International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2013): 6.14 | Impact Factor (2013): 4.438

A Survey on Feature Description Techniques

Hitul Angrish[1], Sandeep Kaur[2]

[1]Student M. Tech (CSE), CGC Technical Campus, Janjheri, Punjab, India

[2]Assistant Professor (CSE), CGC Technical Campus, Janjheri, Punjab, India

Abstract: ***This paper gives us the overview of the different feature description techniques. Feature description evolves feature detection as its first default step. First of all we need to know what features we have to extract according to our problem and then by using an appropriate feature detection algorithm we will locate them in image. Once detected feature description will be done so that matching between those points in two different images could be done.***

Keywords: Edge, Blob, Interest point, Features, Features, Detection, Feature Description.

1. Introduction

The concept of feature detection is a method to compute abstraction of image information at every point of an image and making local decision at that particular point that there is a feature in an image or not under image processing and computer vision. Features thus extracted are in form of connecting regions, isolated points and continuous curves. Subset of the image domain is resulting features.

An image patch near the features found can be produces after successful detection of the features. A high amount of image processing would be needed in this process of extraction whose result is called feature vector also known as feature descriptor. Local histogram and Njets can be mentioned among one of the methods to detect features. The step of feature detection itself can add some additional attributes such as strength of blob and polarity under blob detection and gradient magnitude, edge orientation under edge detection [1].

A. Definition of a Feature

A feature definition changes according to the application type, feature of an image can't be bound to an exact or universal definition. An interesting part of an image can be called as feature. Many computer vision algorithms uses feature as starting point thus whole success of these algorithms depends on how good is the feature detector. Repeatability is necessary property for feature detector between two or more different images of same types to detect that they have same features or not.

Feature detection is the first operation performed on an image. Each and every pixel is checked whether or not there is feature present at that pixel thus feature detection is considered as a low level operation in image processing. Typically as a subpart of an algorithm the feature detector will not process the whole image it will only examine the regions including features of an image. In scale space representation the Gaussian Kernel is used to smooth the image as first built in step in feature detection. The computed images containing the features are expressed in terms of local image derivatives operation [2].

Feature detection is an expensive computation when there is limit of time constraints, for searching particular parts of an image to detect feature to guide the detection stage a higher level of algorithm may be used.

B. Difference Bbetween Feature Detector and Feature Descriptor

From above section now we have idea about features. Once we know what kind of features we have to detect we will detect them with the help of feature detector. In simple terms, **Feature Detection** is a process of to find out some special points in our image and those 'special points' or 'keypoints' are our features which varies from problem to problem.

After finding out the features using a feature detection technique in image (say a), now the same type of feature have to found out in another image (say b). For that we have to take region or subset of image around our 'feature'. For example we have to find a same car in image b for that we concentrate on car shape, kind of glass and its shapes, tires and wheels are simple or with alloys and then what kind of alloys, so basically what we have done is that we have described the car's features. In similar manner the features in image b should also be described so that they could be matched. This process is known as **Feature Description.** Once after finding features and describing them you can match them from other images and align them together or stitch them. A wide variety of applications such as object reorganization, pattern matching etc are of this technique [3].

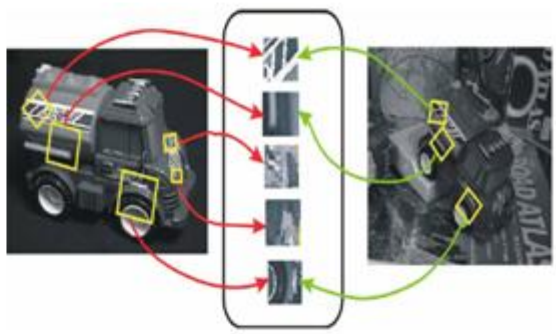

Figure 1: Description and Matching between two Images [4].

2. Types of Image Features

As initial step feature detection is used in variety of vision algorithms thus many feature detecting techniques has been developed. In terms of repeatability, computational complexity and types of features detected these techniques vary widely. For overview purpose features can be divided into following groups:

A. Edges

The points at a boundary between two image regions are known as Edges. Edges have local one dimensional structure locally. In general terms an arbitrary shape including junctions can be an edge. In practice set of points with strong gradient magnitude in an image are said to be Edges. Further to complete the edge description linking together or joining these high gradient points is done with the help of common algorithms called edge linking algorithms. Constraints on some properties like shape, gradient value and smoothness of an edge are placed by these algorithms [2].

B. Corners / Interest Points

In an image point like features are corners and interest points. Interest points and corners are likely interchangeable terms. These have two dimensional structures locally. The corner term is used tradition cause in early algorithms to find corners (rapid changes in direction) first edge detection is done then analysis of the edges. Later algorithms were developed in which there was no longer a requirement for explicit edge detection. For example: In an image gradient by analyzing high levels of curvatures. On some parts of an image points detected were not corners in the traditional meaning like within a dark background a small bright spot. Thus these nontraditional corners were later named as Interest Points [2].

