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Singular Point Comparisons During Panoramic Image Formation

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Abstract: In this study, the review of the most common methods of critical point comparison are analyzed during the solution of various problems of image processing such as, the formation of panoramic images. The order of singular point descriptor obtaining is analyzed, the main types of singular points are revealed and the property characteristics are described obtained by descriptor construction with which may assess their effectiveness. The descriptions of the following descriptors are presented: SIFT, PCA-SIFT, SURF, GLOH, DAISY, BRIEF. The principles and features of their research are described.

Key words: Panoramic images, singular points, singular point descriptors, singular, critical

INTRODUCTION

The issue of a single panoramic image formation from multiple overlapping images captured by different cameras is the combination of their common fragments and "bonding" line correction. One common method of combination is based on the determination of singular points found at both adjacent images (Summa *et al*., 2012) which is an alternative to the approximation of geometric object boundaries, located on two adjacent images (Pritula *et al*., 2014).

Problem determination: The singular point m is the point of the image, the neighborhood of which is O(m) and which may be distinguished from the vicinity of any other point of the image O(n) in some other neighborhood of a singular point of $O_2(m)$. In other words, these are the points in an image differing from the others on some attribute. The mechanisms aimed at the determination of singular points are called detectors.

The result of detector work is a set of singular points for which you may provide a mathematical description using a descriptor. Descriptor is a set of numerical parameters describing the characteristics of an image singular points. In its turn, the descriptors should provide an invariant obtaining of a match between the singular points with respect to the transformations of images.

The input data during the construction of a descriptor is an image and a set of singular points allocated for a given image. The output data is the set of feature vectors for an initial set of singular points. It should be noted that some descriptions solve two problems simultaneously the search of singular points and the development of this point descriptors.

The attributes (descriptors) are developed on the basis on the information about the intensity, color and texture of a singular point. But singular points may be presented as corners, edges or even an object contour, therefore, as a rule, the calculations are made for a certain neighborhood. Ideally, good signs must possess a number of properties: repeatability, locality, representativeness, accuracy, efficiency.

MATERIALS AND METHODS

Main part: The descriptor SIFT (Scale Invariant Feature Transform). For its formation (Lowe, 2004; Szeliski, 2010), first of all, the magnitude and orientation values of a gradient are calculated in each pixel belonging to the neighborhood of a singular point with the size of 16×16 pixels. At that the magnitudes of the gradients are taken into account with theweights proportional to the density function value of normal distribution with the mathematical expectation in a given singular point and a standard deviation equal to half of the neighborhood width (the weights of the Gaussian distribution are used to reduce the impact on the final gradient descriptor calculated in pixels, located further from a singular point). Gaussian is an image is blurred by a Gaussian filter. The blurring operation may be represented as a convolution of an image by the Gaussian Kernel:

$$L(x,y,\sigma) = G(x,y,\sigma)\times 1(xy) \qquad (1)$$

Where:
x, y = Pixel coordinates
σ = Blurring radius
L (x, y, σ) = Gaussian, blurred image
G (x, y, σ) = Gaussian kernel

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

The difference of Gaussians is the image obtained by per pixel subtraction of one Gaussian with the radius σ from neighboring Gaussian with the blurring radius:

$$D(x, y, \sigma) = L(x, y, k\sigma) - L(x, y, \sigma) \quad (3)$$

The histogram of oriented gradients is calculated in each square (4×4 pixels) by adding the weighted value of a gradient magnitude to one of 8 bins (columns) of a histogram. In order to reduce the various "boundary" effects associated with such similar gradients to different squares (which may occur due to the slight shift of a singular point location) the bilinear interpolation is used: the value of each gradient magnitude is accrued not only in the histogram corresponding to the square to which this pixel belongs but also to histograms corresponding to adjacent squares. At that the magnitude value is added with the weight proportional to the distance from the pixel in which this gradient is computed to the center of a corresponding square. All calculated histograms are combined into a single vector, the size of which makes 128 = 8 (the number of bins×4×4 (the number of squares).

The resulting descriptor is converted to reduce the possible effects of illumination changes. The change of an image contrast (the intensity value of each pixel is multiplied by a constant) causes the same change in the values of gradient magnitudes. Therefore, it is obvious that this effect may be leveled by normalizing the descriptor in such a way that its length will be equal to 1. The change of an image brightness (a constant is added to the value of each pixel intensity) does not affect the gradient magnitude values. Thus, SIFT descriptor is an invariant one with respect to affine illumination changes. However, nonlinear illumination changes may occur, for example, due to different orientations of a light source with respect to the surfaces of a three-dimensional object. These effects may cause a large change in relation to the magnitudes of some gradients (in this case, they make a negligible effect on the orientation of a gradient vector). In order to avoid this, the cut-off at a certain threshold is used (the experiment results show that the value of 0.2 is an optimum one) which is applied to the components of a normalized descriptor. After the application of the threshold the descriptor becomes normal again. Thus, the value of the gradient large magnitudes is reduced and the value of these gradient orientation distribution in the vicinity of a singular point is increased.

The descriptor PCA-SIFT (Pritula *et al*., 2014) is essentially the modification of SIFT. Similarly, the magnitude values and gradient orientation are calculated similarly at the initial phase. The area of 41×41 pixels centered at a special point only for each singular point is considered. In fact a gradient map is structured along the vertical and horizontal directions. The result of it is the vector containing 2×39×39 = 3042 elements. Then, the development of the SIFT descriptor is performed according to the scheme described in the previous section. The vector size is reduced to 32 elements by the means of Principal Component Analysis (PCA) for the resulting set of SIFT descriptors.

