FILTERING OF TLS POINT CLOUDS FOR THE GENERATION OF DTM IN SALT-MARSH AREAS.

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ABSTRACT

Marshes are ubiquitous landforms in estuaries and lagoons, where important hydrological, morphological and ecological processes take place. These areas attenuate sea action on the coast and act as sediment trapping zones. Due to their ecosystem functions and effects on coastal stabilization, marshes are crucial structures in tidal environments, both biologically and geomorphologically, and fundamental elements in wetland restoration or coastal realignment schemes. The spatially-distributed study of the geomorphology of intertidal areas using remotely-sensed digital terrain models remains problematic, owing to their small relief, often of the order of a few tens of centimetres, and to the presence of short and dense vegetation, which strongly reduces the number of resolvable ground returns. Here, we present the results of the application of terrestrial laser scanning (TLS) for the generation of a DTM of the bare soil within a tidal marsh in the Venice lagoon. To this aim we apply a new filtering scheme to Terrestrial Laser Scanner data which selects the lowest values within moving windows, whose optimal size is determined with the aid of a limited number of ancillary Differential GPS data in order to maximize resolution while ensuring the identification of true ground returns. The accuracy of the filtered data is further refined using classifications of the intensity of the returns to extract additional information on the surface (ground or canopy) originating the returning laser beam. By using a low-pass filter with window size of the order of 1 m and the maximum likelihood classifier to further refine the detection of ground signals, laser returns coming from low vegetation (about 0.3-1.0m high) can be satisfactorily separated from those coming from the marsh surface. The overall result is a new observation technique producing DTMs and DSMs in areas with very small relief, which is shown to provide unprecedented high-resolution and high-accuracy characterizations of marsh morphology.

1. INTRODUCTION

The dense and accurate recording of surface points allowed by Terrestrial Laser Scanning (TLS) has recently motivated several research efforts towards the development of automated or semi-automated methods for feature extraction, object recognition and object reconstruction (Böhm, 2003; Nagai et al., 2004; Barnea 2007; Gorte, 2007). TLS has been used for a variety of applications like structural monitoring, cultural heritage recording, landslide monitoring, forensic characterizations (e.g. Gordon et al., 2003; Vozikis et al., 2004; Guarnieri and Vettore, 2005). In particular, topographic and geomorphic studies in terrestrial landscapes have largely benefited from the use of TLS technology but there is a distinct lack of applications in intertidal areas. These are critical transition zones between marine and terrestrial systems playing an important role in the geomorphological and biological dynamics of intertidal areas (Marani et al., 2006). Marshes attenuate sea action on the coast and act as sediment trapping zones. Due to their ecosystem functions and effects on coastal stabilization, marshes are crucial structures in tidal environments, both biologically and geomorphologically, and fundamental elements in wetland restoration or coastal realignment schemes. In spite of their important role, the understanding of salt-marsh dynamics still lacks a comprehensive and predictive theory, and only relatively recent times they have been studied using spatially-distributed observations of their biological (Belluco et al., 2006, Wang et al., 2007) and geomorphological (Wang et a., 2008) properties. The study of ecogeomorphic dynamics is indeed complicated by the fact that the processes shaping the biological and geomorphological characters of a salt marsh occur over a wide range of spatial scales, from few centimetres to several kilometres. While the role of large scale features (e.g. the large tidal channels through which water, sediment and nutrient exchanges between a tidal environment and the sea take place) is quite obvious, it is worthwile to emphasise that also small-scale geomorphic features (e.g. within the centimeter to one meter range) are very important in the morphological and ecological evolution of the system. A fundamental problem in intertidal studies is to observationally identify the relationship between terrain morphology, ground elevation, and the spatial distribution of vegetation species, in order to clarify the complex eco-morphological processes governing the temporal evolution of tidal environments (Marani et al., 2007).

The use of high resolution TLS would therefore be highly beneficial both to provide an effective way of monitoring the evolution of tidal landforms and to provide a detailed and accurate basis for intertidal geomorphic studies. Channels or elevation features occurring over scales smaller than a few meters, in fact, cannot be detected using traditional topographic techniques over the entire marsh scale (size of the order of kilometers) nor through airborne LiDAR data, which are characterized by relatively sparse (as compared to TLS) laser return distributions (of the order of ten returns per square meter, many of which, as seen in the following, are reflected by the canopy rather than by the soil surface) and by a large beam size (with respect to canopy elements sizes) (e.g. Montané and Torres, 2006, Rosso et al., 2006).

