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Research Article

A Fuzzy Logic-Based Personalized Method to Classify Perceived Exertion in Workplaces Using a Wearable Heart Rate Sensor

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Knowing the perceived exertion of workers during their physical activities facilitates the decision-making of supervisors regarding the worker allocation in the appropriate job, actions to prevent accidents, and reassignment of tasks, among others. However, although wearable heart rate sensors represent an effective way to capture perceived exertion, ergonomic methods are generic and they do not consider the diffuse nature of the ranges that classify the efforts. Personalized monitoring is needed to enable a real and efficient classification of perceived individual efforts. In this paper, we propose a heart rate-based personalized method to assess perceived exertion; our method uses fuzzy logic as an option to manage imprecision and uncertainty in involved variables. We applied some experiments to cleaning staff and obtained results that highlight the importance of a custom method to classify perceived exertion of people doing physical work.

1. Introduction

Advances in miniaturization, mobile communication, and sensor technologies make Mobile Health (mHealth) system development possible. mHealth is the intersection between Electronic Health (eHealth) and smartphone technologies. This means that the practice of eHealth is assisted by smartphones, which are used to capture, analyze, process, and transmit health-based information from sensors and other biomedical systems [1]. mHealth systems provide healthcare services with cost-effective, flexible, and efficient ways [2]. A mHealth system implemented on a mobile device enables a portable and nonobstructive solution; in addition, the computing and wireless capabilities allow real-time monitoring. This technology allows application deployment on mobile devices for continuous monitoring of people in order to determine, for example, the effort in their physical daily activities.

Humans possess a well-developed system for sensing the strain involved in physical effort. This is called perceived exertion (PE), which is the act of detecting and interpreting the sensations arising from the body during physical exertion [3]. Continuous measurement of physiological parameters in individuals while performing daily or labor activities allows health and well-being preservation or improvement.

Personal exertion estimation during labor activities has a particular interest, given that the effort to perform an activity is different for each person. Misallocation of an activity can affect a person's welfare and health. Workers may have risks associated with the disparity between high physical work demands and capacity/labor skills. These risks include musculoskeletal disorders, cardiovascular disease, prolonged absences, stress, burnout, and early retirements from the labor market [4]. Furthermore, physical strength assessment in ergonomics has additional benefits such as worker selection and placement and job design [5].

The estimation of workers' physical efforts in workplaces can be useful for allocation of employees in the appropriate position, adequacy of physical activities inherent to a job, prevention of accidents due to job demands, disease prevention related to physical demands, etc.

Generic methods known to estimate the physical effort do not take into account important physiological characteristics of individuals [6–8]. For many years, cardiac cost and

metabolic expenditure from physical labor are calculated using formulas and generic tables [6]. Physical exertion is then set, based on standards, such as the maximum heart rate (220-age). While in many cases this may be agile and convenient, it is not always true, as in the case of overweight or habituated people to perform an activity. It is necessary to develop methods that can provide higher accuracy for predicting energy consumption for a wide range of physical activities. This would allow a greater chance of being accurate on when to compare them to scientifically validated methods as doubly labeled water method [9].

Most available solutions for health monitoring offer a generalized physiological measurement, that is, by reference to generic formulas or tables that are not customized to individuals [7, 10]. Many other solutions are focused on predefined activities such as walking and running without considering physiological parameters of each person, giving results that are not clearly differentiated [9, 11].

In [12], a method based on personalized maximum heart rate was proposed as an extension of Chamoux method. This method allows continuous monitoring effort, taking into account the particular physical condition of each person by measuring the heart rate. The goodness of this proposal was evaluated in [13] through a comparative study with the other two methods (original Chamoux and Borg) [10, 14]. It can be stated from these results that the heart rate reflects health conditions (sick, tired, and acclimatized), but to our knowledge, this has not been proven objectively and formally, it can also be stated that the personalized maximum heart rate method allows a better result distribution than that obtained in previous works. However, these results do not consider the habituation to specific work that a person may have, nor the perception of experts about the nature of effort levels.

In this work, we propose a method considering both of these important factors in personalized effort evaluation: the habituation to perform a specific job and expert perception about the nature of effort levels assessment.

Expert knowledge refers to the estimates or judgments made by experts of the analysis and interrelations of problem's quantitative parameters. Usually, the expert knowledge must face situations of vagueness and imprecision. It is because it is complex or not possible to have a complete list of all variables involved in the problem domain. That is, there is no exhaustive list of all factors to take into account for the problem domain. Even knowing all the variables, it can be difficult to obtain concrete data. In addition, this information may be incomplete or even erroneous [15].

Expert perception of effort level is needed because of the nature of effort values reported in previous works based on relative cardiac cost (RCC), which is defined into a rank of values, RCC = [0, 69], and grouped in sets of 10 values—these sets are named as intense = [60, 69], heavy = [50, 59], slightly heavy = [40, 49], and so on [14]. The problem is when we have a value, let us say, RCC = 49, which is considered as slightly heavy, but which could be considered as heavy instead. In order to better define the effort magnitude, we propose to consider RCC sets as diffuse ones, given that there is a gradual progression of values from one set to the next, which allows us to define the membership degree of values to each set.

The habituation of a person to perform a specific activity is needed, because we must consider if this person has the skills needed to execute the activity with a good performance, that is, good performance in the execution of an activity depends more on habituation than on other factors as good physical condition. The habituation of a person to the execution of job activities affects the job after assignment in an important way.

2. State of the Art

For many years, cardiac cost and metabolic expenditure from physical labor are calculated using formulas and generic tables [6]. The use of a custom method becomes more important when monitoring physical activities that require a lot of effort, such as heavy lifting, since such activities are those that can compromise the welfare and health of workers [16].

As established in the ISO 8996 standard [17] for estimating metabolic cost, the use of the heart rate is an option that provides an estimation of effort with a margin of error as plus or minus 10 percent. This method of analysis is surpassed only by custom measurements that require the use of specialized equipment commonly available in laboratories. The latter very precise methods are equipment of indirect calorimetry (oxygen consumption test using a mask) and doubly labeled water (water consumption and urine analysis).

Measuring the heart rate is a valid option to estimate the effort which represents a work activity for an individual, although some limitations must be considered [18]. It is also important to consider that there are other factors influencing significantly, such as environmental conditions (temperature and humidity), weight, age, acclimation, mental stress, and personality [19].

2.1. Fuzzy Logic. A fuzzy logic provides an inference mechanism that allows us to simulate human reasoning into knowledge-based systems. The theory of fuzzy logic provides a mathematical framework that allows modeling the uncertainty of human cognitive processes in a way that can be treatable by a computer [15].

In accordance with [20], two important reasons to employ fuzzy logic are (1) data obtained from sensors measurements could be imprecise and imperfect and (2) fuzzy logic can deal with imprecision and uncertainty due to its properties of performance and intelligibility necessary for the classification process.

2.1.1. Fuzzy Logic Steps. Many solutions of real-world problems require dealing with inaccurate and imprecise data. Humans are able to solve these problems because they make use of cognition but also make use of fuzzy judgments and reasoning. Diffuse classification techniques have the advantage that require a soft decision, that is, a value that describes the degree to which an element belongs to a class. Instead of a hard decision, where one must say precisely whether an element belongs to a class or not, fuzzy logic is a very attractive field within artificial intelligence because it

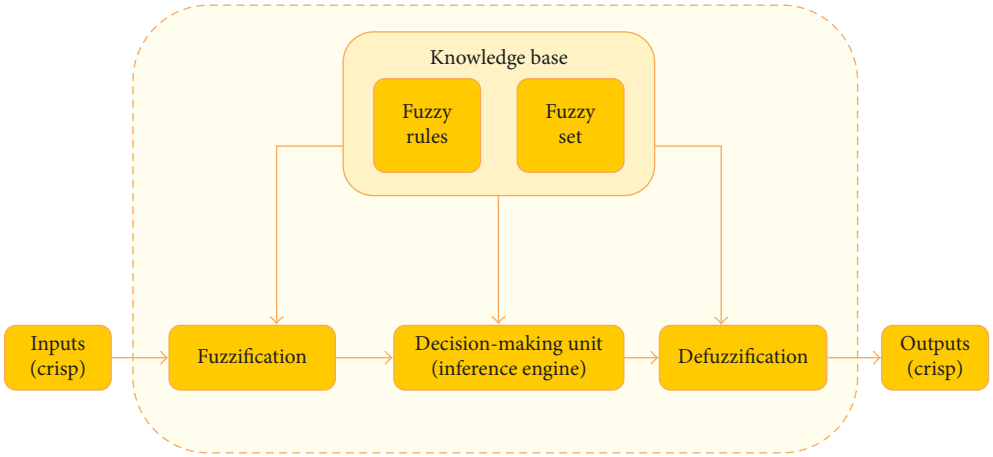

Figure 1: Fuzzy inference system steps.

is based on natural language. That is, it allows us to use linguistic terms to describe problems in a natural way. It does not use terms of relations between precise numerical values.

