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Theory, Technology, Applications

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Factory Automation: Case Study in Production-Line Management

In the automated production line of the new Candy washing machines, the whole manufacturing, assembly and inspection operations are performed and managed by 30 robots.

1. Line Characteristics

The line has been designed to manufacture a new class of washing machines. It can be operated by humans or by robots and its flexibility allows the production of all the different models. The whole line consists of 30 microcomputer-controlled handling robots operating machines, assembly equipment and transfer machines. It is subdivided into a drum manufacturing line, a tub manufacturing line and a drum and tub assembly line. Candy required a flexible line to allow the manufacture of different models in accordance with market requirements for machines with top loading or front loading and of different capacities (drum depths).

The robots used are hydraulically powered and of modular construction with Cartesian axes and movements as follows.

(a) Traversing: the carriage carrying the robot can slide on two columns, blocked at their extremities by floor-mounted pedestals; the traversing stroke can reach 2500 mm.

(b) Rotation: obtained from a rotating table fixed to the traversing carriage; the angle of rotation is 180°.

(c) Vertical: the robot carriage slides on two vertical columns with a maximum stroke of 500 mm.

(d) Horizontal: a second carriage, carrying the robot arm and gripper, slides on two horizontal columns; the arm stroke has a maximum value of 1000 mm.

The maximum weight which can be manipulated is 100 kg.

The modular construction of these robots means that only the axes which provide the movements necessary for a given application need be provided, thus yielding obvious economic benefits. The grippers are designed specially for each workplace and are equipped with the mechanical parts and electronic sensors to fit the various parts to be manufactured.

All the robots are microcomputer-controlled. A master microcomputer provides management of the line and communications between robots.

2. Drum Manufacturing Line

The line that manufactures the drums is shown in Fig.1. It consists of:

(a) one stainless steel sheet roller,

(b) one punching shear press,

(c) one transfer cut pack system,

(d) one calender,

(e) three folding machines,

(f) one shaping machine,

(g) two drum transfers,

(h) two rolling machine tools, and

(i) twelve robots.

At the beginning of the line a coil of strip of the desired

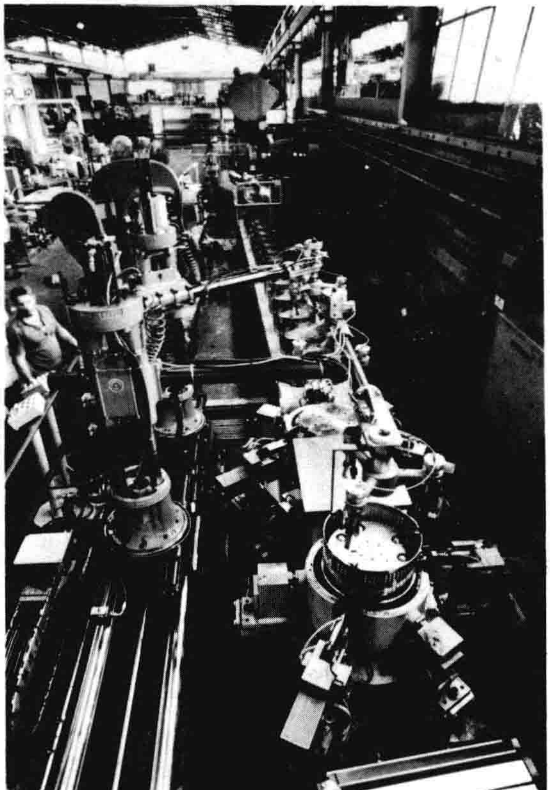

Figure 1
Drum manufacturing line

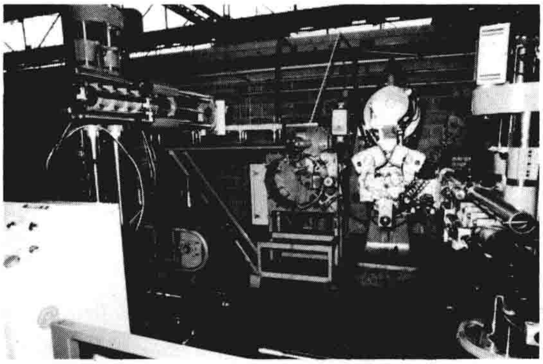

Figure 2
Calendering of bands

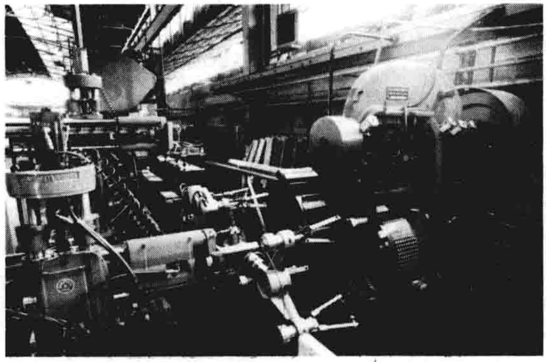

Figure 3
Folding of bands

depth is positioned and automatically unrolled, then cut by the shear press into bands of the right length and packs of a prescribed height. The pack of bands, on requirement by the robot, is fed to workplace A.

