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MOTION-AE: an Intelligent Mobile Application for Aerobic Endurance Training

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ABSTRACT

A significant part in the field of physical activity is represented by aerobic endurance training due to the fact that it depends primarily on aerobic energy generating processes. The stress of aerobic workout induces adaptations in the cardiovascular and respiratory systems which generate an optimal output of performance. Maintaining the heart rate and breathing at a set value of intensity, determined by the individual's unique characteristics, is one way of enhancing the performance output of training. Determining these operating points that ensure desired results are often hard to calculate with classical methods, especially in the presence of nonlinearity of the heart rate variability. This paper presents a mobile application, MOTION-AE, designed for setting the optimal intensity of the aerobic endurance training, using an intelligent decision making method. The software application was tested and validated using data from various subjects. The designed mobile application takes into account the individual's unique characteristics and ensures the optimal intensity of the training session, finding its usefulness in supporting the configuration process of training parameters by specialized professionals.

Keywords: mHealth Systems, Mobile Applications, Intelligent Decision Making, Fuzzy Decision, Aerobic Endurance Training, Heart Rate Variability.

Mathematics Subject Classification: 68T35, 68T37

Computing Classification System: I.2

1. INTRODUCTION

The stress of aerobic workout induces multiple adaptations in a human body that generate an optimal output of performance (Jones and Carter, 2000). The adaptation heart rate to aerobic workout (Carter et al., 2003) is a consequence of the increased delivery of blood to the muscles that generate through their activity a rise in the metabolic demands. Maintaining the heart rate, during training, at a set value of intensity, determined by the individual's unique characteristics, is one way of improving the fitness of a person (Helgerud et al., 2001; Ellison et al., 2012).

There is a strong correlation between the intensity value that needs to be determined for the next training session and its previous value. As the set intensity value goes higher it becomes harder for the subject to maintain the required heart rate. The regulation of intensity in the classical methodologies for improving aerobic endurance training is done in an “off-line” manner.

This means that the intensity for the next training session is settled after the data from the previous one is gathered, transformed and analyzed. There is a degree of subjectivity attached to the interpretation of the actual training intensity (Nawarycz et al., 2012) in relation to the stress of the workout. The integration (Wagholikar and Jo, 2008) of this subjective side of the intensity in an objective instrument could offer an invaluable way of achieving the desired performance (Gou, 2009).

An intelligent decision making instrument using fuzzy logic is the right way to incorporate non-crisp values and therefore is the optimal solution for this situation (Precup et al., 2015; Novotny, 2007; Kenney et al., 2015).

In (Jacobs, 1997), a controller with 36 if-then rules that was applied to a model that had three sets of variables was proposed by the author managed to integrate abstract knowledge from physiology with a decent level of success. Moreover, it has been proved (Rudas et al., 2012) that the human drives and motives can be integrated into a fuzzy logic controller to model the human decision-making. Even though there is a gap in the literature describing the methodology of creating such a controller, the authors proposed a 10 step method that allowed them to include abstract variables like motivation and drives.

Research has been also done into developing an evaluation method of strength exercises using a fuzzy controller (Novatchkov and Baca 2013). In their paper, the two authors surmised that currently there is a lack of application of fuzzy logic controllers in the field of sport and training. With the increasing progress in fuzzy systems implementation, this technology is becoming more and more versatile, with a wide range of applicability, from modelling non-linear systems (Precup et al., 2015) to detection algorithms (Moallen et al., 2015).

Heart rate variability monitors (Achten and Jeukendrup, 2003; Porges, 2007; Weippert et al., 2010) and associated software are powerful tools for athletes and coaches, providing useful information which can be used to adjust training programs for the desired effect. A new trend (Strickland, 2012; Baig and Gholamhosseini, 2013) has appeared in the last few years in the development of sport and fitness software (Emrich, 2014). Researchers and companies around the world started paying attention to mobile applications because of the integration of GPS hardware, accelerometers and other sensors (Ramos et al., 2015).

Furthermore, mobile devices can now connect with smart wearable sensors (Baig et al., 2013; Marin-Perianu et al., 2013) and watches which provide information about heart rate, body temperature and respiratory rate during training. This enables the possibility of developing powerful software tools

(Varriale and Tafuri, 2015; Kenney et al., 2015) for monitoring and improving the overall aerobic endurance and fitness.

Recent trends incorporate devices from specialized toys (Penados et al., 2010) to smartphones (Barkhuus and Polichar, 2011) in which a connection is made between the tangible and virtual worlds (Bekker et al., 2010), in an effort to promote physical activity and, thus, overall well being.

Regarding aerobic training, so far various mobile solutions have been proposed:

- Stand-alone solutions: the device can capture real-time data in flash memory inside device itself (Garmin, 2015; Polar Electro, 2015; Fitbit, 2015).
- Smartphone solutions: applications are developed for Android, iPhone, and Windows mobile OS, which make use of smartphone sensors and features (iTreadMill, 2015; RunKeeper, 2015; Endomonodo, 2015).
- Hybrid solutions: devices that communicate with smartphones to transmit and process data (Nike, 2015; Digifit, 2015; Adidas, 2015).

