Complementary Medicine

Complementary Oncology

Adjunctive Methods in the Treatment of Cancer

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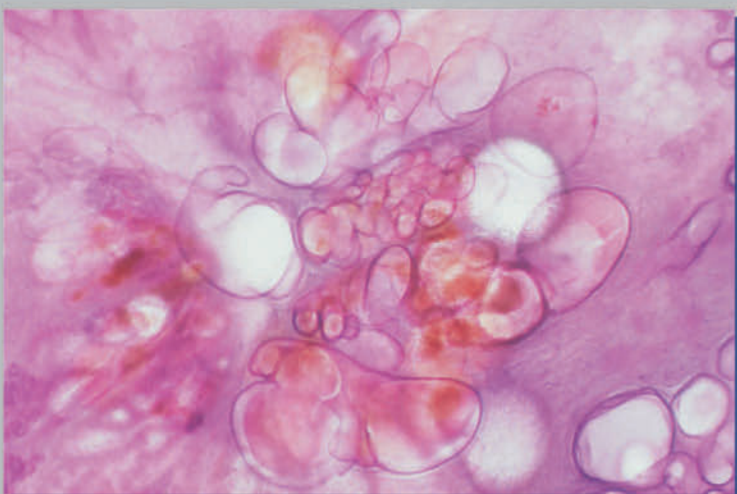

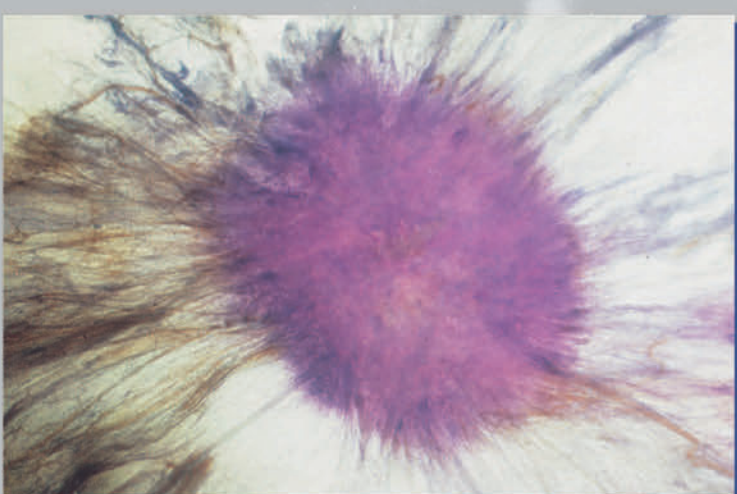

Thieme

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.

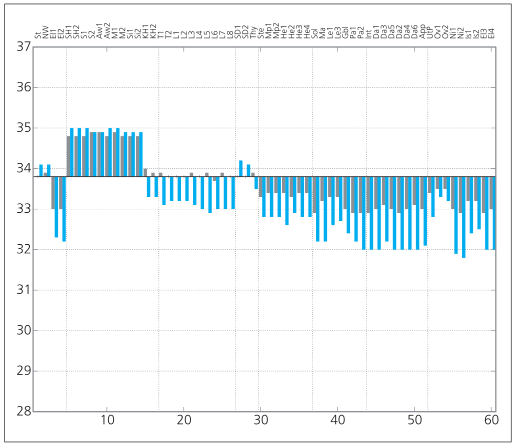

Fig. 5.**6** An ideal thermogram presented in the form of a histogram.

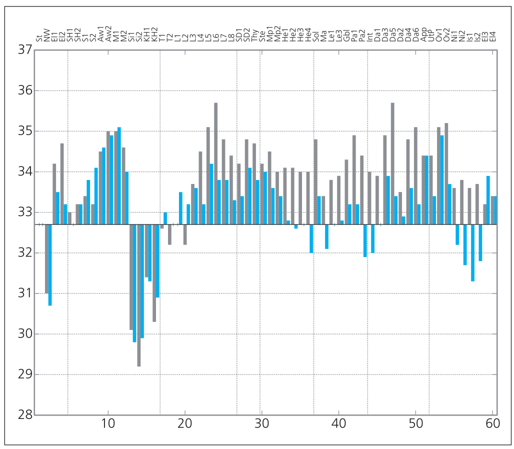

Fig. 5.**7** For comparison, the thermogram of a woman with mammary carcinoma.

