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A Novel Image Matching Technique using SIFT and SURF

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Abstract –**Keypoints-based image matching algorithms have proven very successful in recent years. However, their execution time makes them unsuitable for online applications. Indeed, identifying similar keypoints requires comparing a large number of high dimensional descriptor vectors. Previous work has shown that matching could be still accurately performed when only considering a few highly significant keypoints. In this paper an improved method for assessing the performance of popular image matching algorithms is presented. Specifically, the method assesses the type of images under which each of the algorithms reviewed herein perform to its maximum or highest efficiency. This paper addresses two texture based algorithms (SIFT and SURF).**

Keywords – **Image Matching, SIFT, SURF.**

I. INTRODUCTION

The use of images in human communication is not a new concept, our cave-dwelling ancestors painted pictures on the walls of their caves, usage of maps and building plans for delivering information is almost certainly dates back to pre-Roman times. However the twentieth century has seen the growth and importance of images in all turns of life. Images play a vital part in the fields of medicine, journalism, education, advertising, design, and entertainment.

Technology, in the field of photography and television, has played a key part in facilitating the capture and messaging of image data. However the real engine of the imaging revolution has been the computer, carrying with it a series of methods for digital image detention, storage, processing and broadcast [1].

The establishment of the World-Wide Web in 1990s, permitting users to access data in a range of media from everywhere on the planet, has provided an additional massive stimulus to the exploitation of digital images. The number of images accessible on the Web was recently estimated to be between 10 and 30 million, a figure which some observers consider to be a significant underestimate.

The process of digitisation does not in itself make image collections easier to manage. Some type of cataloguing and indexing is still required, the only difference being that much of the required information can now potentially be derived automatically from the images themselves.
One of the main problems they highlighted was the difficulty of locating a desired image in a large and varied collection. While it is impeccably feasible to find a desired image from a small collection merely by browsing, more actual techniques are required with collections containing thousands of items.

Many computer vision tasks require the analysis of two or more images [2]. Time varying sequences for recognizing parts on a conveyor belt based on their three dimensional shape or for the visual inspection of the geometry of manufactured parts; for the medical diagnosis of beating hearts; for monitoring land use; for deriving topographic maps from satellite or aerial imagery; can only be accomplished if, at least, pairs of related images are available. Other examples include the analysis of slices of computer tomography images. In principle, the inherent goal of these tasks is object reconstruction, that is, the determination of an object's pose or shape [3].

It is a classic difficult problem for a computer to recognize images that is because a computer lacks ability of adaptive learning [4]. The inductive processes embody the universal and efficient means for extracting and encoding the relevant information from the environment, the evolution of intelligence could be seen as a result of interactions of such a learning mechanism with the environment [5]. In consensus with this, any one strongly believe that the pivot of image matching should be arranged around learning processes and to accomplish this task, this paper presents Scale Invariant Feature Transform (SIFT) and Speed Up Robust Features (SURF) based matching technique which outperforms than previous method [6].

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II. Proposed Methodology

Figure 1 shows the basic block diagram for proposed approach. We have taken an image from reference folder to convert it into different colour bands. Then the scale invariant feature transform (SIFT) and speed up robust features (SURF) are calculated for each image and then pooling algorithm is used to extract those keypoints that match the image best. These keypoints are saved in database for matching the query image.

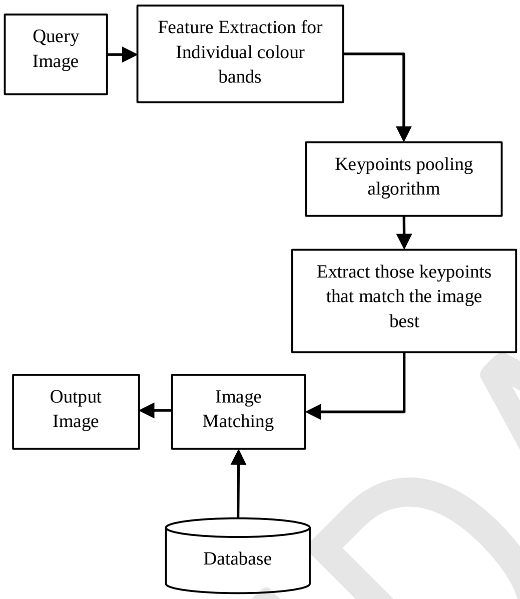

Figure 1: Block diagram for proposed approach

Proposed SIFT and SURF algorithms are explained as follows:

