SAND--97-2724C
SAND97-2724C
CONF-970928--

Neural Networks for Damage Identification

Thomas L. Paez and Scott E. Klenke

Experimental Structural Dynamics Department
Sandia National Laboratories
Albuquerque, New Mexico 87185-0557

ABSTRACT

Efforts to optimize the design of mechanical systems for preestablished use environments and to extend the durations of use cycles establish a need for in-service health monitoring. Numerous studies have proposed measures of structural response for the identification of structural damage, but few have suggested systematic techniques to guide the decision as to whether or not damage has occurred based on real data. Such techniques are necessary because in field applications the environments in which systems operate and the measurements that characterize system behavior are random.

This paper investigates the use of artificial neural networks (ANNs) to identify damage in mechanical systems. Two probabilistic neural networks (PNNs) are developed and used to judge whether or not damage has occurred in a specific mechanical system, based on experimental measurements. The first PNN is a classical type that casts Bayesian decision analysis into an ANN framework; it uses exemplars measured from the undamaged and damaged system to establish whether system response measurements of unknown origin come from the former class (undamaged) or the latter class (damaged). The second PNN establishes the character of the undamaged system in terms of a kernel density estimator of measures of system response; when presented with system response measures of unknown origin, it makes a probabilistic judgment whether or not the data come from the undamaged population. The physical system used to carry out the experiments is an aerospace system component, and the environment used to excite the system is a stationary random vibration. The results of damage identification experiments are presented along with conclusions rating the effectiveness of the approaches.

Keywords
Damage
Health monitoring
Artificial neural networks
Probabilistic neural networks
Bayesian decision analysis
Rosenblatt transform

1. INTRODUCTION

Structural engineering design usually dictates that systems be fabricated to optimum weight and cost specifications, and yet safely sustain the loads applied to them for a preestablished duration. This can be accomplished because great strides are being made in analysis, design, and testing practice, but it is complicated by the fact that loads applied to any real structure are unknown and the material properties and geometry of a structure have random components. In view of this, responses of critical structures must be monitored, and the information used to infer structural functionality and safety.

Many frameworks can be used to assess the relative health of a structure, and this paper presents two of them. They are the classical PNN of Specht (1990), and a PPC that we have developed. The former is an ANN implementation of the Bayes' decision analysis procedure. The latter is a formal statistical procedure that permits us to judge the source of data of unknown origin.

The PNN requires data sets from two or more sources. When presented with a datum of unknown origin, it judges which set of known data is the likeliest source of the unknown datum. The PNN implements Bayes' decision rule representing the probability density functions (PDFs) of the known data sets with kernel density estimators. These were first developed in the form in which they are used today by Parzen (1962), and their form was later generalized to the multivariate case by Cacoullos (1966). A text that summarizes kernel density estimators is that of Silverman (1986). The PNN is briefly described in Section 2.

When one or more measures of structural behavior representing both damaged and undamaged system states are available, they can be used to establish the parameters of a PNN. When corresponding measures of structural behavior are taken from a structure not known to be damaged or undamaged, they can be presented to the PNN for its judgment regarding the state of the system.

The PPC, in contrast, requires a data set from one source. When presented with a datum of unknown origin, it judges whether the datum is a member, an outlier, or a nonmember of the set whose source is known. This tool also uses the PDF representation of Parzen and Cacoullos, but given that representation it defines a transform (see Rosenblatt, 1952) into the space of uncorrelated standard normal random variables. Data of unknown origin are transformed into this space, and a test of hypothesis is performed to judge the source of the data. The PPC is developed in Section 3.

When one or more measures of structural behavior representing undamaged system states are available, they can be used to establish the parameters of a PPC. When corresponding measures of structural behavior are taken from a structure not known to be damaged or undamaged, they can be presented to the PPC for its judgment regarding membership of the data in the set of undamaged data. The data will be judged members, outliers, or nonmembers of the undamaged data set. Details of the approaches used perform the statistical damage diagnoses described above are given in Section 4.

The real test of a damage diagnosis tool is its effectiveness in practical application. The two health monitoring tools considered in this study are applied to the monitoring of damage in a physical system. The system is a stereolithography model of an aerospace component. The system was tested using random vibration and its response measured and used to characterize the undamaged system. Next, a small amount of damage was introduced into the system, and it was retested and characterized again. This step was repeated four more times; each time incremental damage was introduced into the system before retesting. Finally, the PNN and PPC were used to determine whether the incremental damage could be recognized. The results were successful, and are presented in detail in Section 5.

