Evaluation of Disease Severity and Patient Disability Using the LSP Method

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Abstract

We present quantitative models for evaluation of disease severity and patient disability using the LSP method. We use as an example peripheral neuropathy, a common neurological condition with many causes and a wide range of severities. LSP models can incorporate both subjective symptoms and objective impairments; can be used by both doctors and patients to quantitatively evaluate the current level of severity or disability; and can be applied serially to analyze the progression of disease over time and the response to treatment. The presented method is generally applicable to all medical evaluations where it is important to create precise quantitative severity or disability models based on sophisticated logic conditions.

Keywords: LSP method, peripheral neuropathy, disease severity, disability evaluation, OSD, ODD, PDD.

1 Introduction

One of the main goals of soft computing is to develop mathematical models that describe phenomena based on variables that are a matter of degree [17]. Many medical conditions cause symptoms and impairments that are also matters of degree, and which manifest the severity of the condition [11][20][19][14]. In this paper we focus on evaluating the disease severity and patient disability using the LSP evaluation method. We use peripheral neuropathy to exemplify the proposed method.

In the area of evaluation of medical conditions we differentiate three types of evaluation models, and three types of users. The basic types of disease evaluation models are:

- Medical criterion of disease severity
- Models of patient disability
    - Medical disability model
    - Patient disability model

Three main users of evaluation models are:

- Physicians
- Patients
- Social and/or health organizations

Our classification of three fundamental medical evaluation problems and corresponding severity and disability indicators is shown in Fig. 1. We assume that each medical condition can be characterized by a comprehensive set of disease severity and disability attributes (S/D attributes). Appropriate subsets of S/D attributes are then used as inputs for each of the three basic models.

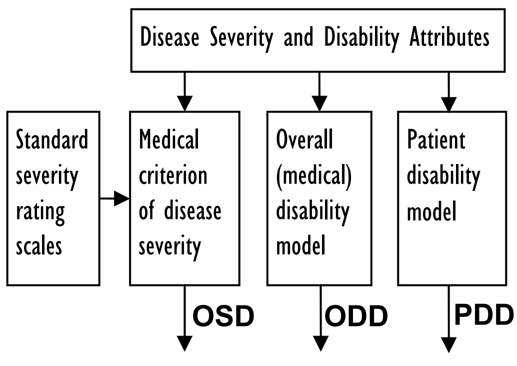

Figure 1. Types of disease evaluation models

Disease severity is the focal point of medical interest. It reflects all symptoms and impairments (loss of anatomic structure or function) caused by the analyzed disease. The goal of severity evaluation is to generate highly standardized indicators that are suitable for comparison of patients and unified assessment of their condition. Disease severity is evaluated by medical examiners based on objective measurements of selected impairment degrees, and quantification of symptoms by patients (e.g. as scores on symptom questionnaires). The end result of evaluation is an *overall severity degree* (OSD). In our models OSD$\in$[0,100%] where 0% corresponds to normal conditions and 100% corresponds to the maximum severity. OSD aggregates all relevant medical inputs and can also incorporate elements from existing severity rating scales [14][9][10][12][13]. A standardized OSD can be used by physicians as a reliable indicator whose threshold values support difficult decisions, particularly those that involve treatments which carry risk of serious adverse effects.

As opposed to the standardized evaluation of disease severity, patient disability refers to the degree of restriction in patient activities. Consequently, the level of disability depends on specific characteristics of each patient, such as his/her age, gender, profession and hobbies. Some patients may be very disabled at a relatively low level of severity. Others may reach a high level of severity without significant disability. Disease severity and patient disability are positively correlated, but are different indicators [9].

Regarding the level of standardization of disability indicators, we distinguish between the patient disability evaluation model and the overall medical disability model. The patient disability evaluation model is designed to be used by patients for self-evaluation and the disability trend estimation. The self-evaluation results can help patients make decisions about accepting or declining proposed treatments. Consequently, inputs to such models consist of S/D attributes that are easily understandable and easily assessed by the patient without technical assistance. The resulting *patient disability degree* (PDD$\in$[0,100%]) reflects the patient's view of his/her own disability.