Scale Invariant Feature Transform (SIFT)

David Lowe in 1991 [7] gave this Scale Invariant Feature Transform (SIFT) wherein he executed this method for object recognition. SIFT has now been effectively actualized in number of different applications [8] also, for example, fingerprint recognition [9] [10], face detection [11] [12], ear recognition [13], continuous hand motion detection [14], iris recognition [15]. SIFT gives us features which are strong to scaling, illumination changes, occlusion, orientation etc.

SIFT [7] is truly an included technique and along these lines it can be separated into following phases:

- Scale Space Extrema Detection
- Key point Localization
- Assigning an orientation to the keypoints
- Generate SIFT features

Therefore, SIFT is a strategy for separating particular invariant features from images that can be utilized to perform dependable coordinating between distinctive images of the same object. The principal stage is to recognize area and sizes of key points utilizing scale space extrema as a part of the DoG (Difference-of-Gaussian) capacities with distinctive estimations of σ, the DoG capacity is convolved of image in scale space divided by a constant factor k as the accompanying mathematical statement:

$$D(x, y, \sigma) = (G(x, y, k\sigma) - G(x, y, \sigma) \times I(x, y) \quad (1)$$

Where, G is the Gaussian function and I is the image. Presently the Gaussian images are subtracted to deliver a DoG, after that the Gaussian image subsample by element 2 and produce DoG for inspected image. A pixel contrasted of 3×3 area with recognize the neighbourhood maxima and minima of D(x, y, σ).

In the key point localization step, key point candidates are limited and refined by disposing of the key points where they dismisses the low differentiation points. In the orientation task step, the orientation of key point is acquired in view of neighbourhood image angle. In depiction generation stage is to figure the neighbourhood image descriptor for every key point taking into account image gradient magnitude and orientation at every image test point in a region pointed at key point [16]; these examples fabricating 3D histogram of slope area and orientation; with 4×4 location grid and 8 orientation bins in every specimen. That is 128-component measurement of key point descriptor.

Algorithm-1

1. **Separate image I to color bands (Ir, Ig,Ib,Igr).**
2. **Extract key points and Features with Sift**
   [D{1},K{1}] = sift(Igr);
   [D{2},K{2}] = sift(Ir);
   [D{3},K{3}] = sift(Ig);
   [D{4},K{4}] = sift(Ib);
3. **Start pool**
   a. Put all the grey features into the pool
      feature= D{1};
      points= K{1};
   b. Finding key points of red which are not present in pool and adding them to pool
      Kr = D{2};
      keyr = K{2};
      i. Match features(feature and Kr) and find the index
      ii. If size of index is greater than Kr
      Then size of index will be the size of Kr

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iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

c. Finding key points of green which are not present in pool and adding them to pool
Kg = D{3};
keyg = K{3};
i. Match features(feature and Kg) and find the index
ii. If size of index is greater than Kg
Then size of index will be the size of Kg
iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

d. Finding key points of blue which are not present in pool and adding them to pool
Kb = D{4};
keyb = K{4};
i. Match features(feature and Kg) and find the index
ii. If size of index is greater than Kg
Then size of index will be the size of Kg
iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

4. **At last total keypoints found in the pool will be used in matching images.**

Speed Up Robust Features (SURF)

SURF [16] is additionally prominently known as inexact SIFT. It utilizes necessary images and proficient scale space development for the effective generation of keypoints and descriptors. SURF fundamentally includes two stages:

- Recognition of Keypoint.
- Description of Keypoint.