RESULTS AND DISCUSSION

The descriptor SURF (Speeded up Robust Features) (Tuytelaars and Mikolajczyk, 2007) is one of those descriptors which simultaneously, performs the search of singular points and develop their description to the change of scale and rotation. Besides, the search of key points have invariant features, i.e., the turned object of a scene has the same set of singular points as the sample.

The determination of special points on the image is performed on the basis of Hessian matrix (FAST-Hessian detector) (Tuytelaars and Mikolajczyk, 2007). The use of Hessian provides invariance concerning the transformation like "turn" but not the invariance concerning the scale change. Therefore, SURF applies the filters of all sizes in order to calculate the Hessian. Suppose that an original image is defined by intensity matrix I, the current pixel under consideration is denoted by X = (x, y) and σ is a filter scale. Then, the Hessian matrix has the following form:

$$H(X, \sigma) = \begin{bmatrix} L_{xx}(X, \sigma) & L_{xy}(X, \sigma) \\ L_{xy}(X, \sigma) & L_{yy}(X, \sigma) \end{bmatrix} \quad (4)$$

Where, L_{xx} (X, σ), L_{xy} (X, σ), L_{yy} (X, σ) convolution approximation of the Gaussian Kernel second derivative with the image I. The determinant of the Hessian matrix reaches extremum at the points of brightness gradient maximum change. Therefore, SURF performs the filtration with a Gaussian Kernel along the whole image and finds the points at which the maximum value of the Hessian determinant is achieved. Note that this passage reveals dark spots on a white background and bright spots on a dark background.

Then, the orientation is calculated for each determined singular point, the prevailing direction of brightness fluctuations. The concept of orientation is close to the notion of a gradient direction but Haar filter is applied to determine the orientation of a singular point (Viola and Jones, 2004). On the basis of available information, the development of descriptors is carried out for each critical point:

- A square area of 20s is built around a point where s is the scale at which the maximum value of Hessian matrix determinant is obtained
- The obtained square area is divided into blocks, therefore the area will be divided into 4×4 region
- More simple features are calculated for each block Thus, the vector is obtained containing four components: 2 2 is a total quadrant gradient, 2 is the sum of point gradient modules

Adescriptor is formed as the result of weighted gradient description bonding for 16 quadrants around a singular point. Descriptor elements are weighted by Gaussian Kernel ratios. Weights are needed for a greater noise immunity in remote locations. The Hessian matrix track is provided in addition to the descriptor. These components are needed to distinguish light and dark spots. The light is negative for bright dots on a dark background and it is positive for dark spots on a bright background.

It should be noted that SURF is used for the search of objects. However, the descriptor does not use the information about objects. SURF treats the image as a whole and highlights the features of the whole image, so it works poorly with simple shape objects.

The descriptor GLOH (Gradient Location-Orientation Histogram) (Mikolajczyk and Schmid, 2004) is the modification of SIFT descriptor which is built in order to improve reliability. The SIFT descriptor is calculated by fact but the polar mesh of area division into bins is used: 3 radial blocks with the radii of 6, 11 and 15 pixels and 8 sectors. The result of it is the vector containing 272 components which is projected in a space with the dimension of 128 by using Principal Component Analysis (PCA).

The descriptor DAISY (Tola *et al*., 2008) was initially introduced to solve the problem of image comparison in case of significant external changes, i.e., this descriptor in contrast to the earlier described works operates on a dense set of pixels within the entire image. The DAISY researchers showed in (Viola and Jones, 2004) that the descriptor works 66 times faster than SIFT, running on a dense set of pixels. The DAISY uses the ideas of GLOH and SIFT descriptor development.

Similarly, GLOH chooses a circular neighborhood of a singular point. At that the bins appear not as partial sectors but as circles.

For each such bins the same sequence of operations is performed as in the algorithm SIFT but a weighted sum of gradient magnitudes is replaced by theconvolution of an original image with the Gaussian filter derivatives, taken in 8 directions. The researchers (Tola *et al*., 2008) showed that the developed descriptor has an invariant nature like SIFT and GLOH. At the same time, in order to solve the problem of comparison when all pixels are considered to be special, it requires less computational costs.

Descriptor BRIEF: The purpose of the BRIEF descriptor (Binary Robust Independent Elementary Features) (Calonder *et al*., 2010) was to ensure the recognition of the same image areas that were shot from different angles. At that there was an objective to minimize the number of performed calculations. Recognition algorithm was reduced to the development of randomize classification trees or a naive Bayes classifier on a training set of images and the subsequent classification of test image parts. In a simplified version, the method of the closest neighbor may be used to search the most similar patch (a separate overlapping portion of an image) in a training sample. A small number of operations is ensured through the provision of feature vector as a binary line and as a result, the use of Hamming distance as the measure of similarity.

The researchers provide the results of experiments (the recognition quality) (Calonder *et al*., 2010) at the selection of point pairs according to the law of even distribution in the patch and the normal distribution with different values of expectations and standard deviations. Let's note that under identical conditions of experiment performance within some test patterns the accuracy of detection by BRIEF is almost 1.5 times higher than with the use of SURF descriptors.

The method based on subband matrices is also interesting from the point of view of analysis and the comparison of images (Zhilyakov *et al*., 2014).

CONCLUSION

The descriptors considered in this study do not exhaust the entire set of existing ones but they are among the most commonly used and computationally fast. The descriptor length is very important at the processing of large numbers of images. The descriptor BRIEF is the most compact one. It is not an invariant one concerning the rotation but this may be achieved if a fragment is turned around a point of interest at a certain angle like for the descriptor SIFT and SURF.

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