

# Towards a Mobile Three-dimensional Modelling System for Underground Structures

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**Abstract**—This paper addresses the three-dimensional modelling of large scale underground galleries, such as traffic tunnels and mines. This work employs techniques from mobile robotics to achieve an autonomous mobile modelling system, adapted to general underground environments. So far, the state-of-the-art methods in underground modelling remain restricted to environments in which pronounced geometric features are abundant. This limitation is a consequence of the scan matching algorithms used to solve the localization and registration problems.

This work aims to extend the modeling capability to structures characterized by uniform geometry and smooth surfaces, as is the case of road and train tunnels.

A visual monocular Simultaneous Localization and Mapping (MonoSLAM) approach based on the Extended Kalman Filter (EKF) and complemented by the introduction of inertial measurements in the prediction step, allows our system to build three-dimensional models and localize himself over long distances, using exclusively sensors carried on board a mobile platform.

By feeding the Extended Kalman Filter with inertial data we were able to overcome the major problem related with MonoSLAM implementations, known as scale factor ambiguity, which emerges from the absence of metric measurements in monocular images. The monocular visual features used in MonoSLAM were extracted by the SIFT algorithm, and inserted directly in the EKF mechanism according to the Inverse Depth Parametrization. Through the 1-Point RANSAC (Random Sample Consensus) wrong frame-to-frame feature matches were rejected.

To build the model, vertical cross-sections of the gallery, acquired by a laser rangefinder sensor, are placed on a common reference frame using the estimated localization.

The system was tested based on a dataset acquired inside a real road tunnel. Results from the localization strategy and the modelling process are presented.

## I. INTRODUCTION

Over the last few years some successful underground mobile modelling implementations were documented [1] [2] [3]. These approaches, designed specifically to operate in mines, are characterized by one common aspect: they all use laser range finder sensors as the main (and in some cases the only) source of information. The model is built by placing laser range finder scans in a virtual three-dimensional world, process called registration. For this purpose, relative position and orientation between scans have to be determined. In previous approaches, this task is accomplished via a scan matching algorithm [7], which restricts the systems to non-uniform structures, since this technique requires that notorious and well-differentiated geometric features stand out along overlapping scans.

Our work extends the underground mobile modelling systems to galleries characterized by very uniform and smooth surfaces, as is the case of traffic tunnels. In this type of scenario the scan matching approaches are condemned to failure, so the previous state-of-the-art systems become ineffective. Without artificial landmarks and no access to global positioning systems, self-localization becomes a hard problem. In inertial based localization the errors accumulated over time cause a monotonic growth in localization uncertainty. On the other hand, a vision based approach may be affected by the lighting conditions, additionally, the parametrization of landmarks far from the cameras raises extra difficulties due to the depth uncertainty.

Similarly to [3], our solution uses 2D laser range finder to gather a sequence of vertical scans along the gallery. Absolute position and orientation of each scan is computed by an independent localization process, that estimates the system's trajectory based on inertial measurements and a sequence of images.

We employ an alternative localization solution to overcome both the structural monotony and the lack of global positioning systems, adopting the SLAM (Simultaneous Localization and Mapping) concept [8] [9] to estimate the platform's localization in 6DoF (Six Degrees of Freedom). Following the traditional approach, the probabilistic SLAM algorithm is based on the EKF (Extended Kalman Filter). Since for landmarks far from the cameras, stereoscopic systems do not provide satisfactory depth measurements, a visual monocular algorithm was implemented instead, ensuring tracking of landmarks at any depth.

In order to identify visual landmarks to be used in the SLAM algorithm, highly distinctive visual features, invariant to scale, rotation and linear illumination variations, are extracted from the images using the SIFT algorithm [11]. To each feature is assigned at least one descriptor, that embodies the image properties in the features' neighborhood. The descriptors are used to establish the frame-to-frame feature matches.

Our system combines another advanced state-of-the-art methods such as Inverse Depth Parametrization [5], and the 1-Point RANSAC algorithm [6], for outlier rejection.

