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Towards an Intelligent System for Clinical Guidance on Wheelchair Tilt and Recline Usage

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Abstract— **We propose to construct an intelligent system for clinical guidance on how to effectively use power wheelchair tilt and recline functions. The motivations fall into the following two aspects. (1) People with spinal cord injury (SCI) are vulnerable to pressure ulcers. SCI can lead to structural and functional changes below the injury level that may predispose individuals to tissue breakdown. As a result, pressure ulcers can significantly affect the quality of life, including pain, infection, altered body image, and even mortality. (2) Clinically, wheelchair power seat function, i.e., tilt and recline, is recommended for relieving sitting-induced pressures. The goal is to increase skin blood flow for the ischemic soft tissues to avoid irreversible damage. Due to variations in the level and completeness of SCI, the effectiveness of using wheelchair tilt and recline to reduce pressure ulcer risks has considerable room for improvement. Our previous study indicated that the blood flow of people with SCI may respond very differently to wheelchair tilt and recline settings. In this study, we propose to use the artificial neural network (ANN) to predict how wheelchair power seat functions affect blood flow response to seating pressure. This is regression learning because the predicted outputs are numerical values. Besides the challenging nature of regression learning, ANN may suffer from the overfitting problem which, when occurring, leads to poor predictive quality (i.e., cannot generalize). We propose using the particle swarm optimization (PSO) algorithm to train ANN to mitigate the impact of overfitting so that ANN can make correct predictions on both existing and new data. Experimental results show that the proposed approach is promising to improve ANN's predictive quality for new data.**

I. Introduction

Pressure ulcers pose serious threats to the quality of life for people with spinal cord injury (SCI) [1, 2]. The reason that people with SCI are vulnerable to pressure ulcers is that SCI can lead to structural and functional changes below the injury level that may predispose individuals to tissue breakdown [3]. Due to the blockade of the sensory pathway to the brain, people may lose the protective mechanism for avoiding prolonged ischemic insults to the compressed tissues. Loss of autonomic nervous system control over the cardiovascular system weakens the vasodilatory response to loading pressure [4]. All these factors are directly responsible for the high occurrence rate of pressure ulcers in individuals with SCI [5, 6].

Reddy *et al*. [7] found that periodically repositioning patients was a key element in the majority of the pressure ulcer prevention protocols. The purpose is to allow the ischemic soft tissues to develop sufficient blood flow and thus avoid prolonged tissue ischemia, which is considered to be the main cause of pressure ulcers [8]. In practice, clinicians recommend periodically adjusting power wheelchair tilt and recline angles so that sitting-induced pressures can be relieved and the ischemic soft tissues can be re-perfused [9, 10].

However, how to effectively use wheelchair power seat functions to enhance skin blood flow is still under-investigated. Our previous study [11] showed that there were no generic rules that were suitable for all the wheelchair users on how to effectively use wheelchair power seat functions. The skin blood flow of people with SCI responded very differently to wheelchair tilt and recline settings. As a result, the clinical guidance on wheelchair tilt and recline usage should be customized for individual persons. We attempted to address this issue by using the artificial neural network (ANN) to classify favorable tilt and recline settings that could result in skin perfusion increase for individual persons [11]. The limitation of that approach, however, is that it can only make discrete classifications, namely, positive, neutral, or negative. It cannot quantify the extent of the positive or negative response to a given tilt and recline setting. Therefore, it cannot predict the optimal tilt and recline angles, which can increase skin perfusion the most.

We propose using ANN to predict the values of skin perfusion change for individual persons with SCI. This study is different from our previous approach [11] in that ANN will predict numerical values instead of discrete classifications. This is the so called regression learning, which is very challenging. The back-propagation algorithm (BP) [12] has been widely used to train ANN. However, BP tends to suffer from the overfitting problem, in which ANN cannot generalize to predict new data (i.e., poor predictive ability) even though it can predict well the existing training data. In order to mitigate the impact of overfitting, we propose to use the particle swarm optimization (PSO) algorithm [13] to train ANN. PSO has emerged as an important population-based stochastic optimization algorithm inspired by flocking birds or schooling fish. It tends to converge faster than other optimization algorithms, such as the well-known genetic algorithm [14], while maintaining similar or better optimization quality. Experimental results demonstrate that the proposed approach is very promising: The ANN trained by PSO generalizes significantly better than the one trained by BP. By combining our previous classification approach [11] and the proposed PSO-based regression approach, our intelligent system can

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cross-validate the outputs of the two approaches to ensure even better prediction quality.

