TELEOPERATION SYSTEM USING NEURAL NETWORK BASED MULTIPLE MODEL
ADAPTIVE PREDICTIVE CONTROL

MR. BUI VAN BIEN

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF MASTER OF SCIENCE
IN MECHANICAL ENGINEERING
SIRINDHORN INTERNATIONAL THAI-GERMAN GRADUATE SCHOOL OF ENGINEERING
(TGGS)
GRADUATE COLLEGE
KING MONGKUT'S UNIVERSITY OF TECHNOLOGY NORTH BANGKOK
ACADEMIC YEAR 2007
COPYRIGHT OF KING MONGKUT'S UNIVERSITY OF TECHNOLOGY NORTH BANGKOK
Abstract

Today, applications of master-slave teleoperation systems can find in many areas from micro to macro scales. In a teleoperation system, the master is moved by a human operator, and the slave is controlled to follow the motion of the master.

Environment model and communication time delays of teleoperation system are usually variant, which will cause bad performance, even instability of the system. We have developed a theoretical framework to design the neural network based multiple model adaptive predictive controller to solve this problem. First, neural network model based of any possible environment is built up. The teleoperation controller is designed under the effects of time delay. The state observer of forward time delay is built for all environment models to predict slave state. The model of total teleoperation system is established. Finally, the control parameters can be given conveniently using the result of transparency analysis. Therefore, the performance of teleoperation system is worked properly.

The proposed control strategy is tested for verification system. In the simulation, the stability and performance result of teleoperation system is achieved under the proposed controller.

(Total 75 pages)

Keywords: teleoperation system, time delay, neural network, multiple models, predictive control
ชื่อ : นาย บูวาน เบียน
ชื่อวิทยานิพนธ์ : ระบบการทำงานทางไกลโดยใช้โครงข่ายประสาทเทียมด้วยการควบคุมแบบการปรับค่าได้ด้วยแบบจำลองหลายชนิด
สาขาวิชา : วิศวกรรมเครื่องกล
มหาวิทยาลัยเทคโนโลยีพระจอมเกล้า พระนครเหนือ
อาจารย์ที่ปรึกษาวิทยานิพนธ์หลัก : ดร. วุฒิ เปีย ภิรมย์
อาจารย์ที่ปรึกษาวิทยานิพนธ์ร่วม : ดร. อนันต์ ศิริสราญ
ปีการศึกษา : 2550

บทคัดย่อ

ในปัจจุบันการประยุกต์การใช้งานของระบบการทำงานทางไกลเป็นแบบแม่-ลูกสามารถพบในหลายส่วนทั้งจากระดับส่วนเล็กไปจนถึงระดับส่วนที่ใหญ่ ในการประยุกต์แบบการทำงานทางไกลนั้น ต้องออกแบบลูกที่ให้เคลื่อนที่โดยศูนย์ควบคุมและในส่วนลูกควบคุมเพื่อให้สามารถควบคุมลูกที่ได้

แบบจำลองสิ่งแวดล้อมและการทำงานหลายสิ่งของระบบการทำงานทางไกลซึ่งปลูกเติบโตจะเปลี่ยนแปลงไปตามที่จะทำให้ประสิทธิภาพของระบบไม่ดี เนื่องจากความไม่มีเสถียรภาพของระบบ เราได้พัฒนาระบบการทำงานแบบที่มีการลดลงที่โครงข่ายประสาทเทียมด้วยระบบควบคุมแบบการทำงานที่จะปรับค่าได้ด้วยแบบจำลองของลูกที่เพื่อแก้ปัญหาในส่วนแรกระบบการควบคุมแบบจำลองสิ่งแวดล้อมที่มีการเปลี่ยนแปลงเพื่อให้ประสิทธิภาพของระบบดีขึ้น สิ่งแวดล้อมที่เปลี่ยนไปได้หลากหลายมีลูกพัฒนาขึ้น มีความควบคุมการทำงานทางไกลของลูกที่เพื่อให้ประสิทธิภาพของระบบที่ดีขึ้น

พารามิเตอร์ที่ใช้ในการควบคุมสามารถส่งผ่านไปใช้งานโดยการวิเคราะห์สิ่งแวดล้อมของระบบ ที่ต้องการปรับค่าให้เหมาะสมกว่า วิธีการควบคุมที่ได้นำเสนอถูกพิสูจน์ร่วมจากผลการทดลองการทำงานของระบบแสดงให้เห็นว่า ความสามารถและประสิทธิภาพของระบบได้รับผลสัมฤทธิ์มากที่ได้ตัวควบคุมที่ได้นำเสนอ

(วิทยานิพนธ์มีจำนวนทั้งสิ้น 75 หน้า)

คำสำคัญ : ระบบการทำงานทางไกล การทำงานแบบโครงข่ายประสาทเทียมแบบจำลองหลาย

ชันด กระบวนการควบคุมการทำงาน
ACKNOWLEDGEMENTS

This work was carried out at The Sirindhorn International Thai-German Graduate School of Engineering (TGGS), King Mongkut’s University of Technology North Bangkok, Bangkok, Thailand. The work could not have been done without the help of many persons, of whom the following are specially acknowledged.

It is difficult to express my gratitude to my advisors, Dr. Vu Trieu Minh and Dr. Anan Suebsomran. With their enthusiasm, their inspiration, their great efforts to explain things clearly and simply, they helped me believe in myself. Throughout my thesis-doing period, they provided encouragement, sound advice, good teaching, and many good ideas. I would have been failed without them.

I also would like to show my sincere thanks to Associate Professor Dr. Suwat Kuntanapreeda, my first year lecturer, for his advice and support throughout I-MME course. I would like to say a big “thank you” to my teachers who have taught me during all master courses. I am indebted to their knowledge, helpful suggestions, and valuable assistances throughout my studying in Thailand.

I would like to thank the Thailand International Cooperation Department (TICA) for the scholarship, which has supported me during my three years of master degree in Thailand. Without their support, it is impossible for me to have a chance to visit and study in Thailand.

Last but certainly not least, I would love to thank my wife, my parents, my sister, brother, and my relatives for their love, care, and encouragement.

Bui Van Bien
# TABLE OF CONTENTS

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract (in English)</td>
<td>ii</td>
</tr>
<tr>
<td>Abstract (in Thai)</td>
<td>iii</td>
</tr>
<tr>
<td>Acknowledgements</td>
<td>iv</td>
</tr>
<tr>
<td>List of Tables</td>
<td>vi</td>
</tr>
<tr>
<td>List of Figures</td>
<td>viii</td>
</tr>
<tr>
<td>Chapter 1 Introduction</td>
<td>1</td>
</tr>
<tr>
<td>1.1 Background and Statement of the Problem</td>
<td>1</td>
</tr>
<tr>
<td>1.2 Teleoperation Controller Design Goals</td>
<td>3</td>
</tr>
<tr>
<td>1.3 The Scope of the Study</td>
<td>4</td>
</tr>
<tr>
<td>1.4 The Utilizations of the Study</td>
<td>5</td>
</tr>
<tr>
<td>Chapter 2 Literature Review</td>
<td>6</td>
</tr>
<tr>
<td>2.1 History</td>
<td>6</td>
</tr>
<tr>
<td>2.2 Applications for Teleoperation System</td>
<td>8</td>
</tr>
<tr>
<td>2.3 Teleoperation Control</td>
<td>13</td>
</tr>
<tr>
<td>2.4 Conclusion</td>
<td>24</td>
</tr>
<tr>
<td>Chapter 3 Neural Network Based Multiple Model Adaptive Predictive Control</td>
<td>25</td>
</tr>
<tr>
<td>3.1 Physical Model</td>
<td>25</td>
</tr>
<tr>
<td>3.2 Neural Network Model based</td>
<td>29</td>
</tr>
<tr>
<td>3.3 Controller Design</td>
<td>35</td>
</tr>
<tr>
<td>3.4 Observer Design</td>
<td>37</td>
</tr>
<tr>
<td>3.5 System Model</td>
<td>40</td>
</tr>
<tr>
<td>3.6 Transparency Analysis</td>
<td>42</td>
</tr>
<tr>
<td>3.7 Conclusion</td>
<td>46</td>
</tr>
<tr>
<td>Chapter 4 Simulation Results</td>
<td>47</td>
</tr>
<tr>
<td>4.1 Simulation Models</td>
<td>47</td>
</tr>
<tr>
<td>4.2 Simulation Results</td>
<td>50</td>
</tr>
<tr>
<td>4.3 Conclusion</td>
<td>63</td>
</tr>
<tr>
<td>Chapter 5 Conclusion</td>
<td>64</td>
</tr>
<tr>
<td>Section</td>
<td>Page</td>
</tr>
<tr>
<td>-------------------------</td>
<td>------</td>
</tr>
<tr>
<td>5.1 Conclusions</td>
<td>64</td>
</tr>
<tr>
<td>5.2 Future Works</td>
<td>65</td>
</tr>
<tr>
<td>References</td>
<td>66</td>
</tr>
<tr>
<td>Appendix</td>
<td>70</td>
</tr>
<tr>
<td>Biography</td>
<td>75</td>
</tr>
</tbody>
</table>
# LIST OF TABLES

<table>
<thead>
<tr>
<th>Table</th>
<th></th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>A-1</td>
<td></td>
<td>71</td>
</tr>
<tr>
<td>The matrix P and Q</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
## LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>2-1</td>
<td>First mechanical master slave manipulator by Ray Goertz</td>
<td>7</td>
</tr>
<tr>
<td>2-2</td>
<td>Master-slaver manipulator</td>
<td>8</td>
</tr>
<tr>
<td>2-3</td>
<td>Da Vinci minimal invasive surgical robot</td>
<td>9</td>
</tr>
<tr>
<td>2-4</td>
<td>Highly dexterous 7 DOF end-effector of Da Vinci robotic system</td>
<td>10</td>
</tr>
<tr>
<td>2-5</td>
<td>ROV with manipulators courtesy</td>
<td>10</td>
</tr>
<tr>
<td>2-6</td>
<td>Robot at International Space Station courtesy</td>
<td>11</td>
</tr>
<tr>
<td>2-7</td>
<td>Single master operators operating multiple robots with a bilateral control system</td>
<td>12</td>
</tr>
<tr>
<td>2-8</td>
<td>The components within a teleoperation system</td>
<td>13</td>
</tr>
<tr>
<td>2-9</td>
<td>The position-position controller architecture</td>
<td>15</td>
</tr>
<tr>
<td>2-10</td>
<td>The position-force controller architecture</td>
<td>16</td>
</tr>
<tr>
<td>2-11</td>
<td>The force-force controller architecture</td>
<td>16</td>
</tr>
<tr>
<td>2-12</td>
<td>The four-channel architecture</td>
<td>17</td>
</tr>
<tr>
<td>2-13</td>
<td>Block diagram of a teleoperation predictive display and control</td>
<td>19</td>
</tr>
<tr>
<td>3-1</td>
<td>Teleoperation system configuration</td>
<td>26</td>
</tr>
<tr>
<td>3-2</td>
<td>Physical model of master and slave manipulator</td>
<td>26</td>
</tr>
<tr>
<td>3-3</td>
<td>Physical model of environment</td>
<td>28</td>
</tr>
<tr>
<td>3-4</td>
<td>The schematic diagram of the bilateral teleoperation system with the proposed control scheme</td>
<td>29</td>
</tr>
<tr>
<td>3-5</td>
<td>Radial basis function network</td>
<td>32</td>
</tr>
<tr>
<td>4-1</td>
<td>The simulation model for the ideal teleoperation system</td>
<td>47</td>
</tr>
<tr>
<td>4-2</td>
<td>The simulation model for teleoperation system with time delay and without time-variant environment</td>
<td>48</td>
</tr>
<tr>
<td>4-3</td>
<td>The simulation model for teleoperation system with time-variant delay and environment</td>
<td>49</td>
</tr>
<tr>
<td>4-4</td>
<td>The simulation model for teleoperation system with noise, time variant delay, and time-variant environment</td>
<td>49</td>
</tr>
<tr>
<td>Figure</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>4-6</td>
<td>The forces of master and slave in the ideal teleoperation system with M1</td>
<td>51</td>
</tr>
<tr>
<td>4-7</td>
<td>The position of master and slave in the ideal teleoperation system with M2</td>
<td>52</td>
</tr>
<tr>
<td>4-8</td>
<td>The forces of master and slave in the ideal teleoperation system with M2</td>
<td>53</td>
</tr>
<tr>
<td>4-9</td>
<td>The position of master and slave in the ideal teleoperation system with M3</td>
<td>53</td>
</tr>
<tr>
<td>4-10</td>
<td>The forces of master and slave in the ideal teleoperation system with M3</td>
<td>54</td>
</tr>
<tr>
<td>4-11</td>
<td>The position of master and slave in the teleoperation system with M1 and M1</td>
<td>55</td>
</tr>
<tr>
<td>4-12</td>
<td>The forces of master and slave in the teleoperation system with M1 and M1</td>
<td>55</td>
</tr>
<tr>
<td>4-13</td>
<td>The position of master and slave in the teleoperation system with M2 and M2</td>
<td>56</td>
</tr>
<tr>
<td>4-14</td>
<td>The forces of master and slave in the teleoperation system with M2 and M2</td>
<td>57</td>
</tr>
<tr>
<td>4-15</td>
<td>The position of master and slave in the teleoperation system with M3 and M3</td>
<td>57</td>
</tr>
<tr>
<td>4-16</td>
<td>The forces of master and slave in the teleoperation system with M3 and M3</td>
<td>58</td>
</tr>
<tr>
<td>4-17</td>
<td>The performance of the RBF neural network without noise</td>
<td>59</td>
</tr>
<tr>
<td>4-18</td>
<td>The position of master and slave in the teleoperation system with time-variant delay and environment</td>
<td>59</td>
</tr>
<tr>
<td>4-19</td>
<td>The forces of master and slave in the teleoperation system with time-variant delay and environment</td>
<td>60</td>
</tr>
<tr>
<td>4-20</td>
<td>The performance of the RBF neural network with noise</td>
<td>61</td>
</tr>
<tr>
<td>Figure</td>
<td>Description</td>
<td>Page</td>
</tr>
<tr>
<td>--------</td>
<td>-----------------------------------------------------------------------------</td>
<td>------</td>
</tr>
<tr>
<td>4-21</td>
<td>The position of master and slave in the teleoperation system with time delays, time-variant environment and noise</td>
<td>61</td>
</tr>
<tr>
<td>4-22</td>
<td>The forces of master and slave in the teleoperation system with time delays, time-variant environment, and noise</td>
<td>62</td>
</tr>
</tbody>
</table>
CHAPTER 1
INTRODUCTION

1.1 Background and Statement of the Problem

In recent years, with reducing the cost and time in the control system, teleoperation has been developed very fast. Teleoperation was first conceived to allow a human operator the ability to perform dangerous tasks on a remote environment while the operator remains at a safe distance. The first practical application of teleoperation was developed to handle nuclear waste. Today, applications of master-slave teleoperation systems can be found in different areas, such as space and submarine explorations, military and public services (e.g., maintenance and repairing of electric lines), agriculture and livestock nourishing, medicine and others.

