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A Survey of Feature Extraction Techniques in Content-Based Illicit Image Detection

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Abstract: For many of today's youngsters and children, the Internet, mobile phones and generally digital devices are integral part of their life and they can barely imagine their life without a social networking systems. Despite many advantages of the internet, it is hard to neglect the Internet side effects in people life. Exposure to illicit images is very common among adolescent and children, with a variety of significant and often upsetting effects on their growth and thoughts. Thus, detecting and filtering illicit images is a hot and fast evolving topic in computer vision. In this research, we tried to summarize the existing visual feature extraction techniques used for illicit image detection. Feature extraction can be separate into two sub-techniques feature detection and description. This research presents the-state-of-the-art techniques in each group. The evaluation measurements and metrics used in other researches are summarized at the end of the study. We hope that this research help the readers to better find the proper feature extraction technique or develop a robust and accurate visual feature extraction technique for illicit image detection and filtering purpose.

INTRODUCTION

In today's world, the Internet became an effective means in the world that leads to a huge revolution in people communicating and making business. Different from any other communication medium, it has a great effect to the communities and given an international dimension to the world. For many of today's youngsters and children, the internet, mobile phones and generally digital devices are integral part of their life and they can barely imagine their life without a social networking systems, online gaming, photographs and videos sharing[1-3]. As much as the positive impact of internet is noticeable, it is hard to neglect its negative impacts. Distributing the illicit contents and more specific the illicit images is one of the most significant negative impacts of the internet. Exposure to illicit contents is very common among adolescent and children with a variety of significant and often upsetting effects on their growth and thoughts[4]. These reasons motivates the researchers to develop new methods and techniques to counter with ever-growing illicit contents.

The fundamental step in content-based illicit image detection is extracting visual features from these images. Due to the importance of the matter and lack of a comprehensive study in the field, we are motivated to prepare a survey on different visual feature extraction techniques on illicit images. The term feature or visual feature which also known as Keypoint refer to interest image primitives and structures such as edge, corner, blob and etc. They are containing the most informative data from an image and they are very important within the field of image processing and computer vision. The method and technique of identifying these features are named feature detector. Once, features are detected, it is required to represent them numerically using feature descriptor techniques. The feature extraction actually consists of these two main steps feature detection and feature description. In other words, feature extraction refers to identifying the meaningful information and features from an image using feature detectors and represents them numerically by feature descriptors. Feature extraction techniques are engaged to discover the image anomalies and discontinuities in order to recognize the semantic of an image. Indeed, these anomalies might give a clue to predict the semantic of an image.

The following sections explain different types of features and then the categorized of detecting techniques based on these features are performed. Feature description techniques afterward is presented in more details and exiting state-of-the-art descriptors in the field are explained. Finally, the evaluation metrics and datasets use for evaluate visual feature extraction are reported.

VISUAL FEATURES TYPES IN CONTENT-BASED ILLICIT IMAGE

Generally, in computer vision society, a Feature is referred to a function of one or more measurements, each of which identifies some informative data and quantifiable property of an object in image. There have been remarkable works on different approaches to extract several kinds of features in these images. From image structure perspective these approaches could be classified as global features, pixel-level features and local features. Figure 1 shows different types of features used in the literature to detect illicit images. The following describes each type of features in more details.

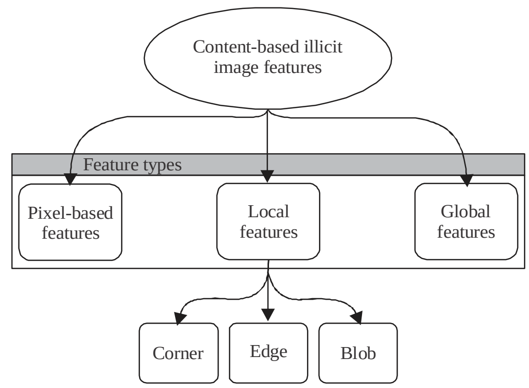

Fig. 1: Different types of features in content-based illicit image detection

Global features: Global feature are evaluated over the whole image or a sub-area of image. Generally, global features presents statistical facts of the image and they are able to generalize the entire image by a single vector. Resolution, image size, dimensions and aspect ratio are some examples of spatial-based global features. The image moments and average image intensity are some semantic-based global features. These features have been used to evaluate images in various research fields. For example, image contents are described by colour histograms in image retrieval applications, although, the foreground and background are mixed together. Many researchers such as[5-8] and etc. used global features for sake of illicit image detection. Global features have some limitations such as dealing with background clutter and occlusion, consequently misleads the feature extraction performance.

