Fuzzy Role Based Expert System for Human Thermoregulation Model

ME290M Final Project
Spring 1999

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May 19, 1999

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Mechanical Engineering

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Abstract

This paper investigated the application of fuzzy rule based expert system (FRBES) to the identification of human thermoregulation system which has long been modeled as a crisp controller without adaptation by earlier approaches. In this project, human body is treated as an adaptive fuzzy logic system. An additional fuzzy controller is implemented and its effect studied. A fuzzy IF-THEN rule base consisting of a set of intuitive fuzzy rules is constructed and applied to the fuzzy thermal controller.

Introduction

An important issue involved in the study of human thermoregulation system is understanding the controlling mechanism which regulates temperatures of all body parts. This system, due to the lack of quantitative data and the difficulty in observation, has not been fully understood. Almost all theories are on hypothetical level and most approaches model the controlling mechanism as a pure mechanical system. In Stolwijk's[1] thermoregulation model, for example, deviation of temperatures in several body parts from their respective "set points" are used as error signals which generate control efforts by causing evaporative heat loss, heat production from shivering or changes in the peripheral blood flow in the appropriate locations in the body. All of these actions, in turn, form a nonlinear controller. This approach, although can be justified in certain thermal conditions, is only a greatly simplified version of what is actually going on inside human body and, inevitably, exhibits inability to emulate the correct response of human body in some conditions.

Several things can be challenged.

1. Human body is adaptive. It is known that human body can adjust to its new thermal environment. Not only some of its physical properties, such as heat capacitance and conductance, can be variant, but also its thermoregulation mechanism. For example, Eskimos, who live in north pole region, cannot sweat. This is a long time adaptation to their environment. Living in such extreme cold condition, sweating is not only expensive in terms of energy but also dangerous. However, if they move to a warmer area, they will, eventually, regain their ability to sweat.
2. It is questionable whether human body adopts a "crisp" thermal control mechanism. Cold and warm are all perceptions and inherently fuzzy. Our knowledge on human sensor mechanism is still incomplete because it is not accessible to observation and study. It is unlikely that human body relies exclusively on numerical sensor input as a way to regulate its thermal states.
3. The so-called thermal comfort index, which has long been investigated but is still not clearly defined, is actually a fuzzy concept. Comfort is a fuzzy perception and the traditional "crisp" approach can hardly model it.

This project tries to attack these problems by incorporating fuzzy logic into the human thermoregulation model.

Basic Concepts of Fuzzy Sets and Fuzzy Logic

Fuzzy Sets and Fuzzy Set Operations

Fuzzy Set: Let U be a collection of objects of interest, and be called the universe of discourse. A fuzzy set F in U is characterized by a membership function μ_F: $U \rightarrow [0,1]$, with $\mu_F(u)$ representing the grade of membership of $u \in U$ in the fuzzy set F. A Fuzzy set can be viewed as a generalization of the concept of an ordinary set whose membership function only takes two values { 0, 1 }.

Figure 1 shows member functions of three fuzzy sets, namely, "Cold", "Neutral" and "Warm", which are three common linguistic descriptions of thermal sensations. The universe of discourse is all possible environment temperatures, i.e. $U = [T_{\min}, T_{\max}]$, where $T_{\min}$ and $T_{\max}$ are minimum and maximum temperatures of a certain thermal condition.

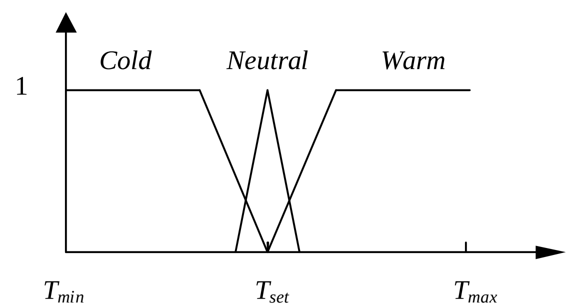

Figure 1 Member functions of three fuzzy sets

Support, Center, and Fuzzy Singleton: The support of a fuzzy F set is the crisp set of all points $u \in U$ such that $\mu_F(u) > 0$. That is,

$$S_F := \{u : u \in U, \mu_F(u) > 0 \}$$

The center of a fuzzy set F includes the point(s) with maximum member function values.

$$C_F := \{u : u \in U, \mu_F(u) \geq \mu_F(v), \text{ for all } v \in U \}$$

If the support of a fuzzy set F is a single point in U at which $\mu_F(u) = 1$, then F is called a fuzzy singleton.

Intersection, Union, and Complement: Let A and B be two fuzzy sets in U, The intersection of A and B, $A \cap B$ is a fuzzy set in U whose member function is given forall $u \in U$ by

$$\mu_{A \cap B}(u) = \min \{ \mu_A(u), \mu_B(u) \}$$

The union of A and B, $A \cup B$ is a fuzzy set in U with member function defined forall $u \in U$ by

$$\mu_{A \cup B}(u) = \max \{ \mu_A(u), \mu_B(u) \}$$

The complement of A, denoted by A', is a fuzzy set in U with member function defined forall $u \in U$ by

$$\mu_{A''}(u) = 1 - \mu_A(u)$$

Note that the definitions of intersection, union and complement given here, when A and B are ordinary sets, are consistent with the corresponding definitions in conventional set theory. It should be mentioned that, however, this definition shows only one possible choice for these operations. The choice of operations corresponds to one's interpretation of the meaning of these operations. Based on different interpretation ranging from intuitive argumentation to empirical or axiomatic justifications, other operators have been suggested in literature.

T-norm: *A* T-norm, denoted by *, is a two place operation from $[0,1] \times [0,1] \rightarrow [0,1]$ which includes fuzzy intersection, algebraic product, bounded product and drastic product, defined as

$\min\{x, y\}$	*fuzzy intersection*
xy	*algebraic product*
$\max\{0, x + y - 1\}$	*bounded product*
x if $y = 1$	
y if $x = 1$	*drastic product*
0 if $x, y < 1$	

where *x, y* are values of two fuzzy member functions.

Fuzzy Relations

Fuzzy Relation: Let *U* and *V* be two universes of discourse. A fuzzy relations is a fuzzy set in the Cartesian product space of *U* and *V*, $U \times V$, and is characterized by a member function $\mu_{R''}(u,v): U \times V \rightarrow [0,1]$ indicating to what extent the relation is true.

