



澳門大學  
UNIVERSIDADE DE MACAU  
UNIVERSITY OF MACAU

---

**WAVELET NEURAL NETWORKS**  
**THE FUSION OF HC AND SC FOR COMPUTERIZED PHYSIOLOGICAL SIGNAL INTERPRETATION**

**LI Bing Nan**

*(B.Eng. Southeast University; M. Sc. University of Macau)*

A thesis submitted for the fulfillment of  
the requirements of the degree of  
**DOCTOR OF PHILOSOPHY**  
in  
**ELECTRICAL AND ELECTRONICS ENGINEERING**

Faculty of Science and Technology  
University of Macau

November 2009



# Wavelet Neural Networks:

## The Fusion of HC and SC for Computerized Physiological Signal Interpretation

---

**LI Bing Nan**

Department of Electrical and Electronics Engineering  
Faculty of Science and Technology  
University of Macau  
Av. Padre Tomás Pereira S. J., Taipa, Macao, China

Copyright © 2009 LI Bing Nan



\* The works in this dissertation were financially supported in part by the Macau Science and Technology Development Fund, and in part by the University of Macau Research Committee.



In presenting this dissertation in partial fulfillment of the requirements for a PhD's degree at the University of Macau, I agree that the Library and the Faculty of Science and Technology shall make its copies freely available for inspection. However, reproduction of this dissertation for any purposes or by any means shall not be allowed without my written permission. Authorization is sought by contacting the author at

Address:

Department of Electrical & Electronics Engineering, Faculty of Science and Technology, University of Macau, Taipa, Macau

Telephone: (853) 83974518

Fax: (853) 28835928

Email: me@bingoon.org



Signature

\_\_\_\_\_

Date

\_\_\_\_\_



## ABSTRACT

# WAVELET NEURAL NETWORKS

## THE FUSION OF HC AND SC FOR COMPUTERIZED PHYSIOLOGICAL SIGNAL INTERPRETATION

by

LI Bing Nan

Thesis Supervisor: Prof. DONG Ming Chui

Thesis Co-supervisor: Prof. VAI Mang I

Department of Electrical and Electronics Engineering, University of Macau, Taipa, Macau

The works presented in this dissertation originate from our years of research on cardiovascular health monitoring at home. Different prototyping systems have been developed in our group for cardiovascular health monitoring. However, it is found in our practice that computerized interpretation of the recorded cardiovascular physiological signals is far more challenging than expected. The biggest challenge comes from the intrinsic physiological signal variability due to pathophysiological artifacts, instrumental inaccuracy and operational inconsistency. All of them alter the morphologies and rhythms of cardiovascular physiological signal substantially. At the same time, there is yet no unanimous solution to discriminate and eliminate abovementioned variability in cardiovascular physiological signals.

This dissertation is focused on integrating hard computing (HC) and soft computing (SC) for computerized physiological signal interpretation. Neural networks are chosen as the delegate of SC for adaptive clustering and supervised classification. Among various HC paradigms, wavelet transform is a well-established technology for unified time-frequency analysis. To attack physiological signal variability, we are interested in the essential components by means of wavelet analysis. Those components are supposed resistant to noises and artifacts. Nevertheless, there is yet no unanimous criterion for the choice of essential wavelet components. Two criteria were examined and evaluated in this dissertation for adaptive wavelet modeling. The first one is oriented to energy maximization. It attempts to select out those strong wavelet components. Actually, many popular schemes of adaptive wavelet modeling, such as wavelet scale maxima, relative wavelet energies and regional wavelet entropies, exactly follow this energy-oriented criterion. The second criterion directing adaptive wavelet modeling is oriented to morphological similarity. In essence, it is desired

to optimize wavelet modeling to approximate the original physiological signals accurately with a compact representation. The refined wavelet components are supposed optimal to the essential signal components, meanwhile are resistant to noises and artifacts. The paradigms of wavelet shrinkage, matching pursuits and wavelet regression networks obey such morphology-oriented criterion for adaptive wavelet modeling.

