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Aims & scope

The *Electrotechnics, Electronics, Automatic Control and Computer Science* series of the Scientifical and Technical Bulletin of the „Aurel Vlaicu" University of Arad will devote it self to the dissemination of the original research results, technical advances and new items in Electrical and Computers Engineering and in Knowledge Engineering.

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Abstract

In computing with words and perceptions, or CWP for short, the objects of computation are words, propositions and perceptions described in a natural language. In science, there is a deep-seated tradition of striving for progression from perceptions to measurements, and from the use of words to the use of numbers.

Reflecting the bounded ability of sensory organs and, ultimately, the brain, to resolve detail, perceptions are intrinsically imprecise. Perceptions are f-granular in the sense that (a) the perceived values of attributes are fuzzy; and (b) the perceived values of attributes are granular, with a granule being a clump of values drawn together by indistinguishability, similarity, proximity or functionality.

F-granularity of perceptions is the reason why in the enormous literature on perceptions one cannot find a theory in which perceptions are objects of computation, as they are in CWP.

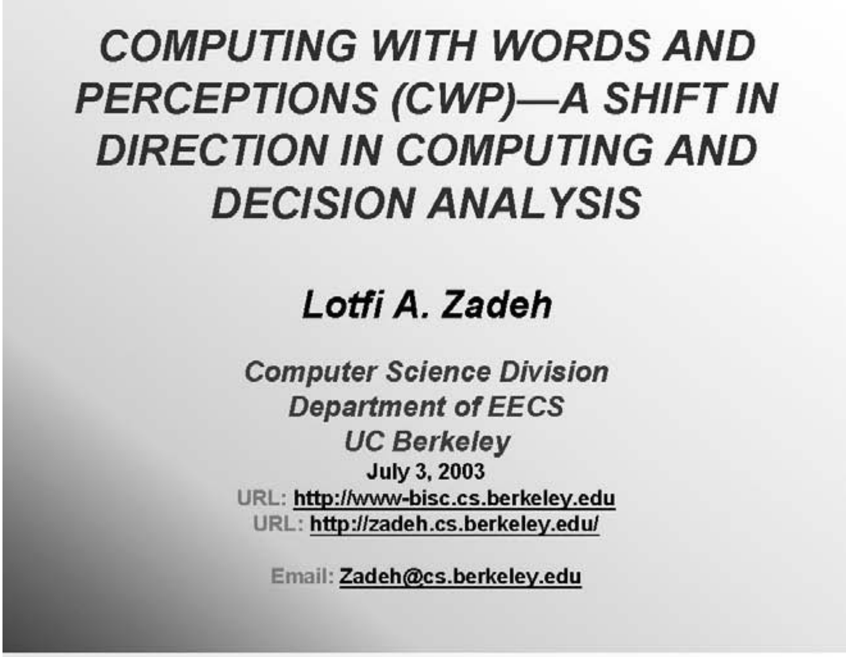
PNL (precisiated natural language) associates with a natural language, NL, a precisiation language, GCL (Generalized Constraint Language), which consists of generalized constraints and their combinations and qualifications.

The principal function of PNL is to serve as a system for computation and reasoning with perceptions. The need for redefinition arises because standard bivalent – classic-based definitions may lead to counterintuitive conclusions.

Computing with words and perceptions provides a basis for an important generalization of probability theory, namely, perception-based probability theory (PTp).

The importance of CWP derives from the fact that it opens the door to adding to any measurement-based theory.

Keywords: *fuzzy, CWP (computing with words), PNL (precisiated natural language), probability theory.*