Precise quantification of a standardized *overall (medical) disability degree* (ODD$\in$[0,100%]) is of interest both to physicians and to organizations that provide health and social services to patients. Such indicators should be designed by medical experts in order to provide support for administrative decisions, such as disability benefits, retirement conditions, etc.

The three severity and disability indicators, OSD, ODD, and PDD reflect various criteria, but they are designed using the same LSP methodology. In order to minimize medical prerequisites for understanding the proposed methodology, in this paper we present a model for computing a PDD for peripheral neuropathy.

The disability and severity rating scales used in clinical practice are regularly based on simplistic additive scoring. These scales enjoy wide acceptance because they are easy to administer. The additive scoring approach yields indicators of low granularity and insufficient precision. Its validity is investigated in [11][16][19].

Current medical rating scales do not use graded logic functions and other useful features of soft computing decision models. The main goal of this paper is to demonstrate how soft computing methods and corresponding software tools can increase the precision of medical evaluations.

2 Limitations of medical rating scales

The primary goal of medical rating scales is to serve as standardized instruments for measuring disease severity or patient disability. Such scales usually score several attributes and add individual points to generate an overall score. The score can be used by medical personnel both to rate disease severity and to support treatment decisions. An impressive number of different rating scales is used in the neurological field [14].

In the area of peripheral neuropathy [1], popular rating scales include the Neuropathy Symptom Score (NSS) and the Neurologic Disability Score (NDS) [9][10], the Overall Disability Sum Score (ODSS) [18] and its modified version the Overall Neuropathy Limitation Scale (ONLS), [12], Walk-12 [13] (same as the Multiple Sclerosis Walking Scale (MSWS) [15]), and others.

The concept of medical rating scales is shown in Table 1. There are K evaluated S/D attributes and each is scored according to the patient's degree of limitation. The patient is asked to select in each row one of N scores that best describes his/her degree of limitation. The value of N is typically small. For example, in the case of ONLS N=3 (1=not affected, 2=affected but not prevented, and 3=prevented); in the case of Walk-12 N=5 (1 = not at all, 2 = a little, 3 = moderately, 4 = quite a bit, 5 = extremely).

Table 1. Scoring of the limitation of abilities

S_{ij} = ability limitation score $S_{i1} < S_{i2} < ... < S_{iN}; 1 \le i \le K$		Limitation level		
		Min	…	Max
Limitations of K abilities (S/D attributes)	Ability #1	S_{11}	…	S_{1N}
	…	…	…	…
	Ability #K	S_{K1}	…	S_{KN}

Minimum score = $S_{11} + S_{21} + ... + S_{K1} = S_{\min}$

Maximum score = $S_{1N} + S_{2N} + ... + S_{KN} = S_{\max}$

Total score $= S = \sum_{i=1}^{K} S_{ij_i}; \quad j_i \in \{1,...,N\}$

Normalized score:

$$S_{norm} = 100\frac{(S - S_{\min})}{(S_{\max} - S_{\min})} \in [0,100\%]$$

Theoretically, individual scores in each row could belong to different ranges, to reflect different levels of importance of the investigated abilities. Unfortunately, this is not the case in many popular scales (including Walk-12); it is assumed that all items have equal importance. The total score satisfies the condition $S_{\min} \le S \le S_{\max}$ and therefore it is useful to apply the normalized score which directly reflects the overall limitation of abilities.

Table 2. The Walk-12 S/D attributes

1 Ability to walk	2 Ability to run	3 Climbing up/down stairs
4 Difficulties in standing	5 Balance problems	6 Length of walk
7 Effort needed to walk	8 Support for walking indoors	9 Support for walking outdoors
10 Slowed down walking	11 Smoothness of walk	12 Need to concentrate on walking

