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Swarm intelligence-based assessment in home care pulmonary monitoring

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Abstract- A swarm intelligence-based procedure to detect a critical condition of a patient, affected by a specific disease, at an early stage in absence of clinician, is proposed. The procedure is conceived for a remote health monitoring system for patients at home, where some physiological parameters related to a specific disease are being monitored. A significant variation in the parameters can lead the patient to a critical state, thus the proposed method is aimed at predicting a possible future bad condition of the patient on the basis of past measures. Moreover, different physiological parameters contribute to diverse degrees in dissimilar diseases, thus a swarm intelligence-based method is proposed for optimizing the weight of each parameters for a more accurate diagnosis. The proposed approach has been tested experimentally under the framework of the industrial research project PADIAMOND (Patient Diagnosis and Monitoring at Domicile) funded by EU.

I. Introduction

Medical diagnosis is a complicated task based on both medical knowledge derived from state of the art and medical judgement inferred from clinician experience. In recent years, many home health monitoring systems have been proposed [1-5], where patients affected by a specific disease are monitored by means of a medical protocol, based on periodical measures of some physiological parameters related to the disease through biomedical transducers. Typically, the acquired data are sent via internet to a remote centre where clinicians analyse the data and take decisions. However, the equipment cannot predict imminent health hazard, and sends a red-alert signal only when one or more physiological parameters overcome the pre-defined thresholds according to the medical protocol.

In the lasts years, some researchers have proposed methods aimed at predicting imminent health hazard of a patient, in a reliable way [6]-[7]. Starting from these works, instruments with some auto-decision making support, suitable to be used as a preventive device for an early diagnosis of problems related to a specific disease, should be a fascinating improvement in telemedicine research area [8].

For this reason, in the present paper, a method for predicting the most plausible critical condition of a patient affected from a specific disease, inside a home health monitoring system, is introduced. In particular, the proposed method has two main characteristics: (i) predicting the future patho-physiological state of a patient through past physiological data and thus forecasting the approach of a critical condition for a patient, before a criticality occurs actually, and (ii) using a swarm intelligence-based method [11] is used to calculate the weights of each parameter in medical diagnosis problem, instead of performing diagnosis by giving equal weights to all parameters, because different physiological parameters can contribute to different degrees in different disease [9]-[10]. Experimental case studies to validate the proposed method are currently in progress on a clinical data base of 78 patients (age 68±7), affected by moderate to severe Chronic Obstructive Pulmonary Disease (COPD) in the framework of the research project PADIAMOND, supported by the company Filia srl in Caserta (Italy) [12]. In the following, in Section II, the proposed method is illustrated, and in Section III, preliminary experimental results are reported.

II. The proposed method

The present work introduces a methodology to predict critical condition of a patient, before criticality occurs actually. Multiple physiological parameters are involved in diagnosis, thus the first step is to define which parameters are to be measured for the considered disease. In the considered case study of COPD a monitoring model of the following 4 parameters has been studied [17]:

1. Forced Expiratory Volume (FEV1%), expressed as percentage of a maximum value assessed by a spirometry test in 1 second;
2. Six-Minute Walking Test [18] (6MWT), a simple stress test, namely consisting in the meters walked in six minutes;

3. MMRC Dyspnea Scale, the score of a test (points from 1 to 4) for the assessment of dyspnea based on the Modified Medical Research Council (MMRC) dyspnea scale [19];
4. Body Mass Index (BMI), the well-known biometric data, expressed as the ratio between the weight and height, associated with body fat and health risk [20].

Each patient underwent to a 12-months follow up, with a monthly monitoring of the clinical variables of interest. The data set as a whole has been split in two equal parts to be used for algorithm tuning and testing. The different forecasting capabilities of the algorithm have been assessed by mixing the sample of patients with thrre groups of patients in (i) severe but stable conditions, (ii) a worsened conditions, and (iii) with improved clinical conditions during the study period.
Moreover, by exploiting only a single data, an accurate decision about the future patho-physiological state of the patient, particularly in a chronic case, is hard to be taken [8]. Therefore, the patient data were fuzzified [13] for transforming periodic measures into likelihoods that the patho-physiological parameter of the patient is high, low, or moderate, according to a set of reference values.
In Fig. 1, the Fuzzy sets for the above mentioned parameters are reported. The membership functions are set according to the limits provided by the World Health Organization.

