12 The Truck Backer-Upper: An Example of Self-Learning in Neural Networks

Derrick Nguyen and Bernard Widrow

12.1 Introduction

The control of severely nonlinear systems has for the most part escaped the attention of control theorists and practitioners. This chapter addresses the issue from the point of view of utilizing self-learning techniques to achieve nonlinear controller design. The methodology shows promise for applications to control problems that are so complex that analytical design techniques either do not exist or will not exist for some time to come. Neural networks can be used to implement highly nonlinear controllers whose weights or internal parameters can be chosen or determined by a self-learning process.

Backing a trailer truck to a loading dock is a difficult exercise for all but the most skilled truck drivers. Anyone who has tried to back up a house trailer or a boat trailer will realize this. Normal driving instincts lead to erroneous movements. A great deal of practice is required to develop the requisite skills.

When watching a truck driver backing toward a loading dock, one often observes the driver backing, going forward, backing again, going forward, etc., and finally backing to the desired position along the dock. The forward and backward movements help to position the trailer for successful backing up to the dock. A more difficult backing up sequence would only allow backing, with no forward movements permitted. The specific problem treated in this paper is that of the design by self-learning of a nonlinear controller to control the steering of a trailer truck while backing up to a loading dock from an arbitrary initial position. Only backing up is allowed. Computer simulation of the truck and its controller has demonstrated workability, although no mathematical proof yet exists. The experimental controller contains twenty six adaptive ADALINE units (Widrow and Hoff 1960) and exhibits exquisite backing up control. The trailer truck can be initially "jackknifed" and aimed in many different directions, toward and away from the dock, but as long as there is sufficient clearance, the controller appears to be capable of finding a solution.

Figure 12.1 shows a computer-screen image of the truck, the trailer, and the loading dock. The critical state variables representing the position of the truck and that of the loading dock are θ_{cab}, the angle of

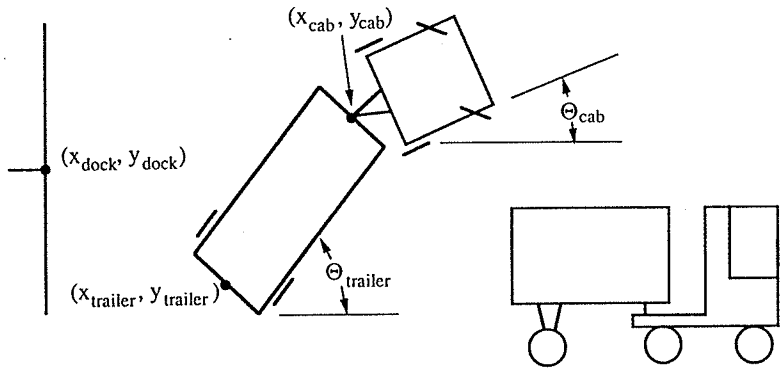


Figure 12.1
The truck, the trailer, and the loading dock.

the truck, x_{cab} and y_{cab}, the Cartesian position of the yoke, $x_{trailer}$ and $y_{trailer}$, the Cartesian position of the rear of the center of the trailer, and x_{dock} and y_{dock}, the Cartesian position of the center of the loading dock. Definition of the state variables is illustrated in figure 12.1.

The truck backs up until it hits the dock, then stops. The goal is to cause the back of the trailer to be parallel to the loading dock, and to have the point $(x_{trailer}, y_{trailer})$ be aligned as closely as possible with point (x_{dock}, y_{dock}). The controller will learn to achieve this objective.

12.2 Training

The approach to self-learning control that has been successfully used with the truck backer-upper involves a two-stage learning process. The first stage involves the training of a neural network to be an emulator of the truck and trailer kinematics. The second stage involves the training of a neural-network controller to control the emulator. A similar approach has been used by Widrow (1986, Widrow and Stearns 1985) and by Jordan (1988). Once the controller knows how to control the emulator, it is then able to control the actual trailer truck. Figure 12.2 gives an overview, showing how the present state vector $state_k$ is fed

to the controller which in turn provides a *steering signal*$_k$ between -1 (hard right) and $+1$ (hard left) to the truck. The time index is k. Each time cycle, the truck backs up by a fixed small distance. The next state is determined by the present state and the steering signal, which is fixed during the cycle.

Figure 12.3 shows a block diagram of the process used to train the emulator. The truck backs up randomly, going through many cycles with randomly selected steering signals. By this process, the emulator "gets the feel" of how the trailer and truck behave. The emulator, chosen as a two-layer neural network, learns to generate the next positional state vector when given the present-state vector and the steering signal. This is done for a wide variety of positional states and steering angles. The two-layer emulator is adapted by means of the backpropagation algorithm (Werbos 1984, Parker 1985, Rumelhart and McClelland 1986) The first layer had six present-state inputs plus the present steering signal input. This layer contained forty-five hidden adaptive ADALINE units producing six next-state predictions. Once the emulator is trained, it can then be used to train the controller.

