EDV in Medizin und Biologie 17 (1/2), 12–20, ISSN 0300-8282

Fuzzy modeling and reasoning in a medical diagnostic expert system*

K.-P. Adlassnig

Summary

CADIAG-2 (Computer-Assisted DIAGnosis) is a data-driven, rule-based fuzzy medical expert system developed for diagnostic screening and on-line consultation in a hospital. It is integrated into the system WAMIS (Wiener Allgemeines Medizinisches InformationsSystem [Vienna General Medical Information System]), the medical information system of the Vienna General Hospital. Extended clinical trials in the fields of gastroenterology and rheumatology have been conducted. First results obtained by testing about 500 clinical cases indicate the applicability of CADIAG-2 in this hospital setting.

This paper describes the main components and the formal concept of CADIAG-2. An example of a diagnostic process in the field of pancreatic diseases is provided for illustrative purpose.

Zusammenfassung

CADIAG-2 (Computerunterstützte Diagnose [Computer-Assisted DIAGnosis]) ist ein medizinisches Expertensystem für diagnostisches Screening und On-line-Konsultation im Krankenhaus. Fuzzy Produktionsregeln bilden die Grundlage der Wissensrepräsentation in diesem System. Der Diagnoseprozeß erfolgt datengetrieben, wobei die Patientendaten aus der Datenbank des medizinischen WAMIS (Wiener Allgemeines Medizinisches InformationsSystem) entnommen werden. Dies wird ermöglicht durch eine umfassende Integration des CADIAG-2 in das System WAMIS. CADIAG-2 wird derzeit in den Gebieten Gastroenterologie und Rheumatologie getestet. Die Ergebnisse der Auswertung der ersten 500 klinischen Fälle demonstrieren die Anwendbarkeit des Systems im Krankenhausbereich.

Die vorliegende Arbeit beschreibt das formale Konzept sowie die wesentlichen Komponenten von CADIAG-2. Ein illustratives Beispiel eines diagnostischen Prozesses aus dem Bereich der Pankreaserkrankungen ist beigefügt.

Schlüsselwörter:

Medizinisches Expertensystem CADIAG-2, Fuzzy Mengen und Fuzzy Logik, Medizinisches Informationssystem WAMIS, Interne Medizin.

1. Introduction

CADIAG-2[1] is a data-driven, rule-based fuzzy medical expert system, integrated into the medical information system WAMIS[2] of the Vienna General Hospital. The Vienna General Hospital is the teaching hospital of the University of Vienna Medical School and is constituted of about 70 medical clinics and institutes. At present, more than 1,200,000 case histories from about 700,000 patients are contained in its central patient data base. Both CADIAG-2 and WAMIS are on-line systems programmed in CICS/VS command level language and PL/1. They run in a time-sharing environment on an IBM 4381 Model P03 under DOS/VS, controlled by VM. For a description of WAMIS see [1, 2].

CADIAG-2 is at present being tested in this hospital setting. It is under retrospective evaluation at the 2nd Department for Gastroenterology and Hepatology (Director: Prof. Dr. G. Grabner) and the Hospital for Rheumatic Diseases of the Social Insurance Institute of Trade in Baden near Vienna (Director: Prof. Dr. G. Kolarz). The latter is associated with the University of Vienna Medical School for joint research. Until now, about 500 clinical cases, each case including up to 800 symptoms, signs, and laboratory test results, have been evaluated. These large symptom patterns consist of findings present, present to a certain degree, and definitely absent. Reports on these evaluations can be found in [3, 4].

CADIAG-2 is a successor of CADIAG-1 [4, 5]. Both systems employ two basic medical concepts for expressing medical associations between symptoms[3] and diseases: (1) the necessity of occurrence of a symptom with the disease; and (2) its sufficiency for concluding the disease. But whereas CADIAG-1 applies some qualitative categories of relationships between symptoms and diseases, expressed mathematically by means of first-order predicate calculus, CADIAG-2 uses two quantitative numbers to characterize the strengths of association between symptoms and diseases. Furthermore, while CADIAG-1 presupposes dichotomous decisions on the presence or absence of symptoms, CADIAG-2 allows uncertainty about these decisions and thus represents borderline symptoms, i.e., symptoms rendering a state between normal and pathological, more adequately. Fuzzy set theory [6] and fuzzy logic [6, 7] provide the necessary framework to formalize and manipulate certain as well as borderline symptoms, allow to propagate and aggregate this information, and to draw diagnostic conclusions. With the means of fuzzy logic, diag-

* This work was supported by a Max Kade Fellowship for Scientific Research and supported in part by the National Science Foundation NSF-IST Grant 8320416 and NASA Grant NCC2-275.

[1] CADIAG stands for *C*omputer-*A*ssisted *DIAG*nosis.

[2] WAMIS is the German acronym for *W*iener *A*llgemeines *M*edizinisches *I*nformations-*S*ystem (Vienna General Medical Information System).

[3] Throughout the text, the term »symptom« is considered to be synonymous with the terms »sign« and »laboratory test result«.

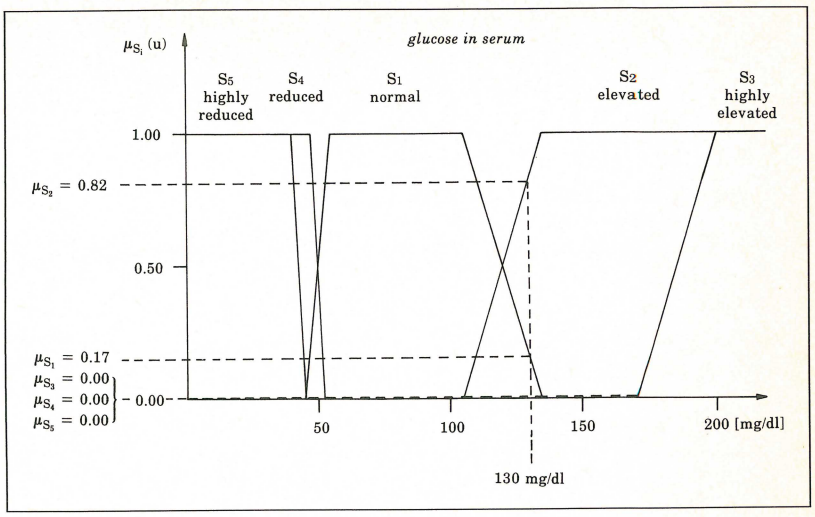

Figure 1. Determination of degrees of compatibility for a quantitative laboratory test result (serum glucose = 130 mg/dl) with the semantic medical concepts *serum glucose normal, elevated, highly elevated, reduced,* and *highly reduced.*

noses can be logically concluded with a certain degree of confidence. Additionally, a heuristic evidence aggregation function calculates a numerical support score for each diagnostic hypothesis. This score expresses the degree to which the given medical evidence supports the inferred diagnosis.

