مجلة كلية التراث الجامعة

العدد التاسع والعشرون

Retrieve an Image and its location from Video stream based on Hybrid Features Extraction methods

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Abstract

For the reason of colossal technological developments, the requirement of image information methods became a significant issue. Due to the visual media need great memory's amounts and calculating power for storage and processing, there is a requirement to worthily index and recapture information visually from the video frames. More Content-Based Image Retrieval (CBIR) methods utilized the low-level characteristics such as texture, color and shape for extracting the characteristics of an image. For numerous works which were available, points of interest were utilized for extraction the identical images with various accuracy and view. The aim of this research was to retrieve an image and its location from video frames based on hybrid features extraction methods. The suggested system for retrieving consists from four stages. In the first stage, a video is loaded on the project screen and all video frames are extracted. Seven moments invariant was employed to extract the features of each frame in the second stage. In the third stage, Speeded up Robust Features (SURF) was employed to detect the features of each frame based on the values of seven moments. In the fourth stage, test image was loaded, extract all features from this image and Manhattan distance method was used to calculate the distance between the values of SURF of the test image and all SURF values of the video frames to match and retrieve an image and its location from video sequence. The experimental results show that the precision and the recall values were high for retrieval when using a hybrid SURF based seven moments methods compare with using SURF method only. For example, the precision for retrieval an image woman was 93% when using hybrid while it was 81% when using SURF only with static threshold also the recall for retrieval image woman was 91% when using hybrid while it was 83% when using SURF only with static threshold.

Keywords—SURF, Seven moments, image retrieval, Manhattan distance, CBIR

استرجع الصورة وموقعها من السلسه الفيديويه بالأعتماد على دمج طرق استخراج الصفات

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الخلاصه

بسبب التطورات التكنولوجية الهائلة ، أصبحت طرق التعامل مع معلومات الصور من المتطلبات المهمة. نظرًا لأن الوسائط المرئية تحتاج إلى كميات كبيرة من الذاكرة وقوة حساب للتخزين والمعالجة ، فهناك حاجة لفهرسة المعلومات واستعادتها بشكل مرئي من صور الفيديو. المزيد من طرق أسترجاع الصور المعتمده على المحتوى *(CBIR)* أستخدمت

الخصائص منخفضة المستوى مثل الملمس واللون والشكل لاستخراج خصائص الصورة. في العديد من الأعمال التي كانت متاحة ، تم استخدام النقاط المهمه لاستخراج الصور المتطابقة بدقة ورؤية مختلفة. كان الهدف من هذا البحث هو استرجاع صورة وموقعها من صور الفيديو بالأعتماد على دمج طرق استخراج الصفات. يتكون نظام الاسترجاع المقترح من أربع مراحل. في المرحلة الأولى ، يتم تحميل مقطع فيديو على شاشة المشروع ويتم استخراج جميع صور الفيديو. ثم يتم استخدام العزوم السبعه الثابتة لاستخراج صفات كل صوره في المرحلة الثانية. في المرحلة الثالثة ، تم استخدام الصفات القوية السريعه (*SURF*) لاكتشاف صفات كل صوره بناءً على قيم العزوم السبعه. في المرحلة الرابعة ، تم تحميل صورة الاختبار واستخراج جميع الصفات من هذه الصورة وتم استخدام طريقة مسافة مانهاتن لحساب المسافة بين قيم *SURF* لصورة الاختبار وجميع قيم *SURF* لصور الفيديو لمطابقة وأسترجاع الصوره و موقعها من تسلسل الفيديو. أظهرت النتائج التجريبية أن الدقة وقيم الاسترجاع كانت عالية عند استخدام طريقة *SURF* الهجينة المعتمده على العزوم السبعه مقارنة باستخدام طريقة *SURF* فقط. على سبيل المثال ، كانت دقة استرجاع صورة المرأة 93٪ عند استخدام الهجين بينما كانت 81٪ عند استخدام *SURF* فقط مع عتبة ثابتة ، كما كانت نسبة استرجاع صورة المرأة 91٪ عند استخدام الهجين بينما كانت 83٪ عند استخدام *SURF* فقط مع عتبة ثابتة.

