Detecting unstructured elements in 3D scanned scenes

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Abstract

This paper presents a technique for detecting unstructured areas in scanned 3D data. For many applications, outdoor 3D scanned data has to be filtered in order to eliminate undesirable artefacts, such as wires, vegetation, small objects, etc. Usually, this task is done manually, but it would be desirable to provide an automatic tool to reduce the preprocessing cost. The proposed technique, which consists in two stages, based on anisotropic diffusion and plane regression respectively, allows us to select most of the uninteresting data. It also has been shown good results with real data.

Keywords: Data filtering, 3D scanner, anisotropic diffusion.

1 INTRODUCTION

3D data acquisition has been turn very popular in recent times, because of the availability of affordable and very accurate scanners. A lot of 3D data is being collected from a variety of sources, outdoor and indoor, for very different purposes, ranging from reconstruction to analysis and measurement. For this reason, 3D data filtering techniques have become a very active research topic, with a variety of applications that include among others robotic vision, civil engineering, archaeology, medicine, etc.

Typical available 3D laser scanner software includes tools for processing the 3D points scanned, which constitute complex sets of data. It is often necessary to remove unwanted objects from the data (workers, equipment, temporary support structures, etc.), so a basic segmentation process is necessary. Without a priori knowledge, automated unsupervised segmentation provides unsatisfactory results [3, 1, 4]. For this reason, current 3D point-cloud management software requires manual or semi-automatic data segmentation. This can be an extremely slow and tedious operation when dealing with large complex models.

Most of the unwanted objects present in a 3D outdoors scene share common geometrical properties. In general, they do not present surface-like structures locally. We will call such objects as unstructured. Typical unstructured objects give rise to point aggregations that are: longitudinal (wires), noisy (bushes or trees branches), and very small and isolated point clusters (small objects).

In our case, we want to detect unstructured elements present in a given scene, using geometric information exclusively. Starting from a point cloud dataset, obtained from a 3D scanner, our technique allows us to detect such type of elements. By eliminating the selected points we can extract relevant structures from the scene, in order to create suitable polygonal meshes for civil engineering applications. It must be emphasized that we do not want to reduce or remove the noise present in the cloud of points, but to detect unstructured objects present into the scene.

In this paper, we propose a two-stage process for detecting such type of structures, based on anisotropic diffusion and plane regression, where 3D data are arranged as a two-dimensional matrix representing the polar coordinates of every point relative to the scanner.

This paper is organized as follows. Section 2 introduces the proposed method. Experimental results, using both synthetic and real data are shown in Section 3. Finally, Section 4 presents our conclusions and further work.

2 PROPOSED METHOD

We start by obtaining the projections of the scanned points over a range matrix I, where the column and row for a given point are determined by his horizontal and vertical angle relative to the scanner position. Each element of the matrix can be a real number, representing the distance of the corresponding point to the scanner, or be undefined if the scanner did not detect anything.

Our technique consist of two phases. The first one applies an anisotropic diffusion process to the range matrix. This process displaces each point along the straight line that connects it with the scanner. Subtracting the resulting matrix and the original one, we can extract the high frequency component of the range matrix. One can expect that unstructured objects give rise to bigger variations in the values of the resulting matrix.

If we generate a matrix with the differences between the original range matrix and the smoothed one, we can see that not only appears big values in nonstructured zones. It also appear significant values inside the regions where the distance to the scanner changes gradually (like the ground, or a inclined wall). This is due to the anisotropic diffusion process modify the values of these regions to reach a central value. The second phase detects such variations in the subtracted matrix, measuring the difference between every actual point and a regression plane, calculated from his neighbours.

2.1 Anisotropic diffusion

Perona and Malik [7] introduced an iterative, non-linear regularisation technique known as *anisotropic diffusion* which regularises grey-valued images while preserving important discontinuities that often contain edge information. This process can be generalised to be applied to colour [5] and disparity (range) images [6]. Our approach is based in the latter case. Being I our range matrix, we will apply this technique in order to remove the high frequencies from it, effectively displacing the points.

Anisotropic diffusion modifies the value on a point as a function of the difference with its neighbours. This difference is weighted by a conduction coefficient c. For the discrete approach of the anisotropic diffusion a four nearest neighbours discretization of the Laplacian operator can be used to update matrix values in each iteration:

$$\begin{aligned} I_{t+1} &= I_t + \lambda [c_N \cdot \nabla N(I) + c_S \cdot \nabla S(I) + \\ &\quad + c_E \cdot \nabla E(I) + c_W \cdot \nabla W(I)] \end{aligned} \tag{1}$$

where ∇ represents the gradient operator, $\lambda \in [0, 1/4]$, and the sub-indices N, S, E and W represent the North, South, East and West neighbours.

