernike moments are attainable by projection of the image intensity function $f(x,y)$ onto the complex conjugate of Zernike polynomials $V_{nm}(\rho,\theta)$, which is defined as

$$A_{nm} = \frac{n+1}{\pi} \iint_{x^2+y^2 \le 1} f(x,y) V^*{}_{nm}(\rho,\theta) dxdy \tag{4}$$

For a digital image, it can be rewritten as [6, 7]:

$$A_{nm} = \frac{n+1}{\pi} \sum_x \sum_y f(x,y) V^*{}_{nm}(\rho,\theta), \quad x^2 + y^2 \le 1 \tag{5}$$

To obtain the Zernike moments of a separated region, the center of the image is considered as the origin, and location of pixel coordinates is ranged over unit circle [6].

III. SUPPORT VECTOR MACHINE

The set of labels can be given as:

$$(y_1, x_1), \ldots, (y_N, x_N), \qquad y_i \in \{-1, 1\} \tag{7}$$

In linearly separable dataset, a vector w and a scalar b can be described as following inequalities [8]:

$$\begin{cases} w.x_i + b \ge +1 & \text{if} \quad y_i = +1 \\ w.x_i + b \le -1 & if \quad y_i = -1 \end{cases} \tag{8}$$

where can be applied on all elements of the training set. We are able to rewrite them in the following single form [8]:

$$y_i \left(w x_i + b \right) \ge 1, \;\; i = 1, 2, 3, .., N \tag{9}$$

Now, we can obtain the distance between two hyperplanes which is equal with $2/\|w\|$. The Lagrangian function is employed to separate (maximize) classes (margin), efficiently by minimizing the value of $\|w\|$ [1].

The constraint of Lagrangian function is formulated as the following form [8]:

$$\mathcal{L}(w, b, \lambda) = \frac{1}{2} w.w - \sum_{i=1}^{N} \lambda_i \left[y_i \left(w x_i + b \right) - 1 \right] \tag{10}$$

IV. THE PROPOSED APPROACH

An overview of the proposed approach is shown in Figure 1. The first step is to separate the image into regions of interest. Then, the features of regions are extracted by Zernike moments and ensemble of SVM classifiers is used for data classification.

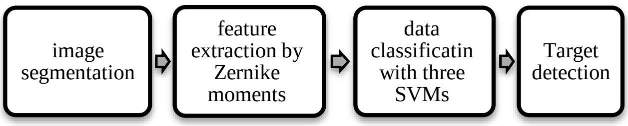

Figure 1. An overview of the proposed approach

V. IMPLEMENTATION OF ZERNIKE MOMENTS

Various types of noise affects on output images of digital cameras and scanners. Noise reduction performs a serious role in image processing applications like object detection, edge detection, image segmentation, compression, etc. [9, 10].

The image is separated by one of the segmentation algorithms to segregate regions, and then the features of each segmented region are extracted. Zernike moments are one of the most robust feature extraction algorithms [2]. It is invariant to scaling, rotation and translation, so it is suitable for feature extraction from video frames. The execution time of applying Zernike moments depends on the size of the input image and order of moments. Since the Zernike moments are invariant to scaling, the image can be shrunk to reduce execution time. To decrease the running time, we must determine the value of input parameters including order of moments and size of images. The number of extracted features depends on the order of Zernike function. Reconstruction error is calculated to find optimum parameters.

The outputs of Zernike moments are reconstructed to find the best parameters when they are compared with the original image. To calculate the reconstruction error, the original image is compared with the reconstructed image to specify the error. The value of difference between original and reconstructed images provides a good criterion for determining the best parameters of Zernike moments. Reconstructed binary image by using Zernike moments is presented in Figure 2.

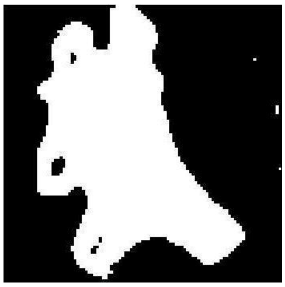

Figure 2. The reconstructed binary image

A. Estimating the Optimal Order

Finding the best order of Zernike moments is one of fundamental challenges, because the number of extracted features and the execution time is directly affected. Therefore, we must determine the optimal value for the order. The optimum order can be achieved by plotting the reconstruction error. Reconstruction error is calculated for different values of order with different image sizes. Optimal order provides the minimum reconstruction error during sequence of images. Reconstruction error with different values of the order are plotted in Figure 3.