Medical expert systems whose design considerations influenced the conception of CADIAG-2 are CASNET [8, 9], MYCIN [10] (see also [11]), INTERNIST/CADUCEUS [12, 13], and EXPERT [14] (see also [15]). CADIAG-2's inference scheme has its roots in work published in [16, 17]. Further approaches to medical decision making applying fuzzy set theory, fuzzy logic, and possibility theory can be found in a survey on medical diagnosis and fuzzy subsets [18]. More recent work ist reported in [19–30].

The aim of this paper is to describe the main components and the formal concept of CADIAG-2. This is illustrated by examples of a CADIAG-2 description of a disease and a diagnostic process, both from the field of pancreatic diseases. Since a detailed and complete description of the mathematical basis of CADIAG-2 can be found elsewhere [3], this is not repeated here, but instead, emphasis is put on the description of the principal mechanisms of CADIAG-2 and their application in a hospital environment.

2. Medical expert system CADIAG-2

2.1. *Knowledge representation*

2.1.1. *Patient data*

In WAMIS, the stored patient records usually contain patient data on a detailed observational level, i.e., detailed history items, signs from physical examinations, quantitative laboratory test results, etc. An interface program, called patient data fuzzy interpreter, accesses the given medical data and transfers them to the CADIAG-2 system. During this step, medical information is abstracted and aggregated and converted into a representation commonly used in diagnostic discourse. This information can then be processed by the fuzzy inference engine.

An example for an abstracted symptom is *elevated glucose level,* set according to the result of the glucose test and the definition of *elevated.* The formal modeling of semantic medical concepts such as *elevated* that considers their inherent uncertainty, i.e., their gradual transition to adjacent medical concepts, is based on fuzzy set theory (see [6]). Adopting this theory, every symptom is considered to be a fuzzy set. Fuzzy sets are defined by fuzzy membership functions that assign to every symptom a degree of membership, expressing the degree of compatibility of a measured concrete value with the semantic concept under consideration. These membership functions are determined by the physician according to numerical ranges for normal and pathological findings, where the physician also indicates the transition zone. At present, about 400 membership functions for about 100 laboratory tests, where the test results are abstracted into classes such as *normal, elevated, highly elevated, reduced,* and *highly reduced,* are included into the patient data fuzzy interpreter. Most of them will be additionally adjusted according to sex and age of the patient during the actual diagnostic process. Figure 1 shows with an example how the degrees of compatibility of a quantitative laboratory test result are determined.

An example for an aggregated symptom is *limited motion in the hand joint,* defined according to physician's degree measurements of the *radial, ulnar, dorsal,* and *volar motion of the hand joint.* These detailed degree measurements are part of the medical documentation in WAMIS. Measurements like this and many other symptoms are simplified as binary symptoms in the WAMIS system. In these cases, the fuzzy logical concept automatically coincides with Boolean logic[4], a subtheory of fuzzy logic. The patient data fuzzy interpreter contains at present about 900 aggregation functions.

Once the abstracted and aggregated symptoms together with their degrees of compatibility have been transferred to the CADIAG-2 system, the degrees of compatibility can be altered by the physician according to his subjective perception of the case. By doing this, even symptoms defined as binary in the documentation system WAMIS can obtain intermediate values.

In more formal terms, degrees of compatibility $\mu_{S_i}(u_k) \in [0,1]$ between a symptom S_i and a measured or observed concrete value u_k, which is a member of the universe of discourse U of the respective symptom S_i, i.e., $u_k \in U$ ($U = \{u\}$), are determined by the patient data fuzzy interpreter and can be altered by the physician consulting CADIAG-2. A degree of zero means *no* and unity *full* compatibility with the meaning of the symptom S_i.

[4] Actually, Kleene's trivalued logical system [31] is used to capture also missing values, i.e., the logical values are 1: »Present«, ½: »Don't know«, and 0: »Absent«.

The degrees of compatibility $\mu_{S_i}(u_k)$ are interpreted as binary fuzzy relationships $\mu_{PS}(P,S_i)$ between the patient P and the symptom S_i, that is,

$$\mu_{S_i}(u_k) = \mu_{PS}(P,S_i). \quad (1)$$

Example 1 (quantitative laboratory test):

$\mu_{\textit{serum glucose normal}}$ (130 mg/dl) = 0.17
$\mu_{\textit{serum glucose elevated}}$ (130 mg/dl) = 0.82
$\mu_{\textit{serum glucose highly elevated}}$ (130 mg/dl) = 0.00
$\mu_{\textit{serum glucose reduced}}$ (130 mg/dl) = 0.00
$\mu_{\textit{serum glucose highly reduced}}$ (130 mg/dl) = 0.00

Example 2 (sign aggregated from detailed information about the *radial, ulnar, dorsal,* and *volar motion of the hand joint*):

$\mu_{\textit{limited motion in the hand joint}}$ (»Yes«) = 1.00

2.1.2. *Medical relationships*

In CADIAG-2, medical knowledge is represented in form of rules. These rules contain relationships between antecedents and consequents. Rules with a single medical entity as antecedent express known associations between medical entities, whereas compound antecedents, which are combinations of symptoms, allow the definition of pathophysiological states and the incorporation of very specific, complex criteria for diagnosing diseases. The evaluation of compound antecedents is carried out by means of fuzzy logic[5].

In CADIAG-2, the overwhelming part of the stored medical knowledge consists of relationships between single antecedents and consequents. The present ratio between single and compound antecedent/consequent rules is about 23,000:120.

Two kinds of relationships – the necessity and sufficiency – define the associations between antecedents and consequents. Causal relationships are not explicitly represented. They are (whenever possible) expressed as associations and captured by associational relationships. In CADIAG-2, the employed relationships are:

- frequency of occurrence O of the antecedent with the consequent (necessity);
- strength of confirmation C of the antecedent for inferring the consequent (sufficiency).

