

KIDNEY ABNORMALITY DETECTION AND CLASSIFICATION USING
ULTRASOUND VECTOR GRAPHIC IMAGE ANALYSIS

WAN MAHANI HAFIZAH BINTI WAN MAHMUD

UNIVERSITI TEKNOLOGI MALAYSIA

KIDNEY ABNORMALITY DETECTION AND CLASSIFICATION USING
ULTRASOUND VECTOR GRAPHIC IMAGE ANALYSIS

WAN MAHANI HAFIZAH BINTI WAN MAHMUD

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy (Biomedical Engineering)

Faculty of Biosciences and Medical Engineering
Universiti Teknologi Malaysia

JULY 2013

Dedicated to

Mak (Fatimah binti Haron) & **Where** (Wan Mahmud bin Wan Idris),
Beloved siblings, relatives, and friends

ACKNOWLEDGEMENT

All praise to Allah, the Almighty, the Benevolent for His blessings and guidance to me and bestowing upon me wisdom, ideas and strength to successfully complete this PhD thesis.

I would like to express my very special thank to my supervisor, Professor Dr. –Ing Eko Supriyanto for his guidance and contribution of time, ideas and energy in making my PhD experience productive and stimulating. The enthusiasm he has as an academia is motivational for me even during the tough time in this PhD pursuit. I am thankful to him for an excellent example he has provided throughout my study period.

Most prominently, I would like to extend my warmest gratitude to my beloved parents and siblings for their precious support, patience and assurance throughout my education in Universiti Teknologi Malaysia (UTM). They always being my stand all through the period of my education, and I will always be appreciative for their never-ending love, sacrifice and generosity. Special thanks to all my fellow friends, especially Diagnostics-RG members and all of those who supported me in any respect during the completion of the project.

ABSTRACT

Ultrasound imaging has been widely used in kidney diagnosis, especially to estimate kidney size, shape and position, and to provide information about kidney function, and to help in diagnosis of structural abnormalities like cysts, stone, and infection. However, the use of ultrasound in kidney diagnosis is operator dependent where the images may be interpreted differently depending on operators' skills and experiences, variations in human perceptions of the images, and differences in features used in diagnosis. Current kidney diagnosis may be improved by implementing automated techniques and computer aided diagnosis systems, but have not been widely explored. Therefore, this study proposed a vector graphic image formation method which enables the ultrasound images to be manipulated for various applications including region of interest (ROI) generation, cysts detection and segmentation and abnormality classification. Automatic kidney ROI generation algorithm able to achieve 89.6% true ROI when tested with 125 kidney images. Besides that, the vector graphic formation helps in detection and segmentation of cysts automatically with high accuracy (true positive area ratio = 0.9584, similarity index = 0.9439, Hausdorff distance = 11.4018) and less execution time (11.4 seconds). Performance evaluation to 50 single cyst images, and 25 multiple cysts images gave accuracy of 92%, and 86.89% respectively. This vector graphic formation also helps in extracting better features that successfully classify kidney ultrasound images into three different groups namely normal, infectious and cystic with testing and validation accuracy of 93.33% and 91.67% respectively ($p < 0.05$). Overall, this study has shown promising results and implementation of these proposed algorithms into current kidney diagnosis technique may help in improving current diagnosis accuracy while reducing human intervention and operator dependency.

ABSTRAK

Pengimejan ultrabunyi telahpun digunakan secara meluas dalam diagnosis ginjal, terutamanya untuk menganggar saiz, bentuk dan kedudukan ginjal, mendapatkan maklumat tentang fungsi ginjal dan membantu mengesan struktur abnormal seperti *cysts*, batu karang dan jangkitan. Namun begitu, penggunaan ultrabunyi dalam diagnosis ginjal sangat bergantung kepada pengendali mesin, dimana imej ginjal akan ditafsirkan secara berlainan bergantung kepada kebolehan dan pengalaman pengendali, kepelbagaian dalam persepsi individu terhadap imej tersebut, dan perbezaan ciri yang digunakan untuk diagnosis. Diagnosis ginjal ini boleh diperbaiki dengan menggunakan teknik automatik dan sistem pengesanan berkomputer. Walau bagaimanapun, teknik ini masih belum dikaji dengan meluas. Justeru, kajian ini mencadangkan kaedah pembentukan imej grafik vektor (*vector graphic image formation*), yang membolehkan imej ultrabunyi dimanipulasikan untuk pelbagai kegunaan termasuk penjanaan rantau berkepentingan (ROI), pengesanan *cysts* dan pengelasan penyakit. Pengujian algoritma ROI secara automatik ke atas 125 imej ginjal menunjukkan ianya mampu mencapai 89.6% ketepatan ROI sebenar. Selain itu, pembentukan imej grafik vektor membantu mengesan dan mengasing *cysts* dengan ketepatan yang tinggi (nisbah kawasan positif = 0.9584, indeks kesamaan = 0.9439, jarak Hausdorff = 11.4018) dan masa yang singkat (11.4 saat). Penilaian prestasi terhadap 50 imej *cyst* tunggal dan 25 imej pelbagai *cysts* memberi ketepatan sebanyak 92% dan 86.89% setiap satunya. Pembentukan imej grafik vektor juga membantu mengekstrak ciri yang lebih baik dan berjaya mengelaskan imej ultrabunyi kepada tiga kumpulan, iaitu normal, jangkitan dan *cystic* dengan ketepatan pengujian dan penentusahihan (*validation*) sebanyak 93.33% dan 91.67% setiap satunya ($p < 0.05$). Secara keseluruhan, kajian ini telah menunjukkan keputusan yang baik, dan pelaksanaan algoritma ini dalam diagnosis ginjal dapat memperbaiki ketepatan pengesanan sedia ada, selain mengurangkan campur tangan manusia dan kebergantungan terhadap pengendali.

TABLE OF CONTENTS

CHAPTER	TITLE	PAGE
	DECLARATION	ii
	DEDICATION	iii
	ACKNOWLEDGEMENT	iv
	ABSTRACT	v
	ABSTRAK	vi
	TABLE OF CONTENTS	vii
	LIST OF TABLES	xi
	LIST OF FIGURES	xiii
	LIST OF ABBREVIATIONS	xviii
	LIST OF SYMBOLS	xx
	LIST OF APPENDICES	xxiii
1	INTRODUCTION	1
	1.1 Research Background	1
	1.2 Problem Statement	4
	1.3 Objectives	4
	1.4 Scope of Research	5
	1.5 Thesis Organization	6
	1.6 Contribution of Research	6
2	LITERATURE REVIEW	8
	2.1 Anatomy of Normal Kidney	8
	2.2 Review of Kidney Test and Diagnosis Techniques	9
	2.2.1 Blood Test	10

2.2.2	Urine Test	12
2.2.3	Kidney Biopsy	13
2.2.4	Imaging Tests	14
2.3	Ultrasound Imaging for Kidney Diagnosis	16
2.3.1	Review of Ultrasound	17
2.3.2	Kidney Risks, Abnormalities and Diseases	20
2.3.3	Ultrasound Image Features	27
2.3.4	Kidney Ultrasound Diagnosis: Variation and Misdiagnosis	29
2.4	Kidney Ultrasound Image Processing and Analysis	32
2.4.1	Image Enhancement and Speckle Reduction	33
2.4.2	Image Segmentation	34
2.4.3	Vector Graphic Image	37
2.4.4	Automatic Kidney Region of Interest Generation	41
2.4.5	Feature Extraction of Kidney US Images	42
2.4.6	Computer Aided Diagnosis (CAD)	43
2.5	Artificial Neural Network (ANN)	46
2.6	Summary	48
3	EXPERIMENTAL DESIGN AND IMPLEMENTATION	50
3.1	Introduction	50
3.2	Data Acquisition	52
3.3	Vector Graphic Image Formation	54
3.4	Automatic Region of Interest Generation of Kidney Ultrasound Images	63
3.4.1	Seed Region Selection	65
3.4.2	Active Contour Rough Segmentation	67
3.5	Automatic Detection and Segmentation of Kidney Cysts in Ultrasound Images	68

3.6	Feature Extraction, Selection and Kidney Ultrasound Image Classification	72
3.6.1	Image Pre-Processing	74
3.6.2	Feature Extraction	77
3.6.3	Feature Selection	81
3.6.4	Image Classification	81
4	RESULT AND DISCUSSION	86
4.1	Introduction	86
4.2	Vector Graphic Image Formation	86
4.2.1	Parameter Optimization	89
4.3	Experiment Result of Automatic Kidney ROI Generation	92
4.4	Experiment Result of Automatic Detection and Segmentation of Kidney Cysts	95
4.4.1	Evaluation Metrics	98
4.4.2	Comparison with Other Segmentation Methods	100
4.4.3	Multiple Cysts Detection	104
4.4.4	Statistical Tests	106
4.4.5	Sensitivity Analysis	111
4.4.6	Limitations	113
4.5	Experiment Result of Feature Extraction, Selection and ANN-based Classification	114
4.5.1	Result of Feature Extraction	115
4.5.2	Feature Selection	118
4.5.3	ANN-based Classification	119
4.6	Summary	124
4.6.1	Usefulness Index	126
5	CONCLUSION AND RECOMMENDATION	128
5.1	Conclusion	128
5.2	Recommendation	130

