3D Keypoint detection with Deep Neural Networks

Elías J. Puma

Escuela Profesional de Ciencia de la Computación,
Universidad Nacional de San Agustín,
Arequipa, PE
Email: eliasj.puma@gmail.com

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 [1] 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 [1] 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

In this paper we have considered auctions in which bidders make offers that are sequentially increasing in value by a unit price in order to minimally surpass the previous highest bid, and modelled them as discrete state-space random processes in continuous time. Analytical solutions are obtained and measures that are of interest to the SB are derived.

The measures that can be computed in this way include the SB's probability of winning the auction, its expected savings with respect to the maximum sum it is willing to pay, and the average time that the SB spends before it can make a purchase. An extension of the model that incorporates price-dependent behaviours of the agents has also been presented.

The model allows us to quantitatively characterise intuitive and useful trade-offs between improving the SB's chances of buying a good quickly, and the price that it has to pay, in the presence of different levels of competition from the other bidders.

There are interesting extensions and applications of these models that can be considered, such as the behaviour of bidders and sellers that may have time constraints for making a purchase, and the possibility of the SB's moving among different auctions so as to optimise measures which represent its self-interest. Another interesting area of study may be to examine bidders who are "rich" and are willing to drive away rivals at any cost, and who may create different auction environments for bidders that have significantly different levels of wealth. Yet another area of interest concerns auctions where items are sold in batches of varying sizes, with prices which depend on the number of items that are being bought.

ACKNOWLEDGEMENTS

This research was undertaken as part of the ALADDIN (Autonomous Learning Agents for Decentralised Data and Information Networks) project and is jointly funded by a BAE Systems and EPSRC (Engineering and Physical Research Council) strategic partnership (EP/C548051/1).

REFERENCES

[1] Gelenbe, E. (2006) Analysis of automated auctions. *ISCIS 2006, LNCS 4263*, Istanbul, Turkey, 1-3 November, pp. 1–12. Springer Verlag, Berlin.

[2] Gelenbe, E. (in press) Analysis of single and networked auctions. Accepted for publication in *ACM Trans. Internet Technology.*

[3] Gelenbe, E. (2007) Dealing with software viruses: A biological paradigm. *Information Security Technical Report*, **12**, 242–250.

[4] Gelenbe, E. (2007) A diffusion model for packet travel time in a random multi-hop medium. *ACM Trans. Sensor Netw.*, **3**, 10:1–10:19.

[5] Gelenbe, E. (2006) Travel delay in a large wireless ad hoc network. *2nd Workshop on Spatial Stochastic Modeling of Wireless Networks (SpaSWiN 2006)*, Boston, 7 Apr., pp. 1–6. IEEE.

[6] Gelenbe, E. (2003) Sensible decisions based on QoS. *Computational Manage. Sci.*, **1**, 1–14.

[7] Zeithammer, R. (2006) Forward-looking bidding in online auctions. *J. Marketing Res.*, **43**, 462–476.

[8] Gagliano, R. A., Fraser, M. D., and Schaefer, M. E. (1995) Auction allocation of computing resources. *Commun. ACM*, **38**, 88–102.

[9] Maes, P., Guttman, R. H., and Moukas, A. G. (1999) Agents that buy and sell. *Commun. ACM*, **42**, 81–91.

[10] Dobson, S., Denazis, S., Fernández, A., Gaïti, D., Gelenbe, E., Massacci, F., Nixon, P., Saffre, F., Schmidt, N., and Zambonelli, F. (2006) A survey of autonomic communications. *ACM Trans. Autonom. Adapt. Syst.*, **1**, 223–259.

[11] Gelenbe, E., Lent, R., Montuori, A., and Xu, Z. (2000) Towards networks with cognitive packets. *Proc. of the Int. Conf. on Performance and QoS of Next Generation Networking*, Nagoya, Japan, Nov., pp. 3–17. Springer, London.

[12] Gelenbe, E., Gellman, M., and Su, P. (2003) Self-awareness and adaptivity for QoS. *Proc. Eighth IEEE Int. Symp. on Computers and Communications (ISCC 2003)*, Kemer-Antalya, Turkey, June, pp. 3–9. IEEE Computer Society, Los Alamitos, California.

[13] Gelenbe, E., Gellman, M., Lent, R., Liu, P., and Su, P. (2004) Autonomous smart routing for network QoS. *Proc. Int. Conf. on Autonomic Computing (ICAC 2004)*, New York, 17-18 May, pp. 232–239. IEEE Computer Society, Los Alamitos, California.

[14] Gelenbe, E., Lent, R., and Xu, Z. (2001) Measurement and performance of a cognitive packet network. *Computer Networks*, **37**, 691–701.

[15] Gelenbe, E., Lent, R., Montuori, A., and Xu, Z. (2002) Cognitive packet networks: QoS and performance. *Proc. 10th IEEE Int. Symp. on Modelling, Analysis and Simulation of Computer and Telecommunications Systems (MASCOTS 2002)*, Ft. Worth, Texas, 11-16 Oct., pp. 3–12. IEEE Computer Society, Los Alamitos, California.

[16] Gelenbe, E., Lent, R., and Nunez, A. (2004) Self-aware networks and QoS. *Proc. of the IEEE*, **92**, 1478–1489.

[17] Gelenbe, E., Liu, P., and Laine, J. (2006) Genetic algorithms for autonomic route discovery. *Proc. IEEE Workshop on Distributed Intelligent Systems: Collective Intelligence and Its Applications (DIS 2006)*, Prague, Czech Republic, 15-16 June, pp. 371–376. IEEE Computer Society, Los Alamitos, California.

