A Camouflage Effect Detection Model for Fixed Targets

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Abstract: The traditional camouflage effect detection mainly implements the evaluation process for a single image, and cannot effectively reflect the statistical characteristics of the target. In order to better simulate the dynamic interpretation process of reconnaissance personnel on the target, a dynamic and statistically characteristic camouflage effect evaluation model is proposed for the problem of camouflage effect detection of fixed targets. Combined with the Mean shift target tracking technology, the model statistically correlates the target with the background eight-link domain and establishes a normalized joint Gaussian distribution. The target's camouflage effect is then evaluated using the distribution of probability density. The experiment performs complete camouflage, partial camouflage and non-disguise on the exit target of a simulated cavern, and calculates the logarithmic amplification probability and statistics of the curve after collecting the data. According to the 3σ criterion, the mean value is compared with a preset threshold value, and corresponds to the original camouflage state, the better camouflage state, and the invalid camouflage state, respectively. The experimental results show that the model can clearly distinguish the different camouflage states.

1. Introduction

In engineering practice, the camouflage problem of a fixed type of target is relatively common. Compared to general objectives, fixed targets have long-term and fixed characteristics, such as defense engineering, cave mouths, and work objectives. Fixed targets are usually located in remote areas. Personnel and ground detection equipment are difficult to reach. Usually, the data is obtained by using drones or satellite reconnaissance means. Therefore, the acquired data is redundant and diverse. For the problem of camouflage detection, the traditional camouflage effect detection application personnel interpret the discovery probability of the target, which requires a lot of manpower and material resources[1]. In recent years, some scholars have proposed many methods for detecting camouflage effects. Some neural network processing based on image features, some based on the establishment of psychology-based stimulation functions, and some based on the distance of background spots[2-5]. These methods can quickly and objectively evaluate the camouflage effect of the target through a large number of calculations. However, the actual reconnaissance process is often dynamic, multi-view joint and statistical, and these methods for evaluating a single image cannot effectively solve this problem.

The research ideas in this paper are as follows. Aiming at the problem of camouflage effect evaluation of fixed targets, and using its characteristics reasonably, a fixed target camouflage effect detection model is established, which can effectively overcome the shortcomings of traditional evaluation methods. The
model adopts the anomaly detection model in machine learning. By quantifying the target feature data and the feature parameters in the disguised state, the camouflage state evaluation process of the target is realized.

2. Model Establishment

2.1. Target and background area division

The eight-way domain method is used to divide the target and background. The method takes the target in the image as a template, and the eight-way domain with the target center as the origin as the direct background of the target. Considering only the background near the target area, not all the image areas are classified as background areas, which is in line with the law of the human eye to read the camouflage effect. Regardless of the proportion of the target in the image during imaging, the target only melts into the background near it, regardless of the background of the far region. In addition, the segmentation method in citation 6 is irregular, and such segmentation requires a large amount of manual segmentation work, which is also disadvantageous for computer processing. So this paper applies the method of rectangular segmentation, and divides the target and background with the smallest adjacency rectangle of the target, as shown in Figure 1. The rectangular segmentation divides a part of the background into the target area. In the state of good camouflage, the target and the background are well integrated, and can be ignored.

![Eight-way domain partition map of target and background area](image)

Figure 1. Eight-way domain partition map of target and background area

Use $A_{ij}^{(k)}$ to represent continuous image data frames. Where k represents the number of frames, and i, j respectively determine the coordinate position of the pixel. The background area number is numbered 1-8 in the order from the upper left corner and the counterclockwise rotation. The target area of the kth frame is represented by $A_0^{(k)}$, $A_1^{(k)}$, $A_2^{(k)}$, ..., $A_8^{(k)}$ respectively represent 1-8 of the kth frame. Let a, b, c, and d be the target segmentation template abscissa, ordinate, length and width, respectively, then the target area is expressed as:

$$A_0^{(k)} = \{A_{i_0,j_0}^{(k)} | a \leq i_0 \leq a + c, b \leq j_0 \leq b + d, i_0, j_0 \in \mathbb{Z}\}$$

Similarly, the eight-way background area can be represented by a similar formula, and each background area has a clear relationship with the target area. The background area No. 3 of the kth frame is expressed as formula 2:

$$A_3^{(k)} = \{A_{i_3,j_3}^{(k)} | a + c \leq i_3 \leq a + 2c, b \leq j_3 \leq b + d, i_3, j_3 \in \mathbb{Z}\}$$

It may be easy to indicate that the horizontal and vertical coordinates of the target area between the adjacent two frames are shifted to the right by $\Delta a$ and $\Delta b$.

$$i^k = i^{k+1} + \Delta a$$
$$j^k = j^{k+1} + \Delta b$$

Therefore, the numerical relationship between each target and the background between successive image data frames can be clearly calculated by the above formula 3 and formula 4.

