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Adaptive neuro-fuzzy inference systems with *k*-fold cross-validation for energy expenditure predictions based on heart rate

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ABSTRACT

This paper presents a new model based on adaptive neuro-fuzzy inference systems (ANFIS) to predict oxygen consumption ($\dot{V}O_2$) from easily measured variables. The ANFIS prediction model consists of three ANFIS modules for estimating the Flex–HR parameters. Each module was developed based on clustering a training set of data samples relevant to that module and then the ANFIS prediction model was tested against a validation data set. Fifty-eight participants performed the Meyer and Flenghi step-test, during which heart rate (HR) and $\dot{V}O_2$ were measured. Results indicated no significant difference between observed and estimated Flex–HR parameters and between measured and estimated $\dot{V}O_2$ in the overall HR range, and separately in different HR ranges. The ANFIS prediction model (MAE = 3 ml kg^{-1} min^{-1}) demonstrated better performance than Rennie et al.'s (MAE = 7 ml kg^{-1} min^{-1}) and Keytel et al.'s (MAE = 6 ml kg^{-1} min^{-1}) models, and comparable performance with the standard Flex–HR method (MAE = 2.3 ml kg^{-1} min^{-1}) throughout the HR range. The ANFIS model thus provides practitioners with a practical, cost- and time-efficient method for $\dot{V}O_2$ estimation without the need for individual calibration.

1. Introduction

Researchers in occupational health and safety have demonstrated the importance of designing jobs according to the physiological capacity of a particular workforce. Studies have shown that such design, based on the balance between physiological capacity of the workforce and energetic demands of physical work, is a key factor in maintaining workforce safety and productivity (Abdelhamid, 1999; Wu and Wang, 2002; Dempsey et al., 2008). Oxygen consumption ($\dot{V}O_2$) reflects energy expenditure (EE) and physical workload associated with physically demanding work (Smolander et al., 2008; Wu and Wang, 2002; Bouchard and Trudeau, 2008).

Direct measurement of $\dot{V}O_2$ requires sophisticated and costly instrumentation; therefore attempts have been made to find alternative estimation methods (e.g., ISO8996, 2004; Smolander et al., 2008).

The Flex–HR method is one of the most widely used methods based on heart rate (HR) measurements (Spurr et al., 1988; Ceesay et al., 1989; Schulz et al., 1989; Garet et al., 2005). This method assumes a linear relationship between HR and $\dot{V}O_2$ above a transition point (Flex point) and a more variable relationship, which uses the average of HR values during rest, below this point (Garet et al., 2005; Valanou et al., 2006). The Flex point is empirically defined as the average of the lowest HR during exercise and the highest HR during rest (Valanou et al., 2006). Accordingly, the Flex–HR method is based on four parameters, namely resting oxygen consumption ($\dot{V}O_2$ rest), the Flex point, the slope, and the intercept of the linear function describing the $\dot{V}O_2$–HR relationship above the Flex point. The main criticism about the Flex–HR method is the impracticality of establishing individual calibration curves at workplaces with large populations, since it takes at least 45 min per participant (Rennie et al., 2001). Another criticism concerns the uncertainty in determining the Flex point due to several factors, such as the physical and physiological characteristics of the population under study, as well as the type and number of physical activities (Garet et al., 2005).

Group calibration methods have been used to estimate energy expenditure from HR (Li et al., 1993; Luke et al., 1997; Rutgers et al.,

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1997; Rennie et al., 2001; Keytel et al., 2005). These methods were based on linear prediction models using regression and mixed-model analyses, which require a large sample size and lack the ability to capture nonlinearity, uncertainty and the true relationship between variables in the human physiological system (Shimizu and Jindo, 1995; Park and Han, 2004).

In recent years, artificial intelligence (AI) techniques have been proposed as alternatives to conventional statistical methods (Jang et al., 1997; Kaya et al., 2003; Yildirim and Bayramoglu, 2006). One of the most effective AI techniques, particularly for nonlinear function approximation, is the adaptive neuro-fuzzy inference system (ANFIS). It combines the unique ability of fuzzy logic to make decisions in uncertain conditions with the learning and adaptive capabilities of artificial neural networks. ANFIS has consistently been demonstrated effective in approximating nonlinear functions, particularly in biomedical engineering (Güler and Übeyli, 2004, 2005; Übeyli and Güler, 2005a,b).

This study presents a new approach to estimating $\dot{V}O_2$ using HR without the need for an individual calibration test. The proposed approach attempts to improve the standard Flex–HR method so as to be suitable for large-scale workplaces. Three ANFIS modules forming the ANFIS prediction model were developed for the estimation of the Flex–HR parameters from measurements that can be easily obtained in field. Once the Flex–HR parameters are estimated, individuals' $\dot{V}O_2$ during different activities can be determined. Laboratory and field data collection were conducted for the ANFIS prediction model development and testing. The ANFIS prediction model was compared with measured $\dot{V}O_2$ values and three $\dot{V}O_2$ estimation methods, namely the standard Flex–HR method, Rennie et al.'s and Keytel et al.'s models.