[18] Gelenbe, E., Liu, P., and Laine, J. (2006) Genetic algorithms for route discovery. *IEEE Trans. on Systems, Man and Cybernetics B*, **36**, 1247–1254.

[19] Gelenbe, E. and Lent, R. (2004) Power-aware ad hoc cognitive packet networks. *Ad Hoc Networks*, **2**, 205–216.

[20] Gelenbe, E., Sakellari, G., and D'Arienzo, M. (2008) Admission of QoS aware users in a smart network. *ACM Trans. Autonom. Adapt. Syst.*, **3**, 4:1–4:28.

[21] Gelenbe, E. (2005) Users and services in intelligent networks. *Asian Internet Engineering Conf. (AINTEC 2005), LNCS 3837*, Bangkok, Thailand, 13-15 December, pp. 30–45. Springer Verlag, Berlin.

[22] Di Ferdinando, A., Rosi, A., Zambonelli, F., Lent, R., and Gelenbe, E. (2008) A platform for pervasive combinatorial trading with opportunistic self-aggregation. *IEEE Int. Symp. on A World of Wireless, Mobile and Multimedia Networks (WOWMOM 2008)*, Newport Beach, CA, 23-26 June, pp. 1–6. IEEE.

[23] Gelenbe, E. and Loukas, G. (2007) A self-aware approach to denial of service defence. *Computer Networks*, **51**, 1299–1314.

[24] Loukas, G. and Oke, G. (2007) A biologically inspired denial of service detector using the random neural network. *Workshop on Socially and Biologically Inspired Wired and Wireless Networks (BIONETWORKS 2007)*, Pisa, Italy, 8-11 October, pp. 1–6. IEEE.

[25] Loukas, G. and Oke, G. (2007) Likelihood ratios and recurrent random neural networks in detection of denial of service attacks. *Proc. Int. Symp. on Performance Evaluation of Computer and Telecommunication Systems (SPECTS 2007)*, San Diego, California, 16-18 July.

[26] Oke, G., Loukas, G., and Gelenbe, E. (2007) Detecting denial of service attacks with bayesian classifiers and the random neural network. *Proc. IEEE Int. Conf. on Fuzzy Systems (FUZZ-IEEE 2007)*, London, UK, 23-26 July, pp. 1964–1969. IEEE.

[27] Krishna, V. (2002) *Auction Theory*, 1st. edition. Academic Press, California and London.

[28] Roth, A. and Ockenfels, A. (2002) Last-minute bidding and the rules for ending second-price auctions: Evidence from ebay and amazon auctions on the internet. *Amer. Econ. Rev.*, **92**, 1093–1103.

[29] Ockenfels, A. and Roth, A. E. (2006) Late and multiple bidding in second price internet auctions: Theory and evidence concerning different rules for ending an auction. *Games Econ. Behav.*, **55**, 297–320.

[30] Bajari, P. and Hortacsu, A. (2003) The winner's curse, reserve prices, and endogenous entry: Empirical insights from ebay auctions. *RAND J. Econ.*, **34**, 329–355.

[31] Popenda, J. (1987) One expression for the solutions of second order difference equations. *Proc. Amer. Math. Soc.*, **100**, 87–93.

[32] Mallik, R. (1997) On the solution of a second order linear homogeneous difference equation with variable coefficients. *J. Math. Anal. Appl.*, **215**, 32–47.

[33] Boese, F. G. (2002) On ordinary difference equations with variable coefficients. *J. Math. Anal. Appl.*, **273**, 378–408(31).

[34] Hillier, F. S., Conway, R. W., and Maxwell, W. L. (1964) A multiple server queueing model with state dependent service rate. *J. Ind. Eng.*, **15**, 153–157.

[35] David, E., Rogers, A., Jennings, N. R., Schiff, J., Kraus, S., and Rothkopf, M. H. (2007) Optimal design of english auctions with discrete bid levels. *ACM Trans. Internet Technology*, **7**, 12:1–12:34.

[36] Gelenbe, E. (1993) Learning in the recurrent random neural network. *Neural Computation*, **5**, 154–164.

[37] Gelenbe, E. and Mitrani, I. (1980) *Analysis and Synthesis of Computer Systems*. Academic Press, New York and London.

[38] Gelenbe, E. and Pujolle, G. (1998) *Introduction to Networks of Queues*. J. Wiley & Sons, Chichester.

[39] Guo, X. (2002) An optimal strategy for sellers in an online auction. *ACM Trans. Internet Technology*, **2**, 1–13.

[40] Lucking-Reiley, D., Bryan, D., Prasad, N., and Reeves, D. (2007) Pennies from ebay: the determinants of price in online auctions. *J. Ind. Econ.*, **55**, 223–233.

[41] Medhi, J. (1994) *Stochastic Processes*. J. Wiley & Sons.

[42] Milgrom, P. R. and Weber, R. J. (1982) A theory of auctions and competitive bidding. *Econometrica*, **50**, 1089–1122.

[43] Oren, S. S. and Rothkopf, M. H. (1975) Optimal bidding in sequential auctions. *Oper. Res.*, **23**, 1080–1090.

[44] Rothkopf, M. H. and Harstad, R. M. (1994) Modeling competitive bidding: a critical essay. *Manage. Sci.*, **40**, 364–384.

[45] Shehory, O. (2002) Optimal bidding in multiple concurrent auctions. *Int. J. Coop. Inf. Syst.*, **11**, 315–327.