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Classifying work rate from heart rate measurements using an adaptive neuro-fuzzy inference system

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A B S T R A C T

In a new approach based on adaptive neuro-fuzzy inference systems (ANFIS), field heart rate (HR) measurements were used to classify work rate into four categories: very light, light, moderate, and heavy. Inter-participant variability (physiological and physical differences) was considered. Twenty-eight participants performed Meyer and Flenghi's step-test and a maximal treadmill test, during which heart rate and oxygen consumption ($\dot{V}O_2$) were measured. Results indicated that heart rate monitoring (HR, HR_{max}, and HR_{rest}) and body weight are significant variables for classifying work rate. The ANFIS classifier showed superior sensitivity, specificity, and accuracy compared to current practice using established work rate categories based on percent heart rate reserve (%HRR). The ANFIS classifier showed an overall 29.6% difference in classification accuracy and a good balance between sensitivity (90.7%) and specificity (95.2%) on average. With its ease of implementation and variable measurement, the ANFIS classifier shows potential for widespread use by practitioners for work rate assessment.

1. Introduction

Despite the global trend towards mechanization, many industries, such as forestry, construction, and mining, still entail physically demanding labor. Excessive physical work demands are the main cause of undue fatigue, which affects workers and leads to lower work performance and quality (Abdelhamid, 1999). Studies have suggested that understanding the physical demands of work is key to protecting safety and health in the workplace and enhancing productivity (Brouha, 1967; Chengalur et al., 2004). Work physiology researchers have underscored the importance of assessing the physiological demands of physical activity, and have fostered the use of categorical scales to measure work rate (e.g., light, moderate, and heavy), with several applications, such as thermal stress assessment (ACGIH, 2009; ISO, 20089, 2008).

There are three main methods for classifying work rate (Table 1). The first one is based on energy expenditure, which can be assessed indirectly by measuring oxygen consumption ($\dot{V}O_2$) (Christensen, 1964; Hettinger, 1970; American Industrial Hygiene Association (AIHA), 1971; Astrand and Rodahl, 1977). This method is costly, invasive, and time-consuming, and it requires sophisticated equipment (Smolander et al., 2008). In the second method, work rate is classified based on variables that can be linearly related to $\dot{V}O_2$, such as heart rate (HR) (Grandjean, 1980). Although this method is considered one of the most practical and useful methods, HR monitoring alone lacks accuracy due to high inter-participant variability (Melanson and Freedson, 1996; Valanou et al., 2006). A third method recommended by the U.S. Department of Health and Human Services (1996) uses the relative oxygen consumption or percentage of maximal oxygen consumption ($\%\dot{V}O_{2max}$) to classify work rate. This method has been demonstrated accurate and is considered the gold standard for classifying work rate (U.S. Department of Health and Human Services (1996); Haskell and Pollock, 1996; Pollock et al., 1998). For practical applications, several studies have recommended using the percent heart rate reserve ($\%HRR = 100 \times (HR - HR_{rest}) \div (HR_{max} - HR_{rest})$) to estimate $\%\dot{V}O_{2max}$ (Haskell and Pollock, 1996; Pollock et al., 1998; American College of Sports Medicine (ACSM), 2014). The %HRR is calculated by estimating the maximal heart rate (HR_{max}), widely computed as 220 − age (Fox et al., 1971; Londeree and Moeschberger, 1982; McArdle et al., 1996; Tanaka et al., 2001; Robergs and Landwehr, 2002).

Today, there is a need for practical and reliable field methods for assessing and classifying work rate. They should use easily

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Table 1
Norms for work rate classification.

Assessment of work rate	$\dot{V}O_2$ (L/min)		EE (Kcal/min)	EE (Kcal/8hr)		HR (bpm)			$\%\dot{V}O_{2max}$ or %HRR
	Christensen (1964)	Åstrand and Rodahl (1977)	AIHA (1971)	AIHA (1971)	Hettinger (1970)	Christensen (1964)	AIHA (1971)	Åstrand and Rodahl (1977)	HHS (1996) and ACSM (2014)
Sitting	–	–	1.5	<720	–	–	60–70	–	–
Very light	0.25–0.3	–	1.6–2.5	768–1200	–	60–70	65–75	–	0–24
Light	0.5–1.0	<0.5	2.5–5.0	1200–2400	<1000	75–100	75–100	<90	25–44
Moderate	1.0–1.5	0.5–1.0	5.0–7.5	2400–3600	1000–1600	100–125	100–125	90–110	45–59
Heavy	1.5–2.0	1.0–1.5	7.5–10.0	3600–4800	1600–2000	125–150	125–150	110–130	60–85
Very heavy	2.0–2.5	1.5–2.0	10.0–12.5	4800–6000	>2000	150–175	150–180	130–150	>85
Extremely heavy	2.5–4.0	>2.0	>12.5	>6000	–	>175	>180	150–170	–