2.1 Workplace A: Band Calendering

At this workplace (Fig. 2) the bands of strip are calendered. The bands are stacked on a conveyor (height 300 mm) and are taken one at a time by the robot and positioned at the calender entry. At the calender exit the band is taken by another robot. The conveyor is positioned at one side of the calender. When all bands of the pack are calendered, the conveyor sends another pack, and so on.

These bands, positioned on the conveyor, are the future front drums. In front of this pack is positioned another pack of the same height; these bands when calendered are the future top drums.

The forms of band to be manipulated having been analyzed, a gripper was designed able to handle all the bands. This gripper has six vacuum suckers connected to a vacuum pump in groups of four plus two. The six suckers allow front drum band handling, whereas the four suckers allow only top drum band handling. They have a soft-landing device to achieve perfect adhesion to the band.

The suckers are fixed at the end of the robot arm in such a way that allows top band pickup without interfering with the pack. Sensors fitted on the gripper are able to detect the presence of a band and stop the arm descent. The microcomputer has memorized all the different programs to allow handling of the bands, top or front.

2.2 Workplace B: Band Folding

At this workplace the bands are folded (Fig. 3). At the calender exit the bands are presented wrapped on a support; they are then picked up and positioned on the folding machine. During this operation the band must be kept in position; afterwards it is rotated 90° and placed on the conveyor. Examining the folding machine we notice that the band must be followed and kept in position of folding. This operation is performed only on front drum bands; the top bands are treated differently. After the loading operations of the folding machine, contact must be maintained with the band rims in order to keep the bands in the right position.

The grippers consist of two groups mounted on a device at the end of the arm. The first group consists of three grippers that take the band at the calender outlet and bring it to the folding machine, holding the band rims to allow folding operations to take place. The second group consists of three grippers that take the band and place it on the conveyor after having rotated it through 90°. The conveyor is equipped with reference devices, as from this moment the folded band must be kept oriented.

2.3 Workplace C: Shaping Rims and Blades

At this workplace (Fig. 4) there are two robots. The first takes the band from the conveyor and rotates it through 110°, then places it oriented on the blade shaping

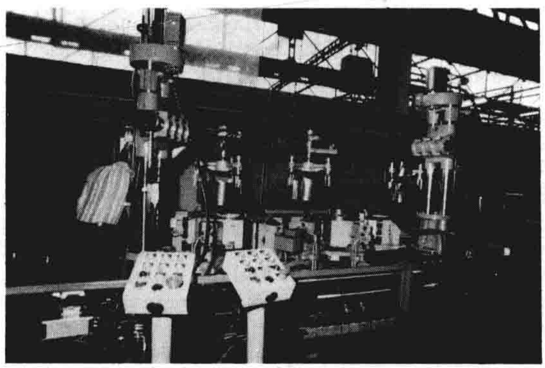

Figure 4
Rims and blades shaping

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machine. The second, simultaneously with the first, takes the band from the blade shaping machine and places it, after rotation through 31°, on the rim shaping machine. Then it draws the band from this latter machine and places it on a conveyor in one of two possible positions, depending on the production needs.

All the grippers have the same configuration. The first robot has three grippers set at 120° to one another, fitted on a device able to rotate through 110°. The second robot has two grippers that can rotate the band through 120°.

2.4 Workplace D: Bottom Plate Folding

At this workplace (Fig. 5) two robots carry out the job. The first robot takes the band from the conveyor and places it oriented on a stepping conveyor which has a template to receive the parts. The second robot takes one bottom plate at a time from one of two pallets, orients the plate into the right position and places it on the band. After positioning of the bottom plate on the band, the robot orders the conveyor to advance to move the band with the bottom plate under the folding machine.

The first robot has a group of three grippers mounted at 120° to one another on the arm extremity. The grippers of the second robot are a group with suckers which have a soft-landing device, a vertical movement of 1000 mm and centering and orientation systems. The sequence of the movements is as follows:

(a) descent onto the pallet and onto the pile wanted,

(b) pickup of one bottom plate,

(c) centering of the bottom plate in relation to the center of the suckers, and

(d) rotation of the bottom plate, by means of optical sensors, until the correct orientation is reached.