2. CLASSICAL PROBABILISTIC NEURAL NETWORK

The classical PNN uses the Bayesian decision analysis cast into an ANN framework to judge the origin of datum z given that data from two random variable sources, X and Y, are known. The known data are denoted $x_j, y_j, j=1,...,N$. The sources X and Y are assumed to be vector random variables with dimension n, and their corresponding realizations are also assumed to be vectors. For the two-source case, the origin of z is determined based on the following Bayesian decision rule

$$\begin{array}{lll} z \in X & if & H_X L_X f_X(z) > H_Y L_Y f_Y(z) \\ z \in Y & if & H_X L_X f_X(z) < H_Y L_Y f_Y(z) \end{array} \quad (1)$$

where $f_X(z)$ and $f_Y(z)$ are the PDFs for the sources X and Y, respectively; H_X and H_Y are the a priori probabilities of sources X and Y; and L_X and L_Y are the losses resulting from incorrect decisions that the sources are Y and X, respectively. Often the a priori probabilities can be determined for the source data, however, the loss factors require some subjective evaluation based on the application from which the source data have come. The key to using Eq. (1) is the ability to estimate the probability density functions $f_X(z)$ and $f_Y(z)$ based on experimental data. These joint PDFs can be approximated using the kernel density estimator (see Parzen (1962), Cacoullos (1966) and Silverman (1986)). The kernel density estimator (KDE) is a data based estimator and one form is

$$\hat{f}_X(z) = \frac{1}{N(2\pi)^{1/2}\|S\|^{1/2}} * \sum_{j=1}^{N} \exp\left(-\frac{1}{2}\left(z-x_j\right)^T S^{-1}\left(z-x_j\right)\right) \tag{2}$$

where most of the notation is described above Eq. (1). Of course, the kernel in this expression, is a multivariate normal PDF. The kernel density estimator is a superposition of N multivariate normal densities centered at each measured realization of X. This summation is normalized so that its hyperspace volume equals one. S is the covariance matrix for the kernel. This matrix can conveniently be approximated by the special form

$$S = \sigma^2 I \tag{3}$$

where I is the identity matrix and σ is the smoothing parameter of the KDE. A small smoothing parameter can cause the estimated density function to show distinct modes at the locations of the training data, while a large value of σ provides greater smoothing or interpolation between points in the density estimation. The following smoothing factor was used in the KDEs of this study.

$$\sigma = 0.9 * \left(4/(n+2)\right)^{1/(n+4)} * \sqrt{\left\{\sum_j std\left(x_j\right)\right\}^2} * N^{-1/(n+4)} \tag{4}$$

where $std(x_i)$ refers to the standard deviation of the ith random variable vector source X, and the other parameters were previously described.

3. PROBABILISTIC PATTERN CLASSIFIER

The PPC is similar to the PNN in that it seeks to distinguish the source of a datum of unknown origin. However, the PPC differs from the PNN in that the PPC seeks to answer the question: Is the datum of unknown origin a member, an outlier, or a nonmember of the data set of interest? It answers this question by: (1) characterizing the data set of interest using the kernel density estimator of Eq. (2), (2) using this expression to develop a transformation to the space of uncorrelated standard normal random variables, then (3) transforming the datum of unknown origin to the standard normal space where we perform a test of hypothesis to judge its membership in the reference set.

We commence the development by assuming that a random variable X is characterized by a collection of data denoted $x_j, j = 1,\ldots,n$. The source and the data it produces may be vector quantities. The kernel density estimator for the data is given by Eq. (2). We seek a transformation from the space of X to the space of uncorrelated standard normal random variables. Such a transformation can be developed using the Rosenblatt transformation (see Rosenblatt, 1952).

The Rosenblatt transformation is a unique and invertible mapping that permits the conversion of vector realizations of random variables with arbitrary joint probability distribution to vector realizations of independent, uniformly distributed random variables on the interval [0,1]. To develop the transformation, note that there is a cumulative distribution function (CDF) estimator that corresponds to the KDE in Eq. (2). It is easy to obtain the CDF estimator because of the form of the covariance matrix in Eq. (3); it is given by

$$F_X(x) = \int_{-\infty}^{\xi_1} d\alpha_1 \ldots \int_{-\infty}^{\xi_n} d\alpha_n \hat{f}_X(\alpha) = \frac{1}{N} \sum_{j=1}^{N} \prod_{k=1}^{n} \Phi\left(\frac{\xi_k - x_{kj}}{\sigma}\right) \tag{5}$$