All of them were further examined in comparison with the fully integrated wavelet networks for adaptive clustering and supervised classification of cardiovascular physiological signals. In general, a wavelet network replaces the neuronal transfer functions in conventional neural networks by wavelet basis functions. Hence the optimization of wavelet modeling and neural networks can be unified as a whole. In practice, we found that wavelet networks suffer from many challenging issues in system architecture, network initialization, optimal evolution, and so forth. On the contrary, the modular integration of wavelet analysis and neural networks owns structural simplicity and implemental flexibility. Nevertheless, the morphology- or energy-oriented paradigm of adaptive wavelet modeling keeps blind to the subsequent clustering or classification. In other words, their performance can not be guaranteed as an overall system for physiological signal interpretation. Therefore we proposed two novel wavelet modeling strategies in this dissertation.

The first scheme, termed as principal wavelet modeling (PWM), incorporates the theories and methods of principal component analysis into adaptive wavelet modeling. The choice of wavelet components are based on neither energy maximization nor morphological similarity, but their clustering distributions in the unified time-frequency space. Theoretically speaking, the PWM is optimal for adaptive clustering of cardiovascular physiological signals. On the other hand, we took advantages of the theories and methods of linear discriminant analysis for the second paradigm of adaptive wavelet modeling, termed as discriminant wavelet modeling (DWM). The adaptive wavelet modeling is hereby oriented to classification optimization directly.

The performance was validated carefully in both small- and large-scale benchmark databases. In terms of ECG beat clustering, the wavelet neural network using novel PWM and FCM achieved the accuracy 64.7%, which was better than those morphology-oriented HBF (57.5%) and MP (53.4%). Coming to ECG classification, the wavelet neural network based on the novel DWM and  $k$ NN (error rate  $10.34 \pm 0.35\%$ ) was fairly good against the energy-oriented WSM ( $13.31 \pm 0.30\%$ ) and the morphology-oriented MP ( $18.75 \pm 0.67\%$ ), but worse than the morphology-oriented HBF ( $8.45 \pm 0.26\%$ ). As a conclusion, neither morphology- nor energy-oriented adaptive wavelet modeling is able to guarantee the global performance for optimal clustering and classification. In contrast, the novel PWM and DWM are robust against physiological signal variability, thus effective for computerized physiological signal interpretation.



## ACKNOWLEDGEMENTS

First and foremost, I am truly indebted to my supervisors – Prof. DONG Ming Chui and Prof. VAI Mang I – for their invaluable mentorship. Only with their patient guidance and endless support, I had the courage to spend seven years on my graduate studies and achieve some decent results. To be frank, Prof. DONG and Prof. VAI offered me the all-round helps, from living allowance to technical facilities, during the past seven years.

The Institute of Systems & Computer Engineering (INESC-Macau) and the Department of Electrical & Electronics Engineering offered me a comfortable and friendly environment, which are of great help to my doctoral study and research. Please allow me to thank the staff in both institutes, including Prof. HAN Ying Duo, Prof. RUI Martins, Prof. LI Yi Ping, Prof. MOK Kai Meng, Prof. QIAN Tao, Prof. CHENG Weiji, Dr. MAK Peng Un, Dr. CHAN Iat Neng, Dr. WONG Chi Kong, Dr. CHAO Sam, Dr. WONG Fai, Dr. WAN Feng, Dr. DAI Ningyi, Mr. CHEANG Sek Un, and many many others.

The works presented in this dissertation are benefited from several research projects supported by the Macau Science and Technology Development Fund (Grant No: 007/2006/A1 and 014/2007/A1) and the University of Macau Research Committee (Grant No: RG071/04-05S/DMC/FST, RG074/04-05S/VMI/FST and RG061/06-07S/VMI/FST). Their generous financial supports are in particular appreciated.

The colleagues in my research group – Mr. LEI Wei Kei, Ms. FU Binbin, Mr. SHI Jun, Mr. FEI Xiaolei, Mr. IEONG Chio In, and Mr. PUN Sio Hang – are worthy of my words for their friendliness, technical supports as well as inspiring discussion. What a happy time to study and work with all of you. In particular, I hope to point out that Mr. LEI and Ms. FU assisted me a lot in my research and experiments.

Finally, but not all, I would like to express my wholehearted gratitude to my family and especially my family-in-law. As a matter of fact, without their understanding, patience and consistent support, what I have done would be nothing at all. To my heart, I hope to dedicate this dissertation to my loves, Ms. SHI Mian and Ms. LI Siyuan.

