

NEURAL NETS FOR ALIGNING OPTICAL COMPONENTS IN HARSH
ENVIRONMENTS—BEAM SMOOTHING SPATIAL FILTER
AS AN EXAMPLE

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The goal of this project is to develop an approach to automating the alignment and adjustment of optical measurement, visualization, inspection, and control systems.

Developments in the last decade in inexpensive computing, fiber optics, sensitive and selective detectors, and motorized mounting hardware have made optical spectroscopy, interferometry, deflectometry, and imaging valuable for non-intrusive measurements and inspections of aerospace flows and structures. Nevertheless, optical techniques still require skilled people for setup, alignment, adjustment, and operation. The simplest dual-beam holography setup for example requires that a technician perform 50 to 100 separate translations and rotations of optical components before a single hologram is recorded. A spectroscopy setup might require 1000 or more actions before data is collected. The human specialist must adjust the optical system for changes in the scene and must realign to compensate for environmental disturbances. These activities are a nuisance in the laboratory and are difficult, impractical, or impossible in harsh and dangerous test and launch environments.

Classical controls, expert systems, and neural networks are three approaches to automating the alignment of an optical system. We in the Instrumentation and Control Technology Division at Lewis Research Center have decided to pursue neural networks based on two judgements.

First, neural networks classify automatically and learn by example. Therefore, they require the least specialized knowledge of controls and optical phenomena. What is more important, the neural networks require the least self-knowledge from a human operator. The human operator need only execute a representative set (training set) of alignments, and no explanations are necessary. Hence, the alignment of a component is reduced to a series of steps, where each step consists of a mapping between input and output observations and actions.

For optical alignment, the input to the human operator and to the neural network can include beam position, beam pattern, and beam brightness as well as a memory or flag of the action taken previously. The output of the human-operator or neural-network controlled component consists of an action (linear or rotational motion) which terminates at a new condition of position, pattern, or brightness. There is no need to know the theoretical details of beam positioning, beam pattern, or beam brightness or to know or measure the positions of the mechanical actuators. In fact, as is the case with a human operator, there is no need to achieve exactly the same result each time a step is executed. This feature is useful in handling the non-linearities and errors present in the very sensitive mechanical actuators. If the training set is representative, then the neural network will eventually achieve and recognize an aligned condition.

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The second reason for selecting neural networks is that neural-network hardware and software are available and being developed and improved. Some of the packages are small enough that one envisions a separate network for each adjustable optical component. The separate nets would receive inputs from one or more visualization systems and would be linked eventually with one another or with a master network. Hence, optical components can be automated and tested one at a time. Full automation can be brought on line gradually.

We are testing our judgments by using neural networks to automate the alignment of the ubiquitous laser-beam-smoothing spatial filter. The spatial filter is challenging and complex enough to be non-trivial, yet is simple enough to be modeled exactly. The most common version of a spatial filter assembly is a pinhole 10 micrometers in diameter and a 20X microscope objective. The pinhole is mounted in an XY stage, and the microscope objective is mounted in a linear stage for focus (Z-axis) control. In alignment, the laser beam is focused through the pinhole. Scattered light, from dust particles for example, is not focused and does not pass through the pinhole. Hence, a smoothed beam exits the filter. Alignment is a 3-degree-of-freedom process: the pinhole is translated perpendicular to the laser-beam axis in the XY plane, and the microscope objective is translated along the axis in Z. There are 2 diffraction regions. Most of the alignment steps are in the first region where the out-of-focus beam fills the pinhole, and a symmetrical pattern of diffraction rings is observed. Several serial adjustments of X, Y, and Z covering total distances of several hundred micrometers each may be required in this region. The second diffraction region occurs within about 10 micrometers of focus, where an asymmetrical, knife-edge pattern may be observed. One or two very slight adjustments are required here to create a symmetrical beam. The brightness of the beam reflected from a backstop may vary by 6 orders of magnitude during an alignment.

A technician created a training set for our initial efforts with neural networks. The training set contained 37 alignments beginning from random positions and a total of 337 alignment steps. The input vector of an alignment step consisted of a flag of the control (X, Y, Z, or none) operated in the previous step, the position of the beam bright spot (x, y) on a backstop, a flag indicating the diffraction pattern (symmetrical rings or knife edge), and the logarithm of the intensity. The output vector of the alignment step consisted of a flag of the control to be operated, the new incremental beam position, and the logarithm of the predicted output intensity. A training set was also created using a model of the spatial filter.

