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**The enhancement of intra-operative
diagnostics and decision-making using
computational methods**

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A thesis submitted in partial fulfilment of the requirements for the degree of
Doctor of Medicine.

The University of Auckland, 2005

ABSTRACT

The data presented and views expressed in this document are the result of multiple published and unpublished studies over the last 25 years. My over-arching goal in this research was to use modern computing power to create functionally useful diagnoses, in real time, from the monitoring systems used during routine anaesthesia and to present these diagnoses in an ergonomic manner. In addition it was intended to incorporate into the anaesthetic monitor, expert systems that help with the management of uncommon situations.

The Australian and New Zealand College guidelines on monitoring during anaesthesia dictate those measurements that should be made during every anaesthetic; from these data evidence can be gathered, integrated, and presented to the clinician. Constraints in this field of research include the inability of the monitors to see, hear or understand the context of operating theatre activities, and computer processing time.

Because many studies are involved the methods are detailed in the main text, and are not summarized here.

Physiological 'envelopes' have been developed, in which the 'normal' variation in physiological variables, during anaesthesia, are enclosed. They have enabled the creation of intelligent alarm systems that can suggest diagnoses. A retrospective off-line study showed that it was possible to diagnose the onset of malignant hyperpyrexia, using fuzzy logic templates, about 10minutes earlier than the clinician. Some variables may be more important than others in making a diagnosis, and the strength of a diagnosis depends on the amount of supporting evidence, the amount of evidence not against the diagnosis and the amount of missing data.

Decision-making (for example to transfuse or not transfuse blood) can also be mathematically modelled so that decision making is more consistent.

Finally, investigation of the ways of displaying data indicates that the output can be very explicit.

My overall conclusion is that real time decision support systems for the management of clinical dilemmas are possible. They can be instantly and easily accessible and can sit discretely in the background of anaesthetic monitors to be activated at will by the anaesthetist.

PREFACE

STATEMENT OF WORK

ACKNOWLEDGEMENTS

PUBLICATIONS AND PRESENTATIONS

STATEMENT OF WORK

The work for this thesis has been carried out over twenty-five years. It began whilst I was working as a Consultant Anaesthetist and Senior Lecturer in Anaesthesia in the city of Nottingham, in the UK. The work was continued in Auckland, at Auckland Hospital, and as an honorary Senior Lecturer and Associate Professor in the Department of Anaesthesiology, Faculty of Medical and Health Science, University of Auckland, New Zealand.

The majority of the work has been at my instigation but much of the work has been co-authored with past and present colleagues.

ACKNOWLEDGEMENTS

I would like to give thanks to the following friends who have contributed to my fumbling attempts at seeing through the fog of uncertainty.

Frank Johnson, Andrew Lowe, Phil Guise, Nigel Robertson, Michal Kluger, Brian Mace, Guy Warman, Brian Pollard, Ron Jones, Tom Healy, Alan Merry, Doug Campbell, Richard Jones, David Kabel, Jim Hunter and many more.

Much praise and thanks must be given to my wife, Penny, who has valiantly put up with my computing over the years.

“I heartily beg that what I have done here may be read with candour; and that the defects I have been guilty of upon this difficult subject may be not so much reprehended as kindly supplied, and investigated by new endeavours of my readers.”

Isaac Newton

The Mathematical Principles of Natural Philosophy

Cambridge, Trinity College,

May 8, 1686.

It is likely that this work will expose my ignorance more than my knowledge. Being pragmatic I hope the end result may be of use to someone with greater skills.

Michael Harrison

September 22nd, 2005

PUBLICATIONS AND PRESENTATIONS

The following publications arose from this work:

My contribution to these publications is tabulated in detail in APPENDIX H

Harrison MJ, Johnson F. Computer assisted decision making in anaesthesia. Br J Anaes 1980; 629P

Harrison MJ, Johnson F. Codifications of anaesthetic information for computer processing. J.Biomed.Engng 1981;3:196-199

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Lowe A, Harrison MJ. Preliminary performance analysis of a shallow-knowledge intelligent monitoring system for anaesthesia (abstract). Anaesthetic Research Group of New Zealand Conference '97, Tauranga, New Zealand.