In the first stage, as opposed to utilizing Difference of Gaussian like as a part of SIFT, integral images are utilized which permit the fast computation of rough Laplacian of Gaussian (LoG) images utilizing a box filter. The computational expense of applying the box filter is free of the span of the filter due to the integral image representation. Determinants of the Hessian matrix are then used to identify the keypoints. So as to be invariant to rotation, it figures the Haar-wavelet responses in x and y direction.

In image I, x = (x, y) is the given point, the Hessian matrix H(x, σ) in x at scale σ, it can be characterize as:

$$H(x,\sigma) = \begin{bmatrix} L_{xx}(x,\sigma) & L_{xy}(x,\sigma) \\ L_{yx}(x,\sigma) & L_{yy}(x,\sigma) \end{bmatrix} \qquad (2)$$

Where Lxx (x, σ) is the convolution result of the second order derivative of Gaussian filter $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the image I in point x, and similarly for Lxy (x, σ) and Lyy (x, σ).

Algorithm-2

1. **Separate image I to color bands (Ir, Ig,Ib,Igr).**
2. **Extract key points of each band with function detect SURF features and extract features of each band with function extract features.**
3. **Start pool**

a. Put all the grey features into the pool
points = gr;
feature = fgr;

b. Finding key points of red which are not present in pool and adding them to pool.
i. Match features (feature and fr) and find the index
ii. If size of index is greater than fr
Then size of index will be the size of fr
iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

c. Finding key points of green which are not present in pool and adding them to pool.
i. Match features(feature and fr) and find the index
ii. If size of index is greater than fr
Then size of index will be the size of fr
iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

d. Finding key points of blue which are not present in pool and adding them to pool.
i. Match features(feature and fr) and find the index
ii. If size of index is greater than fr
Then size of index will be the size of fr
iii. for i = 1:size(index,1)
If sum(index(:,2)==i) is less than 1 for i
Then increase feature size and points size by 1 and add that feature and points of i.

4. **At last total keypoints found in the pool will be used in matching images**

Where,
I=RGB Image

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Ir=Red component of image
Ig=Green component of image
Ib=Blue component of image
Igr=Grey component of image
Kr=Keypoints obtained from Red Component
Fr=Features obtained from Red Component
Kg=Keypoints obtained from Green Component
Fg=Features obtained from Green Component
Kb=Keypoints obtained from Blue Component
Fb=Features obtained from Blue Component
Kgr=Keypoints obtained from Grey Component
Fgr=Features obtained from Grey Component
points=Keypoints used for Image matching after pooling.
features=Features used for Image matching after pooling.