Pixel-level feature: Pixel-level features are evaluating each pixel individually. Pixel position and pixel intensity (gray level) are two prominent pixel-level features. Each pixel in image carries its Spatial-Positioning information which are represented as pair of scalar (x, y). These pairs specify the offset of a particular pixel from the image origin, i.e., in image-processing the image origin is the top-left corner of the image. Special information of pixels might bring useful information when the occurrence of the particular color cluster is a function of its position. Beside pixel position, each pixel has a pixel intensity which specifies the value that the corresponding pixel carries to represent its illumination and chromaticity. Meanwhile, the intensity feature could have different structure that depends on used image color space. For example, the RGB colour space presents pixel intensities in range 0 to 255 which they are identified by three values red, green and blue.

Pixel-level features are unable to directly present the sophisticated and high-level structures such as area, shape, texture and etc. but these features are forming the basis for more informative and sophisticated features. Despite this fact, the pixel-level features have been utilized in many illicit image detection techniques as a part of designed feature vector. For example, skin color information as primary pixel-level feature is indispensable part of many illicit image detector techniques. A number of researches such as Arentz *et al*.[9, 5, 10, 7, 11] have been used pixel-level features for sake of illicit image detection. To tackle the limitations and weaknesses of global features and pixel-level features, the local features were developed.

Local features: Local features could be localized in image by analyzing the local neighborhood of pixels which sharing some attributes such as texture, hue or holding a shape with distinctive border. These features are able to quantify more sophisticated image structures such as corners, blobs and edges. Since, local features are focusing on a group of spatially related pixels at a time, they are less likely to be affected by environmental variables such as illumination variation. Furthermore, these features have been proved that are more robust and give superior performance to background clutter, image noise and occluded scene[12, 11]. Many researchers used local features in various computer vision and image processingfield particularly illicit image detection which some of them are presented in the following.

Shen *et al*.[13] used local feature for sake of breast and pubes detection in illicit images. Diversity in shape, color and breast size of different individuals, makes feature extraction as a challenging task. The other study by Chung *et al*.[14] used the skin textural features to detect the obscene objects in low quality images. The main problem of this technique is that textural features are tend to fade away in low quality images. A very similar study by Li *et al*.[11] used texture and shape features to classify illicit images.

Mofaddel and Sadek also took advantage of local features such as edges detection in order to spot the illicit images. They believe that the number of the edges in the connected skin region helps to detect illicit images. The authors assumed that skin regions are tending to contain less edges compare to other areas. In the other work Zeng, etc., utilized local feature such as shape features, texture coarseness and texture contrast in order to spot illicit images. In a relatively different fashion Zhang *et al*.[15] used Bag of Visual Word model (BoVW) to detect illicit images. A mixture of local and pixel based features including intensity, color, skin and texture were extracted in illicit regions. More recently Zaidan *et al*.[7] used combination of global, pixel-level and local features in order to detect the illicit images.

Since, the local feature are the most common and important feature type in content-based illicit image detection techniques, they are explained in more details in the next section separately.

CATEGORIZATION OF LOCAL FEATURE DETECTOR

The methods or techniques of identifying visual features and keypoints in image are known as feature detector. As is shown in Fig. 1, the visual features can be categorized as follow:

Edge: The term Edge refers to pixel at which the image intensities change abruptly. Image pixels are discontinuous at different sides of edges.

Corner: This feature refers the point where two edges intersect. The corner is also defined as a point where a pair of different edge directions occur in the local neighborhood.

Blob: The blob feature refers to the local regions of interest and it also is divided to interest region detection and interest-point detection.

Based on local feature types, there are many types of feature detector in the literature. Generally, the visual feature detection techniques could be categorized as edge detection, corner detection and Blob detection. Figure 2 shows a taxonomy of different feature detection techniques.

It is noteworthy that there are tight and natural connections between the above mentioned definitions. For example contour/boundary could be obtained by tracking and connecting neighboring edges or for corners points actually a pair of connected contour lines intersect at this point. Meanwhile, an interest point refers to a point in an image with a well-defined position where it is easy to robustly detect. In other words, an interest point can be a corner but it can also be a point on a curve at which the curvature is locally maximal, or it can also be line endings and an isolated point of local intensity maximum or minimum. Table 1 presents some prominent techniques of different feature detector with related categories.