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Churchill Livingstone ISBN 0443028818

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1986 ISBN BE-0407002987

Anaesthesia for Uncommon Diseases, Pollard BJ, Harrison MJ. Blackwell Scientific.

TABLE OF CONTENTS

ABSTRACT	ii
PREFACE	iii
ACKNOWLEDGEMENTS	iv
PUBLICATIONS	v
TABLE OF CONTENTS	viii
LIST OF TABLES	xi
LIST OF FIGURES	xiii
LIST OF ABBREVIATIONS	xix
PART 1 INTRODUCTION... GOALS AND LIMITATIONS	1
PART 2 DIAGNOSIS AND DECISION MAKING	6
2.1 An overview.....	7
2.1.1 Induction and deduction.....	7
2.1.2 Sets (crisp and fuzzy).....	10
2.1.3 Probability.....	12
2.1.4 Neural nets.....	13
2.1.5 Fuzzy logic.....	14
2.1.6 Logistic regression.....	15
2.1.7 Clinical judgment analysis.....	16
2.2 Summary.....	18
PART 3 DECISION SUPPORT SYSTEMS (DSS)	19
3.1 Decision trees.....	20
3.1.1 Fortran, Basic, Prolog, Text.....	22
3.1.2 DSS in the new millennium.....	29
3.1.2.1 Anaesthetic advice.....	29
3.1.2.2 Rare diseases.....	31
3.1.2.3 Drug interactions.....	32
3.2 Transfusion decisions.....	34
3.2.1 Quantification of the physiological state.....	35
3.2.2 Modelling the decision-making (paper exercise).....	44

3.2.3	Modelling the decision-making (clinical audit).....	54
3.3	Summary.....	68
PART 4 DATA COLLECTION AND TIME SERIES ANALYSIS.....		69
4.1	Data Collection and Time series analysis.....	69
4.1.1	The Basic Data set.....	71
4.1.2	Digital Data Collection.....	74
4.1.2.1	Normal systolic blood pressure variation.....	76
4.1.2.2	BP vs BP.....	78
4.1.2.3	BP vs BP vs Time.....	83
4.1.2.4	BP vs Events.....	84
4.1.3	Time series analysis.....	93
4.1.3.1	Moving averages / SDs/ percentiles.....	93
4.1.3.2	Exponential smoothing, Trigg and Hope.....	94
4.1.3.3	A cardiovascular example.....	98
4.2	Summary.....	104
PART 5 DATA AS EVIDENCE.....		105
5.1	Data as evidence.....	106
5.1.1	Simple models	106
5.1.1.1	Details of diagnoses.....	107
5.1.2	Combination of evidence.....	110
5.1.2.1	A Respiratory example.....	111
5.1.2.2	Clusters and Vectors.....	119
5.1.2.3	Belief and Plausibility - Mu values and Courses... ..	121
5.1.3	Examples.....	126
5.1.3.1	Malignant Hyperpyrexia.....	126
5.1.3.2	Change in Cardiac Output.....	127
5.1.3.2.1	Crisp sets.....	128
5.1.3.2.2	Fuzzy sets.....	139
5.1.3.3	Hypovolaemia.....	143

5.1.3.4 Sympathetic Response.....	145
5.2 Summary.....	146
PART 6 ANALOGUE DATA COLLECTION AND ANALYSIS	147
6.1 Analogue waveforms.....	148
6.2 The problem and the goals.....	149
6.3 Progress reports.....	154
6.3.1 Respiratory variability (arterial pressure).....	154
6.3.2 Correlation of arterial and photo-plethysmogram variability ...	166
6.3.3 Sympathetic activity in the photo-plethysmogram	176
6.4 Summary.....	180
PART 7 DATA DISPLAY	181
7.1 An overview.....	182
7.1.1 3D display.....	182
7.1.2 Remote monitoring (Audio / MRI).....	183
7.1.3 Vectors and the diagnostic fan.....	184
7.1.4 Flaming tracks.....	187
7.1.5 Hierarchy of displays.....	188
7.2 Summary.....	190
PART 8 SUMMARY AND CONCLUSIONS.....	191
8.1 Summary.....	192
8.2 Conclusions.....	194
BIBLIOGRAPHY.....	195
APPENDIX A.....Harrison, Kluger, and Robertson, 2000.....	204
APPENDIX B.....Lowe and Harrison, 1999.....	208
APPENDIX C.....JAVA program for respiratory related variability of SBP.....	213
APPENDIX D.....Case Scenarios for transfusion decision-making study.....	218
APPENDIX E.....OSRE analysis of transfusion audit data.....	223
APPENDIX F.....Probabilistic alarms for changes in blood pressure.....	225
APPENDIX G.....Free text details for operating theatre procedures.....	224
APPENDIX H.....Details of my contribution to published work	230
APPENDIX I..... Ethics Committee's approval documents.....	232

