# Adaptive Fuzzy Weighted Template Matching Using Invariant Features for a Tracking Application

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**Abstract:** One of the common research topics for surveillance systems is tracking of a target object. Motions of both observer and target make the problem difficult to handle. In this paper, proposed algorithm tracks a target object on consecutive frames taken from a camera embedded on an unmanned aerial vehicle. Adaptive-fuzzy weighted sum of square distances (SSDs) are utilized for template matching process. SSD is computed by the pseudo-Zernike moments of the reference template and possible matching template around the search point. Fuzzy weights are obtained by taking the advantage of circular projection features. An adaptive fuzzy system is realized by updating the weights of the defuzzifier. Proposed method provides center point of the best matching template which represents the target object to be tracked. Tracking is accomplished under the presence of illumination changes and parallax, and it is seen that the proposed algorithm yields satisfactorily small errors.

Keywords: Pseudo-Zernike moments, circular projections, adaptive fuzzy, template matching, tracking.

## 1. INTRODUCTION

Tracking of the objects is an essential research topic studied in the context of surveillance systems. There are various ways to realize the tracking applications according to the constraints of the problem. The common way for the stationary systems is to detect changes on a static background and extract foreground objects to be tracked (Celenk et al., 2008). In most cases, background modeling with change detection is not suitable for dynamic systems in which the observer is also moving. One main difficulty with moving observers is the disparity of illumination among consecutive frames. Guo et al. (2007) states the use of line and point features with robust alignment to match similar objects between frames by comparing proposed matching algorithm with different matching methods.

The crucial point is to attain a system with best accuracy and least computational complexity. Hence, considering region of interest (RoI) is a good choice to work on rather than original image. Kontitsis and Valavanis (2010) demonstrate that template matching with sum of absolute differences (SAD) can achieve tracking by updating search template using the templates of two consecutive frames. Also, features of the templates can be used to match templates to obtain higher accuracy under geometric transformations (Sibiryakov, 2008). Use of robust and invariant features instead of template itself is a good option to track objects under illumination changes and geometric transformations (Sibiryakov, 2008; Choi and Kim, 2001). Choi and Kim (2001) propose a two stage template matching method to overcome rotational motion and illumination change problems. First stage is the vector sum of the circular projection to verify possible matching templates, and the second stage is to find best matching template according to

Zernike moments extracted from possible matching templates (Choi and Kim, 2001).

In addition to the cited literature, fuzzy logic is also frequently used in pattern recognition and image processing applications with the goal of increasing the accuracy (Cheng et al., 1998; Nozaki and Ishibuchi, 1996). The verbal nature of fuzzy set theory and the diversity of possibilities in choosing the membership functions, inference engine, fuzzifier and deffuzifier make the use of fuzzy logic a good alternative providing many degrees of freedom to the designer. Availability of supervised and unsupervised learning techniques as well as the presence of different rule base structures constitutes the power of fuzzy inference systems. Especially, the experiences of a designer can be incorporated into the design of the fuzzy model and this enables to set up biased initial conditions for the adjustable parameters.

In this paper, a different type of two stage template matching is presented. Pseudo-Zernike moments are used to calculate sum of square distances (SSDs) between template features, and circular projections are taken as the input vectors for the fuzzy system to obtain the weight for SSDs. Also, adaptive fuzzy structure is implemented by updating the weights related to the membership functions according to the circular projections of the best matching template. The tracking result of the proposed system is compared with the template matching with pseudo-Zernike features and fuzzy weighted template matching using pseudo-Zernike features.

This paper is organized as follows: Section 2 explains the algorithmic procedure of the proposed system. Section 3 demonstrates the results and a comparison of the studied methods. Concluding remarks constitute the last part of the paper.

#### 2. PROCEDURE FOR THE PROPOSED SYSTEM

The first step is to determine the reference template which belongs to target object. The reference template will be tracked on the consequent video frames by using the proposed algorithm. Pseudo-Zernike moments and circular projections of the reference template are extracted as reference features for the tracking process.

The proposed tracking algorithm searches the best matching template around the center point of previous best matching template. The template with minimum fuzzy weighted SSD among various possible templates is selected as the point of the target object to be tracked. Fig. 1 expresses the diagram of fuzzy weighted SSD calculation for a possible template by using reference pseudo-Zernike features and circular projections features.

The next step is the update of fuzzy weights related to each membership function. In addition, reference pseudo-Zernike features is updated as the pseudo-Zernike moments of best matching template to handle the problem of template change due to the parallax.



