Development of Speed Up Robust Feature Algorithm for aerial image feature extraction

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Abstract: *Speed Up Robust Feature Algorithm (SURF) has been a very useful technique in the advancement of image feature algorithm. The strategy offers an extremely decent agreement between the runtime and accuracy, especially at object borders and fine structures. It has a wide scope of applications in remote sensing like getting computerized surface models from UAV and satellite images. In this paper, SURF algorithm has been discussed in details to enhance the capability of the system for image feature extraction technique to detect and obtain the maximum feature points from aerial imagery. The algorithms are developed depending upon such phenomena in which a maximum result can be obtained in very less time.*

Key Words: *Speed-up Robust Feature, Pixel, Feature Extraction, Image processing, Algorithm, k-d trees, Digital surface model, Digital elevation model, Scale, Occlusion, Orientation, Clutter, Illumination*

1. INTRODUCTION

In the arena of image feature examination, the photogrammetric feature recognition and image matching are the two important tasks. Their application keeps on developing in every single field day by day. Image matching algorithms performance produce a significant part from simple photogrammetry task like feature detection to the advancement of modern 3D demonstrating software. Moreover, this is an identical dynamic extent of examination in recent times as indicated by the workload and numerous papers around it. Researchers are encouraged to develop new technologies as needs changes and become more demanding. In this context,

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merits saying that numerous techniques are distributed with source code to fulfill the ordinary needs of photogrammetry and computer vision including feature identification, matching, and 3D modeling. 3D modeling has been a progressing research subject in artificial intelligence integrated vision-based photogrammetry for an extended period now [1]. More than 10 years earlier, applications related to 3D models and object restoration had as final objective the visual examination and the application of autonomy. Today, these applications now incorporate the utilization of 3D models in PC design, virtual reality, correspondence, and others. Yet, accomplishing exceptionally dependable coordinating outcomes from a couple of images is the assignment that probably the most prevalent matching methods are attempting to achieve. Yet, none have been all around acknowledged. Furthermore, it appears that the choice the satisfactory technique to finish a matching task altogether relies on upon the sort of image to be matched and in the varieties inside an image and its matching pair in one or huge numbers of the following parameters: a) Scale: At least two elements of the set of images views have different scales. b) Occlusion: The concept of two articles that are spatially isolated in the 3D world may impose by a solitary additional role in the anticipated 2D images plane. For single-view task, for example, object identification, obstructions are ordinarily viewed as aggravation requiring increasingly strong calculations. c) Orientation: The image positions are turned concerning one another. A maximum orientation of 30° is a regular highest value for the massive mainstream of the calculations to play out a compact match. d)Object to be matched: Whether is a planner, textured or edgy object. e) Clutter: This refers to the conditions of the image background. It is often difficult from the algorithm to understand the boundaries of the projected object when it has a cluttered background. f) Illumination: Changes in the enlightenment additionally speak to an ordinary issue for precise component similarities. Current image matching algorithms may perform acceptably well in the nearness of a portion of the image conditions depicted previously. Be that as it may, all in all, none of the algorithms has really finished aggregate invariance to these parameters. A constantly-growing number of researchers around there are attempting to join to the current algorithms the fundamental instruments to accomplish finish invariance to these genuinely regular coordinating issues. In any case, given this is a relative novel research area in photogrammetry, it is at times hard to combine all the vital components into one algorithm without expanding its computational cost. The SURF cluster implementation was applied in various projects for creating digital surface models (DSM) and orthoimages from aerial pinhole as well as satellite images. Over 100 TB of registered images have been fully automatically processed in recent years. The production of DSMs and completely finished recreations from commercial grade cameras is another application for SURF. Comparative reviews have been distributed surveying the execution for image corresponding calculations techniques in a few perspectives. Be that as it may, these reviews just assess the algorithms as far as how well will one perform to the next. This review defeats a portion of the deficits and constraints of the present similar reviews by fusing the investigation of the algorithms utilizing diverse scenes to decide under which conditions they will give optimum outcomes. The challenge is to have the capacity to assess the execution of every algorithm utilizing target criteria. This is expected to guarantee the usage of a legitimate strategy for the testing criteria. An unquestionable requirement is an assessment centered around distinguishing trademark images that when joined with a particular algorithm, will bring about optimal matching. It is too important to decide if algorithms have been tried that are capable of delivering a sufficient result to generate 3D models. Within the procedure of looking for documentation on 3D demonstrating, a great deal of work was discovered that tends to the early element discovery and the later corresponding image [2]. This is a good indicator of their importance to this process. A large portion of the early executions created appeared to function admirably under certain constrained image condition. The genuine test for those creators was to accomplish genuine invariant element identification under any image conditions (i.e. illumination, rotation, blurring, scale, clutter, etc.). The consistency of the early results appears to have been mostly controlled by the type of images used. Robust feature detection, image matching, furthermore, 3D models are ideas that have been around for a lengthy period of time now in the CPU vision area. Be that as it may, it wasn't until the finish of the most recent decade and the start of this one that the issue was truly drawn closer by various analysts and experts working in this field. It is outstanding that accomplishing genuine invariant object recognition has been a standout between the furthermost essential difficulties in computer vision and photogrammetry. Recently, there has been a critical advancement in the utilization and execution of calculations for detecting invariant features in more complex images on a daily basis.