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.

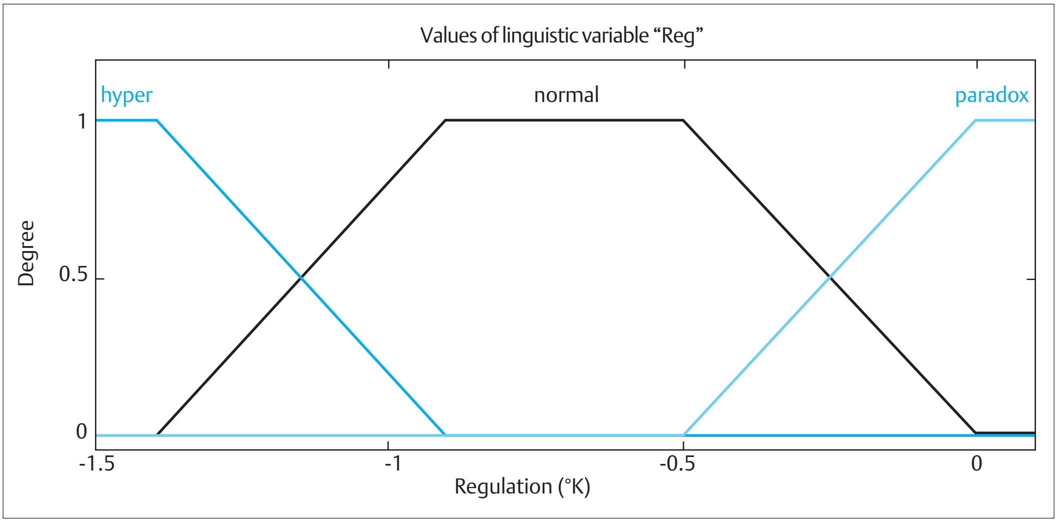

Fig. 5.**8** Definition of linguistic values.