LI Bing Nan

Nov 2009



# TABLE OF CONTENTS

ABSTRACT .....	i
ACKNOWLEDGMENTS .....	iii
TABLE OF CONTENTS .....	v
LIST OF FIGURES .....	ix
LIST OF TABLES .....	xi
LIST OF ABBREVIATIONS .....	xiii
<b>CHAPTER 1: INTRODUCTION .....</b>	<b>1</b>
1.1 RESEARCH BACKGROUND.....	1
1.1.1 CARDIOVASCULAR SYSTEM AND DISEASES .....	3
1.1.2 NONINVASIVE CARDIOVASCULAR HEALTH MONITORING .....	4
1.2 COMPUTERIZED CPS INTERPRETATION .....	7
1.2.1 OVERVIEW OF COMPUTERIZED CPS INTERPRETATION .....	7
1.2.2 CURRENT STATE OF THE ART .....	8
1.3 CHALLENGES AND BOTTLENECK PROBLEMS .....	16
1.4 RESEARCH GOALS .....	17
1.5 STATEMENT OF CONTRIBUTIONS .....	19
1.6 DISSERTATION OVERVIEW .....	21
REFERENCES .....	24
<b>CHAPTER 2: PHYSIOLOGICAL SIGNAL VARIABILITY .....</b>	<b>33</b>
2.1 PHYSIOLOGICAL SIGNAL VARIABILITY.....	34
2.1.1 PATHOLOGICAL ALTERNATIONS .....	34
2.1.2 PHYSIOLOGICAL VARIABILITY.....	36
2.1.3 INSTRUMENTAL INACCURACY.....	38
2.1.4 INCONSISTENT MEASUREMENTS .....	38
2.2 CONVENTIONAL CPS FEATURES .....	39
2.3 PHYSIOLOGICAL WAVEFORM ANALYSIS .....	42
2.3.1 MORPHOLOGICAL ANALYSIS .....	44

2.3.2	EVALUATION AND DISCUSSION .....	47
2.4	CHAPTER SUMMARY .....	50
	REFERENCES .....	52
<b>CHAPTER 3:</b>	<b>PHYSIOLOGICAL SIGNAL MODELING .....</b>	<b>55</b>
	— <i>Attacking Physiological Signal Variability</i>	
3.1	HERMITE TRANSFORM .....	56
3.2	WAVELET ANALYSIS .....	59
3.2.1	UNIFIED TIME-FREQUENCY ANALYSIS .....	63
3.3	EVALUATION AND DISCUSSION .....	67
3.4	CHAPTER SUMMARY .....	72
	REFERENCES .....	74
<b>CHAPTER 4:</b>	<b>ADAPTIVE WAVELET MODELING .....</b>	<b>77</b>
	— <i>Attacking Physiological Signal Variability</i>	
4.1	WAVELET SHRINKAGE .....	78
4.2	MATCHING PURSUITS .....	80
4.3	WAVELET REGRESSION NETWORKS .....	83
4.4	EVALUATION AND DISCUSSION .....	86
4.5	CHAPTER SUMMARY .....	92
	REFERENCES .....	94
<b>CHAPTER 5:</b>	<b>COMPETITIVE WAVELET NETWORKS .....</b>	<b>97</b>
	— <i>Attacking the Deficiency of Models and Knowledge</i>	
5.1	CPS SELF-ORGANIZING .....	100
5.1.1	SELF-ORGANIZING BY ERROR MINIMIZATION .....	101
5.2	NEURAL COMPUTATION .....	103
5.2.1	SELF-ORGANIZING MAPS .....	106
5.3	COMPETITIVE WAVELET NETWORKS .....	108
5.3.1	HYBRID WAVELET NETWORKS FOR CLUSTERING .....	109
5.3.2	COMPETITIVE WAVELET NETWORKS .....	111
5.3.3	PRINCIPAL WAVELET MODELING: A NOVEL PARADIGM .....	113
5.4	EVALUATION AND DISCUSSION .....	117
5.5	CHAPTER SUMMARY .....	121