Note. $\dot{V}O_2$ (L/min) = oxygen consumption in liters per minute; EE (Kcal/min) = energy expenditure in kilocalories per minute; EE (Kcal/8hr) = energy expenditure in kilocalories per 8 h; HR (bpm) = heart rate in beats per minute; $\%\dot{V}O_{2max}$ = percentage of maximal oxygen consumption; %HRR = percent heart rate reserve; HHS= U.S. Department of Health and Human Services.

measured physical and physiological variables, such as HR, and they should account for inter-participant variability. They should also allow dealing with the uncertainty and vagueness inherent in the human physiological system and in various work environments. In recent years, a number of artificial intelligence (AI) techniques have been proposed as alternatives to conventional statistical methods (Kaya et al., 2003; Yildirim and Bayramoglu, 2006). One of the most effective AI techniques, particularly for nonlinear function approximation and pattern recognition (classification), 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. The strength of ANFIS in real life applications is that it works well with small datasets (Montiel et al., 2009; Siow-Wee et al., 2010; Dom et al., 2012) and it does not depend on the assumptions required by conventional statistical methods, such as data normality and independence (Hillenbrand, 2004; Schoemaker, 2006; Shrestha et al., 2007). ANFIS has consistently been demonstrated effective in solving classification problems, particularly in biomedical engineering (Güler and Übeyli, 2004, 2005; Übeyli and Güler, 2005a, 2005b). In addition, ANFIS has been considered a powerful tool in handling the uncertainty that characterizes human physiological and nervous systems (Shimizu and Jindo, 1995; Park and Han, 2004; Petkovic and Cojbasic, 2012; Petkovic et al., 2013).

Kolus et al. (2014) compared ANFIS modeling to four other methods to estimate $\dot{V}O_2$ from HR measurements made during physical activity. The four methods used in the comparison were: an analytical approach using a bi-linear relationship between HR and $\dot{V}O_2$ (Labib and Khattar, 2010), the classical individual calibration using a step-test to establish a participant's HR-$\dot{V}O_2$ relationship (Schulz et al., 1989), the Flex-HR method (Spurr et al., 1988), and actual $\dot{V}O_2$ measurements made during the physical activity. Two types of ANFIS models were developed, one for each participant thus requiring individual calibration and a general model based on all participants' data that can be used without the need for individual calibration. Their results indicated that the ANFIS models yielded better $\dot{V}O_2$ estimates from HR measurements and proved the general model to be the most cost effective, since it yielded estimates comparable to actual $\dot{V}O_2$ measurements without the need for individual calibration that all other methods require. Kolus et al. (2015) used the ANFIS approach to model the parameters of the Flex-HR method and compared the resulting $\dot{V}O_2$ estimates from HR measurements with the standard Flex-HR method, a method from Rennie et al. (2001), a method from Keytel et al. (2005), and actual $\dot{V}O_2$ measurements of the activity. The ANFIS modeling approach provided $\dot{V}O_2$ estimates throughout the HR range that were: 1) comparable to those of the standard Flex-HR and to actual measurements, and 2) better than those of the other two methods. Since use of ANFIS does not require individual calibration, this approach proved to be very cost effective and time efficient from a practitioner's point of view.

The main objective of the present study is to develop a practical approach to classifying work rate using variables that account for inter-participant variability and can be measured easily in actual workplaces. This study presents a new ANFIS-based classifier that uses HR and physical characteristics to classifying work rate. The developed classifier is composed of four ANFIS models, each of which was trained to classify work rate in to one of the four categories: very light (VL), light (L), moderate (M), and heavy (H). The individual models were then combined into an integrated ANFIS classifier (hereinafter, the classifier) that classifies work rate into the four categories.

2. Methods

This research was based on a laboratory study in which participants performed a submaximal step-test and a maximal treadmill test. All participants' data was used to identify potential variables associated with work rate. Then, part of the data (approximately 70%) was used to develop the ANFIS classifier and the remaining data was used to test it and compare its performance to the %HRR classification method.

2.1. Participants

A total of 28 healthy men aged from 20 to 45 years participated in the study (Table 2). 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.