LIST OF TABLES

TABLE 1	Standard Boolean truth table	15
TABLE 2	Functional derangements for some common clinical disorders with drug interactions	33
TABLE 3	Numbers of senior anaesthetic staff at the hospitals studied together with the number of forms returned.	36
TABLE 4	Lower quartile, median of mid-range values and upper quartile values (mm) from Auckland and Middlemore anaesthetists with comparison statistics	39
TABLE 5	Comparisons between the assessments of likelihood of transfusion (Auckland and Middlemore Hospitals) for co-morbidities at two levels of Hb	41
TABLE 6	Examples of clinical scenarios with embedded data	46
TABLE 7	Numbers of senior anaesthetic staff at the hospitals studied together with the number of forms returned	47
TABLE 8	Distribution of values for COR, ON and Hb embedded in the thirty clinical scenarios	47
TABLE 9	Logistic regression parameters for decision to transfuse	48
TABLE 10	Probabilities of transfusion for the 30 clinical scenarios, for the four hospitals	50
TABLE 11	A comparison, using some of the demographic and contextual variables, between the two sets of transfusion audit data	56
TABLE 12	Co-morbidities in the transfusion audit data sets; initial set n= 80 and testing set n=50	60
TABLE 13	Binary logistic regression analysis of seven variables considered of some importance in the decision to transfuse	61
TABLE 14	Patient numbers for those false positives and false negatives for four different model, BLR = Binomial Linear Regression, PM = Probabilistic Model, NN = Neural Net	64

TABLE 15	Patient details: FP= False positive, FN =False Negative, COR = Cardiac output reserve, OGH = Ongoing haemorrhage, ROTH = Risk of tissue hypoxia, PPT = Peer pressure to transfuse	64
TABLE 16	5th and 95th percentile limits for change in systolic blood pressure	81
TABLE 17	Values for systolic blood pressures recorded five minutes after a previous systolic blood pressure measurement, in 10 mm Hg groupings.	100
TABLE 18	The analysis of matches and mismatches between clinicians' decisions and the computer algorithm's indications to intervene, when blood pressure changed	101
TABLE 19	A crude diagnostic matrix	107
TABLE 20	The number of events detected by the algorithm is displayed against the percentage cumulative change in the physiological variable.	133
TABLE 21	The number of events identified by the clinicians classified as False/True, Negative/Positive when related to different threshold values for the computer algorithm	134
TABLE 22	Numbers of events with indication of agreement between clinicians	134
TABLE 23	Events that were identified by at least two clinicians but not detected by the computer algorithm	135
TABLE 24	Factors affecting E_TCO_2 concentration	139
TABLE 25	The linguistic rules for diagnosis of decreased cardiac output and increased ventilation	140
TABLE 26	Patients and times where the respiratory related variability in blood pressure exceeded 10%	156
TABLE 27	Events where SPV% was raised for two minutes or more	157
TABLE 28	Events where the SPV% was raised for very short periods	163

LIST OF FIGURES

FIGURE 1	An overview of techniques used in the making of decisions and diagnoses	7
FIGURE 2	Overlapping sets	10
FIGURE 3	Crisp boundaries	11
FIGURE 4	Fuzzy sets and boundaries	11
FIGURE 5	Schematic diagram of a neural net	14
FIGURE 6	The overlapping shells of techniques for making decisions and diagnoses.	18
FIGURE 7	Patient information with linkage codes	22
FIGURE 8	Anaesthetic advice from Fortran sorting program	23
FIGURE 9	Decision trees branches for inputting medical problems	26
FIGURE 10	Decision trees branches for inputting surgical procedures	27
FIGURE 11	Decision trees branches for inputting procedures and drug therapy	28
FIGURE 12	Partial Decision Support System advice for malignant hyperpyrexia	30
FIGURE 13	Extract from 'Anaesthesia for Uncommon Diseases'	32
FIGURE 14	(a) Example of one cardiac output related statement, the upper and lower range of one individual's perception of the ability of the patient to increase their cardiac output (b) how the group results are amalgamated to produce a 'population' based lower and upper limit for the range of ability to increase cardiac output.	37
FIGURE 15	VAS results from senior specialists at Auckland Hospital when asked how a particular pathology would affect the patient's ability to increase their cardiac output.	38
FIGURE 16	Likelihood of transfusion on a 100mmVAS for a range of co-morbidities at a Hb of 95 gL^{-1} or 80 gL^{-1}	40

