

**UNIVERSITY OF SOUTHERN QUEENSLAND**



**MONITORING THE DEPTH OF ANAESTHESIA USING  
SIMPLIFIED ELECTROENCEPHALOGRAM (EEG)**

A dissertation submitted by

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*To my family*

# Abstract

Anaesthesia is administered routinely every day in hospitals and medical facilities. Numerous methods have been devised and implemented for monitoring the depth of anaesthesia (DoA) in order to guarantee the safety of patients. Monitoring the depth of anaesthesia provides anaesthesia professionals with an additional method to assess anaesthetic effects and patient responses during surgery. The measurement of depth of anaesthesia benefits patients and helps anaesthetists such as “reduction in primary anaesthetic use, reduction in emergence and recovery time, improved patient satisfaction and decreased incidence of intra-operative awareness and recall” (Kelley S. D.).

Clinical practice uses autonomic signs such as heart rate, blood pressure, pupils, tears, and sweating to determine depth of anaesthesia. However, clinical assessment of DoA is not valuable in predicting the response to a noxious stimulus and may vary depending on disease, drugs and surgical technique. Currently available DoA monitoring devices have been criticised in the literature, such as being redundant (Schneider, 2004), not responsive to some anaesthetic agents (Barr G., 1999), and time delay (Pilge S., 2006).

This research proposes new methods to monitor the depth of anaesthesia (DoA) based on simplified EEG signals. These EEG signals were analysed in both the time domain and the time-frequency domain. In the time domain, the Detrended Fluctuation Analysis (DFA), detrended moving average (DMA) and Chaos methods

are modified to study the scaling behaviour of the EEG as a measure of the DoA. In the frequency domain, fast Fourier transform (FFT) and filter bank are used to identify difference states of anaesthesia. In the time-frequency domain, discrete wavelet transforms (DWT) and power spectral density (PSD) function are applied to pre-process EEG data and to monitor the DoA.

Firstly, a new de-noising algorithm is proposed with a threshold  $T_{WE}$ , which is a function of wavelet entropy and the window length  $m$  for an EEG segment. Secondly, the anaesthesia states are identified into awake, light, moderate, deep and very deep anaesthesia states. Finally, the DoA indices are computed using:

- Modified DFA method (MDFA I),
- Modified DFA-Lagrange method (MDFA II),
- Modified detrended moving average method (MDMA),
- Modified Chaos method, combined Chaos and MDMA method,
- Wavelet-power spectral density.

Simulation results demonstrate that our new methods monitor the DoA in all anaesthesia states accurately. These proposed methods and indices present a good responsive to anaesthetic agent, reduce the time delay when patient's hypnotic state changes (from 12 to 178 seconds), and can estimate a patient's hypnotic state when signal quality is poor.

# Certification of Dissertation

I certify that the ideas, experimental work, results and analyses, software and conclusions reported in this dissertation are entirely my own effort, except where otherwise acknowledged. I also certify that the works is original and has not been previously submitted for any other award, except where otherwise acknowledged.

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# Related Publications

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# List of Frequently used Acronyms and Abbreviations

ANN	Artificial Neural Network
ANOVA	Analysis of Variance
AP	Affine Projection
AWL	Adaptive Window Length
BIS	Bispectrum Index
BS	Burst Suppression
BSR	Burst Suppression Ratio
cdf	cumulative distribution function
CDoA	Chaos Depth of Anaesthesia
CsDoA	Chaos-s Depth of Anaesthesia
CFAM	Central Function Analysing Monitor
Ch-MDMA	Chaos-Modified Detrended Moving Average
CSI	Cerebral State Index
CWTs	Continuous Wavelet Transforms
DB	Daubechies Wavelet.
df	degrees of freedom
DFA	Detrended Fluctuation Analysis
DMA	Detrended Moving Average
DoA	Depth of Anaesthesia

DSP	Digital Signal Processing
DTFT	Discrete-Time Fourier Transform
DWT	Discrete Wavelet Transform
ECGs	Electrocardiograms
EEA	Error Estimation Algorithm
EEG	Electroencephalogram
EMG	Electromyogram
EOG	Electroocclugrams
FFT	Fast Fourier Transform
fMRI	functional Magnetic Resonance Imaging
HMSPs	High Magnitude Specified Peaks
IFT	Isolated Forearm Technique
LMS	Least Mean Squares
LOC	Lower Oesophageal Contractility
LOC	Loss of Consciousness
MAC	Minimum Alveolar Concentration
MAC	Monitored Anesthesia Care
MaPS	Maximum Power Spectrums
MDFA1	Modified Detrended Fluctuation Analysis 1
MDFA2	Modified Detrended Fluctuation Algorithm 2
MDMA	Modified Detrended Moving Average
MLAEP	Mid-Latency Auditory Evoked Potentials
MS	Mean Squares
MUSIC	Multiple Signal Classification
NEEA	New Error Estimate Algorithm

OAA/S	Observer's Assessment of Alertness/Sedation
OMT	Ocular Micro Tremor
PCA	Patient Controlled Analgesia
PET	Positron Emission Tomography
PRST	Pressure, Rate, Sweating and Tear
PSD	Power Spectral Density
PSI	Patient State Index
RE	Response Entropy
RLS	Recursive Least Squares
SC	Skin Conductance
SE	State Entropy
SMI	Set-Membership Identification
SM-NLMS	Set-Membership Normalized Least Mean-Squares
SPECT	Single Photon Emission Computed Tomography
SQI	Signal Quality Index
SS	Sum of Squares
TCR	Time to Correct Response
USB	Universal Serial Bus
WDoA	Wavelet DoA
WT	Wavelet Transform



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- *Zone 1* has the space formed by lines  $s=42, F(s)=0$  and  $Z(s),$
- *Zone 2* has the space formed by lines  $s=35, F(s)=30$  and  $Z(s),$
- *Zone 3* has the space formed by lines  $s=25, F(s)=60$  and  $Z(s),$
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