

**A MODIFIED RETINEX ILLUMINATION
NORMALIZATION APPROACH FOR INFANT
PAIN RECOGNITION SYSTEMS**

MUHAMMAD NAUFAL BIN MANSOR

UNIVERSITI MALAYSIA PERLIS

2014

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**A MODIFIED RETINEX ILLUMINATION
NORMALIZATION APPROACH FOR INFANT
PAIN RECOGNITION SYSTEM**

by

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TABLE OF CONTENTS

	PAGE
APPROVAL AND DECLARATION SHEET	i
ACKNOWLEDGEMENTS	ii
TABLE OF CONTENTS	iii
LIST OF TABLES	vii
LIST OF FIGURES	ix
LIST OF ABBREVIATIONS	xi
LIST OF SYMBOLS	xiv
ABSTRAK	xvi
ABSTRACT	xvii
CHAPTER 1 INTRODUCTION	
1.1 Project Background	1
1.2 Problem Statement	3
1.3 Objectives	4
1.4 Scope	4
1.5 Dissertation Outline	5
CHAPTER 2 LITERATURE REVIEW	
2.1 Neonatal Monitoring	8
2.2 Overview of Image Noise	11
2.2.1 Filtering Techniques for Face Recognition	12
2.3 Preprocessing for Face Recognition	13

2.4	Illumination Normalization Method for Face Recognition	13
2.5	Histogram Normalization Method	14
2.5.1	Histogram Equalization (HQ)	15
2.5.2	Histogram Truncation and Stretching (HT)	16
2.5.3	Normal Distribution (ND)	17
2.5.4	Lognormal Distribution (LN)	18
2.5.5	Extreme Value Distribution (EV)	19
2.5.6	Exponential Distribution (EN)	20
2.6	Photometric Normalization Method	21
2.6.1	Single Scale Retinex (SSR)	21
2.6.2	Homomorphic Filtering (HOMO)	23
2.6.3	Single Scale Self Quotient Image (SSQ)	24
2.6.4	Gross and Brajovic Technique (GBT)	25
2.6.5	DCT-Based Normalization (DCT)	27
2.6.6	The Gradientfaces-based normalization technique (GRF)	28
2.6.7	The Large-and Small-Scale Features Normalization Technique (LSSF)	30
2.6.8	The Tan and Triggs Normalization Technique (TT)	31
2.7	Feature Extraction of Infant Pain Images	32
2.7.1	Correlation	33
2.7.2	Principal Component Analysis	33
2.7.3	Linear Discriminant Analysis	34
2.7.4	Independent Component Analysis	35
2.8	Classification of Infant Pain Recognition Scheme	35
2.8.1	k-Nearest Neighbor (kNN)	36
2.8.2	Artificial Neural Network (ANN)	36
2.8.3	Support Vector Machine (SVM)	37
2.9	Proposed Approaches for Infant Pain Recognition System	37
2.10	Summary	39

