Regulation Thermography

Supplemental Articles

A collection of relevant articles and studies regarding the effectiveness of non-invasive digital infrared thermal image systems in the detection of cancer and other forms of disease is available upon request.

This document includes relevant excerpts from the recent publication '*Complementary Oncology'*, by Dr. Josef Beuth and Dr. Ralph W. Moss. Topics include Expert Systems based on *Fuzzy Logic* and *Regulation Thermography*.

Additional research articles are available on request:

Surgery Today
The American Journal of Surgery
Nanyang Technological University
Kingston General Hospital, (Ontario)
The American Cancer Society
Aston University, (UK)

5 Expert Systems in Complementary Oncology

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Introduction

The human organism is a highly complex system with an intricate network of various interrelated causes and effects. Diagnosis, prognosis, and therapeutic planning require a high level of medical expertise and experience. Due to the complex effects a disease exerts on the human organism, it is generally necessary to sift through of a lot of data in order to provide a good diagnosis and prognosis in any individual. Accordingly, the physician uses an extensive set of rules herein.

The evaluation of such medical data is increasingly supported through adaptive diagnostic systems based on mathematical models. In order to apply mathematics in a sensible way, a **mathematical model** of a section of the reality one wishes to work on is required. A mathematician might emulate the growth of bacteria in culture after an infection in otherwise healthy individuals. This model would in this case be a function or graphic depiction illustrating the time dependent amount of a type of bacteria observed in the blood after an infection present in a certain person. Such a function might look as shown in Fig. 5.1 (the units in the graphic are chosen arbitrarily). The progression of this function, e.g., time until the start of the immune response, was calculated by the mathematician by taking mean values of lots of data points. The model of bacterial growth obtained in such a way would, of course, be very simplistic, since it would be independent of other parameters like the person's age or the individual characteristics of the immune system.

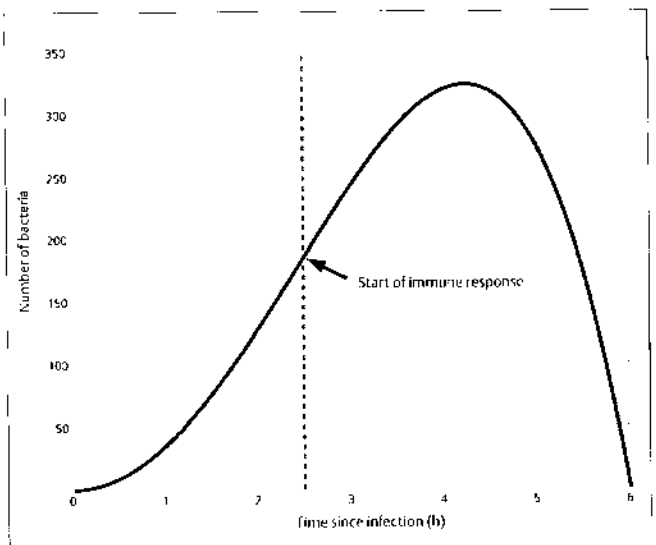

Fig. 5.1 Model for bacterial growth following an infection.

Mathematical modeling is often a complex, longwinded interactive process between experts from within the context of application and the mathematicians producing the model. Once a model is found it is evaluated and analyzed using mathematical methods. Nowadays the computer plays a large part in this. Without it, many of the models would be far too complex and therefore useless. In the evaluation, visualization is often the initial step for translation back into the specific context of application. This entire process is referred to as **simulation**—its computational part as **scientific computing.**

Mathematical Contribution to Diagnosis and Therapy

The diagnosis and therapy of diseases can be conceived as regulatory processes. In individual diagnosis, information on the actual disease state is achieved initially by assessing the medical history of and by questioning the patient, and also through a set of targeted procedures such as radiography and computed tomography or ultrasound. This information serves as the foundation upon which the physician, using his knowledge and experience will come up with a diagnosis and initiate therapeutic measures.

Expert systems can now be of manifold value in the diagnostic and therapeutic setting. A well-functioning expert system can guide doctors to the correct diagnosis by delivery of concrete suggestions for diagnosis, as well as supporting accumulation of the physician's own experience. In other instances, a different group of doctors can play a part in the development of an expert system—knowledge can thereby be integrated and made objective.

A large amount of medical data arise from clinics and private practices. Once used for diagnosis and treatment, these data are often not studied further. Here lies a tremendous potential for the extension, improvement, and safeguarding of existing medical knowledge. Through the application of systematic **data mining**, existing medical hypotheses can be verified and statistically validated. Software systems for automatic recognition of patterns in data can provide the impulse and motivation for research in a new direction.

Expert systems and data mining are pillars that provide the basis for computer-supported medical diagnosis and therapy, which has been gaining considerable importance in recent years. This novel medical field requires the intensive and interdisciplinary collaboration of physicians, mathematicians, computer specialists, physicists, and engineers. In addition to utilizing previously existing medical information more effectively, and learning from it through combination with medical expertise, expert systems could serve as integral components of a system that is yet to be constructed, consisting of interlaced medical data banks that would be provided online for physicians for diagnosis and therapy.

What is an Expert System?

> An expert system is a computer program that simulates an expert within a clearly defined area of expertise and terms of functions.

One example is the "Mycin" system developed in 1972, which helps the physician choose the type and dose of antibiotics. This system is made up of three main components:

- **Consultation component** After insertion of patient data and data pertaining to, say, the bacterial types detected in the blood sample, the system proposes an antibiotic for therapy, including suggestions for dosage. It is crucial to understand that data fed into the system may be vague: in this case, a morphological description of the organisms found in the sample can be given. The system tries to identify these through combination with other information.
- **Explanatory component** Following suggestion for therapy, it can be revealed which data and information was used.