where $\boldsymbol{x}$ is the variate vector and ξ_k is its kth element, x_{kj} is the kth vector element in the jth data point $\boldsymbol{x}_j$, $F(.)$ is the CDF of a standard normal random variable and the other quantities in the expression are defined following Eq. (2). This is the joint CDF of all the random variables, $X_k, k = 1, \ldots, n$, in the vector $\boldsymbol{X}$. From this function all the lower order joint CDFs (including marginal CDFs) and conditional CDFs can be developed. The Rosenblatt transformation is defined as

$$\begin{aligned} u_1 &= F_{X_1}(\xi_1) \\ u_2 &= F_{X_2|X_1}(\xi_2 | \xi_1) \\ &\ldots \\ u_n &= F_{X_n|X_{n-1},\ldots,X_1}(\xi_n | \xi_{n-1},\ldots,\xi_1) \end{aligned} \tag{6}$$

where the $u_j, j = 1, \ldots, n$, are realizations of independent, uniformly distributed random variables on $[0,1]$, the $\xi_j, j = 1, \ldots, n$, are elements of the vector $\boldsymbol{x}$, and the functions on the right hand side are one marginal (the first equation) and several conditional CDFs obtained from Eq. (5). The following shorthand notation can be adopted for Eqs. (6).

$$\boldsymbol{u} = T(\boldsymbol{x}) \tag{7}$$

where $\boldsymbol{u}$ is the vector of elements $u_j, j = 1, \ldots, n$, and $\boldsymbol{x}$ is the vector of elements $\xi_j, j = 1, \ldots, n$.

Because the CDF defined in Eq. (5) is monotone increasing (The standard normal CDF, $\Phi(.)$ is a monotone increasing function.), the transformation of Eqs. (6) and (7) is invertible, therefore,

$$\boldsymbol{x} = T^{-1}(\boldsymbol{u}) \tag{8}$$

Because we can define the forward and inverse transformations in Eqs. (6) through (8) for a vector of random variables $\boldsymbol{X}$ with arbitrary distribution, we can also define the transformation for a vector of random variables $\boldsymbol{W}$ that are uncorrelated with standard normal distribution (i.e., each element of $\boldsymbol{W}$ is normally distributed with mean zero and unit variance.). The forward and inverse transformations may be denoted

$$\boldsymbol{u} = T_{sn}(\boldsymbol{w}) \qquad \boldsymbol{w} = T_{sn}^{-1}(\boldsymbol{u}) \tag{9}$$

where the subscript "*sn*" refers to the fact that these are transformations to and from the standard normal space.

The existence of the transformation in Eq. (7) and the second transformation in Eq. (9) implies that a transformation from a realization of a vector random variable with arbitrary joint probability distribution to a realization of a vector of uncorrelated standard normal random variables can be defined. In terms of the notation in Eqs. (7) and (9), it is

$$w = T_{sn}^{-1}(T(x)) \tag{10}$$

This transformation, developed using the detailed forms of Eqs. (5) and (6), forms the basis of the PPC. The transformation reflects the character of the data source X via its measured realizations $x_j, j = 1,...,N$, because the CDFs in Eq. (6) come from Eq. (5), and Eq. (5) involves the $x_j, j = 1,...,N$.

The PPC operates on the following basis. We consider a datum z of unknown origin, and make the hypothesis that it comes from the random source X. We transform z to the space of realizations of uncorrelated standard normal random variables using Eq. (10). The operation yields

$$w_z = T_{sn}^{-1}(T(z)) \tag{11}$$

Note that the distance from the origin of a random vector in uncorrelated standard normal space is related to the chi squared distribution. Specifically, the square of the distance from the origin of a random vector with dimension n, whose components are standard normal random variables, is chi squared distributed with n degrees of freedom. In view of this, the hypothesis specified above is rejected at the $\alpha \times 100\%$ level of significance if the norm of w_z (i.e., $\|w_z\|$) falls outside the interval $\left[0, \sqrt{\chi^2_{n,1-\alpha}}\right]$, where

$$F_{\chi^2_n}\left(\chi^2_{n,1-\alpha}\right) = 1 - \alpha \tag{12}$$

and $F_{\chi^2_n}(.)$ is the CDF of a chi squared distributed random variable with n degrees of freedom. Otherwise, the hypothesis is accepted at the discretion of the analyst. (The need for discretion arises here because measure of performance may simply not have been one that leads to rejection of the hypothesis; i.e., other measures of structural response may have led to rejection.)