Fig. 1. Fuzzy weighted SSD calculation diagram

## 2.1 Template Features

#### 2.1.1 Pseudo-Zernike Moments

Pseudo-Zernike moments are widely used features in literature because of being robustness to illumination changes and invariant to rotation (Chong et al., 2003; Prokorp et al., 1992; Teh and Chin, 1988). Hence, this paper takes the advantage of pseudo-Zernike moments extracted from the templates on image.

Pseudo-Zernike features are calculated by using pseudo-Zernike polynomials which can be expressed as in (1) (Khotanzad and Hong, 1190; Chong et al., 2003).

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

where *n* and *m* are order and repetition values respectively,  $\rho$  and  $\theta$  are defined in (2), and  $R_{nm}(\rho)$  is the radial polynomial described by (3).

$$\rho = \sqrt{x^2 + y^2}, \theta = \tan^{-1}(y / x)$$
(2)

$$R_{nm}(\rho) = \sum_{s=0}^{n-|m|} (-1)^s \frac{\rho^{n-s} (2n+1-s)!}{s!(n+|m|+1-s)!(n-|m|-s)!}$$
(3)

where  $0 \le |m| \le n$  and  $n \ge 0$ .

 $V_{nm}$  is calculated around a unit circle where  $\rho \leq 1$  is satisfied with x and y which are normalized pixel values with respect to template size (Khotanzad and Hong, 1190; Teh and Chin, 1988). Psedudo-Zernike moments with given  $V_{nm}$  can be obtained as in (4) (Khotanzad and Hong, 1990; Chong et al., 2003; Teh and Chin, 1988).

$$Z_{nm} = \frac{n+1}{\pi} \sum_{x} \sum_{y} f(x, y) V'_{nm}(x, y)$$
(4)

where  $V'_{nm}$  is the conjugate of  $V_{nm}$ , and  $Z_{nm}$  is the *n* order and *m* repetition pseudo-Zernike moment of template f(x, y).

#### 2.1.2 Circular Projections

Circular projections feature as being rotation invariant is a useful tool to describe template by reducing 2D data to 1D feature vector (Choi and Kim, 2002). The philosophy behind this algorithm is to compute the sum all intensities on the defined circles with given radius (Choi and Kim, 2002). Feature vector size can be up to a maximum value of the radius along the template center. The circular projections can be obtained as in (5);

$$c_r = \sum_{x} \sum_{y} f(x, y) p_r(x, y)$$
(5)

where  $c_r$  is the circular projection at radius r, f(x,y) is the template, and  $p_r(x,y)$  is the circle template for radius r in which  $p_r(x,y)$  is 0 if the pixel point is not on the circle, otherwise  $p_r(x,y)$  is equals 1.

The circle templates can be created by rounding Euclidean distance between template points and template centre (Choi and Kim, 2002). Fig. 2 shows the circle templates from radius 1 to 8 respectively.



Fig. 2. Circle templates to calculate circular projections

#### 2.2 Fuzzy System

In this paper, fuzzy system represented in Fig. 1 is used to increase the accuracy of template matching with SSD computed by pseudo-Zernike features. Circular projections are taken to consideration because these features give intensity information on the template at different radius scales.

Fuzzy system decides on the similarity between templates by utilizing their individual circular projections features. The output of the system is used as a coefficient to weight the SSD obtained from pseudo-Zernike features as in Fig. 1. The fuzzy system diagram is demonstrated in Fig. 3 with given circular projections.



Fig. 3. Proposed fuzzy system

In Fig. 3,  $c_1$  to  $c_R$  are the circular projections of the template which is a search template for the best matching,  $P_1$  to  $P_R$  are the circular projections of the reference template,  $F_1$  to  $F_R$  are the related fuzzy blocks for each radius of the circular projections, R is the maximum radius value for the circular projections obtained from the template,  $\psi$  is the output function of the fuzzy system, and Y is the output which is used to weight the SSD of the related template.

Circular projections of the reference template are employed to create membership functions for each fuzzy block to find out the intensity similarity between search template and reference template. Membership functions are expressed as in Fig. 4 and a typical rule structure is as below.  $\mathbb{C}$  represents the fuzzy sets for each rule.

