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A Review of Detector Descriptors' on Object Tracking

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ABSTRACT: The objective here is to present a briefing on the methods and algorithms presented in the field of identifiers and descriptors of key point areas and the manner of obtaining various indicators in order to comply and track the selected objects, compare and reveal their advantages and disadvantages in 2D features in recent decades. Feature detection methods subject to study in this article consist of:Scale-Invariant Feature; Maximally Stable Extremal Regions; Speeded up Robust Features; Features from Accelerated Segment Test; Binary Robust Independent Elementary Features; Efficient Dense Descriptor Applied to Wide-Baseline Stereo; Binary Robust Invariant Scalable Key points; Oriented Binary Robust Independent Elementary Features and Fast Retina Key point.

KEYWORDS: Object Tracking, Detection, Key Points, Index, Binary Descriptors, Detectors.

I.INTRODUCTION

Object tracking is depicted from an algorithm applied in tracking and identifying the location of a moving object chosen by the user or detected by a special feature in every frame of images taken by the camera. Corners, colour, geometrical shapes, dimensions, etc. are extracted and in the next frame, according to this feature, the new position of the object is determined and the rout of the object can be traced. Tracking the selected objects by the user through moving the camera or identify a particular object of interest and its tracking various urban applications such as public transportation, traffic monitoring systems, military systems, rescue and relief and alike. In the recent decades, many studies are run based on image processing for object identification and tracking through scientific and experimental method. The restrictions consist of noises, changes in scene illumination intensity value, change in the observation angle of the object, the creation of obstruction and fragmentation of an object, the emergence of a new object, high processing capacity and necessity for high-speed processing, low image resolution transparency, creation of shadow and its disappearance, distinguishing the background and foreground, change in the dimensions and size of the object due to its closeness the camera and the manner the camera is moved. In the recent studies, many of these restrictions have been removed through proposed methods. Most of the video applications are based on matching the key points in the image. In the past decade a serious challenge is launched towards more robust key points introduction of related algorithms known as the: Scale-Invariant Feature (SIFT), Maximally Stable Extremal Regions (MSER), Speeded up Robust Features (SURF), Features from Accelerated Segment Test (FAST), Binary Robust Independent Elementary Features (BRIEF), Efficient Dense Descriptor Applied to Wide-Baseline Stereo (DAISY), Binary Robust Invariant Scalable Key points (BRISK), Oriented Binary Robust Independent Elementary Features (ORB) and Fast Retina Key point (FREAK) can be introduced.The objective here is to introduce more rapid computable and more compact indexes, while in contrast, the scale, rotation and noise would remain resistant.

II.LITERATURE REVIEW

There exist several benchmark studies for 2D or 3D feature or key point detection methods in computer vision. TinneTuytelaars et al in 2008 [1], introduced an overview of invariant point detectors regarding how they have evolved over time, how they work, and what their respective strengths and weakness are. They begin with defining the properties of the ideal local feature detector. SamueleSalti et al in 2011 [2], proposed a performance evaluation of the state-of-the-art in 3D key point detection, mainly addressing the task of 3D object recognition. The evaluation is carried out by analysing the performance of several prominent methods in terms of robustness to noise, presence of clutter, occlusions and point-of-view variations. Tsz-Ho Yu at el in 2013 [3], assessed the performance of several state-of-the-

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art interest points' detectors in volumetric data, in terms of repeatability, number and nature of interest points. They detailed comparisons, with both quantitative and qualitative measures on synthetic and real 3D data. Cameron Schaeffer in 2013 [4], presented a comparison of two new key point descriptors (BRISK & FREAK) with the SURF descriptor in the context of pedestrian detector with an accuracy of over 90% using FREAK descriptors with a Radial Basis Function SVM classifier through Bag of Words model. Zijiang Song at el in 2013 [5], evaluated a 2D feature detection with respect to invariance and efficiency properties where a long video sequence of traffic scenes is used for testing these feature detection methods. Moreover a brute-force matcher and Random Sample Consensus are used in order to analyse how robust these feature detection methods are with respect to scale, rotation, blurring, or brightness changes.

III.FEATURE DETECTORS AND DESCRIPTORS

The identifiers and descriptors of the applied key points are grouped and introduced in brief.