Sup-Star Composition: Let *R* and *S* be fuzzy relations in $U \times V$ and $U \times W$, respectively. The sup-star composition of *R* and *S* is a fuzzy relation denoted by $R \circ S$ and is defined by

$$\mu_{R \circ S}(u) = \sup_{v \in V}\{ \mu_R(u,v) * \mu_S(v,w) \}$$

where $u \in U$, $v \in V$, and * can be any operator in the class of T-norm defined earlier. It is clear that $R \circ S$ is a fuzzy set in $U \times W$.

Fuzzy relations and compositions are used to obtain the interpretation of fuzzy IF-THEN rules.

Fuzzifier

The *fuzzifier* maps a crisp point $x \in U$ to a fuzzy set *A* in *U*. The most commonly used fuzzifiers are

- Singleton fuzzifier: *A* is a fuzzy singleton with support *x*. That is, $\mu_A(u) = 1$ for u = x and $\mu_A(u) = 0$ for other.
- Nonsingleton fuzzifier: $\mu_A(x) = 1$and $\mu_A(u)$ decreases as *u* moves away from *x*.

Fuzzifier is an essential part of a fuzzy system. It relates numerical information to fuzzy sets.

Defuzzifier

Defuzzifier performs a mapping from fuzzy sets in *V* to a crisp point $y \in V$. There are different methods of doing so, each of which has its own suitable application. For details about defuzzifier, please refer to Li-Xin Wang [5] and Mohammad Jamshidi [7].

UC Berkeley Multinode Human Physiology and Thermal Model

Background

Stolwijk's 25 node model of thermoregulation (Stolwijk and Hardy 1966) set out the fundamental concept, algorithm, physical constants and physiological control sub-systems for many contemporary multinode models (Hwang and Konz 1977). The Berkeley Multinode Comfort Model is based on the Stolwijk model as well as on work by Tanabe in Japan (Tanabe, Stuzuki et al. 1995), but includes several significant improvements over the Stolwijk model. The Stolwijk model is based on six body segments: head, torso, arms, hands, legs, and feet. The Berkeley model (like the Tanabe model) uses sixteen body segments corresponding to the Berkeley segmented thermal manikin (Tanabe, Arens et al. 1994). Each segment in the model is modeled as four body layers (core, muscle, fat, and skin tissues) and a clothing layer. Blood is modeled as a separate series of nodes that provide convective heat transfer between segments and tissue nodes. The model computes heat transfer between each node using a standard finite differencing algorithm with variable time-stepping to optimize computational resources while preserving numerical stability.

The treatment of time as a series of discrete "phases" of variable length enables the model to simulate almost any combination of environmental, clothing and metabolic conditions. Effects of transient and spatially asymmetric conditions that are completely lost in whole-body models such as the 2-node PMV model can be predicted by the model. An example simulation might be a person walking from an air-conditioned building to hot summer outdoor conditions and then getting into a car that has been sitting in the sun, turning on the air-conditioning and driving as the car begins to cool off. Applications include evaluating thermal comfort in spaces with asymmetric or transient thermal environments including automobiles, buildings or outdoors.

This improved Berkeley Multinode Comfort Model is used as a platform and test bed for the fuzzy control system discussed later.

Model Overview

The model treats each body part as lumped thermal mass, called node, and simulates the transit thermal response of body by computing the heat transfer between these nodes. The following improvements have been made over the Stolwijk model:

- Increase in number of body segments from six to sixteen
- Improved blood flow model, including counter flow heat exchange in the limbs
- Addition of a clothing node to model both heat and moisture capacitance
- Addition of heat loss by conduction to surfaces in contact with the body
- Improved convection and radiation heat transfer coefficients
- Explicit radiation heat transfer calculation using angle factors
- Addition of a radiation heat flux model (e.g. sunlight striking the body)

Figure 2 shows a typical segment node structure. This configuration can accommodate most environment conditions and is default implementation. The model, however, is flexible enough and the structure can be modified easily, without recompiling the code, to suit for specific situation.

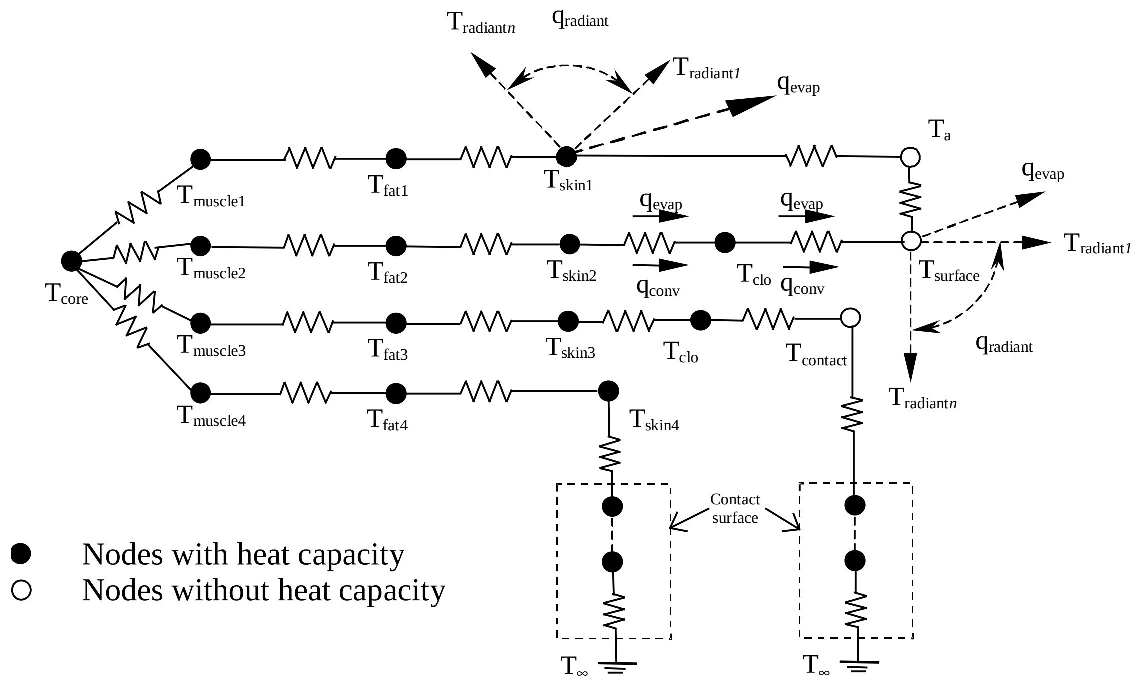

Figure 2. Typical segment node structure showing four parallel heat paths: top, exposed skin with convective and radiant heat loss; second from top, clothed skin with convection and radiant heat loss; third, clothed skin with conductive loss to contact surface; bottom, bare skin

Original Thermoregulation System

The lumped node model of human physiology is a passive system which by itself does not exhibit any control, rather, it represents a complex transfer function between regulator and disturbance. The regulating system receives signals from the passive system and exerts corrective effector action on the passive system if there is deviation from preferred conditions.

