Fast semi-automated point cloud cleaning

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1 Introduction

The Zamani Project is an initiative aimed towards digitally preserving cultural heritage sites in Africa. This goal is achieved by visiting culturally significant sites and documenting their spatial domain. The end result are highly accurate 3D models of documented sites.

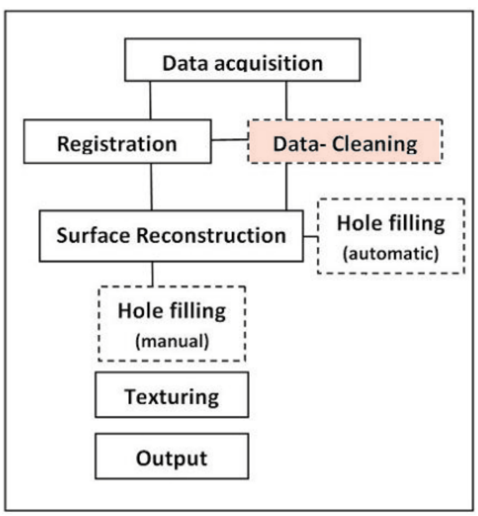

Figure 1: Processing pipeline [6]

The 3D models that are produced is the product of a processing pipeline that starts with data acquisition (see Figure 1) [6]. Laser rage scanners and optical cameras are used to capture the spatial domain. Following this, the point clouds acquired need to be cleaned and registered onto one coordinate space. Cleaning can be performed before or after registration. The surface reconstruction step triangulates the point cloud and produces a geometric model. Missing data or holes can be automatically filled during this step or manually afterwards. Finally, site photography is used to texture the model.

The focus of this project is on the cleaning step of this pipeline. Cleaning involves the removal of unwanted noise from point clouds. Noise can be classified into three categories. Static noise, dynamic noise and instrument noise. Static noise are unwanted objects that do not move. Examples can include vegetation, cars and equipment. Dynamic noise are unwanted objects, such as birds or people, that move through the scan. Instrument noise occurs when part of laser beam hits a near objects and part of it hits a far object. The result is that the average distance of the two objects is recorded.

A typical scan may take an experienced person anywhere between 30 minutes to 2 hours to clean. Given that one requires 500 - 1000 scans to cover a typical heritage site, this stage of the processing pipeline takes a considerable amount of time [6].

In the Zamani project, vegetation is considered to be the most problematic type of noise. The objective of this project is to develop a system to accelerate the removal of vegetation from point clouds.

In the next section shortcomings in existing systems and a overview of related work is presented. The subsequent section will outline the project aims and research questions. Research methods will then be discussed. Finally the project time line will be presented.

2 Background

Point cloud cleaning implies the classification and segmentation of points corresponding to noise. This classification can be performed manually by the user or it can be automated. Various degrees of automation allows users to save time by offloading some aspects of a task to an algorithm. Automation can however compromise accuracy.

In the cultural heritage domain there is a strong emphasis on preserving detail. Every point is considered valuable information. It is thus very important that noise is accurately classified.

2.1 Existing systems

Manual segmentation tools allow users to to achieve the highest degree of accuracy. Lasso selection is one such tool that is available in a number of commercial packages. [3, 2, 9]. It allows the user to draw a two dimensional polygon around points on screen. Unfortunately, hidden points behind the intended selection may be removed accidentally. For this reason it may be tedious to use when noise is hard to isolate. Despite it's shortcomings, lasso selection is currently the primary point cloud cleaning method used by members of the Zamani project. Selection brushes lets the user select points by painting over them with a three dimensional brush. It can give a user more control over which points are removed [3] but is still time consuming.

A limited degree of automated cleaning can be achieved with different families of fill tools. Fill tools recursively add neighbouring points to a selection based on metrics such as distance or intensity [3]. Filling tools are however of little use because they fail to discriminate well between different types of objects. Pointools Edit [3] allows one to perform plane selection. While this tool is undoubtedly useful in many cases, not all selections are planar.