CHAPTER 3 INFANT PAIN SYSTEMS AND PREPROCESSING

3.1	System Overview	41
3.2	Infant Cope Database (COPE)	43
3.2.1	Subjects	43

3.2.2	Procedure	44
3.3	Grayscale Image Representation	46
3.4	Noise Image Representation	46
3.5	Illumination Invariant Representation	47
3.6	Proposed Preprocessing Method	49
3.6.1	Median Filter	49
3.6.2	Adaptive Filter	50
3.6.3	Proposed Adaptive Median Filter	51
3.6.4	Simulation Results	54
3.6.4.1	Peak Signal-to-Noise Ratio (PSNR) Analysis	56
3.6.4.2	Average Peak Signal-to-Noise Ratio (PSNR) Analysis	61
3.6.4.3	Mean Square Error (MSE) Analysis	62
3.6.4.4	Average Mean Square Error (MSE) Analysis	67
3.6.4.5	Image Enhancement Factor (IEF) Analysis	68
3.6.4.6	Average Image Enhancement Factor (IEF) Analysis	73
3.6.4.7	Mean Structural SIMilarity (MSSIM) Index Analysis	74
3.6.4.8	Average Mean Structural SIMilarity (MSSIM) Index Analysis	79
3.6.5	The Modified Retinex Theory Normalization Technique	80
3.6.6	Histogram Equalization (HQ)	85
3.7	Summary	90
CHAPTER 4 FEATURE SELECTION AND CLASSIFIER		
4.1	Introduction	91
4.2	Principal Component (PC) for Various Illumination and Noise Levels	92
4.3	Local Binary Pattern (LBP) Parameter for Various Illumination and Noise Levels	96
4.4	Discrete Cosine Transform (DCT) Coefficients for Various Illumination and Noise Levels	101
4.5	Proposed Features for Various Illumination and Noise Levels	105
4.6	Classification of Proposed Features	106
4.6.1	k-Nearest Neighbor (kNN)	107
4.6.2	Linear Discriminant Analysis (LDA)	108
4.6.3	Artificial Neural Network (ANN)	109
4.6.3.1	Multilayer Perceptron Neural Network (MLP)	110

4.6.3.2 Probabilistic Neural Network (PNN)	111
4.6.3.3 General Regression Neural Network (GRNN)	112
4.6.4 Support Vector Machine (SVM)	113
4.6.4.1 Outline of SVM	114
4.6.5 Fuzzy k-Nearest Neighbor (F-kNN)	116
4.7 Summary	117

CHAPTER 5 PERFORMANCE ANALYSIS OF VARIOUS ILLUMINATION LEVELS

5.1 Introduction	118
5.2 Performance Results under 25 δ Illumination Levels with 10% Noise Level	128
5.3 Average Performance Results under 25 δ Illumination Levels with 10% Noise Level	133
5.4 Performance Results under 50 δ Illumination Levels with 10% Noise Level	142
5.5 Average Performance Results under 50 δ Illumination Levels with 10% Noise Level	147
5.6 Performance Results under 75 δ Illumination Levels with 10% Noise Level	156
5.7 Average Performance Results under 75 δ Illumination Levels with 10% Noise Level	160
5.8 Performance Results under 100 δ Illumination Levels with 10% Noise Level	169
5.9 Average Performance Results under 100 δ Illumination Levels with 10% Noise Level	174
5.10 Summary	175

CHAPTER 6 CONCLUSION AND FUTURE WORK

6.1 Conclusion	177
6.2 Future Work	179

REFERENCES	181
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APPENDIX A (List of publication)	191
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APPENDIX B (Performance Results (Table))	196
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LIST OF TABLES

NO.		PAGE
3.1	PSNR for Various Filters for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	56
3.2	PSNR for Various Filters for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	57
3.3	PSNR for Various Filters for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	58
3.4	PSNR for Various Filters for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	59
3.5	MSE for Various Filters for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	62
3.6	MSE for Various Filters for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	63
3.7	MSE for Various Filters for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	64
3.8	MSE for Various Filters for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	65
3.9	IEF for Various Filters for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	68
3.10	IEF for Various Filters for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	69
3.11	IEF for Various Filters for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	70
3.12	IEF for Various Filters for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	71
3.13	MSSIM for Various Filters for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	74
3.14	MSSIM for Various Filters for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	75
3.15	MSSIM for Various Filters for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	76
3.16	MSSIM for Various Filters for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	77
4.1	Different PC for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	94
4.2	Different PC for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	95

