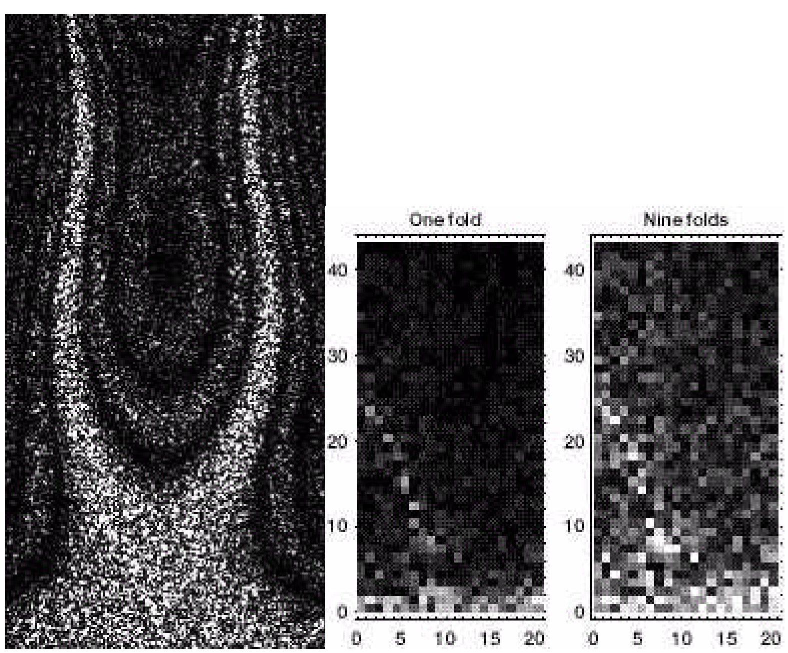
Training Data Optimized and Conditioned to Learn Characteristic Patterns of Vibrating Blisks and Fan Blades

At the NASA Glenn Research Center, we have been training artificial neural networks to interpret the characteristic patterns (see the leftmost image) generated from electronic holograms of vibrating structures. These patterns not only visualize the vibration properties of structures, but small changes in the patterns can indicate structural changes, cracking, or damage (refs. 1 and 2). Neural networks detect these small changes well. Our objective has been to adapt the neural-network, electronic-holography combination for inspecting components in Glenn's Spin Rig.

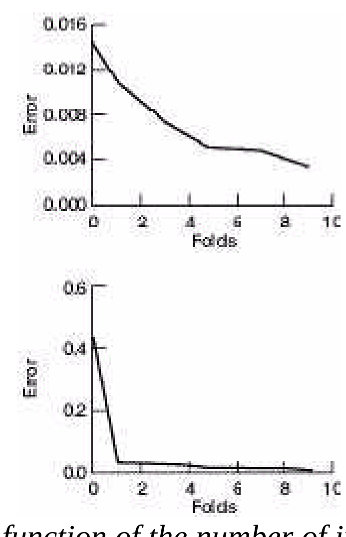
This project has generated an excellent beginning for answering a very important question for NASA's growing involvement with intelligent systems: Given any technology or process such as an artificial neural network, how do you impose a useful intelligence on that technology in an optimum manner? Artificial neural networks are trained by example, using a so-called training set, and training-set-educated systems are popular in general. Optimum training means that the technology learns the training set quickly, learns to distinguish small, but significant, variations in the input patterns, learns to handle noisy data, does not overtrain (overfit the training data), and learns, consequently, to generalize (correctly interpret patterns not in the original training set). Electronic holography of structures is especially useful for testing approaches for training, since models can be used to generate statistically realistic, although far from perfect (ref. 3), training sets.



Left: Characteristic pattern or mode shape of a vibrating blade. Note that the laser speckle effect causes a large intensity fluctuation about the local average. Right: Finite-element-resolution characteristic patterns before and after folding.

Two questions must be answered in preparing training data for any technology: How do you condition the data optimally for the particular technology, and how do you generate statistically optimum training sets in general? We have developed a technique called folding for conditioning characteristic patterns for optimum training of feedforward neural networks. For image processing using feedforward neural networks, the data are usually normalized so that each input node covers the same range. A common practice is to use a minimum-maximum table, where the data for each pixel are scaled into the range -1 to 1. Neural net-works trained in this way learn more quickly, but they are prone to overfit the data. Folding, by contrast, divides the data into intensity ranges, and it scales each range into the full input range of the neural network. The laser speckle effect (the noise covering the leftmost image) has a considerable variation about the average intensity, which ensures that all the positions on the image participate in all folding ranges, whereas the minimum-maximum table imposes an image-position-dependent scaling. The folding-trained networks learn more quickly, are better able to distinguish between damaged and undamaged blades, and generalize better. The images to the right show a finite-element-resolution node pattern for a blade vibrating in its first mode before and after folding. The graphs show the training and test errors as a function of the number of folds.

The discovery of hardware that can emulate intelligent behavior is expected to be fortuitous. The discovery of effective, if not optimum, training procedures for specific kinds of data will provide the practical challenge. Neural-network processing of speckled fringe patterns from vibrating structures provides an excellent theoretical and experimental testbed for this work.



Root mean square error as a function of the number of intensity folds in the neural net training patterns. Top: Training error. Bottom: Test error.

References

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