Through the Inverse Depth Parametrization, undelayed initialization of landmarks within the EKF framework becomes possible. However another major problem of monocular SLAM applications still needs to be solved. A single camera

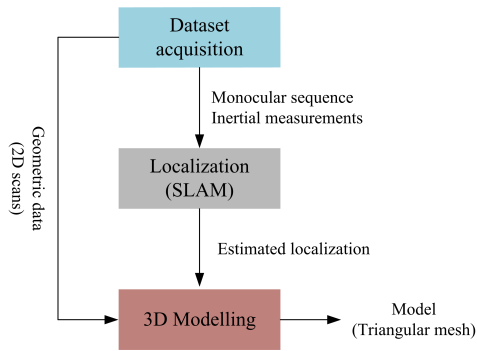


Fig. 1: High level system architecture

moving through the scene does not provide metric measurements, leading to scale ambiguity in the estimated map and motion. As suggested in [4] inertial measurements, provided by a low-cost IMU, feed the filter with metric data in order to prevent the scale factor degeneration. This strategy keeps the map and motion estimates constrained to the meaningful metric system, in our case for distances over more than one hundred meters.

To build the model, all vertical cross sections are replaced on a common reference frame according to the localization estimates, resulting in a point cloud model, which is finally converted into a triangular mesh through the Ball Pivoting Algorithm [10], to reach a more realistic representation without information losses.

This document is organized as follows: Section II presents a brief architecture description with emphasis on the localization and modelling algorithms. Section III is devoted to the dataset acquisition that takes place inside a road tunnel. We then present and discuss our implementation results (Section IV) and finally, Section V, provides a conclusion and sets some future goals.

## II. SYSTEM ARCHITECTURE

Our system is divided into three main blocks, executed by the following order: data acquisition, localization and three-dimensional modelling (see Fig. 1).

In the first step, a sensor platform mounted on board a car is used to collect a wide range of synchronized measurements inside the underground galleries, including images captured by two CCD cameras, 2D scans from two laser range finders and inertial measurements provided by a low cost inertial measurement unit. The platform carries also an INS/GPS system that gives accurate ground truth information, used to measure the performance of our localization strategy.

The localization estimation and modelling tasks are performed offline based on this data, according to the methods described next.

### A. Localization Algorithm

In underground galleries it is expected to find reliable visual features that can be used as reference points to build the SLAM

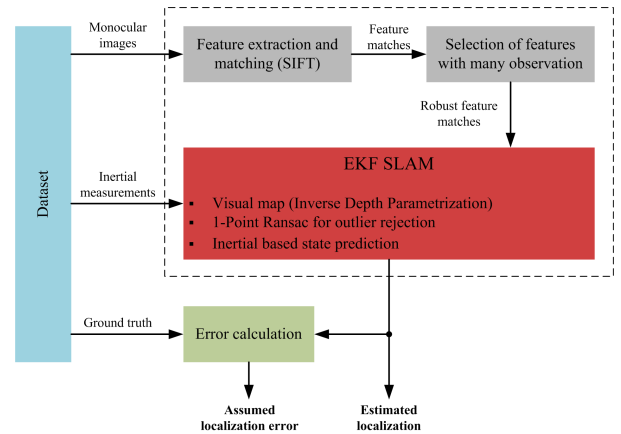


Fig. 2: Localization algorithm overview

map. The process starts with a feature pre-selection stage (see Fig. 2) to fulfill the following objectives:

- Reduce the computational complexity of the SLAM cycle, by performing feature extraction and frame-to-frame matching in advance. The feature extraction is accomplished by the SIFT algorithm [11], that produces descriptors invariant to scale, orientation, and linear illumination changes, used to compute the frame-to-frame feature matches;
- Identify features with a large number of observations and use only those to build the map. By doing so, we pretend to minimize the computational demands, ensuring that all landmarks in the map persist over an acceptable frame interval.

