Texture Segmentation For Classification of Terrain Features In Aerial Images

Divya K[1], Harshavardhini T[2], Mohamed Hanees J[3], Dr .N.V.Shibu[4]
[1, 2, 3] Dept of CSE
[4]Associate Professor, Dept of CSE
[1, 2, 3, 4]Sri Ramakrishna Institute Of Technology

Abstract- *Unmanned autonomous surface vehicles operating in unknown real-world environments need to navigate efficiently. For efficient navigation, it is essential to construct an image map/photo map that can classify and characterize the terrain features of the area it is covering. A photomap thus constructed will be very much effective for safe navigation. To generate a photomap, imagestitching is done to the aerial images taken around the coverage area. An effective stitching method can generate smooth stitching over aerial images. The terrain features are classified mainly into five major types: hills, dark vegetation, deserted, farmland, and water bodies. Gabor convolutional kernel can be used to classify the texture in the aerial image which is stitched. The texture segmented and classified image then undergoes photo mapping. The photo mapping will be helpful for the vehicle to cover the navigable area without making an error. This project work aims to generate a photomap based on image stitching and texture segmentation of terrain features. The input will be a set of aerial photographs of the area for which navigation has to be undertaken by the autonomous surface vehicle.*

Keywords- Image stitching, Gabor Filter, Aerial Image, Texture segmentation

I. INTRODUCTION

Texture segmentation is a method used in image processing that divides an aerial image into smaller regions based on the textures they contain. It can be used to identify specific terrain features, such as roads and buildings, by clustering local colour or texture information extracted from an input images.The aim is to develop an automated system which can segment the image and generate class information based on various terrain features or classes. This process requires extracting objects from the aerial images and attaching them with appropriate labels. Additionally, stitching multiple input imagery’s together would help maintain data continuity while enabling a wider field-of-view coverage.

Image stitching techniques utilizing Gabor filters can then be applied for super-resolution of the source imagery resulting in higher accuracy and resolution classification output. This technique has promising applications for detailed mapping projects involving large scale drone surveys over variety of landscape areas providing valuable data about terrain features which will enhance our understanding of earth's surface complexity further.

This technique involves using image stitching techniques to process multiple source images into a single new composite that contains all relevant information about an object or region's texture. By analyzing this data, gabor filter can accurately identify various terrain features from aerial imagery with minimal ambiguity. With advances in imaging technology, effective use of texture segmentation has become increasingly important in recognizing complex geospatial phenomena from remotely sensed datasets.

The Gabor filter approximates the local frequency of an ideal linear detector and serves as foundation for texture analysis, allowing it to identify different visual characteristics from objects or background within an image. Through this technique, textural differences present across diverse locations on a digital map can be identified and classified accordingly into distinct shapes. In addition, feature-rich information associated with terrain properties such as vegetation density, soil composition and land use type can also be retrieved from segments obtained by the Gabor filters.

II. RELATEDWORK

Here, literature review on different techniques given by various researchers is being presented.

2.1 Seamless Image Stitching by Minimizing False Edges:

Assaf Zomet, Anat Levin, Shmuel Peleg, and Yair Weiss had studied different methods for image stitching, and focused on a novel approach that optimizes over image derivatives. They explored the differences between the proposed approach and alternative methods, and the differences in optimizing under different norms. Even though each stitching algorithm works better for some images and worse for others, they found that GIST1 under l1 always worked well. The use of the l1 norm was especially valuable in overcoming geometrical misalignment of the input images. The drawback of optimizing under l1 is computational, as it is two orders of magnitudes slower than minimizing under l1. Therefore, since, in many cases, the results of GIST1 under l1 is comparable with other methods, they recommend to use this method only when faster methods fail. Image stitching was presented as a search for an optimal solution to an image quality criterion. Encouraged by the results obtained by this approach, they believethat it will be useful to explore alternative criteria for image quality using additional image features and results on statistics of natural images.