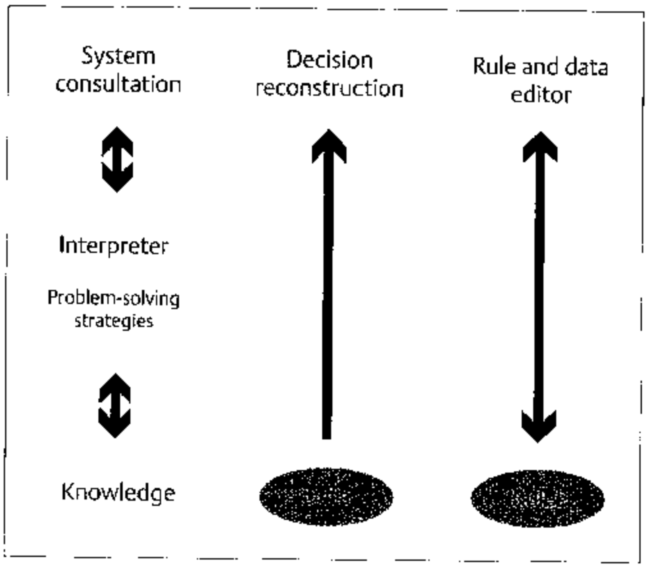

Fig. 5.2 Structure of an expert system.

- **Acquisition component** This component enables new expert knowledge to be integrated into the existing system, or current information to be edited. Entering new information does not require any knowledge of programing, and can be done entirely by the expert.

The structure of the "Mycin" system is prototypical for an expert system. Generally the structure is as shown in the depiction shown in Fig. 5.2, the components of which are to be described shortly. The arrows in the diagram symbolize the flow of data and the direction of flow.

The knowledge of a (medical) expert consists of data and rules, in which the handling of information is defined dependent on specific situations. Data are, for example, the characteristics of bacteria or the effects of certain medications. Accordingly, the fact that certain bacteria can be treated with certain medicines can be defined as a simple rule.

This perspective of expert knowledge is referred to as **rule-based approach** and is used throughout the entire chapter. An alternative is the so-called **object orientation**, in which data and rules are conceptualized as more abstract objects combined.

When considering integration of expert knowledge into a computer program two problem areas should be addressed:

- Data structures must be developed that are well suited for storing and retrieving human expertise—this occurs under the keyword

knowledge representation. The problems surrounding knowledge representation and their possible solutions cannot all be mentioned here, but will be described briefly below, see p. 58, under fuzzy logic, as a possibility of implementing knowledge.

- In association with the implementation of knowledge is its **formalization:** expert depictions of existing knowledge are generally too complex to be directly implemented into respective software. This is due to the complex nature inherent to language itself, but often also due to lack of formal structure. Therefore, before input into the expert system, relevant knowledge must be represented by means of a simple formal language. Ideally, the expert himself performs this translation process. This is especially important, since expert systems should be designed in order to be customized by the user: completeness of knowledge in a certain area can not be expected. This implies that the knowledge can be modified, updated and expanded using a software module, a so-called data and rule editor. Input via this editor ensues in the mentioned formal, but easily written and readable, language. Above all, system users are not expected to have any programming knowledge.

The **expandability of an expert system** is the precursor to learning aptitude: there are various techniques that permit automatic generation of new knowledge from entered data. Such procedures look for structures within the data and interpret them according to the rules of the pertaining expert system. These procedures rely mathematically on multivariate statistics, approximation theory, or cluster analysis. Neuronal networks also play a role.

The actual simulation of experts—the query of a specific situation within the area of expertise of the system—occurs through the **consultation module.** Following entry of data describing the situation, the interpreter analyses these, and compiles the rules needed, then applies these and finally displays the result in a user friendly manner.

Typically, the entered data are not precise. The interpreter must be capable of dealing with poorly delineated situations. Contrary to knowledge, strategies for entry-dependent collocation of the rules are permanently integrated within the system, or more precisely, in the interpreter, and cannot be altered by the user.

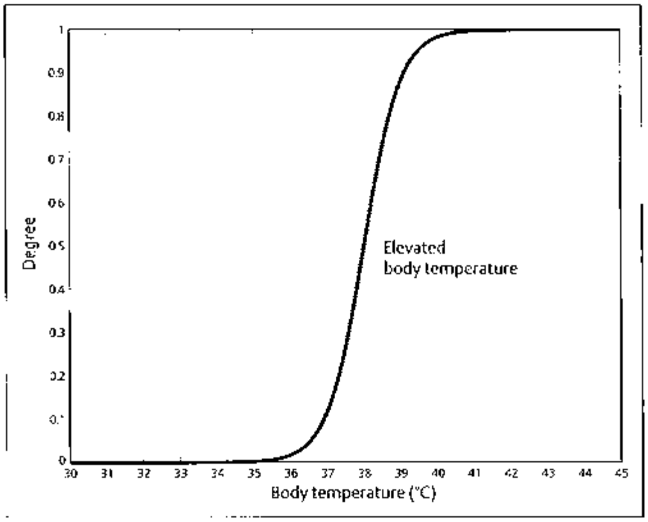

Fig. 5.3 Example of a fuzzy set.

For various ends, it is necessary to fully understand the route from given input data to output data within the expert system: controllability of the system should be mentioned, as should applications in expert training or the test of newly to be integrated knowledge. A structured depiction of the routes from entry to output offers a module for reconstruction of decisions.

Uses in Medicine

The use of expert systems in medicine does not differ much from that in other specialist areas. The following formulated areas of application can easily be transferred to other fields.

- **Relief for the doctor of performing routine tasks** The expert system can take over the classification of patient data for diagnostic purposes, including concrete diagnostic suggestions for the physician. A further field of application is the choice of a specific therapy, oriented according to the individual circumstances of a particular patient.
- **Improved availability of medical expert knowledge** An expert system can be used, among other things, as a specialist book or databank. The internet allows the functionality of expert systems to become available to the wider general public who in turn can use it to improve their health-related behavior and the surveillance of their own health.

- **Support of medical education** A complete expert system provides the user with the option of retrieving explanations for specific conclusions, arrived at by the system in a particular situation. The user can compare his conclusions with that of the system and, if necessary, correct them. Medical models are becoming increasingly realistic through interconnection with expert systems.
- **Objectifying knowledge using formalized depictions** The construction of an expert system requires clear and formal depiction of existing subjective knowledge on a particular circumstance. This enables knowledge to be comprehensible and traceable enabling full utilization of functionality of the expert system. The collaboration of multiple experts on a system makes this approach very effective.
- **Facilitation of validation of knowledge** or rather verification of hypotheses.