# IF $c_i \in \mathbb{C}_i$ THEN $s_r = y_r$



Fig. 4. Structure of the membership functions for the fuzzy blocks

 $y_{r,1}$  to  $y_{r,5}$  are the fuzzy weights for the membership functions at fuzzy block *r*. The parameters of the membership functions of the fuzzy block *r* are  $k_r$ ,  $l_r$ ,  $m_r$ ,  $n_r$ , and  $o_r$ , and these parameters are defined in (6)-(10), respectively.

$$k_r = P_r - \beta g(r) \tag{6}$$

$$l_r = P_r - \alpha g(r) \tag{7}$$

$$m_r = P_r \tag{8}$$

$$n_r = P_r + \alpha g(r) \tag{9}$$

$$o_r = P_r + \beta g(r) \tag{10}$$

where  $P_r$  is the circular projection of reference template at radius r, g(r) is a function based on radius r, and  $\alpha$ ,  $\beta$  and g(r) are coefficients to determine the values of  $k_r$ ,  $l_r$ ,  $n_r$ , and  $o_r$ . g(r) is chosen to be tested with two different function values, perimeter and area of a circle, as in (11) and (12).

$$g(r) = 2\pi N_r \tag{11}$$

$$g(r) = \pi N_r^2 \tag{12}$$

where  $N_r$  is the number of pixels in which the pixel values are 1 on circle template with radius r.

As stated by Thanh and Chen (2007), Mamdani model can be used to identify each fuzzy block output for the proposed fuzzy system (13).

$$s_r = \frac{\sum_{i=1}^{i=5} \mu_{r,i} y_{r,i}}{\sum_{i=1}^{i=5} \mu_{r,i}}$$
(13)

where  $s_r$  is the output of the fuzzy block r. Hence, output of the fuzzy system Y can be expressed as in (14).

$$Y = \psi(\mathbf{s}) = \frac{\sum s_r r}{\sum r_r}$$
(14)

where  $\mathbf{s}$  is the output vector obtained from each fuzzy block, and *Y* is the output of the fuzzy system in which each fuzzy block weighted according to the radius of its input circular projections.

# 2.3 Template Matching

Template matching process is achieved by finding fuzzy weighted SSD for all possible templates around search region. SSD is computed by using pseudo-Zernike features described in section 2.1.1. Circular projections stated in (5) are used to attain the weighting coefficients by fuzzy system described in section 2.2. The fuzzy weighted distance can be shown as in (15).

$$d_{x,y} = \frac{\eta \left(\mathbf{h} - \mathbf{j}_{x,y}\right)^{T} \left(\mathbf{h} - \mathbf{j}_{x,y}\right)}{\mathbf{Y}_{x,y}}$$
(15)

where  $d_{x,y}$  is the fuzzy weighted distance of the template at point (x,y),  $\eta$  is the scaling coefficient, **h** is the pseudo-Zernike feature vector of the reference template,  $\mathbf{j}_{x,y}$  is the feature vector of the template at (x,y), and  $\mathbf{Y}_{x,y}$  is the fuzzy

weighting coefficient obtained from the circular projections of the template at (x,y) with respect to reference template.

Minimum fuzzy weighted SSD obtained from (15) from the possible templates gives the track point for the current frame by taking the centre point of the best matching template. After selection of best matching template, if the minimum fuzzy weighted SSD is between a predefined interval  $T_1$  and  $T_2$ , reference pseudo-Zernike features is assigned as the selected best matching template's pseudo-Zernike moments. This procedure is applied to prevent the affect of parallax.

## 2.4 Adaptive Fuzzy Structure

In adaptive fuzzy weighted SSD template matching, update of the fuzzy weighting parameters  $y_{r,i}$  (13), is preferred to avoid the illumination change problem related to reference template along the video frames instead of updating the reference circular projections.

Update algorithm is based on the membership values of the selected best matching template. Update of the  $y_{r,i}$  is done separately according to each membership values  $\mu_{r,i}$  at each fuzzy block. The pseudo code of the update algorithm is given below:

Table 1. Update scheme for the fuzzy system parameters

for each r		
for each $i$		
$ extsf{if} \mu_{r,i} > 0$ t	hen	$y_{r,i} = y_{r,i} + 0.1 \mu_{r,i}$
else		$y_{r,i} = y_{r,i} - 0.025 \max(\boldsymbol{\mu}_{\boldsymbol{r}})$
<b>if</b> $y_{r,i} > \gamma_{\max}$ <b>t</b>	hen	$y_{r,i} = \gamma_{\max}$
<b>if</b> $y_{r,i} < \gamma_{\min}$ <b>t</b>	hen:	$y_{r,i} = \gamma_{\min}$
endfor		
endfor		

In Table 1,  $\gamma_{max}$  and  $\gamma_{min}$  are the maximum and minimum ranges defined for  $y_{r,i}$  for the proposed system. Initial values of  $y_{r,i}$  for each *r* are selected as [0.5 1 2 1 0.5]. This update procedure provides flexibility for the fuzzy system for correction of illumination changes between consecutive frames.

