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Development of Intelligent Model to Determine Favorable Wheelchair Tilt and Recline Angles for People with Spinal Cord Injury

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Abstract— **Machine-learning techniques have found widespread applications in bioinformatics. Such techniques provide invaluable insight on understanding the complex biomedical mechanisms and predicting the optimal individualized intervention for patients. In our case, we are particularly interested in developing an individualized clinical guideline on wheelchair tilt and recline usage for people with spinal cord injury (SCI). The current clinical practice suggests uniform settings to all patients. However, our previous study revealed that the response of skin blood flow to wheelchair tilt and recline settings varied largely among patients. Our finding suggests that an individualized setting is needed for people with SCI to maximally utilize the residual neurological function to reduce pressure ulcer risk. In order to achieve this goal, we intend to develop an intelligent model to determine the favorable wheelchair usage to reduce pressure ulcers risk for wheelchair users with SCI. In this study, we use artificial neural networks (ANNs) to construct an intelligent model that can predict whether a given tilt and recline setting will be favorable to people with SCI based on neurological functions and SCI injury history. Our results indicate that the intelligent model significantly outperforms the traditional statistical approach in accurately classifying favorable wheelchair tilt and recline settings. To the best of our knowledge, this is the first study using intelligent models to predict the favorable wheelchair tilt and recline angles. Our methods demonstrate the feasibility of using ANN to develop individualized wheelchair tilt and recline guidance for people with SCI.**

I. Introduction

Pressure ulcers significantly affect the quality of life of wheelchair users with SCI. Pressure ulcers have become the second cause of rehospitalization for people with SCI [4]. It is estimated that more than 50% of people with SCI will develop at least one pressure ulcer in their lifetime [13]. Annual U.S. treatment costs of pressure ulcers in people with SCI are approximately $1.3 billion, accounting for 25% of the total cost of treating SCI [3]. It is clear that research regarding the prevention of pressure ulcers remains a priority in people with SCI.

The current clinical practice uses wheelchair power seat function (PSF) to adjust tilt (a change of seat angle orientation while maintaining the seat-to-back angle) and recline (a change of the seat-to-back angle) to reduce seating interface pressure to prevent pressure ulcers. The principle of wheelchair tilt and recline is based on the evidence that turning the patient every 2 hours results in a lower incidence of pressure ulcers [15]. Sitting-induced pressure could be relieved by performing wheelchair tilt and recline [10]. Generally, there is a consensus regarding the use of tilt and recline to reduce seating interface pressure; however, the recommended usage of tilt and recline differs among clinicians and facilities [5].

To determine the efficacy of seating conditions to reduce the pressure ulcers risk, skin blood flow response to loading pressure has been regarded as an accurate way [9][10]. Reactive hyperemia is a transient increase in skin blood flow after ischemia [2]. Both the magnitude and duration of the reactive hyperemia have been shown to relate to the magnitude and duration of the external loads [2]. The purpose of periodically performing pressure-relieving activities (e.g. tilt and recline usage) is to allow the development of reactive hyperemia to re-perfuse the ischemic tissues [10]. Inadequate blood flow increase to ischemic tissues may lead to pressure ulcers [14]. However, at what angle wheelchair tilt and recline usage provides adequate pressure relief for enhancing skin blood flow and soft tissue viability is not clear [9].

We performed a study to investigate the effectiveness of wheelchair tilt and recline on enhancing skin perfusion in 11 wheelchair users with SCI [9]. The main factors include the commonly used tilt and recline angles, including tilt at 15°, 25°, and 35° and recline at 100° and 120°. A combination of 3 tilt and 2 recline angles resulted in 6 testing conditions. Based on the average skin perfusion on each testing condition, we found that as the angles of tilt and recline increase, the average skin perfusion also increases. Although this pattern works well in general, we found that it did not work on some individual cases, in which the increase of tilt and recline angles resulted in decrease of the skin perfusion. In fact, using the average data to classify wheelchair tilt and recline settings shares the same weakness as the current clinical practice that provides uniform guidance on wheelchair tilt and recline usage to patients with SCI. Therefore, it is highly desirable to develop an intelligent system that can predict the favorable wheelchair usage to reduce pressure ulcers risk for individual wheelchair users.