A teleoperation system includes a master station having a manually operable master link coupled to a master actuator, which provides force resistance to operation and movement of the master link, and a slave station having a slave link moveable by a slave actuator in response to command signals. The system also includes a control unit for producing command signals in response to movement of the master link. The control unit consists of five elements: (i) A position transducer is used for producing signals representing the position of the master link; (ii) A force transducer is to produce signals representing the force applied to the master actuator by operation of the master link; (iii) A second force transducer is used for producing signals representing force applied to the slave link by the slave actuator; (iv) A second position transducer is to produce signals representing position of the slave link; (v) A force controller is to respond to the master link position signals: the master actuator force signal and the slave actuator force signal. The slave link position signal produces a force command signal for supply to the slave actuator. The force command signal causes the slave actuator to move the slave link in substantially faithful imitation of movement of the master link. There is always a communications line involved in teleoperation systems since the local controller (master robot) and the remote system (slave robot) are required to be connected at all times. The information
flow from one robotic system to the other can be achieved through various media including the Internet, intranet, satellite, or radio signals. The common shortcoming of these communication systems is that they will make the teleoperation system experience more significant time delays as the distance between the controller and the remote system increases.

The existence of time delay in the communication link is one of the most important problems regarding the stability of teleoperation systems. For the last decade, time delay problem in teleoperation system have been researched in different aspects. Time delays have a destabilizing effect on bilateral teleoperators and this problem is presented by Anderson and Spong [1]. It is shown that delays in the communication block make the standard control law non-passive but by mimicking a lossless transmission line, the system becomes passive and, hence, stable. Aspects of bilateral controller design for teleoperation systems have been presented by Yan and Salcudean [2]. Kikuchi et al. [3] proposed an alternative teleoperation system in dynamic environment with varying communication time delay. The proposed system consists of the stable bilateral teleoperation subsystem using the virtual time delay method, the visual information subsystem that offers pictures in remote site and the environment prediction display subsystem that offers the prediction of the slave manipulator and the environment. Zhu and Salcudean [4] introduced a novel stability guaranteed controller design for bilateral teleoperation under both position and rate control modes with arbitrary motion/force scaling. Ando et al. [5] found the relation between human behavior and time delay based on psychological time theory in teleoperation system. Influence of delay time in teleoperation with visual feedback is quantitatively evaluated and reviewed. Elhaij et al. [6] introduced a new event-based control method for teleoperation systems with haptic feedback, which overcomes the effects of time delay. Itoh et al. [7] proposed a new predictive display method of the motion and the force information for a general network teleoperation without using the virtual environment model. The major contribution of the proposed method was to provide the predictive motion and force information to the human operator without using any virtual model of the real environment even in the constrained space. The proposed method was experimentally applied to a telemanipulation system and the results illustrated the validity of the proposed approach. Shahdi and Sirouspour [8]
introduced an adaptive method for teleoperation in unknown environments. Multiple models describe dynamic behavior of the slave in free motion and in contact with a rigid environment. A multiple-model state estimation technique calculates the mode probabilities based on the available sensory information. The control action is computed by combining the mode-based control signals according to the mode probabilities. To improve transparency and compensate for the effect of time delay, Smith and Van Hashtrudi-Zaad [9] presented a new alternative predictive control that uses the concept of the Smith predictor using neural network. The problem of force-reflecting teleoperation over IP networks is addressed by Polushin et al. [10]. Taking into account time-varying communication delay and possible data packets dropout, they propose a control scheme that guarantees the stability of the overall system. In the case where the communication delay in the forward communication channel is guaranteed to be smooth enough function of time, the proposed scheme also guarantees that the slave tracks the delayed master trajectory with an error bounded by a prescribed constant. A possible extension of the proposed scheme may incorporate some sort of a force control algorithm on the slave side which may improve the performance of teleoperation. Casavola et al. [11] presented a predictive strategy. This is the problem of teleoperating a remotely located precompensated plant subject to input and state-related pointwise-in-time constraints through a communication channel with unknown and possibly unbounded time delay. Within this framework, several predictive teleoperation strategies have been singled out which are well suited to the general problem and individually tailored for the expected communication channel latency. However, all of the mentioned methods can not be directly used to teleoperation systems with time-variant delay and environment.

In this research, we propose a new method to solve time delay problem in teleoperation system using a neural network based multiple model adaptive predictive control. The experimental results from simulations on Matlab environments are used to evaluate the proposed methodology.

1.2 Teleoperation Controller Design Goals

Like any other control systems, the basic design goal of teleoperation controllers is to maintain stability in all circumstances. Stability is defined as a
bounded system response to a bounded input. For linearly modeled systems, the traditional stability analysis tools such as Nyquist criterion or Root Locus technique are available. In the presence of communication time delay, researchers have frequently used stability analysis techniques such as passivity-based tools [1] or Lyapunov theory [12].

The second design goal of teleoperation controllers is performance. Performance in teleoperation systems can be accessed through different criteria, such as task completion time [13], manipulator dexterity, joint effort [14], or telepresence [15,16]. The later is the most commonly used method and can also be referred to as transparency. Transparency is described as “accurate rendering of the environment to the operator”, fulfills the primary objective of teleoperation, which is “projection of human sensing and manipulation ability to remote locations”.

Transparency is quantitatively defined as “a match between the master and the slave positions and forces”, actualizing the condition of direct manipulation [16]. Although in situations that forces or positions are scaled up or down this definition does not apply anymore. Therefore, another definition of transparency has been proposed by Lawrence [17] based on concept of impedance, a quantity that maps the input position of a system to the output force.

1.3 **The Scope of the Study**

The research will focus only on stability and performance of a teleoperation system in case of time-variant environment dynamics and time delay with new control method. We study and investigate the bilateral control issue in teleoperators and we propose a new scheme. The proposed scheme is studied, analyzed, and conditions for stability and robustness are derived. The scheme is also validated by numerical simulation. The simulated system is based on the SIMULINK/MATLAB.

The following chapters of this thesis are organized as follows:

Chapter two: Literature Review. This chapter discusses a brief view on the historical developments and applications of teleoperation systems. A review of the teleoperation control is presented, as well as, a brief background of common teleoperation architectures, which is used to evaluate and compare performances of
previously published teleoperator control laws. Relevant investigations in time delay and predictive strategies and adaptive teleoperation are discussed.

Chapter three: Neural Network Based Multiple Predictive Adaptive Control. The proposed control scheme is described. The physical model and dynamics for one DOF systems are introduced. The neural network model base and slave state predict are explained. The general configuration of the control law is presented, the dynamic equations are derived and the performance of the control law is demonstrated.

Chapter four: Simulation Result. This chapter introduces a case study using the proposed control design approach. The numerical simulation results are also presented.

Chapter five: Conclusions. This chapter summarizes the work presented in this thesis and the contributions made. Suggestions for future work are also discussed.

1.4 Utilization of the Study

The research has benefits as follow:

1.4.1 To supply a new method for teleoperation system.
1.4.2 To investigate the effect of the neural network.
CHAPTER 2
LITERATURE REVIEW

In this chapter, the teleoperation system is reviewed. Section 2.1 presents a brief view on the historical developments of teleoperation systems. Section 2.2 introduces application. Section 2.3 shows a teleoperation system control. Finally, section 2.4 concludes this chapter, with a summary and conclusions.

2.1 History

A teleoperation system or a bilateral telemanipulation system is a complex electro-mechanical system comprehending a master and a slave device, interconnected by a communication channel and controller. Through interaction with the master device, the human operator is able to communicate control signals for the slave. The slave device actually interacts with the (remote) environment, thereby staying under full control of the human operator. Information gathered at the remote side is transmitted back to the human operator through the master device. Usually, this info at least encompasses a camera view of the remote site. Visual information is demonstrated on a screen, possibly using stereovision. If additionally, interaction by exchange of energy occurs through the feedback of force or touch information, the system is called a bilateral telemanipulation system.
Prior to 1945, there were crude teleoperators for earth moving, construction and related tasks. The first master-slave teleoperator shown in Figure 2-1 was developed at the Remote Control Division of the Argonne National Laboratory, near Chicago, under the direction of R. Goertz [18]. Goertz’s master-slave mechanism is implemented with electric-servo manipulators with force feedback in 1950s [19]. Force sensation in the master side is a direct termination of the mechanically coupled systems. Since then a great amount of work has been done in the area by various researchers. Sheridan published a useful survey in 1989 [20]. Hokayem and Spong introduced a recent historical survey [21].

Since a teleoperation system is applied for very delicate tasks, the single most important quality of the system is its stability. Followed after stability, transparency of a teleoperation system is also a key belonging [22]. Transparency of a bilateral system is defined as equivalence of force and position responses of master and slave sides apart from dynamics of the environments [16]. Yokokohji and Yoshikawa introduced
the same concept as kinesthetic coupling formulation and experiment. The ideal kinesthetic coupling allows the operator to manipulate the system as if he were manipulating the object directly [16], or to transfer accurately the task impedances to the master side [17]. Katsura presented that perfect transparency in a bilateral system is not possible [23]. Since perfect transparency of the system is not possible, system designers should try to have the highest transparency possible.

2.2 Applications for Teleoperation System

Since 50’s teleoperation control systems established a wide area for application. Level of telepresence and serviceability in these systems are still way behind the demands. As importance (price) of the human increases in modern society requirements of usable bilateral systems increases. Below various different applications areas of bilateral systems are discussed very briefly.

2.2.1 Hazardous material handling

![Master-slaver manipulator (www.hmw.com)](image-url)
As discussed previously hazardous material handling is the reason for the invention of the master-slave manipulators. Mechanical and servo controlled master slave manipulators are widely used in research and industry. Figure 2-2 shows a master-slave manipulator.

2.2.2 Medical robotics - Minimal Invasive Surgery

Teleoperation systems found its place in biomedical applications also. First mechanical tools used in minimal invasive surgery started to be replaced by the small robotics tools and cameras and after gaining confidence further advanced towards teleoperated surgery workplace are now visible. Intuitive surgical systems inc. produces Da-Vinci surgical system (shown in Figure 2-3). Which compose of a stereo vision system and 4 highly dexterous robotic tools controlled from a station next to the patient. Surgeon can monitor the environment with 3D stereo vision system (shown in Figure 2-4). However, system lacks the force feedback to the surgeon.

**FIGURE 2-3** Da Vinci minimal invasive surgical robot from http://intuitivesurgical.com
FIGURE 2-4 Highly dexterous 7 DOF end-effector of Da Vinci robotic system (http://intuitivesurgical.com)

2.2.3 Underwater robotics

FIGURE 2-5 ROV with manipulators courtesy of www.seaice.com
As deep sea is one of the most dangerous environments for human beings, teleoperation and telepresence is required for construction, research, and military applications. Underwater vehicles are one of the main applications of teleoperation. Underwater remotely operated vehicles (ROV) are mostly controlled with supervisory control algorithms for operation in environments with hard limitations on communication. A remotely operated vehicle also has manipulators for manipulation and similar tasks, bilateral control systems are mostly used in these tools.

2.2.4 Space robotics

**FIGURE 2-6** Robot at International Space Station courtesy of www.space.gc.ca

Like underwater applications, space operation is also very dangerous and costly. Space robots operated from the ground stations is subject to long communication delays due to the distance. Currently there are many researchers working on control of manipulators or observer vehicles at space. Figure 2-6 shows an image of a manipulator currently in use in international space station for assisting astronauts.
2.2.5 Mobile robotics

Recently there are also applications of bilateral control with group of mobile robots in research level. Bilateral control can be applied in many tasks requiring more than one robot at master and slave sides. Cooperated mobile robots can be used in construction and other areas requiring controlled large forces from different sides of an object. Figure 2-7 depicts a bilateral system which single master operating a large object with three mobile robots.

![Diagram of bilateral control system](image)

**FIGURE 2-7** Single master operators operating multiple robots with a bilateral control system [16]

2.2.6 Micro manipulation and assembly

Micromanipulation and micro assembly is one of the hardest tasks for a human being as the forces at the micro world are very different from the human environment. Bilateral control system working with force and position scaling and impedance shaping methods provides a similar environment to the human operator working with the micro objects.
2.2.7 Other possible applications

There are many other possible applications for bilateral control. Exoskeleton human power amplifying robots has been developed in 1970’s. Such exoskeletons can also be used to help disabled people for assistance in walking [16].

Military applications of bilateral control are also considered very attractive for military. Mine inspection and deactivation, remote observation of enemy operations, remotely operated vehicles, aircrafts, tanks, etc are few of many possible applications for military [15].

2.3 Teleoperation Control

2.3.1 Teleoperation system components

A teleoperation system enables a human operator to interact with a real, mostly remote, environment. Figure 2-8 shows the different components within a teleoperator system.

![FIGURE 2-8 The components within a teleoperation system](image)

The “human operator” interacts with the technical system through the haptic interface. In bilateral telemanipulation, the human operator receives force feedback, in most cases combined with visual and/or auditory feedback. Out of the available stimuli, the human operator gathers the desired perceptions and information and determines the following actions. The human operator is the final user and the whole system should be designed in strict accordance to the needs of the human operator and the tasks to be performed.

The “master” is the physical device with which the human operator interacts. The device is capable of acquiring data about the desired manipulation actions, and thus about the task to assign to the slave. Moreover, the master transmits the
appropriate information about the remote site to the human operator. The master may consist of different hardware units, such as a visual display, an auditory unit, tactile devices, joysticks, or consoles. For bilateral teleoperation systems, the master encompasses a haptic interface, which is an active device, able to exert forces on the human operator.

The “communication channel” sends the signals of interest to the other side of the telemanipulator. The information exchange can take place via cable, radio, or even satellite, according to the physical locations of the two devices, the available hardware, and task requirements. The communication channel may be a source of time delay, bandwidth limitations, or loss of information due to communication noise.

The “control” typically is distributed over the different devices. Both master and slave device have local controllers, possibly (but rarely) providing a certain degree of autonomy. An overall control structure determines the variables communicated over the communication line, and coordinates the behaviour of the total system. The controller is responsible for the appropriate behaviour of the slave according to the task assignment by the human operator and the environment the slave is interacting with. The controller also is responsible to offer the human operator the appropriate signals in the right form and as rich in information as possible through the specific master device. Thus, the controller is responsible to yield the user the correct perception about the task execution.

