Toward A New Turbulence Culture

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INTRODUCTION

While evidence of deterministic chaos in turbulence data is now commonly reported, turbulence is still usually treated statistically. The signature of chaos most often reported for turbulence data is a low value for the dimension of the dynamical attractor governing the temporal variability of a measurement at a single spatial location. This means that deterministic algorithms can be found for predicting the future evolution of the turbulence within the limits-to-predictability constraint applicable to chaos, or for retrieving one dynamical variable from another within those same constraints. Such algorithms use a sequence of instantaneous measured observables as input rather than statistical averages of the observables. Since the underlying dynamical model is usually not known, the data are often used to train an artificial neural network to output the desired turbulence quantity.

Examples of the above procedure are described below. These examples have exposed both advantages and limitations of the deterministic treatment of turbulence. Therefore, a proposed new treatment of turbulence is briefly outlined that promises to achieve the optimal balance of stochastic and deterministic data processing. The new method, originated by Crutchfield and Young [1], is termed “e-machine construction.” Incorporating this method in large computer modeling efforts would help to establish a new turbulence culture where data are used to build new models rather than to test old ones.

DETERMINISTIC CHAOS IN STABLE-LAYER TURBULENCE

An example that clearly illustrates an advantage of the deterministic treatment over the statistical treatment of turbulence is the retrieval of humidity gradients in atmospheric stable layers using radar wind profiler signals. In the statistical treatment of the profiler signals, only the absolute value of the gradient is retrieved [2], whereas in the deterministic treatment of the signals reported here, both the sign and the magnitude of the gradient are retrieved.

The experimental data used for this demonstration were radar wind profiler and radiosonde data obtained at Vandenberg, California, in May 1997. Our first step in approaching the humidity retrieval problem deterministically was to notice that the radar vertical Doppler velocity signal usually exhibited clear indications of gravity-wave periodicity embedded in an otherwise random-looking time series. In addition, both the radar backscatter power and the Doppler signal, when sampled at a 3-min time interval, exhibited a low value of the estimated dynamical attractor dimension (a correlation dimension near 4).

A candidate low-dimensional deterministic model for stable-layer turbulence is a truncated spectral model known as the Burgers-Chao model [3] with five nonlinearly coupled velocity and temperature dynamical modes. When humidity is coupled to this model as a passive scalar, the nonlinear gravity-wave motions induce a correlation between the humidity concentration and the vertical velocity that changes sign as the sign of the background humidity gradient changes. Since the radar backscatter is caused primarily by the Bragg structure in the humidity field, the model predicts that the sign of the cross-correlation coefficient between backscatter power and vertical Doppler signals will be in correspondence with the sign of the background humidity gradient. Physically, an upward motion that advects the Bragg structure into higher or lower background humidity will correspond, respectively, to a negative or positive correlation between backscatter power and vertical velocity (using the convention that velocity toward the radar is positive).

The above ideas were validated by the experimental data. The cross-correlation coefficient between the profiler backscatter power and the vertical Doppler velocity sampled every 3 min gives the correct sign of the humidity gradient in 80% of 100 independent samples. We also trained an artificial neural network to output the value of the humidity gradient (including sign) as a function of two sequential measurements each of profiler backscatter power and vertical Doppler velocity. The choice of four inputs to the neural net corresponded to the indicated dynamical attractor dimension near 4. The neural net was trained using a one-hour record of these profiler signals in 44 range gates ranging from 300 m to 6 km and a single radiosonde sounding for the measured humidity gradient. The retrieval function generated by the neural net was tested on 12 separate one-hour profiler records obtained over nine days. Figs. 1a,b compare humidity profiles measured by a balloon sounding with profiles constructed by integrating the neural net-generated humidity gradients using a single balloon-measured value to start the integration. The retrieval shown in Fig. 2b was achieved with inputs to the neural net taken four days after the training data of Fig. 2a.
DETERMINISTIC CHAOS IN MARINE-LAYER TURBULENCE

One of the most striking signatures of deterministic chaos in geophysical turbulence was the identical dynamical attractor dimension indications reported for two independently measured marine boundary-layer observables [4]. Fig. 1a shows the computed correlation dimension for several coincidently measured time series during a multifaceted ocean remote-sensing project known as the San Clemente Ocean Probing Experiment (SCOPE) [4]. The only two observables that demonstrate a definitive, saturated value for the correlation dimension are seen to be the vertically polarized (grazing angle) radar backscatter from the ocean surface and the ocean surface horizontal winds. This finding suggests that a single low-dimensional dynamical system governs both of these observables.