REFERENCES

133

Appendices A – E

148-176

LIST OF TABLES

TABLE NO.	TITLE	PAGE
2.1	Classification of CKD	11
2.2	Kidney diseases affecting kidney size	21
2.3	Comparison of detection of renal stones using ultrasound and CT	30
2.4	The interrater reliability for antenatal hydronephrosis diagnosis of 50 anteroposterior renal pelvis diameter measurements [174]	31
2.5	Summary of segmentation approach for kidney ultrasound images	36
2.6	Comparison of available vector graphic software	39
2.7	Performance levels of CAD schemes for differential diagnosis	44
2.8	Tests for Kidney Diagnosis	48
3.1	MSE and PSNR value of three different filters applied to kidney ultrasound images	59
3.2	ANN data sampling	83
4.1	Vector graphic image of different values of N_{color} and respective execution time	91
4.2	Validation of automatic ROI generation	94
4.3	Comparison of error metrics of the active contour method by Chan and Vese [168], level set method by Li et al. [170], and the proposed method	103
4.4	Comparison of time complexity of the Active Contour method [168], Level-Set method [170], and the	

	proposed method	103
4.5	Determination of TP, FP, FN and TN during cysts detection	106
4.6	Performance evaluation of developed algorithm for single cyst detection	108
4.7	Algorithm testing to 25 multicysts kidney images	110
4.8	Summary findings of N_{color} and R value for detection of cysts in different organs	113
4.9	Manual assessment of three image classes (NR, BI and CD) by experts	115
4.10	Mean and standard deviation value of all features for three classes of kidney ultrasound images	116
4.11	Student t-test results for NR, BI and CD	118
4.12	Classification result of the neural network using significant features	124
4.13	Classification result of the neural network using vector graphic features	124

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
2.1	Anatomy structure of a normal kidney	9
2.2	Healthy and damaged kidney during albumin filtration	12
2.3	Real time kidney biopsy using ultrasound	13
2.4	Kidney images of (a) IVP, (b) CT, (c) MRI, and (d) Ultrasound	15
2.5	Measurement of kidney length (A), width (B) as well as volume (C) using Toshiba Aplio MX ultrasound machine	16
2.6	Doppler ultrasound showing normal resistive index	17
2.7	Frequency of sound waves for ultrasound system (adapted from [49])	18
2.8	Nomenclature related to ultrasound resolution	19
2.9	An example of ectopic kidney (arrow); smaller in size and abnormally rotated [68]	22
2.10	Example of ADPKD [18]; (a) Illustration of polycystic kidney, (b) White line shows US calipers used for measuring purpose (cyst and size) while black line shows some of the cysts detected	23
2.11	An example of mutiple cysts image, with clear visualization of cysts, renal pyramids as well as calyces	25
2.12	Example of acute pyelonephritis kidney image [73]. Left image is 2-dimensional image while right image is Doppler ultrasound image. Yellow arrows in both left and right images show the infected area.	

	For Doppler US image, red and blue colors indicate the blood flow of the area where blue is when the blood flow away from the transducer while red is when the blood flow towards the transducer.	26
2.13	Ultrasound image of kidney with stones. White arrow shows the kidney stone	27
2.14	A normal kidney ultrasound images	28
2.15	Example of vector graphic transformation using market software (a), (c), (e) and (g) Original bitmap image (b) Vectorization using Adobe Illustrator [154], (d) Vectorization using CorelDRAW [155] (f) Vectorization using Vector Magic [113], and (h) Vectorization using AutoTrace [140]	40
2.16	An overall system for breast cancer screening using ultrasound images, consists of an ultrasound imaging device, a whole-breast scanning device and CAD system [162]	45
2.17	Basic diagram of an artificial neural network with one input layer, 2 hidden layers and one output layer. The hidden layers employ a sigmoid and linear transfer function to adjust weight (W) and biases (b) [132]	47
3.1	Workflow design for the study	51
3.2	Sample US images of (a) Normal kidney, (b) Abnormal kidney with infection, and (c) Abnormal kidney with cysts	53
3.3	Flowchart of vector graphic image formation	54
3.4	Formation of vector graphic image with different value of N_{color}	55
3.5	RGB Color Cube for uint8 Images [63]	56
3.6	Minimum variance quantization on a slice of the RGB color cube [63]	57
3.7	Kidney ultrasound, (a) Original image, (b) Wavelet filtering output, (c) Median filtering output, and (d) Wiener filtering output	59
3.8	3 layers of black and white image for $N_{color} = 3$, (a) Layer 1, (b) Layer 2, (c) Layer 3	60

3.9	Shapes plotting of $P = [0; 0; 1; 1]$, $T = [0; 1; 1; 0]$, and $C = 1$	62
3.10	Vector graphic image of kidney ultrasound using $N_{color} = 3$	62
3.11	Flowchart for automatic region of interest generation	63
3.12	Ultrasound Image of (a) normal kidney. Normal kidney always have clear and separate regions of sinus and cortex (b) cystic kidney. Appearance of cyst in kidney leads to unclear separate regions of sinus and cortex	64
3.13	(a) Black and white image after thresholding, (b) output of filtered image that intersect with center window	65
3.14	(a) Image with two remaining regions (region 1 and region 2), (b) region 1 was selected as winning region, (c) Image with three remaining regions (region 1, region 2, and region 3), (b) region 1 was selected as winning region	67
3.15	Kidney ultrasound image with, (a) single cyst, and (b) multiple cysts	69
3.16	Steps for kidney cysts automatic detection and segmentation	70
3.17	Roundness test for both kidney ultrasound image of single and multiple cysts	72
3.18	Steps for kidney ultrasound image classification	73
3.19	Edge detection of kidney in ultrasound image (black contour)	74
3.20	Rotation to zero degree (a) Orientation before rotation, (b) Position of Y_{min} , Y_{max} , X_{min} and X_{max} , (c) Orientation after rotation	75
3.21	Image rotation to zero degree	75
3.22	Output image after cropping	76
3.23	An image with removed background	76
3.24	Development of GLCM from input, I image, with	

	different orientation (0° , 45° , 90° , and 135°) ; adapted from [63]	78
3.25	Kidney vector graphic images for different class (NR, BI and CD) for different value of N_{color} (1,2,3,4,5)	80
3.26	Overall ANN development process	82
4.1	(a) Input image of real kidney, (b) Input image of kidney ultrasound, (c) Output image of (a) after vectorization using Vector Magic, (d) Output image of (b) after vectorization using Vector Magic, (e) Output image of (a) after vectorization using proposed algorithm, and (f) Output image of (b) after vectorization using proposed algorithm	88
4.2	Vector graphic image of different value of N_{color} ($N_{color} = 1$ to $N_{color} = 12$)	90
4.3	(a) Input and (b) Vector graphic image with $N_{color} = 3$, (c) Winning seed region, (d) Active contour rough segmentation result, and (e) Output image of automatic region of interest generation	93
4.4	Example of false positive ROI generation	94
4.5	Kidney images with manually detected cysts boundary by group of experts for (a) single cyst, and (b) multiple cysts	96
4.6	(a) Input image of kidney with single cyst, (b) vector graphic image, (c) Image after binarization, (d) Image after filtering, (e) Cyst detection and segmentation	97
4.7	Areas of TP, FP and FN in image with manual and automatic contours	99
4.8	Segmentation result of (a) manual contour by sonographer, (b) proposed method, (c) active contour method by Chan and Vese [168], (d) level-set method by Li et al. [170]	102
4.9	(a) Input image of kidney with multiple cysts, (b) vector graphic image, (c) Image after binarization, (d) Image after filtering, and (e) Cyst detection and segmentation	105
4.10	Example of mutiple cysts kidney images; (a) Cyst	

	detection by experts (white borders), (b) Cyst detection by developed algorithm (red borders), with true positive cyst regions (red), false negative cyst region (yellow) and false positive cyst region (blue) (TP = 8, FP = 1, and FN = 1)	109
4.11	(a) Input, and (b) output image of segmentation of liver cyst ($R = 0.55$)	112
4.12	(a) Input and (b) output images of segmentation of thyroid cyst ($R = 0.61$)	112
4.13	(a) Input and (b) output images of segmentation of multiple cysts in ovary ($0.55 \leq R \leq 1$)	112
4.14	Output image of multile cysts kidney with unsuccessful (yellow circle) and wrong (blue circle) detection of cysts.	114
4.15	Mean value for three classes of kidney ultrasound images for (a) Intensity histogram features, (b) GLCM features, and (c) Vector graphic features	117
4.16	MSE and testing performance for different neuron number in the hidden layer	120
4.17	MSE and testing performance for different value of learning rate	121
4.18	MSE and testing performance for different value of iteration rate	122
4.19	MSE and testing performance for different value of momentum constant	123

