Robust adaptive control for kite wind energy using evolutionary robotics

Allister Furey, Inman Harvey
Centre for Computational Neuroscience and Robotics
University of Sussex, Brighton, BN1 9QG, United Kingdom

Abstract

Recently designed wind energy systems use large traction kites to drive electricity generation equipment at ground level; this exploits stronger and more consistent winds available at higher altitudes than used by traditional wind turbine systems. These kites require active control; in this study we build upon past work demonstrating the use of evolutionary robotics techniques to build neural network controllers that maximize energy recoverable from wind in a simulated kite system using only information available at ground level from the line angles and forces. Neurocontrollers are evolved under selective pressure to fly the kite in order to maximise forces through the lines, resulting in optimal figure-eight trajectories.

We allow evolution to converge completely and compare the flight trajectory with analytically derived solutions. We consider the robustness of the neurocontrollers to large gust deviations in speed and direction. Finally we address the problem of controlling the kite with different line lengths, which dramatically alters the response properties of the kite.

1. Introduction

The wind resource at high altitude has been known for some time to be of much higher quality in terms of strength and consistency than that exploitable by traditional wind turbine technology. This knowledge has spurred the exploration of a number of high altitude wind concepts using kites. Here we address the control of a kite in simulation using evolved neural network controllers. Initially we continue previous work which has shown that evolution can configure recurrent neural networks to robustly steer a kite in an appropriate trajectory for power generation, using only data available at ground level from line angles and tension data. We then consider a further subset of the operating conditions under which the neural network must maintain robust and adaptive control, namely lateral wind deviations and varying line length.

2. Background

The use of kites for electricity generation was first addressed by Loyd, who demonstrated that steering a tethered airfoil in sweeping crosswind passes maximises the power generated at a ground based generator (Loyd, 1980), as the lines are reeled out from a spool which is coupled to a dynamo. The basis for this strategy is that power generated by a wind generator scales with the cube of the wind speed (Canale *et al*, 2006). This lends itself to the periodic power generation strategy as shown in Figure 1; the difference in energy between that recovered in the reel-out phase A where dynamic manoeuvres are performed to augment apparent wind velocity, and that spent in phase B where the lines are reeled in with the kite at low attack angles, is the net gain of energy. Here we take a bio-inspired method and use evolutionary robotics (ER) techniques to develop controllers for a single four-line kite with in-trial variation in wind speed and wind direction and between-trial line length variation.

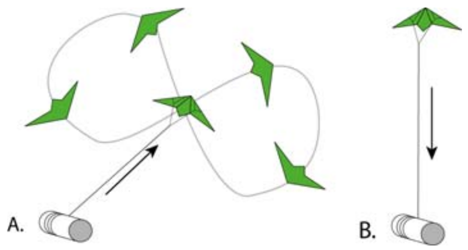

Figure 1. Generation (reel out) phase A and retraction (reel in) phase B.

Presented at the Biological Approaches for Engineering Conference, held 17-19 March 2008 at University of Southampton, Southampton, UK

3. Methodology

Following Furey *et al* (2007), neurocontrollers are selected in an iterative process directly inspired by evolution. The key elements are summarised below, a more precise description is given in the earlier paper.

3.1 Physics simulation

In order to capture some of the dynamics of the kite's flexible structure that affect its flight and response to steering input, the kite is considered to be a collection of particles with mass, whose relative distances are constrained. Assuming that the enforcement of the constraints is not fully rigid, the kite will flex according to the relative forces on different parts of the canopy and the layout of the constraints (see Fig. 2). The kite's canopy is split into 5 slices, the drag (Eq. 1.4) and lift (Eq. 1.2) forces on each section are calculated separately using the section's own angle of attack (α in Eqs 1.2,1.4), area, leading edge vector and apparent wind vector at that section (A ,e and a respectively in eq 1.3.). The drag and lift coefficients (C_L and C_D) are determined using the slice angle of attack (see Furey *et al* 2007). The aerodynamic and gravitational forces upon each slice are distributed among its constituent particles, and acceleration calculated via Newton's second law. In the simulation the particles positions (x in eq 1.1) over time are integrated using the Verlet method as shown in equation 1.1 where a is acceleration and Δt is 0.004, Gauss-Seidel iteration is used to enforce constraints.