Since the demands that medicine places in terms of complexity and operational reliability are considerably higher than in the technical–scientific area, a warning should be given: none of the above mentioned points should be misinterpreted to the extent that competency of a medical expert can be replaced by a computer program.

Fuzzy Logic

The formal representation of knowledge in a computer program is problematic due to a variety of reasons: even when limited to a tightly confined area the knowledge to be integrated is too vast and networked too complexly for real-life applications.

Medical knowledge, in particular, is often vague. Transitions between "healthy" and "pathological" behavior can be blurred. The described entities often demonstrate considerable breadth in variety.

When utilizing rule-based representation of knowledge the networking of existing information is presented through logical rules. In the simplest case this occurs through logical implications, such as rules in the form of "A implies B." To assist in the problem of vaguely defined entities, an expansion of the basic prepositional logic is necessary—the so-called fuzzy logic.

Fuzzy Set

Fuzzy set is a concept that helps to determine the blurry entities in a specialist mathematical field. The term "elevated body temperature" is a typical vaguely defined term often found in medicine. It could be defined mathematically, specified as "body temperature above 37 °C." For application, e.g., within an expert system, a continuous transition between normal condition leading up to the condition of increased temperature would be desirable.

An alternative model would be to give a so-called fuzzy set for the characteristic "elevated body temperature" (Fig. 5.**3**):

This diagram gives you the specific amount at each relevant body temperature at which the body temperature should be considered "elevated." This degree of elevation assumes values between 0 and 1. Values close to 0 are to be interpreted as "(almost) not elevated," while values closer to 1 are to be looked at as "definitely elevated." In analogy to this example, any vaguely defined entity can basically be mathematically expressed.

Linguistic Variables

Expert knowledge partially consists of the formulation of characteristics of specific objects in the respective technical terminology. The re-creation of such formulations in fuzzy logic occurs through the use of linguistic variables: the observed object characteristic receives a name under which it will appear within the expert system. In addition, it must be clarified which properties or values this characteristic may assume. Crucial to this specification is that these values can be numeric, as well as technical, in nature.

For example, the linguistic variable "body temperature" can appear in an expert system. The possible values of this variable were temperatures from within the interval 30–45 °C.

Depending on the mode of application the following more complex construction could make sense: as possible values for "body temperature" the terms "normal," "elevated," or "fever" can be used. Each of these so-called **linguistic values** clearly must be defined more precisely. Since these are obviously blurry entities, specification ensues through indication of the respective fuzzy set, as described above in the example "elevated body temperature."

The advantage of this approach is in the increased viability and it allows the formalization of knowledge that as close to technical terminology as possible.

Fuzzy Rules

Fuzzy rules are expert regulations that are grasped based on fuzzy logic. All fuzzy rules can be traced back to a simple basic structure, namely the logical implication:

"If x equals A, then y equals B."

Both x and y are linguistic variables. The letters A and B stand for linguistic values that these variables can assume. Let us take, for example, the aforementioned linguistic variable "body temperature" for x, and "treatment with aspirin" for y with the linguistic values of "none," "moderate," and "high." A fuzzy rule would then be:

(1) "If body temperature is elevated, treatment with aspirin is moderate."

Now both "elevated" and "high" are blurry linguistic values specified through fuzzy sets. With "moderate" each dose of aspirin is related to a respective degree (how "moderate" is the dosing?). With each given body temperature rule (1) should provide the user with a suggested dosing. How this is to be determined, is the next question that needs to be addressed.

Fuzzy Implication

In Fig. 5.4, the fuzzy set for the linguistic value "elevated" can be seen. The prevailing body temperature is 37.8 °C as marked through a vertical line. The height of the gray area relates to the degree to which the respective temperature is considered "elevated."

Above and to the right is the depiction of the fuzzy set of the linguistic value "moderate." It is cut off at the height of the "elevated" degree belonging to the temperature of 37.8 °C. The remaining fuzzy set is depicted as blue.

The sense for this operation lies in treating all aspirin doses with a "high" degree (namely higher than the degree of elevated body temperature) in the same way. The particular degrees do not play a major role given the concrete body temperature.

When choosing a recommended dose, the smallest dose is taken at which the remaining fuzzy set shows a maximum as marked by a thick vertical line. With these simple procedures one combines low doses with high efficacy.