A fuzzy set can be defined as a set without clear and defined boundaries, in which elements that it contains can have a certain degree of membership ranging from total membership (value 1) to nonmembership (value 0). From this perspective, conventional sets (or crisp sets) can be seen as a particular case of fuzzy sets, a diffuse set that only admits two degrees of membership (one and zero).

Therefore, a diffuse set extends a standard set allowing degrees of membership of an element to the set, measured by the real numbers in the interval [0; 1]. If X is the universe of discourse and its elements are denoted by x, then a fuzzy set A on X is defined as a set of ordered pairs $(x, \mu_A(x))$ such that

$$A = \left\{ x, \frac{\mu_A(x)}{x}, \quad 0 \le \mu_A(x) \le 1 \right\}, \tag{1}$$

where $\mu_A(x)$ in (1) is the membership function of each x in A. In contrast to classical logic where the membership function $\mu_A(x)$ of an element x belonging to a set A could take only two values: $\mu_A(x) = 1$ if $x \in A$ or $\mu_A(x) = 0$ if $x \notin A$, fuzzy logic introduces the concept of membership degree of an element x to a set A and $\mu_A(x) \in [0; 1]$; here we speak about the truth value.

A typical fuzzy logic inference system has four components: the fuzzification, the knowledge base (rules and fuzzy sets), the inference engine, and the defuzzification [15]. Figure 1 shows those main fuzzy inference system steps.

2.1.2. Fuzzification. The first step in fuzzy logic is to take the measured data (crisp data) and determine membership degree of these inputs to associated fuzzy sets. It is done by giving a value to each variable to a membership function set. Naturally, crisp value will be limited to the universe of discourse. Membership functions take different shapes. The two most common functions are triangular and trapezoidal. A triangular membership function with straight lines can formally be defined as follows:

$$\Lambda(x, a, b, c) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & x \ge c. \end{cases} \tag{2}$$

Trapezoidal function is shown in the following equation:

$$f(x, a, b, c, d) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & x \ge d. \end{cases} \tag{3}$$

A Gaussian membership function with the parameters m and σ to control the center and width of the function is defined by

$$G(x, m, \sigma) = e^{-(x-m)^2/2\sigma^2}. \tag{4}$$

The generalized Bell function that depends on three parameters a, b, and c is given by

$$f(x, a, b, c) = \frac{1}{1 + ||(x-c)/a||^{2b}}. \tag{5}$$

Other membership functions are sigmoid-shaped functions and delta functions (single functions). Selecting the membership function will depend on the nature of the problem, the type of data, and the experimental results. A knowledge expert is important to decide which shape will be used.

2.1.3. Knowledge Base (Rules and Fuzzy Sets). Rules are constructed from linguistic variables. Rules are structured in a IF-THEN format. The IF part of the rule is the antecedent and the THEN part of the rule is the consequent. These variables take on the fuzzy values that are represented as words and modeled as fuzzy subsets of an appropriate domain. There are several types of fuzzy rules, we mention only the two main rules:

(i) *Mamdani rules* [21]: These rules are of the following form: if x_1 is A_1, x_2 is A_2, . . ., x_p is A_p, then y_1 is C_1, y_2 is C_2, . . ., y_p is C_p, where A_i and C_i are fuzzy sets that define the partition space. The conclusion of a Mamdani rule is a fuzzy set. It uses the algebraic product and the maximum as T-norm and S-norm, respectively, but there are many variations by using other operators.

(ii) *Takagi/Sugeno rules* [21]: These rules are of the following form: if x_1 is A_1, x_2 is A_2, . . ., x_p is A_p, then $y = b_0 + b_1x_1 + b_2x_2 + \cdots + b_px_p$. In the Sugeno model, the conclusion is numerical. The rules' aggregation is in fact the weighted sum of rules' outputs.

2.1.4. Inference Engine. The fuzzy inference system uses fuzzy equivalents of logical AND, OR, and NOT operations to build up fuzzy logic rules. An inference engine operates on rules to evaluate them. Inference engine takes inputs and applies them to the antecedent part of the rule. If a rule has multiple antecedents, then logical AND, OR, and NOT operations are used to obtain a unique value representing evaluation result. This result (truth value) is applied to the consequent part. The outputs are then added. It is the process of unification of the outputs of all rules, that is, the membership functions of all consequent previously trimmed or scaled outputs are combined, to obtain a single fuzzy set for each output variable.

2.1.5. Defuzzification. The final step of a fuzzy logic system consists of transforming the fuzzy variables obtained by the fuzzy logic rules into crisp values again that can then be used to take a decision or perform some action. There exists different defuzzification methods: centroid of area (COA), bisector of area (BOA), mean of maximum (MOM), smallest of maximum (SOM), and largest of maximum (LOM). In our system, we used COA, and the following equation illustrates it:

$$Z_{\mathrm{COA}} = \frac{\sum_{i=1}^{n} \mu_A(x_i) x_i}{\sum_{i=1}^{n} \mu_A(x_i)}. \tag{6}$$

2.2. Habituation. Habituation is a form of learning in which an organism decreases or ceases its responses to a stimulus after repeated presentations [22]. In perceived exertion, context is about how much a person has repeated a physical activity. Habituation as a state of training affects the heart rate [23]. In labor context, it refers to how frequently workers perform a specific physical activity related to their job.

Habituation to the performance of physical work activities is important because a person not being accustomed to perform a specific physical activity has a perceived effort of about twenty percent higher than a person accustomed to performing such an activity [24, 25].

Several methods have been used to quantify workload, including questionnaires, diaries, physiological monitoring, and direct observation [23]; in this sense, direct observation method can be considered to determine habituation, based on intensity and frequency (workload) of individual daily activities' performance.

3. Related Work

There are several works related to the proposal that we present, but none with the approach (personal perceived exertion), combination of factors (habituation, relative cardiac cost, and degree of membership to a fuzzy group), and application domain (prevention of labor accident risks due to workload fatigue) that is proposed.

The first group contains studies in workplaces oriented to estimate energy expenditure or activity recognition using technological devices. For example, Hwang et al. [26] proposed a measurement approach in energy estimation field. It is expected to provide in-depth understanding and continuous monitoring of worker's physical demands from construction tasks. Their solution was to use the heart rate (HR) to estimate EE according to a linear relationship between HR and EE. Their proposal was to achieve reliable field EE measurement through automatic action recognition using an embedded accelerometer and applying HR-EE relationships for corresponding actions with acceptable HR monitoring accuracy.

Hwang's proposal is based on identifying physical activities, which to date is limited to certain activities such as walking, running, and climbing stairs. That is, we could not identify any physical activity derived from a job; this makes Hwang's proposal not suitable for any type of work where physical activities are performed. On the contrary, our proposal focuses on identifying the personal physical effort involved in the work activity, without needing to identify which is the activity that the worker performs. Another example is shown in [27]; in this case, authors estimate and try to predict energy expenditure predictions based on the heart rate. On the contrary, we are compelled to estimate perceived exertion.

The second group contains works aimed at preserving health at work. For example, Migliaccio et al. [28] used sensors to monitor physical bends performed by construction workers, so it is identified that those physical activities can be risky to health. In this experiment, a heart monitor was used to detect high heart rates which were directly associated with a subject carrying a load. Fusing heart rate data and posture data provided the capability of differentiating safe from unsafe material-handling activities. The main objective of this research was to assist future decision makers in designing ergonomically safe and healthy

work environments. Migliaccio's work focuses on detecting high levels of heart rate and unsafe postures, but the proposal is not personalized.

Aryal et al. [29] present a method for real-time monitoring of physical fatigue in construction workers using heart rate monitoring and infrared temperature sensors. Boosted tree classifiers were trained using the features extracted from the heart rate and temperature sensor signals and used to predict the level of physical fatigue from 12 participants. The study lacks a personalized classification of effort since it uses the Borg scale, which is extremely generic and does not contribute to the personalized detection of the efforts. There is a non-personalized classification because during physical activity, relative effort regarding resting heart rate and personalized maximum heart rate is not considered.

The third group contains those researches based on the fuzzy logic. The fuzzy logic-based tool for modeling human sensitivity to thermal sensation developed by Shimizu and Jindo [30] demonstrated that membership functions capture the ambiguity of classes to categorize thermal sensations. In the same sense, in [31] the theory of fuzzy sets and systems was applied to assess perceived workload involved in manual lifting tasks. In [32] a fuzzy logic-based risk assessment framework to evaluate physiological parameters is proposed; this model is used to avoid emergency situations during sport activity; however, personalized heart rate thresholds used in this proposal are based on generic values [10] from runners and triathletes.

These results support that our hypothesis about the fuzzy logic is convenient for classifying humans' effort perceptions. Additionally, no proposal considers the impact of habituation to work on physical effort, nor the degree of membership that has a cardiac cost value to a defined effort class.