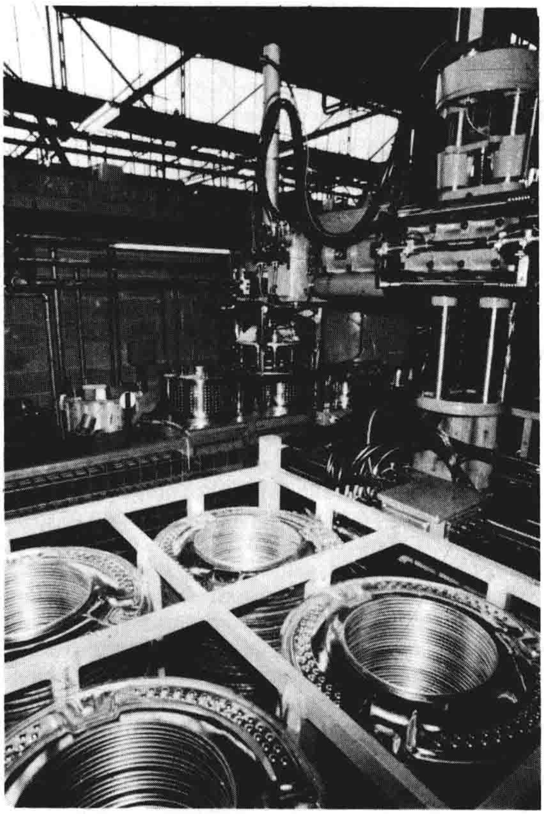

Figure 5
Bottom plate and abutment folding

2.5 Workplace E: Abutment Folding

At this workplace (Fig. 5) the same operations are performed as at workplace D, except that the first robot transfers the drum from conveyor 1 to the conveyor 2, rotating it through 180°. It has a gripper able to take the drum at the side.

2.6 Workplace F: Star Wheel Assembly

There are also two robots at this workplace. The first takes the drum from the conveyor and places it on the riveting machine. The second robot takes an oriented star wheel supplied by a conveyor and places it on the drum in a predetermined position. The riveting machine rivets the star wheel on the drum. The same robot then loads the drum onto a conveyor.

In this case there are standard grippers, pneumatically operated, with special fingers.

2.7 Workplace G: Drum Positioning for Dispatch

The finished drum is conveyed in a specific position to the roller conveyor exit. The robot picks up the drum, taking it by the star wheel, turns its arm through 90° and runs along the overhead conveyor to position the drum at the nearest free position. This robot has a special tracking program allowing it to reach the nearest free position and place the drum, adjusting itself to the overhead conveyor speed if it changes. Tracking and centering are achieved by means of optical sensors.

This robot also has standard grippers, pneumatically operated.

3. Conclusions

The production capacity of this line is 420 drums per hour. Along the whole line, ~70 m long, there are normally only two people ensuring that the right operations are carried out.

Candy has invested in this line to obtain a constant output as well as a large increase in productivity. At the same time, a high quality level has been achieved, as well as the capacity to maintain it unchanged over time, safeguarding it against the inconsistency of human work. The efficiency, assessed over two years, is very satisfactory for standard automatic equipment.

Staff reaction has been very positive, without disturbances, as personnel did not see the introduction of robots as a threat to work but as a change in functions from heavy working conditions to more satisfactory ones; in fact there have been no dismissals.

See also: Industrial Systems: Robot Integration

C. Castoldi

Fate Modelling of Organic Chemicals: Case Study

PEST (Park *et al.* 1980, 1981, 1982) is a dynamic simulation model for evaluating the fate of toxic organic material (TOM) in freshwater environments. It represents the time-varying concentration (in ppm) of a given TOM in each of as many as sixteen carrier compartments; it also computes the percentage distribution and half-life of the TOM in each of the carriers. Possible carriers include phytoplankton, macrophytes, zooplankton, waterbugs, zoobenthos, fish, particular organic matter, floating organic matter, clay and water (with TOM in the dissolved phase).

PEST simulates TOM degradation by hydrolysis, oxidation, phytolysis, microbial metabolism and biotransformation by higher organisms; it simulates TOM transfer by solution, volatilization, sorption, absorption onto gills, consumption, excretion, defecation, biodeposition, mortality and throughflow. These are subject to time-varying environmental factors such as pH, temperature, dissolved oxygen, wind, solar radiation and biomass and condition of organisms.

PEST is an interactive, user-oriented model with ten commands. The user can edit parameters and driving variables, display process-response curves of all combinations of processes and driving variables, run a simulation for any length of time, print any or all state-variable results, debug loadings and rates and graphics-device plots, dump common block contents, and access an extensive help file.