FIGURE 17	Age distribution in initial data set (Hb 70-100 gL ⁻¹) with indication of transfusion rate	58
FIGURE 18	Distribution of VAS scores (mm) for ability to increase CO (in the initial data set, Hb 70-100 gL ⁻¹) with indication of transfusion rate.	58
FIGURE 19	Distribution of VAS scores (mm) for risk of tissue hypoxia ROTH (in initial data set, Hb 70-100 gL ⁻¹) with indication of transfusion rate.	59
FIGURE 20	The likelihood of transfusion vs. the Hb gL ⁻¹	62
FIGURE 21	The likelihood of transfusion vs. the risk of tissue hypoxia as assessed on a VAS	62
FIGURE 22	Heart rate, mean arterial pressure, end-tidal CO ₂ and pulse volume over a period of half an hour during which a fall in cardiac output has fallen	70
FIGURE 23	Effect of a median filter	76
FIGURE 24	Distribution of systolic blood pressures during anaesthesia and surgery	77
FIGURE 25	Present blood pressure (SBP _n) vs. the next SBP (SBP _{n+1})	78
FIGURE 26	Confidence limits for change in systolic blood pressure	79
FIGURE 27	Frequency distribution of changes in systolic blood pressure, the bigger the change the less likely it is to be encountered	79
FIGURE 28	An example of event related changes in MAP, with annotations, designed to clarify the following figures	87
FIGURE 29	Event related changes in MAP	88
FIGURE 30	Event related changes in heart rate	89
FIGURE 31	Event related changes in pulse volume	90
FIGURE 32	The not so subtle effects of smoothing on height and timing of the data points.	93
FIGURE 33	An example of the use of a moving window of standard deviation	94

FIGURE 34	Trigg's Tracking signal (TTS) responding to changes in a variable	96
FIGURE 35	Part of the restructuring of the TTS so that positive changes are positive and negative changes negative	96
FIGURE 36	Demonstration of the restructuring showing that a downward trend above the average and an upward trend below the average both have positive values, which indicates improvement	97
FIGURE 37	One variable analysis with predictions for future range of values	103
FIGURE 38	Integration of intermittent, multiple variable data for diagnostic analysis	103
FIGURE 39	Integration of continuous (analogue data) for diagnostic purposes	103
FIGURE 40	A comparison of respiratory variables between those patients breathing spontaneously and those being ventilated (IPPV)	113
FIGURE 41	A comparison of summed, normalised variables ($E_T\text{CO}_2$, $F_I\text{CO}_2$, RR and RRV) between spontaneously breathing patients and those being ventilated (IPPV)	114
FIGURE 42	The initial neural network used to test the ability to discriminate between those patients breathing spontaneously and those being ventilated	115
FIGURE 43	The final, simple, neural network used to discriminate between the ventilated and non-ventilated patients	115
FIGURE 44	Frequency distribution for calculated values for MOV using the 'Goal-seek' method	116
FIGURE 45	Probability vs 'Goal-seek' calculated values for the area of overlap. For a value > 0.3 the probability is $>98\%$ spontaneous ventilation, <-0.3 IPPV	117
FIGURE 46	Example of the use of cluster analysis in an attempt to separate modes of ventilation	119
FIGURE 47	Vector graph; in this example four variables are plotted on four non-orthogonal axes (y,a,b,x), the resulting sum of these four vectors produces a point +	120
FIGURE 48	Cluster analysis using four vectors; normalised values for $E_T\text{CO}_2$, $F_I\text{CO}_2$, RR and RRV	121