3.1. Heart Rate-Based Methods to Estimate Physical Effort. In this paper, we use methods based on the heart rate because this type of parameter has a 90% accuracy in estimating physical efforts, as it is stated in safety and health standards at work [17].

There are several methods that rely on measuring the heart rate to establish which is the physical effort that a work activity can represent for people [33]. We selected two of them: the Borg rating scale of exertion [10] and the Chamoux method [14].

The Borg scale is widely known and applied in sport and medical domains; it is generic and based on a table where, if a person has a certain value of heart rate, then it has a certain level of effort, and it is called rating of perceived exertion. In Table 1, the Borg scale shows 14 (6 to 20) values grouped in six categories.

In order to interpret the Borg scale, the numbers in the left column correspond to the number of beats of one person during physical activity divided by 10, and the corresponding value in the right column is the perceived exertion (level of effort); for example, if a worker has 110 beats per minute, the level on the scale is 11 and it belongs to slight effort. In this method, it is assumed that the maximum heart rate of a person is 220 minus his/her age in years. A real effort test is not required; therefore, it is a generic value.

Table 1: Borg's scale.

Scale	Description
6	No exertion
7	—
8	—
9	—
10	—
11	Light
12	—
13	Somewhat hard
14	—
15	Hard (heavy)
16	—
17	Very hard
18	—
19	—
20	Maximal exertion

Table 2: Different levels of effort for RCC under Chamoux.

RCC	RCC level	Effort
0–9	RCC1	Very light
10–19	RCC2	Light
20–29	RCC3	Slightly moderate
30–39	RCC4	Moderate
40–49	RCC5	Slightly heavy
50–59	RCC6	Heavy
60–69	RCC7	Intense

Otherwise, Chamoux [14] proposes a lesser-known method, and as far as we know, it is not frequently used. This method requires to measure resting and the maximum heart rate for each person, taking into account several physiological parameters.

The method consists of two steps to estimate the physical effort. This first step is to obtain labor activity's absolute cardiac cost (ACC), which is obtained using the average cardiac frequency (ACF) and the resting cardiac frequency (RCF) for a person at every moment. ACF is obtained from the average value of the frequency of the worker during a day of conventional job. RCF is obtained after a person has slept (8 hours) and is resting.

ACC is obtained by subtracting the resting cardiac frequency (RCF) from the average cardiac frequency (ACF), as shown in the following formula [14]:

$$\mathrm{ACC} = \mathrm{ACF} - \mathrm{RCF}. \tag{7}$$

The second step is to compute the relative cardiac cost (RCC). Therefore, we should get theoretical maximum cardiac frequency (TMCF). Conventionally, the TMCF value is obtained by subtracting the person's age in years from 220. The formula for RCC is as follows [14]:

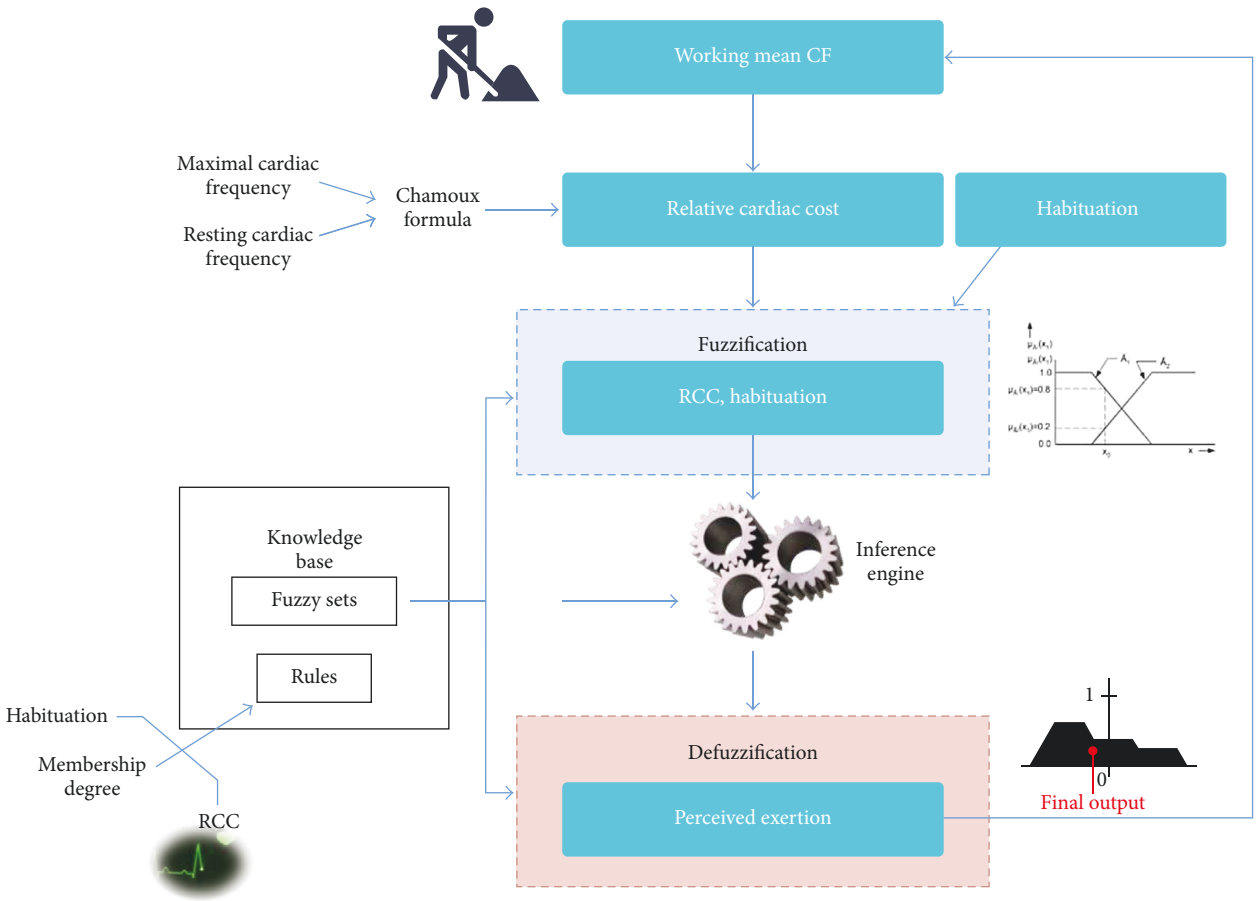

Figure 2: Proposed method (FPC).

$$\mathrm{RCC} = \left(\frac{[\mathrm{ACC} * 100]}{[\mathrm{TMCF} - \mathrm{RCF}]} \right). \tag{8}$$

Effort levels for a worker according to the method of Chamoux are shown in Table 2.

4. Materials and Method

We used a Basis B1 Fitness Wristband as a heart rate monitor, an Omron Sphygmomanometer Model HEM-742INT, and a common stethoscope. We used a treadmill mark BH Fitness Model Prisma M60 to measure personalized maximal cardiac frequency. It was operated without inclination. The prototype to estimate perceived exertion was developed with the Java 6.0 language using the ADT tool v22.3.0-887826. The prototype was implemented over a Samsung Galaxy S4, an Android 4.2.2 (Jelly Bean) Operation System, an octa-core chipset, and a 1.6 GHz Quad + 1.2 GHz Quad CPU.

We propose a method based on the method of Chamoux as it was explicitly created for the work environment, while the Borg method is used in sports. The fuzzy personalized Chamoux-based method (FPC) we propose is illustrated in Figure 2. Our fuzzy inference method is Mamdani type.

The first step of the proposed FPC method is taking cardiac frequency at rest, personalized maximal cardiac frequency, and habituation level. As we decided to customize the Chamoux method, that is, obtaining the value of TMCF parameter for each person, we required each user to perform a maximal exercise stress test using an electric treadmill and we took the value of the heart rate as their TMCF. We refer to this as a personalized Chamoux method [12]. Habituation value was assigned considering how frequent and experienced the user is about a specific labor physical activity.

Users will carry a wearable heart rate monitor to have a continuous monitoring of cardiac frequency during labor activity. From this monitoring, we obtain media cardiac frequency per minute. Having these data, we apply the Chamoux formula, using as maximum cardiac frequency, the personalized value that was obtained during the test with the treadmill. Chamoux formula gives us relative cardiac costs (RCCs) for each worker.

Later, RCC variables were assigned to fuzzy sets, as shown in Figure 3.

