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Improved MOSSE Tracking Algorithm Based On Dimensional Analysis

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Abstract

The classic MOSSE algorithm is often used for real-time target tracking. Aiming at the problem that the fixed filter update rate is difficult to adapt to the drastic change of the target appearance and the target is lost, an improved MOSSE tracking algorithm based on dimension analysis is proposed. This method uses Buckingham theorem to analyze the main factors that affect the update rate of the filter, establishes an update rate prediction model and automatically reloads the update rate. The improved algorithm can improve the robustness and tracking quality of target tracking.

Keywords

MOSSE tracking, Dimensional analysis, Buckingham's theorem, Prediction model, Robustness.

1. Introduction

Target tracking is a hot research direction in machine vision, and its application prospect is broad [1]. In the medical field, multi-target tracking is an auxiliary method of diagnostic technology. Through the application of target recognition technology to medical images, the accuracy of detection can be improved [2]. In the field of transportation, multi-target tracking is an important module in intelligent transportation systems, and it is the key to achieving intelligent traffic monitoring [3]. The development of target tracking has roughly gone through three stages. Classic target tracking methods such as Meanshift [4] identify targets by calculating the probability density of the target on the next frame of image. Particle Filter [5] defines a similarity metric to determine how well a particle matches a target. Because classic methods cannot handle and adapt to complex tracking changes, target tracking algorithms based on deep learning and correlation filtering have replaced the status of classic methods [6]. A typical algorithm, TLD [7], which combines detection and tracking, trains the tracking detector through online learning methods. Representatives of correlation filtering algorithms such as MOSSE [8] find the possible location of the target by calculating the maximum response of the input image.

The above methods can achieve target tracking, but the classical method is not as robust and accurate as the tracking method of deep learning. The target tracking based on deep learning is more biased towards the accuracy of target tracking, and the real-time performance is lower than the target filtering algorithm of correlation filtering. The research object of this paper is the MOSSE tracking algorithm, which has strong real-time performance, but because the filter update rate cannot adapt to changes in the target shape and background environment, and filter deviation accumulates and causes tracking failure [9]. The improved MOSSE tracking improved algorithm analyzes the physical laws and mathematical relationships between the multivariables that affect the tracking quality, and realizes the prediction and automatic reloading of the filter update rate. The algorithm of improved update strategy can be effectively used for real-time tracking of targets in complex environments.

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2. MOSSE Tracking Algorithm

The Assuming input signals s_i, their output response is t_i. The corresponding FFT is represented by S_i and T_i. The optimal filter is determined based on the minimum sum of squares of the difference between the training sample output response and the expected response, as shown in formula (1):

$$M_{opt} = \min_{M^*} \sum_i |S_i \otimes M^* - T_i|^2 \tag{1}$$

export:

$$M_{opt}^* = \frac{\sum T_i \otimes S_i^*}{\sum S_i \otimes S_i^*} \tag{2}$$

A random affine transformation is performed on the tracking frame to obtain training samples s_i, which t_i are generated by a Gaussian function with the peak at the center of s_i.

$$M_i^* = \frac{U_i}{V_i} \tag{3}$$

$$U_i = \lambda T_i \otimes S_i^* + (1-\lambda)U_{i-1} \tag{4}$$

$$V_i = \lambda F_i \otimes F_i^* + (1-\lambda)V_{i-1} \tag{5}$$

The MOSSE tracking filter is the least error mean square filter [10]. Selecting a reasonable update rate can generate an optimal filter for the current frame to avoid tracking failure problems and improve tracking quality.

3. Improved MOSSE Tracking Algorithm

3.1 Algorithm Flow

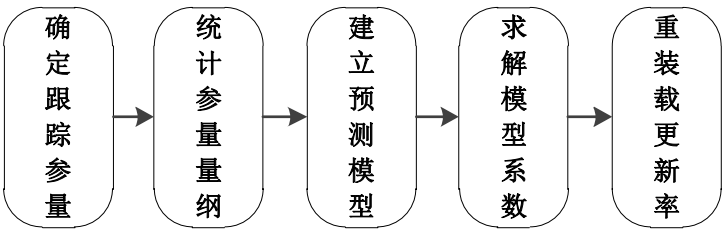

Figure 1. Algorithm flowchart

The MOSSE tracking improvement algorithm flow is shown in Figure 1: First, the main parameters of the tracking process are determined; the second step is to calculate the parameter dimension through the dimension table and the dimension matrix [11]; The fourth step is to solve the partial regression coefficients of the prediction model through the multiple linear regression method. Finally, use the update rate prediction value to generate the current frame optimal filter to complete the target tracking task.