4.3	Different PC for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	95
4.4	Different PC for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	95
4.5	Different LBP Parameter for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	99
4.6	Different LBP Parameter for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	99
4.7	Different LBP Parameter for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	100
4.8	Different LBP Parameter for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	100
4.9	Different DCT Coefficients for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	103
4.10	Different DCT Coefficients for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	103
4.11	Different DCT Coefficients for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	103
4.12	Different DCT Coefficients for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	104
4.13	Comparison of Combination Features with Different Features for the Infant COPE Database at Different Noise Densities under 25 δ Illumination Levels	105
4.14	Comparison of Combination Features with Different Features for the Infant COPE Database at Different Noise Densities under 50 δ Illumination Levels	105
4.15	Comparison of Combination Features with Different Features for the Infant COPE Database at Different Noise Densities under 75 δ Illumination Levels	105
4.16	Comparison of Combination Features with Different Features for the Infant COPE Database at Different Noise Densities under 100 δ Illumination Levels	106
5.1	Performance Results under 25 δ Illumination Levels with 10% Noise Level	121
5.2	Performance Results under 50 δ Illumination Levels with 10% Noise Level	135
5.3	Performance Results under 75 δ Illumination Levels with 10% Noise Level	149
5.4	Performance Results under 100 δ Illumination Levels with 10% Noise Level	162

LIST OF FIGURES

NO.		PAGE
2.1	The Histogram Equalization (HQ) Technique	16
2.2	The Histogram Truncation and Stretching (HT) Technique	17
2.3	The Histogram Normal Distribution (ND) Technique	18
2.4	The Histogram Lognormal Distribution (LN) Technique	19
2.5	The Histogram Extreme Value Distribution (EV) Technique	20
2.6	The Single Scale Retinex (SSR) Technique	23
2.7	Homomorphic Filtering (HOMO) Block Diagram	23
2.8	Homomorphic Filtering (HOMO) Technique	24
2.9	Single Scale Self Quotient Image (SSQ) Technique	25
2.10	Gross and Brajovic Technique (GBT)	26
2.11	DCT-Based Normalization (DCT) Technique	27
2.12	The Gradientfaces-Based Normalization Technique (GRF)	30
2.13	The Large-and Small-Scale Features Normalization Technique (LSSF)	31
2.14	The Tan and Triggs Normalization Technique	32
3.1	The Proposed Study Procedure	42
3.2	The Infant COPE Database	44
3.3	The Infant COPE Grayscale Image	46
3.4	Examples of the Different Noise Levels Effects	47
3.5	Examples of the Various Illuminations Level Image	48
3.6	Examples of the Effects of the Different Filter Methods	53
3.7	Average Peak Signal-to-Noise Ratio (PSNR) Analysis	61
3.8	Average Mean Square Error (MSE) Analysis	67
3.9	Average Image Enhancement Factor (IEF) Analysis	73
3.10	Average Mean Structural SIMilarity (MSSIM) Analysis	79
3.11	The Histogram Equalization (HQ) Image	87
3.12	The Proposed Method Image	88
3.13	Examples of the Effects of the Different Preprocessing Methods	89
4.1	The Infant COPE Database Eigen Face	94
4.2	The basic LBP Operator	96
4.3	The Infant COPE LBP Image	98

4.4	The Infant COPE DCT Image	102
5.1	Average Performance Results under 25 δ Illumination Levels with 10% Noise Level	133
5.2	Average Performance Results under 50 δ Illumination Levels with 10% Noise Level	147
5.3	Average Performance Results under 75 δ Illumination Levels with 10% Noise Level	160
5.4	Average Performance Results under 100 δ Illumination Levels with 10% Noise Level	174

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LIST OF ABBREVIATIONS

AC	Accuracy
AMF	Adaptive Median Filter
ANN	Artificial Neural Networks
AUC	Area under Curve
CDF	Cumulative Distribution Function
CONV	Conventional Validation
COPE	Classification of Pain Expressions
CRIES	Assesses Crying, Oxygen Requirement, Increased Vital Signs, Facial Expression, Sleep.
CROSSV	Cross Validation
DCT	DCT-Based Normalization
DCT	Discrete Cosine Transform
DOG	Difference of Gaussians
ELBP	Elongated Binary Pattern
ELTP	Elongated Ternary Pattern
EN	Exponential Distribution
EV	Extreme Value Distribution
FFNN	Feed Forward Neural Network
F-KNN	Fuzzy- k-Nearest Neighbor
FM	F-Measure
FN	False Negative
FP	False Positive
GBT	Gross and Brajovic Technique
GRF	Gradientfaces-Based Normalization Technique
GRNN	General Regression Neural Network
HCI	Human Computer Interface
HOMO	Homomorphic Filtering
HQ	Histogram Equalization
HT	Histogram Truncation and Stretching
IDCT	Inverse Discrete Cosine Transform
IEF	Image Enhancement Factor

