3D Object Tracking from LiDar Point Clouds: A Salience-Based Model

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Abstract—**The main idea of a 3D object tracking depends on analysis of a vector that represents each pixel by direct comparison of pixel intensities and/or positions acquired at different times. In this research, we will describe a moving representation of a 3D object scanned at different time based on both spatial and spectral relationship between corresponding scanned points. This model is used to monitor a rock slide using terrestrial laser scanners (TLS). Terrestrial laser scanning (TLS) generates a high resolution representation of a surface with an accuracy of sub-centimeters, which is considered as a powerful tool for monitoring topography changes. This paper introduces a selective saliency model based on 3D region-features. The edge regions of the original Lidar point cloud are primarily extracted using spectral saliency. Then a region merging process between the different point clouds acquired at different time is performed, resulting in sub-3D object used for further change detection analysis. Subsequently, we introduce a saliency 3D feature model based on entropy analysis of point neighborhoods. These feature descriptors have been used to provide complete information about the amount and directional changes between different points cloud. Experimental results show that our proposed model attains similar performance with direct point to point comparisons (most accurate method) nevertheless it comes with much better execution time.**

Keywords; LiDar point cloud, terrestrial laser scanning (TLS), saliency feature, object tracking.

I. INTRODUCTION `

Nowadays, Light Detection and Ranging (LiDar) is considered as an effective tool in a remote sensing community, since it has a capability to precisely model the 3-D objects. The system provides a tool to generate a huge amount of three dimensional points (cloud points), it ranges from thousands to million points per second. This capability offers a way for better describing a geometrical structure of the 3D objects. The basic idea of Lidar scanners is to measure the distance to a particular object by illuminating its surface with a stream of laser pulses, then measure the round trip time of the returning pulse. The scanner system uses the measured distance of each pulse and the coordinate location of the scanner to transform a laser point's location into real world coordinate (x, y, z) forming what we call a cloud point of the scene. The cloud points are characterized by reliability and high geometric accuracy, but it suffers from irregularity in the spatial domain (non-uniform sampling) and lack of dense. Vast growing on computer technology and parallel processing leads to use Lidar imagery in a large scale, particularly, in the field of Geomatics, geology, environmental modeling, archaeology and remote sensing.

According to the nature of the Lidar scanning system and its capability to precisely model the surrounded, many researchers attempt to use a terrestrial laser scanner (TLS) to monitor the natural and man-made activities. Gordon et al., 2004 used a laser scanner to measure a structure deformation. Gordon and Brian et al., explain how to use Lidar data for monitoring rock falls from steep slopes [1,2]. Abellán et al., study the validity of using TLS to measure a displacement within mill metric magnitude, he concluded that using unprocessed Lidar data failed to measure such displacement on the other hand he reported that applying preprocessing steps leads to successful detection [3]. Xiao aims of his study to automatic to detect the changes in trees height using different date of Lidar dataset [4].

The main objective of this research is to design a general framework not only able to identify the movements in the rock unit but also determine the direction of movements. Automatically, it calculates the amount and direction of the movements by analyzing the cloud point in two different dates. In this study, we use the terrestrial laser scanner (TLS) to model the rock unit. The used scanner is able to acquire over 250 points per square meter resulting in roughly distribution of point cloud in spatial domain. Aswan, Abo-elreish Mountain-Egypt area is selected as a pilot study area in two different dates, 2012, 2014.

To meet the requirements of the automated change detection of Lidar imagery, many challenges come to the scene. Initially, the registration process is mandatory in and between different data set used in change detection procedures. The Lidar data set usually suffer from misalignment due to the duration between different scans, whether condition or even using different scan systems. Secondly, the distribution of

Lidar cloud point is dense in nature, that it is not uniformly distributed in spatial domain. This is because of the coherent nature of laser pulse or, the scanner has different positions and orientation in each scan time. On the other hand, many obstacles may arise in the trajectory of scanning that may have direct effects on modeling the 3-D objects, subjected to further change detection process: power line cables, large trees this is can be shown in figure 2. In summary, identifying the changes in Lidar data is a tricky challenge; as modeling a 3-D object using Lidar scan may not be accurately modeled due to misalignments, obstacles in scan path, and non-uniform distribution of cloud points. All these factors may leads to detect false changes which, should not be considered in the final results.