In accordance with knowledge obtained in [25], it was used as a condition that establishes that nonhabituated workers increase their perceived exertion by 20% for evaluated activity (sweeping, cleaning windows, and stacking chairs). Another condition was implemented for moderately habituated workers; in this case, their PE was increased 10%. For habituated workers, there is no need to increase

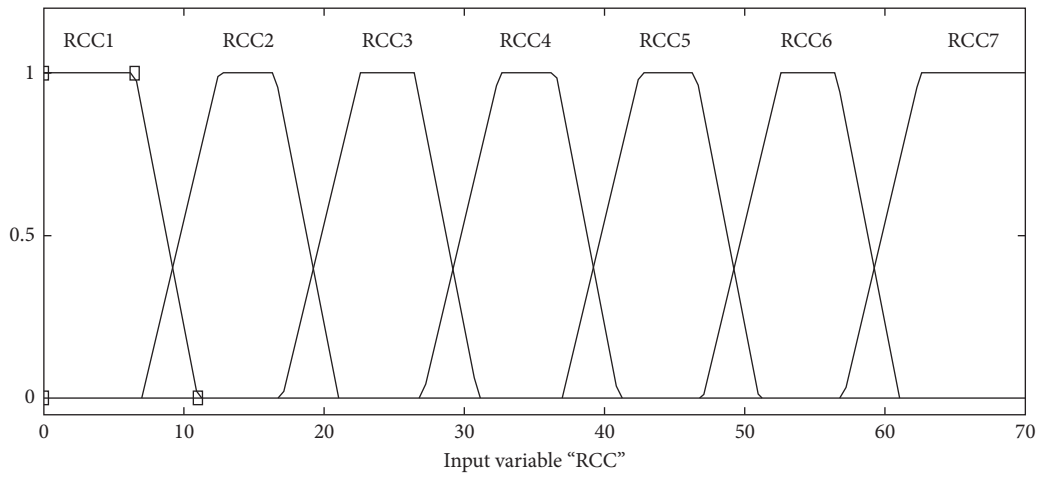

Figure 3: RCC membership function.

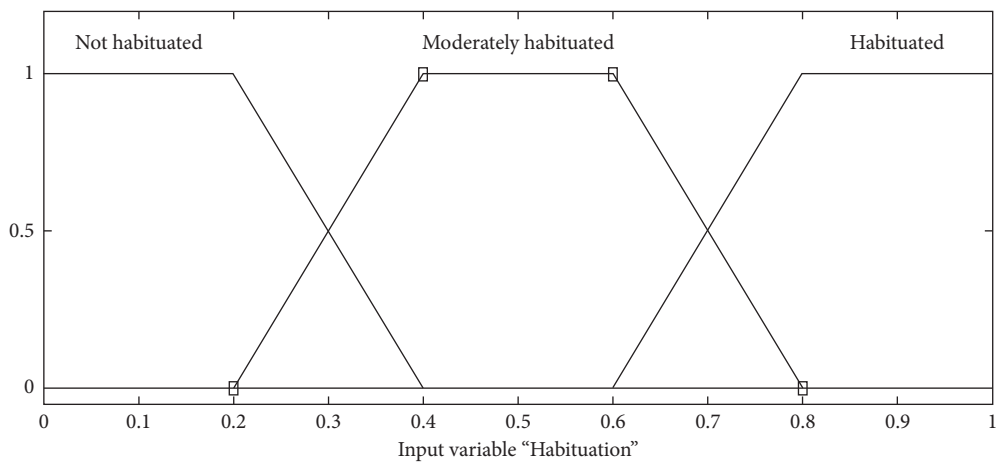

Figure 4: Habituation function.

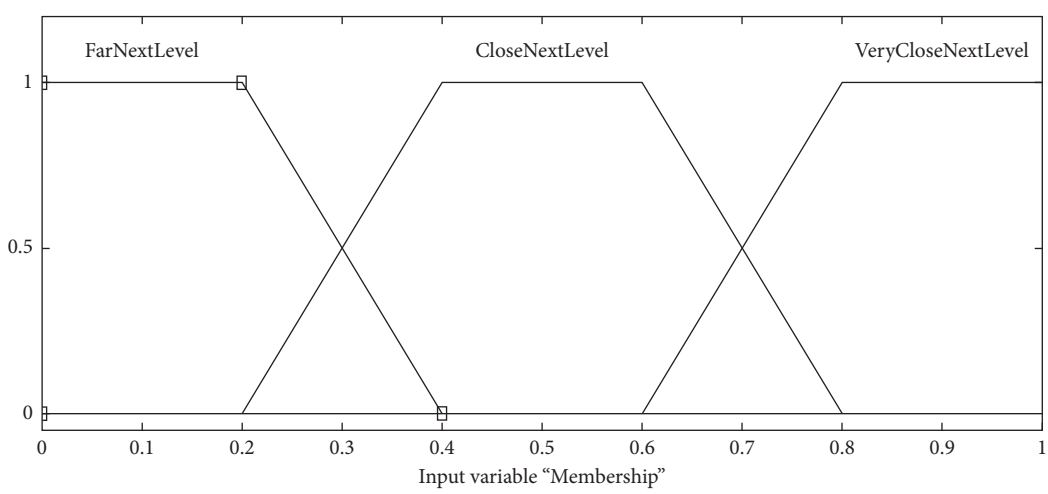

Figure 5: Level of membership function.

If (RCC is RCC1) and (Habituation is habituated) then (perceived Exertion is PE1)

If (RCC is RCC1) and (Habituation is ModeratelyHabituated) and (Membership is FarNextLevel) then (Perceived Exertion is PE1)

If (RCC is RCC1) and (Habituation is ModeratelyHabituated) and (Membership is CloseNextLevel) then (Perceived Exertion is PE1)

If (RCC is RCC1) and (Habituation is ModeratelyHabituated) and (Membership is VeryCloseNextLevel) then (Perceived Exertion is PE2)

If (RCC is RCC1) and (Habituation is NotHabituated) and (Membership is FarNextLevel) then (Perceived Exertion is PE1)

If (RCC is RCC1) and (Habituation is NotHabituated) and (Membership is CloseNextLevel or Membership is VeryClose NextLevel) then (Perceived Exertion is PE2)

Figure 6: Rules for RCC1.

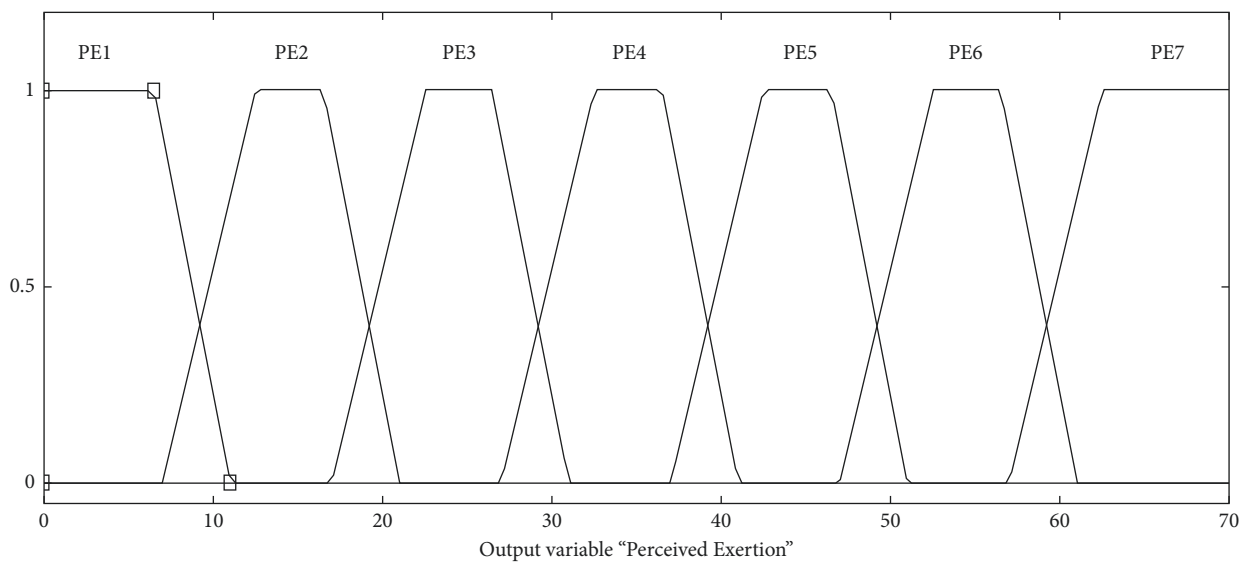

Figure 7: Output variable "perceived exertion."

(compensate) the perceived exertion. Membership function for habituation variable is shown in Figure 4.

Another criterion used to conform the rules is a variable called membership. This variable is used to define when a PE result must be located in the next level. That is, if a worker is moderately habituated and his membership variable is VeryCloseNextLevel, then his PE is upgraded to the next level of PE. If a worker is nonhabituated and his Membership variable equals to CloseNextLevel or VeryCloseNextLevel, then his PE result is upgraded to the next level of PE. Figure 5 illustrates the Membership function.

After that, rule base is constructed, rules are based on knowledge or experience in the domain and these are useful for the inference engine to carry out the process of defuzification. In our proposal, rules make use of the fuzzification of efforts scalar sets defined by Chamoux and habituation impact on the worker.