FIGURE 49	Mu values; how a change in MAP can be allocated a μ value	122
FIGURE 50	The way a time series fits a course can be represented by a μ value	122
FIGURE 51	Allocation of μ values to individual data points in a time series. Courtesy of Dr Andrew Lowe	123
FIGURE 52	Belief and plausibility for two sets of evidence for a sympathetic response	123
FIGURE 53	Using the opinions of experts to determine mu values	126
FIGURE 54	Changes in $E_T\text{CO}_2$, MAP, PV and $E_T\text{AA}$ (mean \pm 2 SEM) during acute cardiovascular events identified by the clinicians. The onset of the event is at time zero, n=18	132
FIGURE 55	Data showing an acute event at about 9:05 am. [MAP mmHg, $E_T\text{CO}_2$ kPa, $E_T\text{AA}$ kPa, Heart rate bpm]. This event was detected by all three clinicians	131
FIGURE 56	Example of a trend template used to determine a significant decrease in $E_T\text{CO}_2$ (Courtesy of Dr Andrew Lowe)	141
FIGURE 57	Normalised output showing diagnosis of a fall in cardiac output, courtesy of Dr Andrew Lowe. The lines of points are normalised values for the measured variables; the shaded area indicates the degree of belief in a significant change in the variable. At point 120 in the time series the belief in significant changes in MAP, $E_t\text{CO}_2$, pulse volume (Mod \equiv pulse modulation) and EtAA are all rising. The combination of all these mu values indicates a high belief that cardiac output has changed (msdCOprod)	142
FIGURE 58	Belief and plausibility values for relative hypovolaemia (modified). Courtesy of Dr Andrew Lowe	144
FIGURE 59	A typical arterial pressure waveform	148
FIGURE 60	A typical plethysmographic trace from a pulse-oximeter	149
FIGURE 61	SPV% and trend data from Pt 5	159
FIGURE 62	SPV% and trend data from Pt 9	160
FIGURE 63	SPV% and trend data from Pt 13	162

FIGURE 64	Systolic pressure variation with respiration	166
FIGURE 65	Pulse pressure variation with respiration	167
FIGURE 66	Transformation of data to compensate for general trends	167
FIGURE 67	Processing of the raw pulse-oximeter plethysmogram involves the creation of upper and lower envelopes, plotting the difference between the two and then plotting the absolute value for this value. The variation in this value is then presented as a percentage of the average absolute value	168
FIGURE 68	Correlation between respiratory related variation in the upper envelope of the plethysmograph wave and the variation in the arterial systolic pressure (Pt 17)	170
FIGURE 69	A Bland-Altman plot for percentage variation in the upper envelope of the plethysmograph wave and the variation in the arterial systolic pressure (Pt 17)	170
FIGURE 70	Correlation and Bland-Altman plots for respiratory related systolic variation from pulse-oximeter plethysmograph and arterial pressure waves, Pt 10	171
FIGURE 71	Correlation and Bland-Altman plots for respiratory related systolic variation from pulse-oximeter plethysmograph and arterial pressure waves, Pt 15	172
FIGURE 72	Correlation and Bland-Altman plot for percentage variation in plethysmograph wave and the arterial pulse pressure (Pt 17)	173
FIGURE 73	Correlation and Bland-Altman plots for pulse variation from pulse-oximeter plethysmograph and arterial pressure waves Pt 15	174
FIGURE 74	Correlation and Bland-Altman plots for pulse variation from pulse-oximeter plethysmograph and arterial pressure waves Pt 10	174
FIGURE 75	Correlation and Bland-Altman plots for respiratory related variability of pulse-oximeter plethysmograph and arterial pressure waves using a peak and trough detection algorithm, Pt17	175
FIGURE 76	A FFT of Pt.9's plethysmogram during a stable period of anaesthesia, it shows the major features. The area of interest for SNA is 0.05 - 0.10 Hz.	177