LIST OF ABBREVIATIONS

3D	-	Three dimensional
AC	-	Active contour
ADPKD	-	Autosomal dominant polycystic kidney disease
AI	-	Adobe Illustrator
ANN	-	Artificial neural network
ARPKD	-	Autosomal recessive polycystic kidney disease
BI	-	Bacterial Infection
BUN	-	Blood urea nitrogen
CAD	-	Computer aided diagnosis
CBIR	-	Content-based image retrieval
CC	-	Cortical cyst
CD	-	Cystic disease
CKD	-	Chronic kidney disease
CT	-	Computed tomography
DICOM	-	Digital imaging and communication in medicine
ESRD	-	End stage renal disease
FBME	-	Faculty of Biosciences and Medical Engineering
FN	-	False negative
FP	-	False Positive
GFR	-	Glomerular filtration rate
GLCM	-	Gray level co-occurrence matrix
GUI	-	Graphical user interface
HD	-	Hausdorff distance
IVP	-	Intravenous pyelogram
MDRD	-	Modification of diet in renal disease
MLP	-	Multilayer perception

MRD	-	Medical renal disease
MRI	-	Magnetic resonance imaging
MRF	-	Markov random field
MSE	-	Mean squared error
NR	-	Normal
PCA	-	Principal component analysis
PDF	-	Portable document format
PSNR	-	Peak signal to noise ratio
RGB	-	RGB image
RI	-	Resistive index
ROC	-	Receiver operating characteristic
ROI	-	Region of interest
RRT	-	Renal replacement therapy
SI	-	Similarity index
SPL	-	Spatial pulse length
SVG	-	Support vector graphics
SVM	-	Support vector machine
TP	-	True positive
US	-	Ultrasound
VBA	-	Visual basic for application
VUR	-	Vesicoulateral reflux
WV	-	Weight vector

LIST OF SYMBOLS

A	-	Area
A_m	-	Pixel set of manual outline
A_a	-	Pixel set of automatic outline
A_z	-	Average ROC curve area
b	-	Biases
BW	-	Body weight
cm	-	Centimeter
C_n	-	Contrast
Cr	-	Correlation
dB	-	Decibel
dl	-	Deciliter
$d(p_i, Q)$	-	Shortest distance of p_i to contour Q
E	-	Energy
EQ	-	Equality test
F	-	Number of cycle
$GLCM(i,j)$	-	GLCM image
gm	-	Gram
H	-	Homogeneity
I_{IN}	-	Input image
$I_{LAYERED}(i)$	-	Layered image
I_{ORI}	-	Original image
I_{VG}	-	Vector graphic image
$I_{WF}(i,j)$	-	Wiener filtered image
kHz	-	Kilohertz
$K(m,n)$	-	Kurtosis
m	-	Meter

MAP	-	Array
mg	-	Milligram
MHz	-	Megahertz
min	-	Minute
ml	-	Milliliter
n	-	Number of bits
MN	-	Size of image
N_{color}	-	Number of colors
N_{pixel}	-	Number of pixel
N_R	-	Number of pixel in region
N_{shape}	-	Number of shape
p	-	Perimeter
R	-	Roundness test
R_{rank}	-	Region rank
$\$$	-	US Dollar
S_{cr}	-	Serum creatinine
$S(m,n)$	-	Skewness
T_C	-	Threshold
T_T	-	Threshold
$u(i,j)$	-	Discrete image
v	-	Speed
v^2	-	Noise variance
$VG2R$	-	Vector graphic ratio in 2 nd layer
$VG3R$	-	Vector graphic ratio in 3 rd layer
$VG4R$	-	Vector graphic ratio in 4 th layer
w	-	Weight
$x(i,j)$	-	Original image
X_{max}	-	Maximum value of X
X_{min}	-	Minimum value of X
$y(i,j)$	-	Output Image
Y_{max}	-	Maximum value of Y
Y_{min}	-	Minimum value of Y
z	-	Axial resolution

μ	-	Local mean
$\mu(m,n)$	-	Mean
σ^2	-	Local variance
$\sigma^2(m,n)$	-	Variance
θ^0	-	Angle
λ	-	Wavelength

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
A	Data, Machines and Operators	148
B	Ultrasound Scanning Procedure	151
C	Source Code for Image Segmentation	169
D	Gantt Chart	174
E	List of Publications	175

CHAPTER 1

INTRODUCTION

1.1 Research Background

Nowadays, kidney diseases have become more common than ever, and are rising throughout the world, especially due to the complication of hypertension and type 2 diabetes mellitus [1]. Diseases in kidney may progress to the end stage renal disease (ESRD) which leads to the need of renal replacement therapy (RRT) and hemodialysis, as well as kidney transplants [1]. In Malaysia only, according to 19th Report of the Malaysian Dialysis and Transplant Registry, newly registered dialysis patients continue to increase, from 2375 in 2002 to 5153 in 2010, and at least 5201 in 2011 [2]. Treatments of the diseases are life saving, but demands a long term commitment at a very high cost. Therefore, other than focusing on the treatment itself, early prevention and detection; including urine test, blood test and imaging test of kidney diseases should become a priority. Early detection of kidney diseases allows a more effective and suitable treatment to the patient [3]. In most cases, patients with early stage of kidney disease can receive treatment that can delay or even prevent kidney damage. In addition, early treatment can also prevent many of heart and vascular conditions, which may complicate kidney disease [4]. Besides that, early detection of kidney disease can avoid further unnecessary biopsy and therapy sessions [5, 6].

Currently, there are several types of tests that can be used to diagnose kidney disease. Kidney function can be assessed by performing blood and urine tests.

Blood test is performed to check on the level of the waste product of blood urea nitrogen (BUN) [7] and creatinine [8, 9] while urine tests is performed to measure the level of certain substances in the urine, such as protein [10, 11], glucose, ketones, blood, and other substances. Excessive amount of waste product in blood and related substance in urine indicate that the percentage of kidney function has reduced [7-11]. Besides that, in order to diagnose any disorders that affect the specialized blood vessels of the kidney, kidney biopsy, a procedure for sampling a small portion of kidney tissue, is performed. In addition, imaging tests including ultrasound [16-19], intravenous pyelogram (IVP), computed tomography (CT) [12-15] and magnetic resonance imaging (MRI) [23] scans are performed to get useful information about kidney size, shape and structures.

Among all imaging techniques, the conventional ultrasound is more preferred to be used in the diagnosis and follow-up of patients with kidney diseases [19]. Ultrasound is more affordable compared to the use of MRI technique, besides being widely available, noninvasive, painless, does not require any contrast agent as being used in IVP and does not expose the patient to any radiation compared to using CT scan [16-19]. Diagnostic capability of ultrasound is based on sound waves that travel along the organ and structures, reflected back and appear in a range of hypoechoic to hyperechoic depending on the organ and structure composition [19]. Ultrasound can act as an excellent way to estimate kidney size, shape and position. Ultrasound can provide information about the kidney function, and help in diagnosis of structural abnormalities like cysts, stones, tumors, abscesses, obstructions, fluid collection, or infection within or around kidneys [19-21]. Besides that, the use of Doppler ultrasound may improve sonographic assessment of kidney dysfunction in relation to changes of kidney blood flow [22].

However, the use of ultrasound in current kidney diagnosis also has limitations. A major drawback of this ultrasonography in kidney diagnosis is that this method is very operator dependant [24-30], in terms of locating, measuring, and analyzing the images. Kidney diagnosis using ultrasound depends on the operator skills to locate the kidney in correct position, especially during the measurement of kidney size, or else the measurement would not be accurate. Besides that, the

diagnosis also requires well trained and experienced operator/ sonographers in analyzing and interpreting the images, especially when dealing with diseases, as compared to normal kidney, as the kidney with diseases may develop various symptoms and changes in the images [19]. An ultrasound image of kidney may be interpreted differently by different operators and the result is relative to the operator expertise, variations in human perceptions of the images, as well as differences in features used in diagnosis. Other imaging modalities such as CT and MRI allow the radiologists to get and view the stack of images of desired organs in different planes, while patient just lay still on the bed. On the other hand, this US technique requires the operator himself to angle and position the transducer on patients' body in correct position. Different position and angle of the transducer gives different output images thus interpretation of the images will differ. Another limitation is that the ultrasound image itself are affected by the speckle noise with variations of gray level intensities, and the presence of this noise makes analysis of ultrasound images, including locating, measuring, detecting and segmenting of desired structure or parameters become more complex and challenging [24, 30].