In this paper we present the results of the application of TLS technology for the generation of a DTM of the bare soil within a tidal marsh in the Venice lagoon. The small relief, typical of tidal marshes, and the presence of dense and low vegetation (about 0.3-1.0 m high), which produces a large proportion of the reflected laser pulses, makes such DTM construction an unusually difficult task. Therefore, new and reliable procedures to separate vegetation and ground returns are needed. The

approach developed and applied here consists in two steps. Firstly, filtering techniques previously developed for aerial LiDAR (Latypov, 2002; Wang et al., 2008) are applied to TLS scans to identify ground returns as the lowest elevation estimate within a moving window, whose optimal size is determined with the help of Differential GPS (DGPS) measurements of soil elevation. Secondly, the initial DTM estimate is refined by applying to the radiometric information, contained in the intensity of the laser return, both supervised and unsupervised classification methods.
The remainder of the paper is organized as follows. In section 2 an overview of the test area is presented, while the survey methodology is described in section 3. We then present the details about laser data classification and achieved results in section 4. We finally conclude the paper in section 5 with a short discussion.

2. STUDY SITE

The Lagoon of Venice (Figure 1a), located in north-east Italy, is a water body with a surface of about 550 km^2 and an average depth of approximately 1.1 m, characterized by a semidiurnal tide with a range of about of about ±0.7m above mean sea level (hereinafter amsl). It is connected with the Adriatic sea by three inlets and receives freshwater inputs from a few tributaries, contributing a quite small water flux, but a relatively large associated input of solutes (e.g. nutrients from agricultural areas). The Lagoon as a whole is currently experiencing a transformation towards a marine system with important environmental implications.

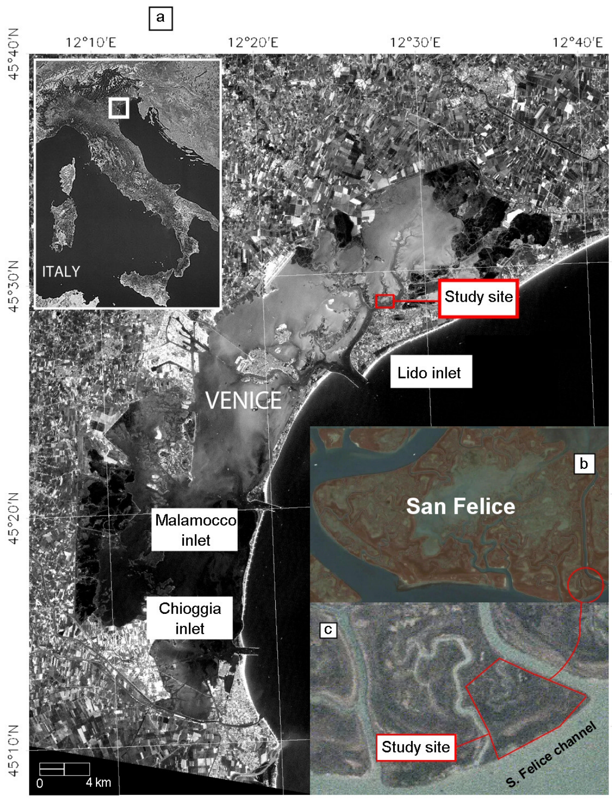


Figure 1. a) Map of the Venice lagoon and location of the studied salt marsh. b) Aerial view of San Felice salt-marsh. The lower-lying areas and the network of small channels are also depicted. c) Close-up view of the surveyed area.