SIFT

This algorithm is introduced by David G. Lowe (1999), [6]. It includes the four major stages: space extremal scale detection, localization of the key points, direction assignment and describes key points. In the first stage the difference of Gaussian (DoG), is applied to identify points of potential interest, which are fixed in relation to orientation. DoG applied instead of the Laplacian to improve computing speed. The localization of the key points, reject the low contrast points and eliminates the response edge. Hessian matrix is applied to calculate the main curve and eliminate the key points which have a ratio between the two main curvatures: bigger than the threshold value. Orientation histogram, consists of sample points gradient orientation in the vicinity of the key points (defined by key point scale), in order to get an orientation attribute. It is suggested that the best results are obtained with a set of 4×4 array histogram, each with eight orientation bins. Thus, SIFT is rector of, a $4 \cdot 4 \cdot 8 = 128$ dimensions [5], Fig. 1 below:

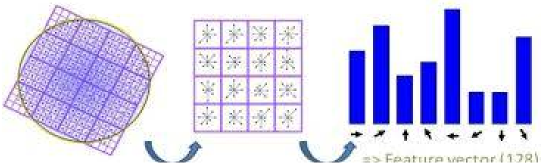

Figure 1: Scale-Invariant Feature Detector

The features of SIFT through high sustainability in relation to the previous trends improves scale change, lighting and local repetitious distortions. The high number of features in a sample image makes resistant detection under partial occlusion in the images disappear area possible. The final stage applicable in repetitious of the mode parameters allows for the approval and more accurate state determination in relation to methods which rely only on indexing. The overall stability of the image key points in relation to image conversions can be judged by the content in Table 1 where, each section obtained by combining the results of 20 different test image and the matching briefs the key points in to 15,000 key points. Each line of the table responds the conversion of a specific image. The key points' percentage are found in places and adapted scales. (Match %) and are adopted in orientation, responded by (Ori %).

Table 1: For various image transformations applied to a sample of 20 images, this table gives the percent of keys that are found at matching locations and scales (Match %) and that also match in orientation (Ori %) [6]

Image transformation	Match %	Ori %
A. Increase contrast by 1.2	89.0	86.6
B. Decrease intensity by 0.2	88.5	85.9
C. Rotate by 20 degrees	85.4	81.0
D. Scale by 0.7	85.1	80.3
E. Stretch by 1.2	83.5	76.1
F. Stretch by 1.5	77.7	65.0
G. Add 10% pixel noise	90.3	88.4
H. All of A,B,C,D,E,G.	78.6	71.8

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Since its initiation SIFT has been through different modifications. Ke and Sukthankar in 2004 [18], applied PCA on the image gradient around the identified designated point. PCA-SIFT reduced descriptor 128 to 36 dimensions by compromising its distinction and increasing the time for the formation of descriptor, which in turn removes the increase in comparative speed. This PCA-SIFT descriptor, a product of a 36-dimensional is for fast comparison, but according to a comparative study by Mikolajczyk et al in 2005 [19], it is proved that PCA-SIFT has less distinction than SIFT, since applying PCA slows down the calculations feature. In the same article, the authors propose a variant of the SIFT named GLOH and proves that even with the previous number of dimensions, it has greater distinction. However, GLOH computation sense, as it applies PCA once more for data compression, is costly. Se et al [20], implemented SIFT on programmable gate array (FPGA) and improved its speed in a big range. In almost two years, Grabneret al [21], used the integral images to estimate the SIFT. Their diagnosis is based on the difference of averages and their description is from, the integral histograms. They obtained the same speed limits provided by SURF in [8], (though in the descriptions, speed is constant), but at the cost of a reduction in quality compared with SIFT. In general, high dimensions in descriptor is a weak point of SIFT in matching step. If a physical object has a smooth border or a smooth piece, their images through the cameras would yield an image of an object with smooth appearance in different positions. This local deformation is well approximated by affine conversion of the image surface. As a result, the problem of solid object detection often leads to calculating the local features of fixed image affine. Similarity invariance (invariance to move, rotate and zoom) is dealt with through SIFT in an accurate manner. In the method proposed by Guoshen Yu and Jean-Michel Morel (2011) [22], Affine-SIFT (ASIFT) simulate, a set of initial images yield by changes made in direction axis detecting of two cameras, for example: longitudinal and altitude angle, something not achievable by SIFT. Consequently the SIFT is implemented automatically on all images produced in this manner. Therefore, ASIFT covers all six conversion of parameters of affine in an effective manner.

MSER

This algorithm is proposed by J. Matas et al (2002), [7], who applied it as a method of detecting bubbles in the images, for example, to find similarities among elements of the image of two pictures in different perspectives. A new set of picture elements, identified as correspondents, are named by two important Extremal features. A new set of element image identified as correspondents (i.e. duplicate conversions, extra regions and skew deviation viewing) regions with two intense major features of uniform image, 1) continuous 1-covered image coordinate uniform image conversion, 2) duplicate conversions, extra regions and skew deviation viewing. This method is sensitive to as natural light effect like changes in daylight or shade movement [5]. Sustainability and efficiency of this algorithm is proven in empirical sense. A major innovation here is the application of a robust similarity measurement in creating experiential correspondence. Despite this resistance, the measurement stability in multiple areas, even those that are considerably greater than MSER application (with differentiation potential) is of concern. Some appropriate estimates of EG (Epi-polar Geometry) are yield on basic spans through comparative robust algorithm on the output generated by the detector MSER. Scale change, lighting conditions, turning off the screen rotation, occlusion, local anisotropic scale change and transmit 3-D view angle transfer are implemented in the test issues. In a test where different images are involved, the following results tabulated in Table 2 are obtained:

Table 2: Experimental results [7]

	TC	Rough EG	Rough $d_\perp$	EG + corr	Fine EG	Fine $d_\perp$	Miss
Bookshelf	85	25	0.48	151	63	0.09	1
Valbonne	49	27	0.17	180	82	0.08	0
Wash	171	42	0.34	220	86	0.08	2
Kampa	303	78	0.34	422	185	0.08	2
Cyl. box	63	23	0.15	102	67	0.09	3
Shout	151	44	0.43	220	86	0.08	1

TC is the number of repeated correspondence, Rough EG is the number of duplicate correspondence with coarse estimate EG, Fine EG is the final correspondence, Rough *dl* and Fine *dl* are the average spacing from lines epi-polar,

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EG + corris the number of correspondence fit to course EG which have passed the tests and is the number of Miss wrong matches obtained manually.

SURF

This algorithm is presented in 2006 by H. Bay et al [8]. SIFT and SURF apply different quantitative methods for feature detection. SIFT forms image pyramid, filters each layer with Sigma Gaussian values and sorts the differences. SURF is inspired by SIFT, but designed with an emphasis on speed, while sharing the weakness of the SIFT. It is said that: “SURF is many times faster than SIFT without any fall in performance". A Haar estimate wavelet that applies bubble detector based on Hessian determinant is applies in SURF. Haar estimate wavelet can effectively be calculated at different scales using integral images. SURF features the package using an approximate second order Gaussian filter box, since the integral images allow calculation of rectangular box filters in a time close to constant. Precise localization of the features needs to be interpolated [5]. The elements witch constitute the SURF feature are shownin Fig. 2 below:

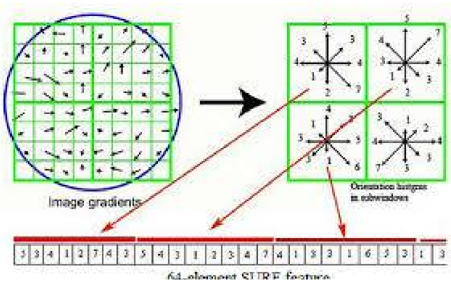

Figure 2: Speeded up Robust Features detector

For comparison, two versions of the Fast Hessian detectors, subject to the size of the initial Gaussian Derivative filter are tested. The FH-9 is the fast Hessian detector with initial filter size of 9 * 9 and FH-15 is the 15 * 15 filter of the version with two of image size input. Thresholds and parameters used are similar here. This detector is compared with (DoG), Harris and Hessian Laplace detectors. The number of points of found interests in average is similar in detectors. The thresholds, according to the number of these points that have been found by DoG, are adapted, as expressed in Table 3:

Table 3: Thresholds, number of detected points and calculation time for the detectors in comparison. (First image of Graffiti scene. 800*640) [8]

detector	threshold	nb of points	comp. time (ms)
FH-15	60000	1813	160
FH-9	50000	1411	70
Hessian-Laplace	1000	1979	700
Harris-Laplace	2500	1664	2100
DoG	default	1520	400

FH-9 is faster than DoG and Hessian Laplace by 5 and 10 times respectively. FH-15 DoG is faster than DoG and Hessian Laplace by 3 and 4 times, respectively. Moreover, most important repeatability of this detector is even better than its counterparts. The improvement in this method is the speed indicator. Almost real time calculation without loss in function can be considered as an important advantage in many on-line vision computerized application. The index is outperforms all new and modern methods. Simplicity in using integral images of this index in terms of speed makes this index robust and re-forms the index-based Laplace indexing in comparative stage faster with no disturbances. SURF algorithm has wide application in camera calibration and object detection.

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Based on the weak point of the original SURF in rotation immutability, Li Li in 2014 [23], introduced on combined algorithm with SURF features of DAISY descriptor. This algorithm, first, compares the SURF Hessian calculation matrix, for SURF Hessian to detect feature points, in a manner that the speed and accuracy of the point features is maintained during the detection process. Next, the image gradient is calculated from the original image and by using the proposed algorithm in DAISY descriptor for the purpose of calculating the main direction of the feature points. After the main direction is chosen the axis focus on the feature point and then rotates towards the main direction. Together with the main, some directions of the rectangular areas in vicinity are selected to calculate the descriptor. The experimental results indicate that this algorithm improves the rotation immutability of the main SURF algorithm, while increasing the run time is low, hence, more accurate matching points are achieved and this presented descriptor is assessed Oxford data collection standard, where pairs of images under different image changes, include: changes in view point, changes in rotate scale, image blurring, JPEG compression, and changes in brightness. The proposed image matching algorithm with SURF feature points and descriptor are combined provide better implementation speed and robustness in relation to the classical algorithms. This algorithm is not ideal for great changes in image scale.