The thermal regulation mechanism used in this model is based on Stolwijk's original theory with little modification. Finer segmentation resulted in an increased number of signals and corresponding gains. Apart from that, however, the control algorithm remains largely the same.

Three types of effector action are, in a qualitative sense, well known. They are sweating, which results in evaporative heat loss, shivering with increased heat production, and vasodilation or vasoconstriction which have the effect of varying skin and muscle blood flow. These action(s) are triggered by error signals -- deviations of body parts temperature from their set points. The gains are modeled by a set of coefficients.

In modeling the regulator, the following assumptions have been made:

1. Sensors are located in head core, muscle, and evenly distributed in the skin.
2. The signals received from these sensors vary linearly with the local temperature within physiological limits, insensible to the rate of change of local temperature. This is in accord with available experimental observation.
3. Each of these sensor systems has zero output at a local temperature corresponding to a set point.
4. Signal from head core plays a far more important role in determining what the major effector action should take, be it increasing heat loss by sweating and/or vasodilation or increasing heat storage by shivering and/or vasoconstriction.

It is not clear what the physical meaning of the set points is. It can be viewed as a kind of thermal neutrality where the regulator has zero output. However, depending upon the physical properties of the body and the environment, these set points may not be the preferred temperatures at which the body tries to stay. In other words, at steady state, body temperatures may be quite different from these set points. This result is not surprising in that, for a linearized system, in order for the steady state to track reference, the closed loop system must have a pole at origin. This may not the case in many situations.

The regulator itself is a complex nonlinear system which combines error signals from sensors all over the body and produces control effort. Temperature of each node is compared against its set point. The deviations of all skin nodes are summarized to form one skin signal. It is multiplied by head core signal. A series of complex, nonlinear operation is performed on these signals then and the final controller output is produced in the form of 4 numerical values -- SWEAT, DILAT, STRIC and SHIVER which indicate the extent of four effector actions discussed before, i.e., sweating, vasodilation, vasoconstriction, shivering, respectively. The passive system model uses these values to regulate evaporative heat loss, heat production and the amount of blood flown to skin. For details of the thermoregulating mechanism, please refer to Stolwijk and Hardy[1].

Fuzzy Controller

The purpose of introducing fuzzy algorithm into the human thermoregulating system is to account for the unmodeled human physiology. Our qualitative knowledge of human thermoregulation is still very limited and the human body is greatly simplified in the model. One big challenge for the original crisp control is that it will produce exactly the same results given the same environment conditions. This is, obviously, not the case for a real body. Human body has adaptation ability which the crisp controller does not model. It is hoped that by applying fuzzy algorithm this situation can be improved.

Another belief is that it would be presumptuous of us to assume that human body is doing crisp thermal control (The reason human body is being modeled as a crisp system is that this is the best we have at hand.). Our choice of fuzzy logic system may not be the best to attack this problem, or even worse, fuzzy logic system may not be the answer at all! However, at this point, it can, at least, serve as a good starting point.

<u>Structure of Fuzzy Model/Control</u>

Figure 3 illustrates the configuration of the fuzzy controller used in this model.

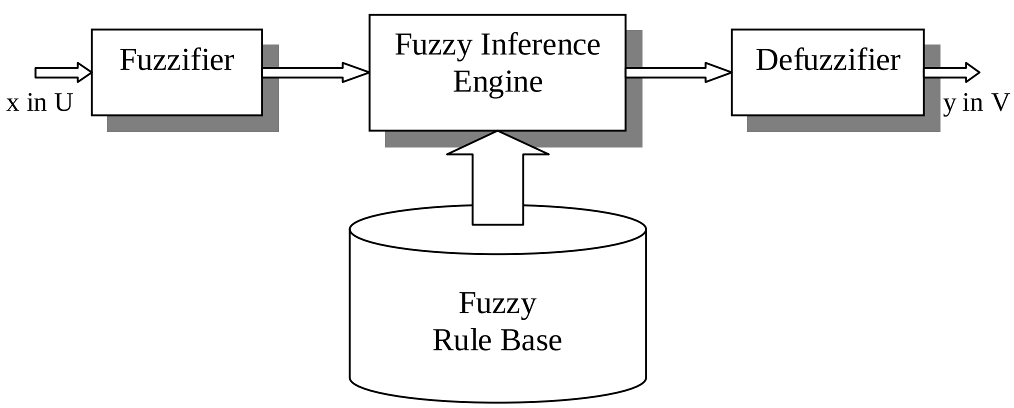

Figure 3 Configuration of the fuzzy controller

Fuzzifier

Although it seems that singleton fuzzifier is widely used, we feel nonsingleton fuzzifier is more suitable in this problem in that we are mapping temperatures to thermal sensations such as COLD, WARM, etc. and we have some intuitively natural membership functions for these fuzzy sets (will be discussed later) that we would like to use.

In this model, thermal sensation, σ, is the linguistic input to the fuzzy controller. σ takes on 7 linguistic values: extremely cold(EC), very cold(VC), cold(C), neutral(N), warm(W), very warm(VW) and extremely warm(EW). The controller, after defuzzification, produces four numerical effector actions mentioned before. Internally, the four effector actions are treated as linguistic variables too. Their linguistic values are out put of the fuzzy inference engine.

Membership Functions

Because of the finer segmentation, each node of the body can have its own set of membership functions for these thermal sensation values which can be best tuned to match each node's role in thermoregulation. Figure 4 shows a typical membership function set for skin node. Since the head core plays a far more important role in determining control action (Stolwijk and Hardy[1].), it has a far narrower Neutral range as shown in figure 5. Also note that the slopes of all its membership functions are sharper and the centers are closer to its set point. This indicates the node is more sensitive to deviation and has more say in the vote of thermal action.