2.2 Adaptive As-Natural-As-Possible Image Stitching:

This system first described the moving DLT method to estimate the local homography and proceed to propose an approach to linearize it in the non-overlapping regions. Then, this paper explain the computation of a global similarity transformation between the reference and the target images. Since many similarity transformations are possible, this paper automatically choose the one with the lowest rotation angle as the best candidate. Finally, the details of the proposed warp, which is constructed by combining the homography or its linearized version across the whole image with the global similarity, are presented.

2.3 Spectral-Spatial Convolutional Neural Networks:

In the year 2018, a classification model based on CNN and spectral-spatial feature learning has been proposed for aerial photographs. With the utilization of advanced regularization techniques such as dropout and batch normalization, the proposed model could balance generalization ability and training efficiency. The use of such methods to improve the CNN model along with other techniques like preprocessing and sensitivity analysis could make these models robust for classifying the given dataset. The network architecture can effectively handle the inter- and intraclass complexity inside the scene.

2.4 Terrain segmentation and roughness estimation using RGB Data:

Vivekanandan Suryamurthy, Vignesh Sushrutha Raghavan, Arturo Laurenzi, Nikos G. Tsagarakis, and Dimitrios Kanoulas et al. In the year 2019, proposed an end-to-end deep convolutional neural network to segment terrains and estimate their roughness. For training the models the system modified a dataset of a few named landscape pictures with their roughness. At last, the proposed system assessed the visual strategy of the CENTAURO robot by performing ongoing errands, like leg reconfigure ration for planning also, adjusting purposes during navigation. This paper plan in combining the vision-based landscape and roughness calculation with other terrain estimations, for example, force/torque-based ones, to empower independent preparation, what's more, control during the robot route.

III. SYSTEM REQUIREMENT SPECIFICATION

System requirements specifications acquired by collecting relevant information for system implementation. It is the system's elaborative conditions that must be met. Furthermore, the SRS provides a complete understanding of the system to understand what this project will achieve without any constraints on how to achieve this goal. This SRS does not reveal the plot to outside characters, but it conceals it.

3.**1 Hardware Requirements:**

- System Processor : i5/i7
- Hard Disk : 50GB.
- Ram : 8 GB/ 12 GB

Any desktop / Laptop system with above configuration or higher level.

3.2 Software Requirements:

- Operating system : Windows 7(64bits OS)
- Programming Language : Python
- Framework : Anaconda
- Libraries :OpenCV,
- IDE : Jupyter Notebook.

IV. PROPOSEDALGORITHM

We will provide a detailed presentation of the proposed algorithm which are as follows. We first describe the image stitching method which requires four steps and proceed to propose an approach to linearize and fit-merge them into single panoramic image. Then, we explain the computation of texture segmentation using gabor filters on the single output from previous steps. Finally, the details of the proposed stitch, which is constructed by combining the homography matrix and filtered images for texture classification is provided.