Based on Table1, it can be observed that despite the advantages of Edge-based featuresdetection techniques they suffering from several weaknesses such as highly sensitive to noise, producing wild edge responses in textured regions, internal noise edges, high computational complexity and low localization accuracy. The Blob-based detection techniques, on the other hand deliver better performance compare to Edge-based technique and detected features are more stable under image transformations. But majority techniques in this category such as well-known SIFT are still carrying the weakness of high computational complexity. Some other weakness of this category are difficulty in determining the extremal measurement among scales, sensitivity to noise, blur and illumination change, sophisticated detection framework and detecting redundant and not related features. Table 1 also shows that the Corner detection techniques generally generate more stable and unique features from image among existing techniques and categories. Therefore, more details of Corner detection techniques and related advantages and weaknesses will be discussed in the following.

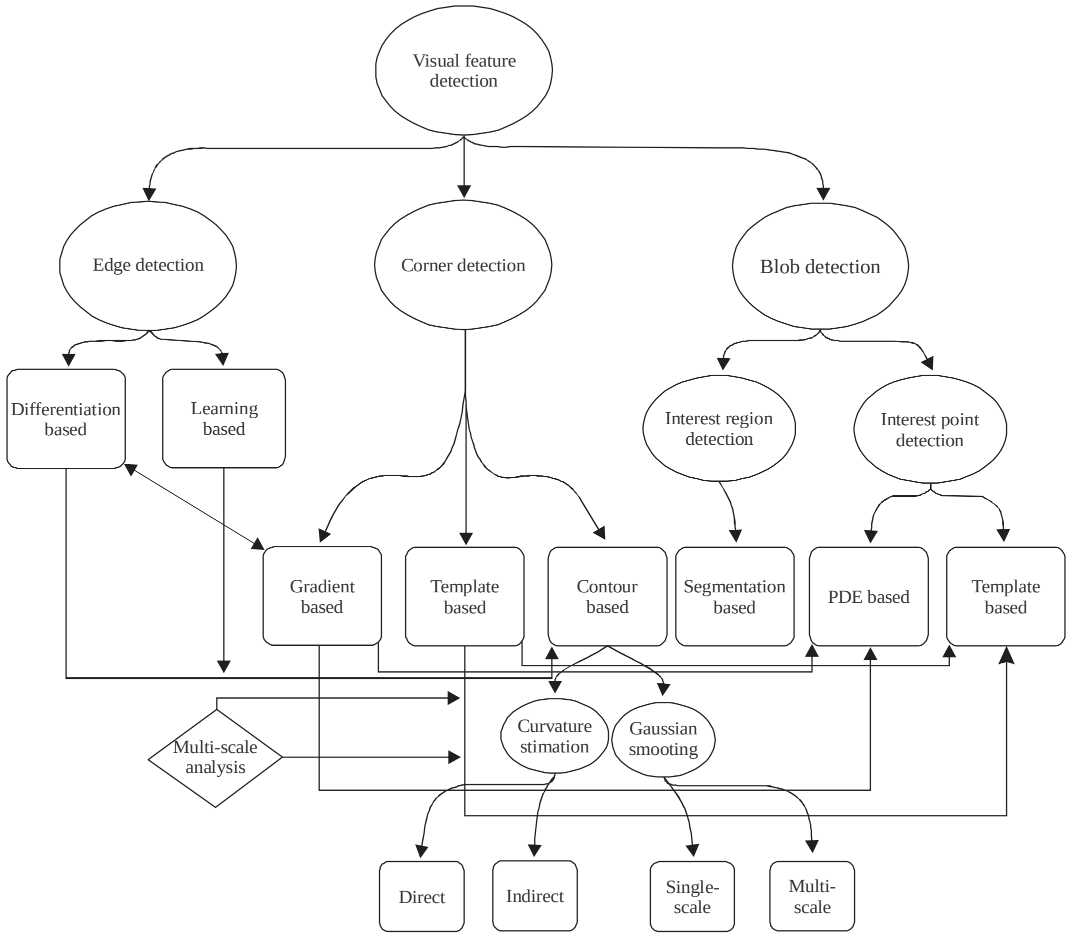

Fig. 2: The taxonomy of visual feature detection techniques. The connections of different categories are also has been shown

Corner detection techniques: As it mentioned before, among different types of local features, the corners contain more informative information and they are unique and stable under different image transformations. Generally, the methods and techniques of detecting corners in the image can be classified in three main group gradient-based, template-based and contour-based which have been shown in Fig. 2 as well. In the following the details of each group are explained.