An extract of the rules used in the proposal is illustrated in Figure 6, specifically for the first level of relative cardiac costs (labeled as RCC1). For each one of the seven RCC levels [RCC1, RCC7] were built a group of rules similar to these.

Later, we use the inference engine fed by the defined rules, where the level of habituation and the degree of membership to relative cardiac costs are part of the rules. The last step is the defuzzification phase. The COA method was applied for defuzzification. The COA defuzzification method effectively calculates the best compromise between multiple output linguistic terms [15]. In this phase, we obtained PE, which is one of all possible outputs (linguistic variables), as shown in Figure 7.

5. Experiments

The tests were conducted on a university campus, and users were potential janitors and janitors. In the experiments, a group of 20 research participants conducted a series of work activities, and heart rate measurements were taken during those activities. These data sets were collected using a population of 20

Table 3: Participants' characteristics.

Subject	Genre	Age	BMI	Habituation level
Worker 1	Male	23	29.62	Habituated
Worker 2	Female	23	21.98	Habituated
Worker 3	Female	23	20.95	Moderately habituated
Worker 4	Male	22	24.72	Habituated
Worker 5	Male	23	28.27	Habituated
Worker 6	Male	23	20.03	Not habituated
Worker 7	Female	24	19.27	Not habituated
Worker 8	Female	33	31.24	Moderately habituated
Worker 9	Female	34	21.68	Habituated
Worker 10	Male	25	28.44	Habituated
Worker 11	Male	28	28.33	Habituated
Worker 12	Male	27	24.38	Habituated
Worker 13	Male	24	33.64	Not habituated
Worker 14	Female	28	29.36	Moderately habituated
Worker 15	Male	34	23.63	Not habituated
Worker 16	Female	36	24.35	Not habituated
Worker 17	Male	33	24.68	Habituated
Worker 18	Female	22	26.29	Not habituated
Worker 19	Female	36	30.44	Not habituated
Worker 20	Male	51	23.12	Habituated

Table 4: Activities in the experiments.

Activity	Description
Sweep the floor	One broom (1 kg) was used in this activity. A hallway (42 m long × 0.5 m width) was the area to sweep. The volunteers started in one corner of the hallway and swept in overlapping strokes in towards the end of the hallway.
Washing windows	The total dimensions of the window were 110 cm × 90 cm. The research participants started at the top and worked down the window. This activity was executed in indoor environments.
Stacking chairs	Placing the entire stack of chairs had a short walk away (3 m). This activity was done using iron chairs (7 kg). During these activities were created several stacks, each stack with 8 chairs; all experiments were done in an indoor hallway. Never were stacked more than ten chairs at a time.

participants; 11 male (28.4 ± 8.5 years, BMI 26.26 ± 3.77) and 9 female (28.7 ± 5.97 years, BMI 25.06 ± 4.45). Participants' characteristics are shown in Table 3.

Three physical activities were defined for every research participant. These activities are described in Table 4.

Personal characteristics and physical conditions (such as age, sex, acclimation, and physical condition) are the attributes that are indirectly reflected when we measure the maximal theoretical heart rate being their maximal personal effort for each user. Together with the heart rate at rest and individualized monitoring in real time during the execution of physical activities, they allow customized estimations. During analysis, these characteristics' results allow us to see that two people with similar characteristics do not necessarily perform the same effort to perform the same activity.

Heart rate was measured using an unobtrusive Basis B1 fitness tracker band. Basis' precision is enough to know how many beats per minute a user heart has. Basis B1 measures our blood pressure, steps, intensity and exertion of our workout, and sleep metrics. This device was placed on the wrist of each worker. The first activity was to sweep a floor using a broom, the second activity was to clean glass windows with a rag, and the last activity was stacking metal structure chairs.

Heart rate values used in all methods (Borg–Chamoux–personalized Chamoux–fuzzy personalized Chamoux) were the average heart rates during the activities.

Experiments related to the three labor activities are shown in Figure 8.

6. Results

In order to compare the resulting values of all methods tested, we made a mapping of the Borg's perceived exertion values (Table 1) with labels used in Chamoux method (Table 2). Scales 6-7 are no exertion (NE), 8-9 are very light (VL), 10-11 are light (L), 12 is slightly moderate (SM), 13 is moderate (M), 14 is slightly heavy (SH), 15-16 are heavy (H), and over 16 is intense (I).

A frequency analysis of results of perceived exertion of the participants obtained for each physical activity was included. In order to do this, we obtained some values describing the features of a collection of data from physical activities performed. For stacking chairs activity, Table 5 shows the number of users for each perceived exertion level grouped by the method.

In Table 5 we can see that the estimated perceived exertion of people using the Borg method is only two levels, the common Chamoux method classifies them into three levels, and the personalized Chamoux and our proposal (FPC) classify them into five levels. The Borg method classifies all people into very light (VL) and light (L); conventional Chamoux classifies 20% into SM, as it only takes into account the age of the people; personalized Chamoux distributes 60% of workers between SM and SH, this is because it takes into account personal maximum effort, in addition to the age of the individual; while the proposed method makes a small rearrangement of the number of people at every level, which results from applying the fuzzy logic for handling uncertainty membership groups and the effect of habituation variable. This indicates that our proposal has a better effort discrimination because of measuring their personal maximum effort, fuzzy sets without clear and defined boundaries, rules base, and habituation-level variable.

In Figure 9(a), the results of perceived exertion are scalar (diffuse for FPC), whereas in Figure 9(b) the results of perceived exertion are linguistic (crisp for FPC). The objective is that the decision-maker can appreciate not only the level of final perceived exertion obtained (after the whole process) but also the level of belonging to that level (scalar values). The same criterion applies for Figures 9(c) and 9(d).

(a) (b) (c)

Figure 8: Activities developed by participants: (a) sweeping floors, (b) cleaning windows, and (c) stacking chairs.

Table 5: Number of users for each effort level during stacking chair activity, grouped by method.

Perceived exertion	Borg	Chamoux	Personalized Chamoux	Fuzzy personalized Chamoux
VL	11	4	0	0
L	9	12	8	6
SM	0	4	6	6
M	0	0	4	5
SH	0	0	2	3

These results can be used in decision-making to preserve or improve the health and quality of life of the worker. This can be done by adjusting their work environment or by measuring physical performance based on their effort for a better allocation of their workload.

As we can see in Figures 9(a) and 9(b), a female worker who is moderately habituated to physical job maintained her perceived exertion level obtained using FPC with respect to the personalized Chamoux with sweeping and cleaning windows activities; however, while she was stacking chairs (which demands more physical effort), her perceived exertion level increased. With regard to not habituated male Worker 6 (Figures 9(c) and 9(d)), his perceived exertion level obtained using FPC increased with respect to the personalized Chamoux with all activities (sweeping, cleaning windows, and stacking chairs). All his FPC perceived exertion levels were higher than the personalized Chamoux perceived exertion levels. We attribute this behavior to the level of habituation. One objective of this proposal is to illustrate how the habituation factor impacts the perceived effort, and the proposal is not focused on an accurate calculation of physical effort or energy expenditure.

Figures 10 and 11 show personalized Chamoux and FPC methods to classify perceived exertions during sweeping.

As we can see, results clearly reflect different perceived exertion levels for individuals even though they perform the same activity. In Figure 10, the results of the FPC method are fuzzy, and in Figure 11, the results of the FPC method are defuzzified.

The statistical results allow us to know that when the activity is physically demanding (activity of stacking chairs), variance and standard deviation values are much higher. This shows that the many factors involved in the process of classifying perceived exertion are clearly reflected in the increase in cardiac frequency.

Figures 12 and 13 illustrate an activity that can be physically demanding if we are not habituated, and they show how the fuzzy personalized Chamoux method is more efficient for classifying individual perceived exertion, which is appreciated particularly for the activity of stacking chairs (Figures 12 and 13). Figure 12 can be very useful for a decision-maker to appreciate how a worker is being impacted for a specific physical activity.

All participants were directly observed during experiments to estimate their physical effort level. Additionally, they were asked about their perceived exertion just at the end of each activity. We obtained that perceived exertion classification using our proposed method is coincident (75% or higher) with respect to our direct observation and answers from participants.