The “slave manipulator” is the robotic device that is in charge of the physical interaction with the (remote) environment. It replicates the user behaviour at the remote side and carries out the required task. It might be equipped with sensors to acquire relevant information about the task development to be sent back to the master.

The “environment” is composed of the various objects the user has to interact with. The environment is remote in the sense that it is mostly hard to access directly. The barrier could be a distance (e.g. space applications, underwater, keyhole surgery), a hazardous environment (e.g. nuclear plants), or even a size (e.g. micromanipulation). The environment can be a priori known or structured (e.g. during assembly) or be unknown and unstructured (as during telesurgery).

Through above five components, information is exchanged in two directions. The control channel enables the human operator to assign tasks to the slave and
control the slave as desired. Through the information channel, information about the
task execution is fed back to the human operator. Both channels mostly are
interconnected, and the information is affected by all of the system components.

Teleoperation control architectures are categorized based on the number and the
type of signals transmitted across the communication channel. Common two-channel
and four-channel architectures are introduced next.

2.3.2 Two-channel architectures

The first teleoperation control architecture was the position-position architecture
[24]. This architecture uses only the position signals from master and slave \((X_m, X_s)\)
and emulates a rubber band between the two devices. In [25] Lawrence discusses a
position based controller and states that this type of controller is best suited for
operation on soft environments, under ideal circumstances. However, to achieve
perfect transparency, in theory the control gains would have to be infinite. Elevating
the controller gains to improve position following cause sluggishness and instability
under significant delay. This is caused by a delay-induced position error, which is
amplified and applied, to the master controller. As a result, this architecture is not
transparent [17].

![FIGURE 2-9 The position-position controller architecture](image)

To improve performance, environment contact force instead of slave position
can be sent directly to the master. This force-position architecture has been adopted
by many researchers since it has been shown empirically to provide better
transparency than the position-position architecture [17]. One drawback of this
architecture is its low stability margin when significant communication delay is
introduced. To improve stability, the transmitted slave force can be attenuated at the
master; however, this improved stability comes at the cost of reduced sensitivity [15].
FIGURE 2-10 The position-force controller architecture

The force-force architecture, in which master and slave forces are exchanged, has been proposed by Kazerooni et al. [26]. To guarantee the stability of the system, \( H_\infty \) control theory and model reduction techniques have been used. Due to the lack of position signals, this architecture suffers from a lack of kinematical coordination between the master and slave. Without any coordinating force the devices can drift if unattended.

FIGURE 2-11 The force-force controller architecture

2.3.3 Four-channel architecture

The four-channel teleoperation architecture uses master and slave position and force signals. This architecture is arguably the only architecture, which can obtain perfect transparency under ideal circumstances over all obtainable frequencies if acceleration is, used [17]. However, good transparency can also be obtained at lower frequencies without the use of acceleration signals [17]. Contrary to this claim, in [27] it has been shown that perfect transparency can be obtained with one less force channel if local force feedback is used.

Although the four-channel architecture can obtain perfect transparency under ideal circumstances, it has been shown to lack stability robustness to communication
delay [28]. To increase stability robustness, damping can be added to the master and slave, which causes a sluggish feel for the operator. To improve this, the amount of artificial damping has been adjusted in [28] to give the operator a more transparent feel.

FIGURE 2-12 The four-channel architecture

2.3.4 Time delay issues

Practically every teleoperation system contains some amount of delay in communication, which are due to the speed limitation of signals through communication medium and controller processing time. Teleoperation systems operating within the same room through serial communication or a dedicated Ethernet connection have a small, constant delay of several tens of milliseconds. Due to the existence of switching equipment, teleoperation systems traveling through the Internet have unpredictable delays with high variability, from 0.1 seconds to as much as 3 seconds [29]. In outer space operations, communication over extremely long distances using radio signals enforces delays approximately minutes [30]. In many applications, the amount of time delay does not need to be large to cause catastrophic effects to uncompensated systems. It has been shown that time delays of less than 50 milliseconds can destabilize force-position bilateral controllers [1].

The first methods of dealing with delay employed a “move and wait” strategy where the operator performs the task in an open loop system. The operator makes a discrete controlled movement, waits for the round-trip delay time and confirms that the control command has been followed by the slave device. In this way the operator
can only commit to a small incremental position change before waiting the delay period for the slave to “catch up”. The operator then makes another move and so forth. Although this strategy is stable, it is very time consuming, makes simple tasks very difficult to perform, and leads to increased operator fatigue [30].

To improve the efficiency, a better understanding of delay is required. The problem of time delay can be understood using passivity theory. The addition of time delay into the communication channel generates energy and causes the energy of the channel to increase, thus rendering it non-passive and unstable [1]. There are several ways to compensate for this increase in energy. Scattering theory has been used to design controllers guaranteeing stability by making the communication channel a passive loss-less transmission line [1]. This architecture guarantee stability under any delay given passivity of the rest of the system. However, as the delay increases, the practicality of this system diminishes due to the reduced transparency. A time domain passivity observer was implemented by Ryu et al. [31] to identify the period in which artificial damping was needed to guarantee passivity of the master-slave system, providing a better compromise between stability and transparency. Adding artificial damping to the system leads to an increased “sluggish” feeling, thus reducing the transparency of the system. $H_\infty$ optimization and $\mu$-synthesis techniques have been employed to optimize performance for guaranteed stability, give fixed and known operator and environment impedances [2].

The above architectures are designed for systems with small communication delays. When the delay increases, the stability is maintained at the cost of significantly reduced performance. Alternative methods such as “supervisory control” and “predictive strategies”, which provide better performance under large communication delays have been developed. Supervisory control has been proposed to address delay by moving the operator outside of the master control loop. The operator monitors and supervises the tasks by sending high-level programs for the slave to execute. The programs operate in a zero delay local control loop at the slave device, frequently reporting back to the operator providing updates [30]. Although supervisory techniques have been shown to improve stability and decrease completion time under large communication delays [30], these architectures require precise
knowledge of all the systems involved in the task. Predictive strategies are presented next.

2.3.5 Predictive strategies

Predictive display and control techniques predict the response of the slave and environment at the master through display and/or kinesthetic feedback. These methods commonly use a dynamic model of the slave and environment for prediction. The general organization of a predictive strategy is shown in Figure 2-12.

![Block diagrams of a teleoperation predictive display and control](image)

**FIGURE 2-13** Block diagrams of a teleoperation predictive display and control

Predictive display methods have been used to compensate for large and varying communication delays [11]. These methods use a real-time graphically simulated task, which uses the dynamic model of the slave and environment. The graphical simulation can be superimposed over top of camera images of the remote task. The operator is then presented with visual information and possibly kinesthetic information, which is provided by the local dynamic simulated environment at the master controller. These strategies decrease the task completion time, provided that the dynamics of the slave and environment are known precisely and the task does not involve extensive contact [30]. Predictive displays often overload the operator with information, do not provide improved transparency, and can lead to increased completion times if there exist uncertainties in the model.
An alternate solution has been devised to compensate for large time delays while also providing kinesthetic feedback using theories developed for chemical processes. Predictive control was first proposed by Smith to address dead time in chemical control loops [32]. In the work proposed by Smith, a linear estimate of a plant is placed within a control loop containing delay, commonly referred to as a “Smith predictor”. Provided that the linear estimate of the plant is accurate, the effect of delay can be moved outside of the control loop, thus improving the stability and performance of the system.

Recently this work has been extended to teleoperation systems where the operator receives kinesthetic force feedback via a master robot locally interfaced with a real-time dynamic simulation of the slave and environment. This local model of the slave and environment dynamics removes the effect of delay in the control loop [33, 34, 35, 36]. The difficulty with using Smith predictors in teleoperation architectures is the use of fixed linear dynamic estimates of the slave and environment (plant). However, in practice the slave and environment exhibit time-varying nonlinear dynamic behavior.

Ganjefar et al. [33] propose the use of wave-based teleoperation techniques with a modified Smith predictor architecture. Munir and Book [35] use a Kalman filter to estimate the position of the slave device and wave variables to transfer information across the communication channel to implement a modified Smith predictor. These systems have good stability robustness to large and varying delay as illustrated by experimental results involving teleoperation over the Internet. However, this architecture requires accurate knowledge of the system dynamics. Any model errors or uncertainties can quickly destabilize the system. As well, to provide optimal performance a good estimate of the communication delay is required.

In [34] Huang and Lewis propose the use of neural networks in the slave controller to remove the nonlinear dynamic effects of the slave and environment so that the remaining linear dynamics can be accurately estimated in a Smith predictor architecture. However, although this work compensates for delay and can do so on nonlinear slave and environment dynamics; it is unable to adjust to said unknown or changing dynamics.
Fite et al. [36] propose another Smith predictor architecture in a teleoperation system. To allow for dynamic uncertainty and variations in the slave and environment dynamics, they propose the use of a Slotine and Li adaptive controller [37] to update the master linear estimate of the slave and environment dynamics. Although this architecture does allow for uncertainty and variation in plant dynamics, it requires that the plant dynamics be linear to provide improved stability and performance. As well, to ensure the convergence of the estimated parameters, the operator must provide a rich enough input, which is persistently exciting. This is difficult in a teleoperation system with significant communication delay due to a lack of stability robustness.

Smith and Van Hashtrudi-Zaad [9] introduced the several new classes of teleoperation predictive control architectures with communication delay that are based on the concept of the Smith predictor. The proposed predictive architectures use neural networks that are trained online to guess and represent the slave and environment dynamics at the master. Using online learning neural networks to estimate slave and environment contact forces allowed to create a nonlinear real-time mapping between master position and slave contact force, making this method suitable for environments displaying nonlinear and time-varying dynamics. To provide a better tradeoff between force matching and NN weight convergence a new method of selecting the learning rate is also proposed. Using the slave and environment dynamic estimate the master controller is capable of predicting the environment contact force and providing the operator with more control over the task, especially when there is substantial delay in the communication channel. Comparing the variations of the proposed NN-based predictive controllers, it was found that the lack of precise cancellation of the delayed transmitted contact force and the estimated force at the master contributed to mild contact oscillations. It was also found that the best performance was obtained when no contact force was transmitted to the master and only contact force estimates generated by the NN at the master are used for control.

2.3.6 Adaptive teleoperation

Another alternative for better trade-off between stability robustness and performance is the use of adaptive controllers that adjust their parameters based on operator and environment contact information or impedance [38]. This type of
controller is also well suited for situations with unstructured of time varying environment dynamics.

In [39], a position-position architecture has been employed with a Slotine and Li direct adaptive controller for slave position tracking with various slave end-effector loads. Under ideal circumstances, this architecture performs well but has difficulty with immobile objects. When in contact with immobile objects the mass parameter becomes elevated and causes a delay in slave movement when out of contact. To improve this, Niemeyer and Slotine propose switching to stiffness control with no adaptation once contact is made [40]. This system has difficulty maintaining stability when communication delay is added to the system.

A two-channel force-position architecture instantaneous impedance identification is proposed in [41]. Using a least mean squares recursive algorithm to quickly identify the environment impedance, Heredia et al. propose a novel adaptive architecture, which can adjust for time varying environments. The instantaneous environment impedance model is used to update position feedforward and force feedback gain to improve transparency. However, algorithms, which use instantaneous values for adaptation, are subject to stability problems when significant delay is present in the communication channel.

Hashtrudi-Zaad and Salcudean improve performance with communication delay by using an indirect Slotine and Li controller at the slave for position tracking [42]. This architecture identifies the environment impedance in a position-position architecture and reflects the identified impedance back to the master controller for impedance matching. This architecture provides good parameter convergence for applications with slow time-varying environments.

In [43], a position-position controller is used which adjusts the master and slave impedances based on the angle between the slave velocity command and the contact force. Without delay, the variable impedance results in reduced impact forces reflected to the master robot and improved velocity control in free motion. However, for surface tracking the algorithm is always attempting to reach a point within the surface, leading to increased friction and unnecessary force application.

Rubio et al. [44] propose a force-force architecture with an added adaptive impedance algorithm at the master and slave to improve transparency and stability in
hard contact. This system provides improved contact stability and performance in contact but is susceptible to kinematical drift. As well, this architecture will not provide stable contact when communication delay is significant in the system.

In [45], Salcudean et al. propose an adaptive algorithm which uses instantaneous position and force values for impedance matching between master and slave. Both master and slave devices are controlled using impedance control with the master and slave impedance adjusted in a dual manner to match high or low environment impedances. This architecture provides good transparency and stability in both free motion and contact but has not been tested with significant time delay.

Zhu and Salcudean [12] proposed a novel adaptive control algorithm that allows for arbitrary motion/force scaling. By considering the operator together with the master and the environment together with the slave as separate systems two adaptive motion/force control algorithm are designed. This allows for strong feedback control and parameter identification of each system, which compensates for any uncertainties and improves stability and performance even with small communication delays of up to 100 milliseconds. The system becomes equivalent to a linearly damped free-floating mass, thus providing good motion tracking. However, this architecture cannot provide good performance and stability with large communication delays over 1 second.

Love and Book [46] proposed identifying environment impedance using recursive least squares identification and adjusting the artificial damping at the master for stability, based on the estimated impedance. As a result, the system provides significantly reduced operator effort and fatigue. This work does not discuss transparency.

Neural networks have been used to realize the input-output behavior of systems demonstrating nonlinear dynamics such as robotic manipulator [47] or to identify the parameter of a nonlinear environment dynamic model [48]. These methods often use off-line learning techniques, which limit their applications. Recently, Chang and Okamura [49] proposed an impedance reflecting neural network teleoperation control architecture that compensated for the changes in end-effector load. Although not discussed in enough detail, the slave controller used an online position-based neural network with an evolutionary algorithm. Using master and slave position errors, the
neural network created a compensation term which are employed in both the master and slave controllers to compensate for slave dynamic uncertainties and load variations.

2.4 Conclusion

This chapter introduces a brief overview of the historical developments and applications of teleoperation systems. The teleoperation control is reviewed. A brief background of common teleoperation architectures, which is used to evaluate and compare performances of previously published teleoperator control laws, is presented. Pertinent investigating in time delay and predictive strategies and adaptive teleoperation are also discussed in detail. However, all of the methods mentioned in this chapter cannot be directly used to teleoperation systems with time-variant delay and environment. Therefore, we proposed a method using neural network based multiple models adaptive predictive control for the teleoperation systems with time-variant delays and environment. The proposed method will be presented in chapter 3.
In this chapter, the proposed teleoperation system control, physical model and dynamics for one DOF systems, neural network model base, controller design, slave state predict, total teleoperation system model, transparency analysis are explained. Section 3.1 presents the physical model. Section 3.2 introduces the neural network model base. Section 3.3 designs the controller. Section 3.4 predicts slave state. The system model will be presented in Section 3.5. Section 3.6 will show the transparency analysis. Finally, the conclusion will be depicted in Section 3.7.