COMPUTING WITH WORDS AND PERCEPTIONS (CWP)—A SHIFT IN DIRECTION IN COMPUTING AND DECISION ANALYSIS
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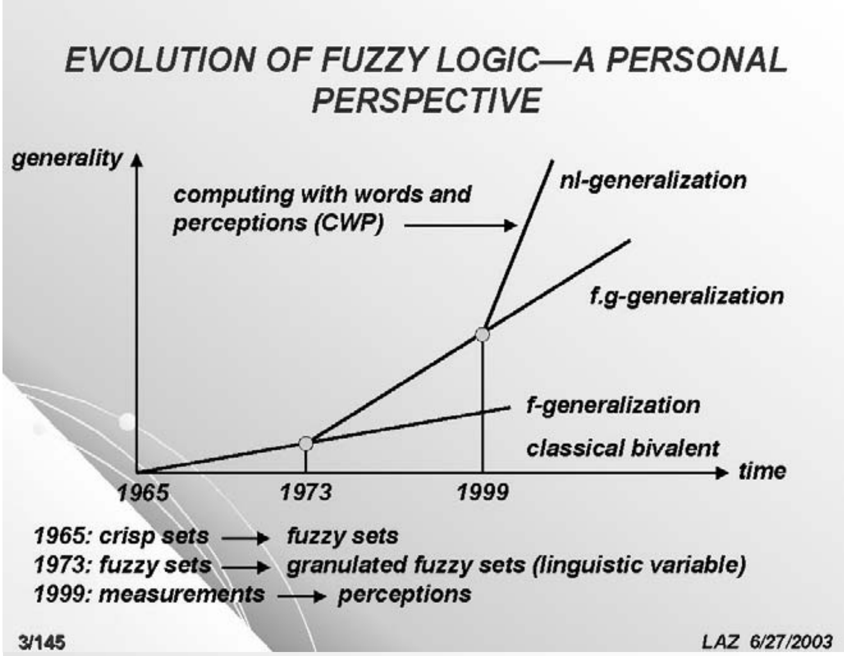
EVOLUTION OF FUZZY LOGIC—A PERSONAL PERSPECTIVE
generality
computing with words and perceptions (CWP)
nl-generalization
f.g-generalization
f-generalization
classical bivalent
time
1965
1973
1999
1965: crisp sets → fuzzy sets
1973: fuzzy sets → granulated fuzzy sets (linguistic variable)
1999: measurements → perceptions
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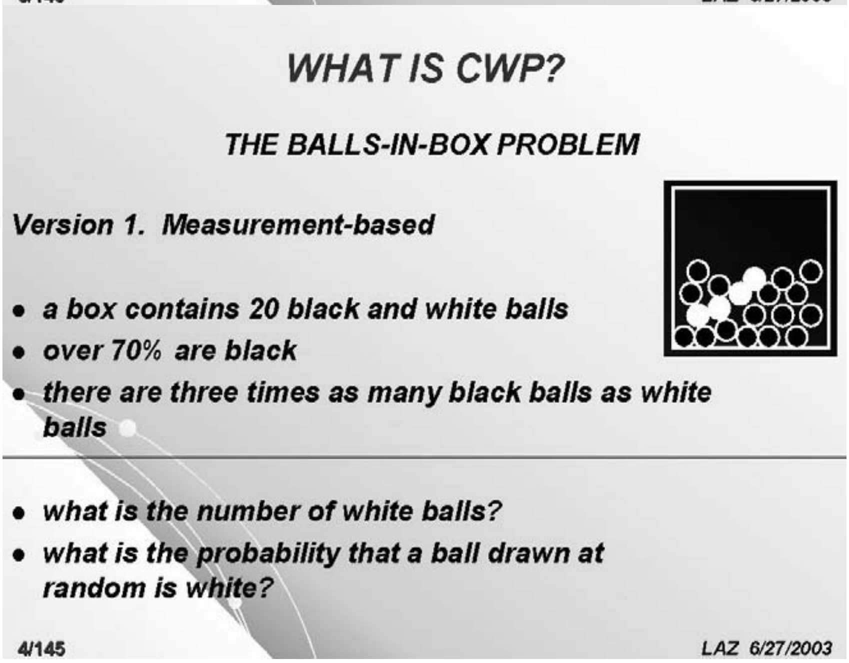
WHAT IS CWP?
THE BALLS-IN-BOX PROBLEM
Version 1. Measurement-based
• a box contains 20 black and white balls
• over 70% are black
• there are three times as many black balls as white balls
• what is the number of white balls?
• what is the probability that a ball drawn at random is white?
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CONTINUED

Version 2. Perception-based

- a box contains about 20 black and white balls
- most are black
- there are several times as many black balls as white balls

- what is the number of white balls?
- what is the probability that a ball drawn at random is white?

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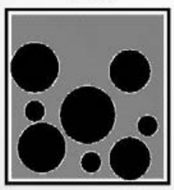
CONTINUED

Version 3. Perception-based

box



- a box contains about 20 black balls of various sizes
- most are large
- there are several times as many large balls as small balls

- what is the number of small balls?
- what is the probability that a ball drawn at random is small?

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MEASUREMENT-BASED

- *a box contains 20 black and white balls*
- *over seventy percent are black*
- *there are three times as many black balls as white balls*
- *what is the number of white balls?*
- *what is the probability that a ball picked at random is white?*

PERCEPTION-BASED (version 1)

- *a box contains about 20 black and white balls*
- *most are black*
- *there are several times as many black balls as white balls*
- *what is the number of white balls*
- *what is the probability that a ball drawn at random is white?*

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COMPUTATION (version 1)