Concerning the limited capabilities of ultrasound in kidney diagnosis as mentioned earlier, it is important to develop some alternative approaches to the current system which perhaps can help medical doctors to do an accurate and effective kidney diagnosis. Computerized method, such as computer aided diagnosis (CAD) system can help in minimizing the dependency of the diagnosis on operators, as well as can make the diagnosis become easily reproducible without or with limited variation in result. Development of automatic system in locating, detecting and analyzing the required images can also be alternative solutions to the stated limitations. Therefore, this study will concentrate on improving the current kidney diagnosis method by implementing certain image processing and analysis methods, preferably utilizing algorithm that can performed automatically, which then can be implemented into any computer aided diagnosis (CAD) system for better kidney assessment and classification. However, it should be noted that the research into the use of automatic system or CAD is not toward eliminating the operators themselves, but much more toward providing the operators/ sonographers/ medical experts a second opinion and help them to increase the diagnosis accuracy, reduce the use of

other imaging modalities that could be harmful, avoid unnecessary biopsy, and save them time and effort.

1.2 Problem Statement

Ultrasound is often the initial imaging tool used because it can be performed comfortably and safely even when the kidney function is impaired. However, the role of ultrasonography in kidney diseases detection and classification is limited by its dependencies on the expertise of the operators or sonographers to detect, measure, segment and analyze structure of kidney during diagnosis. The use of ultrasound requires the operators to angle and position the transducer correctly to get better view of kidney. Besides that, the ultrasound images may be interpreted differently by different operators and the result is relative to the operators' skills and expertise, variations in human perceptions of the images, as well as differences in features used in diagnosis. Not to mention the limitation in the quality of ultrasound image itself due to the speckle noise. This restriction prevents ultrasonography from taking a prominent role in kidney diagnosis. Hence, this study aims to help and improve the existing ultrasonography for detecting, analysing and classifying the kidney risk by proposing some new approaches on kidney image analysis based on ultrasound image features.

1.3 Objectives

There are few objectives for this research study, including:

1. To develop an algorithm for vector graphic image formation from ultrasound images.
2. To develop new algorithm for automatic region of interest (ROI) generation of kidney images.
3. To develop new algorithm for automatic detection and segmentation of cysts in kidney ultrasound images.

4. To develop new features extraction technique for kidney ultrasound images, and evaluate the experimental result by using artificial neural network for kidney risk classification.

1.4 Scope of Research

Few scopes have been set so that the study is conducted within and heading toward the objectives. This project focuses on the kidney ultrasound images (details of images, machines and operators are in Appendix A) where;

1. For the development and analysis of automatic ROI generation of kidney ultrasound images, normal kidney ultrasound images were collected from the Faculty of Biosciences and Medical Engineering (FBME), UTM Johor Bahru by using Toshiba Aplio MX machine with 3.5MHz transducer.
2. For the development of automatic kidney cysts detection as well as analysis of the kidney ultrasound image features, images were taken from patients at Gelderse Vallei Hospital, Ede, The Netherlands and the diagnosis was made by experts by using ultrasound machine Hitachi Aloka Prosound F75 with transducer 3.5MHz.
3. For automatic detection and segmentation of kidney cysts, only cystic (CD) class of images was used, and for feature extraction and classification, all three classes were used (normal (NR), infectious (BI) and cystic (CD)),
4. Kidney images with multiple diseases (kidney with both CD and BI) were excluded to avoid any similar information between groups.
5. The kidney ultrasound images used in this study were in DICOM (Digital Imaging and Communications in Medicine) format and all necessary care had been taken to preserve the quality of the images.
6. All image processing, and analysis methods applied to the kidney ultrasound images were implemented in MATLAB.

1.5 Thesis Organization

This thesis is divided into five major chapters. Chapter 1 includes an introduction, background, objectives and scope of research. The main purpose is to show the motivation of this research and existing limitations of diagnosing kidney using ultrasound imaging. The chapter is summarized with the novelties and contribution of this thesis and its feasibility. Chapter 2 describes this thesis in terms of its background, history and the related works in greater detail. The focus is on the introduction to kidney, reviews on kidney diagnosis, ultrasound in kidney diagnosis, ultrasound image features, as well as kidney ultrasound image processing. Chapter 3 describes the experimental design and implementation including the research materials, data sources acquisitions and manipulation, image processing and analysis, kidney feature extraction and risk classification. Chapter 4 looks into the results and discussion on the proposed methods, with thorough analysis and validation. Lastly, Chapter 5 provides the conclusion for the system testing and evaluation. It also gives some recommendations for further improvement of the system.

1.6 Contribution of Thesis

Generally, some new improvements have been proposed to help sonographers in performing better and more accurate diagnosis of kidneys using ultrasound. The implementation of image processing techniques had been explored, together with the analysis and validation of proposed ideas. The contributions of the thesis are;

1. Development of a new vector graphic formation or image vectorization method. Degradation of ultrasound image by speckle noise can complicate the analysis (detection, segmentation, classification, etc.) of the image during diagnosis, as well as restricting the image to be analyzed visually. Important features may not be extracted due to this condition. Development of this method, enables the user to manipulate the images thus helping the user to extract desired features for required objectives.

2. Development of a new algorithm for automatic generation of region of interest (ROI) of the kidney. To the best knowledge of the author, there are no other automatic algorithms available for kidney ultrasound images. This proposed algorithm can be implemented in real time ultrasonography and help sonographer in locating the correct position of the kidney. Besides that, this algorithm can also be used as a pre-processing method before performing further analysis of the images such as segmentation of the kidney.
3. Development of a new approach of automatic detection and segmentation of kidney cyst in ultrasound images, and the result has been fairly compared with other segmentation methods available. Not only it is automatic, this algorithm can also be used to analyze images with multiple cysts, as well as ultrasound image of other cystic organs. Tested of the algorithm to both single and multiple cysts images also gave high accuracy. Compared to other available methods, this method is able to be executed in a very quick time with high accuracy.
4. Development of new algorithm for feature extraction of kidney ultrasound images based on vector graphic image formation. The kidney ultrasound images are classified into three classes (normal, infectious and cystic) using artificial neural network (ANN) which gives a better accuracy compared to using other commonly used features.

This study is strictly technical, and its emphasis was influenced by the opinions of clinical collaborators. Improvements proposed in this study for the purpose of kidney abnormalities detection and classification can reduce manual measurement, improve consistency, reduce human intervention and operator dependency, avoid competency factor and human errors, while producing reliably meaningful images and measurement, so as to support future studies in a clinical setting.

REFERENCES

1. Dirks, J., Remuzzi, G., Horton, S., Schieppati, A. and Hasan Rizvi, S. A. Diseases of the Kidney and the Urinary System. In: Jamison, D. T., Breman, J. G., Measham, A. R., Alleyne, G., Claeson, M., Evans, D. B., Jha, P., Mills, A. and Musgrove P. eds. *Disease Control Priorities in Developing Countries*. New York: Oxford University Press. 695-706; 2006.
2. Ngo, L. Y., Meng, O. L., Leong, G. B., and Guat, L. D. All renal replacement therapy in Malaysia. *The 19th Report of the Malaysian Dialysis and Transplant Registry*. 2011.
3. Hostetter, T. H. The Importance of Being Tested for Kidney Disease. *Kidney Beginnings: The Magazine*. 2004. 3(1).
4. Hostetter, T. H. Chronic Kidney Disease Predicts Cardiovascular Disease. *New England Journal of Medicine*. 2004. 351(13): 1344–1346.
5. O'Neill, W. C. Chronic renal failure. In: O'Neill W. C. ed. *Atlas of renal ultrasonography*. Philadelphia: W. B. Saunders Company. 41-43; 2001.
6. O'Neill, W. C. Sonographic evaluation of renal failure. *American Journal of Kidney Disease*. 2000. 35:1021-1038.
7. Nolan, B. G., Ross, L. A., Vaccaro, D. E., Groman, E. V. and Reinhardt, C. P. Estimation of glomerular filtration rate in dogs by plasma clearance of gadolinium diethylenetriamine pentaacetic acid as measured by use of an ELISA. *American Journal of Vet Res*. 2009. 70(4): 547-552.
8. Cockcroft, D. W. and Gault, M. H. Prediction of creatinine clearance from serum creatinine. *Nephron*. 1976. 16(1): 31–41.
9. Levey, A. S., Coresh, J., Greene, T., Marsh, J., Stevens, L. A., Kusek, J. W. and Van Lente, F. Expressing the modification of diet in renal disease study equation for estimating glomerular filtration rate with standardized serum creatinine values. *Clinical Chemistry*. 2007. 53: 766–772.