Gradient-based corner detector: The method used in initial studies of corner detection techniques heavily rely on gradients computation. For an example, the Harris corner detection is among the earliest detection algorithm[26] where it works on the auto-correlation of gradients on shifting windows premise to detect corner points. In order to check whether there is a corner, every one of the pixels in the image is examined by considering degree of similarity between a center patch on the pixel to its nearby and largely overlapping patches. In order to estimate the resemblance, the weighted Sum of Squared Differences (SSD) of a pair of patches is calculated that finally led to forming the Harris matrix H as shown in Eq. 1:

$$H = \begin{bmatrix} I_x^2 & I_x I_y \\ I_x I_y & I_y^2 \end{bmatrix} \quad (1)$$

Three options can be taken based on the size of the eigenvalues of Harris matrix λ_1 and λ_2. In the cases that $\lambda_1\lambda_2$ the point is near an edge. But, in the cases when both λ_1 and λ_2 are big, the point should be considered as corner. If none of the cases occur, the point can be found in a flat area. Besides Harris, the early corner detection techniques including Shi-Tomasi detector[56] and KLT[27] were introduced. Cornerness measurement function is the main differences between proposed methods. The high computational complexity and noise sensitivity are the shortcomings of these detectors. To tackle with the high

Table 1: Different feature detection and description categories with some prominent related works in the field

Category	Classification	Detector	Descriptor	Methods	Advantage	Disadvantage
Edge detection	Differentiation based	Y	N	Roberts-cross	Simple implementation	Sensitive to noise
		Y	N	Oriented Energy (OE)	Sub-pixel edge detection	Produces wild edge
		Y	N	Canny[16]	Multi-scale edge analysis	responses in textured
					Hysteresis thresholding	regions
		Y	N	D-ISEF[17]		Internal noise edges
		Y	N	Color boundary		
		Y	N	Sobel		
		Y	N	Harris-laplace[18]		
		Y	N	Prewitt		
		Y	N	LoG		
	Learning based	Y	N	Pb[19]	Suppress the internal edges	High computational
		Y	N	MS-Pb	More related with semantic	complexity
		Y	N	gPb[20]	meanings	Low localization accuracy
		Y	N	tPb[21]		
		Y	N	NMX[22]		
		Y	N	DSC[23]		
		Y	N	Sketch Tokens[24]		
		Y	N	SCG		
		Y	N	SE[25]		
Corner detection	Gradient based	Y	N	Harris detector[26]	Reasonable performance	Quite time consuming
		Y	N	KLT[27]		Noise-sensitive
		Y	N	Shi-Tomasi detector[26]		Unstable under some
		Y	N	LOCOCO[28]		image transfromations
				S-LOCOCO[29]		
	Template based	Y	N	SUSAN[30]	Faster	Unstable under image
		Y	N	FAST	Larger number of	transformation such as:
		Y	N	FAST-ER[31]	detected corners	Illumination change,
		Y	N	AGAST[32]		blur, noise, scale
						Lack of effective and
						precise cornerness
						measurements
						Dataset dependent
	Contour based	Y	N	DoG-curve[33]	More stable than edge	Depend on the contours
		Y	N	ANDD[34]	Unique in local image	acquired by edge
		Y	N	Hyperbola fitting[35]	regions	detection and linking
		Y	N	ACJ[36]	Much related with real	Require preprocessing
		Y	N	ARCSS[37]	corners	steps
		Y	N	JUDOCA[38]	Can be viewed as points	
		Y	N	CPDA[39]	of interest at a fixed scale	
		Y	N	Fast CPDA[40]	Important kinds of blobs	
		Y	N	Eigen values[41]		
Blob detection	Interest point	Y	Y	SIFT[42]	Generate smoothed scale	Sensitive to noise
PDE Based		Y	Y	SURF[43]	spaces	High computation
		Y	Y	Cer-SURF[44]	Detect features affine	complexity
					invariant	Extremal measurement
		Y	Y	Rank-SIFT[45]		among scales is difficult
		Y	Y	DART[46]		to determine
		Y	N	LoG		
		Y	N	DoG		
		Y	N	DoH		
	Interest point	Y	Y	ORB[47]	Faster than PDE based and	not stable under image
	Template based	Y	Y	BRISK[48]	interest region detection	transformations
		N	Y	FREAK[49]		Detecting redundant and
		N	Y	BRIEF[50]		not related features
	Interest region	Y	N	MSER[51]	Better stability rather	Detection framework
	Segmentation based	Y	N	IBR[52]	interest point detection	also becomes much more
		Y	N	EBR[52]	Provide more geometrical	sophisticated than interest
		Y	N	PCBR[53]	parameters for stereo	point
		Y	N	Beta-stable feature[54]	matching	High computation
		Y	N	Salient region[55]		complexity

complexity recent trend shows that many works exploit the approximation of cornerness measurements. As an instance, the authors by Mainali *et al*.[29] introduced a low-complexity corner detector LOCOCO which is based on classical detectors. LOCOCO relies on Harris and KLT cornerness measurements.