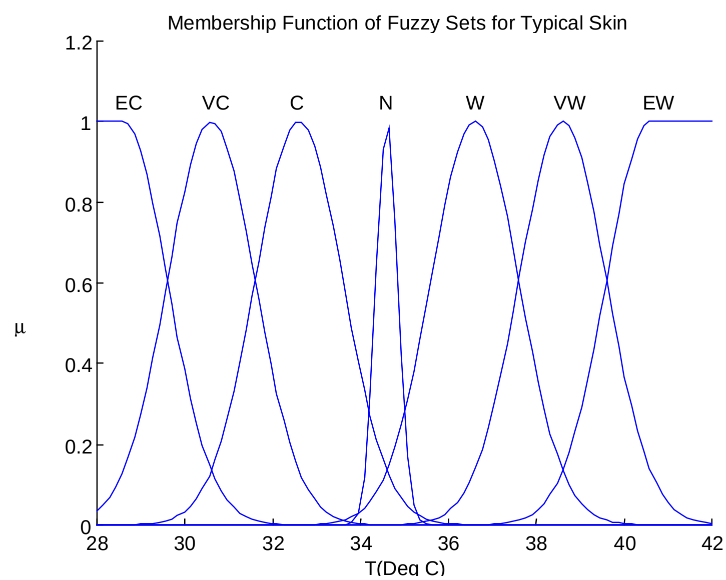

Figure 4 Membership functions for typical skin node

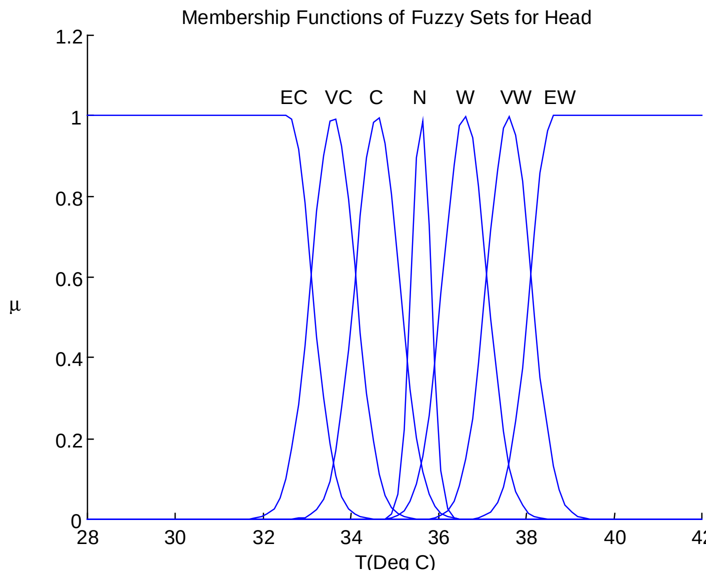

Figure 5 Membership functions for typical head core

Subject studies have indicated that people have asymmetric thermal comfort preference. For example, people prefer a warm back to a cold one. They feel uncomfortable if their back is cold although a colder face can be tolerated, or even preferred. Apart from a higher set point for back skin node, this observation also leads to the asymmetric membership function shown in figure 6. Note that the warm part of the functions have slow slope and centers that are far from set point. This makes back less sensitive to warm and more so to cold.

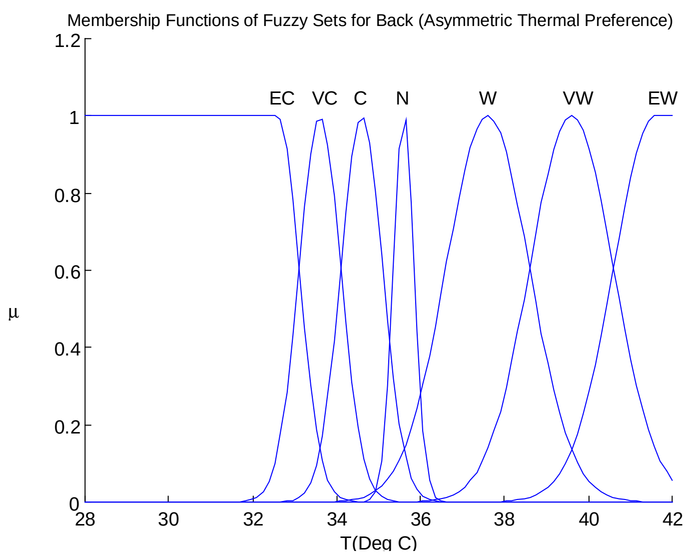

Figure 6 Membership functions for back(asymmetric thermal preference)

Fuzzy Rule Base

In its simplest form, the fuzzy rule regulating human thermal comfort should be

IF σ *= C, THEN u = STRIC and SHIVER (SS), where u is the control effort.*

This is, in plane English, equivalent to saying

IF I am cold, reduce my blood flow to skin and shiver.

Similarly, other rules dealing with different situations can be constructed

IF σ = VC, THEN u = STRIC HARD and SHIVER HARD (SSH)
IF σ = EC, THEN u = STRIC HARDEST and SHIVER HARDEST(SSHST)
IF σ = N, THEN u = 0 (Z)
IF σ = W, THEN u = SWEAT and DILAT (SD)
IF σ = VW, THEN u = SWEAT HARD and DILAT HARD (SDH)
IF σ = EW, THEN u = SWEAT HARDEST and DILAT HARDEST (SDHST)

Fuzzy Inference Engine

Since each node has its own thermal sensation value, σ_i, it is the duty of fuzzy inference engine to combine them and produce an output. We use fuzzy intersection to combine the IF part of the fuzzy rule since in our case the relationship among these conditions is all AND.
Let $\sigma = [\sigma_1, \sigma_2, \ldots \sigma_n]^T$ be the input to the fuzzy inference engine, where n is the number of nodes. The combination of the conditions in the IF part of the fuzzy control rule yields a set of membership function values of σ in the n-dimensional space for the 7 linguistic fuzzy sets. For example, the membership function value of σ for C would be

$$\mu_C(\sigma) = \min \{ \mu_C(\sigma_1), \mu_C(\sigma_2), \ldots \mu_C(\sigma_{1n}) \}$$

Similarly, $\mu_{VC}(\sigma)$,$\mu_{EC}(\sigma)$,$\mu_N(\sigma)$,$\mu_W(\sigma)$,$\mu_{VW}(\sigma)$,$\mu_{EW}(\sigma)$ can also be obtained. These can be viewed as the vote from all body parts on the overall body thermal sensation.

