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PROPOSED SYSTEM FOR CONVERT SATELLITE SURFACE IMAGE TO GEOMETRIC REPRESENTATION (MESH STRUCTURE)

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ABSTRACT

Satellite images provide a wealth of information that is used in various applications such as urban planning, environmental monitoring and terrain analysis. However, converting raw satellite data into a grid image suitable for these applications remains a challenge. this study proposes a three-stage methodology that integrates advanced image processing techniques to transform satellite image surfaces into a mesh image to enhance the utility in e geometric topology. The first phase involves applying intelligent detectors technology to identifying the edges of objects within the satellite image. By detecting high-density change points which are characteristic points at edge intersections especially at corners or angular features formed by objects. In the second stage, these features are processed using SIFT which ensures that scale-invariant features are extracted across different images. The final stage utilizes Delaunay triangulation to create the mesh, effectively converting the satellite image surfaces into a mesh representation. This mesh representation is a type of graph consisting of nodes (representing extracted features) and edges (connecting these nodes). Such a representation opens up new possibilities for analysis and study and providing an organized and detailed depiction of the Earth's surface. The mesh image produced through this methodology can be applied to numerous scientific and practical applications, bridging the gap between raw satellite data and its practical utilization in various fields. The satellite images used in this study are high-resolution raster optical images, commonly employed in applications such as urban mapping, environmental monitoring, and geographic analysis. These types of images are typically captured by satellites like Landsat. Such raster optical imagery provides detailed visual information that is essential for analyzing surface features and patterns. The results demonstrate the effectiveness of the proposed system, achieving a Ki metric value of (104.46) compared to (78.51) in previous approaches, indicating superior mesh quality.

KEYWORDS

Images of Satellite; Canny Algorithm; Smart Detector; Sift; Delaunay Translation Technology; Mesh Image; Mesh Generation.

1. INTRODUCTION

One of the parametric representations occupied by a specific object is the surface, which is an extension of the traditional ground plane (Stillwell, 1995). Parametric structures provide precise information about the geometric shape of the surface, making it of great importance in areas such as image processing to extract distinctive features such as edges and geometric details. In addition, this information is used in geometric applications such as modeling the object's surface in a three-dimensional image and analyzing terrain features in geographic information systems (GIS). The aim of this study is to address the need for developing geometric modeling systems (Welch, 1994). The image resulting from the process of converting the surface into a mesh carries important information within the field of geometric disciplines and can be considered an organized representation of the surface connected in the form of polygons by dividing it into a set of points connected by edges (Botsch, 2010). the method enables accurate modeling and computational analysis of complex geometric shapes. This representation offers many advantages. Mesh image provides a way to approximate smooth surfaces using a limited number of elements, which makes interacting with complex shapes computationally easier by adjusting the density and arrangement of vertices and edges (Botsch, 2007). Mesh image can capture geometric details and accurately represent complex surface features. The primary goal of the conversion process is to reduce the computational complexity inherent in images of raster by transforming the raster image surface into a vector image. Therefore, vector images can be considered less complex and easier to process than the information contained in raster images. For this reason, the conversion process is useful for processing images more simply and efficiently. A mesh image represents the geometric properties of objects on a given surface, and this representation allows for more accurate calculation of surface properties, for example volume and area of surface. Therefore, mesh structure is suitable for analyzing image elements as a numerical analysis method (Szendrei, 2011).

Triangular and quadrilateral structures are fundamental to constructing a graphical representation of objects in an image scene. The surface of the mesh is represented by a structure of irregularly connected triangles, and this structure is based on the octahedral tree method (Byrne, 1994) and the Delaunay method. This study presents the use of the Delaunay algorithm to reconstruct a mesh image based on three key points located on the circumference of a virtual circle, provided that the circle contains no other points; this is an important criterion for the Delaunay algorithm (Dey, 2007).

A surface is a flat two-dimensional space according to the concepts of mathematics and geometry. However, when represented using vector notation, it becomes a three-dimensional surface in Euclidean space. The connection between triangles in a mesh structure allows for the mathematical representation of complex and curved geometric shapes that can be described by parametric equations. Surfaces formed by irregularly connected triangles are fundamental to modeling and analyzing three-dimensional structures in various fields such as computer graphics, geometric, and physics. Therefore, understanding the relationships between connected triangles that represent objects in an image scene is essential. Thus, creating a mesh of an image surface involves partitioning the parametric field of image objects and mapping them as triangles. One technique for partitioning the parametric field of image objects is the Delaunay triangulation algorithm (Cheng, 1996).