A. Algorithm for diagnosis

The algorithm for diagnosis accepts as input the patients data acquired periodically according to the medical protocol (each 4 days in the case reported here), and fuzzifies them on the basis of the membership functions reported in Fig. 1. Successively, on the basis of past collected data, it assess the possibility that the next physiological data will be in low, moderate, or high range, according to the following rule:

$$P_R(x)=\frac{\sum_{i=1}^{n} i\ \mu_R(x)}{\sum_{i=1}^{n} i} \tag{1}$$

where $i = 1,\ldots,n$ is the time sequence of the most recently acquired data, R $\in$ {low, moderate, high}, x $\in$ {w, f, b, d}, represents the result of the six-minutes walking test, FEV1%, BMI and dyspnea, and $\mu_R(x)$ ($\mu_{low}(x)$, $\mu_{moderate}(x)$ and $\mu_{high}(x)$), refers to low, moderate, or high fuzzy set value of the parameter x. Consequently, the value of P(x) corresponding to max ($P_R(x)$) predicts the fuzzy set in which the next state input of the physiological parameter x is going to lie.

B. Inferencing

Inferencing implies providing a decision whether the patient is in critical condition or not. To make this decision, specifics rules based on the value of the assessed probability in (1) have to be defined. According to clinician experience, a typical rule to assess a critical condition for patient affected of COPD is the following:

$$\begin{aligned} & CR_h > CR_m \\ & with \\ & \begin{cases} CR_h = (c_w\ P_{high}(sb) + c_f\ P_{high}(db) + c_b\ P_{high}(b) + c_d\ P_{high}(h)) \\ CR_{m=}\ (c_w\ P_{\text{moderate}}(sb) + c_f\ P_{\text{moderate}}(db) + c_b\ P_{\text{moderate}}(s) + c_d\ P_{\text{moderate}}(f)) \end{cases} \end{aligned} \tag{2}$$

where c_w, c_f, c_b, c_d $\in [0,1]$ are the weight parameters, and CR_h and CR_m are criticality factors which indicate the possibility to be in high critical or moderate critical condition, respectively, for the patient in the next state. A swarm intelligence-based method was used to compute the weight parameters.

C. Swarm intelligence and Particle Swarm Optimization

Swarm intelligence is a modern artificial intelligence discipline that is concerned with the design of multi-agent systems with applications, mainly in optimization problem and in robotics [11]. The design paradigm for these systems is fundamentally different from more traditional approaches. Instead of a sophisticated controller that governs the global behavior of the system, the swarm intelligence principle is based on many unsophisticated entities that cooperate in order to exhibit a desired behavior. Inspiration for the design of these systems is taken from the collective behavior of social insects such as ants, termites, bees, and wasps, as well as from the behavior of other animal societies such as flocks of birds or schools of fish [11].

