Knowledge-Based Systems 67 (2014) 429–438

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

TPLUFIB-WEB: A fuzzy linguistic Web system to help in the treatment of low back pain problems

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ARTICLE INFO

Article history:
Received 11 May 2013
Received in revised form 27 January 2014
Accepted 5 March 2014
Available online 31 March 2014

Keywords:
Low back pain
Health care
Recommender systems
Quality evaluation
Fuzzy linguistic modeling

ABSTRACT

Low back pain affects a large proportion of the adult population at some point in their lives and has a major economic and social impact. To soften this impact, one possible solution is to make use of Information and Communication Technologies. Recommender systems, which exploit past behaviors and user similarities to predict possible user needs, have already been introduced in several health fields. In this paper, we present TPLUFIB-WEB, a fuzzy linguistic Web system that uses a recommender system to provide personalized exercises to patients with low back pain problems and to offer recommendations for their prevention. This system may be useful to reduce the economic impact of low back pain, help professionals to assist patients, and inform users on low back pain prevention measures. TPLUFIB-WEB satisfies the Web quality standards proposed by the Health On the Net Foundation (HON), Official College of Physicians of Barcelona, and Health Quality Agency of the Andalusian Regional Government, endorsing the health information provided and warranting the trust of users.

1. Introduction

Low back pain is a painful and economically costly syndrome that affects two-thirds of adults in developed societies at some point in their lives [1]. It is almost always a self-limiting episode of pain, with a tendency to spontaneous and complete improvement, although there is frequently a transition from acute to chronic disease [2]. Low back pain has an enormous social and economic impact and is a leading cause of absenteeism in all professions. The incidence or progression of chronic low back pain can be influenced by numerous variables, including not only mechanical aspects of the compression system, stress, torque and load levels [3] but also psychological [4], physiological, socioeconomic and psychosocial factors [5]. Physical exercise has proven effective to protect against low back pain and promote recovery from processes that can transform into chronic pain, reducing the number of days off work and helping in the treatment of psychological components of this condition [6].

Recently developed Information and Communication Technology (ICT) applications in healthcare have demonstrated potential for addressing different challenges, including: the development of personalized medicine, i.e., the tailoring of medical decisions, practices, and/or products to individual patients [7], the reduction of healthcare costs [8], and the universalization of health, i.e., the accessibility of care to all citizens, regardless of their resources or place of residence [9].

Recommender Systems (RSs) are one ICT application that may be useful in the healthcare field [10]. RSs offer tools for distinguishing relevant from irrelevant information and delivering it to those who need it, explaining their usefulness for commercial organizations. RSs offer a personalized approach, because each user can be treated in a different way. They may be useful in the diagnosis of chronic disease, offering a prediction of the disease risk to support the selection of appropriate medical advice for patients [11]. Thus, in the field of physiotherapy, RSs may help to achieve an effective personalization of recommended exercises. They could also be useful to experts for supervising the treatment of a greater number of patients.

An essential feature of RSs is an efficient communication between system and users. One possibility for improving system-user communication is the utilization of soft tools to represent the information, as in fuzzy linguistic modeling [12–15]. We propose the use of multi-granular fuzzy linguistic modeling [16] to represent and handle flexible information by means of linguistic labels. The idea is to develop flexible tools to manage the information by

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http://dx.doi.org/10.1016/j.knosys.2014.03.004
0950-7051/

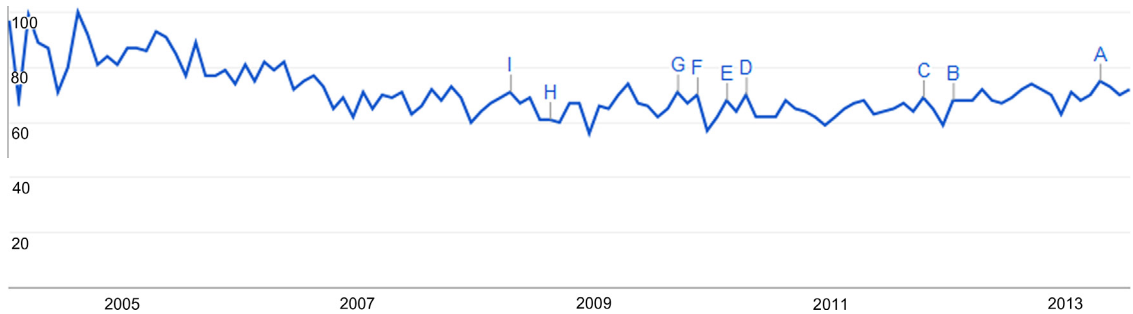

Fig. 1. Google trends for "low back pain".

representing the different concepts of the system with different linguistic label sets.

The aim of this article is to present a novel fuzzy linguistic Web system, designated TPLUFIB-WEB,[1] for individuals with low back pain, providing them with appropriate exercises and information. Expected benefits of the system include:

1. The provision of personalized exercises by using a recommender system.
2. The ability to use it in any place (e.g., at home) and at any time, yielding savings in travel and staffing costs.
3. Its user-friendly nature, designed for individuals with minimal skills and using fuzzy linguistic modeling to improve the representation of user preferences and facilitate user-system interactions.
4. The reliability of the information offered and the selection of exercises, endorsed by a team of experts in physiotherapy from the School of Health Sciences of the University of Granada. We emphasize that the aim was not to develop new exercises or treatments for low back pain but rather to incorporate clinically validated proposals [6,17], including preventive strategies, in a Web tool to facilitate their use by individuals at any time anywhere.

The utilization of the Internet to seek medical information has increased sharply over recent years. Fig. 1 shows the Web search interest in "low back pain" worldwide since 2004 according to the "Google Trends" tool.[2] The maximum search interest is scored as 100, and the interest was 70 by June 2013. As depicted in Fig. 2, the search interest in the Spanish term "*lumbalgia*" in the same month was also very high (90).

