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Pitch function comparison methodology for supporting a smart 3D scanner selection

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ABSTRACT

When working with 3D scanner devices, one of the most critical problems is usually the low quality of the point cloud provided by the scanning device. This problem mainly consists of the following two aspects. The first one is surely the choice of the strategy used to acquire the object shape. Most of the times, the selected strategy is based on selective sampling. This choice proved to be valid, especially when working with Free-Form surfaces: by using a selective sampling strategy is in fact possible to limit point density increase to those regions showing high morphological complexity. The second aspect is the difficulty of identifying which 3D scanner device is the one that better fulfils the specific application needs, which vary depending on the specific scenario in which the costumer/user works (resolution, accuracy, . . .). As far as this last issue is concerned, the presence of many different acquisition technologies and devices on the market is a source of confusion for the users, who sometimes choose the wrong solution instead of finding the most efficient one. Hence, in order to support the potential users in their selection, this paper aims to propose a solution able to integrate the morphological analysis of the object acquired with the costumer needs (resolution, accuracy, . . .) and with the 3D scanner performances in order to help users to identify the optimal solution.

1. Introduction

Reverse engineering and 3D scanners have recently been employed in a wide range of different fields. At present, the use of 3D scanners in the medical field is growing at high rate and is soon going to exceed the use of this kind of devices in the traditional mechanical/manufacturing context. Users belonging to those fields in which reverse engineering and 3D scanners have been employed for many years have generally developed a significant expertise to manage these tools. Unfortunately, the same cannot be said for users belonging to those fields (i.e. medicine, archaeology, . . .) in which 3D scanning devices have been introduced only a few years ago [1–3]. For this reason, several experimentations have been carried out in order to understand which solution would be the best one in these new domains of application. Among these experiments, the most relevant are those performed by using computer tomography (CT) (which is normally employed in the facial trauma diagnosis [4]) and ultrasound systems—a kind of system used to estimate the volume of human kidneys in vivo) [5]. All these studies aim to compare different solutions/strategies in order to understand which would be the best one for the applications mentioned above.

Another field in which 3D scanners have recently been employed is the agricultural one [6] where it is necessary to compare different possible solutions to analyze the drift over time, the effect of material and colour on measurement accuracy, and the ability to map different surface patterns.

While these studies have developed vertical analysis for a specific application field, some other studies [7] have tried to analyze the behaviour of different 3D scanners for generic virtual reality applications. However, none of these studies goes beyond proposing an experimental validation of different possible solution for vertical or horizontal applications; instead, it is necessary to find a more structured methodology, able to support users in their selection of the best 3D scanner device. This structured methodology should work by using quantitative parameters, i.e. the morphology of the acquired object and performances of the 3D scanner.

2. The "Optimal Pitch Function": the concept

While dealing with the approach considered in previous works [8,9], the selective sampling is a point cloud optimization strategy, based on considerations about the local morphological complexity of surfaces, on which the optimal sampled point density is supposed to depend. In other words, the selective sampling approach

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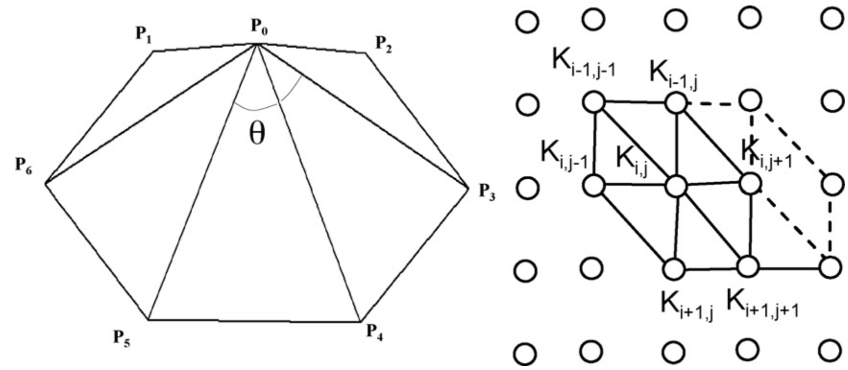

Fig. 1. Graphical representation of curvature K evaluation.

starts from the assumption that the more a surface is complex (from the point of view of local morphology) the higher is the number of points needed to sample it with enough precision. On the other hand, simpler surfaces, i.e. cone-like, plane-like or cylinder-like ones, need fewer points in order to be correctly sampled. In particular, the local morphological complexity of surfaces can easily be measured by using the so-called discrete Gaussian curvature parameter.