1) *State Vector*: The SLAM cycle is implemented according to the EKF method. The state vector stores the localization and map states. Since the system does not have prior information about the environment, the initial state vector includes only 9 states related to the platform's localization: position  $x^n$ , orientation  $\Theta^n$  (expressed in terms of Euler angles) and velocity  $v^n$ , all defined in the local level reference frame.

$$x(k) = \begin{bmatrix} x^n(k) \\ \Theta^n(k) \\ v^n(k) \end{bmatrix} \quad (1)$$

As new landmarks are observed, the state vector is expanded to accommodate the respective states (equation 2).

$$x(k) = \begin{bmatrix} (x \ b)^n(k) \\ L_1(k) \\ L_2(k) \\ \vdots \\ L_n(k) \end{bmatrix} \quad (2)$$

Initially, each landmark  $L_i$  is coded in the SLAM map using the Inverse Depth Parametrization [5], which requires six parameters (Fig. 3): position of the camera's optical center at the moment of first observation  $[x_i^n \ y_i^n \ z_i^n]$ , azimuth  $\theta_i$  and

elevation  $\varphi_i$  angles of the projection ray that passes through the optical center and the landmark, and finally the inverse of the distance  $\rho_i$  between the optical center and the landmark in the world (inverse depth).

$$L_i = [x_i^n, y_i^n, z_i^n, \theta_i, \varphi_i, \rho_i]^T \quad (3)$$

The state uncertainty of this overparameterized representation can be modelled by Gaussian distributions, regardless to the distance between the landmark and the camera, therefore this is an efficient and accurate solution for undelayed initialization of new landmarks within the EKF. The EKF computational complexity grows quadratically with respect to the state vector dimension, so when the uncertainty in the landmark's location reveals a Gaussian behavior, indicated by the linearity index introduced in [13], the conversion to the standard Cartesian representation is accomplished applying the formulabelow:

$$\begin{bmatrix} L_{xi} \\ L_{yi} \\ L_{zi} \end{bmatrix} = \begin{bmatrix} x_i^n \\ y_i^n \\ z_i^n \end{bmatrix} + \frac{1}{\rho_i} m(\theta_i, \varphi_i) \quad (4)$$

being  $[L_{xi}, L_{yi}, L_{zi}]$  the Cartesian coordinates of the landmark and  $m(\theta_i, \varphi_i)$  a unitary vector calculated from the azimuth and elevation angles:

$$m(\theta_i, \varphi_i) = \begin{bmatrix} -\cos(\varphi_i)\sin(\theta_i) \\ \sin(\varphi_i) \\ \cos(\varphi_i)\cos(\theta_i) \end{bmatrix} \quad (5)$$

2) *Landmark Initialization:* From the six parameters that define an Inverse Depth landmark, only the azimuth and elevation angles need to be computed, since the camera position is already defined in the state vector, and the initial inverse depth consists on a fixed value defined in advance. To compute the angles, the feature is first projected from the image to the camera reference frame, using the pinhole camera model. A distortion model is applied next to compensate for the lens distortion. From this operation results a three-dimensional non-unitary vector  $h^c$  with the same orientation as the projection ray. The vector expressed in the navigation frame is given by:

$$h^n = C_b^n C_c^b h^c \quad (6)$$

where  $C_b^n$  and  $C_c^b$  are the rotations matrices from the body frame to the navigation frame and from the camera frame to the body frame, respectively.

From  $h^n$ , the orientation angles can be finally computed as follows:

$$\begin{aligned} \theta_i &= \arctan\left(\frac{-h_x^n, h_z^n}{h_y^n}\right) \\ \varphi_i &= \arctan\left(\frac{h_x^n}{(h_x^n)^2 + (h_z^n)^2}\right) \end{aligned} \quad (7)$$

3) *Landmark Prediction and Outliers Rejection:* At the update step of the Extended Kalman Filter the position of the features observed in the image is compared to the expected projection of the map landmarks in the image. The projection

