Wavefront Prediction using Artificial Neural Networks

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Motivation for Research (1 of 2)

- Atmospheric turbulence results in the aberration of astronomical images of science objects.
- Science objects are not bright enough to image directly.
- Natural or artificial reference sources are used to recover wavefront turbulence and correct for image aberration in real-time.
- Sky coverage of natural reference sources (guide stars) of sufficient brightness is severely limited (P<0.15% of V=10).
Motivation for Research (2 of 2)

• Multi-conjugate Adaptive Optics compensates for multiple turbulence layers.

• Tomography is used to recover information from multiple sources and projections through multiple turbulence layers.

• Machine Learning is used to extend the prediction of wavefront data.
Extensions from Research

• Machine Learning has been successfully used in the following fields:
  – Adaptive Optics
  – Horizontal (continuous) turbulence correction
  – Underwater image restoration
Adaptive Optics

Distorted incoming wavefront

Telescope

Deformable mirror

Wavefront sensor

Image Plane

AO movie credit: Guido Brusa, CAAO, Steward Observatory
How effective is AO?

Seeing, Resolution & Strehl Comparisons by Altitude (from Table 1)
Specific Objectives

• Given a true $C_n^2$ atmospheric profile and $n$-layers of turbulence, determine the minimum number of reference objects required to predict turbulence, with a variance of 0.01 from actual, over a two arcminute, field-of-view.

• Review methods for generating the tomographic matrix, given a variation in the position of reference objects, magnitude and atmospheric profile, given by SCIDAR.
Background Research

- Evolutionary (genetic) algorithm designed to optimise prediction of a time series from a Shack-Hartmann wavefront sensor (Gallant, 2004).

- Multigrid approach to predicting wavefront reconstruction (Barchers, 2004)

- Preprocessing used on images to reduce computation (curse of dimensionality) for real-time correction of turbulence degraded images (Chundi et al., 2004).

- Tomography (3-D slices) used from three PSFs over a large FOV to reconstruct wavefronts for image reconstruction (Ragazzoni et al., 2000).

- Maximum a posteriori (MAP) used to estimate phase over large FOV in Adaptive Optics for image restoration (Fusco et al. (1999)).
Research Targets

• Record and analyse the auto- and cross-correlation decay from data-sets of three or more natural guide stars and a science object, over a large field-of-view (FOV).

• A recurrent ANN will be optimised to use the data-sets to train for prediction of low-order aberration within a large FOV.

• Machine learning will be used to classify atmospheric profiles for specific sites such as at Mt. John observatory.

• Such profiles can be used in a tomographic matrix $M$ (Tallon & Foy), to produce a 3-D representation of the atmosphere for a local site. This will only need to be updated periodically (nightly) using local SCIDAR instrumentation to provide real-time atmospheric corrections.
Current Activities

• Matlab simulations using geometric optics and Elman ANNs for prediction of turbulence over $n$-layers of perturbations.

• Verification of turbulent models using data-sets recorded using the McLellan 1-Meter telescope at Mt. John.

• Developing turbulence structure profiles using ANNs and chaos models.
Collecting atmospheric wavefront profiles

- One telescope, one aperture (for now).
- Imaging multiple objects over a wide field-of-view.
- Two CCD cameras, one placed just outside, the other placed just inside, prime focus.
- Curvature sensing used over collect time-series wavefront data of multiple reference objects over a wide field.

The “breadboard” used to collect data
Why use ANNs for Wavefront Detection / Image Reconstruction?

• Once trained, conversion is fast, direct and does not require a model.

• Non-linear capabilities are inherent in the structure of each artificial neuron. No need to ‘up-wrap’ data from sensor outputs.

• Prediction, auto-association (pattern completion) & classification capabilities can be used.

• Preconditioning of sensor data, e.g. applying the discrete cosine transform (DCT), reduces the curse of dimensionality and can provide real-time performance for adaptive optics.
What is an Artificial Neural Network?

Model of a single Artificial Neuron

- Non-linear output used to approximate the unknown.
- Supervised training used to learn the “model”.
- Inputs are multiplied with pre-calculated weights and summed to implement the linear combiner.

Multi-layer Perceptron Model
Example – Predicting Solar Wind Activity with a Recurrent ANN

- Delay-line in feedback loop provides temporal capabilities.
- State-space configuration but without a prior model.
- Supervised learning.
- Inputs include density, solar magnetic flux and velocity.

Peter Wintoft, 2002.
Image reconstruction over a large FOV

- To what extent can we assume a frozen turbulence hypothesis over an aperture?

- Site profiling and changes in $C_n^2$ over time e.g., current SCIDAR research at Mt. John

- Non-Kolmogorov Statistics

- Given $m$-layers of turbulence over a large FOV, what is the minimum number of point source objects required to reconstruct an image?
Turbulence Prediction over a Large Field

- Laser guide stars (LGSs) are point source objects and have a spherical wavefront; Natural guide stars (NGSs) are considered planar.
- NGSs do not suffer from the undesirable cone effect inherent with LGSs.
- Isoplanatic angle is major limitation with only one guide star.
Multiple point sources from one curvature wavefront sensor*

- Separate telescopes measuring turbulence is a problem due to guiding, synchronisation etc.
- Curvature sensing on one telescope over multiple objects is manageable.
- Wavefront (Zernike) coefficients are extracted over multiple sources within a single, wide field-of-view.

*Curvature and geometric Matlab code and simulations courtesy of Yong Chew.
WF Reconstruction over a large FOV - Methods under evaluation

**Linear (superposition)**
- Principal Components Analysis (PCA)
- Tomography (RLS, SVD)

**Artificial Neural Net**
- Recurrent ANNs
- Prediction using a Multigrid approach

To improve variances over a wide (2 arcmin) FOV, combinations of each of these methods is currently being investigated.
Modal Tomography* using NGSs

The $i$'th NGS can be expanded into a sum of $p$ Zernike polynomials.

$N_i = \sum_{j=1}^{M} N_{ij}$  \hspace{1cm} M-layers of turbulence.

$N_{ij} = A_{ij} W_j$  \hspace{1cm} A set of matrices $A_{ij}$ can be defined, given the geometry of the circular regions.

$N_i = \sum_{j=1}^{M} N_{ij} = \sum_{j=1}^{M} A_{ij} W_j$  \hspace{1cm} Representing in matrix form,

\[
\begin{bmatrix}
N_1 \\
N_2 \\
\vdots \\
N_K \\
\end{bmatrix} =
\begin{bmatrix}
A_{11} & A_{12} & \cdots & A_{1M} \\
A_{21} & A_{22} & \cdots & A_{2M} \\
\vdots & \vdots & \ddots & \vdots \\
A_{K1} & A_{K2} & \cdots & A_{KM} \\
\end{bmatrix}
\begin{bmatrix}
W_1 \\
W_2 \\
\vdots \\
W_M \\
\end{bmatrix}
\]

*Ragazzoni et al. Modal Tomography for Adaptive Optics, 1999

The most accurate tomographic matrix varies in time (Ragazzoni). Prediction, using RNNs will be used to reduce the complexity of this problem.
Modal Tomography Considerations

• Real-time processing is restricted due to high CPU demands.

• Use of ANNs may reduce computational demands but the *curse of dimensionality* needs to be addressed.
Future Research

• Collect wavefront data from multiple source objects over a wide field-of-view.

• Extend Matlab and C++ simulations.

• Establish a testbench in the optics lab.

• Simulate using multiple sources and turbulence in the lab.

• Train a recurrent ANN with lab and field data.

• Develop a self-configuring Forward Matrix.