The number of physiotherapists per 100,000 inhabitants in Spain is low in comparison to other European countries,[3] supporting the need for complementary tele-rehabilitation systems to assess low back pain. The enormous number of health recommendations available on the Web is cause of concern to the user, who needs to be sure of their provenance and reliability. For this reason, measures were taken to guarantee the quality and reliability of the data in our Web system. Thus, TPLUFIB-WEB satisfies the requirements of the World Wide Web Consortium (W3C) Web Accessibility Initiative [18] and of health accreditation bodies, i.e., the Health On the Net Foundation (HON) [19], Official College of Physicians of Barcelona [20] and Health Quality Agency of the Andalusian Regional Government [21].

The paper is organized as follows: Section 2 describes preliminary information pertaining to low back pain, RSs, the fuzzy linguistic modeling and the Web quality evaluation methodologies; Section 3 presents the new Web system, TPLUFIB-WEB; Section 4 addresses the validation of the system, and Section 5 offers conclusions based on the study findings.

2. Preliminaries

2.1. Low back pain

Low back pain is extremely common. Although estimates vary widely, studies in developed countries report point prevalences of 12–33%, one-year prevalences of 22–65%, and lifetime prevalences of 11–84% [22]. The annual prevalence ranges between 15% and 45% and is higher for women aged over 60 years [23]. Most of these episodes are not serious and are self-limiting, but they are recurrent and represent the second most frequent reason for visits to the physician after headaches [24]. Low back pain is defined by: pain, muscle tension, or stiffness localized below the costal margin and above the gluteal folds, with or without sciatica. Low back pain is classified as in [25]:

1. *Specific* low back pain in which the cause is known, e.g., fractures, trauma and systemic diseases. It occurs in only 20% of cases.
2. *Nonspecific* pain located between the lower ribs and the lower limit of the buttocks. It varies depending on the position and physical activity of the individual; it is often accompanied by painful limitation of motion and may be associated with referred pain or radiating pain [26]. No structural alterations are observed in around 80% of cases of low back pain, which are therefore classified as nonspecific low back pain.

Nonspecific low back pain is the leading cause of healthcare spending, but it is very difficult to estimate its total economic impact [27]. According to the study presented in [27], low back pains that become chronic are responsible for 85–90% of total expenditure arising from this disease. These costs are increasing in Spain and in neighboring countries. For instance, in Germany the total expenditure on direct costs due to low back pain is about 7000€/person, and costs for temporary disability due to pain account for 75% of the total cost. In developed countries, low back pain is the leading cause of disability in workers under 45, and the third one in those who are older than 45. Likewise, lumbar spine pathologies were the main cause of loss of working days in Spain in 2010, representing 73.4% of the total [27]. The enormous social and economic costs of this disease has led to the search for multidisciplinary treatments, not only to relieve the pain but also to reduce functional deficits, promote the return to employment, and treat associated psychopathologies.

One of the explanations offered to interpret the ineffectiveness of treatments in low back pain is the lack of success in defining subgroups of patients with a greater likelihood of responding to

[1] Accessible in: http://sci2s.ugr.es/sapluweb/.
[2] http://www.google.com/trends/.
[3] See the report listed at: http://www.pordata.pt/en/Europe/Physiotherapists+per+100+thousand+inhabitants-1925.

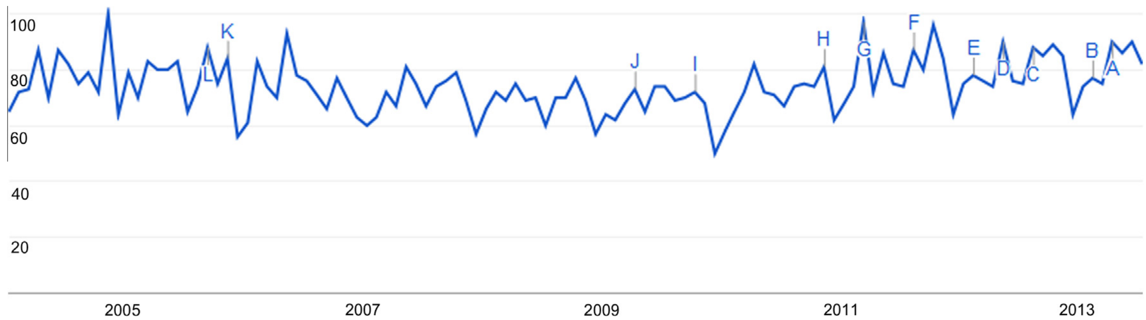

Fig. 2. Google trends for "lumbalgia".

a specific treatment [28]. It has long been acknowledged that exercise is an active therapy that plays a key role in the treatment of nonspecific mechanical low back pain, and it is the most frequently prescribed treatment for chronic low back pain [6]. This requires individualized healthcare measures. Due to the high incidence of lumbar pathology, treatment and prevention programs have been introduced in the workplace in an attempt to reduce its incidence and the associated absenteeism and economic costs [29]. There is a need to reduce the major social and economic burden of low back pain by developing more effective therapeutic and preventive approaches [30].

2.2. Recommender systems

RSs are systems that produce individualized recommendations as output or have the effect of guiding the user in a personalized manner towards appropriate tasks among a wide range of possible options [10].

They are proving to be very useful tools to increase knowledge and provide personalized items in numerous activities such as e-commerce, digital library, and e-marketing, among many others. Well-known examples include Amazon [31] and Google [32,33] and similar operations in which automated tools are applied to filter and spread increasing amounts of information in a simple and timely manner [34,35].

The key components of an RS are [10]:

- *User profiles:* They represent the information needs and preferences of the user. User profiles can be obtained implicitly or explicitly. The *implicit approach* is implemented by inference from observations of the user's behavior, e.g., in systems utilized by the users without the user's awareness. In the *explicit approach*, interaction with the users involves their feedback, which is used to improve and update the user profiles. The construction of accurate profiles is a key task in any SR.
- *Representation of items:* There should be a representation of all important characteristics of the items needed to filter the information; this representation is usually developed by experts.
- *Method of recommendations:* RSs can be characterized by the method used to generate recommendations. Numerous techniques have been proposed to generate recommendations, but we highlight the two main methods:
  – *Content-based method*, which recommends items to a user by matching the content of the item and the user's past experience with similar items, ignoring data from other users.
  – *Collaborative method*, which recommends items to a user based on the explicit or implicit preferences of similar users, ignoring the representation of items.