3.1 Physical Model

Bilateral force-reflecting teleoperators is usually modeled as a two-port network [1], [15], [17], [50]. The advantage of the two-port network exists in the fact that traditional electrical network theory can be used to analyze the system. In this case, the force and position/velocity variables of the teleoperation system correspond to the voltage and current in electrical systems. Because the electrical network theory is already quite mature, the analysis and simulations of teleoperators can be performed more easily. Until now, the network model is still the dominant one in this research field.

As mentioned in the previous chapter, to model a teleoperation system, we need to consider five fundamental elements: the human operator, the master manipulator, the communication channel, the slave manipulator, and the environment. Besides, we need to model their connections. This is not a trivial work, especially when considering that the environment is variant within the control loop.
Figure 3-1 shows a basic teleoperation layout for a bilateral control setting. The operator moves the master manipulator, which in turn causes the slave manipulator to run after its movements. Forces exerted by the environment on the slave are transmitted to the master and are felt by the operator. Under the assumption that each degree of freedom (DOF) has linear uncoupled from the other, the analysis and design will be centered on a one DOF linear system hereunder.

3.1.1 Model of master and slave manipulator

The master and slave manipulator are all modeled as mechanical devices with masses, dampers and springs, shown in Figure 3-2.

First, we define the notations in Figure 3-2 and these notations will be used throughout this thesis. $m_m$, $m_s$, $b_m$, $b_s$, $k_m$, and $k_s$ are the inertia, damping ratio, and stiffness of the master and slave manipulators respectively; $f_h$ is the force applied to
the master manipulator by the human operator and $x_m$ is the position of the master; $f_e$ is the contact force between the slave manipulator and the environment and $x_s$ is the position of the slave. In addition, $u_{dm}$ is the signal return from the slave and $u_d$ denotes the control signal that given by the master through the Internet.

The dynamics of the master and slave manipulators of this physical model are given by the following equations. Note that they are in time domain. For simplicity, the time variable $t$ is dropped.

$$f_h - u_{dm} = m_m \cdot \ddot{x}_m + b_m \cdot \dot{x}_m + k_m \cdot x_m \quad \text{Eq. 3-1}$$

$$u_d - f_e = m_s \cdot \ddot{x}_s + b_s \cdot \dot{x}_s + k_s \cdot x_s \quad \text{Eq. 3-2}$$

3.1.2 Model of communication channel

In a traditional teleoperation system, the communication channel is a private telecommunication line using a communication satellite, a private communication cable, a private radio channel and etc. Therefore, the communication channel is assumed to have a constant time delay.

In this thesis, we considered a problem of teleoperation via Internet where the time delay is significant and variable. In this situation, the time delay of communication channel is random. The equation of communication channel is given as:

$$u_d(t) = u(t - T_R(t)) \quad \text{Eq. 3-3}$$

$$u_{dm}(t) = u_s(t - T_L(t)) \quad \text{Eq. 3-4}$$

where $T_R(t)$ denotes the forward time delay and $T_L(t)$ denotes the backward time delay.

3.1.3 Model of environment

Another issue in a teleoperation controller design is the wide range of (and possible time-variant) environment dynamic display. To model the environment, we
assume that the dynamics of the environment are regulated by a model from a finite set of environment at any given time. They are all modeled as mechanical devices with masses, dampers and springs, shown in Figure 3-3.

![Physical model of environment](image)

**FIGURE 3-3** Physical model of environment

We define the notations in Figure 3-3 and these notations will be used throughout this thesis. $m_e$, $b_e$, and $k_e$ are the inertia, damping ratio, and stiffness of the environment. And the environment model is described as the following equation. Note that it is in time domain. For simplicity, the time variable $t$ is dropped.

$$f_e = m_e \cdot \ddot{x} + b_e \cdot \dot{x} + k_e \cdot x$$  \hspace{1cm} \text{Eq. 3-5}$$

where $m_e$, $b_e$, and $k_e$ are usually unknown and time-variant.

Figure 3-4 shows the proposed control scheme including the predictor and the radial basic function network.

In order to identify the parameters of environment, we builds up neural network model base of any possible environment offline. When the system operates, a neural network model which fits the factual environment best is selected from the environment model base, and the model parameters are transmitted to the master. These are introduced in next section.
3.2 Neural Network Model Based

Neural network is an effective modeling method. However, because of limitation of training speed, neural network shows poor real time modeling capability in the case of time variant dynamics. In order to solve the problem, the radial basis function (RBF) network is used to model environment dynamics in this system. It is a typical local approximation neural network and is easy to approximate local performance of a function and the training speed is fast.

3.2.1 Overview of RBF network

RBF networks have been widely used for function approximation of nonlinear systems. In the initial time, the original RBF method has been used for rigorous multi-variable function interpolation [51] and for this the RBF model demands as many RBF neurons (referred to here as computational units) as data points. This is seldom practical because of the large size of the data points. Broomhead and Lowe [52] removed this strict interpolation restriction and provided a neural network architecture where the number of RBF neurons can be far less than the data points.

The RBF neural network mainly consists of three layers, one input layer, one hidden-layer and one output layer. The number of hidden-layer neurons is a variable to be decided by the user. Different basis functions such as thin-plate spline function,
multi-quadratic function, inverse multi-quadratic function and Gaussian functions have been studied for the hidden-layer neurons but normally they are took as Gaussian. Compared with other types of neural networks like backpropagation feedforward networks, the RBF network has a more compact topology [53] and also requires less computation time for learning [54]. Apart from pattern recognition, RBF networks have been utilized successfully in a number of wide-ranging applications such as time-series prediction [55], in speech recognition [56], in adaptive control [57], etc.

A hierarchically self-organizing learning (HSOL) algorithm was formulated to find the minimal number of hidden units for RBF in [53]. Different types of basis function were analyzed like sigmoidal, sinusoidal and Gaussian. The Gaussian RBF was found suitable not only in generalizing a global mapping but also in refitting local features without much altering the already learned mapping. The learning algorithm recruits new hidden-layer neurons whenever necessary for improving network performance. The network starts with no hidden units and adds a new unit with a larger width in the beginning of the learning which is reduced for the following units until a minimal radius is received. In this algorithm, after adding a new node all the weights are adjusted using backpropagation. In summary, this paper introduced the concept of building up of the hidden neurons from zero to the required number using the inputs with the update of the RBF parameters being done by backpropagation or actually a gradient descent algorithm with its attendant problems.

In [54], Moody and Darken presented a solution for using a smaller number of hidden neurons than that of the data using a local representation for hidden units. For this method the number of hidden units is chosen a “priori” and no special assumptions are made about the basis functions such as orthogonality or being uniformly distributed over the input space. The basis functions used are radially symmetric where the widths can be computed using various \( P \) nearest neighbor methods. They developed a hybrid learning method which mixed the linear self-organized learning scheme (the well-known k-means clustering) for estimating the centers of the basis functions and a linear supervised learning method (the standard LMS algorithm) for estimating the output weights. They clearly showed that the RBF
learning is faster compared to BP because of the combination of locality of representation and linearity of learning schemes.

In a series of papers, Billings and his colleagues [58, 59, 60] have developed RBF neural networks for nonlinear dynamic system identification and they have compared the performance of RBF networks with the standard backpropagation feedforward networks. The results clearly demonstrate that the RBF networks are giving better performance with less network complexity. In their use of RBF schemes they have worked mainly on the batch learning scheme where the entire training set is available. Their scheme is also mentioned to as a hybrid scheme because it consists of an unsupervised learning scheme which estimates the centers of the basis functions and supervised learning scheme which uses the well-known least squares algorithm for determining the output weights. Also, in their original scheme, the number of centers is fixed a “priori” and in an improved version [60] they have indicated a recursive scheme for centre estimation. In all their studies they have selected radial basis functions of the thin-plate type which does not have a width parameter or even when they have chose Gaussian functions, the widths of these functions have been fixed. The unsupervised learning scheme for estimating the centers is the well-known \(k\)-means clustering algorithm. They have presented the results of their scheme on a nonlinear dynamic system identification problem which leads to a nonlinear autoregressive moving average with exogenous inputs (NARMAX) time series prediction problem.

In particular, the RBF network with Gaussian basis functions possess the very desirable mathematical properties of universal approximation and best approximation. Next, the structure of RBF network will be discussed.

3.2.2 The structure of RBF network

The structure of RBF network can be described in Figure 3-5.
FIGURE 3-5 Radial basis function network

Input Layer: This layer consists of the \( n \times d \) input data matrix \( X \),

\[
X = (x_1, x_2, \ldots, x_n)^T \in \mathbb{R}^{n \times d}
\]

where \( x_i \) are \( d \)-dimensional input vectors and \( n \) is the number of input vectors, i.e., size of the input data set.

Hidden Layer: Suppose that the hidden layer consists of \( k \) basis functions \( \phi_j(\cdot), j = 1, 2, \ldots, k \). These functions transform the input data matrix via nonlinear mappings, \( \phi_j(x) = \Phi(\|x - \mu_j\|/\sigma_j), j = 1, 2, \ldots, k \) based on the Euclidean distance between the input vector \( x \) and prototype vector \( \mu_j \). The \( n \times d \) input matrix is thus transformed by the \( k \) basis functions into the following \( n \times d \) matrix \( \Phi \) whose \( j \)th column represents the outputs from the \( j \)th basis function, \( j = 1, 2, \ldots, k \).
\[
\phi = \begin{bmatrix}
\varnothing_1(x_1) & \cdots & \varnothing_k(x_1) \\
\vdots & \ddots & \vdots \\
\varnothing_1(x_n) & \cdots & \varnothing_k(x_n)
\end{bmatrix}
\]  
Eq. 3-7

For the Gaussian RBF, we have \( \varnothing(r) = \exp\left(-\frac{r^2}{2}\right) \) so that the expression for the \( j \)th function mapping can be explicitly written as

\[
\varnothing_j(X) = \exp\left(-\frac{\|X - \mu_j\|^2}{2 \cdot \sigma_j^2}\right) 
\]  
Eq. 3-8

where \( \mu_j \) is the center and \( \sigma_j \) is the width of the \( j \)th basis function. On substituting for \( \varnothing_j(.) \) in equation 3-7, we get the following expression for \( \varnothing \).

\[
\varnothing = \begin{bmatrix}
\exp\left(-\frac{\|x_1 - \mu_1\|^2}{2 \cdot \sigma_1^2}\right) & \cdots & \exp\left(-\frac{\|x_1 - \mu_k\|^2}{2 \cdot \sigma_k^2}\right) \\
\vdots & \ddots & \vdots \\
\exp\left(-\frac{\|x_n - \mu_1\|^2}{2 \cdot \sigma_1^2}\right) & \cdots & \exp\left(-\frac{\|x_n - \mu_k\|^2}{2 \cdot \sigma_k^2}\right)
\end{bmatrix}
\]  
Eq. 3-9

Output Layer: As mentioned above, the column in equation 3-9 represent nonlinear mappings of the input data, produced by the \( k \) basis functions in the hidden layer. The entries in this matrix are then combined linearly according to weights \( w_1, w_2, \ldots, w_k \) associated with the \( k \) basis functions \( \varnothing_1(\cdot), \varnothing_2(\cdot), \ldots, \varnothing_k(\cdot) \), respectively. The resulting values at the output node are then given by

\[
f(X) = \sum_{j=1}^{k} w_j \cdot \exp\left(-\frac{\|X - \mu_j\|^2}{2 \cdot \sigma_j^2}\right) 
\]  
Eq. 3-10

where \( f(X) \) represents the RBF output for input vector \( X \). Thus, for \( n \) input vectors \( (x_1, x_2, \ldots, x_n)^T \), the output layer generates an output vector \( \hat{Y} \) which consist of \( n \) estimates of outputs \( \hat{y}_i \) each corresponding for \( x_i \), i.e.,
\[ \hat{y} = (\hat{y}_1, \hat{y}_2, ..., \hat{y}_n)^T = (f(x_1), f(x_2), ..., f(x_n))^T \]  

Eq. 3-11

3.2.3 RBF network model base

To create and train the radial basis function network, we use the command “newrb” in MATLAB neural network toolbox.

First, we have \( n \) given environment models. With \( i \)-th model, we have been known the value of state of the slave \( P_i = [x_{si} \ \dot{x}_{si} \ \ddot{x}_{si}]^T \) and the environment model parameters \( Q_i = [k_{ei} \ b_{ei} \ m_{ei}]^T \).

Hence, the input vector \( P \) is presented as follows

\[
P = \begin{bmatrix}
x_{s1} & \ldots & x_{sn} \\
\dot{x}_{s1} & \ldots & \dot{x}_{sn} \\
\ddot{x}_{s1} & \ldots & \ddot{x}_{sn}
\end{bmatrix}
\]  

Eq. 3-12

And the associated target vectors \( Q \) is also shown as

\[
Q = \begin{bmatrix}
k_{e1} & \ldots & k_{en} \\
b_{e1} & \ldots & b_{en} \\
m_{e1} & \ldots & m_{en}
\end{bmatrix}
\]  

Eq. 3-13

We use the command “newrb” to quickly create a radial basis network which will approximate the function defined by \( P \) and \( Q \). The function “newrb” adds neurons to the hidden layer of a radial basis function network until it meets the specified mean squared error goal \( \varepsilon \).

At \( t \) time, we get the value of environment model parameters from RBF network

\[
f_e(t) = \begin{bmatrix}
m_e \ b_e \ k_e
\end{bmatrix}^T
\]  

Eq. 3-14

On the other hand, we have the value of parameters of \( n \) environment models...
\[ f_{e1}(t) = [m_{e1} b_{e1} k_{e1}]^T \]
\[ f_{e2}(t) = [m_{e2} b_{e2} k_{e2}]^T \]
\[ ... \]
\[ f_{en}(t) = [m_{en} b_{en} k_{en}]^T \]  

Eq. 3-15

Modeling error is computed according to the following equation

\[ e_i = \sqrt{[m_{et} - \hat{m}_e]^2 + [b_{et} - \hat{b}_e]^2 + [k_{et} - \hat{k}_e]^2} \]  

Eq. 3-16

where \( i = 1, 2, ..., n \).

