Development of a hough transform based algorithm for extraction of buildings from actual and simulated LiDAR data

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Abstract

3D information of buildings is fundamental in several applications. Airborne altimetric LiDAR (Light Detection and Ranging) technique generates terrain data which are dense and accurate, and unlike other remote sensing tools have reliable and accurate height information. This data has potential to be used for building extraction in isolation and in combination with other data. A hough transform based approach for extraction of buildings using LiDAR data is presented in this paper. Building extraction includes identification of data points in LiDAR point cloud which belong to building roofs and fitting of a vector model on these points to reconstruct the building. It is shown that LiDAR data should be smoothed and sparsed prior to hough transform for better result. Algorithms to realize smoothing, sparsing, and hough transformation are presented. Further algorithms that reconstruct a building by locating building edges and corner points are also presented. The results obtained are compared with ground truth using accuracy indices, which are specially developed for this purpose.

1 Introduction

The 3D details of buildings are important geo-information and can be obtained from land surveys, through photogrammetry (aerial or satellite stereo images) or from LiDAR (**Li**ght **D**etection **A**nd **R**anging) data. Accurate 3D geo-information helps in decisions like placement of telecommunication towers, planning of disaster management, land tax evaluation, and many more. Till

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recent past building extraction was being performed mainly by photogrammetry. However, generation of digital surface model (DSM) and extraction of building using photogrammetry is resource and time consuming. LiDAR technology directly provides dense and accurate 3D coordinates of the ground points thus solving the problem of obtaining DSM. This data necessitates development of algorithms to efficiently and accurately extract information from large volume of data.

Various approaches have been attempted for extracting buildings from LiDAR data. Classification of LiDAR data using remote sensing tools has been investigated by Arefi et al. (2003). They generated normalized difference image and also used reflectance data for their classification approach. Researchers have used several different methods for LiDAR data classification, like height segmentation (Maas, 1999), texture based segmentation (Tan and Shibasaki, 2002), reasoning on image segments (Zhan et al., 2002), morphological processing, mathematical model fitting (Vu and Tokunaga, 2002), classification algorithms (Maas, 1999; Voegtle and Steinle, 2003; Elberink and Maas, 2000) etc. Various methods have been combined to increase the efficiency of classification. Both the first and last return data have been used to get better accuracy (Voegtle and Steinle, 2003). Integration of LiDAR data with different data types, like multispectral images (Sohn and Dowman, 2003), reflectance information from LiDAR (Elberink and Maas, 2000), GIS (geographical information system) maps (Tan and Shibasaki, 2002), etc. has been attempted to improve classification accuracy.

This paper discusses building extraction using hough transform, which shows promise as a valuable technique. The term building extraction encompasses two processes-first building identification, which is detection of LiDAR points that belong to a building and second the model fitting (also referred in literature as building reconstruction), in which the identified building surfaces are modelled on a vector framework. Vosselman and Dijkman (2001) have used 3D hough transform to detect planes in LiDAR data. Hofmann et al. (2003) have made a comparison between 2D and 3D hough transform for detecting building planes in LiDAR data. The hough transform can be implemented using a cluster space described by two slope parameters (s_x and s_y) and a distance parameter (d) (Maas and Vosselman, 1999):

$$Z = s_x X + s_y Y + d$$

A triangle is the basic element adopted for computing aforesaid parameters, which are generated using a tessellation scheme on LiDAR data. Due to random error in data (particularly in Z direction) the parameters of these triangular elements vary substantially even if the triangles come from the same roof plane. This variation of parameters can be taken care of by clustering of data(i.e., having higher values of quantization in hough room.) However, in case of high data density, only this measure may not be able to account for the variation in parameters of triangular planes due to random error. So preprocessing of LiDAR data by smoothing, sparsing, or both, prior to hough transform, is desired. Further, how building extraction is dependent upon data characteristics is not known. However, this is fundamental for optimal use of LiDAR data. Finally, in absence of a proper accuracy analysis procedure, it is difficult to compare the performance of different algorithms or the effect of data characteristics. The aforesaid issues have been either partly explored or not explored in existing literature, and are the motivation for this work.

2 Data used

Two data sets have been used in this study. The first data used were collected by ALTM1025 from an altitude of $900m$,with $25000Hz$ measuring rate, swath of $390m$, and an average velocity of $80m/sec$. The ortho-photograph corresponding to this ALTM data is shown in Figure 1. This photograph is used to generate validation data for assessing the building identification accuracy for ALTM data.