Though the general trend is quite clear, the mechanisms shaping the landscape of the Lagoon, as for many other tidal environments, are not well understood and, while some of its parts experience intense erosion, some salt-marshes are actually accreting. Thus accurate observations of marsh topography are key to understand current trends and to achieve a better comprehension of the links between morphological and biological processes shaping intertidal environments, e.g. to link soil elevation, vegetation, microphytobenthos colonization and soil stabilization or erosion processess.
The study site is within the *San Felice* salt marsh, an area of 74 ha about 2 km from the northern inlet of the lagoon (Lido inlet), along the homonymous channel (Figure 1a, b). The marsh, flooded (on the average) twice a day, is characterised by relatively small rates of general erosion and, in some cases, by local accretion. Its elevation ranges from about 0.01 m above mean sea level (a.m.s.l.) to 0.68 m a.m.s.l. (with an average of 0.26 m a.m.s.l.), and its area is mainly colonized by halophytic vegetation, i.e. by vegetation which has adapted, to varying degrees, to very salty environments. The sub-area studied here (Figure 1c) is about 400 m^2 with a nearly constant elevation of 0.15 m a.m.s.l. The vegetation height ranges between 0.3 and 1.0 m (Figure 2).

Figure 2. Detail of the study area in Figure 1c. The marsh is colonized by halophityc vegetation with spatially variable density. The San Felice channel is visible in the background .

3. DATA COLLECTION

As described in (Axelsson, 1999), airborne LiDAR technology is ideally well suited for measuring topography in marsh environments but the accurate determination of ground elevation requires the removal of the laser echoes reflected by the canopy or by other above-ground objects. Airborne LiDAR surveys have been shown to provide spatially-distributed characterizations of intertidal areas (Wang et al., 2008). However the presence of dense vegetation and complex network of small channels with low elevation relief combined with the large footprint and the limited spatial density (of the order of 10 returns/m^2) typical of LiDAR data, lead to a relatively low chance of laser penetration through marsh vegetation. Therefore the resolution of the final DTM potentially suffers from the relatively low probability of canopy penetration by laser beams. TLS can overcome these limitations. In the present case we used a Leica HDS 3000 terrestrial laser scanner and a setup that produced a footprint smaller than 6 mm (at a 50 m distance), a scan resolution of 5 cm and an average return density of 3000 points/m^2 (resulting in the acquisition of about 1.3 million points). Measurements were performed during low tide period to avoid interferences due to water on the marsh surface. To minimize shadowing effects due to the tilting of the laser beam (especially in the channel network), the scanner was mounted on an aluminium custom-built tripod 3 m above the marsh surface (Figure 3). Working in a marshy and often muddy area,

all the equipment has been configured in order to be completely dismounted and packed for easy transportation by car and boat.
The site was fully surveyed with three main scans from different positions to obtain a more uniform sampling of the area. Eight retroreflective targets, identifiable in all acquisitions, were used for scan registration (figure 3). The position of the targets was determined using post-processed GPS survey (2 cm accuracy in all directions) in order to allow accurate georeferencing of the TLS data in the Italian National reference frame. Furthermore, 500 GPS points were collected in RTK mode in a roughly homogeneous manner to be used for calibration and validation of adopted methods for point clouds filtering. During field survey, care was taken to avoid that the plumb pole, used for the GPS antenna, penetrate the ground surface leading to an underestimation of the actual terrain elevation.

Figure 3. The tripod used to rise up the laser scanner. On left and right side two poles holding retroreflective targets are visible in the background.

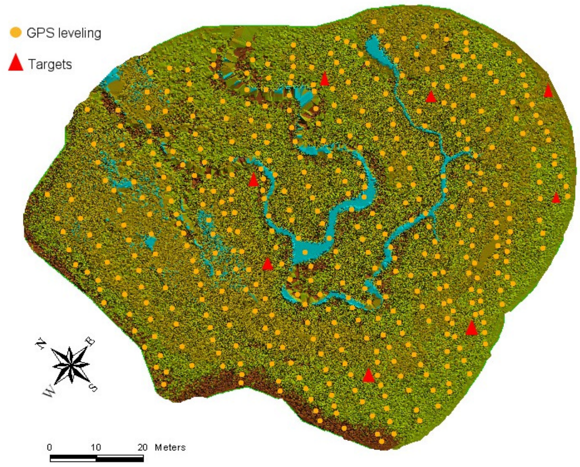


Figure 4. RTK GPS points overlaid onto the TLS-derived DTM after model georeferencing. Red triangles denote the position of the 8 retroreflective targets.