- *measurement-based*

  X = number of black balls

  Y_2 number of white balls

  $X \geq 0.7 \cdot 20 = 14$

  $X + Y = 20$

  $X = 3Y$

  $X = 15$; $Y = 5$

  $p = 5/20 = .25$

- *perception-based*

  X = number of black balls

  Y = number of white balls

  X = most × 20*

  X = several *Y

  $X + Y = 20$*

  $P = Y/N$

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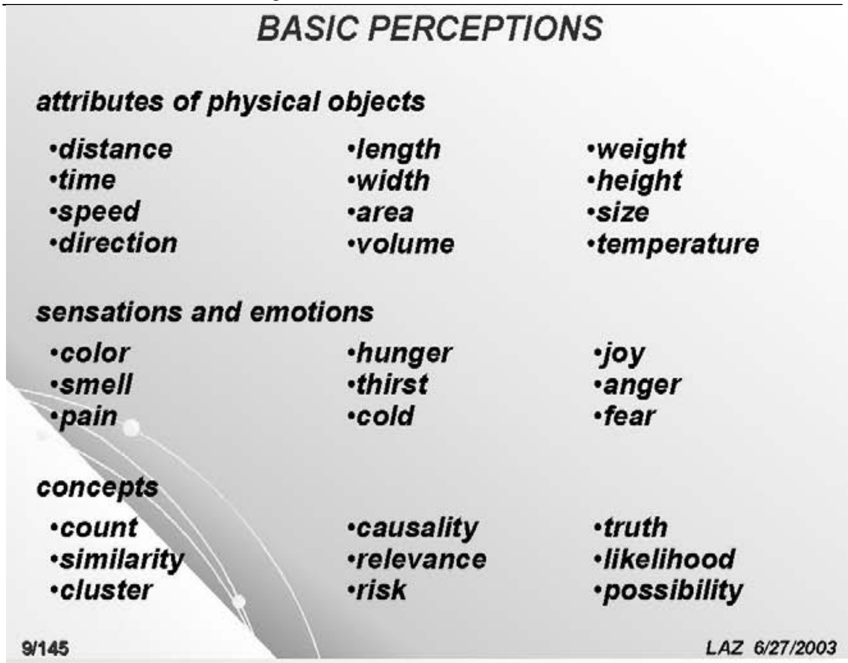
BASIC PERCEPTIONS
attributes of physical objects
•distance
•time
•speed
•direction
•length
•width
•area
•volume
•weight
•height
•size
•temperature
sensations and emotions
•color
•smell
•pain
•hunger
•thirst
•cold
•joy
•anger
•fear
concepts
•count
•similarity
•cluster
•causality
•relevance
•risk
•truth
•likelihood
•possibility
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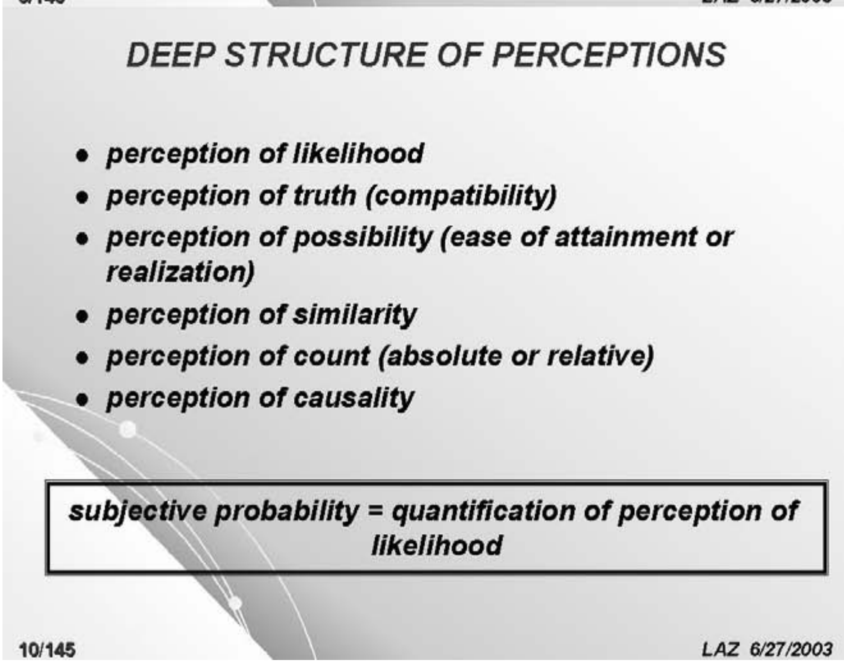
DEEP STRUCTURE OF PERCEPTIONS
• perception of likelihood
• perception of truth (compatibility)
• perception of possibility (ease of attainment or realization)
• perception of similarity
• perception of count (absolute or relative)
• perception of causality
subjective probability = quantification of perception of likelihood
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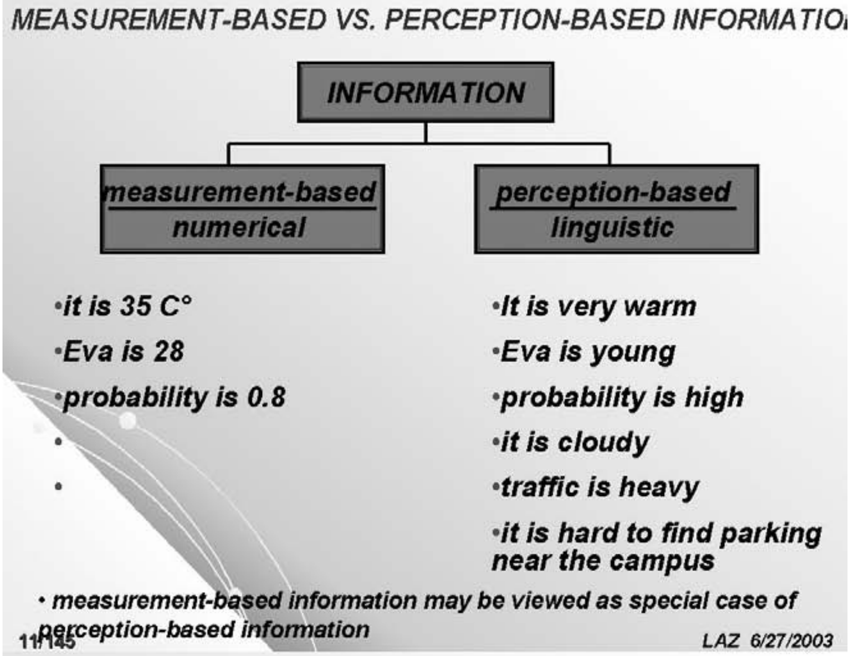
MEASUREMENT-BASED VS. PERCEPTION-BASED INFORMATIO
INFORMATION
measurement-based
numerical
perception-based
linguistic
•it is 35 C°
•Eva is 28
•probability is 0.8
•
•
•It is very warm
•Eva is young
•probability is high
•it is cloudy
•traffic is heavy
•it is hard to find parking near the campus
• measurement-based information may be viewed as special case of perception-based information
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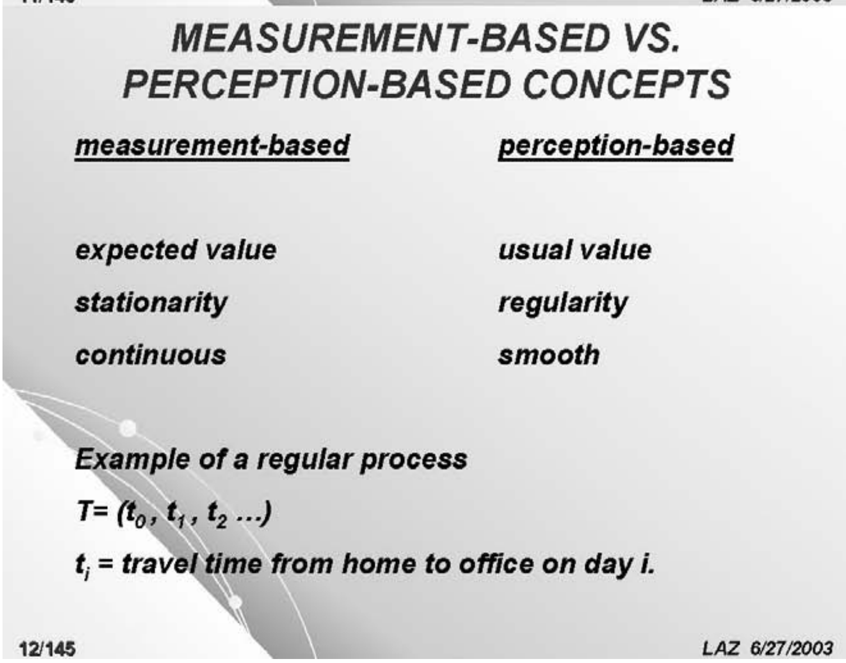
MEASUREMENT-BASED VS.
PERCEPTION-BASED CONCEPTS
measurement-based
perception-based
expected value
usual value
stationarity
regularity
continuous
smooth
Example of a regular process
T= (t0 , t1 , t2 ...)
ti = travel time from home to office on day i.
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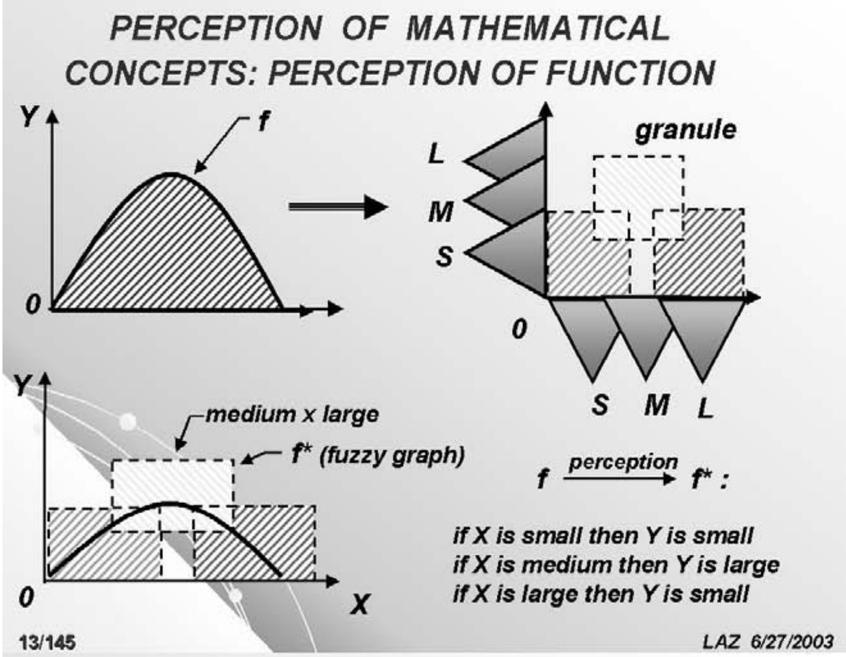
PERCEPTION OF MATHEMATICAL CONCEPTS: PERCEPTION OF FUNCTION
Y
f
0
granule
L
M
S
0
S M L
Y
medium x large
f* (fuzzy graph)
0
X
f perception f* :
if X is small then Y is small
if X is medium then Y is large
if X is large then Y is small
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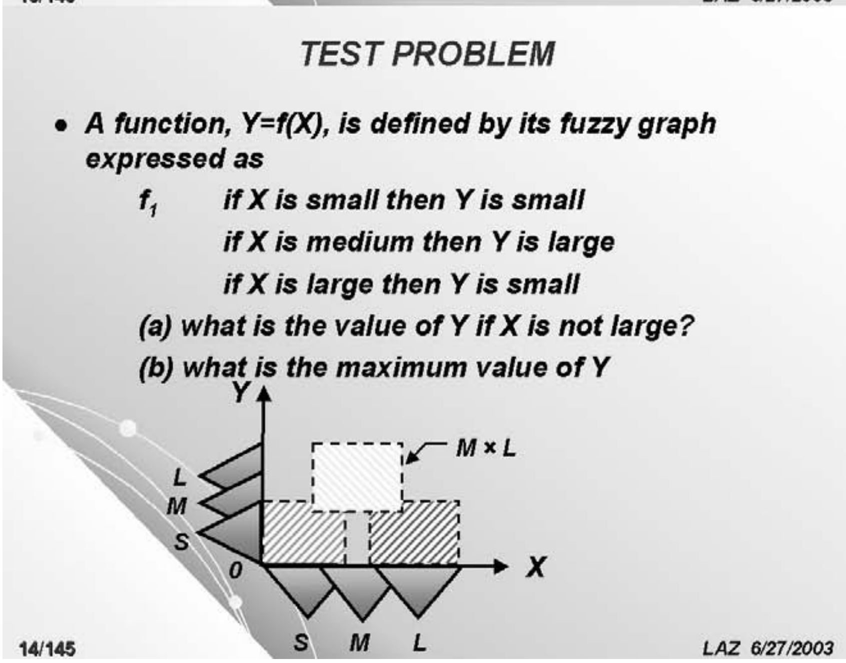
LAZ 6/27/2003