Fig. 1. Othophoto corresponding to ALTM data

The other data used is generated from a LiDAR simulator (Lohani et al., 2006). The simulator offers advantages of generating a wide variety of data thus suitable for accuracy assessment of developed methodology. A total of 45 data sets (consisting of 11 building roof planes) are generated for different settings of flying height, data density, and scan angel. The aim was to assess the effect of these parameters on accuracy of identified buildings.

3 Methodology for building extraction

The methodology for building extraction is divided into two parts. First part consists of identification of group of points corresponding to a roof plane by using hough transform. Second part consists of fitting a model to the points within a group. The following paragraphs describe these steps. Matlab is used for coding the algorithm.

3.1 Detection of building roof points

Building roof points are detected using hough transform. The methodology adopted is shown in Figure 2. LiDAR data in WGS84 are normalized by transforming the coordinates of points to local origin (mean x, mean y, minimum z). This helps to reduce Z intercept parameter (d) of the plane equation $Z = s_x X + s_y Y + d$. This parameter is further constrained in range by specifying the maximum slope of the roofs present in data. The data can be transformed back to original coordinates once the building model fitting is over. The point elevation coordinates are smoothened if the data density is lower (up to 8 points/m^2) while for higher data density both sparsing and smoothing are done.

Each data point is evaluated for smoothing. A plane is fitted to the point under consideration and its neighboring points. The standard deviation of the separation of these points from fitted plane is computed in z direction. If the standard deviation is less than the standard deviation of data error the elevation of the point under consideration is replaced by the corresponding elevation on the fitted plane. This ensures that data are smoothened for random error while preserving the edges. Sparsing is done by removing the neighbours of a point which are within a specified distance from the point. Data points which are on edges, determined using the edge detector on LiDAR image, and which were removed in the process of sparsing are added back. The sparse data produce larger basic computation elements, i.e. triangles, thus minimizing the effect of random error on slope parameters computed.

Data resulting from the above step are triangulated in plan by using 2D delaunay triangulation. Using the coordinates of vertices of triangles the plane parameters, i.e., s_x, s_y, and d are computed for each triangle. Hough room quantization is done based on the specified quantization levels for different parameters. These quantized levels facilitate voting to parameter space. The hough room cells with high frequency of votes are further analyzed. All the triangles with similar plane parameters vote in the same cell. However, all these may not belong to one roof plane. So different point groups in one cell

