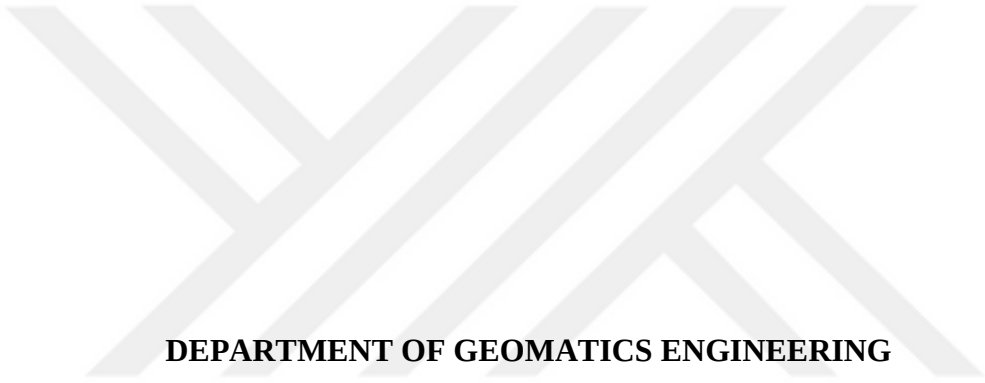


ZONGULDAK BÜLENT ECEVİT UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

STOCHASTIC SURFACE MESH RECONSTRUCTION



DEPARTMENT OF GEOMATICS ENGINEERING

DOCTOR OF PHILOSOPHY THESIS

MUSTAFA ÖZENDİ

NOVEMBER 2018

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GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

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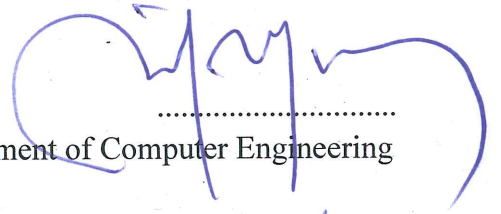
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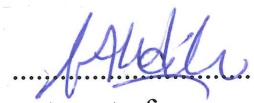
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Mustafa ÖZENDİ

ABSTRACT

Doctor of Philosophy Thesis

STOCHASTIC SURFACE MESH RECONSTRUCTION

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**Zonguldak Bülent Ecevit University
Graduate School of Natural and Applied Sciences
Department of Geomatics Engineering**

Thesis Advisor: Assoc. Prof. Hüseyin TOPAN

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November 2018, 89 pages

This thesis aims at developing a novel methodology for 3D surface mesh generation from Terrestrial Laser Scanners (TLS)-derived point clouds. The methodology has been divided into two main parts. The first part deals with developing a generic and anisotropic point error model, and the following second part is focused on the surface (mesh) reconstruction.

The point error model is capable of computing the magnitude and direction of a priori random errors with regard to direct TLS measurements (vertical and horizontal angle and the range), and it is described in the form of error ellipsoids for each point. A static and repetitive experiment was designed to determine angular precision values. For the determination of the a priori precision of the range observations, a test stand was designed and measured. All the experiments were conducted using three TLSs, namely the Faro Focus 3D X330, the Riegl VZ400 and the Z+F 5010X. Using the test stand measurements, a priori precision for range measurements was modelled as a function of sensor-to-object distance, incidence angle, and surface reflectivity parameters. The error ellipsoid of each point was then computed using the

ABSTRACT (continued)

law of variance-covariance propagation. The validation procedure showed that the proposed point error model works successfully.

The mesh reconstruction method exploits the previously determined error ellipsoids by computing a point-wise quality measure, which takes into account the semi-diagonal axis length of the error ellipsoid. The co-registered point cloud was voxelized, and then managed by the octree data structure. The points with the best quality were selected from the voxelized data in order to use the best data in the subsequent surface mesh reconstruction step. In order to keep the surface resolution versus completeness in appropriate limits, a threshold value was defined for low quality points' elimination. The 3D surface meshes generated from the proposed model outperformed the ones generated from the original point clouds.

Keywords: TLS (Terrestrial Laser Scanner), Range, Incidence Angle, Reflectance, Error Ellipsoid, Anisotropic, Error Model, Variance-Covariance Propagation, Voxel, Octree, Mesh Integration, Surface Generation

Science Code: 616.02.00.

ÖZET

Doktora Tezi

STOKASTİK YÜZEY ÖRGÜSÜ OLUŞTURULMASI

Mustafa ÖZENDİ

Zonguldak Bülent Ecevit Üniversitesi

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Bu çalışmanın amacı YLT cihazı ile üretilen nokta bulutlarından 3B yüzey ağı (mesh) üretilmesi için özgün bir metodolojinin geliştirilmesidir. Bu metodoloji iki ana kısma ayrılmıştır. Birinci kısım genel ve anizotropik nokta hata modeli üretimi ile uğraşırken ikinci kısım yüzey örgü ağı (mesh) oluşturulmasına odaklanmıştır.

Nokta hata modeli, YLT gözlemlerinin öncül rastgele hatalarının hata elipsoidi şeklinde ifade edilmekte ve hatanın hem büyüklüğünü hem de yönünü modelleyebilmektedir. Öncül açısal hassasiyet değerlerinin belirlenebilmesi için sabit bir noktaya kurulan YLT ile tekrarlı ölçüm yapan bir deney tasarlanmıştır. Mesafe ölçümünün öncül hassasiyetinin belirlenmesi için ise bir deney düzeneği tasarlanmıştır ve bu düzenek YLT ile ölçülmüştür. Bütün bu deneyler üç adet farklı YLT ile gerçekleştirilmiştir. Bu YLT'ler Faro Focus3DX300, Riegl VZ400 ve Z+F 5010X tarayıcılarıdır. Mesafe ölçüm hassasiyeti, deney düzeneği taramaları kullanılarak YLT ile nesne arasındaki mesafe, geliş açısı ve yüzey yansıtımı parametrelerinin bir fonksiyonu olarak modellenmiştir. Daha sonar her noktaya ait hata elipsoidi hataların dağılımı yasası

kullanılarak hesaplanmıştır. Doğrulama aşamasında geliştirilen bu nokta hata modelinin başarılı sonuçlar verdiği gösterilmiştir.

Örgü ağı (mesh) oluşturulmasının ilk adımı nokta bazlı kalite ölçütünün hesaplanmasıdır ki bu ölçüt hata elipsoidinin yarı-köşegen uzunluğudur. Daha sonra, birleştirilmiş nokta bulutu sekizli ağaç yapısı altında yönetilen hacimsel elemanlara (voxel) ayrılmıştır. Gereksiz noktalar her hacimsel eleman için en kaliteli nota seçimi ile çıkarılmıştır. Bu yöntemin gereksiz noktaları uygun bir biçimde çıkarmadığı için ayrıca bir de eşik değeri tanımlaması yapılmıştır. Bu şekilde yeni elde edilen nokta bulutundan üretilen 3B yüzey ağının (mesh) original nokta bulutu ile elde edilen 3B yüzey ağından (mesh) çok daha kaliteli olduğu gözlemlenmiştir.

Anahtar Kelimeler: YLT (Yersel Lazer Tarama), mesafe, geliş açısı, yansıtım, hata elipsoidi, anizotropik, hata modeli, variance-kovaryans dağılımı, voksel, sekizli ağaç, örgü entegrasyonu, yüzey oluşturma

Bilim Kodu: 616.02.00.

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LIST OF SYMBOLS AND ABBREVIATIONS

SYMBOLS

$(P_1, P_2, P_3, P_4, P_5)$	: Scanner positions
(X, Y, Z)	: Cartesian coordinates of a point
ρ	: Range
α	: Vertical angle
θ	: Horizontal angle
c_l	: Speed of light in vacuum
Δt	: Travel time of laser pulse
$\Delta\phi$	: Phase shift
f	: Frequency of sine wave
$[x_i \ y_i \ z_i]^T$	: Cartesian coordinates of i-th point
$r_i = [\rho_i \ \alpha_i \ \theta_i]^T$	: Spherical coordinates of i-th point
$p_{i,j}$	: The point addressed with i-th row and j-th column
S_p	: Neighboring valid points
$\vec{n}$	: Local surface normal
γ	: Incidence angle
$\vec{l}$	: Laser beam vector
$\bar{p}$	: Centroid of V_p
C	: Covariance matrix
$\vec{v}_j$	: Eigenvector of C
λ_j	: Eigen values of C
p_{TLS}	: TLS stand point
Σ_{rr}	: A priori covariance matrix of a point in spherical coordinate system
$(\sigma_p^2, \sigma_\alpha^2, \sigma_\theta^2)$	: A priori variances of range, vertical angle and horizontal angle
Σ_{xx}	: Covariance matrix of a point in Cartesian coordinate system
J_{xr}	: Jacobian matrix
$\lambda = [\lambda_1, \lambda_2, \lambda_3]$	: Eigenvalues of Σ_{xx}

LIST OF SYMBOLS AND ABBREVIATIONS (continued)

$z = [z_1 \ z_2 \ z_3]$	: Eigenvectors of Σ_{xx}
$(\sqrt{\lambda_1}, \sqrt{\lambda_2}, \sqrt{\lambda_3})$	: Dimensions of semi-axes of the error ellipsoid
$\vec{I}$	: Unit vector
$(\sigma_\rho, \sigma_\alpha, \sigma_\theta)$	: A priori precision values of range, vertical angle and horizontal angle
A, B, C, D	: Plane coefficients
d_i	: Off-plane distance of a point I
m	: Empirical a priori precision of the range measurement
a, b, c, d	: Scanner parameters
e	: Constant distance accuracy provided by the manufacturer
m_{90}^w	: RMSE of the off-plane distances for white plate at 90m
m_{10}^w	: RMSE of the off-plane distances for white plate at 10m
m_{90}^b	: RMSE of the off-plane distances for black plate at 90m
m_{10}^b	: RMSE of the off-plane distances for black plate at 10m
I	: Reflectance value
I_T^b	: Reflectance threshold
I_{90m}^b	: Average reflectance value of black plate at 90m
I_{10m}^b	: Average reflectance value of black plate at 10m
Q_{p_i}	: Quality measure of a point
V	: Voxel space
v_i	: i-th voxel

ABBREVIATIONS

ALS	: Aerial Laser Scanner
FEM	: Finite Element Model
FOV	: Field of View
ICP	: Iterative Closest Point
IVIA	: IMAGO Volumetric Integration Algorithm
MAT	: Medial Axis Transform
PCA	: Principal Component Analysis
POI	: Point of Interest
SDF	: Signed Distance Function

LIST OF SYMBOLS AND ABBREVIATIONS (continued)

TLS	: Terrestrial Laser Scanner
VRIP	: Volumetric Range Image Processing
3D	: Three Dimensional





CHAPTER 1

INTRODUCTION

1.1 MOTIVATION

In the last a few decades, developments in electronics and optics have made it possible to produce affordable, accurate and high resolution Terrestrial Laser Scanners (TLS). Also, these developments have led cost-efficient processing of dense point cloud data both in terms of field-work and office-work time. Such possibilities have made the TLS technology a feasible tool for innumerable applications in fields such as 3D modelling of objects, deformation monitoring, object recognition, segmentation, forestry, architectural planning, preservation of cultural heritage and reverse engineering. Among them, 3D modelling is of great importance. Once the seamless and watertight 3D model is created, many further applications can be realized. 3D modelling is an active field of the research in which scientists from photogrammetry, remote sensing, computer vision and computer graphics carry out extensive studies.

3D model generation methods are generally classified into two major categories on the basis of sensor type - either active sensors such as laser scanners, or passive sensor such as digital cameras (Remondino and El-Hakim 2006). Active sensor-based 3D modelling methods are categorized as involving Triangulation- or Time Delay-based methods as shown in Figure 1.1.

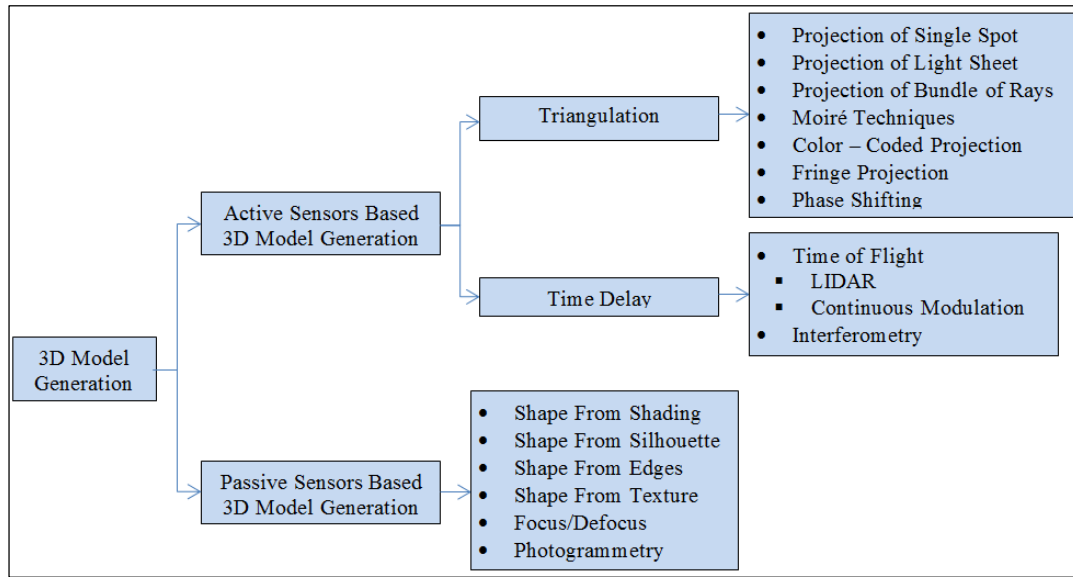


Figure 1.1 Classification of 3D model generation methods by Remondino and El-Hakim (2006).

Another classification scheme is proposed by Vosselman and Maas (2011). In this study, optical 3D measurement techniques are classified into two major categories: Triangulation- and Light-based methods. Triangulation methods are divided in two types: passive systems, based on stereo image processing, and active methods based on light sheet or strip projection methods. TLSs are in the category of Light-based measurement techniques. This measurement can be performed by directly measuring the travel time of the laser pulse, or by the phase measurement of continuous waves of the laser beam. This classification is depicted below in Figure 1.2.

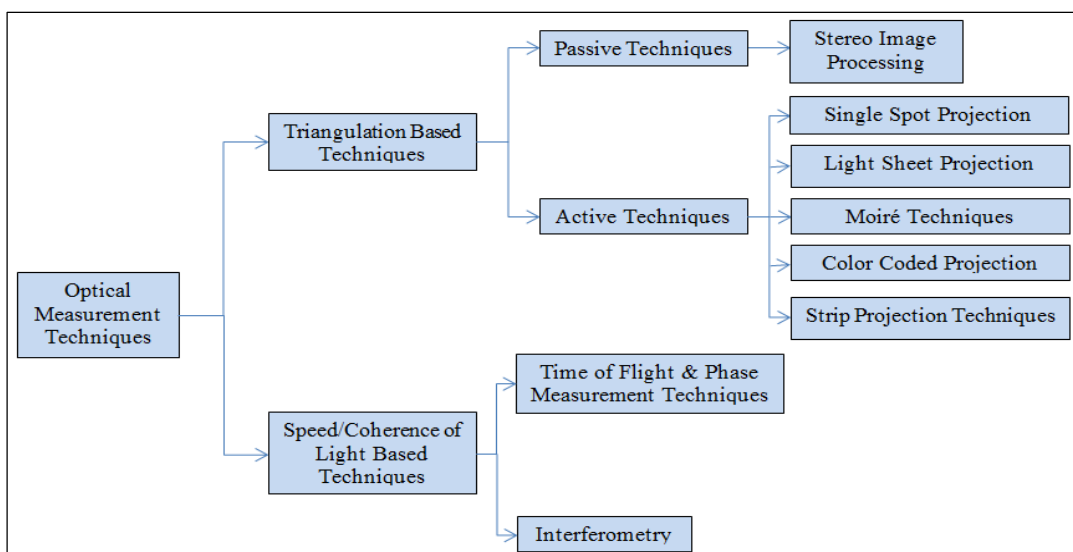
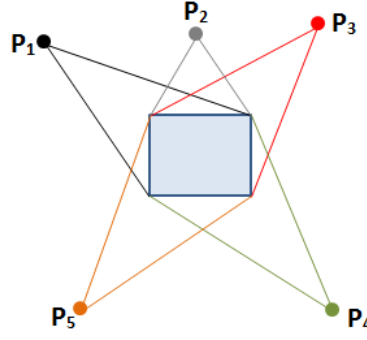


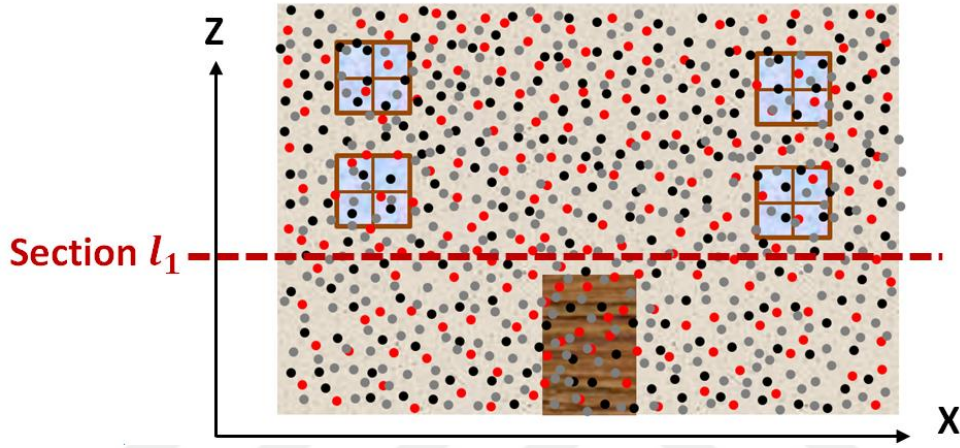
Figure 1.2 Classification scheme of Vosselman and Maas (2011).

The 3D model of an object should be complete, geometrically accurate, noise- and error-free (Wheeler et al. 1998). Due to the fact that a single scan will not fully capture the entire geometry of an object, it has to be scanned from multiple viewpoints, where successive scans overlap in a certain ratio. Consequently, it will be possible to model the entire surface of the object. The 3D model generation pipeline is composed of the following steps: data acquisition, co-registration, mesh reconstruction and geometric model building. In the data acquisition step, a target object or scene must be scanned from various viewpoints to be able to obtain full coverage of the object's surface. Each individual scan is described through the use of different local coordinate systems. These scans need to be aligned into a common coordinate system using the process known as co-registration. Up to the present time, many methods have been developed for point cloud co-registration. The most common co-registration approach is the Iterative Closest Point (ICP) (Besl and McKay 1992, Chen and Medioni 1992 and Zhang, 1994). There exist several variants and improvements (Akca and Gruen 2005). For a comprehensive survey on the subject, the reader is referred to Gruen and Akca (2005) and Tam et al. (2013). The mesh reconstruction step follows the co-registration step. In this step, multiple scans of the object have to be combined and assembled into a single description of the entire surface in a unique coordinate system. As the final step of the pipeline, a 3D model of the object can be generated with or without texture, depending on the user requirements. Projects conducted by Levoy et al. (2000), Bernardini et al. (2002), Ikeuchi et al. (2003) and Akca (2012) provide us with useful examples of a complete 3D reconstruction pipeline.

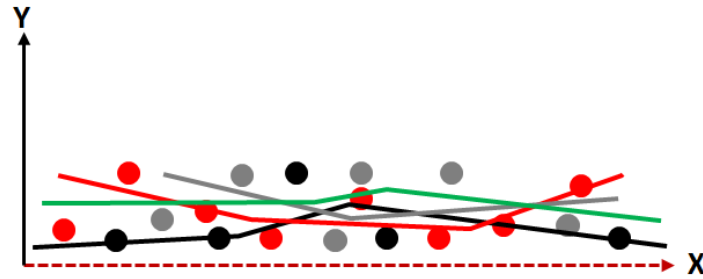
After the co-registration step, all scans of the target object or scene are aligned into a common coordinate system. Even though these scans are part of the same coordinate system, generating a single and entire 3D model of the target object is not possible using these standalone scans. The process which combines multiple observations (scans) and creates a single unified surface model, is referred to as mesh reconstruction. The mesh reconstruction process can be illustrated as in Figure 1.3. The geometry of the target object or scene is described by means of a point cloud which is composed of multiple individual scans. At this point, the question arises "Which points have to be used for mesh generation?" This thesis work will answer this question by combining multiple scans into an integrated point cloud and selecting the points in high quality among them. This derived point cloud is used for 3D surface mesh generation.



a) Top view of the scanning plan.



b) Co-registered Point Clouds From P_1 , P_2 , and P_3



c) Choosing Appropriate Points for Mesh Generation

Figure 1.3 Continued Mesh reconstruction illustration. The target object is scanned from five viewpoints (P_1 , P_2 , P_3 , P_4 , P_5) for full coverage. (a) After co-registration, the surface of the target object is described by scans obtained from P_1 (black points), P_2 (gray points), P_3 (red points). (b) Cross-section of l_1 and small portion of P_1 , P_2 , P_3 (c) where black, gray and red lines represent meshes generated from point clouds P_1 , P_2 , P_3 respectively, and the green line represents the consensus mesh (i.e. the mesh generated from the most appropriate points).

This process is considered as being a difficult problem due to the noisy nature of the scan data and holes (Bernardini and Rushmeier 2002). Mesh reconstruction plays an important role in

geospatial applications, computer vision and computer graphics' communities because the unified surface model, which is the output of the mesh reconstruction step, can be used as the resultant 3D model of the object of interest.

Terrestrial Laser Scanners (TLSs) have the advantage of fast data acquisition with large spatial coverage and high spatial resolution. These advantages make the TLSs a major 3D data acquisition tool for surface reconstruction tasks. The quality of a scan point depends on both sensor space and object space parameters such as the operating principle of the hardware, atmospheric conditions, and the properties of target object reflectivity and scanning geometry. Similar to all other measurement techniques, TLS measurements are subject to random errors. These errors propagate through the steps of data processing, namely pre-processing, co-registration, mesh reconstruction and 3D model generation. For this reason, the investigation of the random error pattern of each individual point is essentially important for the validation of 3D surface meshes generated from TLS-derived point clouds.

In practice, the target object has to be scanned from multiple standpoints to ensure full coverage. Such a scanning configuration will result in a certain degree of overlap between consecutive scans. In this case, some parts of the target object will be sampled by more than one point cloud that will have different random error patterns or positional uncertainties. Moreover, the TLS-derived data is very noisy. These facts make the 3D surface generation from TLS-derived data a challenging task. Nowadays, the most common solution with regard to this problem is subsampling the data and then generating the 3D surface mesh. This solution manipulates the data set and does not take the random error of individual points into account. However, the random error characteristic of each individual point is unique. While the random error of some points is very small, some other points may have huge random errors in terms of magnitude, and such points should be neglected when it comes to further processing. Such an approach will yield 3D models with minimum random error and less noise. Motivated by this aspect, we are aiming to accomplish the following objectives:

1. The investigation of the most significant random error sources for TLS-derived point clouds,
2. The development of a practical and generic point error model for TLS-derived data,
3. The development of a stochastic mesh reconstruction method based on the developed point error model.

1.2 OVERVIEW OF THE THESIS CONTENT

Chapter 2 provides a comprehensive review of the literature on point error models and mesh generation methods. The literature review in terms of surface mesh reconstruction has been divided into four main groups. Moreover, the surface mesh related studies performed by the photogrammetry and remote sensing community have also been investigated in Section 2.2.5.

Chapter 3 starts with explanations related to basic equations of TLS-derived point cloud data. The essentials include observations of TLS, the data structure of TLS-derived point clouds, and the method used for local surface and incidence angle estimation. The second part of Chapter 3 introduces the developed anisotropic point error model in detail. The point error model requires the determination of a priori precision values. The determination of these values is explained comprehensively in Section 3.3. Chapter 3 ends with a validation of the proposed point error model.

Chapter 4 tackles the mesh reconstruction problem. At first, a quality measure is defined for TLS-derived points. Secondly, the voxelization of co-registered point clouds is covered, and the selection of the best quality points is introduced in Section 4.2. At the end of this chapter, the experimental study which covers the entire workflow is described in detail.

The last chapter contains concluding remarks. Finally, the limitations of the research and improvement strategies are mentioned in the last section of the thesis.

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CHAPTER 2

REVIEW OF PREVIOUS WORK

2.1 RELATED WORK ON THE POINT ERROR MODEL

As is the case in other measurement techniques, TLS measurements are contaminated with the appearance of both random and systematic errors and also the outliers. The systematic errors are eliminated by proper design of the hardware and/or appropriate calibration procedures in today's technological level. Thus, they are out of the scope of this thesis.

The random error of a point measured by TLS depends on the hardware design, the scanning geometry, the surface properties, the atmospheric conditions and the environment. Specifically, angular (mechanical) stability, sensor-to object distance, incidence angle of the incoming laser beam, and surface reflectivity are the most significant causes of error. The surface reflectivity and imperviousness are very important characteristics. The laser light may penetrate to some kind of surfaces, such as marble (Godin et al. 2001, Akca et al. 2006a).

These facts result in a heteroscedastic (point dependent), anisotropic and inhomogeneous point error distribution (Matei and Meer 1999, Ohta and Kanatani 1998, Williams et al. 1999). The anisotropic error nature of TLS sensors implies that the error distribution for each individual point is different. This characteristic of scanners is simulated by Williams et al. (1999) using the Monte Carlo simulation technique and is depicted in Figure 2.1.

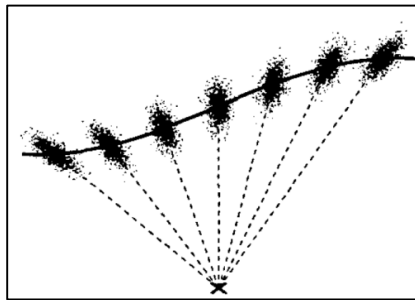


Figure 2.1 Error distribution of a laser scanner over the line of sight. The solid line represents the true surface and X represents the viewpoint of laser scanner. Adopted from Williams et al. 1999).