In the rest of this paper, we briefly overview ANN and the PSO algorithm in Section II, and then describe the method designed to collect skin perfusion data and the method to train ANN in Section III. Finally, we present the experimental results in Section IV, discuss the proposed method in Section V, and conclude the paper in Section VI.

II. Background

A. Artificial Neural Network

Pictorially, an artificial neural network is a layered graph consisting of nodes (i.e., neurons) organized into layers and edges (i.e., weighted connections) connecting nodes between layers. Although there is no limitation on the number of layers, in practice, we do not choose a network with more than four layers because an ANN with four layers can learn any function with arbitrary accuracy [15]. After a network structure is determined, the weights of the connections will determine the quality of learning. Therefore, an appropriate training algorithm is very important to train ANN through adjusting the weights.

B. Particle Swarm Optimization (*PSO*)

In PSO, a particle is identified by its position and velocity in a multi-dimensional space. The position of a particle encodes a potential solution to the problem to be solved. The initial population of particles is often randomly generated. PSO needs a fitness function to evaluate the performance of particles. PSO proceeds in iterations and terminates when the stop criteria are satisfied. In each iteration, the particle with the best fitness value is considered as being located at the "global best" position (*gBest*). In addition, each particle keeps its personal best position (*pBest*) in history. Knowing both *gBest* and *pBest*, a particle p_i can "fly" towards the *gBest* and *pBest* with a certain velocity $v_i[t] = (v_i^1[t], v_i^2[t],\ldots, v_i^N[t])$ at time t in an N dimensional space. Therefore, the updated velocity (v_i) and position (pos_i) in the dth dimension at time $t + 1$ are calculated by [13]:

$$v_i^d[t+1] = v_i^d[t] + l_1 \times \gamma_1 \times (pBest_i^d[t] - pos_i^d[t]) + l_2 \times \gamma_2 \times (gBest^d[t] - pos_i^d[t]) \quad (1)$$

$$pos_i^d[t+1] = pos_i^d[t] + v_i^d[t+1] \quad (2)$$

where γ_1 and γ_2 are two random numbers in the range of (0, 1); l_1 and l_2 are learning factors. After all particles have updated their positions, the fitness function is used again to evaluate the performance of each particle. *gBest* as well as the personal *pBest* might be changed. Then, the particles will fly towards the new *gBest* and *pBest*. This process will repeat until meeting the stop criteria.

III. Method

An experimental study was conducted to establish the relationship between wheelchair power seat function usages and the resulting skin blood flow responses [4]. The study involved 11 wheelchair users with SCI consisting of 1 African American, 1 American India, and 9 white participants. More details regarding the experiment protocol and participants' information can be found in [4]. In this section, we only briefly introduce how data were collected in the experiment.

We considered the clinically recommended tilt (i.e., 15°, 25°, and 35°) and recline (i.e., 100° and 120°) angles in our study. As a result, a total of 6 tilt and recline testing conditions were created. Each testing condition lasted for 5 minutes to relieve the seating pressure, which was caused by sitting upright for 5 minutes without performing tilt or recline. Skin perfusion was continuously measured throughout the experiment. The skin perfusions measured in the aforementioned two 5-minute periods can help us determine the ratio of the skin perfusion change resulted from performing wheelchair tilt and recline.

$$\beta = b_1 / b_0 \quad (3)$$

where b_0 was the skin perfusion measured when the research subject sat upright for 5 minutes and b_1 was the skin perfusion measured when wheelchair tilt and recline functions were performed in the next 5 minutes.

A. Modeling Participants

By nature, this is a feasibility study. We simplified the modeling of participants by considering attributes that were once reported to be related to the occurrence of pressure ulcers [16]. Specifically, we model a participant with 5 attributes, namely, age (a), sex (s), level of injury (l), duration of the SCI (d), and completeness (c). Formally, a research participant is modeled with a 5-tuple $\langle a, s, d, l, c\rangle$.

B. Modeling Inputs and Outputs

By training ANN, we attempt to learn a function g: $D \rightarrow R$. D is the input domain, in which each data item is modeled in a 7-tuple, namely, $\langle a, s, d, l, c, t, r\rangle$, where a, s, d, l, c are the 5 attributes discussed above; t and r represent a tilt and recline setting. All training data were obtained from the 11 participants.