2.2. Target Tracking

Knowing the target coordinate position of each frame is a prerequisite for calculating the similarity
feature data. The target area \( A_{0}^{1} \) of the start frame can be obtained by manual labeling or global query matching (in the case of a known target structure). If the rest of the frames are acquired in the same way, the work efficiency will be greatly reduced. Therefore, it is necessary to use the target tracking algorithm to obtain the values of \( \Delta a \) and \( \Delta b \). Target tracking algorithms can be divided into four categories: active contour based tracking, feature based tracking, region based tracking, and model based tracking [7]. Among them, the feature-based tracking algorithm has an advantage of being insensitive to changes in scale, deformation, and brightness of moving objects [8]. This paper selects the Mean shift tracking algorithm based on the gray histogram feature. The algorithm was proposed by Fukunaga in 1975 [9], which uses the non-parametric estimation of density gradient to achieve fast tracking of moving target regions.

The target area has \( n \) pixels \( (n = i_{0} \times f_{0}) \), its absolute position is represented by \( z_{i} \), and \( z_{i}^{*} \) indicates its relative position, then the target area model \( q_{u} \) is:

\[
q_{u} = C \sum_{i=1}^{n} K_{E}(\|z_{i}^{*}\|^{2}) \delta[b(z_{i} - u)]
\]

The \( \delta \) and \( b \) functions determine whether the color value at \( z_{i} \) belongs to \( u \). The normalized parameters \( C \), \( \delta \) function and \( z_{i}^{*} \) are calculated as follows:

\[
C = 1 / \sum_{i=1}^{n} K_{E}(\|z_{i}^{*}\|^{2})
\]

\[
z_{i}^{*} = \left( \frac{(x_{i}-x_{0})^{2}+(y_{i}-y_{0})^{2}}{x_{0}^{2}+y_{0}^{2}} \right)^{0.5}
\]

\[
\delta(x) = \begin{cases} 1 & x = 0 \\ 0 & x \neq 0 \end{cases}
\]

When establishing the target model, the Epanechnikov kernel function is used, which is expressed as follows:

\[
K_{E}(x) = \begin{cases} c(1 - ||x||^{2}) & ||x|| < 1 \\ 0 & \text{others} \end{cases}
\]

When the k-1 frame is set, the center area where the target is located is \( f_{0} \), the candidate target center area is \( f \), and the probability of the candidate area is:

\[
p_{u}(f) = C \sum_{i=1}^{n} K_{E}\left(\frac{f_{0}-z_{i}}{h}\right) \delta[b(z_{i} - u)]
\]

Where \( h \) is the kernel function window size.

In this paper, the Bhattacharyya coefficient is used to establish the probability density function in the similarity measure, which is described as formula 11:

\[
\rho(p,q) = \sum_{i=1}^{m} \sqrt{p_{u}(f)q_{u}(f)}
\]

After the Taylor expansion is performed on the probability density function, the approximate expression can be obtained:

\[
\rho(p,q) \approx \frac{1}{2} \sum_{i=1}^{m} \sqrt{p_{u}(f)q_{u}(f)} + \frac{c}{2} \sum_{i=1}^{n} w_{i} K_{E}\left(\frac{f_{0}-z_{i}}{h}\right) \delta[b(z_{i} - u)]
\]

\[
w_{i} = \frac{1}{2} \sum_{u=1}^{m} \frac{q_{u}}{\sqrt{p_{u}(f)}} \delta[b(z_{i}) - u]
\]

Deriving the formula 12, we can get it after finishing:

\[
f_{t+1} = f_{t} + \frac{\sum_{i=1}^{n} w_{i} K_{E}\left(\frac{f_{0}-z_{i}}{h}\right)}{\sum_{i=1}^{n} w_{i} K_{E}\left(\frac{f_{0}-z_{i}}{h}\right)}
\]

Finally, the iterative process ends by limiting the number of iterations or setting an iteration change threshold. The coordinate change value can be calculated as shown in formula 15:

\[
\Delta f = f_{\text{end}} - f_{0} = (\Delta a, \Delta b)
\]

2.3. Feature Extraction

The feature extraction in the existing camouflage effect analysis model is mainly considered from the aspects of image color, texture, and spot shape. These features are selected from the perspective of human eye observation. However, the calculation of these features does not have a good analytical theory to guide the evaluation of camouflage effects. Based on this, this paper considers the selection of features
from the following three aspects. The first aspect is to look at the pixel space of the target and background, rather than the feature space of the image. The second aspect uses prior information to evaluate existing features, thereby avoiding the extraction of complex image information. In the third aspect, in order to avoid losing the structural information on the space and increasing the calculation speed, the rotation transformation and the contraction transformation of the image are not considered, otherwise the calculation amount will be greatly increased, and the real-time requirement cannot be achieved.

