Adaptive Electromagnetic Control of Artificially Induced Disturbances

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Abstract
A numerical simulation of the control of artificially induced disturbances over a single electromagnetic tile is presented. The tile consists of a pair of magnets and electrodes and is operated in a weakly conducting fluid as both a flow sensor and actuator. The tile is located beneath the lower wall of a channel consisting of two free slip non permeable walls which are infinite in extent in the cross flow direction. Time varying sinusoidal vertical velocity disturbances are imposed on a uniform flow at the channel entrance and convected downstream. As a result a sequence of upward and downward vertical velocities are passed over the tile. The control objective is to dampen the upward velocity disturbances as they pass over the tile while leaving the downward velocity disturbances unhindered. The dampening of the upward velocities loosely approximates the control of the ejection events of a turbulent boundary layer. For an arbitrary sequence of disturbances a control algorithm continually varies the Lorentz force strength as a function of the instantaneous velocity field. This information, in conjunction with the modeled responses of the sensor, is then used to train a neural network. The neural network has demonstrated its ability to control other sequences of artificially induced disturbances of a similar nature.

Introduction
The flow of a weakly conducting electrical fluid (such as seawater) can be manipulated by subjecting it to an electromagnetic field. Over the last decade researchers have sought to utilise this phenomenon for the control of the turbulent boundary layers of such fluids with the primary aim being the reduction of the turbulence intensity and frictional drag. The technique is known as Electromagnetic Turbulence Control (EMTC).

The electromagnetic field is generated by an array of electrodes and magnets mounted just beneath the boundary layer wall surface. The interaction of the electric and magnetic fields, produced by the electrodes and magnets respectively, generates a field known as a Lorentz force field. It is this force that the electrically conducting fluid responds to. Each pair of electrodes, consisting of an anode and cathode, along with the common magnet pair they share is known as a Lorentz force actuator.

To date research efforts have almost invariably concentrated on the application of either constant [3,5] or pulsed [1,10] Lorentz force fields. This paper presents the results of a preliminary numerical investigation into the application of an adaptive Lorentz field. The field is adaptive in that it's strength is timed dependent and varied in accordance with the control requirements of each instantaneous flow field.

The preliminary investigation involves the manipulation of sinusoidal wave disturbances using a single Lorentz Force actuator (see figure 1). These disturbances are loose approximations to the ejection events found in turbulent boundary layers. The ejections, as well as the resultant bursts and sweeps, form a sequence of events that have been identified as the major contributors to the high fictional drag associated with turbulent flows [8]. In the field of EMTC the two main strategies have been to either directly suppress the ejection events using wall normal Lorentz forces [10] or to manipulate the low speed streaks that form simultaneous to the ejection events using streamwise Lorentz forces [5]. Preliminary investigations into the adaptive control of low speed streaks are also being made by the authors.

The adaptive control is achieved as follows. An algorithm embedded in the numerical model of the Navier-Stokes solver generates the appropriate time sequence of Lorentz forces. The algorithm utilises velocity information only obtainable from the numerical model and so on its own is of little practical value. As a result the responses of an electromagnetic flow sensor have also been modeled.

The time sequence of Lorentz forces together with the corresponding flow sensor responses have been used to train a neural network. For each instantaneous flow field the network receives the sensor signal and computes the appropriate Lorentz force to apply. The neural network has been tested against a range of sinusoidal velocity disturbances and has successfully manipulate the flow.

Figure 1: Sinusoidal vertical velocity disturbances convected in a channel flow. Lower channel wall shows the subsurface electromagnetic tile consisting of an electrode pair (aligned in the streamwise direction) and a magnet pair (aligned in the spanwise direction).

Channel and Electromagnetic Tile Particulars
The channel is 50mm long by 25mm wide by 8.4mm high. The electrodes maximum current is 150 mA and the magnets have a maximum magnet flux density of 0.6 Tesla. The electrode pair is aligned at right angles to the magnet pair (see figure 2) thus producing a primarily wall normal Lorentz force field. The electrical conductivity of the fluid is 4.5 S/m.

Numerical Methods
The fractional step scheme of Kim and Moin [6] is used to solve the Navier-Stokes equations.

The magnetic flux density field (B) is generated by distributing a current density across the surface of the magnets and using the Biot-Savart Law to determine the field induced by these currents.
The electric field ($\mathbf{E}$) is generated by distributing a charge density across the surface of the electrodes and using Coulomb's Law to determine the field induced by the charges. Multiplying the electric field by the electrical conductivity ($\sigma$) of the fluid produces the current density field. The cross product $\sigma \mathbf{E} \times \mathbf{B}$ then gives the Lorentz field. The responses of the electromagnetic sensor are calculated using the method of Bevir [2].