3.2 Specific Steps

3.2.1 MOSSE Tracking Parameters and Dimensional Statistics

The dimensional analysis method is a mathematical analysis method that starts from analyzing the dimensions of the physical quantities involved in a phenomenon and solves the relationship between the physical quantities in the phenomenon under study [12]. The tracking quality has a direct relationship with the update rate and affects the update rate. Factors include the size of the tracking target, the speed of the movement, the degree of deformation, and the complexity of the background. Because different physical quantities have different dimensions and dimensional units, they must be dimensionlessly processed [13-15].

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According to the basic principle of dimensional analysis, the parameters and dimensions of MOSSE tracking are established in the length-mass-time (L-M-T) system. "None" in Table 1 indicates that the physical quantity is a dimensionless parameter.

3.2.2 Establishment of Update Rate Prediction Model

There are 6 main parameters involved in MOSSE tracking, so these parameters can be expressed by functions:

$$F(\lambda, v, \Delta l, l, t, \eta) = 0 \tag{6}$$

Or

$$\lambda = f(v, \Delta l, l, t, \eta) \tag{7}$$

Table 1. Parameters and dimensions of MOSSE tracking

	parameters	dimension
1	Template update rate λ	none
2	Target speed v	LT^{-1}
3	Target diagonal deformation Δl	L
4	Target diagonal length l	L
5	Frame time interval t	T
6	Target background complexity η	none

In order to facilitate the statistical analysis of the dimensions of the six parameters, Table 1 can be written in the form of a dimension matrix, see Table 2.

Table 2. Dimensional matrix of MOSSE tracking

	λ	v	Δl	l	t	η
L	0	1	1	1	0	0
M	0	0	0	0	0	0
T	0	-1	0	0	1	0

According to the analysis in Table 2, the rank of the easy-to-verify dimensional matrix is 2. According to the principle of selecting the basic quantity, this example selects the target diagonal deformation of the geometric similarity variable Δl, and performs dimensional analysis on the similarity variable v as the basic physical quantity. You get 4 independent variables: $\pi_1 = \lambda$, $\pi_2 = \frac{l}{\Delta l}$, $\pi_3 = \frac{vt}{\Delta l}$, $\pi_4 = \eta$.

Available dimensionless formula:

$$\lambda = f(\frac{l}{\Delta l}, \frac{vt}{\Delta l}, \eta) \tag{8}$$

Converting formula (8) to a power form is:

$$\lambda = \varphi_0 (\frac{l}{\Delta l})^{\varphi_1} (\frac{vt}{\Delta l})^{\varphi_2} (\eta)^{\varphi_3} \tag{9}$$

Where: φ_0 is coefficient; φ_1、φ_2 and φ_3 are indices.

Take the logarithm of both sides of equation (9) to get:

$$\begin{aligned} \ln(\lambda) &= \ln(\varphi_0) + \varphi_1 \ln(\frac{l}{\Delta l}) \\ &+ \varphi_2 \ln(\frac{vt}{\Delta l}) + \varphi_3 \ln(\eta) \end{aligned} \tag{10}$$

The prediction model of the update rate is established, and its constant terms and partial regression coefficients need to be determined through tracking simulation experiments.

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4. Test Experiment

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4.1 Parameter Setting and Regression Analysis

Before verifying the model established by Buckingham's theorem, the partial regression coefficients of the constant term and the remaining terms in formula (9) need to be solved. The experimental platform is an independently developed motion tracking simulator based on the Flash and OpenCV environments. The simulator allows the user to input the background picture and track the target plug-in, and set the geometric parameters and motion parameters of the target plug-in. After the tracking scene is established, the user needs to edit the tracking algorithm. After the algorithm is successfully imported, click the execute button. The motion simulator is initialized according to the input parameters and enters the running state. There are three positioning frames around the tracking target, the red positioning frame is the target reference frame, the green positioning frame is the MOSSE recognition frame, and the blue positioning frame is the improved MOSSE recognition frame.

