Abstract: Geospatial data extraction from aerial images becomes more and more important with the advances in technology. Extracting building profiles is one of the key elements in geospatial applications. rooftops are detected through a variety of approaches. In that rooftop detection is the main and difficult task. Building model reconstruction from aerial imagery constitutes the key element in various geospatial applications which includes three dimensional map reconstruction, urban environmental planning, telecommunication purposes, and military simulations. This task is very difficult because of the complexity and diversity of 3-D objects and also the shape of rooftops. Rooftop detection has been done through a large variety of approaches but most of them are limited to process very simple profiles. This work presents a method for extracting 2-D rooftop footprints from aerial imagery with the help of corners to detect very complex profiles because corner contains the most important shape information about image. Corner is an important local feature of image with rotation invariance so that processing corners can reduce the amount of data calculations and improves image processing speed. In this work corner detection is done based on two different approaches the first one is Harris corner detector which correctly detects corners but the operation is complex, abundant and time consuming with vast computations. And the next one is SUSAN corner detector this also detects corners correctly but with higher efficiency and better noise immunity capacity. Then the detected corners are connected in a particular way to get final rooftops. The main objective of this work is to present a fast and accurate system for finding rooftops.

Keywords: Aerial Image Processing; Corner Detection; Building Extraction; Harris Corner Detector; SUSAN Corner Detector.

I. INTRODUCTION

Three Dimensional building model reconstructions becomes an active research area in the last decades. In that rooftop detection is the main and difficult task. Building model reconstruction from aerial imagery constitutes the key element in various geospatial applications which includes three dimensional map reconstruction, urban environmental planning, telecommunication purposes, and military simulations. This task is very difficult because of the complexity and diversity of 3-D objects and also the shape of rooftops. Rooftop detection has been done through a large variety of approaches but most of them are limited to process very simple profiles. This work presents a method for extracting 2-D rooftop footprints from aerial imagery with the help of corners to detect very complex profiles because corner contains the most important shape information about image. Corner is an important local feature of image with rotation invariance so that processing corners can reduce the amount of data calculations and improves image processing speed. In this work corner detection is done based on two different approaches the first one is Harris corner detector which correctly detects corners but the operation is complex, abundant and time consuming with vast computations. And the next one is SUSAN corner detector this also detects corners correctly but with higher efficiency and better noise immunity capacity. Then the detected corners are connected in a particular way to get final rooftops. The main objective of this work is to present a fast and accurate system for finding rooftops.

II. RELATED WORK

Two Dimensional rooftop extractions is the main task for 3-D building model reconstruction and it has been addressed through a variety of approaches. In a previous work of automatic extraction of buildings by C. Vestri and F. Devernay they model buildings from a single range data image, a digital elevation model (DEM). The system consists of two stages: The first stage is to segment the DEM into local planar surfaces to recover various parts of the buildings. The second stage is the vectorisation of the boundaries to obtain the model of buildings. This system is restricted to buildings with flat rooftops but it is able to model buildings of all shapes. Curve evolution/energy-based and model-based methods are very popular for building extraction. In a previous model-based work by Z. J. Liu, J. Wang and W. P. Liu they used probabilistic Hough transform for building extraction. They divided their work into two different phases: building roof extraction and shape reconfiguration. In the first phase, high resolution satellite imageries are fused for color information enhancement and for spatial resolution improvement. Then on the fused image multi resolution image segmentation is applied, resulting in the formation of different level of polygon primitives providing different view at different resolution. The classification is based on fuzzy rule decision tree classifier. Building roofs are detected and extracted by fuzzy evaluating the shape, context, texture and spectral information.
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In another work by M. S. Nosrati and P. Saeedi, they detected rooftops of polygonal shape with no angular constraint or with any angular constraint in aerial imageries based on line intersections. This approach uses edge definitions and their relationships with each other to create a set of potential vertices. Using a graph representation, polygonal roofs are presented as closed roofs thereby detecting rooftops. The major drawback of their work was time complexity that increases with the number of vertices. The other drawbacks are the assumption of only straight lines and the issue of gabled rooftops. In our work, we extract 2-D rooftop footprints from aerial imagery by combining the strength of energy-based approaches with those of corners to detect complex profiles. Two corner detection algorithms are used for the purpose. Harris corner detector and SUSAN corner detector. A polygonal rooftop outline is generated from the detected corners. The system is ported to be applicable on satellite images.