If \( e_m \) is smallest, \( m \)th environment model which fits best to current environment dynamics is selected.

### 3.3 Controller Design

From section 3.1 we know that the control signal sent by the master to the slave is \( u(t) \). In conventional control methods such as [17], [22], it is necessary to transmit position, velocity and acceleration signals between the master and slave. But acceleration is difficult to measure. It makes the system difficult to realize. In order to guarantee transparency, \( u(t) \) should include force, position and velocity signal as follows

\[ u(t) = f_{11} \cdot x_m(t) + f_{12} \cdot \dot{x}_m(t) + c \cdot f_h(t) \]  

Eq. 3-17

where \( f_{11}, f_{12}, \) and \( c_{11} \) are feedback coefficients and \( f_1 = (f_{11} f_{12}) \).

In incorporating equation 3-17 and 3-3 yields

\[ u_d(t) = f_{11} \cdot x_m(t - T_h(t)) + f_{12} \cdot \dot{x}_m(t - T_R(t)) + c_{11} \cdot f_h(t - T_R(t)) \]  

Eq. 3-18

Because time delay causes \( u_d(t) \neq u(t) \), we use \( x_s(t), \dot{x}_s(t), \) and \( f_e(t) \) to adjust \( u_d(t) \) as follow
\[ u_d(t) = f_{11} \cdot x_m(t - T_R(t)) + f_{12} \cdot \dot{x}_m(t - T_R(t)) + f_{13} \cdot x_s(t) + f_{14} \cdot \dot{x}_s(t) + c_{11} \cdot f_h(t - T_R(t)) + c_{12} \cdot f_e(t) \]  
Eq. 3-19

where \( f_{12}, f_{13}, \) and \( c_{12} \) are feedback coefficients.

Similar with \( u_d(t) \), \( u_s(t) \) should also include force, position and velocity signal

\[ u_s(t) = f_{23} \cdot x_s(t) + f_{24} \cdot \dot{x}_s(t) + c_{22} \cdot f_e(t) \]  
Eq. 3-20

where \( f_{23}, f_{24}, \) and \( c_{22} \) are feedback coefficients.

Substituting equation 3-20 and 3-4 yields

\[ u_{dm}(t) = f_{23} \cdot x_s(t - T_L(t)) + f_{24} \cdot \dot{x}_s(t - T_L(t)) + c_{22} \cdot f_e(t - T_L(t)) \]  
Eq. 3-21

Because time delay causes \( u_{dm}(t) \neq u_s(t) \), we use \( x_m(t - T(t)), \dot{x}_m(t - T(t)), \) and \( f_h(t - T(t)) \) to adjust \( u_{dm}(t) \) as follow

\[ u_{dm}(t) = f_{23} \cdot x_s(t - T_L(t)) + f_{24} \cdot \dot{x}_s(t - T_L(t)) + c_{22} \cdot f_e(t - T_L(t)) + f_{21} \cdot x_m(t - T(t)) + f_{22} \cdot \dot{x}_m(t - T(t)) + c_{21} \cdot f_h(t - T(t)) \]  
Eq. 3-22

where \( T(t) = T_R(t) + T_L(t) \), \( f_{21}, f_{22}, \) and \( c_{21} \) are feedback coefficients.

In \( u_{dm}(t) \) there contains state of the slave at time \( t - T_L(t) \) and \( u_{dm}(t) \) can response control effect of \( u(t - T(t)) \) on the slave. Accordingly , \( u_{dm}(t + T(t)) \) can response the control effect of \( u(t) \). As a result, if we use predicted value of \( u_{dm}(t + T(t)) \) as feedback value from the slave, then the master will feel that there do not exist time delay. Correspondingly, the effect of time delay on transparency is eliminated completely. Predicted value of \( u_{dm}(t + T(t)) \) is labeled as \( \hat{u}_{dm}(t + T(t)) \):
\[
\hat{u}_{am}(t + T(t)) = f_{21} \cdot x_m(t) + f_{22} \cdot \dot{x}_m(t) \\
+ f_{23} \cdot \hat{x}_s(t + T_r(t)) + f_{24} \cdot \dot{\hat{x}}_s(t + T_r(t)) \\
+ c_{21} \cdot f_h(t) + c_{22} \cdot \hat{f}_e(t + T_R(t))
\]

Eq. 3-23

where \( \hat{f}_e(t + T_R(t)) \), \( \hat{x}_s(t + T_R(t)) \), and \( \dot{\hat{x}}_s(t + T_R(t)) \) are predicted values of \( f_e(t + T_R(t)) \), \( x_s(t + T_R(t)) \), and \( \dot{x}_s(t + T_R(t)) \).

According to the environment model, \( \hat{f}_e(t + T_R(t)) \) can be calculated by the following equation.

\[
\hat{f}_e(t + T_R(t)) = m_e \cdot \hat{x}_s(t + T_R(t)) + b_e \cdot \dot{\hat{x}}_s(t + T_R(t)) \\
+ k_e \cdot \ddot{x}_s(t + T_R(t))
\]

Eq. 3-24

And the predicted values \( \hat{x}_s(t + T_R(t)) \), and \( \dot{\hat{x}}_s(t + T_R(t)) \) can be realized through time forward observer.

### 3.4 Observer Design

For the sake of predicting \( x_s(t + T_R(t)) \), and \( \dot{x}_s(t + T_R(t)) \), substituting equation 3-19 in 3-2, we have

\[
f_{11} \cdot x_m(t - T_R(t)) + f_{12} \cdot \dot{x}_m(t - T_R(t)) + c_{11} \cdot f_h(t - T_R(t)) \\
+ f_{13} \cdot x_s(t) + f_{14} \cdot \dot{x}_s(t) + c_{12} \cdot f_e(t) - f_e(t) = m_s \cdot \ddot{x}_s(t) \\
+ b_s \cdot \dot{x}_s(t) + k_s \cdot x_s(t)
\]

Eq. 3-25

We define

\[
\bar{u}_d(t) = f_{11} \cdot x_m(t - T_R(t)) + f_{12} \cdot \dot{x}_m(t - T_R(t)) \\
+ c_{11} \cdot f_h(t - T_R(t))
\]

Eq. 3-26

Equation 3-25 becomes the following equation
\[ u_d(t) = m_s \cdot \dot{x}_s(t) + (b_s - f_{14}) \cdot \dot{x}_s(t) + (k_s - f_{13}) \cdot x_s(t) \\
+ (1 - c_{12}) \cdot f_e(t) \]  
Eq. 3-27

Substituting equation 3-5 into 3-27, we have

\[ u_d(t) = m_s \cdot \dot{x}_s(t) + (b_s - f_{14}) \cdot \dot{x}_s(t) + (k_s - f_{13}) \cdot x_s(t) \\
+ (1 - c_{12}) \cdot (m_e \cdot \dot{x}_s(t) + b_e \cdot \dot{x}_s(t) + k_e \cdot x_s(t)) \]

Hence

\[ u_d(t) = (m_s + (1 - c_{12}) \cdot m_e) \cdot \dot{x}_s(t) \\
+ ((b_s - f_{14}) + (1 - c_{12}) \cdot b_e) \cdot \dot{x}_s(t) \\
+ ((k_s - f_{13}) + (1 - c_{12}) \cdot k_e) \cdot x_s(t) \]  
Eq. 3-28

Converting equation 3-28 into state-space models, we have

\[ \dot{x}_s(t) = A_s \cdot \ddot{x}_s(t) + B_s \cdot u_d(t) \]
\[ \ddot{y}(t) = C_s \cdot \ddot{x}_s(t) \]  
Eq. 3-29

where \( \ddot{x}_s(t) = \begin{bmatrix} x_s(t) \\ \dot{x}_s(t) \end{bmatrix} \), \( C_s = \begin{bmatrix} 1 & 0 \end{bmatrix} \), \( B_s = \begin{bmatrix} 0 \\ \frac{1}{m_s + (1 - c_{12}) \cdot m_e} \end{bmatrix} \), and

\[ A_s = \begin{bmatrix} 0 & 1 \\ \frac{(k_s - f_{13}) + (1 - c_{12}) \cdot k_e}{m_s + (1 - c_{12}) \cdot m_e} & \frac{(b_s - f_{14}) + (1 - c_{12}) \cdot b_e}{m_s + (1 - c_{12}) \cdot m_e} \end{bmatrix} \]

In order to predict \( u_{dm}(t + T(t)) \), we have to prognosticate \( x_s(t + T_R(t)) \), and \( \dot{x}_s(t + T_R(t)) \), firstly, state-space equation of the slave at time \( t + T_R(t) \) should be accomplished. As a result, we switched equation 3-29 into the future by \( T_R(t) \) units and yields
\[
\dot{x}_s(t + T_R(t)) = (1 + \dot{T}_R(t)) \cdot A_s \cdot \ddot{x}_s(t + T_R(t)) \\
+ (1 + \dot{T}_R(t)) \cdot B_s \cdot \ddot{u}_d(t + T_R(t)) \tag{Eq. 3-30}
\]
\[
\bar{y}(t + T_R(t)) = C_s \cdot \ddot{x}_s(t + T_R(t))
\]

However, it is difficult to compute \(\dot{T}_R(t)\). According to the characteristic of Internet, we model \(\dot{T}_R(t)\) as uncertain parameter, and equation 3-30 becomes

\[
\dot{x}_s(t + T_R(t)) = (A_s + \Delta A_s) \cdot \ddot{x}_s(t + T_R(t)) \\
+(B_s + \Delta B_s) \cdot \ddot{u}_d(t + T_R(t)) \tag{Eq. 3-31}
\]
\[
\bar{y}(t + T_R(t)) = C_s \cdot \ddot{x}_s(t + T_R(t))
\]

where \(\Delta t = \dot{T}_R(t)\), \(\Delta A_s\) and \(\Delta B_s\) are modeled as uncertain parameters, \(\Delta A_s = \Delta t \cdot A_s\), \(\Delta B_s = \Delta t \cdot B_s\).

When the time delay is constant, \(\dot{T}_R(t) = 0\), namely there do not exist uncertain parameters. It is a special case of this article.

Now we predict \(\ddot{x}_s(t + T_R(t))\) using the following observer

\[
\dot{z}(t) = A_s \cdot z(t) + B_s \cdot (f_1 \cdot \ddot{x}_m(t) + c_{11} \cdot f_h(t)) \\
+ L \cdot (\bar{y}(t + T_R(t)) - y_s(t)) \tag{Eq. 3-32}
\]
\[
y_s(t) = C_s \cdot z(t)
\]

where \(L\) is the observer gain, and \(\ddot{x}_m(t) = \begin{bmatrix} x_m(t) \\ \dot{x}_m(t) \end{bmatrix}\)

Since the master cannot measure \(\bar{y}(t + T_R(t))\), the observer cannot be realized. 

We can only use output error of time \(t - T_L(t)\) to adjust the observer as follows

\[
\dot{z}(t) = A_s \cdot z(t) + B_s \cdot (f_1 \cdot \ddot{x}_m(t) + c_{11} \cdot f_h(t)) \\
+ L \cdot (\bar{y}(t - T_L(t)) - y_s(t - T_R(t) - T_L(t))) \tag{Eq. 3-33}
\]
\[
y_s(t) = C_s \cdot z(t)
\]
Let observing error \( e(t) = \ddot{x}_s(t + T_R(t)) - z(t) \), then

\[
\dot{e}(t) = A_s \cdot e(t) + \Delta A_s \cdot \ddot{x}_s(t + T_R(t)) - L \cdot C_s \cdot e(t - T_R(t) - T_L(t)) + \Delta B_s \cdot (f_1 \cdot \ddot{x}_m(t) + c_{11} \cdot f_h(t))
\]

\text{Eq. 3-34}

\subsection{3.5 System Model}

Using \( \ddot{u}_{dm}(t + T(t)) \) in equation 3-23 to take the place of \( u_{dm}(t) \) in equation 3-1, we have

\[
f_h(t) = \left( f_{21} \cdot x_m(t) + f_{22} \cdot \dot{x}_m(t) + f_{23} \cdot \ddot{x}_s(t + T_R(t)) + f_{24} \cdot \dot{x}_s(t + T_R(t)) + c_{21} \cdot f_h(t) + c_{22} \cdot \dot{f}_e(t + T_R(t)) \right)
\]

\text{Eq. 3-35}

\[
= m_m \cdot \ddot{x}_m(t) + b_m \cdot \dot{x}_m(t) + k_m \cdot x_m(t)
\]

Rearranging equation 3-35 yields

\[
m_m \cdot \ddot{x}_m(t) + (b_m + f_{22}) \cdot \dot{x}_m(t) + (k_m + f_{21}) \cdot x_m(t) = - \left( f_{23} \cdot \ddot{x}_s(t + T_R(t)) + f_{24} \cdot \dot{x}_s(t + T_R(t)) + c_{22} \cdot \dot{f}_e(t + T_R(t)) \right)
\]

\text{Eq. 3-36}

\[
+(1 - c_{21}) \cdot f_h(t)
\]

Substituting equation 3-24 into 3-36 and modifying, we have

\[
m_m \cdot \ddot{x}_m(t) + (b_m + f_{22}) \cdot \dot{x}_m(t) + (k_m + f_{21}) \cdot x_m(t) = - \left( (f_{23} + c_{22} \cdot k_e) \cdot \ddot{x}_s(t + T_R(t)) + (f_{24} + c_{22} \cdot b_e) \right)
\]

\text{Eq. 3-37}

\[
\cdot \dot{x}_s(t + T_R(t)) + c_{22} \cdot m_e \cdot \ddot{x}_s(t + T_R(t))
\]

\[
+ (1 - c_{21}) \cdot f_h(t)
\]

Using \( z(t) \) and \( \dot{z}(t) \) to substitute \( \ddot{x}_s(t + T_R(t)) \), \( \dot{x}_s(t + T_R(t)) \), and \( \ddot{x}_s(t + T_R(t)) \) in equation 3-37 generates
\[ \ddot{x}_m(t) + \left(\frac{b_m + f_{22}}{m_m} + B_e \cdot B_s \cdot f_{12}\right) \cdot \dot{x}_m(t) + \left(\frac{k_m + f_{21}}{m_m} + B_e \cdot B_s \cdot f_{11}\right) \cdot x_m(t) = \]

\[ \left(1 - c_{21}\right) \cdot f_h(t) - \left(A_e \cdot z(t) + B_e \cdot \dot{z}(t)\right) \]

Eq. 3-38

where \( A_e = \left[ \frac{(f_{23} + c_{22} \cdot k_e)}{m_m} \quad \frac{(f_{24} + c_{22} \cdot b_e)}{m_m} \right] \), and \( B_e = \left[ 0 \quad \frac{c_{22} \cdot m_e}{m_m} \right] \)

