A Spectral Approach to Ghost Detection

Daniel Maturana, *Distinguished Lecturer in Parapsychology and Volology*, David Fouhey, *Senior Ufologist and Ghost Hunter*

Abstract—A large number of algorithms in optimization and machine learning are inspired by natural phenomena. However, so far no research has been done on algorithms inspired by *super*natural phenomena. In this paper we survey our groundbreaking research on in this direction, with algorithms inspired on ghosts, astral projections and aliens, among others. We hope to convince researchers of the value of not letting research be constrained by reality.

Index Terms—Spectral and Astral Methods, Trans-Dimensional Group Lasso, Ghosts, Occult, Hauntology, Crystal Energy, Supernatural, Paranormal

1 Introduction

Many algorithms in optimization and machine learning are inspired by natural phenomena. Some examples, in no particular order, include[1]

- Falling down a slope. [Robbins and Monro (1951)]
- Climbing up a hill. [Kernighan (1970)]
- Gravity [Rashedi (2009)]
- Iron cooling down [Hastings (1970)]
- DNA mutation and crossover [Goldberg (1989)], [Rechenberg (1971)], [Smith (1980)]
- Immune system behavior [Farmer et al. (1986)]
- Meme spreading [Moscato (1989)]
- Ant colony exploration [Dorigo (1992)]
- Honeybee mating behavior [Haddad et al. (2006)]
- Bee colony exploration [Karaboga (2005)]
- Glowworm communication [Krishnanand and Ghose (2009)]
- Firefly communication [Yang (2008)]
- Musicians playing in tune [Geem et al. (2001)]
- Mosquito swarms [Kennedy and Eberhart (1995)]
- Honeybee swarms [Nakrani and Tovey (2004)]
- Locust swarms [Buhl (2006)]
- Krill swarms [Gandomi (2009)]
- Cat swarms [Chu et al. (2006)]
- Magnetism [Tayarani (2008)]
- "Intelligent" water drops falling. [Shah (2009)]
- River formation [Rabanal (2008)]
- Frog leaping [Huynh (2008)]
- Monkey search behavior [Mucherino]
- Cuckoo search behavior [Yang and Deb (2009)]
- Bat echolocation [Yang (2010)]
- Galaxy evolution [Shah-Hosseini (2011)]
- Spirals [Tamura and Yasuda (2011)]

Clearly the bottom of this barrel has been thoroughly scraped. Therefore we propose to move towards algorithms inspired by *super*natural phenomena. In this paper we survey our groundbreaking work on algorithms on this area. We give a brief synopsis of each of our main results and conclude with some ideas for future research.

• *D. Fouhey and D. Maturana are with The Robotics Institute, Carnegie Mellon University, Pittsburgh, PA 15213.*

1. After reading this list you may be inspired to create a hyper-heuristic called "The Zoo Algorithm". Don't bother, we call dibs on the idea.

2 Related work

Outside of the occasional use of oracles, there is no real use of supernatural phenomena within computer science. The most closely related bodies of work are ancient and esoteric methods of prediction such as necromancy (performing prediction by posing queries to the deceased), and multilevel modeling.

3 Algorithms

3.1 A spectral approach to ghost detection

Ghost detection is a task that is currently painstakingly done by humans, often with high false positive rate and astoundingly low true positive rates, as documented in *Ghost Hunters* and *Most Haunted USA*. It is possible these researchers have been using unsuitable priors on ghost presence. We proposed to use the proven effectiveness of machine learning and computer vision to build a system for automatic ghost detection.

As can be seen in Figure 1, local "spectral" power is a strong cue to ghost presence. We created a system based on spectral analysis. We trained a Support Vector Machine with thousands of labeled examples to detect ghosts. Some example detections showing the effectiveness of our approach are shown in Figure 2.

3.1.1 Application: automatic ghost removal

Often ghosts, orbs and other supernatural appearances can show up and ruin otherwise perfectly fine pictures. We have developed a Photoshop plugin to automatically detect and remove these annoyances. An example result is shown in Figure 3.