10. Hillege, H. L., Fidler, V., Diercks, G. F., van Gilst, W. H., de Zeeuw, D., van Veldhuisen, D. J., Gans, R.O., Janssen, W. M., Grobbee, D. E. and de Jong, P. E. Urinary albumin excretion predicts cardiovascular and noncardiovascular mortality in general population. *Circulation*. 2002. 106(14): 1777–1782.
11. Tesch, G. H. Review: Serum and urine biomarkers of kidney disease: A pathophysiological perspective. *Nephrology*. 2010. 15(6): 609-616.
12. Smith, R. C. and Coll, D. M. Helical computed tomography in the diagnosis of ureteric colic. *BJU Int*. 2000. 86 (1): 33–41.
13. John, R. Radiological diagnosis of kidney stones, *Nephrology*, 2007. 12: 34-36.
14. Kang, K. Y., Lee, Y. J., Park, S. C., Yang, C. W., Kim, Y. S., Moon, I. S. Koh, Y. B., Bang, B. K. and Choi, B. S. A comparative study of methods of estimating kidney length in kidney transplantation donors, *Nephrol Dial Transplant*. 2007. 22: 2322–2327.
15. Glodny, B., Unterholzner, V., Taferner, B., Hofmann, K. J., Rehder, P., Strasak, A. and Petersen, J. Normal kidney size and its influencing factors - a 64-slice MDCT study of 1,040 asymptomatic patients, *BMC Urology*. 2009. 9:19.
16. Hagen-Ansert, S. Urinary system. In: Hagen-Ansert, S. ed. *Textbook of Diagnostic Ultrasound*. St. Louis, MO: Mosby. 893–913; 1995.
17. Pollack, H. M. and McClennan, B. L. In: Pollack, H. M., McLennan, B. L., Dyer, R, et al., eds. *Clinical urography*. Philadelphia: Saunders. 826-831; 2000.
18. Jadranka, B. P. and Alenka V. P. Ultrasonography in chronic renal failure, *European Journal of Radiology*. 2003. 46: 115-122.
19. Gheissari, A. The Place of Ultrasound in Renal Medicine. *Saudi Journal of Kidney Diseases and Transplantation*. 2006. 17(4):540-548.
20. Thurston, W. and Wilson, S. R. The Urinary Tract. In: Rumack, C. M., Wilson, S. R. and Charboneau, J. W. eds. *Diagnostic Ultrasound*. China: Elsevier Mosby. 321-393; 2005.
21. Kabala, J. E. The Kidney and Ureters. In: Sutton, D. ed. *TextBook of Radiology and Imaging*. London: Churchill Livingstone. 929-987; 2003.

22. Oyuela-Carrasco J, Rodriguez-Castellanos F, Kimura E, et al. Renal length by ultrasound in Mexican adults. *Nefrologia*. 2009. 29(1): 30-34.
23. Bakker, J., Olree, M., Kaatee, R., de Lange, E. E., Moons, K. G., Beutler, J. J. and Beek, F. J. Renal Volume Measurement: Accuracy and Repeatability of US Compared with That of MRI Imaging. *Radiology*. 1999. 211(3): 623-628.
24. Dahdouh, S., Frenoux, E. and Osorio, A. Real time kidney ultrasound images segmentation: a prospective study, *Proc. of SPIE*. 2009. 7265: 1-9.
25. Martin-Fernandez, M. and Alberola-Lopez, C. An approach for contour detection of human kidneys from ultrasound images using Markov random fields and active contours. *Medical Image Analysis*. 2005. 9: 1-23.
26. Shrimali, V., Anand, R. S. and Kumar, V. Current trends in Segmentation of Medical Ultrasound B-Mode Images: A Review. *IETE Technical Review*. 2009. 26(1): 8-17.
27. Saini, K., Dewal, M. L. and Rohit, M. Ultrasound Imaging and Image Segmentation in the area of Ultrasound: A Review. *International Journal of Advanced Science and Technology*. 2010. 24: 41-60.
28. Noble, J. A. and Boukerroui, D. Ultrasound Image Segmentation: A Survey. *IEEE Transactions on Medical Imaging*. 2006. 25(8): 987-1010.
29. Martin-Fernandez, M. and Alberola-Lopez, C. A Bayesian Approach to *in vivo* Kidney Ultrasound Contour Detection Using Markov Random Fields. *MICCAI*. 2002. 397-404.
30. Kop, A. M. and Hegadi, R. Kidney Segmentation from Ultrasound Images using Gradient Vector Force. *IJCA Special Issue on Recent Trends in Image Processing and Pattern Recognition*. 2010. 104-109.
31. Hafizah, W. M. and Supriyanto, E. Automatic Generation of Region of Interest for Kidney Ultrasound Images Using Texture Analysis. *International Journal of Biology and Biomedical Engineering*. 2012. 6(1): 26-34.
32. Hekmatnia, A and Yaraghi, M. Sonographic measurement of absolute and relative renal length in healthy isfahani adults. *Journal of Research in Medical Sciences*. 2004. 2: 1-4.
33. Emamian, S. A., Nielsen, M. B., Pedersen, J. F. and Ytte, L. Kidney dimensions at sonography: correlation with age, sex, and habitus in 665 adult volunteers. *AJR Am J Roentgenol*. 1993. 160: 83-86.

34. Bircan, O., Oner, G., Saka, O., Ravasoglu, T. and Akaydin, M. The estimation of kidney sizes in Turkish population. *Journal of Islamic Academy of Sciences*. 1993. 6(3): 197-201.
35. Fernandes, M. M. R., Lemos, C. C. S., Lopes, G. S., Madeira, E. P. Q., Santos, O. R., Dorigo, D. and Bregman, R. Normal renal dimensions in a specific population. *International Braz J Urol*. 2002. 28 (6): 510-515.
36. Geelhoed, J. J. M., Taal, H. R., Steegers, E. A. P., Arends, L. R., Lequin, M., Moll, H. A., Hofman, A., van der Heijden, A. J. and Jaddoe, V. W. V. Kidney growth curves in healthy children from the third trimester of pregnancy until the age of two years. The Generation R Study. *Pediatr Nephrol*. 2010. 25: 289–298.
37. Finco, D. R. Kidney functions. In: Kaneko, J. J., Harvey, J. W. and Bruss, M. L. eds. *Clinical biochemistry of domestic animals*. New York: Academic Press Inc. 441; 1997.
38. Stevens, L. A. and Levey, A. S. Measurement of kidney function. *Med Clin North Am*. 2005. 89: 457-473.
39. Levey, A. S., Coresh, J., Balk, E., Kausz, A. T., Levin, A., Steffes, M. W., Hogg, R. J., Perrone, R. D., Lau, J. and Eknoyan, G. National Kidney Foundation Practice Guidelines for Chronic Kidney Disease: Evaluation, Classification, and Stratification. *Ann Intern Med*. 2003. 139: 137-147.
40. Sirwal, I. A., Banday, K. A., Reshi, A. R., Bhat, M. A. and Wani, M. M. Estimation of Glomerular Filtration Rate (GFR), *JK Science*, 2004. 6(3): 121-123.
41. Davies, D. F. and Shock, N. W. Age changes in glomerular filtration rate, effective renal plasma flow, and tubular excretory capacity in adult males. *J Clin Invest*. 1950. 29: 496-507.
42. Lindeman, R. D., Tobin, J. and Shock, N. W. Longitudinal studies on the rate of decline in renal function with age. *J Am Geriatr Soc*. 1985. 33: 278-85.
43. National Kidney Foundation. K/DOQI clinical practice guidelines for chronic kidney disease: evaluation, classification, and stratification. *American Journal of Kidney Diseases*. 2002. 39(1): S1–266.
44. Hull, J. H., Hak, L. J., Koch, G. G., Wargin, W. A., Chi, S. L. and Mattocks, A. M. Influence of range of renal function and liver disease on predictability of creatinine clearance. *Clin Pharmacol Ther*. 1981. 29: 516.