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Machine-learning techniques can capture characteristics of interests based on examples (i.e., training data) even though the underlying nature, principles, and/or probability distributions are unclear. As a result, machine-learning techniques are well suited in this study because many factors, such as level of injury, completeness, duration of injury, etc., may interact with each other to affect skin perfusion. However, the nature and principles with regard to how these factors interact remain unknown [6]. In this study, we use artificial neural network (ANN) to construct an intelligent model that considers multiple factors and is able to predict whether a tilt and recline setting would increase skin perfusion for individual wheelchair users with SCI. ANN is a powerful computational model with many appealing properties, such as learning capability, adaptability, and ability to generalize [1]. All these properties are desirable in this study.

To the best of our knowledge, no such intelligent models are currently available. Hence, the goals of this study are to (1) demonstrate the feasibility of using machine-learning techniques to construct such an intelligent model; and (2) investigate methods to determine the attributes relevant to skin perfusion and build the intelligent model based on the relevant attributes. The experience learned from this study will benefit investigators in this area.

The rest of the paper is organized as follows. In Section II, we present the methods used in this study. Then, we show the experimental results in Section III, present the discussion in Section IV, and conclude in Section V.

II. Methods

We performed a study [9] to investigate the blood flow response to wheelchair tilt and recline usage in 11 wheelchair users with SCI. The main factors include the commonly used tilt and recline angles, including tilt at 15°, 25°, and 35° and recline at 100° and 120°. The factorial design created 6 testing conditions (A_1B_1, A_2B_1, A_3B_1, A_1B_2, A_2B_2, and A_3B_2) as shown in Table I. The order of the 6 testing conditions was randomly assigned to the subjects. Skin blood flow was continuously measured through the experiment. Each condition lasted for 10 minutes. The first 5-minute was the sitting-induced ischemic period (no tilt or recline). The skin perfusion b_0 was measured during the ischemic period. The next 5-minute was the pressure reduction period caused by performing wheelchair tilt and recline, during which the skin perfusion b_1 was measured. The skin perfusion increase was computed by the ratio:

$$\beta = b_1 / b_0 \qquad (1)$$

In addition, the subject assumed a sitting posture of 35 degree tilt and 120 degree recline for a duration of 5 minutes to restore blood flow supply to ischemic tissues between each conditions [10]. Each subject spent 90 minutes to complete the experimental protocol. 11 participants with 6 testing conditions produced 66 skin perfusion data.

TABLE I
A REPEATED MEASURES FACTORIAL DESIGN

	Wheelchair Tilt Angle (A)		
Wheelchair recline angle (B)	15° (A_1)	25° (A_2)	35° (A_3)
100° (B_1)	A_1B_1	A_2B_1	A_3B_1
120° (B_2)	A_1B_2	A_2B_2	A_3B_2

A. Traditional Statistical Analysis

We used traditional statistical approach to analyze skin blood flow response to wheelchair tilt and recline usage based on the average skin perfusion increase ratio $\bar{\beta}$ on each testing condition. The averaged data demonstrates a strong pattern: as the angles of tilt and recline increase, the average skin perfusion increase ratio $\bar{\beta}$ also increases. The wheelchair tilt should be at least 35° for enhancing skin perfusion over the ischial tuberosity when combined with recline at 100° and should be at least 25° when combined with recline at 120° [9].

Although the above pattern works well in general, we found that it did not work on some individual cases, in which the increase of tilt and recline angles resulted in decrease of skin perfusion. We used the average skin perfusion ratio $\bar{\beta}$ to classify data in the same testing condition. Specifically, if $\bar{\beta} > 1$ on a particular testing condition (i.e., a particular tilt and recline setting), then we classify all the data on this testing condition as positive. On the other hand, if $\bar{\beta} <= 1$, all the data on this testing condition is classified as negative. Based on this method, the classification accuracy rate is only 59.38%. Therefore, the traditional way to investigate blood flow response to wheelchair tilt and recline usage is not satisfying.

B. Using ANN to Study Blood Flow Response to Wheelchair Tilt and Recline Usage

Since no such intelligent models are currently available, there is no previous experience to follow. In this study, we explore methods to determine the attributes relevant to skin perfusion and, then, build the intelligent model based on the relevant attributes.

