A MODIFIED RETINEX ILLUMINATION NORMALIZATION APPROACH FOR INFANT PAIN RECOGNITION SYSTEM

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by

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A thesis submitted
in fulfillment of the requirement for the Doctor of Philosophy

SCHOOL OF MECHATRONIC ENGINEERING
UNIVERSITI MALAYSIA PERLIS

2014

A MODIFIED RETINEX ILLUMINATION NORMALIZATION APPROACH FOR INFANT PAIN RECOGNITION SYSTEMS

MUHAMMAD NAUFAL BIN MANSOR

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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

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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

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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
υ_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 x N window centered at $g(x,y)$
m_L	Local Mean
Φ_i	Vector image
ω_k	Eigen-Vector
$B_{p,q}$	Weights functional

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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 3x3,5x5 or 7x7 telah digunakan. Keputusan kuantitif seperti Puncak Isyarat kepada nisbah gangguan (PSNR), Purata Kuasa Dua Ralat (MSE), Faktor Peningkatan 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 stiap 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), Kemugkinan 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.

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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 Discriminat 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*), Precession , F-Measure and Time Consumption .

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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.

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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.

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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.

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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, precession, recall, f-measure and execution time under different noise and illuminations levels.

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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.

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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