The rock movement's detection framework proposed in this research includes isolating the rock units from other features such as background, trees and power cables. Then, this isolation procedure should be followed by complementary algorithmsto identify the nature of the changes. In this research, we propose a general model based on image saliency for change detection purpose.

II. Overview of points cloud change detection

Generally speaking, change detection is the process of Monitoring an object or phenomenon at different instant of time. Basically, it involves the ability to enumerate the object changes in terms of geometric structure, direction of changes and sometimes changes in physical properties. In remote sensing community change detection plays an important role in various applications, it's frequently used for the purpose of urban planning, shoreline erosion, growing of forest, assessing damages [5]. Recently, using Lidar Data in the remote sensing field added another aspect to the change detection definition. As the Lidar points cloud possess height information of the objects, it added new applications: structure deformation, monitoring rock falls, landslide, and earthquake effects [6].
We use the following mathematical notations to define the changes between two point clouds. Let Pcl1 and Pcl2 are the two points cloud, in this research, we assume that the two point clouds are perfectly aligned to each other. Each point cloud represents surface model S1 and S2 respectively, we seek to find the continuous regions Ri of point cloud that denotes the difference in space between S1 and S2. The change regions consist of scanned point (x, y, z) exist in one Lidar scan and subjected to positional change in the other scan.
The first step in any change detection algorithm is to preciously align the two cloud points. This issue is beyond the scope of this research, we assume that the two data set is registered to each other. In literature, there are two main categories for comparing points cloud, the first category is a rasterizing process, in which, the point clouds are transformed into Digital Elevation Model DEM via interpolation procedures. Then the two DEMs are directly compared to each other to highlight areas of changes [7, 8]. The second category used for comparison in this research is to use the individual cloud point to directly decide whether those points have been changed during different scans. The huge number of scan points represent an obstacle to complete this task in appropriate time, so many authors use a hierarchal representation of the points cloud to perform point to point comparison. An octree is an example of such representation [9].

III. Salience detection for 3D sparse data

In computer vision, the salience detection is a mechanism to assist viewers to which part of a scene should be paying more attention, especially in complex scenes.
The salience value of a certain point/region indicates how much this point differs from its surrounded. The higher value of salience, leads to more paid attention to this point/region. Accordingly the scene visualization can be improved by calculating salience values in the scene. Moreover, salience could be used as an indicator of visualization goodness.
Recently, salience detection has been used in a large scale in the field of image processing and pattern recognition. Ran Shi et. al. Proposed a new technique based on region diversity maximization to detect salient object [10], Rapantzikos et al. Use a spatiotemporal feature for action recognition [12], also salience detection has been used in image/video compression [13], salient object segmentation [14], image retrieval [15]. On the other hand, many authors have developed algorithms to use salient points for 3D point. Color saliency and spatial salience will be discussed in the following subsections.

A. *Spectral saliency*

The spectral saliency of an object, a pixel, or a region is an indicator by which its pre-attentively distinctive with respect to it's surrounded. It depends mainly the luminance values of different pixels. For the image I the spectral saliency at pixel position (i,j) is defined as a posterior probability as:

$$S_i = \Pr(y_i = 1|F) \quad (1)$$

Where F is the feature matrix that contain feature vectors in a local neighborhood. West et al. provided through their work in object recognition and segmentation several features based on principal component analysis of point neighborhood, that better describe Lidar point could: anisotropy, sphericity, omnivariance, planarity, eigenentropy [16]. These features are calculated from principal components analysis PCA. Hermann Gross enhances the use of these feature descriptors in modeling application [17]. Also, these features have been used for optimal neighborhood selection [18].

B. *Spatial saliency*

Salience map, in order to detect the movement of an object from two different cloud point, we calculate the salience based on point positions to detect movement cues. The spatial saliency of a point/region express "how much it stands out from its surroundings" the used measure is coordinate distance (x, y, z). Our analysis based on the following rule "the spatial distribution of the moved part of an object has more deviation than the fixed part of an object" i.e. the moved object has differing distribution than original one. Accordingly the moving information of each point cloud is calculated based on component entropy [16].

IV. General Framework for Point Cloud Change Detection

To achieve a change detection on Lidar data set, we introduce a general framework to identify the difference between two point clouds. Firstly, we extract the edge region around the relevant object based on spectral (color) saliency. Then, spatial saliency is calculated of only points that possess lower spectral salience value; it only represents the region around the object edge. The amount and direction of change are calculated according to the spatial salience of the edge points. Figure-1 depicts the general framework of the proposed procedures.