Specifically, we want to determine a function $f(a_1, a_2, \ldots, a_k, t, r) \rightarrow \{0, 1\}$, where $a_1, a_2, \ldots, a_k$ are attributes (or factors) of participants, such as level of injury, duration of injury, etc, and t and r are a particular tilt and recline setting. The purpose of the function f is that given a patient modeled with attributes $\langle a_1, a_2, \ldots, a_k \rangle$, the function f will determine whether the tilt and recline setting $\langle t, r \rangle$ will result in skin perfusion increase (denoted by 1; otherwise, 0).

To determine the function f, we need to (1) prepare training data for machine-learning algorithms; (2) determine the set of attributes $\{a_1, a_2, \ldots, a_k\}$ that is relevant to skin perfusion; and (3) establish an intelligent model based on the relevant attribute set such that function f can accurately classify existing and unseen data.

1) To prepare training data. We collected participants' attributes that are reported to be risk factors for pressure ulcers, including age (a), gender (g), duration of injury (d), level of injury (l), and completeness (c) [6][7]. The reason that we also consider demographic attributes is that SCI individuals with certain demographic attributes may be more vulnerable to pressure ulcers [6]. With existing information, we are able to derive an additional attribute, namely, age at onset of SCI (o) with $o = a - d$. Combining all the attributes together, we obtain a raw model for a participant as:

$$\langle a, g, d, l, c, o\rangle \in P \qquad (2)$$

where P is the set of participants and a, g, d, l, c, and o are attributes defined as above. Then, the set of raw data is defined as:

$$D = \{\langle a, g, d, l, c, o, t, r, \beta\rangle \mid \langle a, g, d, l, c, o\rangle \in P, \langle t, r\rangle \in \Gamma\} \qquad (3)$$

where P is the set of participants defined in (2); Γ is the set of tilt and recline settings; and β is the skin perfusion increase ratio defined in (1).

Based on D, we prepare the training data for attribute selection and classification algorithms. For any data $\langle a, g, d, l, c, o, t, r, \beta\rangle \in D$, it is transformed into an example pair $(\langle a, g, d, l, c, o, t, r\rangle, y)$, where $\langle a, g, d, l, c, o, t, r\rangle \in P \times \Gamma$; $y = 1$ iff $\beta > 1$ and, otherwise, $y = 0$. The data item $\langle a, g, d, l, c, o, t, r\rangle$ serves as the input to the machine-learning algorithms and y is the expected output. Then, all the training data is put into a set X as follows:

$$X = \{(\langle a, g, d, l, c, o, t, r\rangle, y) \mid \langle a, g, d, l, c, o\rangle \in P, \langle t, r\rangle \in \Gamma, \text{and } y \in \{0, 1\}\} \qquad (4)$$

2) To determine the relevant attributes. We take two steps to determine a subset of the attributes that is relevant to skin perfusion from the raw training data X (defined in (4)). In the first step, we use correlation-based feature subset selection (CFS) algorithm [8] to obtain a set of relevant attributes. CFS is a state-of-the-art attribute selection algorithm and is highly ranked in attribute selection repository [17]. We call the set of attributes returned from CFS as the core attributes set. This core set, however, may miss some relevant attributes. Hence, in the second step, we gradually add the remaining attributes to the core set, one attribute at a time. Each time when an attribute is added to the core set, we use ANN to construct the function f based on the new core attributes set.

3) To establish the intelligent model by using ANN. Artificial neural network (ANN) provides a general and practical method for learning functions from examples (training data). An ANN consists of a set of processing units (neurons) that communicate among themselves by sending signals. The signals travel through weighted connections between neurons. Upon receiving signals, these neurons accumulate the inputs and produce outputs according to their internal activation functions. The outputs can serve as inputs for other neurons, or can be a part of the network outputs [12]. Learning is achieved through adjusting the weights of connections between neurons.

Specifically, we use two approaches to build function f and examine its generalization ability. (1) We use all the data to train ANN and use the same set of data to test how well the learned function f classifies these data. We call this approach as "train and test with the same set". When the training set is small, overfitting can easily happen. Overfitting refers to a situation where the classification algorithm may perfectly classify training data, but cannot generalize to correctly classify new data that is not observed before. Hence, (2) we perform N-fold cross-validation to minimize overfitting impacts. N-fold cross-validation refers to dividing the training data into N different sets. This approach runs ANN N times, each time using a different set as the testing set and combining the rest $N - 1$ sets as the training set. Therefore, ANN is always tested with unseen data at each time. The N results from the folds are averaged to produce a single accuracy estimation [12]. The 10-fold cross-validation is the most commonly used method [11].