TEST PROBLEM
• A function, Y=f(X), is defined by its fuzzy graph expressed as
f1 if X is small then Y is small
if X is medium then Y is large
if X is large then Y is small
(a) what is the value of Y if X is not large?
(b) what is the maximum value of Y
Y
M × L
L
M
S
0
X
S M L
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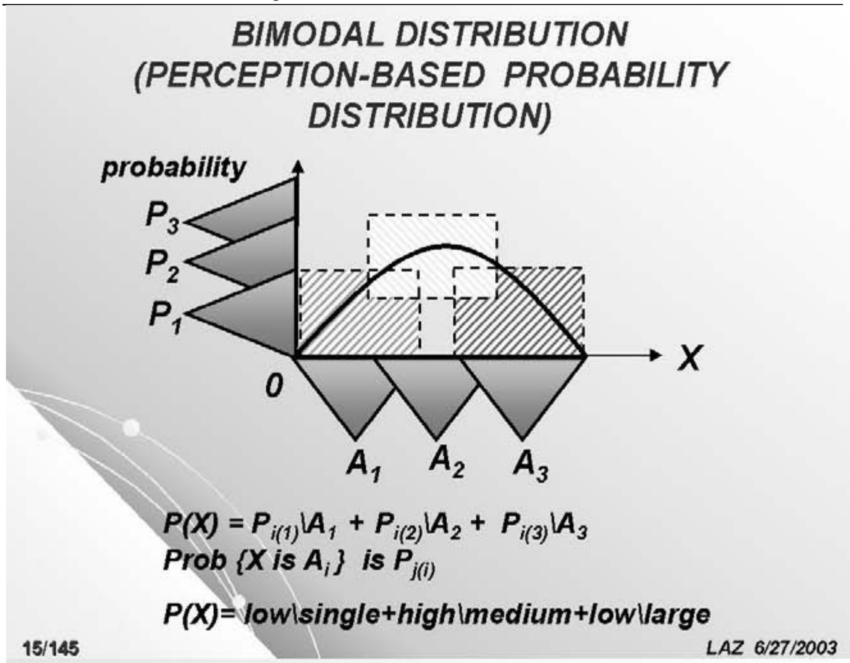
LAZ 6/27/2003