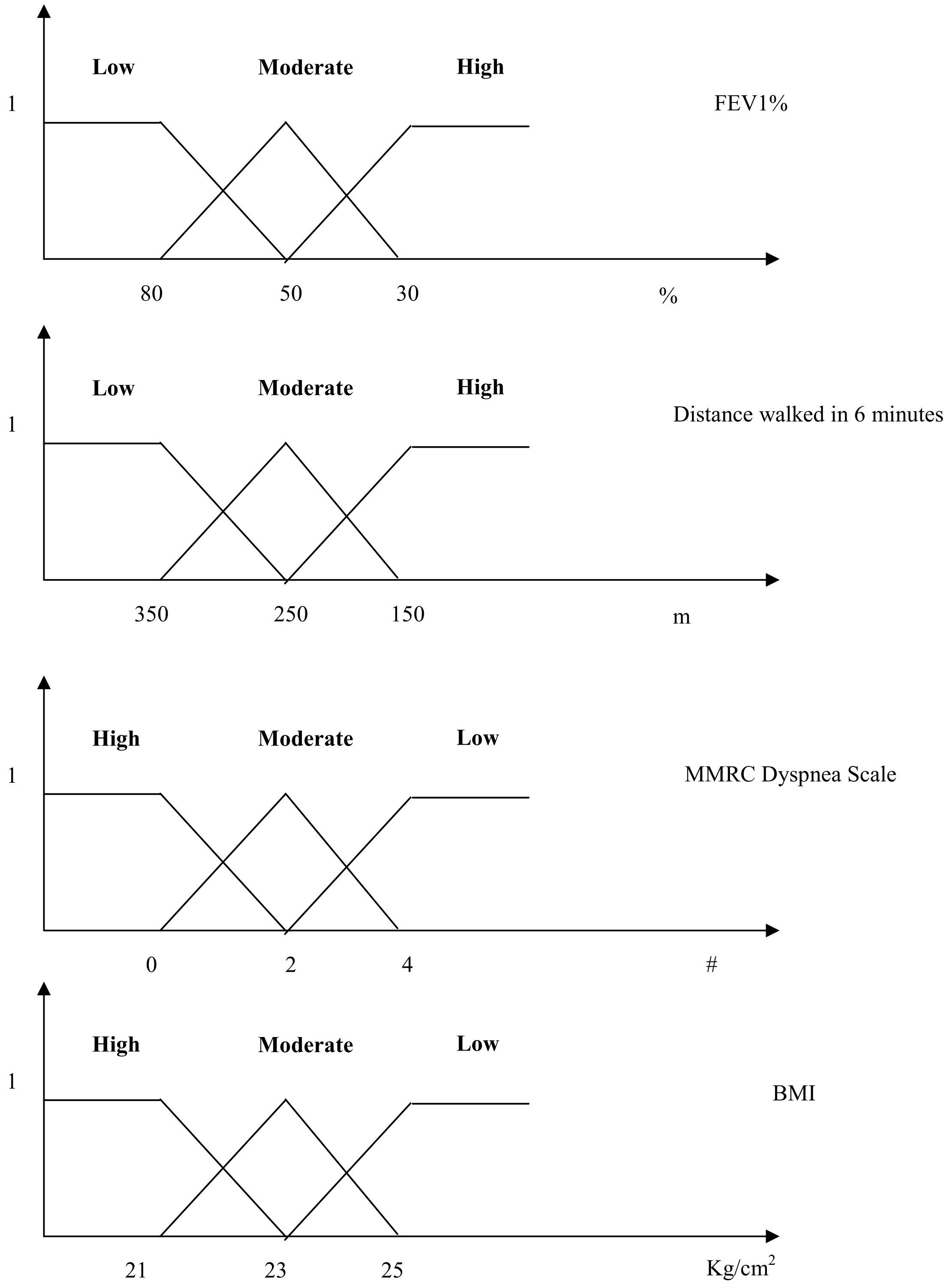

Figure 1. Plot of membership functions for the physiological parameters

Mainly swarm intelligence methods in optimization problems are Ant Colony Optimization (ACO)[14] and Particle Swarm Optimization (PSO) [15]. The first is inspired from foraging behavior of social ants, and it is typically used for combinatorial optimization problem, while the latter is derived from birds flocking and it is normally applied to optimization problem in continuous landscape.
Find the weight parameters in (2) is essentially an optimization problem in continuous domain. For this reason, in the present paper, the Authors focus on PSO algorithm as tool for optimization.
In PSO, each particle (i.e. potential solution) 'moves' within its search space. As each optimization procedure, a fitness function has to be defined and maximized (or minimized) according to the problem itself. The *velocity* of each particle is modified iteratively by its *personal best position* (i.e., the best position found by the particle so far, and that has the highest scoring according with the fitness function), and the *global best position* found by all other particles. As a result, each particle searches around a region defined by its personal best position and the best position from all its neighbours. Let's v_i to denote the velocity of the *i-th* particle in the swarm, x_i to denote its position, p_i to denote the personal best position and pg the best position found by particles in its neighborhood. In the PSO algorithm, v_i and x_i, for $i = 1, \ldots, n$, are updated according to the following two equations [15]:

$$\begin{aligned} v_i &= v_i + \varphi_1 \otimes (p_i - x_i) + \varphi_2 \otimes (p_g - x_i) \\ x_i &= x_i + v_i \end{aligned} \tag{3}$$

where $\varphi_1 = c_1 R_1$ and $\varphi_2 = c_2 R_2$. R_1 and R_2 are two separate functions each returning a vector comprising random values uniformly generated in the range [0,1], and c_1 and c_2 are acceleration coefficients.
This is an iterative procedure that terminates when the pre-defined condition is achieved. Fig. 2 shown the basic procedure for PSO.

```
Random generation of initial swarm position

repeat
   for each particle i do
      if fitness(x_i) > fitness(p_i) then p_i= x_i
      p_g=max(p_neighbours)
      update v_i (eq. 3)
      update p_i (eq. 3)
   end for
until termination criteria is achieved
```

Figure 2. Basic procedure of PSO

D. Determination of weights of physiological parameters using Particle Swarm Optimization

To determine the weights of the parameters in (2), first of all a fitness function has to be defined. The fitness function proposed for the problem here, uses *i* past measurements for each of the physiological parameters $x \in W=\{w, f, b, d\}$. The basic idea is to find (for each parameter) the best weight coefficient that minimize the squared distance between the actually value of the fuzzified physiological parameter and that assessed by eq. (1) over a time sequence $i=1 \ldots n$. Hence, the fitness function that has to be minimized is:

$$F = \sum_{x \in W} \left[\frac{1}{n} \sum_{i=1}^{n} \left(\mu_R^{'}(x_i) - c_x P_R(x_i) \right)^2 \right] \tag{4}$$

where $\mu'_R(x_i)$ is the actual value of the fuzzified physiological parameter x at *i-th* measurement, $P_R(x_i)$ is the probability that the physiological parameter x is in the state R $\in$ {low, moderate, high}computed by means of eq. (1), and c_x is the weight coefficient of parameter x that has to be estimate by PSO described in section II.C.