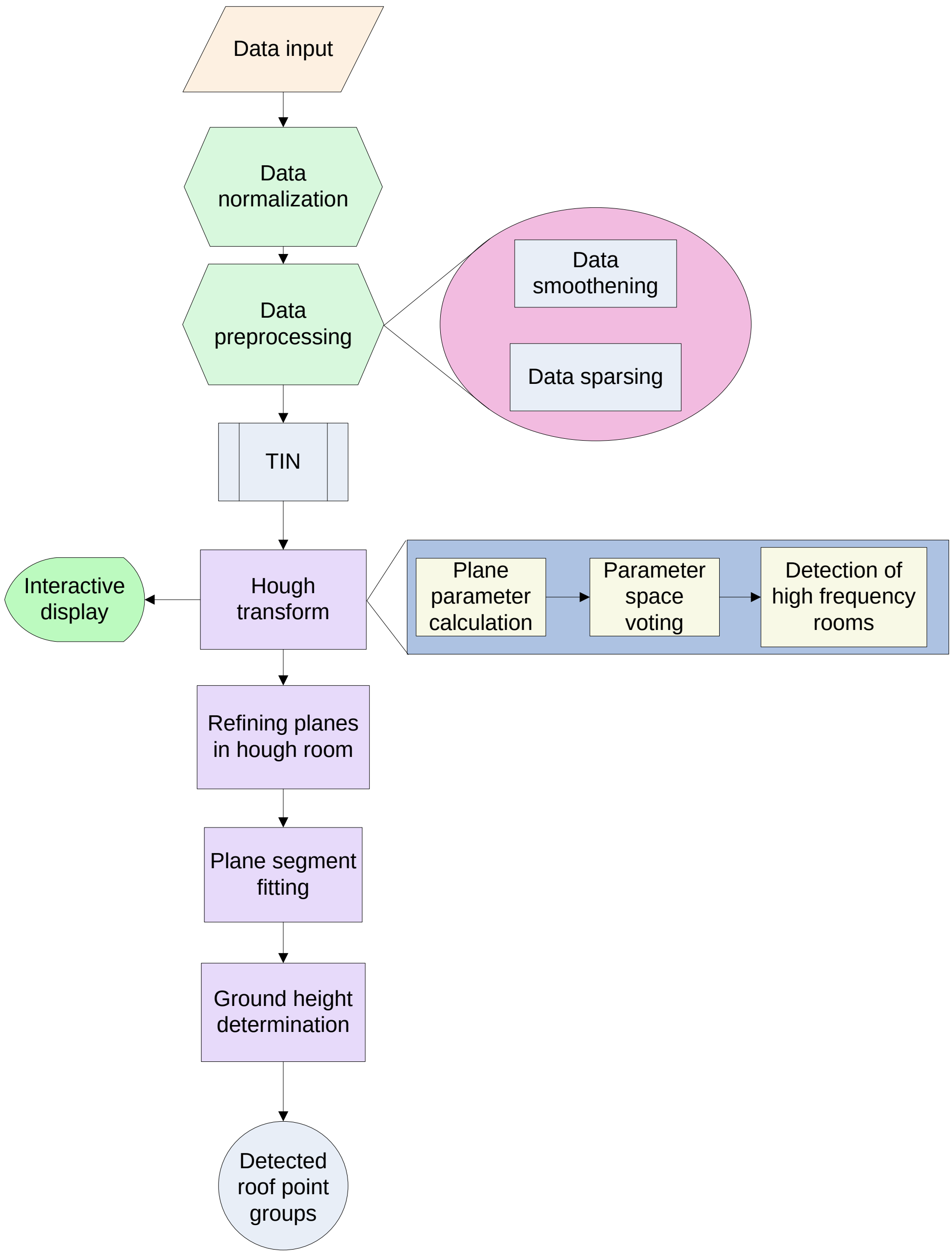

Fig. 2. Methodology for identification of group of data points belonging to a roof plane.

need to be separated. This is realised by gridding all the points of a cell to a binary image with grid size being equal to the average data spacing. Grid elements where a data point is present are made TRUE while the rests become FALSE. A morphological closing operator (with a 3 X 3 structuring element) is operated on resulting binary image to close the holes in the data group. All the elements of a 8-connected point group are given a unique ID using an indexing algorithm. The IDs are mapped back to the points in the hough room. The point groups, having area and number of points larger than the specified thresholds, are kept for further analysis.

Following the above, a segmentation based fitting is carried out to collect all the points belonging to one roof in one point group. This is done by starting with a point group and fitting a plane to it by least squares. The perpendicular distance of neighbouring points (within a distance threshold) to the fitted plane is calculated. If the point is within 3σ of the elevation error it is included in point group and the plane parameters are updated. This is done till no other point is being included into the group. This step helps to merge groups having different IDs but belonging to the same roof.

3.2 Building model fitting

LiDAR points identified corresponding to building roofs in the above step are represented using a vector framework. This is realized by fitting a plane to the point group by least squares and finding the edges of the point group. The steps used for building model fitting are shown in Figure 3. For detection of the edge points the roof point group is converted to binary raster with a pixel size equal to average data spacing. Holes in raster data are filled by morphological closing. Boundary pixels are determined using bwboundaries() function of the matlab software. The roof group points are mapped onto the raster and the points corresponding to edge pixels are selected for further fitting of line by contour approximation and orthogonalization. An algorithm, similar in concept to (Douglas and Peucker, 1973), but specifically adapted to identify roof edges has been developed for this purpose.

In this, two points having maximum separation in the boundaries are flagged as control points. The distance of other points is calculated from the line formed by joining the control points. The point at maximum distance from this line is again flagged as control point. Consideration of the direction of contour ensures that the points only on one side of the line are evaluated for selection. Again the distance of points is calculated from the lines formed. The point at maximum distance from it's nearest contour line is made a control point if it's distance from the contour line is greater than a threshold distance. This is done till all the points are within threshold distance (half the minimum side length specified for building) from nearest contour line. Then lines are fitted to all points between two consecutive control points. The longest line is taken as the main orientation of building and other lines are made orthogonal to that line. The lines obtained are later intersected to get the corners of the roofs.