K-NN	K-nearest neighbor
LBP	Local Binary Pattern
LDA	Linear Discriminant Analysis
LN	Lognormal Distribution
LSSF	Large- and Small-Scale Features Normalization Technique
LSVM	Linear Support Vector Machine
MAX	Median
MIN	Minimum
MLP	Multilayer Perceptron Neural Network
MRT	Modified Retinex Normalization Technique
MSE	Mean Square Error
MSSIM	Mean Structural SIMilarity Index
NF	New Feature
ND	Normal Distribution
NICU	Neonatal Intensive Care Unit
NIPS	Neonatal Infant Pain Scale
NNSOA	Neural Network Simultaneous Algorithm
N-PASS	Neonatal Pain, Agitation and Sedation Scale
OSH	Optimal Separating Hyperplane
PCA	Principal Component analysis
PIPP	Premature Infant Pain Profile
PNN	Probabilistic Neural Network
PRE	Precession
PSNR	Peak Signal-to-Noise Ratio
REC	Recall
SE	Sensitivity
SP	Specificity
SSIM	Structural SIMilarity Index
SSQ	Single Scale Self Quotient Image
SSR	Single Scale Retinex
SVM	Support Vector Machine
SVMLIN	SVM Linear kernel
SVMMLP	SVM MLP kernel
SVMPOL	SVM Polynomial kernel

SVMRBF	SVM RBF kernel
TN	True Negative
TP	True Positive
TT	Tan and Triggs Normalization Technique

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LIST OF SYMBOLS

$I(x,y)$	Image on (x,y) coordinate
$J(i)$	Probability image
v_i	Number of pixels
i_{out}	Latest intensity value
$g(x)$	Allotment function
K	order grouped
β	Scale parameter
$R(x,y)$	Reflectance on (x,y) coordinat
$L(x,y)$	Illumination on (x,y) coordinat
T	Non linear function
Qk	Quotient images
Mk	Weighting factors
k	Scale Parameter
$WkGk$	Weighted Gaussian kernels
G	Gradientfaces
δ	Delta factor
$\frac{1}{I}$	Gain
ψ	Small neighborhood
Ω	Image domain
ρ	Anisotropic diffusion coefficients
λ	Smoothness constraint
h	Grid interval
f	Ratio of total intensity difference
\hat{f}	Output Image
W	Current $N \times N$ window centered at $g(x, y)$
m_L	Local Mean
Φ_i	Vector image
ω_k	Eigen-Vector
$B_{p,q}$	Weights functional

W_{opt}	Finest projection
x_L	Projected sets
Y^i	Observed values

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Pengubahsuaian Normalisasi Iluminasi Retinex dalam Pendekatan Mengesan Kesakitan pada Bayi