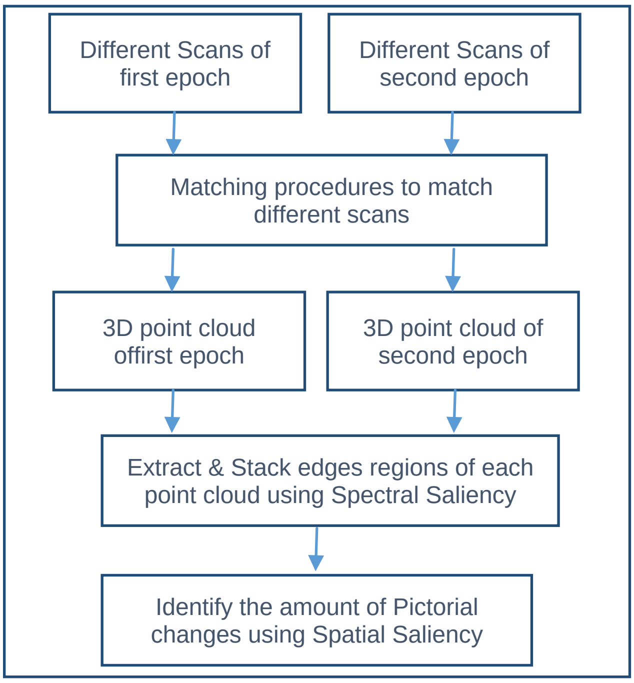

Figure 1. General framework for Identification of Pictorial changes between point clouds

A. Detection of an object edge

After preprocessing step, for each point cloud we compute the spectral salience which is based mainly on the point color information. The spectral salience S_P (color similarity) for each Lidar point Pl_i is calculated with all its neighborhoods, according to:

$$S_P = \frac{1}{m} \sum_{j=1, j \neq i}^{n} \exp(-D_{i,j}) \qquad (2)$$

Where m is number of point neighborhood, $D_{i,j}$ indicates the spectral Euclidean distance between $Pl_i and Pl_j$. Equation-2 shows how much the investigated point differs from its surrounded. The point is assigned to a small value if adequately differ from its neighborhood. The exponential term in equation-1 is considered as a spectral amplification factor, to increase the color difference value in the spectral salient measure.

B. Detection of an object edge

After preprocessing step, for each point cloud we compute the spectral salience which is based mainly on the point color information. The spectral salience S_P (color similarity) for each Lidar point Pl_i is calculated with all its neighborhoods, according to:

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Where m is number of point neighborhood, $D_{i,j}$ indicates the spectral Euclidean distance between $Pl_i and Pl_j$. Equation-3 shows how much the investigated point differs from its surrounded. The point is assigned to a small value if adequately differ from its neighborhood. The exponential term in equation-1 is considered as a spectral amplification factor, to increase the color difference value in the spectral salient measure.

C. Points cloud change detector

In our proposed change detector algorithm, for each point in the Lidar point cloud with lower spectral saliency, the spatial saliency is evaluated (these points only represent the region around the object edge).
The main object of this part, is to calculate the amount and direction of changes by developing a multidirectional approach based on the spatial salience measure, such approach not only introduce the quantity of changes but also provide information about the directional changes between different points cloud acquired at different time.

The edge part of the two point cloud point acquired at different cloud point Pl_1 and Pl_2 are merged together to constitute stacked point cloud $D = Pl_1 \cup Pl_2$. The algorithm begins with analyzing the neighborhoods of each point (N) in Pl_1 with respect to Pl_2, we define the neighborhood as all points from second point cloud Pl_2 , that satisfy the multi directional distance metric (δ) with respect to the candidate point in the first point cloud , Pl_1.

In this study, the component entropy is used as a selected feature to indicate the changes in point cloud, component entropy is described by equation-4

$$H_{\sigma,0}(x) = H_\sigma(V_x \cup \{x\}) \qquad (4)$$

We consider Ch(x) as a factor represents the salience function for measure the quantity and direction of changes.

$$Ch(x) = H(i) - H^*(i) \quad (5)$$

Where, H(i) is the initial component entropy of the candidate point neighborhood, H*(i) is the component entropy after removal the investigated point , which is considered as a baseline estimation.