Each technique has its advantages and disadvantages, according to the setting. However, a hybrid approach can also be adopted to compensate for their weaknesses and benefit from their strengths [10,36].

- *The set of historic ratings:* These are provided by the users when they experience an item or update a previous rating.

2.3. Fuzzy linguistic modeling

This subsection describes the 2-tuple fuzzy linguistic modeling and multi-granular fuzzy linguistic approach used to represent the linguistic information in TPLUFIB-WEB.

In some situations, the information cannot be precisely assessed in a quantitative manner but can be qualitatively evaluated. For instance, attempts to qualify phenomena related to human perception often require the use of words in natural language rather than numerical values. In other cases, precise quantitative information cannot be stated because it is unavailable or the cost of its computation is too high, and an approximate value can be useful. Very good results have been obtained by using Fuzzy Sets Theory to model qualitative information [37]. The two main methods for managing qualitative information are [13]:

1. The *classical* linguistic approach, based on the use of labels whose semantics is represented by means of fuzzy sets and their associated membership functions. In this case, the combination of the labels is processed by Zadeh's extension principle [37].
2. The *ordinal* linguistic approach, based on the use of labels whose semantics is established on an ordered structure defined on the labels. In this case, the combination of labels is processed by direct computation on the labels, using the indexes associated with the labels and with no need to deal with membership functions [38].

In an ordinal linguistic approach, the semantics of the linguistic labels is established by assuming that the labels are uniformly and symmetrically distributed around the central assessment in the set of linguistic terms. Linguistic symbolic computational models are defined to manage ordinal linguistic information. One of the most widely used computational models is the 2-tuple linguistic computational model. This model was introduced in [39] to avoid the loss of information that occurs when an approximation function (e.g., rounding operation) is used in a linguistic symbolic model based on convex combination [38].

2.3.1. The 2-tuple fuzzy linguistic approach

Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set with odd cardinality, where the mid-term represents an indifference value to which the remaining terms are symmetric. For instance, we could use the following set of terms with 7 labels: $S = \{N, VL, L, M, H, VH, P\}$, where $s_0 = N = None$, $s_1 = VL = Very\_Low$, $s_2 = L = Low$, $s_3 = M = Medium$, $s_4 = H = High$, $s_5 = VH = Very\_High$, and $s_6 = N = Perfect$.

We assume that the semantics of labels is given by means of fuzzy subsets defined in the $[0,1]$ interval, which are described by their membership functions $\mu_{s_i} : [0,1] \rightarrow [0,1]$, and we consider all terms distributed on a scale in which a total order is defined, i.e., $s_i \leqslant s_j \iff i \leqslant j$. We consider linear triangular membership functions to be adequate to capture the vagueness of these linguistic assessments. This representation is achieved by three elements (a, b, c), where a is the point at which the membership is 1 and b and c are the left and right limits of the definition domain of the triangular membership function. For example, the following semantics, represented in Fig. 3, can be assigned to a set of seven terms via triangular membership functions:

$P = Perfect = (1, 0.83, 1)$ $VH = Very\_High = (0.83, 0.67, 1)$
$H = High = (0.67, 0.5, 0.83)$ $M = Medium = (0.5, 0.33, 0.67)$
$L = Low = (0.33, 0.17, 0.5)$ $VL = Very\_Low = (0.17, 0, 0.33)$
$N = None = (0, 0, 0.17)$

In this fuzzy linguistic context, if a symbolic method [40] aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, \ldots, g\}$, then an approximation function is used to express the result in S : β is represented by means of 2-tuples (s_i, α_i), where $s_i \in S$ represents the linguistic label of the information, and α_i is a numerical value expressing the value of the translation from the original result β to the closest index label, i, in the linguistic term set $(s_i \in S)$.

Definition 1 [39]. Let $S = \{s_0, \ldots, s_g\}$ be a linguistic term set and $\beta \in [0, g]$ a value representing the result of a symbolic aggregation operation, then the 2-tuple that expresses the equivalent information to β is obtained with the following function:

$$\Delta : [0, g] \rightarrow S \times [-0.5, 0.5) \tag{1}$$

$$\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} s_i & i = round(\beta) \\ \alpha = \beta - i & \alpha \in [-.5, .5) \end{cases} \tag{2}$$

where $round(\cdot)$ is the usual rounding operation, s_i has the closest index label to "β" and "α" is the value of the symbolic translation. For all Δ there exists Δ^{-1}, defined as $\Delta^{-1}(s_i, \alpha) = i + \alpha$.

Example 1. Let $S = \{s_0, s_1, s_2, s_3, s_4, s_5, s_6\}$ be the linguistic term set, and let $\beta = 2.8$ be the result of a symbolic aggregation operation. The 2-tuple that expresses the equivalent information to β is $\Delta(\beta) = \Delta(2.8) = (s_3, -0.2)$, because $round(\beta) = 3$ and $\beta - i = -0.2$.

The computational model is completed by presenting the following operators:

1. Negation operator: $Neg((s_i, \alpha)) = \Delta(g - (\Delta^{-1}(s_i, \alpha)))$.
2. Comparison of 2-tuples (s_k, α_1) and (s_l, α_2):
   - If $k < l$ then (s_k, α_1) is smaller than (s_l, α_2).
   - If $k = l$ then
     (a) if $\alpha_1 = \alpha_2$ then (s_k, α_1) and (s_l, α_2) represent the same information,
     (b) if $\alpha_1 < \alpha_2$ then (s_k, α_1) is smaller than (s_l, α_2),
     (c) if $\alpha_1 > \alpha_2$ then (s_k, α_1) is larger than (s_l, α_2).