The Gaussian curvature approach for differentiable surfaces can be easily extended to point cloud analysis by using a triangulated model. Due to the Gauss–Bonnet theorem, the discrete Gaussian curvature value can be easily calculated as the angular excess of each triangulated neighbourhood, which have been previously generated through the Delaunay's approach.

The Gaussian discrete parameter provides an intrinsic curvature value which enables the operator to assess the discrepancy between the actual local geometry and the planar one by employing the following formula:

$$K = 2\pi - \sum_i \vartheta_i, \quad i = 1, \ldots n, \tag{1}$$

where K represents the Gaussian curvature value. This curvature value is calculated for each discrete neighbourhood, which consists of several triangles individuated by index I and sharing the same central node. As a consequence, there are as many triangulated neighbourhoods as there are points in the point cloud. For this reason, each point can be "labelled" with a specific curvature value (Fig. 1).

Due to this procedure it will be possible to associate every point cloud to a database composed by the preliminary points' Cartesian coordinates (Fig. 2a) and by the corresponding Gaussian discrete curvature values ("curvature map") (Fig. 2b).

Hence, taking into account that the curvature map reflects the morphological complexity of the preliminary sample and that the point density is proportional to the curvature value, it can be stated that it is possible to create an operative automatic approach by translating the curvature map into an "optimal pitch map", which can subsequently be employed for a new scanning session.

Due to the adoption of this reference parameter, a discrete value for local complexity can be easily measured for every triangulated neighbourhood (i.e. for the area composed by those triangles sharing the same central node) which forms the approximating surface. The whole set of curvature values associated to the points of the cloud (i.e. to every triangulated neighbourhood) constitute the so-called curvature map. This map shows the global behaviour of the approximating triangulation, as far as morphological complexity is concerned. The originally scanned object has a real surface, which results of both designing choices and manufacturing uncertainty. Furthermore, it has to be noticed that the scanning device used to carry out the acquisition phase, is a real measuring instrument, hence it is itself affected by uncertainty. The presence of non-Free-Form features on sampled surfaces is the main cause of the gap between originally scanned surfaces and final rebuilt models. All these elements survived the pre-processing point selection but do not submit to the classical "Free-Form" definition (concerning smoothness and regularity of the surface). Instead, they have been gathered under the name of "disturbance" since they contribute to generate the surface morphological local complexity (Fig. 3).

By using a geometrical and statistical model to evaluate the contribution of the "disturbance" to the local morphological complexity, it has been possible to transform the curvature map into a

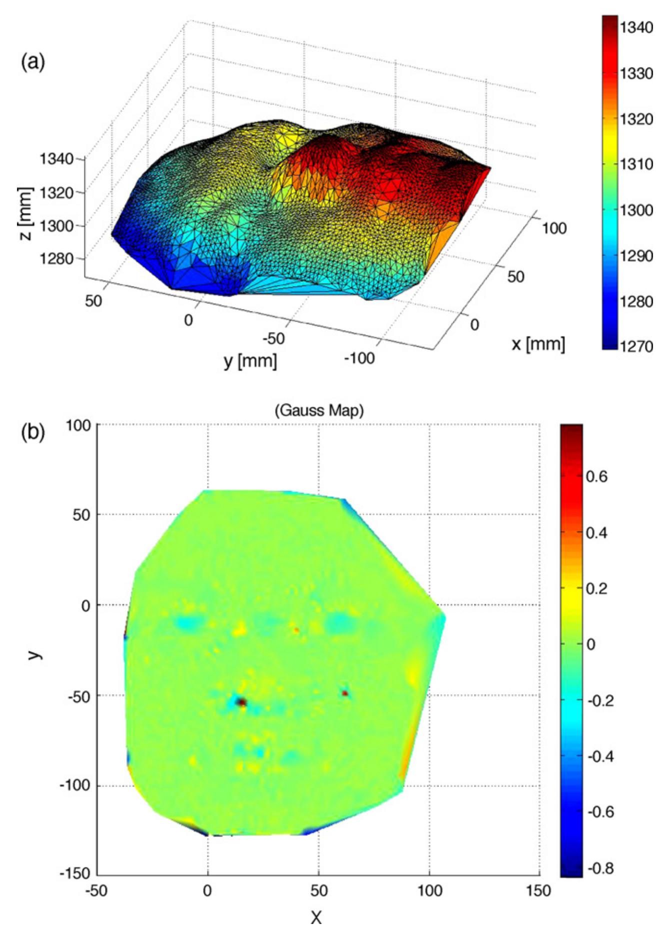

Fig. 2. (a) Geometrical representation of a scanned surface (*the colour-map describes z-coordinate values* [mm]); (b) curvature map for the same surface (*the colour-map describes curvature K values*).