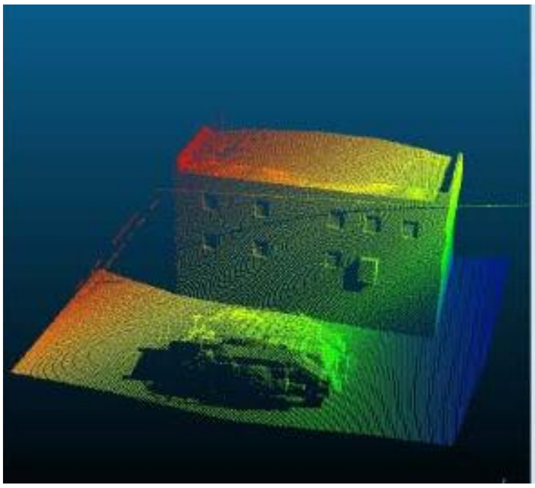
In general, we consider a point that maximizes the change of information within the neighborhood as a changed point. Points will be marked as no change if the salient function provides nearly zero value, and the sign of the salient function indicates the direction of changes.

V. Experimental Results

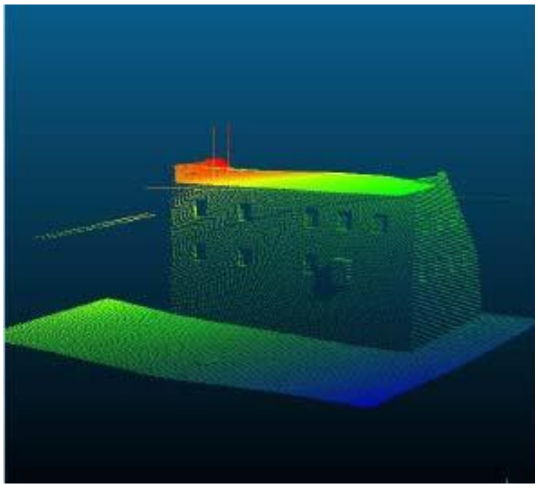
Two experiments are conducted to confirm the cogency of the proposed framework. Start with a simple synthesis LiDAR Data, followed by the more complex real scanned data. The algorithm was used to estimate a displacement/direction vector field between the query and reference images.

A. *Site and event description*

The first data set as shown in Figure (2) was generated by the simulated LiDAR camera [20]. The data information contain both of spatial information (xyz), spectral information (RGB) and camera index (camera frame corresponding to the imaged point). The succeeding data model represents the application of rockfall. Abo el-reish Mountain area is selected to monitor the rock-movement.



(a)



(b)

Figure 2. Example of simulated LiDar Scan data. (a) The LiDar scanned contains a vehicle (b) the vehicle is absent from the reference scan data.

3D Optech ILRIS terrestrial laser scanner is used to collect LiDAR cloud point accompanied with Nikon D700-SLR camera to acquire an RGB image. The scanner operates on (acquisition rate 125000 points/sq. meter with accuracy 0.2 cm at distance of 100m). Figure (3) shows the study area scanned on December 2012 and October 2013.

VI. Point Cloud Preprocessing

The matching process is carried out of individual scans for the same point cloud (in this study each point cloud is formed from four scans taken at different view direction) different scans should have an overlap 20% at least to ensure accurate matching. The matching process is also applied to sequential point cloud taken at different epochs. This enables to quantify the difference between objects. Commercial Software Polyworks has been used to carry out the preprocessing step [21]. The following point summarizes these steps:

A. *Alignment of different scans.*

For the same scene, different scans are aligned to each other, this is achieved by accurately manual selecting common tie points in adjacent scans.

B. *Refinment alignment process.*

To fine tune the manual matching step, an iterative procedure with an Iterative Closest Point (ICP) algorithm is used to minimize the registration errors [19, 22, 23].