FAST

This algorithm is introduced by E. Rosten and T. Drummond in 2006, [9]. The Illustration of this method is observed in Fig. 3 below:

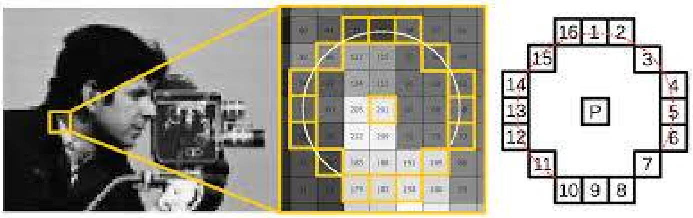

Figure 3: Feature Detection through Accelerated Segment Test

FAST is based on the SUSAN corner detector [10], where corner is a circular area to specify the neighbourhood pixels clearer or darker. However, case of FAST, not the entire area, but only the pixels on the circle of the detector segment are calculated. Similar to SUSAN, FAST algorithm applies a Bresenham of a circle 3.4 diameter of pixel as the mask in testing. For a full accelerated segment, test the 16 pixels should be compared with the core value where, the following two tests are performed: 1) the candid points are identified through the sectioning test on every pixel. To obtain the best results: Let IP define the lighting of the subject pixel P, provided that *n* pixels are in a Bresenham circle with radii of 3 and 9 p, darker than IP-t or lighter than IP+t, where *t* is the threshold value, the test is passed. The sequence of questions to categorize a pixel is obtained through ID3 algorithm, which improves the speed of this process considerably. Thus the first test, generates many marginal answers around the point in question and an extra criterion is added to implement for a non-maximal stop. Since the second test is run for the fraction of image point extracted from the first test, the process test time here is short [5]. The time results for selection of a specific detector on (768*288) grounds belonging to a PAL P/sec as a percentage of process cost/frame where approximately 500 characters are identified per field are presented in Table 4 below:

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Table 4: Timing results for a selection of feature detectors run on fields (768*288) of a PAL video sequence in milliseconds, and as a percentage of the processing budget per frame. Approximately 500 features per field are detected [9]

Detector	Opteron 2.6GHz		Pentium III 850MHz	
	ms	%	ms	%
Fast $n = 9$ (non-max suppression)	1.33	6.65	5.29	26.5
Fast $n = 9$ (raw)	1.08	5.40	4.34	21.7
Fast $n = 12$ (non-max suppression)	1.34	6.70	4.60	23.0
Fast $n = 12$ (raw)	1.17	5.85	4.31	21.5
Original FAST $n = 12$ (non-max suppression)	1.59	7.95	9.60	48.0
Original FAST $n = 12$ (raw)	1.49	7.45	9.25	48.5
Harris	24.0	120	166	830
DoG	60.1	301	345	1280
SUSAN	7.58	37.9	27.5	137.5

Advantages: compared to the other corner detectors available it is faster by many fold and having a high level of repeatability subject to multiple variations in character types.
Disadvantage: not resistant against high levels of noise; able to respond to lines with one pixel with specified angles, when the circle expansion eliminates the line and being affiliated to one threshold.
ElmarMair et al (2010) introduced a common comparative algorithm based on an accelerated segment test [24]. This is a corner detecting manner based on the AST which is more efficient, and more universal. Instead of considering only one limited configuration space, like FAST, it is suggested to apply a more detailed configuration space in order to provide a more practical solution. For this purpose, at any given time only one question is of concern. The idea is that one of the pixels is selected for the test and a question is selected for the design, followed by assigning the question for the pixel and the answer for drawing conclusion on pixel and the next addressed question. The search for a corner reduces to a traverse of a binary decision tree. Thus, it is necessary to determine which pixel is raised and what type of required questions are applied. Consequently, the configuration, space is increased by adding two additional “non-brighter” and "non-darker" modes. The speed and repeatability of FAST are compared with other modern algorithms introduced by Edward Rosten et al (2010), [25]. In their experiments, FAST-9 outperforms Harris, DOG or SUSAN. Note that this method is based on the AST with the capability to repeat FAST resemblance. Based on practical experiences, the tree is optimized in a 4-state space configuration and yields an increase in the speed average about 13% in relation to FAST-9. To mask 12 pixels, the ideal tree can be found in 6-state tree and an increase in speed from 23% to 30% if Ps = 0.1 and Ps = 1/3. By applying AGAST-5 decision tree on the 8 pixels mask a 50% increase in performance is yield.