III. SIMULATION RESULTS

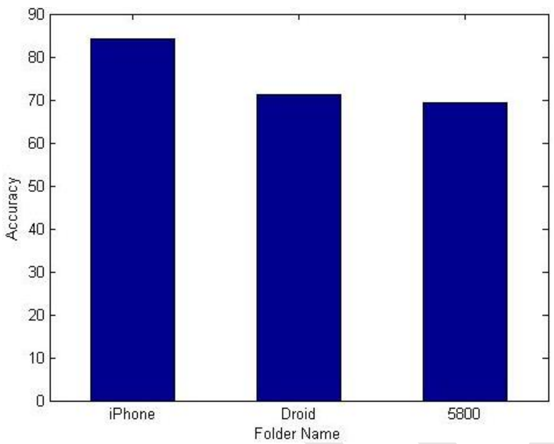

Figure 1: Accuracy graph for SIFT

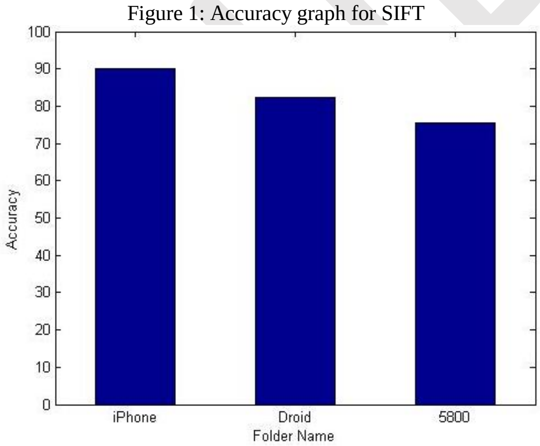

Figure 2: Accuracy graph for SURF

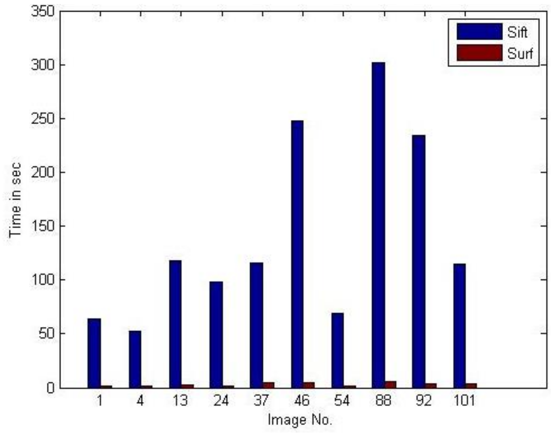

Figure 3: Comparative result of "colour to colour"

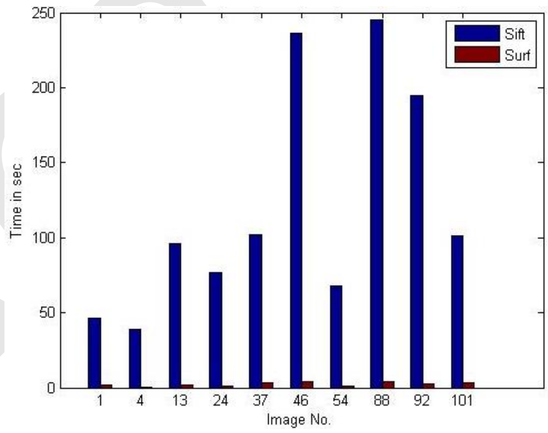

Figure 4: Comparative result of "colour to grey"

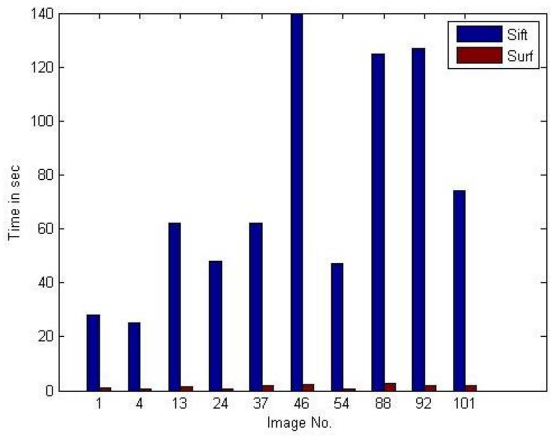

Figure 5: Comparative result of "grey to colour"

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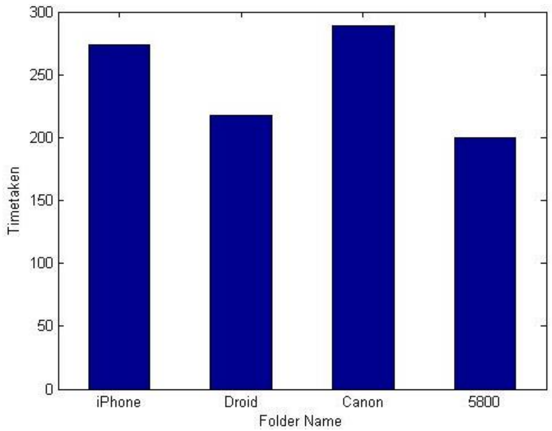

Figure 6: Time taken by SIFT in finding accuracy of folders

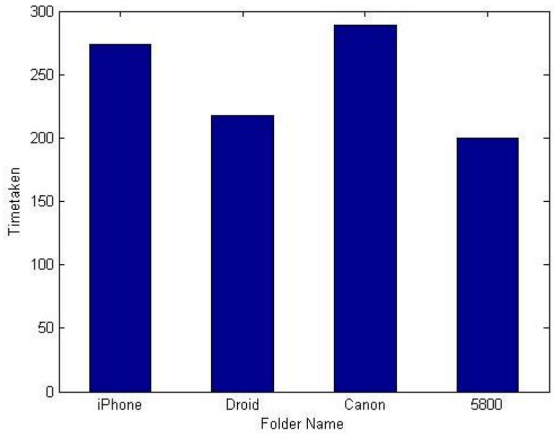

Figure 7: Time taken by SURF in finding accuracy of folders

Table 1: Comparisons of results of SIFT and SURF algorithm (Accuracy and Time Taken)