These relationships are interpreted as binary fuzzy relationships between antecedents and consequents. They take their values μ_O and μ_C in $[0,1] \cup \{v\}$ with v: »No relationship«. Linguistic terms λ_O and λ_C such as *always, often, seldom, never, strong, weak,* etc., have been found semantically useful in order to characterize these relationships, although numerical values are stored in the knowledge base of CADIAG-2 (see [3, 32]). The general form of the CADIAG-2 rules is:

IF *antecedent* THEN *consequent* WITH (O, C). (2)

The relationship tupels (O, C) contain linguistic and numerical values λ_O and μ_O, and/or λ_C and μ_C. An antecedent is a sufficient criterion for concluding a consequent if the strength of confirmation is $\mu_C = 1.00$; it is a necessary criterion if the frequency of occurrence is $\mu_O = 1.00$; and it is an excluding criterion if the frequency of occurrence is $\mu_O = 0.00$ and the strength of confirmation is $\mu_C = 0.00$. Relationships with intermediate degrees are supportive criteria. Graded adverse criteria are not considered in CADIAG-2.

Example 3 (supportive):
IF *elevated pancreatic oncofetal antigen (POA) in serum*
THEN MAY BE *pancreatic cancer*
with (λ_O = *often* [μ_O = 0.80], λ_C = strong [μ_C = 0.70]).

Example 4 (necessary and sufficient):
IF (IF NOT) *rheumatoid arthritis,* and
splenomegaly, and
leukopenia under 4 giga/l
THEN (THEN NOT) *Felty's syndrome*
with (λ_O = *always* [μ_O = 1.00], λ_C = *always* [μ_C = 1.00]).

Example 5 (excluding):
IF *positive rheumatoid factor*
then not *seronegative rheumatoid arthritis*
with (λ_O = *never* [μ_O = 0.00], λ_C = *never* [μ_C = 0.00]).

The relationships frequency of occurrence $\mu_O = 1.00$ and strength of confirmation $\mu_C = 1.00$ are also applied to establish symptom and disease taxonomies. In these taxonomies, present sub-terms are sufficient criteria for inferring super-terms, e.g., *bacterial arthritis* implies *arthritis.* But vice versa, super-terms are necessary criteria for the presence of sub-terms, e.g., criteria excluding *infectious arthritis* also exclude all kinds of *infectious arthrites* such as *bacterial* and *viral arthrites, arthritis* by *fungi* or *rickettsiae.*

In CADIAG-2, the frequency of occurrence and strength of confirmation are expressible as proportions of the cardinalities of sets of patients. They can be numerically calculated from sample patient data with already diagnosed patients. Although the frequency of occurrence and the strength of confirmation suggest an interpretation as conditional probabilities – P(S/D) as frequency of occurrence and P(D/S) as strength of confirmation – the property of the symptoms of having attached degrees of compatibility $\mu_{PS}(P,S_i)$, unequal zero or unity, prevents a pure probabilistic calculation.

The formal apparatus allowing to calculate proportions of fuzzy sets is found in the concept of the relative sigma-count. For a general exposition on the cardinality of fuzzy sets see [33].

Provided that the patient data base contains N patients, we calculate for the frequency of occurrence

$$\mu_{SD^O}(S_i,D_j) = \Sigma\,\text{Count}(S_i/D_j) = \frac{\Sigma\,\text{Count}(S_i \cap D_j)}{\Sigma\,\text{Count}(D_j)} = \frac{\sum_{k=1}^{N} \text{Min}\,[\mu_{PS}(P_k,S_i); \mu_{PD}(P_k,D_j)]}{\sum_{k=1}^{N} (\mu_{PD}(P_k,D_j))} \quad (3)$$

and for the strength of confirmation

$$\mu_{SD^C}(S_i,D_j) = \Sigma\,\text{Count}(D_j/S_i) = \frac{\Sigma\,\text{Count}(S_i \cap D_j)}{\Sigma\,\text{Count}(S_i)} = \frac{\sum_{k=1}^{N} \text{Min}\,[\mu_{PS}(P_k,S_i); \mu_{PD}(P_k,D_j)]}{\sum_{k=1}^{N} (\mu_{PS}(P_k,S_i))}. \quad (4)$$

[5]) In fact, an extension of fuzzy logic allowing variables to take values in $[0,1] \cup \{v\}$ with v: »Don't know« is used (see [3]).

If there are only degress of compatibility $\mu_{PS}(P_k,S_i) \in \{0,1\}$ and clinical diagnoses $\mu_{PD}(P_k,D_j) \in \{0,1\}$ in the sample patient data base, i.e., if their is no uncertainty about the assignment of measured or observed findings into symptom categories and no uncertainty about the clinical diagnoses for these patients, then the above-mentioned calculations coincide with the calculations for P(S/D) and P(D/S).

The Σ Count interpretations for symptom combination/disease, symptom/symptom, and disease/disease relationships are conducted analogously to symptom/disease relationships.

Table 1 shows as an example the stored medical description of *pancreatic cancer,* a disease belonging to the differential diagnostic group of pancreatic diseases, a subgroup of gastroenterology in CADIAG-2 .

Table 1. The medical documentation of *pancreatic cancer* in CADIAG-2 with the relationships frequency of occurrence $\mu_{SD^O}(S_i,D_j)$ and strength of confirmation $\mu_{SD^C}(S_i,D_j)$. An empty place means that there is no known or a totally unspecific relationship between the symptom and the disease.