45. Jelliffe, R. W. Creatinine clearance: Bedside estimate (letter). *Ann Intern Med.* 1973. 79: 604.
46. Post, T. W. and Rose, B. D. Urinalysis in the diagnosis of renal disease. *Up To Date.* 2006. 13: 3.
47. Alev, K. Renal Measurements, Including Length, Parenchymal Thickness, and Medullary Pyramid Thickness, in Healthy Children: What Are the Normative Ultrasound Values?. *American Journal of Roentgenology.* 2010. 194: 509-515.
48. Platt, J. F. Doppler ultrasound of the kidney, *Semin Ultrasound CT MR.* 1997. 18(1): 22-32.
49. Tilakaratna P., Ultrasound Basics, in howequipmentworks.com.
50. Keogan, M., Kliewer, M., Hertzberg, B., DeLong, D. M., Tupler, R. H. and Carroll, B. A. Renal resistive indexes: variability in Doppler US measurement in a healthy population. *Radiology.* 1996. 199: 165–169.
51. Platt, J., Rubin, J., Ellis, J. and DiPietro, M. A. Duplex Doppler US of the kidney; differentiation of obstructive from nonobstructive dilatation. *Radiology.* 1989. 171: 515–517.
52. Friedland, G. W., Devries, P. A. and Nino-Murcia, M. Congenital anomalies of the urinary tract. In Pollak, H. M. ed. *Clinical Urography. An Atlas and Textbook of Urologic Imaging.* Philadelphia: WB Saunders. 559-787; 1990.
53. Hildebrandt, F., Jungers, P. and Grunfeld, J. P. Medullary cystic and medullary sponge renal disorders. In: Schrier, R. and Gottschalk, C. eds. *Diseases of the kidney.* Little Brown and Company (Inc). 499-520; 1997.
54. Israel, G. M. and Bosnia, M. A. Calcification in cystic renal masses: is it important in diagnosis? *Radiology.* 2003. 226: 47-52.
55. Krol, E., Rutkowski, B., Czarniak, P., Kraszewska, E., Lizakowski, S., Szubert, R., Czekalski, S., Sułowicz, W. and Więcek, A. Early Detection of Chronic Kidney Disease: Results of the PolNef Study. *American Journal of Nephrology.* 2008.
56. Kwon, T. W., Sung, K. B. and Kim, G. E. Experience of an abdominal aortic aneurysm in a patient having crossed ectopia with fusion anomaly of the kidney. *J Korean Med Sci.* 2004. 19: 309-310.
57. Lalli, A. F. Renal enlargement. *Radiology.* 1965. 84: 688-691.

58. Absy, M., Metreweli, C., Matthews, C. and Al Khader, A. Changes in transplanted kidney volume measured by ultrasound. *Br J Radiol.* 1987. 60(714): 525–529.
59. Dean, R. H., Kieffer, R. W., Smith, B. M., Oates, J. A., Nadeau, J. H. J., Hollifield, J. W. and DuPont, W. D. Renovascular hypertension Anatomic and renal function changes during drug therapy. *Arch Surg*, 1981. 116: 1408-1415.
60. McRae, C. U., Shannon, F. T. and Utley, W. L. F. Effect on renal growth of reimplantation of refluxing ureters. *Lancet.* 1974. 1:1310-1313.
61. Cheong, B., Muthupillai, R., Rubin, M. F., et al. Normal Values for Renal Length and Volume as Measured by Magnetic Resonance Imaging. *Clin J Am Soc Nephrol.* 2007. 2: 38 – 45.
62. Eknoyan, G., A Clinical View of Simple and Complex Renal Cysts, *J Am Soc Nephrol*, 2009. 20: 1874 –1876.
63. Matlab, Image Processing Toolbox, 2004.
64. Gupta, S. K., Eustace, J. A., Winston, J. A., Boydston, I. I., Ahuja, T. S., Rodriguez, R. A., Tashima, K. T., Roland, M., Franceschini, N., Palella, F. J., Lennox, J. L., Klotman, P. E., Nachman, S. A., Hall, S. D. and Szczech, L. A. Guidelines for the Management of Chronic Kidney Disease in HIV-Infected Patients: Recommendations of the HIV Medicine Association of the Infectious Diseases. *Society of America Clinical Infectious Diseases.* 2005. 40: 1559-1585.
65. Snyder, S. and Pendergraph, B. Detection and Evaluation of Chronic Kidney Disease, *American Family Physician.* 2005. 72(9): 1723-1732.
66. DeBruyn, R. and Gordon, I. Imaging in cystic renal diseases. *Arch Dis Child.* 2002. 83: 401-407.
67. Farmer, K. D. and Gellet, L. R. The sonographic appearance of acute focal pyelonephritis: 8 years' experience. *Clin Radiol.* 2002. 57(6): 483-487.
68. Asghar, M. and Wazir, F. Prevalence of renal ectopia by diagnostic imaging. *Gomal Journal of Medical Sciences.* 2008. 6(2): 72-76.
69. Gambaro, G., Fabris, A., Citron L, et al., An unusual association of contralateral congenital small kidney, reduced renal function and hyperparathyroidism in sponge kidney patients: on the track of the molecular basis. *Nephrol Dial Transplant.* 2005. 20: 1042-1047.

70. Nahm, A. M., Henrique, D. E. and Ritz, E. Renal cystic disease (ADPKD and ARPKD). *Nephrol dial transplant*. 2002. 17: 311-314.
71. Badani, K. K., Hemal, A. K. and Menon, M. Autosomal Dominant polycystic kidney disease from aetiology, evaluation, postsurgical treatment options to current practice. *J. postgrad med*. 2004. 50: 222-226.
72. Kawashima, A., Sandler, C. M. and Goldman, S. M. Imaging in acute renal infection. *BJU Int*. 2000. 86(1): 70-79.
73. Cavorsi, K., Prabhakar, P. and Kirby, C. Acute pyelonephritis. *Ultrasound Quarterly*. 2010. 26(2): 103-105.
74. Parmer, M. Kidney stones. *BMJ*. 2004. 328: 1420-1424.
75. Amato, M., Lussini, M. L. and Nelli, F. Epidemiology of nephrolithiasis today. *Urol Int*. 2004. 72(1): 1-5.
76. Middleton, W. D., Dodds, W. J., Lawson, T. L. and Foley, W. D. Renal calculi: sensitivity for detection with US. *Radiology*. 1988. 167: 239-244.
77. Ather, M. H., Jafri, A. H. and Sulaiman, M. N. Diagnostic accuracy of ultrasonography compared to unenhanced CT for stone and obstruction in patients with renal failure. *BMC Med Imaging*. 2004. 4: 2-6.
78. Bates, R. H. and Robinson, B. S. Ultrasonic transmission speckles imaging. *Ultrasonic Imaging*. 1981. 3(4): 378-394.
79. Hende, W. R., Ritenour, E. R. and Hoffmann, K. R. Medical Imaging Physics. *Medical Physics*. 2003. 30: 730.
80. Madabhushi, A. and Metaxas, D. N. Combining low-, high-level and empirical domain knowledge for automated segmentation of ultrasonic breast lesions. *IEEE Trans. Med. Imaging*. 2003. 22(2): 155-169.
81. Fenster, A. and Downey, D. B. 3-D ultrasound imaging: A review. *IEEE Engineering in Medicine and Biology Magazine*. 1996. 15(6): 41-51.
82. Guo, Y., Cheng, H. D., Tian, J. and Zhang, Y. A Novel Approach to Speckle Reduction to Ultrasound Image. *Proceedings of the 11th Joint Conference on Information Sciences*. 2008.
83. Abd-Elmoniem, K. Z., Youssef, A. M. and Kadah, Y. M. Real-Time Speckle Reduction and Coherence Enhancement in Ultrasound Imaging via Nonlinear Anisotropic Diffusion. *IEEE Transaction on Biomedical Engineering*. 2002. 49(9): 997-1014.

84. Thyagarajah, K., Raja, K. B., and Madheswaran, M. Analysis of Ultrasound kidney Images using Content Descriptive Multiple Features for Disorder Identification and ANN based Classification. *Proc. of the International Conference on Computing: Theory and Applications*. 2007.
85. Yu, Y. and Acton, S. T. Speckle Reducing Anisotropic Diffusion. *IEEE Transaction on Image Processing*. 2002. 11(11): 1260-1270.
86. Tagare, H. D., Jafe, C. and Duncan, J. Medical image databases: A content-based retrieval approach. *Journal of the American Medical Informatics Association*. 1997. 4(3): 184-198.
87. Vasantha, M., Bharathi, V. S. and Dhamodharan, R. Medical Image Feature, Extraction, Selection and Classification, *International Journal of Engineering Science and Technology*. 2010. 2(6): 2071-2076.
88. Albregtsen, F. Statistical Texture Measures Computed from Gray Level Cooccurrence Matrices. Image Processing Laboratory, Department of Informatics, University of Oslo, November 5, 2008.
89. Haralick, R. M., Shanmugam, K. and Dinstein, I. Textural Features for Image Classification. *IEEE Trans. on Systems, Man and Cybernetics*. 1973. 3: 610-621.
90. He, D. C., Wang, L. and Juibert, J. Texture Feature Extraction. *Pattern Recognition Letters*. 1987. 6: 269-273.
91. Trivedi, M. M., Haralick, R. M., Connors, R. W. and Goh, S. Object Detection based on Gray Level Cooccurrence. *Computer Vision, Graphics, and Image Processing*. 1984. 28: 199-219.
92. Chai, H. Y., Wee, L. K., Swee, T. T., Hussain, S. Gray-Level Co-occurrence Matrix Bone Fracture Detection, *WSEAS Transactions on Systems*. 2011. 10(1): 7-16.
93. Gotlieb, J. C. C. and Kreyszig, H. E. Texture Descriptors based on Co-occurrence Matrices. *Computer Vision, Graphics, and Image Processing*. 1990. 51: 70-86.
94. Connors, R. W. and Harlow, C. A. A theoretical comparison of texture algorithms. *IEEE Trans. on Pattern Analysis and Machine Intell.* 1980. 2: 204-222.