The error distribution is elliptical where the major axis is aligned with the line of sight direction as shown by Figure 2.1. This is because the error in this direction is greater than the directional error.

The basic TLS observations are the range (i.e. the sensor-to-object distance), and the horizontal and vertical angles. In addition, TLSs can measure the amplitude of the reflected laser beam (the so called intensity) which is a quantity of the reflectivity of the object surface. The precision of the range measurement was theoretically approximated by Hebert and Krotkov (1992) taking into account the physical, optical and electronic characteristics of the sensor, and the reflectivity of the observed scene. It was shown that this model is not sufficiently accurate in practice (Young Min et al. 2008). An additive error model was presented in Williams et al. (1999) to improve the co-registration quality by means of the covariance matrix of points. Another covariance matrix-based anisotropic error model was developed for a commercial structured light system which uses the photogrammetric collinearity equations in point positioning (Guehring 2001). While the error model proposed by Okatani and Deguchi (2002) fundamentally considers the range measurement error, it omits angular measurement errors. In this model the scan data was smoothed depending on the variance of each point. A similar approach was used in Sagawa et al. (2002) to refine data iteratively, similar to the ICP algorithm. This approach was further improved in estimating the degree of uncertainty by relating the ranging precision and the amplitude of the reflected light (Sagawa et al. 2005b, Sagawa et al. 2006). For stochastic modelling, precision values provided by the manufacturer can be used to compute the covariance matrix of each point (Scaioni 2012). However, such an approach will not yield a point-dependent error model because each point will have the same value. Moreover, the incidence angle and the surface reflectivity parameters are not considered in this method. In Bae et al. (2009), the effect of the incidence angle on the ranging precision was reported. This approach can hardly be implemented in practice due to its complexity.

The incidence angle of the incoming laser beam has a significant effect on range precision. This effect can be quantified as the cosine of the incidence angle as reported in Soudarissanane et al. (2011). This formulation was advanced in order to compute point-wise covariance matrices, provided that the manufacturer's precision values are available (Grant et al. 2012). Moreover, the same formulation can be used in surface reconstruction-related studies (Baselgia et al. 2014). The point cloud precision was alternatively evaluated by means of the error ellipsoids (Chen et al. 2015, Chen et al. 2016). Schaer et al. (2007) extended the state-of-the-art

computations so that the effect of a laser spot (foot print) was considered in addition to the manufacturer-provided precision numbers and the incident angle. However, the reflectivity of the object surface and the linearity error of range were not included in the computations. Mezian et al. (2016) developed a positional uncertainty model specifically for mobile terrestrial LiDAR sensors. Their model estimates the error ellipsoids of each point using the manufacturer-provided precision numbers, while neglecting the effects of the incidence angle and the surface reflectivity. In a recent study, the precision of the distance measurement of a Z+F Imager 5006 TLS was stochastically modelled using raw intensity values (Wujanz et al. 2017). However, this model cannot be used for TLSs for which the manufacturers do not provide the raw intensity values.

This large number of studies show the relevance of the problem. A fully satisfying solution, which mathematically formulates the physical nature of the instrumental and environmental errors, has still to be designed, realized and justified. This work presents a generic and anisotropic point error model which is capable of computing the magnitude and direction of a priori random errors, described in the form of error ellipsoids, which are associated with every individual point of the cloud. Unlike the aforementioned studies, the proposed point error model includes a priori precision values in terms of range and angular (horizontal and vertical) observations. In addition, a mathematical model was developed for the range precision taking into account the most falsifying parameters, namely the distance between the TLS and the target object, the incidence angle of the incoming laser beam and the surface reflectivity.

2.2 RELATED WORK ON MESH RECONSTRUCTION

The surface mesh reconstruction problem is an active research area where there are numerous studies mostly from the computer vision and the computer graphics communities. In the literature, developed methodologies are categorized based on two main criteria. The first criteria is based on the structure of the input data, i.e. mesh reconstruction from unorganized points and organized points (Khatamian and Arabnia 2016, Berger et al. 2016) as shown in Figure 2.2.

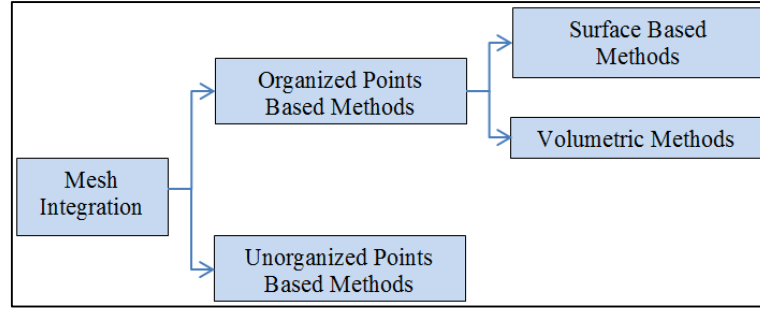


Figure 2.2 Categorization scheme of mesh reconstruction methods depending on the type of the input data.

On the other hand, the second criteria classifies mesh reconstruction approaches based on the type of assumption and approach (Bernardini and Rushmeier 2002, Junior et al. 2012). This classification categorizes meshing approaches into Delaunay-Based, Surface-Based, Parametric Surfaces-Based and Volumetric Methods groups as represented in Figure 2.3.

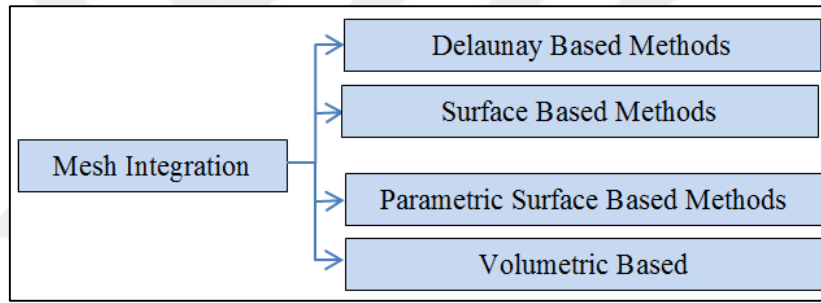


Figure 2.3 Meshing methods classified based on integration approach.

In the following sub-chapters, we will elaborate the state-of-the-art works of this second group.

2.2.1 Delaunay - Based Methods

Delaunay-based methods use unorganized point clouds as an input, allowing a Delaunay complex to be established. Such a complex is composed of the entire data and provides connectivity information with regard to the points. The integrated surface can then be extracted from this complex by sculpting. A good review of these methods is presented in Edelsbrunner (1998). Subcomplexes of the Delaunay triangulation of the point set are called alpha-shapes, and can be used for reconstruction (Bernardini et al. 1999a). Amenta et al. (2001) described a method which approximates the Medial Axis Transform (MAT) using union balls. This new MAT is then used for defining the object surface as a new piecewise-linear approximation referred to as a power crust. A similar yet improved method is suggested by Kolluri et al. (2004)

and is referred to as eigencrusts. This method differs from others by introducing spectral partitioning and the normalized cuts method and aims to create a watertight surface. Another watertight surface construction algorithm entitled cocones is proposed in Dey and Goswami (2003).

Mesh reconstruction can also be considered as a data clustering problem. Zhou and Liu (2008) have conducted experiments on the integration of point clouds by means of clustering. They developed a framework based on k-means clustering. They detected corresponding points between overlapping registered range images using a k-means clustering algorithm. They then minimized the dissimilarity between the original corresponding points and their integrated ones. The integrated point set is triangulated using the Delaunay method described in Dey and Goswami (2003). Zhou et al. (2009) improved this method by introducing adaptive segmentation, surface classification and c-means clustering. In these clustering-based works it is reported that accumulative registration errors and scanning noise can be reduced.

2.2.2 Surface-Based Methods

Surface-based methods take the surfaces of each scan or partial surfaces of the target object or scene as input. As a result of integration, a single triangular mesh (or surface) is reconstructed which defines the target object or scene.

After generating a 3D description of surfaces, Rutishauser et al. (1994) applied mutual approximation on overlapping portions of surface descriptions in order to reduce the measurement error, and then followed this by retriangulation which yields the final integrated model. Moreover, the integration method is supported by an anisotropic Gaussian error model. Turk and Levoy (1994) proposed a method which integrates meshes incrementally. This method first detects and then removes overlapping portions, followed by clipping one mesh using another as reference, and then it zippers along the clipped boundaries. Finally, a consensus surface is found by means of weighted averaging in the direction of surface normal. The error in the registration of the range images propagates through the final model of the object. However, an approach aimed at registering range images simultaneously, may minimize the error (Shum et al. 1995). In this study, range images are registered simultaneously using Principal Component Analysis (PCA) with missing data. This is considered to be a weighted least squares minimization problem. Soucy and Laurendeau (1992a, 1992b, 1995) described an

integration method which also aims to model the non-redundant surfaces of free-form objects. This method first detects overlapping areas using canonic subsets of the Venn diagrams, followed by resampling, averaging and merging. A similar approach is presented in Pito (1996) which employs co-measurements for integration purposes. Co-measurements are defined as triangles that have sampled the same region of the object from each viewpoint. For integration purposes, co-measurements that have the highest confidence value are used. The confidence value is calculated for each vertex, and an average is used for individual triangles. Redundant triangles are removed, and the neighborhood relationship is defined for the remaining triangles. The gaps between these triangles are filled by retriangulation. To ensure the fidelity of the final model, the determination of the inlier and outlier observations is a significant process. Masuda et al. (1996) first determines inliers and outliers, and the registration and geometric model generation is then performed, employing only reliable points. Finally, each new scan is integrated on it by simply averaging, as proposed in Chen and Medioni (1991). In order to generate a smooth surface without any loss of detail, Dorai et al. (1998) have proposed a weighted averaging algorithm for the integration of pairwise range images. This algorithm first defines a plane for the overlapping portions of range images to the Z axis, followed by an intersection of the same curves on the surfaces of this plane. After intersection, the weighted average is computed for the same curve pairs and assigned as an integrated point. Since the weighted average is computed, the resulting model yields smooth surfaces. Otherwise, joining parts would yield rougher surfaces.

A novel region growing algorithm entitled the Ball-Pivoting algorithm was presented by Bernardini et al. (1999b). This algorithm constructs an interpolating triangulation incrementally. It first finds a seed triangle which is touched by a ball of a certain radius. It then pivots the ball and adds triangles to the seed triangle. Another incremental integration method is described in Sappa and Garcia (2000). This method detects the overlapping portions of the range images that are to be merged. When the overlapping regions are removed, integration boundaries are defined. In the second step, the integration boundaries are projected onto a so-called integration plane. Finally, using the constrained Delaunay algorithm, the edges are retriangulated in order to construct an integrated mesh.

The incremental integration method proposed in Zhou and Liu (2005) is capable of integrating both point clouds and meshes. It involves four steps. The first step relating to overlapping area detection is accomplished by applying a threshold to the distance between points belonging to

the meshes to be merged. After determining the overlapping area, corresponding points are detected, and points to be used in merging step are labeled as confident points based on the incidence angle. At the merging step, these confident points are used, depending on their confidence level, as the weighting factor. Finally, a single point set and corresponding normal values are obtained and transformed for the next computation. The same method is presented in Zhou et al. (2006) with one difference. In this study, measurement and registration error is taken into consideration robustly. Registration error and measurement noise is present in the scanning data. Integration methods should take into consideration this important fact. To be able to eliminate the registration error and measurement noise, this approach shifts points along their normal direction. For generating a model of a 3D object, range images that have different resolutions may be required. Morooka and Nagahashi (2006) have developed a method in order to solve this problem. The method is composed of four main steps: First, the detection of overlapping areas, followed by corresponding point determination between range images. The third step is the integration of corresponding points, and finally there is the reconstruction of new patches belonging to the overlapping area. The saliency-guided integration scheme proposed by Song et al. (2012) aims to provide an integration method which minimizes the registration error. Since points that are in salient regions of a scan are more sensitive to registration errors, scans are partitioned into salient and non-salient regions using an MRF (Markov Random Field). After partitioning, ICP is applied for the adjustment of points, and finally point shifting is used for the integration of points.

2.2.3 Parametric or Deformable Surface-Based Methods

A parametric surface is defined in Euclidean space using a parametric equation. It is widely used in computer graphics. A deformable surface can be considered as an approximation of a surface which is deformed by external forces such as pressure. For instance, a balloon or water surface acts as deformable surfaces. A balloon deforms when a certain pressure is applied to it, and a water surface acts similarly. In addition to external forces, reaction of the surface and some constraints exist. Scientists have made attempts to solve the surface mesh reconstruction problem using this surface concept.

The work proposed in Sclaroff and Pentland (1991) can be considered as pioneering in this field. They developed an approach which is based on the Finite Element Model (FEM). Another approach employs a polyharmonic Radial Basis Function for the integration of point clouds

(Carr et al. 2001). Ohtake et al. (2003) presented a novel approach for shape representation which is capable of integrating very large point clouds. The main principle of this approach is to partition the data, and approximate each of these partitions separately. This is followed by blending. This approach is improved in Fleishman et al. (2005) by using robust statistics methods. Sharf et al. (2006) made an attempt to solve the problem by computing a watertight surface which is the result of incrementally deforming an initial mesh along an energy field of the point cloud. Kazhdan et al. (2006) considered integration as a spatial Poisson problem which supports a hierarchy of a locally-supported basis function which yields a well-conditioned sparse linear system. This approach is improved by the implementation of a parallel computing algorithm (Bolitho et al. 2009). For the solution of the Poisson problem, a screening term is introduced in addition to the mathematical framework, and this effort increases the quality of the integration (Kazhdan and Hoppe 2013).

Level set methods can also be used. For example, Whitaker (1998) proposed an approach which calculates the maximum a posteriori for the consensus surface as a nonlinear optimization problem. During the calculation of the deformable surface, level-set models are used. Another level-set related approach is proposed in Zhao et al. (2001). In addition to level-sets, fast sweeping and tagging methods are also employed in this work.

A common drawback of these methods is the limitation in terms of representing the sharp corners of objects, and uncertainty in the balance between a smoothing effect and noisy surface removal (Gomes et al. 2014, Hornung and Kobbelt 2006, Junior et al. 2012).

2.2.4 Volumetric Methods

The mesh generated as a result of volumetric integration is usually represented implicitly by means of voxels which yield a 3D cuboid data structure. Similar to images, each cuboid cell, which is a voxel in this case, has a value computed using a Signed Distance Function (Field). The values of voxels correspond to the distance between the voxel and the object surface. The sign of the distance shows whether the voxel is inside or outside the object. Generally, a negative value shows that the voxel is inside the object, while a positive value shows that the voxel is outside the object, and a distance value of zero means that the voxel is on the object's isosurface. Even though the main idea behind volumetric integration is as aforementioned, algorithms vary according to the calculation of the distance.

The work of Hoppe et al. (1992) can be considered as one of the pioneering approaches. They developed an approach which first generates a Signed Distance Function (SDF) from unorganized points using a Euclidean Minimal Spanning Tree, and then applied the marching cube algorithm to reconstruct the polygon mesh (Lorensen and Cline 1987). Curless and Levoy (1996) developed the Volumetric Range Image Processing (VRIP) algorithm which initially creates a dense volumetric grid. For each voxel, the weighted signed distance of points to the nearest range surface is computed in a line of sight direction. Consequently, computation time is decreased, and only reliable measurements are taken into consideration. This method was used in the digital Michelangelo project of Levoy et al. (2000). A similar algorithm is developed in Hilton et al. (1996a, 1996b). This algorithm used heuristics to determine the distance to be used in calculation of the distance field. A similar method is developed by the same authors which is capable of integrating 3D point clouds acquired with the use of hand-held sensors (Hilton and Illingworth 2000). However, it is claimed by Wheeler et al. (1998) that these methods will result in inaccurate integration because of the computation approach. In order to eliminate these effects, Wheeler et al. (1998) put forward an algorithm entitled Consensus Surfaces. This algorithm also partitions the space into voxels and calculates the SDF. However, it differs from other methods by warranting the observations to be locally coherent for the calculation of the average values that result of the SDF. This algorithm was used in The Great Buddha Project (Ikeuchi et al. 2003). An extension of the Consensus Surface algorithm is presented which uses photometric attributes such as laser reflectance strength, intensity and color (Sagawa et al. 2001a). This algorithm creates the Consensus Surface by means of appearance, and it is also capable of eliminating noise and outliers. This algorithm is also used for Parallel Processing-related integration (Sagawa et al. 2001b). Sagawa et al. (2005a) took their work a step further by adaptively partitioning the space into voxels. They took into consideration the curvature of the object; a higher curvature means more voxels, while a lower curvature means fewer voxels. In addition to these efforts, the Consensus Surface algorithm is also used for effective nearest neighbor search, hole filling, and the completion of unobserved parts' applications (Sagawa and Ikeuchi 2003, 2008, Sagawa et al. 2003). The work presented in Sun et al. (2003) also employs color for integration purposes.

A different volumetric approach is presented by Johnson and Kang (1996). They tried to solve the problem from a probabilistic occupancy grids viewpoint. In this work, the space is initially sampled using voxels, followed by the calculation of surface probability based on a proximity and sensor model. In the final step, each voxel surface shape and probability is stored in a vector

form. The direction of this vector is the consensus surface normal. A major advantage of this method is its applicability for different type of sensor, because a significant component of the methodology is the sensor model which is capable of integrating textured 3D data. Rusinkiewicz et al. (2002) presented a volumetric integration method which is capable of working in real time, by calculating the average normal for points falling in the same 3D grid. In terms of representing the target object volumetrically, Pulli et al. (1997) proposed a method which creates a hierarchical volumetric representation of the object, and then reconstruct a triangle mesh from this representation. It aims to remove outliers, automatically filling gaps and ensure fast computing.

The study presented in Masuda (2002) solves the registration and integration problems simultaneously. This approach has the advantage of being free from the cumulative registration error by utilizing minimization of the error function. This approach differs from others in terms of shape representation, discrete samples of the object surface being used, and integration and registration being performed iteratively. Similarly, Zach et al. (2007) developed a method minimizing the error function using total variation and fidelity terms. The main objective of this study is to develop an integration method which is robust in terms of outliers, and capable of obtaining smooth surfaces of the target object. Rocchini et al. (2004) proposed a method which requires user interaction. This method first determines the intersections between meshes and a reference voxel which is parameterized by the user. It then merges intersections along the grid lines using a distance threshold. This method claims to be able to perform the integration process in shorter time when compared to the previous approaches. The volumetric fusion technique that presented in Yemez and Wetherilt (2007) uses a hybrid method for merging. It uses shapes from silhouettes and shapes from optical triangulation. Fuhrmann and Goesele (2011) proposed a method which is based on the previously-mentioned VRIP (volumetric range image integration). However, they introduced a hierarchical signed distance field which takes into consideration the scale issue.

In order to perform reconstruction as perfect as possible, the available approaches may be appropriately synthesized. Junior et al. (2012) have proposed an IMAGO Volumetric Integration Algorithm (IVIA) method that mixes VRIP and Consensus Surface algorithms. This method not only eliminates the disadvantages of VRIP and Consensus Surface algorithms, but also takes advantage of them. IVIA performs the surface reconstruction in two steps; it first creates an integrated volumetric representation using VRIP, while in the second step it detects

and removes outliers. Moreover, this work compares the performance of VRIP, Consensus Surface and IVIA.

Octree data structure is another volumetric representation of 3D data, and can be used to store the SDF (Zeng et al. 2013). One of the most recent work, presented by Zhou and Koltun (2013), proposed a volumetric method which is based on POI (Points of Interest). In this work, a POI pose estimation is first performed, and then a projective SDF scheme is defined which maintains the POI geometry. Additionally this method minimizes and distributes residual error that results from registration. Paulsen et al. (2010) also used the SDF concept for integration. However, they differ from the other works by regularizing the calculated SDF using the Markov Random Field.

2.2.5 Previous Work in the Photogrammetry & Remote Sensing Domain

The photogrammetry and remote sensing community have produced 3D data using numerous methods and sensors such as TLSs, Aerial Laser Scanners, and close range, aerial and spaceborne imaging systems. The generated 3D model is generally representing the bare terrain as a DTM (Digital Terrain Model) or object surface as a DSM (Digital Surface Model). Even though the production of 3D model is a well-known issue, the integration or fusion of different quality models coming from different sources is gaining attention recently. Agugiaro and Kolbe (2012) proposed a deterministic method with the purpose of integrating two registered triangular mesh-based surfaces that have different resolutions. This work focused on defining a transition surface between high resolution and low resolution surfaces that allows the gradual transition from low resolution to high resolution. The result of this algorithm yields a surface which is topologically and geometrically continuous. Another 3D model integration scheme is presented by Papasaika (2012) which aims at the integration of different quality registered multi-temporal and multi-sensor DEMs (Digital Elevation Models), in order to produce a more accurate, reliable and complete product. In this study, integration is performed using weighted averaging and sparse representations methods. To be able to calculate weighted averages, certain metrics such as slope, aspect, roughness and edginess are employed. One of the most recent studies to be carried out on this topic is that of Kuschik and d'Angelo (2013). Their approach solves the problem by considering it as an optimization problem. To achieve this objective, they employed Total Variation-based methods for minimizing energy functions.



CHAPTER 3

GENERIC AND ANISOTROPIC POINT ERROR MODEL FOR TLS DERIVED POINT CLOUDS

3.1 FUNDAMENTALS OF TERRESTRIAL LASER SCANNING

TLSs can measure and record the geometry and attribute information (e.g. amplitude, imagery, texture, echo count) of visible surfaces belonging to the target objects or scenes by utilizing a technique that does not require direct contact with the surface. The data obtained as a result of scanning is a 3D digital representation of the environment. This is in the form of 3D point clouds of the surface within the Field of View (FOV) provided by the scanner. The point cloud data file provided by TLSs is generally composed of line storage (X , Y , Z), cartesian coordinates, and the intensity information with regard to individual points.

3.1.1 TLS Observations

TLS systems operate in a spherical coordinate system that measures the sensor-to-object distance or range (ρ), vertical (α) and horizontal (θ) angles in the form of direct observations (Figure 3.1). In addition, TLSs can measure the amplitude or so-called intensity of the reflected laser beam which is a quantity of the reflectivity of the object surface.

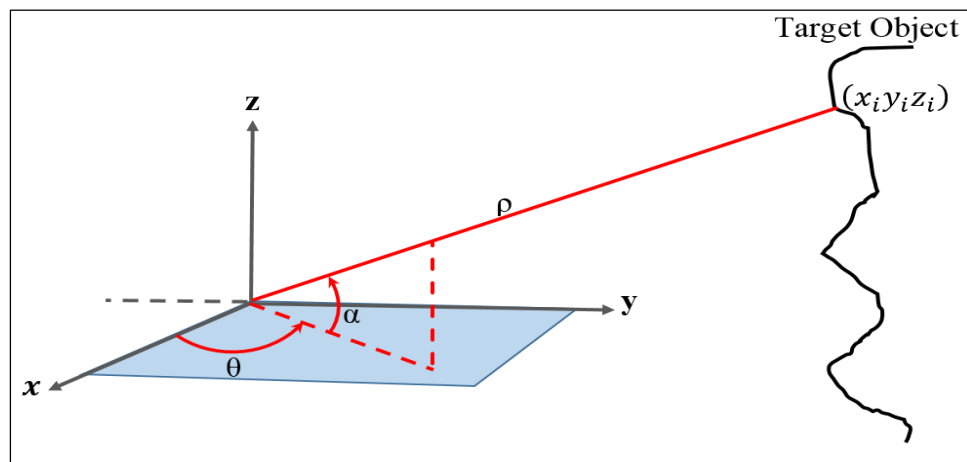


Figure 3.1 The direct observations of a TLS system.

The range measurement methods used in TLSs are divided into two categories (Soudarissanane, 2016): Time of Flight and Phase Based methods. A Time of Flight-based TLS emits short laser pulses and measures the travel time between the laser source and the reflective target surface. With this method the sensor-to-object distance or range (ρ) can be determined using Equation 3.1.

$$\rho = \frac{c_l \Delta t}{2} \quad (3.1)$$

where ρ is the range, c_l is the speed of light in a vacuum, and Δt is the travel time. Time of Flight-Based TLSs are capable of ranging longer distances, and obtaining less noisy data when compared to Phase-Based TLSs.

A Phase-Based TLS emits a modulated continuous wave to the target object. In this ranging method the time Δt is determined using Equation 3.2.

$$\Delta t = \frac{\Delta \phi}{2\pi f} \quad (3.2)$$

where $\Delta \phi$ is the phase shift, and f is the frequency of the sine wave. When the Δt defined in Equation 3.2 is replaced in Equation 3.1, the ranging formula can be obtained in Equation 3.3.

$$\rho = \frac{c_l \Delta \phi}{4\pi f} \quad (3.3)$$

Phase-Based TLSs provide higher measurement rates. However, the point cloud data contains noise in greater magnitude. In addition, Phase-Based TLSs are limited in terms of very long distances.

TLSs emit laser signals to a target object with known vertical (α) and horizontal (θ) angles. Angular measurements with TLSs are performed electro-optically with the use of high resolution angular encoders associated with the rotating mirror system of the TLS (Ingensand 2006, Schulz 2007). The rotating mirror system of the TLSs rotate both in horizontal and vertical directions with a defined step width. At each horizontal step, the rotating mirror system of the TLS rotates vertically, and at each vertical step performs a range measurement. Consequently, the TLS generates unique spherical coordinate values (ρ, α, θ) for each point.

Most of the TLSs output the Cartesian coordinates $[x_i \ y_i \ z_i]^T$ rather than the spherical coordinates $[\rho_i \ \alpha_i \ \theta_i]^T$ for the users. The relationship between Cartesian and spherical coordinate system can be easily established.