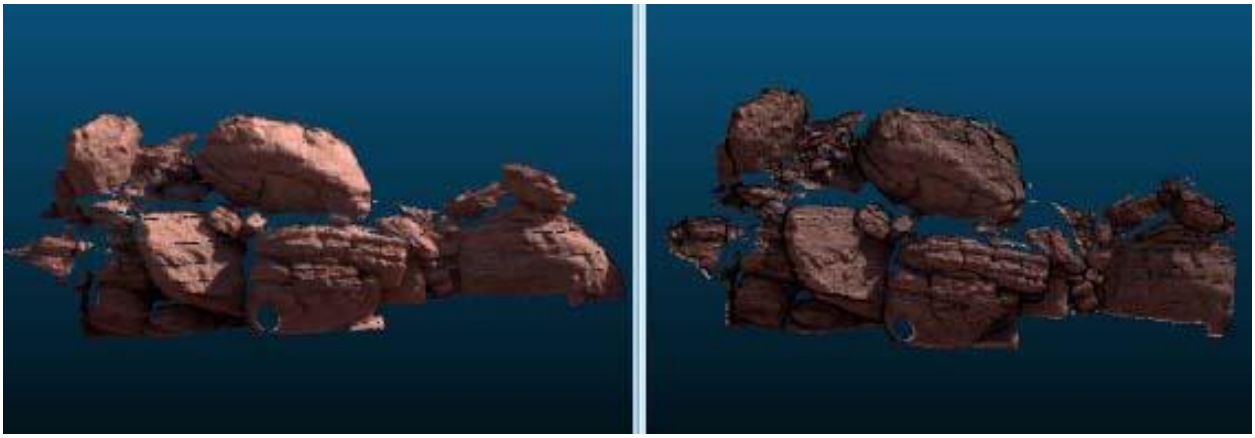


Figure 3. Example real LiDar scan data from the optech ILRIS acquired at different time, this reepresents an extracted section of the original data; due to the scanner position the angular nature affect the rock positions

Figure 4.Photographic image of the study area: part of Aswan area, Egypt

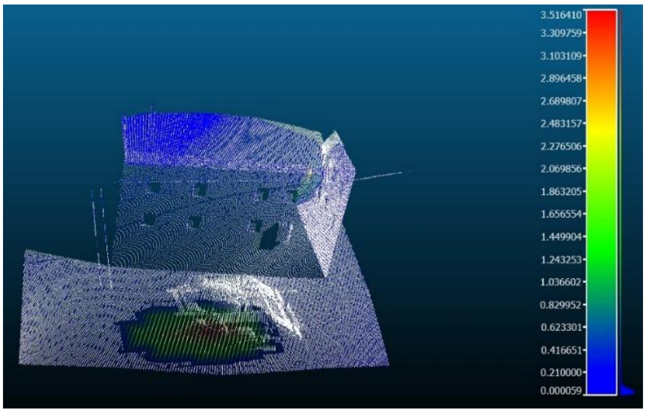
VII. EVALUATION AND DISSUASION

The output results of simulated and real TLS measurements are shown in figures 5 and 6. The values of displacement and direction of movement for each cloud point are represented by different colors. The direction of movement was omitted regardless to the simulated data, since the displacement direction regardless of the vehicle is meaningless. Performance evaluation of proposed algorithm includes comparison with the following two strategies for cloud point change detection.

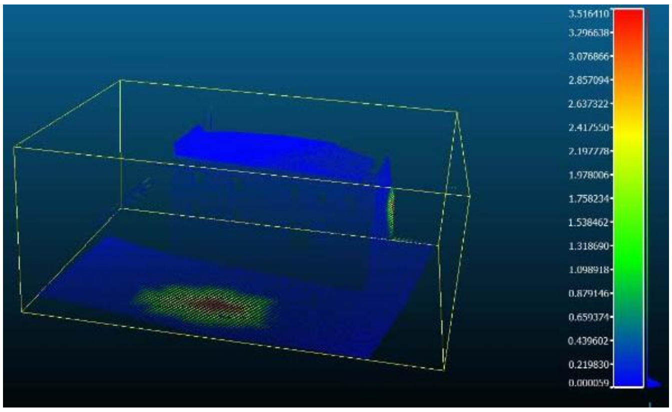
In the first method, the point cloud is reorganized as a hierarchical organization of data using an octree data structure [24]. The change analysis is accomplished by direct node-to-node comparison. It's a method which attempts to isolate different patches of data that possibly differ. On the other hand, the second method inspects the changes between point clouds by examining the shortest distance comparison of each individual point [25]. Hausdorff distance [26] method was used through this strategy, where the distance (D) is measured for each point of a first cloud point to its closest point in the second cloud.

