Fuzzy Systems:

An Introductory Paper

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What are fuzzy systems?

Before the above question can be answered, two things need to be defined: *system* and *fuzzy*. There are a number of different definitions defined for both terms. Instead of attempting to compile various different definitions and judge their correctness, this paper will try to describe practical interpretations of the terms. A system can be considered as a collection of parts working together, accepting some inputs (stimuli), processing, then producing some outputs (responses). This simple view of a system is illustrated in Figure 1.

Normally, a word fuzzy would put a negative impression on anything it describes. It indicates things that are blurred, ambiguous, imprecise, or vague. They basically are undesirable values when constructing a system. However, in reality, not everything is so precise. We, as human beings, survive in this imprecise world due to our ability to deal with imprecision. We, most of the time in our everyday life, use our common sense reasoning or qualitative judgment rather than quantitative computation. For an example, think of yourself when you drive a car into a curve, what do you do? You would never quantitatively calculate the degree at which you need to turn the steering wheel nor the speed you need to drive your car according to the condition of the curve. You would *simply look* at the curve and the traffic, then automatically and qualitatively come up with a response to turn the steering wheel and to adjust your car's speed without any explicit number-calculation. You would *hardly even look* at your speedometer.

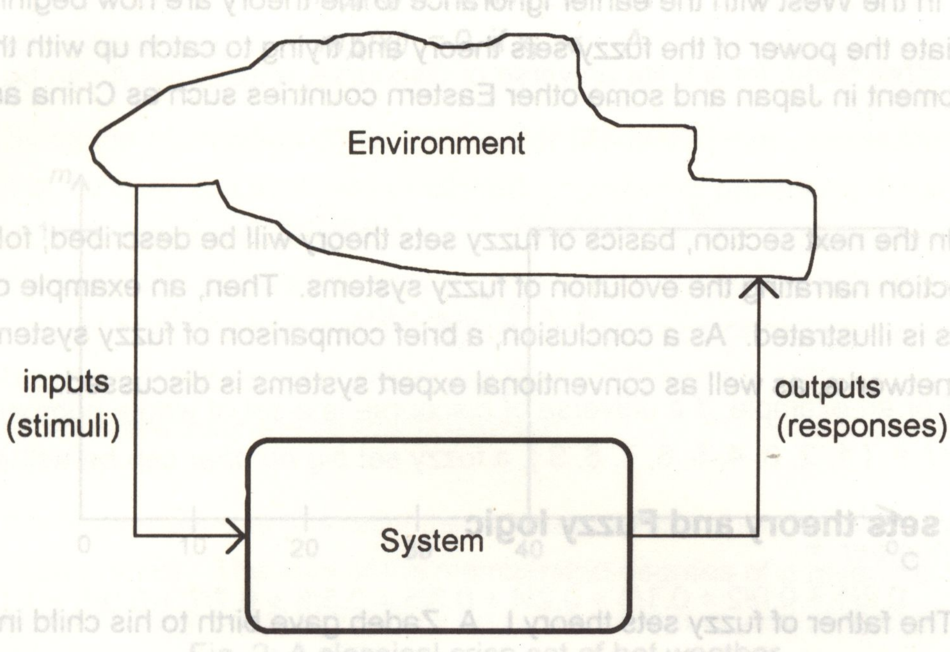

Fig. 1: A system as a black box

Therefore, in order to endow machines with such human intelligence, we need to equip those machines with a tool that qualitatively takes into account the imprecision and processes it as we, human beings do, rather than avoids the imprecision. Researchers in the field of Artificial Intelligence (AI) have tried to produce so-called *intelligent* systems based on symbolic processing and predicate logic for decades. However, their achievements were quite limited. This is due to the fact that human intelligence depends largely on qualitative judgment rather than quantitative computation. In order for machines to possess such level of intelligence, they must be built to exhibit human's qualitative reasoning.

With the fuzzy sets theory, we make computer think like human rather than the other way around. We employ fuzzy sets theory in building qualitatively intelligent systems so-called *fuzzy systems*. Fuzzy systems can effectively and intelligently deal with imprecision in real-world the way human can. A number of fuzzy systems with commercial applications have been produced in recent years. Such systems include automatic train operators, automobile cruise controllers, elevator controllers, camera and camcorder stabilizers, fuzzy washing machines, fuzzy microwave ovens, etc. Those products have primarily been produced in Japan and sold worldwide. Even though the fuzzy sets theory was originated in US, Japanese researchers have proven the worthiness of the underlying theory and are now helping Japanese industry make quite a good deal of money.

People in the West with the earlier ignorance to the theory are now beginning to appreciate the power of the fuzzy sets theory and trying to catch up with the development in Japan and some other Eastern countries such as China and Korea.

In the next section, basics of fuzzy sets theory will be described, followed by a section narrating the evolution of fuzzy systems. Then, an example of fuzzy systems is illustrated. As a conclusion, a brief comparison of fuzzy systems with neural networks, as well as conventional expert systems is discussed.

Fuzzy sets theory and Fuzzy logic

The father of fuzzy sets theory L. A. Zadeh gave birth to his child in his classical paper *Fuzzy Sets* [Zadeh65] in 1965. Fuzzy sets theory generalize the dichotomy world of classical sets theory to incorporate multivaluedness.