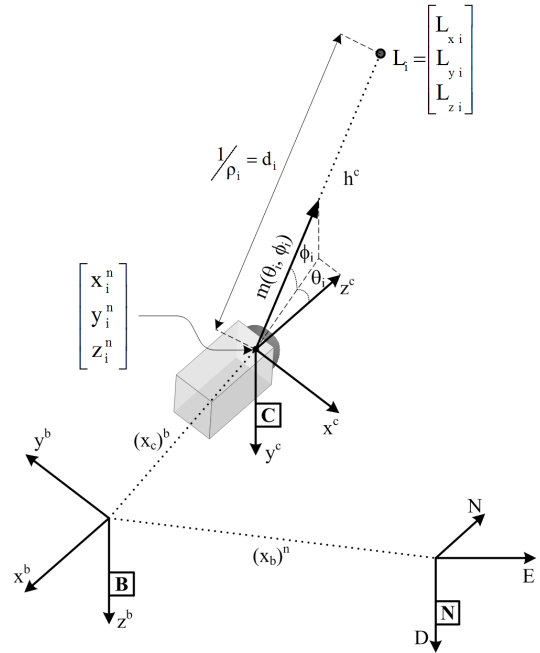


Fig. 3: Reference frames and Inverse Depth Parametrization

of a landmark in the map to the image starts with the projection from the navigation frame to the camera frame:

$$h^c = C_b^c C_n^b \rho_i \begin{bmatrix} x_i^n \\ y_i^n \\ z_i^n \end{bmatrix} - (x_b)^n - C_b^n (x_c)^b + m(\theta_i, \varphi_i) \quad (8)$$

The distortion model is then applied to  $h^c$ , followed by the pinhole model, to determine the projection in the image.

Finally, wrong feature matches are rejected through the 1-Point RANSAC algorithm [6], that takes into account the prior probabilistic distributions maintained by the EKF to reduce the minimal sample size to only one feature match, significantly reducing the computational complexity associated with the standard RANSAC algorithm.

4) *Inertial Based State Prediction:* To avoid the scale factor ambiguity, the main limitation of monocular SLAM caused by the absence of metric information, inertial measurements from a low cost IMU are injected in the EKF prediction step. Since the map landmarks are static, only the platform localization states are subjected to the motion model, that consists on the inertial mechanization in the local level reference frame, respecting the following equations:

$$\begin{aligned} x^n(k) &= x^n(k-1) + v^n(k)\Delta t \\ \Theta^n(k) &= \Theta^n(k-1) + E_b^n w^b(k)\Delta t \\ v^n(k) &= v^n(k-1) + C_b^n a^b(k) + g^n \Delta t \end{aligned} \quad (9)$$

where the IMU inputs are identified by  $a^b$  and  $w^b$ , respectively the linear accelerations and angular velocities, measured in the body reference frame.  $C_b^n$  is the direction cosine matrix obtained from the platform orientation and  $E_b^n$  is a 3 by 3 matrix that converts the angular velocities into the Euler angles

rateofchange:

$$E_b^n = \begin{bmatrix} 1 & \sin(\varphi)\tan(\theta) & \cos(\varphi)\tan(\theta) \\ 0 & \cos(\varphi) & -\sin(\varphi) \\ 0 & \sin(\varphi)\sec(\theta) & \cos(\varphi)\sec(\theta) \end{bmatrix} \quad (10)$$

### B. ModellingAlgorithm

The three-dimensional model is constructed by placing all gallery cross-sections, taken by the vertical laser rangefinder, into a common coordinate system.

First, laser rangefinder scans, initially expressed in polar coordinates, are converted to the Cartesian coordinate system with origin matching the center of the laser rangefinder. Next, specific position and orientation of each scan is derived from the two closest localization points in time. Given the calibration parameters that describe the spatial relationship between sensors, and using the calculated scan localization, all vertical cross-sections are transformed to the local level frame according to the formula below:

$$P^n = C_b^n C_c^b C_l^c P^l - (x_l)^c - (x_c)^b - (x_b)^n \quad (11)$$

where  $P^n$  is the final point in the local level frame, whereas  $P^l$  refers to the original point in the sensor Cartesian system. The rotation matrices  $C_c^b$  and  $C_l^c$  establish the rotation from camera to body and laser to body reference frames, respectively. Whereas  $(x_c)^b$  defines the camera position in the body frame and  $(x_l)^c$  the laser position with respect to the camera frame. Finally  $C_b^n$  and  $(x_b)^n$  enclose the rigid body transformation from the body to the local level reference frame.