The model is written in standard FORTRAN IV and will run in 22 K on a PDP11 with overlaying. It has also been run on an IBM 3033. The program is modular and well structured and is easy to understand. System-dependent features are restricted to two optional subroutines: one that handles operations such as file numbering and time calls and one that provides an interface to graphics terminals and plotters.

PEST is a process-oriented evaluative model. As such, it is intended to be used primarily to indicate the relative importance of the various processes under well-defined environmental conditions and to determine the environmental compatibility of particular organic materials. The model can also assist in the extrapolation of data from laboratory experiments and microcosms, to natural environments.

It combines detailed chemical kinetics and bioenergetics to permit examination and evaluation of the behavior of toxic organic materials in the context of the entire aquatic ecosystem. PEST is capable of simulating the time-varying concentration of a toxic organic material (TOM) in each of as many as sixteen carrier compartments. The sixteen state variables can be parametrized to represent a variety of TOM-carrier associations typical of aquatic ecosystems.

The state-variable equations are ordinary differential equations with source and sink terms for the various processes that result in additions to, and losses from, the carriers. The source and sink terms for the state variables are represented by process equations. Most of the process equations are nonlinear and involve several environmental factors. Output from the model includes

(a) the time-varying concentration of the toxic material in each carrier (in ppm),

(b) the percentage distribution of the toxic material among the carriers, and

(c) the half-lives of the toxic material in each carrier.

One can also obtain plots of the degradation rates, both as they vary through time and as a function of environmental factors.

The model has been verified with process-level laboratory data for several compounds and with ecosystem data from fish ponds in Missouri and Israel, from an experimental stream in Minnesota, and from a reservoir in Iowa. The site constants and environmental driving variables for these ecosystems constitute useful "prototype" data sets that enhance the value of the model for evaluative purposes.

Data requirements depend on the intended use of the model. If PEST is to be used as an evaluative model, as originally intended, then default data on prototype sites (such as the verification sites) may be sufficient to characterize the behavior and fate of a toxic organic material; therefore, site data would be unnecessary. If the model is to be applied as a diagnostic tool in order better to understand the fate of a compound at a particular site, then an accurate characterization of the site is required. If the problem involves bioconcentration in a particular group of organisms, then it will be necessary to characterize accurately the metabolic requirements and feeding preference of the organism.

The philosophy of verification has been to use available parameter values, confirm the validity of the process equations by inspecting the process-response curves (such as are presented in the previous section), and then apply the model to the particular site without calibration. If the fit to the observed data is not acceptable the formulations are re-examined and improved, but the parameter values are not changed. This approach was taken because it was felt that there would not be opportunity or rationale for "fine-tuning" the parameter values in PEST using observed data when it was used as an evaluative model for new compounds.

See also: Toxic Chemicals Assessment: Simulation Modelling; Water Quality Modelling: Case Study; Aluminum and the Fate of Nutrients and Toxic Substances in Terrestrial and Freshwater Environments; Limnology: Dispersion of Toxic Substances

Bibliography

Park R A, Connolly C I, Albanese J R, Clesceri L S, Heitzman G W, Herbrandson H H, Indyke B H, Loche J R, Ross S, Sharma D D, Shuster W W 1980 Modeling transport and behavior of pesticides and other organic materials in aquatic environments. Report No. 7, Center for Ecological Modelling, Rensselaer Polytechnic Institute, Troy, New York

Park R A, Connolly C I, Albanese J R, Clesceri L S, Heitzman G W, Herbrandson H H, Indyke B H, Loche J R, Ross S, Sharma D D, Shuster W W 1982 *Modeling the Fate of Toxic Organic Materials in Aquatic Environments,* Research Report EPA-600/S3-82-028. US Environmental Protection Agency, Athens, Georgia

Park R A, Indyke B H, Heitzman G W 1981 Predicting the fate of coal-derived pollutants in aquatic environments. In: Mitsch W J, Bosserman R W, Klopatek J M (eds.) *Energy and Ecological Modeling; Developments in Environmental Modelling 1.* Elsevier, New York, pp. 115–21

R. A. Park

Fault Trees

A fault tree is a hierarchical representation of the probabilities for failure of various functions of a system.

See also: Trees

A. P. Sage

Feature Selection: Fuzzy Classification

Classification is a technique which enables us to look for regularities in a broad sense. Classification problems may be divided into two categories: pattern recognition and clustering. In pattern recognition it is assumed that the names of classes and samples characterizing these classes are known; the aim is to place new objects into the classes using a sort of inductive generalization based on the knowledge derived from these samples. In clustering, the aim is to partition a given collection of objects into a number of classes in such a way that objects within each class are strongly similar to each other, while objects of different classes are appreciably less similar. The first step in solving both problems is the selection of significant characteristics of the objects considered. This step is called feature selection and it may be treated as a kind of data reduction.