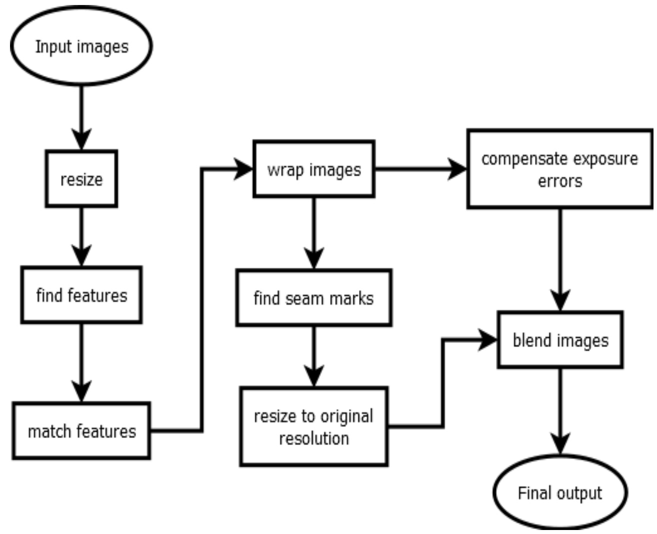

figure4.1: Flowchart forimage stitching-1

Image stitching algorithm requires four easy steps which is shown in detailedfigure4.1 (image stitching classes). Detecting key points (DoG, Harris, etc.) and extracting local invariant descriptors (SIFT, SURF, etc.) from any of the two input images is the first step(input images figure 5.1). Followed by this is matching the descriptors between the images. Using the RANSAC algorithm the system will estimate a homographic matrix using the matched feature vectors which is key points extracted above. Finally we get the output(as shown in figure 5.2) by applying a warping transformation using the homographic matrix and fit these images and merge them into one to form a single panorama(figure 5.3).

Descriptors are vectors that describe the local environment around a given key point. The key points are found by calculating the Gaussian blur difference of the image at different levels. This means that the image is blurred with varying degrees of Gaussian blur, from slightly blurry to more blurry, etc. These images are then subtracted from each other, resulting in images with different levels of Gaussian blur. The resulting images are stacked on top of each other to look for extreme points that differ locally, these are key points.

Descriptors are vectors that outline the immediate surroundings of a certain important location. Calculating the variance of the image's Gaussian blur at various levels allows for the identification of key spots. That indicates that the image has gaussian blur at varying intensities, ranging from barely perceptible to significantly perceptible. Following that, those images are subtracted from one another to produce a difference of images with varying degrees of Gaussian blur. The resulting pictures are piled on top of one another to seek for important spots—extreme points that are locally distinguishable.

It translates the matching points of one image to another in the homography matrix. This is crucial to the panorama's creation. In order to wrap one image over the other and make panoramas, it is necessary to compute the homography of two photos. This homography matrix is computed using the RANSAC technique. The stitch() function or method of the stitcher class performs the actual stitching. It puts these actions into practice. The most recent version of OpenCV includes this feature. A list of photos is accepted as an argument by the stitch() method. It gives back a tuple (status, output), where status is a bool value that is True if the stitching was successful and false otherwise. The resulting panorama is the output.

4.1 SIFT

A feature detection approach is SIFT (Scale-Invariant Feature Transformation). This is a local description which uses gradient vector histograms as its foundation. Since SIFT is scale-invariant, as its name implies, which is opposed to a Harris detector can detect features at any scale.

4.2 Homography

The Homography matrix describes the transition of two pictures. To define how one image matches the other, keypoint coordinates (obtained via SIFT) are required. The following equation can be used to describe the homography matrix:

$$\lambda * x' = H * x$$

where x' is a point in the transformed image's coordinate system, x is a point in the base image's coordinate system, H is the homography matrix, and λ is a coefficient. If this system includes coordinates, the same equation will be as follows:

$$\lambda * [x'\ y'\ 1] = H * [x\ y\ 1]$$

We need to remove the so-called outliers before executing the homography calculation. An outlier is a key point that does not fit the "true" model instantiated by the "true" set of parameters within an error threshold that determines the maximum deviation attributable to noise effects.

4.3 RANSAC

RANSAC, or Random Sample Consensus, is an iterative approach for estimating mathematical model parameters from a set of observed data that includes outliers.

When are to be given no impact on the estimations' values. It operates on outlier-saturated datasets and can handle datasets with more than 50% outliers. Other algorithms (such as LMeD) are practical limited by that percentage, also known as the breaking point. RANSAC operates on two fundamental processes that are repeated indefinitely: hypothesis and test.

Hypothesis: In this stage, minimum sample sets are chosen at random from the input data, and model parameters are calculated using just items from the minimal sample set. The minimum sample set has the least cardinality necessary to estimate model parameters.

Test: The second RANSAC stage determines which components of the full dataset agree with the model instantiated with the parameters calculated in the first step. The set of such elements is referred to as the consensus set. When the likelihood of discovering a better-ranked consensus set falls below threshold, the process is terminated.