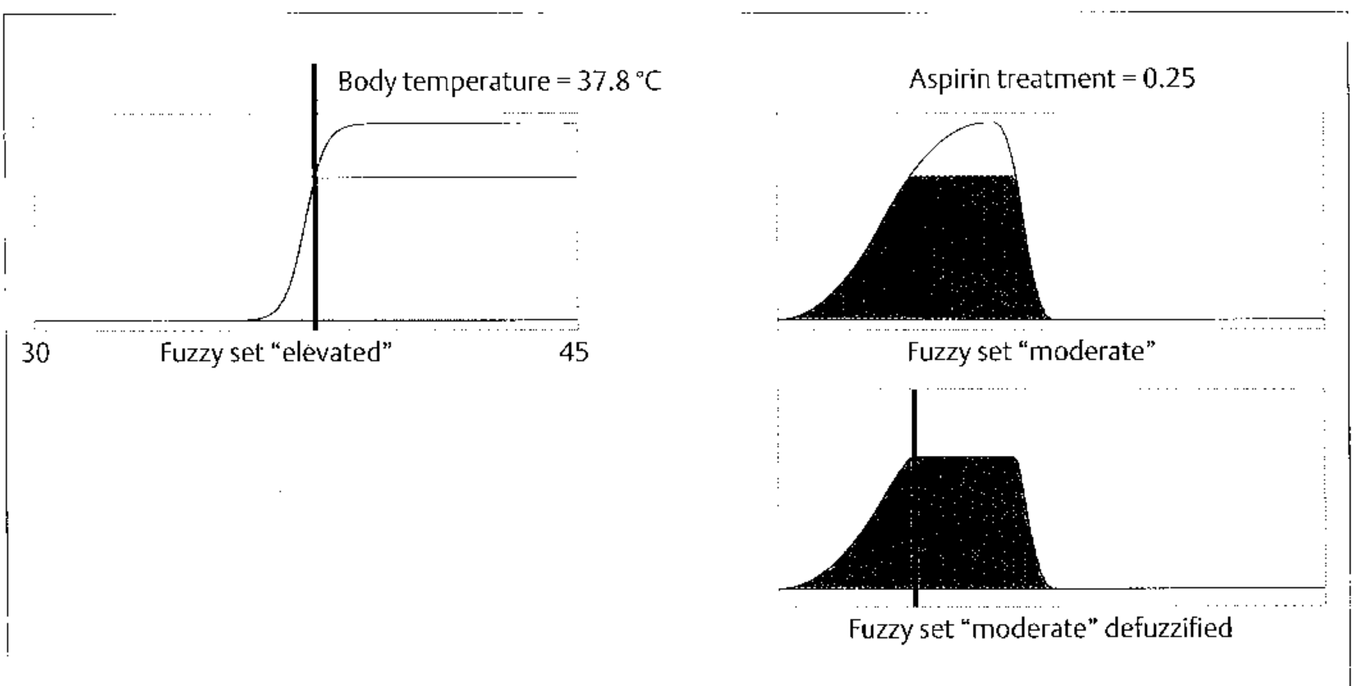

Fig. 5.4 Fuzzy implication and defuzzification.

The method shown is referred to as "fuzzy implication." The change of the initial fuzzy set, through cut-off and designation of a recommended dose, only offers one possibility from a slew of options from which, oriented according to the respective application, the designer of an expert system can choose. The designation of the recommended doses is generally referred to as "**defuzzification**" because a sharply defined numeric value is determined from a fuzzy set.

Fuzzy-Logical Operations

When generating more complex fuzzy rules the use of logical operators such as "and" and "or" is unavoidable. In the case of basic prepositional logic the meaning of such operations are clear, but not in the event of fuzzy logic: an expression such as "x equals A" is, in this case, always fulfilled to a certain degree that is determined by the respective fuzzy set.

If one constructs expressions of the type "(x equals A) and (y equals B)," one must calculate in each event the degree of fulfillment of "(x equals A) and (y equals B)" from the degree of fulfillment of "x equals A" and "y equals B." This occurs through declaration of a general calculation provision for the fuzzy set of an expression determined through conjunction of "and"—and "or"— interconnections based on the fuzzy sets of its components. All the mathematical details cannot be presented here.

Combination

The complexity of expert knowledge, and thereby also of expert systems, is caused for the most part due to a combination of rules with the same linguistic variables, but opposing influences on the values of these variables.

Taking a look, for example, at the following two fuzzy rules:

1. If body temperature equals fever, then high aspirin dose
2. If trouble with stomach lining, then moderate aspirin dose

In this case, the recommended dose for aspirin must be ascertained from two opposing rules. Basically, this can occur if one determines the degree of the variables for "aspirin treatment" separately

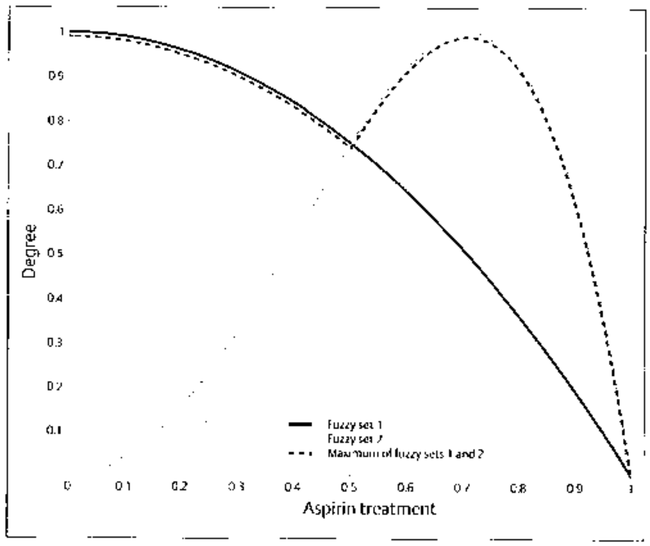

Fig. 5.5 Aggregation of two fuzzy set. The blue (or gray) line indicates the linguistic value "moderate" or "high" of the co-variable "aspirin treatment." The dotted line indicates their maximum.

for both rules according to the depicted procedure (see above Fuzzy implication). A weighted average of the two values can then be taken. The weights can be adjusted according to the importance of the rules.

However, fuzzy logic uses a more complex approach: as in the case of logic operations, the new fuzzy quantity is first established by superposing the modified fuzzy quantities for the linguistic values "high" and "moderate." One refers to this step as aggregation, and, as with defuzzification, a lot of possibilities exist for the aggregation procedure that can be chosen depending on the specific application. Fig. 5.5 shows the formation of a maximum of two fuzzy sets in such an aggregation procedure.

Example: Interpretation of Regulation Thermograms

Regulation thermography offers a typical example for the application of a rule-based expert system. This diagnostic procedure of complementary medicine is based on recognition and evaluation of pathological patterns in body temperature. In the field of complementary medicine within oncology, much expert knowledge exists for the detection of breast cancer and gastrointestinal cancers using the methods of thermography. It plays a part, not only when determining patterns to be recognized, but also in their interpretation for diagnosis.

Regulation Thermography

The functions of the human body depend largely on its temperature. In order to maintain an optimal distribution of temperature throughout the body, it possesses a complex control and regulating system, the center of which is located in the hypothalamic region of the brain. For example, in reaction to incoming impulses in this region from cold or warm receptors, the production of heat in the organism can be regulated by increasing or decreasing metabolic activity. Regulatory impulses run from the brain to the skin as well, where they can influence the amount of heat that is perspired through contraction of blood vessels. The nerves through which these impulses pass can interact with nerves running within the spinal column from the internal organs to the brain. In this way a pathological disturbance within an organ can lead to a change in thermal regulation of the skin—this is referred to as a **reflex arc**.

Regulation thermography attempts to measure and interpret these changes in the regulatory behavior. The goal is to associate certain changes in regulatory behavior with specific diseases. According to expert opinion, this is possible: an extensive pool of pathological temperature patterns and their diagnostic interpretation is available.