Refer to figure 12.4. The identical blocks labeled C represent the controller. The identical blocks labeled T represent the truck and trailer emulator. Suppose that the truck is engaged in backing up. Let C be chosen randomly and be initially fixed. The initial state vector s_0 is fed to C, which produces the steering signal output which sets the steering angle of the truck. The backing up cycle proceeds with the truck and trailer soon arriving at the next state s_1. With C remaining fixed, the backing up process continues from cycle to cycle until the truck hits something and stops. The final state s_K is compared with the desired final-state (the rear of the trailer parallel to the dock with proper positional alignment) to obtain the final state error vector ϵ_K. This error vector contains three elements (which are the errors of interest), $x_{trailer}$, $y_{trailer}$ and $\theta_{trailer}$, and is used to adapt the controller C.

The method of adapting the controller C is illustrated in figure 12.5. The final-state error vector ϵ_K is used to adapt the blocks labeled C, which are maintained identical to each other throughout the adaptive process. The controller C is a two-layer neural network. The first layer has the six state variables as inputs, and this layer contains twenty five adaptive ADALINE units. The second or output layer has one adaptive ADALINE unit and produces the steering signal as its output.

The procedure for adapting C goes as follows. The weights of C are chosen initially at random. The initial position of the truck is chosen at random. The truck backs up, undergoing many individual back up

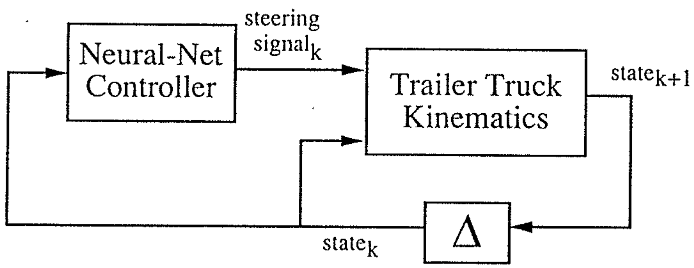


Figure 12.2
Overview diagram.

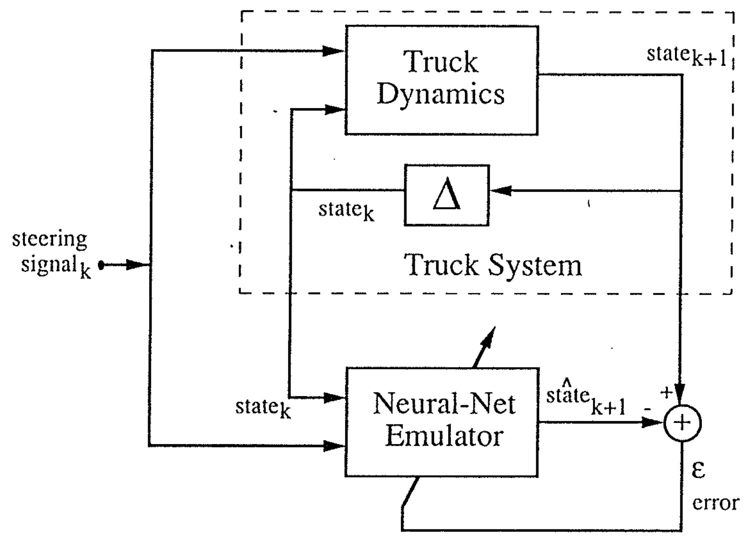


Figure 12.3
Training the neural-net truck emulator.

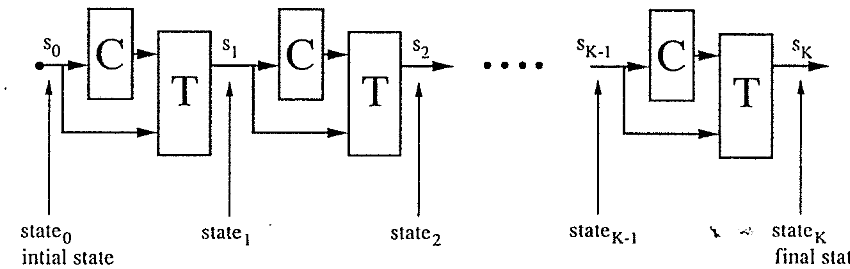


Figure 12.4
State transition flow diagram.

cycles, until it stops. The final error is used by backpropagation to adapt the controller. Each of the C blocks could be tentatively adapted by backpropagation if they were independent of each other, but the actual weight changes in C are taken as the sum of the tentative changes. In this way, the C blocks are maintained identical to each other. The weights are changed by this constrained backpropagation algorithm to reduce the sum of the squares of the components of the final-state error ϵ_K by following the negative of the gradient, using the method of steepest descent. The entire process is repeated by placing the truck and trailer in another initial position, and allowing it to back up until it stops. Once again, the controller weights are adapted. And so on.

