A Novel Shuttle Walking Model Using Networked Sensing and Control for Chronic Obstructive Pulmonary Disease: A Preliminary Study

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Abstract — Exercise training is a crucial component of pulmonary rehabilitation for patients with chronic obstructive pulmonary disease (COPD). Based on fuzzy logic control and wireless sensor networking, we develop an approach with calibration, rehabilitation, artifact/safety monitoring and endpoint decision (CRASE) to perform adaptive subject exercise training and monitoring. This preliminary study investigates an exercise training model with overload principle and safety concern. The experimental results show that the proposed CRASE scheme is promising to efficiently put exercise training into practice for home-based rehabilitation.

Keywords— pulmonary rehabilitation; chronic obstructive pulmonary disease; fuzzy control; wireless sensor networking.

I. INTRODUCTION

Chronic obstructive pulmonary disease (COPD) is a chronic inflammatory disease of the airways characterized by progressive downhill of the lung functions and frequent systemic involvement [1]. The characteristics of COPD are the presence of lots of immunocytes in airways and the decrease of forced expiratory volume in one second (FEV1) due to airflow limitation. The most recent international treatment guideline suggests that early introducing of pulmonary rehabilitation (PR) and pharmacological management may help improve the quality of life and reduce the frequency of acute exacerbation [2], [3]. The incremental shuttle walking test (ISWT) has recently been proposed as an effective and reproducible alternative to the conventional 6-min walking (6MWT) in exercise tolerance evaluation of patients with COPD [4]. The initial procedure of the conventional ISWT is that the subject walks a 10-meter distance between two cones with a walking speed of 30 m/min as defined in Stage 1 (Table I). This walking speed increases 10 meters per minute until the speed reaches 140 m/min as defined in Stage 12. The endpoint of the test is determined when the subject is too short of breathing to keep up with the pace or is unable to complete the shuttle in the limited time [5]. The total distance and predicted \( VO_2 \) max = 0.025 * distance + 4.19 may be the outcome for pulmonary rehabilitation.

Although the ISWT conforms overload principle [6] and inflexible termination criterion of the training testing [5] may not help improve the max oxygen uptake (\( VO_2 \) max) of the subject. Moreover, because of the difficulty for defining the crisp endpoint with the predicted maximum heart rate (MHR = 220 - Age) [7] which depends on subjects’ oxygen uptake, rest, deep breath and other non-physiological factors, it is essential to adaptively control the intensity and endurance in training-sensitive zone with safety consideration such that improving cardiorespiratory fitness is achievable. The recent study shows that the increment of endurance walking capacity with ground walk training is more than that with upright cycle ergometer in pulmonary rehabilitation for people with COPD [8]. Currently, the design of walking exercise with overload and training-sensitive zone guidance is not reported in the literature.

Accordingly, in contrast to the conventional ISWT method which surveys the subject manually [9], we develop an adaptive shuttle walking (ASW) as an exercise training model and propose the Calibration, Rehabilitation, Artifact/Safety monitoring and Endpoint decision (CRASE) protocol, which applies networked sensing and fuzzy characteristics to explore the performance in adaptive shuttle walking subjects, to optimize the shuttle walking endpoint, and to interpret the measurements in the cases as natural language variables such as “fast” and “too slow” with the developed fuzzy

<table>
<thead>
<tr>
<th>Stage</th>
<th>Speed (m/min)</th>
<th>Shuttles per min</th>
<th>Distance m/stage</th>
<th>Total distance (m)</th>
<th>( VO_2 ) max (ml/kg.min)</th>
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<tr>
<td>1</td>
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<td>3</td>
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<tr>
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<td>120</td>
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<tr>
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<td>140</td>
<td>14</td>
<td>140</td>
<td>1020</td>
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</tr>
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</table>
rules. Thus, a pair of sensors can be applied to estimate the walking distance of a subject. Moreover, measuring physical vital signals can be served as the basis for safety monitoring. Based on the walking distance information and the vital signals of the subject, the sensor nodes are able to apply fuzzy logic control for generating the guidance during the process of pulmonary rehabilitation. Therefore, this preliminary study may become the groundwork of implementation for designing an efficient exercise training system. The organization of this paper is as follows: Section II describes the system model and derives an adaptive distributed solution that relies on fuzzy sensor networking. Section III summarizes the rehabilitation performance of the proposed protocol. Finally, Section IV draws conclusions and shows future research directions.