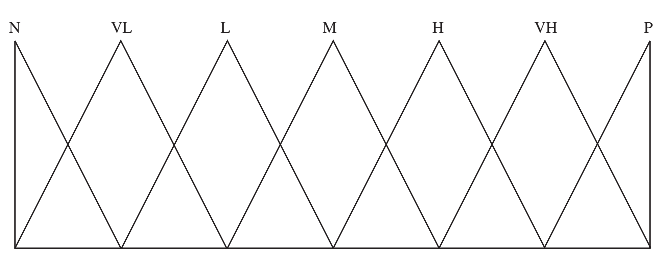

Fig. 3. A set of seven linguistic terms with its semantics.

3. Aggregation operators: The aggregation of information consists of obtaining a value that summarizes a set of values; therefore, the result of the aggregation of a set of 2-tuples must be a 2-tuple. The literature offers numerous aggregation operators that allow the combination of information according to different criteria. Any existing aggregation operator can be readily extended to deal with linguistic 2-tuples, using functions Δ and Δ^{-1}, which transform numerical values into linguistic 2-tuples. This rule is also valid in the case of the opposite transformation. Some examples are:

Definition 2 (*Arithmetic Mean*). Let $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples, the 2-tuple arithmetic mean $\bar{x}^e$ is computed as:

$$\bar{x}^e[(r_1, \alpha_1), \ldots, (r_n, \alpha_n)] = \Delta\left(\sum_{i=1}^{n} \frac{1}{n} \Delta^{-1}(r_i, \alpha_i)\right) = \Delta\left(\frac{1}{n}\sum_{i=1}^{n}\beta_i\right). \tag{3}$$

Definition 3 (*Weighted Average Operator*). Let $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{w_1, \ldots, w_n\}$ be their associated weights. The 2-tuple weighted average $\bar{x}^w$ is:

$$\bar{x}^w[(r_1, \alpha_1), \ldots, (r_n, \alpha_n)] = \Delta\left(\frac{\sum_{i=1}^{n} \Delta^{-1}(r_i, \alpha_i) \cdot w_i}{\sum_{i=1}^{n} w_i}\right) = \Delta\left(\frac{\sum_{i=1}^{n} \beta_i \cdot w_i}{\sum_{i=1}^{n} w_i}\right). \tag{4}$$

Definition 4 (*Linguistic Weighted Average Operator*). Let $x = \{(r_1, \alpha_1), \ldots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{(w_1, \alpha_1^w), \ldots, (w_n, \alpha_n^w)\}$ be their linguistic 2-tuple associated weights. The 2-tuple linguistic weighted average $\bar{x}_l^w$ is:

$$\bar{x}_l^w[((r_1, \alpha_1), (w_1, \alpha_1^w)), \ldots, ((r_n, \alpha_n), (w_n, \alpha_n^w))] = \Delta\left(\frac{\sum_{i=1}^{n} \beta_i \cdot \beta_{W_i}}{\sum_{i=1}^{n} \beta_{W_i}}\right), \tag{5}$$

with $\beta_i = \Delta^{-1}(r_i, \alpha_i)$ and $\beta_{W_i} = \Delta^{-1}(w_i, \alpha_i^w)$.

2.3.2. Linguistic hierarchies to model multi-granular linguistic information

When different experts have varied degrees of uncertainty in relation to a phenomenon, several linguistic term sets with a different cardinality (granularity of uncertainty) are necessary. The use of different label sets to assess information is also necessary when an expert has to evaluate different concepts. In these situations, we need tools to manage multi-granular linguistic information [41,16].

Multi-granular fuzzy linguistic modeling based on a 2-tuple fuzzy linguistic approach and the concept of linguistic hierarchy were proposed in [41]. A *Linguistic Hierarchy, LH,* is a set of levels *l (t,n (t))*, i.e., $LH = \bigcup_t l(t, n(t))$, where each level t is a linguistic term set with different granularity $n(t)$ from the remaining levels of the hierarchy. The levels are ordered according to their granularity, i.e., a level $t + 1$ provides a linguistic refinement of the previous level t. We can define a level from its predecessor level as: $l(t, n(t)) \rightarrow l(t + 1, 2 \cdot n(t) - 1)$. A graphical example of a linguistic hierarchy is shown in Fig. 4. Using this *LH*, the linguistic terms in each level are the following:

- $S^3 = \{a_0 = Null = N, a_1 = Medium = M, a_2 = Total = T\}$.
- $S^5 = \{b_0 = None = N, b_1 = Low = L, b_2 = Medium = M, b_3 = High = H, b_4 = Total = T\}$.
- $S^9 = \{c_0 = None = N, c_1 = Very\_Low = VL, c_2 = Low = L, c_3 = More\_Less\_Low = MLL, c_4 = Medium = M, c_5 = More\_Less\_High = MLH, c_6 = High = H, c_7 = Very\_High = VH, c_8 = Total = T\}$.

A family of transformation functions among labels from different levels was defined in [41] to combine multi-granular linguistic information with no loss of information:

Definition 5. Let $LH = \bigcup_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \left\{s_0^{n(t)}, \ldots, s_{n(t)-1}^{n(t)}\right\}$. The *transformation function* between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ is defined as:

$$TF_{t'}^{t} : l(t, n(t)) \rightarrow l(t', n(t')) \tag{6}$$

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta\left(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t') - 1)}{n(t) - 1}\right) \tag{7}$$

To define the computational model, a level is selected that makes the information uniform (e.g., the highest granularity level), allowing use of the operators defined in the 2-tuple fuzzy linguistic approach.

2.4. Web quality evaluation

Quality criteria are applied by most studies and initiatives to describe, evaluate, and analyze the quality of Health websites, focusing on the quality of the information they provide [42]. These criteria can range from those dictated by common sense or used in evaluating the contents of printed publications [43] to extensive sets of criteria developed in quality initiatives, including URAC [44] or MEDCERTAIN [45].