Regulatory behavior is determined by the twofold measurement of the test person's body temperature on defined parts of the body (**areas**). The first measurement ensues after the test person has undressed in an examination room with standardized temperature and humidity. The room temperature should be below normal body temperature, which induces a cold stimulus that, in turn, stimulates the regulatory system of the body. After a defined period of time the measurement is repeated. The body will then have reacted to the cold stimulus. The comparison between the first and second measurements allows a conclusion to be drawn as to the regulatory activity of the skin.

The entirety of the measured temperatures is referred to as a **regulation thermogram**. Fig. 5.6 depicts an ideal thermogram in form of a histogram: shown as the temperature values of 60 areas. Abbreviated designations for areas can be seen on the horizontal axis above on the diagram, the first temperature measurements are the black rectangles and the second are blue. All rectangles refer to the horizontal black line, the forehead temperature (measured first). The individual temperature values can be read on the left vertical axis. Figure 5.7 depicts a pathological thermogram of a woman with breast cancer.

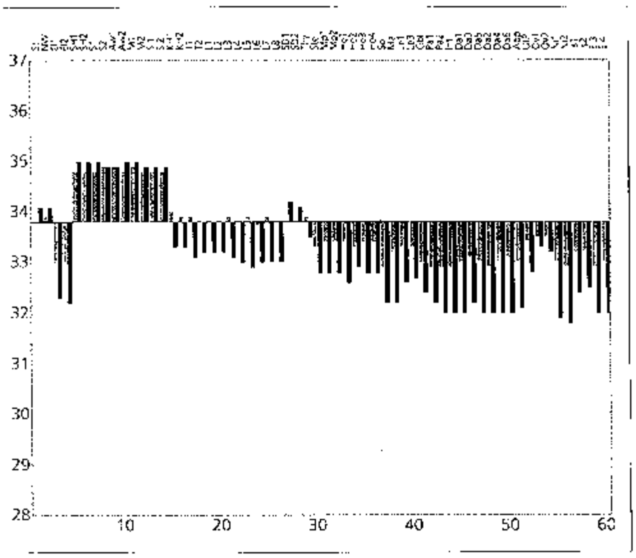

Fig. 5.6 An ideal thermogram presented in the form of a histogram.

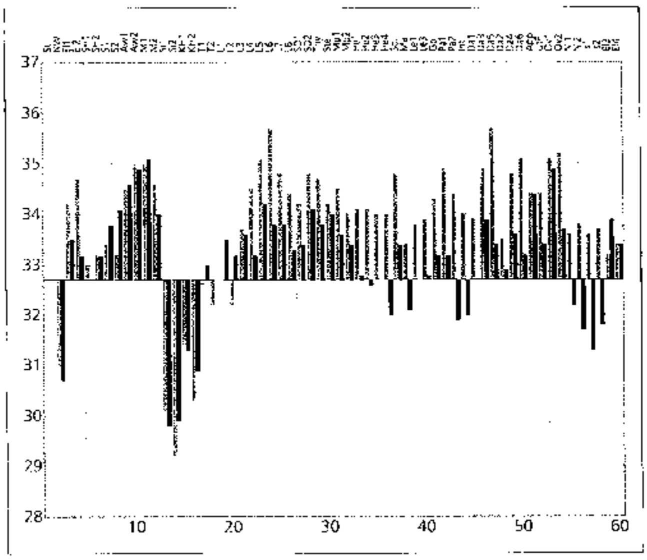

Fig. 5.7 For comparison, the thermogram of a woman with mammary carcinoma.

Fuzzy Modeling of Expert Knowledge

The regulation thermogram encompasses temperature measurements at 110 areas. Expert knowledge of pathological activity in three areas within the thoracic regions—the sternum, as well as the two asymmetrically aligned pectoral muscle areas—serves as an example in the following thermogram.

These areas are used during evaluation of thermograms in reference to breast cancer in women. All further numeric values mentioned are more or less accurate (according to current scientific standards), but are to be taken merely as examples.

The following validation criteria are applied to all three areas:

- **Absolute temperature** For each area, the difference between the first value at the area and the first value on the forehead is tested. Differences in temperature smaller than −0.8 °K and bigger than +0.2 °K are considered pathological. The first event is termed a **cold area**, while the latter case is considered a **hot area**. Overstepping or falling short of the indicated boundaries is considered to be all the more pathological, the more pronounced the deviation.
- **Regulation** In this case, the difference between the first and second measurement is observed for each area. If the difference falls below −1.1 °K, this indicates a so-called **hyperregulation.** Exceeding beyond the value −0.25 °K, a phenomenon known as **paradoxical regulation**, is also considered pathological. When comparing hyperregulation with paradoxical regulation, the first is regarded to be less pathological.

The pathologies of absolute temperature and regulation should be added for a combined overall rating. This occurs according to the following guidelines:

- Regulation pathologies carry more weight than absolute temperature.
- When both pectoral muscle areas exhibit different activities, the more pathological of the two is included in the final assessment.
- Activity of the sternum area and the more pathological pectoral muscle areas are of equal importance.

The valuation rules suggest fuzzy modeling using two linguistic variables: "Abs Temp" as one variable to designate the absolute temperature of one area, with the linguistic values "normal," "cold," and "warm"; "Reg" as another variable with the values "normal," "hyper," and "paradox" to record the observed regulation.

Now these linguistic values need to be specified through indication of fuzzy sets. Figure 5.**8** shows the fuzzy amounts of the values of the variable "Reg." These were determined using temperature values denoted in the valuation rules, otherwise modeling was kept fairly simple, since no further information was specified.

An observed regulation of −0.1 °K as measured at the sternum area was classified, for example, as paradoxical with a degree of pathology approximately 0.8, as normal with a degree of approximately 0.2, and as hyperregulation with a degree of 0.

