Noise and Adaptive Systems

In the early 90's, the University of Sussex played a key role in showing the world what evolutionary robotics has to offer, with Cliff, Husbands and Harvey's 1993 publication [1]. Their work was centred around visually guided robots, and they were amongst the first to genetically evolve the control-network architecture of autonomous robots. After showing promising results, they laid the foundations for a myriad of further works, many of which at the University of Sussex. Floreano and Mondada [2] showed it possible to evolve simple behaviours directly on a real robot, however with it taking 60 hours to train their Khepera robot to navigate a static environment, there was clearly room for improvement. Particularly when you consider their agent was performing nearly at an optimal level after only 50 of the 100 generations. The obvious solution would be to carry out the evolutionary process within a simulation, however Brooks [3] illustrated a few key reasons which may cause problems for this simulative approach. Unlike a real robot, simulations are conducted in a stable coordinate system, with knowledge of the absolute position of all objects. Simulated sensors are able to return perfect information, void of any uncertainty. In addition, there are of course many physical laws that need be accounted for in the real world, such as friction, inertia, mass, and critically – noise, which can affect all aspects of such a system.

In spite of this, Miglino, Nafasi and Taylor [4] built on the work by Floreano et al by using a simulation of a simplified environment to evolve the weights of a recurrent neural network controller which demonstrated an exploration ability of that environment. However they were now able to carry out their evolution of 6 times the amount of generations, at 20 times the speed (600 generations in 3 hours). Although the observed fitness values did correlate, the paths taken by their genotypes did differ either side of the reality gap. Does noise have a role to play in achieving behavioural consistency between the simulated and non-simulated environments? This would ratify the findings of Nick Jakobi [5], that even complex motor behaviours can be evolved in minimal simulations and impeccably transferred into reality. That being the case however, where do the limitations of such roles lie?

Stefano Nolfi, Orazio Miglino and Domenico Parisi [6] investigated an alternative approach, a hybrid one, in which the evolutionary process is continued post reality gap transfer for a few generations to allow the system to adjust to the non-idealistic conditions of the real world. Although there was a significant drop in the fitness of individuals when transferred on to a real robot, these quickly reached a level akin to those achieved within the simulation after just a few additional generations evolved locally. This quick readjustment period demonstrates that to some extent at least, the problems posed by noise can be overcome by parameter fine-tuning, rather than being indicative of any fundamental flaws with the simulatory evolution strategy. This approach is not without its flaws however - as well as being time consuming, evolving a behaviour within a real robot usually requires some form of human intervention between every iteration to reset the agent. This would not be possible in environments that are adversely suited to human survival, or otherwise inaccessible – take the example of a behaviour being evolved for a distant planetary rover.

The significance of the detrimental role played by noise with regards to an adaptive system, and specifically its resultant transferability from a simulation, depends largely on its nature. In the case of a non-visually guided return to home behaviour for example, I hypothesize noise to be somewhat less of a concern than it would otherwise pose, the key reason for this being that the agent won't be exhibiting reactive behaviour as a result of sensor-read environmental stimulus (as with a visually guided agent), and instead any input will come intrinsically.

Although noise does affect actuators as well as sensors, the effects on actuators are likely to be negligible in comparison. High quality actuators that promise great precision are becoming more affordable year on year, so any noise that may be present is likely to be of a far more consistent and limited nature regardless of the environment. In terms of a sensory guided system however, this would rely purely on external stimulus and I anticipate will suffer far more due to noise as a result once bridged over the reality gap. The effects of noise are now two-fold, sensors are vulnerable to the same sort of intrinsic noise that affects actuators (e.g measurement uncertainty), but they are also susceptible to environmental noise, to which there is no limit in potential magnitude. This problem is again compounded when we consider that sensor readings, when they reach certain thresholds, dictate reactive behaviours, and the disruption of when these thresholds are met is likely to be catastrophic to the performance of an adaptive system. This would substantiate what is expressed in the Google AI blog [7] regarding visual perception to constitute the widest part of the reality gap.