Any point in a spherical coordinate system is defined as $r_i = [\rho_i \ \alpha_i \ \theta_i]^T$ where $i = 1, 2, \dots, n$ is the number of points in the data set. The Cartesian coordinates $[x_i \ y_i \ z_i]^T$ of any i -th point can be computed from the spherical observations $r_i = [\rho_i \ \alpha_i \ \theta_i]^T$ as:

$$\begin{bmatrix} x_i \\ y_i \\ z_i \end{bmatrix} = \begin{bmatrix} \rho_i \cos(\alpha_i) \cos(\theta_i) \\ \rho_i \cos(\alpha_i) \sin(\theta_i) \\ \rho_i \sin(\alpha_i) \end{bmatrix} \quad (3.4)$$

Reverse transformation from the Cartesian coordinates $[x_i \ y_i \ z_i]^T$ to the spherical coordinates $[\rho_i \ \alpha_i \ \theta_i]^T$ can be performed using the following equations:

$$\rho_i = \sqrt{x_i^2 + y_i^2 + z_i^2} \quad (3.5a)$$

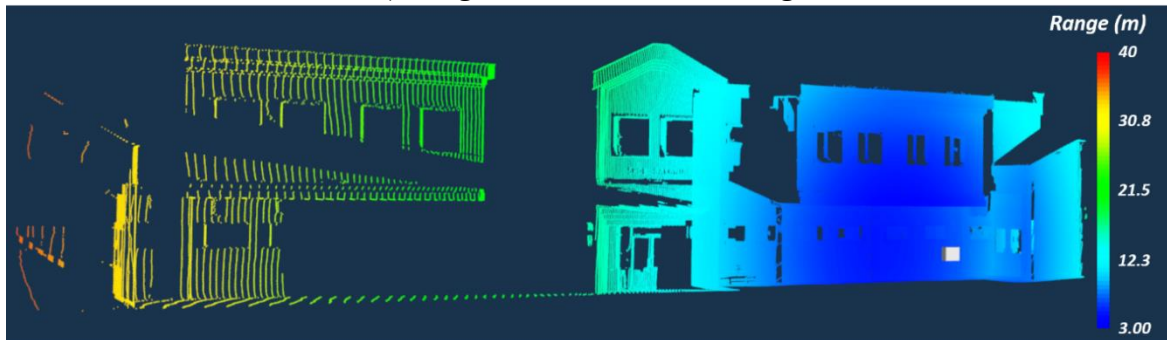
$$\alpha_i = \tan^{-1} \left(\frac{z_i^2}{\sqrt{x_i^2 + y_i^2}} \right) \quad (3.5b)$$

$$\theta_i = \tan^{-1} \left(\frac{y_i^2}{x_i^2} \right) \quad (3.5c)$$

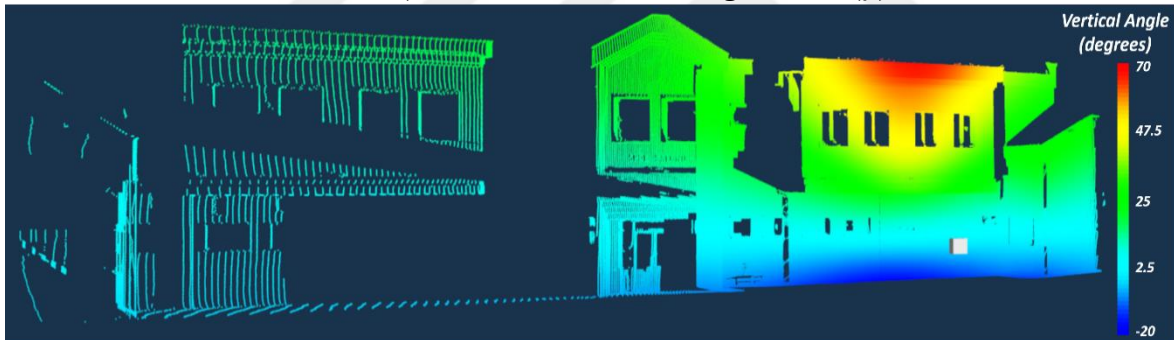
Figure 3.2 depicts the computed spherical coordinates of a point cloud of a building. The point cloud was acquired using a Faro Focus 3D X330 scanner.



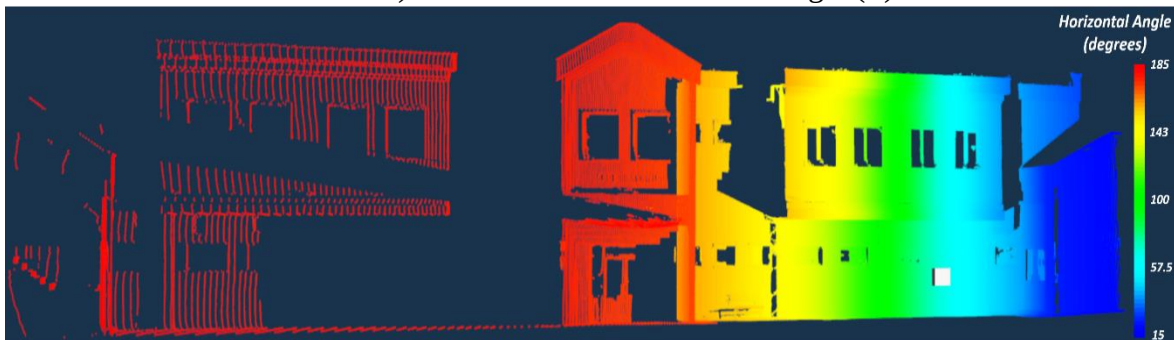
a) Image of the scanned building.



b) Points colored with range values (ρ).



c) Points colored with vertical angle (α).



d) Points colored with horizontal angle (θ).

Figure 3.2 Point cloud visualized using the spherical coordinate values.

The scanning principle of the TLS is important in the calculation of vertical and horizontal angles. For scanners that perform panoramic scanning, Equations (3.5b) and (3.5c) should be modified. If

$\theta < 0^\circ$, 180° must be added to Equation (3.5c) and in Equation (3.5b) must be subtracted from 180° . Otherwise, if $\theta \geq 0^\circ$, there is no need to modify Equations (3.5b) and (3.5c) (Lichti 2010a, Lichti 2010b).

Apart from the positional data, TLSs record an additional attribute data entitled the intensity of each point. Intensity is generally used for the visual improvement of point clouds (Carrea et al. 2016). Intensity can be defined as the power of the backscattered signal from the object. While some TLSs provide both reflectance and intensity values, some of them provide only one of them. For example, the point cloud processing software of the Faro Focus 3D X330 displays intensity values on the screen, but only outputs reflectance values. While intensity strongly depends on the incidence angle and distance, reflectance only depends on the surface properties. Reflectance values can be obtained by applying distance and angle corrections to the intensity values. In the literature this process is referred to as intensity calibration (Jaakkola et al. 2008, Kaasalainen et al. 2008). Figure 3.3(a) shows a scanned scene, and Figure 3.3(b) shows the scene with measured intensity values. The higher surface reflectivity results in higher intensity values (white). Contrarily, if the surface is highly absorbent, the resulting intensity values are relatively low (black).



(a)



(b)

Figure 3.3 A scene (a) scanned with Faro Focus 3D X330 scanner and visualized with intensity values (b).

3.1.2 TLS Data Structure

The raw point cloud data generated by TLSs is in a kind of structured form. This structured point cloud is arranged in a rectangular grid similar to 2D images. TLSs scan the environment either in column-ordered or in row-ordered manners. Thus, if the topological structure of the point cloud is already known, the neighbouring information of any point can be determined easily. A hypothetical example is illustrated in Figure 3.4.

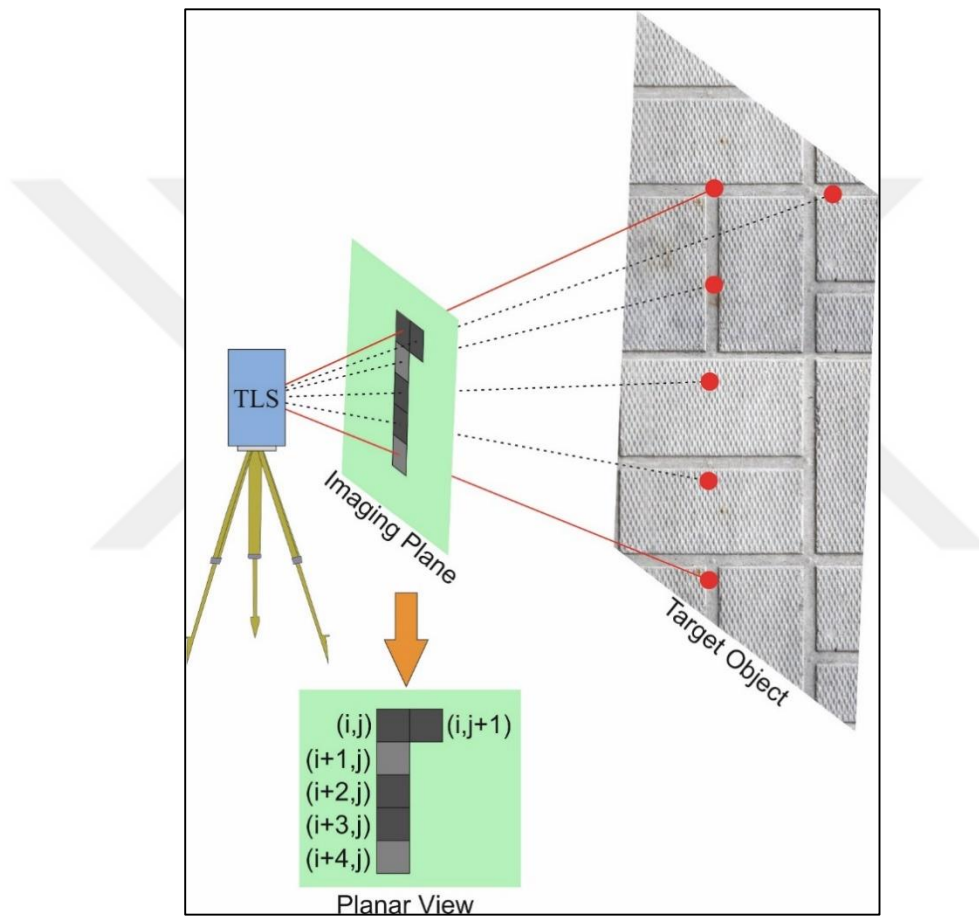


Figure 3.4 The formation of the structured point cloud.

When each laser beam is intersected with a virtual imaging plane, the structured point cloud is obtained where each point is addressed with a row (i) and column (j) index number. For each row and column, the corresponding Cartesian coordinate and the intensity (or reflectance) values are stored in the data file.

In scanning projects, for some points the emitted laser beam may not return. This results in invalid points (or holes) in the dataset. This situation is shown in Figure 3.5.

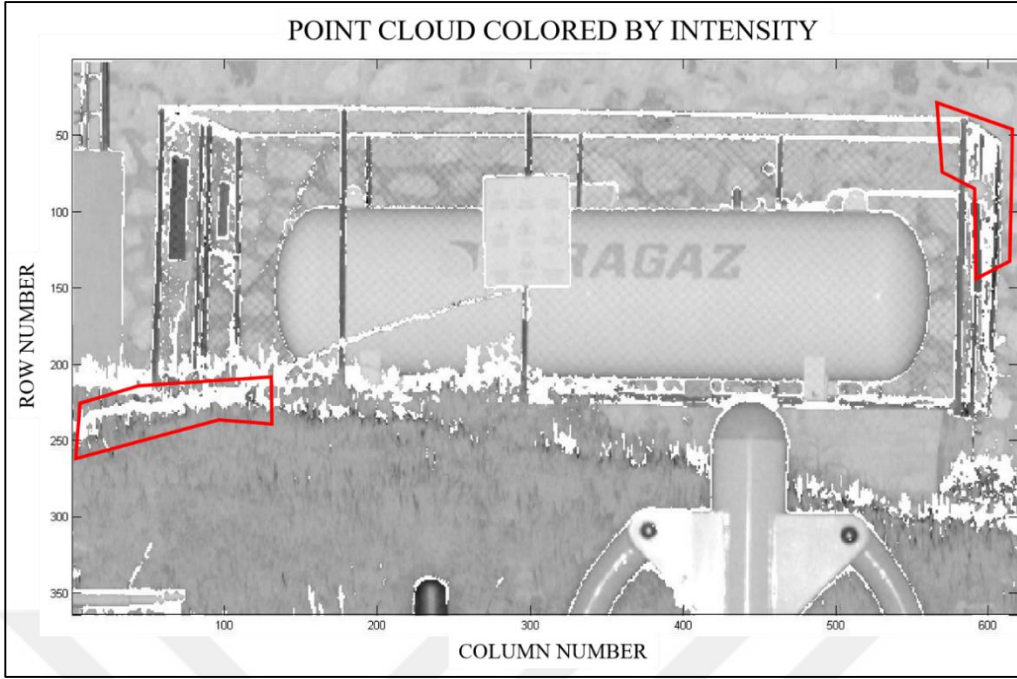


Figure 3.5 Valid and invalid points in point cloud data.

Figure 3.5 shows a planar view of a propane tank surrounded by wire fences. Each point is addressed with a row and column number. Since there is no returning laser beam, some points are invalid. These invalid points are colored as white, and some of them are delineated by red polygons.

For any point $p_{i,j}$, which is addressed with i -th row and j -th column, the list of first degree neighboring valid points S_p is defined as:

$$S_p = \{p_{(i-1,j-1)}, p_{(i-1,j)}, p_{(i-1,j+1)}, p_{(i,j-1)}, p_{(i,j)}, p_{(i,j+1)}, p_{(i+1,j-1)}, p_{(i+1,j)}, p_{(i+1,j+1)}\} \quad (3.6)$$

In the case of single scans, this approach is useful and computationally efficient for performing the closest point queries. However, for unstructured point clouds such as co-registered point clouds, where the gridded structure is lost, this approach will not work.

3.1.3 Estimation of Local Surface Normal and Incidence Angle

Once a target object is scanned with a TLS, it is sampled with a dense point cloud. As a result of this sampling process, some basic information about the surface, such as orientation and

curvature, is no longer available (Klasing et al. 2009, Rusu 2009). The local surface normal is a convenient tool for recovering surface orientation and curvature. Moreover, the local surface normal descriptor can be used for the estimation of the incidence angle of the incoming laser beam. The local surface normal ($\vec{n}$) and incidence angle (γ) are illustrated in Figure 3.6.

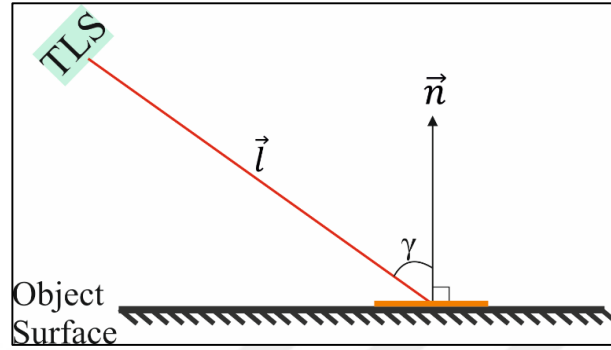


Figure 3.6 Illustration of the local surface normal ($\vec{n}$) and incidence angle (γ). The tangential plane to the local surface shown in orange. The laser beam vector is represented by $\vec{l}$.

The local surface normal ($\vec{n}$) can be defined as the normal of a plane tangent to a local surface. For the estimation of $\vec{n}$ of a point p_i , valid neighbors V_p should be determined, as is explained in the previous section. It was shown that the eigenvalue decomposition of the covariance matrix of a neighboring point set V_p can be used for $\vec{n}$ estimation (Schaer et al. 2007).

Let V_p consists of n valid neighboring points of the point p_i . The centroid of this point set $\bar{p}$ can be defined as follows:

$$\bar{p} = \frac{1}{n} \sum_{i=1}^n p_i \quad (3.7)$$

The covariance matrix C for point p_i can be computed using Equation 3.8:

$$C = \begin{bmatrix} p_i - \bar{p} \\ \vdots \\ p_n - \bar{p} \end{bmatrix}^T \cdot \begin{bmatrix} p_i - \bar{p} \\ \vdots \\ p_n - \bar{p} \end{bmatrix} \quad (3.8)$$

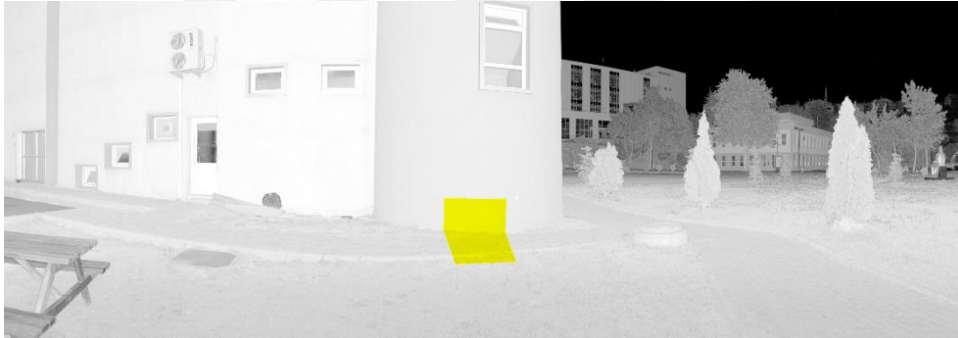
The covariance matrix C is symmetric and semi-definite. The eigenvalues decomposition shown in Equation 3.9 of the covariance matrix C will result in local surface normal $\vec{n}$:

$$C \cdot \vec{v}_j = \lambda_j \cdot \vec{v}_j, \quad j \in \{0,1,2\} \quad (3.9)$$

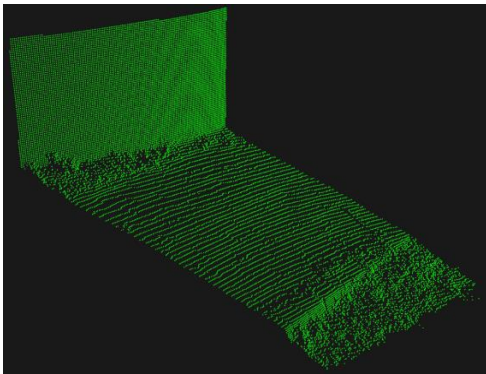
Since C is symmetric and semi-definite, λ_j are real numbers, and the associated $\vec{v}_j$ form the orthogonal frame. The $\vec{v}_j$ associated with the smallest λ_j approximates the local surface normal and constitutes $\vec{n} = (n_x, n_y, n_z)$. The sign (positive or negative case) of local surface normals should be consistent with respect to the TLS stand point (p_{TLS}). If required, the sign should be swapped. This condition can be satisfied using Equation 3.10:

$$\begin{cases} \vec{n} \cdot (p_{TLS} - p_i) < 0 \Rightarrow \vec{n} = -1\vec{n} \\ \vec{n} \cdot (p_{TLS} - p_i) > 0 \Rightarrow \vec{n} = \vec{n} \end{cases} \quad (3.10)$$

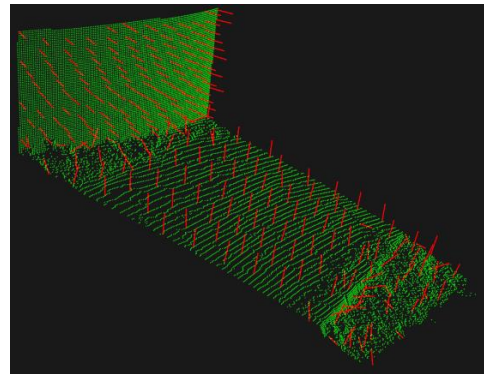
Using Equation 3.10 it is guaranteed that all local surface normals are consistently oriented through the TLS. Figure 3.7 represents computed local surface normals for a small portion of the point cloud obtained using a Faro Focus TLS.



a) Intensity image of the scanned scene. The yellow area is selected for local surface normal computation. Data acquired with a Faro Focus 3D X330 scanner.



b) Point cloud of the selected area



c) Point cloud and computed local surface normals (red). The surface normals are plotted at every 75th point.

Figure 3.7 Illustration of the local surface normals.

The incidence angle (γ) as depicted in Figure 3.6, can be defined as the angle between the incoming laser beam ($\vec{l}$) and the local surface normal ($\vec{n}$). Using Equation 3.11, the incidence angle (γ) can be easily computed:

$$\gamma = \cos^{-1} \left(\frac{\vec{n} \cdot \vec{l}}{|\vec{n}| |\vec{l}|} \right) \quad (3.11)$$

The variation of incidence angle with respect to the position of the TLS is visualized in Figure 3.8.

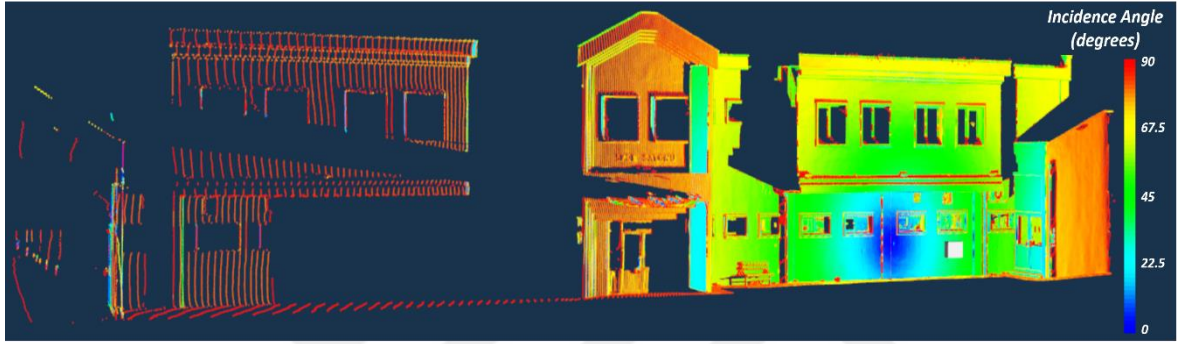


Figure 3.8 Point cloud colored by incidence angle. The TLS stand point is labelled with a white cube.

Figure 3.8 shows that as the laser beam hits the target surface perpendicularly, the incidence angle gets closer to 0° . The smaller the incidence angle is the greater the returning laser beam. This yields less positional uncertainty.

3.2 THEORETICAL BACKGROUND OF THE ANISOTROPIC POINT ERROR MODEL

As mentioned in Section 3.1.1, any TLS measured point $r = [\rho, \alpha, \theta]^T$ is defined in a spherical coordinate system. However, the corresponding Cartesian coordinates are provided to users. The transformation from spherical coordinates to Cartesian coordinates and the reverse transformation are straightforward using Equations 3.4 and 3.5. The a priori covariance matrix of any point r_i can be established using the a priori precision values of the direct observations:

$$\Sigma_{rr} = \begin{bmatrix} \sigma_\rho^2 & 0 & 0 \\ 0 & \sigma_\alpha^2 & 0 \\ 0 & 0 & \sigma_\theta^2 \end{bmatrix} \quad (3.12)$$

where, σ_ρ^2 , σ_α^2 and σ_θ^2 represent a priori variances of the range (ρ), vertical (α) and horizontal (θ) angles, respectively. Non-diagonal elements of this matrix are zero under the following assumptions:

1. The TLS is well-calibrated, thus the range and angular measurements are free of systematic errors,
2. There is no physical correlation between the direct observations.

Since the range and angle measurement units operate independently from each other, the second assumption is valid.

Using the law of error propagation, the covariance matrix Σ_{xx} of a point in the Cartesian coordinate system can be defined as:

$$\Sigma_{xx} = J_{xr} \Sigma_{rr} J_{xr}^T \quad (3.13)$$

where J_{xr} is the Jacobian matrix of the partial derivatives of the Cartesian coordinates (Equation 3.4) with respect to the range (ρ), and the vertical (α) and horizontal (θ) angle observations as shown in Equation 3.14.

$$J_{xr} = \begin{bmatrix} \frac{\partial x}{\partial \rho} & \frac{\partial x}{\partial \alpha} & \frac{\partial x}{\partial \theta} \\ \frac{\partial y}{\partial \rho} & \frac{\partial y}{\partial \alpha} & \frac{\partial y}{\partial \theta} \\ \frac{\partial z}{\partial \rho} & \frac{\partial z}{\partial \alpha} & \frac{\partial z}{\partial \theta} \end{bmatrix} \quad (3.14)$$

Because the error ellipsoid is able to represent the magnitude and direction of the random error of the associated point, it is an appropriate tool for the assessment of positional uncertainty. Once the covariance matrix Σ_{xx} of a point is obtained, the error ellipsoid parameters of a point can be calculated by solving the eigenvalue problem given in Equation 3.15.

$$(\Sigma_{xx} - \lambda \vec{I})z = 0 \quad (3.15)$$

where, $\vec{I}$ is the unit matrix, $\lambda = [\lambda_1, \lambda_2, \lambda_3]$ are the eigenvalues, and $z = [z_1 \ z_2 \ z_3]$ is the eigenvector of the covariance matrix Σ_{xx} .

An error ellipsoid can be defined in terms of its semi-axis dimensions and orientation. The dimensions of the semi-axes of the error ellipsoid are the square root of the eigenvalues ($\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$, $\sqrt{\lambda_3}$). The axes orientations of the ellipsoids are given by the eigenvectors $z = [z_1 \ z_2 \ z_3]$. Vertical and horizontal directions can be computed as shown in Equation 3.16.

$$\text{Vertical Direction} = \tan^{-1} \left(\frac{z_3}{\sqrt{z_1^2 + z_2^2}} \right) \quad (3.16a)$$

$$\text{Horizontal Direction} = \tan^{-1} \left(\frac{z_1}{z_2} \right) \quad (3.16b)$$

A hypothetical error ellipsoid is illustrated in Figure 3.9. The semi-major axis of the ellipsoid is aligned with the laser beam vector. This situation indicates that the error in the line of sight direction is higher than the ones in the lateral directions.