The proposed method consists of four stages: extracting edges from image, identifying features or key points and then creating links to form non-overlapping, interconnected triangles between those features, as illustrates in Fig.1.

specifically triangular shapes. The proposed method for converting raster images into meshes addresses two important aspects that should be highlighted: the creation of a triangular mesh structure and interest points that define the objects present in the satellite image scene.

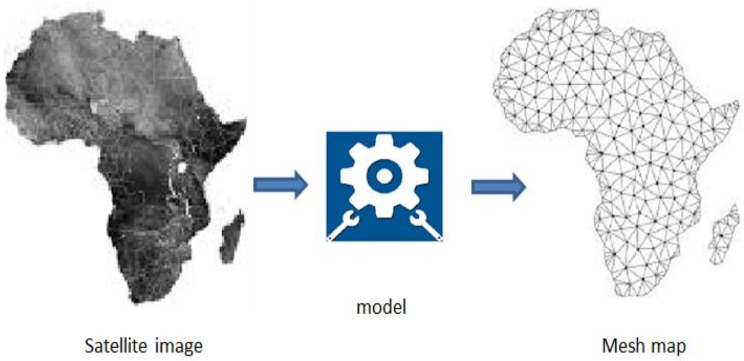


Fig 1 Satellite Image and Mesh Structure

2. RELATED WORKS

This paper addresses the challenges of reconstructing two-dimensional surfaces from satellite images and transforming objects in the image surface into a less complex geometric structure in terms of data and mathematical calculations. This transformation has been studied in previous research by training computers on end-to-end deep learning techniques using a monochrome image for example, graph-based convolutional neural networks (Shin, 2016) are used to create a direct mesh model. Some researchers have also proposed a new approach called Pixel2Mesh for converting color images into 3D meshes, with the core of the research idea based on the use of CNNs (Wang, 2018). This proposed system uses two stacked modules to efficiently generate high-quality skeletal volumes by first representing the object's topological skeleton through a set of skeletal points, and then constructing a mesh over those skeletal points to ensure the object's boundaries are preserved through correct connections (Tang, 2021).

Other researchers have proposed an approach for converting an image surface into a mesh using contour lines, in which the contour lines are processed and converted into a mesh image with the aim of reducing computational complexity during computer processing, rather than using the color image. The processing mechanism focuses on the conversion by identifying the grid lines that intersect most frequently with the contour lines; grid points are then easily determined along these lines using spline-type mathematical curve algorithms (Cheng, 1986).

Other researchers have proposed an advanced methodology for representing objects by dividing the space surrounding the object into specific geometric regions based on key points located both inside and outside the object, using VOMAC (Voronoi-based Object Model for Arbitrary Complex Objects) (Gavrilova, 200). Some researchers have proposed a method for converting 3D raster images into models with high computational accuracy. The method relies on segmenting the most prominent structures in the image scene and defining the boundaries of each object; these boundaries are then converted into a finite element mesh using a technique known as "principal normalization" while preserving the fine details of the objects in the image without resorting to smoothing or simplification operations (Young, 2008).

Researchers have proposed a method based on techniques for the automatic generation of finite element meshes, utilizing Delaunay and Advancing Front algorithms to create a mesh. The method incorporates the mechanism of 'adaptive meshing' to improve accuracy by redistributing elements based on the error in the numerical solution. Errors are estimated using a posteriori error estimator (Lo, S. H, 2002).

In a study presented by Fotinos in 2013, a method was developed for converting a raster image into a mesh composed of a finite number of elements. The method relies on processing the image data without using pre-processing operations to generate a mesh that reflects the specific elements in the image scene. The method utilized optimization techniques to adaptively distribute nodes according to object boundaries and areas of contrast in the image. (Foteinos, 2013). Researchers have proposed a research framework called 'Image2mesh' that constructs a 3D model from a single image. The method utilised a convolutional neural network (CNN) to extract significant features from the two-dimensional image and ignore the scattered points in the image; the method works directly by forming a three-dimensional surface in the form of a mesh. Initially, the Initial Shape Module is used as a starting point for the 3D reconstruction process. This step produces a spherical mesh, and to adjust the mesh by iterative deformation layers are applied to fit the shape of the object to be reconstructed (Pontes, 2018).