Pancreatic cancer	μ_{SD^O}	μ_{SD^C}
Anamnesis/known present disorder(s)		
age, 17–29 years	0.03	
age, 30–50 years	0.08	
age, 51–80 years	0.09	0.01
sex, male	0.59	
sex, female	0.41	
(heavy) smoker	0.35	
alcoholism	0.20	0.01
diabetes mellitus	0.20	0.02
latent diabetes	0.55	0.02
venous thrombosis	0.35	0.03
Present symptoms		
tiredness	0.52	
weakness	0.55	0.01
lack of concentration	0.23	
malaise	0.60	
decrease in physical/mental powers	0.50	
major debilitation	0.26	0.02
jaundice	0.54	0.02
nausea	0.44	
vomiting	0.34	
anorexia	0.50	0.01
weight loss	0.82	0.05
subfebrile temperature	0.25	0.01
bloating	0.18	
pain, abdominal	0.86	0.06
pain, abdominal, epigastric region, diffuse	0.08	
pain, abdominal, right epigastric region	0.54	
pain, abdominal, mid-epigastric region	0.20	
pain, abdominal, left epigastric region	0.04	
pain, abdominal, deterioration at hyperlordosis	0.35	0.03
pain, abdominal, radiation to the back	0.33	
pain, abdominal, radiation to the side(s)	0.05	
pain, abdominal, radiation to the hypogastrium	0.03	
pain, abdominal, persistent, mild	0.09	0.01
pain, abdominal, persistent, intensive	0.16	0.01
pain, abdominal, intermittent, mild	0.45	0.02
pain, abdominal, intermittent, colicky	0.16	0.01
pain, abdominal, acute onset	0.16	
pain, abdominal, insidious onset	0.70	0.02
pain, abdominal, unrelated to food intake	0.66	
pain, abdominal, postprandial	0.34	
defecation, constipation	0.18	0.01
defecation, diarrhea	0.23	0.01
defecation, steatorrhea	0.09	0.02
defecation, light stools	0.40	
defecation, tarry stools	0.07	0.03
miction, dark urine	0.38	
anemia-signs	0.45	0.02
depression	0.33	
Physical examination		
general condition, normal	0.15	
general condition, ill	0.85	0.01
nutritional status, normal	0.25	
nutritional status, reduced	0.75	0.02
strength, normal	0.30	
strength, reduced	0.70	0.01
skin, subicteric	0.06	0.02
skin, icteric	0.54	0.02
skin, subcutaneous fat necrosis	0.10	0.03
skin, thrombophlebitis, migrans	0.10	0.03
lymphnodes (LN), palpable LN metastasis	0.09	0.30
eyes, sclerae, icteric	0.60	
abdomen, ascites	0.28	0.01
abdomen, systolic murmur, left epigastrium	0.17	0.05
abdomen, palpable abdominal mass	0.30	0.05
abdomen, liver, hepatomegaly	0.50	0.01
abdomen, liver, palpation, suspicion (susp.) of liver metastasis	0.55	0.30
abdomen, gall bladder, Courvoisier's sign	0.35	0.07
abdomen, spleen, splenomegaly	0.30	0.01
Laboratory findings		
blood sedimentation rate (BRS), increased	0.75	0.01
serum, alkaline phosphatase (AP), elevated	0.72	
serum, glucose, elevated	0.48	0.02
serum, bilirubin, elevated	0.60	0.02
serum, glutamic-oxaloacetic transaminase (SGOT), elevated	0.65	0.02
serum, glutamic-pyruvic transaminase (SGPT), elevated	0.65	0.02
serum, lactate dehydrogenase (LDH), elevated	0.46	0.02
serum, gamma-GT (γGT), elevated	0.65	0.02
serum, amylase, elevated	0.21	0.02
serum, lipase, elevated	0.21	0.02
serum, electrophoresis, alpha-2 globulin, elevated	0.60	
serum, electrophoresis, beta-globulin, elevated	0.60	
serum, pancreatic oncofetal antigen (POA), elevated	0.80	0.65
serum, CA-19-9, elevated	0.80	0.65
serum, carcinoembryonic antigen (CEA), elevated	0.68	0.30
hemogram, leucocytosis	0.32	0.01
urine, amylase, elevated	0.10	
urine, glucose, elevated	0.20	
stool, hemoccult test, positive	0.45	0.03
stool, chymotrypsin, pathological finding	0.70	0.20
stool, fat content, increased	0.09	0.20
Clinical investigations		
exocrine pancreatic function test(s), pathological finding	0.80	0.50
X-ray, hypotonic duodenography, susp. of inflammatory/malignant pancreatic tumor	0.38	0.05
X-ray, endoscopic retrograde choledochopancreatography (ERCP), susp. of pancreatic tumor	0.85	0.80
X-ray, selective arteriography, susp. of pancreatic tumor	0.85	0.85
X-ray, computerized tomography (CT), susp. of pancreatic tumor	0.85	0.85
ultrasonography (US), susp. of pancreatic tumor	0.80	0.70
percutaneous aspiration biopsy (US/CT-guidance), positive cytology	0.65	1.00

2.2. *Inference engine*

2.2.1. *Inference and chaining*

The fuzzy inference mechanism applied in CADIAG-2 (for a formal, detailed description see [3]) allows inference under uncertainty. The basic rule on which the inference mechanism relies is the compositional rule of fuzzy inference advanced in [7]. It accepts patient's symptoms with attached degrees of compatibility and infers diagnoses with a certain degree of confidence expressing the degree to which the diagnosis can logically be concluded from given medical evidence. From the logical point of view, only the strength of confirmation can be applied for carrying out inferences from given symptoms (modus ponens). An exception is the case in which the frequency of occurrence is $\mu_O = 1.00$ and the respective criterion is definitely absent. It can then be inferred that the conclusion has to be rejected (Boolean modus tollens).

The formal representation is:

$$\begin{array}{l} P \text{ has } S_i \text{ with } \mu_{PS}(P,S_i), \text{ and} \\ \text{If } S_i \text{ implies } D_j \text{ with } \mu_{SD^c}(S_i,D_j), \\ \hline \text{Then P has } D_j \text{ with } \mu_{PD}(P,D_j). \end{array} \qquad (5)$$

This modus ponens syllogism is calculated using the Max-Min composition that provides very secure and reliable inference values and is considered to be »conservative«. For many symptoms S_i in patient P the formula is stated as:

$$\mu_{PD}(P,D_j) = \max_{S_i} \text{Min}\,[\mu_{PS}(P,S_i); \mu_{SD^c}(S_i,D_j)]. \qquad (6)$$

The compositional rule of inference is not only applied for drawing conclusions from given symptoms, but also for conclusions from given combinations of symptoms. Furthermore, inferences among symptoms and among diseases are based on the same principle.

Chaining is carried out by employing the same rule in subsequent steps, e.g.,

$$\begin{array}{l} P \text{ has } S_i \text{ with } \mu_{PS}(P,S_i), \text{ and} \\ \text{If } S_i \text{ implies } S_j \text{ with } \mu_{SS^c}(S_i,S_j), \text{ and} \\ \text{If } S_j \text{ implies } D_i \text{ with } \mu_{SD^c}(S_j,D_i), \text{ and} \\ \text{If } D_i \text{ implies } D_j \text{ with } \mu_{DD^c}(D_i,D_j), \\ \hline \text{Then P has } D_j \text{ with } \mu_{PD}(P,D_j). \end{array} \qquad (7)$$

Out of efficiency reasons, CADIAG-2 processes a fixed number of inference steps: (1) symptom/symptom inference to complete and extend patient's initial symptom pattern; (2) symptom/disease inferences; (3) symptom combination/disease inferences with symptoms as evidence only, at this point a primary set of diagnoses is obtained; (4) disease/disease inferences to complete and extend the primary set of diagnoses; (5) again symptom combination/disease inferences, but not with symptoms and already inferred diseases as evidence; and finally (6) again disease/disease inferences to complete and extend the final set of diagnostic results.