In summary, we transform the datum z using Eq. (11), compute the norm of w_z, then observe whether $\|w_z\|$ falls within $\left[0, \sqrt{\chi^2_{n,1-\alpha}}\right]$. If it does, then we may conclude that z is a realization of the random variable X; otherwise, we conclude that it is not. It is anticipated that, on average, $(1-\alpha) \times 100\%$ of the realizations z that come from the random source X will fall in the interval. When we perform a test under practical conditions, we will often set the significance level in the range 0.1% through 5%. In a heuristic sense, we can conclude that when $\|w_z\|$ is outside the interval $\left[0, \sqrt{\chi^2_{n,1-\alpha}}\right]$, but not too much greater than $\sqrt{\chi^2_{n,1-\alpha}}$, then z may simply be an outlier of the random variable X. When $\|w_z\|$ is much greater than $\sqrt{\chi^2_{n,1-\alpha}}$, then we conclude that z did not arise from the random source X.

4. APPLICATION OF PROBABILISTIC NEURAL NETWORKS TO STRUCTURAL HEALTH MONITORING

The current research effort has focused on the development of two PNN software codes (the classical PNN and the PPC) to address the health of mechanical structures based on experimental data. These ANN approaches use measures of system response (and sometimes input) data to characterize the dynamic behavior of a component. The PNN uses measures of both damaged and undamaged system behavior to characterize a structure; the PPC uses only the latter. Once these models have been developed with measured response data, they can be used to enhance the decision making process related to the health of the structure. On-line measurements of both inputs and responses of an operating system, such as equipment on a production or manufacturing line, can be used to train the ANN. Once trained, the ANN can be used to monitor system health, either in real-time, or via post processing of data. There is no limitation on the types of structural response measures that can be used in the ANN training process to help assure that change in structural response or structural damage is clearly detected.

There are several key elements that are required to develop a useful PNN. First, the selection of a KDE plays an important role in the ANN development process. The KDE is an estimator of the PDF required in the decision analysis. Second, the selection of appropriate measures of structural response are needed that help to clearly reveal structural damage. These elements are a critical part of the development of a PNN that can be used to establish a measure of system health.

There are limitations to using these ANNs. Care needs to be taken when calculating multivariate density estimates. The size of the exemplar or training set needed in kernel density estimation increases dramatically as the order or dimensionality of the density estimation increases (Silverman, 1986). Thus, the requirement for large amounts of experimental data in estimating the probability densities might cause some limitations of these ANN techniques. Also, these two techniques are currently limited to assessing whether damage has occurred in a structure and they do not provide a method for determining the location or extent of the damage in the structure. In addition, the type of smoothing chosen in the kernel density estimation could limit not only the accuracy but also the computational speed of the estimation. Finally, when the sample set is large, the choice of kernel estimator may be very important in reducing the computation time of the probability density estimation (Silverman, 1986).

5. NUMERICAL EXAMPLE

An aerospace housing component was selected as test case hardware for generating experimental data where the health of the system could be monitored under different structural conditions. A test design tool called the Virtual Environment for Test Optimization (VETO) was used to design an optimal experiment for this housing component. The frequency band of interest was selected to include the first five vibration modes of the structure. A solids model of the aerospace housing component was used to generate a rapid prototype component through a stereolithography process. The testing was performed on this stereolithography component. Figure 1 shows a test setup photo.

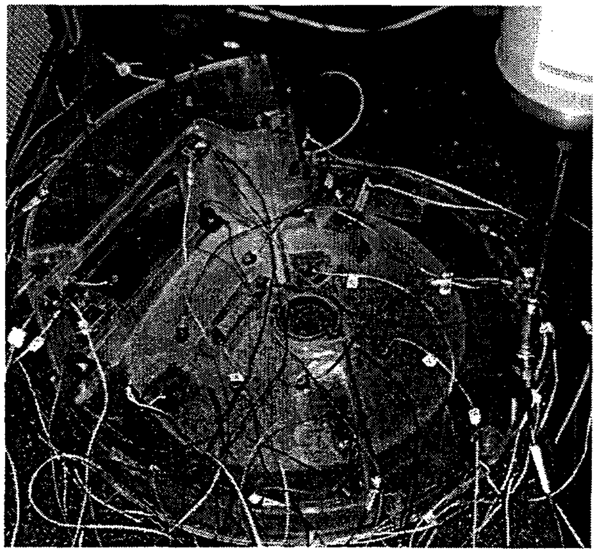

Figure 1. Experimental test setup.

