Aiding in the Treatment of Low Back Pain by a Fuzzy Linguistic Web System

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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 recommender systems, which have already been introduced in several health fields. In this paper, we present TPLUFIB-WEB, a novel 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. A strong part of TPLUFIB-WEB is that it 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.

Keywords: Low back pain, health care, recommender systems, fuzzy linguistic modeling, quality evaluation.

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. 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 [3].

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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 [4], the reduction of healthcare costs [5], and the universalization of health, i.e., the accessibility of care to all citizens, regardless of their resources or place of residence [6]. *Recommender Systems* (RSs) are one ICT application that may be useful in the healthcare field [7]. RSs assist users in their decision making processes to find relevant information. They could be seen as a Decision Support System, where the solution alternatives are the information items to be recommended and the criteria to satisfy are the user preferences and needs [8,9]. 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 [10]. Thus, in the field of physiotherapy, RSs may help to achieve an effective personalization of recommended exercises.

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

1. The provision of personalized exercises by using a recommender system.
2. The ability to use it in any place 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 [11,12].
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 [3,13], 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. Figure 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 Figure 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 (see the report listed at: `http://www.pordata.pt/en/Europe/Physiotherapists+per+100+thousand+inhabitants-1925`), supporting the need for complementary tele-rehabilitation systems to assess low back

[1] Accessible in: `http://sci2s.ugr.es/sapluweb/`
[2] `http://www.google.com/trends/`

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[3] and of health accreditation bodies, i.e., the Health On the Net Foundation (HON)[4], Official College of Physicians of Barcelona[5] and Health Quality Agency of the Andalusian Regional Government[6].

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

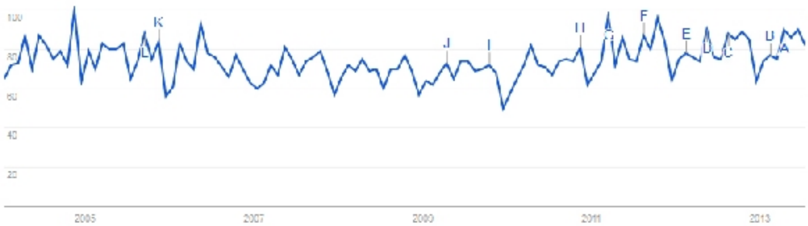

Fig. 2. Google trends for "lumbalgia"

The paper is organized as follows: Section 2 describes preliminary information pertaining to recomender systems and the fuzzy linguistic modeling; 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 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

[3] http://www.w3.org
[4] http://www.healthonnet.org/
[5] http://wma.comb.es/es/home.php
[6] http://www.juntadeandalucia.es/agenciadecalidadsanitaria

among a wide range of possible options [7]. In order to provide personalized recommendations, system requires knowledge about users, such as ratings provided of already explored items [7,14]. To maintain available this knowledge it implies system should keep also user profiles that contain also users preferences and necessities. Nevertheless, the way system acquires this information depends on the recommendation scheme used. The system could obtain the information about users either in an *implicit* way, that is analyzing their behavior, or *explicitly* requiring user to specify their preferences.

One of the most popular method used to obtain recommendations is the collaborative approach [7]. In this approach the recommendations for a user are based on the ratings provided by other users similar to this user. Another method more simple but not less important is the content-based approach [7]. This approach 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. These aproaches work with the set of historic ratings, which are provided by the users when they experience an item or update a previous rating.

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 [7,15,9].

2.2 Fuzzy Linguistic Modeling

The fuzzy linguistic modeling is a tool based on the concept of *linguistic variable* [16] which has given very good results for modeling qualitative information in many problems in which quantitative information can not be assessed precisely [17].

The 2-tuple FLM [18] is a continuous model of representation of information that allows to reduce the loss of information typical of other fuzzy linguistic approaches (classical and ordinal, see [16]).

Let $S = \{s_0, ..., s_g\}$ be a linguistic term set with odd cardinality. We assume that the semantics of labels is given by means of triangular membership functions and consider all terms distributed on a scale on which a total order is defined. In this fuzzy linguistic context, if a symbolic method aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$,. 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 $(s_i \in S)$.