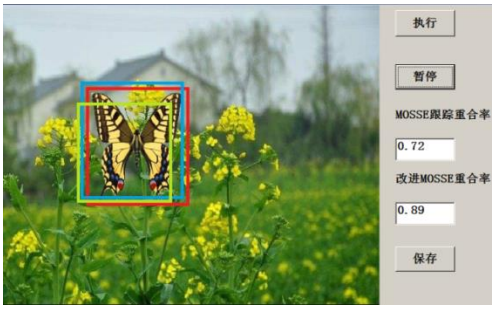

Figure 2. Motion tracking simulator flowchart

The initialization parameters of the motion simulator are set as follows: the target diagonal length is 150 pixels (Dots), the frame rate is set to 24fps, the target initial speed is 4.5m / s and the increment is 0.5m / s, and the target background is initially complicated. The degree is 0.50 and is increased by 0.02 steps. The background complexity is quantified according to the proportion of the gray distribution interval that exceeds a certain threshold to the total interval after the original image is grayed. The initial diagonal deformation of the target is 5Dots in 5Dots increments, and the default resolution of the image is 100DPI. After the simulation experiment is finished, click the Save button to generate an Excel spreadsheet of the simulation data. Ten groups of data are selected as the fitting data of the update rate prediction model, as shown in Table 3.

Table 3. MOSSE tracking simulation data

	λ	$\frac{l}{\Delta l}$	$\frac{vt}{\Delta l}$	η
1	0.114	30.00	147.64	0.50
2	0.126	15.00	82.02	0.52
3	0.140	10.00	60.15	0.54
4	0.147	7.50	49.21	0.56
5	0.161	6.00	42.65	0.58
6	0.171	5.00	38.28	0.60
7	0.188	4.29	35.15	0.62
8	0.196	3.75	32.81	0.64
9	0.215	3.33	30.99	0.66
10	0.228	3.00	29.53	0.68

The simulation data was imported into MATLAB for multivariate linear regression analysis, and the point estimates and interval estimates of the regression coefficients [16] are shown in Table 4.

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Table 4. Estimation of regression coefficients for the update rate prediction model

Regression coefficients	Point estimation	Interval estimation	
$\ln(\varphi_0)$	4.1347	-5.8175	14.0868
φ_1	1.4508	-1.6020	4.5037
φ_2	-1.5646	-4.8143	1.6850
φ_3	4.9438	-1.0015	10.8892

Draw a scatter plot of the prediction model, as shown in Figure 3. The scatter plot can intuitively reflect the relationship between $\ln(\lambda)$ with the three independent variables $\ln(\frac{l}{\Delta l})$ 、 $\ln(\frac{vt}{\Delta l})$ and $\ln(\eta)$,the dependent and independent variables are roughly linear, Based on the comprehensive judgment of partial regression coefficient and scatter plot, $\ln(\eta)$ is the factor that affects $\ln(\lambda)$ with a larger weight.

The partial regression coefficient in Table 4 is substituted into formula (9), and the final prediction formula of the update rate is shown in formula (11):

$$\lambda = 62.4708(\frac{l}{\Delta l})^{1.4508}(\frac{vt}{\Delta l})^{-1.5646}(\eta)^{4.9438} \tag{11}$$

Three statistics for testing regression models: $R^2 = 0.9979$, $F = 941.4835$,corresponding F, $p < 0.05$,statistically verify the prediction model.

