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Model Based Optimization of The Cardiopulmonary Resuscitation (CPR) Procedure

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Abstract— **This paper is concerned with the optimization of the cardiopulmonary resuscitation (CPR) procedure, which plays a critical rule in saving the life of patients suffering from cardiac arrest. In this paper, we define the performance index for optimization using the oxygen delivery. A model developed earlier is used to calculate the oxygen delivery through CPR. The free parameters of this model which depend on the rescuer performance are ventilation time, compression speed, tidal volume, and fraction of oxygen in the inspired air. Two different optimization problems are carried out. First, a global optimization is implemented to discover the best values of the free parameters which maximize the oxygen delivery. In addition to this, a sequential optimization scheme is explored which uses a two step optimization in each CPR sequence to maximize the oxygen delivery. Results show that the sequential optimization procedure will enhance the performance of the CPR significantly.**

I. INTRODUCTION

Cardiopulmonary resuscitation (CPR) is performed in emergency conditions on patients suffering from cardiac arrest to maintain blood flow and oxygen delivery to the brain and other vital organs until further treatments are performed on the patient [1]. CPR involves chest compression and artificial respiration. Chest compressions helps to pump blood from the heart to restore blood circulation in the body and mouth by mouth ventilation provides manual respiration.

Since 1966 the American Heart Association (AHA) has been providing and developing guidelines for step by step procedures of the cardiopulmonary resuscitation (CPR). The developed guidelines have been saving many lives by emphasizing early recognition, activation and defibrination; in addition, they showed the importance of early access to emergency medical care. The prospect of saving lives demonstrates the importance of resuscitation research and clinical translation [2]. In spite of its relative success, an open area in resuscitation research remains to be an appropriate modification of the CPR procedure. Optimization of the CPR parameters could vastly improve the rule of this procedure in emergency conditions and help save the lives of patients.

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The compression to ventilation ratio is certainly an important parameter in the CPR procedure. The issue of best compression to ventilation ratio has gained a lot of attention among researchers in the field of CPR due to its importance in increasing the performance of CPR [3]–[7]. In many practical conditions the compression to ventilation ratio, based on the traditional ABC (airway, breathing circulation) method, is $15:2$ [8]. This means that, the rescuer does the chest comprehension 15 times, pauses to give two ventilations, and then repeat this procedure until patient's recovery. The other important parameter in the CPR procedure is ventilation time. The ventilation time is defined as the pause for the ventilation following the compressions; experimental models has been used to assess the role of ventilation time in reducing the coronary perfusion pressure [9].

In this paper, we intend to employ Computational intelligence (CI) techniques to this problem. CI techniques have increasingly attracted attention from researchers in the biomedical field, as a result of their superior performance in comparison with traditional stochastic approaches in prediction, modeling and classification of biomedical signals [10], [11]. Data mining facilitates data exploration using data analysis methods with sophisticated algorithms in order to discover unknown patterns. The spectrum of CI techniques include data mining algorithms and techniques like artificial neural networks (ANNs) [12], support vector machine (SVM), adaptive neuro-fuzzy inference system (ANFIS), etc. [13].

II. MATERIALS AND METHODS

The main objective of this paper is to design an optimal procedure for CPR which would maximize the systemic oxygen delivery. The research so far has focused on finding the optimal value for the compression to ventilation ratio which maximizes the oxygen delivery and keeps it constant during the complete CPR procedure.

A. Calculating the Oxygen Delivery

Systemic oxygen delivery can be calculated using a simple equation presented in [8]:

$$D_{O_2} = \bar{Q} \times \Delta C_{O_2} \tag{1}$$

where, $\bar{Q}$ is the mean forward blood flow during CPR and ΔC_{O_2} is the oxygen concentration in blood. An analytical expression for $\bar{Q}$ based on the CPR parameters is derived in [8] and presented in Eq. (2)

$$\bar{Q} = Q_{max} \frac{x}{\frac{T}{t} + x} \tag{2}$$

where, T is the average time required for one ventilation, t is the time for one full compression and x is the compression to ventilation ratio. The values of T are different for ideal and practical conditions and in this paper we only focus on the practical conditions; however, the developed method could easily be used for the ideal condition.