In classical sets theory, an element in a universe of discourse utterly either belongs or does not belong to a given set. It is a world of black or white, yes or no. When an element x_i belong to a set A, it is written,

$$x_i \in A.$$

While the same element x_i does not belong to a set B is written,

$$x_i \notin B.$$

The classical crisp sets are adequate for classifying certain things such as classifying whole numbers as odd or even numbers. Unfortunately, they are not good enough to meaningfully classify many other real-world objects. For an example, how can one use a classical set of temperatures measured in degree Celsius to describe *hot* weather? Imagine if one uses a threshold temperature as a cut-off point, say at 40 degree, one would have to consider the temperature of 40 degree and above as hot. What about 39 degree? Isn't it somehow hot? Is there a big enough difference between 40 degree and 39 degree to consider one *hot* and the other one *not hot*? This situation is depicted in Figure 2, using a characteristic function m, where

$$m_A(x_i) = 1, \text{ if } x_i \in A,$$
$$m_A(x_i) = 0, \text{ if } x_i \notin A.$$

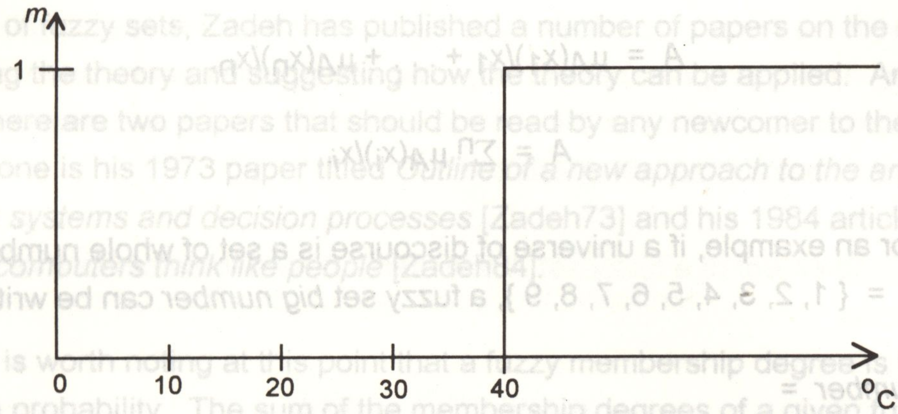

Fig. 2: A classical crisp set of hot weather

The problem here stems from the sharp boundary of the classical crisp set. The fuzzy sets theory solves the problem by accommodating the naturally imprecise nature of the majority of real-world objects. Instead of the dichotomy membership, i.e. either *belong to* or *not belong to*, of an object with respect to a given set, fuzzy sets theory employs *graded* membership. Every element in the universe of discourse U is assigned a membership grade ranging from 0 (non-member) to 1 (full-member) that represents the degree to which an element belongs to a given fuzzy set. This introduces the concept of (continuous) membership function μ which maps an element x_i in a universe of discourse U to a real number in a closed interval [0,1]. This real number represents the membership degree of the element x_i with respect to a fuzzy set A. The said membership function can be written as,

$$\mu_A : U \rightarrow [0,1],$$

or, in other words,

$$0 \leq \mu_A(x_i) \leq 1.$$

For an infinite universe of discourse, a fuzzy set A can be represented as

On the other hand, for a finite universe of discourse, a fuzzy set A can be written,

$$A = \mu_A(x_1)/x_1 + \ldots + \mu_A(x_n)/x_n,$$

or,

$$A = \Sigma^n \mu_A(x_i)/x_i.$$

For an example, if a universe of discourse is a set of whole numbers from 1 to 9, $U = \{ 1, 2, 3, 4, 5, 6, 7, 8, 9 \}$, a fuzzy set *big number* can be written as

big number =

0.0/1 + 0.0/2 + 0.1/3 + 0.2/4 + 0.3/5 + 0.5/6 + 0.7/7 + 0.9/8 + 1.0/9

Based on the concept of membership function above, a fuzzy set representing *hot weather* can be shown graphically in Figure 3.

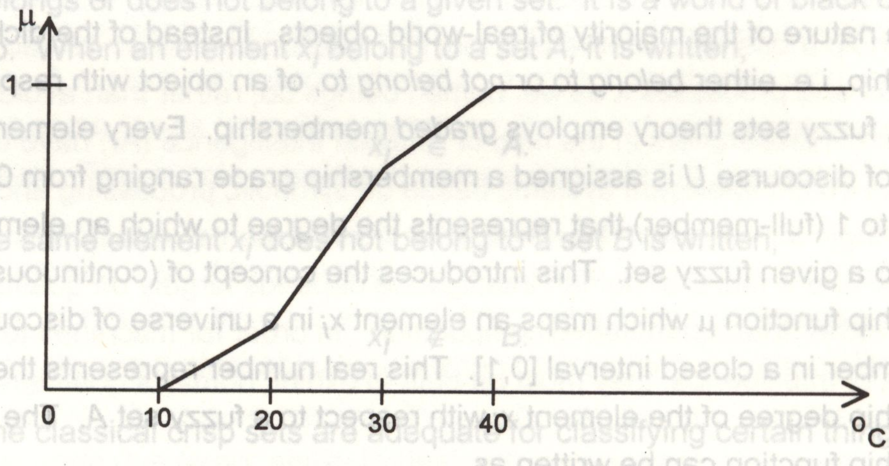

Fig. 3: A fuzzy set representing hot weather

Since a fuzzy set normally represents meaningful but imprecise real-world concepts such as hot, warm, fast, slow, tall, beautiful, etc., a membership degree naturally represents the degree of *compatibility* or *fit* of an element with respect to the given real-world concept. The fuzzy sets theory has equipped us with a mathematical tool for representing and manipulating natural concepts appearing in *rules of thumb* or *common sense* knowledge. Thus, the theory has given birth to a new kind of logic with which imprecise but meaningful reasoning can be achieved, namely *fuzzy logic*.

Since the publication of his 1965 paper [Zadeh65] that defines the concept of fuzzy sets, Zadeh has published a number of papers on the subjects extending the theory and suggesting how the theory can be applied. Among those, there are two papers that should be read by any newcomer to the field; the first one is his 1973 paper titled *Outline of a new approach to the analysis of complex systems and decision processes* [Zadeh73] and his 1984 article on *Making computers think like people* [Zadeh84].

It is worth noting at this point that a fuzzy membership degree is by no means a probability. The sum of the membership degrees of a given fuzzy set does not necessarily equal to 1. They do not represent values of random variables. On the other hand, they do represent the degrees of compatibility of the elements in question with respect to the imprecise concept represented by the given fuzzy set. Moreover, every classical crisp set can be considered and manipulated in the framework of the fuzzy sets theory as a limiting case.