In the case of Walk-12 we use 12 S/D attributes shown in Table 2. Consequently,

$$K = 12, \quad N = 5, \quad S_{ij} = j, \; j = 1,..,5$$

$$S_{11} = ... = S_{K1} = 1, \quad S_{\min} = 12$$

$$S_{1N} = ... = S_{KN} = 5, \quad S_{\max} = 60$$

$$S_{norm} = 100(S - 12)/48$$

Each of the 12 Walk-12 S/D attributes has equal weight. The granularity of this scale (the increment of S_{norm} caused by a single increment of one of the attributes) is $\gamma = 100/[K(N-1)] = 100/48 = 2.08\%$. The maximum effect of any attribute (the difference between the case without limitations and the case with extreme limitations) is $\delta = 100/K = 100/12 = 8.3\%$. So, according to Walk-12, the difference between a patient who is almost unable to climb up or down stairs and a patient who performs this activity without any problem is only 8.3%. Furthermore, the ability to run is initially weighted equally as the ability to walk even though walking is much more important for most daily activities. The importance of standing in Walk-12 is only 1/12 even though standing is indispensable for a number of professions. Such properties, considered isolated, are highly questionable. The only reason why the results of such rating scales are not meaningless is that all the analyzed abilities are highly correlated, and the positive correlation significantly compensates for errors in additive scoring models [4].

The presented properties of Walk-12 are typical for all simple additive scoring scales. The main disadvantages of the simple additive scoring approach are:

- All S/D attributes are equally important.
- Addition of points prevents the use of more appropriate logic aggregators of inputs.
- Increasing the number of inputs decreases their relative importance.
- Redundant questions artificially increase the relative importance of correlated inputs.

Walk-12 is an example of a standardized medical rating scale. Patients of different gender and age are evaluated using the same criteria and Walk-12 requests patients to "answer all questions even if some seem irrelevant to you." This approach clearly reflects the standpoint of the medical examiners, with the intention that all examiners use the same instrument and generate consistent scores. Of course, this approach is not appropriate for evaluating patient disability.

3 The LSP method for soft computing of OSD, ODD, and PDD

The Logic Scoring of Preference (LSP) [6][21] is a quantitative evaluation method based on the Continuous Preference Logic (CPL) [8]. In the area of medical evaluation the LSP method can be used for building complex criteria for the evaluation of the disease severity and patient disability based on a set of S/D attributes.

The structure of LSP criteria is summarized in Fig. 2. A general database of S/D attributes is used for selecting a subset of n attributes that are appropriate inputs for one of the three fundamental evaluation models that generate

OSD, or ODD, or PDD. Some inputs are provided by the doctor, and others are provided by the patient. Inputs include objective measurements, expert assessments, and subjective ratings of symptoms.

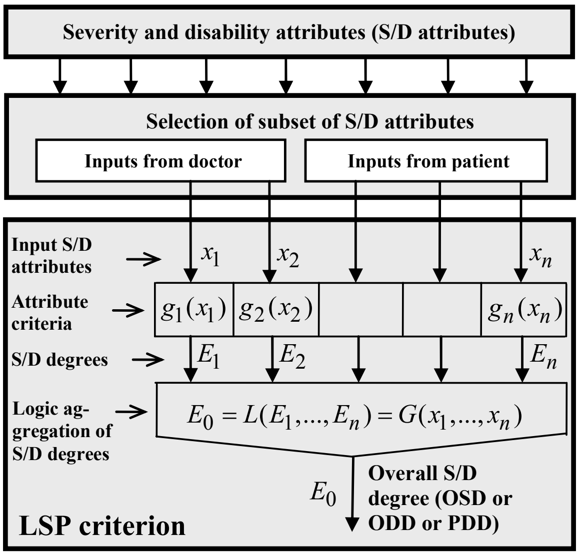

Figure 2. The structure of an LSP criterion

For each S/D attribute we create an individual attribute criterion that determines the individual degree of severity/disability (S/D degree). E.g., a typical elementary attribute criterion for the patient's length of walk L is shown in Fig. 3.

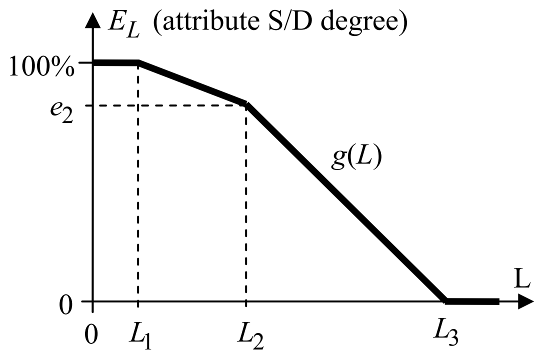

Figure 3. An elementary attribute criterion $E_L = g(L)$ for the length of walk L