An analytical expression for ΔC_{O_2} based on the CPR parameters is derived in [8] and presented in Eq. (3).

$$\Delta C_{O_2} = \frac{s(v_T - v_D) f_I}{(v_T - v_D) + Q_{max} stx} \tag{3}$$

where, s is the slope of the oxygen-hemoglobin dissociation curve, v_T is tidal volume, v_D is the deadspace volume and f_I is the fraction of oxygen in the inspired gas.

Finally, we express oxygen delivery in terms of the following equation, Eq. (4):

$$D_{O_2} = Q_{max} \frac{sx(v_T - v_D) f_I}{(T/t + x) \times ((v_T - v_D) + Q_{max} stx)} \tag{4}$$

B. Global Optimization

To find a maximum of the oxygen delivery calculated by Eq. (4) in the real world where the rescuer performance can vary greatly, one can implement a global optimization method. In this paper, to find the global maximum of the oxygen delivery we divide the model parameters to two groups: patient specific parameters and CPR parameters. Patient specific parameters are the parameters that vary from patient to patient and do not depend on the rescuer performance and include s, v_D and Q_{max}. CPR parameters are the parameters that depend on the rescuer performance and could vary over the compression/ventilation periods and include T, t, v_T and f_I. The algorithm is implemented here using the simulated annealing method.

C. Simulated Annealing

Simulated annealing is a powerful method to solve combinatorial optimization problems. The objective of combinatorial optimization is to minimize the user defined cost function of a system characterized by a large number of solutions. [14]. The simulated annealing methods have been largely used in engineering applications as well as in biomedical research [15], [16].

Annealing as defined in [17] *is the process of slowly cooling a physical system in order to obtain states with globally minimum energy*. By simulating such a process, solutions near a global minimum can be found for very large optimization problems. To define the simulated annealing we should first define the *energy* of the system and how it relates to the *temperature* of the system. The Helmholtz free energy of a physical system is defined by Eq. (5).

$$F = \sum_i p_i E_i + T \sum_i p_i \log p_i \tag{5}$$

where, p_i is the probability of occurrence of state i, E_i is energy of the system in state i and T is the *temperature* of the system. This equations will result in the conclusion that low energy ordered states are strongly favored at low temperatures. Based on the above definition the simulated annealing could be described as the following twofold scheme [14].

- A schedule that determines the rate at which the temperature is lowered.
- An algorithm that iteratively finds the equilibrium distribution at each new temperature in the schedule by using the final state of the system at the previous temperature as the starting point for the new temperature.

Simulated annealing is particularly well suited for solving combinatorial optimization problems [14]. We use the simulated annealing method for all optimization problems in this paper.

D. Sequential Optimization

For a second perspective, we design an optimal procedure for the CPR using a sequential optimization scheme. In this scheme, instead of finding the global maximum for oxygen delivery before performing the CPR and keeping the parameters constant during the resuscitation, we optimize the oxygen delivery at every sequence of the CPR. We first maximize the oxygen delivery based on optimizing the compression to ventilation ratio, perform the CPR and then maximize the oxygen delivery based on maximizing the CPR parameters. These new parameters are then used as the starting point of the next sequence, and this procedure is continued until the last sequence.

The schematic of the sequential optimization algorithm is presented in Fig. (1) and can be described as follows.

1) Start with nominal values.
2) Optimize the oxygen delivery based on the x.
3) Perform the CPR.
4) Optimize the CPR parameters to maximize the oxygen delivery based on x calculated in Step 2.
5) Go to Step 2 and repeat until the final sequence.

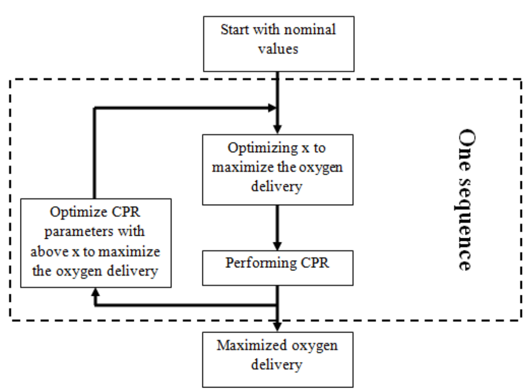

Fig. 1. Schematic of the sequential optimization algorithm. The algorithm is combined of two parts and after each CPR sequence the optimization is carried out again.