2. SPEED UP ROBUST FEATURE (SURF)

Speeded Up Robust Features (SURF) is a newly developed system, which will probably turn into the next defected highlight indicator in the business. In contrast to its fundamental rival, SIFT, SURF was created to provide faster and more powerful execution. Utilizing the question acknowledgement assignment, it is demonstrated how SURF is applied for vigorously recognize protests in images taken under various extraneous and natural settings. The undertaking of discovering point correspondences between two images of a comparative scene or protest is a piece of numerous PC vision applications. Image enrolment, camera alignment, question acknowledgment, and image recovery are only a couple of these applications. This is accomplished depending on necessary for image complications; by expanding on the qualities of the main existing finders and descriptors (particularly, utilizing a Hessian network-based measure for the identifier, and a dissemination-based descriptor); and by rearranging these techniques to the basic [3-5].

This prompts a blend of novel discovery, portrayal, and coordinating strides. The look for discrete image point correspondences could be parted into three fundamental strides. The most significant property of an intrigue point indicator is its repeatability. The repeatability communicates the unwavering quality of an indicator for finding the same physical plotting focuses under various review conditions. Next, the region of each interest point is addressed by a component vector. This descriptor must be particular and, in the meantime, powerful to clamour, identification relocations, and geometric and photometric disfigurements. At long last, the descriptor vectors are coordinated between various images. The coordinating depends on a separation between the vectors, e.g. the Mahalanobis or Euclidean separation. The measurement of the descriptor directly affects the time this takes, and fewer measurements are alluring for quick plotting point coordinating. In any case, bring down dimensional element vectors are by and large less unmistakable than their high-dimensional counterparts. The main concentration is on a scale and in-plane turn invariant identifiers and descriptors. These appear to offer a decent tradeoff between highlight unpredictability and power to normally happening distortions.

Skew, anisotropic scaling, and point of view impacts are thought to be second-arrange impacts, that passage secured to some degree by the general heartiness of the descriptor. Concerning the photometric disfigurements, it is expected that a basic direct model with a predisposition (counterbalance) and difference scale can be calculated and analysed [6]. Neither identifier nor descriptor utilizes shading information.

The input image is dissected at various scales with an exact conclusion part to ensure invariance to scale changes. The distinguished plotting focuses are furnished with a turn and scale-invariant descriptor. Besides, a straightforward and effective first-line ordering method, in light of the differentiation of the interesting point with its encompassing, is proposed.