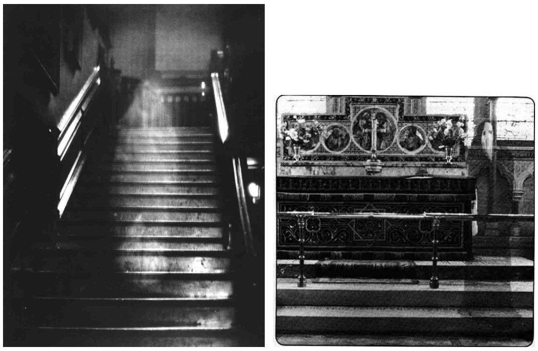

Fig. 1. Ghosts.

Fig. 2. Example detections.

3.2 Paranormal distribution modelling

The so-called "Normal" distribution is a relatively well known probability distribution function used to model various phenomena such as (TODO). It is not very interesting, which is why we propose to replace it with the Paranormal distribution. The formulation was inspired by the terrible and forbidden secrets in a manuscript found among the ruins of a nameless city in Iran.

$$X \sim \mathrm{PN}(\text{⚲}, \text{➾}^{\star}, \text{♉}^{\odot}_{\llcorner}, \nwarrow_{\circledcirc}, \text{ℛ})$$

We can not write out the analytic formula for this distribution; we foolishly tried to derive it but were nearly driven mad by the dark and twisted symbols contained within. The best we can do to convey the idea is the diagram in Figure 4.

3.2.1 Occult variables

While indubitably powerful, the expressiveness of the paranormal distribution is limited by its unimodality. To enhance the power of paranormal distributions we introduce mixtures of paranormal distributions:

$$Z \sim \mathrm{Mult}(\text{§}_1, \ldots, \text{§}_K)$$
$$X|Z \sim \mathrm{PN}(\text{⚲}_k, \text{➾}^{\star}_k, \text{♉}^{\odot}_{k\llcorner}, \nwarrow_{k\circledcirc}, \text{ℛ}_k)$$

where Z is an *occult* variable (also known as "latent" or "hidden" variables in less esoteric literature) that indexes the parameters of the Paranormal distribution (see Figure 5). Naturally, estimation in such a model is fiendishly complex. We resort to maximizing the likelihood with the esoteric optimization algorithms outlined in Section 3.4.

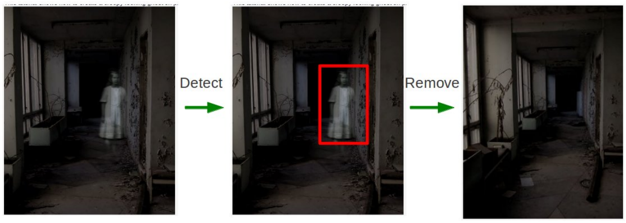

Fig. 3. Automatic ghost removal.

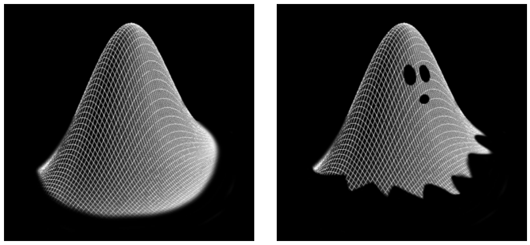

Fig. 4. The normal (left) and paranormal (right) distributions.

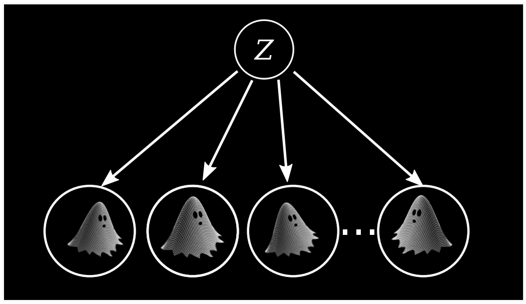

Fig. 5. Mixtures of paranormal distributions with occult variables.