Anisotropic diffusion uses a conduction coefficient c that is 1 inside each region and 0 at the boundaries. We have used the following expression for c [7]:

$$g(x) = \frac{1}{1 + (x/K)^2} \tag{2}$$

Where x is an estimate of the range matrix gradient magnitude for the corresponding point, and K is just a threshold according to which the boundaries with contrast bigger than K will remain and the rest will tend to disappear. This value can be fixed manually or be the *noise estimator* described by Canny [2]: the accumulated histogram of the absolute values of the image gradient can be determined and the value of K is chosen that leaves 90% of the histogram values below.

The number of iterations can be established manually. When the process finishes, we obtain the smoothed image I'. If we compare the smoothed image I' with the original I we can see important differences in noisy zones. We will then calculate a new matrix $M = I - I'$.

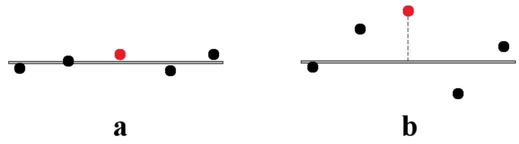

Figure 1: Unstructured point detection. a) Structured set of points, the distance between the point (red) and the ones used to estimate the regression plane (black), is small. b) Unstructured set of points: the distance between the red point and the plane is bigger.

2.2 Plane regression

Regions belonging to structured objects present one characteristic in M: their values can be locally adjusted to a plane with small error. We use this in a similar manner to [8], to discriminate between unstructured and structured regions. To find the best plane that adjusts the points we consider the row and column indices of the matrix as the X and Y coordinates and the values themselves as the Z coordinate. For each value inside the matrix, we can use its neighbour values to fit a plane and measure the distance between the plane and the value itself. If the value corresponds to a structured region, the distance with the plane will be very small (See Figure 1). This way we generate a new difference matrix, M', filled with the distances between every value to its corresponding regression plane, allowing us to characterize the unstructured regions.

The final selection stage will be performed by thresholding the difference matrix M' estimated in the regression phase. We use as a threshold the inflection point calculated over the histogram of M'. Isolated points are directly marked as unstructured.

3 EXPERIMENTAL RESULTS

3.1 Experimental setup

We have tested our technique on several synthetic and real world scenes. Synthetic scenes have been obtained by simulation, from a simple world composed by several simple structured objects (ground and buildings), and unstructured ones (trees, bushes and electric wires), giving us a cloud of approximately 530.000

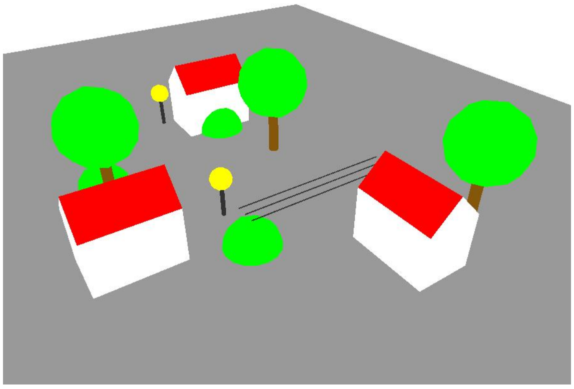

Figure 2: Synthetic scene used in experiments.

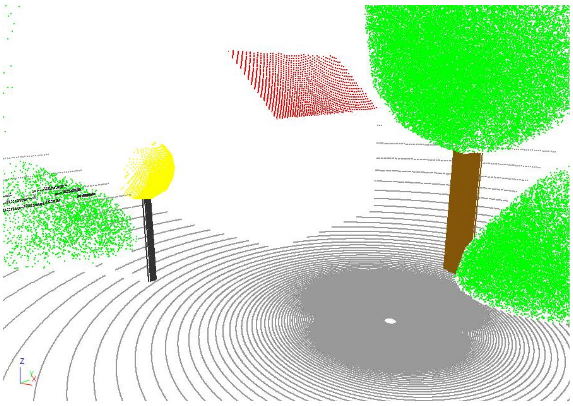

Figure 3: Synthetic cloud of points used in the experiments, generated from the scene in figure 2. showing a building, a street light, and some vegetation.

points (See Figures 2 and 3). Vegetation leaves have been simulated using randomly placed points inside a sphere.

The real world scene (Figure 4) has been obtained outdoors using a mid range laser scanner (Callidus CP 3200), showing an ancient stone bridge, surrounded by vegetation, with approximately 400.000 points. The point cloud also contains some wires, belonging to the scanning station.

We have the ground truth only for the synthetic scene, so we will show numerical results for that image only.

For the diffusion process, the following parameters have been used for all the experiments: 100 iterations, $\lambda = 0.25$, and K such that leaves an 80% of the accumulated histogram.