3. INTEGRAL IMAGES

The quick calculation of box sort convolution filters is considered. SURF approximates and uses box filters as shown below in fig. 1 at area x = (x; y) which talk about the whole of all pixels in the information image inside a rectangular locale framed by the source and x, as shown in the given equation 1.

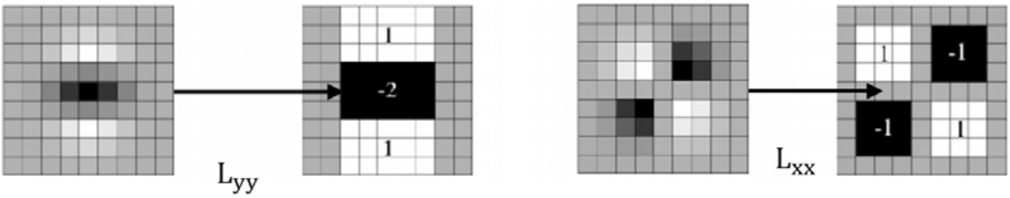


Fig. 1: SURF approximations using box filters

$$\boldsymbol{I_{\Sigma}}\,(\boldsymbol{x},\boldsymbol{y}) = \sum_{\boldsymbol{i=0}}^{\boldsymbol{i\leq x}} \sum_{\boldsymbol{j=0}}^{\boldsymbol{j\leq y}} \boldsymbol{I}(\boldsymbol{i},\boldsymbol{j}) \tag{1}$$

When the fundamental image has been registered, it takes three increases to ascertain the whole of the powers over any upstanding, rectangular territory. Subsequently, the estimation time is autonomous of its size. This is vital in our methodology, as we utilize enormous filter sizes.

4. HESSIAN MATRIX BASED INTEREST POINTS

The detector depends on the Hessian framework in light of its great execution in precision. Even more decisively, we identify mass-like structures at areas in which the determinant is extreme.

As opposed to the Hessian-Laplace identifier by Mikolajczyk and Schmid [7], we depend on the determinant of the Hessian additionally for the scale determination, as done by Lindeberg [8]. Given an element of both space x = (*x; y*) in an image, the Hessian matrix Ή (x, σ) in x at scale σ is defined as follows in equation 2.

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

where $L_{xx}(x,\sigma)$ is considered as the convolution of the Gaussian second order derivative $\frac{\partial^2}{\partial x^2} g(\sigma)$ with the images at a point x, and correspondingly for $L_{xy}(x,\sigma)$ and $L_{yy}(x,\sigma)$. Gaussians are ideal for scale-space examination [9-10], but in practice, it is essential to discretize and crop that particular segment. This shortcoming holds for Hessian-based detectors in over-all. The repeatability conquers a maximum number of multiples of $\frac{\pi}{2}$, because of the square state of the filter. In any case, the locators still perform well, and the slight diminishing in execution does not exceed the benefit of quick convolutions brought by the discretization and cropping.

As real filters are non-perfect regardless and given Lowe's prosperity with his LoG approximations, we push the estimate for the Hessian network much further with box filters These are rough second-order Gaussian derivatives and can be assessed at an exceptionally low computational cost utilizing necessary images. The estimation time, in this way, is independently depending upon the filter extent [11]. Detector depends on the Hessian framework due to its great execution in precision. More decisively, we identify blob-like structures at areas in which determinants are extreme. Rather than the Hessian-Laplace locator by Mikolajczyk and Schmid, we depend upon the basis of Hessian likewise for the scale determination, as done by Lindeberg.

5. SCALE SPACE REPRESENTATION

The interest points of correspondences frequently require their correlation in images where they are seen at different scales, the scale-spaces are regularly realized as an image pyramid. The images are over and again smoothed with a Gaussian and after that sub-inspected so as to accomplish a more elevated amount of the pyramid [12].