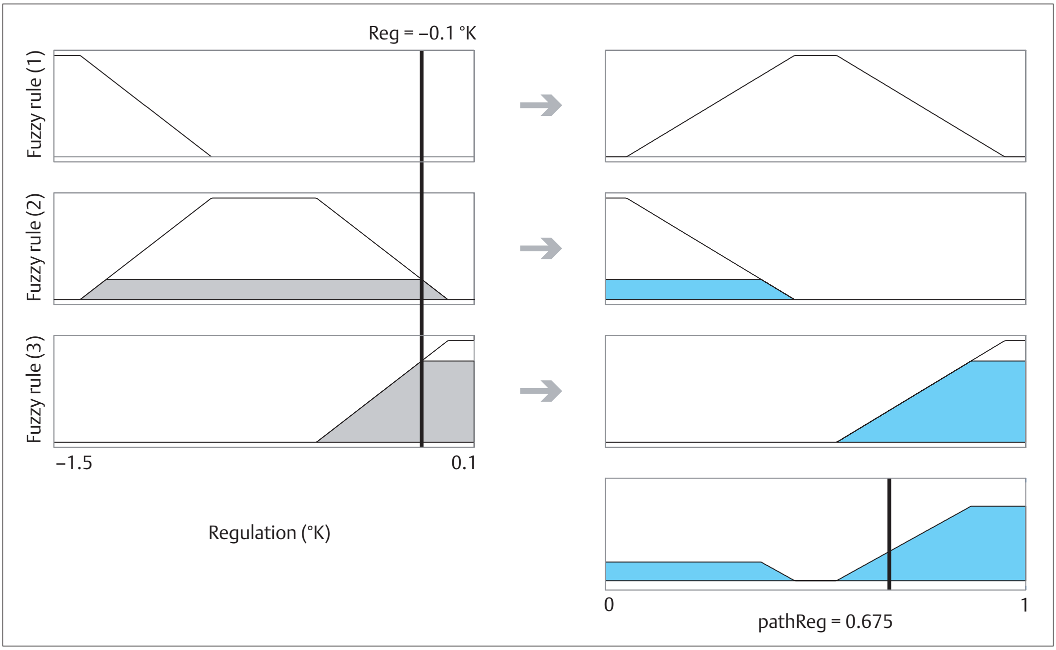

Fig. 5.**9** Evaluation of a block of three fuzzy rules.

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.

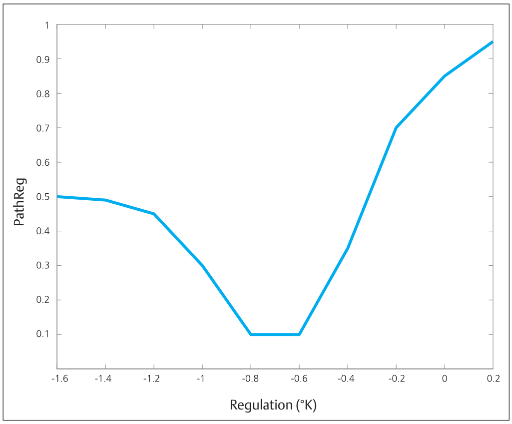

Fig. 5.**10** Correlation between regulation and degree of pathology.

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

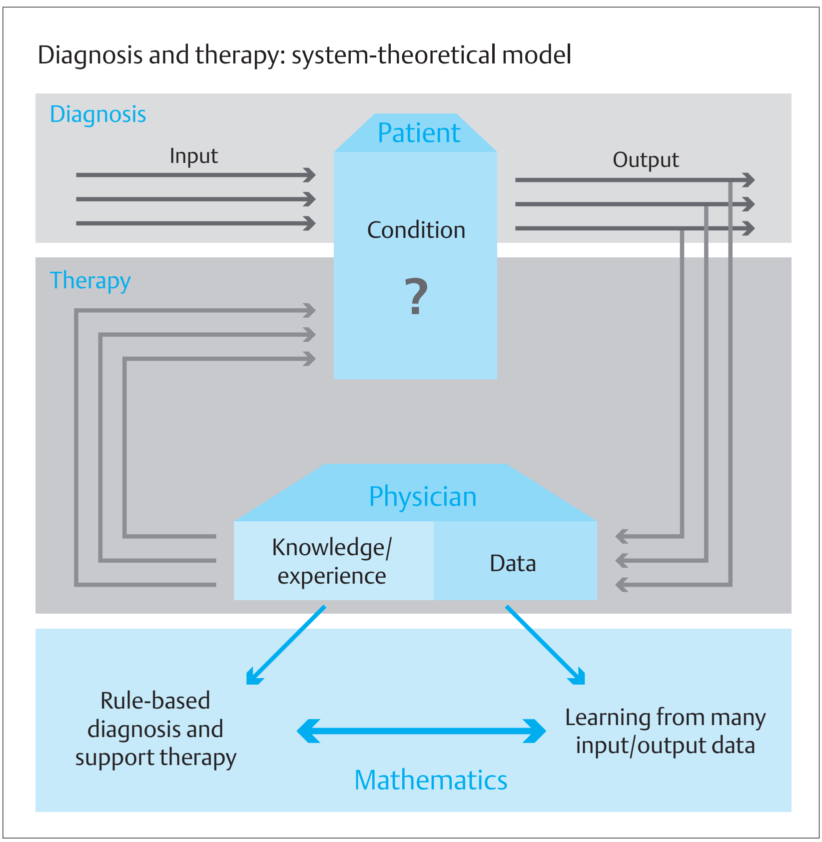

Fig. 5.**11** Structure of an expert system for regulation thermography.

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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