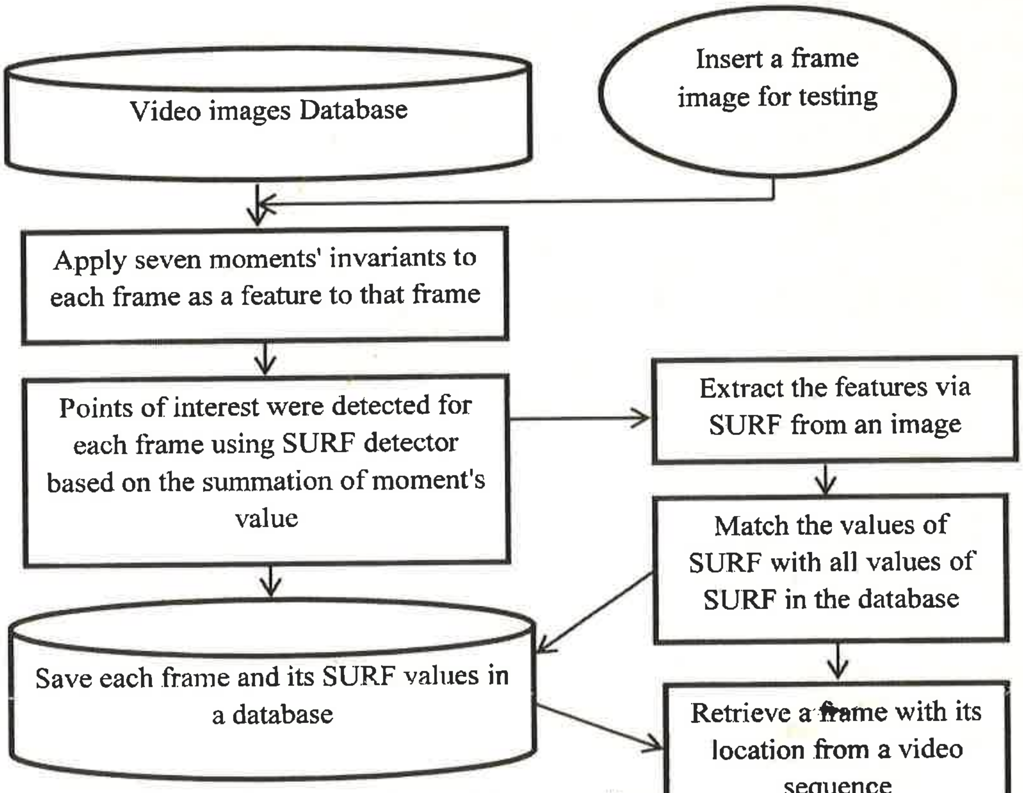
1. Introduction

The retrieval of an image is the study field which can be concerned with searching, scanning, and recapturing digital images of the expanded database. Content Based Image Retrieval (CBIR) can be seen as a quick and dynamic advancement research region for the retrieval of an image domain. It is a mechanism for images retrieving by similarity of a collection. Retrieval can be depended on the characteristics that automatically elicitation from the images. Numerous systems of CBIR that depend on descriptors' features are established and advanced. A feature captures a certain visual property of an image. A descriptor can be encoded of an image in a way which can be allowed it to compare and match with other images. The descriptors of an image features in general could be either local or global. The global descriptors of the feature can be described the visual content of the whole image, while local feature can be described an image's spot for example, a small set of content image pixels. The superiority of a global descriptors elicitation is increasing feature's extraction speed and calculating the similarity. Global features remain too solid for image representation. Specially, they can more sensitive to position and consequently may fail for identifying significant visual features. The approaches of local feature supply best retrieval efficiency and big discriminative force in resolving vision troubles than global features [1]. Smallest Univalue Segment Assimilating Nucleus (SUSAN) is a special detector which offers considerably higher performance. It is very fast in detecting corners as key-points and consumes only a fraction of the time available during detection of corner with more features, and on low power hardware [2]. Fast Retina Keypoints (FREAK) was proposed as a fast retina's key-point descriptor [3]. The retina's organization imitated, utilizing a circular grid that receptive ranges are suggested of several sizes. The dissimilarity of intensity among receptive ranges pairs can be calculated and classification binary vector. Especially the receptive ranges focus is maximal at the center of the pattern, similar to the fovea of a retina. FREAK was estimated at matching function that shows high detection's performance for an object. The descriptors of Binary Robust Invariant Scalable Keypoints (BRISK) [4] and A Fast Local Descriptor for Dense Matching (DAISY) [5] compare intensities pairs via utilizing a circular manner. Compare to descriptors' state art like Scale Invariant Feature Transform (SIFT), Binary Robust Invariant Scalable Keypoints (BRISK) or Speed Up Robust Feature

(SURF), it outperformed them, whilst being faster and simpler. For a modern descriptor like CS-FREAK [6], a fundamental grid simplified via lessening the sensitive ranges' numbers and the nearness density will encode boosting the precision of matching. For a different job type, FREAK used for videos actions realization via extend to a descriptor that encoded motion this can be known Modified Fast Retina's Key-point descriptor (MoFREAK) [7].The descriptors biologically inspired have fundamentally been utilized for recognition of an object task [5]. For filtering, Difference of Gaussian (DoG) can simulate the performance of retina that utilized for classification the texture. In this action, it can be proposed a modern descriptors group of bio-inspired for scene job categorization [8]. The aim of this research was to retrieve an image and its location from video frames based on hybrid between features extraction seven moments' invariants method and SURF detector method.