B. Estimating the Size of the Input Image

Scale invariant of moments defines that the output of Zernike moments is similar for both small and large images. So, by resizing images, the outputs of Zernike moments are approximately constant. For finding the optimal smallest size of each image, the reconstruction error is calculated for the output of moments at different size of images.

Figure 4 demonstrates the characteristics of scale invariant of these moments. According to Figure 4, the errors are approximately located in the same interval for image sizes ranged from 30×30 to 100×100 and the slope of the error becomes smooth. The diagrams of the reconstruction errors show stationary manner after order 20. The error is reducing gradually with a light slope in large sizes of images. The reconstruction error increases to a high value in small sizes of images. It decreases when the size of images increases. But the error reduction is constant in the large sizes of images and calculating Zernike moments takes high runtime. We can increase the response times by reducing the size of images without changing the results of output. According to Figure (4), the size of images ranged from 30×30 to 80×80 pixels are suitable as input of Zernike moments.

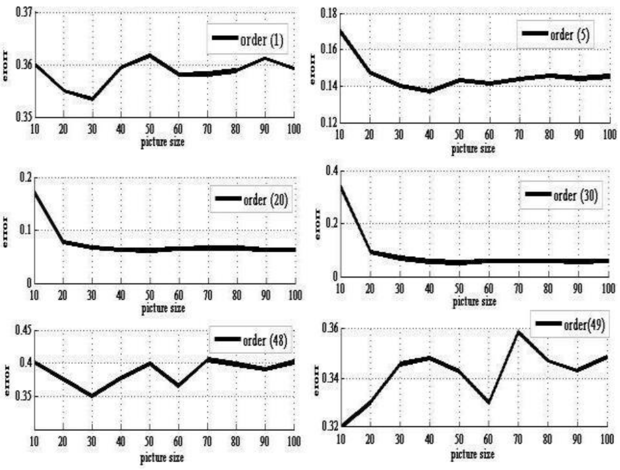

Figure 3. Reconstruction error for different orders

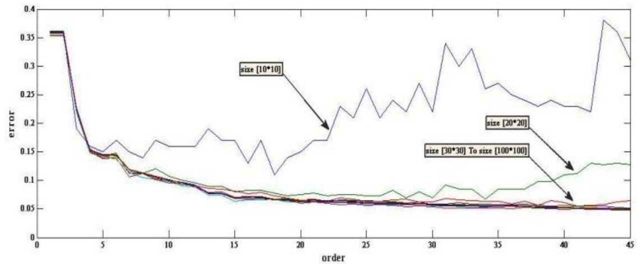

Figure 4. Reconstruction error for different images size (10×10 to 100×100)

VI. CLASSIFICATION DATA BY SVM

The supervised SVM classifier divides data into separate classes. In the first step, the SVM is trained by training set. Thus, SVM classifies new input data by using the trained dataset. To obtain satisfactory accuracy, we exert different SVM kernel functions on datasets. The parameters must be tuned with kernel functions. Training data maps into high-dimensional kernel space is done by Kernel function. A structure resulted from SVM training function is included information about the trained classifier. There are lots of errors in data classification by SVM and the value of this error varies with different kernel functions. SVM performance has been evaluated by employing different kernel functions displayed in Table 1.

Several SVM classifiers are used to reduce errors in data classification. According to the results of Table 1, it seems that would be reasonable to use kernel functions such as linear, quadratic and polynomial forms. In this case, the correct identification for a class object is equal to 98.73, and it is 91.32 for non-object class. After training the SVM, the original data can be classified.

Table 1. Separation rates for different kinds of kernels utilized in SVM

Kernels / Classes	Linear	quadratic	Polynomial	rbf	Mlp
Object	57.77	42.38	95.07	100	90.95
Non-Object	60.33	64.46	41.32	0.2	18.38

VII. ERROR REDUCTION APPROACHES FOR TARGET DETECTION

Several kinds of errors have influences on the results of the algorithm. Objects have a slight displacement in two consecutive frames. So, the current location of the object is marked based on its position in the previous frame. After finding the target, they are stored in a matrix, which is called the history matrix. History matrix keeps path and location of objects in the consecutive frame. Fuzzy logic describes each segmented region with its number. Based on fuzzy logic, a number is assigned to each segment in the matrix. If the value of number is high, the segment is a likely target. This resulted value is expressed in the form of percentage. History matrix is shown in Figure 5.

Figure 5. History matrix

After identifying the target, the average values obtained from three kernels of SVM are stored in the history matrix. To update the history matrix, we use the weighted average to increase the influence of the history matrix. If the target is not found in one of the frames, we can determine its approximate location by using the history matrix. When a target is detected, the probability of being target increases in the matrix. If the target has not been detected, its value decreases within the matrix.