There were an extremely high number of people skeptic, rejecting, or even opposing the theory, on the ground that fuzzy sets theory is imprecise and non-rigorous. Some people even insisted that the fuzzy sets theory is redundant, any imprecision the theory is supposed to handle can be dealt with by the probability theory. Those charges were misleading. First of all, the fuzzy mathematics itself is *not* fuzzy. It is rather a quite rigorous mathematical framework that tries to deal with imprecision in the real-world. Secondly, only small portion of imprecision in the real-world is expressible in terms of randomness to which probability theory can be applied. As a simple example, can the fuzzy set hot weather above be interpreted or described in terms of probability (distribution) by any means?

Apart from the oppositions, there have been a group of far-sighted researchers working on both theoretical extension and application of the theory. They have produced numerous published papers. There have been establishments of publications and organizations devoted to the theory and related research. Among those, the prominent ones include *International Fuzzy Systems Association* (IFSA) and *International Journal of Fuzzy Sets and Systems*.

In the fuzzy sets theory, all set-operations of the classical sets theory are redefined in terms of operations on the membership degree. This is a true generalization of the classical sets theory under which the classical crisp sets are included as limiting cases. However, unlike the classical sets theory, an operation in the fuzzy sets theory could have more than one mathematical definition. The appropriateness of any given definition depends on the application context. Below is the summarization of popular and simple definitions of basic fuzzy set operations.

Complement of a fuzzy set *A* is written $\neg A$, and the membership function is defined as,

$$\mu_{\neg A}(x_i) = 1 - \mu_A(x_i).$$

Therefore, a fuzzy set *not hot* which is a complement of the fuzzy set *hot* given in Figure 3, can be shown as in Figure 4 below.

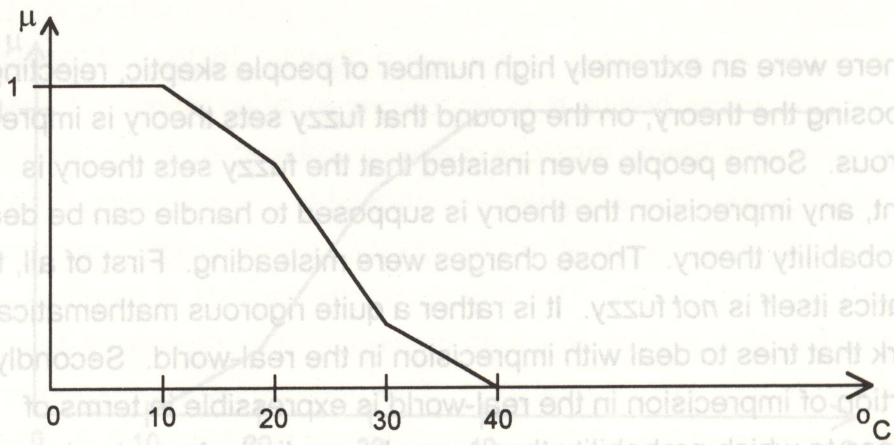

Fig. 4: A fuzzy set representing not hot

Union of fuzzy sets *A* and *B* can be written as $A \cup B$ whose membership function is defined as,

$$\mu_{A \cup B}(x_i) = \mu_A(x_i) \vee \mu_B(x_i) = \max(\mu_A(x_i), \mu_B(x_i)).$$

A fuzzy set *hot or not hot* which is a union of fuzzy set *hot* and fuzzy set *not hot* is shown in Figure 5.

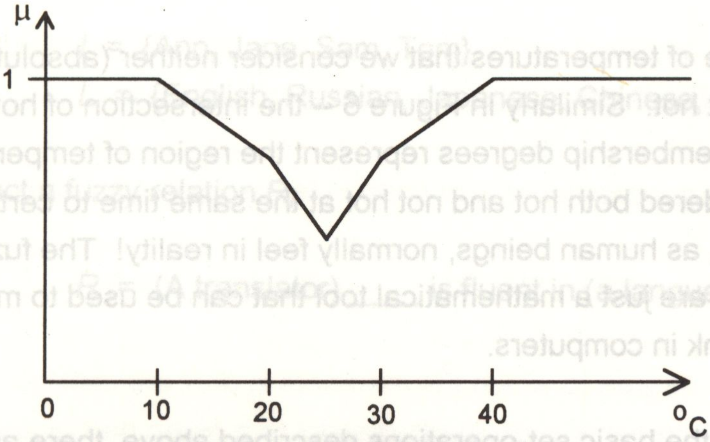

Fig. 5: A fuzzy set of hot *or* not hot

Intersection of fuzzy sets *A* and *B* can be written as $A \cap B$ whose membership function is defined as,

$$\mu_{A \cap B}(x_i) = \mu_A(x_i) \wedge \mu_B(x_i) = \min(\mu_A(x_i), \mu_B(x_i)).$$

A fuzzy set *hot and not hot* which is an intersection of fuzzy set *hot* and fuzzy set *not hot* is shown in Figure 6.

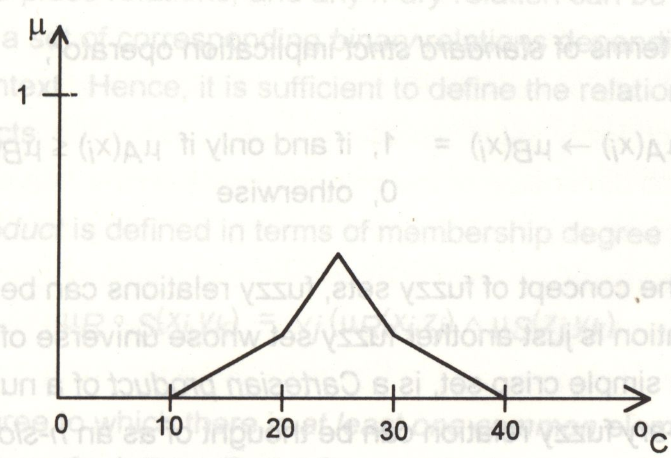

Fig. 6: A fuzzy set of hot *and* not hot

Note that in Figure 5 -- the union of hot and not hot, there is a region that membership function has value less than 1. This simply reflects the fact that there is a range of temperatures that we consider neither (absolutely) hot nor (absolutely) not hot. Similarly in Figure 6 -- the intersection of hot and not hot, the non-zero membership degrees represent the region of temperatures which could be considered both hot and not hot at the same time to certain degree. This is how we, as human beings, normally feel in reality! The fuzzy sets theory and fuzzy logic are just a mathematical tool that can be used to mimic the way we feel and think in computers.