The excitation used in the experiment was a stationary random vibration; acceleration response was measured at 55 locations. Using the visualization software within the VETO environment, two separate locations on the housing structure were selected for the introduction of damage. The basis for the selection of these locations was made by animating the vibration modes of interest while observing maximum strain energy density on the structure. Five separate damage cuts - each of one-quarter inch depth - were introduced at two locations with high strain energy density.

The selection of independent response measures for training the PNN was an important factor in developing a useful tool to measure the health of the housing component. The goal in choosing these measures was to minimize the dimension of the ANN while preserving or amplifying the response differences as damage was introduced into the structure. Responses measured at five locations were used in the analyses. It was determined that measures of static flexibility at the five measurement locations on the housing component would be used to train the PNNs to detect structural damage. Selecting static flexibility as the measure of structural response to use in the ANN applications required some analysis to be completed on the experimental data. Large sample sets of data were collected from input as well as for each of these response locations on the structure. Thirty-nine frequency response function (FRF) realizations were calculated using smaller blocks of this large sample set of data. An approximation of the static flexibility was calculated given each of these FRF realizations. The method for estimating the static flexibilities was to average the low frequency FRF behavior to asymptotically approximate these measures. The difficulty in determining these estimates was in selecting an appropriate frequency range to make the calculations. A typical FRF measure is shown in Figure 2.

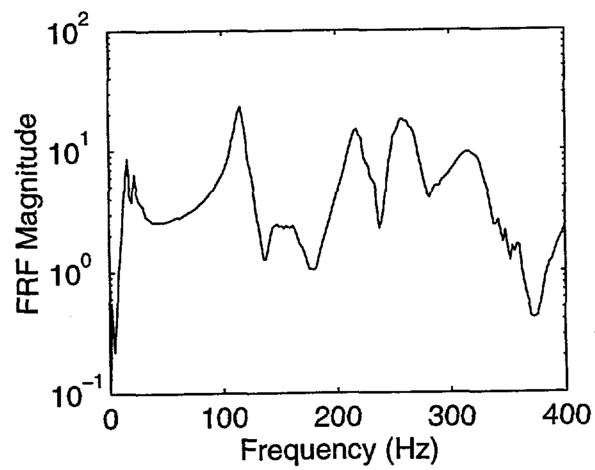

Figure 2. Typical frequency response function.

The first case study utilized these measures of static flexibility at the five selected locations on the housing structure as input to the classical PNN. Operation of the classical PNN requires data from at least two known sources; one set of static flexibilities from the undamaged case and one or more sets of static flexibilities from the group of damaged cases. When the classical PNN was presented with data from an unknown source (this unknown data was taken from the sample set of undamaged or damaged flexibilities and was subsequently not used as PNN training data), the PNN would judge the origin of that data based on the Bayesian decision criterion shown in Eq. (1). The a priori probabilities given the two known sources of data were 0.5 and the loss factors were set to 1. The results from the classical PNN study were perfect with the code predicting the correct origin of an unknown source 78 out of a possible 78 times in all damage cases. Because of the obvious difficulties in graphically presenting the results of a five-dimensional density, two of the five locations on the housing structure were arbitrarily selected for displaying results from the classical PNN. Figure 3 shows the two-dimensional scatter plot of the static flexibilities plotted against one another for the undamaged (o) and five successive damaged cases (+). The differences between the undamaged and damaged cases for these two static flexibility measures are quite apparent enabling the PNN to easily detect the origin of an unknown source. The classical PNN was able to distinguish the damaged from the undamaged data in all cases, including the most lightly damaged case.

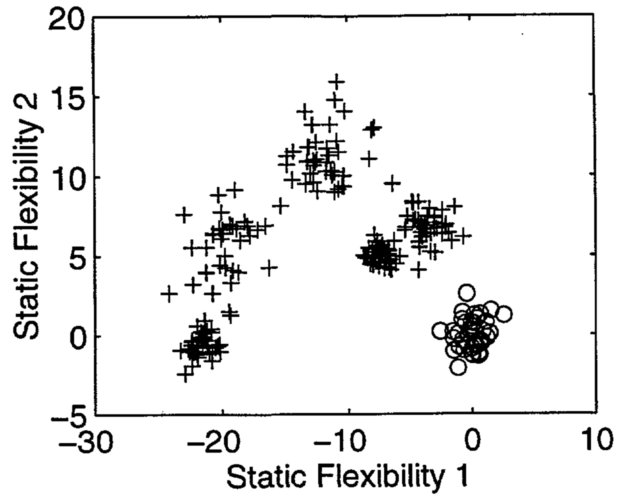

Figure 3. Scatter plot of static flexibilities.