If the patient can walk only some very small distance $L_1 \geq 0$, then we consider that the corresponding S/D degree is 100%. If $L = L_2$ then $E_L = e_2 < 100\%$. Finally, if $L \geq L_3$ then there is no impairment and $E_L = 0$. The criterion function $E_L = g(L)$ is usually defined as a piecewise linear approximation. In such cases the elementary attribute criterion can be symbolically denoted as a set of breakpoints:

$$EC(L) = \{(L_1,100),(L_2,e_2),(L_3,0)\};\ L_1 < L_2 < L_3$$

It is important to note that all attribute criteria generate S/D degrees that are continuous functions of the values of S/D attributes. This process yields better accuracy than the discrete rating scales.

After defining n individual S/D degrees, we are ready to aggregate them and generate the desired overall patient's S/D degree (OSD or ODD or PDD). At each step of the aggregation process we select two groups of parameters: the relative importance of inputs, and the logic properties of the aggregation operator. The logic aggregators are based on a fundamental CPL function called the Generalized Conjunction/Disjunction (GCD) [7][8].

In the simplest case of two variables and equal weights of inputs the GCD is symbolically denoted $z = x_1 \Diamond x_2$, $x_1 \in I$, $x_2 \in I$, $z \in I$, $I = [0,100\%]$ (or, in the case of strictly logic interpretation, $I = [0,1]$). GCD can be modeled using various means, and in this paper we use models based on the weighted power mean [2]:

$$W_1 x_1 \Diamond ... \Diamond W_k x_k := \sum_{i=1}^{k} (W_1 x_1^r + ... + W_k x_k^r)^{1/r}$$

$$0 < W_i < 1, \quad i = 1,...,k, \quad \sum_{i=1}^{k} W_i = 1, \quad k \geq 2$$

The relative importance of the inputs is defined using their weights $W_1,...,W_k$. If $r > 1$ then GCD is a model of replaceability (graded disjunction). If $r < 1$ then GCD is a model of simultaneity (graded conjunction). By selecting the appropriate values of r we determine a desired conjunction degree (andness) and the desired disjunction degree (orness) [7][8].

By combining the basic conjunctive and disjunctive aggregators we can make compound logic aggregators of any level of complexity. The simplest compound aggregators are partial absorptions [8][21]: the conjunctive partial absorption aggregates mandatory and desired inputs and the disjunctive partial absorption aggregates sufficient and desired inputs. The fundamental CPL aggregators can be classified as follows [7]:

1. Disjunctive aggregators (replaceability)
   1.1. Full disjunction (D)
   1.2. Partial disjunction
      1.2.1. Hard partial disjunction (HPD)
      1.2.2. Soft partial disjunction (SPD)
2. Neutral aggregator (A, arithmetic mean)

3. Conjunctive aggregators (simultaneity)
   3.1. Partial conjunction
      3.1.1. Soft partial conjunction (SPC)
      3.1.2. Hard partial conjunction (HPC)
   3.2. Full conjunction (C)
4. Compound aggregators
   4.1. Disjunctive partial absorption (DPA)
   4.2. Conjunctive partial absorption (CPA)
   4.3. Complex aggregators

The special cases of GCD satisfy the following conditions:

HPD and D: $1\Diamond y = 1, \quad y < 1$

SPD: $y/2 < 1\Diamond y < 1, \quad y < 1$

A: $x\Diamond y = (x+y)/2$

SPC: $0 < 0\Diamond y < y/2, \quad y > 0$

HPC and C: $0\Diamond y = 0, \quad y > 0$

The weighted power mean can model the following special cases of GCD: D ($r = +\infty$), SPD ($1 < r < +\infty$), A ($r = 1$), SPC ($0 < r < 1$), and HPC ($-\infty < r \le 0$). To realize a continuous transition from disjunction to conjunction with 16 equidistant steps of andness/orness we use the following special cases of GCD:
D ($r = +\infty$), D++ ($r = 20.63$), D+ ($r = 9.52$), D+- ($r = 5.8$), DA ($r = 3.93$), D-+ ($r = 2.79$), D- ($r = 2.018$), D-- ($r = 1.449$), A ($r = 1$), C-- ($r = 0.619$), C- ($r = 0.261$), C-+ ($r = -0.148$), CA ($r = -0.72$), C+- ($r = -1.655$), C+ ($r = -3.51$), C++ ($r = -9.06$), C ($r = -\infty$).
Therefore, SPD is modeled using aggregators D++, D+, D+-, DA, D-+, D-, and D--. SPC is modeled using C-- and C-, and HPC is modeled using C-+, CA, C+-, C+, and C++. The presented values of exponent r correspond to the case of two variables (for more variables these values are slightly different [5]).