Besides the basic set-operations described above, there as many as 9 different definitions of an *implication* operator, $\rightarrow$. This leads to different interpretations of *subsethood*, $\subseteq$. Bandler and Kohout have investigated the different definitions of the implication operator and presented very interesting discussion in [BaKo80a] and [BaKo80b]. It could be defined that the *degree* to which a fuzzy set *A* is a *subset* of a fuzzy set *B* is,

$$\pi(A \subseteq B) = \wedge_i (\mu_A(x_i) \rightarrow \mu_B(x_i)).$$

Hence, the classical interpretation of subset in the fuzzy sets theory which asserts that

$$A \subseteq B \quad \text{if and only if} \quad \forall x_i \in U, \ \mu_A(x_i) \leq \mu_B(x_i),$$

can be defined in terms of *standard strict* implication operator,

$$\mu_A(x_i) \rightarrow \mu_B(x_i) = \begin{cases} 1, & \text{if and only if } \mu_A(x_i) \leq \mu_B(x_i) \\ 0, & \text{otherwise} \end{cases}$$

Based on the concept of fuzzy sets, fuzzy relations can be defined. In fact any fuzzy relation is just another fuzzy set whose universe of discourse, instead of being a simple crisp set, is a *Cartesian product* of a number of crisp based sets. An *n-ary* fuzzy relation can be thought of as an *n-slot open sentence* or an *n-place predicate* such that when elements, one from each crisp based set, are put in appropriate slots, the truth value of the sentence can be determined in the close interval [0,1].

For an example, given two based sets of interpreters *I* and languages *L*,

$$I = \{\text{Ann, Jane, Sam, Tom}\}$$
$$L = \{\text{English, Russian, Japanese, Chinese, Thai}\}$$

we can construct a fuzzy relation R,

R = (A translator) ____ is fluent in (a language) ____

as follows.

	English	Russian	Japanese	Chinese	Thai
Ann	0.9	1.0	0.6	0.0	0.0
Jane	1.0	0.0	0.8	0.5	0.2
Sam	0.8	0.0	0.8	1.0	0.7
Tom	1.0	0.9	0.0	0.0	0.0

According to the above fuzzy relation, it can be interpreted that Jane is a native English speaker, who is pretty good in Japanese, speaks some Chinese and very little Thai, but does not know Russian at all.

Having defined fuzzy relations, we can manipulate them using the relational products defined below. Note that the most commonly used relations are *binary* or *two-place* relations, and any *n-ary* relation can be reduced in various ways to a set of corresponding *binary* relations depending on the application's context. Hence, it is sufficient to define the relational products only for *binary* products.

Circle product is defined in terms of membership degree as

$$\mu_{R \circ S}(x_i, y_k) = \vee_j (\mu_R(x_i, z_j) \wedge \mu_S(z_j, y_k)).$$

This gives a degree to which there is *at least one common* element z_j with respect to x_i and y_k of relations R and S respectively.

Triangle subproduct is defined in terms of membership degree as

$$\mu_{R \lhd S}(x_i, y_k) = \wedge_j (\mu_R(x_i, z_j) \rightarrow \mu_S(z_j, y_k)).$$

This yields the degree to which the elements z_j of R *include* the corresponding elements z_j of S with respect to a given pair of x_i and y_k.

Triangle superproduct is defined in terms of membership degree as

$$\mu_{R\,|>\,S}(x_i,y_k) = \wedge_j\,(\mu_R(x_i,z_j) \leftarrow \mu_S(z_j,y_k)).$$

This yields the degree to which the elements z_j of R *are included in* the corresponding elements z_j of S with respect to a given pair of x_i and y_k.

Square product is defined in terms of membership degree as

$$\mu_{R\,\square\,S}(x_i,y_k) = \wedge_j\,(\mu_R(x_i,z_j) \leftrightarrow \mu_S(z_j,y_k)).$$

This yields the degree to which the elements z_j of R *exactly match* the corresponding elements z_j of S with respect to a given pair of x_i and y_k.

Here, $\rightarrow$ is a fuzzy implication operator, $\leftarrow$ is dual to $\rightarrow$, and $\leftrightarrow$ represents *if and only if*, i.e. $\rightarrow$ and $\leftarrow$. Detailed discussion on various aspects of fuzzy relations can be found in [BaKo80a] and [BaKo88].

Meanwhile, Kosko has presented a very interesting idea of *sets as points in cubes*. For a finite universe of discourse $U = \{ x_1, ..., x_n \}$ of n elements, we can represent a fuzzy powerset $F(2^U)$ as an *n-dimensional* unit hypercube $I^n = [0,1]^n$. Then, each fuzzy set is represented as a point in the hypercube. The coordinate in each dimension of the point depends on the membership degree of the corresponding element with respect to the given fuzzy set. The corners of the hypercube represent all *crisp* subsets of the universe of discourse. This can be illustrated by an example of a *two-dimensional* hypercube representing a fuzzy powerset of $U = \{ x_1, x_2 \}$ in Figure 7. Here two fuzzy sets,

$$A = 0.7/x_1 + 0.4/x_2 \text{ and } B = 0.3/x_1 + 0.8/x_2$$

are shown as points in the hypercube. Further discussion on this *sets as points* idea can be found in [Kosko92].