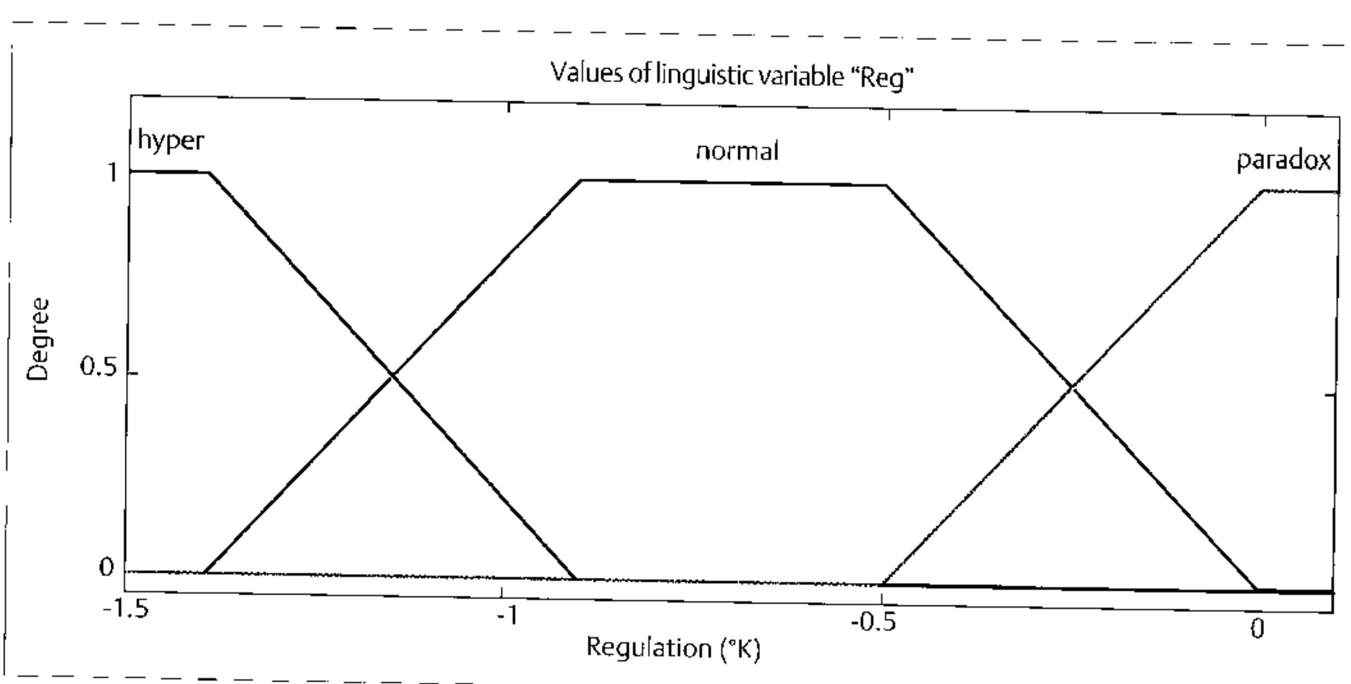

Fig. 5.**8** Definition of linguistic values.

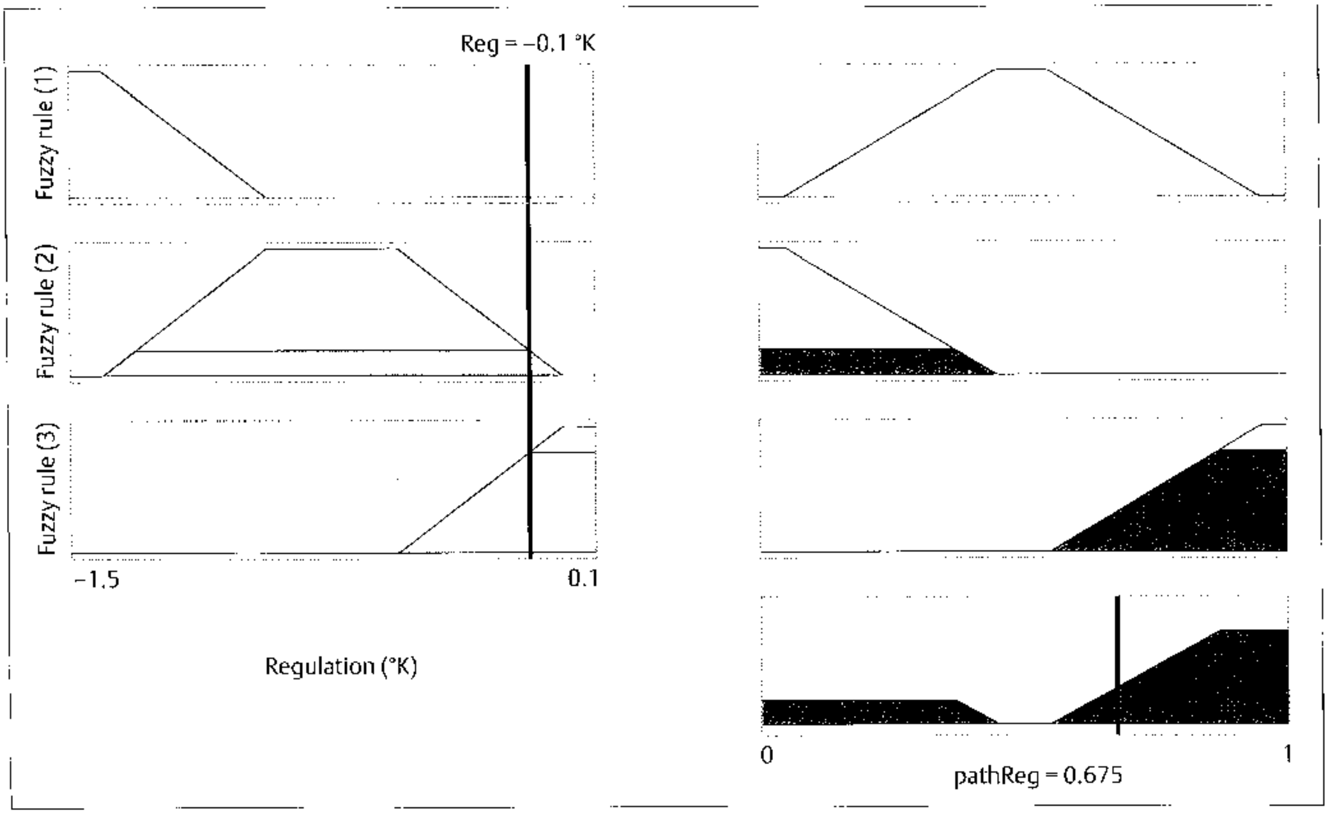

Fig. 5.9 Evaluation of a block of three fuzzy rules.