There is still no consensus on a single set of quality criteria for evaluating health-related websites [46,47]. The lack of a standard set of norms has led researchers to adopt varied criteria in their studies, making it very difficult to compare published results [48]. The most frequently adopted quality criteria are variations of what might be called "criteria of transparency" of the publishing world [43], with assessments of web content depending on the same factors as those considered for printed publications:

1. *Authoring:* Authors of the content and their affiliations and credentials must be clearly specified.

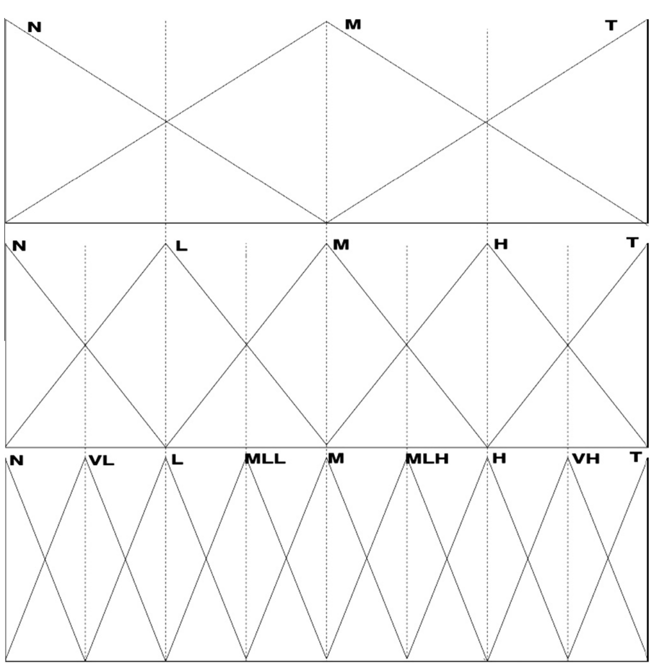

Fig. 4. Linguistic hierarchy of 3, 5 and 9 labels.

2. *Attribution:* References and sources of published content must be identified.
3. *Declaration:* There should be a clear statement on the ownership of the site and any sponsorship/advertising or media, trade, or financial relationships that may constitute a potential conflict of interest.
4. *Validity:* Websites should indicate the date of the on-line publication of information and the date of the most recent update of related Web pages.

Some authors have only used criteria derived from printed publications [49], but the evaluation of Web content requires the application of additional quality criteria in relation to privacy policies, the ability to encrypt sensitive information, the usability and accessibility of the website [46], and the possibilities of interaction with the authors of the content.

3. TPLUFIB-WEB: A Web platform to help in the treatment of low back pain problems

TPLUFIB-WEB is accessible at: http://sci2s.ugr.es/sapluweb/. The system structure has three main components (see Fig. 5):

1. *A multimedia database of exercises* for recommendation to patients according to their pathology.
2. *A database of patient profiles* that stores the characteristics of each patient, not only the internal representation of their diagnostics but also their personal evaluations obtained after user-system interaction.
3. *A personalized method for generating exercise recommendations* that implements the hybrid recommendation policy based on information from the multimedia and patient profile databases.

Different sets of linguistic labels $(S_1, S_2, \ldots)$ are used to represent the different concepts necessary for the system activity. These label sets, S_i, are selected from among those that compose a LH, i.e., $S_i \in LH$. The number of different label sets used is limited by the number of LH levels. In many cases, therefore, the label sets S_i and S_j can be associated with the same LH label set but with different interpretations according to the concept to be modeled. The different concepts assessed in the system are:

- The *membership degree* of patient diseases with respect to each of the defined diagnostic subgroups, which is labeled in S_1.
- The predicted *degree of relevance* of exercise for a patient, which is labeled in S_2.
- The *degree of similarity* between the diseases of two patients or between exercises, which is labeled in S_3.
- The *degree of satisfaction* with a recommended exercise expressed by a patient, which is labeled in S_4.

Following the LH depicted in Fig. 4, level 2 (5 labels) was used to represent the degrees of membership and satisfaction ($S_1 = S^5$ and $S_4 = S^5$) and level 3 (9 labels) to represent the degrees of predicted relevance ($S_2 = S^9$) and similarity ($S_3 = S^9$).

3.1. Multimedia database

A multimedia database was developed that contained exercises for all possible pathologies. Exercises can be exchanged among different subgroups in the construction of a customized program for each patient. Instruction videos were recorded for reproduction on computers and mobile devices. It is very important to obtain an adequate representation of exercises, because these are the

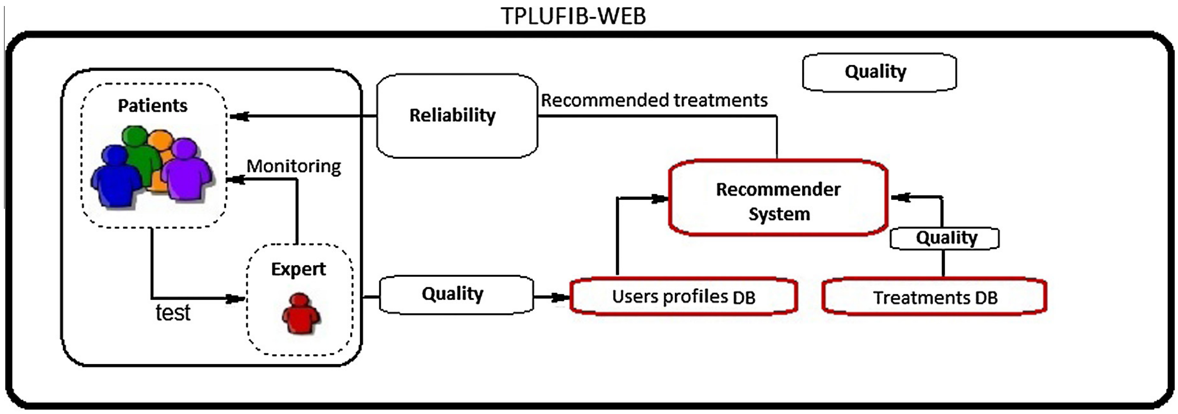

Fig. 5. Operating scheme.

items to be recommended by our system. Given that each exercise is suitable for a diagnostic subgroup with a specific pathology, these subgroups are used to represent the corresponding exercises. We first considered patients with a previous diagnosis of chronic mechanical low back pain based on different symptoms, establishing the following five diagnostic subgroups: muscle weakness, lumbar instability, psychometric variables, flexibility, and postural syndrome.