Finally, for comparison with previous results published in [8], it is to be noted that the optimal value of x was computed by Eq. (6):

$$x^* = \frac{1}{t}\sqrt{\frac{(v_T - v_D)T}{Q_{max}s}} \tag{6}$$

By substituting the x^* from (6) into (4) the maximum oxygen delivery can be calculated.

III. RESULTS

The nominal values and ranges of the parameters are presented in Table (I). As described earlier the parameters are divided into two groups: patient specific parameters and CPR parameters. Among the patient specific parameters, s and v_D are considered constant in the literature [8]. We vary Q_{max} in the range of $[700 \quad 1100]$ to simulate a wide range of patients. We vary the CPR parameters in the range of $[min - SD \quad min + SD]$, where, SD is the standard deviation. The reason to limit the range to one SD is to avoid sharp changes in the simulation of the rescuer performance.

TABLE I

PARAMETER VALUES AND THEIR RESPECTIVE RANGES. SD IS STANDARD DEVIATION. PARAMETERS ADAPTED FROM [8]

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Parameter	Mean± SD	Unit
	CPR Parameters	
T	0.133±0.01	Min
t	0.01±0.001	Min
v_T	800±200	ml gas
f_I	0.16±0.02	ml O_2 / ml gas
	Patient Parameters	
v_D	150	ml gas
Q_{max}	900±200	ml blood/ min
s	1.5	ml gas / ml blood

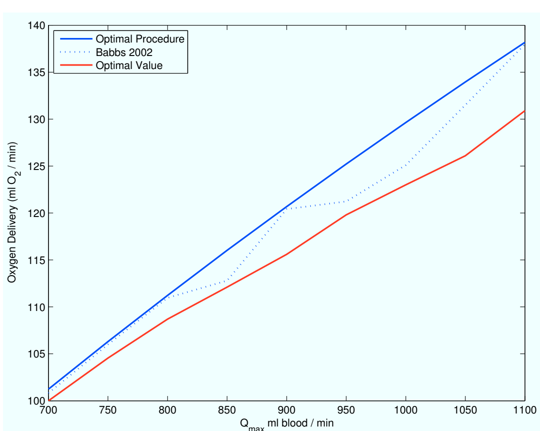

Fig. 2. Comparison of results obtained from three different method described in the paper

Results obtained from our proposed methods are presented in Fig. (2) along with a comparison with the results from [8]. The results show that the sequential optimization scheme proposed in this paper gives the best values for maximum oxygen delivery.

The method presented by Babbs and Kern [8] performs better than the global optimization method but still needs to be improved. The global optimization scheme as shown in this figure will not result in the best CPR performance. Fig. (2) also shows that the performance of the global optimization scheme is decreased by increasing the maximum forward blood flow, Q_{max}. The reason is that oxygen delivery is increased by increasing Q_{max} and consequently the global optimization scheme becomes more inefficient. The very interesting result observed from Fig. (2) is that unlike the method presented in [8], the performance of sequential optimization scheme described in this paper is consistent.

The advantage of the sequential optimization technique used in this paper stems from its sequence adaptation effect. As presented in Fig. (3) the oxygen delivery is increased during CPR. This figure also shows that the oxygen delivery reaches its steady state after the fourth cycle from which it is clear that the sequential optimization scheme has a fast adaptation rate.