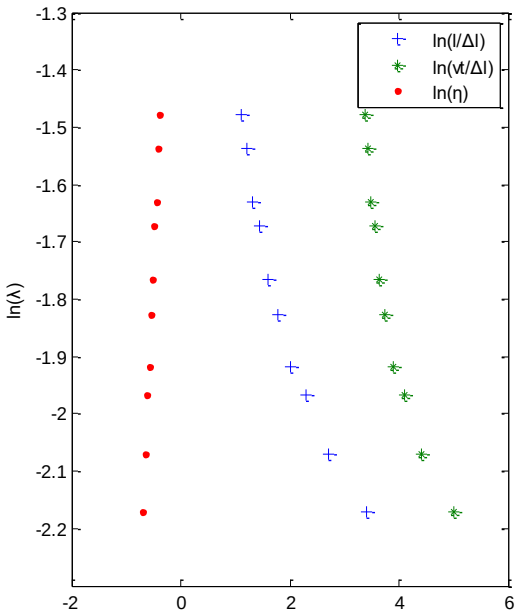

Figure 3. Scatter diagram of the prediction model

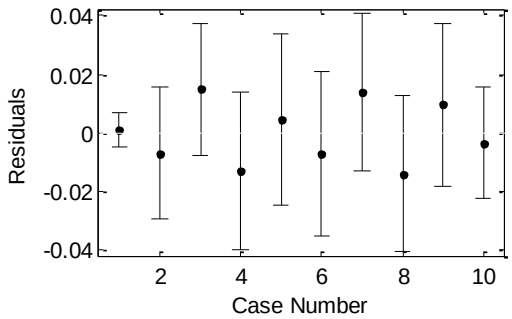

Figure 4. Analysis of residuals of prediction model

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The deviation between the estimated value and the true value of the update rate generated by the prediction model is shown in Figure 4. The confidence intervals of the residuals contain zero abnormal points not found, and the residuals fall more evenly in the horizontal region, indicating that the selected model has Rationality [17].

4.2 Prediction model validation

According to the simulation data of the motion tracking simulator, the constant terms of the update rate prediction model and the partial regression coefficients of the independent variables were obtained. The three statistics of the regression model and the residual analysis of the prediction model were used to verify the update rate from a theoretical level. The rationality of the prediction model and its feasibility at the practical level need to be proved by actual test experiments.

Previous analysis shows that there are five parameters that affect the update rate of the filter, which are the target motion speed, target diagonal deformation, target diagonal length, frame time interval, and target background complexity. In this test experiment, the target diagonal deformation was selected, and 5Dots was used as the initial deformation value. Eight groups of experiments were performed, and each group increased the deformation amount by 5Dots compared with the previous group. The remaining constants are set as follows: the target movement speed is set to 6m / s, the target diagonal length is 150Dots, the frame rate is 24fps, and the background complexity is set to 0.56. In order to ensure the confidence of the test experiments, each set of test experiments is performed 20 rounds of tracking comparisons. Whether the target is deformed in each frame and the number of continuous deformation frames is randomly generated by the simulator [18]. The test results of the 8 groups of experiments are shown in Table 5. The table lists the comparison results of the success rate and tracking quality of the classic MOSSE tracking and the improved update strategy of each group of experiments.

Table 5. Update rate prediction model test experiments

	Success rate(%)		Tracking quality(%)	
	classic	improve	classic	improve
1	96	99	85	91
2	93	98	86	87
3	89	96	84	88
4	83	92	85	86
5	76	88	86	85
6	67	83	82	86
7	56	76	78	85
8	43	70	73	82

The data in the table can be concluded as follows: For the same moving target tracking, the improved MOSSE tracking success rate is significantly better than the classic MOSSE tracking algorithm, and the tracking quality is also improved to a certain extent.

Test experiments verify the robustness and accuracy of the improved algorithm. Through case study of target tracking failure, it is found that the main reason for tracking failure is the lag of filter update, that is, whether it is classic MOSSE tracking or MOSSE with improved update strategy Tracking has a limited update rate. If the target increases its deformation or continues to deform so that the deformation rate is greater than the update rate, and the rate difference continues to accumulate, the target tracking will eventually fail. Two major advantages are robustness and robustness.

5. Concluding Remarks

Aiming at the problem of high tracking loss rate of the classic MOSSE algorithm, this paper proposes an improved MOSSE tracking algorithm based on dimensional analysis. This method estimates the update rate of the next frame by establishing an update rate prediction model with reference to the

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target state. Under the circumstances, improve the tracking quality. The next step of this article is to study the failure cases of MOSSE tracking targets, establish a failure model, and propose a reliable algorithm that can recover lost targets.

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