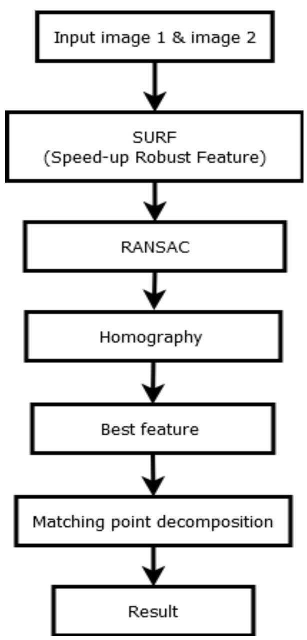

figure 4.2: Flow of image stitching

The SIFT technique is used to extract the features points of each newly taken picture. The homography matrix produced by the SIFT method displays the matching spots between two pictures. Using the RANSAC method, this matching is modified to remove outlier matches (Fischler and Bolles, 1981). The RANSAC technique was used to fit a basic matrix iteratively utilizing the normalized. The crucial matrix is decomposed using the camera's intrinsic properties to produce the relative orientations of the matched pictures. In addition, the homography transformation between the picture pairs is computed to aid in the stitching process. Thus the image stitching algorithm as shown in figure 4.2 works.

4.4 Gabor Convolutional Kernel

The stitched and blended image is now should be segmented using textures. For texture segmentation, the gabor function is used. Gabor convolutional function is a complex sinusoid which is modulated by Gaussian, which satisfies the requirements of monotonicity and differentiability, i.e.

$$g(x,y,\omega,\theta,\psi,\sigma)=exp(-x'+y'^2/2\sigma^2)exp(i(\omega x'+\psi))$$
$$x'=x\cos\theta+ y sin\theta$$
$$y'=-xcos\theta+ycos\theta$$

As we are using real values the complex function converts into

$$g(x,y,\omega,\theta,\psi,\sigma)=exp(-x'^2+y'^2/2\sigma^2)cos(\omega x'+\psi)$$

Gabor filters have been shown to be an effective technique for extracting spatially confined spectral characteristics, which are employed in a variety of pattern analysis applications. In real-world image processing applications, features are often retrieved using a bank of Gabor filters, the parameters of which are determined following the technique. The following equations provide the Gabor filter frequencies ωn and orientations θm :

$$\omega n=\pi/2(\sqrt{2})^{-(n-1)}$$
$$\theta m=\pi/8(m-1)$$
$$n=1,2,\ldots,5m=1,2,\ldots,8$$

The σ is set by $\sigma\approx\pi/\omega$, which allows to define the relationship between σ and ω. The ψ is set by uniform distribution U(0, π).

A gabor filter applies textons – directional edge templates – over a given space at scales defined by orientation parameters like area size, rotation angle or tilt relative scaling factor σ Between 0 And 1 Equal To θ; sinusoidal modulation frequency f defines coefficient between -3f9+3f8 With 3 different kernel sizes 8×8 , 12×12 16x16; gaussian blurriness strength sigma s Captured through average deviation Of data set From zero mean Value Support multi scale Algorithms As well As Edge Detection Operations Through Computations Involving Spatial Frequency Changes Via Natural Numer Vs Fourier Transforms Application Such Technology Characterizing Two Dimensional Grayscale Histograms. Thus, we get the output of our system which is a segmented photomap. The Obtained output (figure 5.4) is a image which is converted into gray scale and segmented using gabor filters .

V. CONCLUSION

In this study, we've introduced a brand-new texture segmentation technique for categorizing terrain characteristics in aerial pictures using Gabor filters and image stitching, which is a useful tool set for stakeholders to get high-resolution representations of their surroundings. Due to the numerous parameters involved, including wavelength and variance that are set based on particular geographic conditions, this technique makes precise mapping possible and produces a more detailed representation from stitched photos. While seamlessly aligning these acquired frames, it gives users the ability to detect minute differences within the data sets it has collected. This was followed by a conclusion that offered effective edge identification recognition capabilities together with improved accuracy from recognizing textural patterns among categorizing regions using terrestrial streams.