# 3. RESULTS AND EXPERIMENTS

In this paper, the video source is used as in COMETS Project in which the video is taken from a camera embedded on an aerial vehicle for surveillance duty (access address given as: http://www.comets-uavs.org/results/perception.shtml).

Video source contains frames with 279×339 size. Template size is taken as 17×17 for template matching process, and according to that circular projection radius varies from r = 1 to r = 8. Possible matching templates are searched around 8 pixel intervals from the previous best matching template center point which is the search point for best matching template.

Proposed algorithm adaptive fuzzy weighted SSD (AFW-SSD) is compared to two algorithms which are the basis

elements of the proposed system. Hence, the tracking improvement satisfied by the proposed system can be shown exactly. Comparison is made according to an error measure which is the distance of the track point to the approximate centre of the target object. First algorithm is based on matching the pseudo-Zernike features by finding minimum SSD among possible templates around search point. This algorithm includes the feature update procedure stated in section 2.3. Second algorithm is fuzzy weighted SSD (FW-SSD) matching algorithm; however, parameter update depicted in Table 1 is not utilized on each frame. On the other hand, pseudo-Zernike features and circular projection features is updated as to be reference features if the condition is satisfied as in section 2.3.

Comparisons are made by different values of the parameters  $\alpha$ ,  $\beta$  and g(r) defined in (6) to (10) to observe the performance of the proposed system. Fig. 5 shows the error graph when  $\alpha = 5$ ,  $\beta = 15$  and g(r) as (11), and the mean and variance of error of the three algorithms for these parameter selection are given by Table 2. Fig. 6 demonstrates the error graph when  $\alpha = 8$ ,  $\beta = 24$  and g(r) as defined in (11), and the mean and variance of error of the three algorithms for these parameter selection are given by Table 3. Fig. 7 depicts the error graph when  $\alpha = 5$ ,  $\beta = 15$  and g(r) defined as in (12), and the mean and variance of error of the three algorithms for these parameter selection are given by Table 4. Fig. 8 and Fig. 9 demonstrate the tracking results for the proposed AFW-SSD algorithm with two different parameters.

Experimental results prove that using circular projection information for fuzzy structure is helpful to track target object. Moreover, utilizing an adaptive system as proposed in this paper also enables a better tracking which surpasses the compared algorithms on overall performance by means of mean and variance of error. FW-SSD and AWF-SSD also succeeds good performance regarding the time consumption by having 8 - 9 fps and low error statistics with respect to SSD having 13 - 14 fps and high error statistics.

Table 2. Mean and Variance of Errors for Fig. 5

	Mean	Variance
SSD	9.7219	25.19991
FW-SSD	4.4678	4.5950
AFW-SSD	4.0641	4.0285

Table 3. Mean and Variance of Errors for Fig. 6

	Mean	Variance
SSD	9.7219	25.19991
FW-SSD	6.8669	13.0554
AFW-SSD	4.9324	8.1343

Table 4. Mean and Variance of Errors for Fig. 7

	Mean	Variance
SSD	9.7219	25.19991
FW-SSD	7.0029	15.6775
AFW-SSD	4.2106	5.6246

### 4. CONCLUSIONS

Proposed algorithm focuses on the adaptive fuzzy weighted sum squared distance template matching algorithm to track a target object under parallax and illumination changes. The results depict that the proposed system realizes the tracking application with an acceptable accuracy. In determining the parameters in fuzzy system, the experimental observations have been utilized. The results emphasize the effectiveness of the proposed system.

# 5. ACKNOWLEDGMENTS

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Fig. 5. Error graphs  $\alpha = 5$ ,  $\beta = 15$  and g(r) as (11)



Fig. 6. Error graphs  $\alpha = 8$ ,  $\beta = 24$  and g(r) as (11)



Fig. 7. Error graphs  $\alpha = 5$ ,  $\beta = 15$  and g(r) as (12)



Fig. 8. Tracking results for proposed system  $\alpha = 5$ ,  $\beta = 15$  and g(r) as (11)



Fig. 9. Tracking results for proposed system  $\alpha = 5$ ,  $\beta = 15$  and g(r) as (12)