Once the building roofs are detected the roofs which are close (within a threshold) to each other are intersected to get the line of intersection of roofs. Next

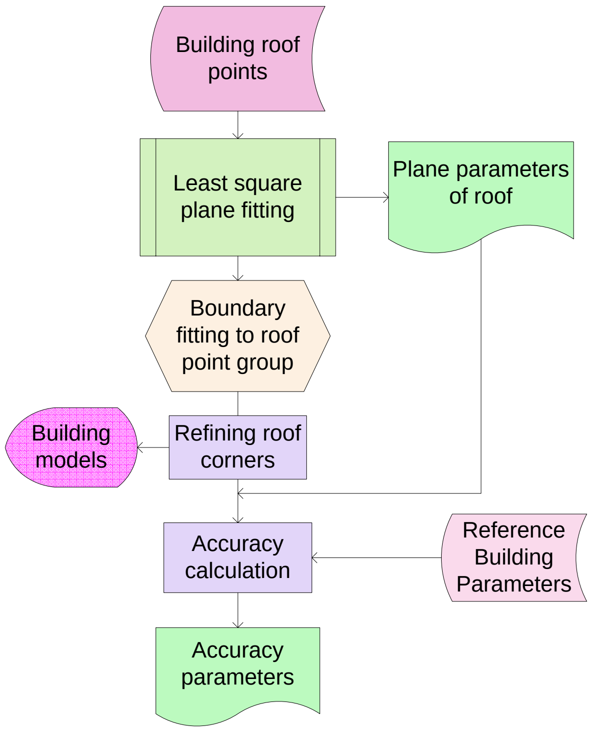

Fig. 3. Steps of building model fitting and accuracy analysis

step is to find the height of the point group above ground. This is accomplished based on the difference of the elevation of edge point group and their neighbours on ground. Point group height helps to differentiate roofs from the planar surfaces formed due to flat ground. Using the corner coordinates of the roofs the building models can be plotted.

4 Development of accuracy indices

To assess the quality of buildings extracted using the ground truth a set of accuracy measures is proposed below.

- **Corner distance**: Mean value of distance between corresponding nearest corner of extracted and reference building.

$$Cde = \frac{\sum_{i=1}^{n} dist(\mathrm{P}_i^{ref}, P_i^{ext})}{n}$$

  where Cde is corner distance accuracy of a building, P_i^{ext} and P_i^{ref} are i_{th} corner point of identified and reference buildings respectively, $dist(A, B)$ is function which calculates distance between points A and B, and n is the number of corners of the building.

- **Slope accuracy** : This is difference of absolute values of reference building slope and actual slope detected.

$$SD_i = |Sl_{ref}|_i - |Sl_{ext}|_i$$

where SD_i is slope difference, Sl_{ref} and Sl_{ext} are slopes of reference and extracted buildings, respectively, and i represents the direction of slope (S_x or S_y direction).
- **Area difference**: This is calculated using formula:

$$Area\ difference = \frac{Area(Poly_{ref}) - Area(Poly_{ext})}{Area(Poly_{ref})}$$

where $Area(Poly_x)$ is area calculation function for calculation of area of $Poly_x$ polygon. $Poly_{ref}$ is reference building polygon and $Poly_{ext}$ is extracted building polygon.
- **Perimeter difference**: This is calculated using formula:

$$Perimeter\ difference = \frac{Peri(Poly_{ref}) - Peri(Poly_{ext})}{Peri(Poly_{ref})}$$

where $Peri(Poly_x)$ is perimeter calculation function for $Poly_x$. Other terms are as defined above.
- **Area Overlap**: This index is calculated using formula:

$$Area\ overlap = \frac{Area(Poly_{ref} \bigcap Poly_{ext})}{Area(Poly_{ref})}$$

where all the terms are defined as above.
- **Area extralap**: This is calculated as:

$$Area\ extralap = \frac{Area(Poly_{ext} - Poly_{ref})}{Area(Poly_{ref})}$$

The corner distance and slope accuracies are reported in meters and degrees, respectively, while the rest of the indices are unitless. Further, the aforesaid indices are defined for an individual building. To define accuracy for all buildings together in a data set, the accuracy indices of individual buildings are averaged. The standard error of mean is also computed.

5 Result and discussion

The buildings identified and reconstructed for ALTM data are shown in Figure 4. Further, the accuracy indices for building identification from ALTM data