The result of logic aggregation of individual S/D degrees is an overall S/D degree that quantitatively evaluates the severity or disability associated with the analyzed medical condition.

The presented LSP method is a generalization of scoring techniques. It combines sophisticated scoring with complex and flexible logic conditions based on soft computing models, and consequently it is suitable for precise evaluation of medical conditions. The advantages of our approach can be summarized as follows:

- Computation of a single OSD/ODD/PDD from any number of heterogeneous inputs.
- Flexibility to develop sophisticated quantitative severity criteria that have adjustable logic conditions between symptoms (or impairments) and adjustable degrees of their importance.
- Ability to customize severity and disability criteria according to opinions and needs of physicians and/or patients.
- Ability to efficiently track the development of severity and disability over any time interval.
- Use of software tools [3] to optimize the cost/benefit ratio of evaluation.

4 A case study of the evaluation of PDD for peripheral neuropathy

The first step in the PDD evaluation process is the development of the PDD attribute tree. The following tree contains 39 PDD attributes (in lay terminology) that can be adjusted according to the needs of the majority of patients:

PERIPHERAL NEUROPATHY

1 SENSORY SYMPTOMS
  11 Numbness
    111 Numbness of feet
      1111 Numbness of toes
        11111 Numbness of toes tips
        11112 Numbness of entire toes
      1112 Numbness of sole (nonuniform distribution)
        11121 Minimum numbness of sole
        11122 Maximum numbness of sole
      1113 Numbness of the upper surface of feet
    112 Numbness of hands
      1121 Numbness of fingertips
      1122 Numbness of fingers and hands
  12 Pain
    121 Pain in feet
      1211 Pain in toes
      1212 Pain in soles
    122 Pain in hands
      1221 Pain in fingertips
      1222 Pain in fingers and hands
  13 Tingling/Itching
    131 Tingling/itching in feet
    132 Tingling/itching in hands

2 MOTOR SYMPTOMS
  21 MUSCLE WEAKNESS
    211 Muscle weakness in legs
      2111 Muscle weakness in feet
      2112 Muscle weakness in calves
      2113 Muscle weakness in thighs
    212 Muscle weakness in arms
      2121 Muscle weakness in hands
      2122 Muscle weakness in arms/shoulders
  22 MOBILITY IMPAIRMENTS (PATIENT TESTS)
    221 Impaired standing
      2211 Short standing (<1h; e.g. teaching)
      2212 Medium standing (1 to 2h)
      2213 Long standing (more than 2h)

- **222 Impaired walk**
  - **2221 Fast (short) run**
  - **2222 Slow run**
  - **2223 Fast walk**
  - **2224 Slow walk**
- **223 Impaired climbing**
  - **2231 Impaired rising on toes**
  - **2232 Impaired toe walk**
  - **2233 Impaired jumping**
  - **2234 Impaired stair-climbing**
  - **2235 Impaired slopes (10% or more)**
- **224 Impaired (fast) transitions**
  - **2241 Impaired arising from chair**
  - **2242 Impaired arising from squat**
  - **2243 Impaired arising from floor**

23 INCOORDINATION

- **231 Imbalance**
  - **2311 Imbalance with closed eyes**
  - **2312 Imbalance with open eyes**
- **232 Tremor**
  - **2321 Tremor in legs**
  - **2322 Tremor in arms**
- **233 Clumsiness**
  - **2331 Clumsiness in legs**
  - **2332 Clumsiness in arms**