In this process, confirmed diagnoses are obtained from given evidence (symptoms, symptom combinations, and diseases) and confirming relationships. Excluded diagnoses are determined from given evidence with excluding relationships or from definitely absent evidence whose occurrence was indicated as absolutely necessary. Diagnostic hypotheses are generated if uncertain evidence is combined with confirming relationships and/or certain or uncertain evidence is combined with supportive, but not confirming relationships. In case of diagnostic hypotheses, it is tested if

$$\varepsilon \leq \mu_{PD}(P,D_j) \leq 0.99, \qquad (8)$$

where ε is a threshold precluding diagnoses with too little evidence. Usually, ε is assigned a small value, say, between 0.1 and 0.4, to allow a very »liberal« hypothesis generation.

2.2.2. *Combination of evidence*

Because the values $\mu_{PD}(P,D_j)$ for diagnostic hypotheses, inferred with the compositional rule of inference (Eqn. 6), are both independent of the number of pieces of evidence supporting diagnosis D_j and their frequency of occurrence with the consequent, a heuristic function (Eqn. 9) was introduced considering the number of present and partly present symptoms with supportive relationships to diseases D_j and calculating support scores SS_{D_j} according to which all diagnostic hypotheses are ranked in descending order. These scores reveal very clearly how strongly the various hypotheses are supported. The formula with which the support scores are calculated is an unnormalized function and the individual score becomes the higher the more symptoms support the hypothesis. It considers the degrees of presence (compatibility values) of the symptoms and weights the associated frequency of occurrence and strength of confirmation according to given weights α and β. At present, the value α is 0.09 and β is 0.91, thus $\alpha + \beta$ yields 1.00. The weights cause that the strength of confirmation determines the support score ten times stronger than the frequency of occurrence. The formula is:

$$SS_{D_j} = 100 \sum_{i=1}^{m^*} \Big\{ \alpha \text{MIN}[\mu_{PS}(P,S_i); \mu_{SD^o}(S_i,D_j)] + \beta \quad \text{MIN}[\mu_{PS}(P,S_i); \mu_{SD^c}(S_i,D_j)] \Big\}, \qquad (9)$$

where m^* is the number of present or partly present symptoms occurring in the medical documentation of diagnosis D_j.

Table 3 shows the diagnostic results inferred from the patient data given in Table 2. The above-described fuzzy inference engine was applied to obtain these results. The diagnostic process was carried out in the differential diagnostic group of pancreatic diseases, containing at present *acute* and *chronic pancreatitis, pancreatic cancer, cystic pancreatic fibrosis, pancreatic pseudocyst, annular pancreas, insulinoma, glucogonoma, Zollinger-Ellison syndrome* and *Verner-Morrison syndrome.*

2.3. *Explanation system, examination proposal generation, and unexplained symptom generation*

As explanation, CADIAG-2 presents every item of evidence that contributed to the respective diagnostic result along with its frequency of occurrence and its strength of confirmation. Usually, these are many single symptoms and only few symptom combinations. Diagnostic hypotheses are always presented with their calculated degrees of compatibility to the patient and their achieved support scores (cf. Table 3).

A natural component of an iteratively working, data-driven medical expert system is the generation of further useful examinations at the end of each iteration cycle. CADIAG-2 advances examination proposals for each of the diagnostic

hypotheses. All symptoms or symptom combinations that will improve the fuzzy inference results or the support scores but were not investigated or determinable yet are offered. They are categorized according to their degree of risk for the patient and their costliness (cf. Table 4).

Unexplained disorders or positive findings are those symptoms in the patient's symptom pattern that cannot be accounted for by any of the inferred diagnostic results. They make it necessary to continue the diagnostic process and search for other diagnoses the patient may suffer from. These symptoms

Table 2. Patient data of a clinical case from the 2nd Department for Gastroenterology and Hepatology (Director: Prof. Dr. G. Grabner) including data from patient's history, present symptoms, signs, laboratory test results, and clinical findings. The data were evaluated by the patient data fuzzy interpreter, which assigns to every symptom, sign, test result, and finding a degree of compatibility $\mu_{PS}(P,S_i)$ of the measured or observed concrete value with the semantic concept under consideration.

Patient's medical data

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Anamnesis/known present disorder(s)		
1.00	age, 30–50 years		
1.00	sex, female		
1.00	known previous disorder, peptic ulcer		
1.00	known present disorder, gastric ulcer		
1.00	known present disorder, duodenal ulcer		
1.00	known present disorder, multiple gastro-intestinal (GI)-ulcerations		
	Present symptoms		
1.00	malaise		
1.00	decrease in physical/mental powers		
1.00	nausea		
1.00	vomiting		
1.00	anorexia		
1.00	weight loss		
1.00	pain, abdominal		
1.00	defecation, diarrhea		
	Physical examination		
1.00	general condition, ill		
1.00	nutritional status, normal		
1.00	strength, normal		
1.00	abdomen, tenderness, diffuse		
1.00	liver, palpation, susp. of liver metastasis		
	Laboratory findings		
1.00	BSR, increased		
1.00	serum, AP, elevated		
0.80	serum, potassium, reduced		
1.00	serum, SGOT, elevated		
1.00	serum, SGPT, elevated		
1.00	serum, LDH, elevated		
0.90	serum, γGT, elevated		
1.00	serum, cholesterol, elevated		
0.33	serum, triglycerides, elevated		
	Clinical investigations		
1.00	gastric analysis, BAO > 15 mval hydrochl. acid/hour		
1.00	gastric analysis, BAO/PAO > 0.6		
0.40	gastric analysis, volume > 200 ml/hour		
1.00	X-ray, hypotonic duodenography, susp. of inflammatory/ malignant pancreatic tumor		
1.00	X-ray, ERCP, susp. of pancreatic tumor		
1.00	X-ray, CT, susp. of pancreatic tumor		