4. DATA PROCESSING

The whole data processing workflow was subdivided in three different steps, detailed in the following sub-sections: a) scan registration, b) model georeferencing and c) data classification. The first step was performed using the Cyclone application (Leica Geosystems), while the algorithms developed to perform steps b) and c) were implemented in Matlab.

4.1 Scan registration

At the end of each main scan, the 8 retroreflective targets were measured with a resolution of 2 mm. Point clouds were then aligned together by manual matching the corresponding targets between scan pairs. The registration RMS error obtained in this way was 5 mm.

4.2 Model georeferencing

Once aligned, the 3D model of the study area and the GPS meaurements were georeferenced in the same reference frame (figure 4). Parameters required for the transformation were derived by matching the laser coordinates of the 8 retroreflective targets as determined by TLS and GPS measurements. This matching yielded a residual RMS error of 2.2 cm. Then a 7 parameter transformation was applied to the RTK-GPS data in order to co-register the GPS levelling with the aligned point cloud.

4.3 Data classification

In this section we describe the procedure applied to the aligned 3D model, derived by TLS measurements, in order to automatically separate the laser returns coming from the low vegetation from those coming from the marsh surface.
The separation of ground and canopy returns is an essential step in the retrieval of salt-marsh DTM. As noted above, this phase may be problematic due to the relatively low chance of a bare soil return in the presence of dense vegetation (Figure 2) and to the low stature of the plants, which makes it potentially difficult to distinguish ground and plant elevations. Here we use a filtering technique developed for LiDAR observations (Wang et al., 2008) to obtain a first-cut discrimination and then apply classifiers to the laser return intensity to provide an improved discrimination of vegetation vs. bare soil reflections.
The analysis was firstly carried out on a limited portion of the study site, then the processing method providing the most satisfactory results was applied to the whole area.
The initial filtering procedure consists in selecting, as ground returns, the minimum TLS elevation estimates within a moving window of fixed size R. The idea behind this procedure is that for small window sizes and depending on the canopy density the likelihood of a ground return is small so that the minimum TLS estimate will be appreciably higher than the actual elevation of the soil. As the window size is increased it becomes more likely that at least one of the laser pulses within the window has actually penetrated the canopy and has been reflected by the ground. In order to determine the optimal size of the moving filter window, we use a calibration subset (control points) composed by 50% of the available GPS ground elevation observations available in the area considered. The laser return with minimum elevation (Z_{min}) within a neighborhood of size R (with 0.2 m < R < 2.0 m) centered at each of these GPS reference observations (Z_{gps}) is considered as the best TLS estimate of ground elevation. The difference Z_{gps} - Z_{min} between the elevation of each GPS control point and the corresponding selected TLS return is thus the estimation error. The dependence of the mean and/or standard deviation of this error on the neighborhood size R is used to select the minimum value of R allowing a pre-determined level of accuracy. In order to ensure an evaluation of the estimation error independent from the calibration information, the same procedure is applied again by

exploiting the reference GPS observations (check points), not used in the calibration. A scatter plot of DGPS vs. TLS elevations is then produced for each value of R as a validation.
Figure 5 shows the dependence of the mean and Root Mean Square (RMS) errors on the radius chosen to produce the laser estimate of ground elevation. As expected both parameters decrease for increasing window size. The mean error (blue dots) initially rapidly approaches zero, but a slight positive bias remains (about 1 cm) when R > 1.4 m. Conversely, the RMS error (red circles) decreases with increasing radius. Considering that the surveyed area is almost completely covered by halophityc vegetation with variable density, the presence of the small bias suggests that the penetration of a laser pulse to the ground surface is not a certain event, even when a large amount of laser returns is considered.