The assessment of an area as pathologically active is determined based on linguistic variables, separately for absolute temperature and regulation, respectively. For regulation, "PathReg" is the variable used, for example. Attributed linguistic values would be "negative" (no pathological activity), "positive" (pathological activity is present) and "suspicion" (suspicion of pathological activity). As already described, a fuzzy set is determined for these linguistic values based on pre-existing knowledge.

The expert rulings for assessment of regulation of each of the three respective areas can now be expressed by way of fuzzy rules as follows:

1. If (Reg = hyper), then (PathReg = suspicion)
2. If (Reg = normal), then (PathReg = negative)
3. If (Reg = paradoxical), then (PathReg = positive)

The application of this block of rules should offer the user a "degree of pathology" for regulation observed in the respective area. Figure 5.9 demonstrates the process for determining the degree of pathology for an entered value of –0.1 °K for the regulation: it is at approximately 0.68, clearly indicating a pathological activity in the observed area (0.0 = nonapplication of a fuzzy assertion; 1.0 = accuracy of a fuzzy assertion).

In Figure 5.9 the first three lines of the graphic stand for the three fuzzy rules in the sequence of appearance (1–3): on the left side you see the fuzzy sets for each of the linguistic values of the variable "Reg" of the respective rule. The vertical line represents the observed regulatory value of –0.1 °K; the height of the gray areas denote the degree of truth of the denotations "Reg = hyper," "Reg = normal" or "Reg = paradox."

On the right side you see the fuzzy sets for the linguistic values of the variables "PathReg." The heights of the blue surfaces show the true values for "PathReg = suspected" or "PathReg = negative," or "PathReg = positive."

The last line of the graphic entails the result of aggregation and defuzzification: the end result—the degree of pathology of regulation at an area—is depicted by a vertical bar.

Figure 5.10 gives an overall oversight of the dependency of the degree of pathology on regulation in areas observed.

In a similar way, expert behavior on activity of absolute temperatures can be gathered with the help of linguistic variables for absolute temperatures and likewise linguistic variables for the degree of pathology of absolute temperature.

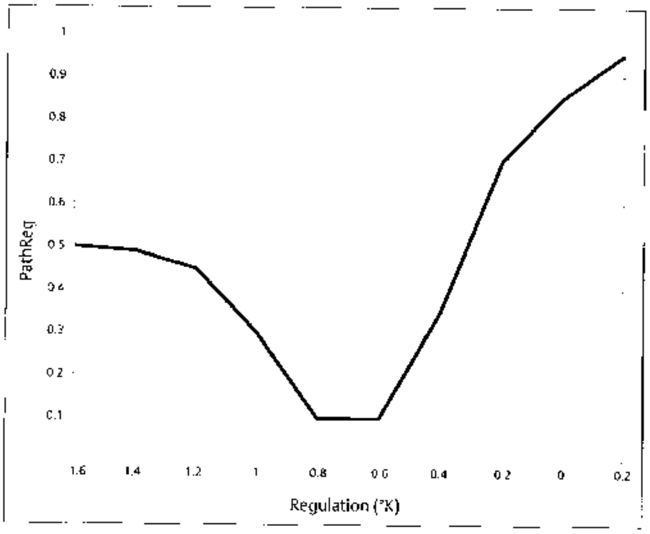

Fig. 5.**10** Correlation between regulation and degree of pathology.

Finally, the determined degree of pathology for absolute temperatures and regulations of all three areas must be combined to yield a single value.

This occurs in two steps: first, a weighted mean value is determined from the degrees of pathology and regulation for each area. The fact that regulation carries more weight is accounted for. In the second step the third line of expert rules are followed by combining the mean with the maximum of the just calculated degree of pathology in the three areas.

The minimum degrees of pathology can be seen to lie between −0.8 °K and −0.6 °K. The visible increment in degree of pathology in the left branch of the function graphic shows the increasing hyperregulation. The right branch shows paradox regulation. According to expert opinion, much higher degrees of pathology are reached here in comparison to the left branch. One can discern the minimum degrees of pathology to fall between the values −0.8 °K and −0.6 °K. The notable increase in degree of pathology of the left branch of the function of the graph indicates the increasing hyperregulation. Paradox regulation is represented by the right branch in the graph. Here considerably higher degrees of pathology are reached than in the left branch.

— Design of an Expert System for Regulation Thermography

Regulation Thermography lends itself not only to the presentation of knowledge via fuzzy logic, but also other points important for the programming of a medical expert system can be elucidated with this example.

Creating a Body of Rules

The construction of fuzzy rules on the basis of existing knowledge is basically also possible for the layman. Nonetheless, some steps are necessary during this process, which may require the collaboration between a medical expert and mathematician: the choice of methods to be used for logical implication as well as aggregation and defuzzification. These methods are, for the most part, determined at the beginning of the development process of a system and are left unaltered in the once functioning expert system. Nevertheless, they are dependent on mode of application and must be chosen via engagement with a medical expert.

Specification of linguistic values of fuzzy sets is a different story: in this case expert knowledge is incorporated, and the special structure of fuzzy sets must be determined. In the example of "elevated body temperature" this is given by the curve depicted in blue (see Fig. 5.**3**, p. 57).

The medical expert normally does not have a preconceived notion of such a structure. This frequently evolves either indirectly from existing knowledge or it must be determined through the iterative process of trial and error: a backbone network appropriate for the respective linguistic value is primarily set up, and then changes are made to the details until they show the desired activity within the expert system. The latter can naturally only be appraised in dialogue with a medical expert.

Automatic Generation of Rules/ Hypotheses

The adaptive process for the definiton of fuzzy sets described above can partially be automated, given the appropriate data: a physician must specify the desired output for a sufficiently large amount of input data into the expert system, based on his or her expertise. Following entry of this training data set into the expert system, the actual output is compared with the desired output. On the basis of comparison, the system is modified. This process is repeated until a satisfactory accord between desired and actual output is achieved. The modification does not necessarily need to be performed manually, but can be done using a computer software program.