Laplacian of the image is another method used to solve the issue of obtaining a scalar value to estimate the quantity of second derivative. Noise usually highly intensifies by second derivatives, so, the smoothed Laplacian that can be calculated through convolving the image which has the Laplacian of a Gaussian (LoG) is able to decrease such noise. Meanwhile the maxima of the LoG over different scales can provide stable locations[57]. In Harris-Laplace[58], also found that it would be possible to employ such method to detect features. Also, it is possible to build image pyramids then calculate C_H in every layer of those pyramids. Only the features located at a local maxima of the LoG in scales and local maximum of C_H in the image plane should be chosen.

The shortcoming of gradient based corner detection techniques is that they are highly sensitive to noise because the calculation of gradient is naturally noise-sensitive. Moreover, it is necessary to use the pixels inside the window to calculate the matrix for measurement function. Unfortunately, it makes the computational complexity significantly high. Furthermore, detecting unwanted points as corner point is another drawback of traditional gradient based corner detection.

Template-based corner detector: Template based corner detectors are another category of feature detectors. In template based detection techniques, keypoints could be found by comparing the intensity of center pixels and it's surrounding pixels. The cornerness measurement function should be devised from the association between center pixel intensities and the surrounding pixels. An example of template based corner detector is the traditional SUSAN (Smallest Univalue Segment Assimilating Nucleus) where all pixels in the circular mask and the center pixels are compared with one another and the differences in intensity is recorded[30]. Points that have the lowest USAN value are referred to as USAN measurement. In general, the template-based corner detection requires multiple comparisons and computational cost in this method is less compared to gradient based methods. Although, the SUSAN detector delivers remarkable repeatability but many of the features were located on edge structures and not on corners[59].

In order to facilitate detecting keypoints through Template-based techniques, the new Template-based generation include machine learning algorithms such as decision trees are introduced recently. The researchers in Rosten and Drummond[31] proposed a test criteria, which relies on a circular template of diameter 3.4 pixels contains 16 pixels; this test is named FAST (Features from Accelerated Segment Test). The criteria of FAST is, when a minimum of S contiguous pixels, darker or brighter than the center pixel intensity plus a threshold t, occur in the circle, then a point can be considered as a corner. Assume the center as P_0 and the pixel intensity as $I(P_0)$. A point P_0 can be considered as a corner if the minimum number of S connected pixels are brighter than $(I(P_0)+t)$ or darker than $(I(P_0)-t)$. In order to reduce time, the order of pixels should be compared with a decision tree. In addition, a thicker circular template through FAST-ER is applied in order to increase the stability of detected corners. More details are explained in Appendix B. Another type of FAST derivations named AGAST (Adaptive and Generic Accelerated Segment Test) is proposed[32]. In this technique, an optimal decision tree is constructed using backward induction in order to increase the speed. Meanwhile, a group of different decision trees are trained with several dissimilar sets of specified train images. Using these trees, AGAST becomes more generic to cater different environments. In the process of identifying features, templates play an essential role. Since, isotropy is a positive feature of circular templates, these kind of templates are selected to determine corners.

In order to achieve a better accuracy, the pixel intensity in sub-pixel level must be necessarily computed by interpolation. Usually, the amounts of computational cost and the robustness become larger in a template with more thickness. As an advantage of Template-based approaches is that not only much time is saved, it also detected more quantity of features (e.g., FAST, FAST-ER, AGAST) compared to gradient based approaches. Nonetheless, Aanæs *et al*.[60] revealed that in different image transformation, the quantity of detected FAST keypoints are not stable enough. The lack of effective and precise cornerness measurements in template based approach is the other shortcoming of this approach. Furthermore, some database-dependent problems might arise when using machine learning techniques, in spite of the fact that the computational cost of corner detection decreases.

Contour-based corner detector: The third category includes approaches based on edge or contour and boundary detection to locate the features in image. The notions of corners, specifically in contour based detection cannot be easily distinguished[61]. The purpose of such approaches is to detect the intersecting points of contours that edges produce or the points that have the maximum curvature in the planar curves. The crossed contours can be connected with n-junction such as T-, L-, X- and Y-junctions. The emphasis of the experts who initially studied on the early contour based corner and junction detection was on the processing of binary edges, in general.