The leaves of the above decomposition tree are PDD attributes that can be directly evaluated to generate the attribute disability degrees. We included a set of tests for mobility impairments that a patient can evaluate according his/her age and the needs of his/ her activities. For example, the following criterion for stair-climbing (2234) is based on the number of stairs a patient can climb without having to stop and rest:

$$EC_{2234}(stair) = \{0,100),(50,0)\}$$

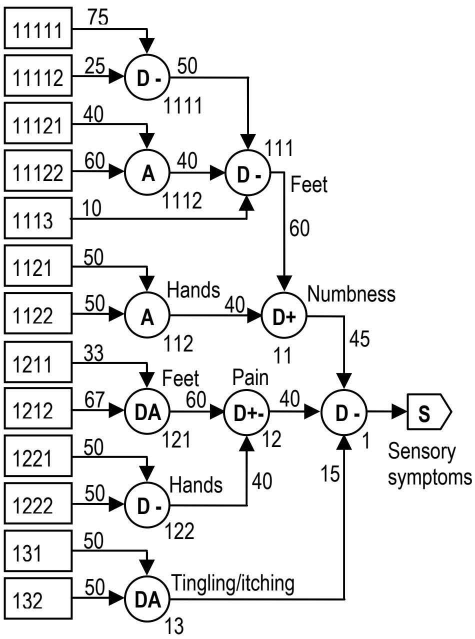

Figure 4. Aggregation of sensory symptoms

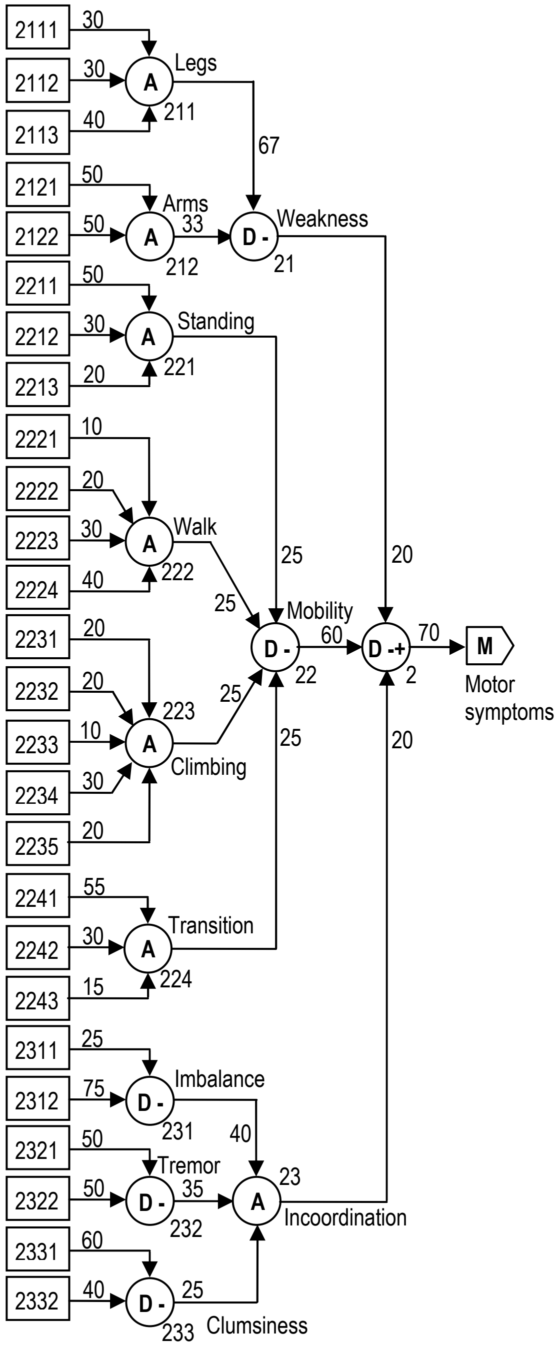

Figure 5. Aggregation of motor symptoms

This criterion reflects a patient in the age group where climbing 50 stairs denotes normal ability.

The logic aggregation of sensory and motor attribute disability degrees is shown in Figs. 4-5. The majority of aggregators are partial disjunctions or arithmetic means. The reason for predominantly disjunctive aggregators is clearly apparent in the case of pain: any of several sources of pain is sufficient to create discomfort and need for medications.

