3D Keypoint detection with Deep Neural Networks

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3D keypoint detection plays a fundamental role in the Computer Vision field, detection of these salient points in the local surfaces of a 3D object is important in order to perform certain tasks such as registration, retrieval and simplification. There has been a lot of research in the field of 3D keypoint detection, most of them take a geometrical approach which have a good performance but lack flexibility to adapt to changes such as noise and high curvature points that are not keypoints to human preference. A good approach seems to be machine learning methods that can be trained with human annotated training data. In this paper a new method is proposed using deep neural network with sparse autoencoder as the regression model due to their great ability for feature processing. The analysis shows this method outperforms other methods that are widely used.

Keywords: Keypoint detection; Deep Neural Networks; 3D Model; Sparse Autoencoders

1. INTRODUCTION

Several computer-dependent areas are benefited of the applications that 3D Models have in them. The growth of 3D data has increased in the latter years with the availability of low-cost 3D capture devices, and the ability to analyse, proccess and select relevant information from them is an active research area.

3D interest point detection is a difficult task for several reasons. First, there are not any definitions for what a interest point is, most of the approaches consider the high level of protusion in a local area as a keypoint characteristic. So, in planar sections of an area vertices have a low interest level and in local areas with diferent structures the interest level will be the opposite. Second, vertex density is different for every 3D model which makes harder the task of selecting a local area. Third, information obtained from a 3D model are only vertex positions and connectivity between them which means the interest level will depend only from the information we can retrieve from different calculations. These are not the only reasons but are sufficient for explaining why this method is prepared to handle these difficulties.

In this paper we extend the work in [?] to study the outcome of strategies that a designated bidder may follow in an English auction, in the presence of a collection of other bidders, under the assumption that this "special bidder" (SB) observes the parameters resulting from the auction as a collective (many bidders and the seller) system. Note that in [?] bidders are lumped together in a pool, where everyone shares a similar behaviour; whereas in this work we propose a generalisation in that the SB is allowed to have its own activity (bidding) rate which may differ from the other bidders', and examine how the SB should select its bidding rate in a self-serving manner.

We first sketch the model to be studied, and then in Section **??** we analyse it in detail. The manner in which the model provides performance measures of interest to the SB and to the seller, is discussed in Section **??** where we first discuss how the SB can behave in order to optimise outcomes that are in its best interest, and provide numerical examples to illustrate the approach and the model predictions. We then explore how the SB can try to achieve balance and compete with the other bidders in Section **??**. Finally Section **??** generalises the analysis to the case where the bidding rates depend on the current price attained in the auction. Conclusions are drawn in Section 2 where we also suggest further work.

2. CONCLUSIONS

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