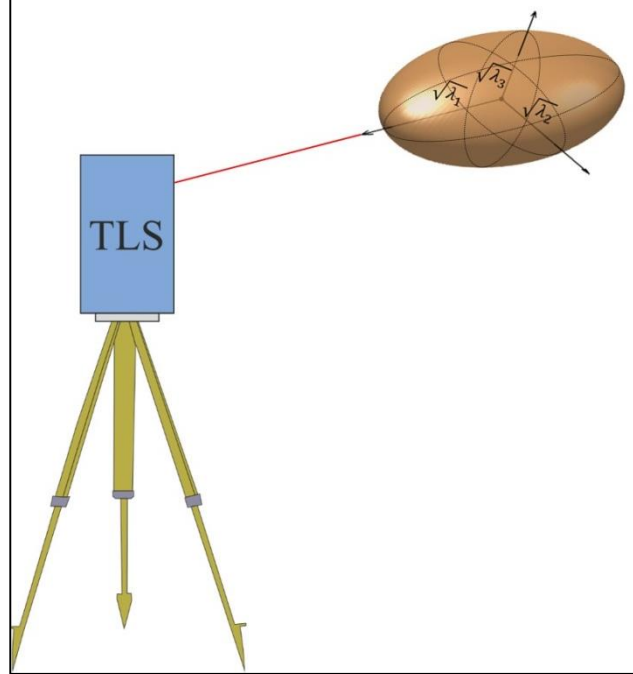


Figure 3.9 Illustration of an error ellipsoid with respect to the TLS position.

At this step, the error ellipsoid of every individual point can be computed, provided that the a priori precision values of the direct measurements ($\sigma_\rho, \sigma_\alpha, \sigma_\theta$) in Equation 3.12 are given. This situation is illustrated in Figure 3.10 for a sample point cloud.

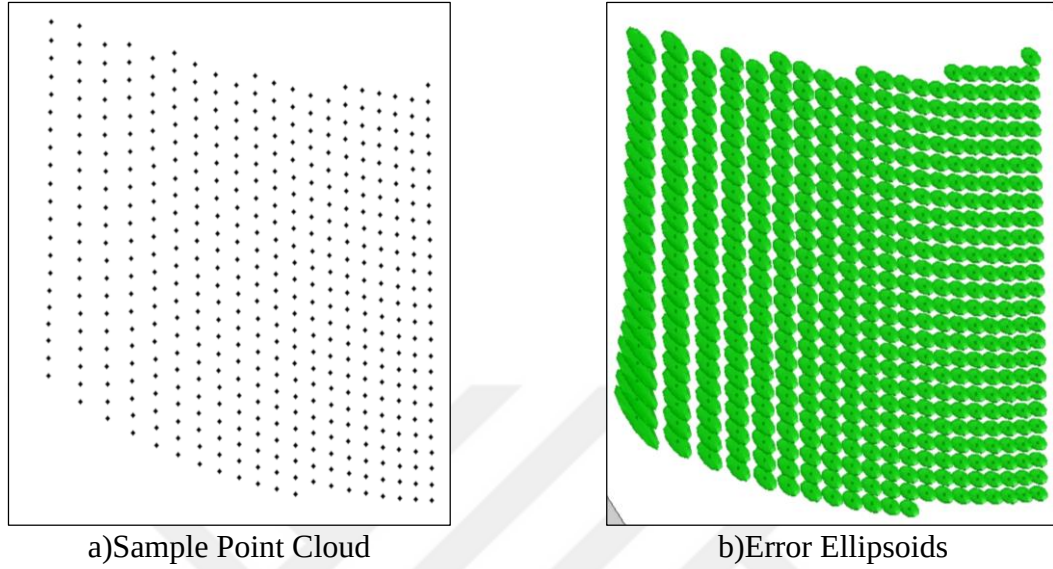


Figure 3.10 Error ellipsoids of a sample point cloud.

However, the a priori precision values ($\sigma_\rho, \sigma_\alpha, \sigma_\theta$) are unknown. For the determination of these values, a practical methodology is developed which will be explained in detail in the following section.

3.3 DETERMINATION OF A PRIORI PRECISION VALUES: A PRACTICAL METHODOLOGY

Range (ρ), vertical (α) and horizontal (θ) angles are the direct observations of a TLS which obviously have their own a priori precision values. Since the TLS manufacturers do not publicly or standardly share these values, a practical methodology is designed and realized for how to determine them. The methodology does not require specific laboratory conditions and equipment; rather it is practical, so that it can be conducted in real world environments by any TLS user. As the range measurement varies in a certain sight-of-line direction, the vertical and horizontal angle measurements remain the same. Thus, the ranging mechanism of the TLS does not have any effect on the angular precision (Schulz 2007). Therefore, the determination of the angular precision and that of the range precision are realized in two separate parts of the experiment.

The first part is a static and repetitive measurement configuration for the determination of a priori precision values of the vertical (σ_α) and horizontal (σ_θ) angles. The second part is the measurement of a test stand which contains four plates in white, light gray, dark gray and black colors for the determination of the a priori precisions of the range observations (σ_ρ). The test stand measurements were performed in a recursive manner so that the sensor-to-object distance, the incidence angles and the surface reflectivity are parameterized.

All experiments were conducted in almost the same atmospheric conditions for three different TLSs, namely a Faro Focus 3D X330, a Riegl VZ400 and a Z+F 5010x. Even though TLSs allow users to perform scanning in different resolution and quality options, all the scanners were set to a moderate resolution and quality level. The selected resolution and quality levels are appropriate for modelling ordinary buildings. The technical specifications of the tested TLSs are summarized in Table 3.1.

Table 3.1 Technical specifications of the tested TLS systems.

			
	Faro Focus 3D X330	Riegl VZ400	Z+F 5010x
Laser Class	Laser Class 1	Laser Class 1	Laser Class 1
Range Measurement Error	$\pm 2\text{mm @ } 25\text{-}50\text{m}$	$\pm 3\text{mm @ } 100\text{m}$	Linearity Error $\leq 1\text{mm}$
Ranging Method	Phase Measurement	Time of flight	Phase Measurement
Beam Divergence	121.0^{cc} (0.19 mrad)	222.8^{cc} (0.35 mrad)	$<191.0^{\text{cc}}$ (0.30 mrad)
Wavelength	1550nm	Near Infrared	1500nm
Angular Step Width (Hor.)	100^{cc}	26.7^{cc}	2.2^{cc}
Angular Step Width (Ver.)	100^{cc}	26.7^{cc}	4.4^{cc}
Field of View (Ver./Hor.)	$333.3^{\text{g}} / 400^{\text{g}}$	$111.1^{\text{g}} / 400^{\text{g}}$	$355.6^{\text{g}} / 400^{\text{g}}$

All TLSs scan the target object with laser beams classified as Laser Class 1, which means that this laser beam is not hazardous to eye or skin. Among the tested TLSs, the Riegl VZ400 is the only one that measures distance with the Time of Flight principle. Even though the Riegl VZ400 is capable of measuring long distances, its range measurement error is the largest. The angular step width values can be considered as the resolution of the TLS. For example, the step width parameters of the Z+F 5010x scanner are the smallest, which leads the highest resolution. According to their FOV, the Riegl VZ400 can be classified as a hybrid scanner while the others can be classified as panoramic scanners (Staiger, 2003).

3.3.1 Angular precision (σ_α and σ_θ) determination

The angular precisions of a TLS can be defined as the repeatability of the angle observations. The vertical and horizontal angle measurements are independent of the object space conditions such as temperature, surface reflectivity, distance, etc. Rather, they are the result of mechanical movements of the laser beamer in the vertical and horizontal directions. It is a mechanical stability problem. The greater the precision, the less the scatter of the vertical and horizontal angle values resulting from repetitive scans.

The precision of the vertical and horizontal angles are assessed by repeated scans of the same environment when the TLS is set up in such a way as to be firmly static. In our case, the same environment was scanned five times from the same station. The repetitive scans were performed with four-to-six minute time intervals to verify that the TLS is completely stable, and the heating and cooling of the device is at a moderate level. As a result of this measurement configuration, it is expected that each point should coincide with its conjugates in the other scans. However, the imperfect mechanical structure of angular encoders results in a certain dispersion of conjugate points. This situation is shown for the five conjugate points of the same laser ray in Figure 3.11 for three tested TLSs.

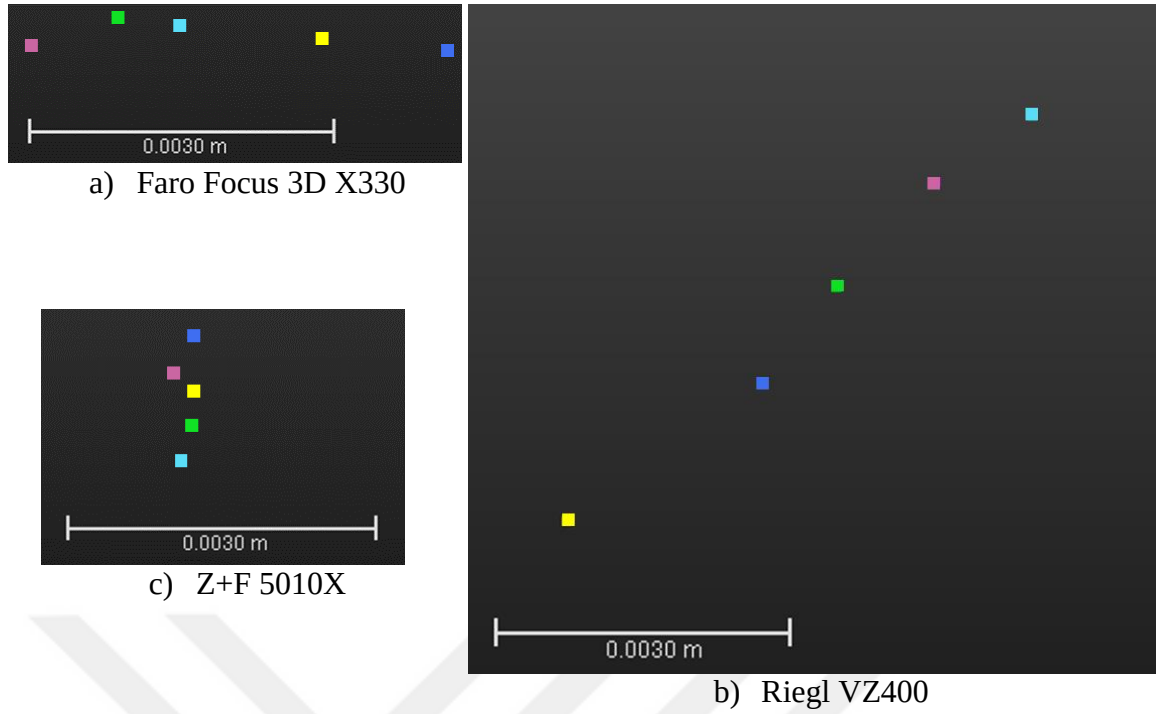


Figure 3.11 Distribution of the conjugate points of a laser ray as a result of five repeated scans.

In Figure 3.11, the views are rendered along the lateral direction. The ordinate is the vertical angle direction, and the abscissa is the horizontal angle direction. Conjugate scan points resulting from the 1st, 2nd, 3rd, 4th and 5th scans are represented by yellow, green, cyan, blue and purple colors, respectively. It is apparent from Figure 3.11 that the angular precisions of the tested scanners are not equivalent along the vertical and horizontal directions, both in terms of magnitude and direction. The Faro scanner exhibits a better vertical angle precision than a horizontal one. The situation with regard to the Z+F scanner is completely the reverse. The Riegl scanner shows similar precision, both for the horizontal and vertical angles, although with larger magnitudes than is the case with the Faro and Z+F scanners. The same pattern is observed for points in different directions and at different distances. It is observed that the distribution pattern is similar for the same scanners. For this reason, it can be concluded that the angular a priori precision is the scanner variant numbers, and not the point variant.

The deviation at conjugate points is closely related to the angular a priori precision values. After the scanning procedure, five conjugate points from the same laser ray were selected, and corresponding vertical (α) and horizontal (θ) angles were computed from Cartesian coordinates using Equations 3.5(a) and 3.5(b). This computation is repeated for at least four laser rays which were fired in the four main directions with respect to the TLS. For each laser ray, the root mean square error (RMSE) values of the vertical (α) and horizontal (θ) angle discrepancies were

computed. Finally, the mathematical mean of these four RMSE values was calculated and was considered as a measure of the a priori angular precision. This procedure was repeated for all tested scanners leading to the final precision values of the vertical and horizontal angles (σ_α and σ_θ) as tabulated in Table 3.2.

Table 3.2 Angular precision values for the tested TLSs

Faro Focus 3D x 330		Riegl VZ 400		Z+F 5010x	
σ_α	σ_θ	σ_α	σ_θ	σ_α	σ_θ
18.8 ^{cc}	76.2 ^{cc}	94.5 ^{cc}	107.2 ^{cc}	26.7 ^{cc}	3.8 ^{cc}

The Z+F scanner has the least vertical and horizontal step widths (Table 3.1), and accordingly the least vertical and horizontal angle precision numbers (Table 3.2). The same relation does not exist between the Faro and Riegl scanners. Although the Riegl scanner has five times less step width values than the Faro scanner, the Faro scanner has considerably better precision values. This is due to the better internal stability of the Faro scanner. It can be summarized that in vertical direction Faro scanner has the best precision and in horizontal direction Z+F 5010x scanner has the best precision.

The angular precision of the TLSs have been already investigated in previous studies. Schulz (2007) studied the angular precision of the Z+F 5003 TLS. Spherical targets were used, and ten repeated scans were performed for different scanning modes of the scanner. The results of this work are given in Table 3.3.

Table 3.3 Angular precision of the Z+F 5003 determined in Schulz (2007)

Scanning Mode	RMSE(σ_θ)	RMSE(σ_α)
Super High	11.1 ^{cc}	11.1 ^{cc}
High	22.2 ^{cc}	33.3 ^{cc}
Middle	66.6 ^{cc}	55.5 ^{cc}

In another study, the horizontal and vertical precision of the Z+F 5003 were determined as being 124^{cc} and 68^{cc} respectively, using intensity images (Parian and Gruen 2005). Some works aimed at the self-calibration of TLSs and also investigated their angular precision. For example, the horizontal and vertical precision of a Trimble (Mensi) GS200 was determined as 153.3^{cc}

and 121.1^{cc} respectively, as a result of repeated measurements (Chow et al. 2010). In order to determine angular precision, the repeated measurements method is the most-commonly used. The results of our study are consistent with the previous studies.

3.3.2 Range precision (σ_ρ) determination

3.3.2.1 Data-driven range precision

Range precision (σ_ρ) depends not only on the sensor space (instrumental) parameters, but also on many object space (environmental) parameters. Among these, the most effective ones are the distance from the TLS to the object, the incidence angle of the incoming laser beam, and the reflectivity of the object surface. Thus, the range precision is point variant, and should be determined for each point individually. In order to determine the a priori range precision (σ_ρ), a test stand, which is appropriate for both indoor and outdoor use, was constructed (Figure 3.12).



Figure 3.12 The test stand containing the four plates in white, light gray, dark gray and black colors.

The test stand consisted of four glass plates on which A3 sized papers with different reflectance properties were glued. The white one is ordinary unprinted paper. The light and dark gray papers were printed using a laser printer. The black one was sprayed homogeneously with a fully black (matte) spray in order to absorb a large extent of the incoming beam. The test stand

was placed at distances ranging from 10m to 90m in steps of 20m from the scanner. At each step, the test stand was positioned with 0°, 30° and 45° orientation angles with respect to the TLS so that it enabled investigation of the effects of the distance, the incidence angle and the reflectivity. This experiment configuration is depicted in Figure 3.13.

Four-to-six minutes time delays were allowed between the consecutive scans to make sure that the operation temperature of the scanner was reduced. A total of 15 scans of the test stand were acquired for each of the three scanners. Such an experimental configuration allows for the simultaneous parameterization of the sensor-to-object distance, the incidence angle and the surface reflectivity.

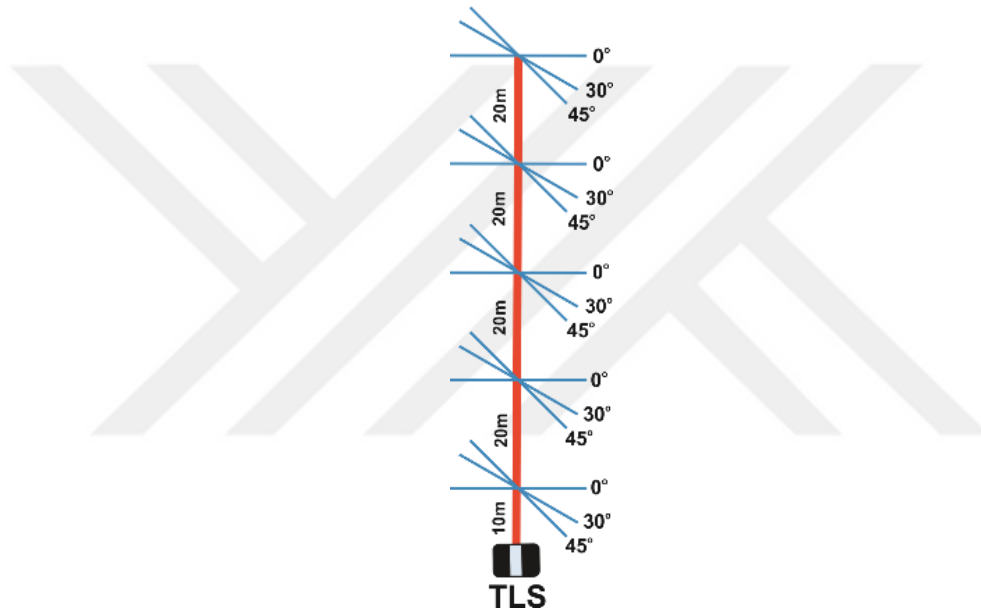


Figure 3.13 The scan plan showing the top view of the experimental configuration. The locations and orientations of the test stand are represented with the blue lines.

Once the measurements were completed, data points on the plates were cropped and saved in separate files. Assuming that the plates are exactly planar, the least squares plane fitting was computed for each plate using the conventional least squares parameter estimation method. The following plane equation was employed:

$$Ax_i + By_i + Cz_i + D = 0 \quad (3.17)$$

where A, B, C and D are the coefficients of the respective planes and (x_i, y_i, z_i) represent the coordinates of the points which lie in the plane. After the four plane coefficients were computed

using the redundant point observations, the off-plane distance (d_i) of every i -th scan point was computed using Equation 3.18.

$$d_i = \frac{Ax_i + By_i + Cz_i + D}{\sqrt{A^2 + B^2 + C^2}} \quad (3.18)$$

The RMSE of the off-plane distances d_i was computed, represented by the symbol (m), and considered as the empirical (data driven) a priori precision (σ_ρ) of the range measurements.

$$m = \pm \sqrt{\frac{\sum d_i d_i}{n - 1}} \quad (3.19)$$

The (m) values of each plate at varying distances (10, 30, 50, 70 and 90 meters), orientation angles (0, 30 and 45 degrees) and reflectivity (black, dark gray, light gray and white papers) were computed. This procedure was repeated for each of the three scanners Faro, Riegl and Z+F, and graphically depicted in Figures 3.14, 3.15 and 3.16, respectively.

Figures 3.14, 3.15 and 3.16 clearly demonstrate how the range precision σ_ρ changes when the distance, the laser incidence angle and the surface reflectivity change. Moreover, the σ_ρ of the black objects worsens when compared to gray and white colored objects. The incidence angle of the laser ray is another dominating factor in terms of deteriorating the point-positioning quality, especially for the black objects. On the other hand, the perturbation of σ_ρ for dark gray, light gray and white objects is small. The point quality and quantity was so bad for the black plates of the Z+F 5010X scanner at 90m 30°, 90m 45° and 70m 45° distances and orientation angles, respectively, that the m values could not be calculated (Figure 3.16).

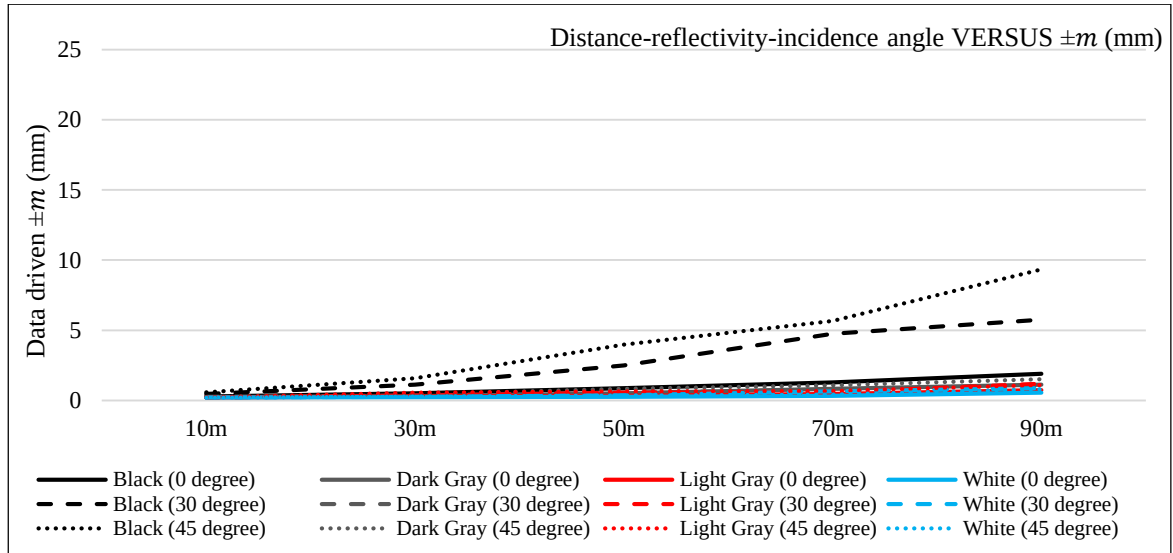


Figure 3.14 Data driven empirical σ_ρ values for the Faro Focus 3D X330 scanner.

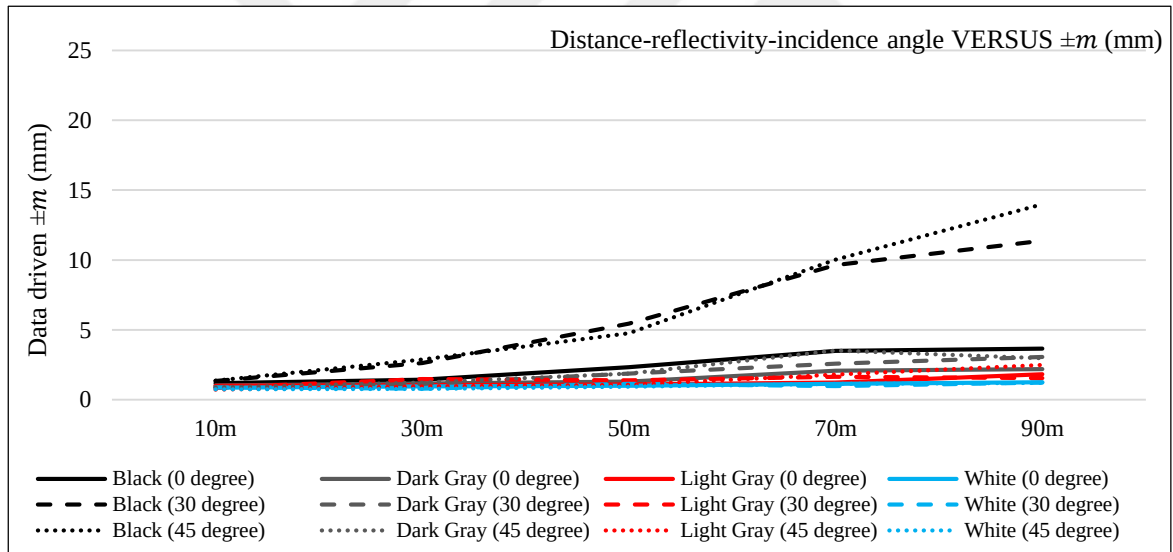


Figure 3.15 Data driven empirical σ_ρ values for the Riegl VZ400 scanner.

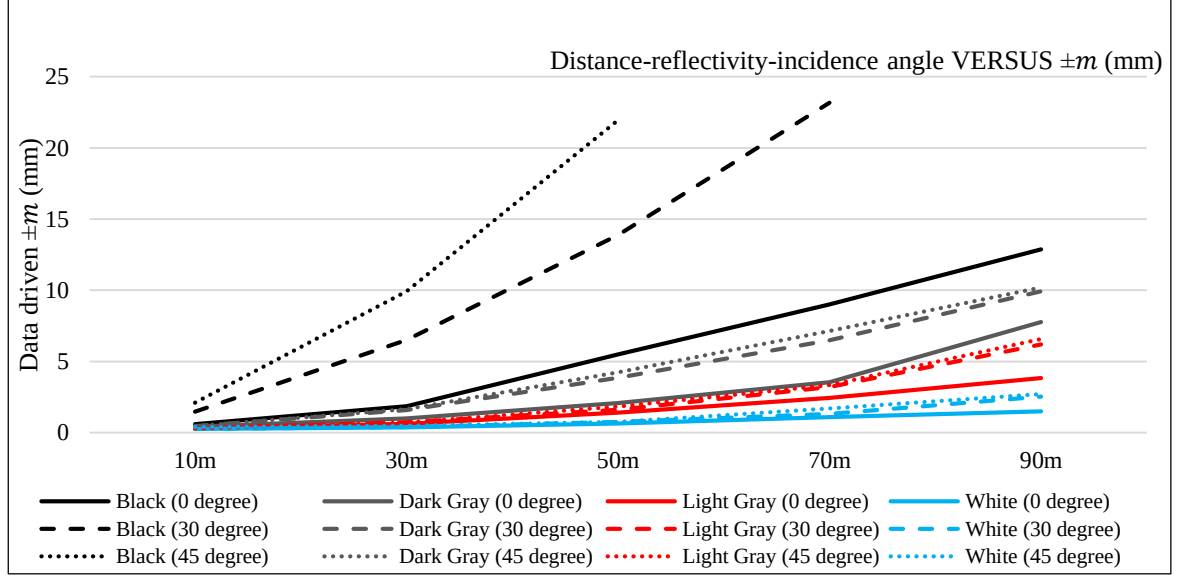


Figure 3.16 Data driven empirical σ_ρ values for the Z+F 5010X scanner.