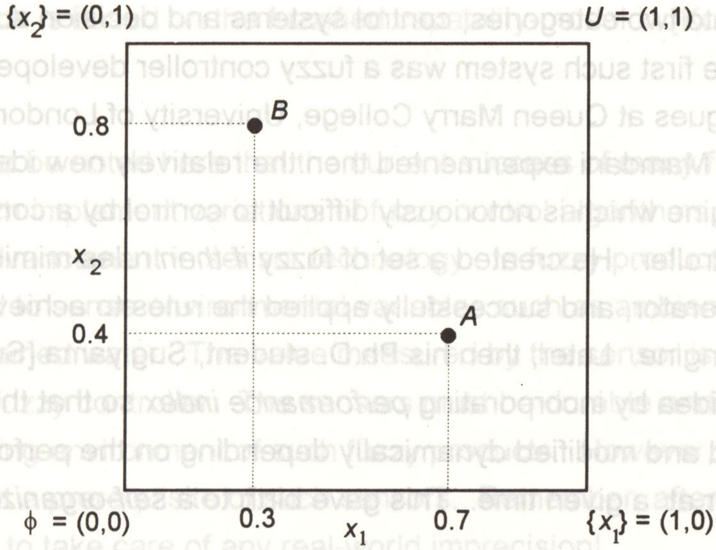

Fig. 7: Sets as points

The discussion above can be summarized as follows. As a result of an application of fuzzy sets theory to inference process, an unconventional logic, namely *fuzzy logic* has been invented. With fuzzy logic, we normally reason with statements whose truth values are graded rather than strictly true or false. This may seem very unsettling to some (old-fashioned) logician. However, the fuzzy logic, being able to deal with imprecision, covers much larger area of discourse than the classical strict logic does. Moreover, the fuzzy logic indeed includes the strict logic in its limiting cases. Instead of having a computer reason with a strict and unnatural statement like "If the temperature is not above 40 degree Celsius this afternoon, we will let the children swim for 30 minutes," with fuzzy logic, we can make a computer comfortably reason with a more natural statement such as "If it is *not too hot* this afternoon, we will let the children swim for *about half an hour*."

Fuzzy systems: the evolution

Based on the discussion about fuzzy sets theory and fuzzy logic in previous section, the term *fuzzy systems* can be defined as any systems that utilize fuzzy sets theory and fuzzy logic in its process. Applications of fuzzy sets theory and fuzzy logic permeate wide variety of disciplines such as engineering, artificial intelligence, decision support systems, information processing and retrieval, psychology, medicine, meteorology, etc. Most prevailing fuzzy systems currently fall into two categories; control systems and decision support systems. Historically, the first such system was a fuzzy controller developed by Mamdani and his colleagues at Queen Marry College, University of London in 1974 [Mamdani74]. Mamdani experimented then the relatively new idea with a control of a steam engine which is notoriously difficult to control by a conventional numerical controller. He created a set of fuzzy *if-then* rules mimicking the action of a human operator, and successfully applied the rules to achieve good control of the steam engine. Later, then his Ph.D. student, Sugiyama [Sugiyama86] expanded the idea by incorporating *performance index* so that the fuzzy rules can be created and modified dynamically depending on the performance of the fuzzy controller at a given time. This gave birth to a *self-organizing fuzzy control system*.

Spurred by the development of the first fuzzy controller, a number of researchers around the world have worked on various fuzzy systems. The pioneer works were done mostly in Japan and few European countries. One of those has become a major mile-stone of fuzzy systems development, Japan's Sendai automated subway system. The subway system which was opened in 1987 used a fuzzy control system developed by Hitachi in lieu of a human operator. The fuzzy control system reportedly operates the subway with better performance than its human operator counterpart in various aspects -- smoother acceleration and braking, better accuracy in stopping at a platform, and less energy consumption. Since the success of the Sendai subway system, many Japanese companies have caught a *fuzzy fever* developing wide variety of fuzzy products ranging from consumer products such as fuzzy rice cooker, fuzzy microwave oven, fuzzy air-conditioning system, fuzzy camcorder, fuzzy refrigerator, fuzzy washing machine, etc. to high-tech products such as fuzzy expert system, fuzzy VLSI chip, etc. A recent survey article in BYTE, *Putting Fuzzy Logic into Focus*, by Barron [Barron93] summarizes the current trend in applications of fuzzy systems and related technologies.

While majority of researchers focus on fuzzy rule-based systems, there are still a number of different ways in applying fuzzy sets theory and fuzzy logic. In their 1988 book, *Fuzzy Sets, Uncertainty, and Information*, [KlFo88], Klir and Folger discuss various theoretical frameworks upon which fuzziness can be measured and captured for further manipulation. Another interesting application of fuzzy sets theory and fuzzy logic is the use fuzzy relations in analysis of computer security and protection model. Kohout and Bandler describes a technique which is based on the fuzzified capability-model in [KoBa81] and [KoBa87].

It should be noted here that the current success of many fuzzy consumer products, which implement variations of fuzzy control algorithms, is partly owing to the rapid advancement in sensor technology. In fuzzy products, at least one sensor is used to sense environmental variables such as ambient temperature or dirtiness of drained water. The value measured by the sensor is used as an input into the fuzzy controller. The sensors must be durable and operable in normal operating environment of such fuzzy products. However, utmost accuracy is not a prerequisite of such sensors. Remember, after all we have fuzzy systems to take care of any real-world imprecision!

Fuzzy systems: an illustration

This section briefly discusses an example of fuzzy systems in order to give an idea on how such systems work. Among various types of fuzzy systems, the fuzzy rule-based systems are the simplest to construct and the most widely used in the market. A (very) simplified version of fuzzy system for the control of traffic signal on a main street is used as an example to illustrate the idea behind fuzzy rule-based systems. Three common sense rules for controlling a traffic signal based on the flow rate of traffic could be described as follows.

if traffic speed is Fast *then* green light is Short
if traffic speed is Normal *then* green light is Medium
if traffic speed is Slow *then* green light is Long

The next step here is to define fuzzy sets that represent the linguistic variables of the if-part, namely Fast, Normal, and Slow, as well as those of the then-part, Short, Medium, and Long. Those linguistic variables could be defined as shown in Figure 8 and 9, respectively.