BIMODAL DISTRIBUTION
(PERCEPTION-BASED PROBABILITY DISTRIBUTION)
probability
P_3
P_2
P_1
0
X
A_1
A_2
A_3
$P(X) = P_{i(1)}\backslash A_1 + P_{i(2)}\backslash A_2 + P_{i(3)}\backslash A_3$
Prob $\{X \text{ is } A_i\}$ is $P_{j(i)}$
P(X)= low\single+high\medium+low\large
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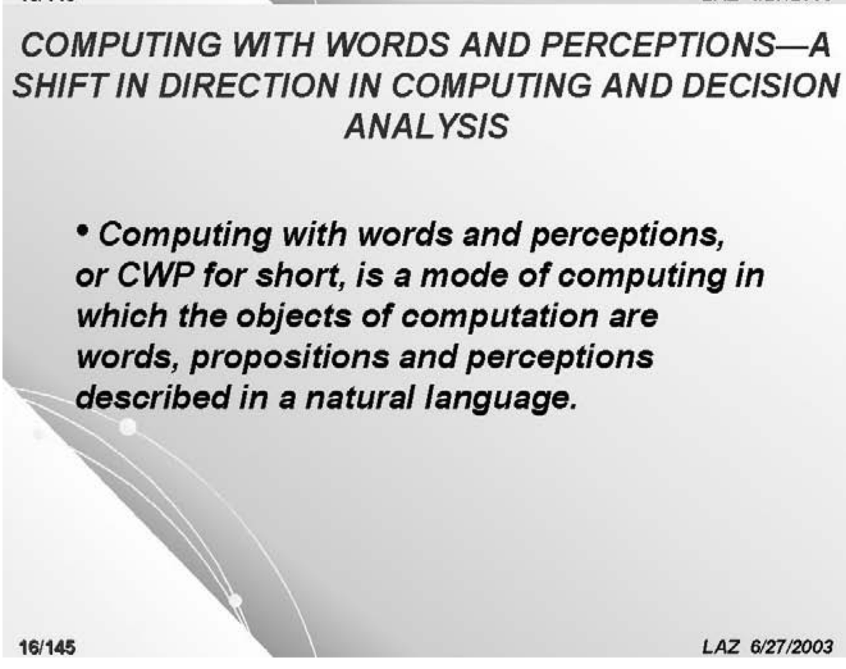
LAZ 6/27/2003


COMPUTING WITH WORDS AND PERCEPTIONS—A SHIFT IN DIRECTION IN COMPUTING AND DECISION ANALYSIS
• Computing with words and perceptions, or CWP for short, is a mode of computing in which the objects of computation are words, propositions and perceptions described in a natural language.
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1. INTRODUCTION

The control of the non-linear and time variable plants demands a high quality self-adaptation, covering a wide range of possible combinations of the parameters of the system. A conventional control fails when it has to deal with contradictory clauses. For instance the integrative effect of the PID controller may produce notable overshoots and oscillations during the vari-able regimes but in the same time its help is welcome during the steady ones. The adjustment of a dc drive controller for ordinary speeds does not matches at low speeds, because of to the non-linearity of the friction load torque, which is growing when the speed is decreasing.
However these contradictions may be managed by the help of the fusion of several controllers each one designed for a specific operating regime. The fuzzy fusion of the controllers became in the last years a reliable solution to this problem.
The goal of this lesson is to offer a simple and reliable method for the on-line identification of each regime that could possible produce contradictions when adjusting a PID basic controller. The lesson is based on a previous paper [8].