A fuzzy IF-THEN rule is interpreted as a fuzzy implication. The existence of many different definitions of fuzzy implication results in different interpretations of fuzzy IF-THEN rules (Li-Xin Wang, []). Most of them, however, require before-handed knowledge of membership function of output, thus lack simplicity and intuition. And their reliability is doubtful. Remember that although the goal of fuzzy logic is reasoning with uncertainty and non-numerical information, its implementation is, at least at this stage of computing technology, exactly the opposite. That is, it relies on the exact numerical computation and a certain algorithm to achieve a sense of uncertainty and fuzzy. In an effort to keep the inference simple and intuitive, I proposed, and implemented, a simple direct mapping of IF-THEN rules.

Consider the following fuzzy rule

IF x is A THEN y is B

where A and B are fuzzy sets and $x \in U$, $y \in V$ with the membership function $\mu_A(x)$ and $\mu_B(y)$. Our goal is to find $\mu_B(y)$ given $\mu_A(x)$. Instead of the complicated implication, a simple, monotonic relationship between $\mu_A(x)$ and $\mu_B(y)$ is used. That is, the rule is interpreted as

$$\mu_B(y) = R(\mu_A(x))$$

where R:[0,1]->[0, 1], is a monotonic function and is determined by the specific situation we are dealing with, our confidence in this particular rule, as well as the amplification capability of the rule. Figure ?? shows several possible choices of mapping. It should be noted that, since we have the freedom to choose R, we are not losing any control over modeling the problem. On the contrary, proper choice of R may enable us to best characterize our problem. Form figure ?? we can see that the simplest mapping would be

$$\mu_B(y) = \mu_A(x)$$

However, we may consider a larger gain if we have evidence to indicate this is the case. This depends on the nature of the rule. For example, if x is input to a system with a large gain and y is its output and the rule states

IF x is big THEN y is big.

In this case a function with a large slope may be appropriate since a small input can produce a big output. Figure ?? also shows the cases where $\mu_A(x)$ and $\mu_B(y)$ are not linearly related. This may be suitable for some problem where our confidence in the rule of the output should vary with the degree with which x is in A.

The results of this implementation are quite good(See the section Results).

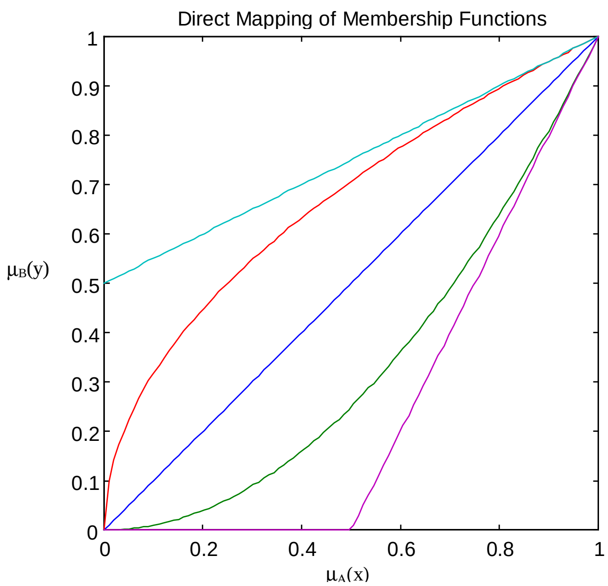

Figure 7 Direct rule mapping

The output of fuzzy inference engine would be a set of membership function values of u for all the possible effector actions which are treated as fuzzy sets.

$\mu_{SS}(u)$, $\mu_{SSH}(u)$, $\mu_{SSHST}(u)$, $\mu_Z(u)$, $\mu_{SD}(u)$, $\mu_{SDH}(u)$, $\mu_{SDHST}(u)$

Defuzzifier

Defuzzifier performs a mapping from fuzzy sets in V to a crisp point $y \in V$. Again we are faced by different choices (Lin-Xin Wang [5]). Here center averaged defuzzifier is used. That is,

$$u^f = \frac{\sum_{i=1}^{M} \bar{u}_i (\mu_{B^i}(u^i))}{\sum_{i=1}^{M} \mu_{B^i}(u^i)} \qquad (*)$$

where $\bar{u}_i$ is the center of fuzzy set B^i, i.e., $\mu_{Bi}(\bar{u})$ achieves maximum value and $\mu_{Bi}(u^i)$ is the membership function of the proposed control for fuzzy set B^i.

In our application, B^i's correspond to the fuzzy sets *SS, SSH, SSHST, Z, SD, SDH* and *SDHST*. Each of these fuzzy sets has a center $\bar{u}_i$ which represents the maximum control it is proposing. For example,

$$\bar{u}_{SS} = \begin{bmatrix} STRIC_n \\ SHIVER_n \\ 0 \\ 0 \end{bmatrix}$$

where $STRIC_n$ and $SHIVER_n$ are real numbers indicating the normal level of vasoconstriction and shivering. The final output, after the defuzzification, is the membership function weighted average of all the fuzzy set centers.

It is tempting to implement the control given in equation (*) directly. However, it must be noted that since all the error signals are transformed and weighted only by their membership functions, the numerical correctness of the controller given by equation (*) depends on

1. Good choice of membership functions that characterize the linguistic variables perfectly, including their weight in the final vote for thermal sensation and control action, and
2. Correct identification of the centers of the control fuzzy sets.

The strength of fuzzy logic system, on the other hand, is its ability to reason with nonnumerical information and model the intuitive knowledge of an expert. This nature makes it not good at finding a sheer numerical solution. Also the dimension of the solution space it is dealing with is infinite in that we have infinite combinations of membership functions, fuzzifier and defuzzifier, let along the numerous choices of fuzzy implications. Therefore it is hard to find a satisfactory solution in such a limited time. As suggested in Li-Xin Wang (Li-Xin Wang[], pp60), a pure fuzzy logic controller may not be sufficient for controlling a system.

Based on the above observation, in this project, the fuzzy controller is used as an intuitive correction to the original numerical controller which at least models the right trend of thermoregulation system.