3.3 Dimensionality shifting with astral projections

There are several algorithms in the literature to reduce the dimensionality of the data with discriminative or informative projections, such as principal component analysis (PCA) or linear discriminant analysis (LDA). There are also various kernel algorithms to implicitly or explicitly increase the dimensionality of data to a Hilbert space that increases class separability. But no algorithms exist so far to *trascend* and *shift* between dimensions. We propose to achieve this by projecting the data onto the astral plane. In the astral plane everything is possible: see Figure 6. As a useful side effect of this approach we can estimate the quality of the projection by its OOBE (Out Of Body Error).

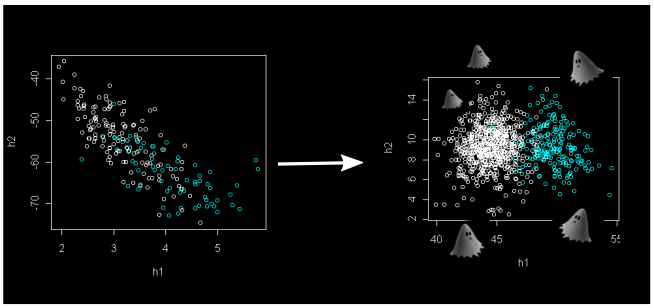

Fig. 6. Projection onto the Astral plane.

3.4 Esoteric optimization methods

The methods described above often require the solution of high-dimensional, trans-dimensional and non-linear optimization problems. To solve them we have developed various novel optimization algorithms.

3.4.1 Supernatural gradient descent via demon invocation

The so-called "Natural" gradient descent algorithm [Amari (1999)] is a popular variation of gradient descent for optimization, with an update written as

$$x_{n+1} \leftarrow x_n - \gamma_n \left(J^T J\right)^{-1} \nabla f(x_n)$$

we propose a supernatural gradient descent instead:

$$x_{n+1} \leftarrow x_n - \gamma_n \text{☆}^{-1} \nabla f(x_n)$$

In this algorithm we replace $J^T J$ with an invocation of demons that will rapidly drag our solutions to the depths of hell. A necessary condition for this to work is the sacrifice of at least one goat, a practice first popularized in the Deep Belief Net literature. We conjecture the amount of livestock that must be sacrificed is proportional to the difficulty of the problem, i.e., different classes of problems may be characterized by their goat-complexity.

3.4.2 ALIENS

The last resort. See Figure 7.

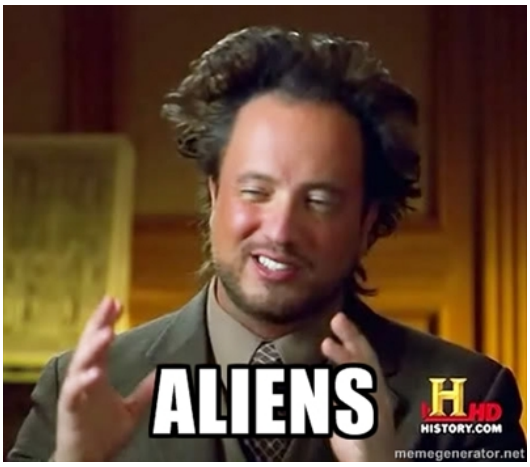

Fig. 7. ALIENS

4 Conclusion and future work

We have summarized our groundbreaking work on algorithms inspired by supernatural phenomena. We are currently working on various new papers in this vein, described below.

4.0.3 Learning Hauntologies

Learning ontologies is a popular topic in the Artificial Intelligence literature. We propose to learn Hauntologies, a related but more esoteric and powerful way to describe knowledge.

4.0.4 Crystal-energy-based models

Energy-based models are a popular way to describe dependencies between variables. However inference in these models is often intractable. We propose Crystal-energy-based models, which leverage the magical healing power of crystals to solve this problem.