Once a new exercise is entered into the system, it obtains an internal representation that is mainly based on its appropriateness for each diagnostic subgroup. We therefore use the *vector model* [50] to represent the membership degree of a given exercise in each one of the five diagnostic subgroups. Thus, an exercise *i* is represented as:

$$VT_i = (VT_{i1}, VT_{i2}, \ldots, VT_{i5}),$$

where each component $VT_{ij} \in S_1$ is a linguistic assessment that represents the fitness degree of exercise *i* with respect to the diagnostic subgroup *j*. These fitness degrees are determined by the physiotherapists when they insert new exercises into the system.

3.2. Patient profiles database

The patient profiles database stores the patients' pathological conditions, which are used to personalize the exercises. The results of a series of tests undergone by patients [17] are analyzed by experts to establish the pathology used to represent their respective profiles. The representation of the pathologies is also based on the same features as those applied for representation of the exercises. After obtaining the test results, the experts assess the membership of the patient's pathology in each one of the five diagnosis subgroups. The *vector model* [50] is again used to represent the membership degree of the patient in each diagnostic subgroup. Hence, a patient *i* is represented as:

$$VP_i = (VP_{i1}, VP_{i2}, \ldots, VP_{i5}),$$

where each component $VP_{ij} \in S_1$ is a linguistic assessment (i.e., a 2-tuple) that represents the fitness degree of *i* for each subgroup *j*.

The tests used to establish the pathology of each patient are set according to three kinds of variables:

1. *Physical variables.* We include tests for storing the physical characteristics of the patients. These tests must be performed in the presence of a physiotherapist, because some require the use of specific instruments:
   - Test to measure the anthropometric characteristics.
   - Test using an approved dual inclinometer (ACUMAR).
   - Test to measure isometric muscle strength of the lumbar extensors and hip (Sorensen test).
   - Test of aerobic capacity.
2. *Functional variables.* These are specific to patients with chronic nonspecific mechanical low back pain and include the following:
   - PILE: Lifting capacity.
   - ASLR: Motor control of the lumbopelvic region in patients with chronic nonspecific mechanical low back pain.
   - Robin McKenzie's Questionnaire.
3. *Psychometric variables.* These were evaluated with the following instruments:
   - Visual analog scale of pain perception.
   - SF12 general health questionnaire.
   - McGill pain questionnaire.
   - Oswestry Disability Index.
   - Tampa Kinesophobia Scale.
   - Emotional well-being questionnaire.

The functionality of these tests has been previously demonstrated, and all have been evaluated with satisfactory results [6]. We have incorporated them in TPLUFIB-WEB, and they are prepared for on-line application. We highlight the dynamic nature of the patient profiles, which will be supplemented and updated during the feedback phase. For this purpose, patients will be asked to provide assessments of exercises previously recommended by the system.

3.3. Method of generating recommendations of exercises

TPLUFIB-WEB is based on a hybrid recommendation strategy, which switches between a content-based and a collaborative approach to share information on exercise effectiveness among patients with similar pathologies (see Fig. 6). The former approach is applied when a new exercise is entered into the system and the latter when a new patient is registered or when previous recommendations to a patient are updated, whenever the system has received sufficient ratings.

Because the exercises and the patient pathologies are both represented by vectors, the cosine measure [50] is used to estimate the similarity between two vectors, $\sigma_l(V_1, V_2) \in S_1$. We use the modified cosine measure in order to work with 2-tuple linguistic information:

$$\sigma_l(V_1, V_2) = \Delta\left(g \times \frac{\sum_{k=1}^{n}(\Delta^{-1}(v_{1k}, \alpha_{v1k}) \times \Delta^{-1}(v_{2k}, \alpha_{v2k}))}{\sqrt{\sum_{k=1}^{n}(\Delta^{-1}(v_{1k}, \alpha_{v1k}))^2} \times \sqrt{\sum_{k=1}^{n}(\Delta^{-1}(v_{2k}, \alpha_{v2k}))^2}} \right) \quad (8)$$

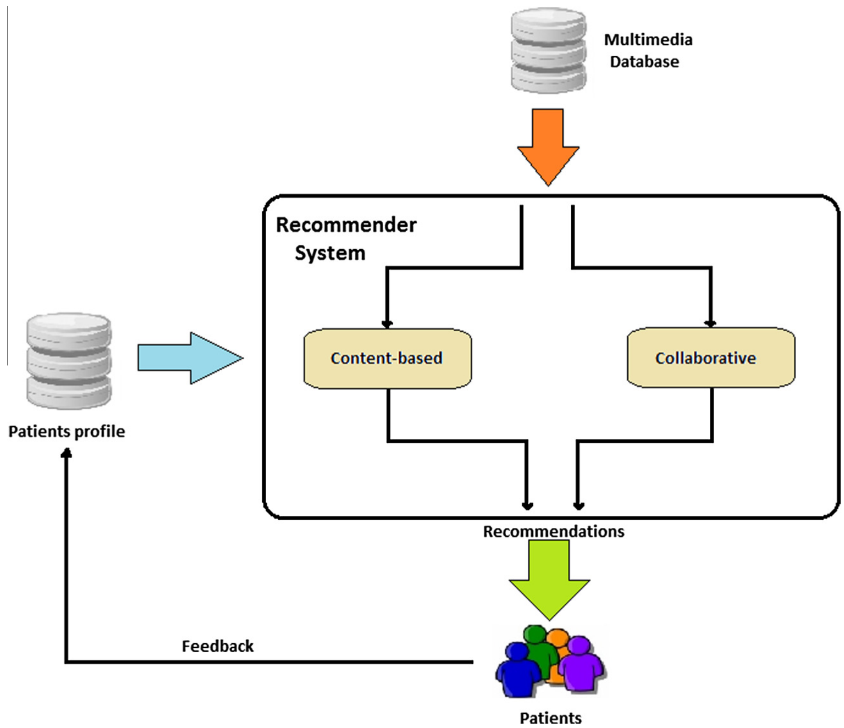

Fig. 6. Recommendations scheme.

with $\sigma_l(V_1, V_2) \in S_3 \times [-0.5, 0.5]$, and where g is the granularity of the term set used to express the similarity degree, i.e., S_3, n is the number of terms used to define the vectors (i.e. the number of diagnosis subgroups that have been considered) and (v_{ik}, α_{vik}) is the 2-tuple linguistic value of the diagnostic subgroup k in the exercise or patient vector V_i (label of S_1).