BRIEF

This algorithm is introduced by M. Calonder et al (2010), [11]. This is a multipurpose point descriptor with features able to be combined with other selected detectors. This descriptor applies binary strings. This descriptor, even when relatively low number of bits is in use, is very distinctive and can be calculated through simple insensitive differential. This descriptor is resistant against common photometric classes and geometric conversions of image. The similarity between descriptions can be evaluated through Hamming distance which usually is very efficient in calculations rather than L2-norm. The objective of BRIEF is to achieve real time programs, while living a substantial empty space in the memory in devices with weak computational abilities [5]. Assessing this method is based on two criteria: Spend time in CPU and criterion identification. In the first, the CPU clock is measured through a few repeated operation. In the second, the ratio of correct level number to the desired points (r=nc/N) is defined. BRIEF algorithm consists of 4 major subcategories [11]:
1- Recognition rate as a function of descriptor size: here the results indicate that BRIEF-64 has a better performance than SURF and U-SURF unlike BRIEF-32 and BRIEF-16 is restricted.
2- Influence of features detectors: BRIEF slightly outperforms SURF and U-SURF at GenSurE points of SURF.
3- Sensitivity to orientation: BRIEF not designed to be stabilized against the rotation, however, results indicate that it can tolerate a little rotation. Since the U-SURF does not modify orientation, its behaviour is somewhat similar to, or slightly worse than BRIEF, that is, up to 10 to 15 degrees, where a slight decline is observed followed by a rapid

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reduction in SURF which seeks to compensate for changes in orientation in large spins; hence, a better performance which highlights the issue where change against rotation has a cost. Another point is that, response to planar rotations is a function of the estimators' quality rather than the index.

4- Estimating speed: time to comply with the second number of bits used in absolute values in a range of useful BRIEF change, but remains extremely low. Moreover, at least in theory, these times can be calculated using the POPCNT of SSE 4.2 is almost zero. The results of timing and calculations of the vectors described and fit for 512 key points on a machine that offers 2.66 GHz / Linux x86-64, measured in milliseconds are tabulated in Table 5 below:

Table 5: Timing results for the second and third steps for 512 key points, measured on a 2.66 GHz/Linux x86-64 machine, in milliseconds [11]

	BRIEF-16	BRIEF-32	BRIEF-64	SURF-64
Descriptor computation	8.18	8.87	9.57	335
Matching (exact NN)	2.19	4.35	8.16	28.3

In conclusion, reconstruction and matching algorithms BRIEF not only for the index much faster than other methods do, As long as the stability of the rotation for the big screen as a requirement is not raised, the higher detection rates. This valuable feature on devices that have computing power are limited.

DAISY

This algorithm is proposed by Engine Tola et al in 2010, [12]. This is a local image descriptor, DAISY, efficient in dense computation. They presented an algorithm based on EM (Expectation Maximization) to calculate the density depth and obstruction maps of wide baseline image pairs through DAISY. Efficiency of DAISY is due to the fact that most calculations consist of discrete convolutions, and that the calculation of joint histogram among close descriptors does not occur more than once. An increase in speed is due to replacing the weighted sums. Through previous descriptors and convolution of the sums, which can quickly be calculated through a circular symmetric kernel, weighting is achieved. The proposed method even when applied in small images for stereo reconstruction, yields good results, that is, it can be applied in video string resolution processes which is less static in image. Applying a descriptor would make this algorithm resistant against many photometric and geometric variations. The development of this descriptor is inspired from SIFT and GLOH but can be calculated for designated objectives much faster. Unlike SURF, this algorithm does not introduce artefacts that reduce concentrated matching functions. It should be noted that this proposed method is the first that seeks to estimate the density of pairs of image depth maps with a wide base line. This is a good case where many trials to accurately estimate the depth and obstruction are compare against other descriptors, where the scenes of ground truth is scanned with a laser. They tested this method on a variety of indoor and outdoor scenes with different variations in geometry and photometry, and the result support the claim that their algorithm is robust and responsive to these issues; Fig. 4.

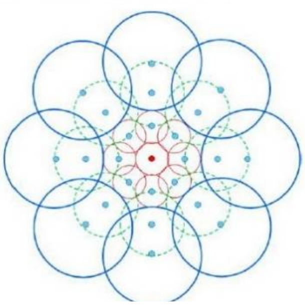

Figure 4: Structure of DAISY descriptor

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The details of the comparison of this algorithm with SIFT presented in [12, 13], are tabulated in Table 6 as follows:

Table 6: Computation time in seconds on an IBM T60 laptop [12, 13]

Image Size	DAISY	SIFT
800x600	3.8	252
1024x768	6.5	432
1280x960	9.8	651

BRISK

This algorithm is introduced by S. Leutenegger et al in 2011, [14]. BRISK is a method for the detection, description and comparison of key points. This method combines DAISY and BRIEF in order to obtain the advantage of rapid convergence and appropriate numerical stability by occupying minimum space in memory. The authors reveal a comprehensive assessment of the benchmark data sets, high performance quality which is in compliance with BRISK compared to modern algorithms and dramatically lower computing costs (in most cases they illustrate faster degree of SURF). Speed is subject to application of a scale-space FAST-based detector accompanied with bit-string descriptor [5].