Workers' personal perceived exertion (PPE) was a linguistic label (belonging to Table 2) that participants assigned

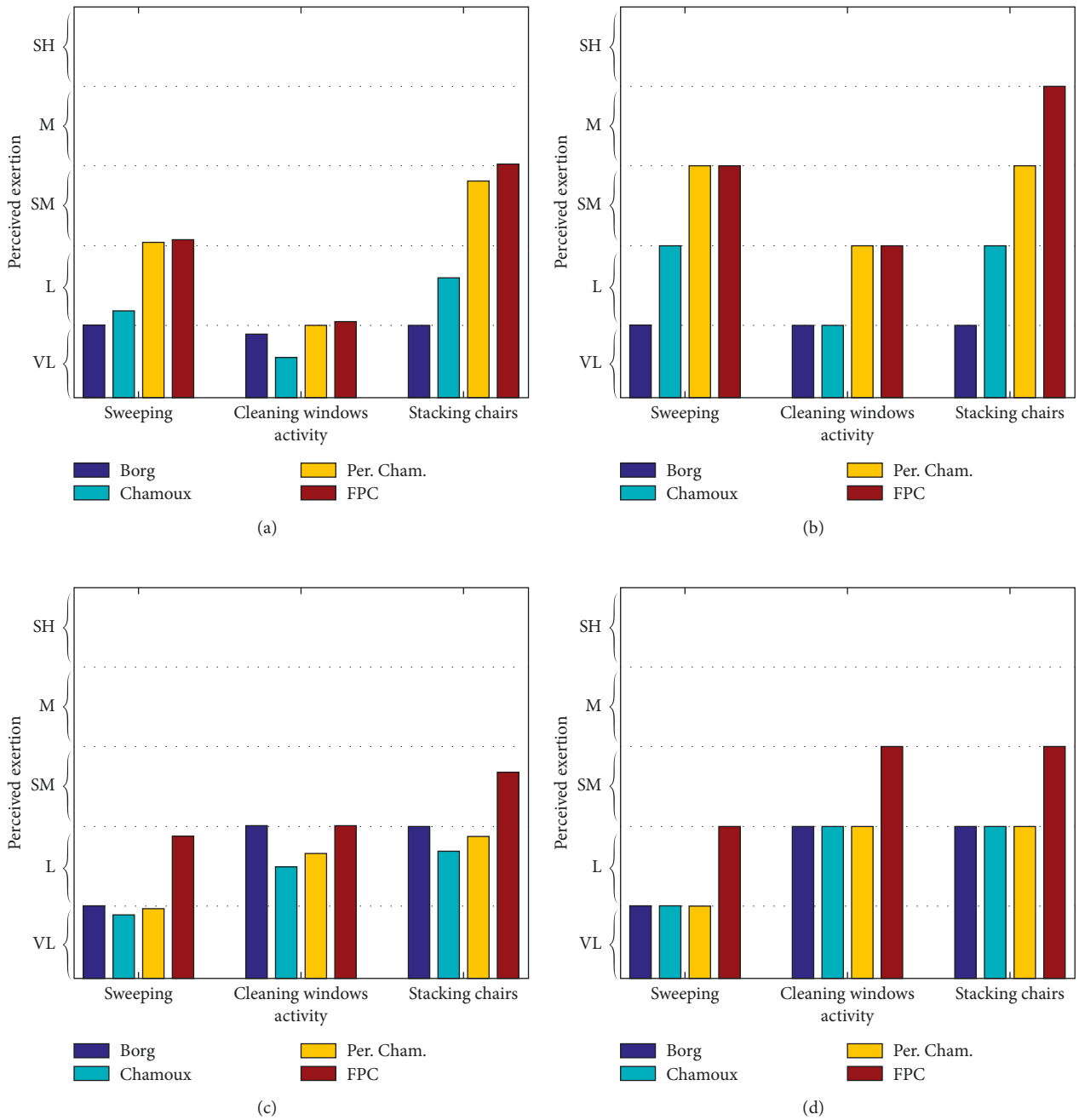

Figure 9: Perceived exertion: sweeping, cleaning windows, and stacking chairs. (a) Worker 3 (moderately habituated female—scalar values), (b) Worker 3 (moderately habituated female—linguistic values), (c) Worker 6 (not habituated male—scalar values), and (d) Worker 6 (not habituated male—linguistic values).

to each developed activity, representing their effort perception. We compare PPEs with FPC results to evaluate our proposal. Matching percentages were 75%, 75%, and 80% for sweeping, cleaning windows, and stacking chairs, respectively. As an example, in Figure 14, it is appreciated a comparison of workers' PPE versus linguistic outputs provided by our proposal for the sweeping activity.

We have designed a prototype for logging and informing users about their perceived exertion levels and historical records during activities. Figure 15 shows the prototype for Android devices.

The disk located at the bottom of the interface simulates a semaphore. The colors used represent the different levels of perceived exertion (from very light to intense). The green color represents the lowest levels of effort, and the red color represents the intense effort. The yellow color is used for moderate efforts. The purpose of the disk in the interface is that a given user can visualize in each moment and, in real time, the percentage of monitoring time that he/she has been in each level of perceived exertion, in accordance with our proposed method. Recording of perceived efforts is useful for rapid decision-making by the supervising manager, for

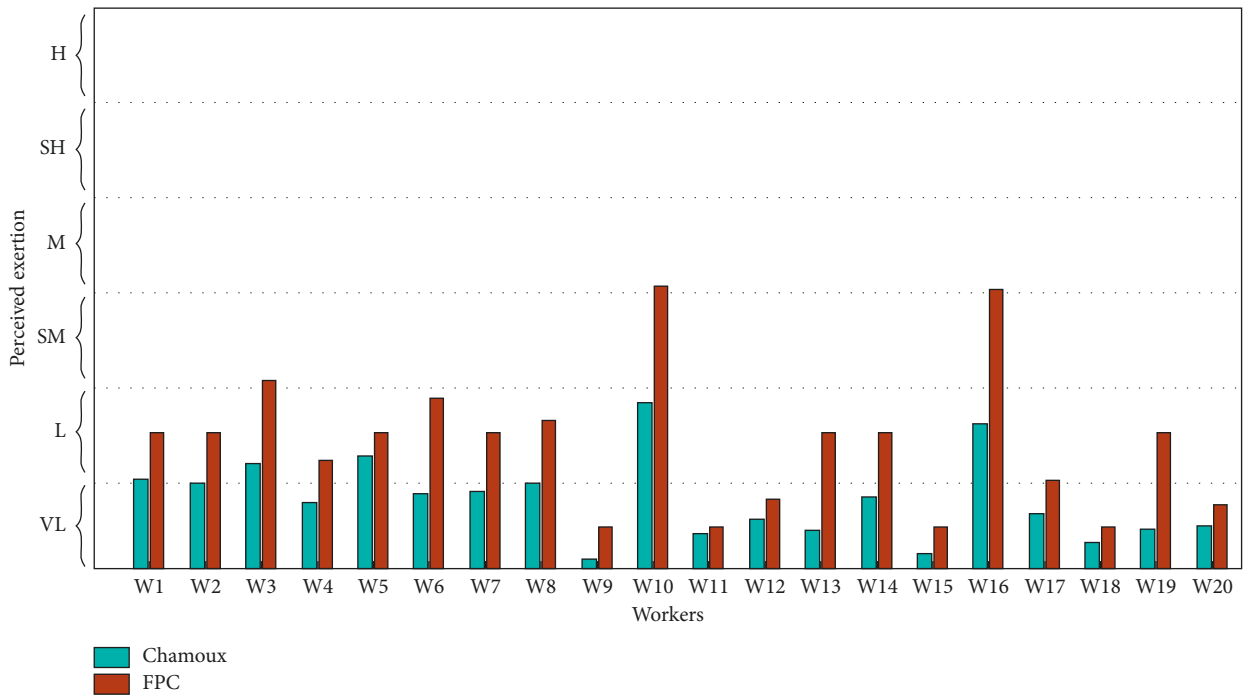

Figure 10: Sweeping activity (scalar results).