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Physical examination		
1.00	general condition, reduced	0.85	0.01
1.00	nutritional state, normal	0.25	
1.00	strength, normal	0.30	
1.00	liver, palpation, susp. of liver metastasis	0.55	0.30
	Laboratory findings		
1.00	BSR, increased	0.75	0.01
1.00	serum, AP, elevated	0.72	
1.00	serum, SGOT, elevated	0.65	0.02
1.00	serum, SGPT, elevated	0.65	0.02
1.00	serum, LDH, elevated	0.46	0.02
0.90	serum, γGT, elevated	0.65	0.02
	Clinical investigations		
1.00	X-ray, hypotonic duodenography, susp. of inflammatory/malignant pancreatic tumor	0.38	0.05
1.00	X-ray, ERCP, susp. of pancreatic tumor	0.85	0.80
1.00	X-ray, CT, susp. of pancreatic tumor	0.85	0.85

μ_{PD} **0.50** **Verner-Morrison Syndrome (10 symptoms: 171.4 points)**

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Present symptoms		
1.00	malaise	0.72	0.01
1.00	weight loss	0.65	0.05
1.00	defecation, diarrhea	0.30	0.11
	Physical examination		
1.00	general condition, reduced	0.78	0.02
1.00	nutritional state, normal	0.40	
1.00	strength, normal	0.30	
1.00	liver, palpations, susp. of liver metastasis	0.30	0.08
	Laboratory findings		
0.80	serum, potassium, reduced	0.90	0.02
	Clinical investigations		
1.00	X-ray, ERCP, susp. of pancreatic tumor	0.85	0.50
1.00	X-ray, CT, susp. of pancreatic tumor	0.85	0.50

μ_{PD} **0.50** **Glucagonoma (5 symptoms: 134.4 points)**

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Present symptoms		
1.00	weight loss	0.80	0.07
	Physical examination		
1.00	liver, palpation, susp. of liver metastasis	0.30	0.08
	Laboratory findings		
1.00	serum, cholesterol, elevated	0.38	0.01
	Clinical investigations		
1.00	X-ray, ERCP, susp. of pancreatic tumor	0.85	0.50
1.00	X-ray, CT, susp. of pancreatic tumor	0.85	0.50

μ_{PD} **0.50** **Insulinoma (5 symptoms: 122.3 points)**

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Present symptoms		
1.00	nausea	0.20	0.02
1.00	vomiting	0.15	0.01
	Physical examination		
1.00	liver, palpation, susp. of liver metastasis	0.30	0.08
	Clinicqal investigations		
1.00	X-ray, ERCP, susp. of pancreatic tumor	0.85	0.50
1.00	X-ray, CT, susp. of pancreatic tumor	0.85	0.50

Table 3. This Table shows diagnostic results of a CADIAG-2 diagnostic process with the data given in Table 2. The achieved inference values μ_{PD} (P,D_j), which are greater or equal the threshold ε ($\varepsilon = 0.10$ for pancreatic diseases) are printed out on the left hand side of this disease name. On the right hand side, one can find both the number of symptoms supporting the hypothesis and the calculated support score SS_{D_j}. The diagnostic hypotheses are ranked according to the support scores in descending order. The symptoms, which led to the generation of the hypotheses, are printed out together with their degrees of compatibility μ_{PS} (P,S_i) with the patient and their frequencies of occurrence μ_{SD^O} (S_i,D_j) and strengths of confirmation μ_{SD^C} (S_i,D_j) to the hypotheses. An empty place means that there is no known or a totally unspecific relationship between the symptom and the disease. The diagnosis with the highest point number *(Zollinger-Ellison Syndrome)* was also the clinical diagnosis for this patient.

Diagnostic hypotheses with explanations

μ_{PD} **0.50** **Zollinger-Ellison Syndrome (15 symptoms: 325.7 points)**

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Anamnesis/known present disorder(s)		
1.00	age, 30–50 years	0.70	0.02
1.00	sex, female	0.40	
1.00	known present disorder, duodenal ulcer	0.79	0.30
1.00	known present disorder, multiple GI-ulcerations	0.10	0.35
	Present symptoms		
1.00	nausea	0.20	0.01
1.00	vomiting	0.26	0.01
1.00	weight loss	0.65	0.05
1.00	defecation, diarrhea	0.36	0.05
	Physical examination		
1.00	liver, palpation, susp. of liver metastasis	0.30	0.08
	Laboratory findings		
0.80	serum, potassium, reduced	0.36	0.03
	Clinical investigations		
1.00	gastric analysis, BAO > 15 mval hydrochl. acid/hour	0.80	0.30
1.00	gastric analysis, BAO/PAO > 0.6	0.80	0.30
0.40	gastric analysis, volume > 200 ml/hour	0.80	0.30
1.00	X-ray, ERCP, susp. of pancreatic tumor	0.85	0.50
1.00	X-ray, CT, susp. of pancreatic tumor	0.85	0.50

μ_{PD} **0.85** **Pancreatic cancer (22 symptoms: 317.4 points)**

μ_{PS}		μ_{SD^O}	μ_{SD^C}
	Anamnesis/known present disorder(s)		
1.00	sex, female	0.41	
	Present symptoms		
1.00	malaise	0.60	
1.00	decrease of physical/mental powers	0.50	
1.00	nausea	0.44	
1.00	vomiting	0.34	
1.00	anorexia	0.50	0.01
1.00	weight loss	0.82	0.05
1.00	pain, abdominal	0.86	0.06
1.00	defecation, diarrhea	0.23	0.01

Table 4. Because the diagnoses presented in Table 3, which are the result of the CADIAG-2 diagnostic process with the data given in Table 2, could not be confirmed yet, proposals for further examinations are presented. The provided list contains the achieved inference values μ_{PD} (P,D_j), the calculated support scores, according to which the hypotheses are ranked, a list of symptoms not yet examined along with their frequencies of occurrence μ_{SD^O} (S_i,D_j) and strengths of confirmation μ_{SD^C} (S_i,D_j) to the hypotheses. The proposed examinations are categorized into three classes: Class-1-symptoms are those that can be examined very easily and that are cheap; Class-2-symptoms include more specific investigations; and Class-3-symptoms are invasive and/or expensive procedures.