Figure 12.6 and figure 12.7 show details of one of the state transition stages of figure 12.5. One can see the structure of controller C and of emulator T, and how they are interconnected. Each stage of figure 12.5 amounts to a four-layer neural network. The entire process of going from an initial state to the final state can be seen from figures 12.4 and 12.5 to be analogous to a neural network having a number of layers equal to four times the number of backing up steps when going from the initial state to the final state. The number of steps varies of course with initial position of the truck and trailer.

The diagram of figure 12.5 was simplified for clarity of presentation. The output error does not go directly to the C-blocks as shown, but backpropagates through the T-blocks and C-blocks. Thus, the error used to adapt each of the C-blocks does originate from the output error ϵ_K, but travels through the proper backpropagation paths. For purposes

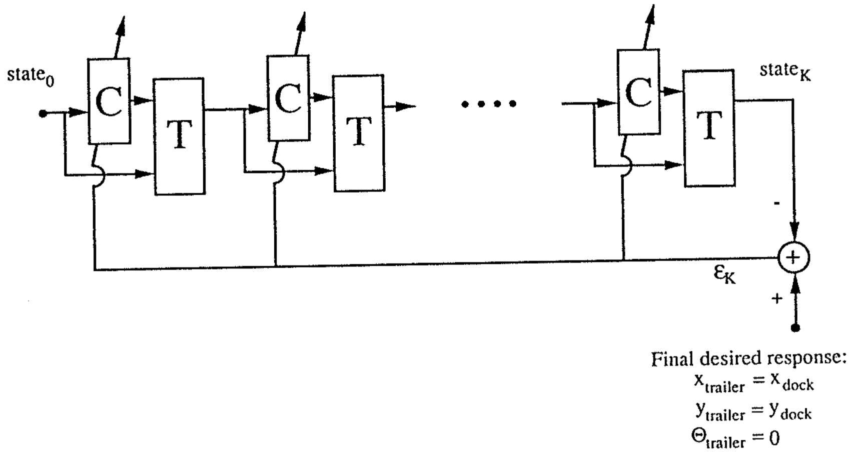


Figure 12.5
Training the controller with backpropagation.

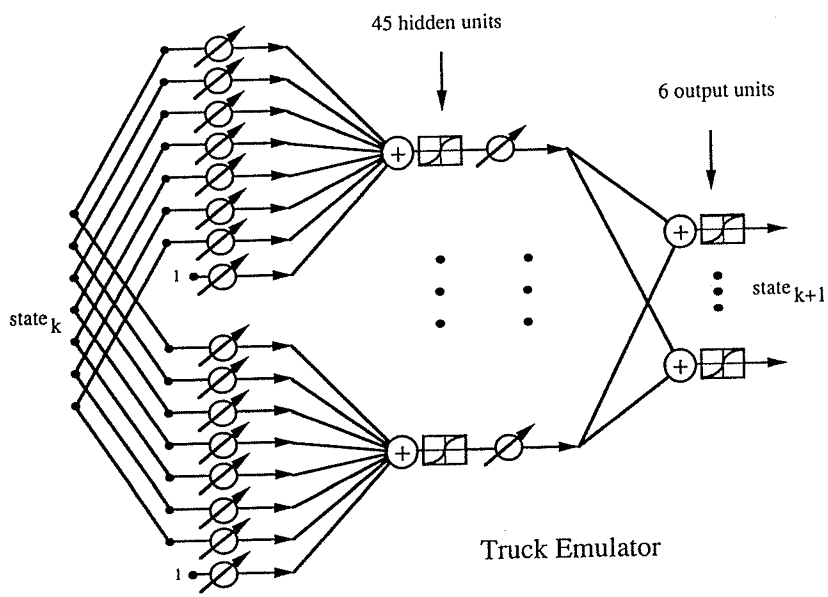


Figure 12.6
Details of emulator and controller.

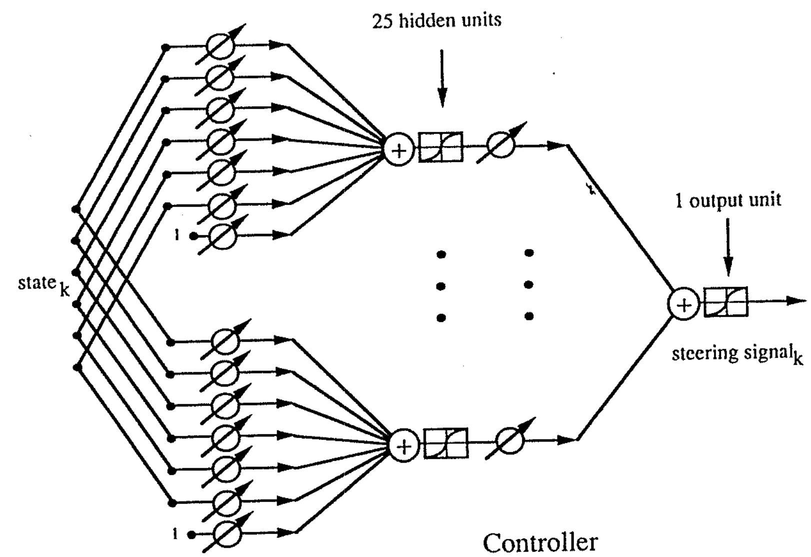


Figure 12.7
Details of emulator and controller.

of back-propagation of the error, the T-blocks are the truck emulator. But the actual truck kinematics are used when sensing the error ϵ_K itself.