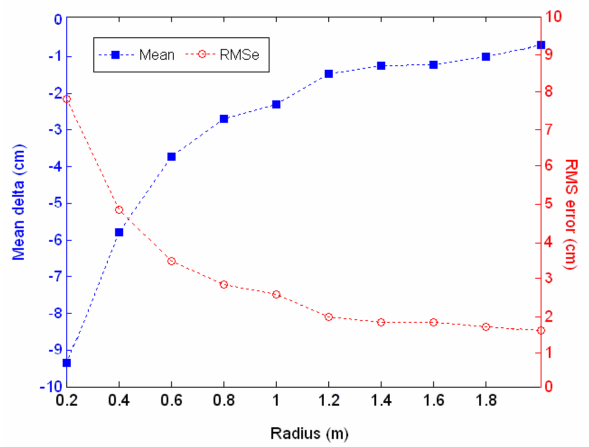
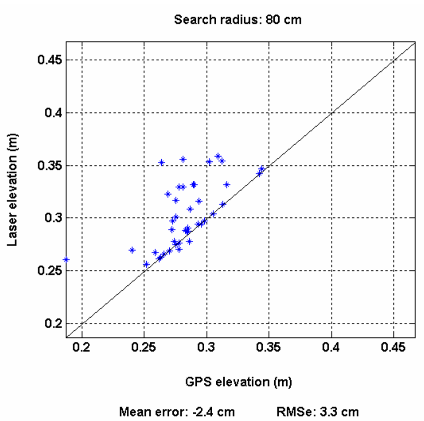


Figure 5. Mean and RMS error of the laser estimation error as functions of the size of the local search neighborhood.

A scatter plot of DGPS measurements vs. TLS estimates (Figure 6) reveals, however, that just minimal errors actually affect the filtered laser returns. Most points lie close to the 45-degree line for window sizes as low as R=0.8 m, showing that, even though complete canopy penetration occurs relatively infrequently, a large part of the reflections are caused by very low canopy elements. Assuming as discriminating criteria the DTM resolution and the minimal residual errors associated with the searching window size, a grid spacing of 1.4 m was considered as the optimal tradeoff between accuracy in elevation and resolution.



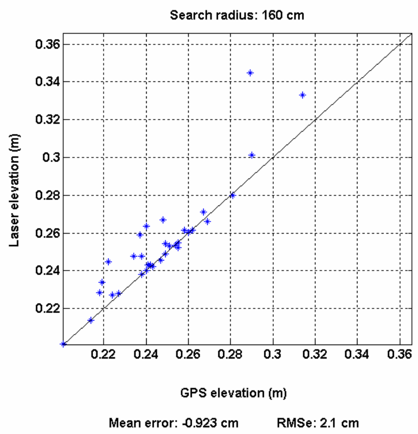


Figure 6. Scatter plot of GPS measurements vs. laser estimates of ground elevation.

Even though TLS estimation errors after filtering are quite small (see first row in Table 1), it is useful to see whether the persisting bias due to vegetation reflections which have not been eliminated by the filtering procedure can be attenuated. Here we exploit the information contained in the intensity of the returning pulses to attempt a classification of the surface elements (canopy, soil, and water) responsible for the reflections. This approach is particularly attractive because the TLS instrument operates in the 'green' part of the spectrum (central wavelength of the band is located at 532 nm).
We experimented the application of two classifiers: the K-means algorithm and the (Gaussian) Maximum Likelihood Classifier (MLC) (Mather, 1999). Different combinations of filtering and classification techniques were applied according to the following scheme:

1) Minimum elevation filtering: a grid DTM with resolution 1.4 m is produced by assigning to each pixel the minimum TLS elevation estimate within each pixel;
2) Minimum elevation filtering + K-means: the result of 1) is refined by discarding, as not belonging to the soil surface, all laser returns assigned to the water or vegetation classes by the application of the K-means algorithm;
3) Minimum elevation filtering + Maximum Likelihood: the result of 1) is refined by discarding, as not belonging to the soil surface, all laser returns assigned to the water or vegetation classes by the application of the Maximum Likelihood classifier;
4) K-means: selection of 'true' ground returns according to the results from the K-means algorithm. In this case the result is not a gridded DTM but a collection of (x,y,z) coordinates of soil elevations;
5) K-means + Minimum elevation filtering: the filtering defined in 1) is applied to the results of 4);
6) Maximum Likelihood Classification: selection of 'true' ground returns according to the results from the Maximum Likelihood classifier. As in 4) the result is composed by collection of (x,y,z) coordinates of soil elevations;
7) Maximum Likelihood Classification + Minimum elevation filtering: the filtering defined in 1) is applied to the results of 6).

Such scheme was designed in order to evaluate the effectiveness of the classification based on laser elevation with respect to supervised and supervised methods, based on the Intensity data only.