3. PROPOSED SYSTEM

The proposed method for converting a surface into a mesh involves a sequence of four consecutive stages that use several different techniques, with the input for each subsequent stage depending on the output of the previous stage. The result is the conversion of the input raster image into a mesh based on key points of interest extracted from the original image. These extracted key points represent the features of the original image, which will be represented by nodes within the mesh structure. These nodes are connected by edges, and this connection follows specific criteria rather than being random. The structure consisting of nodes and edges is a type of geometric representation known as a mesh. Fig. 2. illustrates the steps followed in converting the color raster image into a geometric representation (mesh).

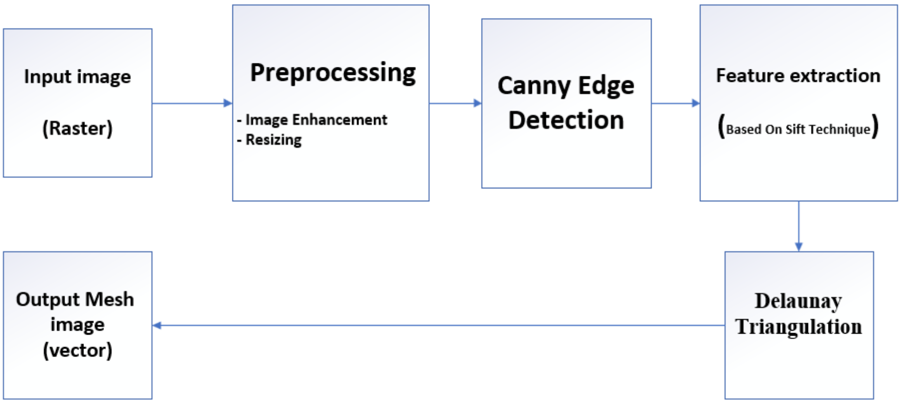


Fig 2 Rster-Image Mesh transformation Diagram

Name of Algorithm: Convert RasterImage to Mesh

Algorithm Name: Convert RasterImage to Mesh
The Input
set of raster images obtain from satellites.
The Output
structure of Mesh.
start:
    For all raster image Do
        change color image into grayscale
        Apply Sobel filters to handle contrast and edge problem
        Use Sobel filters to enhance image clarity and address edge issues.
        Change image size to 256×256
        Apply Canny algorithm to determine objects edges in image
        Using the SIFT algorithm to detect image keypoints
        Use Delunay method to build Mesh
    End

3.1. Prestage of processing

first part of proposed method involves preprocessing satellite images, which consists of converting the image from color to grayscale to reduce computational complexity; this is considered the first step in the pre-processing of the images fed into the proposed model. The second step involves resizing all images to 256×256 pixels to standardize their dimensions, followed by process of enhancing the edges of objects in image using the Sobel filter to remove weak features and preserve strong, important. This preprocessing serves as a step toward extracting geometric details, such as keypoints in image, thus transforming image into a structured format.

3.2. Edge detection stage

The second stage of the proposed model involves detecting the edges of the objects in the image using the Canny algorithm. objective of this process is to strengthen the proposed system's methodology for determining the important edges in the image, which leads to highlighting the key points located on the detected edges. Fig. 3. illustrates the edges of the image objects in a gray-scale image

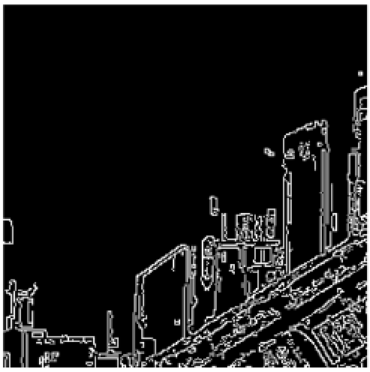


Fig 3. Results of Canny algorithm

edge detection process can be summarized by the following (Papari, 2011):

1. Noise reduction: To obtain strong features, the image is smoothed by applying a Gaussian filter. The general formula is: (Canny,1986)

$$\text{Gau}\,(x, y) = \frac{1}{2\pi\sigma^{2}} e^{-\frac{x^2+y^2}{2\sigma^{2}}} \tag{1}$$

The symbol σ represents the standard deviation of the Gaussian distribution. Image noise is removed using a Gaussian filter.