12.3 Summary and Results

The truck emulator was able to represent the trailer and truck when jackknifed, in line, or in any condition in between. Nonlinearity in the emulator was essential to represent the truck and trailer. The angle between truck and trailer were not small. *Sin* θ could not be represented approximately as θ. Nonlinearity in the controller was also essential. Self-learning processes were used to determine the parameters of both the emulator and the controller. Thousands of backups were required to train these networks. Without the learning process however, substantial amounts of human effort and design time would have been required to devise the controller.

The training of the controller was divided into several "lessons." In the beginning, the controller was trained with the truck initially set to points very near the dock and the trailer pointing at the dock. Once the controller was proficient at working with these initial positions, the problem was made harder by starting the truck farther away from the dock and at increasingly difficult angles. This way, the controller learned to do easy problems first and more difficult problems after it mastered the easy ones. There were sixteen lessons in all. In the easiest lesson the trailer was set about half a truck length from the dock in the x direction pointing at the dock, and the cab at a random angle between ± 30 degrees. In the last and most difficult lesson the rear of the trailer was set randomly between 1 and 2 truck lengths from the dock in the x direction and ± 1 truck length from the dock in the y direction. The cab and trailer angle was set to be the same, at a random angle between ± 90 degrees. The controller was trained for about 1000 truck backups per lesson during the early lessons, and 2000 truck backups per lesson during the last few. It took altogether about 20000 backups to train the controller.

The controller learned to control the truck very well with the above training process. Near the end of the last lesson, the root mean square error of $y_{trailer}$ was about 3 percent of a truck length. The root mean square error of $\theta_{trailer}$ was about 7 degrees. There is no error in $x_{trailer}$ since a truck backup is stopped when $x_{trailer} = x_{dock}$. One may, of course, trade off the error in $y_{trailer}$ with the error in $\theta_{trailer}$ by giving them different weightings during training.

Results with the adaptive controller are illustrated in figures 12.8 through 12.10. The controller has already been trained and its weights remained fixed for all the experiments. The truck and trailer were placed in a variety of initial conditions, and backing up was effected in each case. Initial and final states are shown in the computer screen displays, and the dynamics of backing up is illustrated by the time-lapse plots.

The truck backer-upper learns to solve sequential decision problems. The control decisions made early in the backing up process have substantial effects upon final results. Early moves may not always be in a direction to reduce error, but they position the truck and trailer for ultimate success. In many respects, the truck backer-upper learns a control strategy that is like a dynamic programming problem solution. The learning is done in a layered neural network. Connecting signals from one layer to another corresponds to idea that the final state of a backing up cycle is the same as the initial state of the next backing up cycle.

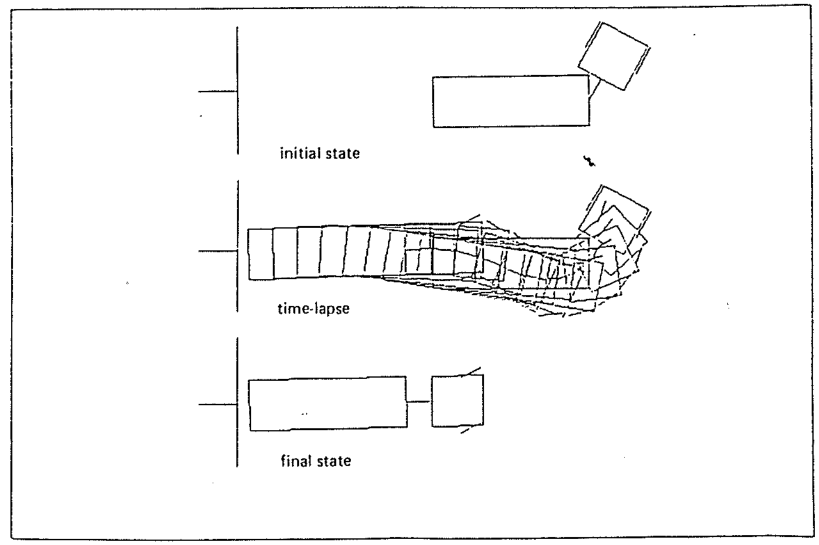


Figure 12.8
Results of training.