Lowe deducts these pyramid layers so as to get the DoG (Difference of Gaussians) images where the limits and masses can be found. Because of the utilization of box filters and indispensable images, we don't need to iteratively apply a similar filter to the yield of a recently separated layer, however rather can put on box filters of any magnitude at the very same speed straightforwardly on the first image and even in corresponding (in spite of the fact that the last isn't exploited here) [13-15]. Therefore, the scale space is dissected by up-scaling the filter measure as opposed to iteratively lessening the image estimate.

The yield of the 9×9 filter, presented in the past segment, is considered as the underlying scale layer, to which we will allude as scale s = 1:2 (resembling Gaussian derivatives with σ = 1:2). The accompanying layers are gotten by separating the image with bit by bit greater veils, considering the discrete idea of essential images and the particular structure of our filters.

Besides, as we don't need to break down the example of the image, there is no association. On the drawback, box filters safeguard high-recurrence parts that can become mixed up in zoomed-out variations of a similar scene, which can restrain scale-invariance [16]. The scale space is isolated into octaves.

An octave speaks to a progression of filter reaction maps gotten by convolving a similar information image with a filter of expanding the size. Altogether, an octave envelops a scaling component of 2 (which suggests that one needs to dramatically increase the filter measure. Every octave is subdivided into a consistent number of scale levels. Because of the discrete idea of essential images, the base scale distinction between 2 ensuing scales relies upon the length l0 of the positive or negative projections of the incomplete second request subsidiary toward determination (*x* or *y*), which is set to 3rd of the filter measure extent. For the 9×9 filter, this length l0 is 3.

For two progressive dimensions, we should expand this size by at least 2 pixels (one pixel on each side) so as to keep the size uneven and consequently guarantee the nearness of the focal pixel. These outcomes in an all-out increment of the veil measure by 6 pixels. The development of the scale-space begins with the 9×9 filter, which figures the blob reaction of the image for the littlest scale. At that point, filters with sizes 15×15, 21×21, and 27×27 are connected, by which much in excess of a scale change of 2 has been accomplished. Be that as it may, this is required, as a 3D non-most extreme concealment is connected both spatially and over the neighbouring scales. Henceforth, the first and last Hessian reaction maps in the stack can't contain such maxima themselves, as they are utilized for reasons of correlation as it were.

In this way, after insertion, the littlest conceivable scale is σ = 1.6 = $1.2\frac{12}{9}$ relating to a filter size of 12 × 12, and the most elevated to σ = 3.2 = $1.2\ \frac{24}{9}$. Similar contemplations hold for different octaves. For each new octave, the filter measure increment is multiplied (going from 6 to 12 to 24 to 48).

In the meantime, the inspecting interims for the extraction of the intrigue focuses can be served also for each new octave. This diminishes the calculation time and the negative inexactness is practically identical to the image sub-testing of the traditional methodologies. The filter magnitudes for the second octave are 15, 27, 39, 51.

A third octave is registered with the filter sizes 27, 51, 75, 99 and, if the first image measure is as yet bigger than the relating filter sizes, the scale-space examination is done for a fourth octave, utilizing the filter sizes 51, 99, 147, and 195. Note that more octaves might be broken down, however, the quantity of distinguished interest focuses per octave rots all-around rapidly.

The extensive scale changes, particularly between the primary filters inside these octaves (from 9 to 15 is a difference in 1.7), renders the testing of scales very rough. In this way, we have additionally executed a scale-space with better testing of the scales. This first pairs the span of the image, utilizing direct introduction, and afterwards begins the primary octave by sifting with a filter of size 15.

Extra filter sizes are 21, 27, 33, and 39. At that point a second octave begins, again utilizing filters which presently increment their sizes by 12 pixels, after which a third and fourth octave pursue.

Presently the scale change between the initial two filters is just 1.4 (21/15). The most minimal scale for the exact adaptation that can be recognized through quadratic insertion is as appeared in equation (3).

$$S = (1.2\frac{18}{9})/2 = 1.2 \tag{3}$$

As the Frobenius average remains constant for our filters at any scope, they are already scale normalized, and not any additional allowance of the filter response is mandatory [17-19].