As it shown in Fig. 2 before, the contour-based corner detectors could be categorized into various groups from different points of view such as the type of curvature estimation techniques, to measure the cornerness of the locations or the number of Gaussian smoothing scales to remove the noise from the curve. It can be categorized in two main groups: Classification based Gaussian smoothing and classification of the curvature estimation techniques. The classification based Gaussian smoothing also classified into two groups based on the number of used Gaussian smoothing scales: single-scale and multi-scale corner detectors. Note that the difference between using Gaussian smoothing in contour-based corner detectors and intensity-based detectors is that the in first group the Gaussian smoothing is applied the extracted edges where as in second group the Gaussian smoothing is applied on the original image. In most cases, the smoothing scale for a detector is chosen based on the empirical results[62, 63, 39].

In the past 20 years, Curvature Scale-Space (CSS)[64] which is single-scale corner detectors has been broadly utilized due to its good performance in localization accuracy of the corner points. It uses a coarse smoothing scale to estimate the curvature value for each pixel along the curve and then identifies approximate locations of the corners. Then, it applies a finer scale to track these locations to improve the localization of these corners. Awrangjeb and Lu[39] proposed the CPDA detector to enhanced CSS detector and they attempted to solve this weakness by using different scales for curves with different lengths. However, choosing the right set of scales for various curves' length is still difficult. In the other study a technique for image corner detection was suggested by Mokhtarian and Suomela[64] which relies on CSS depiction. In order to separate the FP corner points from the candidate corners, thresholding is applied. Generally, in CSS-based detectors, an edge extraction process is a sensitive procedure that may cause diagonal lines to be aliased on the edge and the original corner point in the contour to be missed. The edge map is not influenced by anti-aliasing but localization accuracy of the detectors and the FP rate are influenced by these issues.

In contrast, multi-scale detectors such as[65, 66, 40, 67] use a range of smoothing scales on all the curves of the image and later they combine or select the measured cornerness from all versions of the curves. For example, Rattarangsi and Chin[65] first applied Gaussian multi-scales for detecting and localizing corners of planar curves. The author constructed a map of curvature maxima that includes relevant information on the maxima of absolute curvature of the curves. He analyzed the behavior of the scales and the interaction of the two neighborhood corner locations. Then, the curves of different scales were transformed into a tree that provided simple but concise representation of the corners. Finally, a multiple-scale corner detection scheme was developed using a coarse-to-fine tree parsing technique. The main disadvantage of multi-scale detectors is that the cornerness of same locations is being measured in multiple scales which is computationally very expensive. Although, both multi-scale and single-scale corner detectors have their weaknesses own and strengths, according to reported evaluations, single-scale detectors perform relatively better considering both efficiency and effectiveness.

The classification of the curvature estimation techniques can be generally classified in two groups: direct and indirect techniques. The direct techniques identify the corners on high curvature points using geometric-based or algebraic measures[39, 68]. The indirect techniques are usually based on polygonal approximation of the curve, while the corner locations are extracted after doing this approximation. The direct techniques typically look for the robust corner locations where can also be found under various image transformations. However, the detection of a higher number of robust corners is always appreciated. On the other hand the locations detected by the indirect techniques are mostly used to represent the boundary of the shapes or pattern[69, 70]. Since, this research is focusing on the robustness of each detected corner and not the overall robustness of a group of corners belongs to a specific object in an image, the indirect techniques of corner detection are outside the scope of this research.

The corner detectors proposed by Farzin etc. which are based on the curvature scale space often use the Euclidean curvature, a derivative-based technique, to estimate the curvature values. These methods consider a very small neighborhood such as 2 by 2 pixel block on both sides of the candidate location. As a result, the estimated curvature is very sensitive to local variations and noise along the curve. These corner detectors typically detect many false and weak corner locations. The behavior of the curvature scale space and its properties have been investigated by Rattarangsi and Chin[65, 71].

One of the best contour-based corner detectors reported in the literature is the CPDA corner detector[39]. Essentially, the CPDA technique is a way of estimating the curvature values of a 2-D planar curve using a single chord[72]. Later, Awrangjeb by[39] proposed a strong angle detector based on the CPDA technique with multiple chords. The proposed detector applies chords which intersect curve segments of different lengths, to estimate curvature values on each corner point along the curves extracted by the edge detector. Then the estimated curvature values of each chord are normalized. After that, the curvature values estimated by the chords at each corner point were multiplied to obtain the final curvature value for each corner location. Finally, the points corresponding to the local maxima of the multiplied values are chosen as candidate corners and these corners are further refined to determine the final set of corners. Although, the CPDA detector is reported to achieve one of the lowest localization error and the highest repeatability among existing compatible detectors in the literature, it has several weaknesses such as it detects many weak or false corners, the estimated curvature values are not proportional to the original angle of the corner and it has the potential to miss some corners on curves which have several corners closely located to each other. Furthermore, the CPDA detector is also computationally very expensive.