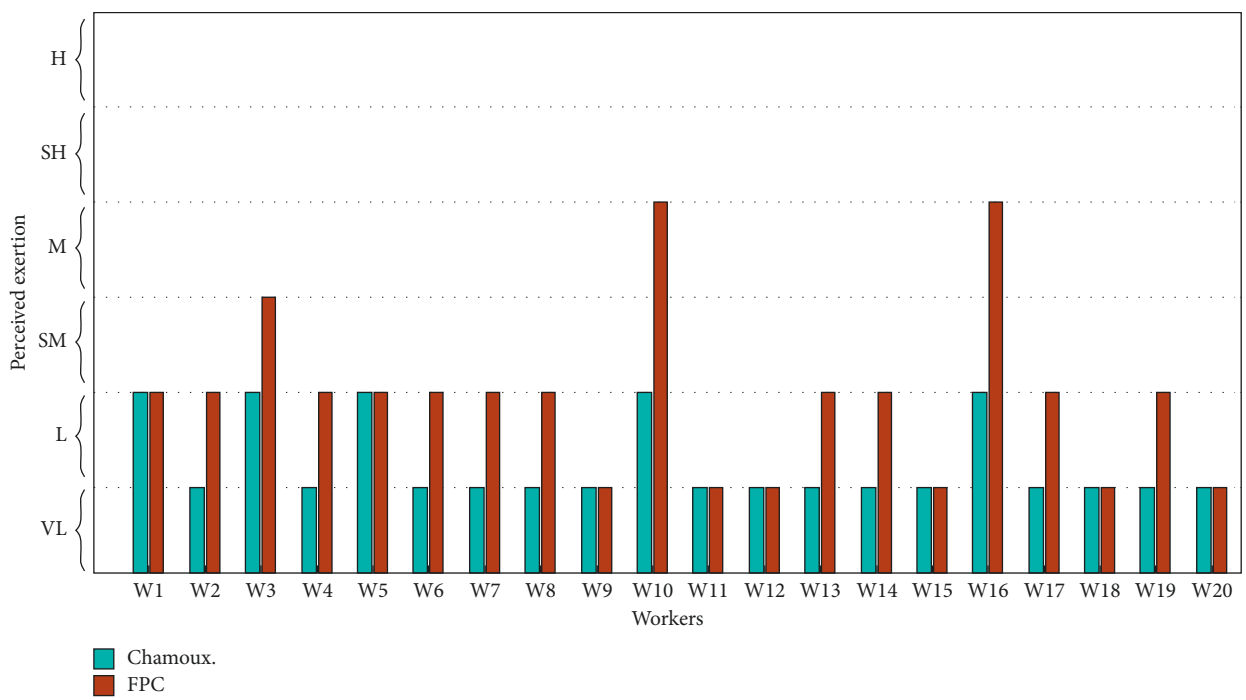

Figure 11: Sweeping activity (linguistic results).

example, for reassignment of tasks or scheduling of rest periods.

7. Discussion

The smartwatch presented several failures when data started to be captured, that is why a period of at least three minutes was monitored before the value of cardiac frequency was taken. However, as cardiac frequency values entered to formulas were averaged, some noise effects do not impact the results. We think that technological advances will let that future devices be more precise in sensing.

Considering habituation as a factor in the method of estimating perceived effort allows in turn improving

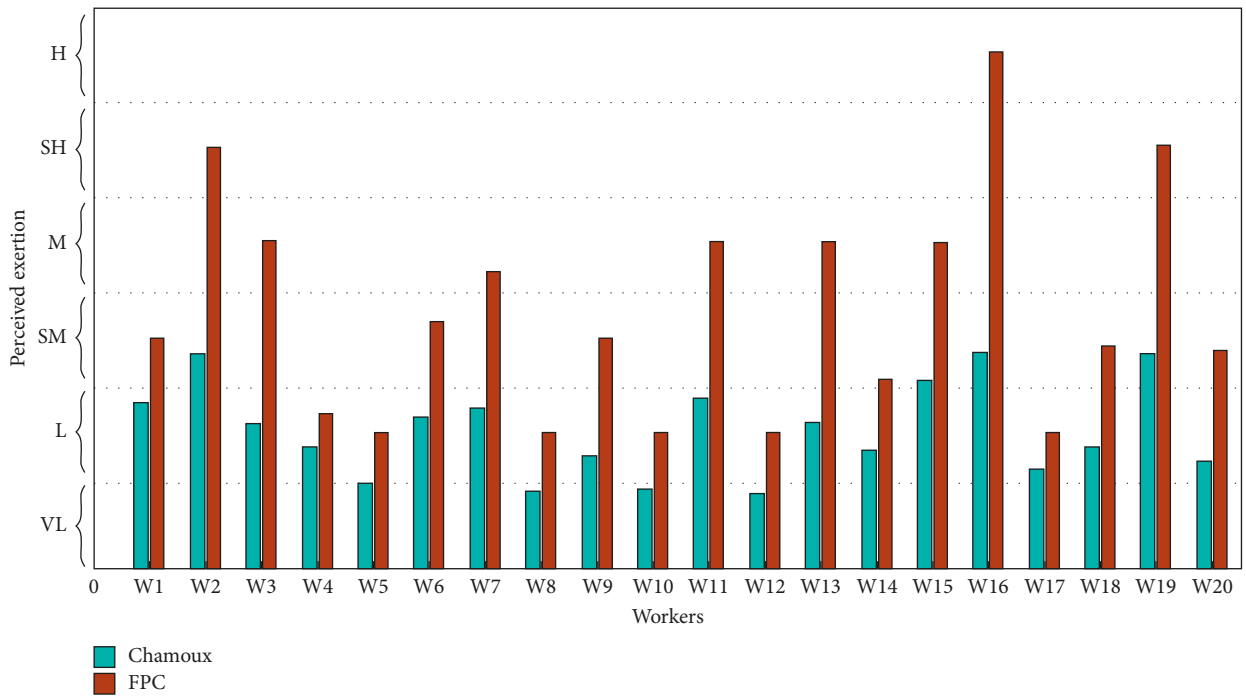

Figure 12: Stacking chair activity (scalar results).

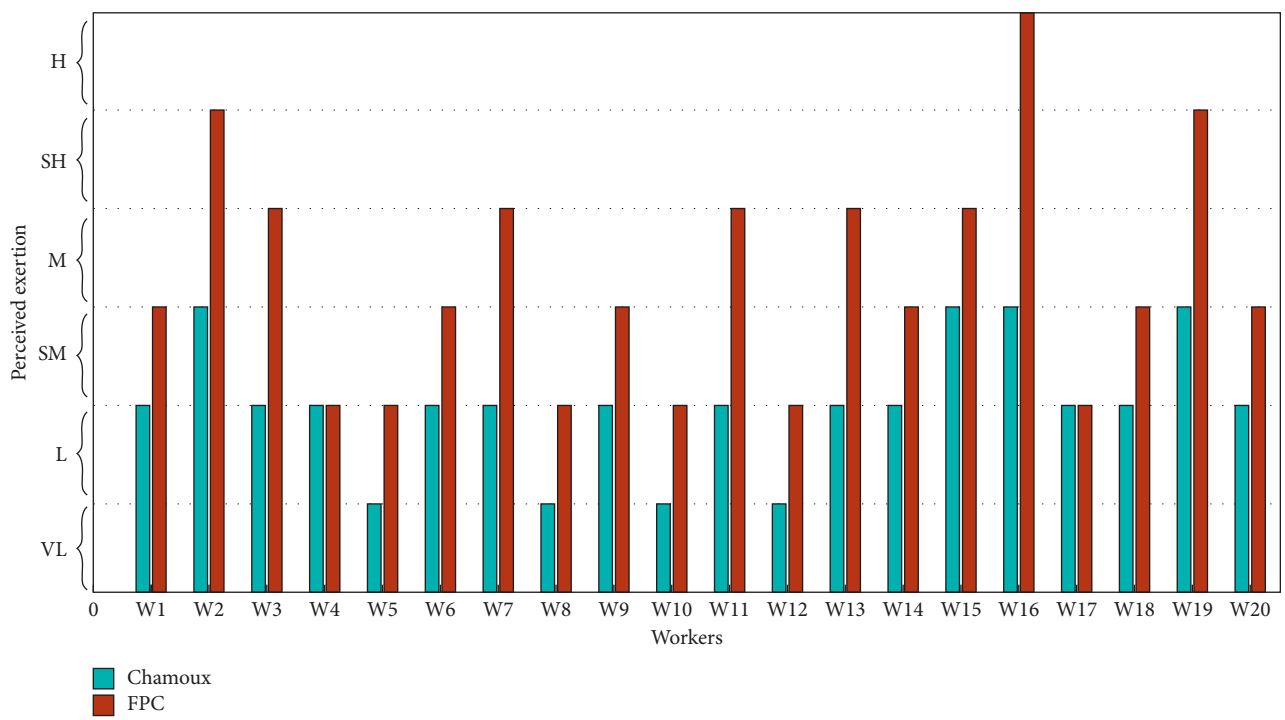

Figure 13: Stacking chair activity (linguistic results).

decision-making, for example, when a worker should be selected for a job with physical activities. Habituation is important because an unhabituated worker will have a greater perceived effort with respect to another worker who is accustomed, as studies reveal [24, 25].