2. Suggested Methodology

The suggested system for retrieving an image and its location consists from four stages. Figure1 illustrated the flowchart of the suggested methodology.



2.1. Features Extraction using Seven Moments Inva

Figure 1: Block diagram of the proposed system for frame retrieval from a video sequence

One of the most important tools to get significant features is Moments. Moments are defined simply as "scalar quantities to characterize a function". One of the most common Invariant Moments is the geometric Moments. Suppose (F (x, y)) defined a 2-Dim image in a spatial model. A Geometric moment of arrangement *(p + q)* is illustrated in Eq.1 .

$$m_{p,q} = \sum_x \sum_y x^p y^q F(x,y) \qquad (1)$$

for(p , $q = 0$, 1 , 2 , ...).The central of moments are defined via Eq.2

$$x_c = m_{1,0} / m_{0,0}$$
$$y_c = m_{0,1} / m_{0,0}$$
$$(2)$$

Where xc and yc offers at Eq. 2 defined the region's center of an object. Hence the Central moments of order up to 3 can be defined in Eq.3

$$\left.\begin{aligned}
\mu_{0,0} &= m_{0.0}\\
\mu_{1,0} &= 0\\
\mu_{0,1} &= 0\\
\mu_{2,0} &= m_{2,0} - x_c m_{1,0}\\
\mu_{0,2} &= m_{0,2} - y_c m_{0,1}\\
\mu_{1,1} &= m_{1,1} - y_c m_{1,0}\\
\mu_{3,0} &= m_{3,0} - 3x_c m_{2,0} + 2m_{1,0} x_c^{\,2}\\
\mu_{1,2} &= m_{1,2} - y_c m_{1,1} - x_c m_{0,2} + 2y_c^{\,2} m_{1,0}\\
\mu_{2,1} &= m_{2,1} - 2x_c m_{1,1} - y_c m_{2,0} + 2x_c^{\,2} m_{0,1}\\
\mu_{0,3} &= m_{0,3} - 3y_c m_{0,2} + 2y_c^{\,2} m_{0,1}
\end{aligned}\right\} \qquad (3)$$

The normalized moments' central, indicate $\eta_{p,q}$ as illustrated in Eq.4.

$$\eta_{p,q} = \mu_{p,q} / \mu^{\gamma}{}_{0,0} \qquad (4)$$

Where $\gamma = p + q/2$

For Eq.4, (p + q = 2, 3,…,p*q) . A group of seven *transformations moments invariant* constructed vial 2nd order and 3rd order moments via Eq.5 [9].

$$\left.\begin{array}{l}
\phi 1 = \eta_{2,0} + \eta_{0,2} \\
\phi 2 = (\eta_{2,0} + \eta_{0,2})^2 + 4\eta_{1,1} \\
\phi 3 = (\eta_{3,0} - 3\eta_{1,2})^2 + (3\eta_{2,1} - \eta_{0,3})^2 \\
\phi 4 = (\eta_{3,0} + 3\eta_{1,2})^2 + (3\eta_{2,1} + \eta_{0,3})^2 \\
\phi 5 = (\eta_{3,0} - 3\eta_{1,2})(\eta_{3,0} + 3\eta_{1,2})[(\eta_{3,0} + 3\eta_{1,2})^2 \\
- 3(\eta_{2,1} + \eta_{0,3})^2] + (3\eta_{2,1} - \eta_{0,3})(\eta_{2,1} + \eta_{0,3}) \\
[3(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} + \eta_{0,3})^2] \\
\phi 6 = (\eta_{2,0} + \eta_{0,2})[(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} - \eta_{0,3})^2] \\
+ 4\eta_{1,1}(\eta_{3,0} + \eta_{1,2})(\eta_{2,1} - \eta_{0,3}) \\
\phi 7 = (3\eta_{2,1} - \eta_{0,3})(\eta_{3,0} + \eta_{1,2})[(\eta_{3,0} + \eta_{1,2})^2 \\
- 3(\eta_{2,1} + \eta_{0,3})^2] + (3\eta_{1,2} - \eta_{3,0})(\eta_{2,1} + \eta_{0,3}) \\
[3(\eta_{3,0} + \eta_{1,2})^2 - (\eta_{2,1} - \eta_{0,3})^2]
\end{array}\right\} \quad (5)$$

This group of normalized moments central is constant to rotation, translation and scale alterations for an image [9].