A structure used here is for improving the process of identifying and tracking of object. Data obtained for each target is stored in the structure including the exact location of segment, region, center of intensity, the number of pixels, and the pixel values. This structure makes it possible to access the location of targets in subsequent frames. Therefore, if target is not found, it is stored in the structure so that it may be repeated in following frames. The most frequent targets remain for a long time in structure, because it is most likely repeated in the next frame. We define a variable to store the last number of the frame that contains the target.

This variable is used to remove targets that were not repeated in a long time. Target identification is displayed in Figure 6.

Figure 6. Target detection

VIII. COMPARISON WITH OTHER ALGORITHMS

Some kinds of algorithms have been proposed with the aim of detecting and tracking moving objects in video surveillance. Most algorithms of video surveillance are optimized for a particular activity. This algorithm has been compared with other algorithms to evaluate the success rate of detection of moving targets. The first algorithm is exploited for detecting and counting cars in a video sequences using foreground detector based on Gaussian mixture models (GMMs). The GMM is one of usual technique for image segmentation [11]. The second algorithm is one of the examples of MATLAB that shows performing automatic detection and motion-based tracking of moving objects in a video.

Third and fourth algorithms have been implemented based on the Kalman filter. The Kalman filter is one of the useful tools for predicting. The outputs of algorithms are achieved with an identical data set to compare the success rates (precision and efficiency) of different algorithms. By analyzing the outputs of different algorithms, each algorithm calculates the percentage of correct diagnosis. Correct identification rate is computed by analyzing the outputs of the algorithm. The comparison between algorithms in different backgrounds is presented in Table 2. Detection targets in a simple background, relatively simple background, and complex background are plotted in Figures 7, 8, and 9, respectively.

Figures 7, 8, 9 are the other form of representation of Table 2. Each one is included two diagrams. One of them is related to accurate recognition of target (red) and the other one is connected to detection of non-objects (blue). Our proposed algorithm has the highest rate of recognition of target in the sequence of images and also is able to decrease errors in detection of non-objects within three backgrounds.

Table 2. Comparison of algorithms

data \ algorithms		Algorithm 1	Algorithm 2	Algorithm 3	Algorithm 4	Proposed Algorithm
Simple background	object	72%	84%	81%	67%	97%
	non-object	47%	20%	11%	22%	1%
Relatively simple background	object	69%	78%	30%	47%	85%
	non-object	70%	60%	89%	66%	23%
Complex background	object	12%	16%	38%	20%	80%
	non-object	99%	94%	64%	79%	42%