3.2 Results obtained

Figures 5 and 6 show the clouds of points projected over the range matrices. As we can see, there are large areas of undefined points, corresponding mainly to the sky, where the laser beam did not return to the scanning station. These points will be simply ignored in the processing stages.

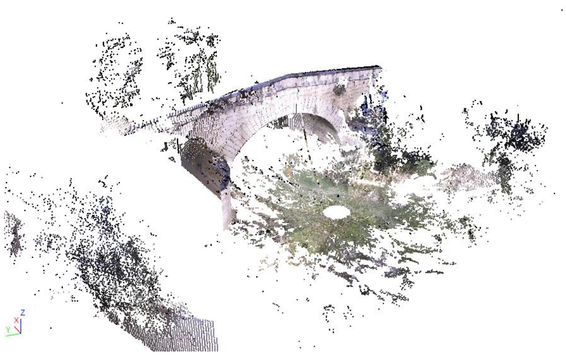

Figure 4: Cloud of points obtained outdoors by a mid range scanner.

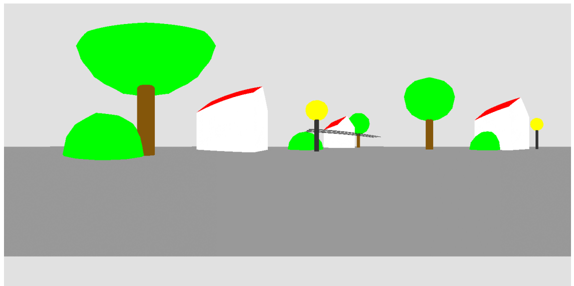

Figure 5: Projected points corresponding to the synthetic scene, using the real colours of the scene. Undefined points are shown in grey.

Figure 6: Projected points corresponding to the real scene, using the real colours of the scene. Undefined points are shown in white.

Figure 7 shows the results obtained from the synthetic cloud of points, using regression planes computed over a neighbourhood defined by a centred window size of 3. It can be seen that most of the unstructured points are correctly marked, and some of the structured points, specially those placed in high curvature areas, are marked also as unstructured. Particularly interesting is the case of the street lights, whose poles are labeled as unstructured. In fact, these objects are only slightly thicker than the electric wires.

Some numerical results are shown in Table 1. The best results have been obtained with smaller window sizes. This is due to the better tolerance to curvature in the arrangement of the points in the neighbourhoods of the structured points.

Figure 8 shows the results obtained for the real scene. It can be seen that most of the bushes are se-

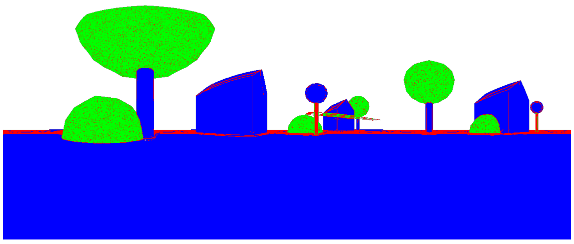

Figure 7: Results for the synthetic cloud in fake colors (blue: correct match for structured regions; green: correct match for unstructured regions; red: incorrect match). Neighbourhood window size: 3.

Window Size	Unstructured	Structured
3	92.34%	97.18%
5	92.00%	96.77%
7	89.23%	97.28%
9	89.98%	96.53%

Table 1: Accuracy levels achieved for the synthetic scene, varying the neighbourhood window size.

Figure 8: Results for the real scene. Points detected as unstructured are marked in red. Neighbourhood window size: 9.

lected correctly. The upper border of the bridge is marked also as unstructured. This is due to the presence of small bushes in this part of the bridge. We can also see that the vegetation of the ground has been not marked, because of his small height.

4 CONCLUSIONS AND FUTURE WORK

Our method can detect and mark most of the unstructured elements in outdoors 3D scenes. These unstructured elements correspond in most of the cases with undesirable objects in the scanned scene (wires, vegetation, etc.).

The first stage, composed by an anisotropic diffusion process followed by a subtraction, eliminates the low frequency components of the cloud of points, and the plane regression stage detects locally the lacking of structure. As a result, we obtain a labelling for each point, indicating the presence (absence) of local structure.

Numerical results show that the proposed method is accurate enough to give an initial estimation of the structures of interest in a cloud of points.

It is worth to mention that our method is currently used in a 3D data manipulation software, as part of a supervised point selection tool for civil engineering applications, with good results.

As a future work, we plan to test our method with other kinds of scenes, containing objects of different scales. We want also to take into account the colour information in the selection process. Finally, our method can be combined with object detection techniques to select mixed compound objects, such as trees, which have unstructured parts (leaves) and structured ones (trunk).

5 ACKNOWLEDGMENTS

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