FIGURE 77	FFT power (0.05 – 0.1Hz) and changes in MAP (mmHg min ⁻¹). The records are displayed in descending magnitude of change in MAP.	178
FIGURE 78	Three dimensional plot of current and historical data with fixed normal ranges	183
FIGURE 79	Skeleton of diagnostic fan showing individual variables on spokes,	185
FIGURE 80	Combinations of variables can be made to produce individual point (x.y) for the strength of a diagnosis	185
FIGURE 81	These diagrams show how diagnoses might be presented with some indication of the strength of the diagnosis.	186
FIGURE 82	Hierarchy of display data; face icon always visible, strength of diagnosis determines switch to more detailed information using the user's choice of display.	188
FIGURE 83	Development of data display	189

LIST OF ABBREVIATIONS

AI	Artificial intelligence
ASA	American Society Anaesthesiologists' assessment score (I – V E)
BIS	Bi-spectral index
BLR	Binary logistic regression
BP	Blood pressure
BPV	Blood pressure variability
CHF	Congestive heart failure
CJA	Clinical judgment analysis
CO	Cardiac output
COPD	Chronic obstructive pulmonary disease
COR	Cardiac output reserve
COR	Clinical operating range (for physiological variables)
CVP	Central venous pressure
Des	Desflurane
DSS	Decision Support System
ECG	Electrocardiogram
E _T AA	End-tidal concentration of anaesthetic agent
E _T CO ₂	End-tidal concentration of carbon dioxide
F _E O ₂	Fractional expired concentration of oxygen
FFT	Fast Fourier Transform
F _I AA	Fractional inspired concentration of anaesthetic agent
F _I CO ₂	Fractional inspired concentration of carbon dioxide
F _I O ₂	Fractional inspired concentration of oxygen
FN	False negative
FP	False positive
gdL ⁻¹	Grams per decilitre
Hal	Halothane
Hb	Haemoglobin or haemoglobin concentration
HF	High frequency
HRV	Heart rate variability
IABP	Intra-arterial blood pressure
IPPV	Intermittent positive pressure ventilation
Iso	Isoflurane
kPa	kilo Pascal
LF	Low frequency
LRE	Logistic regression equation
MAC	Minimum alveolar concentration
MAP	Mean arterial blood pressure
MOV	Mode of ventilation
N ₂ O	Nitrous oxide
NIBP	Non invasive blood pressure
NMT	Neuromuscular transmission monitor
NN	Neural networks
NPV	Negative predictive value
NZ	New Zealand
OGH	Ongoing haemorrhage
ON	Oxygen need
P1	Invasive arterial pressure channel on Datex-Ohmeda monitor

P(E)	Probability of the individual being in a subset
P(H)	Unconditional probability of event H
PA	Pulmonary artery
PCF	Patient condition factor
PCWP	Pulmonary capillary wedge pressure
PE (H)	Probability of the event occurring if patient was in subset
PH (E)	Fraction of events in a set of patients
Pleth	Plethysmographic trace from pulse-oximeter
PPNT	Peer pressure not to transfuse
PPT	Peer pressure to transfuse
PPV	Positive predictive value
PR	Pulse rate
Pt	Patient
PVD	Peripheral vascular disease
RAPV	Respiratory-related arterial pressure variability
ROTH	Risk of tissue hypoxia
RR	Respiratory rate
RRV	Respiratory rate variability
SBP / SABP	Systolic blood pressure / Systolic arterial blood pressure
Sevo	Sevoflurane
SNA	Sympathetic nervous activity
SpO2	Oxygen saturation of Hb measured using pulse-oximetry
SPV	Systolic pressure variability
SQL	Structured Query Language
TIA	Transient ischaemic attack (transient cerebral ischaemia)
TN	True negative
TP	True positive
TSW	Time series workbench
TTS	Trigg's tracking signal
TURP	Transurethral resection of prostate
Tx	Transfusion
V (max, min, ave)	Variable (maximum, minimum, average)
VAS	Visual analogue scale
Xt	Value of variable X at time t
y	'year old' as in '80y'

PREFACE

STATEMENT OF WORK

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PUBLICATIONS AND PRESENTATIONS

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The majority of the work has been at my instigation but much of the work has been co-authored with past and present colleagues.

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“I heartily beg that what I have done here may be read with candour; and that the defects I have been guilty of upon this difficult subject may be not so much reprehended as kindly supplied, and investigated by new endeavours of my readers.”

Isaac Newton

The Mathematical Principles of Natural Philosophy

Cambridge, Trinity College,

May 8, 1686.

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Michael Harrison

September 22nd, 2005