Optik 126 (2015) 3276–3282

Contents lists available at ScienceDirect

Optik

journal homepage: www.elsevier.de/ijleo

Fast contour torque features based recognition in laser active imaging system

Canjin Wang[a,b,*], Tao Sun[a], Tinfeng Wang[a], Juan Chen[a]

[a] State Key Laboratory of Laser Interaction with Matter, Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Science, Changchun, Jilin, China
[b] University of Chinese Academy of Sciences, Beijing, China

ARTICLE INFO

Article history:
Received 15 July 2014
Accepted 3 August 2015

Keywords:
Laser active imaging
Recognition
Contour torque
Affine invariant
Feature regions

ABSTRACT

Recent years laser active imaging system are widely used as a useful detection artifice. While many denoising and enhancing algorithms have been proposed, target recognition in laser active imaging is still a new domain that few researches have been done. Classical recognition methods often break done due to the characteristic of laser active imaging. In this paper we present a novel target recognition method based on fast contour torque features (FCTF). The proposed fast contour torque features contain abundant information of the target, such as the size, position, darkness and shape regularly of the contours. Meanwhile the features are invariant to rotation, scaling and affine transform, and can be computed efficiently.

We first extract feature regions by MSER algorithm, and transform them into circular areas, so the regions are invariant to affine transform. Then local invariant features of the feature regions were extracted by fast contour torque feature descriptor and we input into the trained SVM classifier for identify. Comprehensive experiments show that our approach achieves higher recognition rate in rotation and affine transformation as state-of-art method, and meet the real-time requirement in laser active imaging.

1. Introduction

Laser active imaging is a new detection method which performs better than the passive imaging system under conditions of poor visibility due to laser's high intensity and high collimation [1,2]. With laser active imaging systems, it is possible to classify and identify targets of interest at night, which has broad application prospects in the military, civilian security and other fields [3–5]. Nowadays researches on target recognition for laser active imaging system is still in its infancy at home and aboard and few can learn from literature. Due to the difference of imaging mechanism and imaging conditions, with respect to the target recognition under visible passive imaging, active laser illumination target recognition has the following characteristics:

(1) An inherent noise – speckle noise is introduce by laser's coherence, thus blurring the image details;
(2) CCD noise and noise caused by atmospheric transport decrease image contrast, seriously affecting the image quality;
(3) Uneven illumination in target's different areas increases the difficulty of target segmentation;
(4) When the laser power is changed, the gray level and contrast of target and the background are changed;
(5) Due to laser's monochromatic, the color characteristics of the target are difficult to obtain;
(6) Real-time requirement for the system needs to complete the identification process within a single frame time.

These characteristics above make most identification methods based on gray, texture and color are difficult to apply in the laser active imaging target recognition system, which increases the difficulty of identification.

For the features of laser active imaging, we proposed a recognition method based on fast contour torque features (FCTF). The features are invariant to rotation, scale and affine transform, with which we could real-time, accurately identify the target. The proposed method comprises three steps: first, detect the target's feature regions with MSER and transform them into circular areas; second, calculate FCTF for each feature areas; third, input the FCTFs into trained SVM for recognition.

* Corresponding author at: State Key Laboratory of Laser Interaction with Matter, Changchun Institute of Optics, Fine Mechanics and Physics, Chinese Academy of Science, Changchun, Jilin, China. Tel.: +86 05973622339.
E-mail address: wcjpsh@126.com (C. Wang).

http://dx.doi.org/10.1016/j.ijleo.2015.08.014

2. Related work

Relative to grayscale and color information, the contour of the target is easier to extract in laser active imaging. Contour features provide information about the target's shape and play an important role in target recognition. Currently recognition methods based on contour features include: Belongie [6] proposed shape context feature descriptor, in which contour points distribution histogram were added up in polar coordinates. When discontinuity occurs in the contours, the targets can still be identified. Jurie et al. [7] proposed a scale-invariant feature detection algorithm. They regarded the extreme region of the edge energy and entropy as a significant area of the region, then used the space distribution of the annular neighborhood points in the region to construct feature vectors. Fergus et al. [8] segmented contour and boundary by double tangency points, and tested their methods by identifying the constellation model. To identify shape-changed objects in video sequences, Kumar [9] proposed a Bayesian model graph structure. Shotton et al. [10] proposed to randomly sample rectangle from the training picture and generate contour fragments detection operator. Opelt [11] outlines principles to find fragments from the fragments pool based on the principle that the occurrence probabilities of the positive examples are the maximum and that of the negative examples are minimum. Zhu [12] proposed a technique for grouping the contour and segmented the contours in different scales. The algorithms above contain complex calculations and do not take into account complex motion of the target. When objects perform affine transformation, these algorithms may fail. Therefore, they are not applicable to occasions that have high demands on real-time and recognition accuracy, such as laser active imaging.