The control is implemented in the following way

$$u = u^0 (I_n + W\Delta)$$

where u^0 is the original numerical controller, I_n is identity matrix of proper dimension, $W \in R^{n\times n}$ is a predefined weighting matrix, Δ is $n\times n$ diagonal matrix whose entries are elements of normalized fuzzy controller u^f, i.e.,

$$\Delta = diag\{u_1^f, u_2^f, \ldots u_n^f\}$$

Normalizing the output of fuzzy controller to be within the range of [0, 1] is essential in that the fuzzy controller is being used as a correcting factor rather than the actual control action whose scale is not best anticipated by the linguistic rules. Making them unitless can best utilize our intuitive control rules. It is also easy to select the fuzzy set centers. For example, since we have 3 levels of intensity of vasoconstriction and shivering (*SS, SSH, SSHST*), it is intuitive, once they are normalized, to select centers for these fuzzy sets as following:

$$\bar{u}_{SS} = \begin{bmatrix} 1/3 \\ 1/3 \\ 0 \\ 0 \end{bmatrix}, \quad \bar{u}_{SSH} = \begin{bmatrix} 2/3 \\ 2/3 \\ 0 \\ 0 \end{bmatrix} \text{ and } \quad \bar{u}_{SSHST} = \begin{bmatrix} 1 \\ 1 \\ 0 \\ 0 \end{bmatrix}$$

The other centers can be selected in the same way.

$$\bar{u}_{SD} = \begin{bmatrix} 0 \\ 0 \\ 1/3 \\ 1/3 \end{bmatrix}, \ \bar{u}_{SDH} = \begin{bmatrix} 0 \\ 0 \\ 2/3 \\ 2/3 \end{bmatrix}, \ \bar{u}_{SDHST} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix} \text{ and } \bar{u}_{Z} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$$

W can be selected to determine the weight and scale of the fuzzy controller. Note that since it is a $n \times n$ matrix, it maps the fuzzy controller from and into all directions. This is another powerful nub to tune the controller to fit specific situation.

Implementation

The model has been implemented in an object-oriented (OO) approach using C++. Much effort has been spent to make the data structure and simulation procedure resemble the physical model as much as possible. In addition, we have kept the internal model structure very flexible, so that changes to the model can be implemented easily, often without recompiling the code. For example, the node structure is read from text input files so that adding a node or reconfiguring existing nodes only requires modifying program input. The choice of an object-oriented language has greatly simplified this approach.

Several objects are defined to represent each element of the physical model. The *node* object is the basic unit in this object structure. All the actual simulation procedures – heat production, heat transfer and regulating control mechanism -- are done within node objects. Multiple nodes are organized into a tree-like structure which is maintained by a higher level object, the s*egment* object. A segment also has a *blood* object which contains an *artery* and a *vein*. Figure 8 shows the relationship of these objects. The *body* consists of several *segments* that are connected with each other via blood. Nodes exchange heat with their adjacent nodes via conduction and as well as with blood.

Nodes in each segment form a linked tree. Multiple parallel branches may be included in each segment to simulate different heat flow paths. The structure of each segment does not need to be identical. This provides the capability to model different body parts having quite different physical structures and/or non-identical environmental conditions. For example, if the subject is wearing shorts, the model will generate both a clothed and a bare-skin path for the thigh segment. If the subject is wearing long pants, only the clothed path will be generated.

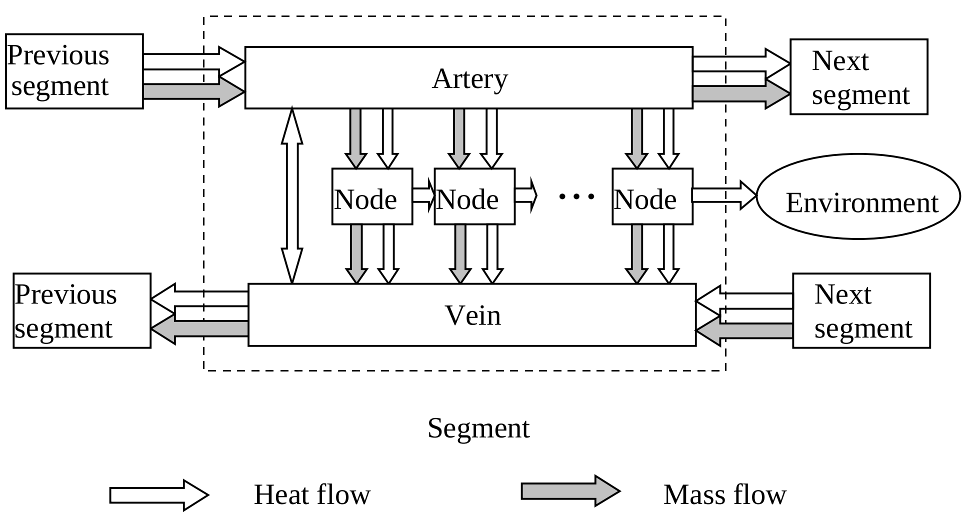

Figure 8. Segment object schema

3D Visualization

This model also has a graphic user interface with 3D visualization implemented using OpenGL©. It is capable of updating body temperature in real time. Simulation results are mapped to the 3D objects and shown with different color. Figure 9 is the screen image after one simulation. Different temperatures are represented by different colers. Figure 10 shows the solar load of a car. Solar load is used as an input to the human physiology model and is a very important thermal factor while simulating the thermal conditions inside a car.