After applying formula (11) to all points of all scans, a point cloud model is achieved (see Fig. 4). Usually, the interpretation of point clouds is not easy due to a lack of surfaces. To improve the scene's perception, original surfaces are reconstructed by converting the point cloud into a triangular mesh, using the Ball Pivoting Algorithm (BPA) [10]. Through BPA, a realistic world representation can be attained without data losses (see Fig. 4).

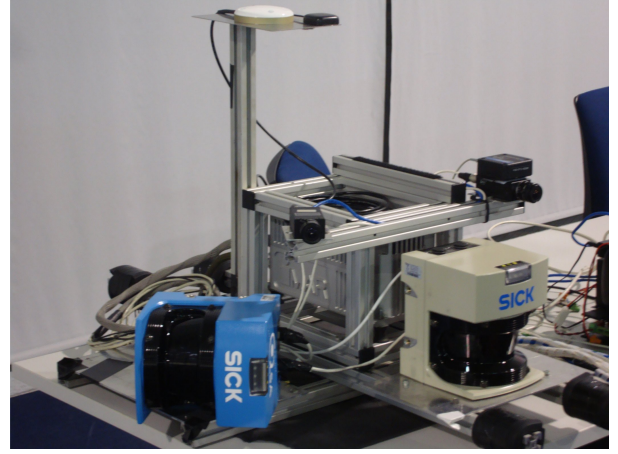
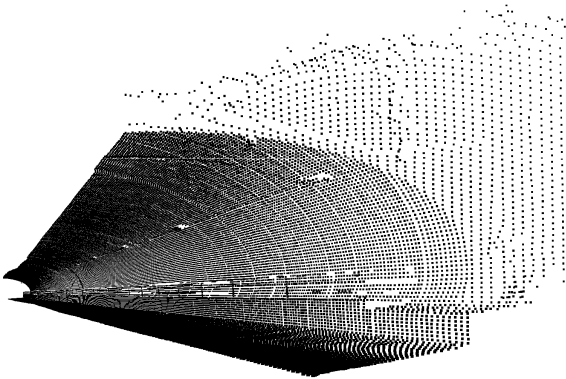


Fig. 5: Sensor platform used for data acquisition

To reduce the noise and produce smoother surfaces, a Laplacian filter is applied to the whole triangular mesh, computing a new position for each vertex according to local information given by adjacent points.

Both the point cloud model and the triangular mesh are coded in the VRML format to be displayed in a virtual reality application.

### III. DATASET ACQUISITION

Solving the localization and modelling problems demands previous acquisition of a variety of measurements. To this purpose, different types of sensors were assembled in a rigid platform (see Fig. 5), which in turn is mounted on top of a car.

The vertical cross-sections are taken by the vertical laser rangefinder (SICK LMS-200) at 75 Hz with an angular resolution of  $1^\circ$ . There are two pointing-forward cameras (JAI CB-080GE), arranged in a stereoscopic configuration, with a resolution of 1032(h) x 778(v) and controlled by an external trigger at a frame rate of 7 fps. Only the images from the left camera are used in our SLAM system.

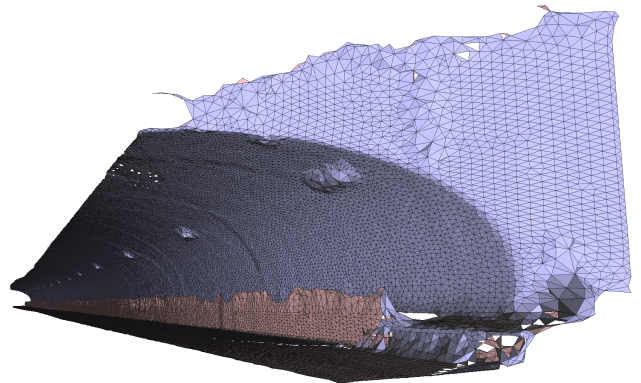


Fig. 4: Three-dimensional model of a road tunnel: point cloud (left) and triangular mesh produced by the Ball Pivoting Algorithm (right).