Considering the relationship between image features and camouflage effects, the following six image features are selected to characterize the similarity of eight backgrounds and targets.

- **H-histogram feature relationship in HSV space:**
  \[
  \rho_1 = \frac{\| \mathbf{H} \| \| \mathbf{H'} \|}{\| \mathbf{H} \| \| \mathbf{H'} \|}
  \]
  (16)

- **S-histogram feature relationship in HSV space:**
  \[
  \rho_2 = \frac{\| \mathbf{S} \| \| \mathbf{S'} \|}{\| \mathbf{S} \| \| \mathbf{S'} \|}
  \]
  (17)

- **Image gray histogram feature relationship:**
  \[
  \rho_3 = \frac{\| \mathbf{G} \| \| \mathbf{G'} \|}{\| \mathbf{G} \| \| \mathbf{G'} \|}
  \]
  (18)

- **Peak signal to noise ratio characteristic relationship**: [10-12]
  \[
  \rho_A = 10 \log_{10} \left( \frac{(2^n - 1)^2}{MSE} \right)
  \]
  (19)

- **Perceived hash feature relationships.** To make the calculation faster, after reducing the image to an 8×8 gray matrix, calculate [13-15]:
  \[
  \mu_x = \frac{1}{64} \sum_{i=1}^{64} x_i
  \]
  (20)

  \[
  \mu_y = \frac{1}{64} \sum_{i=1}^{64} y_i
  \]
  (21)

  \[
  \rho_5 = \sum_{i=1}^{64} b(x_i, \mu_x) \oplus b(y_i, \mu_y)
  \]
  (22)

  Where \( \oplus \) denotes an exclusive OR operation and function \( b \) is calculated as follows:

  \[
  b(x, y) = \begin{cases} 
  1 & x \geq y \\
  0 & y \geq x 
  \end{cases}
  \]
  (23)

- **Autocorrelation model feature relationship** [16,17]:
  \[
  \rho_6 = \frac{\sum_{m=1}^{n} \sum_{n=1}^{m}(A_{mn} - \bar{A})(B_{mn} - \bar{B})}{\sqrt{\sum_{m=1}^{n}(A_{mn} - \bar{A})^2 \sum_{m=1}^{n}(B_{mn} - \bar{B})^2}}
  \]
  (24)

### 2.4. Parameter Estimation and Effect Evaluation

It can be known from Lyapunov's theorem that the superposition of multiple random variables approaches a normal distribution. The distribution of image feature samples is affected by various complex factors and can be approximated as obeying a normal distribution. Therefore, as long as the parameters of the normal distribution are estimated, the feature distribution parameters in the case where the entire camouflage state is good can be obtained. The parameters are estimated using a first-order estimation method. Let the sample feature set be \( P = \{p_{uf}^i\} \), where \( u=1,...,m \), \( f=0,...,8 \). \( p_{uf}^i \) represents the \( f \)th background of the \( u \)th frame data in the training sample. When \( f=0 \), it represents the target. Then the feature representation of the sample can be represented by a three-dimensional matrix \( A \):

\[
A = \{a_{ijk}\}
\]

(25)

\[
a_{ijk} = \rho_j(p_{k1}, p_{k1}^j)
\]

(26)

Therefore, the parameters of the sample distribution can be estimated:

\[
\mu_{ij} = \frac{1}{m} \sum_{k=1}^{m} a_{ijk}
\]

(27)

\[
\sigma_{ij} = \frac{1}{m} \sum_{k=1}^{m} (a_{ijk} - \mu_{ij})^2
\]

(28)

According to the above model, the flow chart of the feature parameter extraction of the algorithm is shown in Figure 2. After reading the training data, the target area is selected to obtain the background eight-way domain (if the background is in the edge area, the complete eight-way domain cannot be
obtained, then it is lost.). Calculate the feature to obtain the mean variance while tracking and establish a normalized joint distribution. The algorithm flow chart of the effect evaluation process is shown in Figure 4. The data to be detected is read and the eight-way domain is acquired, and the feature is substituted into the normalized joint distribution to calculate the joint probability density. Since the value fluctuation range is \(0 \sim 6.94 \times 10^{-20}\), it is not conducive to the setting of the threshold. In order to enhance the sensitivity of the density value, the result is first magnified 10 times and then the logarithm is obtained. The process is as follows:

\[
r = \sum_{j=1}^{8} \sum_{i=1}^{6} \ln 10 p_N \left( \frac{a_i^j - \mu_i^j}{\sigma_i^j} \right)^{k}
\]