Fully automated segmentation tools are found in many industrial packages. Packages exists that automatically segment a laser range scan into ground points, vegetation and buildings [10, 11, 1]. Vegetation detection in VR Mesh Studio [10] is based on a noise metric. In the heritage domain buildings often exhibit uneven surfaces. Such surfaces can be mistaken for vegetation as is seen in Figure 2.

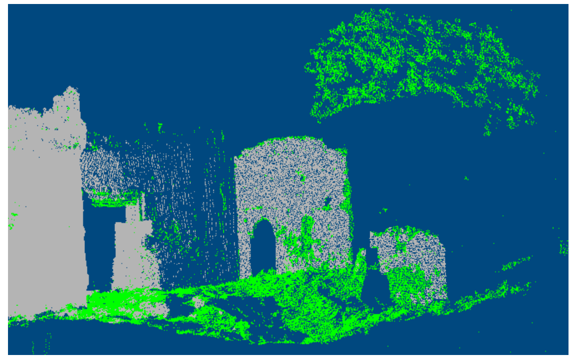

Figure 2: Automated segmentation of vegetation [11]

In 3DReshaper [9] a point clustering approach is used to automatically segment a point cloud. Distinct objects are isolated by looking at the distance between neighbouring points. This approach may be somewhat effective on point clouds with a constant density. However, raw point clouds from laser scans decrease in density as one moves away from the origin. Applying this technique on a raw scan produces large clusters at the origin and increasingly smaller clusters one moves further away (See Figure 3).

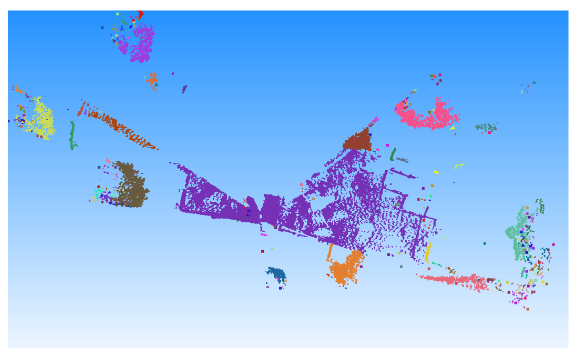

Figure 3: Distance clustering [9]

Meshlab [12], is the only known open source system that provides point cloud cleaning features. It is primarily aimed at processing triangulated meshes. Point cloud editing features were recently introduced

	Segmentation feature			
Package name	Simple	Semi automated	Fully automated	Open source
Terrascan [10]			ground points, vegetation, buildings	✗
Pointools Edit [3]	lasso select rectangle select, ball and cube brush select	floodfill with distance threshold, floodfill based on colour or intensity similarity, plane select		✗
VR Mesh Studio [11]		power lines	ground, vegetation, roofs, planes	✗
Carlson PointCloud [1]			clear isolated and duplicate points, extract bare earth	✗
3D Reshaper [9]	lasso select		clustering with distance metric, clustering colours, remove isolated points	✗
Cyclone [2]	lasso select	floodfill based on smoothness similarity		✗
Meshlab [12]	point picking	plane select	isolated point removal	✓

Table 1: Existing systems

in the form of point picking and plane selection tools. These features are somewhat slow when used on larger point clouds. They are also not sufficient to perform a point cloud cleaning task.

2.2 Related work

Little research is available relating to the cleaning or classification of cultural heritage data. Extensive research have however been conducted in point cloud classification in the context of robot navigation and other domains.

In robot navigation objects need to be identified in real time in order to inform actions. The general approach taken in such a classification task is to use point features to characterize basic surface characteristics. Subsequently machine learning techniques are used to classify points into higher level features. Point features can be far more efficiently calculated than alternative approaches such as model fitting.

Point features are calculated by considering the neighbourhood around a given point. A point normal is probably the most basic point feature. Fast Point Feature Histograms (FPFH) is a more complex point feature that has been shown to discriminate well between basic geometric surfaces [5]. Rusu et al. used FPFHs to train both Conditional Random Fields (CRF) and Support Vector Machines (SVM) to classify basic geometric shapes. The classifiers where tested on a scan taken of a table scene with plates, cutlery and condiments. Different arrangements of the scene had between 70k and 80k points.