2. Gradient calculation: Use Sobel operators to determine the direction and magnitude of the gradient. The first-order derivatives of the Sobel operators are used to calculate the gradients. Sobel operators in the horizontal (Gau_x) and vertical (Gau_y) directions (Chen, 2023):

$$Gau_x = \begin{matrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{matrix} \quad , \quad Gau_y = \begin{matrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{matrix}$$

3. Local Maxima Extraction: Maintain local maxima in the gradient direction to reduce the thickness of the edges.

4. Double threshold: two thresholds for classifying pixels as having strong or weak edges..

5. Edge tracing: If weak and strong edges are connected, they are joined to complete the edges.

3.3. Scale-Invariant Feature Transform (SIFT) stage

Scale-Invariant Feature Transform (SIFT) is used to identify and characterize local features in images (Gbash, 2017). The SIFT technique finds interest points and calculates their descriptors, which are invariant to scale, rotation, and partially invariant to illumination and affine transformations. It involves:

- Constructing a scale space using Gaussian blurring, to find possible interest points by looking for local maxima in the scale space. as following:

The space of measures L(x, y, σ) to Img(x, y) is transformed by various measures through the construction of a representation Gau(x, y, σ) (Lowe, 2004):

$$L(x, y, \sigma) = Gau(x, y, \sigma) * Img(x, y) \quad (2)$$

$$Gau(x, y, \sigma) = \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \quad (3)$$

- Detection of key points, which are local extrema in the 'Difference of Gaussians' (DoG). This is done to detect fixed points of interest when applying the DoG which corresponds to 'Laplacian of the Gaussian' (LoG). (DoG) is calculated by taking the difference between two adjacent pixels in images that have undergone Gaussian blurring: Fig.4 demonstrates the application of Gaussian blurring and the computation of (DoG) across different bands.

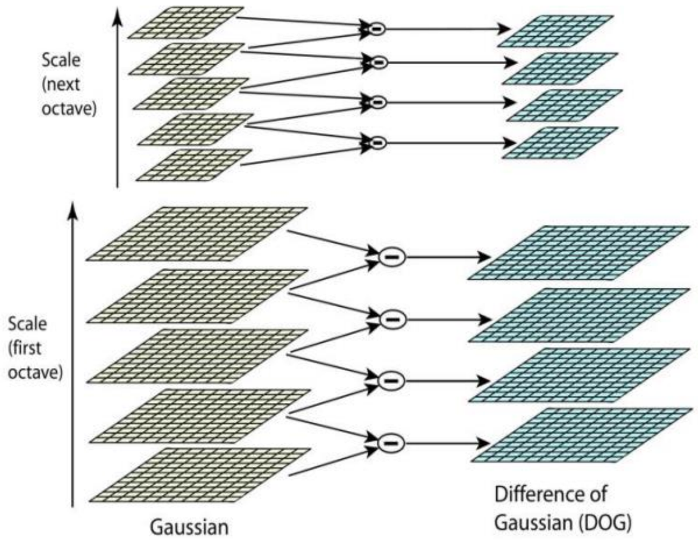


Fig 4 Generating variations in the Gaussian image

$$D(x, y, \sigma) = L(x, y, H\sigma) - L(x, y, \sigma) \quad (4)$$

symbol H indicates is static value.

Identifying Local Maxima: The keypoints in DoG images are considered local maxima, and each pixel is compared with its 26 neighboring pixels within a 3×3 neighborhood.

- Refine the locations of points of interest and remove unstable points.

To estimate the location of the maximum values, potential keypoints are identified, their locations are determined with precision, and unstable points are removed. To do this, a three-dimensional quadratic function must be fitted to the local sample points. The metric function D (x, y, σ) is generalized using a Taylor expansion as follows (Lowe, 2004):

$$\check{D}=D+\frac{\partial D}{\partial x}x+\frac{\partial D}{\partial y}y+\frac{\partial D}{\partial \sigma}\sigma+\frac{1}{2}\,[x\ \ y\ \ \sigma\,]\begin{bmatrix}\frac{\partial D^2}{\partial x^2} & \frac{\partial^2 D}{\partial x\partial y} & \frac{\partial^2 D}{\partial x\partial \sigma}\\ \frac{\partial^2 D}{\partial y\partial x} & \frac{\partial^2 D}{\partial y^2} & \frac{\partial^2 D}{\partial y\partial \sigma}\\ \frac{\partial^2 D}{\partial \sigma\partial x} & \frac{\partial^2 D}{\partial \sigma\partial y} & \frac{\partial^2 D}{\partial \sigma^2}\end{bmatrix}\begin{bmatrix}x\\ y\\ \sigma\end{bmatrix} \tag{5}$$