Folders Name	**Accuracy of Folders**		**Matching Time (in min)**	
	SIFT	**SURF**	**SIFT**	**SURF**
5800	69.36	75.39	348.14	20.42
IPHONE	84.15	90.06	426.71	22.79
DROID	71.19	82.33	673.67	25.06

Table 2: Grey to colour result

IMAGE NO.	**SIFT**			**SURF**		
	KEYPOINTS		**TIME TAKEN(IN SEC)**	**KEYPOINTS**		**TIME TAKEN (IN SEC)**
	FOUND	**MATCHED**		**FOUND**	**MATCHED**	
1	1019	149	28	529	73	1
4	906	96	25	209	21	0.5
13	2172	496	62	659	115	1.3
24	1599	163	48	250	25	0.5
37	1961	114	62	1120	64	2
46	3996	187	140	1392	29	2.4
54	1356	287	47	335	94	0.7
88	4312	0	125	1422	123	2.5
92	4426	257	122	904	67	1.7
101	2030	212	74	1128	118	2

It is found that the SIFT has detected more number of features keypoints compared to SURF but it is suffered with speed. Time taken to match the image from grey to colour is less than matching the image from colour to colour.

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Table 3: Colour to grey result

IMAGE NO.	SIFT			SURF		
	KEYPOINTS		TIME TAKEN (IN SEC)	KEYPOINTS		TIME TAKEN (IN SEC)
	FOUND	MATCHED		FOUND	MATCHED	
1	1718	249	46.1	803	111	1.5
4	1430	169	39.4	336	35	0.7
13	3164	615	96.3	889	137	1.6
24	2722	337	77.7	391	56	0.8
37	3184	227	102	1809	109	3.1
46	6811	320	236	2051	37	3.9
54	1887	560	68	618	197	1.2
88	7184	1218	245	2128	156	3.7
92	5537	860	195	1390	139	2.4
101	2703	434	101	1586	153	2.7

It is found that the number of keypoints of RGB image is more than the number of keypoints of grey image. Time taken to match the image from colour to grey is less than matching the image from colour to colour and also found that the SIFT has detected more number of features keypoints compared to SURF but it is suffered with speed.

Table 4: Colour to colour result

IMAGE NO.	SIFT			SURF		
	KEYPOINTS		TIME TAKEN(IN SEC)	KEYPOINTS		TIME TAKEN (IN SEC)
	FOUND	MATCHED		FOUND	MATCHED	
1	1718	249	63.8	803	111	1.6
4	1430	169	52.4	336	35	1.2
13	3164	615	117.8	889	137	2.3
24	2722	337	97.8	391	56	1.2
37	3184	227	115.9	1809	109	4.3
46	6811	320	247.7	2051	37	4.9
54	1887	560	68.9	618	197	1.7
88	7184	0	302	2128	156	5.2
92	5537	0	234.6	1390	139	3.4
101	2703	434	114.8	1586	153	3.9

In this case time taken to match the colour image colour image is more than matching of colour to grey image and grey to colour image and also found that the SIFT has detected more number of features keypoints compared to SURF but it is suffered with speed.

IV. CONCLUSION

This paper shows an improved image matching approach for identifying SIFT and SURF keypoints that are important for image matching. For this purpose, we investigated different image features for characterizing SIFT and SURF keypoints.

In previous research work [6], they used SIFT only. Although this research work provides comparison of matching time and accuracy for SIFT and SURF and it was found that the SURF algorithm outperforms than the SIFT algorithm.

As future work we will consider combining different image features to improve the matching accuracy. Additionally, we will consider

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investigating techniques for reducing the complexity of the pre-processing phases.

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