Several commercial neural network packages were procured which involve both hardware and software. The work reported herein was accomplished with a Hecht-Nielsen neurocomputer which consists of a co-processor for a PC and a substantial package of software. The software includes C language subroutines which will instruct the co-processor to execute a number of published neural network algorithms and a compiler for creating custom designed neural networks. A system of neural networks was created to learn the training set and to control the alignment of the spatial filter. The training set was pre-classified into 13 classes using an unsupervised network (Adaptive Resonance Theory 2). Unsupervised networks classify vectors according to some criterion such as Euclidean distance. Each of the classes was then used to train a back propagation network. Back propagation networks learn the mapping between input and output vectors which minimizes the mean squared error between actual responses and the correct responses of the training set. Learning is encoded in weighted connections between processing elements or neurons.¹ The

system of networks can respond to inputs not in the original training set and, hence, has a certain generalization ability.

There are many networks; their effectiveness must be judged by performance. The network system described above was used to direct the alignment of an actual spatial filter. A technician was the eyes and hands for this test. The technician aligned the filter and then backed off the XYZ controls for arbitrary mis-alignment. The input vectors were passed to the network. The technician performed the actions directed by the output vectors of the network. The network was able to direct a satisfactory alignment; it also knew when to stop the alignment process.

The neural network was also tested with inputs generated by a physical model of the spatial filter. The physical model included random errors to simulate the non-linearities and errors in the mechanical drives. The neural network was able to execute sets of alignment steps beginning at arbitrary starting points and terminating at aligned states.

Future work will be directed toward the gradual achievement of the following goals. An electrical-mechanical interface will be created between the neural network and the spatial filter assembly. A machine vision system consisting of a camera, frame grabber, and software will supply the input vectors to the neural network. The neural network will be transferred to miniature, commercially available hardware. A hands-off, self-aligning spatial filter will be demonstrated.

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1. D. E. Rumelhart, G. E. Hinton, and R. J. Williams, "Learning Internal Representations by Error Propagation," in **Parallel Distributed Processing, Volume I: Foundations**, D. E. Rumelhart, J. L. McClelland, and the PDP Research Group, MIT Press, 1986, pp. 318-362.

OBJECTIVE

- AUTOMATE OPTICAL MEASUREMENT SYSTEM

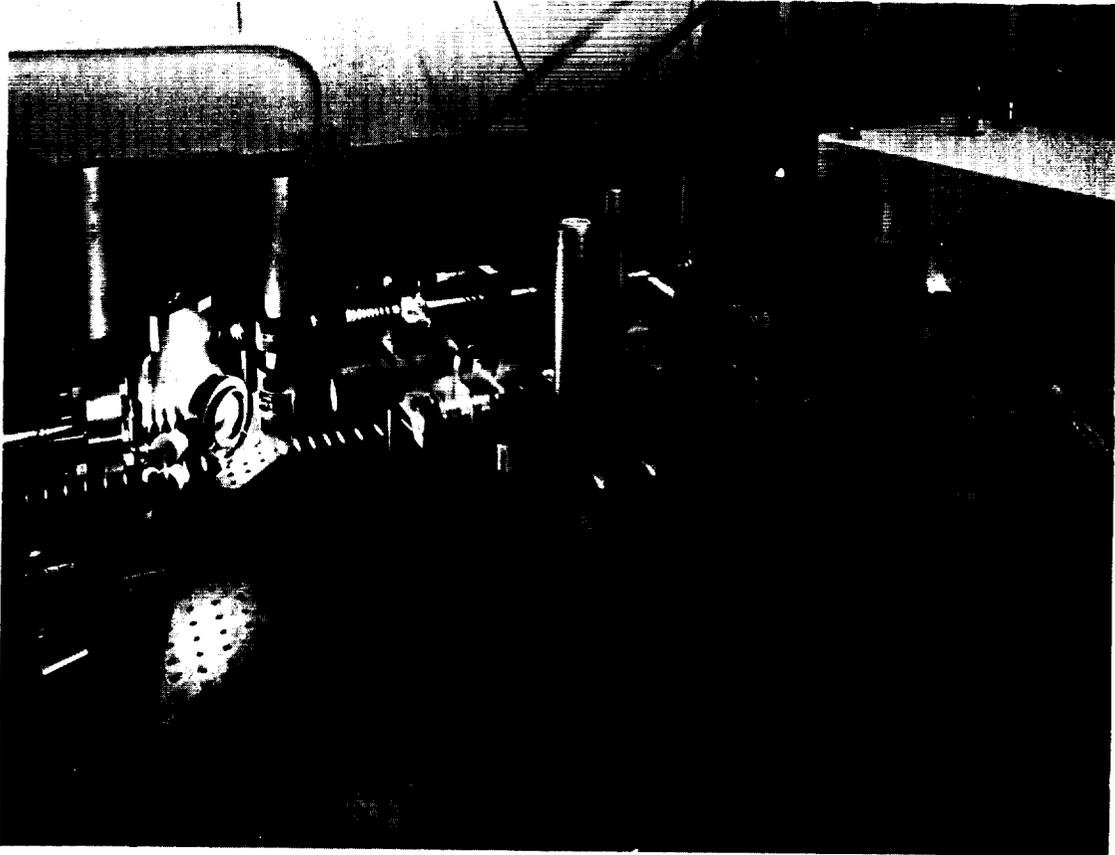
Alignment
Adjustment
Operation
Realignment