III. CORNER DETECTION

Corner detection is of relevant research value and has an increasing attention in recent years. Corner is an important local feature of image which is almost freed from the influence of light conditions and with rotation invariance. Even though corner holds only about 0.5% pixels of the image it contains the most important shape information, so that processing corners can greatly reduce the amount of data calculations and also improve the image processing speed. Corner detection is frequently used in motion detection, image matching, tracking, 3-D modeling, object recognition, panorama stitching. A lot of corner detection algorithms were present but the main algorithms fall under two categories: corner detection based on boundary and corner detection based on grayscale. In corner detection based on boundary, firstly the image is segmented to extract the boundary and then the points on boundary are found as corners. This type of algorithms is restricted in the range of application. The performance of the algorithms depends on the initial image segmentation and edge extraction results so that any error of the previous work may affect the detection results.

In corner detection based on grayscale, image processing is done directly on the original image; these algorithms are widely used because they don’t require pre-segmentation of image, edge extraction and other preliminary works as in corner detection based on boundary. Experimental results show that this algorithm is fast and real-time. Harris operator and SUSAN operator algorithms are based on grayscale. Harris operator detects corners by differential operations, Gaussian filtering and gradient calculations. Therefore this becomes more complex, abundant and sensitive to noise. The SUSAN operator which is proposed by smith detects corners without differential operations and with higher efficiency and better noise immunity capacity.

A. Corner Detection Based on Harris corner detector

The Harris Corner Detector algorithm was developed by Chris Harris and Mike Stephens in 1988. Harris corner detector has large invariance to rotation, illumination, variation, scale and image noise. This operator is based on the local auto-correlation function of signal; auto-correlation function measures the local changes of the signal with patches shifted by a small amount in different direction. In this paper, we present an approach for rooftop detection from aerial images with the help of corners to detect complex profiles. Image corners are first assessed from detected edges. Edges of each building boundary are found using canny operator. Then a polygonal rooftop outline is generated from the detected corner sets. To detect corners of each rooftop, we define blobs of different shape in the original color image which means within each blob there must be a rooftop and these blobs are obtained from a blob detection algorithm through k-means clustering of the hue and saturation (HS) components of the images.

Figure1. Filtered version of the input image and histogram of the HS components of the image. (a) Color image; (b) filtered image; (c) HSV image; (d) H image; (e) S image; (f) histogram of H; (g) histogram of S; (h) 2-D histogram of H S.

The steps include firstly a filter with up-size/down-size (ratio of 8) with bi-cubic interpolation is applied to smooth the original RGB image; this smooth image is then transposed into hue-saturation-value color space. This step is done to remove the dependency between the color and brightness information. A k-means clustering algorithm is applied on the HS components. K-means clustering partitions the 2-D pixels (HS components) into k clusters through an iterative scheme so that it minimizes the sum of the intra-cluster sums of the distances (of HS data) between pixels and cluster centroids. Two parameters have to be specified: The number of desired clusters (k), which is data dependent and the initial cluster centroids ( \( \mathbf{k}_i \) ). These two parameters are determined automatically for each image through the 2-D histogram analysis of the HS values.

\[
k = \left| \left( H_{HS} \right)_k = \text{regional maximum} \right| \tag{1}
\]
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\[ k_c, = HS \left( \left( \text{regional maxima} \right) \right) \]  

Here, \( x \) denotes a bin. \( \text{(regional maxima)} \) represents the set of peaks in the 2-D histogram \( H_{HS} \) and \(|...|\) is the cardinality. That means the number of clusters \( k \) is equal to the number of peaks and the cluster centroids \( k_{C_i} \) are given by the HS components of the peaks. According to blob detection algorithm each of the resulting clusters from \( k \)-means clustering algorithm is now processed to obtain blobs that represent rooftops by the following steps:

- Morphological cleaning is carried on each cluster (with a squared structural element of 5x5 pixels) to remove very small/narrow objects and isolated pixels.
- Each cluster is split to get meaningful blobs where strong canny edges are present. This is done by dilating the edge map by a circular structuring element of radius 2 pixels and then setting the dilated edge points to 0 in the cluster masks.
- Every blob is now subjected to individual processing.
  - Image border
  - Eccentricity
  - Size
  - Vegetation

Image border represents the blobs which are on the border of the image are discarded because we need rooftops that are fully contained within the image. Eccentricity means all eccentric blobs are removed. In other words blobs which don’t satisfy the condition are removed.

\[ \frac{L_{\text{minor}}}{L_{\text{major}}} > 0.4725 \]  

Here \( L_{\text{minor}} \) and \( L_{\text{major}} \) are the minor and major axes of the ellipse. This threshold value was selected to prevent any rooftop being discarded and also blobs without having extreme shape/size are discarded. Blobs corresponding to vegetation are removed. Green vegetation (grass or trees) can be distinguished from rooftops based on the saturation component of the HSV color space. A vegetation mask \( M_V \) is created from pixels that have a saturation value over 0.4 and to strengthen the approach a second constraint related to hue is added, hue value must be centered on the green value (0.333). A tolerance spanning from yellow (H=0.1) to cyan (H=0.5) is allowed.