The aggregation of motor (M) and sensory (S) symptoms can be based on three versions of the final aggregator presented in Fig. 6. In the first version, the final aggregator is a medium partial disjunction of sensory and motor symptoms. In other words, either sensory or motor symptoms affect the overall PDD, but their relative importance is quite different. The motor impairments are considered substantially more important than the sensory impairments (70% vs. 30%). This criterion assumes that sensory problems can be tolerated and/or compensated more easily than motor impairments which cause overt disabilities and can substantially reduce the quality of life.

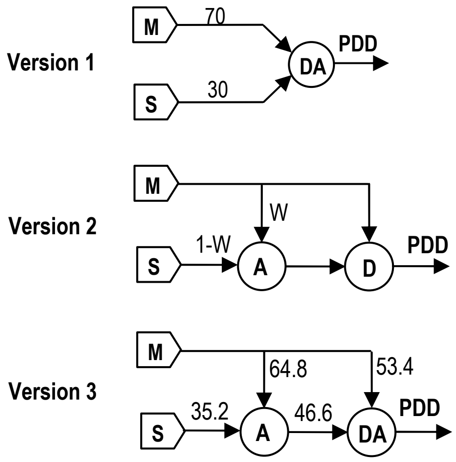

Figure 6. Aggregation of sensory and motor symptoms

The second and third versions of the final aggregator use the disjunctive partial absorption (DPA) aggregators. The DPA aggregator in version 2 is used when we need asymmetric logic relationships of motor and sensory symptoms. If motor symptoms M are considered *sufficient* to cause the overall disability, and sensory symptoms S are considered an *auxiliary component* that partially affects PDD, then DPA is an appropriate aggregator of M and S:

$$PDD = M \vee [WM + (1-W)S], \quad 0 < W < 1$$

$$= \begin{cases} M, & M > S \geq 0 \\ WM + (1-W)S, & S > M \geq 0 \end{cases}$$

$$= \begin{cases} M, & S = 0 \\ (1-W)S, & M = 0 \end{cases}$$

So, if motor symptoms are greater than sensory symptoms then the PDD is fully determined by M, and S does not affect PDD (it is totally absorbed). If the total absorption of S is not desirable, then we can define a DPA that supports a partial absorption of S, shown as version 3 in Fig. 6. Requested asymmetric properties of M and S can be defined using a table of desired {M, S, PDD} triplets. Such a table is shown in Fig. 7. If M=50% (significantly high) and S is low (10%) we want a PDD that is 45% (close to M). In the reverse case, where M is low (10%) and S is significant (50%) we want a moderate impact of S on PDD (20%). To compute the parameters of the DPA aggregator (shown in Fig. 6 Version 3, and in Fig. 7) we can use ANSY (a training tool for preferential neurons described in [5]).

M	S	PDD
0.5	0.1	0.45
0.1	0.5	0.2

$$PDD = [0.534M^{3.929} + 0.466(0.648M + 0.352S)^{3.929}]^{1/3.929}$$

Figure 7. The training set and the final form of the DPA aggregator

The presented case study shows all the main steps in the design of criteria for the evaluation of patient disability or disease severity, and the computation of the overall indicators OSD, ODD, and PDD.

The practical use of the LSP method in medical applications is supported by the LSPmed software tool that is developed in [3].

5 Conclusions

The goals of this project were to develop LSP models and a corresponding software tool (LSPmed) for the quantitative evaluation of medical conditions. The evaluation process can be used both by physicians and by patients. Physicians can use the LSP evaluation methodology to precisely analyze the development and severity of disorders over long periods of time. Patients can use similar methodology and corresponding decision support tools to decide when it is reasonable to accept therapies that can cause adverse effects. In all cases the user (either a doctor or a patient) interacts with LSPmed by answering a list of questions which are then used to compute an overall quantitative severity/disability indicator in the range [0, 100%]. By repeating this process at regular time intervals it is possible to quantitatively analyze the level of severity (and/or disability) as a function of time, and in response to therapy. The advantage of the LSP method is that the criteria for evaluation can be complex, with a large number of inputs, and with sophisticated logic and semantic relationships between them. Both the evaluation method and the LSPmed software tool can be applied to many different medical conditions.

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