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SIMPLE HOLOGRAPHY SETUP



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APPROACHES TO AUTOMATION OF ALIGNMENT

- DISCIPLINES
 - Classical Controls
 - Expert Systems
 - Neural Networks
- CHOICE == NEURAL NETWORKS

REASONS FOR CHOICE

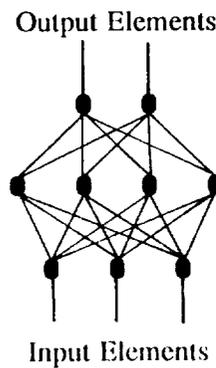
- NEURAL NETWORKS REQUIRE

LEAST SPECIALIZED KNOWLEDGE,
LEAST SELF-KNOWLEDGE OF OPERATOR,
A REPRESENTATIVE TRAINING SET.

- NEURAL NETWORKS CLASSIFY.
- NEURAL NETWORKS GENERALIZE.
- NEURAL NETWORKS ARE AVAILABLE

in Software,
in Hardware.

NEURAL NETWORK



- PROCESSING ELEMENTS WITH LOCAL MEMORY AND NON-LINEAR ACTIVATION FUNCTION
- WEIGHTED CONNECTIONS

OPTICAL ALIGNMENT

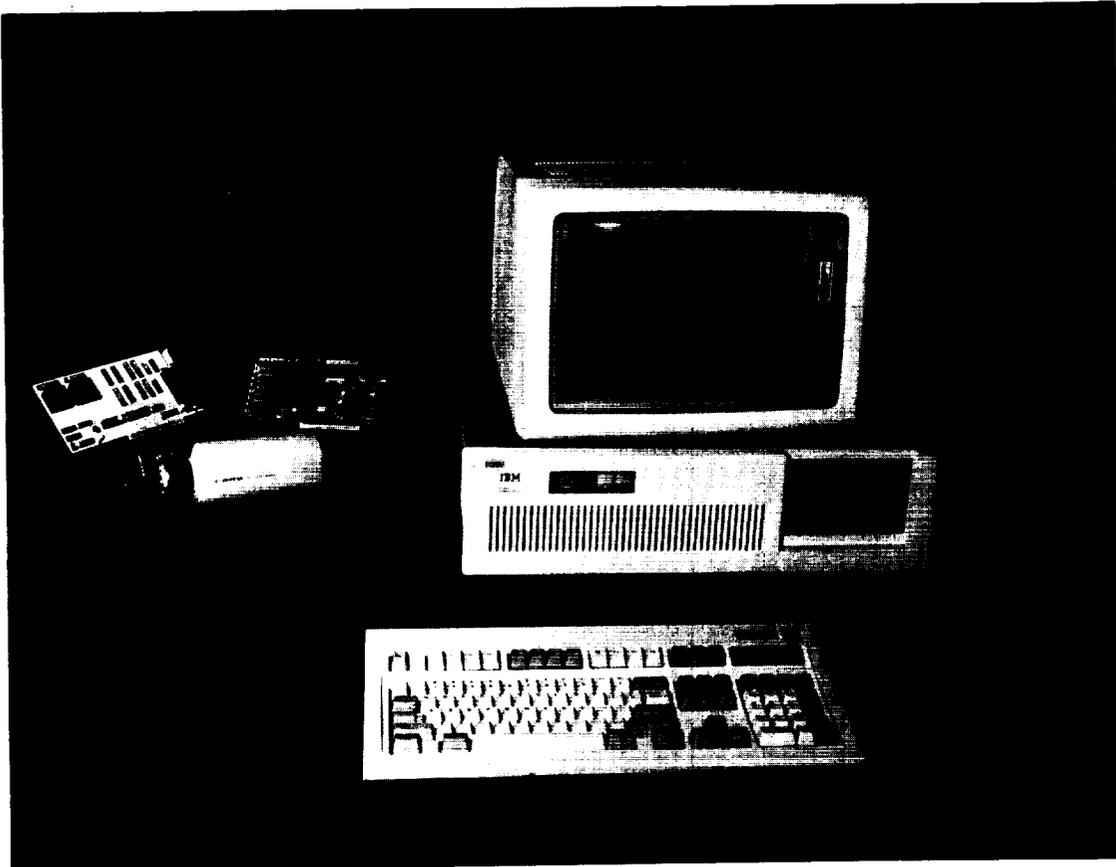
- INPUTS TO HUMAN OPERATOR AND NET

- Light Beam Position
- Light Beam Pattern
- Memory of Last Action
- Light Beam Brightness

- OUTPUTS

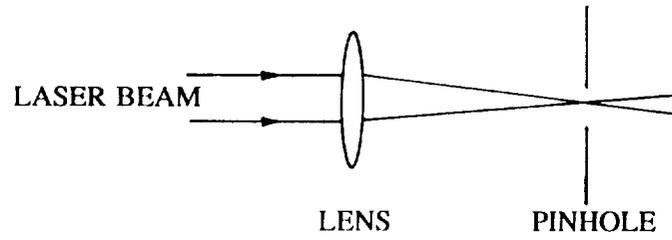
- Action (Linear or Rotational Motion)
- New Position, Pattern, or Brightness