3. Extracting feature areas

Moving targets often perform rotation, scaling, illumination changes and affine transformation. In order to recognize targets accurately, we hope the extracted features are also invariant to the transformation above.

3.1. Maximally stable extremal regions

Lots of researches have been done on affine invariant region extraction methods: Lindeberg [13] proposed a shape adaptive smoothing algorithm, which estimated affine invariant regions in scale space using second moment matrix iteratively. Baumberg et al. [14] first sought Harris corners in scale space, and use them as the centers to iteratively estimate affine invariant regions. Tuytelaars et al. [15] improved Baumberg's method, they constructed affine invariant regions by locating edge points around Harris corners. These regions were more stable. Matas [16] proposed MSER (maximally stable extremal regions). The regions separated by different thresholds were merged and the most stable areas were defined as MSER. Mikolajczyk [17] promoted two kinds of famous feature points to affine invariant regions, which were known as Harris-affine and Hessian-affine. Mikolajczyk [18] then compared the performance of different affine invariant region detectors in viewpoint changes, scale changes and image compression, and concludes that MSER has the highest repetition rate, especially for homogeneous regions. In laser active imaging, the target is generally homogeneous and with high contrast, so we use MSER into laser active imaging recognition.

Let $S=\{0, 1, \ldots, 255\}$, a grayscale image $I: D \subset Z^2 \to S, A \subset D$ is the four-neighbor connection relationship, Q is a sub-region of D, if for any pixel $p, q \in Q$,

$$pAa_1, a_1pa_2, \ldots, a_nAq \tag{1}$$

where $a_i \in Q$, $i=1, \ldots, n$, then we call Q an extremal region.

Let ∂Q be the boundary of Q, the pixels in ∂Q do not belong to Q, but are adjacent to at least one of pixels in Q.

$$\partial Q = \left\{q | q \in D - Q, \exists p \in Q, qAp\right\} \tag{2}$$

where p is one of pixels in Q.

For any $p \in Q$, $q \in \partial Q$, if $I(p) > I(q)$, we call Q the maxima region, if $I(p) < I(q)$, we call Q the minimum region.

For nested extreme regions get by different threshold $\{Q_1, Q_2, \ldots, Q_i, \ldots\}$, let

$$q(i) = \frac{|Q_{i+\Delta} - Q_{i-\Delta}|}{|Q_i|} \tag{3}$$

where $|\bullet|$ means the number of regions, Δ is the threshold width. If $q(i^*)$ is the local minima of $q(i)$, we call Q_{i^*} the maximally stable extremal regions.

Let the threshold change from 0 to 255 and segment the image, with formula (3) we can get the positive maximally stable extremal regions MSER+. The reverse the image and segment it we can get the negative maximally stable extremal regions MSER−. The whole MSER = MSER+∪MSER−. In order to speed up the computation, we sorted the pixels first by box sorting method, of which computational complexity is $O(n)$. The we extracted and restored the consequent regions by the structure of spanning tree. After the optimization above the computational complexity of MSER is O (nloglogn).

3.2. Ellipse fitting and region conversion

The feature regions extracted by MSER are of any shapes. On the one hand, the boundary of MSER is not included in the feature region, which does not facilitate the extraction of the contour feature. On the other hand, the invariant feature of an arbitrary shape is difficult to construct. So we fitted the MSER regions to regular circular regions.

Let Σ be the covariance matrix of Q, which is

$$\Sigma = \begin{bmatrix} M_{20} & M_{11} \\ M_{11} & M_{02} \end{bmatrix} \tag{4}$$

where

$$M_{20} = \frac{1}{M_{00}} \sum\sum_{Q} (x-x_u)^2 I(x, y) \tag{3}$$

$$M_{11} = \frac{1}{M_{00}} \sum\sum_{Q} (x-x_u)(y-y_u) I(x, y) \tag{5}$$

$$M_{02} = \frac{1}{M_{00}} \sum\sum_{Q} (y-y_u)^2 I(x, y) \tag{6}$$

$$M_{00} = \sum\sum_{Q} I(x, y) \tag{7}$$

$$x_u = \frac{1}{M_{00}} \sum\sum_{Q} xI(x, y) \tag{8}$$

$$y_u = \frac{1}{M_{00}} \sum\sum_{Q} yI(x, y) \tag{9}$$

A matrix A maps the unit circle centered at $P_u(x_u, y_u)$ to a ellipse, which is

$$[A(X-P_u)]^T \Sigma^{-1} [A(X-X_u)] = 1 \tag{10}$$

where

$$(X-P_u)^T (X-X_u) = 1 \tag{11}$$