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IKDSIFT: An Improved Keypoint Detection Algorithm Based-on SIFT Approach for Non-uniform Illumination

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Abstract

In this paper, we propose an improved keypoint detection algorithm of object-based recognition for non-uniform illumination, called IKDSIFT, which is implemented using the SIFT approach, morphological operations, Top-Hat filtering and various techniques in pre-processing procedures. The number of keypoint rate of data sets was compared. Data sets consist of three hundred 150x150 images and thirty 851x566 images with different uniform and non-uniform illumination. The experimental results show that the number of keypoint detection is reciprocal to peak selection thresholds. The best algorithm is the proposed IKDSIFT, followed by the SIFT. The ASIFT performs the worst. Additionally, the SIFT and ASIFT can detect some peak selection thresholds while the IKDSIFT can detect all ranges of the peak and obtains the best result comparing to other ones. Hence, the proposed algorithm looks promising to be used for recognizing under non-uniform illumination.

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Keywords: Object-based recognition; Keypoint detection; Non-uniform illumination; SIFT approach.

1. Introduction and Related work

Object class detection has become one of the most focused areas and one of the fundamental challenges in

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computer vision in the new century. They have been utilised in many real-world applications, for instance, NASA Mars Rover images, image reconstruction, robot localisation, video data mining, building panoramas stitching[1], etc. Because of many factors such as the different absorption, reflection properties, and background noise caused by uneven illumination, many approaches have been proposed to overcome these issues[2]. So, object-based recognition leads to many challenging problems. Elementary characteristics that are hopefully invariant over different appearances are different locality, distinction, quantity and invariance, especially non-uniform illumination conditions. By 2004, David G. Lowe proposed a local feature description approach known as *Scale-invariance Feature Transformation* (SIFT)[3]. However, the SIFT approach performs the best under scale and rotation changes, but not illumination change[4] since normalising the vector is caused by the illumination changes. Hence, these problems are investigated in this paper. The SIFT is based on a local feature description approach[3] that is known for its invariance under rotation, translation, scale changes, blur changes, affine transformation, illumination changes, and other transformations. The procedure of SIFT consists mainly of four steps: 1) scale-space extrema detection, 2) keypoint localisation, 3) orientation assignment, and 4) keypoint descriptor. Firstly, the SIFT uses a *Difference of Gaussian* (DoG) function, Eq. (1), to do convolution on the image. We obtain different scale images by changing σ. To find interest points that are extremals (maximum or minimum) with regard to both scale and space, various versions of the original image that have greater and greater Gaussian blurring applied to them are created.

$$G(x,y,\sigma)=\frac{1}{2\pi\sigma^2}e^{-(x^2+y^2)/2\sigma^2} \tag{1}$$

Then, the images which are close in the similar resolution are subtracted to get a DoG pyramid. In other words, subtracting an image from its more-blurred neighbour image gives the DoG. Finally, points that are maximum or minimum in their 3x3x3 = 27 neighbourhood–9 pixels in the less-blurred image, 9 pixels in its own image and 9 pixels in the more-blurred image are marked. The DoG function is a kind of an improvement of a Gauss-Laplace algorithm (see Eq. (2))

$$D(x,y,\sigma)=(G(x,y,k\sigma)-G(x,y,\sigma))*I(x,y) = L(x,y,k\sigma)-L(x,y,\sigma) \tag{2}$$

where $I(x,y)$ denotes an input image, and k denotes a scale coefficient of an adjacent scale-space factor. Secondly, points that have poorly localised along an edge are rejected. The interpolation to locate the keypoint accurately in scale and space is then deployed. Thirdly, $m(x,y)$ assigns a direction to each keypoint based on local image gradients and $\theta(x,y)$ creates a 36-bin orientation histogram and looks for peaks in the histogram (Eq. (3)). It is possible for a keypoint to be assigned multiple orientations.

$$\begin{aligned} m(x,y) &= \sqrt{(L(x+1,y)-\mathrm{L}(x-1,y))^2+(L(x,y+1)-\mathrm{L}(x,y-1))^2} \\ \theta(x,y) &= \tan^{-1}\left(\left(L(x,y+1)-\mathrm{L}(x,y-1)\right)\big/\left(L(x+1,y)-\mathrm{L}(x-1,y)\right)\right) \end{aligned} \tag{3}$$

Finally, each keypoint is summarised in a way which allows it to be compared with other keypoints, while retaining its various robustness properties. Then we calculate 16 separate orientation histograms in a 4x4 neighbourhood around each keypoint. The histograms are calculated with respect to the keypoint scale and orientation which have been distinct in previous steps. Each histogram has 8 orientation bins. The contents of all of the histograms are concatenated to form a 128-element (16x8) vector. This vector is called the keypoint descriptor. Normalising the vector makes it more robust to illumination changes. Now, we will briefly discuss the related work on a local scale invariant features. Firstly, proposed *Top-Hat transformation*[5], which consists of steps as follows: 1) Let $f(x)$ and $b(x)$ be two discrete functions defined on two-dimensional discrete space F and B, respectively, 2) The opening (○) and closing (•) morphological operations are applied to $f(x)$ and $b(x)$, 3) The Top-Hat operator is divided into opening and closing Top-Hat operators ($OTH_{f,b}$ and $CTH_{f,b}$, respectively) defined by

$$OTH_{f,b}(x)=(f-f\circ b)(x) \tag{4}$$

$$CTH_{f,b}(x)=(f\bullet b-f)(x) \tag{5}$$

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