• Determining consistent orientations of key points. The local gradient directions of the image are used to identify a consistent orientation for each key point. This ensures that the result remains stable when the image is rotated. The direction θori(x, y) and magnitude Mag (x, y) of the gradient are calculated using following formula (Lowe, 2004):

$$\mathrm{Mag}\ (x, y) = \sqrt{\big(L(x+1,y)\big) - L(x-1,y))^2 + \big(L(x,y+1)\big) - L(x,y-1))^2} \tag{6}$$

$$\theta ori\ (x, y) = \tan^{-1}\Big(\frac{L(x,y+1) - L(x,y-1)}{L(x+1,y) - L(x-1,y)}\Big) \tag{7}$$

A set of keypoints is used to create a histogram of gradient directions. The peak height in the histogram represents the current direction. To identify additional prominent heights (secondary directions), other keypoints can be generated.

Local image gradients are processed to generate a description for each key point and identify the characteristics of the surrounding area. Fig. 5 illustrates how distribution maps of gradients are created within the subregions surrounding each key point in order to represent features of local image. The processing steps are as follows (Han, 2008):

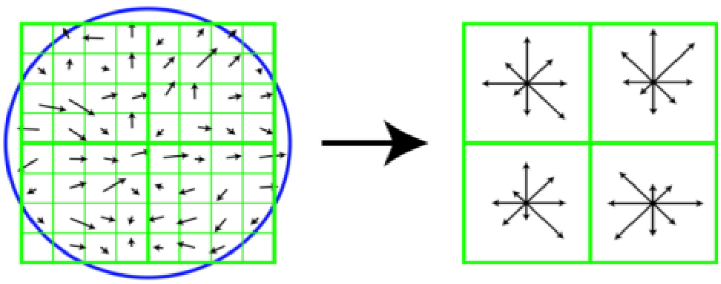
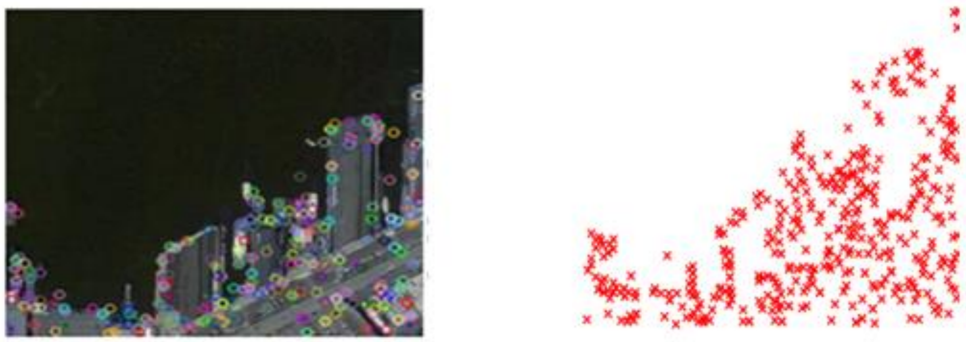


Fig 5 KeyPoints Descriptor Calculation

calculation of Gradient: Gradient values and directions are calculated within a 16×16 grid surrounding the key points.

Orientation Histograms: Directional plots: four 4×4 regions are located within the 16×16 region. A directional Histograms consisting of eight sections is constructed for each region. Depending on the direction of the gradient, each section calculates the weighted cumulative values of the gradient magnitude.

Descriptor vector: To improve stability in the face of lighting and contrast changes, the output vector consisting of 128 elements (4×4×8) are standardized. information of coordinate for SIFT features are obtained during the coordinate extraction stage, and the coordinate extraction function is used to obtain coordinates (x, y) for each feature. Fig.6 illustrates the keypoints extracted from the image using the SIFT algorithm.



(A) interset points on object (B) interest points (X,Y)

Fig 6 Key Points by Sift Technique

3.4. Delaunay Triangulation stage

The general idea behind the use of the Delaunay triangulation technique is to connect points of interest obtained by applying the SIFT technique within a specific plane to form interconnected irregular triangles (Casals, 2006). One of the key features of this technique is that it is designed to maximize the minimum angle to prevent distortion in narrow triangles.