FIGURE 2: Magnet and Electrode Geometry. Computational Meshing is also shown. All dimensions are in mm.

Combining Sensor and Actuator Roles
The concept of utilising the same electrode and magnet pairs for the dual roles of sensor and actuator was first proposed by Snarski [11]. In that study the sensor and actuator were configured for the detection and manipulation of the streamwise velocities. A similar approach is presented here with the detection and manipulation directed primarily toward the wall normal component of the flow.

Combining the roles of sensor and actuator into the one device gives rise to some important issues when considered in conjunction with the concept of a continuously adaptive Lorentz field. The Lorentz field of the actuator must be periodically switched off in order to obtain the flow sensor readings. Technically this results in a pulsed Lorentz field. However if the duration for which the actuator is inactive is many times smaller than the smallest time scale of the flow, then the concept of a continuously adaptive Lorentz field is still preserved. The length of each inactive period is largely dependent on the response time of the electric field which in turn is a function of the permittivity and electrical conductivity of the fluid. An estimate can be made using the electric field charge relaxation time as detailed by Haas [4]. For seawater this is in the order of nano seconds.

Sinusoidal Wave Test
Single and composite sinusoidal wave disturbances have been used to assess the capabilities of both the control algorithm and the neural network. The wave disturbances are convected in a channel flow. Free slip conditions are used on the upper and lower channel walls, periodic boundary conditions are used in the spanwise direction and a convective outflow condition [9] is used at the exit. Free slip walls, rather than no slip walls, are used to help sustain the sinusoidal disturbances. The waves are generated by perturbing the wall normal velocities at the channel inlet as a sinusoidal function of time.

The sinusoidal waves have been formulated in such a way that they provide a loose approximation to the ejection events found in a low Reynolds number turbulent channel flow [7]. The Reynolds number is defined by the bulk mean velocity and the channel half height. The wave disturbances are centred at a height of 4.2mm above the lower wall corresponding to the expected position of the ejection events. The convective speed and RMS amplitude of the waves are also taken at this height using the mean velocity profile and wall normal velocity fluctuations profile of Kim, Moin and Moser [7] respectively.

Twenty five single sinusoidal waves have been used were each wave is taken from a 5x5 matrix of frequency and amplitude combinations. The frequencies range from 2.956 Hz to 7.883 Hz giving wavelengths from 16mm to 6mm. The RMS of the amplitudes range from 70% to 130% of the wall normal velocity fluctuation RMS given in [7].

The composite sinusoidal waves are generated by superimposing twenty five single sinusoidal waves. The frequency range is as detailed above while the amplitudes have been appropriately scaled to ensure the RMS of the composite amplitude is as given in [7]. A random number generator is used to determine the phase relationships between the single waves. This ensures that the actuator/sensor is exposed to a unique wave for each test run.

The Control Algorithm
The control algorithm is incorporated into the numerical model of the flow so that the Navier-Stokes equations are used to determine the appropriate actuating force for each instantaneous flow field. For an arbitrary flow simulation the algorithm generates the required sequence of actuating forces which, in conjunction with the sensor signals, is then used to train a neural network enabling it to control other flows of a similar nature.

Since the attenuation of the upward velocities is analogous to the suppression of the ejection events in a turbulent boundary layer, the control objective is therefore to attenuate the upward velocity phases of the sinusoidal waves while leaving the downward velocity phases unhindered (see figure 3). At each time step a search is made in the immediate vicinity of the actuator for a local peak in the vertical velocity field. When a peak is identified its magnitude is recorded. This serves as the initial value in the control sequence. A desired value is also selected. This is the target magnitude of the vertical velocity as it leaves the vicinity of the actuator. An estimate is also made of the time taken for the peak to be convected over the actuator and a sequence of intermediate target values are then generated over this time interval.

Each control sequence begins by seeking only a small rate of attenuation in the peak. This is more for the benefit of providing the neural network with a smoothly varying actuator control than for the flow control itself. The rate of attenuation is then progressively increased reaching a maximum near the middle of the control sequence and then tapered off over the final stages. Tapering the attenuation in this fashion ensures that the peak does not leave the vicinity of the actuator with any excess energy from the forcing.