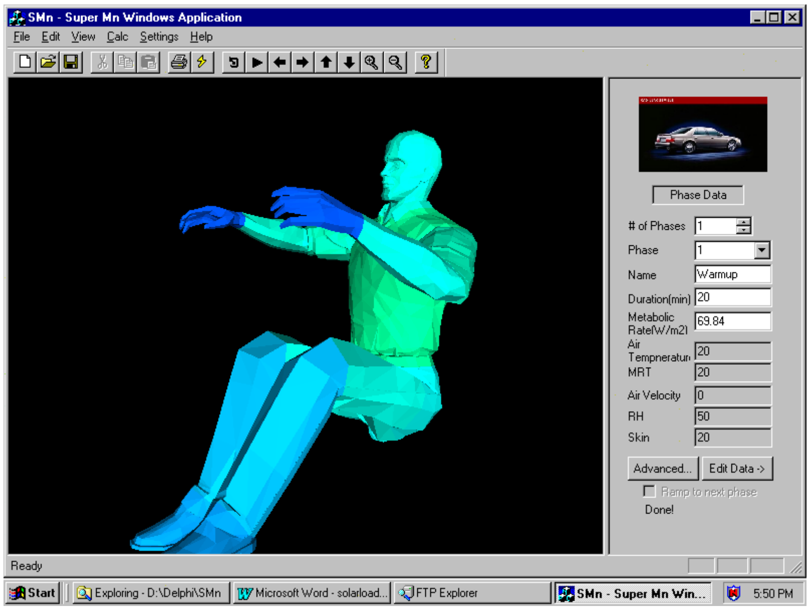

Figure 9 Body temperature 3D visualization

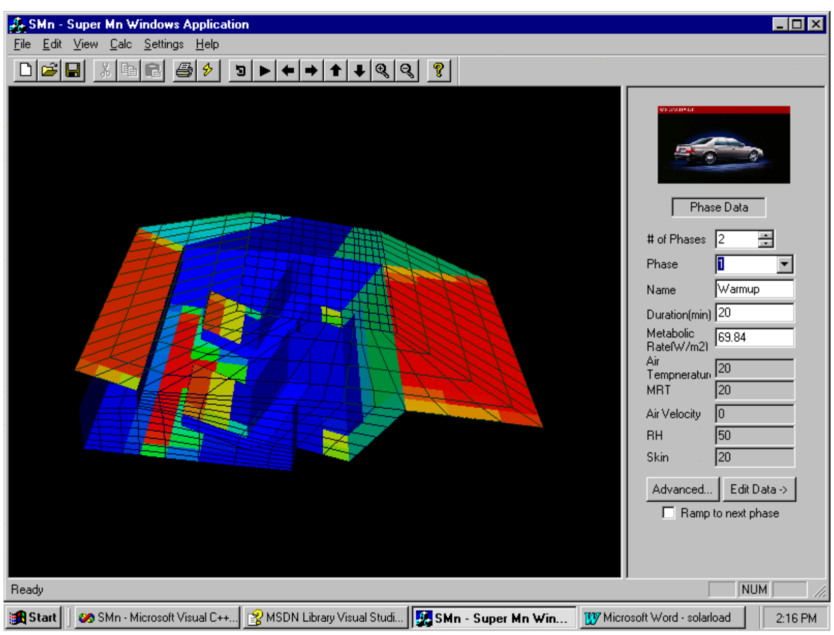

Figure 10 Solar load of a car

Results

Initial Validation

A sound mathematical platform is essential for successfully implementing and testing the control theory. This initial stage of validation is not an effort to obtain realistic result which matches experimental data. Rather, its purpose is to gain confidence in the mathematical correctness of the model.

A greatly simplified version of the model, with constant blood flow rate and temperature, ignoring evaporative heat loss, is governed by the following differential equation:

$$\frac{dT}{dt} = AT + Bu$$

Where

$$A = \begin{bmatrix} -(\frac{C_1}{M_1} + \frac{bf_1}{M_1}) & \frac{C_1}{M_1} & 0 & 0 \\ \frac{C_1}{M_2} & -(\frac{C_1}{M_2} + \frac{C_2}{M_2} + \frac{bf_2}{M_2}) & \frac{C_2}{M_2} & 0 \\ 0 & \frac{C_2}{M_3} & -(\frac{C_2}{M_3} + \frac{C_3}{M_3} + \frac{bf_3}{M_3}) & \frac{C_3}{M_3} \\ 0 & 0 & \frac{C_3}{M_4} & -(\frac{C_3}{M_4} + \frac{bf_4}{M_4} + \frac{Hce}{M_4} + \frac{Hre}{M_4}) \end{bmatrix}$$

$$B = \begin{bmatrix} I_n & BF & Ha & Hr \end{bmatrix}, u = \begin{bmatrix} q \\ T_b \\ T_a \\ T_r \end{bmatrix}, T = \begin{bmatrix} T_1 \\ T_2 \\ . \\ T_n \end{bmatrix}$$

and

$$BF = \begin{bmatrix} \frac{bf_1}{M_1} & 0 & 0 & 0 \\ 0 & \frac{bf_2}{M_2} & 0 & 0 \\ 0 & 0 & \frac{bf_3}{M_3} & 0 \\ 0 & 0 & 0 & \frac{bf_4}{M_4} \end{bmatrix}, q = \begin{bmatrix} q_1 / M_1 \\ q_2 / M_2 \\ . \\ q_n / M_n \end{bmatrix}, T_b = \begin{bmatrix} T_{b1} \\ T_{b2} \\ . \\ T_{bn} \end{bmatrix}$$

$$Ha = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{Hce}{M_n} \end{bmatrix}, Hr = \begin{bmatrix} 0 \\ 0 \\ 0 \\ \frac{Hre}{M_n} \end{bmatrix}$$

T_i is temperature of the ith node, M_i is heat capacity and bf_i is besal blood flow rate. H_a and H_r are heat transfer coefficients.

This equation can be easily solved by MATLAB using OED23. Figure 11 shows the comparison between simulation result(a) and the MATLAB solution(b) for one segment, Head. It could be seen that they match each other perfectly.

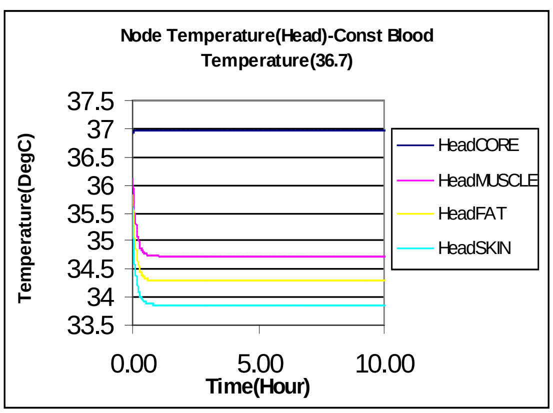

Figure 11a. Simulation result

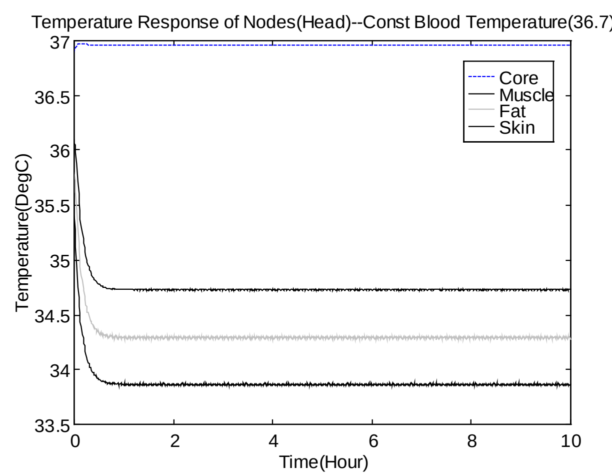

Figure 11b. MATLAB solution

Performance of Fuzzy Controller

It has been found that fuzzy controller gives us more control over the response of the model. By varying its parameters, *W*, member functions, etc., we can tune the model to achieve the response we desired.