When a new exercise i is entered into the system, a content-based approach is used to recommend it to appropriate patients because no ratings are available:

1. Compute the linguistic similarity degree $\sigma_l(VT_i, VP_p) \in S_3$, between the vector VT_i representing the new exercise and the vectors of all patients in the system (VP_p).
2. The system selects the patients with a similarity degree above a previously established linguistic threshold $\delta \in S_3$. Assuming that $S_3 = S^9$, exercise i is considered appropriate for patient p if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$, i.e., if the linguistic similarity degree is higher than the mid linguistic label.
3. If exercise i is considered appropriate for patient p, then the system recommends i to p with an estimated relevance degree $i(p) \in S_2 \times [-0.5, 0.5]$, which is obtained as follows:
   (a) Look for all exercises stored in the system that were previously assessed by p, i.e., the set of exercises $K = \{1, \ldots, k\}$ such that the linguistic satisfaction assessment $p(j) \in S_4$, $j \in K$ and $\sigma_l(VT_j, VP_p) \geqslant (s_4^9, 0)$.
   (b) Then,

$$i(p) = \bar{x}_l^w((TF_{S_2}^{S_4}(p(1), 0), TF_{S_2}^{S_3}(\sigma_l(VT_i, VT_1))), \ldots, (TF_{S_2}^{S_4}(p(k), 0), TF_{S_2}^{S_3}(\sigma_l(VT_i, VT_k)))), \quad (9)$$

where $\bar{x}_l^w$ is the linguistic weighted average operator (Definition 4) and $TF_{t'}^t$ is the transformation function between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ (Definition 5).

As mentioned above, TPLUFIB-WEB also applies a collaborative approach to generate recommendations. The number of ratings rises with the increase in patients using the system, thereby allowing a collaborative approach to be adopted. Moreover, when new patients are entered into the system, they receive recommendations about existing exercises that may be of interest to them. Because these patients have not yet evaluated any exercise, the collaborative approach is used to generate these recommendations. Specifically, we implement an item-based collaborative approach that considers the assessments provided by patients with similar pathologies to the patient receiving the recommendation. However, this approach has been slightly modified by the addition of a first step in which only the exercises considered appropriate by the pathologist are recovered.

To estimate (when no ratings are yet scored) or upgrade the relevance of a exercise i for a patient p:

1. Compute the linguistic similarity degree $\sigma_l(VT_i, VP_p) \in S_3$, between vector VT_i representing exercise i and vector VP_p representing the pathology of patient p.
2. The system considers exercise i to be appropriate for patient p if the similarity degree is greater than a pre-established linguistic threshold $\gamma \in S_3$. If $S_3 = S^9$, i is considered appropriate for p if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$, i.e., when the linguistic similarity degree is higher than the mid linguistic label.
3. Then, if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$, the set of patients $\aleph_p$ with a similar pathology to that of p, usually called *nearest neighbors*, is identified. This is done by calculating the linguistic similarity degree between VP_p and the vectors of all patients already in the system $(VP_y, y = 1, \ldots, n$ where n is the number of patients), i.e., we calculate $\sigma_l(VP_p, VP_y) \in S_3$. Because $S_3 = S^9$, patient y is considered a nearest neighbor to p if $\sigma_l(VP_p, VP_y) > (s_4^9, 0)$, i.e., if the linguistic similarity degree is higher than the mid linguistic label.
4. Retrieve the assessments of the exercise i provided by the nearest neighbors of p, i.e., the linguistic satisfaction assessments $y(i) \in S_4$, for all $y \in \aleph_p$.
5. Exercise i is recommended to p with a predicted relevance degree $i(p) \in S_2 \times [-0.5, 0.5]$. This is calculated as follows:

Table 1
Survey's results.

Q: 1–6		Q: 7–9		Q: 10	
Yes	68.43%	Very Good	52.52%	Average (over 10)	8.84
Yes, but not completely	29.03%	Good	45.45%		
No	2.54%	Regular	1.53%		
		Bad	0.50%		
		Very Bad	0.00%		

$$i(p) = \bar{x}_l^w((TF_{S_2}^{S_4}(y_1(i),0), TF_{S_2}^{S_3}(\sigma_l(VP_p, VP_{y1}))), \ldots, (TF_{S_2}^{S_4}(y_n(i),0), TF_{S_2}^{S_3}(\sigma_l(VP_p, VP_{yn})))), \quad (10)$$

where $y_1, \ldots, y_n \in \aleph_p, \bar{x}_l^w$ is the linguistic weighted average operator (see Definition 4) and $TF_{t'}^t$ is the transformation function between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ (Definition 5).

3.4. Feedback phase

When patients have completed the recommended exercises, they are asked to assess the relevance of these recommendations in order to update their patient profiles. TPLUFIB-WEB receives the user feedback in this way. Patients communicate their linguistic evaluation judgements to the system, $rc \in S_4$, indicating their satisfaction with the recommendations (higher values of rc = greater satisfaction). Future recommendations are strengthened by taking account of patients' ratings, and the user-system interaction required is minimal in order to facilitate the sending of this important information.