II. THE CRASE PROTOCOL

This section presents the procedures of calibration, rehabilitation, artifact/safety monitoring and endpoint decision (CRASE) protocol, which achieves adaptive shuttle walking for patients with COPD. The proposed exercise training system consists of three sensor nodes, a clusterhead node, a reference sensor node, and a physiological sensor node. Each node is embedded with microprocessor-based instruments [10] (e.g. analog to digital converter, micro-controller, data storage, RF and I/O interface etc.) as a basic module.

A. The Procedures of Exercise Training

The exercise training of a subject with COPD is guided by the developed approach. As the subject initiates the sensor components, the CRASE protocol performs system calibration automatically and instructs the subject through sound guidance (as shown in Figure 1), which encourages the subject to prolong the walking distance for improving the $\text{VO}_2\text{max}$ based on networked sensing and fuzzy logic control. The rehabilitation (Reh.) stage and the intensity level of exercise training are determined by the output of the CRASE protocol.

B. Adaptive Shuttle Walking and Networked Sensing

As depicted in Figure 2, the environment of ASW may be based on wireless networked sensing. For the proposed training model, the clusterhead node (Nch) performs as a base station, which initiates the system calibration for excluding the unexpected errors and executes the procedure of training exercise. The reference sensor node (Nr) measures the walking distances and the walking speed, and then transmits the information to the Nch. The physiological sensor node (Np) samples the heart rate (HR) of subject and transmits the HR to the Nch. As receiving the messages from the Nr and the Np, the Nch performs signal processing (per five seconds) and fuzzy control scheme (obtaining the average values of measured signals per shuttle) for providing the guidance to the subject.

For dealing with the unexpected errors (e.g. heart rate decreasing to “0”), system calibration is essential to eliminate the artifact of a sensor. If the system detects the end point from fuzzy for any safety risk (e.g. MHR over 95%), the system will enter “Recovery” phase and guide the patient to gradually stop the exercise. Accordingly, the developed model will execute the exercise training under subject safety consideration and artifact checking.

C. Fuzzy Control

This subsection describes the design principle of the fuzzy control scheme. Variable "MHR\%" is estimated by the physiological sensor node (Np) and variable "Difference" is calculated by the clusterhead node (Nch) in this study. These two variables are the inputs of exercise training and the corresponding outputs of fuzzy system will control the training processes. As the heart rate of the subject reaches 90% of MHR or decreases dramatically, the training procedure enters the Rest Checking phase or adjusts the training intensity to a level below (as shown in Figure 1). As the subject’s heart rate is under the training-sensitivity zone or increasing the walking distance is applicable with respect to the rehabilitation level, the training intensity adjusts to a level above or jumps to a higher intensity level. The fuzzy...
inputs, the fuzzy outputs, and the fuzzy rules are described as follows.

1) Fuzzy Inputs: The fuzzy input 1 is the percentage of MHR within the training-sensitivity zone [7]. We specify a range of values as input 1, \([\text{min max}] = [20 100]\); the member functions (as shown in Figure 3 (left)) are ‘VS’: ‘trapmf’, [20 20 30 35]; ‘S’: ‘trimf’, [30 50 70]; ‘F’: ‘trapmf’, [60 70 90 100]; ‘TF’: ‘trimf’, [90 100 100], where VS = very slow, S = slow, F = fit, and TF = too fast.

The fuzzy input 2 is the difference between the rehabilitation level and the individual walking speed, \(\Delta V\) (m/sec). The endpoint is determined when the individual is too short of breathing to keep up with the pace [5]. Here a range of values are specified as input 2, \([\text{min max}] = [-2 2]\); the member functions (as shown in Figure 3 (middle)) are ‘N’: ‘trapmf’, [-2 -2 -1 0]; ‘S’: ‘trimf’, [-0.5 0 0.5]; ‘P’: ‘trapmf’, [0 1 2 2], where N = negative, S = small, and P = positive.

2) Fuzzy Output: The fuzzy output is the degree of rehabilitation with the average per shuttle. We specify a range of values as fuzzy output, \([\text{min max}] = [0 1]\); the member functions (Figure 3 (right)) are denoted as ‘Maintain’: ‘trimf’, [0.25 0.5 0.75]; ‘Check’: ‘trimf’, [0 0 0.1]; ‘Stop’: ‘trimf’, [0 0.1 0.25]; ‘Down’: ‘trimf’, [0.1 0.25 0.5]; ‘Up’: ‘trimf’, [0.5 0.75 1]; ‘Up_Jump’: ‘trimf’, [0.75 1 1].