Figures 3.14, 3.15 and 3.16 are rendered using the data-driven method. Each figure requires data from 15 scans of the pre-fabricated test stand. This empirical workload is heavy, and not practical for ordinary scanning projects. This fact gives rise to the need for a model-driven method in order to determine the range precision σ_ρ using an appropriate mathematical model and less fieldwork. The following sub-section introduces this model.

3.3.2.2 Model-driven range precision

In the previous section, it has been demonstrated that there is a strong relationship between range precision (σ_ρ) and the object-space parameters in the form of scanner-to-target distance (ρ), incidence angle (γ) and target reflectivity (I). The distance (ρ) and the incidence angle (γ) are computed through the Cartesian coordinates using Equation 3.5(a) and 3.11. The target reflectivity (I) is a measure of the intensity value of the returning signal. The range precision σ_ρ is unique for each point, and can be formulated as a function of (ρ, γ, I). This model-driven formula has to fulfil the following conditions which are the results of the analysis of the trend patterns of m values given in the data-driven graphics in Figures 3.14, 3.15 and 3.16.

1. As the distance increases, σ_ρ increases linearly.
2. As the incidence angle increases, the returned signal weakens. This results in a deterioration of σ_ρ . The degree of deterioration is a factor of the $\frac{1}{\cos(\gamma)}$ function (Baselgia et al. 2014, Grant et al. 2012, Soudarissanane et al. 2011).
3. As the surface reflectivity decreases, so as the target surface absorbs more of the incoming laser light. Consequently, σ_ρ increases non-linearly as a quadratic function of the distance.

Based on these conclusions, the following formula for the model-driven range precision (σ_ρ) was developed:

$$\sigma_\rho = \frac{c + (d * \rho) + f(I)}{\cos(\gamma)} \quad (3.20)$$

and

$$f(I) = \begin{cases} a + b * \rho^2 & , \text{ for } I < I_T^b \\ 0 & , \text{ elsewhere} \end{cases} \quad (3.21)$$

where a, b, c and d are the coefficients (to be determined), ρ is the scanner-to-point distance, γ is the incidence angle and I is the intensity value. If provided by the associated software of the scanner, it is recommended that the reflectance value is used, which is the normalized and distance effect eliminated version of the intensity value. The coefficients a, b, c and d are constant for each scanner, and the direct observations (ρ, γ, I) are variable for each point.

The part $c + (d * \rho)$ of the equation is the linear distance error, where c is the constant error and d is the slope of the regression line. The function $f(I)$ is the error contribution of the target reflectivity. It is a quadratic function of the distance. The cubic or linear functions can also be considered. The linear distance error and the target reflectivity error are additive terms. The denominator term $\cos(\gamma)$ is the error due to the incidence angle, which intensifies or attenuates the additive error terms.

The coefficients a, b, c and d are the scanner (sensor space) parameters which can be derived by means of a simplified experimental set up, instead of conducting the full extent of the

fieldwork experiment (given in Figure 3.12 and Figure 3.13). The four plates are too many given the fact that dark gray and light gray plates behave similar to the white plate. Therefore, only two colours (black and white) can be used.

The simplified experimental set up requires two highly absorbent planar objects (black plates) and two highly reflective planar objects (white plates). The black and white plates can be scanned at close and far distances such as at 10 and 90 meters, respectively. Their orientations are kept perpendicular to the TLS so that the incidence angles become zero degrees. This simplified experimental configuration is shown in Figure 3.17.



Figure 3.17 Simplified experimental configuration. The black and white plates are marked with red arrows.

Such a simplified experimental configuration can reliably recover the scanner variant a, b, c and d parameters. The four m values (the RMS error of the off-plane distances) are calculated using Equation 3.19 for the first set of black-and-white-plates located at 10 meters and the second set located at 90 meters. A hypothetical graph of these m values is plotted in Figure 3.18.

In Figure 3.18, ordinate values m stand for the RMSE of the off-plane distances, where the subscript means the distance between the TLS and the plate (10m or 90m) and the superscript

means the color of the plate (b (black) or w (white)). The scanner variant parameters a , b , c and d of Equations 3.20 and 3.21 are computed by the following steps:

1. The parameter c is the constant error of the TLS. This is the amount of the shift of the line of the white plates (the red line in Figure 3.18) from the range axis (abscissa). Parameter c is the summation of the constant distance accuracy (e) provided by the manufacturer and m_{10}^w which is the intercept of the red line.

$$c = e + m_{10}^w \quad (3.22)$$

2. The parameter d is the slope of the red line (Figure 3.18) and can be computed as in Equation 3.23, which is a kind of linear interpolation. Although the formula is defined to start from the close distance (10 meters), it can be straightforwardly applied for the points whose distances are $\rho < 10$ meters. The discrepancies are minor, and do not change the results significantly.

$$d = \frac{m_{90}^w - m_{10}^w}{90 - 10} = \tan(\beta) \quad (3.23)$$

3. The parameters a and b can be calculated by solving the following equation system:

$$\begin{aligned} a + b * 10^2 &= m_{10}^b - m_{10}^w \\ a + b * 90^2 &= m_{90}^b - m_{90}^w \end{aligned} \quad (3.24)$$

4. I_T^b is the threshold for the black reflectance values. If the reflectance value (I) of any point is smaller than the threshold I_T^b , the a priori precision value is attenuated as much as the function $f(I)$ as shown in Equation 3.20. The threshold I_T^b is defined as the maximum of the average reflectance values belonging to the black plates positioned at 90m and 10m from the TLS.

$$I_T^b = \max\{I_{90m}^b, I_{10m}^b\} \quad (3.25)$$

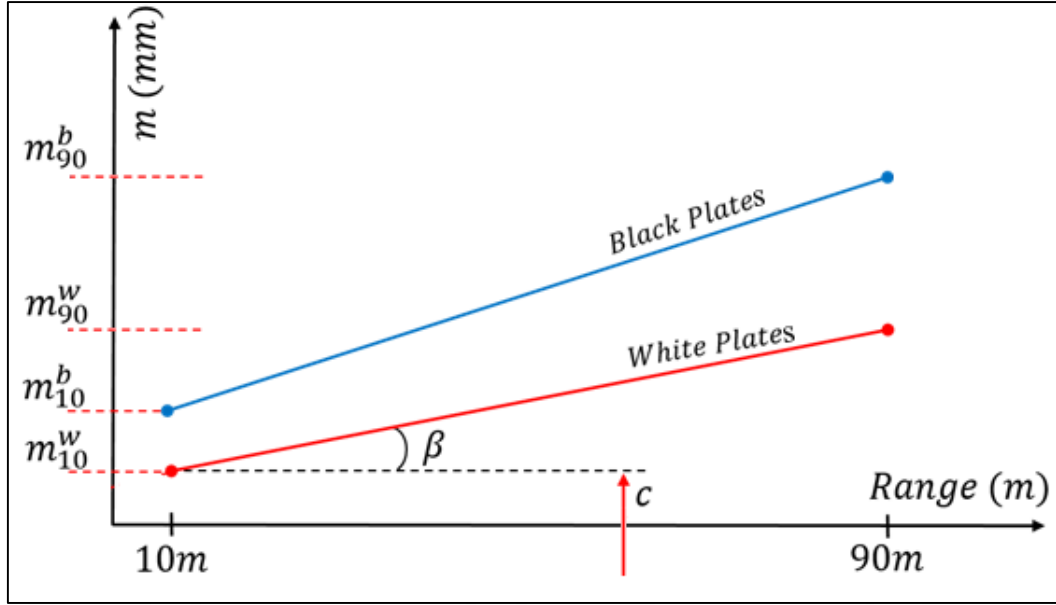


Figure 3.18 Two sets of the black-and-white-plates are located at 10m and 90m distances, respectively. All of the four plates are at the rotation of 0 degrees of incidence angles.

The experiment and associated computations (Equations 3.20-3.25) have been conducted for all of the three scanners. The computed parameters are tabulated in Table 3.4. The threshold I_T^b values are the large numbers for the Faro and Riegl scanners, as their reflectance numbers are over-exposed and their histograms are non-symmetric.

Table 3.4 Parameters of the model-driven a priori range precision formula for the three scanners.

TLS brand	a	b	d	e (mm)	m_{10}^w (mm)	I_T^b [0-255] gray level
Faro Focus 3D X330	0.042	0.000163	0.0042	2	0.21	191
Riegl VZ400	0.297	0.000262	0.0047	3	0.86	133
Z+F 5010X	0.203	0.001380	0.0157	1	0.25	23

Once the coefficients a, b, c and d are computed, the model-driven range precision σ_ρ is calculated with the formula given in Equations 3.20 and 3.21 using the functions of the (ρ, γ, I) variables. These model-driven σ_ρ values are plotted in Figures 3.19, 3.20 and 3.21 for comparison with the data driven σ_ρ values given in Figures 3.13, 3.14 and 3.15.

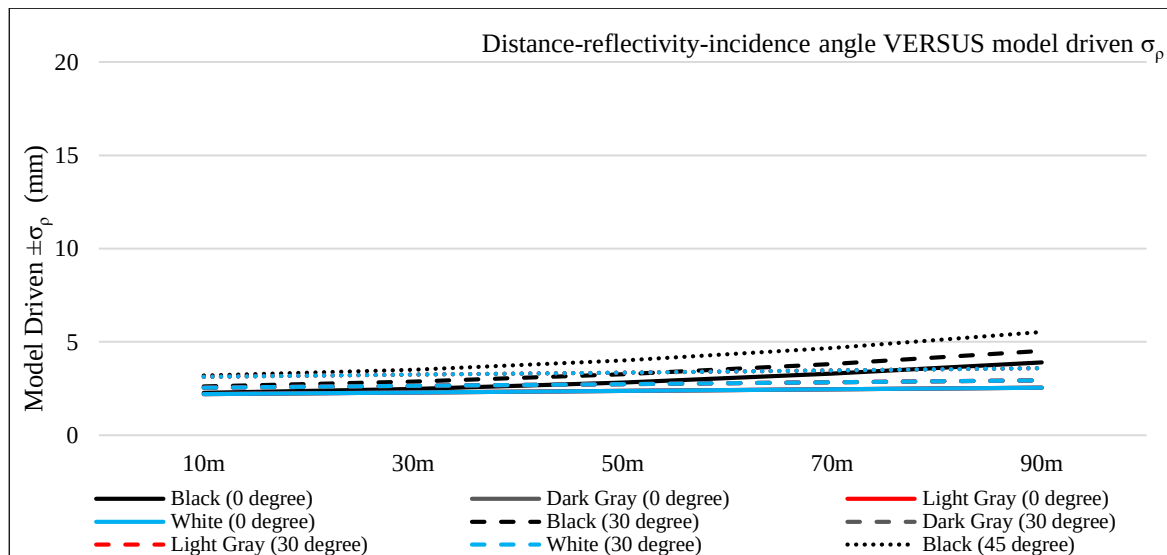


Figure 3.19 Model driven σ_ρ values for the Faro Focus 3D X330 scanner.

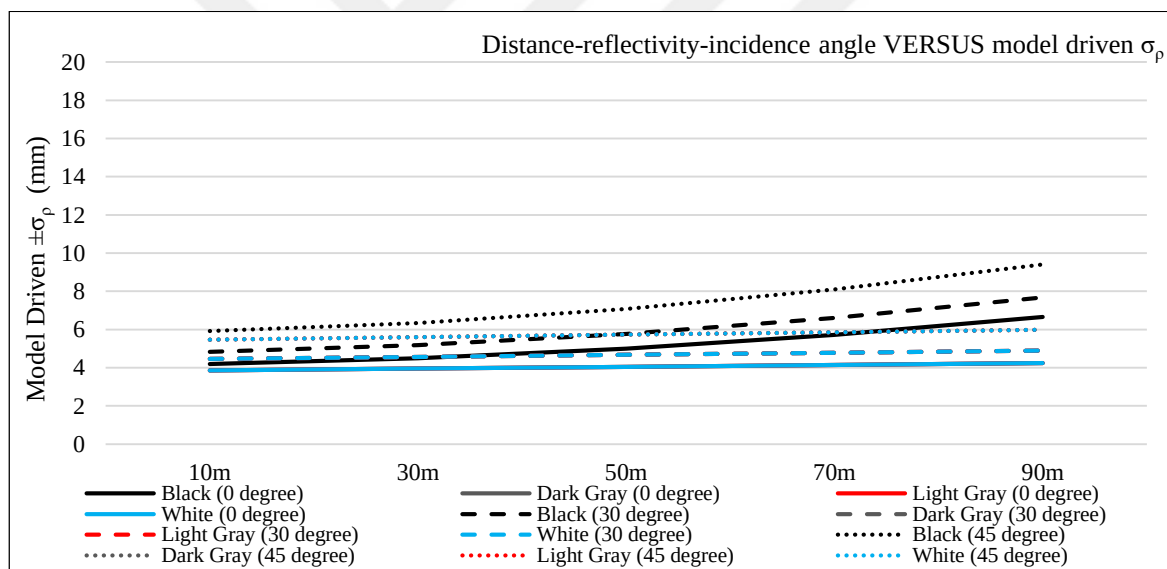


Figure 3.20 Model driven σ_ρ values for the Riegl VZ400 scanner.

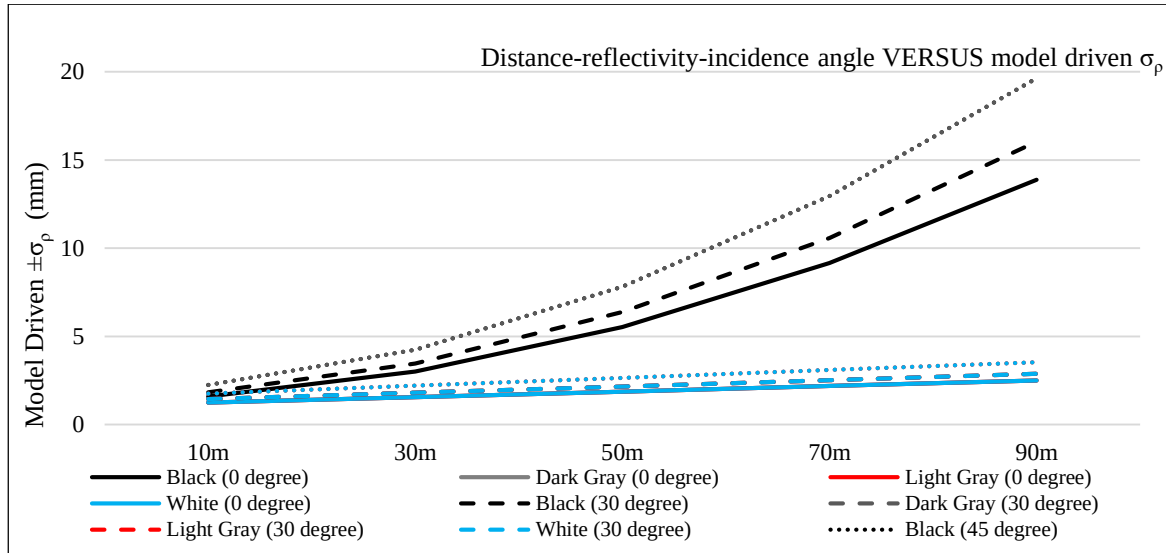


Figure 3.21 Model driven σ_ρ values for the Z+F 5010X scanner.

The model-driven graphics of Figures 3.19-3.21 are the imitations of the data-driven (empirical) graphics of Figures 3.14-3.16. They are practical and can be rendered with less fieldwork. The formula for the range precision of the model-driven approach fulfils the requirements mentioned above. The precision values σ_ρ of highly absorbent (black) objects are much higher when compared to those of the dark gray, light gray and white objects. The precision values σ_ρ of the non-black objects are almost linear, and variations are very small. The precision values σ_ρ of the non-black objects overlap as expected, because the model-driven approach treats the non-black objects as being one class. In conclusion, the model-driven σ_ρ values are compatible with the ones obtained by the data driven versions given in Figures 3.14-3.16.

3.4 INTENSITY OR REFLECTANCE VALUE

TLSs record intensity values directly for each point. When the distance and angle corrections are applied to the intensity values, reflectance values can be obtained. All scanners used in this study can output reflectance values. In order to see the reflectance properties of the plates (Figure 3.12), the mean of the reflectance value for each plate is plotted as shown in Figures 3.22, 3.23 and 3.24.

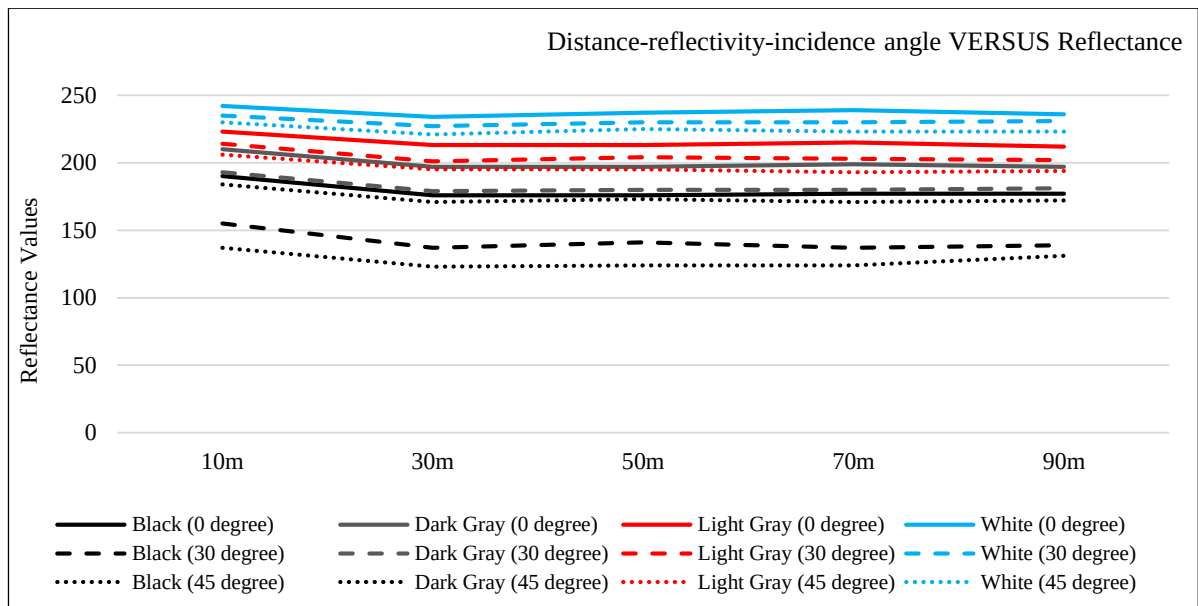


Figure 3.22 Reflectance values recorded by the Faro Focus3D X330.

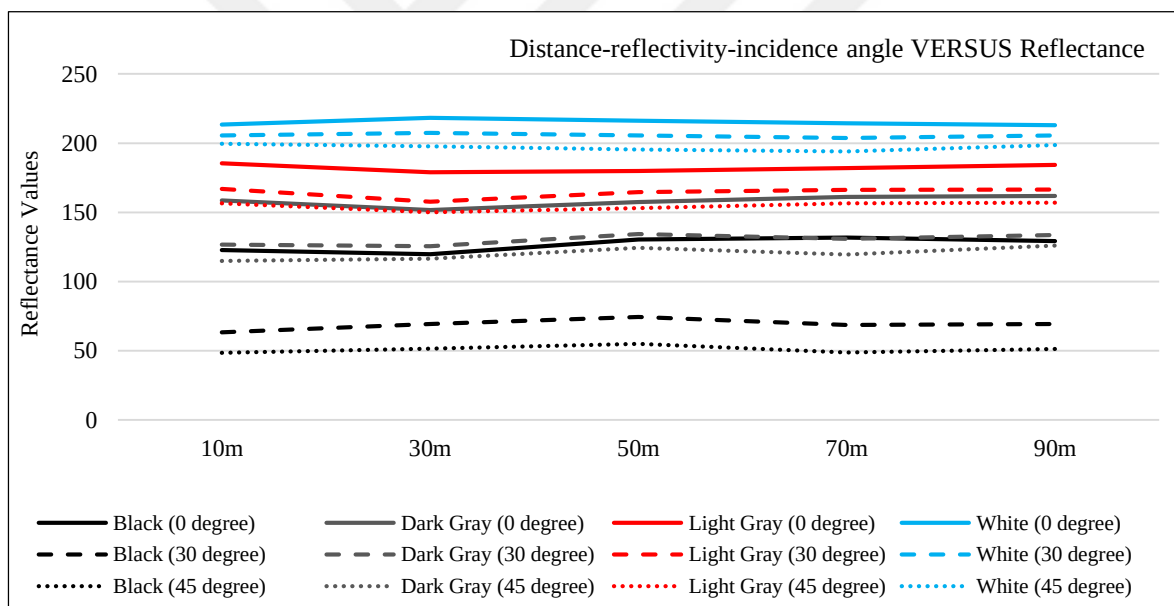


Figure 3.23 Reflectance values recorded by the Riegl VZ400.

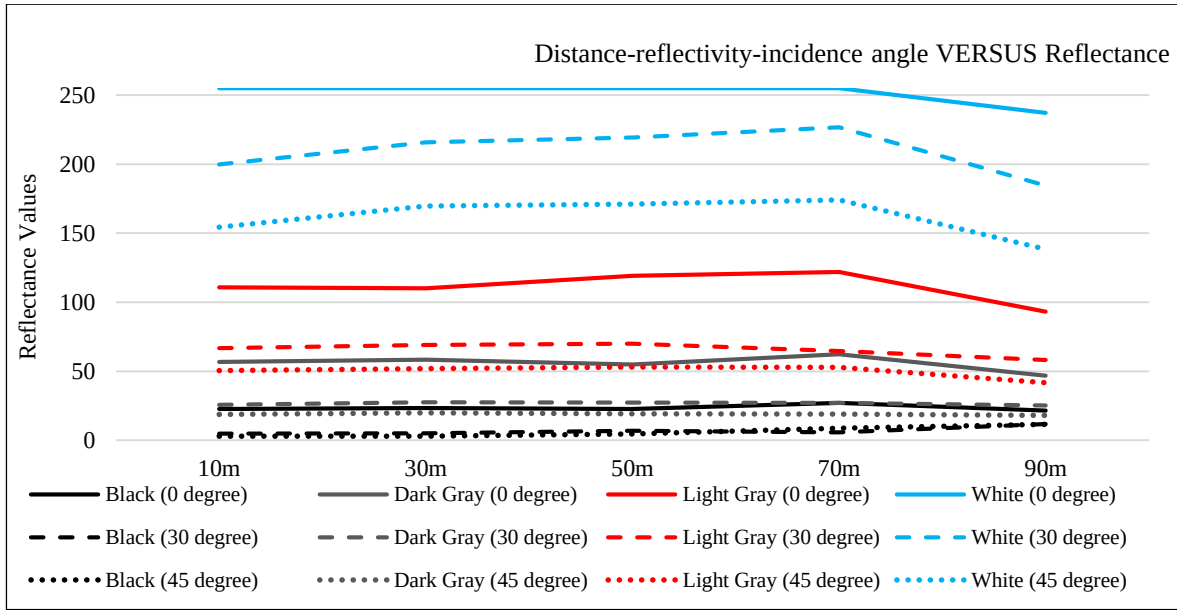


Figure 3.24 Reflectance values recorded by the Z+F 5010X.

The reflectance values shown in these figures are sampled in 8 bits. Even if the objects (plates) are the same, the range of reflectance values varies for each scanner. For example, the Faro scanner recorded reflectance values of between 100 and 250. On the other hand, the Riegl VZ400 recorded reflectance values of between 50 and 250 while the Z+F 5010x scanner recorded reflectance values for the same plates of between 0 and 255.

Figures 3.22, 3.23 and 3.24 show that the effect of distance on intensity is corrected successfully. Contraversially, the effect of the incidence angle is still present. The class boundaries are distinct and do not obscure the each other. Therefore, we recommend using the reflectance values rather than the intensity in the computations.

3.5 VALIDATION OF THE PROPOSED POINT ERROR MODEL

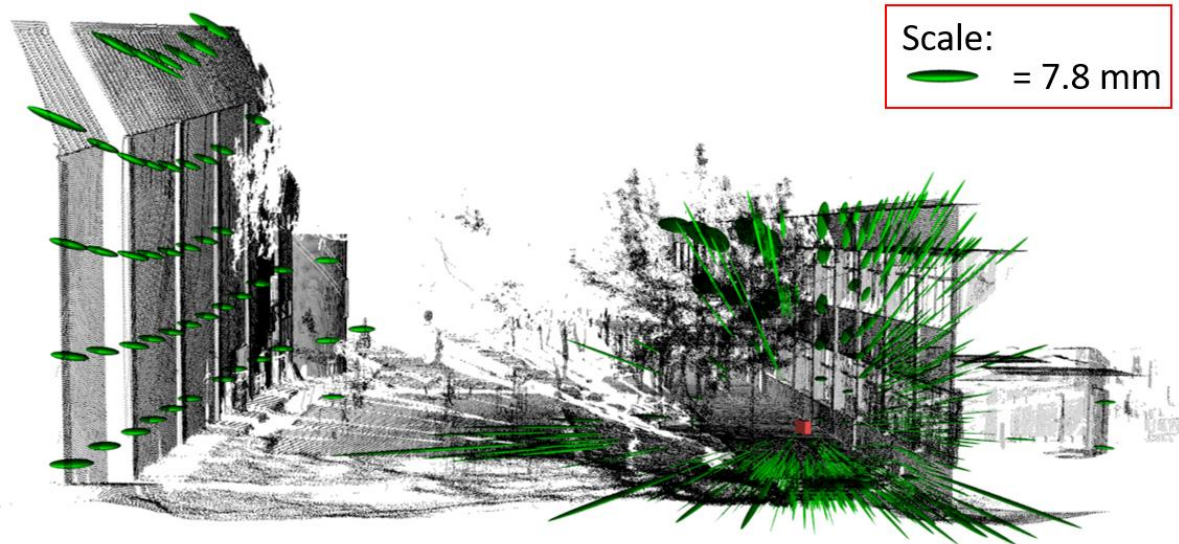
In order to validate the performance of the proposed error model, a test scene was chosen and scanned with the aforementioned TLSs from the same stand point. This test scene consisted of the façades of buildings (Figure 3.25) and a playground in the campus area of the Zonguldak Bülent Ecevit University (Zonguldak, Turkey).