Fig. 6: Preparation for the data acquisition experiment in the tunnel area

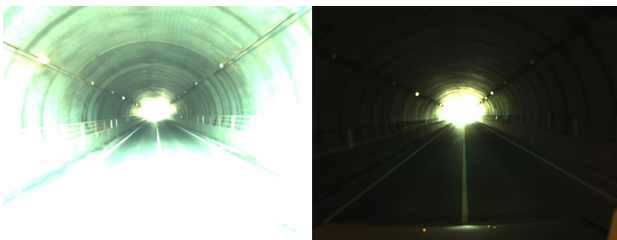


Fig. 7: Image instability as a consequence of the illumination variations along the tunnel.

The low cost IMU (MicroStrain 3DM-GX1), placed above the left camera, gives the linear acceleration and angular velocity measurements used in the EKF prediction step, at a frequency of 100Hz.

Ground truth with a 400Hz rate is obtained by the INS/GPS system (iMARiNAV-FMS-E) placed in the center of the platform. This system provides raw inertial data and GPS measurements acquired outside the gallery, that are post-processed in a commercial software (Waypoint Inertial Explorer) to produce an accurate trajectory estimation. This trajectory is only used as ground truth to evaluate the SLAM performance.

All system reference clocks are synchronized with respect to GPS clock, to assure a consistent time base.

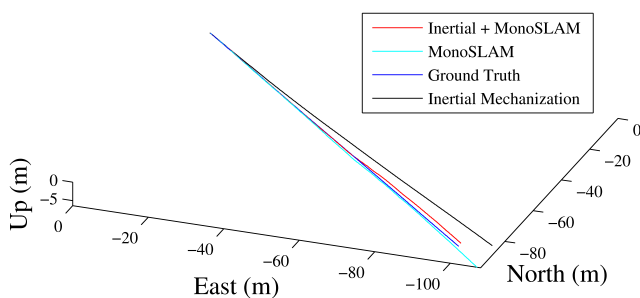


Fig. 8: Three-dimensional representation of the trajectories computed by the following methods: SLAM fusing inertial and visual data (red line), inertial mechanization (black line), monocular SLAM (light blue line) and ground truth (dark blue line)

The data acquisition experiment took place on a road tunnel with approximately 140 meters located at VilardeLuz – Porto (see Fig. 6). To ensure the acquisition of equally spaced cross-sections of the tunnel walls, the vehicle moved at a nearly constant velocity of 35 Km/h. All data were correctly logged. However, the images reflect the huge lighting variations between the interior and exterior of the tunnel, as a consequence of using fixed gain and non-HDR (High Dynamic Range) cameras (see Fig. 7).

#### IV. RESULTS

An accurate localization estimate is crucial to obtain a reliable model reproducing the real gallery characteristics. Since the ground truth is very close to the real trajectory, we were able to determine the error associated with our estimated localization. Furthermore, to realize the benefits of fusing inertial and visual measurements, both inertial navigation and MonoSLAM approaches were implemented, and the results are compared with the ones achieved by our approach.

The trajectories computed by these methods are outlined in Fig. 8. Although the path calculated by MonoSLAM apparently overlaps the ground truth, this approach shows the worst results due to the scale ambiguity, accumulating an error of 11.7 meters. As expected, inertial navigation drifts with time due to error integration, resulting in a total drift of 8.7 meters. Our approach produces the smallest error, showing the advantage of inertial and visual data fusion, with a maximum value of 1.29 meters and an error of 0.95 meters at the final position, equivalent to 0.7% of the total displacement. The insertion of inertial measurements in the MonoSLAM mechanisms successfully prevents the scale factor ambiguity, whereas visual data contributes to the inertial drift compensation, particularly to the orientation states correction.