III. RESULTS

In this section, we first present the result of the set of core relevant attributes returned from the attribute selection algorithm CFS. Then, we discuss how to refine the core attributes set and build the intelligent model.

A. Core Relevant Attributes

By running CFS on the set of raw training data X (defined in (4)), we obtained a subset of attributes,

$$C = \{\text{level of injury, age, duration of injury}\} \qquad (5)$$

The order of the attributes in C is arranged according to their relevance to skin perfusion according to CFS. To check whether the core set misses any other relevant attributes, we add the remaining attributes to the core set C, one at a time. Then, we use ANN to check whether the inclusion of the new attribute will improve the classification accuracy.

B. Construction of the Intelligent Model

By projecting the core attributes onto the raw data set X, we obtain a core data set X_{core}. Then, we train ANN to learn function f based on X_{core}. As discussed before, we train and test ANN with two different approaches, namely, "train and test with the same set" and "10-fold cross-validation". From Table II, we can see that the learned function can correctly classify almost all the data (96.88%). However, overfitting does happen because the accuracy rate for 10-fold cross-validation drops to 70.31%.

TABLE II
EXPERIMENTAL RESULTS

	Train and test with the same set	10-fold cross-validation
X_{core}	96.88%	70.31%
$X_{core} \cup$ {gender}	100%	75%
$X_{core} \cup$ {completeness}	100%	70.31%
$X_{core} \cup$ {*aos*}	96.88%	70.31%
$X_{core} \cup$ { *gender*, *completeness* }	96.88%	71.83%
$X_{core} \cup$ {*gender*, aos}	98.57%	75%
$X_{core} \cup$ {gender, aos, completeness}	100%	75%

Next, we gradually add attribute to the core attributes set and repeat the above experiments. By adding "gender" to the core attribute set, the accuracy rates increase substantially on "train and test with the same set" and "10-fold cross-validation". This result suggests that "gender" should belong to the core attribute set *C*. Thus, we obtain a new core set C' = {level, duration of injury, age, gender}.

Next, we continue to add the remaining attributes to the new core set C' and repeat the experiments as above. The results show that the accuracy rates cannot be further improved.

IV. DISCUSSION

There are two purposes in this study. First of all, we demonstrate the feasibility of using machine-learning techniques to classify whether a given tilt and recline setting would be favorable for skin perfusion for individual wheelchair users with SCI. Specifically, we use ANNs to learn the classification function *f*. When using function *f* to classify existing data, it can classify all the data correctly (e.g., see row "$X_{core \cup \{\text{gender}\}}$" in Table II). However, with a small data set, overfitting is likely to happen. The commonly used approach to minimize overfitting impact is 10-fold cross-validation [11]. Our experimental results show that the highest accuracy rate with 10-fold cross-validation is 75% (e.g., see row "$X_{core \cup \{\text{gender}\}}$" in Table II), which is still satisfying. In comparison, the accuracy rate of the traditional method, i.e., the average data in each tilt and recline setting is used to perform classification, is only 59.38%. Therefore, it is desirable to use machine-learning techniques to study blood flow response to wheelchair tilt and recline usage.

The second purpose of this study is to investigate methods to construct an intelligent model that contains relevant attributes to skin perfusion and is able to predict favorable wheelchair tilt and recline usage for individual wheelchair users with SCI. As a start point, we use a highly ranked attribute selection algorithm, namely, CFS [8], to obtain a core attributes set. Since attributes may interact with each other to take effect, the core attributes set may miss some relevant attributes. We gradually add the remaining attributes to the core set and see if the classification accuracy rates could be further improved. The experimental results show that adding "gender" to the core attribute set substantially improves the classification accuracy. Therefore, "gender" is put into the core attributes set. We continue to add the remaining attributes to the new core set, however, the accuracy rates cannot be further improved. Therefore, the current model includes attributes of "level of injury", "duration of injury", "age", and "gender", which will be validated by more participants in the subsequent study.

V. CONCLUSION

In summary, the use of machine-learning techniques is promising in building an intelligent model that considers the correlations among different factors. The function *f* learned by using ANN significantly outperforms traditional statistical approach in accurately classifying favorable wheelchair tilt and recline settings.