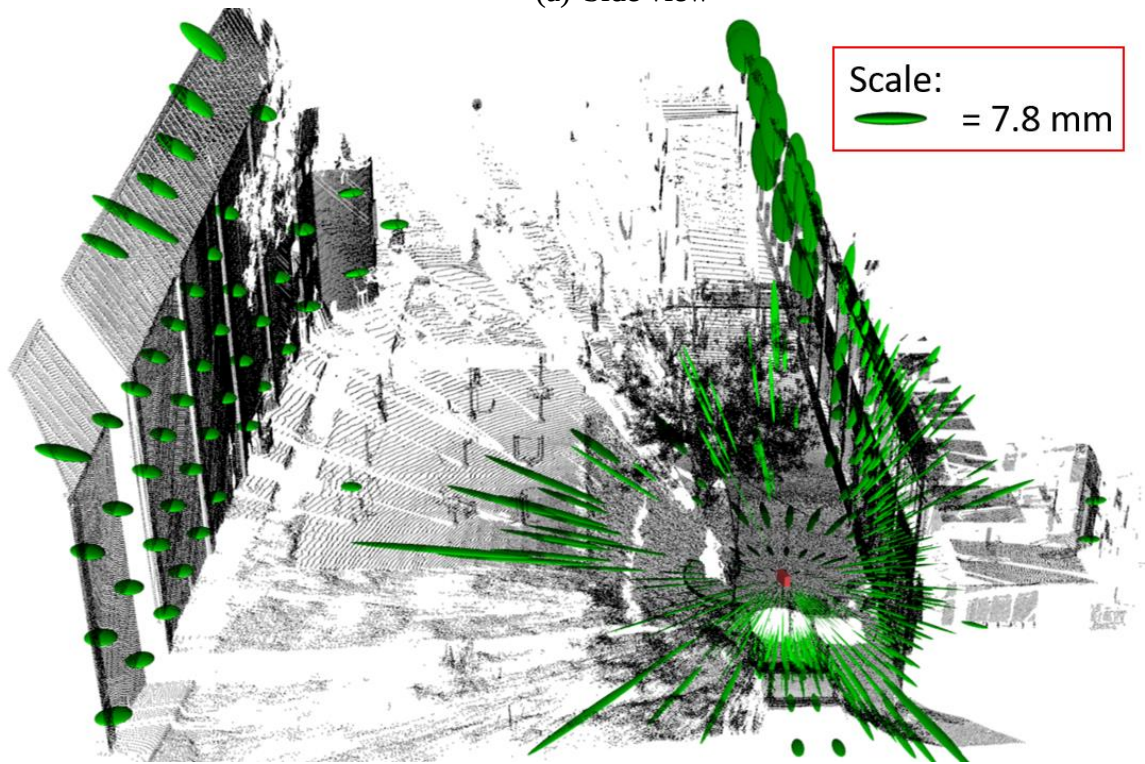
Figure 3.25 The test scene used for the validation.

The error ellipsoid parameters of each point for each scan were calculated as described in the method detailed in Section 3.2. The validation of the proposed point error model was investigated using these ellipsoids. The error ellipsoids for the Faro Focus 3D X330, the Riegl VZ400 and the Z+F 5010X derived point clouds are illuminated, respectively, in Figures 3.26, 3.27 and 3.28. The MATLAB programming environment was used for the computations. The VTK (Visualization Tool Kit) and C++ were used for visualization purposes.

The test environment contains all the relevant parameters, varying scanner to object distances, incidence angles and surface reflectivity. The incidence angle is one of the majorly effecting parameters. As the incidence angle approaches to the extreme values, the corresponding error ellipsoids have elongated shapes. Oppositely, the ellipsoids resemble to spheres where the incidence angles approach to zero degree angles.

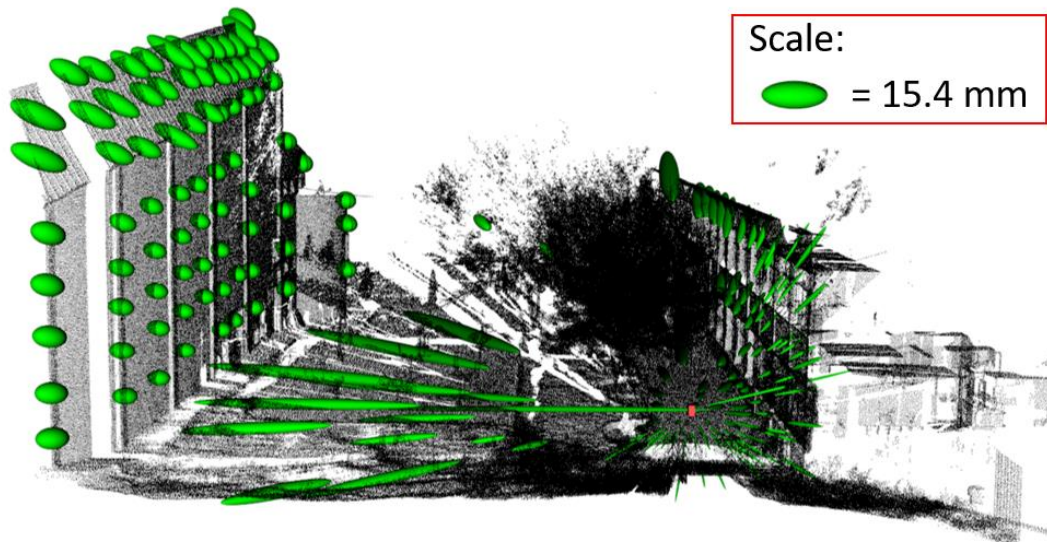


(a) Side view

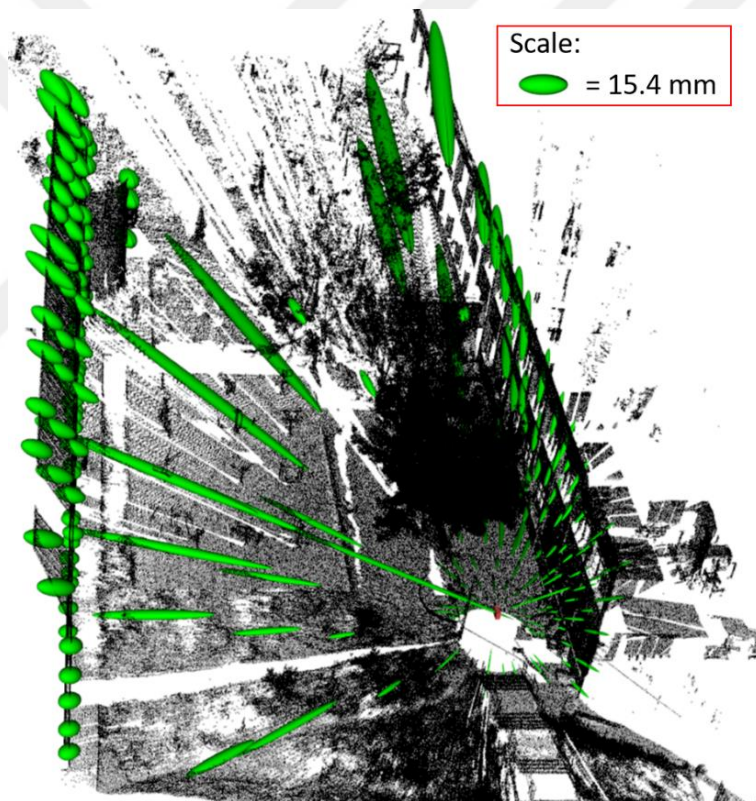


(b) Oblique view

Figure 3.26 Side view (a) and oblique view (b) of a point cloud of the test scene acquired by the Faro Focus 3D X330 scanner. The TLS station is labelled by the red cube. The estimated error ellipsoids are represented in green. The ellipsoids are plotted at every 200-th point.

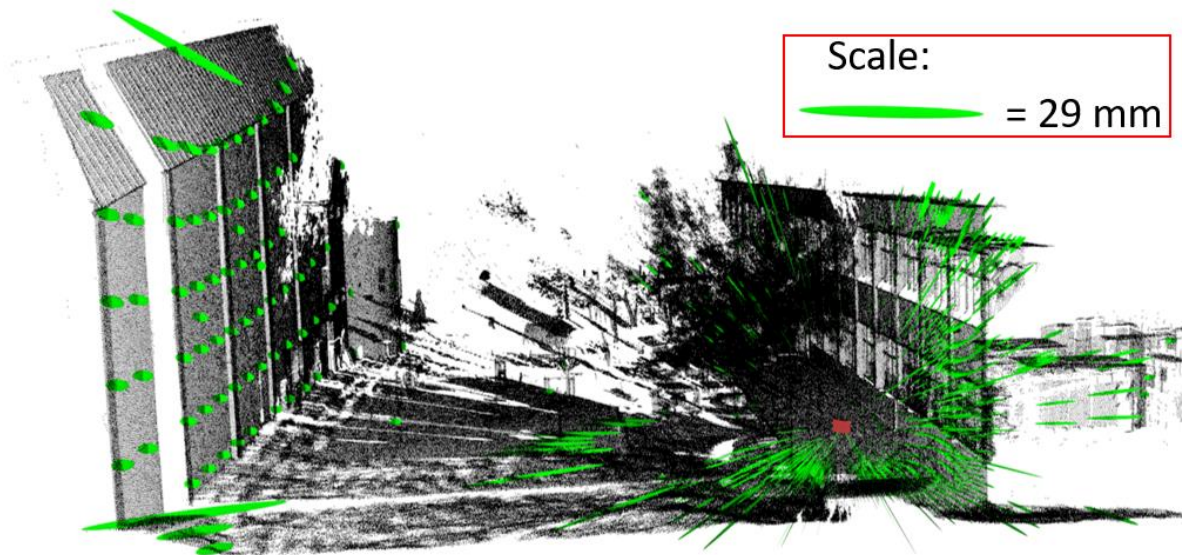


(a) Side view

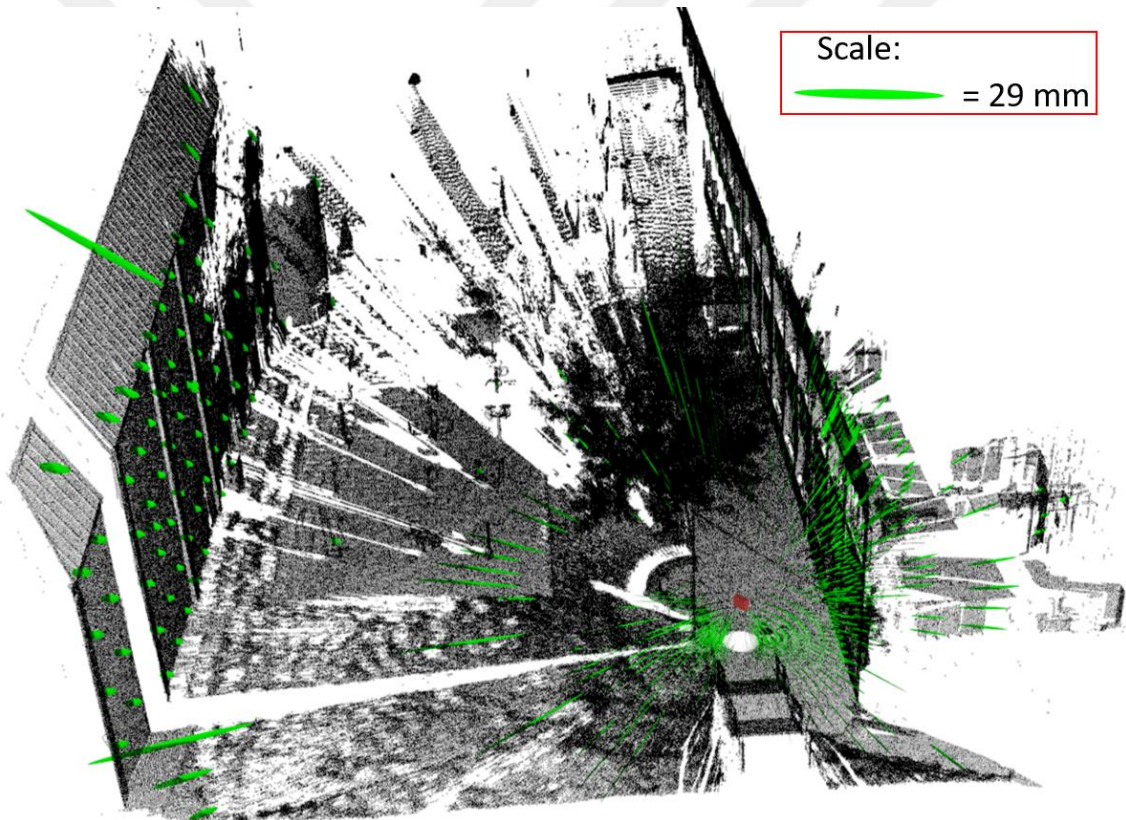


(b) Oblique view

Figure 3.27 Side view (a) and oblique view (b) of a point cloud of the test scene acquired by the Riegl VZ 400 scanner. The TLS station is labelled by the red cube. The estimated error ellipsoids are represented in green. The ellipsoids are plotted at every 150-th point.



(a) Side view.



(b) Oblique view.

Figure 3.28 Side view (a) and oblique view (b) of a point cloud of the test scene acquired by the Z+F 5010X scanner. The TLS station is labelled by the red cube. The estimated error ellipsoids are represented in green. The ellipsoids are plotted at every 300-th point.

Based on the error ellipsoids plotted in Figures 3.26 - 3.28, several conclusions can be drawn. As the distance increases, the ellipsoids become more elongated in the line of sight direction. Apart from the distance, as the incidence angle increases and as the surface is highly absorbent,

the elongation of the ellipsoid becomes much more drastic. This situation reveals the fact that in a point cloud, each individual point has different positional uncertainty, and the proposed point error model can successfully determine this uncertainty. This information is remarkably important when the millions of messy points are subject to object modeling, quality assessment, comparison and data fusion tasks.





CHAPTER 4

SURFACE MESH RECONSTRUCTION

4.1 A QUALITY MEASURE FOR TLS-DERIVED POINTS

The positional uncertainty of each point is unique, and depends on the a priori precision values of direct observations ($\sigma_\rho, \sigma_\alpha$, and σ_θ). Therefore, error ellipsoid characteristic of each individual point is also unique. The proposed error ellipsoid is well defined mathematical representation of the physical reality, since it is formed by use of the most influential error sources. The size, shape and orientation of the error ellipsoid provide useful information about the metric quality of point.

Let a point p_i be associated with the error ellipsoid that has semi-axis lengths $\sqrt{\lambda_1}$, $\sqrt{\lambda_2}$, and $\sqrt{\lambda_3}$, where $\sqrt{\lambda_1}$ is the semi-major axis of the ellipsoid. $\sqrt{\lambda_1}$ can be considered as a quality measure of the point p_i . However, $\sqrt{\lambda_1}$ is independent of angular a priori precision values ($\sigma_\alpha, \sigma_\theta$). This is not optimal. The quality measure should be composed of both angular and the range a priori precision values. The semi-diagonal axis length of bounding box of the error ellipsoid in Figure 4.1 includes both angular and range a priori precision values. In this case, the quality measure of a point p_i can be defined as in the following equation:

$$Q_{p_i} = \text{Semi-diagonal axis length} = \sqrt{(\sqrt{\lambda_1})^2 + (\sqrt{\lambda_2})^2 + (\sqrt{\lambda_3})^2} \quad (4.1)$$

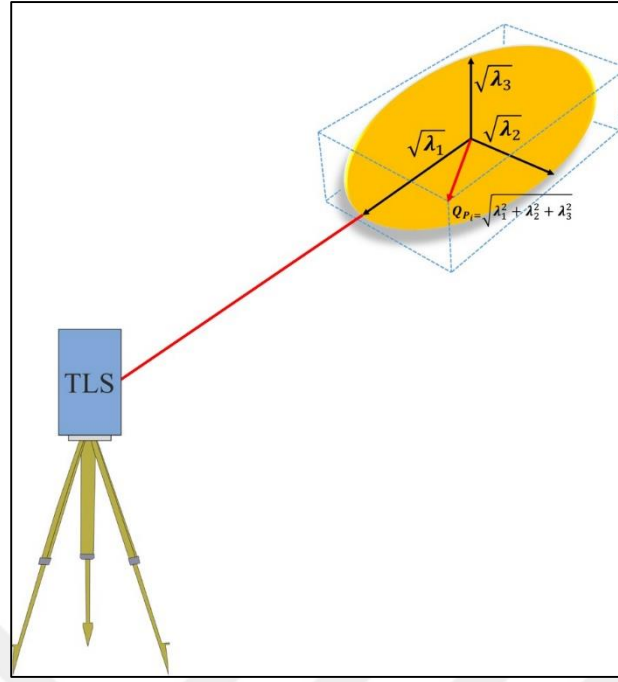


Figure 4.1 Illustration of an error ellipsoid and Q_{p_i} with respect to the TLS.

In order to visualize the Q_{p_i} quality measure values, a test object was chosen and scanned with the aforementioned TLSs from the same stand point. This test object was the façade of a building (Figure 4.2) in the campus area of the Zonguldak Bülent Ecevit University (Zonguldak, Turkey). It is capable of demonstrating the effect of varying scanner to object distances, incidence angles and surface reflectivity. The Q_{p_i} was computed for each point, and visualized as shown in Figures 4.3, 4.4 and 4.5 for each TLS, respectively.



Figure 4.2 The test object is a building façade.

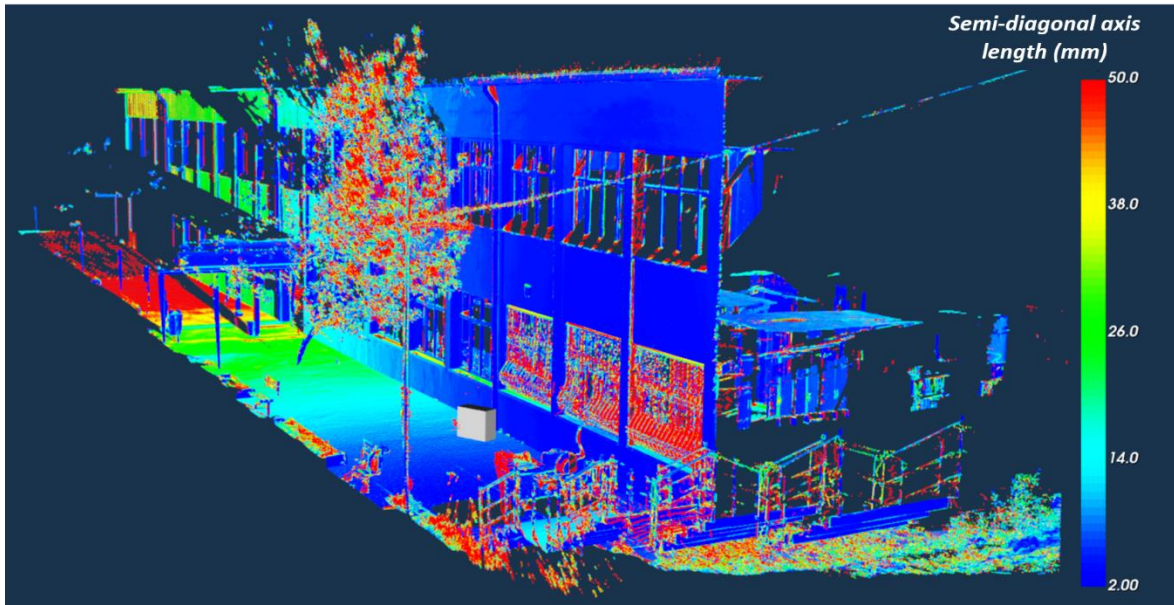


Figure 4.3 Visualization of Q_{p_i} values (semi-diagonal axis length) for the Faro scanner. The TLS station point is indicated by the white cube. The blue colours show the good quality points and the red colours for the bad quality points.

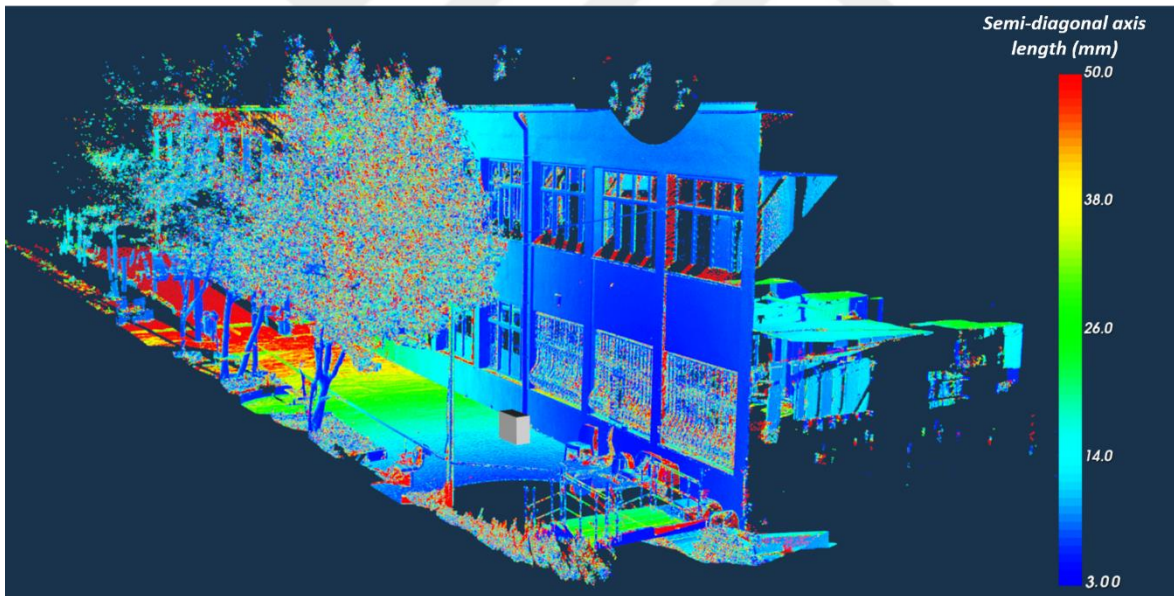


Figure 4.4 Visualization of Q_{p_i} value (semi-diagonal axis length) for the Riegl scanner. The TLS station point is indicated by the white cube. The blue colours show the good quality points and the red colours for the bad quality points.

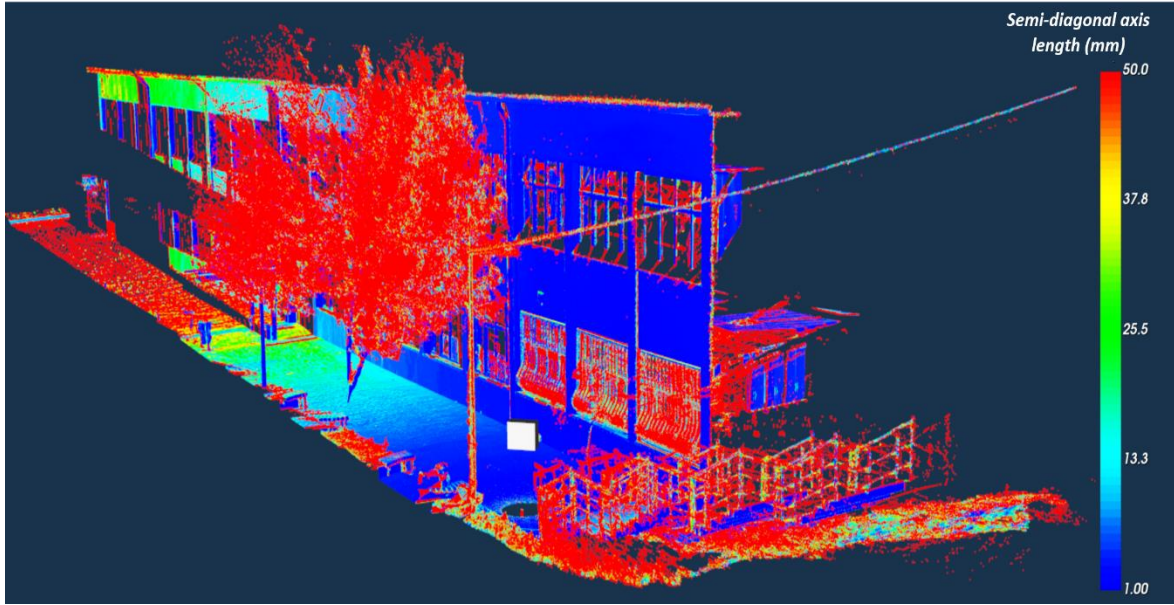


Figure 4.5 Visualization of Q_{p_i} value (semi-diagonal axis length) for the Z+F scanner. The TLS station point is indicated by the white cube. The blue colours show the good quality points and the red colours for the bad quality points.

