



UNIVERSITI PUTRA MALAYSIA

**BAYESIAN NETWORK CLASSIFIERS FOR DAMAGE DETECTION IN ENGINEERING
MATERIAL**

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**BAYESIAN NETWORK CLASSIFIERS FOR DAMAGE
DETECTION IN ENGINEERING MATERIAL**

By

ADDIN OSMAN MOHAMED ADDIN

**Thesis Submitted to the School of Graduate Studies, Universiti
Putra Malaysia, in Fulfilment of the Requirement for the Degree of
Doctor of Philosophy**

February 2007



DEDICATION

The author would like to dedicate this Doctoral dissertation to the soul of his mother Hawa Mohamed Suleiman, his father Osman Mohamed Addin, his daughter Waad Addin, and all his brothers and sisters . The author is deeply grateful to his parents for their patience in raising him up, dedication, and willingness to explore the world.



Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman: Associate Professor Ir. Mohd. Sapuan Salit, PhD

Institute: Advanced Technology

The automation of damage detection in engineering material using intelligent techniques (e.g. Neural networks) has not been matured enough to be practicable and needs more techniques to be implemented, improved, and developed. Nevertheless, the Neural networks have been implemented extensively for the damage detection, but in elementary ways. The damage detection and prediction are very important processes, since the damages have the potential of growing and leading to catastrophic loss of human life, and decrease in economy (e.g. airline crashes, space shuttle explosions, and building collapses).

Bayesian networks have been successfully implemented as classifiers in many research and industrial areas and they are used as models for representing uncertainty in knowledge domains. Nevertheless, they have not been thoroughly investigated and implemented such as Neural networks for the damage detection. This thesis is dedicated to introduce them with the axiom of damage detection and implement them as a competitive probabilistic graphical model and



as classification tools (Naïve bayes classifier and Bayesian network classifier) for the damage detection. The Bayesian networks have two-sided strengths: It is easy for humans to construct and to understand, and when communicated to a computer, they can easily be compiled. Changes in a system model should only induce local changes in a Bayesian network, where as system changes might require the design and training of an entirely new Neural network.

The methodology used in the thesis to implement the Bayesian network for the damage detection provides a preliminary analysis used in proposing a novel feature extraction algorithm (*f*-*FFE*: the *f*-folds feature extraction algorithm). The state-of-the-art shows that most of the feature reduction techniques, if not all, which have been implemented for the damage detection are feature selection not extraction. Feature selection is less flexible than feature extraction in that feature selection is, in fact, a special case of feature extraction (with a coefficient of one for each selected feature and a coefficient of zero for any of the other features). This explains why an optimal feature set obtained by feature selection may or may not yield a good classification results.

To validate the classifiers and the proposed algorithm, two data sets were used, the first set represents voltage amplitudes of Lamb-waves produced and collected by sensors and actuators mounted on the surface of laminates contain different artificial damages. The second set is a vibration data from a type of ball bearing operating under different five fault conditions. The Bayesian network classifiers and the proposed algorithm have been tested using the second set.



The studies conducted in this research have shown that Bayesian networks as one of the most successful machine learning classifiers for the damage detection in general and the Naïve bayes classifier in particular. They have also shown their efficiency when compared to Neural networks in domains of uncertainty. The studies have also shown the effectiveness and efficiency of the proposed algorithm in reducing the number of the input features while increasing the accuracy of the classifier. These techniques will play vital role in damage detection in engineering material, specially in the smart materials, which require continuous monitoring of the system for damages.



Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia
sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

**PENGELAS RANGKAIAN BAYESAN BAGI PENGESANAN
KEROSAKAN DALAM BAHAN KEJURUTERAAN**

Oleh

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Pengautomatan pengesanan kerosakan bahan kejuruteraan menggunakan teknik pintar (contohnya rangkaian Nural) masih belum matang dan memerlukan lebih banyak teknik dilaksanakan, diperbaiki dan dibangunkan supaya menjadi lebih praktikal. Namun begitu, rangkaian Neural telah banyak dilaksanakan untuk pengesanan kerosakan tetapi masih di peringkat permulaan. Pengesanan dan ramalan kerosakan adalah proses yang sangat penting kerana kerosakan berpotensi membesar dan membawa kemusnahan nyawa yang dahsyat dan menjejaskan ekonomi (contohnya kapal terbang terhempas, letupan kapal angkasa lepas dan keruntuhan bangunan).