Bellman, Kalaba and Zadeh were the first to propose the use of fuzzy set theory in classification (Bezdek 1981).

1. Statement of the Problem

Let $W = \{w_1, \ldots, w_n\}$ be a set of objects. To handle them we assign to each $w \in W$ the values of a finite set of parameters (called features) considered relevant for the object. This way w is associated with a mathematical object $\boldsymbol{x} = \boldsymbol{m}(w) = [m_1(w), \ldots, m_s(w)]$ where m_i is the measurement procedure connected with feature i and $m_i(w)$ is the feature value. (There are usually many mathematical objects $\boldsymbol{x}$ that may be associated with w.) We call $\boldsymbol{x}$ a feature vector or pattern, and we denote X the set of all patterns so obtained. Usually it is assumed that $X \subset \mathbb{R}^s$ ($\mathbb{R}$ is a set of reals). However in practical problems, features may very often be valued only linguistically (e.g., in diagnosis). Fuzzy set theory offers powerful tools for such cases (Zadeh 1976, Sanchez *et al.* 1980). Now suppose that c is a number of classes into which the objects from X should be placed. Again in practical problems we focus on the question of how closely the value of $\boldsymbol{x}$ agrees with the characteristics distinguished for the ith class, rather than whether $\boldsymbol{x}$ is a member of class i. This is because the substructure in real data is rarely so distinct that every member in the collection X is most realistically described as a full member of a single subset. Moreover, especially in large-scale systems, classes may be defined in a vague way only. To overcome these difficulties we introduce the function $u_i : X \rightarrow [0, 1]$ (called membership function) that allows every individual $\boldsymbol{x} \in X$ partial membership in all of c subsets. In general, information of this kind is not of a probabilistic nature.

To give conceptual frames for the classification theory, Zadeh (1976) has pointed that in practice man uses "opaque" algorithms A_{op} to classify objects (i.e., their explicit description is not available). These algorithms act on real objects $w \in W$. Following this idea, the classification procedure consists of two main steps:

(a) feature selection: select a small set of possible simple measurement procedures $\boldsymbol{m}$ in order to turn w into $\boldsymbol{x}$;

(b) convert the opaque algorithm A_{op} into a transparent one A_{tr} (i.e., with known explicit description) such that the results $A_{op}(w)$ and $A_{tr}[\boldsymbol{m}(w)]$ lead to the same conclusion.

2. Fuzzy Clustering Methods

The simplest formulation of the problem may be stated as follows. Let $w_i, w_j \in W$ and $\boldsymbol{x}_i, \boldsymbol{x}_j$ denote their mathematical representations. The aim is to find an algorithm A_{tr} such that

$$A_{tr}(\mathbf{x}_i, \mathbf{x}_j) = A_{op}(w_i, w_j) = r(\mathbf{x}_i, \mathbf{x}_j) = r_{ij}, \quad i, j = \overline{1, n} \quad (1)$$

where r_{ij} represent grades of similarity between patterns $\mathbf{x}_i$ and $\mathbf{x}_j$. This way we obtain a mapping $r: XxX \rightarrow [0, 1]$ called a fuzzy relation (Dubois and Prade 1980). The immediate implementation of this idea leads to the use of a similarity relation, i.e., the fuzzy relation that is reflexive, symmetrical and transitive. The similarity relation should provide the inferences of the form

IF "it is desirable to classify w, v in the same cluster"
AND "it is desirable to classify v, z in the same cluster"
THEN "it is desirable to classify w, z in the same cluster."

Apply the standard fuzzy logic rules (Dubois and Prade 1980) to this statement we obtain the concept of (max–min) transitivity, i.e., a fuzzy relation is transitive iff

$$r_{ij} \geq \max_{1 \leq k \leq n} [\min(r_{ik}, r_{kj})] \quad (2)$$

Such a defined similarity relation is an equivalence relation and it possesses the property: all its α-cuts are equivalence relations, where by α-cut we mean a nonfuzzy subset r_α of XxX consisting of pairs for which $r(\mathbf{x}_i, \mathbf{x}_j) \geq \alpha$. Here, α means the minimal strength of relationship among the elements of r_α. Moreover $r_{\alpha_1} \subseteq r_{\alpha_2}$ if $\alpha_1 > \alpha_2$.