Table 1. Key equations

$x^{t+1} = 2x - x^{t-1} + a\Delta t^2$	(1.1)
$F_L = \vec{L}\frac{1}{2}C_L(\alpha)dV_a^2 A$	(1.2)
$\vec{L} = \frac{a}{\lVert a \rVert} \times e$	(1.3)
$F_D = \frac{a}{\lVert a \rVert}\frac{1}{2}C_D(\alpha)dV_a^2 A$	(1.4)
$a_j^t = \sigma\left(\sum w_{ij} a_i^{t-1}\right) - \theta_j$	(1.5)

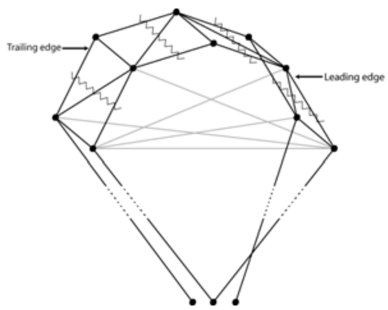

Figure 2. Configuration of constraints and particles. Slices marked by zigzag lines.

3.2 Genetic Algorithm and Neural Network

We use a simple microbial genetic algorithm (Harvey 2001), with a population of genotypes or artificial 'DNA', randomly initialised, specifying possible parameter values. A wind trace is generated with a heuristic that produces the wind speed modulated at different rates and amplitudes around a predetermined background wind speed. Two neurocontrollers are then picked at random from the population and their fitnesses, the average of the component of the aerodynamic force in line with the lines, are determined. The worse performer's DNA is overwritten by the better, with a small random mutation of ± 0.01 applied to every parameter. This process continues for several hundred iterations, each consisting of 15 competitive trials. There is no restriction on the form of the flight trajectory, fitness is the only criteria and suitable flight patterns should emerge from the evolutionary process. We use a simple discrete time recurrent neural network due to its faster evolution relative to continuous time recurrent neural networks in previous work. As mentioned above, we do not feed the network with explicit position data of the kite, only data available from line angles and tension is allowed, the sensor values are subject to significant Gaussian noise with a standard deviation of 2% of the sensor range. There are 5 input nodes, which take their activation values directly from the simulation, describing (1) average line azimuth and (2) elevation, (3) average line force, (4) difference in line force and (5) azimuth between the left and right lines of the kite The activation a at each hidden and output neuron j at time t is given by equation 1.5 where σ is the logistic sigmoid function, θ the threshold, w_{ij} the weight from neuron i to neuron j. The six hidden nodes and the single output node have full recurrency, taking input from every other node and themselves. The activation value of the output node specifies the difference in left and right steering line length in the simulation.

3.3 Experimental protocol

We evolve a population of 30 neurocontrollers to produce the highest average aerodynamic force in line with the flying lines over a 42 second trial. Here we consider three scenarios, in the first the wind amplitude varies ±4ms^{-1} according to the heuristic described above. In the second we use the same type of heuristic to generate lateral deviations of the wind of ±20^{o} around a central point during the tests. The ground attachment points and azimuth sensor readings are not rotated with the wind or direction of force as real kite hardware could be. In the third we consider the control of the kite under varying wind speed, but also with the line length varying from trial to trial. Across the whole set of experiments there is no explicit sensory information given to the network that relates directly to the factors being varied: wind speed, wind direction or line length.

4. Results

Figure 3 (left) was presented previously in Furey *et al* 2007 and represents the trajectory of the kite in a 42 second trial when controlled by the best performing neurocontroller after 200 generations. Whilst being a figure eight, it is clearly suboptimal as the eight in not centred downwind as is required in order to make most efficient use of a given wind. Figure 3 (right) however shows that after a further 800 generations of evolution, the figure eight is fully lying on its side and almost exactly centred downwind. The loop is qualitatively similar to the lying eight presented in (Houska *et al* 2007), with one half of the loop larger than the other. The DNA from the experiment described above was used to seed the population for the second experiment where relatively small lateral deviations of ±15^{o} were introduced to the wind. Figure 4 demonstrates a trajectory of the best performing neurocontroller after 600 generations, being flown with the 15 degree lateral deviation shown below. Unlike in the first experiment, where the controllers performed robustly across all of the range of

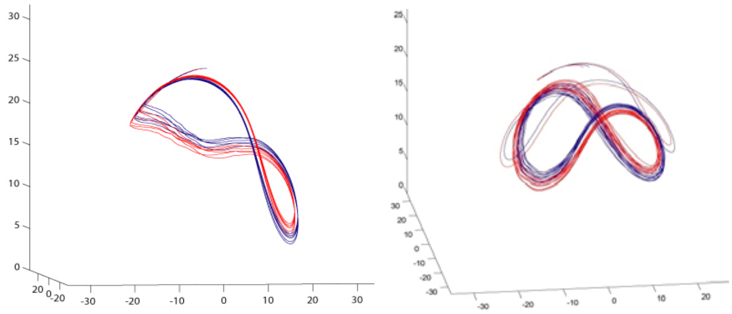

Figure 3. Plot of best evolved controller's trajectory over 42 seconds after 200 (left) and 1000 (right) generations respectively. All axes in meters.