REFERENCES .....	123
<b>CHAPTER 6: WAVELET CLASSIFICATION NETWORKS</b> .....	125
— <i>Attacking the Deficiency of Models and Knowledge</i>	
6.1 NEURAL COMPUTATION AND SUPERVISED LEARNING.....	127
6.1.1 SUPERVISED LEARNING .....	130
6.1.2 SUPERVISED NEURAL NETWORKS FOR CLASSIFICATION.....	131
6.2 WAVELET NETWORKS FOR CLASSIFICATION.....	133
6.3 A NOVEL WAVELET CLASSIFICATION NETWORK.....	139
6.3.1 CONCEPT .....	139
6.3.2 MODELING .....	140
6.3.3 CLASSIFYING .....	143
6.4 EVALUATION AND DISCUSSION .....	144
6.5 CHAPTER SUMMARY .....	147
REFERENCES .....	149
<b>CHAPTER 7: EXPERIMENTS</b> .....	151
— <i>On computerized Physiological Signal Interpretation</i>	
7.1 PREPARATION OF BENCHMARK DATABASES.....	153
7.1.1 PREPROCESSING .....	154
7.1.2 SEGMENTATION .....	155
7.1.3 POST-PROCESSING .....	157
7.2 ECG BEAT CLASSIFICATION.....	158
7.2.1 BENCHMARK DATABASE .....	158
7.2.2 EXPERIMENTS.....	160
7.3 CARDIOVASCULAR AGING EVALUATION .....	168
7.3.1 BENCHMARK DATABASE .....	169
7.3.2 EXPERIMENTS .....	169
7.4 ANALYSIS OF ARRHYTHMIC PREMATURE BEATS .....	172
7.4.1 BENCHMARK DATABASES .....	173
7.4.2 EXPERIMENTS .....	174
7.5 CHAPTER SUMMARY.....	180
REFERENCES .....	182

<b>CHAPTER 8: CONCLUSION AND FUTURE WORKS</b> .....	185
8.1 DISSERTATION SUMMARY .....	185
8.2 FUTURE WORKS .....	188
REFERENCES .....	191



## LIST OF FIGURES

ID	PAGE NUMBER
Figure 1 – 01	The circulatory system ..... 3
Figure 1 – 02	Cardiac electrical conduction system ..... 5
Figure 1 – 03	12-lead ECG monitoring ..... 5
Figure 1 – 04	Noninvasive monitoring of arterial blood pressure waveforms ..... 6
Figure 1 – 05	Arterial blood pressure waveforms ..... 7
Figure 2 – 01	The recorded arterial pulse waveforms with noises and artifacts ..... 33
Figure 2 – 02	Normal vs. pathological ECGs ..... 35
Figure 2 – 03	Normal vs. pathological ABP waveforms ..... 36
Figure 2 – 04	The ABP waveforms from youths vs. those from elders..... 37
Figure 2 – 05	Accidental instrumental failure ..... 38
Figure 2 – 06	Different ABP waveforms from the same subject..... 39
Figure 2 – 07	ECG features for cardiovascular health interpretation ..... 41
Figure 2 – 08	ABP waveform features for cardiovascular health interpretation ..... 42
Figure 2 – 09	CPSs before and after preprocessing ..... 43
Figure 2 – 10	ECG signals before and after normalization..... 45
Figure 2 – 11	ABP waveforms before and after normalization ..... 46
Figure 2 – 12	Nonlinear sampling for morphological feature characterization ..... 46
Figure 2 – 13	Whisker diagrams of morphological samples ..... 48
Figure 2 – 14	A diagram of ideal correlation coefficients ..... 49
Figure 2 – 15	Correlation coefficients of morphological sampling features ..... 50
Figure 3 – 01	The first 8 HBFs without dilation and translation ..... 57
Figure 3 – 02	Modeling normalized CPSs by 7-order Hermite decomposition ..... 58
Figure 3 – 03	Illustrative comparisons between different signal analytical techniques ..... 60
Figure 3 – 04	Comparisons between CWT and DWT ..... 61
Figure 3 – 05	DWT by cascade filter banks ..... 62