It should be noted that more large time sequence determines more accurate estimating of the weight coefficients c_x, but improves the complexity of the optimization problem.

III. Preliminary experimental results

Experimental validation of the proposed method is currently ongoing using collected data of 63 patients affected from COPD and provided by Salvatore Maugeri Foundation in the framework of the research project Padiamond.
To validate the overall procedure, results from the proposed methods was compared with GOLD (Global Initiative for Chronic Obstructive Lung Disease) guideline criteria [16], a standard method for assess the critical condition of patients affected from COPD. This criteria is based on FEV1 and FVC measurements. In table 1 is reported the four criticality indexes and how to assess them.

Criticality index		
I Low	FEV1/FVC< 0.7	FEV1> 80%
II Moderate	FEV1/FVC< 0.7	50%<FEV1< 80%
III High	FEV1/FVC< 0.7	30%<FEV1< 50%
IV Severe	FEV1/FVC< 0.7	FEV1< 30%

Table 1: COPD criticality index (GOLD guideline)

Since the experimental validation of the proposed method is currently ongoing, as preliminary results, in the following the Authors reports results for a 47 year old patient (male), COPD affected. Tab. 2 shown the prediction of a critical condition. In particular, the data prediction was computed using 5 past fuzzyfied measurements of the physiological parameters (tab.2). The values of CR_h and CR_m ($CR_h > CR_m$) indicate that the most probable next condition will be high critical.

C_w=0.9			C_f=0.97			C_d=0.80			C_b=0.49		
w_{low}	w_{mod}	w_{high}	$Fev1_{low}$	$Fev1_{mod}$	$Fev1_{high}$	d_{low}	d_{mod}	d_{high}	BMI_{low}	BMI_{mod}	BMI_{high}
0.00	0.49	0.51	0.00	0.40	0.60	0.00	0.40	0.60	0.00	0.40	0.60
0.00	0.20	0.80	0.00	0.35	0.65	0.00	0.23	0.77	0.00	0.40	0.60
0.00	0.20	0.80	0.00	0.34	0.66	0.00	0.30	0.70	0.00	0.40	0.60
0.00	0.13	0.87	0.00	0.40	0.60	0.00	0.20	0.80	0.00	0.40	0.60
0.00	0.23	0.77	0.00	0.35	0.65	0.00	0.10	0.90	0.00	0.40	0.60
$P(sp)_{low}$	$P(sp)_{mod}$	$P(sp)_{high}$	$P(f)_{low}$	$P(f)_{mod}$	$P(f)_{high}$	$P(s)_{low}$	$P(s)_{mod}$	$P(s)_{high}$	$P(b)_{low}$	$P(b)_{mod}$	$P(b)_{high}$
0.00	0.2107	0.7893	0.00	0.3647	0.6453	0.00	0.2040	0.7960	0.00	0.40	0.60
CR_m = 1.0231						CR_h = 2.9012					

Table 2: Prediction of criticality condition for a 47 year old patient COPD affected. Data was computed using 5 past measurements of the physiological parameters. The values of CR_h and CR_m indicate that the most probable next condition will be *high critical*

Such result was confirmed from the actual state of the patient assessed by means of GOLD criteria and reported in tab. 3. In such table, the first 5 values refer to the past condition of the patient (as for the proposed method in tab.2), while the *6-th* indicates an actually high criticality, as predict through the proposed procedure.

	FEV1	index
T_1	51%	moderate
T_2	49%	high
T_3	48%	high
T_4	50%	high/mod.
T_5	49%	high
T_6	48%	high

Table 3: Criticality index for a 47 years old patient COPD affected. The indexes are assessed by means of GOLD criteria

Conclusions

In the present paper, a method to predict a critical condition of a patient, affect to a specific disease, at an early stage in absence of clinician, based on swarm intelligence optimization procedure, is presented. The proposed method can be useful to applied to the home health monitoring systems, in which some physiological parameters related to a specific disease are being monitored. Although the experimental validation is currently in progress, some preliminary results shown encouraging performance.

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