Substituting equation 3-33 into 3-38 and altering, we possess

\[ \ddot{x}_m(t) + \left(\frac{b_m + f_{22}}{m_m} + B_e \cdot B_s \cdot f_{12}\right) \cdot \dot{x}_m(t) + \left(\frac{k_m + f_{21}}{m_m} + B_e \cdot B_s \cdot f_{11}\right) \cdot x_m(t) = \]

\[ - \left(A_e + B_e \cdot A_s\right) \cdot z(t) + B_e \cdot B_s \cdot \left( f_{11} \cdot \ddot{x}_m(t) + c_{11} \cdot f_h(t)\right) + B_e \]

\[ \cdot L \cdot C_s \cdot e(t - T(t)) + \left(1 - c_{21}\right) \cdot f_h(t) \]

Eq. 3-39

Shifting equation 3-39 yields

\[ \ddot{x}_m(t) + \left(\frac{b_m + f_{22}}{m_m} + B_e \cdot B_s \cdot f_{12}\right) \cdot \dot{x}_m(t) + \left(\frac{k_m + f_{21}}{m_m} + B_e \cdot B_s \cdot f_{11}\right) \cdot x_m(t) = \]

\[ \left(1 - c_{21}\right) \cdot f_h(t) + \left(A_e + B_e \cdot A_s\right) \cdot z(t) + B_e \cdot B_s \cdot L \cdot C_s \cdot e(t - T(t)) \]

Eq. 3-40

Converting equation 3-40 into state-space models and changing, we have:

\[ \dot{x}_m(t) = A_m \cdot \ddot{x}_m(t) + B_m \cdot f_h(t) \]

\[ - \left(A_z \cdot \ddot{x}_s(t + T_R(t)) - e(t)\right) + B_z \cdot e(t - T(t)) \]

Eq. 3-41

\[ y_m(t) = C_m \cdot \ddot{x}_m(t) \]
where \( A_m = \begin{bmatrix} 0 & 1 \\ \frac{m_m f_{21}}{m_m} + B_e \cdot B_s \cdot f_{11} & \frac{m_m f_{22}}{m_m} + B_e \cdot B_s \cdot f_{12} \end{bmatrix} \), \( B_m = \begin{bmatrix} 0 \\ \frac{m_m c_{21}}{m_m} + B_e \cdot B_s \cdot c_{11} \end{bmatrix} \), \( A_z = \begin{bmatrix} A_m & -A_z & A_z \\ (B_s + \Delta B_s) \cdot f_{11} & A_s + \Delta A_s & 0 \\ \Delta B_s \cdot f_{11} & \Delta A_s & A_s \end{bmatrix} \), and \( B_z = \begin{bmatrix} 0 \\ B_m \\ (B_s + \Delta B_s) \cdot c_{11} \end{bmatrix} \).

From equation 3-31, 3-34, and 3-41, the model of the total system is described as

\[
\dot{x}(t) = A \cdot x(t) + A_t \cdot x(t - T(t)) + B \cdot f_h(t) \quad \text{Eq. 3-42}
\]

\[
y(t) = C \cdot x(t)
\]

where \( x(t) = \begin{bmatrix} \ddot{x}_m(t) \\ \ddot{x}_e(t) \end{bmatrix}, A = \begin{bmatrix} A_m & -A_z & A_z \\ (B_s + \Delta B_s) \cdot f_{11} & A_s + \Delta A_s & 0 \\ \Delta B_s \cdot f_{11} & \Delta A_s & A_s \end{bmatrix}, \]

\[
A_t = \begin{bmatrix} 0 & 0 & -B_z \\ 0 & 0 & 0 \\ 0 & 0 & -L \cdot C_s \end{bmatrix}, B = \begin{bmatrix} B_m \\ (B_s + \Delta B_s) \cdot c_{11} \end{bmatrix}, \text{and } C = \begin{bmatrix} C_m & 0 & 0 \\ 0 & C_s & 0 \\ 0 & 0 & 0 \end{bmatrix}
\]

### 3.6 Transparency Analysis

Lawrence [17] presented one of the first comprehensive papers to explore the trade-off between transparency and stability in bilateral teleoperation system. When a teleoperation system is ideal, the operator feels as if he or she were personally on the scene, namely feels as if he or she were operating direct to the environment. If we use impedance to describe, it is

\[
\frac{F_e(s)}{X_e(s)} = \frac{F_h(s)}{X_m(s)} \quad \text{Eq. 3-43}
\]

where \( F_e(s), X_e(s), F_h(s), \) and \( X_m(s) \) are the Laplace transform of \( f_e(t), x_e(t), f_h(t), \) and \( x_m(t) \). From equation 3-5, we have

\[
\frac{F_e(s)}{X_e(s)} = m_e \cdot s^2 + b_e \cdot s + k_e \quad \text{Eq. 3-44}
\]
Because of ideal system \((T_L = T_R = 0)\), substituting equation 3-19 and 3-5 into 3-2 and modifying, yields

\[
f_{11} \cdot x_m(t) + f_{12} \cdot \dot{x}_m(t) + c_{11} \cdot f_h(t) \\
= (m_s + (1 - c_{12}) \cdot m_e) \cdot \ddot{x}(t) \\
+ \left((b_s - f_{14}) + (1 - c_{12}) \cdot b_e\right) \cdot \dot{x}(t) \\
+ \left((k_s - f_{13}) + (1 - c_{12}) \cdot k_e\right) \cdot x(t) \tag{Eq. 3-45}
\]

Using Laplace transform, equation 3-45 shifts as follows

\[
(f_{11} + f_{12} \cdot s) \cdot x_m(s) + c_{11} \cdot F_h(s) \\
= \left(m_s + (1 - c_{12}) \cdot m_e\right) \cdot s^2 \\
+ \left((b_s - f_{14}) + (1 - c_{12}) \cdot b_e\right) \cdot s \\
+ \left((k_s - f_{13}) + (1 - c_{12}) \cdot k_e\right) \cdot X(s) \tag{Eq. 3-46}
\]

Or

\[
Z_{m1} \cdot X_m(s) + c_{11} \cdot F_h(s) = Z_{s1} \cdot X(s) \tag{Eq. 3-46}
\]

where

\[
Z_{s1} = \left(m_s + (1 - c_{12}) \cdot m_e\right) \cdot s^2 + \left((b_s - f_{14}) + (1 - c_{12}) \cdot b_e\right) \cdot s + \left((k_s - f_{13}) + (1 - c_{12}) \cdot k_e\right), \text{ and } Z_{m1} = (f_{11} + f_{12} \cdot s)
\]

Plugging equation 3-22 and 3-5 into 3-1 and changing, we get

\[
m_m \cdot \ddot{x}_m(t) + (b_m + f_{22}) \cdot \dot{x}_m(t) + (k_m + f_{21}) \cdot x_m(t) \\
= (1 - c_{21}) \cdot f_h(t) \\
- \left((f_{23} + c_{22} \cdot k_e) \cdot x(t) + (f_{24} + c_{22} \cdot b_e) \cdot \dot{x}(t) \\
+ c_{22} \cdot m_e \cdot \ddot{x}(t)\right) \tag{Eq. 3-47}
\]

Equation 3-47 can be expressed in Laplace transform as follows
\[(m_m \cdot s^2 + (b_m + f_{22}) \cdot s + (k_m + f_{21})) \cdot X_m(s)\]
\[= (1 - c_{21}) \cdot F_h(s) \quad \text{Eq. 3-48}\]
\[-((f_{23} + c_{22} \cdot k_e) + (f_{24} + c_{22} \cdot b_e) \cdot s + c_{22} \cdot m_e \cdot s^2) \cdot X_s(s)\]

We define

\[Z_{m2} = m_m \cdot s^2 + (b_m + f_{22}) \cdot s + (k_m + f_{21})\]
\[Z_{s2} = ((f_{23} + c_{22} \cdot k_e) + (f_{24} + c_{22} \cdot b_e) \cdot s + c_{22} \cdot m_e \cdot s^2)\]

Equation 3-48 becomes

\[Z_{m2} \cdot X_m(s) = (1 - c_{21}) \cdot F_h(s) - Z_{s2} \cdot X_s(s) \quad \text{Eq. 3-49}\]

From equation 3-46 and 3-49, we get

\[(Z_{s2} \cdot Z_{m1} + Z_{s1} \cdot Z_{m2}) \cdot X_m(s)\]
\[= ((1 - c_{21}) \cdot Z_{s1} + c_{11} \cdot Z_{s1}) \cdot F_h(s)\]

Or

\[\frac{F_h(s)}{X_m(s)} = \frac{(Z_{s2} \cdot Z_{m1} + Z_{s1} \cdot Z_{m2})}{((1 - c_{21}) \cdot Z_{s1} + c_{11} \cdot Z_{s1})} \quad \text{Eq. 3-50}\]

Substituting equation 3-44 and 3-50 into 3-43, we have

\[\frac{(Z_{s2} \cdot Z_{m1} + Z_{s1} \cdot Z_{m2})}{((1 - c_{21}) \cdot Z_{s1} + c_{11} \cdot Z_{s1})} = m_e \cdot s^2 + b_e \cdot s + k_e \quad \text{Eq. 3-51}\]

Changing and homologizing equation 3-51 yields
\[(1 - c_{21}) \cdot (m_s + (1 - c_{12}) \cdot m_e) - c_{11} \cdot c_{22} \cdot m_e \cdot m_e
\]
\[
= (m_s + (1 - c_{12}) \cdot m_e) \cdot m_m
\]
\[
\text{Eq. 3-52}
\]

\[
(1 - c_{21}) \cdot (m_s + (1 - c_{12}) \cdot m_e) - c_{11} \cdot c_{22} \cdot m_e \cdot b_e
\]
\[
+ ((1 - c_{21}) \cdot (b_s - f_{14} + (1 - c_{12}) \cdot b_e) - c_{11} \cdot f_{24} + c_{22} \cdot b_e) \cdot m_e
\]
\[
= (b_s - f_{14} + (1 - c_{12}) \cdot b_e) \cdot m_m
\]
\[
+ (m_s + (1 - c_{12}) \cdot m_e) \cdot (b_m + f_{22}) + c_{22} \cdot m_e \cdot f_{12}
\]
\[
\text{Eq. 3-53}
\]

\[
(1 - c_{21}) \cdot (m_s + (1 - c_{12}) \cdot m_e) - c_{11} \cdot c_{22} \cdot m_e \cdot k_e
\]
\[
+ ((1 - c_{21}) \cdot (b_s - f_{14} + (1 - c_{12}) \cdot b_e) - c_{11} \cdot f_{24} + c_{22} \cdot b_e) \cdot b_e
\]
\[
+ ((1 - c_{21}) \cdot (k_s - f_{13} + (1 - c_{12}) \cdot k_e) - c_{11} \cdot f_{23} + c_{22} \cdot k_e) \cdot m_e
\]
\[
= (k_s - f_{13} + (1 - c_{12}) \cdot k_e) \cdot m_m
\]
\[
+ (b_s - f_{14} + (1 - c_{12}) \cdot b_e) \cdot (b_m + f_{22})
\]
\[
+ (m_s + (1 - c_{12}) \cdot m_e) \cdot (k_m + f_{21}) + c_{22} \cdot m_e \cdot f_{11}
\]
\[
+ (f_{24} + c_{22} \cdot b_e) \cdot f_{12}
\]
\[
\text{Eq. 3-54}
\]

\[
(1 - c_{21}) \cdot (b_s - f_{14} + (1 - c_{12}) \cdot b_e) - c_{11} \cdot (f_{24} + c_{22} \cdot b_e) \cdot k_e
\]
\[
+ ((1 - c_{21}) \cdot (k_s - f_{13} + (1 - c_{12}) \cdot k_e) - c_{11} \cdot f_{23} + c_{22} \cdot k_e) \cdot b_e
\]
\[
= (k_s - f_{13} + (1 - c_{12}) \cdot k_e) \cdot (b_m + f_{22})
\]
\[
+ (b_s - f_{14} + (1 - c_{12}) \cdot b_e) \cdot (k_m + f_{21})
\]
\[
+ (f_{24} + c_{22} \cdot b_e) \cdot f_{11} + (f_{23} + c_{22} \cdot k_e) \cdot f_{12}
\]
\[
\text{Eq. 3-55}
\]

\[
(1 - c_{21}) \cdot (k_s - f_{13} + (1 - c_{12}) \cdot k_e) - c_{11} \cdot (f_{23} + c_{22} \cdot k_e) \cdot k_e
\]
\[
= (k_s - f_{13} + (1 - c_{12}) \cdot k_e) \cdot (k_m + f_{21})
\]
\[
+ (f_{23} + c_{22} \cdot k_e) \cdot f_{11}
\]
\[
\text{Eq. 3-56}
\]
Consequently, when equation 3-52, 3-53, 3-54, 3-55, and 3-56 exist, the system will achieve excellent transparency.

3.7 Conclusion

In this chapter, we have developed a theoretical framework to design the neural network based multiple model adaptive predictive controller. It consists of six main parts: the physical model, the RBF network to approximate the value of environment force at any time, the teleoperation controller, the time forward state observer, the system model, and the transparency analysis.

First, we get the dynamic equations of the master and slave manipulators as well as the dynamic equations of environment from the physical model. Time delay of communication channel is random.

Second, RBF network is created and trained by the function “newrb” in MATLAB neural network toolbox. At instant time, the value of environment force which comes from RBF network is compared with the value of given environment forces, respectively. The environment model which fits best to current environment dynamics is selected.

Third, teleoperation controller is designed under the effects of time delay. Result is $u_d$ and $u_{dm}$ are introduced.

Next, the time forward state observer is built for all environment models to predict slave state. The observer is predicted the slave state at $(t + T_R(t))$ time.

Next, we also established the model of total teleoperation system.

Finally, the control parameters can be given conveniently using the result of transparency analysis. Therefore, the performance of teleoperation system is good. The stability of teleoperation system will be shown in the next chapter.
CHAPTER 4
SIMULATION RESULTS

This chapter discusses some of the results of the experimental simulations. Section 4.1 presents the simulation models. Section 4.2 introduces the simulation results. Section 4.3 is the summary of this chapter.

4.1 Simulation Models

The proposed teleoperation model was developed using MATLAB/SIMULINK. For the sake of comparison, four models of teleoperation system were built. The first simulation model for teleoperation system was created assuming that it will not have any time delays. This model is a direct coupling between the master and the slave. The results received from this model represent the ideal performance for a teleoperation system, as there are no time delays involved. This model is presented in the Figure 4-1.