This model defines a set of transformation functions between numeric values and 2-tuples $\Delta(\beta) = (s_i, \alpha)$ and $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ [18].

In order to establish the computational model a negation, comparison and aggregation operators are defined. Using functions Δ and Δ^{-1} that transform, without loss of information, numerical values into linguistic 2-tuples and viceversa, any of the existing aggregation operators (i.e. arithmetic mean, weighted average operator or linguistic weighted average operator) can be easily extended for dealing with linguistic 2-tuples [18].

In any fuzzy linguistic approach, an important parameter to determine is the "granularity of uncertainty", i.e., the cardinality of the linguistic term set S. When different experts have different uncertainty degrees on the phenomenon or when an expert has to assess different concepts, then several linguistic term sets with a different granularity of uncertainty are necessary [19]. In [19] a multi-granular 2-tuple FLM based on the concept of linguistic hierarchy is proposed.

A *Linguistic Hierarchy, LH,* is a set of levels *l(t,n(t))*, where each level t is a linguistic term set with different granularity $n(t)$ from the remaining of 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 Figure 3. Using this LH, the linguistic terms in each level are the following:

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

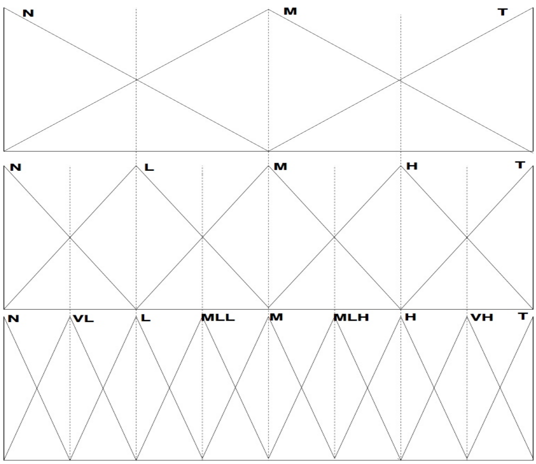

Fig. 3. Linguistic Hierarchy of 3, 5 and 9 labels

In [19] a family of transformation functions between labels from different levels was introduced. This family of transformation functions is bijective. This result guarantees that the transformations between levels of a linguistic hierarchy are carried out without loss of information.

3 TPLUFIB-WEB: A Web System to Help in the Treatment of Low Back Pain Problems

TPLUFIB-WEB is accessible at: `http://sci2s.ugr.es/sapluweb/`. Figure 4 shows the system structure. The system structure has three main components (see Figure 4):

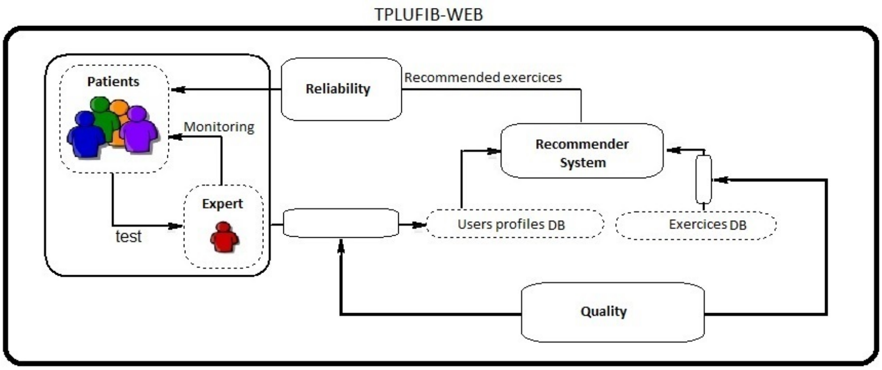

Fig. 4. Operating scheme

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 ($S_1, S_2, ...$) are used to represent the different concepts necessary for the system activity; we selected the LH presented in section 2.2. The different concepts assessed in the system are the following:

– 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.