6. INTEREST POINT DESCRIPTION AND MATCHING

Our descriptor portrays the circulation of the power contained inside the intrigue point neighborhood, like the angle data separated by any other algorithms and its variations. We expand on the conveyance of first request Haar wavelet reactions in x and y course as opposed to the inclination, abuse basic images for speed, and utilize just 64 measurements. This diminishes the ideal opportunity for highlight calculation and coordinating, and has demonstrated to in the meantime increment the heartiness.

Besides, we show another ordering step in view of the indication of the Laplacian, which increments the power of the descriptor, as well as the coordinating rate (by a consideration of two the best case).

We allude to our indicator descriptor conspire as SURF (Speeded-Up Robust Features). The initial step comprises the settling of a reproducible introduction in light of data from a round locale around the interest point.

By then, we build up a square region changed in accordance with the picked presentation and concentrate the SURF descriptor from it. At long last, components are coordinated between two images.

7. ORIENTATION ASSIGNMENT

So as to be invariant to image turn, we recognize a reproducible introduction for the intrigue focuses. For that reason, we initially ascertain the Haar wavelet reactions in x and y-bearing inside a roundabout neighbourhood of range 6s around the interest point, with s the scale at which the interest point was distinguished [20].

The testing step is scale ward and picked to be s. With regards to the rest, additionally, the extent of the wavelets is scale reliant and set to a side length of 4s. Just six tasks are expected to register the reaction in x or y-heading at any scale. When the wavelet reactions are determined and weighted with a Gaussian ($\sigma = 2s$) focused at the interest point, the reactions are spoken to as focuses in a space with the even reaction quality along the abscissa and the vertical reaction quality along the ordinate.

The overwhelming introduction is evaluated by computing the entirety of all reactions inside a sliding introduction window of size 3, The level and vertical reactions inside the window are summed [21-23]. The two summed reactions at that point yield a nearby introduction vector. The extended such vector over all windows characterizes the introduction of the intriguing point. The span of the descending window is a constraint which must be picked cautiously. Little sizes fire on single commanding slopes, extensive sizes will in general yield utmost in vector distance that is not straightforward. Both outcome in a misorientation of the interest point.

8. DESCRIPTOR-BASED ON SUM OF HAAR WAVELET RESPONSES

For the extraction of the descriptor, the initial step consists of building a square district revolved around the intriguing point and situated along the introduction chose in the past segment. The extent of this window is 20s the district is part up consistently into littler 4X4 square sub-areas. This jam essential spatial data. For each sub-locale, we process Haar wavelet reactions at 5×5 normally dispersed example focuses. For reasons of effortlessness, we call d_x the Haar wavelet reaction in the flat course and d_y the Haar wavelet reaction in the vertical heading (Filter measure 2s), SURF is, up to some point, comparative in the idea as SIFT, in that they both spotlight on the spatial conveyance of angle data. Though, SURF beats SIFT in for all goals and determinations for all cases. We trust this is because of the way that SURF coordinates the angle data inside a sub-fix, while SIFT relies upon the introductions of the individual slopes [24-27]. The descriptor is increasingly unmistakable and not much slower to register, however slower to coordinate because of its higher dimensionality.

9. FAST INDEXING FOR MATCHING

For quick ordering amid the coordinating stage, the indication of the Laplacian (for example the hint of the Hessian lattice) for the fundamental interest point is incorporated. Ordinarily, the interest focuses are found at mass sort structures. The indication of the Laplacian recognizes splendid masses on dim foundations from the switch circumstance. This component is accessible at no additional computational expense as it was at that point processed amid the location stage. In the coordinating stage, we possibly come close highlights on the off chance that they have a similar kind of complexity, Hence, this negligible data considers quicker coordinating, without diminishing the descriptor's execution. Note this is additionally of favourable position for further developed ordering strategies. For example, for k-d trees, this additional datum characterizes a significant hyperplane for a part of the information, instead of arbitrarily picking a component or utilizing highlight insights [28-30]. It has been fascinating and tedious to execute the calculation starting from the earliest stage. If I somehow happened to utilize the SURF calculation to a genuine issue, later on, this experience will be significant while adjusting an open source usage to my requirements. Having more eyes on the code can help advance points of interest and guarantee adjusts usage. This would free assets to research distinctive varieties of parameters and systems.