Rangkaian Bayesian telah dilaksanakan dengan jayanya sebagai pengelas dalam pelbagai bidang penyelidikan dan industri dan pengelas ini digunakan bagi mewakili ketidakpastian dalam domain ilmu. Namun begitu pengelas ini tidak pernah dikaji dan dilaksanakan secara terperinci berbanding rangkaian Neural bagi pengesanan kerosakan. Tesis ini ditujukan khas memperkenalkan



rangkaian Bayes dengan aksiom bagi pengesanan kerosakan dan melaksanakan pengelasan ini sebagai model bergraf kebarangkalian kompetitif dan sebagai perkakas pengelasan (pengelas Naïve bayes dan pengelas rangkaian Bayes) bagi pengesanan kerosakan. Rangkaian Bayes mempunyai kekuatan dua bahagian. Ia mudah dibina dan difahami oleh manusia dan bila ia dihubungkan dengan komputer, ia mudah disusun. Perubahan dalam model sistem harus hanya mengaruh perubahan setempat dalam rangkaian Bayes, sedangkan perubahan sistem mungkin memerlukan reka bentuk dan latihan rangkaian Neural baru secara keseluruhan.

Metodologi yang digunakan dalam tesis ini bagi melaksanakan rangkaian Bayes untuk pengesanan kerosakan memberikan analisis permulaan yang digunakan dalam mencadangkan satu algoritma penyarian sifat asli (f -FFE: algoritma penyarian sifat f -lipat). Keadaan semasa menunjukkan bahawa kebanyakan teknik pengurangan sifat, jika tidak semua, yang telah dilaksanakan bagi pengesanan kerosakan adalah pemilihan sifat dan bukannya penyarian. Pemilihan sifat kurang fleksibel berbanding penyarian sifat di mana pemilihan sifat adalah sebenarnya satu kes khusus bagi penyarian sifat (dengan pekali satu bagi setiap sifat yang terpilih dan pekali sifar bagi sifat yang lain). Ini menerangkan kenapa set sifat optimum yang diperolehi menggunakan pemilihan sifat mungkin atau tidak akan menghasilkan keputusan pengelasan yang baik.

Bagi mengesahkan pengelas dan algoritma yang dicadangkan, dua set data telah digunakan, set yang pertama mewakili amplitud voltan bagi gelombang Lamb yang dihasilkan dan dikumpulkan oleh penderia dan penggerak yang



dicagakkan di atas permukaan laminat yang mengandungi pelbagai kerosakan buatan. Set yang kedua adalah data getaran daripada sejenis gelas bebola yang beroperasi di bawah lima keadaan rosak yang berbeza. Pengelas rangkaian Bayesian dan algoritma yang dicadangkan telah diuji menggunakan set yang kedua.

Kajian yang telah dibuat dalam penyelidikan ini menunjukkan bahawa rangkaian Bayesian adalah salah satu pengelas pembelajaran mesin yang paling berjaya bagi pengesanan kerosakan secara umum dan pengelas Naïve bayes secara khusus. Pengelas ini telah menunjukkan kecekapan mereka berbanding rangkaian Neural dalam domain ketidakpastian. Kajian ini telah juga menunjukkan keberkesanan dan kecekapan algoritma yang dicadangkan dalam mengurangkan bilangan sifat masukan sementara menambahkan ketepatan pengelas. Teknik ini akan memainkan peranan penting dalam pengesanan kerosakan untuk bahan kejuruteraan, terutamanya dalam bahan pintar, yang memerlukan pemantauan sistem secara berterusan bagi kerosakan.

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Once, Isaac Newton (English mathematician and physicist, 1642 - 1727) said:

If I have seen further it is by standing on the shoulders of giants.

The writing of a dissertation is a tedious, lonely, and isolating experience, yet it is obviously not possible to successfully be completed, firstly, without the help of "ALLAH" and secondly, without standing on the shoulders of many giants. First and foremost, the author would like to acknowledge and appreciate the generosity and unlimited help of his supervisor Associate Professor Ir. Dr. Mohd. Sapuan Salit and his supervisory committee members, Associate Prof. Dr. Mohamed Othman and Dr. Elsadig Mahdi. They have always allowed him freedom to define and determine his own research directions. They have also offered him valuable comments and suggestions, which played a vital role in successfully completing the thesis.

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I certify that an Examination Committee has met on **23/February/2007** to conduct the final examination of Addin Osman Mohamed Addin on his Ph.D. thesis entitled "Bayesian networks for damage detection in engineering material" in accordance with Universiti Pertanian Malaysia (Higher Degree) Act 1980 and Universiti Pertanian Malaysia (Higher Degree) Regulations 1981. The Committee recommends that the candidate be awarded Doctor of Philosophy. Members of the Examination Committee are as follows:

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UPM or other institutions.