Table I. Accuracy and computation coast comparison

Approach	**Simulated Dataset**		**Real Dataset**	
	Accuracy	Exec. Time (sec.)	Accuracy	Exec. Time (Sec.)
Proposed Method	100%	**0.78(s)**	**85%**	**1.97**
Clustering Approach	100%	1.34(s)	65%	4.693
Minimum Distance Approach	100%	2.67(s)	**85%**	8.6543

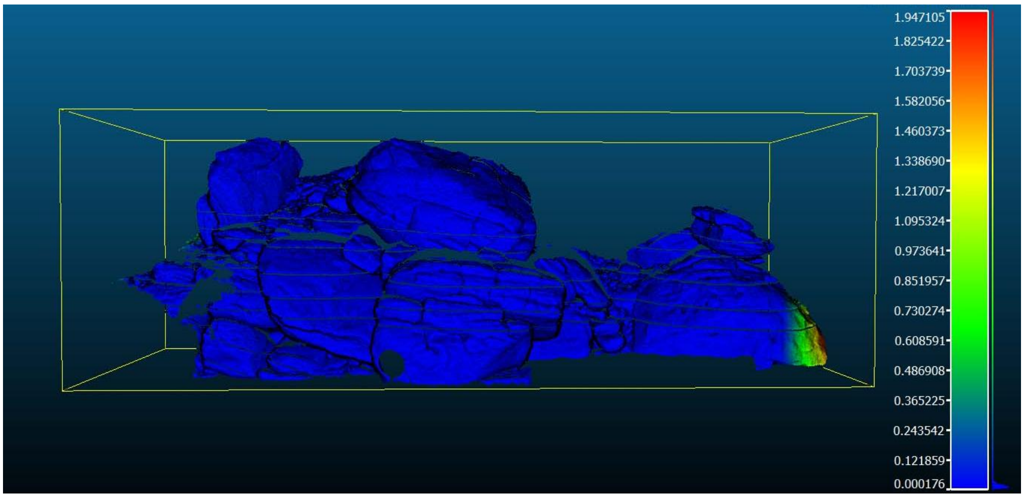


(a)

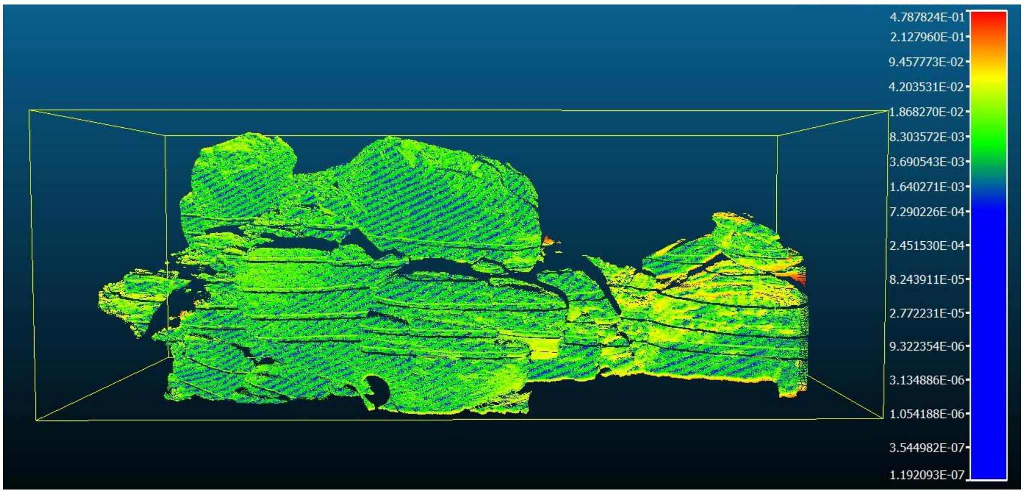


(b)

Figure 5.output point cloud presented in gradient colours, different colour shades represent the directional changes between the different point clouds acquired at different times; ; Reddish and greenish shades dots signify possibly change events, while bluish represent stable actions within resolution cell accuracy (a) the proposed method. (b) Clustering algorithm.



(a)



(b)

Figure 6.Output point cloud presented in gradient colours, different colour shades represent the directional changes between the different point clouds acquired at different times; Reddish shades dots signify possibly Rockall events while bluish and greenish represent stable actions within resolution cell accuracy: (a) proposed method. (b) Clustering algorithm.