10. EXPANSION OF IMAGE PROCESSING ALGORITHM

Digital image processing forms the basis of an aerial image. With this goal, the image-processing algorithms, such as image pre-processing (image enhancement) algorithm and image feature extraction algorithm, etc. are developed in this project work.

These algorithms are advanced in demand to process images for extracting various image features to be utilized by predictive models for prediction of aerial imagery [31-33]. Thus, these algorithms form the basis of the software required for the digital image processing algorithm system proposed in this project work. This section describes in detail the developments of these algorithms. In addition to these algorithms, the software needs to be equipped with appropriate predictive models; their detailed description has been carried out in this paper.

11. DEVELOPMENT OF IMAGE PRE-PROCESSING (IMAGE ENHANCEMENT) ALGORITHM

The key-capacity of image pre-handling is to improve the procured image in manners that expansion the odds for the accomplishment of the resulting image preparing activities. Image pre-preparing essentially plans to improve the nature of the procured image by smothering undesired bends or by upgrading the highlights of intrigue [34]. Suppression of undesired distortions refers to corrections of geometric distortions, grey-level, and blurring as well as removal of noise.

Enhancement of features of interest includes enhancing image contrast. Development of image pre-processing algorithm concerns with making provisions in the software for the following tasks: (i) Writing the acquired image frames to a disk file and reading the same, (ii) Removal of noises from the desired images, (iii) Creation of a structuring element, (iv) Performing morphological opening operation on the noise-removed images, (v) Performing image background subtraction, and (vi) Adjusting the contrast of the background-subtracted required images.

12. DEVELOPMENT OF IMAGE FEATURE EXTRACTION ALGORITHM

Development of image feature extraction algorithm concerns with creating provisions for the following tasks in the inspection software: (i) Zooming-in of the pre-processed image, (ii) Computation of a set of four grey-level co-occurrence matrices (GLCMs), from the zoomed-in grayscale image, (iii) Computation of three statistical features, such as contrast, energy, and homogeneity, since individually of the GLCMs, (iv) Computation of the mean of the four values of each of the image statistical features mentioned in (ii) above, (v) Computation of three other statistical features, such as entropy, range, and standard deviation, from the zoomed-in grayscale image, (vi) Computation of Discrete Cosine Transform (DCT) co-efficient from the zoomed-in grayscale image, (vii) Computation of the mean and the standard deviation of the DCT co-efficient, (viii) Computation of Discrete Fourier Transform (DFT) co-efficient from the zoomed-in grayscale image, (ix) Computation of the mean and the standard deviation of the DFT co-efficient, Detailed descriptions of the computational details of the above-mentioned image features are presented in the experimental analysis section.

13. EXPERIMENTAL RESULTS AND ANALYSIS

To make the experimental data more persuasive we did all the simulation in the given situations:

1. Hardware details: CPU Intel Core i3-8145u 2.10 GHz, RAM 2G, Local video memory 2176M;
2. Software development tools: Visual Studio 2008 & OpenCV 2.1.