The basic idea behind simple Delaunay shapes is based on the fundamental geometric concept of the Voronoi diagram, which provides a mathematical method for dividing a given region into distinct areas, such that each area takes into account the distance to a specific point and contains all points close to that specific point (Gavrilova, 2008). This region is called a Voronoi region. Consequently, regions are formed that cover space without gaps, and the Voronoi tessellation is defined. The dual covering of a Voronoi diagram is known as a "Delaunay covering," in which the centers of the polygonal regions represent the vertices of simple, non-overlapping triangles. Fig. 7 illustrates a Delaunay partition.

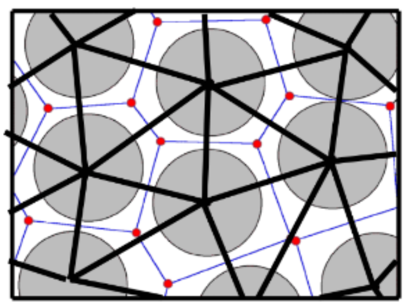


Fig 7 Voronoi Diagram

4. SET OF DATA

The images used in this study are satellite images of various cities on Earth captured by satellites. Converting these images into geometric representations is essential for further analysis and applications in the field of computer vision, for example, in image processing by utilizing the hidden geometric information contained within the images. The images used are of the city of Seattle (200 images) (Zhao, 2021). Fig.8 presents a sample of the satellite images used.

Fig.8 An Images Selection of Seattle city

5. DISCUSSION OF RESULTS

Based on the outcomes obtained from the proposed method for converting satellite images into a mesh structure, the results can be better illustrated by taking a sample of the converted images, to which the pre-processing steps have been applied, resulting in a size of 256×256 pixels and conversion to greyscale, as shown in Fig. 9 image (A). The system then moves on to the second stage, which involves revealing the fine edges of objects in the image using the Canny detector, as shown in image (B) of Fig. 9, so that the image displays most of the edges of the objects in the original image. The system then proceeds to the third stage, which utilizes the SIFT technique, where image (C) of Fig.9. shows all the key points in the image that lie on the significant, sharp edges extracted by the Canny detector, Finally, the proposed system proceeds to the fourth stage, which involves connecting these points in two-dimensional space via edges to form irregular, interconnected triangles using the Delonay triangulation technique, as shown in image(D) of Fig.9.

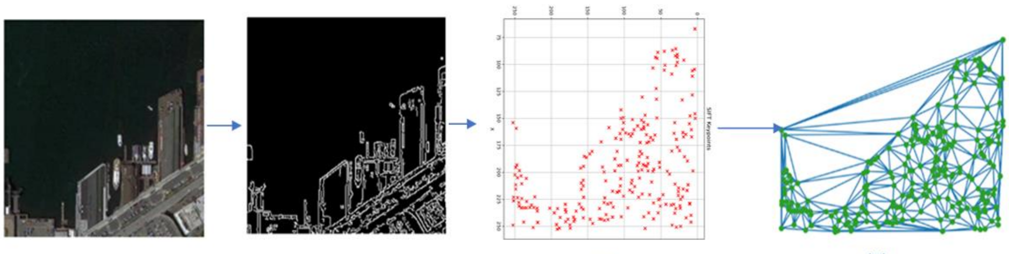


Fig 9 Steps of proposed model

To evaluate the image resulting from the conversion to grayscale, reliable methods were used, specifically the Canny algorithm for consistent edge detection, as shown in image (B) of Fig.9. An algorithm effectively highlights the important and strong edges, supporting the interest points extracted using the SIFT technique. The key points represent the existing corners located on the edges extracted from image (b) in Fig.10, which were extracted using SIFT, a reliable method for extracting corners from edges.

Finally, the Delaunay triangulation method was used to generate triangles, ensuring that the vertices of each triangle lie on the circumference of a circle and that no other points lie within that circle. The result is a mesh representation of the surface that reflects the objects present in image. Fig.10 illustrates conversion of a set of satellite images into a mesh.