ADDIN OSMAN MOHAMED ADDIN

Date: 01 April 2007



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LIST OF ABBREVIATIONS

Latin Letters

Symbol	Description
a	New ball bearing
A	Variable with n states (a_1, a_2, \dots, a_n)
b	Outer race completely broken
c	Broken cage with one loose element
c	Classifier
C	Number of class labels
d	Damaged cage, four loose elements
D	Entire data
D_n	A data set (d_1, d_2, \dots, d_n) with n features
e	No evident damage, badly work ball bearing
E	Set of directed ares between variables
G	Network structure
GUI	Graphical user interface
J	Number of variables
K	Number of classes
m	Number of amplitudes in a folder
k	Number of clusters
V	Set of variables
V_1	Variable number one
V_2	Variable number two
V_m	A data set with m features
V_n	variable number n



$P(A)$	Probability distributions over variable A .
t	Total number of variables in each damage type
TAN	tree augmented Naïve bayes
$WEKA$	The Waikato environment for knowledge analysis
w_n	An element representing class label
X	A data set with n variables (x_1, x_2, \dots, x_n)
X	Original feature space
X'	Reduced feature space
x_c	Class label
x_i	Probability of A been in state a_i
χ^2 -test	Statistical hypothesis test

Greek Letters

Symbol	Description
f	Mapping function
f	Number of folders
ω	Class label that takes a value of $1, 2, \dots, C$

Abbreviations

Symbol	Description
<i>Age</i>	The age of material
<i>Amps</i>	A set of n amplitudes $(amp_1, amp_2, \dots, amp_n)$
<i>Amplitude</i>	The value of the wave's amplitude
<i>ARFF</i>	Attribute-relation file format
<i>ASH</i>	Aluminum sandwich honeycomb



<i>BN</i>	Bayesian networks
<i>BP</i>	Back propagation
<i>CFRP</i>	Carbon-fiber reinforced polymers
<i>Classify</i>	Function Classify
<i>CLI</i>	Command line interface
<i>CMs</i>	Composite materials
<i>CPTs</i>	Conditional probability tables
<i>DAG</i>	Directed acyclic graph
<i>Damage</i>	Presence of damage in material
<i>DDF</i>	Digital damage fingerprints
$D(X_i pa(X_i))$	Data involving only X_i and $pa(X_i)$
<i>EM</i>	Expectation-Maximization algorithm
<i>EM</i>	Engineering material
<i>FF</i>	Feed-forward
<i>f-FFE</i>	f -Folds feature extraction algorithm
<i>FFT</i>	Fast Fourier transformation
<i>fold(1)</i>	Folder number one
<i>fold(2)</i>	Folder number two
<i>fold(f)</i>	Folder number f
<i>LCMs</i>	Laminated composite materials
<i>LTF-C</i>	The local transfer function classifier
<i>LTF-Cimulator</i>	Simulator of local transfer function classifier
<i>LW</i>	Lamb waves
<i>MAP</i>	Maximum Posteriori
<i>Maxs</i>	Maximum values of a cluster
<i>MDL</i>	Minimum Description Length
<i>Means</i>	Mean values of a cluster



<i>MEMS</i>	Micro-electro mechanical systems
<i>Mins</i>	Minimum values of a cluster
<i>ML</i>	Machine learning
<i>NewAmp</i>	A data set
<i>NDE</i>	Nondestructive evaluation
<i>NDT</i>	Nondestructive testing
N_{ijk}	The number of samples in D for which $X_i = k$ and $pa(X_i) = j$
<i>NN</i>	Neural network
$P(D S)$	Cooper-Herskovits scoring function
<i>PMGs</i>	Probabilistic graphical models
<i>PZT</i>	Piezoelectric Transducer
$Score_a$	Score for the <i>DAG</i> S_a after the change
$Score_b$	Score for the <i>DAG</i> S_b before the change
<i>SMH</i>	Structural health monitoring
S_{opt}	Bayesian network structure
S	Bayesian network structure
<i>SUN</i>	Selective unrestricted bayesian network classifier
<i>ToolDrop</i>	Tool dropped on the material



CHAPTER 1

BACKGROUND

1.1 Introduction

Recently, there has been a tremendous growth in the usage of engineering material (*EM*) in all types of engineering structures (e.g. aerospace, automotive, and sports). *EM* is used to create a diversity of products, from computer chips and television screens to golf clubs and snow skis. *EM* includes metals, plastics, semiconductors, steel, aluminum honeycombs sandwich (*AHS*), and laminated composite materials (*LCMs*). *LCMs*, *AHS*, and steel find wide usage in automobile and airplane parts on account of their stiffness and strength [1].

In practical situations, material failure or damage may occur during manufacturing processes or in-service. The manufacturing related damages are like foreign object inclusion, porosity, and resin rich areas. In-service damages can happen in the case of aeronautical materials because a tool is dropped during maintenance, there is a bird or hail strike in plain flight, perhaps runway debris striking the aircraft during takeoff or landing [2].

The damages have the potential of growing and leading to catastrophic loss of human life, and decrease in economy. Examples of real-life damages can be shown as airline crashes, space shuttle explosions, and building and bridge collapses. The early detection and characterization of *in situ* damages in *EM* are very significant to ensure their structural health and integrity, prevent them