ABSTRAK

Kesakitan bayi dipantau di dalam Neonatal Jagaan Unit Rapi (NICU). Kesakitan pada bayi dapat dikesan dengan mengkaji perubahan mimik muka mereka. Walaupun keputusan yang diperolehi amat memberangsangkan, ianya tidak cukup dalam aspek gangguan dan perubahan iluminasi. Penyaring Penyesuai Median (AMF) untuk menapis gangguan telah dicadangkan. Purata dan varian nilai median digunakan untuk menghasilkan pemberat yang bersesuaian dengan imej menggunakan $3 \times 3, 5 \times 5$ or 7×7 telah digunakan. Keputusan kuantitatif seperti Puncak Isyarat kepada nisbah gangguan (PSNR), Purata Kuasa Dua Ralat (MSE), Faktor Peninggian Imej (IEF) dan Indeks Persamaan Purata Struktur (MSSIM). Keputusan purata menunjukkan peningkatan dengan 40.63 db untuk PSNR, 6.01 untuk MSE, 258.09 untuk IEF dan 0.97 untuk MSSIM. Dalam kajian ini juga iluminasi normalisasi baru yang dikenali sebagai Pengubahsuaian Retinex Teknik (MRT) untuk mengesan muka dalam perbezaan iluminasi dengan menggabungkan normalisasi histogram dan gabungan kombinasi ciri telah dicadangkan. Kaedah ini telah dibandingkan dengan kaedah seperti (SSR) Skala Tunggal Retinex, (HOMO) Kaedah Homomorphic, (SSQ) Skala Tunggal Nisbah Imej, Gross dan Brajovic Teknik (GBT), (DCT) Kaedah DCT, (GRF) Teknik perubahan muka, (TT) Kaedah Tan dan Triggs, and Teknik Besar dan Kecil (LSSF) untuk menilai kecekapannya. Kaedah ini tidak memerlukan maklumat luaran tentang bentuk muka dan iluminasi malahan boleh digunakan pada setiap imej secara berasingan. Kajian dijalankan menggunakan imej COPE data. Keputusan yang ditunjukkan amat memberangsangkan. Pengambilan pencirian tunggal seperti Analisis Komponen Prinsipal (PCA), Corak Tempatan Dedua (LBP) dan Transformasi Sudut Berasingan (DCT) menghasilkan keputusan yang baik. Walaubagaimanapun gabungan ketiga-tiga pengambilan pencirian ini menghasilkan ketepatan yang amat memberangsangkan. Kaedah MRT bersama gabungan pengambilan pencirian mendapat keputusan >90% pada sepuluh klasifikasi seperti Jiran Terdekat K (k-NN), Fuzi Jiran Terdekat K (Fuzzy k-NN), Pembezaan Analisis Lurus (LDA), Masukan Terus Rangkaian Neural (FFNN), Kemungkinan Rangkaian Neural (PNN), Regresi Umum Rangkaian Neural (GRNN), Mesin Pembantu Vektor Lurus (SVMLIN), Mesin Pembantu Vektor Fungsi Asas Radial (SVMRBF), Mesin Pembantu Vektor Pelbagai Lapisan (SVMMLP) dan Mesin Pembantu Vektor polinomial (SVMPOL) dalam beberapa pengukuran prestasi seperti sensitivity, spesifikasi, ketepatan, luas bawah lengkung (AUC), Cohen's kappa (k), kepersisan, Pegukur F dan masa proses.

A Modified Retinex Illumination Normalization Approach for Infant Pain Recognition System