FIGURE 4-1 The simulation model for the ideal teleoperation system
The second simulation model for teleoperation system has time delays introduced in the system but this system does not have time-variant environment. This model is evaluated the ability of the time forward state observer to predict slave state. The results obtained from this model introduce the performance for a teleoperation system with time delay. This model is shown in the Figure 4-2.

![Simulation Model](image)

**FIGURE 4-2** The simulation model for teleoperation system with time delay and without time-variant environment

The third simulation model for teleoperation system is the proposed control scheme based on this thesis. This system has time-variant delay and environment. This model is evaluated the RBF neural network based multiple model adaptive predictive control for teleoperation system. The results got from this model represent the performance for a teleoperation system with time-variant delay and environment. This model is represented in the Figure 4-3.
FIGURE 4-3 The simulation model for teleoperation system with time-variant delay and environment

FIGURE 4-4 The simulation model for teleoperation system with noise, time variant delay, and time-variant environment
The fourth simulation model for teleoperation system has noise, time-variant delay, and time-variant environment introduced in the system. This model is introduced in the Figure 4-4. The results prove the proposed control scheme is good for this system.

In next section, we will discuss about simulation results for all models. The advantages of the neural network based multiple model adaptive predictive control for teleoperation systems are demonstrated.

4.2 Simulation Results

The main objective of the simulation is to monitor the tracking performance of the RBF neural network based multiple model adaptive predictive control for teleoperation system with time-variant delay and environment. The performance of the proposed method can be judged by comparing its results with others. In the simulations, the models are tested for time-variant delay and environment. The master position signal $x_m$, slave position signal $x_s$, human force signal $f_h$, and environment force signal $f_e$ of each model are plotted and compared.

In the simulation, the parameters of the master and slave manipulator are selected as $m_m = 1.5\text{kg}$, $b_m = 0.45\text{N.s/m}$, $k_m = 1\text{N/m}$, $m_s = 1.5\text{kg}$, $b_s = 0.45\text{N.s/m}$, and $k_s = 1\text{N/m}$. The initial conditions of the system in state space form are $x_m = 0\text{rad}$, $\dot{x}_m = 0\text{rad/sec}$, $x_s = 0\text{rad}$, $\dot{x}_s = 0\text{rad/sec}$, and the error signal $e = 0$, $\dot{e} = 0$.

4.2.1 Simulation results of the ideal teleoperation system

The parameters of environment model M1 are selected as $m_{e1} = 1.1\text{kg}$, $b_{e1} = 0.6\text{N.s/m}$, and $k_{e1} = 0.6\text{N/m}$. The parameters of controller are chose as $c_{11} = 30$, $f_{11} = 2$, $f_{12} = 1$, $f_{21} = 1456$, and $f_{22} = 987$. The others are calculated by satisfying the condition of transparency as $c_{12} = -27.636$, $c_{21} = -29$, $c_{22} = 28.636$, $f_{13} = -1.8182$, $f_{14} = -1.3682$, $f_{23} = -1456.2$, and $f_{24} = -986.63$. The simulation results are represented in Figure 4-5 and 4-6.
FIGURE 4-5 The position of master and slave in the ideal teleoperation system with M1

FIGURE 4-6 The forces of master and slave in the ideal teleoperation system with M1
The parameters of environment model M2 are selected as $m_{e1} = 1.0$ kg, $b_{e1} = 0.4$ N.s/m, and $k_{e1} = 0.8$ N/m. The parameters of controller are chose as $c_{11} = 20$, $f_{11} = 2$, $f_{12} = 1$, $f_{21} = 1500$, and $f_{22} = 1200$. The others are calculated by satisfying the condition of transparency as $c_{12} = -17.5$, $c_{21} = -19$, $c_{22} = 18.5$, $f_{13} = -2.2$, $f_{14} = -1.15$, $f_{23} = -1499.8$, and $f_{24} = -1199.8$. The simulation results are shown in Figure 4-7 and 4-8.

The parameters of environment model M3 are selected as $m_{e1} = 1.5$ kg, $b_{e1} = 0.7$ N.s/m, and $k_{e1} = 0.5$ N/m. The parameters of controller are chose as $c_{11} = 30$, $f_{11} = 2$, $f_{12} = 1$, $f_{21} = 1497$, and $f_{22} = 1356$. The others are calculated by satisfying the condition of transparency as $c_{12} = -28$, $c_{21} = -29$, $c_{22} = 29$, $f_{13} = -1.5$, $f_{14} = -1.25$, $f_{23} = -1497.5$, and $f_{24} = -1355.8$. The simulation results are presented in Figure 4-9 and 4-10.

![Figure 4-7](image-url)  
**FIGURE 4-7** The position of master and slave in the ideal teleoperation system with M2.
FIGURE 4-8 The forces of master and slave in the ideal teleoperation system with M2

FIGURE 4-9 The position of master and slave in the ideal teleoperation system with M3
4.2.2 Simulation results of the teleoperation system with time delays and without time-variant environment

The time forward state observer based predictive controllers for teleoperation system is designed. Time forward observer is used to predictive the slave state. Time delay in communication channel is random, $T_R(t)$ denotes the forward time delay, and $T_L(t)$ denotes the backward time delay. In experiment case, $0 \leq T_R(t), T_L(t) \leq 5$ and $T = T_R(t) + T_L(t)$.

The parameters of environment model M1 are selected as $m_{e1} = 1.1\text{kg}$, $b_{e1} = 0.6\text{N.s/m}$, and $k_{e1} = 0.6\text{N/m}$. The parameters of controller are chose as $c_{11} = 30, f_{11} = 2, f_{12} = 1, f_{21} = 1456$, and $f_{22} = 987$. The others are calculated by satisfying the condition of transparency as $c_{12} = -27.636, c_{21} = -29, c_{22} = 28.636, f_{13} = -1.8182, f_{14} = -1.3682, f_{23} = -1456.2$, and $f_{24} = -986.63$. The simulation results are represented in Figure 4-11 and 4-12.

**FIGURE 4-10** The forces of master and slave in the ideal teleoperation system with M3
FIGURE 4-11 The position of master and slave in the teleoperation system with time delays and M1

FIGURE 4-12 The forces of master and slave in the teleoperation system with time delays and M1
The parameters of environment model M2 are selected as \( m_{e1} = 1.0 \text{kg}, \) \( b_{e1} = 0.4 \text{N.s/m}, \) and \( k_{e1} = 0.8 \text{N/m}. \) The parameters of controller are chose as \( c_{11} = 20, f_{11} = 2, f_{12} = 1, f_{21} = 1500, \) and \( f_{22} = 1200. \) The others are calculated by satisfying the condition of transparency as \( c_{12} = -17.5, c_{21} = -19, c_{22} = 18.5, \) \( f_{13} = -2.2, f_{14} = -1.15, f_{23} = -1499.8, \) and \( f_{24} = -1199.8. \) The simulation results are shown in Figure 4-13 and 4-14.

The parameters of environment model M3 are selected as \( m_{e1} = 1.5 \text{kg}, \) \( b_{e1} = 0.7 \text{N.s/m}, \) and \( k_{e1} = 0.5 \text{N/m}. \) The parameters of controller are chose as \( c_{11} = 30, f_{11} = 2, f_{12} = 1, f_{21} = 1497, \) and \( f_{22} = 1356. \) The others are calculated by satisfying the condition of transparency as \( c_{12} = -28, c_{21} = -29, c_{22} = 29, \) \( f_{13} = -1.5, f_{14} = -1.25, f_{23} = -1497.5, \) and \( f_{24} = -1355.8. \) The simulation results are presented in Figure 4-15 and 4-16.

**FIGURE 4-13** The position of master and slave in the teleoperation system with time delays and M2
FIGURE 4-14 The forces of master and slave in the teleoperation system with time delays and M2

FIGURE 4-15 The position of master and slave in the teleoperation system with time delays and M3
FIGURE 4-16 The forces of master and slave in the teleoperation system with time delays and M3

4.2.3 Simulation results of the teleoperation system with time-variant delay and environment

Next, we combine the RBF network and the time forward state observer based predictive controllers for teleoperation system with time-variant delay and environment. In experiment case, time delay in communication channel is random and $0 \leq T_R(t), T_f(t) \leq 5$ and $T = T_R(t) + T_f(t)$. There are three environment models M1, M2, M3, at instant time; we do not know what current environment is. Therefore, RBF network will be used to estimate which fits best environment at instant time. The parameters of controller resemble above. The simulation results are shown in Figure 4-17, 4-18, and 4-19.
FIGURE 4-17 The performance of the RBF neural network without noise

FIGURE 4-18 The position of master and slave in the teleoperation system with time-variant delay and environment
4.2.4 Simulation results of the teleoperation system with time-variant delay, time-variant environment, and noise

Finally, we develop the proposed control scheme for the teleoperation system with time-variant delay, time-variant environment, and noise. In experiment case, time delay in communication channel is random and $0 \leq T_R(t), T_L(t) \leq 5$ and $T = T_R(t) + T_R(t)$. The parameters of controller resemble above. The simulation results are represented in Figure 4-20, 4-21, and 4-22.
FIGURE 4-20 The performance of the RBF neural network with noise

FIGURE 4-21 The position of master and slave in the teleoperation system with time delays, time-variant environment and noise
4.2.5 Discussion

Sample results of force, and position of the master and slave manipulators of all ideal teleoperation systems are presented in the Figure 4-5 to 4-10. It shows that the teleoperation system have no time delay.

The Figure 4-11 to 4-16 show the positions and forces of the master and slave manipulators of all teleoperation systems with time delays and without time-variant environment. In Figures 4-11, 4-13, and 4-15, the master position is uniform with the slave’s about $T_R$ units later. In Figures 4-12, 4-14, and 4-16, the human force, and the environment force is also similar about $T_R$ units later. All models are stable. We can conclude that prediction is exact.

The results of the RBF neural network based multiple model adaptive predictive control for teleoperation system with time-variant delay and environment are represented in the Figure 4-17 to 4-19. The master position and force are consistent with the slave’s about $T_R$ units later. The performance of the RBF neural network is

**FIGURE 4-22** The forces of master and slave in the teleoperation system with time delays, time-variant environment, and noise.
0.111963. The environment is detected by RBF neural network. The system is stable under proposed controller.

To estimate the proposed RBF neural network based multiple model adaptive predictive control, we add the noise into the teleoperation system. The simulation results are shown in the Figure 4-20 to Figure 4-22. The system is stable under the effect of noise.

4.3 Conclusion

The results suggest that the master and slave are stable under the proposed control method. The master curves are consistent with the slave’s about $T_R$ units later. It has seemed that there is no backward time delay. We can conclude that the neural network based multiple model adaptive predictive control is exact and the performance is good.
CHAPTER 5
CONCLUSION

This thesis aims at improving the performance of an internet based teleoperation system with time-variant environment. This chapter summarizes the thesis and provides directions for its future work. Section 5.1 concludes the gained results and the effect of the proposed methodology. Section 5.2 suggests further works in order to improve the accuracy of the proposed control scheme.

5.1 Conclusions

This thesis primarily addresses the development of a theoretical framework to design the neural network based multiple model adaptive predictive controller for an Internet based teleoperation system with time-variant environment. Using predictive strategies and RBF network, the stability and the performance of teleoperation system with communication delays and time-variant environment can be significantly improved. Besides, the effect of measurement noise will be also presented.

To solve the problem, time-variant environment, a RBF neural network is proposed. The neural network is trained off-line using the given environment models. At instant time, the value of environment force, which comes from RBF network, is compared with the value of given environment forces, respectively. The environment model, which fits best to current environment dynamics, is selected.

The issue of communication delay in teleoperation systems is discussed. Using the time forward state observer, a novel neural network based multiple model adaptive predictive control strategy is proposed.

The proposed control strategy is tested and verified. In the simulation, the stability and performance of teleoperation system is good under the proposed controller.

Hence, this thesis proves the fact that the proposed control strategy is able to minimize the effects of time-variant delay and environment in teleoperation system.
As the control strategy was tested for a number of test cases, it also proves that this approach is robust.

5.2 Future Works

This section outlines some of the possible future work that can be carried out in the field of teleoperation based on this thesis.

5.2.1 To develop a rigorous stability proof for the proposed neural network based multiple model adaptive predictive architecture. Although the experimental results provide validation of the effectiveness of the proposed architecture, a stability analysis would strengthen the claims made.

5.2.2 To apply the proposed control scheme described in this thesis to control of a teleoperation system with disturbances.