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Results for the Control Algorithm

The control algorithm has been subjected to the twenty five separate sinusoidal wave disturbances described earlier. The efficiency of the control was assessed by both inspection of the controlled waves themselves and by comparing the variation in actuator energy expenditure against a variation in wave amplitude and frequency. Inspection of the controlled waves revealed no evidence of either excessive forcing of the upward velocity phases or redundant forcing of the downward velocity phases. Plots of actuator energy against wave amplitude showed a near linear relationship demonstrating that the algorithm has appropriately adjusted the actuator energy in accordance with the energy of the wave being controlled. Plots of actuator energy against wave frequency also exhibited a near linear relationship, but only over the lower range of wave frequencies. At frequencies above the midrange there was a slow decrease in actuator energy. This however has been explained by the observed natural attenuation of vertical velocity amplitude for the high frequency waves.

The smoothness of the actuator control was also assessed. This is an important criterion, not so much with respect to the manipulation of the wave itself but more so with respect to the training data for the neural network. Minimising any random fluctuations will provide a stronger chance for the convergence of the training. In general the control algorithm has produced a smooth sequence of actuating forces. However discontinuities still exist at the beginning and end of each control interval. This can be addressed by further stretching of the target values in the control sequence. A further, and more extreme discontinuity occurred for the higher frequency waves. At frequencies above 7.883 Hz the wavelength became shorter than the physical length of the actuator. In these cases the actuator experienced two adjacent wave peaks simultaneously. The algorithm does not yet have the facility to smoothly transition control from one peak to another without first passing through a period of inactivity. In any case it is reasonable to expect that the actuator will be ineffective in controlling flow structures below a certain size.

The Neural Network

A three layer neural network has been used consisting of an input layer, one hidden layer and an output layer (see figure 4). The input layer consists of the 30 most recent sensor signals. The output layer produces the actuator strength corresponding to the instantaneous state of the flow. The hidden layer consists of 31 processing elements. The three layers are fully connected. All processing elements use a sigmoidal transfer function. The network is trained using back propagation.

Results for the Neural Network

The sensor and actuator data generated from the control of an arbitrary composite wave was used to train the neural network to associate small time sequences of the sensor signal with the corresponding actuator strength applied at the end of each time sequence.

Sensor time sequences were chosen rather than instantaneous sensor signals since the time sequences provided not only a measure of the instantaneous condition of the flow but more importantly an indication of the direction in which the flow was developing. It was found that although the neural network could successfully replicate this training data (see figure 5), poor flow control was achieved when the network was embedded in the flow simulation and tested against other arbitrary composite waves. The problem was not the neural network itself but the sensitivity of the sensor signal to the flow structure being controlled (in this case the streamwise profile of wall normal velocities at 4.2mm above the lower wall).

Prior to the activation of the actuator the sensor provides a good measure of the state of the wall normal velocities 4.2mm above the lower wall. To a large extent this due to the simplified nature of the sinusoidal waves were the only significant velocity fluctuations are those in the wall normal direction. However once the actuator is activated secondary flow structures are introduced. These are primarily in the form of large spanwise jets generated as the downwardly forced fluid hits the channel lower wall (see figure 6). The strength and proximity of the spanwise jets to the sensor ensure that they become the dominant feature detected.
The sensor signal is swamped by the effect of the spanwise jets thereby significantly reducing its sensitivity to the wall normal velocities further away from the wall (see figure 7).

![Figure 6: Cross stream velocity vectors showing the large spanwise jets induced by the actuator as it forces fluid towards the channel lower wall. Lengths are non dimensionalised by a reference value of 50mm.](image)

Figure 6: Cross stream velocity vectors showing the large spanwise jets induced by the actuator as it forces fluid towards the channel lower wall. Lengths are non dimensionalised by a reference value of 50mm.

The ability of the sensor to detect the state of the sinusoidal waves is severely diminished due to the introduction of secondary flow structures from the actuating forces. Substituting the current sensor with an ‘ideal’ sensor resulted in excellent flow control against a range of composite sinusoidal waves.

**Future Work**

Clearly the next stage of research involves improving the relationship between the sensor signals and the vertical velocity disturbances. Changing the lower channel wall to a more realistic non slip wall should make a marked difference by substantially reduce the velocities immediately adjacent to the sensor thereby making it more sensitive to velocity fluctuations further away from the wall. Options for reorientation of the sensor will also be explored.

**Conclusions**

A preliminary investigation into the control of sinusoidal wave disturbances using a continuously adaptive Lorentz field has been presented. An electromagnetic sensor coupled to a pretrained neural network provides the control guidance. The neural network has been trained using information generated by a control algorithm embedded in the numerical model of the flow. The ability of the sensor to detect the state of the sinusoidal waves is severely diminished due to the introduction of secondary flow structures from the actuating forces. Substituting the current sensor with an ‘ideal’ sensor resulted in excellent flow control demonstrating the strong potential for the application of neural networks to electromagnetic flow control.

**References**


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