4.0.5 Supernatural K-optimality

We are currently studying the Kabbalah, arguably the most K-optimal esoteric text, with the hopes of applying this deep esoteric knowledge to the study of Kardashian Kernel methods [Fouhey and Maturana (2012)].

References

[Chu et al. (2006)] Shu-Chuan Chu, Pei-Wei Tsai, and Jeng-Shyang Pan. Cat swarm optimization. In *Proceedings of the 9th Pacific Rim international conference on Artificial intelligence*, PRICAI'06, pages 854–858, Berlin, Heidelberg, 2006. Springer-Verlag. ISBN 978-3-540-36667-6. URL http://dl.acm.org/citation.cfm?id=1757898.1758002.

[Dorigo (1992)] M. Dorigo. *Optimization, Learning and Natural Algorithms*. Politecnico di Milano, Italie, 1992.

[Farmer et al. (1986)] J.D. Farmer, N. Packard, and A. Perelson. The immune system, adaptation and machine learning. *Physica D*, 22:187–204, 1986.

[Geem et al. (2001)] Z.W. Geem, J.H. Kim, and G.V. Loganathan. A new heuristic optimization algorithm: harmony search. *Simulation*, 76:60–68, 2001.

[Goldberg (1989)] D.E. Goldberg. *Genetic Algorithms in Search, Optimization and Machine Learning*. Kluwer Academic Publishers, 1989. ISBN 0-201-15767-5.

[Haddad et al. (2006)] O. B. et al. Haddad, Abbas Afshar, and Miguel A. Mario. Honey-bees mating optimization (hbmo) algorithm: a new heuristic approach for water resources optimization. *Water Resources Management*, 20:661–680, 2006.

[Hastings (1970)] W.K. Hastings. Monte carlo sampling methods using markov chains and their applications. *Biometrika*, 57:97–109, 1970.

[Huynh (2008)] Thai-Hoang Huynh. A modified shuffled frog leaping algorithm for optimal tuning of multivariable pid controllers. In *Industrial Technology, 2008. ICIT 2008. IEEE International Conference on*, pages 1–6, April.

[Karaboga (2005)] D. Karaboga. An idea based on honey bee swarm for numerical numerical optimization. *Technical Report-TR06*, 2005.

[Kennedy and Eberhart (1995)] J. Kennedy and R. Eberhart. Particle swarm optimization. In *Proceedings of IEEE International Conference on Neural Networks*, volume IV, pages 1942–1948, 1995.

[Kernighan (1970)] R. Kernighan. An efficient heuristic procedure for partitioning graphs. *Bell System Technical Journal*, 49:291–307, 1970.

[Krishnanand and Ghose (2009)] K. Krishnanand and D. Ghose. Glowworm swarm optimization for simultaneous capture of multiple local optima of multimodal functions. *Swarm Intelligence*, 3:87–124, 2009.

[Moscato (1989)] P. Moscato. On evolution, search, optimization, genetic algorithms and martial arts : Towards memetic algorithms. *Technical Report C3P 826*, 1989.

[Mucherino] Antonio Mucherino. Climbing trees like a monkey. http://www.antoniomucherino.it/en/research.php.

[Nakrani and Tovey (2004)] S. Nakrani and S. Tovey. On honey bees and dynamic server allocation in internet hosting centers. *Adaptive Behavior*, 12, 2004.

[Rechenberg (1971)] I. Rechenberg. *Evolutionsstrategie – Optimierung technischer Systeme nach Prinzipien der biologischen Evolution*. 1971. ISBN 3-7728-0373-3.

[Robbins and Monro (1951)] H. Robbins and S. Monro. A stochastic approximation method. *Annals of Mathematical Statistics*, 22: 400–407, 1951.