To cluster a given data collection we start from a reflexive and symmetric relation s (expressed as a matrix $S = [s_{ij}]$) defined on XxX. The values s_{ij} are determined subjectively or using some similarity index (e.g., cosine function, Tanimoto measure, etc). To find the similarity matrix R we "multiply" (in the sense of max–min composition defined by Eqn. (2)) matrix S q times ($q \leq n - 1$). Other algorithms to find similarity relations are mentioned in Dubois and Prade (1980) and elsewhere. Thresholding (in the sense of α-cuts) matrix R we build a nested hierarchy of hard (i.e., nonfuzzy) partitions. Dunn (1974) has shown that because (max–min) transitivity is equivalent to the ultrametric inequality, the resultant hierarchies are in fact a subset of single linkage hierarchies known from graph theoretic methods for clustering. This method was proposed by Tamura *et al.* (1971) and was used, for example, in an information retrieval system (Negoita and Ralescu 1975).

Ruspini (1980) has observed that the application of Łukasiewicz's Aleph-1 logic to the IF . . . THEN statement displayed above leads to the concept of (max-T) transitivity:

$$r_{ij} \geq \max_{1 \leq k \leq n} [\max(r_{ik} + r_{kj} - 1, 0)] \quad (3)$$

The reflexive, symmetric and (max-T)-transitive relation is called a likeness relation. Likeness relations form the largest class of equivalence relations (similarity relations are very sparse among them) and they have been studied extensively by Bezdek (1981). Ruspini (1980) has shown that a necessary and sufficient condition for the existence of fuzzy clusters is that a relation R defined on XxX be a likeness relation. All fuzzy sets that are elements of the quotient X/R are clusters and can therefore be chosen as components of a clustering of X. This observation provides a basis for new clustering techniques.

Ruspini was also the first to suggest the use of the objective function method for fuzzy clustering, and Bezdek (1981) applied this methodology in a very constructive manner by introducing the infinite family of fuzzy ISODATA algorithms. The motivation was that the hard ISODATA (Duda and Hart 1973) always yields some partitions even when compact and well separated clusters do not exist. Hence, when it is not known in advance that such clusters are actually present, inferences drawn from hard ISODATA partitions can be erroneous. Following Ruspini a fuzzy nondegenerate partition of the set X is defined by specifying a set of functions $u_i: X \rightarrow [0, 1]$, $i = \overline{1, c}$ satisfying the conditions

$$\sum_{i=1}^{c} u_i(\mathbf{x}) = 1, \qquad \sum_{\mathbf{x} \in X} u_1(\mathbf{x}) > 0 \quad (4)$$

The first condition ensures that each $\mathbf{x} \in X$ must have a total membership in X of unity (this membership may vary arbitrarily among the fuzzy subsets partitioning X), while the second condition means that each of c clusters is nonempty. It is convenient to represent a fuzzy partition as a matrix $U = [u_{ik}]$ where $u_{ik} = u_i(\mathbf{x}_k)$. The set of all partitions so defined forms a fuzzy nondegenerate partition space denoted M_{fc}. In particular it contains the space of all hard partitions M_c (defined by the characteristic function $h_i: X \rightarrow \{0, 1\}$). The M_{fc} provides a useful mathematical structure for classification of models (Bezdek 1981): it is a closed, compact and convex subset in one positive orthant v_{cn} (the vector space of all ($c \times n$) matrices) with cardinality card (M_{fc}) $= n(c - 1)$. (This is a very significant dimensionality reduction in comparison with $\dim(M_c)$). Studying the connection between M_{fc} and R_T (the space of all likeness relations defined on XxX) it was shown (Bezdek 1981) that the composition U^T (sum, min) U induces a unique likeness relation that enables one to convert fuzzy membership of patterns into a metrical relationship among these patterns.

To find a fuzzy partition U, Bezdek proposed the global criterion function

$$J_m(U, \mathbf{v}) = \sum_{k=1}^{n} \sum_{i=1}^{c} u_{ik}^m \|x_k - v_i\|^2, \quad m > 1 \quad (5)$$

where $U \in M_{fc}$, $\mathbf{v} = (\mathbf{v}_1, \ldots, \mathbf{v}_c)$, $\mathbf{v} \in \mathbb{R}^s$ is a fuzzy centroid and $\|\cdot\|$ is any differentiable norm on $\mathbb{R}^s$. The algorithm consists of the following steps.

Step 1: Choose an initial partition U_0.

Step 2: Compute the fuzzy centroids $\boldsymbol{v}_i$ due to equation

$$\boldsymbol{v}_i = \sum_{k=1}^{n} u_{ik}^m \boldsymbol{x}_k \Big/ \sum_{k=1}^{n} u_{ik}^m, \quad i = \overline{1, c} \tag{6}$$

Step 3: Compute U according to

$$u_{ik}^{-1} = \sum_{j=1}^{c} (\|x_k - v_i\|/\|x_k - v_j\|)^{2/(m-1)}, \quad i = \overline{1, c}, \quad k = \overline{1, n} \tag{7}$$

Step 4: Find the maximum membership defect $|U - U_0|$. If less than some prespecified tolerance ϵ then stop; otherwise relabel $U \rightarrow U_0$ and go to Step 2.