Figure 12 is the steady state responses of average skin temperature to a step environment change. The condition is 20°C air temperature with 0 air velocity and 30% relative humidity. Both the outputs of the model with and without fuzzy controller are plotted. Note that the response with fuzzy controller stabilizes at a lower temperature This is exactly the result we desired because the original result is a little high compared experimental data. The fuzzy controller is tuned to drag it down.

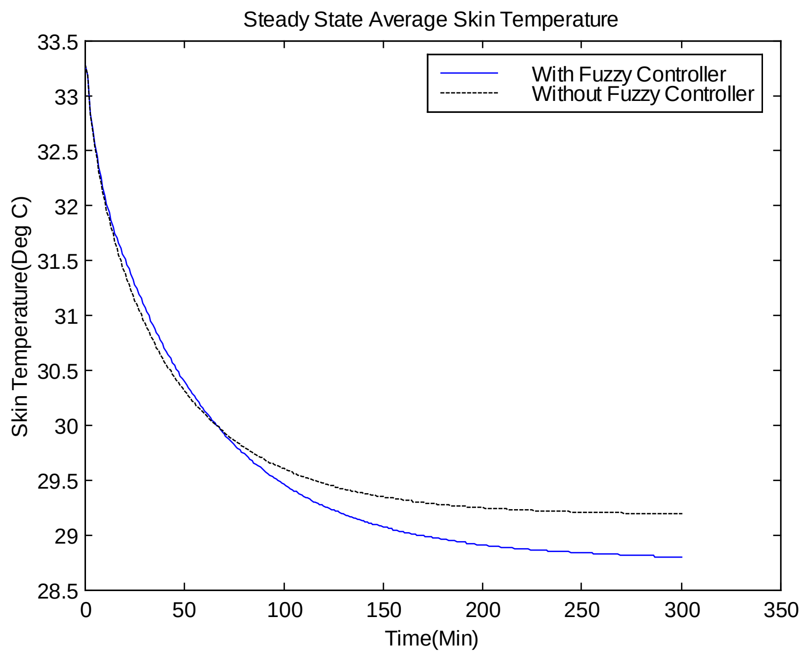

Figure 12. Steady state

Figure 13 is a more realistic scenario where simulation results are compared against measurement data. The initial experiment was done by Stolwijk and Hardy (.Stolwijk and Hardy 1966, Stolwijk 1971) to investigate the response of human subjects to environmental step changes. In their studies, subjects wearing shorts were transferred from normal to high temperature environment, or from high temperature environment to normal condition. Figure 13 shows the results of one such experiment in which subjects were put into a chamber with temperature as high as 43°C for about hour, then moved to a cold environment with temperature of 17°C. The last stage is to return the subjects to the 43°C environment again. After fine tuning the fuzzy controller, the result matches measurement data perfectly.

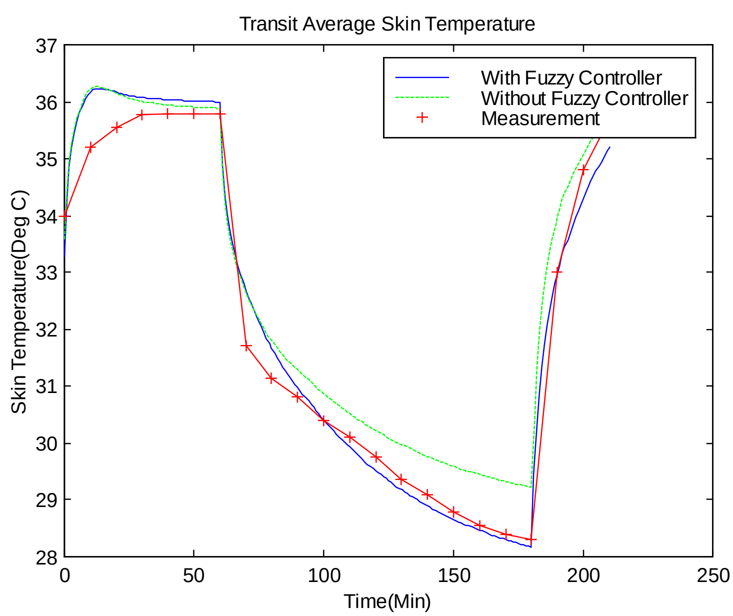

Figure 13. Comparison with measurement data

Conclusion

It is far too early to call it a success because there are still so many unknowns. Also measurement data is scarce, making validation difficult. However, this project shows that fuzzy controller has great potential, offering more freedom than traditional controller, for modeling systems with unidentified dynamics. In fact, sometimes it does such a good job that caution should be taken not to over tune the controller to fit a particular set of data too well because, due to lack of information about the data source, this may not be the condition we are modeling.

Due to limited time, many other possible explorations are left undone (We have so many nubs here!). However fuzzy controller has shown its potential and we may pursue in this field in the future.

Future Work

1. Explore the advantage of using different fuzzy logic system. The very nature and goal of fuzzy logic determined that there are a lot of fuzzy systems for modeling the same system. As mentioned in section ??, besides the existence of many interpretations of fuzzy IF-THEN rule which results in different mappings of fuzzy inference engines, we also have different types of fuzzifiers and defuzzifiers. The combinations of these provide a rich pool of choices. With the progress of our understanding of a particular problem, we sure would find better fuzzy logic systems which fit our most up-to-date empirical knowledge.
2. Investigate the effect of other types of member functions. Again, as a benefit of our improved understanding of the real problem, other member functions may be found to be superior.
3. Try to gain intuitive understanding of the controller. For example, the weighting matrix W has 16 entries. That means it can modify the fizzy controller in all directions. So far only identity matrix is used, giving up most of the choices. It should be most interesting to study its impact to a full extent.

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