The process of automation of system modification can be taken even a step further: given a training data set that is extensive enough, fuzzy rules can directly be extracted from the latter using various mathematical procedures, and integrated into the system's rule databank. The physician is then able to read these rules and verify their meaning, possibly even testing them as hypotheses.

Neuronal Networks

Instead of using training data sets to develop fuzzy rules, the desired system output can also be reproduced directly by creating a mathematical mapping. When input and output data are numerical values, they lend themselves well to neuronal networks. They can be easily and swiftly modified to account for additional new training data sets, thereby enabling a constant stream of learning.

The disadvantage vs. the automatically generated fuzzy rules is that the developed depictions using neuronal networks are generally not useful for medical interpretation. Combination of fuzzy rules with neuronal networks is widely used and usually leads to improvement in quality of output.

In the realm of complementary oncology, regulation thermog raphy is used, among others, for

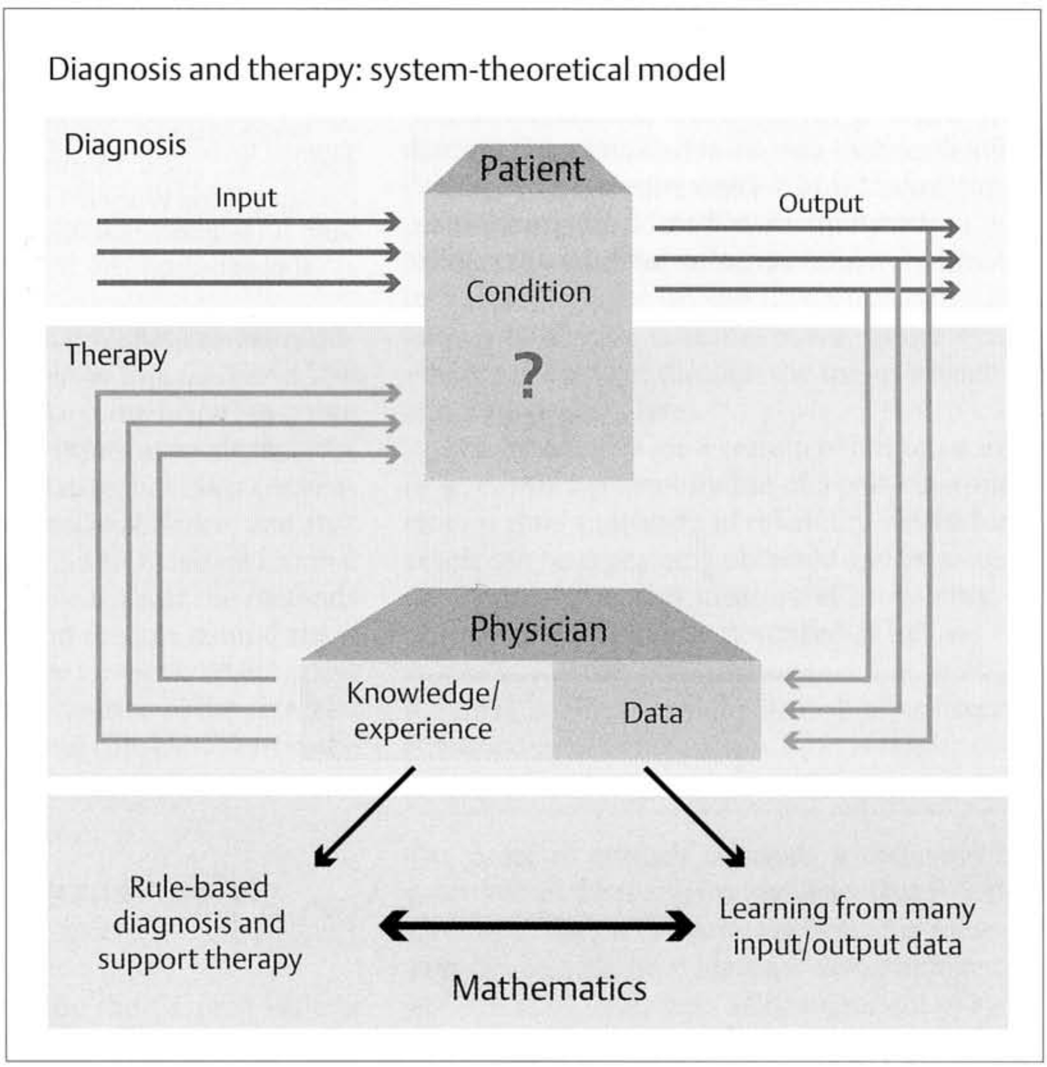

Fig. 5.11 Structure of an expert system for regulation thermography.

early detection of cancer. Depending on the pathological temperature patterns in the thermogram a six-point scale (0–5) is devised to indicate tumor-cell activity (TCA): A TCA of 0 designates "no trace of tumor-cell activity detectable within the body." The more pronounced the observed pathological patterns are, the higher the value will be for TCA.

From the 220 temperature values comprising the thermogram, the TCA is determined to represent the classification profile. This is a situation in which neuronal networks can be applied directly: a neuronal network trained on the basis of a data set commensurate in size can deliver an approximated TCA classification of new thermograms not entailed within the training data set.

Within the context of expert systems for regulation thermography there is yet another area of application for neuronal networks: expertise for determination of TCA classification can be divided into "global" and "local" rules. The thermogram can be subdivided into 10 groups of areas that do not overlap. For each of these groups of areas there is a set of expert rules that are only used by this group and indicate a "degree of pathology" when taken together. The degrees of pathology of the individual groups are ultimately merged through "global" rules for TCA. These rules are far more difficult to determine than their "local" counterpart. It therefore makes sense to (additionally) utilize well-suited neuronal networks at this point: as input the degrees of pathology of the groups of areas are taken, and as output the TCA of a thermogram is measured.

In total, the result for the case of regulation thermography is the following extension (Fig. **5.11**) of the expert system structure shown in Fig. **5.2**: a neuronal network has been added for approximate estimation of TCA directly from the thermogram. A so-called neuro-fuzzy system allows for extraction of rules from a set of data as well as providing a neuronal network for determination of TCA from the 10 degrees of pathology of the area groups. Both components can be delivered and trained with data via a training module as specified by a medical expert.

Further Reading

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