In terms of negating the mal effects of noise, there are a couple of different approaches that can be taken, such as building resistance to noise. For example, as explored in Brogan's 1991 publication [8], the feedback loops present in a recurrent neural networks offer robustness to noise. If the same considerations are held when designing the hardware aspects of such a system, this can yield positive results with certain robot-environment interaction dynamics. Additionally, noise has a further role to play, however this time a redeeming one - the careful and deliberate incorporation of noise during simulation. As scrutinized by Jakobi et al [9], perhaps the foremost method of tackling this issue, is to proportionally model empirically validated noise within the simulation as to more closely mirror those conditions found in the real world. This combined with a real robot designed with resistance to noise in mind can achieve very positive results.

Mondada and Verschure [10] were able to achieve behaviours akin to one another in each environment without the modelling of noise, however performance in the real robot was substantially less robust. There are of course very real limitations to this technique of noise modelling depending on the quantity and nature of said noise, modelled noise is not identical to its real world counterpart, it aims to create a similar degree of inaccuracy even if how it does so is fundamentally different. These differences will result in a growing discrepancy between the environments as more noise is introduced. It may seem apparent why a simulation with insufficient noise can lead to a less successful transfer over the reality gap, but the same is true with too much noise, as the evolved behaviour then becomes dependant on it and its performance then suffers without it.

Whilst carrying out some experimentation of my own, I initially evolved an agent to respond to a single light source in a simulation void of noise. Once transferred into a real robot, it was able to mirror this behaviour only whilst in a strictly controlled environment that was pitch black apart from the one light source. As soon as the system was placed in any typical real-life scenario with any level of ambient light, it would suffer drastically. I then introduced noise in the form of random normally-distributed variation in the light sensors within the minimal simulation during the evolutionary phase, and to my surprise, this performed significantly more competently, and very consistently once transferred and placed in a much more typical environment. I was surprised with the level of success that this had achieved, as I had concerns that the noise was not empirically validated as the findings of Jakobi et al [9] showed necessary. The noise in our scenario takes the form of ambient light of a constant intensity as opposed to it varying in all directions in accordance with a normal distribution, and so I hypothesised a more effective way to mirror this to be to scale down the detected light intensities in the simulation during the CMA-ES optimisation. Such to reduce the contrast that becomes relied upon between light intensities when aiming at the source versus not, as the key impact of our well-illuminated testing environment is the abating of this disparity.

This modification brought severe detriment to the performance of the agent, and it was with this failure that I realised the error of my earlier thinking. Since the random normally-distributed noise was applied over 36,000 iterations during the evolution of the genotype, this created a gaussian smoothing effect of sorts to the detected contrast between the intended light source, and the ambient light, upon which the evolved behaviour was based. These softer boundaries much more accurately replicated the conditions of the real-world environment, whilst my alternative approach actually rewarded the agent to respond to lower levels of light, allowing noise to have more of an impact.

In conclusion, noise is arguably the most major hurdle when transferring a controller for an adaptive system between simulation and reality. But as we have explored, it has more roles to play than exclusively the detriment it has become known for - I believe I have substantiated the findings of Jakobi et al [9] such that a 'fighting fire with fire' approach of using empirically validated noise to overcome its otherwise adverse effects, may be the key to conquering the reality gap. During my experimentation I also proved the value in doing so – evolving a controller in just 35.1 seconds, that would have a theoretical lower-bound of 16.7 days (discounting any inevitable delays such as reset times or the modification of genotypes) if done so without a simulation.

I would love to broaden my understanding of the topic through various points of further investigation; how versatile is this method of noise modelling? What other agent-environment interaction scenarios can this method of noise modelling be applied to (e.g audio-stimulated behaviours)? Provided we can suitably mirror the necessary mechanics within a minimal simulation, I anticipate the role of noise will continue to be a critical one, with near limitless potential if suitably handled.

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