ABSTRACT

Pains in newborn babies are monitored in a Neonatal Intensive Care Unit (NICU) for medical treatment. Pain in newborns can be detected by studying their facial appearance. Even though the outcome is acceptable, it is not adequately vigorous to be used in unpredictable, non-ideal situations such as noise and varying illumination environment. First, to improve the noise cancellation robustness an adaptive median filter (AMF) is proposed. Mean and variance of median values are selected to generate a weight for each window part of the images such as 3x3, 5x5 or 7x7. Various linear and nonlinear filters are adopted to eliminate the noise in the images. Quantitative comparisons are performed between these filters with our AMF in terms of Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Image Enhancement Factor (IEF) and Mean Structural SIMilarity (MSSIM) Index. The average results show improvement in terms of 40.63 db for PSNR, 6.01 for MSE, 258.09 for IEF and 0.97 for MSSIM respectively. In this work a novel method of illumination invariant normalization known as Modified Retinex Normalization (MRT) for preprocessing of infant face recognition is proposed. This is based on a modified retinex model that combines with histogram normalization for filtering the illumination invariant. The proposed method is compared to other methods like Single scale Retinex (SSR), Homomorphic method (HOMO), Single Scale Self Quotient Image (SSQ), Gross and Brajovic Technique (GBT), DCT-Based Normalization (DCT), Gradientfaces-based normalization technique (GRF), Tan and Triggs normalization technique (TT), and Large-and small-scale features normalization technique (LSSF) for evaluation with Infant Classification of Pain Expressions (COPE) database. Several experiments were performed on COPE databases. Single PCA, LBP and DCT feature extraction information yielded a good recognition result. However, by summing these three, it gives more robustness to noise and illumination classification rate because the sum rule was the most resilient to estimate errors and gives higher than 90% accuracies of pain and no pain detection. The new illumination normalization and combination of features gives higher results of more than 90% on five different classifiers with various algorithms such as k -nearest neighbors (k -NN), Fuzzy k -nearest neighbors (FkNN), Linear Discriminant Analysis (LDA), Feed Forward Neural Network (FFNN), Probabilistic Neural Network (PNN), General regression Neural Network (GRNN), SVM Linear kernel (SVMLIN), SVM RBF kernel (SVMRBF), SVM MLP kernel (SVMMLP) and SVM Polynomial kernel (SVMPOL) with different performance measurement such as Sensitivity, Specificity, Accuracy, Area under Curve (AUC), Cohen's kappa (k), Precision, F-Measure and Time Consumption.

CHAPTER 1

INTRODUCTION

1.1 Project Background

Newborn babies are monitored in a Neonatal Intensive Care Unit (NICU) for medical treatment include perinatal asphyxia, major birth defects, sepsis, neonatal, and Infant respiratory distress syndrome due to immaturity of the lungs. These infants are nurtured in an incubator, where their vital bodily function indicators such as blood pressure, temperature, heart rate, oxygen concentration and respiration are continuously observed. To avoid disturbed sleep caused by bright lights which leads to anxiety, the incubator is covered with a blanket to reduce the intensity of light. The drawback of this practice is that visual inspection of the infant throughout most of the time is impaired. In other words, ache and distress cannot be assessed by observing crucial functions. There are growing concerns that early detection of pain and distress may be important for the infant's development which prompts us to widen a model for an automated video surveillance system that can detect ache and distress in neonates.

Distress in newborns can be detected by studying their facial appearance (Grunau et al., 1987; Stevens et al., 1996; Chen et al., 2005). In particular, the appearance of the mouth, eyebrows and eyes are reported to be significant facial features for detecting the occurrence of distress and ache. This has resulted in the development of scoring systems to evaluate the intensity of distress, based on facial appearance and physiological

parameters. The scoring systems provide early signals to care takers when newborns experience ache or distress, so proper actions can be taken in an instant.

So far, only one automatic video-surveillance system (Brahnam et al., 2006; Brahnam et al., 2007) for pain detection in newborn babies has been reported. In this system, enlarged images of an infant are taken in diverse situations: using a painful method (heel lance) and during other non-painful situations such as friction, crying, resting and air stimulus. After manual rotation and scaling, pixel-based classifiers, such as Linear Discriminant Analysis and Support Vector Machines (Brahnam et al., 2006; Brahnam et al., 2007; Martinez & Kak, 2004; Abdi, 2007; Perriere & Thioulouse, 2003) were applied for sorting the facial expressions. Even though the outcome is acceptable, it believe that this is not adequately vigorous to be used in unpredictable, non-ideal situations such as under varying noise and illumination environment, where the newborn's face is partly covered by plasters or tubing.

Illumination is one of the basic characteristics of a visible surface and it provides information for scene interpretation (Gao et al., 2003; Chen et al., 2000). Recent developments in this field have shown that there is room for improvements. Most of the traditional face recognition algorithms are satisfactory under controlled conditions. However, when dealing with performance degrading issues such as variation in pose, noise, illumination, and facial expression, their accuracy greatly diminished (Gao et al., 2003; Chen et al., 2000). As the performance of a face recognition technique is significantly affected by various illumination and noise effects, illumination and noise are known to be the key factors that play an important role in human face recognition system design.