The output results of the simulated and real LiDar data set are shown in figures 5 and 6 the different changes are mapped into diverse color. It ranges from blue to red, where bluish represents stable object dynamics, while the reddish signifies the severe changes. As we miss the existence of ground truth information for the real Lidar area, we manually inspect 20 sites to identify whether changes in object positions are correctly identified. With respect to the simulated data, vehicle is detected as changed object in all algorithms, this is expected as this is considered as a simplified example, and on the other hand the proposed method achieved the best execution time. In the real LiDar data, 8 check points has been correctly detected as no change, 3 rock edges are mis-classified as changes and 9 points are correctly classified as movable points. With overall accuracy 85%. The accuracy assessments of different approaches are listed in table 1. The computational time of the proposed algorithm and other strategies are listed in table 1. The results have been made on laptop i7-2.9 Ghz-6 GB Ram. The first scan of the building and vehicle site composed of 185,695 points. The second data set consists of 1,425,866. As shown in table 1, a proposed method and the minimum distance approach achieve similar accuracy. However the minimum distance approach needs much more time.

VIII. CONCLUSIONS

Terrestrial laser imaging provides an efficient way for rockfall monitoring that can be further utilized for function and managing risks. In this paper, we develop a general purpose 3D object movement tracking. The proposed method is based on the saliency model of an input information. The saliency model uses both spectral and spatial information to provide an adequate information about the amount and direction of an object movements. Generally, it provides better performance compared to other methods. The most significant aspect of a proposed model is that the saliency model can handle huge amount of LiDar scan data in appropriate time. The proposed saliency model presented in this research is used to screen failure dynamics within laser resolution limit in some part of Aswan, Egypt area in order to enable hazard monitoring.

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REFERENCES

[1] Gordon, S., Lichti, D., and Stewart, M.: Structural Deformation Measurement using Terrestrial Laser Scanners, in: Proceedings

[2] of 11th International FIG Symposium on Deformation Measurements, Santorini, Greece, 25–28 May 2003, 8 pp., 2003.

[3] Brian D. Collins, Ph.D., P.E., M.ASCE and Greg M. Stock, Ph.D., P.G."Lidar-based rock-fall hazard characterization of cliffs" GeoCongress 2012 © ASCE 2012.

[4] Abellán, A., Jaboyedoff, M., Oppikofer, T., and Vilaplana, J. M.: Detection of millimetric deformation using a terrestrial laser scanner: experiment and application to a rockfall event, Nat. Hazards Earth Syst. Sci., 9, 365-372, doi:10.5194/nhess-9-365-2009, 2009.

[5] Wen Xiao; Sudan Xu; Sander Oude Elberink; George Vosselman "Change detection of trees in urban areas using multi-temporal airborne lidar point clouds" Proc. SPIE Vol. 8532, Remote Sensing of the Ocean, Sea Ice, Coastal Waters, and Large Water Regions 2012, 853207 (19 October 2012); doi: 10.1117/12.974266

[6] ASHBINDU SINGH (1989) Review Article Digital change detection techniques using remotely-sensed data, International Journal of Remote Sensing, 10:6, 989-1003, DOI: 10.1080/01431168908903939

[7] T. Oppikofer, M. Jaboyedoff, L. Blikra, M.-H. Derron, and R. Metzger, "Characterization and monitoring of the A° knes rockslide using terrestrial laser scanning" Nat. Hazards Earth Syst. Sci., 9, 1003–1019, 2009

[8] S.-E. Chen. Laser scanning technology. In J. A. M. Rodriguez, editor, Laser Scanning Technology for Bridge Monitoring. InTech, 2012. ISBN 978-953- 51-0280-9.

[9] D. Girardeau-Montaut, M. Roux, R. Marc, and G. Thibault. Change detection on point cloud data acquired with a ground laser scanner. In International Archives of the Photogrammetry, Remote Sensing, and Spatial Information Sciences, volume XXXVI Pt. 3/W 19, pages 30–35, 2005.

[10] H. H. Chen and T. S. Huang. A survey of construction and manipulation of octrees. In Computer Vision, Graphics, and Image Processing, volume 43, pages 409–431, 1988.