Future research will be concerned with:

- Determination of complexity of emulator as related to complexity of the system being controlled.
- Determination of complexity of controller as related to complexity of emulator.
- Determination of convergence and rate of learning for emulator and controller.
- Proof of robustness of control scheme.
- Analytic derivation of nonlinear controller for truck backer-upper, and comparison with self-learned controller.
- Relearning in the presence of movable obstacles.

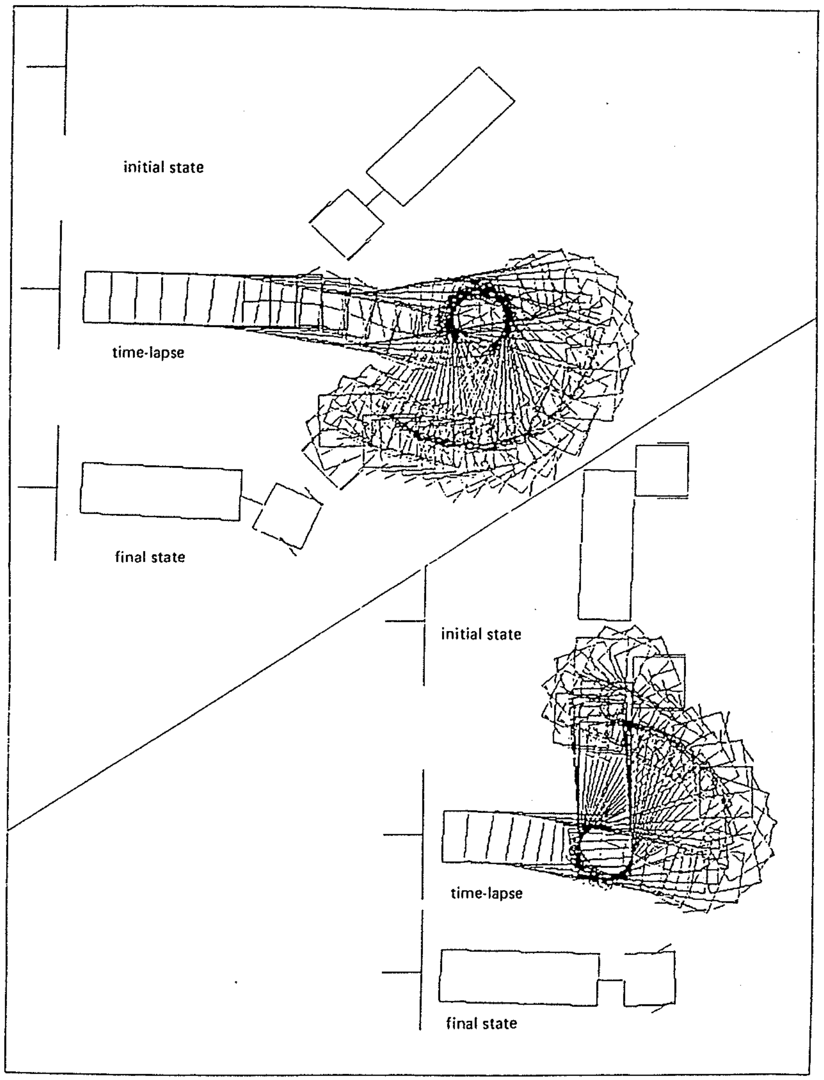


Figure 12.9
Results of training.

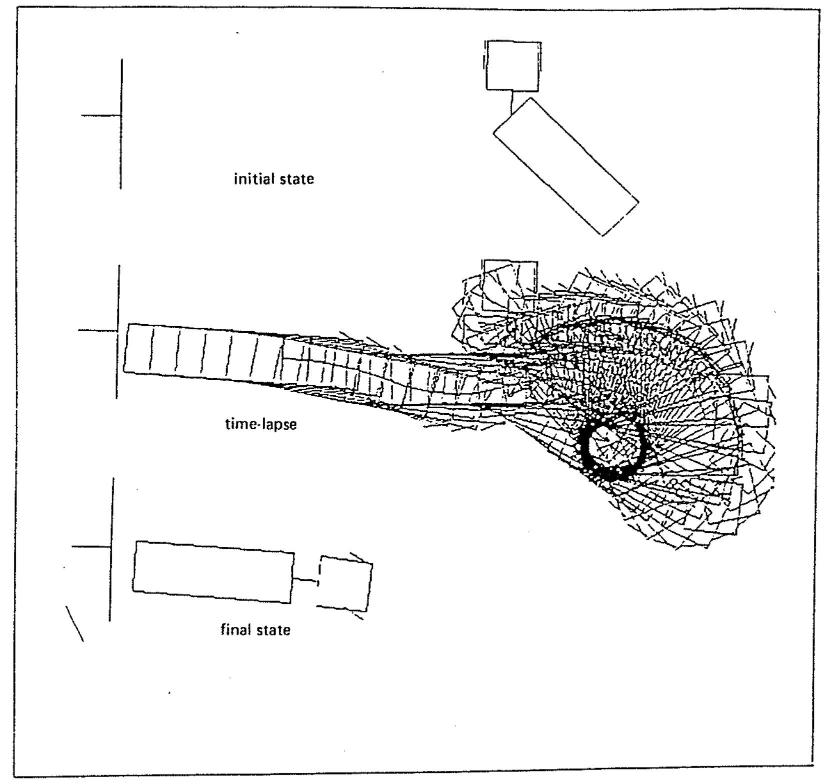


Figure 12.10
Results of training.