2. THE BASIC ASSUMPTIONS

The first question that comes in our mind when dealing with barely controllable plants (highly nonlinear, death time, mathematically unknown, etc.) is: “how would a human operator control this plant?” Many specialists may disregard this heuristic approach, but still it has fundamental advantages over the numerical algorithms: it can always be applied! Of course the performances may be not optimal, and a rigorous solution to the stability problem is not possible, but in turn the costs of the development of new products is getting lower and special applicative measures against instability can always be

In the following paragraphs we will focus on the adaptive correction. The adaptive control rules could be grouped into four clusters according to the next classification of the main operating regimes: variable (G1), steady (G2), oscillating (G3) and unstable (G4). This point of view is not the only possible, other classifications being as well productive. The clusters of rules must respect in great shapes the next linguistic commitments:

- G1: < *Gain* is **medium** and *Integrative* is **zero** >
- G2: < *Gain* is **great** and *Integrative* is **great** >
  (1)
- G3 & G4: < *Gain* is **small** and *Integrative* is **zero** >

The *Integrative* variable is generated by Direct controller.
The differences between G3 and G4 are not fundamental. If necessary they may be separated by the help of supplementary criteria, for example with the help of the product of the first and second derivatives of the control error, that is positive for unstable systems [3]. Anyway, *Gain* must be reduced in order to reject the oscillations and/or to stabilize the system, in the sense of the Nyquist stability criterion. Due to the non-linearity of the plant, an optimal crisp value of the *Gain* would have no sense.
In the next table a possible structure of adaptive PD fuzzy-interpolative corrector is presented.

$$H(s) = \frac{1}{s^3 + 3 \cdot s^2 + 3 \cdot s + 1} \tag{3}$$

Fig. 4 presents the time performances of FFSAIC when controlling four different plants:

$$H_1(s) = \frac{1}{s^2 + 2 \cdot s + 1} \tag{4}$$

$$H_2(s) = \frac{e^{-0.025s}}{s^2 + 0.2 \cdot s + 1} \tag{5}$$

$$H_3(s) = \frac{e^{-0.025s}}{s^2 + 20 \cdot s + 1} \tag{6}$$

$$H_4(s) = \frac{e^{-0.025s}}{s^3 + 3 \cdot s^2 + 3 \cdot s + 1} \tag{7}$$

If linear PID controllers would control them, the tested plants would produce extremely different responses, one of them being fully unstable.

6 CONCLUSIONS

The identification of the operating regime of the closed loop control systems may be obtained by the means of the *qualitative* analyse of the phase trajectory of the control error. Adaptive actions based on this approach are able to improve the control of highly nonlinear and/or important dead times plants.

This analysis may be achieved with the help of fuzzy-interpolative controllers. A family of fuzzy self-adaptive interpolative controllers FSAIC is designed to implement this kind of operation. The adaptive part of FSAIC is a fuzzy-interpolative PD corrector.

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1. INTRODUCTION

1.1. General Things

In the field of control engineering new topics continue to flourish and develop. In common with general scientific investigations the new concept of fault detection and process monitoring emerge as a new growth area in process control. This innovative concept coalesces into a new sub-discipline. A little maturity has been acquired by the new concept. Archival publications and monographs may be study in the international scientifically literature. The reason of developing fault detection and diagnosis is based on new real time instrumentation technologies in manufacturing plant installations. Process operators are using process data to minimize plant downtime and optimize plant operations. The traditional routes to fault detection were model based and them the process has to be well understood. An alternative group of methods has emerged which do not require the use of an explicit model. Model-free and non-parametric methods for fault detection, process optimization and control design are in current development.

Many technical processes are operating now under automatic control based on the progress of control theory. A general scheme for the organization of process automation tasks in several levels is presented in fig. 1 [Ise95].

The measurement and manipulation takes place at in the lowest level. The next level contains feedforward and feedback control. Here some variables u, y are adjusted according to conditions v or reference variables w. The second level contains supervision; it is the monitoring level, which serves to indicate undesired or unpermitted process (fault detection) states and to take appropriate actions (based on fault identification and diagnosis) as process recovery, fail-safe, shut-down, triggering of redundance systems or reconfiguration schemes. The higher

electrical drives applications may be developed. Data from the process – electrical drive – may be collect and applied to the monitoring techniques to detect, isolate and diagnose various fault. The process monitoring techniques can be modeled, simulated and implemented using commercial software as Matlab and Simulink [Bea94, Che92, Lot93, Vol2'0/1, 2].

These researches are focused on the approach based on fuzzy logic and neural networks, as new concepts developed versus the conventional concepts as statistical quality control, analytical methods, knowledge base methods, canonical variant analysis or Fisher discriminate analysis.