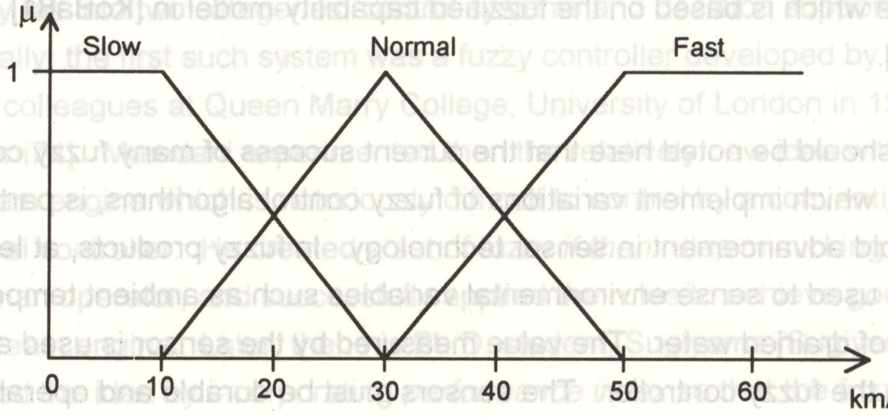

Fig. 8: Fuzzy sets representing Fast, Normal, and Slow

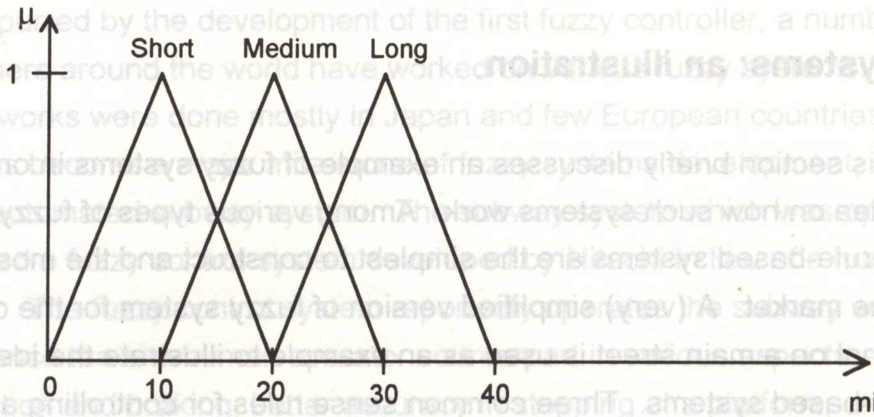

Fig. 9: Fuzzy sets representing Short, Medium, and Long

Each rule could be represented graphically in terms of a pair of two fuzzy sets below.

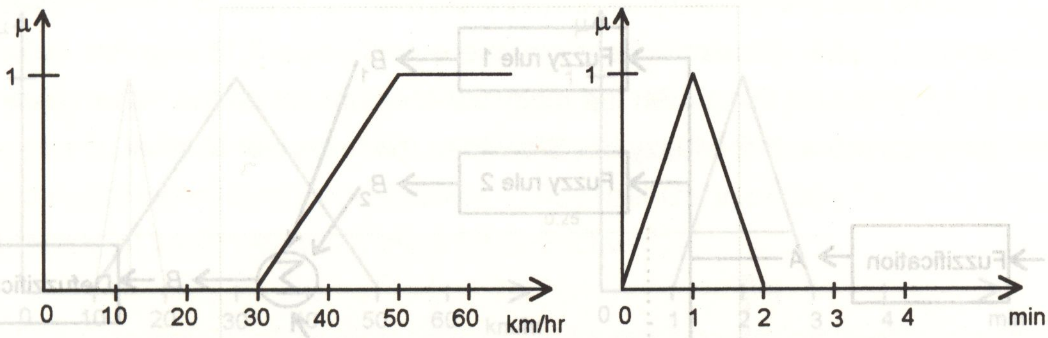

Fig. 10: *if* traffic speed is Fast *then* green light is Short

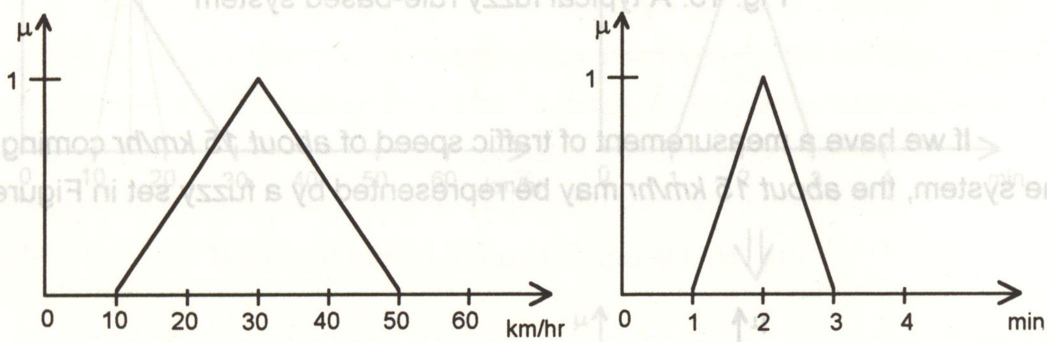

Fig. 11: *if* traffic speed is Normal *then* green light is Medium

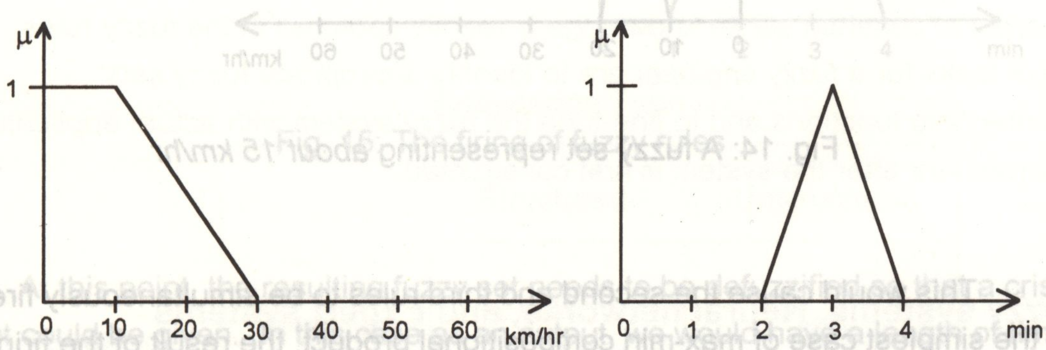

Fig. 12: *if* traffic speed is Slow *then* green light is Long

A fuzzy rule-based system of the type exemplified here can be depicted by a schematic diagram in Figure 13.