- Exploration of other areas of application for self-learning neural networks.

Acknowledgments

This research was sponsored by SDIO Innovative Science and Technology Office and managed by ONR under contract #N00014-86-K-0718, by the Department of the Army Belvoir Research, Development, and Engineering Center under Contract #DAAK70-89-K-0001, and by a grant from the Thomson CSF Company.

This material is based on work supported under a National Science Foundation Graduate Fellowship. Any opinions, findings, conclusions, or recommendations expressed in this publication are those of the authors and do not necessarily reflect the views of the National Science Foundation.

References

Jordan, M. I. (1988). Supervised learning and systems with excess degrees of freedom. COINS Technical Report 88-27, Massachusetts Institute of Technology, Cambridge, MA.

Parker, D. B. (1985). Learning logic. Technical Report TR-47, Center for Computational Research in Economics and Management Science, Massachusetts Institute of Technology, Cambridge, MA.

Rumelhart, D. E., and McClelland, J. L., eds. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition.* Vol. 1, Foundations, chap. 8. Cambridge, MA: MIT Press.

Werbos, P. (1984). Beyond regression: New tools for prediction and analysis in the behavioral sciences. Ph.D. diss., Harvard University, Cambridge, MA.

Widrow, B. (1986). Adaptive inverse control. In *Adaptive systems in control and signal processing*, International Federation of Automatic Control, July. Pergaman Press, Lund, Sweden.

Widrow, B., and Hoff, M. E., Jr. (1960). Adaptive switching circuits. *IRE WESCON Convention Record*, pt. 4:96–104.

Widrow, B. and Stearns, S. D. (1985). *Adaptive signal proccessing.* Englewood Cliffs, NJ: Prentice Hall.