In this experiment, we select two different angles of shooting aerial images given in fig. 2 (a) and (b). The experimental procedures are as follows: By extracting all the features each image is analyzed with all the edge, corner and surface detection techniques:

- Step 1. Creating a path for two images and changing image model from RGB to gray, respectively:

img1=cv2.imread('/home/workstation/PROJECT/images/le1.jpg',0) # Original image – ensure grayscale

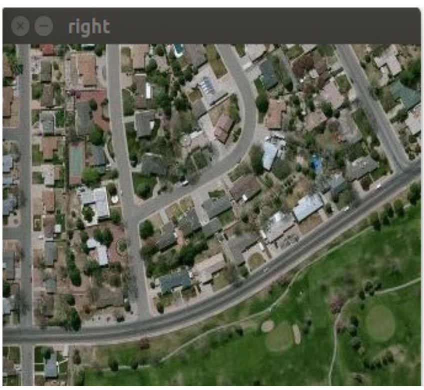
img2 = cv2.imread('/home/workstation/PROJECT/images/re1.jpg',0) # Rotated image - ensure grayscale

- Step 2. Convolution of the SURF function to calculate the Integral image and Hessian matrix and to execute the feature points.
- Step 3. Calculating the feature point and Haar wavelet responses and orienting the interest point descriptor.
- Step4. Producing the feature point matching as shown in figure 3.

We calculate the SURF algorithm feature point extraction efficiency from different angular aerial images given in table 1.

According to the versatile scale factor, the SURF calculation has a decent capacity to choose and locate the key component focuses on an expanding coordinating rate.

Therefore, it can empower proficient enlistment for RGB images at a different scale and angle from aerial imagery platform. The results obtained on the basis of SURF algorithm as they are working in some organized feature extraction models are suggestive of the fact that the images taken from several altitudes can be processed with a particular user and system speed.



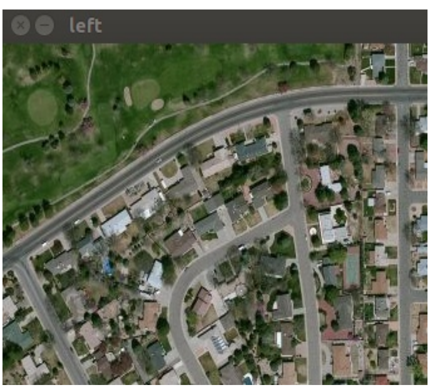


Fig. 2: (a) Reference data 1 and (b) Reference data 2

Fig. 3 Desired output for SURF algorithm as comparing both (a) and (b) datasets

Table 1: SURF algorithm user and system time for the experiment

Algorithm	User time	System time
Surf algorithm for image feature extraction	0.059s	0.001s

14. CONCLUSIONS

The project work undertaken addresses several critical problems and pertinent research issues in the field of image feature matching (SURF). The focus of this project work is to develop an efficient image-processing algorithm based on image feature extraction. The validation of the methodology as proposed is done through experimentation on aerial image processing and obtaining feature points from it. Modeling and prediction of Digital Surface Modeling (DSM), as carried out in this project work, result in an exploration of the potential of several combinations of aerial image features as tools for computer-based image processing. It is worth mentioning in this context that the potential of the combinations of image features considered for modeling and prediction of surface elevation and modeling remain unexplored in the existing approaches proposed in the literature. Modeling and prediction results as obtained may form a basis for setting guidelines for selecting an appropriate combination of image features for a particular type of computerized image enhancing algorithm. Application of the SURF algorithm for image feature extraction technique approach as proposed for digital image processing results in considerable improvement in the level of accuracy of image processing as compared to the existing approaches. Thus, the proposed approach may be effectively utilized in situations where matching algorithms are required to extract feature points from aerial images.

15. FUTURE SCOPE OF WORK

Future Scope of Work: As per the literature survey and the work going around this technique, it is clearly notable that the SURF algorithm for image feature extraction technique is gaining huge importance in the development of the image processing algorithms. It is a very effective tool to detect and extract the feature points from aerial imagery. Researches in the arena of Digital Surface Modeling (DSM) and Digital Elevation Model (DEM), SURF algorithm is slowly replacing the existing approaches. Integrating this method with the utilization of drones in capturing aerial images will not be only cost effective but also time-saving.

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