C. Blobs / Regions Of Interest Or Interest Points

Description of an image structure in terms of regions is given by Blobs. Corners are point like structures in an image whereas blobs consists of a preferred point e.g. a center of gravity thus many blob detectors are also used in interest point operations. Particular area in an image too smooth to be detected by corner detectors can be easily detected by a blob detector.

Suppose an image is being shrunk and processed under corner detector. In shrunk image sharp points would be detected by corner detector but which were usually smooth in an original image. At this point the main difference between a blob detector and corner detector becomes visible .At a greater level, the difference can be prevented by using a suitable method of that scale. Determinant of Hessian (DoH) and Laplacian of Gaussian (LoG) despite of being blob detectors are also described in corner detection articles cause of their reaction to different structures of an image at different levels of scale [2].

D. Ridges

A ridge is a natural term for elongated objects. In practical terms one dimensional curve which represents an axis of symmetry with additional attribute of local ridge width linked with each ridge point can be thought as ridge. Generalization of a medial axis form a grey level image is done using a ridge descriptor. Extracting ridge features from a general grey level image is very hard with the use of an algorithm as compared to extracting a blob, corner or an edge. Road extraction in maps, satellite images and blood vessels extraction in medical science are most common applications of ridge descriptors [2].

3. Key Techniques

A. SIFT

It stands for **Scale Invariant Feature Transform**, it was developed by David Lowe in 1999. In computer vision SIFT is used in detection of local features present in an image and description of them. Robotics Navigation, Gesture Recognition, 3D Modeling, Objects Recognition, Video Tracking, Individual identification of wildlife are some of the applications for this algorithm.

In SIFT first objects keypoints are extracted and stored in database from reference image. Feature comparison by comparing each feature individually is done between new image and features from the database to detect an object's feature vectors on basis of their respective Euclidean distance. In next step location, scale and orientation of the object that matches the keypoints from database are determined and filtered out in new image. Cluster with three or more matches are passed further for processing by discarding outlines and for detailed model verification. In the end a particular set of features which indicates the presence of an object accurately is selected [5].

C. DSIFT

DSIFT stands for **Dense Scale Invariant Feature Transform,** it was originally proposed by Bosch in 2006. It is simply a denser version of SIFT. A dense version of SIFT is implemented under this technique. Under this descriptors for keypoints can be quickly processed by an object. Keypoints are densely or closely packed sampled having same orientation and size. For multiple images of similar size DSIFT can be reused [5].

Dense-SIFT algorithm makes some new assumptions:

(a) The location of each keypoint is not from the gradient feature of the pixel, but from a predesigned location.
(b) The scale of each keypoint is all the same which is also predesigned.
(c) The orientation of each keypoint is always zero. With these assumptions, DSIFT can acquire more feature in less time than SIFT does.

D. HOG

HOG (Histogram of Oriented Gradients) was first described by two researchers named Bill Triggs and Navneet Dalal in 2005 CPRV paper. In their research work the main focus is on the detection of pedestrian in still images, further work lead to detection of humans in video and films and even some classes of animals and vehicles found commonly could be detected in static imagery [6].

In object detection Histogram of Oriented Gradients are widely used. In HOG first an image is divided into small square cells and gradient histogram is taken, a block-wise pattern is used for normalizing the result for each cell and a descriptor is returned. For object detection an image window descriptor could be used for stacking cells into squared regions in an image, like in Support Vector Machine classifier.

E. SURF

SURF stand for **Speeded up Robust Features** first described by Herbert Bay in May 2006. It is a local feature detection which robust in nature meaning it has some extent of fault tolerance. 3D reconstruction and object recognition are main applications of SURF. It is basically inspired from SIFT but having some improvements over it, as claimed by its author SURF is many times faster and robust in processing different transformation in images then SIFT. Sums of 2D Haar wavelet responses are bases of SURF and make it an efficient in using integral images [7].

Hessian blob detector are determined by the use of an integer approximation, with the integral image i.e. three integer operations can be processed very quickly. For detection of features around the point of interest response of Haar wavelet is summed up. Once again computation of these could be done with the help of an integral image. This algorithm is patented in USA and it is part of artificial intelligence which is able to train a machine to determine contents from interpreted images. Then the information is used for operation like reorganization of faces, objects tracking and reorganization, extraction of interest points and to make 3D scenes.

F. BRIEF

BRIEF stands for **Binary Robust Independent Elementary Features** are pro-posed by Calonder in 2010. It is the simplest of the methods. It uses a sampling pattern consisting of 128, 256, or 512 comparisons (equating to 128,256, or 512 bits), with sample points selected randomly from an isotropic Gaussian distribution cantered at the feature location.