The outputs are defined by the template rhythm of sound guidance depicted in Table I: (1) Maintain: The rehabilitation level (RL) is followed with the average per shuttle. We specify the training-sensitivity zone; (2) Check: The individual should check Np or Nr before doing the exercise; (3) Stop: The individual should stop the exercise for reaching the end point or safety consideration; (4) Down: RL decreases the training intensity to a level below after current shuttle; (5) Up: RL increases the training intensity to a level above after current shuttle; (6) Up_Jump: RL directly increases two stages of exercise rhythm after current shuttle.

3) Fuzzy Rules: Based on the training-sensitivity zone and overload principle as suggested in Table I, twelve fuzzy rules are developed. Table II expresses the fuzzy logic in terms of fuzzy IF-THEN rules, which implements a mapping of input functions into output functions. For instance, **IF MHR (%) is F (fit) AND \(\Delta V\) (m/sec) is N (negative), THEN the output (i.e. the degree of rehabilitation with the average per shuttle) is ‘Maintain’**.

<table>
<thead>
<tr>
<th>TF</th>
<th>F</th>
<th>S</th>
<th>VS</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>Stop</td>
<td>Maintain</td>
<td>Maintain</td>
</tr>
<tr>
<td>S</td>
<td>Down</td>
<td>Up</td>
<td>Up</td>
</tr>
<tr>
<td>P</td>
<td>Down</td>
<td>Up</td>
<td>Up_Jump</td>
</tr>
</tbody>
</table>

III. CASE STUDY AND PERFORMANCE EVALUATION

For the purpose of comparison, the fuzzy inference system is applied to simulate the endpoint decision and survey the performances of two subjects undergoing the conventional ISWT with artificial monitoring and undergoing the proposed CRASE protocol and ASW model, respectively. Note that the recorded physical data of real subjects with the conventional ISWT are applied for each case study.

Subject 1: A 68 y/o male with MHR = 152 who ended up the test because of shortness of breath (SOB). Figure 4 shows that the total walking distance was 375 m (Stage 7) with a duration of 250 seconds and heart rate reached 222 beats per minute at 190 seconds by manual monitoring. Using the proposed CRASE protocol to survey the recorded data, decision of “Up” is made in Stage1, 2, 3 and 4, respectively. Check point of “Safety” is at 190 seconds. Afterwards, the CRASE output should be “Down” before entering Stage 6 and should be “Stop” at 255 seconds. Thus, the proposed CRASE shows the outputs of “Up”, “Up”, “Up”, “Up”, and “Stop” in Stage (S) 1, S2, S3, S4, S5 and S6, respectively.

Subject 2: 61 y/o male with MHR = 159 who ended up the test because of SOB. The total walking distance was 160 m (Stage 4) through 160 seconds and heart rate reached 126 beats per minute at 145 seconds by manual monitoring (Figure 5). Similarly, Using the proposed CRASE protocol
to survey the record data, the decision is “Up”, “Up”, “Up” in Stage (S) 1, S2 and S3, respectively. Check point of “Artifact” is at 150 seconds. After that, the control output of CRASE should be “Maintain” at 160 seconds, which encourages the subject to go through ASW with “Maintain” and to improve the performance in the $V\text{O}_2$ max of the subject rather than to terminate the test with the artificial monitoring. Therefore, the proposed CRASE shows the outputs of “Up”, “Up”, “Up”, “Artifact”, and “Maintain” in Stage (S) 1, S2, S3, S4, and S5, respectively.

Observe that for Subject 1, the proposed ASW detects the “Safety” event which is neglected by the conventional ISWT with manual stage of decision making. For Subject 2, the proposed adaptive approach detects the “Artifact” event and suggests exercise training should keep “Maintain” rather than “Stop” for improving the strength of Subject 2. Therefore, the conventional ISWT is lack of safety checking and flexible adjustment of intensity level of training exercise for a patient with COPD, which implies that the proposed CRASE protocol shows strong potential for use in overload principle and work load within training-sensitive zone.

IV. Conclusion

An adaptive approach (CRASE) is proposed to survey the ISWT cases that had been monitored manually. The preliminary study shows that the CRASE is able to create an effective exercise training model with overload principle and safety concerns. Instead of using the conventional manual monitoring of ISWT for the patients with COPD, the proposed CRASE scheme can be an innovative approach of training exercise with networked sensing and automatic ubiquitous control. Accordingly, with CRASE it is possible to put exercise training into practice for efficient and protected home-based rehabilitation. Future plans will involve generalizing the method to investigate the quality of home-based rehabilitation in patients with COPD and to consider the hardware implementation of the CRASE protocol.

REFERENCES