2.2. Features Detection using SURF Detector

SURF (Speeded UP robust Features) algorithm was a robust detector for a local features and the algorithm of the extractor used in numerous applications of the computer vision such as recognition of an object and 3D reconstruction. SURF is preferable method sufficient in real time implementation. The detection of interest points which is performed by calling the vector descriptor in an algorithm of SURF was based on theory of a scale space [10].

2.2.1 Integral Images

An algorithm of SURF employed integer approximations like Hessian's determinant blob detector that can be calculated rapidly with an integral image. It can permit for rapid calculation of box kind convolution filters. The ingress of an integral image ($I_\Sigma(x)$) at a position ($x = (x,y)^T$) can be illustrated in Eq.6.

$$I_\Sigma = \sum_{i=0}^{i<x} \sum_{j=0}^{j<y} I(i,j) \qquad (6)$$

In the moment that the integral image has been calculated, it can take 3 addendums to compute the intensities' summation onto each upright_ rectangular region as illustrated in

Figure 2. Subsequently, the computation time was separate from its size. This is significant for an approach as it employed big sizes of the filter sizes [10].

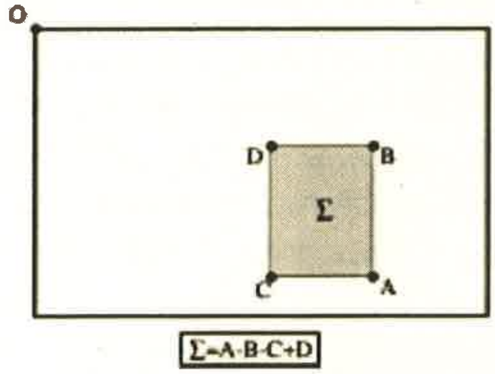


Figure 2: Using integral images, it takes only 3 additions and 4 memory accesses to calculate the total of the intensities inside a rectangular region of each size[11].

2.2.2 Hessian Matrix Based Interest Points

The detector can depend on the Hessian matrix due to its good accuracy performance. It detects a blob as structures at positions where the determinant was max. Specified a point (x = (x; y)) in the image (I), the matrix of Hessian (H(x, σ)) in (x) at scale (σ) was determined by Eq.7

$$\mathrm{H}(\mathrm{x},\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{x}y(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \qquad (7)$$

where $L_{xx}(x, \sigma)$ is the convolution of the (Gaussian second order derivative $\partial^2/\partial x^2 g(\sigma)$) in the image (I) at point (x), and Gaussians are optimum for analysis of the scale space.
In application, it has to be cropped and discretized as illustrated in Figure 3 left_ half.

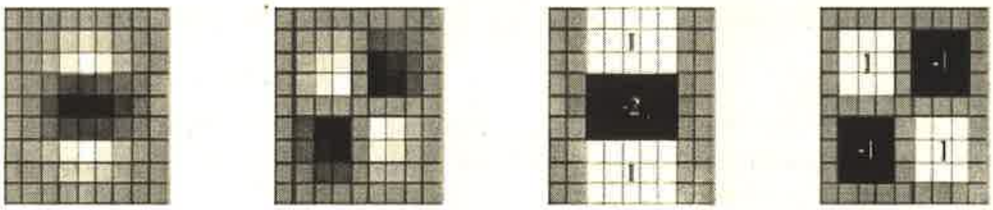


Figure 3: Left tor ight Gaussian_second_order_partial_derivative for L_{xy} (xy-direction), L_{yy} (y- direction) and, respectively [10]

The (9 × 9) box filters in Fgure 3 are approximations of (Gaussian with σ = 1.2) and perform the lowest scale to calculate the blob restraint map [10].

2.2.3. Scale Space Representation

The points of interest required to be established at various scales not least due to the correspondences searching often needs their comparison in the images where they are visible at various scales, scale spaces are generally executed as a pyramid of an image. Repeatedly the images are smoothed by a Gaussian approach and then subsampled for higher level achievement of the pyramid. Due to the employ of integral images and box filters, it does not have to apply iteratively the similar filter to the outcome of a previously filtered-layer, but it employed box filter of each size at precisely the similar speed immediately on the main image and even in parallel. Therefore, a scale-space was analyzed via up_scaling a size of the filter instead of reducing iteratively the size of an image as illustrated in Fgure 4. The outcome of (9×9) filter is treated as the initial scale layer and it can refer like scale (s = 1.2. The following layers were acquired via filtering the image with progressively bigger masks and taking into account the particular filters' structure and the discrete type of integral-images [10].