The Sampling pattern of BRISK is illustrated in Fig. 5 below:

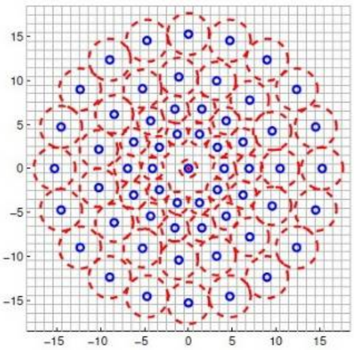

Figure 5: The BRISK sampling pattern with N=60 points: the small blue circle denote the sampling locations; the bigger, red dashed circles are drawn at a radius σ corresponding to the standard deviation of the Gaussian kernel used to smooth the intensity values at the sampling points [14]

BRISK provides a higher speed in matching algorithm performance. The unique characteristics of BRISK can be useful in wide range of applications (specifically work with difficult real-time constraints or computational limitations). BRISK provides high-low quality features for such time consuming applications. The result of the first image of the graffiti sequence are detected and tabulated in Table 7, and the time of matching is tabulated in Table 8. The values are averaged over 100 runs. The times reveal how distinct the BRISK is. Calculating the index and identifying it to the degree of amplitude faster than SURF, known as the fastest non-variable characteristics against rotation and scale are considered here. It is noteworthy that BRISK is capable of scaling for faster implementation by reducing the number of sampling points in the cost structure at competitive expense, payable in certain applications. Obviously, in addition to stability, scale or rotation in non-necessary applications can be removed in order to increase the speed and quality compliance.

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Table 7: Detection and extraction timings for the first image in the Graffiti sequence (size: 800*640 pixels) [14]

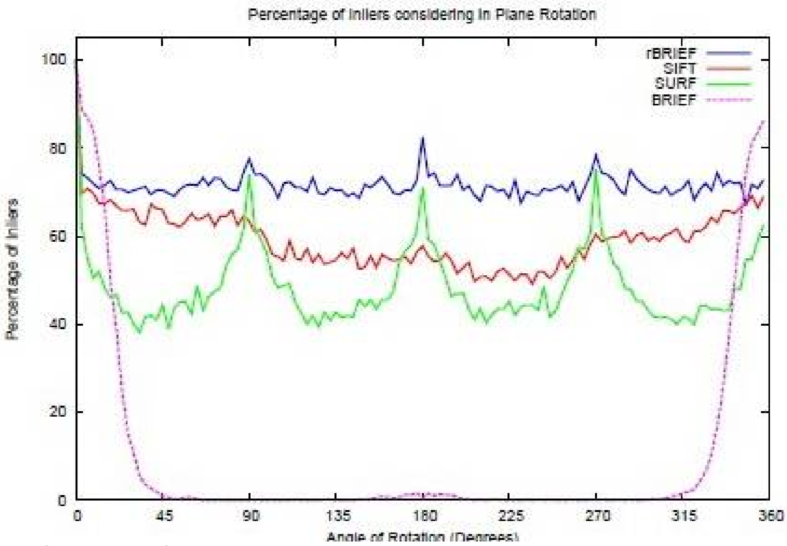
	SIFT	SURF	BRISK
Detection threshold	4.4	45700	67
Number of points	1851	1557	1051
Detection time [ms]	1611	107.9	17.20
Description time [ms]	9784	559.1	22.08
Total time [ms]	11395	667.0	39.28
Time per point (ms)	**6.156**	**0.4284**	**0.03737**

Table 8: Matching timings for the Graffiti image 1 and 3 setup [14]

	SIFT	SURF	BRISK
Points in first image	1851	1557	1051
Points in second image	2347	1888	1385
Total time [ms]	291.6	194.6	29.92
Time per comparison [ns]	**67.12**	**66.20**	**20.55**

ORB

This algorithm is introduced by E. Rublee et al (2011), [15]. This is a standard method for oriented FAST and rotated BRIEF. This algorithm applies FAST in pyramids, to identify sustainable key points and to select the most robust features of FAST on Harris response by orientating them through the first ranking times, finding and describing nodes throw BRIEF, (where the coordinates of a random point pairs (or K-tuples) are rotated based on the measured direction) is calculated [5]. The following graph illustrates the above mentioned 5 methods performances:



Graph 1: Matching performance of SIFT, SURF, BRIEF with FAST, and ORB (oFAST +rBRIEF) under synthetic rotations with Gaussian noise of 10 [15]

The standard BRIEF operand drops drastically after about 10 degrees. SIFT outperforms SURF in relation to the expanding effects at 45 degree do to its Haar wavelet. ORB with more than 70% inlier, illustrates the best performance. ORB unlike SIFT is relatively safer against Gaussian noise front.