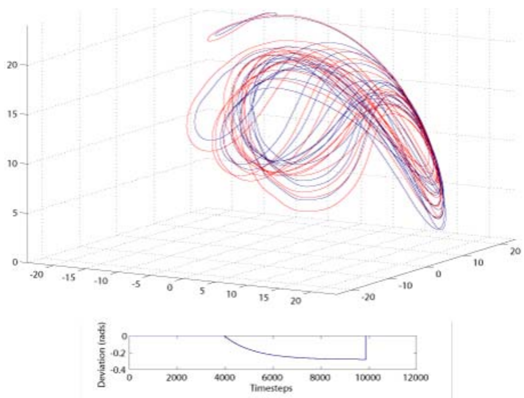

Figure 4. Trajectory of the best evolved agent when subjected to the 15 degree lateral gust shown below.

variation that they were exposed to in evolution, in the case of lateral deviation consistent non-crashing trajectories were only experienced for deviations of 7-8 degrees either side; greater deviations than this would increasingly cause crashes or the neurocontroller would get 'stuck' at a certain point in the wind window before resuming its normal course upon the cessation of the lateral gust. The third experiment produced some unexpected results, controllers were produced that could fly the kite without crashing within a range of line lengths, however, the general pattern of the

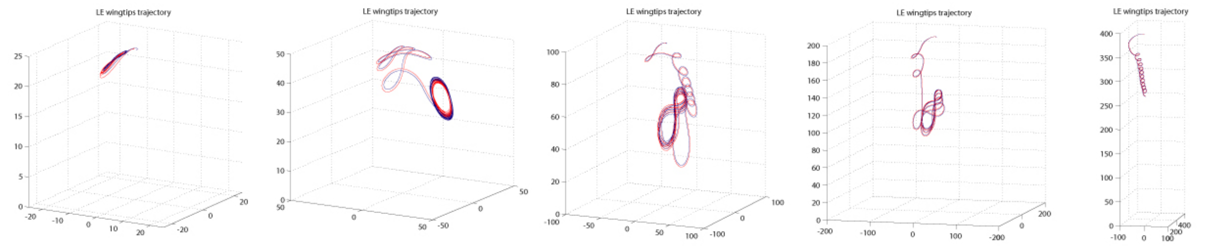

Figure 5. Trajectory of the best evolved agent at line lengths of 25,50,100,200 and 400m respectively.

trajectory itself varied to a large extent depending on the line length. Figure 5 demonstrates the progression of trajectories from 25 to 400m line length using the same neurocontroller. Note the near circular trajectory at 50m which has been shown to be a local optima (Houska, 2007). Interestingly, the successful controllers generalised well to the variation in terms of keeping the kite aloft, controllers evolved to fly the kite with line lengths between 20 and 100 metres could also fly the kite successfully at 200 meters and more. In terms of maximising the aerodynamic forces, all the populations tested here sacrificed the performance at short line lengths in order to generalise to longer lengths.

5. Discussion

We have shown in the first experiment that ER can generate neurocontrollers that fly a kite in an appropriate trajectory to maximise forces through the lines in a wind of varying amplitude. When evolution is allowed to converge, the trajectory qualitatively resembles those derived through mathematical techniques. Secondly it was demonstrated that neurocontrollers could be evolved to be robust to small lateral wind deviations. The relatively poor performance in this task was potentially influenced by the experimental setup in which the base was not rotated meaning that actuator limits were being saturated. Finally ER was shown to generate controllers with good line length generalisation, the trajectory variations seen are likely determined by the evolutionary process working with networks with limited temporal dynamics. This will be addressed in future work, along with the problem of control under reel-out, and active control of reel-out speed.

6. References

Canale M, Fagiano L, Ippolito M, Milanese M, Control of tethered airfoils for a new class of wind energy generator. Proc. 45th IEEE Conference on Decision and Control, 2006, 4020-2046

Furey A and Harvey I Evolution of Neural Networks for Active Control of Tethered Airfoils. Proc. The 9th European Conference on Artificial Life, 2007 746-756. Springer.

Harvey, I., Artificial Evolution: a Continuing SAGA, In Evolutionary Robotics: From Intelligent Robots to Artificial Life, T. Gomi (ed.), 2001, Springer-Verlag.

Houska B Diehl M, Optimal Control for Power Generating Kites, 2007, Internal Report 07-98, ESAT-SISTA, K.U.Leuven

Lansdorp B and Ockels WJ Comparison of concepts for high-altitude wind energy generation with ground based generator. Proc. 2nd China IREETEC 2005, 409-417.

Loyd M Crosswind Kite Power. Journal of Energy, 1980, 4(3) 106-111 AIAA