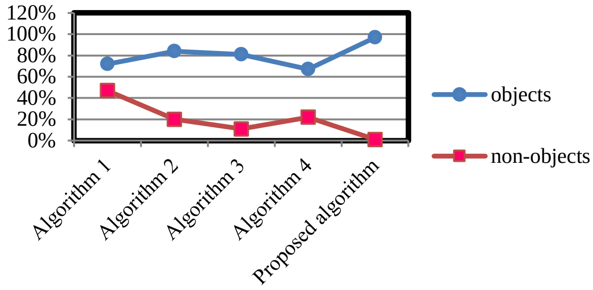

Figure 7. Diagram of detection targets in a simple background

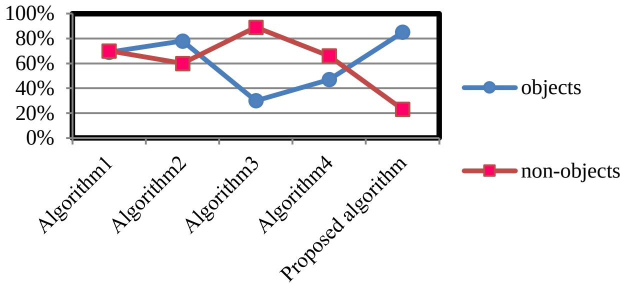

Figure 8. Diagram of detection targets in a relatively simple background

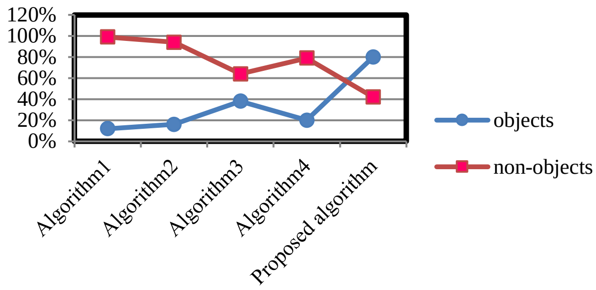

Figure 9. Diagram of detection targets in complex background

The most of the surveillance algorithms in the field of image processing identify all moving object in sequence of image. But proposed approach is just optimized for particular targets. Zernike moments are invariant to scaling, rotation and translation, so it is suitable for feature extraction from video frames. By employing Zernike moments and support vector machine, we are able to finding specific targets. Fuzzy logic has been applied to prevent the loss desired targets. Manage several support vector machine (ensemble of classifiers) reduces classification errors and increase efficiency. Zernike feature extraction requires a lot of time, so execution time is increased for the detection and tracking.

IX. CONCLUSION

In this study, the features extraction method from the image segments is introduced using Zernike polynomials. Zernike moments are applied to the datasets with optimized parameters. The classifier SVM is used to classify the data. It is trained and tested with three kinds of kernels to reduce the classification error and increase the detection accuracy. Finding targets in a sequence of images is based on fuzzy logic. The data extracted from target is stored in a structure that provides access to the target path. Using both Zernike moments and SVM as a hybrid algorithm allows us to determine special-purpose targets. Zernike moments offer unique features that are invariant to scaling, translation, and rotation, which is efficient for detecting targets in video frames.

REFERENCES

[1] S. Sharma, P. Khanna, "Computer-Aided Diagnosis of Malignant Mammograms using Zernike Moments and SVM", Springer, 2014.

[2] M. Javaherian, H. Safari, A. Amiri, S. Ziaei, "Automatic Method for Identifying Photospheric Bright Points and Granules Observed by Sunrise", Springer Science, 2014.

[3] H.J. Kim, W.Y. Kim, "Eye Detection in Facial Images Using Zernike Moments with SVM", ETRI Journal, Vol. 30, No. 2, April 2008.

[4] S. Daniel Madan Raja, A. Shanmugam, "Zernike Moments Based War Scene Classification Using ANN and SVM: A Comparative Study", Binary Information Press, Journal of Information and Computational Science, 2011.

[5] H. Mahi, H. Isabaten, Ch. Serief, "Zernike Moments and SVM for Shape Classification in Very High Resolution Satellite Images", The International Arab Journal of Information Technology, Vol. 11, No. 1, January 2014.

[6] A. Khotanzad, Y.H. Hong, "Invariant Image Recognition by Zernike Moments", IEEE Transactions Analysis and Machine Intelligence, Vol. 12, No. 5, pp. 489-49, May 1990.

[7] M. Cheriet, N. Kharma, C.L Liu, Y.C. Suen, "Character Recognition Systems: A Guide for Students and Practitioners", John Wiley & Sons, November 2007.

[8] C. Cortes, V. Vapnik, "Support-Vector Networks", Machine Learning, Vol. 20, No. 3, pp. 273-297, Kluwer Academic Publishers, Boston. Manufactured in The Netherlands, 1995.

[9] M. Momeny, M. Nooshyar, M. Abdipour, "Introduction of a New Adaptive Trimmed Median Filter to Remove High Density Impulsive Noise In Natural Images", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 19, Vol. 6, No. 2, pp. 31-35, Jun 2014.

[10] M. Momeny, M. Nooshyar, "A Novel and Efficient Method for Reduction Degradation Caused by High Density Impulsive Noise in Digital Images", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 18, Vol. 6, No. 1, pp. 108-113, Mar 2014.

[11] M.A. Balafar, "Fast and Robust Gaussian Mixture Model for MRI Brain Image Segmentation", International Journal on Technical and Physical Problems of Engineering (IJTPE), Issue 15, Vol. 5, No. 2, pp. 8-14, Jun 2013.

BIOGRAPHIES

Elaheh Yakhti Fard was born in Zanjan, Iran. She received the B.Sc. degree from Zanjan Branch, Islamic Azad University, Zanjan, Iran. Currently, She is a M.Sc. degree student in the same university. Her research interests are artificial intelligence and image processing.

Ali Amiri was born in Zanjan, Iran. He received the B.Sc. degree in Computer Software Engineering from Zanjan Branch, Islamic Azad University, Zanjan, Iran. He received the M.Sc. degree from Iran University of Science and Technology, Tehran, Iran, and the Ph.D. degree from Iran University of Science and Technology, Tehran, Iran in Computer Engineering, Artificial Intelligence and Robotic, in 2006 and 2011, respectively. Currently, he is an Assistant professor of Computer Engineering Department at University of Zanjan, Zanjan, Iran.