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Table 9: Results for performance of ORB relative to SIFT and SURF [15]

	inlier %	N points
Magazines		
ORB	36.180	548.50
SURF	38.305	513.55
SIFT	34.010	584.15
Boat		
ORB	45.8	789
SURF	28.6	795
SIFT	30.2	714

According to the results presented in Table 9, ORB performs better than SIFT and SURF when it comes to external data sets; similar to that of the internal sets.
The results tabulated in Table 10 are of the set of 2686 images in 5 scale for the same number of properties and scale have been conducted. This time on 24, 640 * 480 have been averaged Pascal set of images. ORB once the domain of the SURF and more than two times faster than SIFT.

Table 10: ORB comparing to SURF and SIFT on the same data, for the same number of features and the same number of scales [15]

Detector	ORB	SURF	SIFT
Time per frame (ms)	**15.3**	217.3	5228.7

FREAK

This algorithm is introduced by A. Alahi et al in 2012, [16], which is a new key location descriptor inspired from the human visual system with more accuracy. The neuroscience has advanced the understanding of and how the image is transferred to the brain image. There exist the believe that the human retina codes the details by using the difference of Gaussian (DoG) with different image size images extracted with the exception of action potentials. It is proposed to mimic a similar approach to design FREAK image in the index and grid sampling of the retina, which then circular, with the difference that a higher density near the centre point is used. The density with distance from the centre decreases exponentially as shown in Fig. 6.

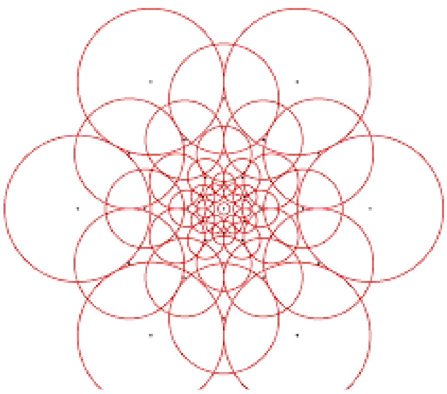

Figure 6: Fast Retina Key point sampling pattern

Each sampling point needs to be smoothened in order to become less sensitive to noise ratio. To implement the retina model, different kernel for each sample point, like BRISK. The Difference between FREAK and BRISK sample pattern

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is the exponential change in size and the overlapping receptive fields. Each circle indicates the standard deviation of the Gaussian kernels applied on the corresponding sampled points. Experimentally it is assessed that any change in Gaussian kernels with respect to retinal log-polar structure leads to a better performance. In addition, the overlapping in receiving enhances performance. The developers of FREAK recommended that saccadic search through the indices to multi-step analysis, be imitated. Through search by 16-bit the FREAK Index, which represents the great information, starts and if the distance was less than a threshold, for finer analysis of data, compared with the next bits, continue to be. As a result, classification of comparison takes place which even increases the compliance stage. More than 90% of the selected bits are discarded through the first 16-bit FREAK Index. For comparison, two test environments are considered: Sets introduced by SchimidMikalasczyu and the specialized framework similar to the one suggested on-line [17]. In both the test environments, FREAK is ranked as the most robust against all changes in the image subject to test. SIFT is the worst index in the first test environment, similar to that of the BRISK. The calculation time of the fixed indexes against the scale and rotation are compared in Table 11. All algorithms are implemented on an Intel dual-core 2.2 GHz, where one of the cores is applied. FREAK is even faster than BRISK, although BRISK is twice faster than SIFT and SURF.

Table 11: Computation time on 800*600 images where approximately 1500 key points are detected per image. The computation times correspond to the description and matching of all key points [16]

Time per keypoint	SIFT	SURF	BRISK	FREAK
Description in [ms]	2.5	1.4	0.031	0.018
Matching time in [ns]	1014	566	36	25