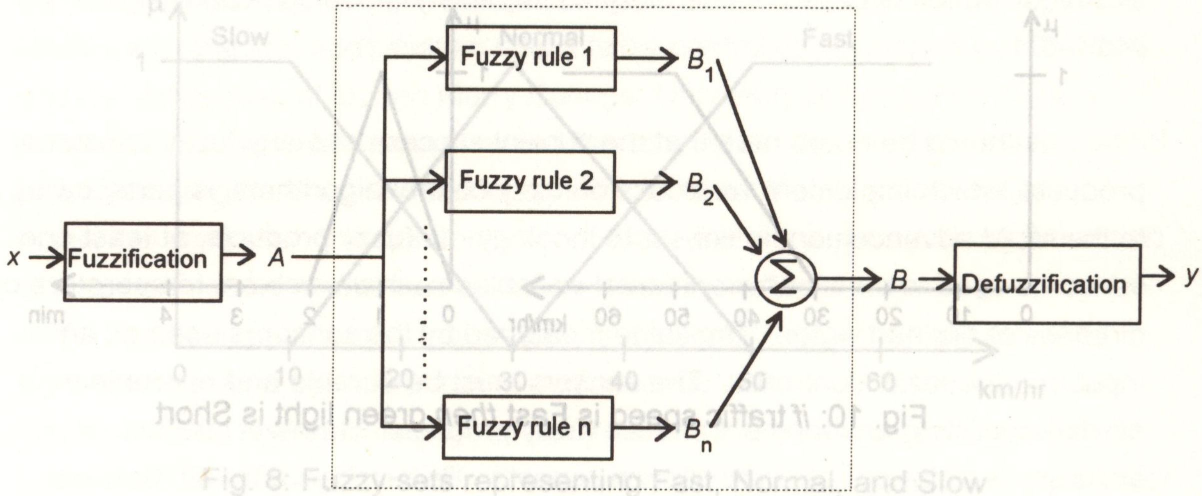

Fig. 13: A typical fuzzy rule-based system

If we have a measurement of traffic speed of *about 15 km/hr* coming to the system, the *about 15 km/hr* may be represented by a fuzzy set in Figure 14.

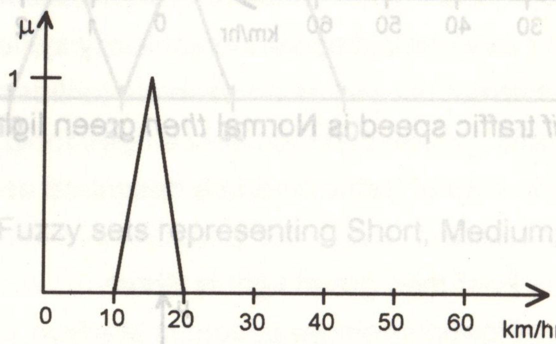

Fig. 14: A fuzzy set representing *about 15 km/hr*

This would cause the second and third rules to be simultaneously fired. In the simplest case of max-min compositional product, the result of the firing could be shown graphically as in Figure 15.