Grazing-angle radar backscatter from the ocean surface is far from simple, involving shadowing, diffraction, specular reflection, and other processes not operating at the smaller incidence angles. Since a deterministic dynamical model that couples grazing-angle radar backscatter to surface winds is not known, we again utilize a neural network to generate a desired retrieval function, in this case a function for retrieving surface...
horizontal wind and wind stress from grazing-angle radar backscatter.

As in the humidity retrieval problem above, the input to the neural net is a set of sequential values of the radar signal. In this case, six sequential values of backscatter power were used to correspond with the value of near 6 found for the correlation dimension. The neural net was trained on the last half of an 8-h measured time series, and its retrieval performance was computed on the first half. This allowed the results to be presented as a function of average wind speed since the wind speed increased throughout the first half [4]. The block averaging time used for the samples was 20 s. The neural net retrieval performance, specified as rms error, is shown in Fig. 2b. The larger retrieval errors found for stress retrieval are consistent with the vertical wind not exhibiting the low value of correlation dimension found for the horizontal wind.

A NEW TREATMENT OF TURBULENCE: e-MACHINES

The ability of the deterministic treatment to retrieve the sign of the humidity gradient clearly illustrates that a statistical characterization of stable-layer turbulence is not capturing all of the relevant information available to an observer. Also, deterministic neural net algorithms for detecting ocean surface ice [5] and internal wave features [6] in a background of radar sea clutter have been shown to outperform statistical regression algorithms that treat the sea clutter background statistically.

On the other hand, these comparisons have generally not demonstrated a robustness of the performance of the deterministic algorithms over large datasets. Generally, a neural net trained on a finite dataset will outperform statistical regression and other algorithms that use statistical processing of the same dataset, but the performance gap will generally diminish as the algorithms are applied over datasets at a greater distance, either temporally or spatially, from the training data.

The explanation for this may be that while a local turbulent geophysical process may continue to exhibit signatures of low-dimensional chaos, the process does not necessarily remain on the same dynamical attractor indefinitely. Flow parameter changes may induce bifurcations of the attractor. Even if this does not occur, long transients may continually occur that take the dynamics from one low-dimensional attractor to another [7]. These types of transitions may be induced stochastically, i.e., through weak coupling to a dynamical system that cannot be characterized deterministically. Clearly, an optimal model of such a system should involve a combination of deterministic and probabilistic structure.

The proposed "new turbulence culture" continues to use data to build new models rather than test old ones. In this sense the approach is similar to the neural network-based algorithm development described above. A new feature is that probabilistic structure be added to the modeling. In effect, we look for a new "language" for turbulence modeling based on emergent features of turbulence that would replace the reductionist-based language of the Navier Stokes equations. The emergent features are discovered in the data rather than externally imposed, and they include probabilistic as well as deterministic structure. This is the e-machine program put forward by Crutchfield and Young [1]. The e-machines are finite-automata computer algorithms designed to capture the optimal amount of deterministic and probabilistic structure from a dataset in order to predict the future evolution of a chaotic dynamical system within a user-specified error, . An essential part of the e-machine program is the determination of the "statistical complexity" of the machine, which is essentially the memory capacity needed to construct the machine causal states. Keeping such an account of the machine needed to compute a specified accuracy result is what makes the e-machine program such a practical solution to geophysical turbulence problems. Computers are usually involved in a patchwork of different processing steps for geophysical turbulence data, whether within a deterministic or statistical modeling framework. The e-machine approach offers a needed unified approach for assuring optimal use of computer resources for turbulence applications and for basic understanding of the emergence behavior of turbulence.

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