MULTISCALE MODELING OF HUMAN ADDICTION: A COMPUTATIONAL HYPOTHESIS FOR ALLOSTASIS AND HEALING

A Dissertation Presented

by

YARIV Z. LEVY

Submitted to the Graduate School of the University of Massachusetts Amherst in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

February 2013

Computer Science

© Copyright by Yariv Z. Levy 2013

All Rights Reserved

MULTISCALE MODELING OF HUMAN ADDICTION: A COMPUTATIONAL HYPOTHESIS FOR ALLOSTASIS AND HEALING

A Dissertation Presented

by

YARIV Z. LEVY

Approved as to style and content by:

Andrew G. Barto, co-Chair

Jerrold S. Meyer, co-Chair

Sridhar Mahadevan, Member

Neil E. Berthier, Member

Lori A. Clarke, Department Chair Computer Science

DEDICATION

To my parents,

to my family,

and to my friends.

ACKNOWLEDGMENTS

I express my deepest gratitude to my co-Advisors, Professor Andrew G. Barto and Professor Jerrold S. Meyer. Professor Barto taught me why essence is the most elegant art of science, and Professor Meyer planted the seeds which bloomed.

I am grateful to the other members of my committee, Professor Sridhar Mahadevan and Professor Neil E. Berthier. Professor Mahadevan encouraged me to be meticulous, and Professor Berthier showed me how a good question can lead to a better answer.

I also express my deepest gratitude to Professor Dino J. Levy who taught me the fundamentals of drug addiction and encouraged me throughout my work. I was also guided and encouraged by Professor Hava T. Siegelmann during the early stages of my research.

I was fortunate to meet and interact with many colleagues, fellows, and teammates during the course of my stay at University of Massachusetts Amherst. I thank them for their curiosity, encouragement, and support.

۷

I wish to thank the staff of the Department and of the University, including the Computer Science Administrative assistants, the Computer Science Computing Facility, the UMass Amherst Libraries, and the UMass Physical Plant Division. Their help was essential for successful completion of my PhD.

My work was supported in part by the National Science Foundation under NSF Grant #CNS-0619337. Any opinions, findings, conclusions or recommendations expressed here are the author's and do not necessarily reflect those of the sponsor.

ABSTRACT

MULTISCALE MODELING OF HUMAN ADDICTION: A COMPUTATIONAL HYPOTHESIS FOR ALLOSTASIS AND HEALING

FEBRUARY 2013

YARIV Z. LEVY

B.Sc., ECOLE POLYTECHNIQUE FEDERALE DE LAUSANNE M.Sc., ECOLE POLYTECHNIQUE FEDERALE DE LAUSANNE Ph.D., UNIVERSITY OF MASSACHUSETTS AMHERST

Directed by: Professor Andrew G. Barto and Professor Jerrold S. Meyer

This dissertation presents a computational multiscale framework for predicting behavioral tendencies related to human addiction. The research encompasses three main contributions. The first contribution presents a formal, heuristic, and exploratory framework to conduct interdisciplinary investigations about the neuropsychological, cognitive, behavioral, and recovery constituents of addiction. The second contribution proposes a computational framework to account for real-life recoveries that are not dependent on pharmaceutical, clinical, and counseling support. This exploration relies upon a combination of current biological beliefs together with unorthodox rehabilitation practices, such as meditation, and proposes a conjecture regarding possible cognitive mechanisms involved in the recovery process. Further elaboration of this investigation leads on to the third contribution, which introduces a computational hypothesis for exploring the allostatic theory of addiction. A person engaging in drug

vii

consumption is likely to encounter mood deterioration and eventually to suffer the loss of a reasonable functional state (e.g., experience depression). The allostatic theory describes how the consumption of abusive substances modifies the brain's reward system by means of two mechanisms which aim to viably maintain the functional state of an addict. The first mechanism is initiated in the reward system itself, whereas the second might originate in the endocrine system or elsewhere. The proposed computational hypothesis indicates that the first mechanism can explain the functional stabilization of the addict, whereas the second mechanism is a candidate for a source of possible recovery.

The formal arguments presented in this dissertation are illustrated by simulations which delineate archetypal patterns of human behavior toward drug consumption: escalation of use and influence of conventional and alternative rehabilitation treatments. Results obtained from this computational framework encourage an integrative approach to drug rehabilitation therapies which combine conventional therapies with alternative practices to achieve higher rates of consumption cessation and lower rates of relapse.

viii

TABLE OF CONTENTS

ACKN	IOWLEDGMENTS	V
ABSTRACT vii		
LIST OF TABLES xii		
LIST	OF FIGURES	.xiii
CHAP	PTER	
1.	INTRODUCTION	1
	1.1 Historical account of addiction in humankind1.2 Maturing out of addiction and natural recoveries1.3 Contributions	4 8 .10
2.	BACKGROUND: BIOLOGICAL MODELS OF ADDICTION	.14
	 2.1 The physical dependence model 2.2 The positive reinforcement model 2.3 The incentive-sensitization model 2.4 The opponent-process model 2.5 The allostatic model 2.6 The disease model 2.7 The impaired response inhibition and salience attribution model 	.16 .18 .19 .20 .21 .24 .27
3.	RELATED WORK: COMPUTATIONAL MODELS OF ADDICTION	.29
	 3.1 Epidemiological models	.30 .32 .35 .36 .39 .43
4.	FIVE-STEPS TOWARD A COMPUTATIONAL MODEL	.48
	4.1 Formalization of the biology underlying addiction4.2 Demonstration of expandability	.50 .51