Figures 4.2–4.4 reveal the fact that point quality is closely related to the incidence angle, range and surface reflectance parameters. As the distance and incidence angle decreases, point quality increases. On the other hand, as the surface reflectance decreases, point quality decreases as well. Even though trees and iron guardrails are closer to the TLS, the point quality of these objects is quite low especially at the edges. This is due to the surface discontinues where the laser beam cone hits multiple objects along the sight of line and the incidence angle approaches to very large numbers. Because the Riegl scanner measures range on a Time of Flight basis, the point cloud of this scanner contains very limited noise when compared to the Faro and Z+F scanners. For this reason, the point quality of the tree and guardrails are very high in the case of the Riegl data.

4.2 VOXEL-BASED BEST POINT SELECTION

In the TLS projects, more than one scan is usually required from multiple viewpoints to ensure full coverage of the target object or the scene. Moreover, consecutive scans should have overlap to some extent. This data acquisition procedure is followed by the co-registration of individual scan data. Co-registration is simply the process of transforming all scan data into a common coordinate system. After the co-registration, in the overlapping parts of the data, the same object surface is sampled at multiple times. For example, assume that the same part of a building is

scanned four times from different TLS stand points. In other words, this part of the building is sampled four times. This is data redundancy. An optimum solution has to be found for the question of which point to select among those four to represent the same object surface.

In the TLS projects generally, the same part of the object is sampled by means of a large number of messy points that are of different quality. Figure 4.6 depicts this scenario.

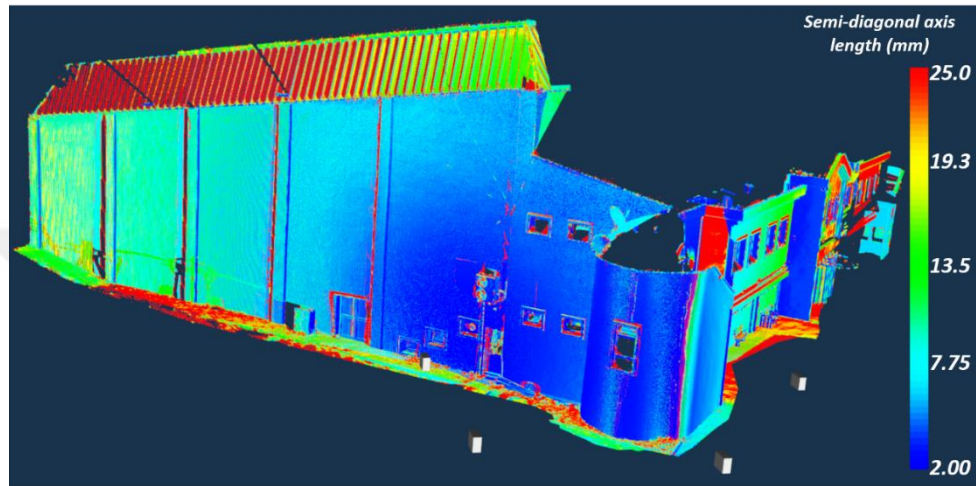


Figure 4.6 Visualization of point quality in a co-registered point cloud.

The point cloud shown in Figure 4.6 is composed of four scans. It contains approximately 20 million points. The TLS stand points are shown by white cubes. The figure clearly shows that the same part of the object is sampled with a very large number of points of differing quality. This fact is especially visible with regard to the cylindrical part of the object which is sampled by points that have quality ranging from 2mm to 25mm (or more). This is a feature that users often encounter during the surface mesh generation from TLS-derived point cloud data. It results in erroneous and very noisy data as represented in Figure 4.7, the surface of this cylindrical structure is made of smooth plaster.

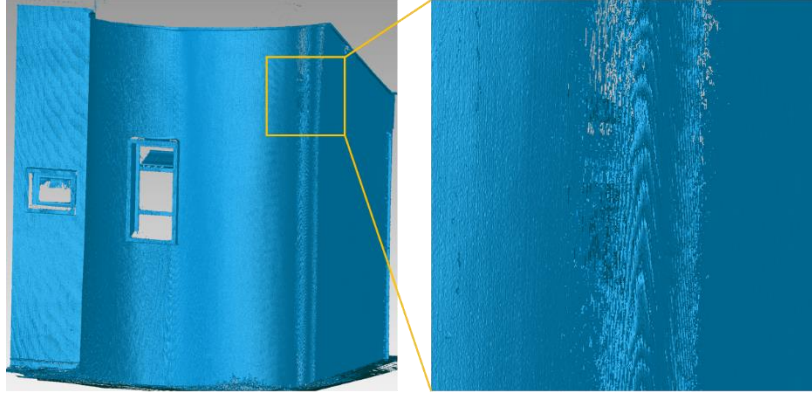


Figure 4.7 Surface mesh of the original TLS data. Surface mesh of the cylindrical structure (left) and close view of the area marked with orange box.

In order to create error-free and smooth surfaces from multiple co-registered point clouds, various surface mesh reconstruction methods have been developed as mentioned in Chapter 2. The mesh reconstruction method proposed in this study can be classified as a volumetric method because it is based on the voxelization of the data space.

Similar to a pixel which is a raster cell in 2D, a voxel is a cuboid element in 3D space. Voxel representation is widely used in computer graphics' applications because it is a very efficient way of representing and analyzing 3D volumetric data. Since 3D point cloud data occupies 3D volumetric space, it can also be considered as volumetric data. The voxelization of a point cloud can be defined as the process of partitioning the 3D data space into voxels recursively, until a certain criteria is satisfied, such as the dimensions of the voxel or the number of points lying in the voxels.

The management of the voxel structure of a point cloud can be done effectively using the octree data structure. An octree data structure is a modified version of a 2D quadtree data structure for 3D data space. The octree is a hierarchical data structure at the top of which there is a root node which is a voxel containing the entire data set. The division of the root node into 8 branches results in lower level octants or voxels. The recursive division of these octants creates lower levels of the tree structure. In the case of the voxelization of a point cloud, the division process is performed by dividing the data domain spatially using Cartesian coordinates. This concept of voxelization with an octree data structure is illustrated in Figure 4.8. The root node is at the top of the tree, namely depth 0. The root node is divided into 8 voxels at the depth 1 level, voxels 0, 1, 2, 3, 4, 5, 6 and 7 are created. At the depth 2 level, the position of voxels 11 and 50 are shown in clour.

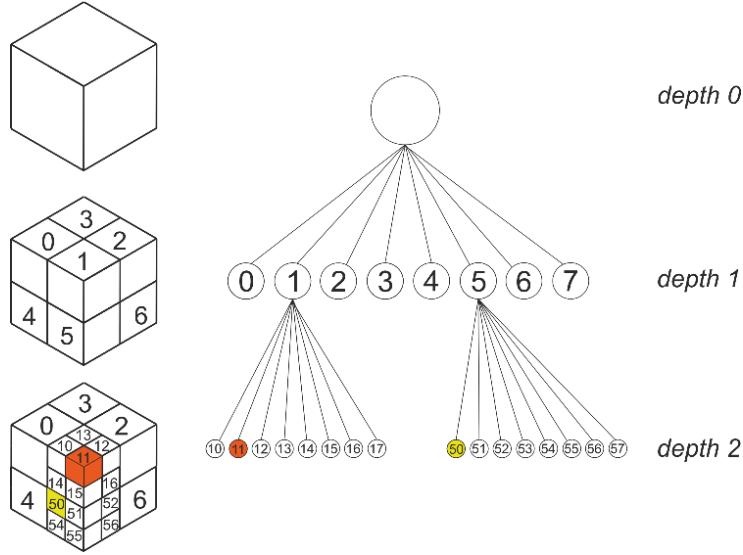


Figure 4.8 Octree-based voxelization of data domain.

In our study, the PCL (Point Cloud Library) was used for voxelization purposes (Rusu and Cousins, 2011). The PCL is an open source library developed for processing of 2D/3D images and point clouds, and it is free for both commercial and research uses. A point cloud can be managed by means of voxels with a user-defined voxel size parameter using the PCL. For example, the point cloud shown in Figure 4.9(a) is voxelized using the PCL library. For the voxelization of this point cloud, the voxel size parameter is selected as 0.5m for better visualization. The resulting voxels are shown in Figure 4.9(b) in the form of red cubes. In this example only non-empty voxels are presented.

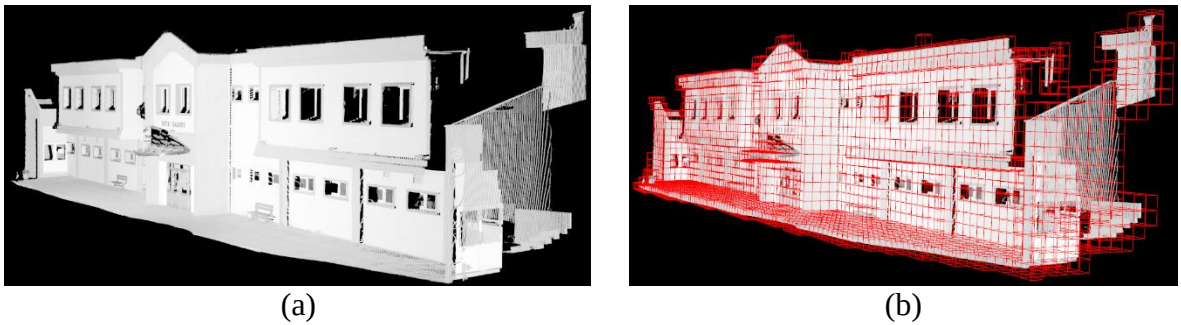


Figure 4.9 Example of voxelization of a TLS-derived point cloud.

As a consequence of the voxelization process, each point is associated with an ID number addressing of its voxel. Thanks to this structure, the list of points lying in each voxel can be easily determined. Due to the fact that the octree is a hierarchical data structure, there is no overlap between adjacent voxels. Each point is addressed to only one voxel. Depending on the point

density, the number of points within each voxel varies. While some voxels contain only one point, some may contain more than one point. In the case of a co-registered point cloud, a voxel may contain more than one points acquired from multiple scans as depicted in Figure 4.10.

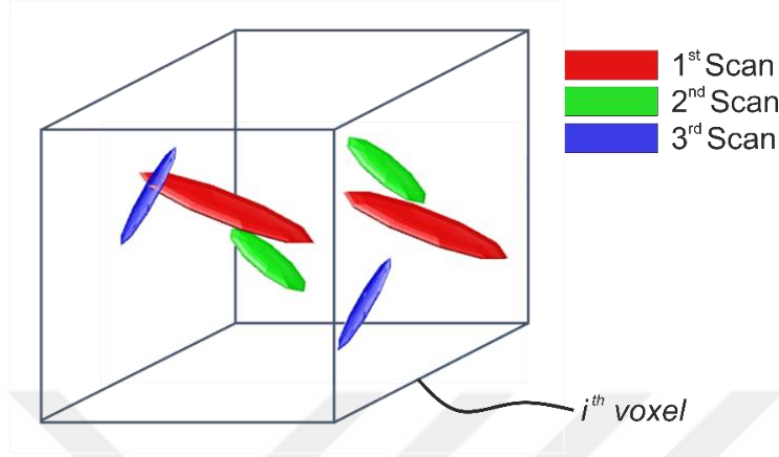


Figure 4.10 Illustration of a voxel and its points.

In Figure 4.10, a voxel and the error ellipsoids of six points lying in this voxel are depicted as a hypothetical example. The voxel contains points acquired from three different TLS stand points, represented by red, green and blue colors. The orientation of the error ellipsoids coming from different scans differ, because it is known that the major axes of the error ellipsoids are aligned with the line of sight of the TLS. Moreover, the dimensions of the error ellipsoids also differ. This is an expected case because the error ellipsoids are characterized depending on range, incidence angle and surface reflectivity. The micro object surface represented by this voxel is sampled by six points. Only the best quality point (among those six) will be used in the subsequent surface reconstruction step.

The proposed mesh reconstruction method is a novel voxel-based method which is capable of integrating partially overlapping co-registered TLS scan data, and decimating them into a new cloud which contains only the best quality points. This newly generated point cloud has to contain minimum scanning noise, registration error and outliers. Also, it has to represent cartographic details of the target object sufficiently. In order to keep the required level of details, the voxel size should be selected adaptively. If the target object contains very small details, then the voxel size should be small. On the other hand, if the target object is regular and the level of detail is very low, the selected voxel size should be larger. Once the voxelization is performed successfully, the next step is the selection of the point with the best quality in each

voxel. As a result, the integrated point cloud containing the best points is created. The surface mesh is reconstructed from this integrated point cloud, which results in the optimal surface.

The best quality point with minimum Q_{p_i} (Equation 4.1) selection procedure is as explained below:

Suppose that, as a result of voxelization, the partially overlapping co-registered point cloud is sampled with a voxel space V which contain n voxel elements as shown in Equation 4.2.

$$V = \{v_1, v_2, v_3, \dots, v_n\} \quad (4.2)$$

where each voxel is represented by v . Thanks to the octree data structure, the set of points lying in each voxel is known. For any voxel v_i , the set of points can be defined as:

$$v_i = \{p_1, p_2, p_3, \dots, p_k\} \quad (4.3)$$

where k is the number of points lying in the voxel v_i . For each voxel, the number of points k may vary.

Quality measure Q_{p_i} is computed for every k point in the voxel v_i . The point whose error ellipsoid has the minimum semi-diagonal axis length (Equation 4.1) is the best quality points for this voxel v_i .

$$BestQuality(v_i) = \min\{Q_{p_1}, Q_{p_2}, Q_{p_3}, \dots, Q_{p_k}\} \quad (4.4)$$

After the best quality point selection procedure is repeated for all voxels, the integrated point cloud is obtained. This point cloud is then used as input for the subsequent surface mesh reconstruction step. An experimental study to reconstruct the surface mesh model of a building is described in the following section.

4.3 3D SURFACE MESH RECONSTRUCTION: AN EXPERIMENTAL STUDY

The workflow of the used procedure for the 3D surface mesh generation is depicted in Figure 4.11.

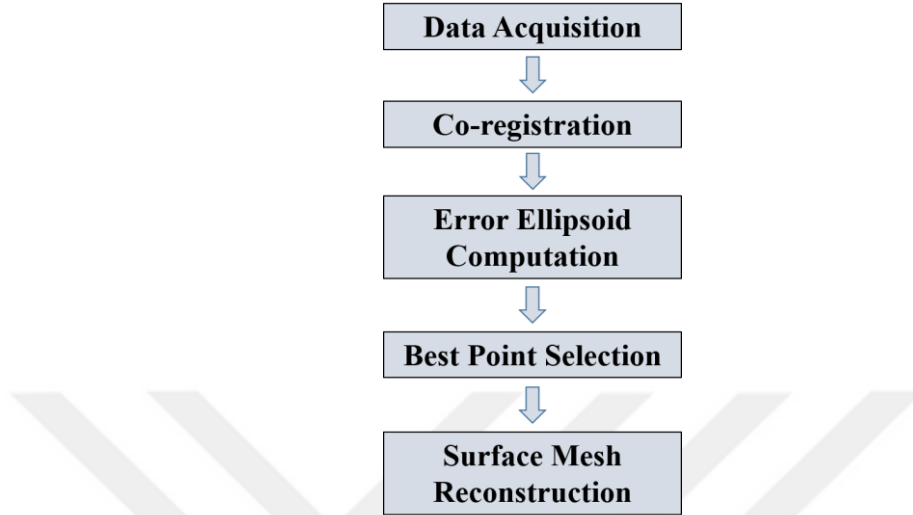


Figure 4.11 The workflow for 3D modelling from TLS-derived point clouds.

The first step is obviously data acquisition. The target object or scene is scanned from multiple viewpoints for full coverage. The consecutive scans should be partially overlapping for a better co-registration.

In this study, the façade of a building in the campus area of the Zonguldak Bülent Ecevit University (Zonguldak, Turkey) was chosen. The building is an ordinary building without fine detail, mostly containing planar components as shown in Figure 4.12.



Figure 4.12 The selected building façade for 3D surface mesh reconstruction.

The selected façade of the building was scanned using a Faro Focus 3D X330 scanner. Some of the technical specifications of the scanner are given in Table 3.1. The façade was scanned

from three stand points. These stand points were chosen in such a way that all details of the façade can be scanned (Figure 4.13).

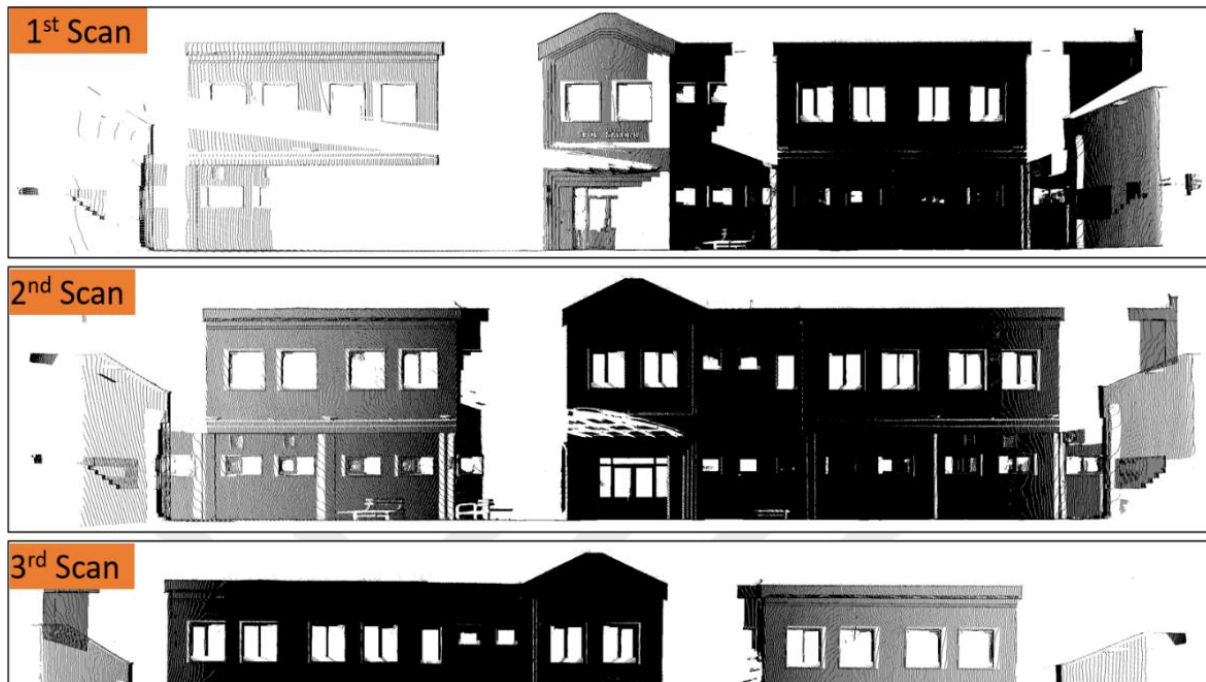


Figure 4.13 Three point clouds of the building façade acquired by the Faro Focus 3D X330 scanner.

As expected, the point density in the scans increases as the distance between the TLS and the façade decreases. Some parts of the façade can not be scanned in individual scans because of occlusions. Thanks to the scans acquired from multiple viewpoints, the occlusion problem is solved, and the façade is fully covered by all three scans. These three scans were co-registered using Faro Scene v5.5, which is the bundled software of the Faro scanners. The mean error of co-registration is reported less than 2mm by the software. After the co-registration process, all scans are aligned into the same coordinate system. The co-registered point cloud (Figure 4.14) contains almost 5.2 million points.

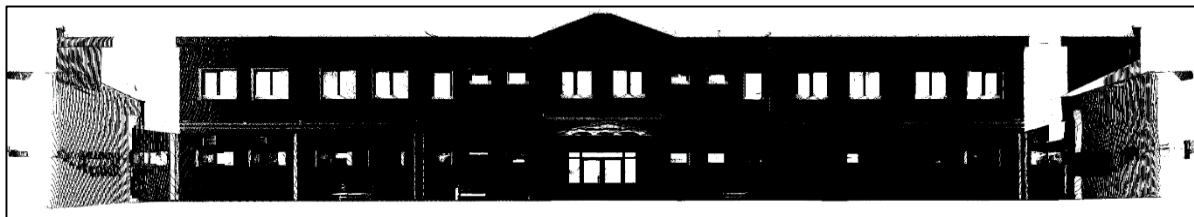


Figure 4.14 The co-registered point cloud acquired by the Faro Focus 3D X330.

The third step of the 3D modelling workflow (Figure 4.11) is the error ellipsoid computation. The error ellipsoids of each point of all three scans are computed as described in Section 3.2. The a priori precision values of the angular measurements ($\sigma_\alpha, \sigma_\theta$) were determined with the method explained in Section 3.3.1. The a priori precision for range measurement (σ_ρ) was determined as described in Section 3.3.2. The computed error ellipsoids are illustrated in Figure 4.15.

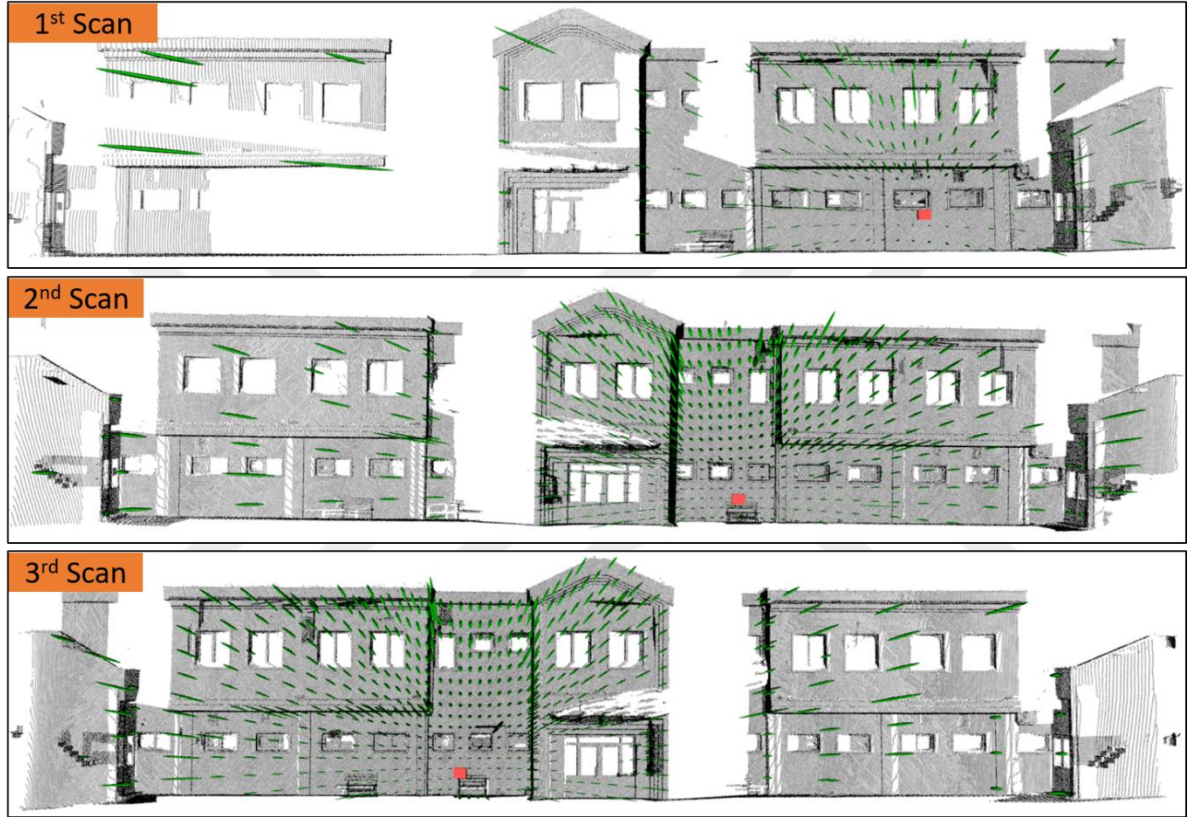


Figure 4.15 Three point clouds of the building facade scene acquired by the Faro Focus 3D X330 scanner. The TLS stations are indicated by the red cubes. The estimated error ellipsoids are represented in green. Every 200-th error ellipsoid is plotted for a better visualization purpose.

As the points get closer to the TLS station, and as the incidence angle approaches to zero, the error ellipsoids get smaller. In contrary, the ellipsoids get larger as the incidence angle and/or distance increases, and the surface reflectivity decreases. The smaller the error ellipsoid is the less the positional uncertainty, which means increased point positioning quality. Moreover, it can be observed that the same part of the target object is sampled by three point clouds, and each of them differ in terms of point quality. At this step, the corresponding error ellipsoids

were computed for each individual point of every point cloud. The best point selection in terms of positional quality will be followed in the next step.

Given the points and their error ellipsoid parameters, the quality measure of each individual point was computed using Equation 4.1, which is the length of the semi-diagonal axis of error ellipsoids. The computed point quality measures are visualized in Figure 4.16.