To evaluate the validity of c, two measures of partition fuzziness are considered:

$$F(U) = \mathrm{tr}(UU^{\mathrm{T}}), \qquad H(U) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik} \log u_{ik} \tag{8}$$

Minimization of H (or maximization of F) leads to an optimal choice of c for $U \in M_{fc}$. For $m = 2$ the result of the algorithm usually reflects the actual fuzziness of the clusters in X. (The case $m = 1$ corresponds to hard ISODATA.)

Fuzzy ISODATA ensures that the misinterpretation of the substructure of X is less probable in comparison with a hard algorithm. Fuzzy ISODATA has been applied to medical taxonomy, to Bayesian unsupervised learning, and to feature selection for binary data (Bezdek 1981).

Other clustering techniques are reviewed by Negoita and Ralescu (1975), Dubois and Prade (1980) and Bezdek (1981).

3. Fuzzy Pattern Recognition

Using Zadeh's terminology, a pattern recognition procedure may be formulated: having the set of measurement procedures $\boldsymbol{m}$ convert given opaque algorithm A_{op} into a transparent one such that acting on $\boldsymbol{m}(w)$ yields the same conclusions as A_{op}.

Conceptually the simplest algorithm is that based on the fuzzified Bayes approach. The fuzzification may be performed in a number of ways. The first gives the concept of the probability of a fuzzy event (Dubois and Prade 1980). Assume that each of classes F_i is described as a fuzzy set $F_i = \{h_i(z_j)/z_j, \quad j = \overline{1, s}\}$ where z_j denotes the name of the jth feature and $h_i(z_j) \in [0, 1]$ is a grade of intensity of this feature for class i. The probability that the object belongs to F_i given by sample $\boldsymbol{x}$ is: $P(F_i|\boldsymbol{x}) = P(\boldsymbol{x}, F_i)/P(\boldsymbol{x})$ where $P(\cdot)$ are probabilities of fuzzy events. The rule for choosing an appropriate class corresponds to the minimization of the probability P_{e} of discrimination error (Duda and Hart 1973). When we use a sequence $x(k) = (\boldsymbol{x}_1, \ldots, \boldsymbol{x}_k)$ of independent elementary observations and $k \rightarrow \infty$, the upper bound for P_{e} no longer converges to zero in average value (Asai *et al.* 1977). This provides the rule for when to stop observations. The second way of implementing the fuzzification Bayes approach offers the theory of fuzzy measure (Seif and Aguilar-Martin 1980). As in the discrete case, belief function is a fuzzy measure and we obtain the third mutation of the Bayes approach. The model built using this concept has an interesting property: it includes the possibility of discovering new classes (Smets 1981).

The next method involves the use of the linguistic approach to classification (Sanchez *et al.* 1980). Here it is assumed that classes and patterns are both defined linguistically. Each class F_i is defined by a statement of the form "z_1^i is Z_1^i and . . . and z_s^i is Z_s^i" where Z_j^i are linguistic terms like "decreased," "normal," etc., modelled by corresponding membership functions defined on the appropriate universes Y_j. All feature values x_j of pattern $\boldsymbol{x}$ are also evaluated linguistically. The grade $u_i(\boldsymbol{x})$ of belongingness of a given object to a class i is computed as

$$u_i(\boldsymbol{x}) = \min_{1 \leqslant j \leqslant s} \left\{ \sup_{y \in Y_j} [\min(h_{Z_j^i}(y), h_{x_j}(y))] \right\} \tag{9}$$

A review of another pattern recognition technique (including syntactic methods) is given in Dubois and Prade (1980) and in Bezdek (1981).

4. Feature Selection

This problem is both significant and difficult. Conceptually it may be stated as in point (a) of Sect. 1. Whenever X is binary valued, the optimal $\boldsymbol{v}_i$s arising from fuzzy ISODATA (see Eqn. 6) possess theoretical properties relevant to this problem (Bezdek 1981). The learning scheme used by Seif and Aguilar-Martin (1980) may also be of use: resulting fuzzy measure expresses the grades of importance of particular features. An overview of many popular approaches to feature selection in a nonfuzzy case is available in Duda and Hart (1973).