2. Methods

This study used three data sets (i.e., training, validation and test), each of which was obtained from different sets of participants. Training data were obtained from 28 laboratory subjects performing a step-test in a laboratory environment. Validation data were obtained from 22 forest workers (i.e., brushcutters) performing a morning step-test near their work site (field step-test). Since these two data sets (training and validation) were used for ANFIS prediction model development (training data set for model training, and validation data set for parameters optimizing), they will be referred to as the learning data set for the remainder of the paper (Fig. 1). The third data set (test set) was obtained from a different group of eight forest workers (i.e., tree-planters) who performed a morning step-test near their work site followed with actual forest work. This set was used to test the accuracy of the developed model and compare its performance in estimating work $\dot{V}O_2$ with that of traditional models.

Brushcutting work included regeneration release and precommercial thinning, which are young forests vegetation management methods (Wiensczyk et al., 2011). Both treatments involve cutting all competing vegetation within a 1 m area around desired young trees so as to foster their growth by allowing light and soil resources to reach them. This work is typically performed using a motor–manual brushsaw. While being very similar task-wise, they are performed at different moments in the silvicultural treatments sequence. Regeneration release is usually prescribed in the first two to five years after reforestation while precommercial thinning is performed when young trees reach 1.5 m in height and a bigger basal diameter. Brushcutters free selected young trees by operating the brushsaw (average load of about 10 kg) while walking back and forth in 2 m wide strips for an average of 87% out of the total 17.5 h needed to treat one hectare of reforested land (SD = 8.9 h; n = 91) (Dubeau et al., 2012). Precommercial thinning is usually more time consuming (e.g., 23.5 h/ha) but showed a similar proportion of effective time in previous studies (84.7%; n = 129) (LeBel and Dubeau, 2007). Tree-planting work consisted in finding a proper microsite, making a hole using a carrot extractor or a shovel, inserting a seedling (young nursery tree), compacting the soil around it and moving to the next proper microsite. In this study, tree-planters typically walked most of the day to plant trees at a mean rate ranging between 5.3 and 15.5 s/tree (depending on seedling size and weight) for an average of 77% out of a mean 8.2-h workday (SD = 0.7 h). They started a cycle by gathering seedlings (initial carried weight ranging between 7.0 and 18.0 kg), then proceeding to plant them following prepared furrows until their load was empty, then refilled seedlings, took a short rest pause and started the next cycle.

2.1. Participants

Fifty-eight healthy men aged from 21 to 64 years participated in the research. Fifty subjects, including 22 brushcutters from various areas in the Province of Quebec and 28 healthy males from various background drawn either from clients attending physical activities at the University of Montreal sport center facilities or from the local population through advertisement, hereafter referred to laboratory subjects, constituted the learning data set participants. The remaining eight subjects were tree-planters and constituted the test data set participants (Table 1). Participants had to pass the pre-activity readiness questionnaire (PAR-Q) before being accepted for the study (Chisholm et al., 1975; Shephard, 1988). No participants were competitive athletes and none regularly used medication. The study was approved by the Human Research Ethics Committee of Polytechnique Montréal. All participants signed a written informed consent form prior to partaking in the study.

2.2. Procedure

2.2.1. Learning data collection

The 50 learning data set participants performed the Meyer and Flenghi (1995) step-test either during the day in a laboratory (for the 28 laboratory subjects) or in the morning close to the work site prior to beginning the day's work (for the 22 brushcutters). This step-test ability to predict maximum aerobic capacity has been validated against the maximal multistage 20-m shuttle run test (Meyer and Flenghi, 1995) and against a maximal treadmill test (Imbeau et al., 2009). It has the following advantages: simple, cost-effective, and practical, it can be implemented safely without imposing high cardiac strain, particularly for older and less active individuals. An additional advantage is that step frequency (15 steps per min paced with a metronome) is sufficiently low for any worker to be able to keep pace at all four step heights, for superior

Table 1
Participants' physical characteristics.

Characteristics	Learning set (n = 50), Mean (SD)		Test set (n = 8), Mean (SD)
	Brushcutters (n = 22)	Laboratory subjects (n = 28)	Tree planters (n = 8)
Age (years)	53.5 (7)	34.8 (8.8)	24.6 (2.4)
Weight (kg)	76.9 (9.7)	78.4 (10.3)	75 (12.9)
Height (m)	1.74 (0.06)	1.74 (0.08)	1.75 (0.05)
BMI (kg m^{-2})	25.3 (2.6)	25.9 (2.6)	24.4 (3.2)
HR_{rest} (bpm)	63.8 (9)	73.8 (9.4)	70.2 (13.6)
$\dot{V}O_2$ max (ml kg^{-1} min^{-1})	40.1 (8.7)	44.7 (6.3)	57.1 (15.7)

Note. SD: standard deviation; BMI: body mass index (kg m^{-2}); HR_{rest}: resting heart rate (bpm); $\dot{V}O_2$ max: maximal oxygen consumption (ml. kg^{-1}. min^{-1}).