Although, the existing corner detector techniques have massive improvement in terms of time complexity, there remain open issues and inherent limitations in terms of accuracy and true detection rate of corner points. Detecting the real corners in the images, is an important issue in corner detection methods. Furthermore, in the popular corner detectors such as Harris, FAST, FAST-ER and CPDA there are many detected points which are wrongly detected as a coroner. Dependency of contour-based corner detector to the output of edge detector also is the other weakness of this detectors. Usually there is a gap between two end points of the detected lines by edge detector which require more processing to tackle these appeared gaps in edge map of image. We believe that the appropriate approaches to detect the real corner points should take advantage of the contour/boundary that occur at a corner point.

Various feature detectors in different categories such as Edge-based, coroner-based and blob based has been explained in this section. A number of researches and techniques alongside their advantages and weaknesses has presented as well. The method and techniques which represent and quantifies these detected features (known as feature descriptor) will be discussed in the next section.

Feature descriptor: Once keypoints are located by detector, in the next step we are interested to associate every feature with a signature or a unique identifier which could later be used in identifying the corresponding feature from the other image. These signatures or identifiers that are used to describe keypoints are termed feature descriptors. Usually a feature descriptor represents either a subset of the total pixels in the neighborhood of the detected keypoints or other measures generated from the keypoints and deliver a robust feature vector. Based on the literature, descriptor techniques can be categorized into two types: descriptors based on geometric relations, descriptors based on pixels of the interest region. The strength and weaknesses of each group will be discussed in the following.

Descriptors based on geometric relations: In descriptors based on geometric relations, the descriptors use the relationship between the keypoint locations such as the distance from, or angle of, the neighboring keypoints. Zhou *et al*.[8] proposed a descriptor in which a Delaunay triangle in improved version of SUSAN[30] was constructed and then the interior angles as the properties of the descriptor were calculated. Since, the interior angles of the Delaunay triangle do not change with scale or rotation transformations, their proposed descriptor was invariant to rotation and uniform scaling. Meanwhile, their proposed descriptor is weak against non-uniform scale or affine transformations[73]. Awrangjeb and Lu[74] proposed a curvature descriptor for keypoint matching between two images. They used the information such as the keypoint location, absolute curvature values and the angle with its two neighborhood corners which is provided by their proposed CPDA[39] keypoint detector. Despite the low dimension and ease of constructing descriptors based on geometric relations, the research on this type of descriptor appears to be limited in the literature due to several weakness. One of main weaknesses of this group is that the distinctiveness of the keypoint locations in such representation is relatively low which leads to either miss-matches or many false matches. Furthermore, this type of descriptor constantly uses the iterative process to look for the best possible matches. Another problem of geometric relations-based descriptors is that the matching process is known to become too slow.

Descriptors based on pixels of interest region: The second group of descriptor is the descriptors based on pixels of the interest region which uses the pixels of the interest region to represent the features. Independency between features and robustness to occlusion are the main advantages of these group of descriptors. Generally, these descriptor can be classified in two main groups binary and non-binary descriptors. In the following section they are described in more details.

Non-binary descriptor: One of the most well-known descriptors in the literature is the SIFT[42] descriptor. According to a survey by Mikolajczyk and Schmid[75] and recent survey by Khan *et al*.[76], robustness against rotation and viewpoint changes has ranked SIFT descriptor at the top of the list. However, the main weakness of SIFT descriptor is its high dimensional feature vector which reduces the speed of this descriptor. Additionally, SIFT descriptor does not perform very well against blur and illumination change.

To counter high dimensional issue, PCA-SIFT[77] proposed to reduce the descriptor vector size from 128-36 dimensions, however, its distinctiveness and increased time for descriptor formation almost negates the increased speed of matching[78]. The other descriptor belonging to SIFT-like family method is GLOH[75] descriptor which is more distinctive but also more expensive to compute than SIFT[43].

According to Leutenegger *et al*.[48] what is probably the most appealing feature descriptor at the moment is the SURF[79] which is the fastest descriptor among the SIFT-like descriptors yet gives comparable performance similar to SIFT[80]. Similarly, SURF descriptor relies on local gradient histograms. A 64 or 128-dimension feature vector is generated by efficiently computing Haar-wavelet responses with integral images. Meanwhile, for large-scale applications such as 3D reconstruction or image retrieval, the dimensionality of the feature vector is too high. Hashing functions or Principal Component Analysis (PCA), are used to reduce the dimensionality of these feature descriptors[81].