- GOAL—STRING INPUT-OUTPUT STEPS TO ACHIEVE ACCEPTABLE ALIGNMENT

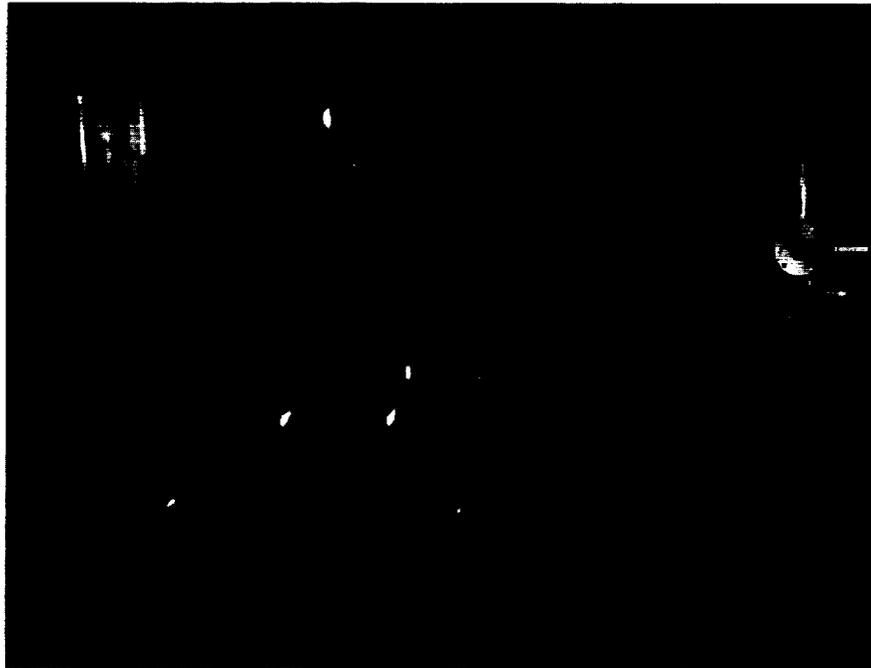


TEST

- LASER-BEAM-SMOOTHING SPATIAL FILTER



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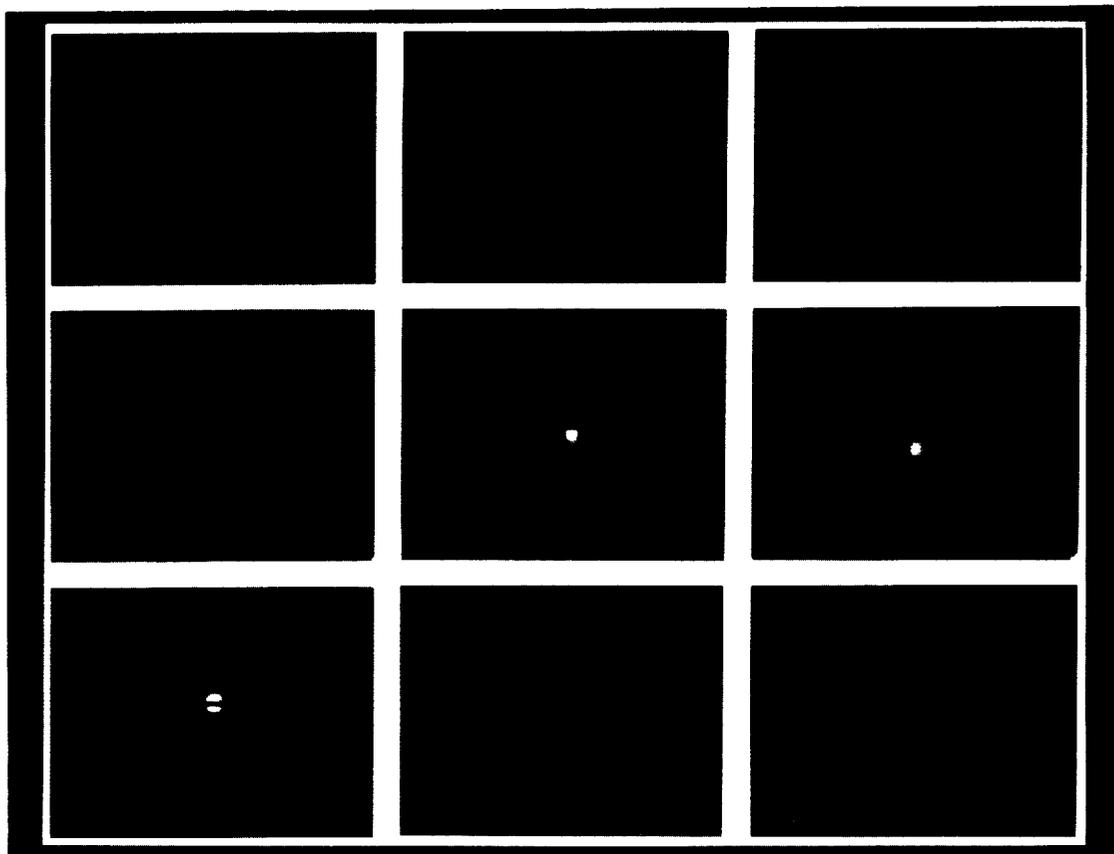
TYPICAL LABORATORY ALIGNMENT

- FILTER == 10 μm PINHOLE IN XY STAGE;
20X MICROSCOPE OBJECTIVE IN
Z STAGE.
- TWO GENERIC BEAM PATTERNS
- ALIGNMENT IN 5 TO 10 STEPS
- TOTAL MOTION IN X OR Y OR Z ==
SEVERAL HUNDRED MICROMETERS.
- BRIGHTNESS VARIATION == 6 ORDERS OF
MAGNITUDE.

TRAINING SETS

- TECHNICIAN: 37 ALIGNMENTS, 337 TOTAL STEPS
- PHYSICAL MODEL OF SPATIAL FILTER

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FUTURE EFFORT

- HANDS AND EYES FOR SPATIAL FILTER

Actuators

Frame Grabber and Camera

- TEST FULL SELF-ALIGNMENT OF SPATIAL FILTER.
- MINIATURIZATION AND SELF-CONTAINMENT
- ENVIRONMENTAL TESTS

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