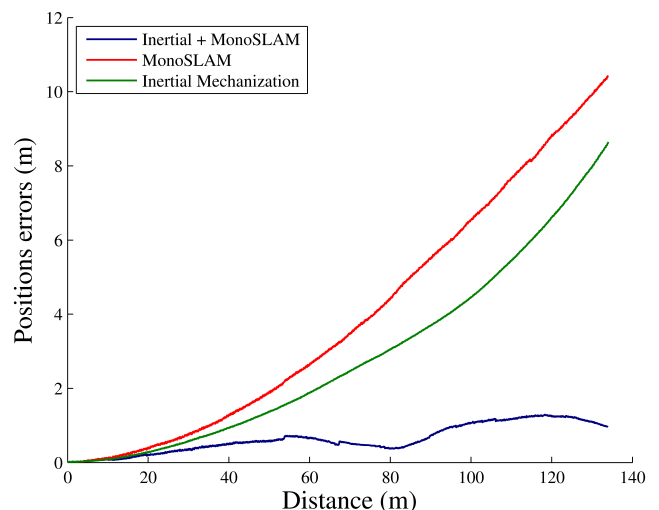


Fig. 9: Position errors produced by each localization strategy: SLAM fusing inertial and visual data (blue line), inertial mechanization (green line) and monocular SLAM (red line)

It can be seen in Fig. 9 that, at some instants, the inertial MonoSLAM position errors momentarily increase. This behavior coincides with a considerable number of landmarks being converted from the inverse depth to the Cartesian representation. As documented in [13], the conversion induces errors in landmark states, that are propagated to the localization states. Nevertheless, in the moments after a visible error attenuation, which indicates the ability of the SLAM mechanism to filter this perturbation. The aleatory oscillations exhibited in the inertial MonoSLAM position error are characteristic of a random walk situation.

The point cloud model in Fig. 4 was built using the localization estimates. As previously mentioned, the point cloud models can become really hard to understand, depending on the viewpoint and scale. In order to reach a more explicit and realistic representation, a triangular mesh is constructed from the point cloud without data losses, through the Ball Pivoting Algorithm. In the final step the surfaces are filtered by a Laplacian smoother (Fig. 10).

## V. CONCLUSION

The development of a mobile modelling system for large scale underground environments raises some difficult challenges, especially when dealing with monotonous geometry. Based on inertial and visual data we have implemented a localization method that does not depend on the geometric properties of the environment, thus it is specifically suited to operate in smooth shape galleries like traffic tunnels.

Through localization results the benefit of fusing inertial data within the MonoSLAM strategy became evident. In the most aggressive configuration, with a pointing forward camera, forward motion and large illumination variance, our localization estimator reached an error of 0.95% of the total displacement, which constitutes a quite impressive accomplishment given the low cost sensors used.

Despite the poor image quality, reliable visual features and descriptors were extracted by the SIFT algorithm, exploiting the algorithm's immunity to rotation scale and linear illumination variations, enabling robust frame-to-frame feature matching.

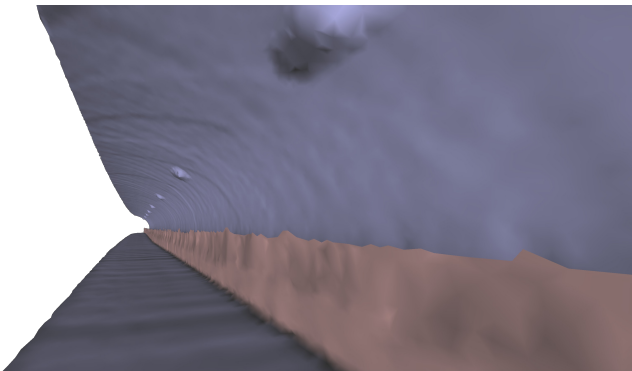


Fig. 10: Triangular mesh model after Laplacian filtering.

In the future, localization accuracy could be improved by adding other types of information, for instance, laser range finder measurements to provide a better approximation of the landmarks initial depth. A stereo vision system will also be implemented to enable instant computation of close landmark coordinates. The use of cameras with larger field of view will also be beneficial, enabling the observation of landmarks with high parallax and hence low depth uncertainty.

In order to enhance the models' realism, the mesh triangles will be filled with texture captured by the cameras.

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