Our long-term goal is to construct a comprehensive model that considers demographic, neurological, and medical factors that are relevant to pressure ulcers. Besides classifying whether a given tilt and recline setting will increase skin perfusion for a wheelchair user with SCI, the intelligent model will also predict (1) the optimal tilt and recline setting that increases skin perfusion the most; and (2) the optimal duration and frequency to perform tilt and recline to effectively reduce pressure ulcers risk.

In addition, we will set up a Web site to make the intelligent model publicly available. People with SCI will simply input some information, such as age, gender, level, duration of injury, etc., then the system will provide suggestions on favorable/optimal tilt and recline settings for them. Therefore, our system will truly aid people with SCI to have a healthier tomorrow.

REFERENCES

[1] E. Alba and J. F. Chicano, "Training neural networks with GA hybrid algorithms", in *Proceedings of the Genetic and Evolutionary Computation Conference—GECCO* 2004, ser. *Lecture Notes in Computer Science*, K. D. *et al*., Ed., vol. 3102. *Springer Verlag*, Berlin, Germany, 2004, pp. 852–863.

[2] M.R. Bliss, "Hyperaemia", *J Tissue Viability* 1998;8:4-13.

[3] D.W. Byrne and C.A. Salzberg, "Major risk factors for pressure ulcers in the spinal cord disabled: a literature review", *Spinal Cord* 1996; 34:255-63.

[4] D.D. Cardenas, J.M. Hoffman, S. Kirshblum, and W. McKinley, "Etiology and incidence of rehospitalization after traumatic spinal cord injury: a multicenter analysis", *Arch Phys Med Rehabil*, 2004; 85:1757–1763.

[5] B.E. Dicianno, J. Arva, J.M. Lieberman, *et al*, "RESNA position on the application of tilt, recline, and elevating legrests for wheelchairs", *Assist Technol* 2009;21:13-22.

[6] S.L. Garber, D.H. Rintala, K.A. Hart, and M.J. Fuhrer, "Pressure Ulcer Risk in Spinal Cord Injury: Predictors of Ulcer Status Over 3 Years", *Archives of Physical Medicine and Rehabilitation*, Volume 81, Issue 4 , Pages 465-471, April 2000.

[7] A. Gélis, A. Dupeyron, P. Legros, C. Benaïm, J. Pelissier, and C. Fattal, "Pressure ulcer risk factors in persons with spinal cord injury Part 2: the chronic stage", *Spinal Cord* (2009) 47, 651–661.

[8] M. A. Hall, "Correlation-based Feature Subset Selection for Machine Learning", *Proc.* 17*th Int'l Conf. Machine Learning*, pp. 359-366, 2000 Hamilton, New Zealand.

[9] Y.K. Jan, M. Jones, M.H. Rabadi, R.D. Foreman, and A. Thiessen, "Effect of wheelchair tilt-in-space and recline angles on skin perfusion over the ischial tuberosity in people with spinal cord injury", *Archives of Physical Medicine and Rehabilitation* 2010, 91(11): 1758-1764.

[10] M. Makhsous, M. Priebe, J. Bankard, *et al*., "Measuring tissue perfusion during pressure relief maneuvers: insights into preventing pressure ulcers", *J Spinal Cord Med* 2007;30:497-507.

[11] G.J., McLachlan, K.A. Do, and C. Ambroise, Analyzing microarray gene expression data. *Wiley*, 2004.

[12] M. Mitchell, Machine Learning, *McGraw-Hill Science*, *Engineering*, *Math*, 1997

[13] National Spinal Cord Injury Statistical Center, "Annual report for the Spinal Cord Injury Model Systems (public version)", Birmingham: University of Alabama; 2006

[14] J. Nixon, G. Cranny, and S. Bond, "Pathology, diagnosis, and classification of pressure ulcers: comparing clinical and imaging techniques", *Wound Repair Regen* 2005;13:365-72.

[15] M. Reddy, S.S. Gill, and P.A. Rochon, "Preventing pressure ulcers: a systematic review", *JAMA* 2006;296:974-84.

[16] D. Rumelhart, G. Hinton, and R. Williams, "Learning Representations by Backpro-pagation Errors". *Nature* 323 (1986) 533-536.

[17] Z. Zhao, F. Morstatter, *et al*., "Advancing Feature Selection Research", Available: http://featureselection.asu.edu/index.php