5.1 Future work

Texture segmentation is a process used to identify and divide an image into various texture regions for classification. By using Gabor filters, it is possible to detect the characteristics of each texture region which can be further used in terrain feature analysis. Additionally, image stitching allows two or more images taken at different times to form one larger combined aerial view of the terrain surface. This technique can also be beneficial when performing automated co-registration tasks and object detection in aerial imagery. Future work includes exploring other methods such as convolutional neural network based models and improved textural features extraction techniques from Landsat 8 satellite data for better segmenting and classifying features on Earth's surfaces.

5.2 Result

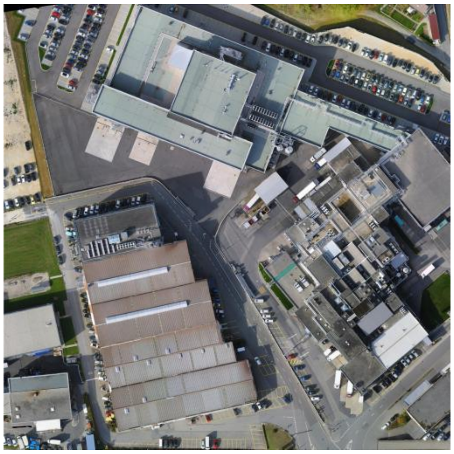

figure5.1: Set of input Aerial Images

figure5.2:Panorama of input images(unblended and uncroped).

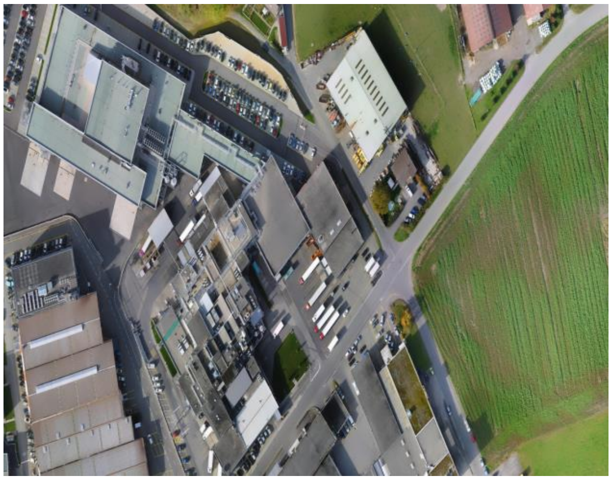

figure5.3:Panorama of input Aerial Images.

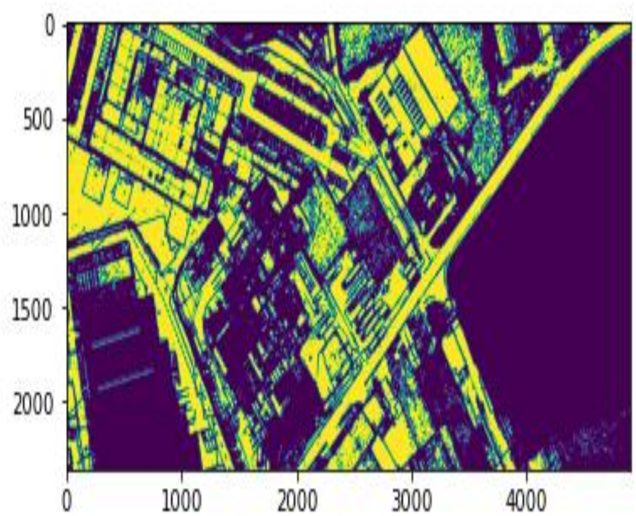

figure5.4: Texture segmented image.

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