Figure 3 – 06	An illustrative DWT by filter banks .....	63
Figure 3 – 07	The 3-order Gaussian derivative and its pseudo-frequency .....	65
Figure 3 – 08	Feature characterization by wavelet-based time-frequency analysis .....	66
Figure 3 – 09	Whisker diagrams of HBF coefficients.....	68
Figure 3 – 10	Whisker diagrams of relative wavelet energies .....	69
Figure 3 – 11	Whisker diagrams of regional wavelet entropies .....	69
Figure 3 – 12	Whisker diagrams of wavelet scale maxima .....	70
Figure 3 – 13	Feature correlation coefficients of adaptive HBFs .....	70
Figure 3 – 14	Feature correlation coefficients of relative wavelet energies .....	71
Figure 3 – 15	Feature correlation coefficients of regional wavelet entropies .....	71
Figure 3 – 16	Feature correlation coefficients of wavelet scale maxima .....	72
Figure 4 – 01	Modeling CPSs by 10-order wavelet shrinkage .....	79
Figure 4 – 02	Adaptive orthonormal WBFs for ECG modeling by matching pursuits .....	81
Figure 4 – 03	Modeling CPSs by 7-order matching pursuits .....	82
Figure 4 – 04	A feed-forward WRN .....	84
Figure 4 – 05	Modeling CPSs by a 7-order WRN.....	86
Figure 4 – 06	The goodness of ECG signal modeling by different techniques .....	87
Figure 4 – 07	The goodness of ABP waveform modeling by different techniques .....	88
Figure 4 – 08	Whisker diagrams of the coefficients of wavelet shrinkage models .....	89
Figure 4 – 09	Whisker diagrams of the coefficients of matching pursuit models .....	89
Figure 4 – 10	Whisker diagrams of the coefficients of WRN models .....	90
Figure 4 – 11	Feature correlation coefficients of the models by wavelet shrinkage .....	90
Figure 4 – 12	Feature correlation coefficients of the models by matching pursuits .....	91
Figure 4 – 13	Feature correlation coefficients of the WRN models .....	91
Figure 5 – 01	Biological vs. artificial neural networks .....	104
Figure 5 – 02	Comparison between PWM and other strategies for adaptive wavelet modeling	116
Figure 5 – 03	Selected arrhythmia ECG beats from MAD.....	117



Figure 5 – 04	Adaptive ECG arrhythmia clustering with a hybrid wavelet network of WSM and SOM .....	118
Figure 6 – 01	Various transfer functions in ANN .....	129
Figure 6 – 02	Schematic diagram of probabilistic wavelet networks for classification .....	134
Figure 6 – 03	Schematic diagram of perceptron wavelet networks for classification .....	135
Figure 6 – 04	Fisher’s linear discriminant analysis .....	141
Figure 6 – 05	Comparison between DWM and other strategies for adaptive wavelet modeling .....	143
Figure 7 – 01	Computerized physiological signal delineation .....	156
Figure 7 – 02	Selected ECG beats from MAD.....	161
Figure 7 – 03	Adaptive ECG beat clustering by integrated HBFs and FCM .....	162
Figure 7 – 04	Adaptive ECG beat clustering by integrated MP and FCM.....	164
Figure 7 – 05	Adaptive ECG beat clustering by integrated WSM and FCM .....	165
Figure 7 – 06	Adaptive ECG beat clustering by integrated PWM and FCM .....	166
Figure 7 – 07	The distribution of k values against the age and gender group .....	170
Figure 7 – 08	Adaptive wavelet models against the age and gender groups.....	171
Figure 7 – 09	Excerpted lead-MLII ECG beats from MIT/BIH database .....	175
Figure 7 – 10	Excerpted lead-V1 ECG beats from MIT/BIH database.....	176
Figure 7 – 11	Selected lead2 ECG beats from MGH database.....	177
Figure 7 – 12	Selected ABP waveforms from MGH database.....	178
Figure 8 – 01	Adaptive wavelet modeling by energy maximization .....	186
Figure 8 – 02	Adaptive wavelet modeling by morphological similarity .....	187
Figure 8 – 03	Comparison between different strategies for adaptive wavelet modeling .....	188