\[ M_v(x,y) = \begin{cases} 1, & S(x,y) > 0.4 \text{ and } 0.1 < H(x,y) < 0.5 \\ 0, & \text{otherwise.} \end{cases} \]  

Here \( x \) and \( y \) denote pixel coordinates and \( S \) and \( H \) the saturation and hue bands. The remaining blobs are labeled after these processing steps and this procedure is repeated for every cluster of \( k \)-means clustering algorithm results then all blobs from each and every cluster are put together. According to Harris detection algorithm, there is a response threshold parameter \( (R) \) and this response parameter is different for different feature points of an image, which means for a corner the value of \( R \) is large, \( R \) is negative with large magnitude for an edge and \( |R| \) is small for a flat region.

To compute \( R \) includes the following steps: compute the \( x \), \( y \) coordinate derivatives of the image and then compute the products of derivatives at every pixel and then computing the sum of the products of derivatives at each pixel. After these steps Harris define a matrix with these parameters and the response at each pixel is found then they used this response value as a threshold for corner detection.

In this work, Harris response threshold parameter is initially set to 50, which is designed to detect an average number of one corners per square meter. If the number of detected corners is less than this value, then the response threshold will be reduced by 5% automatically through an iterative step and the corners are detected again. This iteration is continued until at least the average number is achieved. The non-maximal suppression is carried out at the pixel level. The detected corners at this stage is denoted by \( c_{\text{init}} \). With sensitivity settings for Harris corner detector ensures that no important corner is missed, but at the same time it causes corner overcall. An edge constraint is applied to remove corners that are not located on the dilated edge map of the image; this is done to reduce the number of detected corners. The dilated edge map is defined by

\[ M_{\text{DE}} = M_E \oplus S_C = \{ (x,y) | (x,y) \in S_C \land M_E \neq 0 \} \]  

Where \( x, y \) denotes the pixel co-ordinates from the grayscale version of the original image, \( M_E \) represents the edge map obtained from canny edge detection and \( S_C \) denoting a squared structuring element of 3x3 pixels. The corner set is then found from image pixels satisfying the following condition.

\[ C = \{ (x,y) | (M_{\text{DE}})_x,y = 1, (x,y) \in C_{\text{init}} \} \]  

A. Corner Detection using SUSAN Corner Detector

SUSAN means Smallest Univalue Segment assimilating Nucleus Algorithm is a low level image processing algorithm which was proposed by S. M. Smith and J. M. Brady of Oxford University in 1997. In particular this algorithm is for edge and corner detection and for structure preserving noise reduction. Nonlinear filtering is utilized to define which parts of the image are closely related to each individual pixel which means each pixel has associated with it a local image region which is of similar brightness to that pixel. The noise reduction method uses this region as the smoothing neighborhood and the new feature detectors are based on the minimization of this local image region. Hence, the resulting methods are fast, accurate and noise resistant. In the algorithm, the concept of USAN is proposed for the first time. The concept is defined as scanning the whole image by a circular mask (having a centre pixel which is known as the nucleus). A circular mask is placed at each point in the image and for each point the brightness of each pixel within the mask is compared with that of the nucleus.
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The feature points in an image are flat region points, edge points or corners. And for different feature points of an image, there is different size of USAN. For flat region point of an image the USAN area is larger than half of the circular mask’s area, USAN area of an edge point is equal to half of the circular mask’s area and USAN area of a corner point is smaller than half of the circular mask’s area. The sharper the corner is, the smaller the USAN area is. Therefore, corners can be detected by setting brightness difference threshold and USAN’s area threshold. Consideration of the above lead directly to the formulation of SUSAN principle: An image processed to give as output USAN area has edges and two dimensional features (corners) strongly enhanced, with the two dimensional features more strongly enhanced than edges. This gives rise to the acronym SUSAN. SUSAN edge and corner enhancement uses no image derivatives that are why the performance in the presence of noise is good. The integrating effect together with its non-linear response gives strong noise rejection. The theory of SUSAN operator can be expressed as follows:

SUSAN operator is implemented using circular masks (sometimes known as windows). Digital approximation to circles has been used either with constant weighting or with Gaussian weighting. The usual radius is 3.4 pixels (giving a mask of 37 pixels) and the mask considered for this work is 7x7 mask window. The 37 pixel circular mask is used in all feature detection experiments. The mask is placed at each point in the image and for each point the brightness of each pixel within the mask is compared with that of nucleus (the center point). Setting the brightness difference threshold between either pixels or nucleus within mask as \( t \) implementing the similarity function:

\[
c(\vec{r}, \vec{r}_o) = \begin{cases} 1 & \text{if } |I(\vec{r}) - I(\vec{r}_o)| < t \\ 0 & \text{otherwise} \end{cases}
\]