BRIEF is a recent feature descriptor that uses simple binary tests between pixels in a smoothed image patch. Its performance is similar to SIFT in many respects, including robustness to lighting, blur, and perspective distortion. However, it is very sensitive to in-plane rotation. BRIEF grew out of research that uses binary tests to train a set of classification trees. Once trained on a set of 500 or so typical keypoints, the trees can be used to return a signature for any arbitrary key point [8].

G. ORB

ORB stands for **Oriented FAST and Rotated BRIEF** was proposed by Ethan Rublee in 2011 that can be used in computer vision tasks like object recognition or 3D reconstruction. It is based on the visual descriptor BRIEF (Binary Robust Independent Elementary Features) and the FAST keypoint detector. Its aim is to provide a fast and efficient alternative to SIFT.

It and overcomes the lack of rotation invariance of BRIEF. ORB computes a local orientation through the use of an intensity centred which is a weighted averaging of pixel intensities in the local patch assumed not be coincident with the center of the feature. The orientation is the vector between the feature location and the centred. While this may seem unstable, it is competitive with the single orientation assignment employed in SIFT [9].

H. BRISK

BRISK stands for **Binary Robust Invariant Scalable Keypoints** it was proposed by Stefan Leutenegger in 2011. It involves taking sample pattern of smoothed pixels around feature then separating pairs of pixels into two subsets that is of short-distance pairs and long-distance pairs then computation of local gradient in long-distance pairs is done. Sum of gradients to determine feature orientation is done in next step after that rotation of short-distance pairs using orientation is done and in the last construction of binary descriptor from rotated short-distance pairs is done.

BRISK is a 512 bit binary descriptor that computes the weighted Gaussian average over a select pattern of points near the keypoint. The comparison of specific pairs values of Gaussian windows, leading to either a 0 or a 1, depending on which window in the pair was greater is done. The pairs are preselected in BRISK for usage. Thus the creation of binary descriptors that work with hamming distance instead of Euclidean, and can be made to run extremely quickly using special SSSE hardware instructions for up to a 6x speedup [10].

I. FREAK

FREAK stands for **Fast Retina Key point** it was proposed by Alexandre Alahi in 2012**.** FREAK is also a binary descriptor and latest in the series of binary descriptors. It has an improvement over BRISK in pair selection methods and sampling pattern. Its applications involve object detection, motion estimation, tracking, classification and image registration.

In FREAK 43 weighted Gaussians at a location are evaluated around the keypoints, but the pattern formed by these Gaussians is inspired by the biological retina patter present in the eye. The pixels being averaged overlap, and are much more concentrated near the keypoint. More accurate description of keypoints is done in this way. The cascade for comparison of these pairs is also used in the actual FREAK algorithm and to speed up the matching process puts the 64 most important bits in front. FREAK's matching step will speed up by an order of magnitude [11].

4. Conclusion

A search for the perfect detection and matching technique is still going on. Image descriptors plays critical role in the field of object detection and matching because for an appropriate or perfect match a proper description of features are needed first. In this paper a basic survey on various old and new descriptor techniques has been provided. There has not been a proper paper found containing all these techniques at one place, so our effort is to get all the basic information of all the techniques in one place for ease of future researchers and scholar students.

References

[1] Computer Vision: http://en.wikipedia.org/wiki/Computer_vision
[2] Feature Detection: http://en.wikipedia.org/wiki/Feature_detection
[3] Understanding Features :http://docs.opencv.org/master/df/d54/tutorial_py_features_meaning.html
[4] IJCV, 74(1):59–73. Matlab Tutorials: SIFTtutorial/tutorial.m (utvis). CSC2503: Feature Descriptors, Detection and Matching c D.J. Fleet and A.D. Jepson, 2011.
[5] Lowe, David G. (1999). "Object recognition from local scale-invariant features". *Proceedings of the International Conference on Computer Vision* **2**. pp. 1150–1157.doi:10.1109/ICCV.1999.790410
[6] Histogram of Oriented Gradients: http://en.wikipedia.org/wiki/Histogram_of_oriented_gradients
[7] Speeded Up Robust Features : http://en.wikipedia.org/wiki/SURF
[8] Michael Calonder, Vincent Lepetit, Christoph Strecha, and Pascal Fua, et al. “Brief: Binary robust independent elementary features.” Computer Vision–ECCV 2010. Springer Berlin Heidelberg, 2010. 778-792.
[9] Ethan Rublee, Vincent Rabaud, Kurt Konolige, Gary Bradski "ORB: an efficient alternative to SIFT or SURF", Computer Vision (ICCV), 2011 IEEE International Conference on. IEEE, 2011.
[10] Stefan Leutenegger, Margarita Chli and Roland Y. Siegwart. BRISK: Binary Robust Invariant Scalable Keypoints. ICCV 2011.
[11] Alexandre Alahi, Raphael Ortiz, Pierre Vandergheynst. FREAK: Fast Retina Keypoint. In IEEE Conference on Computer Vision and Pattern Recognition, 2012.