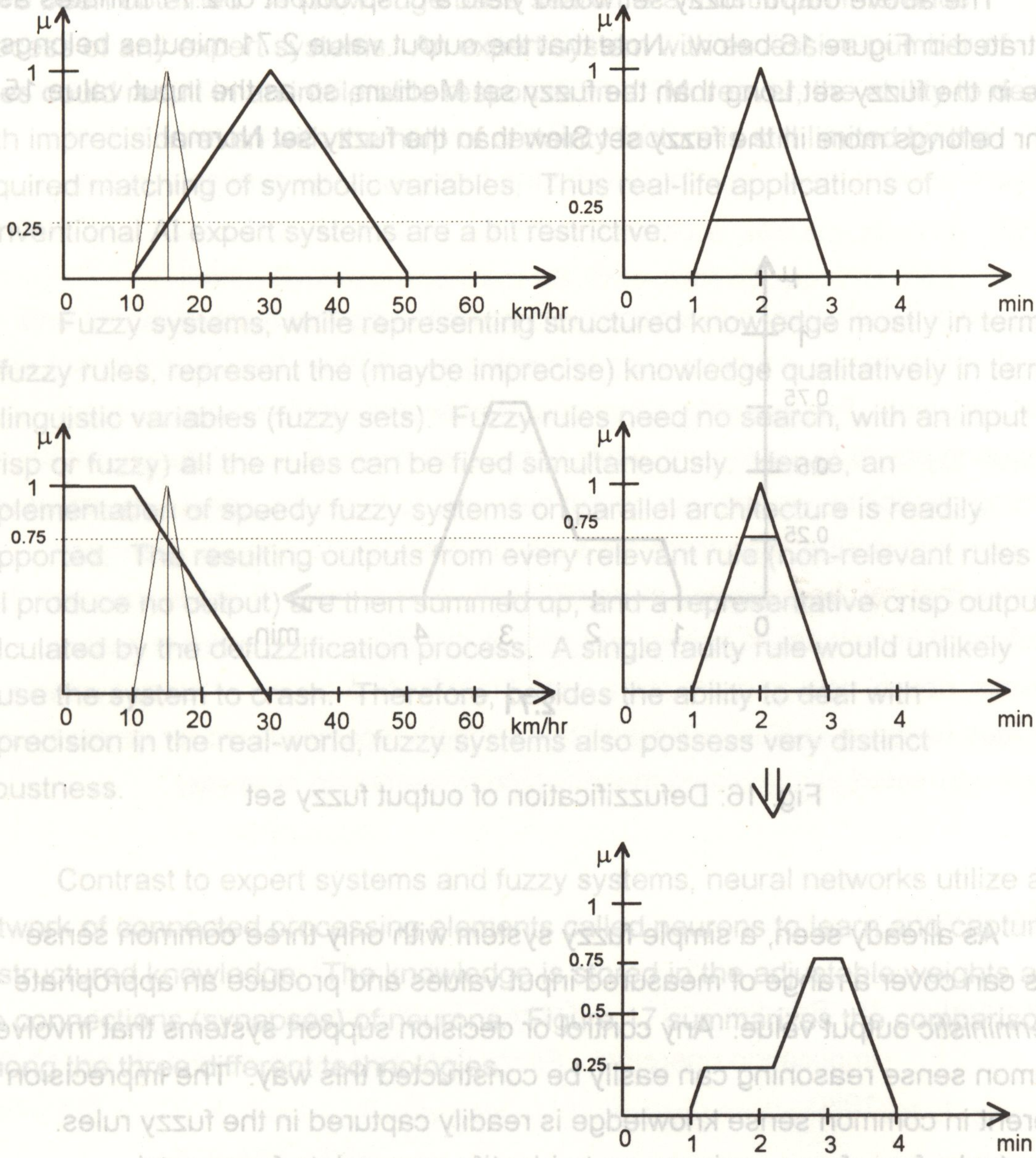

Fig. 15: The firing of fuzzy rules

At this point, the resulting fuzzy set needs to be defuzzified so that a crisp output could be given. In this case as an output, we would have a length of time in minutes that the green light should be on. One of the ways to perform defuzzification is to calculate the center of gravity of the resulting output fuzzy set. This can be done using the following formula, where *B* is an output fuzzy set.

$$c.g. = \Sigma^n \mu_B(x_i)\, x_i \,/\, \Sigma^n \mu_B(x_i)$$

The above output fuzzy set would yield a crisp output of 2.71 minutes as illustrated in Figure 16 below. Note that the output value 2.71 minutes belongs more in the fuzzy set Long than the fuzzy set Medium, so as the input value 15 km/hr belongs more in the fuzzy set Slow than the fuzzy set Normal.

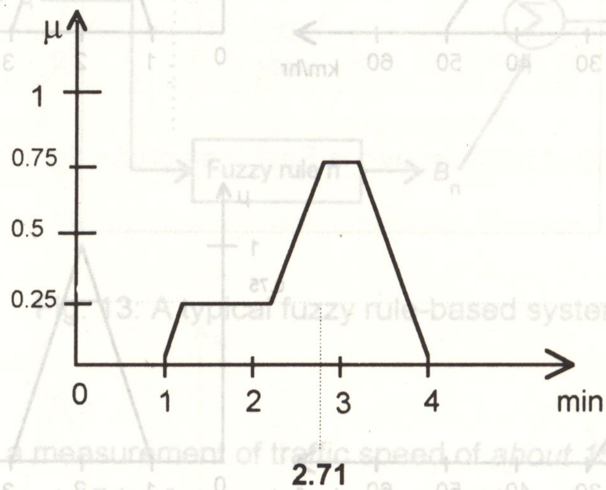

Fig. 16: Defuzzification of output fuzzy set

As already seen, a simple fuzzy system with only three common sense rules can cover a range of measured input values and produce an appropriate *deterministic* output value. Any control or decision support systems that involve common sense reasoning can easily be constructed this way. The imprecision inherent in common sense knowledge is readily captured in the fuzzy rules. Major tasks for a *fuzzy engineer* are to identify appropriate fuzzy sets' membership functions and to fine-tune the fuzzy system with actual application environment after the system is first constructed.

Fuzzy systems, Neural networks, and Expert systems

Both fuzzy systems and neural networks represent numerical approach to capturing human intelligence in machines. On the other hand, expert systems use symbolic representation of structured knowledge in terms of rules and require predicate logic for the manipulation of facts and rules to reach some conclusion. Even though expert systems sometimes incorporate certainty factors, they are used in the computation only after symbolic pattern matches have been obtained. A knowledge base search is a must in an inference process of any expert systems. An expert system with excessive number of rules could result in an intolerable response time. Moreover, the ability to deal with imprecision even with the help of certainty factors is still limited by the required matching of symbolic variables. Thus real-life applications of conventional AI expert systems are a bit restrictive.

Fuzzy systems, while representing structured knowledge mostly in terms of fuzzy rules, represent the (maybe imprecise) knowledge qualitatively in terms of linguistic variables (fuzzy sets). Fuzzy rules need no search, with an input (crisp or fuzzy) all the rules can be fired simultaneously. Hence, an implementation of speedy fuzzy systems on parallel architecture is readily supported. The resulting outputs from every relevant rule (non-relevant rules will produce no output) are then summed up, and a representative crisp output is calculated by the defuzzification process. A single faulty rule would unlikely cause the system to crash. Therefore, besides the ability to deal with imprecision in the real-world, fuzzy systems also possess very distinct robustness.

Contrast to expert systems and fuzzy systems, neural networks utilize a network of connected processing elements called neurons to learn and capture unstructured knowledge. The knowledge is stored in the adjustable weights at the connections (synapses) of neurons. Figure 17 summarizes the comparison among the three different technologies.

		Knowledge Type	
		Structured	Unstructured
System Framework	Symbolic	Expert Systems	N/A
	Numerical	Fuzzy Systems	Neural Networks

Fig. 17: Fuzzy systems, Neural networks and Expert systems

With continuous research efforts in Japan, Korea, and China together with a momentum being picked up in the US and European countries, it can be most certainly foreseen that fuzzy systems will permeate many aspects of our everyday life in the very near future. Right now there already are a few of software development tools for developing fuzzy systems available in the market.

As a conclusion to this paper, it is worth noting that fuzzy systems and neural networks are *not* competing technologies. Rather, they complement each other very well. For example, since neural networks require excessive computing power to implement, while fuzzy systems by themselves do not have learning capability, we can use neural networks to learn the previously structure-unknown knowledge, then translate such knowledge into appropriate fuzzy systems that can be executed more efficiently in real-time. Even in the case that structure of knowledge is known and can be directly implemented in fuzzy systems, neural networks are still a useful tool for fine-tuning of fuzzy systems. A unique textbook of Kosko [Kosko92] is strongly recommended for anybody who is interested in combining these two complementing systems.

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Biography

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