## LIST OF TABLES

ID		PAGE NUMBER
Table 1 – I	Advances of computerized ECG interpretation in chronicle .....	9
Table 1 – II	Advances of computerized ABP interpretation in chronicle .....	13
Table 3 – I	Spectral resolution of 3-order Gaussian wavelet .....	66
Table 5 – I	Heuristic rules defining a normal ECG .....	98
Table 5 – II	The confusion matrix of adaptive clustering by the pseudo wavelet network .....	119
Table 5 – III	Clustering performance of wavelet neural networks .....	120
Table 6 – I	Performance evaluation of three types of supervised classifiers .....	145
Table 6 – II	Classification performance of the novel DWM.....	146
Table 7 – I	Selected ECG beats from the MAD database .....	159
Table 7 – II	The confusion matrix of adaptive clustering by HBFs and FCM .....	163
Table 7 – III	The confusion matrix of adaptive clustering by MP and FCM .....	164
Table 7 – IX	The confusion matrix of adaptive clustering by WSM and FCM .....	165
Table 7 – X	The confusion matrix of adaptive clustering by PWM and FCM .....	166
Table 7 – XI	Performance evaluation of supervised classification on MAD database .....	167
Table 7 – XII	Supervised wavelet neural networks for premature ECG beat analysis .....	176
Table 7 – XIII	Supervised wavelet neural networks for premature ECG beat analysis .....	178
Table 7 – IV	Supervised wavelet neural networks for premature ABP beat analysis .....	179

## LIST OF ABBREVIATIONS

<b>ABP</b>	Arterial Blood Pressure	<b>ANN</b>	Artificial Neural Network
<b>AESC</b>	Arial Escape Beats	<b>ART</b>	Adaptive Resonance Theory
<b>AR<sup>2</sup></b>	Adjusted R-square	<b>BPV</b>	Blood Pressure Variability
<b>CVD</b>	Cardiovascular Diseases	<b>AWT</b>	Adaptive Wavelet Modeling
<b>CVS</b>	Cardiovascular System	<b>CPS</b>	Cardiovascular Physiological Signal
<b>DBP</b>	Diastolic Blood Pressure	<b>CWN</b>	Competitive Wavelet Network
<b>ECG</b>	Electrocardiograms	<b>CWT</b>	Continuous Wavelet Transform
<b>ES</b>	Expert System	<b>DWM</b>	Discriminant Wavelet Modeling
<b>FCM</b>	Fuzzy C-Means	<b>DWT</b>	Discrete Wavelet Transform
<b>FL</b>	Fuzzy Logics	<b>FLD</b>	Fisher Linear Discriminant
<b>FN</b>	False Negatives	<b>GCV</b>	Generalized Cross-Validation
<b>FP</b>	False Positives	<b>IIR</b>	Infinite Impulse Response
<b>GA</b>	Genetic Algorithms	<b>LBBB</b>	Left Bundle Branch Block
<b>HBF</b>	Hermite Basis Function	<b>MAD</b>	MIT/BIH Arrhythmia Database
<b>HC</b>	Hard Computing	<b>MGH</b>	MGH/MF Waveform Database
<b>HRV</b>	Heart Rate Variability	<b>MRA</b>	MultiResolution Analysis
<b>IQR</b>	Inter-Quartile Range	<b>PAC</b>	Premature Atrial Contractions
<b>kNN</b>	<i>k</i> -Nearest Neighbor	<b>PCA</b>	Principal Component Analysis
<b>MAP</b>	Mean Arterial Pressure	<b>PNN</b>	Probabilistic Neural Network
<b>MLP</b>	Multilayer Perceptrons	<b>PUD</b>	Pulse waveform Delineator
<b>MP</b>	Matching Pursuits	<b>PVC</b>	Premature Ventricular Contractions
<b>NN</b>	Neural Networks	<b>PWM</b>	Principal Wavelet Modeling

<b>RBF</b>	Radial Basis Function	<b>QMF</b>	Quadrature Mirror Filters
<b>SBP</b>	Systolic Blood Pressure	<b>RBBB</b>	Right Bundle Branch Block
<b>SC</b>	Soft Computing	<b>RWE</b>	Relative Wavelet Energies
<b>SOM</b>	Self-Organizing Maps	<b>SVM</b>	Support Vector Machines
<b>TP</b>	True Positives	<b>SVPB</b>	Supraventricular Premature Beats
<b>VF</b>	Ventricular Flutter	<b>VEB</b>	Ventricular Escape Beat
<b>WBF</b>	Wavelet Basis Function	<b>WCN</b>	Wavelet Classification Network
<b>WP</b>	Wavelet Package	<b>WRN</b>	Wavelet Regression Network
<b>WT</b>	Wavelet Transform	<b>WSM</b>	Wavelet Scale Maxima