[11] R. Shi, Z. Liu, H. Du, X. Zhang, and L. Shen, "Region diversity maximization for salient object detection," IEEE Signal Process. Lett., vol. 19, no. 4, pp. 215-218, Apr. 2012.

[12] K. Rapantzikos, Y. Avrithis, and S. Kollias, "Dense saliency-based spationtemporal feature points for action recognition," IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2009.

[13] C. Guo and L. Zhang, "A novel multiresolution spatiotemporal saliency detection model and its applications in image and video compression," IEEE Trans. Image Process., vol. 19, no. 1, pp. 185-198, Jan. 2010.

[14] C. Guo and L. Zhang, "A novel multiresolution spatiotemporal saliency detection model and its applications in image and video compression," IEEE Trans. Image Process., vol. 19, no. 1, pp. 185-198, Jan. 2010.

[15] Z. Liu, R. Shi, L. Shen, Y. Xue, K. N. Ngan, and Z. Zhang, "Unsupervised salient object segmentation based on kernel density estimation and two-phase graph cut," IEEE Trans. Multimedia, vol. 14, no. 4, pp. 1275-1289, Aug. 2012.

[16] H. Fu, Z. Chi, and D. Feng, "Attention-driven image interpretation with application to image retrieval," Pattern Recogn., vol. 39, no. 9, pp. 1604-1621, Sep. 2006.

[17] Karen F. West, Brian N. Webb, James R. Lersch, Steven Pothier, Joseph M. Triscari, and A. Evan Iverson, "Context-driven automated target detection in 3D data," in Proceeding of SPIE, Firooz A. Sadjadi, Ed., Bellingham, WA, 2004, SPIE, vol. 5426, pp. 133–143, SPIE.

[18] Hermann Gross and Ulrich Thoennessen, “Extraction of lines from laser point clouds,” in Symposium of ISPRS Commission III Photogrammetric Computer Vision PCV ’06,Wolfgang F¨orstner and Richard Steffen, Eds., G¨ottingen, Germany, 2006, ISPRS, vol. XXXVI-3 of ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, pp. 86–91, Copernicus Publications.

[19] J´erˆomeDemantk´e, Cl´ement Mallet, Nicolas David, and Bruno Vallet, “Dimensionality based scale selection in 3D LIDAR point clouds,” in WG V/3, I/3, I/2, III/2, III/4, VII/7, V/1 ISPRS Workshop Laser Scanning 2011, Derek D. Lichti and Ayman F. Habib, Eds., G¨ottingen, Germany, Aug. 2011, ISPRS, vol. XXXVIII-5/W12 of ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, pp. 97–102.

[20] Besl, P.J., McKay, N.D., 1992. Method for registration of 3-D shapes. Robotics-DL, International Society for Optics and Photonics, pp. 586–606.

[21] http://www.math.tamu.edu/~hielsber/USC/ChangeDetection/MOUT.htm

[22] InnovMetric: PolyWorks: 3-D scanner and 3-D digitizer software from InnovMetric Software Inc., http://www.innovmetric.com/Manufacturing/home.aspx, access: 7 May 2009.

[23] Guarnieri, A., Pirotti, F., Pontin, M., and Vettore, A.: 3-D Surveying for structural analysis applications, edited by: Kahmen, H., and Chrzanowski, A., 3rd IAG / 12th FIG Symposium, Baden, Austria, 22–24 May 2006, 6 pp., 2006.

[24] Teza, G., Galgaro, A., Zaltron, N., and Genevois, R.: Terrestrial laser scanner to detect landslide displacement fields: a new approach, Int. J. Remote Sens., 28, 3425–3446, 2007.

[25] MarjTonini and Antonio Abellan, Rockfall detection from terrestrial LiDAR point clouds: A clustering approach using R”, JOURNAL OF SPATIAL INFORMATION SCIENCE Number 8 (2014), pp. 95–110 doi:10.5311/JOSIS.2014.8.123

[26] T. Oppikofer, M. Jaboyedoff, L. Blikra, M.-H. Derron, and R. Metzger1, “Characterization and monitoring of the Arknes rockslide using terrestrial laser scanning”, Nat. Hazards Earth Syst. Sci., 9, 1003–1019, 2009.

[27] W. Liu, S. Chen, and E. Hauser. Lidar-based bridge structure defect detection.

[28] In Experimental Techniques. Wiley Online Library, 2011.