[Shah-Hosseini (2011)] Hamed Shah-Hosseini. Principal components analysis by the galaxy-based search algorithm: a novel metaheuristic for continuous optimisation. *International Journal of Computational Science and Engineering*, 6:132–140, 2011.

[Smith (1980)] S.F. Smith. *A Learning System Based on Genetic Adaptive Algorithms*. University of Pittsburgh, 1980.

[Tamura and Yasuda (2011)] K. Tamura and K. Yasuda. Spiral dynamics inspired optimization. *Journal of Advanced Computational Intelligence and Intelligent Informatics*, 15:1116–1122, 2011.

[Yang (2008)] X.-S. Yang. *Nature-Inspired Metaheuristic Algorithms*. Luniver Press, 2008. ISBN 1-905986-28-9.

[Yang (2010)] X.-S. Yang. *A New Metaheuristic Bat-Inspired Algorithm http://arxiv.org/abs/1004.4170, in: Nature Inspired Cooperative Strategies for Optimization (NISCO 2010) (Eds. J. R. Gonzalez et al.), Studies in Computational Intelligence,*. Springer, Berlin, 2010.

[Yang and Deb (2009)] X.-S. Yang and S. Deb. *Cuckoo search via Lvy flights, in: World Congress on Nature and Biologically Inspired Computing (NaBIC 2009)*. IEEE Publication, USA, 2009.

[Shah (2009)] Shah-Hosseini, Hamed (2009) "The intelligent water drops algorithm: a nature-inspired swarm-based optimization algoirthm". International Journal of Bio-Inspired Computaton 1 (1/2): 71-79.

[Rashedi (2009)] Rashedi, E.; Nezamabadi-pour, H.; Saryazdi, S. (2009). "GSA: a gravitational search algorithm". Information Science 179 (13): 2232-2248.

[Gandomi (2009)] Gandomi, A.H.; Alavi, A.H. (2012). "Krill Herd Algorithm: A New Bio-Inspired Optimization Algorithm". Communications in Nonlinear Science and Numerical Simulation. doi:10.1016/j.cnsns.2012.05.010.

[Tayarani (2008)] Tayarani, M. H.; Akbarzadeh, M. R.. "Magnetic Optimization Algorithms a new synthesis". IEEE World Congress on Evolutionary Computation, 2008.(IEEE World Congress on Computational Intelligence).

[Rabanal (2008)] Using River Formation Dynamics to Design Heuristic Algorithms by Pablo Rabanal, Ismael Rodrguez and Fernando Rubio, Springer, 2007. ISBN 978-3-540-73553-3

[Buhl (2006)] Buhl, J.; Sumpter, D.J.T.; Couzin, D.; Hale, J.J.; Despland, E.; Miller, E.R.; Simpson, S.J. et al. (2006). "From disorder to order in marching locusts" (PDF). Science 312 (5778): 1402-1406. doi:10.1126/science.1125142. PMID 16741126.

[Atashpaz-Gargari (2007)] Atashpaz-Gargari, E.; Lucas, C (2007). "Imperialist Competitive Algorithm: An algorithm for optimization inspired by imperialistic competition". IEEE Congress on Evolutionary Computation. 7. pp. 4661-4666.

[Amari (1999)] [Amari, S. and Douglas, S.C.] "Why natural gradient?". Proceedings of the International Conference on Accoustics, Speech and Signal Processing, 1998. pp. 1213–1216 vol.2

[Fouhey and Maturana (2012)] "The Kardashian Kernel". Proceedings of SIGBOVIK 2012.

Daniel Maturana Daniel comes from Chile. He is a devout Catholic and listens to reggaeton.

David Fouhey David Fouhey received an A.B. from Middlebury College in Computer Science and Home Economics in 2011. He is currently a Ph.D. student at the Robotics Institute at Carnegie Mellon University. In his spare time, he enjoys reality TV, Americanized mexican food, and reading the *New York Times* wedding section. In 2010, he served as a U.N. Ambassador on a fact-finding mission into the difference between yoga pants and leggings.