The ML classifier requires the definition of reference responses (intensity of the returns) for each of the classes of interest (vegetation, bare soil, and water in the present case). To this aim a set of laser returns from areas which were visually identified to represent the classes of interest (Figure 7) was extracted from the (georeferenced) TLS point cloud. The intensities of these returns were used to estimate the statistics (mean and variance) defining the probability distributions assumed to be representative of each class (Figure 8). It should be noted that samples extracted to estimate the training parameters for the vegetation class were not optimal, as the operator could not correclty separate laser returns due to vegetation from the ones coming from the bare soil below. By the way, it is important to note that the application of the K-means clustering algorithms does not require the definition of the responses (return intensities) representative of each class of interest and thus presents a relevant operational advantage.

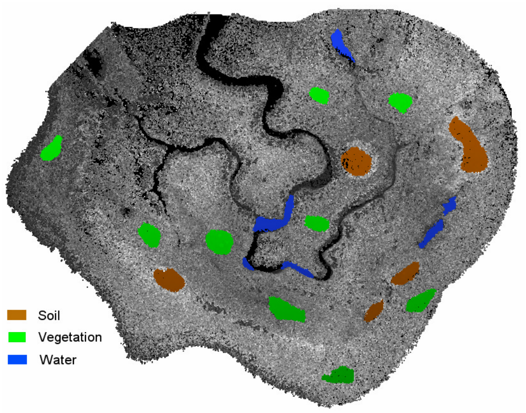


Figure 7. Training sets for the Maximum Likelihood estimate. Vegetation samples are depicted in green, soil samples in brown and water samples in blue. Black areas mean no data.

The best results, as measured by mean and RMS errors (see Table 1), were obtained by first filtering elevations and subsequently classifying the filtered TLS returns through the Maximum Likelihood algorithm. It is worth noting that the improvement obtained using the K-means and Maximum Likelihood classifiers are very similar. This would suggest the use of the unsupervised algorithm because it does not require the evaluation of the reference spectral responses for the classes of interest. Conversely, the use of just a spectral classifier (K-means and MLE), i.e. without any pre- or post-filtering, did not yield satisfactory results, particularly in comparison with those from the filtering approach alone.

Results presented in table 1 were obtained considering a DTM with a 1.4 m grid spacing and the 250 RTK GPS points not used in the calibration, as reference. In the classification trials involving the K-means algorithm the initial centroid positions for the three classes of interest (vegetation, bare soil, and water) were computed through random sampling of intensity data.

As shown in table 1, the application of either spectral data clustering method followed by the minimum elevation filtering does not yield estimation accuracies similar to those obtained from the application of the two processing steps in the reverse order (i.e. first the filter and then the spectral classifier). The classification of the spectral information thus removes some of the local minimum TLS elevation estimates. This likely happens because some of the bare soil returns are misclassified as vegetation or water returns (see overlaps in the corresponding intensity distributions in Figure 8) and thus eliminated prior to filter application. Similarly, some vegetation returns are misclassified as soil returns and thus remain in the set of TLS estimates from which the local minimum elevation is selected.

The final DTM with a grid resolution of 1.4 m is shown in figure 9.