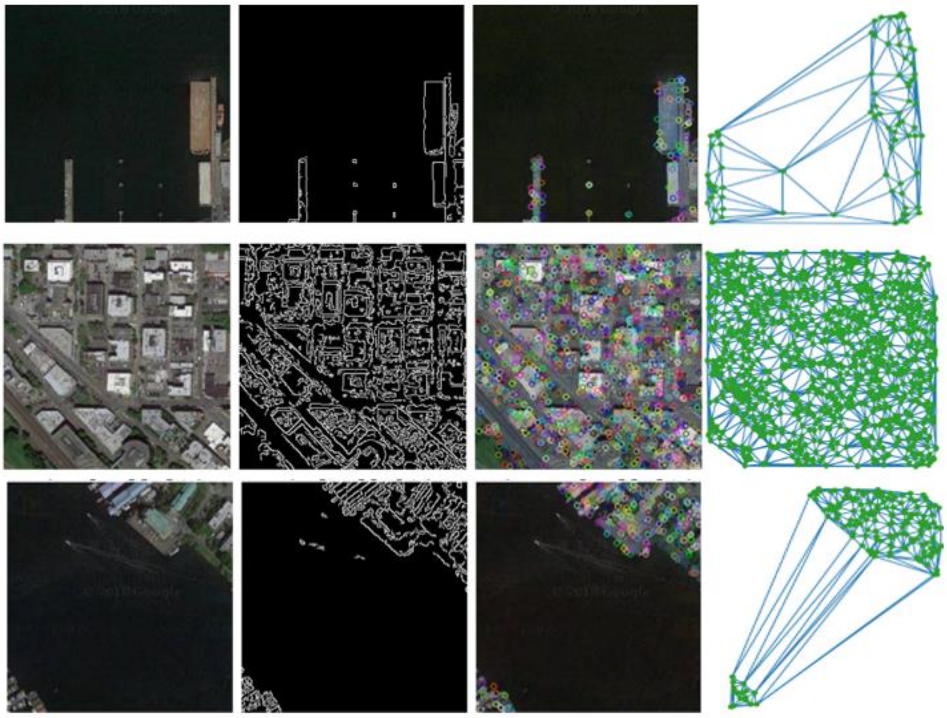


Fig.10 Proposed System Results

The Ki equation is a geometric metric designed to evaluate the quality of triangles formed using the Delonay technique. The main idea behind the metric is based on the lengths of the triangle's sides: (xy), (yz), and (zx); in other words, the distances between the triangle's vertices are calculated. Using the distance equation (Dai, 2020):

$$L = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \tag{9}$$

The symbol L represents the length of each side of the triangle, and then apply the Ki equation as follows:

$$ki = \frac{2 \cdot ca \cdot bc}{ca + ab + bc} \tag{10}$$

The numerator represents the multiplication of two specific sides, multiplied by two. This term reflects the balance between these two sides relative to each other, while the denominator represents the circumference of the triangle. The performance of the proposed model was compared with that of previous models derived in similar studies, using the quality metric Ki. The results demonstrated the superiority of the proposed model, as higher values of the quality measure Ki reflect better geometric quality of the triangles comprising mesh. A quantitative comparison was conducted between mesh generated by proposed system and mesh extracted using the model by Silva model (Da Silva, 2010), as detailed in Table 1.

Table 1 result comparing with another model

model	AB	BC	CA	Ki metric
proposed model	101	213	99	102
Silva model	97	160	85	80

6. CONCLUSIONS

This study presented a robust methodology for converting surfaces into a geometric representation (mesh structure), employing a four-stage approach to transform satellite image surfaces by integrating various techniques (intelligent detection, SIFT, and Delonay triangulation). This approach maintains high accuracy while preserving geometric and topological characteristics. The results demonstrate the effectiveness of this method in accurately modeling the terrain in the image.

This approach positions the proposed system as a powerful tool for applications such as urban development, environmental monitoring, and geographic studies. The system shows significant improvements over existing methods and the Ki-index values it achieved reflect the efficiency and quality of the generated network structures. In addition, the principle of integrating SIFT edge detection techniques provided a framework that yielded reliable results, particularly regarding the geometric features hidden in the raster image.

Future work may focus the model's methodology could be expanded to process various types of remote sensing datasets, such as multispectral and hyperspectral imaging. Furthermore, incorporating advanced machine learning techniques and image processing methods could enhance the system's flexibility and efficiency. This would result in a highly capable tool for diverse applications, such as transforming faces or objects into geometric mesh structures.

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