R is the output domain, which contains the skin perfusion changes resulted from performing wheelchair tilt and recline functions, i.e., β in Equation (3). Therefore, given a participant $\langle a, s, d, l, c\rangle$ and a tilt and recline setting $\langle t, r\rangle$, the function g will predict the skin perfusion increase ratio β. This is regression learning since function g will predict the real values of β.

C. Modeling Particles

To use a particle to represent a solution to an ANN, we need to know the structure of the ANN, including the number of layers and the number of nodes in each layer, as well as the weights of connections between nodes. In this study, we used the network structure 7-7-1, i.e., 7 nodes in the input and hidden layers, respectively, and 1 node in the output layer. All the connections are ordered such that their corresponding weights can be put into an array. Therefore, a particle is modeled with a weight array. In our experiments, each population consists of 25 particles and the weight arrays are

randomly generated in the initial population.

D. Fitness Function

Figure 1 shows the algorithm for the fitness function. The fitness function takes two arguments, namely, a weight array p (i.e., a particle that represents a possible solution to the ANN) and the training data set D. Given a particle (i.e., weight array) p, the fitness function calculates the percentage of correct predictions against the entire training data D. Initially, the number of correct predictions is set to 0 (line 1).

```
/*p is a particle represented by a weight array */
/*D is the training data set*/
Function Fitness (p, D)
1.  correct ← 0
2.  for each data item i ∈ D do
3.      predicted ← ANN(p, i)
4.      if in_same_category(predicted, actual(i)) then
5.          if(|predicted – actual(i)| < τ)
6.              correct ← correct + 1.0
7.          else
8.              correct ← correct + 0.5
9.          end if
10.     end if
11. end for
12. return correct / sizeof(D)
```

Figure 1. Fitness Function

Since the ANN structure is fixed to be 7-7-1 in this study, the weight array p will enable the ANN to make predictions for each data item i in D (lines 2 and 3). The algorithm first checks whether the predicted value is in the same category as the actual value of i (line 4). To see why this step is necessary, let us see an example, in which the actual and predicted skin perfusion ratios for data item i are 1.10 and 0.95, respectively. Such a prediction is unacceptable because the actual value indicates that the corresponding tilt and recline are beneficial (since the skin perfusion increases) while the predicted value suggests that the tilt and recline setting could be harmful (since the skin perfusion decreases). On the other hand, if the predicted value is 1.25, although the absolute difference is the same as that of 0.95, this prediction is acceptable because it carries the same meaning as the actual value, i.e., the skin perfusion increases as a result of performing wheelchair power seat functions.

In general, if the actual skin perfusion increase ratio (i.e., actual(i)) is greater than 1, it suggests that the corresponding tilt and recline setting is beneficial. If actual(i) is less than 1, the corresponding setting may be harmful. There is a third case, in which actual(i) is very close to 1. For example, if actual(i) = 0.995, then it is uncertain whether this is a true negative case. Hence, we set a threshold σ such that

- if actual(i) > 1 + σ, then it is positive;
- if 1 – σ ≤ actual(i) ≤ 1 + σ, then it is neutral; and
- if actual(i) < 1 - σ, then it is negative.

In this study, we set σ = 0.1 because the skin perfusion ratio β is in the range of [0, 2] and σ = 0.1 sets a reasonable range [0.9, 1.1] for the neutral cases.

If the predicted and actual values are in the same category, the algorithm will check whether the difference is less than the threshold τ (line 5). If true, the algorithm increases the correct predictions by 1 (line 6). Otherwise, the algorithm only counts it as half-correct and increases the correct predictions by 0.5 (line 8). We set τ = 0.1 such that the predicted and actual values will be close. If the predicted and actual values are in different categories, they carry different meanings and are thus considered to be a wrong prediction.

E. Two Experiments

We perform two different experiments to examine the prediction quality and generalization capability of the trained ANN. In the first experiment, we use the entire data set to train the PSO-based ANN. After the training is finished, we test the trained ANN by using the same set of data. The disadvantage of this approach is that we cannot examine whether the trained ANN can generalize to predict new (i.e., unseen) data.

The second experiment, called 11-fold cross-validation, is designed to examine the ANN's generalization ability. We divide training data into 11 mutually exclusive folds. Each fold is only associated with a single human subject. We train the ANN with 10 folds and use the one that is left out to test the ANN. This experiment is performed 11 times on all the folds. Then, the averaged accuracy rate on all the folds will be used as the final accuracy. The benefit of this experiment is that we can always test the ANN with a new human subject.