Bongsoo Suh et al (2013) introduced a key point indicators inspired derived from retinal calculations derived from top-name FREAK 2, provided [26]. FREAK applies only two field algorithms to calculate an index. To improve the strength index, the method for calculating the index over two fields through information is applied in the fields of retinal ganglion cells which carefully select the fields for calculation, after which a big index data set is built these are trained to reduce the indexes to 53. They also illustrated that their indicators compare and identify objects in different positions including the provided test images in the third sets of problem. Considering the number of features that apply this method, the relatively good performance is achieved. They applied only 53 characteristics which are significantly less than both SIFT algorithm and initial FREAK. Because there are fewer features, less time is spent on index calculation. In case a quick approximation, detection and object identification is required, this method can be applied with fewer features that provide for almost online calculations. For some test images, this model works well, however when the object is significantly configure, the performance is not good enough. In the simplest case, a linear averaging of neighbouring background intensities is considered, which seems to be due to approximation of biophysical calculations of limitations in simplification performance. This can be improved by considering a higher level of retinal features' calculations, that is a more complex and non-linear characteristic. A. Alahi et al (2014) applied FREAK to discover pedestrians' real time in urban settings with low resolution cameras, [27]. A sensor-less strategy is applied behind the shadows of the foreground to extract and classify real time product. A series of compact binary strings are introduced to model the presence of pedestrians between the cameras for comparative purposes. The proposed system does meet the practical requirements of the transportation system. This system is weak in real-time occupation and filling the computational and memory bandwidth operation. The system performance is assessed when the features extracted are weak and sensing devices are of low quality. Experimental results envision possibility and feasibility of the system.

IV.CONCLUSION

The feature detection functionality of 9 methods is reviewed in this article. There exist many views on the performance of these feature detection algorithms. The SIFT has the best strength with respect to rotation and changes in scale, while the issue of time is confirmed again. BRIEF and FAST yield better results in increasing brightness and ORB is better in reducing brightness. ORB also shows good performance in blurred images. A briefing of the chronology of these nine methods is presented in the figure below for better exposure of this concept.

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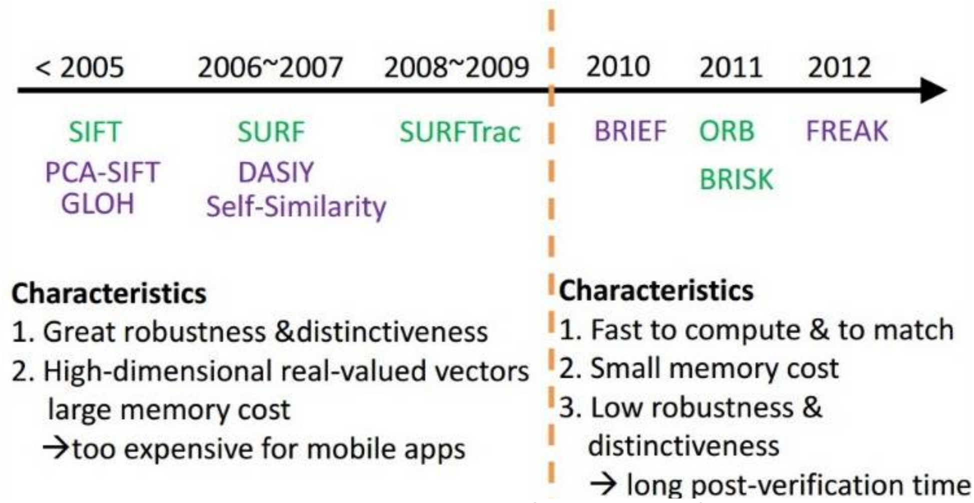

Figure 7: Development and bottlenecks of existing local features [28]

The findings of this review study are tabulated in the following Table:

Table 12: Comparing Results

Algorithm	**Ranking** (1 for higher and 9 for lower)	**Accuracy Percentage**	**Speed Coefficient**	**Notes**
SIFT	9	_	_	● It includes the four major stages. ● DoG applied instead of the Laplacian to identify points of potential interest. ● Hessian matrix is applied to calculate the main curve and eliminate the key points.
MSER	8	_	_	● A method for detecting bubbles in the images.
SURF	7	85%	1	● SURF is inspired by SIFT, designed with an emphasis on speed. ● A Haar estimate wavelet that applies bubble detector based on Hessian determinant is applies in SURF.
FAST	6	_	_	● FAST is based on the SUSAN corner detector. ● FAST algorithm applies a Bresenham of a circle 3.4 diameter of pixel as the mask in testing.
BRIEF	5	_	2	● This descriptor applies binary strings. ● This descriptor is resistant against common photometric classes and geometric conversions of image.
DAISY	4	_	_	● A local image descriptor, efficient in dense computation. ● Efficiency of DAISY is due to that most calculations consist of discrete convolutions.

BRISK	3	87%	_	● BRISK is a method for the detection, description and comparison of key points. ● This method combines DAISY and BRIEF.
ORB	2	_	_	● This is a standard method for oriented FAST and rotated BRIEF.
FREAK	1	91%	3	● It is a new key location descriptor inspired from the human visual system. ● The Difference between FREAK and BRISK sample pattern is the exponential change in size and the overlapping receptive fields. ● Saccadic search through the indices to multi-step analysis, be imitated.

Source: Authors

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