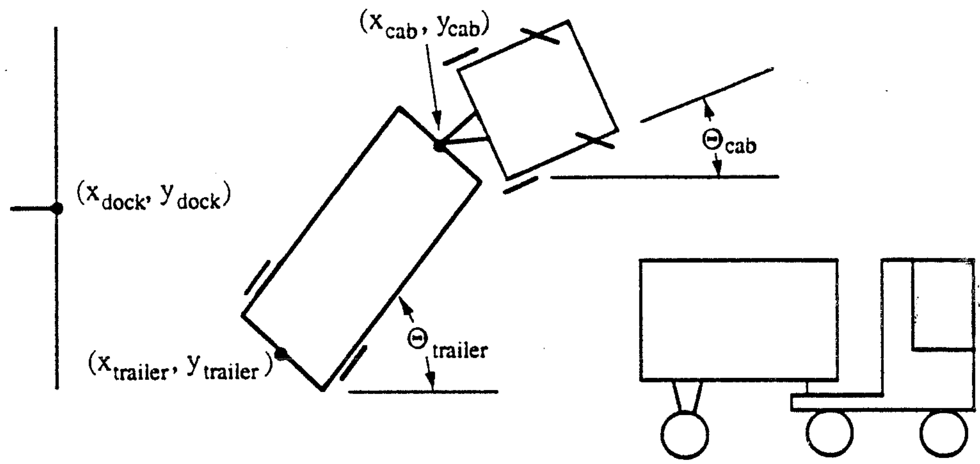


Figure 12.1

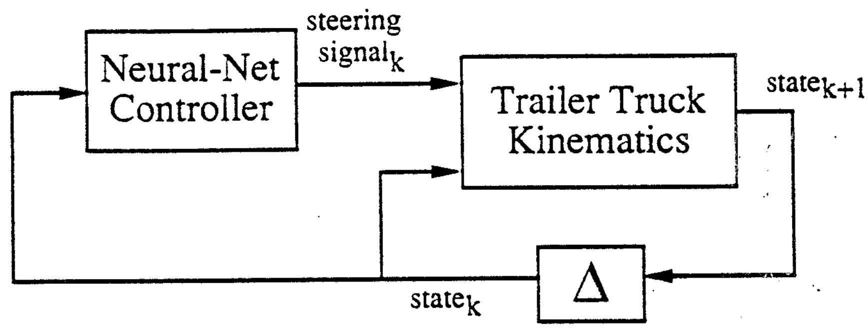
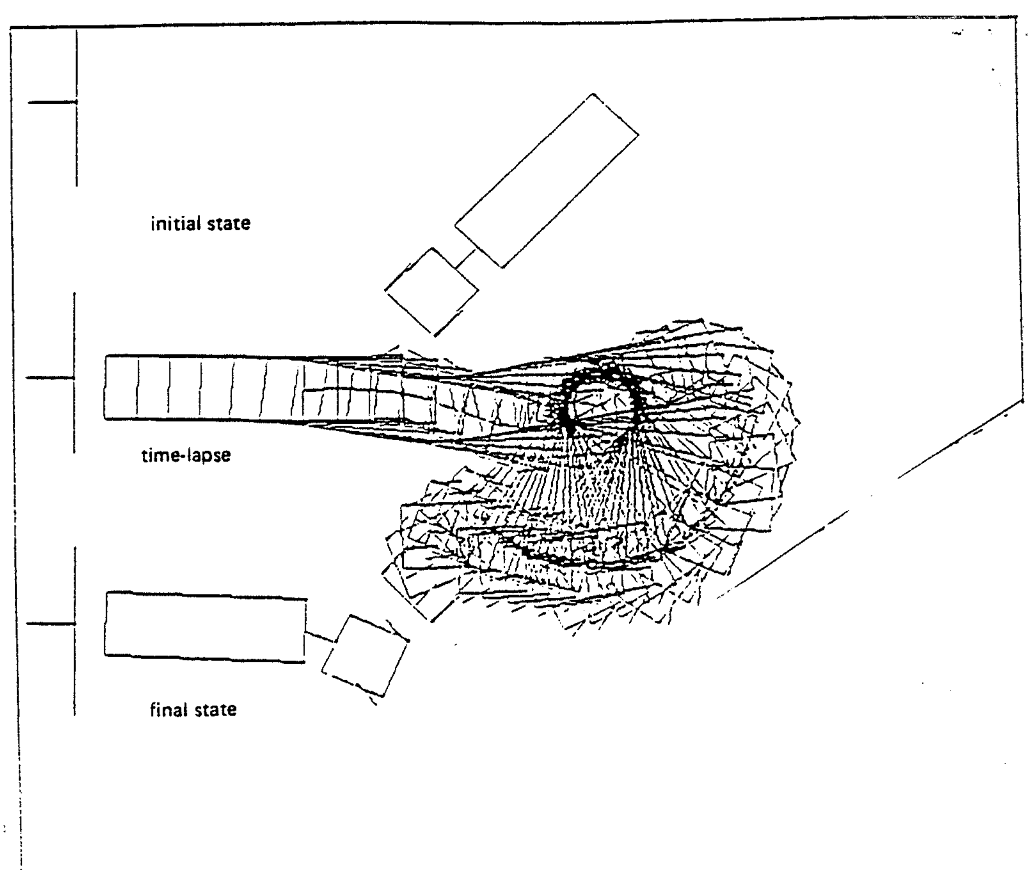


Figure 12.2
Overview diagram.



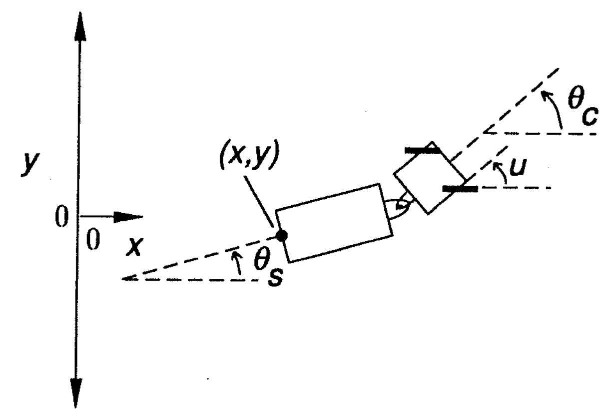


Figure A.4
The tractor-trailer truck backs up at a constant speed. The objective is to position the rear of the trailer at $(x, y) = (0, 0)$ by adjusting the angle, u, of the front wheels.

A.5 Tractor-Trailer Truck Steering

A.5.1 Introduction

Nguyen and Widrow (1989) demonstrated the application of a neural network to the problem of learning to steer a tractor-trailer truck backing up at a constant speed. Their problem definition, with minor modifications, is repeated here. The cab's front wheels move a fixed distance backward with each step. Steering is accomplished by changing the angle of the front tires with respect to the orientation of the cab. The goal is to guide the back of the trailer to a point on a loading dock with the trailer perpendicular to the dock. Refer to the diagram in figure A.4 to relate the following state variables to the physical layout of the problem.