We use the set with 5 labels to represent the degrees of membership and satisfaction ($S_1 = S^5$ and $S_4 = S^5$) and 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 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. An exercise i is represented as a vector $VT_i = (VT_{i1}, VT_{i2}, ..., VT_{i5})$, 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.

For instance, suppose that a new exercise x, specially designed to improve the lumbar instability and postural syndrome, is inserted. Then, the physiotherapist would select for it the diagnostic sugroups 2 and 5 with a membership degree "Total" because they are in the positions 2 and 5 respectively; these membership degrees belong to the label set S_1, i.e. in our proposal the set S^5, with labels $b_0, b_1, ..., b_4$. The rest of the disgnostic subgroup have a membership degree with a value of "None". So, x is represented as: $VT_x = ((b_0, 0), (b_4, 0), (b_0, 0), (b_0, 0), (b_4, 0))$.

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 [13] 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. A patient i is represented as a vector $VP_i = (VP_{i1}, VP_{i2}, ..., VP_{i5})$, 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.

For instance, suppose a patient p whose pathology is muscle weakness and some flexibility. Then, the physiotherapist would select for it the diagnostic sugroups 1 and 3 with a membership degree "Total" and "Medium" respectively, because they are in the positions 1 and 3; these membership degrees belong to the label set S_1, i.e. in our proposal the set S^5, with labels $b_0, b_1, ..., b_4$. The rest of the disgnostic subgroup have a membership degree with a value of "None". So, p is represented as: $VT_p = ((b_4, 0), (b_0, 0), (b_2, 0), (b_0, 0), (b_0, 0))$.

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. 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. We rely on a matching process by similarity measures among vectors. Particularly, we use the standard cosine measure, but defined in a linguistic context:

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

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 know if it could be appropriate for a patinent p, as follows:

1. Compute $\sigma_l(VT_i, VP_p) \in S_3$. As $S_3 = S^9$, exercise i is considered appropriate for patient p if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$
2. 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.
   (b) To aggregate all the ratings of p over these exercises, weigthed by the similarity between i and each of the exercises. To do that we use the linguistic weighted average operator [18].

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

1. Compute $\sigma_l(VT_i, VP_p) \in S_3$. If $S_3 = S^9$, i is considered appropriate for p if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$.

2. If i is appropriate, 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 $\sigma_l(VP_p, VP_y) \in S_3$, between p and the vectors of all patients already in the system (VP_y, $y = 1..n$ where n is the number of patients). Because $S_3 = S^9$, patient y is considered a nearest neighbor to p if $\sigma_l(VP_p, VP_y) > (s_4^9, 0)$.
3. Retrieve the exercises positively rated by the nearest neighbors of p.
4. Each exercise i of recovered in the previous step is recommended to p with a predicted relevance degree $i(p) \in S_2 \times [-0.5, 0.5]$, computed as the aggregation of all the ratings, weighted by the similarity between e and their nearest neighbors. To do that we use the linguistic weighted average operator [18].

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 strenghened 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 [3,13]. Furthermore, it is not our intention to validate the performance of the recommendation system in a strict sense. We have focused on the quality of TPLUFIB-WEB and the confidence that it inspires.

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:
   – Health on the net foundation, HONcode[7], 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)[8], a non-profit organization started in 1999 to provide benchmarks for reliability and service and improve the quality of health information on the Internet.

[7] http://www.healthonnet.org/
[8] http://wma.comb.es/es/home.php

2. *Quality of the website.* The system complies with the protocols laid down by the Health Quality Agency of the Andalusian Regional Goverment[9], 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[10], 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. The next three questions regard their ability and efficiency in using the website. The last item asked for a global evaluation of the health website, on a scale of *0 to 10*.

   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. The usability and efficiency of the website was rated as "*Very Good* or *Good*" by 95% of the responders, and the patients evaluated the website with an average global score of 8.84 out of 10.

5 Concluding Remarks

This study presents a fuzzy linguistic Web tool named TPLUFIB-WEB, which incorporates a recommender system to provide personalized exercises to patients with low back pain. 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.

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.

[9] http://www.juntadeandalucia.es/agenciadecalidadsanitaria
[10] http://www.w3.org

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