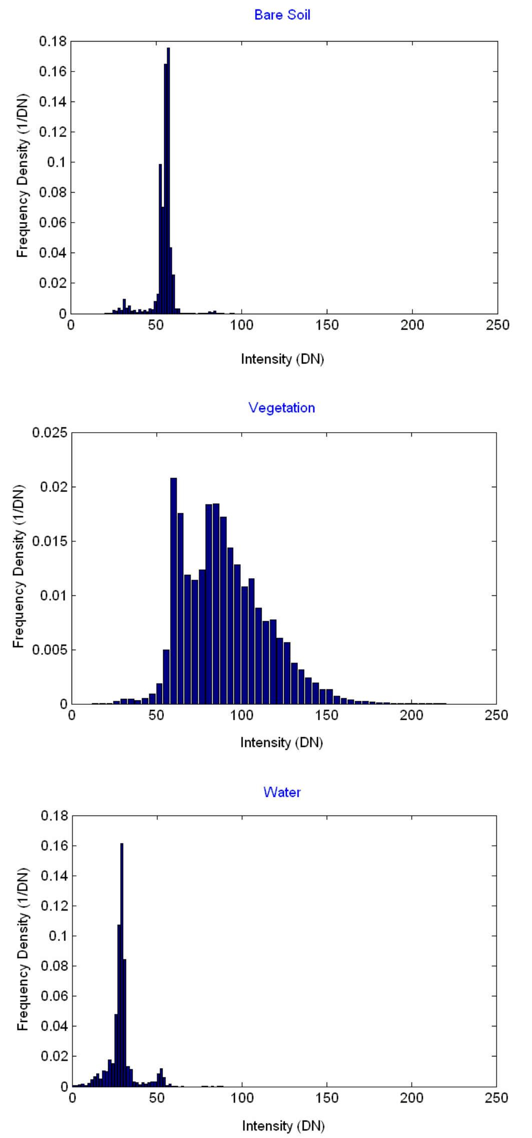


Figure 8. Frequency distributions of the intensity of the returning laser beam for the three classes considered (soil, vegetation, and water). Values on the vertical axis indicate the number of returns normalized with respect to the total number of samples per class.

Radius / Filter	R = 60 cm		R = 100 cm		R = 160 cm	
	Mean error (cm)	RMSe (cm)	Mean error (cm)	RMSe (cm)	Mean error (cm)	RMSe (cm)
Z min	-3.5	3.7	-2.5	2.8	-1.2	1.9
Z min + K-means	-2.2	2.9	-1.6	2.0	-0.7	1.1
Z min + MLC	-2.1	2.9	-1.7	2.0	-0.6	0.9
K-means	-7.9 (Mean error)			11.2 (RMSe)		
K- means + Z min	-2.8	3.2	-2.0	2.5	-1.0	1.3
MLC	-7.6 (Mean error)			10.4 (RMSe)		
MLC +Z min	-2.9	3.2	-2.1	2.6	-0.9	1.2

Table 1. Results of the different combinations of classification procedures investigated. The best accuracy is achieved by exploiting both the optimized filtering procedure and the information contained in the intensity of the laser returns.

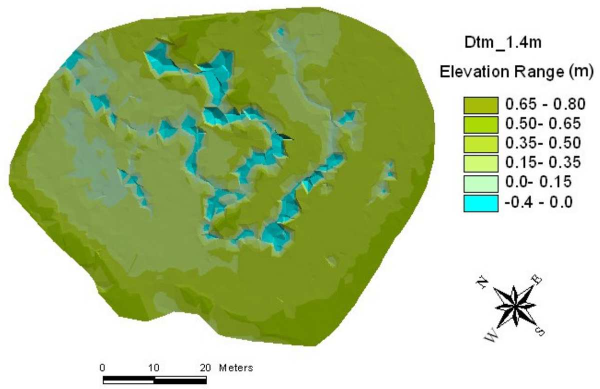


Figure 9. The final DTM obtained after filtering of TLS elevation data and MLE classification of related intensity data.

5. CONCLUSIONS

In this paper we have presented the results of the application of TLS technology for the generation of a DTM of the bare soil within a tidal marsh in the Venice lagoon. Achieved results show that this technology can provide high accuracy with moderate operational efforts. The effects of vegetation on the estimation of the DTM can be minimized by the combined use of a filtering technique and of classification of the spectral information carried by the laser beam. The use of reference GPS ground elevation observations allowed the definition of the optimal size of the filtering window (140 cm in this case).

In summary, we have shown that the development of suitable post-processing techniques allows one to derive straightforward and accurate characterizations of marsh morphology from TLS observations. Further improvements may be achieved by optimizing both data acquisition and processing stages. For instance the salt-marsh could be surveyed from a higher number of different positions, thereby decreasing the angle of incidence of the laser beam and thus increasing the likelihood of complete penetration through the canopy. Scan resolution (here 5 cm on average) can be reduced as well, thus saving the time for fieldwork. However this could potentially decrease the likelihood of laser beam penetration, overall in more densely vegetated areas, resulting in a DTM of lower resolution. A topic for future research concerns with the improvements in discriminating between ground and vegetation: it is likely that better results can be achieved by exploiting different kind of filtering algorithms.

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