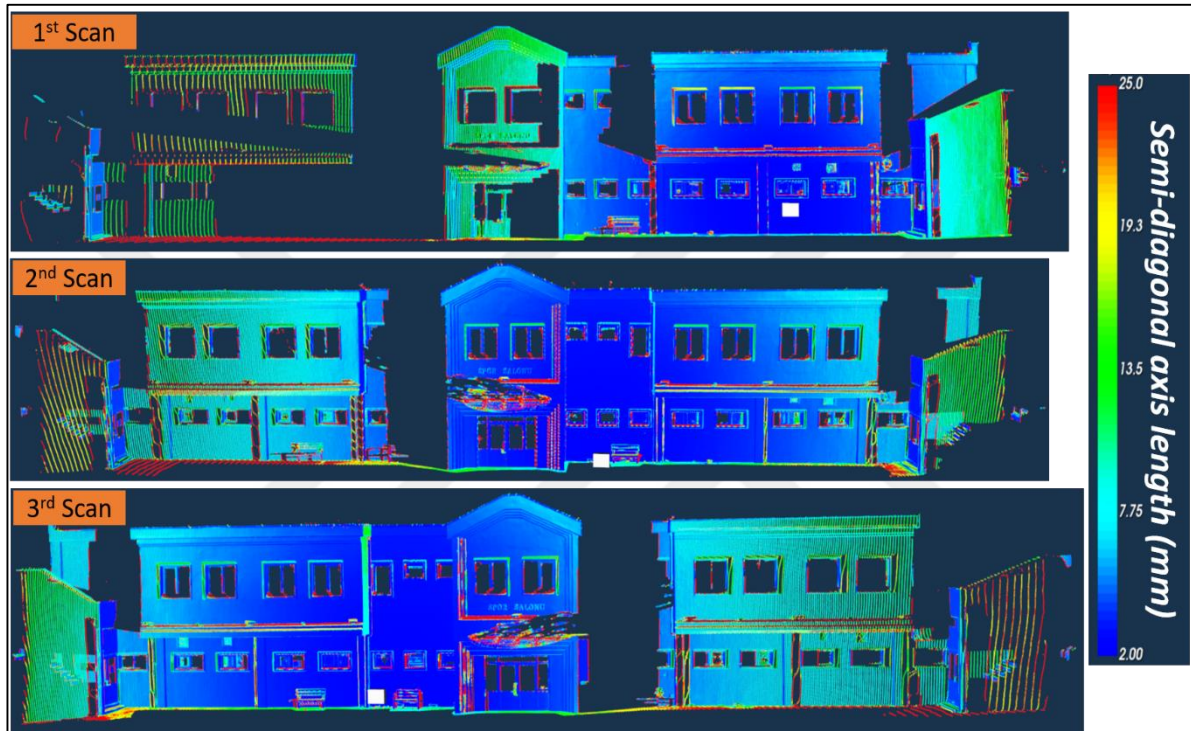


Figure 4.16 Visualization of point quality of the three scans acquired by the Faro Focus 3D X330 scanner. The TLS stations are indicated by the white cubes.

Similar to the error ellipsoid characteristics, the quality of a point depends on the distance to the TLS, the incidence angle of the incoming laser beam, and the surface reflectance properties. In the Figure 4.16, the point quality is represented with the color scale, varying between blue and red. The blue color corresponds to high quality, and red corresponds to low quality points. Surface discontinuity, poor surface reflectance and higher incidence angles yield very low quality points. These points are represented by yellow-to-red colors. While in one scan the same part of the façade is measured with high quality points, in other scans the same part may be measured with low quality points. For example, the wall at the right hand end of the façade is measured with high quality points in the 1st scan, but the same wall is measured with low quality points in the 2nd and 3rd scans. This fact is more obvious when the three scans are merged, and the point quality is visualized (Figure 4.17).

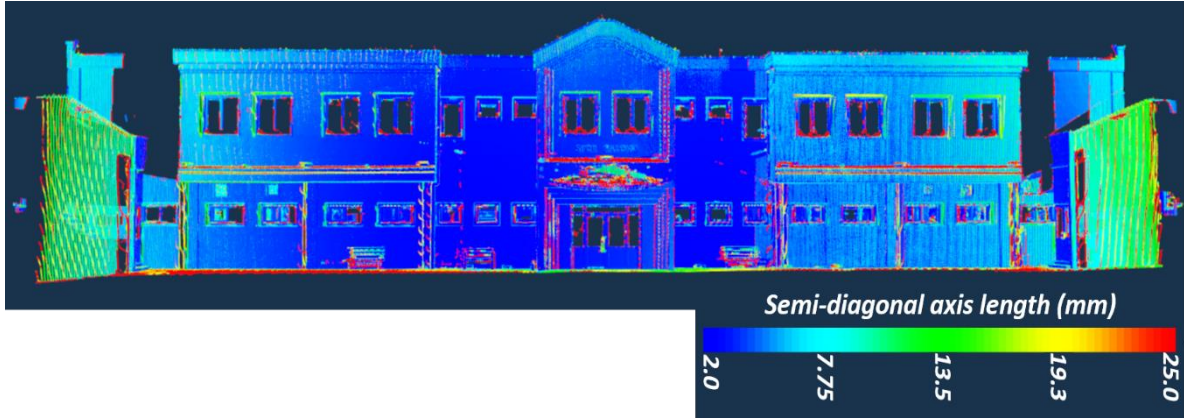


Figure 4.17 Visualization of the point quality of the merged point cloud.

The co-registered point cloud is messy and redundant as shown in Figure 4.17. This data set contains 5.2 million points obtained from three scans. It is not appropriate for surface mesh generation.

A decimated point cloud was created using the voxel-based best point selection method explained in Section 4.2. The voxel size is selected as 2x2x2 mm. After voxelization, the best quality point is selected as given in Equation 4.4. The new point cloud contains 1.4 million points (Figure 4.18).

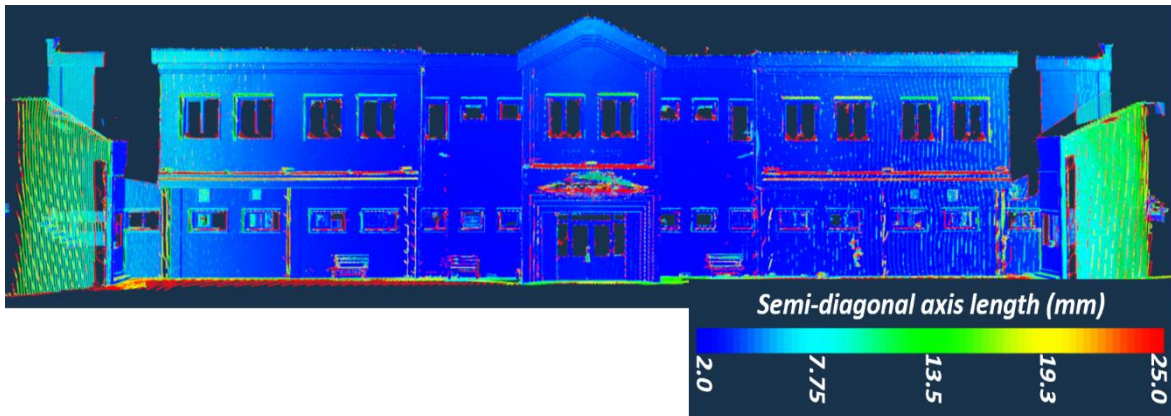


Figure 4.18 Visualization of point quality of the integrated point cloud.

When the original co-registered point cloud (Figure 4.17) and the integrated point clouds (Figure 4.18) are compared, it is obvious that a great number of points of very low quality have been eliminated. This situation is clearer with regard to the right hand side of the façade. However, there exist still some very low quality points shown in red colour which are particularly located at surface discontinuities. The reason why these points are not eliminated

is due to voxelization. At these parts of the dataset, voxels contain points all with very low quality, and even the best quality of them is still in low quality. Since such a dataset will result in a noisy and erroneous surface mesh, these low quality voxels should be eliminated. For this reason, an extra criterion is defined for Equation 4.4. If the selected point's quality value is worse than a threshold, this point (and voxel) is eliminated. We empirically defined this threshold value as 6 mm. By this threshold value we ensure that reconstructed surface mesh has a positional quality of 6 mm or better everywhere.

The procedure is as follow: the best quality point is selected for each voxel, if the quality metric is less than 6mm. If not, the voxel is skipped. The integrated point cloud after this new criterion has 1.1 million points (Figure 4.19).

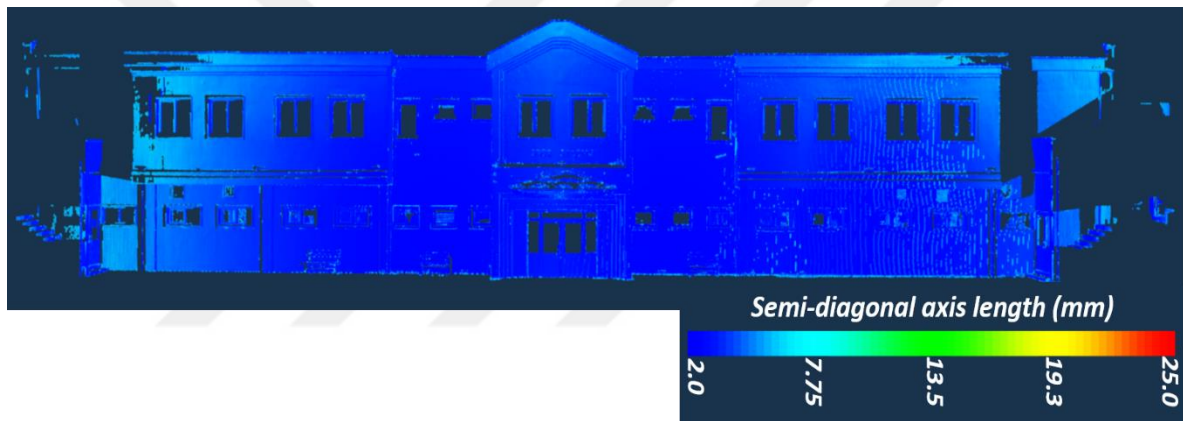


Figure 4.19 Visualization of the point quality of the integrated point cloud. Points with quality metrics of greater than 6 mm are eliminated.

The quality of points in Figure 4.19 are much higher than those shown in Figures 4.18 and 4.17. With the new criteria, low quality points are eliminated. This integrated point cloud is ready for surface mesh reconstruction.

The final step of the workflow is the 3D surface mesh reconstruction. In this study, Geomagic Wrap 2015 and MeshLab v2016.12 software were used for mesh generation purposes. Geomagic Wrap is a commercial software which can import point cloud data in various formats, and allows users to generate 3D surface meshes in a workflow (Geomagic 2018). It is flexible and user friendly software (Akca et al. 2006b, Akca et al. 2007). This software generates 3D surface meshes using a Delaunay-based algorithm (Edelsbrunner et al. 1998). On the other hand, MeshLab is a scientific software that can be used free of charge (Cignoni et al. 2008). MeshLab can also import point cloud data in various formats. It provides Ball Pivoting

(Bernardini et al. 1999b), the Visualization and Computer Graphics Library (Cignoni and Ganovelli 2018) and Screened Poisson Surface Reconstruction algorithms (Kazhdan and Hoppe 2013) for 3D surface mesh generation applications.

Firstly, Geomagic Wrap 2015 was used to generate surface meshes from the “original” point cloud (Figure 4.17) and from the “best” point cloud (Figure 4.19). The results are shown in Figure 4.20. In this figure the mesh in the first row was generated using the “original” points cloud. The mesh in the second row was generated using the “best” point cloud. For better visual investigation, the parts marked by a red rectangle were enlarged at the third, fourth and fifth rows. In this representation, the letters “a” and “b” stands for the mesh generated from the “original” point cloud, and the mesh generated from the “best” point cloud, respectively.

Secondly, the 3D surface meshes of the “original” point cloud (Figure 4.17) and the “best” point cloud (Figure 4.19) were generated using the academic software MeshLab. The Ball Pivoting algorithm was chosen among the available mesh generation algorithms. The created meshes are shown in Figure 4.21. Similar to Figure 4.20, the mesh generated from the “original” point cloud, and the mesh of the “best” point cloud were shown in the first and second rows respectively. The zoom-in views of selected parts were shown on the third, fourth and fifth rows, respectively.

In general, the meshes generated from the “best” point cloud outperform the one generated from the “original” point cloud. Since low quality points have been eliminated, the meshes generated from the “best” point cloud contain less noise and error. Moreover, as the number of points decreased, the computation time became more efficient. When MeshLab and Geomagic software are compared, the mesh generated using Geomagic is better than that generated using MeshLab. Moreover, computationally, the Geomagic software outperforms the MeshLab software.

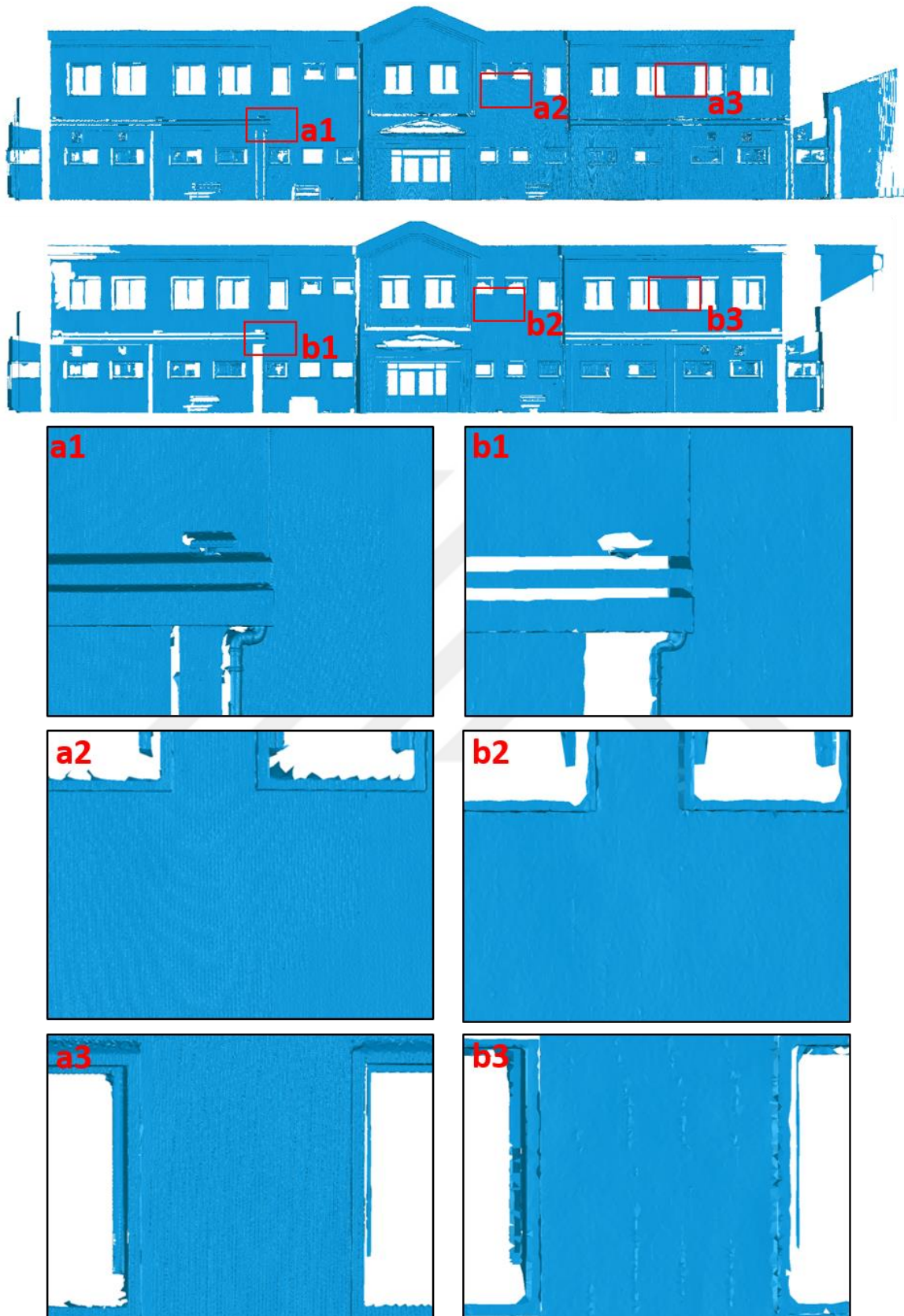


Figure 4.20 3D surface meshes generated with the Geomagic Wrap 2015 software.

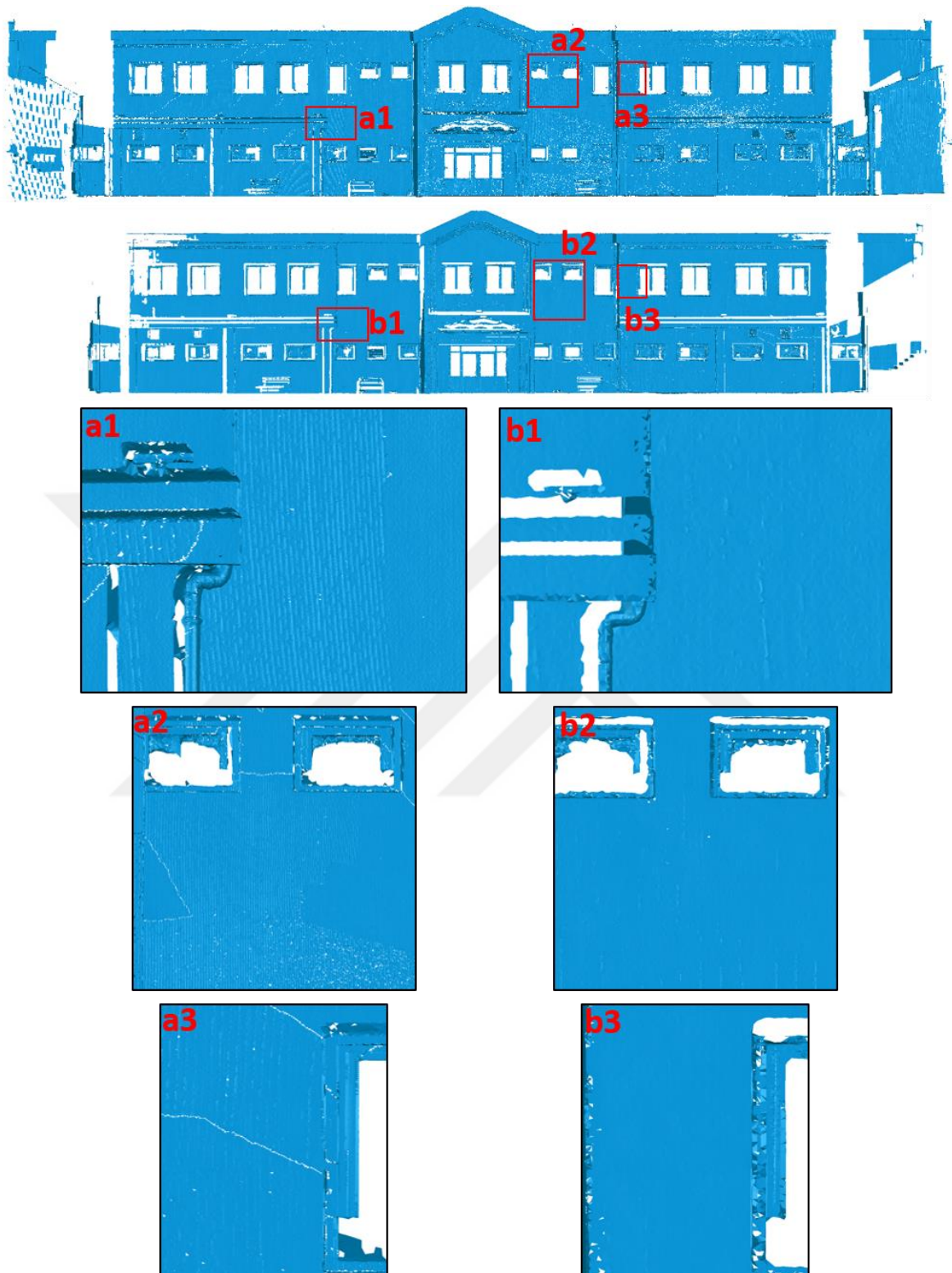


Figure 4.21 3D surface meshes generated with the MeshLab v2016.12 software.

CHAPTER 5

CONCLUSIONS AND OUTLOOK

5.1 CONCLUSIONS

A novel methodology has been introduced for surface mesh reconstruction from TLS-derived point clouds. The work has been divided into two main parts. While the first part deals with developing a generic and anisotropic point error model, the second part focuses on the mesh reconstruction by appropriately exploiting the error model.

The aim of the point error model is to estimate the random error pattern of every individual point. It is generic, because it can be applied to any brand of TLS data without use of any sensor specific or vendor given information. It is anisotropic, because each point has its own particular error pattern.

The efforts with regard to the point error model begins with an estimation of a priori precision values of the horizontal (σ_θ) and vertical (σ_α) angles, which are the scanner variant numbers. Therefore, the angular a priori precision values are constant for each point of the data set. The angular a priori precision values were determined by means of a static and repetitive measurement configuration. The same environment was scanned five times from the same stand point, using the Faro Focus 3D X330, Riegl VZ400 and Z+F 5010X scanners. The scanning was followed by the computation of the vertical (α) and horizontal (θ) angles associated with the conjugate points selected from the four main directions with respect to the TLS position. For each direction, the RMSE values of the vertical (α) and horizontal (θ) angles were computed. The average of those four RMSE values was considered as a priori angular precision. The conclusion can be drawn from these computations that the a priori precision values of vertical (α) and horizontal (θ) angles are not equivalent. The Riegl scanner has the worst angular precision values in both (lateral) directions. In the horizontal direction, the Z+F 5010X scanner has the best precision, and in the vertical direction Faro Focus scanner demonstrates

the best precision values. Moreover, it was shown that the methodology and results for the angular precision values are consistent with the related literature.

The second step of the point error model development is the determination of a priori range precision (σ_ρ). Even though there are many parameters that affect the range precision, the most significant ones are the distance between the TLS and the object (ρ), the incidence angle (γ) and the surface reflectivity (I). The influence of these parameters was investigated by means of outdoor experiments where a specifically designed test stand was used. The experiments were carried out in almost the same conditions with the aforementioned TLSs. The experiment was started by the computation of empirical (data-driven) a priori range precision (σ_ρ) values. The least square plane fitting of each planar plate mounted on the test stand was determined. Once the least square plane equation was obtained, the RMSE of the off-plane distances was computed for each plate. The RMSE value computed at this step was considered as the empirical (data-driven) a priori precision (σ_ρ) values of the range measurements. The results of this experimental study apparently showed that the range precision of a TLS is closely related to the distance between the TLS and the object (ρ), the incidence angle (γ) and the surface reflectivity (I). Apart from this analogy, we are able to analytically determine the quantity of each factor.

Since the experimental approach is not practical for ordinary TLS projects, a practical methodology was provided for a model-driven range precision determination. This methodology contains an experimental part and a computational part. The experimental part was designed in such a way that all TLS users can perform it easily. In the computational part, the range precision was formulated in a way that it is capable of considering the distance between the TLS and the object (ρ), the incidence angle (γ) and the surface reflectivity (I) parameters. It was observed that the model-driven range precision values are consistent with the data-driven values. The presented methodology is in generic form. It can be applied to all TLS brands.

Once the a priori precision values are determined, the law of error propagation was applied for the computation of the error ellipsoid parameters of each point. As a result of the proposed point error model, an error ellipsoid can be attached to each point in the cloud. The error ellipsoid of each point is formed depending on the distance between the TLS and the object (ρ), the

incidence angle (γ) and the surface reflectivity (I) parameters, which implies that the proposed error model is anisotropic. The performance of the point error model was validated in real world scenarios using the scan data acquired by the aforementioned TLSs. The computed error ellipsoids show that the proposed error model works properly with real data sets.

The second main part of this thesis is the stochastic mesh reconstruction methodology. The first step is the computation of quality measures for TLS-derived points. The size and shape of the error ellipsoids provide useful information about the point quality because it is formed by the most influential error sources. Since the semi-diagonal axis of the error ellipsoid includes both angular and range a priori precision values, the quality measure of a point can be considered as the length of the semi-diagonal axis of its ellipsoid.

In the co-registered point clouds the same part of the target object is sampled multiple times which results in redundancy. The surface mesh generated using this redundant data is noisy and erroneous, because both high quality and low quality points are included. In order to generate a noiseless and error-free consensus surface, the low quality points have to be removed from the original point cloud. The method proposed for the removal process is voxel-based. The original co-registered point cloud was partitioned into voxels (voxel size = $2\text{cm} \times 2\text{cm} \times 2\text{cm}$) using the PCL library. The management of the voxel structure was done with the use of an octree data structure. After the voxelization, the point with minimum quality measure is kept and the rest are removed for each voxel. Consequently, a reduced point cloud was created which results in a less noisy 3D surface mesh. Contrary to expectations, the integrated point cloud still contains some very low quality points, because some voxels only contain such useless points. In order to eliminate these points, an additional criterion was employed. This criterion was applied for each voxel, and if the selected point's quality measure was worse than a threshold value, this point was removed. The final integrated point cloud was used for 3D surface mesh generation, in which Geomagic Wrap 2015 and MeshLab v2016.12 software were used. From the generated 3D surface meshes it can clearly be observed that the proposed mesh reconstruction, which takes advantage of the point error model, outperforms the meshes generated from the original co-registered point clouds.

5.2 OUTLOOK AND FUTURE WORKS

Even if the satisfactory and encouraging results have been obtained using the presented methods, there are some limitations and open issues to be considered for the further improvement. These are as listed below:

1. As mentioned in Section 3.3.2.2, with the proposed range precision formulas (Equations 3.20 and 3.21) the distinction can be made successfully between black and white objects. However, the gray values are considered as white objects. In the case of other brands of TLSs, it may be necessary to modify Equation 3.21. Thus, gray objects' error contribution to range precision will be taken into account. However, this brings additional complexity to the model and deteriorates the practicality.
2. Phase measurement-based TLSs acquire very dense point clouds which inevitably contain significant amounts of gross errors. A gross error elimination method may potentially increase the quality of the 3D surface meshes.
3. Prior to the generation of the 3D surface mesh, the co-registered point cloud has to be partitioned into voxels as described in Section 4.2. The voxelization process requires the user to input the size of the voxels. This is an important parameter because it specifies the level of detail of the final 3D surface mesh. In the experimental studies, this parameter was determined empirically. A deterministic method that automatically computes the size parameter will further improve this work.
4. As stated in Section 4.3 an extra criterion has to be applied to points after selection from the voxels. Like with the voxel size, this parameter was also determined empirically. A method for automatic selection of this threshold will advance the procedure.
5. The methods presented in this work can also be applied to co-registration, quality assessment and data fusion tasks with some modifications.

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