Results showed that the CRF took 0.09 seconds to classify a point cloud with 97.36% accuracy while SVM classified the cloud in 1.98 seconds with 89.67% percent accuracy. FPFH in conjunction with CRFs for real time point cleaning of larger clouds seems promising. Cultural heritage data is however likely to exhibit far more noise. Using this unmodified approach to classify noise is not expected to produce acceptable results.

A more involved approach was taken while trying to recognize objects in urban environments. Urban datasets are more similar to the data that one is likely to find in the cultural heritage domain. **?** uses a four step process to recognize objects. Firstly potential locations of objects are identified by looking at point density. Object are then isolated from background noise using graph cuts. To achieve this two cost functions are introduced. The first penalizes neighboring nodes being of a different type while the second cost function penalizes nodes that are far away from the object center. It was shown that this approach is superior to distance clustering. As in [5], a classifier is trained and used to label isolated points. Unlike [5], a feature vector describing the segmented shape is used. Shape features including spin images, shape volume and other features are used to classify objects such as cars and street lights. Contextual features such as the distance of an object from a known feature such as a road is also taken into account.

While recognition of specific objects are of little use

Some success has been achieved in automatically segmenting sites into surfaces and edges through the use of Principle Component Analysis [8]. What makes the segmentation of heritage data hard, is that scanned structures can exhibit very complex geometries that is hard to classify [8].

Approaches Point features Classification of point features Probabilistic Machine learning Heuristics

Approaches: genaral classification of point coulds Aerial scans with markov network [7] City classification [**?**] Sonar [**?**] FPFH [5] [**?**] segment cultural heritage sites Spinas [8] to segment trees Canopy and 3d modeling paper [**?**] Aerial one again [7]

Impementations PCL

A variety of point feature schemes that are used extensively in robotics, could potentially be exploited in the cultural heritage domain. A number of popular point feature algorithms have been implemented and is freely available in the Point Cloud Library [4]. These include Fast Point Feature Histograms, Spin images, Global Fast Point Feature Histogram [4].

Classification can be achieved by though either heuristic schemes [8] or probabilistic models [7, 5]. Approaches based on machine learning have been shown to be effective.

3 Research question

La la

4 Aims (expand)

Why am I doing it?

Inputs, outputs How many points How large do point set become we only deal with small point sets

In collaboration with geomatics

The aim of this research is to produce a system that will allow users to clean cultural heritage data in a fast and effective manner. The focus will be on finding ways to remove the most problematic artefacts as identified by the Zamani project. In descending order of importance, the focus will thus be on removing vegetation, people, and equipment.

Existing point feature schemes will be investigated, as well as heuristic and machine learning approaches to segmentation. In order to ensure fast response times, cleaning methods will be accelerated with OpenCL.

5 Evaluation

Overall:

Performance metrics Total time taken to clean Given cleaning objectives Measure accuracy Perform diff against benchmark scan Compare old vs new Prior training to account for practice effects of leica point cloud Time performance

Each tool Interview : Expert user opinion Sufficient accuracy Confidence information

Remember to try clean out points in scan 1 that was already clean in scan 2.

What about pairwise registration and scanning framework?

Quantitative study (Expert users) Geomatics students Should be experienced

The system will be evaluated in a user study. The speed and accuracy of the existing system will be compared to Zamani's current system [2]. Interviews will also be conducted to assess the usability of the system.

5.1 Milestones

Task	Due date
Research Proposal	June 2012
Point Cloud Cleaning Framework	July 2012
Basic Cleaning Tools	August 2012
Clean Isolated Vegetation	2012
Background Chapter	November 2012
Clean All Vegetation	January 2013
System Design Chapter	February 2013
Implementation Chapter	March 2013
Conference Paper	June 2013
First Thesis Draft	July 2013
Final Draft	August 2013

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