A.5.2 Plant

State

	x, y	coordinates of center of rear of trailer (m)
	θ_s	angle of trailer, measured from positive x with counterclockwise being positive (degrees)
	θ_c	angle of cab, measured from positive x with counterclockwise positive (degrees)

Control

u steering angle of front wheels relative to cab orientation, counterclockwise positive (degrees)

Constraints

$x > 0$	the loading dock is at $x = 0$
$\lvert\theta_s - \theta_c\rvert \leq 90°$	the angle between the cab and trailer cannot be more than 90°
$-70° \leq u \leq 70°$	steering range of front wheels is limited

Initial Conditions

$x[0]$	a random variable from uniform distribution from 0 to 100
$y[0]$	a random variable from uniform distribution from −50 to 50
$\theta_s[0]$	a random variable from uniform distribution from −90° to 90°
$\theta_c[0]$	a random variable from uniform distribution from $\theta_s[0] - 10$ to $\theta_s[0] + 10$

Equations of Motion

$$
\begin{aligned}
A &= r \cos u[t] \\
B &= A \cos(\theta_c[t] - \theta_s[t]) \\
C &= A \sin(\theta_c[t] - \theta_s[t]) \\
x[t+1] &= x[t] - B \cos \theta_s \\
y[t+1] &= y[t] - B \sin \theta_s \\
\theta_c[t+1] &= \tan^{-1}\left(\frac{d_c \sin \theta_c[t] - r \cos \theta_c[t] \sin u[t]}{d_c \cos \theta_c[t] + r \sin \theta_c[t] \sin u[t]}\right) \\
\theta_s[t+1] &= \tan^{-1}\left(\frac{d_s \sin \theta_s[t] - C \cos \theta_s[t]}{d_s \cos \theta_s[t] + C \sin \theta_s[t]}\right)
\end{aligned}
$$

where $\tan^{-1}$ is from −180° to 180°.

Parameters

r	0.2 m	distance front tires move in one time step
d_c	6.0 m	length of cab, from pivot to front axle
d_s	14.0 m	length of trailer, trailer rear to pivot

A.5.3 Controller Input and Output

Input $x[t]$, $y[t]$, $\theta_s[t]$, and $\theta_c[t]$

Output $u[t]$

A.5.4 Objective

The objective of this control problem is to move the center of the rear of the trailer having coordinates (x, y) as close as possible to the center of the loading dock at coordinates $(x_{dock}, y_{dock}) = (0, 0)$ using only backward movements of the cab. The cab starts in a random position and orientation relative to the dock, with a random angle between the cab and trailer. Each trial terminates when any corner of the trailer or cab contacts the plane of the dock. Let T be the time step at which a trial is terminated. The squared error in the positioning of the truck is given by

$$(x_{dock} - x[T])^2 + (y_{dock} - y[T])^2 + (0 - \theta_s[T])^2,$$

since x_{dock}, y_{dock}, and $0°$ are the desired values for $x[T]$, $y[T]$, and $\theta_s[T]$, respectively. Additionally, the desire for a minimum time solution can be incorporated by minimizing T.

A.5.5 Relevance

The truck backer-upper is representative of many sequential decision problems. The control decisions made early in the backing up process have substantial effects upon final results. Early moves may not always be in a direction to reduce error, but they position the truck and trailer for ultimate success. In many respects, this truck steering problem requires a control strategy that is like a dynamic programming problem solution.

A.5.6 Extensions

The problem could be extended by including obstacles in the problem. A trial would then terminate either by contacting the loading dock or one of the obstacles. The same set of fixed obstacles could be utilized for all training and testing, adding fixed constraints to the control problem. New positions for the stationary obstacles could be determined for each trial, requiring a more general capability of planning with constraints. The obstacles could also be allowed to move during each trial, providing [illegible] and dynamic replanning.

The objective can be modified to incorporate the desire for particular truck paths over others in addition to the goal of reaching the loading dock. The results of learning can be biased toward shorter paths or paths requiring smaller steering angles by adding appropriate terms to the error function.

A.5.7 Results

Computer simulations of the truck and a neural network controller by Nguyen and Widrow (1989 and Chapter 12) have demonstrated workability, although no mathematical proof yet exists. Their approach involved the combination of a neural network that learned to generate good steering commands and a second neural network that learned to predict the next state of the truck. After much experience, the truck could be initially "jackknifed" and aimed in many different directions, toward and away from the dock, but as long as there was sufficient clearance the controller appeared to be capable of finding a solution.

References

Nguyen, D. and Widrow, B. (1989). The Truck Backer-Upper: An Example of Self-Learning in Neural Networks. In *Proceedings of the International Joint Conference on Neural Networks*. Washington, DC, June 18–22.

A.6 Ship Steering

A.6.1 Introduction

Figure A.5a shows an overhead view of a ship cruising on an ocean. The ship's state is given by its position, orientation, and turning rate. The ship starts at a particular position and orientation and is to be maneuvered at a constant speed through a sequence of gates. In a real ship, the turning rate would be indirectly controlled by changing the rudder angle. Here, a desired turning rate is specified directly by the controller. There is a time lag between changes in the desired turning rate and the actual rate, modeling the effects of a real ship's inertia and the resistance of the water.