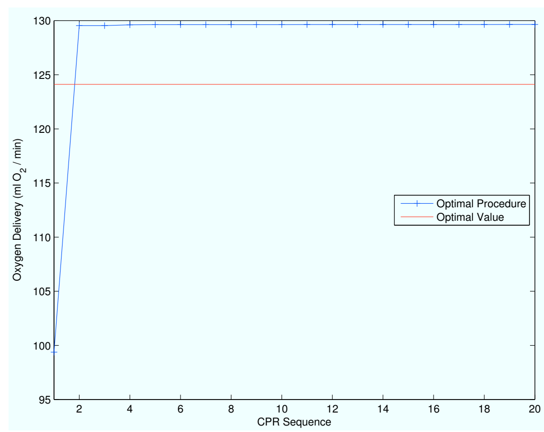

Fig. 3. Oxygen delivery as a function of sequence in the CPR procedure. Q_{max} is set to 1000 ml blood/min

The optimized compression to ventilation ratio is presented in Fig. (4). This plot again shows how the sequential optimization adapts itself to increase the maximum oxygen delivery.

The optimized compression speed in minutes is presented in Fig. (5). This figure combined with Fig. (4) shows that decreasing the compression speed and also decreasing the compression to ventilation ratio together will increase the oxygen delivery.

IV. CONCLUSIONS

This paper is concerned with optimization of the cardiopulmonary resuscitation (CPR) procedure which plays a crucial rule in saving the life of patients suffering from cardiac arrest. Most of the research so far has focused on optimizing the compression to ventilation ratio to maximize the performance of the CPR procedure. This paper is the first effort to consider a broader picture.

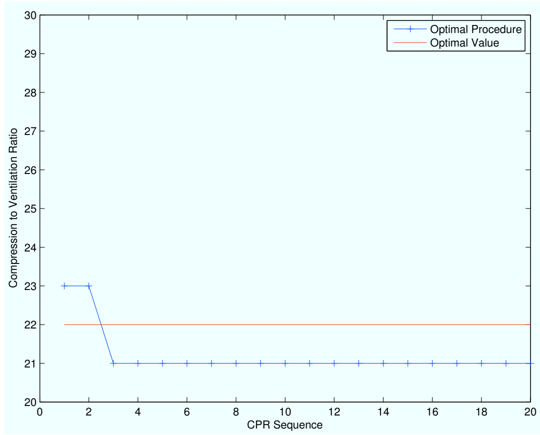

Fig. 4. Compression to ventilation ratio as a function of sequence in the CPR procedure. Q_{max} is set to 1000 ml blood/min.

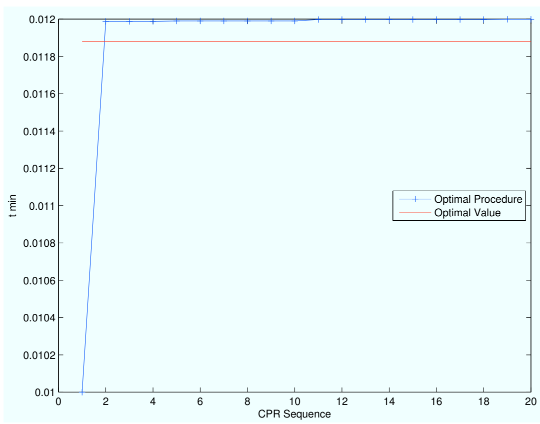

Fig. 5. Compression time as a function of sequence in the CPR procedure. Q_{max} is set to 1000 ml blood/min.

Defining oxygen delivery as the performance measure, a model developed by [8] is used to calculate the oxygen delivery through the CPR. This model consists of several parameters which are divided into two groups of patient specific parameters and CPR or rescuer dependent parameters. Among the patient parameters the maximum forward blood flow (Q_{max}) is the parameter that is considered to be varied from one patient to another. The free parameters of this model which depend on the rescuer performance are ventilation time, compression speed, tidal volume, and fraction of oxygen in the inspired air.

We look at two approaches. The first is to optimize the oxygen delivery by finding the optimal values of the free parameters which maximize the oxygen delivery and to "perform" the CPR process with these optimal values. In the second approach we apply a sequential optimization scheme which uses a two-step optimization algorithm in each CPR sequence to maximize the oxygen delivery. In the sequential optimization scheme, at each sequence, the rescuer performs the CPR with some optimal value of the compression to ventilation ratio and then maximizes his/her performance based on the compression to ventilation ratio he has done and will do the CPR again with new optimized compression to ventilation ratio. Results show that the designed sequential optimization procedure will increase the performance of the CPR.

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