By the logarithmic amplification probability limit, the value varies from \(-\infty \sim 66.41\). It can be seen that the range of variation of the data is significantly larger, which can effectively reduce the calculation error. In order to effectively distinguish different camouflage effect states, and considering the 3σ criterion of the Gaussian distribution, the result is divided into three-level camouflage states. They are the original camouflage state \((r \geq 0)\), the better camouflage state \((0 > r \geq -1000)\), and the failed camouflage state \((r < -1000)\).

3. Experiment and Result Analysis

The experimental process was carried out in a southern suburb of Nanjing in 2018, and continuous aerial imaging acquisition was performed on a certain simulate export target. The altitude of the aircraft is about 50 meters, and the flight conditions are selected in the morning, noon, afternoon, sunny, rainy days and other time periods. The data collected after the masquerading is completed is used as a training sample, as shown in Figure 4. The image in the full camouflage state is used as the test data of the original camouflage state; the image in the partial camouflage state is used as the test data of the better camouflage state; the image in the non-camouflage state is used as the test data of the failed camouflage state, and the three types of data are separately collected 25 frames.

Figure 2. Joint distribution process flow chart

Figure 3. Flow chart of camouflage effect evaluation process

Figure 4. Three camouflage states in the experimental data
Figure 5. Probability density plot of three camouflage states

The probability density graph shown in Figure 5 is calculated by separately calculating the three types of data to be detected shown in Figure 4. The abscissa represents the number of frames of the data to be detected, and the ordinate represents the logarithmic amplification probability density value. Mathematical statistics on these three curves yield the results shown in Table 1. It can be concluded from the figure and the table that in the state of complete camouflage, the mean value of the curve is 58.2364, which is in accordance with the original camouflage state; in the state of partial camouflage, the mean value of the curve is -727.6583, which is in accordance with the better camouflage state; in the state of not camouflage, the curve The average value is -1005.2298, which is in compliance with the failure camouflage state. The mean data of the curve reflects its camouflage state very well. The fluctuation of the curve is relatively stable, and the variance and the extreme difference are relatively stable, indicating that the model can run smoothly during the dynamic detection process. From the full camouflage state to the partial camouflage state, the arrangement orientation of the camouflage net is changed and the ornaments arranged above are removed, but the curve is already close to the threshold of the failed camouflage state. This indicates that the sample data is not sufficiently expressed for the data space, and the next step should be to supplement the sample data reasonably. Overall, the model provides an accurate reflection of changes in the target camouflage state.

| Three camouflage states | Statistical data | range |
|-------------------------|------------------|-------|
| Completely camouflage   | 58.2364          | 5.8953| 21.5698 |
| Partially camouflage    | -727.6583        | 6.9555| 29.0336 |
| Not camouflage          | -1005.2298       | 8.1569| 22.8956 |

4. Conclusion

Based on the target tracking and anomaly detection techniques, this paper proposes a dynamic camouflage effect evaluation method. The model can extract features from the well-prepared state to establish a normalized joint Gaussian distribution, and evaluate the target from multiple frames of images and multiple angles. Different from the static evaluation method of single image, the model establishment process uses the feature data when the camouflage state is good, which can reflect the target state more objectively. Six correlation characteristics were selected. From the histogram and the mean variance table of the experimental data, it can be concluded that when the camouflage state is stable, the data dispersion range is relatively regular, which basically conforms to the trend of Gaussian distribution. This shows that using the Gaussian distribution to simulate the variation range of the camouflage state, it can well handle the influence of factors such as illumination, weather, and shooting angle. By increasing the number of samples, the distribution of feature data can be more comprehensively and correctly reflected. In the experimental process, a certain simulate export target was completely camouflaged,
partially camouflaged and not camouflaged. The aerial imaging acquired multi-frame data and calculated its logarithmic amplification probability density and the mean value of the statistical curve. The results were 58.2364, -727.6583 and -1005.2298, respectively. Compared with the set threshold range, it corresponds to the original camouflage state, the better camouflage state and the invalid camouflage state. The experimental results show that the model is effective and the calculation results can better reflect the camouflage state of the target.

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