See also: Computer-Assisted Medical Diagnostic Systems: Fuzzy Methods

Bibliography

Asai K, Tanaka H, Okuda T 1977 On discrimination of fuzzy states in probability space. *Kybernetes* **6**, 185–92

Bezdek J C 1981 *Pattern Recognition with Fuzzy Objective Functions*. Plenum, New York

Dubois D, Prade H 1980 *Fuzzy Sets and Systems: Theory and Applications*. Academic Press, New York

Duda R, Hart P 1973 *Pattern Classification and Scene Analysis*. Wiley-Interscience, New York

Dunn J C 1974 A graph theoretic analysis of pattern classification via Tamura's fuzzy relation. *IEEE Trans. Syst., Man Cybern.* **4**, 310–13

Negoita C V, Ralescu D A 1975 *Applications of Fuzzy Sets to System Analysis*. Birkhauser, Basel
Ruspini E H 1980 Recent developments in mathematical classification using fuzzy sets. In: Lasker G E (ed.) *Applied Systems and Cybernetics*. Pergamon, Oxford, pp. 2785–90
Sanchez E, Gouvernet J, Bartolin R, Vovan L 1980 Linguistic approach in fuzzy logic of the WHO classification of dyslipoproteinemias. In: Lasker G E (ed.) *Applied Systems and Cybernetics*. Pergamon, Oxford, pp. 2884–89
Seif A, Aguilar-Martin J 1980 Multi group classification using fuzzy correlation. *Fuzzy Sets Syst.* **3**, 109–22
Smets P 1981 Medical diagnosis: fuzzy sets and degrees of belief. *Fuzzy Sets Syst.* **5**, 259–66
Tamura S, Higuchi S, Tanaka H 1971 Pattern classification based on fuzzy relations. *IEEE Trans. Syst., Man Cybern.* **1**, 61–66
Zadeh L A 1976 Fuzzy sets and their application to pattern classification. In: Ryzin J (ed.) *Classification and Clustering*. Academic Press, New York

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Feedback Control: History

Before the middle of the nineteenth century the types of feedback device in use were limited: control or regulation was largely synonymous with the governor. It is only since World War II that a rapid growth in the use and understanding of feedback mechanisms has occurred. However, feedback devices were known in antiquity; in the writing of the Greeks of the Hellenic period there are numerous examples of feedback devices, the earliest known device being the waterclock of Ktesibios (about 300–275 BC). It was not until the seventeenth century that any feedback systems, designed independently from the ancient devices, appeared in Europe. The first was the temperature regulator of Cornelis Drebbel and this was followed by many more temperature regulators.

The replacement of human muscle power by animal, water, wind and other sources of power marked a fundamental change in technological thought, for in the separation of the provision of power and the operation of the process of production, that is, the manipulation of the tool or the machine, the need for control or regulation became apparent. In the eighteenth century the use of nonmanual power sources became more widespread and, as a consequence, the need to regulate the prime mover—be it wind, water, animal power (at the end of the eighteenth century an automatic goad for a horse was proposed) or the newly available steam power—became urgent. It was also during this period that an understanding of the concept of feedback began to develop, although not through the consideration of mechanical devices but through "political economy." The word feedback, however, was not used until the twentieth century: it came into use in connection with the development of the electronic amplifier (Bennett 1979).

1. Hellenic Period

The inventions of the Hellenic period are usually associated with the names of three mechanicians—Ktesibios, Philon and Heron—and it is among their works that the earliest known feedback devices are to be found. Ktesibios, who lived in Alexandria and served as a mechanician to the Ptolemys, is thought to have lived in the first half of the third century BC and is credited with the first known feedback mechanism: a float valve regulator for a waterclock. The mechanism is shown in Fig. 1.

The principle of operation of this type of waterclock is that the time is told by the level of water in the receiving vessel and hence, for accurate timekeeping, the rate of flow of water into the vessel has to be constant. A constant flow rate can be obtained if the level of water in the supply vessel BCDE is maintained at a constant level; the float G in the box senses the level of the water and its tip acts as a valve which opens as the water level falls and closes as the level rises. The operation is shown in block diagram form in Fig. 2.

The measurement of time was important to the highly organized societies which existed and continued to exist in the Mediterranean area. As a consequence, the float valve continued, over many centuries, to be an important component in the design and construction of waterclocks, since these provided the most accurate and reliable means of measuring time intervals.

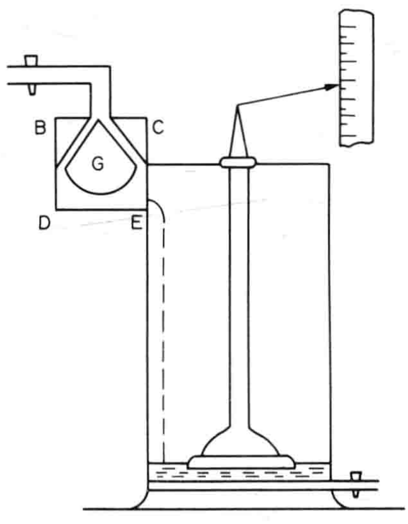

Figure 1
Float valve regulator for the waterclock of Ktesibios (after Mayr 1970)

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