95. Wu, J. C. M. and Chen, Y. C. Statistical Feature Matrix for Texture Analysis. *Computer Vision, Graphics, and Image Processing; Graphical Models and Image Processing*. 1992. 54: 407-419.
96. Vibhakar, S., R. S. Anand, Vinod Kumar, Comparing the Performance of Ultrasonic Liver Image Enhancement Techniques: A Preference Study. *IETE Journal of Research*. 2010. 56(1).
97. Hafizah, W. M., and Supriyanto, E. Comparative Evaluation of Ultrasound Kidney Image Enhancement Techniques. *International Journal of Computer Applications*. 2011. 21(7): 15-19.
98. Donoho, D. L. Denoising by soft-thresholding. *IEEE Trans. Inform. Theory*. 1995. 41: 613-627.
99. Yue, Y., Croitoru, M. M., Bidani, A., Zwischenberger, J. B., and Clark, J. W. Ultrasound speckle suppression and edge enhancement using multiscale nonlinear wavelet diffusion. *Proceeding of IEEE Engineering in Medicine and Biology 27th Annual Conference*. 2005.
100. Sudha, S., Suresh, G. R., and Sukanesh, R. Speckle noise reduction in ultrasound images by wavelet thresholding based on weighted variance. *International Journal of Computer Theory and Engineering*. 2009. 1(1).
101. Nicolae, M. C., Moraru, L., and Onose, L., Comparative approach for speckle reduction in medical ultrasound images. *Romanian J Biophys*. 2010. 20(1): 13-21.
102. Mallat, S., and S. Zhong, Characterization of signals from multiscale edges. *IEEE Trans. Pattern Anal. Machine Intell*. 1992. 14(7): 710-732.
103. Wu, C. H. and Sun, Y. N. Segmentation of kidney from ultrasound B-mode images with texture-based classification. *Computer methods and programs in biomedicine*. 2006. 84: 114-123.
104. Xie, J., Jiang, Y. and Tsui, H. Segmentation of Kidney from Ultrasound Images Based on Texture and Shape Priors. *IEEE Transactions on Medical Imaging*. 2005. 24(1): 45-57.
105. Raja, K. B., Madheswaran, M. and Thyagarajah, K. A General Segmentation Scheme for Contouring Kidney Region in Ultrasound Kidney Images using Improved Higher Order Spline Interpolation. *International Journal of Biological and Life Science*. 2006. 2(2): 81-88.

106. Leventon, M., Grimson, E. and Faugeras, O. Statistical shape influence in geodesic active contours. *Proc. IEEE Comput. Vis. Pattern Recogn.*, 2000. 316-322.
107. Belaid, A., Boukerroui, D., Maingourd, Y., and Lerallut, J. F. Phase Based Level Set Segmentation of Ultrasound Images. *Information Technology and Applications in Biomedicine*. 2009. 1.
108. Sun, J., Liang, L., Wen, F., and Shum, H. Y. Image Vectorization using Optimized Gradient Meshes. *ACM Transactions on Graphics*. 2007. 26(3).
109. Hilaire, X., and Tombre, K. Robust and accurate vectorization of line drawings. *IEEE Trans. on PAMI*, 2006. 28(6): 890–904.
110. Zou, J. J., and Yan, H. Cartoon image vectorization based on shape subdivision. In *Proceedings of Computer Graphics International*. 2001. 225–231.
111. Chiang, J. Y., Tue, S. C., and Leu, Y. C. A new algorithm for line image vectorization. *Pattern Recognition*. 1998. 31(10): 1541-1549.
112. Janssen, R. D. T., and Vossepoel, A. M. Adaptive Vectorization of Line Drawing Images. *Computer Vision and Image Understanding*. 1997. 65(1): 38–56.
113. Vector Magic Software. *Vector Magic Inc*. 2007.
114. Raja, K. B., Reddy, M. R., Swaranamani, S., Suresh, S., Madheswaran, M. and Thyagarajah, K. Study on Ultrasound Kidney Images for Implementing Content Based Image retrieval System using Regional Gray-Level Distribution. *Proc. of International Conference on advances in infrastructures for electronic business, education, science, medicine, and mobile technologies on the internet*. 2003. 93.
115. Yap, M. H. and Ewe, H. T. Region of interest (ROI) detection in ultrasound breast images. *Proc. of MMU International Symposium on Information and Communications Technologies (M2USIC)*, 2005. 5-8.
116. Yap, M. H., Edirisinghe, E. A. and Bez, H. E. A novel algorithm for initial lesion detection in ultrasound breast images. *Journal of Applied Clinical Medical Physics*. 2008. 9(4): 2741.
117. Cheng, H. D., Shan, J., Ju, W., Guo, Y. and Zhang, L. Automated breast cancer detection and classification using ultrasound images: A survey. *Pattern Recognition*. 2010. 43(1): 299-317.

118. Yan, G. and Wang, B. An automatic kidney segmentation from abdominal CT images. *Proc. of Intelligent Computing and Intelligent Systems (ICIS)*. 2010.
119. Freiman, M., Kronman, A., Esses, S. J., Joskowicz, L. and Sosna, J. Non-parametric Iterative Model Constraint Graph min-cut for Automatic Kidney Segmentation. *MICCAI*. 2010. 73-80.
120. Tang, Y., Jackson, H.A., Filippo, R.E.D., Nelson, M.D., Moats, R.A.: Automatic renal segmentation applied in pediatric MR Urography. *Diss. ETH*. 2010. 12-19.
121. Tamilselvi, P. R. and Thangaraj, P. Noise suppression and improved edge texture analysis in kidney ultrasound images. *Proc. Of Innovative Computing Technologies (ICICT)*. 2010.
122. Karthikeyini, C., Raja, K. B. and Madheswaran, M. Study on Ultrasound Kidney Images using Principal Component Analysis: A Preliminary Result. *Proc. Of Fourth ICVGIP*. 2004. 190 – 195.
123. Raja, K. B., Madheswaran, M. and Thyagarajah, K. Ultrasound kidney image analysis for computerized disorder identification and classification using content descriptive power spectral features. *J Med Syst*. 2007. 31(5): 307-317.
124. Raja, K. B., Madheswaran, M. and Thyagarajah, K. Evaluation of Tissue Characteristics of Kidney for Diagnosis and Classification Using First Order Statistics and RTS Invariants. *IEEE-ICSCN*. 2007. 483-487.
125. Raja, K. B., Madheswaran, M. and Thyagarajah, K. Quantitative and Qualitative Evaluation of US Kidney Images for Disorder Classification using Multi-Scale Differential Features. *ICGST International Journal on Bioinformatics and Medical Engineering*. 2007. 7(1): 1-8.
126. Raja, K. B., Madheswaran, M. and Thyagarajah, K. A Hybrid Fuzzy-Neural System for Computer-Aided Diagnosis of Ultrasound Kidney Images Using Prominent Features. *Journal of Medical Systems*. 2008. 32(1): 65-83.
127. Raja, K. B., Madheswaran, M. and Thyagarajah, K. Texture pattern analysis of kidney tissues for disorder identification and classification using dominant Gabor wavelet. *Machine Vision and Applications*. 2010. 21: 287–300.
128. Manikandan, S. and Rajamani, V. Automated and feature extraction and retrieval of ultrasound kidney images using maxi-min approach. *International Journal of Computer Applications*. 2010. 4(1): 42-46.