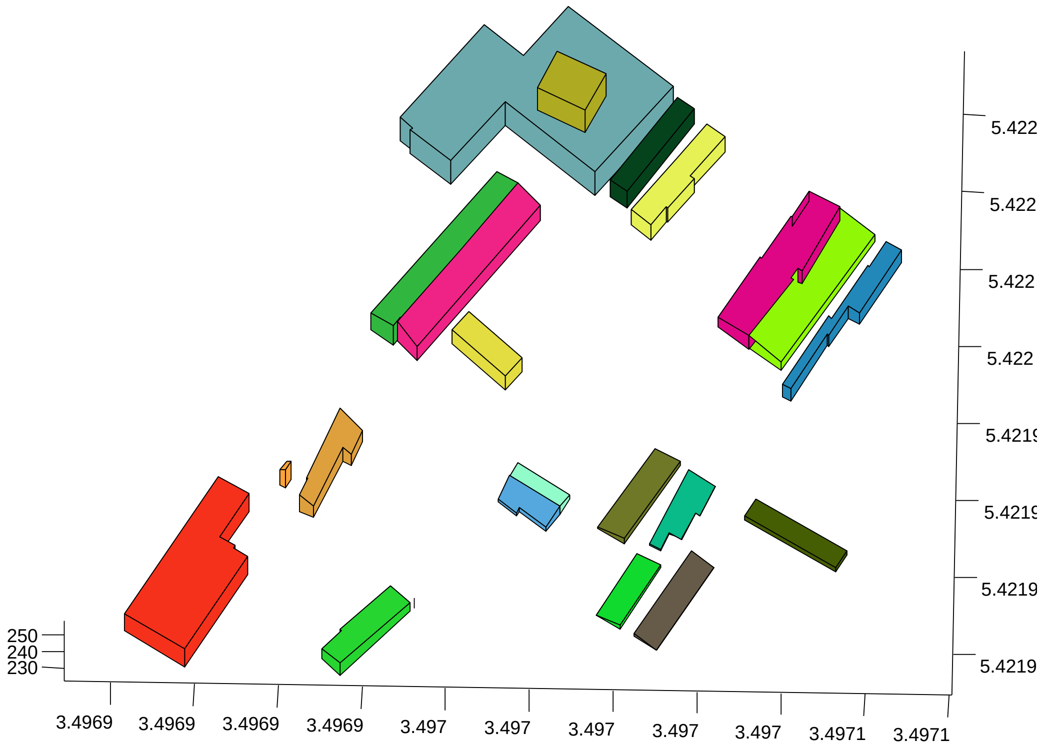

Fig. 4. Final building models for ALTM data. Shades are used only to distinguish different planes. Easting and Northing in $10^6 m$ units. Altitude in m units.

Table 1
Accuracy indices for ALTM data

Accuracy index	Mean value	Standard error
Corner distance	$2.14m$	$0.22m$
Area difference	0.14	0.02
Perimeter difference	0.07	0.02
Area overlap	0.82%	0.03%
Area extralap	0.07%	0.03%

are shown in Table 1. The slope indices are not computed in absence of the ground truth.

The result shown in Figure 5 is for the simulated data obtained from an altitude of 500m with scan angle 20° and the data density of 8 points/m^2. The building models generated from 45 data sets are compared with their truth (the parameters of buildings used for simulating the data) using the accuracy indices proposed above. The extracted building models (shown in Figure 5) and their accuracy analysis indicate satisfactory performance.

Detailed discussion on accuracy analysis and effect of three chosen parameters

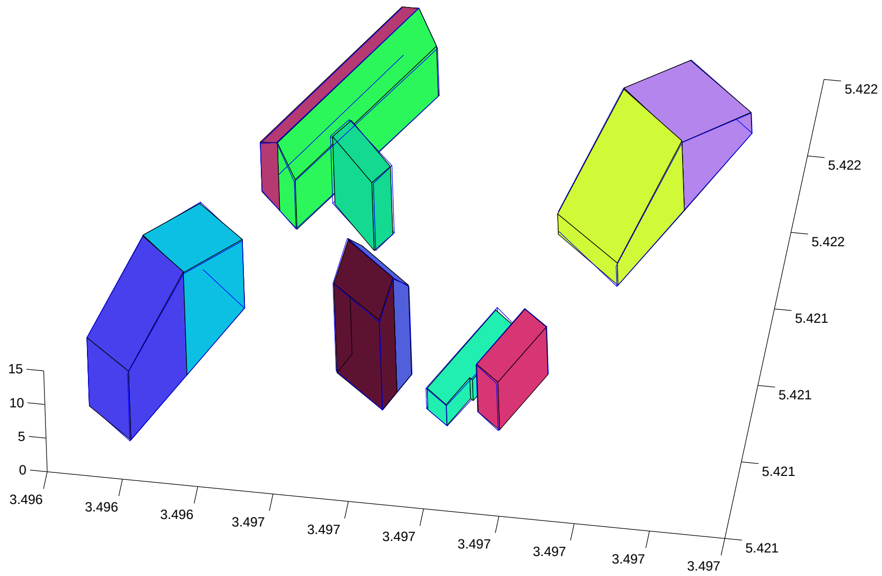

Fig. 5. Final building models for simulated data. Shades are used only to distinguish different planes. Easting and Northing in $10^6 m$ units. Altitude in m units.

on building identification accuracy is being presented in (Lohani and Singh., 2007). The main findings indicate that (Figure 6) the flying height and scan angle variation do not affect building identification. However, as seen in Figure 6(c) all accuracies improve with data density.