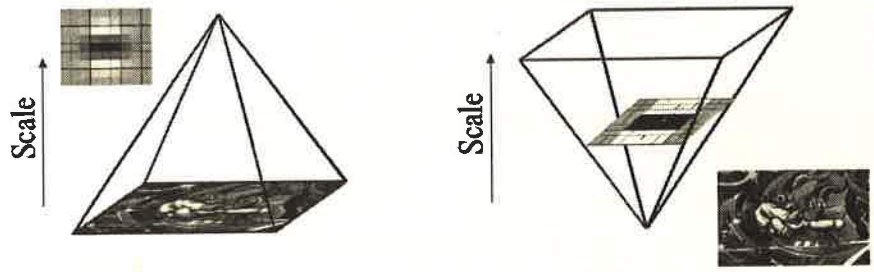


Figure 4: Instead of reducing iteratively the size of an image left, the employed of integral-images permit the up_scaling of the filter at fixed cost right [10].

2.2.4. Interest Point Localization

For points of interest localization in an image and through scales, a non-maximum repression in $(3 \times 3 \times 3)$ neighborhood was employed. The maxima of Hessian matrix determinant are then interpolated within scale. The interpolation of a scale space was particularly significant in this situation, as the difference in scale between the first layers of each octave is comparatively large. Figure 5 illustrates a paradigm of the detected points of interest by employing Fast-Hessian detector [10].

Figure 5: Points of interest detected in a Sunflower domain. This type of scene displays the quality of the features which are extracted via employing Hessian detector [10].

After localization the features of all frames, the Manhattan used via Eq. (8). The Manhattan distance between two components can be calculated by the summation of differences of their identical elements. The distance formula among the points X=(X1, X2, etc.) within the points Y=(Y1, Y2, etc.) can calculate via Eq.(8) [12].

$$d = \sum_{i=0}^{n} |x_i - y_i| \qquad \textbf{(8)}$$

3. Suggested Algorithm for Image Retrieval with its Location

The suggested algorithm can be explained as follow:

Input : video stream, image to be test and matched
Output : Retrieve an image and its location from video stream

begin // For Training phase

Step1:- Enter AVI video and Extract the frames from video stream and put the results in database **(Imgs)**

Step2:-For k=1 to No. of frames **do**

2.1 select a frame **IMG[k]** from a database
2.2 Compute the seven moments values for **IMG[k]** using Eq.5
2.3 Summed the values of seven moments into one value and put the result into **S[k]**
2.4 Apply SURF detector method based on the value of **S[k]** as a threshold
2.5 Store all the features that resulted from SURF detector in a database **(D)**

End for // for k loop

Step 3: //For Retrieving an image with its location phase

3.1 Enter the tested image of English letter , apply step2.2 step 2.3 and step 2.4 and then find the values of the SURF **(VT)** for the tested image.
3.2 Compute the Manhattan distance between all values of SURF for each frame in the database **(D)** and **(VT)** using Eq.(8) .

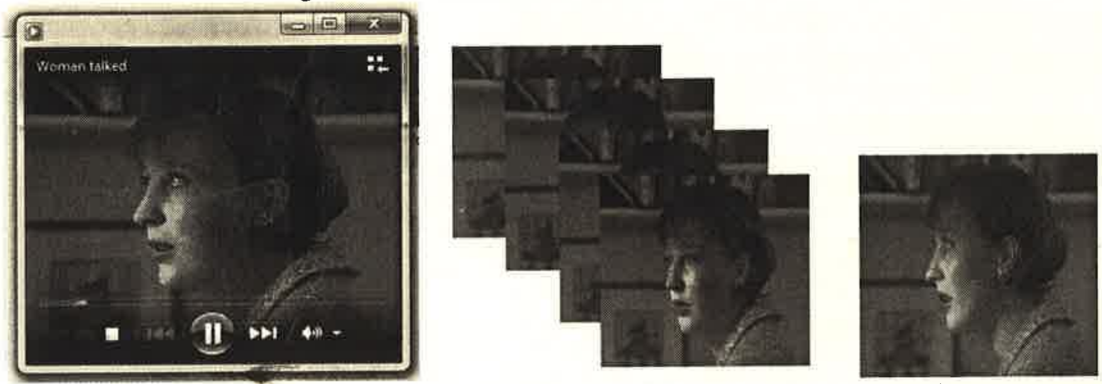
3.3 Retrieve the corresponding frame from the database **(D)** and its location based on the value of Manhattan.

End.