Where \( \vec{r}_o \) is the position of the nucleus in the two dimensional image, \( \vec{r} \) is the position of any other point within the mask, \( I(\vec{r}) \) is the brightness of any pixel in the mask, \( c \) is the output of the comparison, \( I(\vec{r}_o) \) brightness of the mask’s nucleus. In practice, more stable and efficient similarity comparison function is often used.

\[
c(\vec{r}, \vec{r}_o) = e^{-\frac{(|I(\vec{r}) - I(\vec{r}_o)|)}{t}}
\]

Where, \( t \) is the similarity threshold for distinguishing target from the background. This comparison is done for each pixel within the mask and a total \( n \) of the outputs is made.

This total \( n \) is just the number of pixels in the USAN, in other words it gives the USAN’s area. The value of \( t \) determines the minimum contrast of the features to be detected and the maximum amount of noise which will be ignored. Setting area threshold as \( g \) and \( n \) is compared with this fixed threshold \( g \) (geometrical threshold) which is set to exactly half of \( R_{max} \) where \( R_{max} \) is the maximum value which \( n \) can take. The initial corner response is then created by using the function.

\[
R(\vec{r}_o) = \begin{cases} g - n(\vec{r}_o) & n(\vec{r}_o) < g \\ 0 & \text{otherwise} \end{cases}
\]

Where \( R(\vec{r}_o) \) is the initial corner response. After this non-maximum suppression is carried out. When finding corners in the absence of noise, there is no need for the geometric threshold at all. In a nutshell, the algorithm performs the following steps at each image pixel.

- Place a circular mask (with a center pixel known as nucleus) at each point in the image.
- Calculate the number of pixels (within the circular mask) which have similar brightness to the nucleus (USAN).
- Subtract the USAN size from the geometric threshold (a fixed threshold value).
- Apply non-maximum suppression to find corners.

IV. EXPERIMENTAL RESULTS

Rooftop detection using two corner detection methods are described.

Figure 2. Results of k-means clustering algorithm (a) k-means segmentation results using HS components; (b) First cluster; (c) after morphological cleaning; (d) after cluster splitting; (e) after edge dilation; (f) after image border removal and eccentricity removal.
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Figure 3. (a) First cluster after the removal of blobs that doesn’t have extreme shape and size and also after the removal of blobs corresponding to vegetation; (b) first cluster after individual processing; (c) second cluster; (d) second cluster after morphological cleaning; (e) second cluster after cluster splitting; (f) second cluster after edge dilation.

Figure 4. (a) Second cluster after image border removal; (b) second cluster after eccentricity removal; (c) second cluster after the removal of blobs that doesn’t have extreme shape and size; (d) second cluster after the removal of blobs corresponding to vegetation; (e) second cluster after individual processing; (f) third cluster.

These two algorithms perform well for aerial/satellite image which includes flat and gabled rooftops, simple and complex profiles. A single set of parameters is used for images of all types. The presence of weak edges combined with similar colored background may yield to over detection when edges cannot be recovered from RGB or HSV color spaces. The processing time depends on the dimensions of the input image (number of corners) and here the processing time is comparatively less for corner detection using SUSAN operator. Gaussian filtering is applied to input aerial images, the input image and its filtered version and the Hue-Saturation image components are shown in Fig. 1. Figures from 2 to 9 shows the experimental results.

Figure 5. (a) Third cluster after morphological cleaning; (b) third cluster after cluster splitting; (c) third cluster after edge dilation; (d) third cluster after image border removal and eccentricity removal; (e) third cluster after the removal of blobs that doesn’t have extreme shape and size; (f) third cluster after the removal of blobs corresponding to vegetation.

Figure 6. (a) Fourth cluster; (b) fourth cluster after morphological cleaning; (c) fourth cluster after cluster splitting; (d) fourth cluster after edge dilation; (e) fourth cluster after image border removal and eccentricity removal; (f) fourth cluster after the removal of blobs that doesn’t have extreme shape and size and also after the removal of blobs corresponding to vegetation.
V. CONCLUSION

This work gives an approach for fast 2-D rooftop extraction from aerial imagery. Rooftop detection algorithm is based on corner detection. In these work corners of each building boundary is found using two different algorithms Harris corner detector and SUSAN corner detector. Both of the algorithms perform well for the most complex building profiles. Experimental results for various aerial images confirm the methods ability to extract building rooftops accurately and completely.

VI. REFERENCES