6 Conclusion

The hough transform based approach with data smoothing and sparsing to reduce the effect of random error is effective in extracting buildings accurately. The building modeling algorithm works satisfactorily and produces a vector model of building for display and other purposes. However, extraction of edge points of building needs further improvement. From accuracy analysis it is clear that building extraction accuracy mainly depends on data density and there is generally no significant improvement after 8 points/m^2. The flying height and scan angle variations do not affect accuracy.

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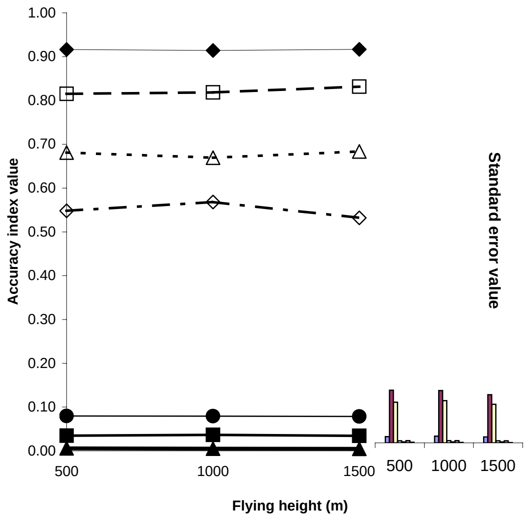
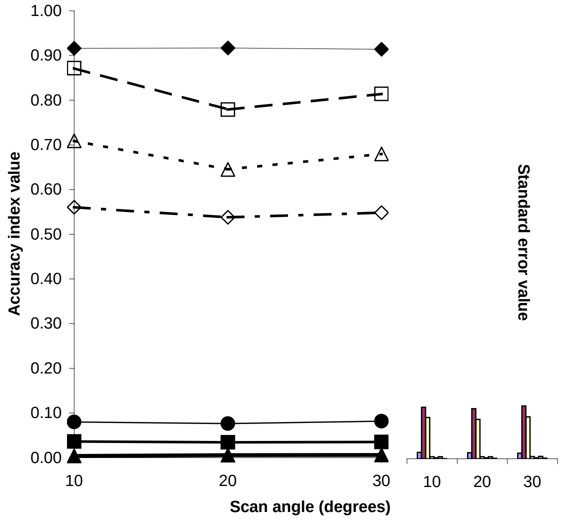
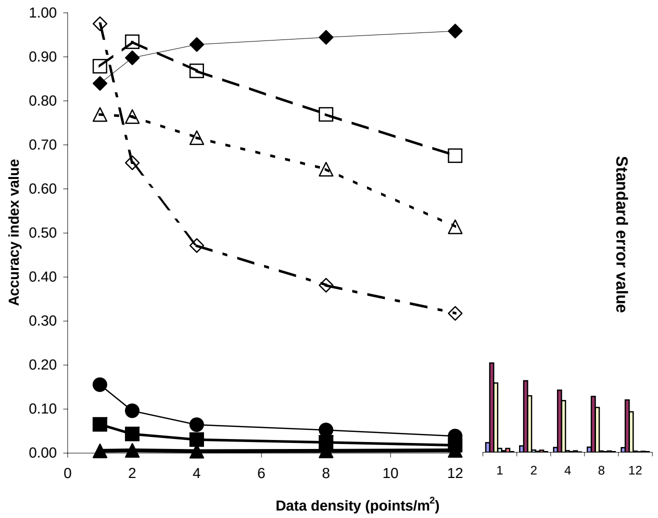


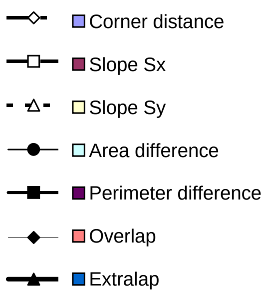
(a) With flying height



(b) With scan angle



(c) With data density



(d) Legend for mean and standard error

Fig. 6. Variation of accuracy indices and their standard error for the variation in one parameter and irrespective of values of other parameters

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