IV. Results

As a baseline, BP was used to train ANN to perform the same experiments. The purpose is to compare whether using PSO to train ANN was superior to using BP. For the first experiment that used the entire data set, the BP-based approach correctly predicted all the training data, i.e., the accuracy rate was 100%. In comparison, the PSO-based approach achieved an accuracy rate of 80.7%. Here, we have a stricter definition for "correct" predictions than the one defined in the fitness function in Figure 1. The criteria include (1) the predicted value should be in the same category as the actual value; (2) the absolute difference between the predicted and actual values should be less than 0.1; and (3) the half correct cases in Figure 1 are considered as wrong predictions.

TABLE I
EXPERIMENTAL RESULTS FOR 11-FOLD CROSS-VALIDATION

Fold	BP-based	PSO-based
#1	0%	50%
#2	0%	50%
#3	33.3%	33.3%
#4	0%	33.3%
#5	0%	83.3%
#6	16.7%	66.7%
#7	0%	50%
#8	0%	100%
#9	33.3%	50%
#10	16.7%	50%
#11	16.7%	50%
Average	11%	56%

However, the ANN trained by BP suffered from serious

overfitting problems. Table I shows the experimental results on the 11-fold cross-validation. The ANN trained by BP generalized poorly on each fold. On average, its accuracy rate was only 11%. In comparison, the ANN trained by PSO generalized significantly better. Its average accuracy rate was 56%.

V. Discussion

To ensure a fair comparison, the BP- and PSO-based approaches used the same network structure for ANN, i.e., 7-7-1.

With the learned function g, we will be able to predict the optimal wheelchair tilt and recline settings that will result in the most significant skin perfusion increase. Given the ranges of commonly used tilt and recline angles, such as tilt at [15°, 45°] and recline at [90°, 120°], we can design a simple algorithm by using function g to try all the combinations of tilt and recline angles in the ranges. The ones resulting in the largest output will be the candidate optimal settings. Formally, we can summarize the algorithm with the following formula: $argmax_{\langle t,r\rangle \in \Gamma}\ (g(a, s, d, l, c, t, r))$, where Γ is the set of tilt and recline settings.

Moreover, the learned function g can be used to cross-validate the outputs of another function f [11] that was designed to classify the skin perfusion changes into three discrete categories, i.e., positive (1), neutral (0), and negative (-1). Given a data item $\langle a, s, d, l, c, t, r\rangle$, we will be confident with the predictions in the following three cases:

- $g(a, s, d, l, c, t, r) > 1 + \sigma$ iff $f(a, s, d, l, c, t, r) = 1$;
- $g(a, s, d, l, c, t, r) < 1 - \sigma$ iff $f(a, s, d, l, c, t, r) = -1$; and
- $1 - \sigma \le g(a, s, d, l, c, t, r) \le 1 + \sigma$ iff $f(a, s, d, l, c, t, r) = 0$.

where "iff" means "if and only if"; σ is the threshold to separate neutral cases from the positive and negative cases as discussed in Section III.D.

A. Study Limitations

This study is a feasibility study since we only have data from 11 participants. We are recruiting more research participants to enroll in the study. In addition, the architecture of the ANN used in this study may not be optimal to generate the best results. Unfortunately, no general rules are available to find the optimal structure [15]. In the subsequent study, we will apply the trial-and-error approach to enumerate possible structures of ANN to find the optimal one. This approach is feasible because an ANN can learn any functions with arbitrary accuracies by a network with 4 layers [15].

VI. Conclusion

In this paper, we employed a regression learning approach to determine a function g that can be used to predict the skin perfusion change as a result of performing wheelchair power seat functions. The PSO algorithm was used to train ANN to mitigate the impacts of overfitting. Experimental results showed that the ANN trained by PSO generalized significantly better than the one trained by BP. With the learned function g, we can predict the optimal wheelchair tilt and recline settings that may increase the skin perfusion the most. To ensure the prediction quality, we can use our previously learned classification function f [11] to cross-validate the outputs of the learned function g. With more training data becoming available, we expect that our intelligent system will be more accurate at providing clinical guidance on how to effectively use wheelchair tilt and recline functions for individuals with SCI.

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