In the control of the electrical drives there is a large push to assure higher security of the electrical drive, to reduce electrical machine rejection rates and to satisfy the increasing stringent safety of the entire process controlled by the electrical drives and its environment. To meet the higher standards, the electrical drives contain a large number of variables operating under closed-loop control. The standard process controllers, for example PID controllers, are designed to maintain satisfactory operations by compensating for the effects of disturbances and changes occurring in the process. While these controllers can compensate for many types of disturbances, there are changes in occurring in the electrical drives that the controllers cannot handle adequately. These changes are called *faults*. More precisely, a fault is defined as a no permitted deviation of at least one characteristic property or variable of the system (resistance, inductance, moment of inertia, friction coefficient, voltage, flux or current, or quality criteria, as for example the overshoot).

The types of faults occurring in industrial systems include process parameter changes, disturbance parameter changes, actuator problems and sensor problems. Short circuit of the motor resistance or friction coefficient rising are examples of process parameter changes. A disturbance parameter change can be an extreme change of in the load torque or in the ambient temperature. An example of an actuator problem is a destroyed transistor in the power converter, and a sensor producing biased measurements is an example of a sensor problem. To ensure that the process operations satisfy the performance specifications, the faults in the process need to be detected, diagnosed and removed. These tasks are associated with *process monitoring*. Different methods were developed for process monitoring.

The goal of process monitoring is to ensure the success of the planned operations by recognizing anomalies of the behavior. The information not only keeps the plant operator and maintenance personnel better informed of the status of the process, but also assists them to make appropriate remedial actions to remove the abnormal behavior from the process. As a result proper process monitoring, downtime is minimized, safety of plant operations is improved and manufacturing costs are reduced. As industrial systems have become more highly integrated and complex, the faults occurring in modern processes present monitoring challenges that cannot be treated with conventional methods. The weakness of the linear methods of detection and diagnosis have led to a surge of research concentrated to the methods of the artificial intelligence as fuzzy logic and neural networks. The growth of the research activity can also be explained by the fact that industrial systems are becoming more heavily instrumented, resulting in larger quantities of data available for use in process monitoring and that modern computers are becoming more powerful. The availability of data collected during various operating fault conditions is essential to process monitoring. The storage capacity and computational speed of modern computers enable process monitoring algorithms to be computed when applied to large quantities of data [Chi01].

The electrical drives, controlled in real time with digital equipments and software of high performances, are at this moment suitable for the implementation of such monitoring algorithms [Har94].

1.2. Process Monitoring Procedures

The four procedures associated with process monitoring are [Chi01]: *fault detection, fault identification, fault diagnosis and process recovery.*

Fault detection is determining whether a fault occurred. Early detection may provide invaluable warning on emerging problems, with appropriate actions taken to avoid serious process upsets.

Fault identification is identifying the observation variables most relevant to diagnosing the fault. The purpose of this procedure is to focuses the plant operator's and engineer's attention on the subsystems most pertinent to the diagnosis of the fault, so that the effect of the fault can be eliminated in a more efficient manner.

Fault diagnosis is determining which fault occurred, in other words, determining the cause of the observed out-of-control status. It can be more specifically defined as determining the type, location, magnitude and time of the fault. The fault diagnosis procedure is essential to the counteraction or elimination of the fault.

Process recovery, also called *intervention*, is removing the effect of the fault and it is the procedure needed to close the *process monitoring loop*. Whenever a fault is detected, the fault identification, fault diagnosis and process recovery procedures are employed in the respective sequence, otherwise, only the fault detection procedure is repeated.

The schema of the process monitoring is presented in fig. 2. Whenever a fault is detected, the fault identification, fault diagnosis and process recovery procedures are employed in the respective sequence, otherwise only the fault detection procedure is repeated.

It is not necessary to implement all four procedures in a process monitoring. For example, a fault may be diagnosed (the procedures of fault diagnosis) without identifying the variables

faults. For fault detection limits must be placed on the measures. A fault is detected whenever one of the evaluated measures is outside the imposed limits. In this way, a measure is able to define a wrong behavior of the process accordingly the out of control status. In these measures the values of the variables can be compared with the values of other variables to determine the variable most affected by the fault. Developing and comparing measures that accurately represent the different faults of the process can also diagnose faults.

The goal of process monitoring is to develop measures that are maximally *sensitive* and *robust* to all possible faults. Faults are manifested in several ways and no the all faults may be detected and diagnosed with only a few measures. Each measure characterizes a fault in different manner; one measure will be more sensitive to certain faults and less sensitive to other faults relative to other measures. This motivates using multiple process monitoring measures, with the proficiency of each measure determined for the particular process and the possible faults.

Possible monitoring measures can be classified as being associated with one or more of approaches [Chi01]: *data driven, analytical* and *knowledge-based*. The data driven measures are derived directly from process data. Modern industrial systems as the electrical drives are large-scale systems. They are equipped with a lot of instruments, which produce large amount of data. Too much information is beyond the capability of an operator to assess the process operations from observing the data. The data driven techniques have the ability to transform the high-dimensional data into a lower dimension, in which the important information is captured. The improvement of a large-scale process monitoring scheme may be done using statistical techniques. The disadvantage of the data driven techniques is that their proficiency is highly dependent on the quantity and quality of the process data.

The analytical approach uses mathematical models often constructed from the primary mathematical and physical laws of the processes. The analytical approach is applicable to information rich systems, with available satisfactory models and enough sensors. Most analytical measures are based on parameter estimation, observer based design and parity relations. The applications of the analytical approach are made on systems with a small number of inputs and outputs and states. Because the analytical approaches need detailed models in order to be effective it is difficult to apply these measures to large-scale systems. Whenever, the analytical measure may be apply to the electrical drives, because they have a small number of inputs and outputs and also they have good state space models. The main advantage of the analytical approach is the ability to incorporate physical understanding of the process into the monitoring strategy. In other words, when detailed models are available, the analytical measures have good performances. The electrical drives are systems suitable for application of the analytical measures. Models of the electrical are developed.

