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,

Computer systems and the Internet have enabled a wide variety of automated trading schemes which are in use for stocks, commodities, derivatives and other financial instruments. More recently, the Internet has also allowed individuals to buy and sell various items in an open and easily accessible manner. Thus we can envisage a future when large parts of the economy will be driven by sequences of automated and interconnected trading patterns.

Auctions are a convenient mechanism for formalising the rules with which such automating trading schemes can be conducted, and they have been widely used for many centuries in human based trading and commerce. In recent work the stochastic behaviour of collections of bidders acting in an auction has been analysed through the use of discrete state-space and continuous time probability models [1]. The approach constructs stochastic dynamical models of auctions and bidders, and then obtains the steady-state behaviour to compute significant properties of both the “one-shot” outcome, and the long-run repetitive outcome of auctions. One-shot properties include the probability distribution and the expected sale price, while long-term properties include the income per unit time obtained by the seller over a large number of transactions. In [2] the model has been extended to study a network of interconnected auctions, where bidders are allowed to move freely between auctions, and an analytical solution has been obtained. These mathematical techniques, and their variants, have also been successfully deployed in other diverse range of problem areas: from biological applications in modelling populations of viruses and agents [3], to communication systems in minimising packet travel time across a wireless network [4, 5], and choosing adaptive routing decisions [6].

In reality, knowledge of the existence of opportunity and availability to purchase similar goods in the future may influence a bidder to choose to forgo the opportunity of procuring a good at a high cost, and instead wait in the hope of securing a better deal later. We can also imagine situations where goods are reusable resources that are not sold per se, but rented out and returned to the seller at the end of some period, so that bidder agents who are not in urgent need to obtain a good immediately may defer a purchase. Interesting work along these lines, where bidders exhibit rational forward-looking behaviour when deciding strategies for the current auction can be found in [7]. A possible application for auctions of reusable goods in allocating computing resources is given in [8].

When we discuss automated auctions, we will invariably imagine software agents representing human counterparts in the digital marketplace [9], acting autonomously and yet guided by its design objectives to fulfill the interests of their owners to the best possible extent. In such instances it is crucial that the underlying communications infrastructure is designed to allow and support the user, i.e. the agent, to set the criteria for its service requirements. For example, a bidder agent may have certain specific needs with respect to its connectivity to the seller, and so may request for a network path with the minimum overall delay to the seller be established, or an agent physically located on a mobile node may prefer a connection that consumes the minimum power, or any weighted combination of its other goals. In this regard, auctions, or any digital marketplace activity for that matter, will benefit from autonomic communications [10] where emphasis is placed to insulate the user experience and services from changes, whether predicted or not, to the underlying infrastructure. In particular, a self-aware network, as proposed and implemented in the *cognitive packet network* (CPN) [11, 12, 13], accomplishes this by online internal probing and measurement mechanisms that are used for self-management, so that it adapts itself to provide the user the best effort quality of service (QoS). The CPN performs these corrective actions by using random neural networks with reinforcement learning [14, 15, 16], and finds newer routes with improved QoS using genetic algorithms [17, 18]. In a wireless mobile ad hoc network environment, where power efficiency is an overriding concern, the CPN has been extended to incorporate power-awareness [19], and the problem of controlling the admission of new users into the network while preserving the QoS of all users has been addressed in [20].

Beyond ensuring QoS for users, at a different level of abstraction, the ongoing research in autonomic communications has a broader objective of providing an intelligent platform for efficient interaction between digital objects such as users and services [21], or as in our context between buyer and seller agents. An important aspect of applying the “intelligence”, as discussed in [22], is in creating new knowledge based on collected raw sensitive data, through a knowledge network which, in turn, can be used to enhance economic efficiency. In this example, it is shown that a good allocation efficiency can be achieved in a trading application where the aggregated knowledge is used to create new markets so that sellers can respond to buyers’ needs as they arise.

Security is another vital feature in a communication network, especially when transactions involving e-commerce activities such as auctions are conducted; the servers running these applications are easy targets for attackers, either as a malicious act of sabotage or for profitable gains. The denial of service (DoS) attack is a particularly critical threat, since it is easy to launch, and by its usually distributed nature, difficult to protect against. Thus an autonomic approach to defending the network, based on self-monitoring and adaptive measures, has been suggested in [23], and several biologically inspired DoS detectors have been evaluated in [24, 25, 26].

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.

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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.