The second case study utilized the same measures of static flexibility as input to the PPC. In this case, the PPC requires data from only a single source, such as the undamaged set of flexibilities, and seeks to judge whether or not the data from an unknown origin comes from that source. The Rosenblatt transformation was used to map the static flexibility data from the space of the kernel density estimator into the space of uncorrelated, standard normal random variables. This transformation was also used to transform the data from an unknown source, static flexibility data from the damage cases, into the standard normal space. A distance from the origin was used as criterion to judge whether the data from the unknown source (data from successive damage cases) came from the known undamaged source. An acceptance region, distances from the origin considered as part of the undamaged source, was established based on the use of the chi square distribution. A chi square random variable with five degrees of freedom has a 99.9% probability of a distance from the origin less than 4.53. The results for the five damage cases input into the PPC are shown in Figure 4 as well as the maximum distance from the origin in standard normal space at which a 5-dimensional datum could be considered a realization of a 5- vector of uncorrelated standard normal random variables (4.53). (This is the straight line at β=4.53.) This figure shows the trend that as damage increases in the structure the distance measure in standard normal space also increases. The data near beta = 12 correspond to the first damage case. The data near beta = 50, 90 (smoother curve), and 110, correspond to the second, third, and fourth level damage cases, respectively. The data near beta = 90 (more erratic curve) correspond to the fifth level damage case. At this time it is not clear to us why the fifth level damage case yields lower beta values than the fourth level damage case.

6. CONCLUSIONS

The results obtained using both the classical PNN and the PPC were quite successful. The damage in the aerospace housing component was identified, even in the most lightly damaged case, using both techniques. These ANNs clearly offer a robust method for assisting in the identification of damage in structures.

There are, however, a number of limitations in using these ANN techniques. The first is the limitation of these methods to provide or determine the location and extent of the structural damage. Further research in these ANNs will explore the combining of these techniques with data condensation methods to assist identifying the location and ultimately the extent of the structural damage. Some additional research will focus on the sensitivity of these ANNs to boundary conditions. Studies will be done to assess the effects that changing test configurations might have on the ANN results.

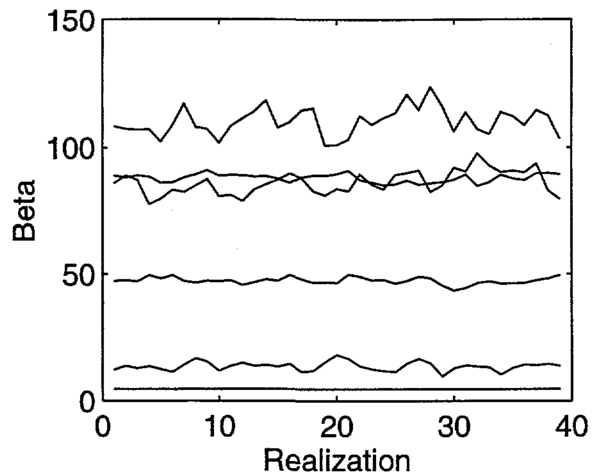

Figure 4. Plot of distance from the origin of data in standard normal space.

Acknowledgment
Sandia is a multiprogram laboratory operated by Sandia Corporation, a Lockheed Martin Company, for the United States Department of Energy under Contract DE-AC04-94AL85000.

7. REFERENCES

Cacoullos, T., (1966) Estimation of a Multivariate Density. *Annals of the Institute of Statistical Mathematics* (Tokyo), Vol. 18(2), pp. 179-189.

Parzen, E., (1962) On Estimation of a Probability Density Function and Mode. *The Annals of Mathematical Statistics*, Vol. 33, pp. 1065-1076.

Rosenblatt, M., (1952) Remarks on a Multivariate Transformation, *The Annals of Mathematical Statistics*, Vol. 23, pp. 470-472.

Silverman, B.W., (1986) Density Estimation for Statistics and Data Analysis. Chapman and Hall, New York.

Specht, D.F., (1990) Probabilistic Neural Networks. *Neural Networks*, Vol. 3, pp. 109-118.