Although recent proposals have determined rates in perceived exertion, these results do not consider individual factors related to worker experience or the physical activity performance. This is, for activities that cannot be controlled in terms of the intensity with which users perform them

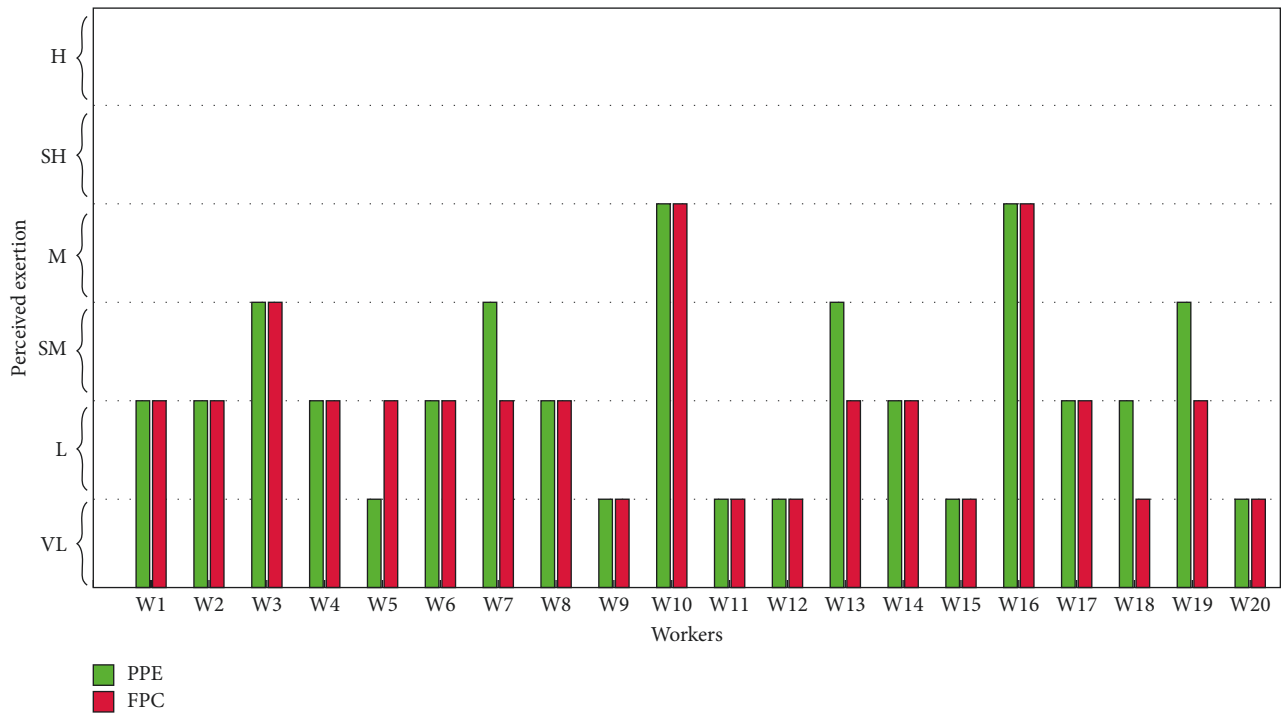

Figure 14: Sweeping activity (personal perceived exertion versus FPC method results).

(e.g., sweeping), each user executes them according to their personality, unlike activities performed on an electric treadmill where the speed at which they walk or run is controlled, so many studies only offer average energy expenditure values for daily activities. For this reason, in some cases for the same activity, a moderately habituated person may have a perceived exertion slightly greater than an unhabituated person.

Perceived exertion assessment in labor physical activities must consider factors such as physical condition, obesity, and hypertension; environmental factors like temperature, humidity, and altitude; or even factors affecting individual physical response in the performance of physical activities such as habituation and acclimatization. Recent proposals do not include these factors in perceived exertion assessment, which can lead to inaccurate decision-making in the allocation of a job post, for example.

The proposed method can handle any of these factors; habituation is an example of how this can be done. To handle other factors (like nutrition), variables and their domains have to be known (such as the quantity (kg and liters) and quality (calories) of food ingested and the time (hours and min) spent between the consumption of food and the performance of the activity), as well as their impact on perceived exertion, that is, the weight to be given to each variable in estimating the effort.

Habituation is considered as the training experiences based on tasks repetition, which conduces to a better physical activities' performance and changes in perceived exertion.

It has been stated in recent works that considering individual characteristics like maximum effort in activities' performance conduces to a better perceived exertion assessment. Published results of perceived exertion are based on one of the following methods: Borg method which considers a HR = [60, 220] to define a 14-value scale [22, 28] going from no exertion to maximal exertion, Chamoux method considering person age (220 – age) as the baseline to define a 70-value scale RCC = [0, 69], grouped in sets of 10 values each going from very light to intense, and extended Chamoux which considers individual maximum exertion as the baseline. However, effort level transition in those scales based on HR values may not correspond to perceived

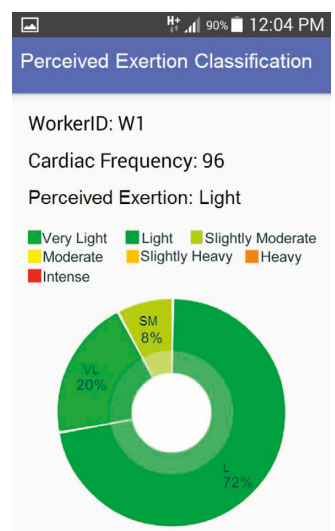

Figure 15: Perceived exertion prototype.

exertion (as perceived by the worker), due to lack of habituation, that is, when considering habituation, a compensation value has to be added to personal exertion for less habituated ones.

Since the assessment of perceived effort and habituation are based on human experience, the fuzzy logic can be used in such evaluations, given that discrete and continuous membership functions of a fuzzy set are intended to capture a person's thinking. Fuzzy membership functions can be determined subjectively in practical problems based on an expert's opinion. Membership functions can be considered as a technique to formalize empirical problem solving that is based on experience rather than the knowledge of theory.

Fuzzy membership function of habituation takes one of three values: no habituated, moderate habituation, and habituated. Fuzzy set values are defined in [0, 1] interval: border values are for a nonhabituated person and a habituated one, respectively. The membership degree was determined by worker experience and direct observation of workers performing physical activities. Values from fuzzy membership function of habituation, CCR, 20% compensation for nonhabituated and 10% compensation for moderate habituated, are inputs for fuzzy membership function of perceived exertion. Fuzzy membership function of perceived exertion takes one of 7 values: very light, light, slightly moderate, moderate, slightly heavy, heavy, and intense, each one taking ten values in [0, 69] interval.

Habituation contribution to perceived exertion assessment is a more realistic result in terms of human experience. As it can be seen in the results (Figure 9), perceived exertion can change to the next level when considering habituation. We think by experience that when a person is not accustomed to perform labor physical activities, the higher the hardness of activities is, the higher the level of perceived effort is. This is true when considering that the membership of one value to a set is binary, that is, a person is habituated or not to perform an activity; however, when considering fuzzy sets, the membership is defined by a function that takes its values in the interval [0, 1]. The closer the degree of membership is to 1, the more the element will be in the set, and the closer the degree of membership is to 0, the less the element will be in the set.

Results obtained in this study clearly establish the importance of considering factors such as habituation to physical activities performance in the evaluation of perceived exertion of workers. Adjustment of perceived exertion levels achieved with fuzzy logic allows us to improve decision-making for the allocation of jobs, the planning of workloads, or even the reduction of risks of fatigue accidents.

8. Conclusions

The contributions of this proposal are the ability to classify perceived exertion of people in daily activities, to improve their safety and health. This is because it is formally established that the effort of a person can be estimated based on his/her cardiac frequency. A standard effort can be estimated for each activity as a reference to analyze the gap with the personalized perceived exertion estimated by our proposed method to perform those activities; the usefulness of measuring the personalized effort of workers in their work environment to preserve their health; and the possibility to determine that a person is conducting his/her activities in a comfortable way, that is, in accordance with his/her personal capacities, abilities, and habituation to improve performance, safety, and welfare state.

This is not a proposal to accurately measure the physical effort but emphasizes the importance of customizing the measurement process and mentions that it is hardly possible to have a generic method, given a large number of variables that must be considered. The intention is to show how the effort estimation varies when considering a custom value as the maximum personal cardiac frequency, as well as imprecision and uncertainty of variables affecting methods to classify perceived exertion.

Using the fuzzy logic, it was possible to verify the importance of the degree of membership of a variable to a fuzzy set, because depending on the degree of membership it is possible that the perceived exertion can be increased (next label) as a result of the rules used by the inference engine. This situation is more suited to real life where although a variable belongs to a certain group, there is a level of belonging to that group, which should be considered because it may be more correct to classify the variable as belonging to a nearby set.

The proposed method for the classification of perceived exertion considers how to add possible variables, as exemplified by the inclusion of habituation and the way it affects, as obtained in related studies. Analysis of our results reveals that an objective method of estimating individual effort should consider custom values in the parameters to capture the widest possible set of variables involved in the estimation of perceived exertion. Therefore, the decision to perform a stress test for obtaining the maximum heart rate is important, because with this action, indirectly, we are including many factors such as age, sex, body mass index, and acclimation.

We conclude that the use of a wearable device with capacities of measurement of physiological parameters together with fuzzy logic computational methods provokes expert knowledge that represent a viable automatic solution for perceived exertion classification.

Future work includes other factors involved such as environment, gender, body mass index, and mental stress. Another type of sensors must be considered, as well as the combination of heterogeneous sensors. The perceived exertion should be objective; direct observation gives an idea of the results, but it is based on experience and questionnaires. Habituation to physical effort requires further study; to our knowledge, there are no studies analyzing the impact of habituation to perform physical activities in the perceived exertion of workers. Additionally, it is important to extend FPC method definition to integrate the implementation into a smartphone.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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