Diagnostic hypotheses with examination proposals

μ_{PD} **0.50** **Zollinger-Ellison Syndrome (325.7 points)**

	μ_{SD^O}	μ_{SD^C}
Class-1-symptom		
abdominal pain, peptic ulcer-like	0.86	0.10
Class-2-symptoms		
serum, gastrin, elevated	0.10	0.60
serum, gastrin, significantly elevated	0.90	0.90
secretin-provocative-test, abnormal finding	0.93	0.90

μ_{PD} **0.85** **Pancreatic cancer (317.4 points)**

	μ_{SD^O}	μ_{SD^C}
Class-3-symptoms		
percutaneous aspiration biopsy (US/CT-guidance), positive cytology	0.65	1.00

μ_{PD} **0.50** **Verner-Morrison Syndrome (171.4 points)**

	μ_{SD^O}	μ_{SD^C}
Class-2-symptoms		
serum, magnesium, reduced	0.60	0.02
serum, VIP, abnormal finding	0.88	0.90

μ_{PD} **0.50** **Glucagonoma (134.4 points)**

	μ_{SD^O}	μ_{SD^C}
Class-2-symptoms		
serum, glucagon, elevated	0.98	0.88
arginine-stimulation test, specific abnormal finding	0.98	0.90
glucose-suppression test, specific abnormal finding	0.92	0.90

μ_{PD} **0.50** **Insulinoma (122.3 points)**

	μ_{SD^O}	μ_{SD^C}
Class-2-symptoms		
serum, insulin, elevated	0.95	0.80
serum, proinsulin, elevated	0.95	0.80
serum, C-peptide, elevated	0.95	0.80

are determined by the CADIAG-2 system and presented to the consulting physician. The physician can then switch to other diagnostic areas and try to confirm of hypothesize further diseases (cf. Table 5).

3. Conclusion

The practicability of CADIAG-2's concept of knowledge representation and fuzzy inference was confirmed by applying the expert system to about 500 clinical cases. The comparison of the CADIAG-2 diagnoses with clinical and pathological diagnoses yielded an accuracy of up to 93 % [3, 4].

The present goal is to advance with the clinical trials at the test clinics and gain further experience regarding the behavior of the system and the acceptance by the physicians, nurses, and medical technicians. These trials are also supposed to possess an educational function at the Vienna General Hospital in such a manner that the prospective medical users learn to apply and utilize these tools.

Furthermore, strong efforts are being made to improve and extend the medical documentation and incorporate further medical specialties.

Acknowledgement

The author gratefully acknowledges the contributions of G. Kolarz, M.D., W. Scheithauer, M.D., P. Peichl, M.D., H. Effenberger, M.D., and G. Grabner, M.D. Without their work, this project would not have been possible. The author is especially thankful to W. Scheithauer, M. D., who documented the group of pancreatic diseases and helped to prepare the example given in the tables. The author is also indebted to W. Bogard, M.Sc., A. Hatvan, M.Sc., F. Lipomersky, and P. Sachs for programming various parts of CADIAG-2. Furthermore, the author would like to thank I. Gröger and G. Sedivy for their help in managing the knowledge acquisition and the patient data documentation.

Table 5. Two findings out of patient's data (Table 2) could not be accounted for by the obtained diagnostic results (Table 2). There are now two possibilities: Either the consulting physician decides that these findings remain unexplained or further diagnoses in this or in other diagnostic areas have to be searched for.

Unexplained symptoms	
μ_{PS}	
	Present symptoms
1.00	abdomen, tenderness, diffuse
	Laboratory findings
0.90	serum, triglycerides, elevated

Literature

1. GRABNER, H., A. MARKSTEINER, W. DORDA, W. WOLF, G. GRABNER (1981): A Medical Information System. Conception and Clinical Usage. J. Clin. Comp. **10,** 154–169.
2. GRABNER, G. (Ed.) (1985): WAMIS – Wiener Allgemeines Medizinisches Informations System. Springer-Verlag, Berlin.
3. ADLASSNIG, K.-P., G. KOLARZ, W. SCHEITHAUER (1985): Present State of the Medical Expert System CADIAG-2. Meth. Inform. Med. **24,** 13–20.
4. ADLASSNIG, K.-P., G. KOLARZ, W. SCHEITHAUER, H. EFFENBERGER, G. GRABNER (1985): CADIAG: Approaches to Computer-Assisted Medical Diagnosis. Comput. Biol. Med. **15,** 315–335.
5. SPINDELBERGER, W., G. GRABNER (1968): Ein Computerverfahren zur Diagnostischen Hilfestellung. In: Fellinger, K. (Ed.) Computer in der Medizin – Probleme, Erfahrungen, Projekte. Verlag Brüder Hollinek, Wien, 189–221.
6. ZADEH, L. A. (1965): Fuzzy Sets. Information and Control **8,** 338–353.
7. ZADEH, L. A. (1973): Outline of a New Approach to the Analysis of Complex Systems and Decision Processes. IEEE Transactions on Systems, Man, and Cybernetics **SMC-3,** 28–44.
8. WEISS, S. M., C. A. KULIKOWSKI, S. AMAREL, A. SAFIR (1978): A Model-Based Method for Computer-Aided Medical Decision-Making. Artificial Intelligence **11,** 145–172.
9. WEISS, S. M., C. A. KULIKOWSKI, A. SAFIR (1978): Glaucoma Consultation by Computer. Comput. Biol. Med. **8,** 25–40.
10. SHORTLIFFE, E. H. (1976): Computer-Based Medical Consultation: MYCIN. Elsevier, New York–Oxford–Amsterdam.
11. BUCHANAN, B. G., E. H. SHORTLIFFE (Eds.) (1984): Rule-Based Expert Systems – The MYCIN Experiments of the Stanford Heuristic Programming Project. Addison-Wesley Publishing Company, Reading/Massachusetts.
12. MILLER, R. A., H. E. POPLE, J. D. MYERS (1982): INTERNIST-I, An Experimental Computer-Based Diagnostic Consultant for General Internal Medicine. New England Journal of Medicine **307,** 468–476.
13. MILLER, R. A. (1984): INTERNIST-1/CADUCEUS: Problems Facing Expert Consultant Programs. Meth. Inform. Med. **23,** 9–14.
14. WEISS, S. M., C. A. KULIKOWSKI (1979): EXPERT: A System for Developing Consultation Models. Proc. IJCAI, Tokyo, 942–947.
15. WEISS, S. M., C. A. KULIKOWSKI (1984): A Practical Guide to Designing Expert Systems. Rowman & Allenheld Publishers, New Jersey.
16. SANCHEZ, E. (1979): Compositions of Fuzzy Relations. In: Gupta, M. M., R. K. Ragade, R. R. Yager (Eds.) Advances in Fuzzy Set Theory and Applications. North-Holland Publishing Company, Amsterdam, 421–433.
17. SANCHEZ, E. (1979): Medical Diagnosis and Composite Fuzzy Relations. In: Gupta, M. M., R. K. Ragade, R. R. Yager (Eds.) Advances in Fuzzy Set Theory and Applications. North-Holland Publishing Company, Amsterdam, 437–444.
18. ADLASSNIG, K.-P. (1982): A Survey on Medical Diagnosis and Fuzzy Subsets. In: Gupta, M. M., E. Sanchez (Eds.) Approximate Reasoning in Decision Analysis. North-Holland Publishing Company, Amsterdam, 203–217.
19. BELFORTE, G., B. BONA, C. CRAVETTO, S. FREDIANI, M. MILANESE, M. MOLINO, L. SAITTA, R. TEMPO (1985): Selection and Assessment of Laboratory Tests for the Evaluation of Liver Functional Impairment. Meth. Inform. Med. **24,** 39–45.
20. BORTOLAN, B., R. DEGANI (1983): Comparative Evaluation of Three Models of Fuzzy Decision-Making in Electrocardiography. In: Van Bemmel, J. H., M. J. Ball, O. Wigertz (Eds.). MEDINFO 83. North-Holland Publishing Company, Amsterdam, 537–540.
21. KERRE, E. E. (1982): The Use of Fuzzy Set Theory in Electrocardiological Diagnostics. In: Gupta, M. M., E. Sanchez (Eds.). Approximate Reasoning in Decision Analysis. North-Holland Publishing Company, Amsterdam, 277–282.
22. FIESCHI, M., M. JOUBERT, D. FIESCHI, G. BOTTI, M. ROUX (1983): A Program for Expert Diagnosis and Therapeutic Decision. Med. Inform. **8,** 127–135.
23. LESMO, L., M. MARZUOLI, G. MOLINO, P. TORASSO (1984): An Expert System for the Evaluation of Liver Functional Assessment. Journal of Medical Systems **8,** 87–101.
24. LESMO, L., L. SAITTA, P. TORASSO (1982): Learning of Fuzzy Production Rules for Medical Diagnosis. In: Gupta, M. M., E. Sanchez (Eds.). Approximate Reasoning in Decision Analysis. North-Holland Publishing Company, Amsterdam, 249–260.
25. MILANESE, M., B. BONA, S. FREDIANI, L. SAITTA, C. CRAVETTO, G. MOLINO (1984): A Sequential Protocol for the Optimization of Diagnostic Procedures in Hepatology. Journal of Medical Systems **8,** 73–85.