4. Experimental Results

The outcomes of suggested method are offered and discussed at this part. The suggested method is executed in C#. Four types of databases like **(Woman)** video, **(Airehorse)** video, **(Scoter)** video and **(Tracery)** video are employed for evaluation the suggested method. Database images are colored, and with size 320 × 240 pixels. The suggested method consists form multiple steps:-

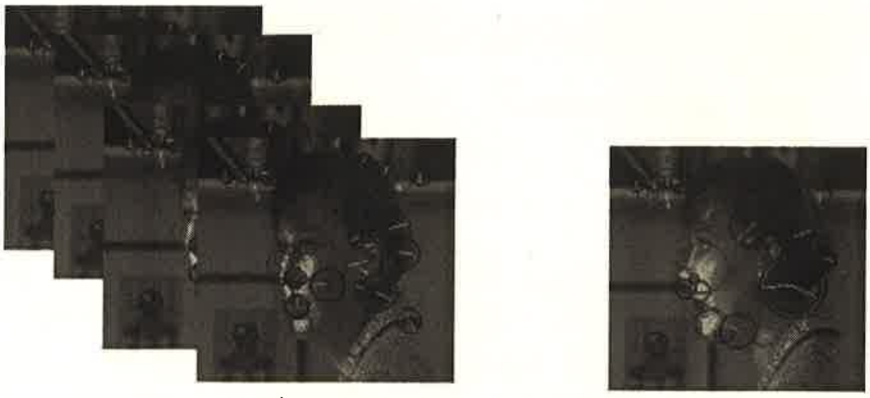
1) At the first step, loading the video stream and tested image as shown in the Figure 6 for **Woman** video and Figure 9 for **Airehorse** video.



a) b) c)

Figure (6): Women video, a) input video b) Frames extraction from women video c) input test image from women dataset to retrieve its location in a video stream

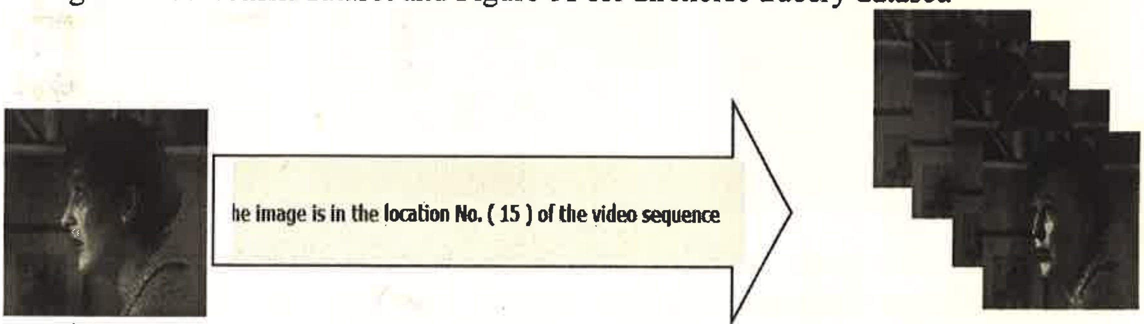
2) Seven moments invariant was employed to detect the features from each frame in the second stage.
3) In the third stage, SURF was employed to detect the features of each frame based on the values of seven moments. The values of seven moments are summed and the result of the summation used as a threshold in SURF detector method. The results of SURF detector can be displayed in Figure 7 for **woman** video and Figure 10 for **airehorse** video.



a) b)

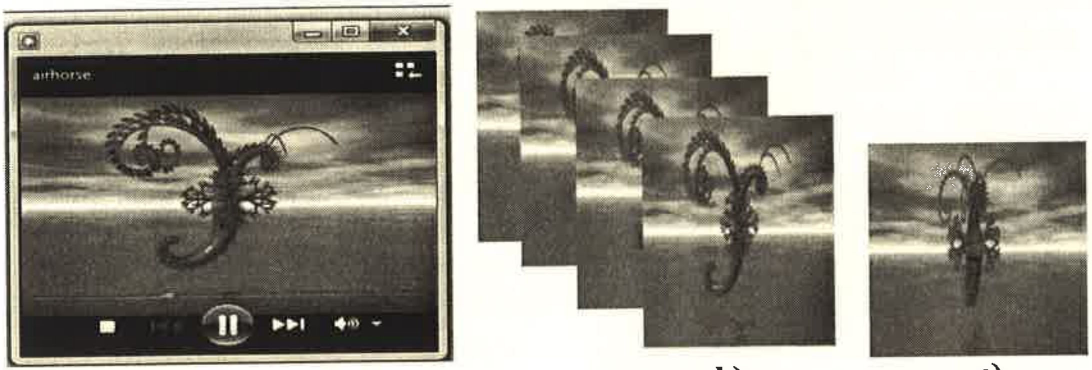
Figure 7: SURF detector on Woman video a) video frames b) test image

4) In the fourth stage, Manhattan distance method was used to calculate the distance between the values of SURF of the test image and all SURF values of the video frames to match and retrieve an image and its location from video sequence as exhibited at Figure 8 for women dataset and Figure 11 for airehorse tracery dataset.