129. Ibrahim, F., Faisal, T., Mohamad Salim, M. I. and Taib, M. N. Non Invasive Diagnosis of Risk in Dengue Patients Using Bioelectrical Impedance Analysis and Artificial Neural Network. *Med Biol Eng Compute*. 2010. 48: 1141-1148.
130. Ubeyli, D. E. Implementing Automated Diagnostic System for Breast Cancer Detection. *Expert System with Application*. 2007. 33: 1054-1062.
131. Esteva, H., Bellotti, M. and Marchevsky, A. M. Neural network for the estimation of prognosis in lung cancer. In: Naguib, R. N. G. and Sherbet, G. V. eds. *Artificial Neural Network in Cancer Diagnosis, Prognosis and Patient Management*. Boca Raton, Florida: CRC Press LLC, 2001. 29-37.
132. Matlab. *Matlab ANN Toolbox*. 2004.
133. Haykin, S. S. *Neural Networks: A Comprehensive Foundation*. New York: Prentice Hall. 1999.
134. Sun, M. and Sclabassi, R. J. The Forward EEG Solutions can be computed using Artificial Neural Networks. *IEEE Transactions on Biomedical Engineering*. 2000. 47: 1044-1050.
135. John, T., Wei, Z. Z. and Barnhill, S. D. Madyastha, R. Understanding Artificial Neural Networks and Exploring their Potential Applications for the Practicing Urologist. *Urology*. 1998. 52: 161-172.
136. Sinha, S. K. and Fieguth, P. W. Projection Neural Network Model for Classification of Pipe Defects. *J Autom Constr*. 2005. 15(1): 73.
137. Liu, B., Cheng, H.D., Huang, J., Tian, J., Liu, J., and Tang, X., Automated segmentation of ultrasonic breast lesions using statistical texture classification and active contour based on probability distance. *Ultrasound in Medicine & Biology*. 2009. 35(8): 1309-1324.
138. Belaid, A., Boukerroui, D., Maingourd, Y., and J-F. Lerallut, Phase Based Level Set Segmentation of Ultrasound Images. *Information Technology and Applications in Biomedicine*. Larnaca: Cyprus .2009.
139. Udupa, J. K., LaBlanc, V. R., Schmidt, H., Imielinska, C., Saha, P. K., Grevera, G. J., Zhuge, Y., Currie, L. M., Molholt, P., and Jin, Y. Methodology for evaluating image-segmentation algorithms. In *Proceedings of SPIE: Medical Imaging*. 2002. 266-277.
140. AutoTrace. 2002. <http://autotrace.sourceforge.net/>.

141. Herth, F. J. F., Yasufuku, K., Eberhardt, R., Hoffmann, H., Krasnik, M., and Ernst, A. Resistance index in Mediastinal Lymph nodes: A feasibility study. *Journal of Thoracic Oncology*. 2008. 3(4): 348-350.
142. York, G., and Kim, Y. Ultrasound Processing and Computing: Review and Future Directions. *Annual Review of Biomedical Engineering*. 1999. 1: 559-588.
143. Sadava, D., Hillis, D. M., Heller, H. C., and Berenbaum, M. R. In: *Life: The Science of Biology*, Ninth Edition. Sinauer Associates. 1100; 2010.
144. Hafizah, W. M., Supriyanto, E., and Yunus, J. Feature Extraction of Kidney Ultrasound Images Based on Intensity Histogram and Gray Level Co-occurrence Matrix. In *Proceeding of Sixth Asia Modelling Symposium*. 2012. 115-120.
145. Intravenous Pyelogram, Radiography.org, *Radiological Society of North America Inc.*, 2013.
146. Chan C. P. I., Young Lady with Intestinal Obstruction Symptoms, In *Hong Kong Society of Critical Care Medicine*. 2009.
147. Ferrer, F. A., McKenna, P. H., Bauer, M. B., Miller, S. F., Accuracy of Renal Ultrasound Measurements for Predicting Actual Kidney Size, *J Urol*. 1997. 157(6): 2278-2281.
148. David B. Larson, Mariana L. Meyers and Sara M. O'Hara, Reliability of Renal Length Measurements Made With Ultrasound Compared With Measurements From Helical CT Multiplanar Reformat Images, *American Journal of Roentgenology*. 2011. 196(5): 592-597.
149. Dunmire, B., Sorensen, M., Kucewicz, J., Bailey, M., Cunitz, B., Harper, J., Sapozhnikov, O., Crum, L., Accuracy of kidney stone size in conventional ultrasound Bmode imaging, *The Journal of the Acoustical Society of America*. 2012. 131(4): 3289.
150. Hyer, R., Acute Abdominal Pain: CT or US? American College of Emergency Physicians News, *Elsevier Global Medical News*, 2011.
151. UBM Medica, Strategies could lead way to a better grip on ultrasound, 2005.
152. Glor, F.P., Ariff, B.; Hughes, A.D.; Verdonck, P.R.; Thom, S.A.Mc.G.; Barratt, D.C.; Xu, X.Y., Operator dependence of 3-D ultrasound-based computational fluid dynamics for the carotid bifurcation, *IEEE Transactions on Medical Imaging*. 2005. 24(4): 451 – 456.

153. Michele G. Sullivan, Renal Ultrasound Predicts Kidney Stones, Need for Intervention, American College of Emergency Physicians News, *Elsevier Global Medical News*, 2008.
154. Adobe Illustrator, *Adobe Systems*, 1987.
155. CorelDRAW. *Corel Corporation*, 1989.
156. Hwang, K.-H., H., Lee, J.G., Kim, J.H., Lee, H.-J. Om, K.-S., Yoon, M., and Choe, W., Computer aided diagnosis (CAD) of breast mass on ultrasonography and scintimammography. In *Proceedings of 7th International Workshop on Enterprise Networking and Computing in Healthcare Industry*. 2005. 187-189.
157. Doi, K., Computer-aided diagnosis in medical imaging: Historical review, current status and future potential, *Computerized Medical Imaging and Graphics*. 2007. 31: 198–211.
158. Jiang, Y, Nishikawa, R. M., Schmidt, R. A., Metz, C. E., Giger, M. L., Doi, K., Improving breast cancer diagnosis with computer-aided diagnosis. *Acad Radiol*. 1999. 6: 22–33.
159. Huo, Z., Giger, M. L., Vyborny, C. J., Metz, C. E., Breast cancer: effectiveness of computer-aided diagnosis-observer study with independent database of mammograms. *Radiology*. 2002. 224: 560–568.
160. Aoyama, M., Li, Q., Katsuragawa, S., Li, F., Sone, S., Doi, K., Computerized scheme for determination of the likelihood measure of malignancy for pulmonary nodules on low-dose CT images. *Med Phys*. 2003. 30: 387–394.
161. Li F, Aoyama M, Shiraishi J, Abe H, Li Q, Suzuki K, et al. Radiologists' performance for differentiating benign from malignant lung nodules on high-resolution CT by using computer-estimated likelihood of malignancy. *AJR* 2004. 183:1209–1215.
162. Y. Ikedo, D. Fukuoka, T. Hara, H. Fujita, E. Takada, T. Endo, T. Morita, Development of a fully automatic scheme for detection of masses in whole breast ultrasound images, *Medical Physics*. 2007. 34(11): 4378–4388.
163. Mimics, *Materialise*, 1991.
164. Amira: 3D Analysis Software for Life Sciences, *Visualization Sciences Group*, 2004.
165. Avizo: 3D Analysis Software for Scientific and Industrial data, *Visualization Sciences Group*, 2004.

166. 3D-Doctor, *Able Software Corp.*, 1994.
167. Vikram Chalana and Yongmin Kim, A Methodology for Evaluation of Boundary Detection Algorithms on Medical Images, *IEEE Transaction on Medical Imaging*. 1997. 16(5): 642-652.
168. Chan, T. F., Vese, L. A., Active Contours Without Edges, *IEEE Transaction on Medical Imaging*. 2001. 10(2): 266-277.
169. Mumford, D., and Shah, J., Optimal approximation by piecewise smooth functions and associated variational problems, *Commun. Pure Appl. Math.* 1989. 42: 577–685.
170. Li, C., Xu, C., Gui, C., and Fox, M. D., Level Set Evolution Without Re-initialization: A New Variational Formulation, *Proceedings of CVPR'05*. 2005. 1: 430-436.
171. Zhu, W. Zeng, N., Wang, N., Sensitivity, Specificity, Accuracy, Associated Confidence Interval and ROC Analysis with Practical SAS® Implementations, *NESUG*. 2010.
172. Craig, D. W., Goor, R. M., Wang, Z., Paschall, J., Ostell, J., Feolo, M., Sherry, S. T., and Manolio, T. A., Box 1 | Risk-assessment definitions applied to sharing GWAS aggregate data sets, *Nature Reviews Genetics*. 2011. 12: 730-736.
173. Parikh, R., Mathai, A., Parikh, S., Sekhar, G. C., and Thomas, R., Understanding and using sensitivity, specificity and predictive values, *Indian J Ophthalmol*. 2008. 56(1): 45–50.
174. Pereira, A. K., Reis, Z. S. N., Bouzada, M. C. F., de Oliveira, E. A., Osanan, G. and Cabral, A. C. V., Antenatal Ultrasonographic Anteroposterior Renal Pelvis Diameter Measurement: Is It a Reliable Way of Defining Fetal Hydronephrosis?, *Obstetrics and Gynecology International*. 2011. 2011 (861865): 1-5.