26. SAITTA, L., P. TORASSO (1981): Fuzzy Characterization of Coronary Disease. Fuzzy Sets and Systems **5**, 245–258.
27. SANCHEZ, E., J. GOUVERNET, R. BARTOLIN, L. VOVAN (1982): Linguistic Approach in Fuzzy Logic of the W.H.O. Classification of Dyslipoproteinemias. In: Yager, R. R. (Ed.) Fuzzy Set and Possibility Theory – Recent Developments. Pergamon Press, New York, 582–588.
28. SMETS, P. (1983): Fuzzy Set Theory for Medical Decision Making. In: Beneken, J. E. W., S. M. Lavelle (Eds.) Objective Medical Decision-Making; Systems Approach in Acute Disease. Springer-Verlag, Berlin, 7–19.
29. SOULA, G., E. SANCHEZ (1982): Soft Deduction Rules in Medical Diagnostic Processes. In: Gupta, M. M., E. Sanchez (Eds.). Approximate Reasoning in Decision Analysis. North-Holland Publishing Company, Amsterdam, 77–88.
30. SOULA, G., B. VIALETTES, J.-L. SANMARCO (1983): Protis; A Fuzzy Deduction-Rule System: Application to the Treatment of Diabetes. In: Van Bemmel, J. H., M. J. Ball, O. Wigertz (Eds.). MEDINFO 83. North-Holland Publishing Company, Amsterdam, 533–563.
31. RESCHER, N. (1969): Many-Valued Logic. McGraw Hill-Book Company, New York.
32. ADLASSNIG, K.-P., G. KOLARZ (1982): CADIAG-2: Computer-Assisted Medical Diagnosis Using Fuzzy Subsets. In: Gupta, M. M., E. Sanchez (Eds.). Approximate Reasoning in Decision Analysis. North-Holland Publishing Company, Amsterdam, 219–247.
33. ZADEH, L. A. (1981): Test Score Semantics for Natural Languages and Meaning Representation via PRUF. Technical Note 247, AI Center, SRI International, Menlo Park CA. Also in: Rieger, B. B. (ed.). Empirical Semantics. Brockmayer, Bochum, 281–349.

Date of receipt: February 3rd, 1986.
The author's address: Dr. med. Klaus-Peter Adlassnig, Department of Medical Computer Sciences, University of Vienna, Garnisongasse 13, A-1090 Vienna, Austria.

EDV in Medizin und Biologie **17** (1/2), 20–27, ISSN 0300-8282

On the use of growth and decay functions for modelling stem profiles

C. Brink and K. von Gadow

Summary

One of the most useful tools for modelling the effects of environmental and stand treatment factors on stem form is a simple taper equation. This article presents four new taper functions for modelling stem profiles. These are not derived de novo, but from known growth and decay functions. The paper demonstrates that it is possible to modify any growth or decay function with certain structural properties to serve as a taper function.

Zusammenfassung

Wenn man die Auswirkungen von Umgebungs- und Behandlungsfaktoren auf die Form von Baumschäften untersuchen will, empfiehlt sich die Anwendung einer flexiblen Schaftgleichung mit begrenzter Parameterzahl. Eine Spline Approximation ist für diesen Zweck unbrauchbar. In diesem Beitrag werden vier neue Schaftgleichungen vorgestellt. Die Gleichungen werden nicht de novo, sondern von bekannten Wachstums- und Zerfallfunktionen abgeleitet. Es wird gezeigt, daß es möglich ist, jede Wachstums- oder Zerfallfunktion mit bestimmten strukturellen Eigenschaften so zu modifizieren, daß sie als Schaftgleichung verwendet werden kann.

1. Introduction

Foresters need to be able to estimate the stem form of trees and how it is affected by environment and stand treatment. One method of modelling the stem form of a tree involves the use of a taper, or stem profile equation which expresses radius r as a function of height h.

One of the first attempts to model the stem profile is BEHRE's (1923) hyperbola (see PRODAN (1965), p. 62):

$$q = \frac{x}{a+bx} \qquad (1.1)$$

where

x = relative tree height;
q = relative tree diameter;
a,b = parameters to be estimated.