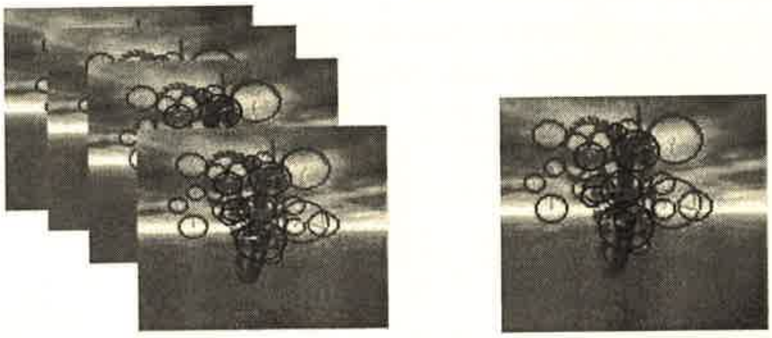
a) b)

Figure 8: Retrieve the location of tested image in a video sequence
a) test image b) video frames



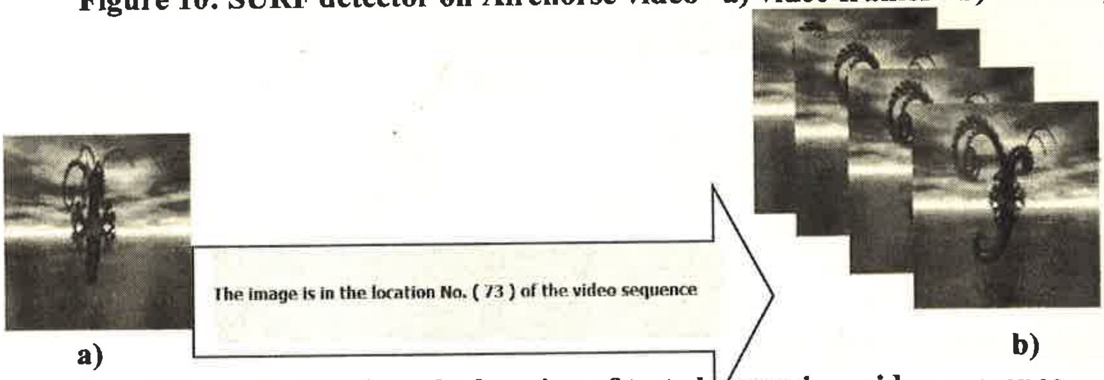
a) b) c)

Figure 9: Airhorse video, a) input video b) Frames extraction from airhorse video c) input test image from women dataset to retrieve its location in a video stream



a) b)

Figure 10: SURF detector on Airehorse video a) video frames b) test image



a) b)

Figure 11: Retrieve the location of tested image in a video sequence
a) test image b) video frames

5. The Performance of Proposed Methodology

The performance of the retrieval system is measured via employing the measurements of recall and precision. The recall gauged the system's capability of recovering whole images that are pertinent whilst the precision gauges the system's capability for recovering only the pertinent images [13]. Eq.(9) [14] is applied to calculate the accuracy of the retrieval adequacy:

$$P = \frac{P_T}{P_T + P_F} \qquad (9)$$

Where P_T explains how many images are correctly acquired from the data-sets of an image while P_F explains how many images that are incorrectly acquired from the datasets of an image. The recall performance of the retrieval system can be calculated using Eq.(10) [14], the parameter of M explains how many pertinent images are not recovered [13].

$$R = \frac{P_T}{P_T + M} \qquad (10)$$

Table (1) shows the values of precision and recall for four samples tested image (**Woman, Airhorse, Scoter** and **Tracery**) when using both SURF only and hybrid SURF features detector with Seven moments features detector.

Table (1) precision and recall values for retrieving samples words

Image Name	Precision Values with using SURF Detectors		Recall Values with using SURF Detectors	
	SURF based on Seven Moments	SURF Only	SURF based on Seven Moments	SURF only
Woman	93%	81%	91%	83%
Airhorse	89%	77%	93%	80%
Scoter	84%	79%	88%	80%
Tracery	92%	86%	91%	81%

6. The Retrieval Speed of Proposed Methodology

It was saw that the retrieval speed was higher when using hybrid SURF features detector with seven moments features detector. Table (2) illustrates the retrieval speed for four samples tested image (**Woman, Airhorse, Scoter** and **Tracery**) when using both SURF only and hybrid SURF features detector based on Seven moments features detector.