4. Validating TPLUFIB-WEB

As previously stated, all the exercises recommended by TPLUFIB-WEB have already been approved by physiotherapists [6,17] and there are no new or experimental exercises. Furthermore, it is not our intention to validate the performance of the recommendation system in a strict sense. Given the importance of developing systems being worthy of the trust of users, we have focused on the quality of TPLUFIB-WEB and the confidence that it inspires. Hence, this section addresses the quality of TPLUFIB-WEB as a valid tool for recommending exercises to patients and providing reliable information.

TPLUFIB-WEB satisfies the following quality criteria:

1. *Reliability of information provided*. The health Web underwent an accreditation process to ensure compliance with ethical codes and user rights and satisfactory fulfillment of quality standards. To date, the quality of the system has been accredited by the following:
   - HONcode [19], certifying that the website was reviewed by the HONcode Team at a given date and complies with the eight principles of this code.
   - The Official College of Physicians of Barcelona (COMB) [20], a non-profit organization started in 1999 to provide benchmarks for reliability and service and improve the quality of health information on the Internet.
2. *Quality of the website.* The system complies with the protocols laid down by the Health Quality Agency of the Andalusian Regional Government [21], designed to guarantee the reliability of the information and paying special attention to the protection and rights of patients. Accordingly, TPLUFIB-WEB is governed by very strict rules and fulfills the requirements of the World Wide Web Consortium (W3C) Web Accessibility Initiative [18], including compliance with XHTML 1.0 and CSS standards to facilitate use of the website on all types of device/platform.
3. *Usability.* Evaluation of the user-friendliness of the system is based on the responses of TPLUFIB-WEB users themselves to a questionnaire hosted on the home page during the trial period (one month). In that period, 64 individuals completed the survey, which comprises ten items. The first six questions are related to their understanding of the information by patients (possible responses: *Yes; Yes, but not completely; No*). The next three questions regard their ability and efficiency in using the website (possible responses: *Very Good; Good; Regular; Poor; Very poor*. The last item asked for a global evaluation of the health website, on a scale of *0 to 10*.
   The questions were as follows:
   (a) Do you understand clearly the information that appears on the Web?
   (b) Are the contents of the site commensurate with the level of knowledge you have about back pain?
   (c) You can access documents related to physiotherapy through the website. Do you think that the documents you have accessed are highly specialized?
   (d) What is your opinion about the clarity of the description, presentation and format of the exercises in the printed version?
   (e) Have you been able to complete the "Initial assessment of the health of your back"?
   (f) Have you been able to do the individualized exercises and "back school" exercises proposed in videos properly in your home or workplace?
   (g) How do you rate the videos on the individual physiotherapy exercises (presentation, quality and content)?
   (h) How do you rate the possibility of carrying out, in your home or workplace, the "individualized physiotherapy exercises and personalized monitoring over the Internet"?
   (i) How do you rate the "back school" videos (presentation, quality and content)?
   (j) How would you rate your overall satisfaction with the website on a scale from 0 to 10? (0 = "very poor" and 10 = "very good").

The results obtained are displayed in Table 1. Note that the weighting of each question differs according to its importance, as shown in Table 2. Fig. 7 depicts the distribution of the average website evaluation rates based on the questionnaire responses.

The results demonstrate that the website is very positively perceived by its users. The patients were able to understand the received information and perform the exercises themselves (questions 1–6). The usability and efficiency of the website was rated as "*Very Good* or *Good*" by 95% of the responders (questions 7–9), and the patients evaluated the website with an average global score of 8.84 out of 10.

Table 2
Weighting of each question.

Question	1	2	3	4	5	6	7	8	9
Weight over 10	1	1	1.5	1.5	2	2	0.5	0.5	1

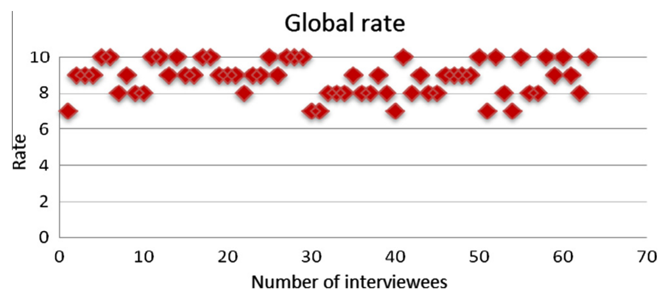

Fig. 7. Distribution of rates in question 10.

5. Concluding remarks

ICTs represent a major breakthrough in healthcare, including physiotherapy. The results of our research on its application in the case of patients with low back pain may be also relevant to other diseases. The effectiveness of physical activity for low back pain handling is well documented, and the present study demonstrates that an ICT recommender system is viable for patients with low back pain. The system can support patients' participation in this activity.

This study presents a fuzzy linguistic Web tool named TPLUFIB-WEB, which incorporates a recommender system to provide personalized exercises to these patients. A physiotherapist establishes the pathology of a patient after evaluating the results of different tests, which are used to generate the recommendations. The website also provides patients with advice for handling future problems. The main benefits of this system deal with the personalization and the possibility of following the exercises anywhere and at anytime, potentially contributing to the reduction in the economic impact of low back pain.

We have applied TPLUFIB-WEB in a real environment, and the experimental results demonstrate that acceptance of the system by users and patients is very high and that it may be able to achieve major costs savings for national health systems and patients by enhancing the effectiveness of each health professional involved. The reliability and quality of the information provided by the system has been maximized by following guidelines established by independent bodies, including the HONcode [19], Official College of Physicians of Barcelona [20], and Health Quality Agency of the Andalusian Regional Government [21] and by complying with the standards proposed by the World Wide Web Consortium (W3C) [18].

Further research is warranted to explore other ICT applications in healthcare, especially in areas in which the physical presence of the health professionals is not wholly necessary and minimal supervision is adequate. There is also a need to improve the proposed recommendation approach, investigating new methodologies for the generation of recommendations.

Acknowledgments

This study received funds from National Projects TIN2010-17876 and TIN2010-22145-C02-01, and Regional Projects P09-TIC-5299 and P10-TIC-5991.

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