	4.3 Qualitative validation	53
	4.4 Dynamical properties analysis	54
	4.5 Sensitivity analysis	56
	4.6 Concluding remarks	58
5.	HYPOTHESIS-DRIVEN FRAMEWORK FOR MATURING OUT	60
	5.1 A Multiscale Model of Addiction	60
	5.2 Methods	64
	5.2.1 Probability of a recovery process	66
		00
	5.3 Results: plausible scenarios of drug-seeking and maturing out	69
	5.3.1 Baseline simulations	69
	5.3.2 Direct Influence of the Recovery Process	70
	Recovery Process	70
	5.4 Analysis: a cognitive learning mechanism to enable maturing	75
	5.5 Concluding Remarks	78
6.	A COMPUTATIONAL HYPOTHESIS FOR ALLOSTASIS	81
	6.1 Introduction	82
	6.2 Methods: Computational framework for allostasis	85
	6.2.1 Model validation and provisional assumption	91
	6.3 Results	92
	6.3.1 Baseline: constant reward set point and constant	
	baseline reward threshold	94
	6.3.2 Case Study 1: Allostatic state trajectory during	
	escalation of drug consumption	97
	conventional therapies	99
	6.3.4 Case Study 3: Allostatic state trajectory during	
	alternative medical treatments	101
	6.4 Concluding remarks	110

7.	DISCUSSION AND CONCLUSION	111
	7.1 Biological conjectures and limitations 7.2 The model's high dimensionality	
	7.3 Conclusion: implications for treatments	116
APF	PENDICES	
Α.	SUPPLEMENTARY METHODS	
В.	SUPPLEMENTARY FIGURES	
C.	SUPPLEMENTARY TABLE	

BIBLIOGRAPHY	r	 148

LIST OF TABLES

Table Pa	ıge
Table 1: Data about the US narcotics users population in 1955 and therelated former addicts population at the end of 19596	8
Table 2: Values of the parameters as used in Figures 13 to 3714	8

LIST OF FIGURES

Figure	ge
Figure 1: Neuropsychological, cognitive, behavioral and recovery scales are the four aspects considered in mathematical and computational models of addiction	2
Figure 2: Recapitulation of 10 investigations of maturing out from heroin addiction undertaken between 1962-1980	9
Figure 3: Epidemiological, economic, pharmacological, dopaminergic, and knowledge repository models of addiction are mostly concerned with two scales of observations	0
Figure 4: The knowledge repository (KR) model presented in this dissertation takes into account the four scales of observations considered in previous formal models of addiction4	9
Figure 5: Prior to execution, the model's phenomenological and mathematical inter-correlations were analyzed, and when necessary a functional control was crafted and refined by analysis of the model's output5	7
Figure 6: Diagram of the computational model, where the output of the model <i>G</i> (<i>t</i>) represents the tendency for drug-seeking behavior6	3
Figure 7: Mean and standard errors of the mean for 100 simulations of B.T.'s profile at 35 years old, 600 time steps long (25 days) without any effect of $h(t)$ 7	2
Figure 8: Mean and standard errors of the mean for 100 simulations of B.T.'s profile at 35 years old, 600 time steps long (25 days) under the direct effect of $h(t)$ 74	3
Figure 9: Mean and standard errors of the mean for 100 simulations of B.T.'s profile at 35 years old, 600 time steps long (25 days) under the effect of $h(t)$	4
Figure 10: Simulations of a virtual subject having different cognitive inclinations7	6

Figure 11: Comparison of simulations using the original and the cognitively unbiased values of <i>γ</i> 80
Figure 12: Diagram of the computational model. Time units differ: t is in minutes and t^* in hours. Output $M(t)$ is the mood estimation within the allostatic framework
Figure 13: Baseline (T_s and T_o are constant)
Figure 14: Case Study 1 (cognitive weights and reward components) 104
Figure 15: Case Study 1 (mood and health state assessments)105
Figure 16: Case Study 2 (cognitive weights and reward components)106
Figure 17: Case Study 2 (mood and health state assessments)107
Figure 18: Case Study 3 (cognitive weights and reward components) 108
Figure 19: Case Study 3 (mood and health state assessments)109
Figure 20: Details of the baseline presented in Figure 13130
Figure 21: Details of Case Study 1 presented in Figures 14 and 15131
Figure 22: Comparison of different probabilities defining the associative learning between the drug and its pleasurable effect132
Figure 23: Details of simulations presented in Figure 22133
Figure 24: Details of Case Study 2 presented in Figures 16 and 17134
Figure 25: Comparison of different probabilities defining the durability of <i>H</i> for conventional therapies, with both T_s and T_o time- dependent
Figure 26: Details of simulations presented in Figure 25136
Figure 27: Comparison of different probabilities defining the durability of H for conventional therapies, with T_s constant
Figure 28: Details of simulations presented in Figure 27138
Figure 29: Comparison of different probabilities defining the durability of <i>H</i> for conventional therapies, with T_o constant

Figure 30: Details of simulations presented in Figure 29	140
Figure 31: Details of Case Study 3 presented in Figures 18 and 19	141
Figure 32: Comparison of different probabilities defining the durability of H for alternative treatments, with both T_s and T_o time- dependent	142
Figure 33: Details of simulations presented in Figure 32	143
Figure 34: Comparison of different probabilities defining the durability of H for alternative treatments, with T_s constant	144
Figure 35: Details of simulations presented in Figure 34	145
Figure 36: Comparison of different probabilities defining the durability of H for alternative treatments, with T_0 constant	146
Figure 37: Details of simulations presented in Figure 36	147