Table (2) illustrates the retrieval speed for both hybrid SURF based on Seven Moments and SURF only detectors methods

Image Name	Retrieval Speed SURF based on Seven Moments	Retrieval Speed for SURF only
Woman	0.0074	0.055

Airhorse	0.0137	0.0338
Scoter	0.0142	0.0917
Tracery	0.0139	0.0410

7. Advantages of hybrid Seven Moments with SURF Detector

Proposed method for retrieve an image from the scene is based on hybrid SURF algorithm with seven moments invariant. It enhanced the performance of image retrieval by selecting the strongest features detector. The algorithm of Speeded Up Robust Features (SURF) has been employed and implemented for retrieval an image and its location from a video stream .SURF can be operated by minimizing the space of search for potential points of interest inside the scale space image pyramid. The tracked interest points that are resulted are more recurrence and noise free. For dealing with images that contain blurring and rotation, SURF is best. Seven moments invariant can be employed with SURF method to build integral images .The integral images can be used to enhance the speed of image matching. The features that are extracted from video images are matched using Manhattan distance measure. Apply seven moments invariant along SURF algorithm of feature; tracking and matching adequacy is better, fast and more efficient than Scale Invariant Feature Transform SIFT algorithm. Since SURF make use of integral images, it is good for processing blur images, SURF is designed to be rotation invariant, it is responsible for fast feature elicitation. Mixing between seven moments features extractor with SURF detector is implementing to betterment the qualification of the retrieving process. The experimental results show that the precision and the recall values were high for retrieval when using a hybrid SURF based seven moments methods compare with using SURF method only as illustrated in table(1). For example, the precision for retrieval an image woman was 93% when using hybrid while it was 81% when using SURF only with static threshold also the recall for retrieval image woman was 91% when using hybrid while it was 83% when using SURF only with static threshold. Also the retrieval speed was high for hybrid detectors methods because it takes less time as illustrated in table (2).

8. Drawbacks of Using (SIFT, FREAK, BRISK , DAISY and SUSAN)

a. **SIFT:-** SIFT algorithm has a local feature detector and local histogram-based descriptor. It detects sets of interest points in an image and for each point it computes a histogram-based descriptor with 128 values. The major drawback is the dramatic increase in the computational load.

b. **FREAK:-** FREAK, one of the latest methods introduced .In this algorithm the functionality of human eye is mimicked, allowing the accomplishment of tracking selected objects in real time system. This method has a significant resistance against changes in scene, brightness and JPEG computation, while like its counterparts it is still weak in frequent rotations, high scale change, and too many changes in viewpoint angles. These weaknesses can constitute specific themes for feature studies in this respect.

c. **BRISK:-** 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 which reveal a comprehensive assessment of the benchmark data sets, high performance quality. 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. Assessing this method is based on two criteria: Spend time in CPU and criterion identification.

d. **DAISY:-** DAISY is a novel keypoint descriptor originally conceived for stereo matching via dense computation. DAISY is used for the dense extraction of the features exploited for image matching. DAISY is the worst invariant descriptor, allowing no correct match for angles between 50° and 300°.

e. **SUSAN:-** SUSAN was recognized by circular mask. If compared to the brightness of pixel mask with the nucleus of the mask brightness, then a mask's region can be introduced which own the same (or similar) brightness as the nucleus [10]. This mask's region was called "USAN", stand for "Univalue Segment. The major drawbacks of this algorithm it require more time for extraction the features and also requires much space to store the extracted features because they produce more features.

Conclusions

The aim of this research was to retrieve an image and its location from video frames based on hybrid features extraction methods. The suggested methodology employed hybrid seven moments and SURF detector for elicitation points of interest from a video frames which is faster. The complexity and speed are higher when using seven moments because the time taken to calculate the seven moment's equations is very little. Since SURF make use of integral images, it is good for processing blur images, SURF is designed to be rotation invariant, it is responsible for fast feature elicitation. Mixing between seven moments features extractor with SURF detector is implementing to betterment the qualification of the retrieving process. The experimental results show that the precision and the recall values were high for retrieval when using a hybrid SURF based seven moments methods compare with using SURF method only as illustrated in table(1). For example, the precision for retrieval an image woman was 93% when using hybrid while it was 81% when using SURF only with static threshold also the recall for retrieval image woman was 91% when using hybrid while it was 83% when using SURF only with static threshold. Also the retrieval speed was high for hybrid detectors methods because it takes less time as illustrated in table (2).

Future Works

The following future works can be added:-

1) It can use a suggested methodology to retrieve an object from a video frames.
2) It can use a suggested methodology to deal with small English letters, digits and special characters.
3) It can use FAST detector to increase the retrieval speed.
4) It can use SURF or SIFT descriptor to improve the retrieval system.
5) Multi-level neural networks and support vector machine can be used in the retrieval system.

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