The knowledge-based approach uses qualitative models to develop process monitoring measures. The knowledge-based approach is well suited for systems with non-available detailed models, with complex and nonlinear models. The knowledge-based measures are based on causal analysis, expert systems or pattern recognition. Like the analytical approach the applications of the knowledge-based measures are on system with a small number of inputs, outputs and states. The electrical drives are non-linear systems with complex models. For an easier application of the knowledge-based measures software packages must be developed.

mean, value and relate it to the standard deviation may improve the decision. Membership fuzzy logic functions may be used to specify the universe of discourse for a such approach.

1.4.2. Fault Diagnosis Methods

The task of fault diagnosis consists of determining the type of fault with as much possible such as the fault size, location and time of detection. The diagnosis procedure is based on the observed symptoms of the process.

Based on heuristic knowledge and inference mechanism for diagnosis e*xpert systems* are used to imitate the reasoning of human experts when diagnosing faults. The experience from a domain can be formulated in terms of rules, which can be combined with the knowledge from the physical-mathematical laws that are ruling the process or with a structural description of the system. Expert systems are able to capture human diagnostic reasoning that are not expressed into mathematical models.

Pattern recognition techniques use associations between data patterns and fault classes without an explicit modeling of internal process states or structures. Examples are *artificial neural networks* and *self organizing maps*. These techniques are related to the data driven techniques in terms of modeling the relation between data pattern and fault classes. Neural networks are black boxes that learn the pattern entirely from the training sessions [Chi01].

All methods based on data-driven, analytical and knowledge based approaches have their advantages and disadvantages, so that no single approach is best for all applications. Usually the best process monitoring scheme uses multiple statistics or methods for fault detection, identification and diagnosis. A good approach is to incorporate several techniques for process monitoring as neural network with fuzzy logic and expert systems. This can be beneficial also in the application of the electrical drives.

2. FUZZY LOGIC APPLICATIONS FOR PROCESS MONITORING

2.1. General Things

Many control systems are based today on fuzzy logic. The development of the fuzzy control theory offers alternative techniques for process monitoring strategies, which describes human reasoning in linguistic form. The fuzzy supervision knowledge-based may replace a human operator. Fuzzy logic provides a systematic framework to process vague variables and knowledge. There are some automation functions for which the fuzzy logic may offer attractive possibilities and advantages.

The main elements in the process information, as: input variables, the process classes, the automation functions and the output variables have different degrees of vagueness. The crisp information may be treated with fuzzy logic.

With regard to the *input signals* usual measurement equipment is designed to deliver signals with precise mean values and low standard deviations. *Low cost sensors* may have imprecise outputs with biased values and large standard deviations. *Non directly measurable variables* can only be calculated or estimated based on other measurement variables and analytical models and therefore imprecise to some extent. Also *linguistic values* of a human operator may be processes. Hence, the degree of precision and imprecision of the input variables may vary within fairly broad ranges.

The description of the static and dynamic behavior in form of a mathematical models plays a crucial role as well for the design of the technical processes as for a systematic design of high performance control systems. Processes from different process classes (mechanical, electrical, thermal, chemical and biological) may be described using basic physical- mathematical principles. Theoretical modeling can be applied using energy balance equations, state equations and phenomenological laws. The structure of the mathematical model is obtained with lumped parameter or distributed parameter (ordinary or partial differential equations). By this way quantitative models based on physical laws result and one can distinguish the following cases [Ise95]. *Analytical process models*, they are quantitative models. If the structure is known, the parameters can be determined experimentally by parameter estimation and identification methods. Quantitative process models result from proper combination of theoretical and experimental modeling. If physical laws in the form of equations cannot express the internal behavior, as for not well-defined process, some qualitative information on the causalities may be expressed as *rules*: *If <condition> then <conclusion>*. The condition part contains as inputs the memberships of facts to the premise and possibility their logical connection by *AND*, *OR* and *NOT*. The conclusion part describes the logical consequence on the output. Then one can distinguish h*euristic process models* (qualitative models) [Ise95].

The functions of the process automation (*control, supervision, management, man-machine interface*) are usually organized according to the levels shown in fig. 1. For *supervision* the basic task is to check if variables exceed tolerances. These tolerances are usually a compromise between small values to early detect faulty behavior and large values to avoid false alarms subject to normal process fluctuations. In reality these tolerances are not crisp but fuzzy variables. Moreover, in many cases fault diagnosis means to treat vague process knowledge and therefore to apply rules [Chi01, Ise95].

The man-machine interface is designed for human interaction. Basic tasks of the human operator are higher-level tasks as supervision, management and redundancy for all control functions. The actions of human operators are based on qualitative knowledge and many be better describes by rules than by precise algorithms. The information in process automation generally changes from using precise algorithms at the lower levels to using more rules at the higher levels.

4. CONCLUSION

In the fault detection and diagnosis fuzzy logic provide a systematic framework to process vague variables and vague knowledge. As the vagueness in fault detection is high the potential of fuzzy logic grow to higher levels.

The supervision of the process requires the treatment of quantitative and qualitative knowledge. Here fuzzy logic approaches are especially attractive for symptom generation with fuzzy thresholds, linguistically described observed symptoms and the approximate reasoning with multi levele fuzzy rule based systems fro fault symptom tree structures.