As a result, the existing state-of-the-art feature descriptors mentioned above are mostly based on gradient-based information which is relatively expensive to compute due to using square root and tangent operations with the pixel intensities. In the following the different approaches which lead to binary descriptor will be explained.

Binary descriptors: Recently, progress in the computer vision community has shown that a simple pixel intensity comparison test can be efficient to generate a robust binary feature descriptor. Calonder *et al*.[50] proposed a binary feature descriptor using a simple intensity difference test which is called BRIEF. The advantage of BRIEF descriptor is its high descriptive power with low computational complexity during feature construction and matching processes. To obtain descriptor vector, intensity of 512 pairs of pixels is used after applying a Gaussian smoothing to reduce noise sensitivity. The positions of the pixels are randomly pre-selected according to Gaussian distribution around the patch center. The high matching speed is achieved by replacing usual Euclidean distance with Hamming distance (bitwise XOR followed by a bit count). As the main weakness of BRIEF descriptor is that it is not invariant to some transformation such as rotation and scale changes unless it is coupled with detector providing it. Calonder *et al*.[50] also mentioned that unnecessary orientation invariant property should be avoided because it reduces the recognition rate.

Rublee *et al*.[47] improved BRIEF descriptor and proposed Oriented Fast and Rotated BRIEF (ORB) descriptor which is invariant to rotation and robust to noise. Similarly, Leutenegger *et al*.[48] proposed a scale and rotation invariant binary descriptor which is named BRISK. To build the descriptor bit-stream using a specific sampling pattern, a limited number of points are selected and Gaussian smoothing is applied to avoid aliasing effects. To build the descriptor, pairs of smoothed points is used. These pairs are divided into long-distance and short-distance subsets in which short-distance subset is used to build binary descriptor after rotating and scale normalization, the sampling pattern and the long-distance subset is used to estimate the direction of selected patch.

Inspired by human visual system, Alahi *et al*.[49] proposed FREAK binary descriptor which uses learning strategy of ORB descriptor and DAISY-like sampling pattern[82]. A number of comprehensive surveys on detectors can be found in Mikolajczyk and Schmid [75, 83, 12, 76, 84]. Appendix B presents more details of binary descriptors BRISK and FREAK.

Despite the advantages of binary descriptors such as high performance in constructing a descriptor vector, low memory consumption and suitability for real-time and mobile-based applications, in terms of accuracy they suffer from weaknesses such as low accuracy in some image transformations. In addition, the accuracy of non-binary descriptors is a challenging and complex process and requires many adjustments and considerations.

Evaluation metrics: The evaluation of visual feature detector is very important. A convincing evaluation framework is required to promote the research significantly. Broadly speaking, the evaluation metrics defines how well a system meets the information needs of its users. The effectiveness of illicit image feature detection techniques are evaluated for accuracy and false detection rates. These evaluation measures are widely used and well established in the literature for performance measurement purposes. Table 2 summarized the existing evaluation metrics of illicit image feature detection techniques.

Table 2: Existing evaluation measures used for illicit image feature detection techniques

Performance measures	Description
Accuracy	
True Positive Rate (TPR) also known as True Detected Rate (TDR)	$\text{TPR} = \frac{\text{TP}}{\text{TP+FN}}$
True Negative Rate (TNR)	$\text{TNR} = \frac{\text{TN}}{\text{TN+FP}}$
Recall also known as sensitivity	Number of correctly matched regions with respect to the number of corresponding regions between two images of the same scene $\text{Recall} = \frac{\text{Number of Correct Matches(CM)}}{\text{Number of Correspondences}}$
Precision also known as False Matches Rate (FMR)	Number of false matches relative to the total number of matches
Error (Pixel)	
Localization Error (L_e)	Measure the accuracy of detected feature locations $L_e = \sqrt{\frac{1}{N}\sum_{i=1}^{N_r}\left[\left(x_{ti}-x_{oi}\right)^2+\left(y_{ti}-y_{oi}\right)^2\right]}$

CONCLUSION

Distributing illicit images is one of the most significant negative impacts of the internet. Exposure to these images significantly affects on children and adultness and they often leads to upsetting effects on their growth and thoughts. This research summarized existing visual feature extraction techniques used for illicit image detection. Feature extraction consists of two main step feature detection and feature description which they were categorized in several types and groups in this research. The state-of-the-art techniques in each groups were presented as well. Finally, different evaluation measurements and metrics used in the literature were summarized. We hope that this research help the readers to contribute and develop of robust and accurate visual feature extraction technique for illicit image detection and filtering purpose.

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