5.2.3 To include the experimentation on a real platform.
REFERENCES


APPENDIX A

DATA USED IN TRAINING RBF NEURAL NETWORK
TABLE A-1  The matrix P and Q

<table>
<thead>
<tr>
<th></th>
<th>P^i</th>
<th>Q^i</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.4668</td>
<td>2.5608</td>
<td>1.4462</td>
</tr>
<tr>
<td>4.4128</td>
<td>3.0144</td>
<td>-0.4095</td>
</tr>
<tr>
<td>7.0306</td>
<td>2.0644</td>
<td>-1.3198</td>
</tr>
<tr>
<td>8.4050</td>
<td>0.6835</td>
<td>-1.3160</td>
</tr>
<tr>
<td>8.5063</td>
<td>-0.3912</td>
<td>-0.7843</td>
</tr>
<tr>
<td>7.8296</td>
<td>-0.8563</td>
<td>-3.7972</td>
</tr>
<tr>
<td>5.5076</td>
<td>-3.3420</td>
<td>-1.1813</td>
</tr>
<tr>
<td>1.9471</td>
<td>-3.4378</td>
<td>0.8144</td>
</tr>
<tr>
<td>-0.8985</td>
<td>-2.1103</td>
<td>1.6428</td>
</tr>
<tr>
<td>-2.1853</td>
<td>-0.4924</td>
<td>1.4618</td>
</tr>
<tr>
<td>-2.0515</td>
<td>0.6428</td>
<td>0.7687</td>
</tr>
<tr>
<td>-1.1488</td>
<td>1.0416</td>
<td>3.6945</td>
</tr>
<tr>
<td>1.3030</td>
<td>3.4144</td>
<td>1.0694</td>
</tr>
<tr>
<td>4.8853</td>
<td>3.4158</td>
<td>-0.8866</td>
</tr>
<tr>
<td>7.6816</td>
<td>2.0424</td>
<td>-1.6630</td>
</tr>
<tr>
<td>8.8975</td>
<td>0.4252</td>
<td>-1.4436</td>
</tr>
<tr>
<td>8.7090</td>
<td>-0.6825</td>
<td>-0.7358</td>
</tr>
<tr>
<td>7.7829</td>
<td>-1.0495</td>
<td>-3.6662</td>
</tr>
<tr>
<td>5.3353</td>
<td>-3.4007</td>
<td>-1.0515</td>
</tr>
<tr>
<td>1.7714</td>
<td>-3.3950</td>
<td>0.8870</td>
</tr>
<tr>
<td>-1.0056</td>
<td>-2.0259</td>
<td>1.6552</td>
</tr>
<tr>
<td>-2.2096</td>
<td>-0.4179</td>
<td>1.4342</td>
</tr>
<tr>
<td>-2.0180</td>
<td>0.6816</td>
<td>0.7292</td>
</tr>
<tr>
<td>-1.0953</td>
<td>1.0442</td>
<td>3.6639</td>
</tr>
<tr>
<td>1.3465</td>
<td>3.3950</td>
<td>1.0563</td>
</tr>
<tr>
<td>4.9056</td>
<td>3.3914</td>
<td>-0.8843</td>
</tr>
<tr>
<td>7.6802</td>
<td>2.0249</td>
<td>-1.6528</td>
</tr>
<tr>
<td>8.8842</td>
<td>0.4188</td>
<td>-1.4329</td>
</tr>
<tr>
<td>8.6941</td>
<td>-0.6799</td>
<td>-0.7290</td>
</tr>
<tr>
<td>7.7731</td>
<td>-1.0428</td>
<td>-3.6645</td>
</tr>
<tr>
<td>4.4602</td>
<td>-4.8686</td>
<td>-1.6198</td>
</tr>
<tr>
<td>-0.5127</td>
<td>-4.4269</td>
<td>2.1837</td>
</tr>
<tr>
<td>-3.5277</td>
<td>-1.3976</td>
<td>3.3839</td>
</tr>
<tr>
<td>-3.3693</td>
<td>1.4948</td>
<td>2.0984</td>
</tr>
<tr>
<td>-1.1829</td>
<td>2.5094</td>
<td>-0.0584</td>
</tr>
<tr>
<td>1.0121</td>
<td>1.6398</td>
<td>2.5329</td>
</tr>
<tr>
<td>3.5090</td>
<td>2.9248</td>
<td>0.0285</td>
</tr>
<tr>
<td>6.1072</td>
<td>1.9807</td>
<td>-1.6731</td>
</tr>
<tr>
<td>7.1694</td>
<td>0.1251</td>
<td>-1.7804</td>
</tr>
<tr>
<td>6.5463</td>
<td>-1.1956</td>
<td>-0.7529</td>
</tr>
<tr>
<td>5.1789</td>
<td>-1.3422</td>
<td>0.4005</td>
</tr>
<tr>
<td>4.1570</td>
<td>-0.6117</td>
<td>-3.0741</td>
</tr>
<tr>
<td>2.3464</td>
<td>-2.6245</td>
<td>-0.8271</td>
</tr>
<tr>
<td></td>
<td>$P^i$</td>
<td></td>
</tr>
<tr>
<td>---</td>
<td>------</td>
<td>---</td>
</tr>
<tr>
<td>-0.3153</td>
<td>-2.3532</td>
<td>1.1950</td>
</tr>
<tr>
<td>-1.9038</td>
<td>-0.7182</td>
<td>1.8120</td>
</tr>
<tr>
<td>-1.7923</td>
<td>0.8206</td>
<td>1.1062</td>
</tr>
<tr>
<td>-0.6109</td>
<td>1.3448</td>
<td>-0.0496</td>
</tr>
<tr>
<td>0.5579</td>
<td>0.8656</td>
<td>3.2068</td>
</tr>
<tr>
<td>2.6478</td>
<td>2.8901</td>
<td>0.7317</td>
</tr>
<tr>
<td>5.5050</td>
<td>2.4626</td>
<td>-1.3843</td>
</tr>
<tr>
<td>7.1123</td>
<td>0.6556</td>
<td>-1.9474</td>
</tr>
<tr>
<td>6.8896</td>
<td>-0.9600</td>
<td>-1.1220</td>
</tr>
<tr>
<td>5.5784</td>
<td>-1.4495</td>
<td>0.1238</td>
</tr>
<tr>
<td>4.3477</td>
<td>-0.8824</td>
<td>-3.1181</td>
</tr>
<tr>
<td>2.2795</td>
<td>-2.8376</td>
<td>-0.6882</td>
</tr>
<tr>
<td>-0.5134</td>
<td>-2.3962</td>
<td>1.3707</td>
</tr>
<tr>
<td>0.6559</td>
<td>0.8544</td>
<td>3.1327</td>
</tr>
<tr>
<td>2.3305</td>
<td>2.2863</td>
<td>0.8270</td>
</tr>
<tr>
<td>4.8541</td>
<td>2.5914</td>
<td>-0.1568</td>
</tr>
<tr>
<td>7.2555</td>
<td>2.1105</td>
<td>-0.7331</td>
</tr>
<tr>
<td>8.9572</td>
<td>1.2615</td>
<td>-0.9042</td>
</tr>
<tr>
<td>9.7790</td>
<td>0.4021</td>
<td>-0.7768</td>
</tr>
<tr>
<td>9.8360</td>
<td>-0.2409</td>
<td>-3.1620</td>
</tr>
<tr>
<td>8.2786</td>
<td>-2.5995</td>
<td>-1.5464</td>
</tr>
<tr>
<td>5.1551</td>
<td>-3.4041</td>
<td>-0.1291</td>
</tr>
<tr>
<td>1.8602</td>
<td>-3.0254</td>
<td>0.7931</td>
</tr>
<tr>
<td>-0.6875</td>
<td>-2.0031</td>
<td>1.1654</td>
</tr>
<tr>
<td>-2.1058</td>
<td>-0.8427</td>
<td>1.0962</td>
</tr>
<tr>
<td>-2.4484</td>
<td>0.1031</td>
<td>3.4352</td>
</tr>
<tr>
<td>-0.9075</td>
<td>2.6873</td>
<td>1.7197</td>
</tr>
<tr>
<td>2.3721</td>
<td>3.6105</td>
<td>0.1948</td>
</tr>
<tr>
<td>5.8911</td>
<td>3.2525</td>
<td>-0.8118</td>
</tr>
<tr>
<td>8.6472</td>
<td>2.1844</td>
<td>-1.2320</td>
</tr>
<tr>
<td>10.2100</td>
<td>0.9482</td>
<td>-1.1757</td>
</tr>
<tr>
<td>10.6200</td>
<td>-0.0725</td>
<td>-3.5021</td>
</tr>
<tr>
<td>9.0800</td>
<td>-2.7114</td>
<td>-1.7613</td>
</tr>
<tr>
<td>5.7598</td>
<td>-3.6627</td>
<td>-0.2098</td>
</tr>
<tr>
<td>2.1848</td>
<td>-3.3088</td>
<td>0.8173</td>
</tr>
<tr>
<td>-0.6225</td>
<td>-2.2286</td>
<td>1.2490</td>
</tr>
<tr>
<td>-2.2204</td>
<td>-0.9734</td>
<td>1.1955</td>
</tr>
<tr>
<td>-2.6458</td>
<td>0.0657</td>
<td>3.5185</td>
</tr>
<tr>
<td>-1.1056</td>
<td>2.7180</td>
<td>1.7713</td>
</tr>
<tr>
<td>2.2249</td>
<td>3.6759</td>
<td>0.2133</td>
</tr>
<tr>
<td>P</td>
<td>Q</td>
<td>P'</td>
</tr>
<tr>
<td>---</td>
<td>---</td>
<td>---</td>
</tr>
<tr>
<td>5.8140</td>
<td>3.3228</td>
<td>-0.8189</td>
</tr>
<tr>
<td>8.6339</td>
<td>2.2394</td>
<td>-1.2534</td>
</tr>
<tr>
<td>10.2400</td>
<td>0.9795</td>
<td>-1.2004</td>
</tr>
<tr>
<td>10.6690</td>
<td>-0.0642</td>
<td>-3.5225</td>
</tr>
<tr>
<td>5.8980</td>
<td>-2.4863</td>
<td>-0.8051</td>
</tr>
<tr>
<td>3.1933</td>
<td>-2.7468</td>
<td>0.2183</td>
</tr>
<tr>
<td>0.6697</td>
<td>-2.1977</td>
<td>0.8035</td>
</tr>
<tr>
<td>-1.0855</td>
<td>-1.2834</td>
<td>0.9618</td>
</tr>
<tr>
<td>-1.9041</td>
<td>-0.3774</td>
<td>0.8115</td>
</tr>
<tr>
<td>-1.9231</td>
<td>0.2883</td>
<td>3.1734</td>
</tr>
<tr>
<td>-0.3158</td>
<td>2.6488</td>
<td>1.5402</td>
</tr>
<tr>
<td>2.8520</td>
<td>3.4419</td>
<td>0.1135</td>
</tr>
<tr>
<td>6.1764</td>
<td>3.0462</td>
<td>-0.8105</td>
</tr>
<tr>
<td>8.7366</td>
<td>2.0078</td>
<td>-1.1793</td>
</tr>
<tr>
<td>10.1530</td>
<td>0.8362</td>
<td>-1.1045</td>
</tr>
<tr>
<td>10.4860</td>
<td>-0.1150</td>
<td>-3.4377</td>
</tr>
<tr>
<td>8.9331</td>
<td>-2.6994</td>
<td>-1.7180</td>
</tr>
<tr>
<td>5.6426</td>
<td>-3.6197</td>
<td>-0.1908</td>
</tr>
<tr>
<td>2.1165</td>
<td>-3.2575</td>
<td>0.8161</td>
</tr>
<tr>
<td>-0.6425</td>
<td>-2.1854</td>
<td>1.2355</td>
</tr>
<tr>
<td>-2.2049</td>
<td>-0.9465</td>
<td>1.1778</td>
</tr>
<tr>
<td>-2.6120</td>
<td>0.0755</td>
<td>3.5027</td>
</tr>
<tr>
<td>-1.0692</td>
<td>2.7144</td>
<td>1.7609</td>
</tr>
<tr>
<td>2.2536</td>
<td>3.6650</td>
<td>0.2088</td>
</tr>
<tr>
<td>5.8303</td>
<td>3.3100</td>
<td>-0.8185</td>
</tr>
<tr>
<td>8.6383</td>
<td>2.2288</td>
<td>-1.2499</td>
</tr>
<tr>
<td>10.2360</td>
<td>0.9730</td>
<td>-1.1960</td>
</tr>
<tr>
<td>10.6610</td>
<td>-0.0665</td>
<td>-3.5186</td>
</tr>
<tr>
<td>9.1199</td>
<td>-2.7187</td>
<td>-1.7712</td>
</tr>
<tr>
<td>5.7887</td>
<td>-3.6765</td>
<td>-0.2129</td>
</tr>
<tr>
<td>2.1992</td>
<td>-3.3230</td>
<td>0.8192</td>
</tr>
<tr>
<td>-0.6209</td>
<td>-2.2395</td>
<td>1.2535</td>
</tr>
<tr>
<td>-2.2272</td>
<td>-0.9794</td>
<td>1.2005</td>
</tr>
<tr>
<td>-2.6562</td>
<td>0.0643</td>
<td>3.5225</td>
</tr>
<tr>
<td>-0.0826</td>
<td>4.4323</td>
<td>2.2993</td>
</tr>
<tr>
<td>4.7843</td>
<td>4.6226</td>
<td>-1.6728</td>
</tr>
<tr>
<td>8.1829</td>
<td>1.8959</td>
<td>-3.3011</td>
</tr>
<tr>
<td>8.4993</td>
<td>-1.1013</td>
<td>-2.3535</td>
</tr>
<tr>
<td>6.5557</td>
<td>-2.4291</td>
<td>-0.2656</td>
</tr>
<tr>
<td>4.2982</td>
<td>-1.8188</td>
<td>-2.7032</td>
</tr>
<tr>
<td>1.5728</td>
<td>-3.1672</td>
<td>0.0094</td>
</tr>
<tr>
<td>-1.2241</td>
<td>-2.1160</td>
<td>1.8271</td>
</tr>
<tr>
<td>-2.3424</td>
<td>-0.1051</td>
<td>1.9171</td>
</tr>
</tbody>
</table>
## Table A-1 (continued)

<table>
<thead>
<tr>
<th>P^1</th>
<th>Q^1</th>
<th>Q^1</th>
<th>Q^1</th>
<th>Q^1</th>
<th>Q^1</th>
</tr>
</thead>
<tbody>
<tr>
<td>-1.6454</td>
<td>1.3072</td>
<td>0.7936</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>-0.1625</td>
<td>1.4463</td>
<td>-0.4491</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>0.9315</td>
<td>0.6466</td>
<td>2.9956</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>2.7406</td>
<td>2.5915</td>
<td>0.7770</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>5.3525</td>
<td>2.2951</td>
<td>-1.1952</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>6.8896</td>
<td>0.6791</td>
<td>-1.7786</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>6.7573</td>
<td>-0.8229</td>
<td>-1.0710</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>5.5883</td>
<td>-1.3210</td>
<td>0.0644</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>4.4467</td>
<td>-0.8389</td>
<td>-3.2147</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>2.3772</td>
<td>-2.8779</td>
<td>-0.7501</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>-0.4769</td>
<td>-2.4678</td>
<td>1.3702</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>-2.0945</td>
<td>-0.6692</td>
<td>1.9449</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>-1.8849</td>
<td>0.9490</td>
<td>1.1289</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>-0.5806</td>
<td>1.4471</td>
<td>-0.1149</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>0.6517</td>
<td>0.8872</td>
<td>3.1229</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>2.7261</td>
<td>2.8443</td>
<td>0.6872</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>5.5246</td>
<td>2.4001</td>
<td>-1.3749</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>7.0805</td>
<td>0.6204</td>
<td>-1.9078</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>6.8430</td>
<td>-0.9551</td>
<td>-1.0866</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>5.5507</td>
<td>-1.4208</td>
<td>0.1349</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
<tr>
<td>4.3498</td>
<td>-0.8554</td>
<td>-3.1308</td>
<td>0.8000</td>
<td>0.4000</td>
<td>1.0000</td>
</tr>
</tbody>
</table>
BIOGRAPHY

Name : Mr. Bui Van Bien
Thesis Title : Teleoperation System using Neural Network Based Multiple Model Adaptive Predictive Control
Major Field : Mechanical Engineering

Biography

I graduated from Hanoi University of Technology, Hanoi, Vietnam with a bachelor degree in Mechanical Engineering major in 2003.

My contact address is Faculty of Engineering, Haiphong University, 171 Phan Dang Luu Street, Kienan District, Haiphong, Vietnam. My e-mail address is muoiba@gmail.com