To address this limitation, this dissertation proposed a distress detection scheme and depicts a pilot method with the following properties: first, the identification of distress will be based on analyzing the whole face region in an automated way. With this information, the behavioral circumstances of the infant either in pain or normal can be detected. Images of surrounding factors such as the visibility of plasters and tubes on the infant are excluded in this work. However, other challenging circumstances, such as the changes in noise and illumination environment, which characteristically lead to suboptimal surroundings, need to be considered.

1.2 Problem Statement

Many issues hinder research efforts in the field of infant face recognition. Variation exists in every imaging approaches, and finding fast, simple algorithms that are robust to variation is difficult (Brahnam et al., 2006; Brahnam et al., 2007). Categorizing the variation may be helpful in the development of effective face recognition algorithms (Matthew, 2003). Intrinsic sources of variation include identity, facial expression, speech, gender, and age (Daugman, 1997). Extrinsic sources of variation include viewing geometry pose changes, illumination (shading, color, self-shadowing), imaging processes (resolution, focus, imaging noise), and other objects (occlusions, shadowing, and indirect illumination).

These sources of variation may or may not hinder the recognition process depending on the algorithm used. It is possible that the variation due to factors such as facial expression, lighting, occlusions, noise and pose is larger than the variation due to identity (Daugman, 1997). That makes identification under such varying environments a

difficult task. However, human proficiency at face recognition (Hochberg et al., 1967) has motivated enormous research in this area despite these challenges. Thus, this work seeks to solve the problems of infant face recognition system in different noise levels and illumination with new filter and new illumination normalization approach.

1.3 Objectives

The objectives of this research are as follows:

- 1) To develop a new approach based on filter under varying conditions of noise level in preprocessing phase.
- 2) To develop a new illumination normalization approach under varying conditions of illumination level.
- 3) To determine the most salient and discriminative features by adopting the feature selection for optimizing on the accuracy of the decision making systems.
- 4) To evaluate the performance of the new illumination normalization method for detecting illumination invariant capability in terms of sensitivity, specificity, accuracy, area under curve, Cohen's kappa, precision, recall, f-measure and execution time under different noise and illuminations levels.

1.4 Scope

As mentioned in the introduction, it seems not much attention is given to research on monitoring of infants in Neonatal Intensive Care Units (NICU). This work may answer many of the misconceived problems. In this work, one approach to Human

Computer Interface (HCI) for monitoring infant pain is presented. Most of the infants represent their pain through their facial appearance, and hence monitoring the whole body movement is not a viable solution. The facial appearance need to be monitored by the nurses at selected intervals and reported to doctors for possible further treatments. Detection of facial changes is very crucial for further treatment. This work is only limited to the face from infant COPE database. The database of whole images in this work only consists of upfront images and does not deal with different poses. Within this work, only common features such as PCA, LBP and DCT are adopted. However, different parameters and coefficient of features under different illumination levels and noise are adopted. Salt and pepper noise is employed rather than other noise because this type of noise always appears in digital images and is mostly adopted as a benchmark for filter performance evaluation. The proposed filter is tested with various quantitative measurements such as Peak Signal-to-Noise Ratio (PSNR), Mean Square Error (MSE), Image Enhancement Factor (IEF) and Mean Structural SIMilarity (MSSIM) Index. In this work, selected noise and illumination levels on the face of infant is investigated. Certain performance measurement such as Sensitivity, Specificity, Accuracy, Area under Curve (AUC), Cohen's kappa (k), Precession, F-Measure and Time Consumption are measured to validate the proposed illumination normalization technique.

1.5 Dissertation Outline

The chapters of this dissertation largely follow the order in which the work was done. The scope and objective of the work is presented in this chapter. The second chapter is a literature review encompassing most of infant monitoring research. This