Devices from Garmin (Garmin, 2015), Suunto (Polar Electro, 2015), and Fitbit (Fitbit, 2015) are considered stand-alone devices. Their main advantages are that data captured with these devices is accurate (because of the integrated high quality sensors), and are easy to wear. For the user to have access to the recorded data the device requires to connect to a computer via USB or wireless network. The disadvantage of using stand-alone devices is the computer dependency for data processing. If the users want to see their performances, compare their training data with previous historical data, and so on, they need a specialized computer software and connection to view it.

iTreadMill (iTreadMill, 2015), RunKeeper (RunKeeper, 2015), and Endomondo (Endomonodo, 2015) are applications that use only smartphones. They are capable of recording data from the user training sessions, compare them with previous historical data and give the user the possibility of sharing it on social networks. The disadvantages of using the smartphone devices are that data recorded with the integrated sensors is not accurate and they cannot record some useful information like the user's heart rate. Thus, applications using only mobile devices are, unfortunately, limited.

Hybrid solutions take advantage of wearable systems (for data accuracy) and smartphone features. Nike+ (Nike, 2015), Digifit (Digifit, 2015), MiCoach (Adidas, 2015) are hybrid solutions offered by companies and are well established on the market. The disadvantage of these solutions is that users have to mount their smartphone on their arm. Not everyone is comfortable with this idea, especially when they can damage their mobile devices.

MOTION-AE improves the training intensity in an off-line manner. It combines some advantages of stand-alone devices with the advantages of smartphones, but it is not a hybrid solution. The data needed for the application can be recorded with any wearable system and so, the data used for deciding the level of the next workout's intensity is accurate. The decision making application is independent of the wearable system, in the sense that users can record training data and then introduce it into the application. The wearable device does not have to be connected with the smartphone and users can leave their smartphone at home during training.

This paper is organized as follows. Section 2 describes the methodology of using heart rate variability in aerobic endurance training, whereas Section 3 describes the design of the fuzzy module. Section 4 of the paper presents the development of the MOTION-AE application. Section 5 contains numerical results and discussion, while Section 6 presents the conclusions.

2. USING HEART RATE VARIABILITY IN AEROBIC ENDURANCE TRAINING

Heart rate is not constant from one beat to another but it alters during this cycle. The beat-to-beat interval, also known as R-R interval, is the time gap between each peak of a heart beat (Garet et al, 2010). The variation of this interval is called Heart Rate Variability (HRV). The measurement of the R-R interval shows that the HRV varies during breathing cycles: it speeds up during inhalation and slows down during exhalation (Taylor and Eckberg, 1996).

The analysis of the beat-to-beat variation can be used for monitoring the training or recovery. If the measurements are accurate, there is a possibility to detect the variations of the R-R interval in such a way that one can determine the physiological stress and fatigue on the body during training (Aubert et al., 2003). If the time between heartbeats has a wider range of variability then it means that the subject is more relaxed and unloaded (free from fatigue).

The imbalance between training or competition and recovery is known as overtraining (Hynynen et al., 2006). Other stress factors and monotony of training may induce the overtraining syndrome. HRV does not seem to be influenced by short term overtraining, but long-term exposure to such a state can lead to burnout (Earnest et al., 2004). Insufficient rest and recovery may influence the effects of the training program in a negative way. The HRV gives an objective view of the activity of sympathetic and parasympathetic neural systems. The increase or decrease in the activity of these systems reflects the fatigue levels of the cardiovascular system (Lehmann et al., 1993).

The intensity of a workout can be conceptualized in the form of the load that the person who undergoes the training is subjected to (i.e. speed of running, weights, number of repetitions per minute). To interpret the HRV one needs to know the reference of the R-R interval and the R-R interval at the beginning of the workout day. The R-R interval reference value is the difference between the natural logarithm of the average value of the R-R interval from the past 10 days and its standard deviation. The number that is left represents the overall reference that must be compared to the new R-R interval value. If the reference is greater than the R-R interval for the workout day, the intensity of the training can be increased. On the other hand, if the reference is smaller, the intensity must be decreased. After each new training day, a new reference must be computed with the same method and compared with the new R-R interval value.

Measurement of HRV for use in monitoring training and recovery involves analysis of the beat-to-beat variation. By accurately measuring the time interval between heartbeats, the detected variation can be used to measure the psychological and physiological stress and fatigue on the body during training. The step by step method to identify this is as follows:

- Recording the values of the HRV for 10 days
- Calculating the reference point for HRV based on the 10 previous values
- Comparing the 11th recording with the reference
- Calculating the new reference to compare for the any following work day.

Using the MOTION-AE application presented in this paper, the optimal intensity can be adjusted according to individual needs. The use of our software gives a more gradual and controlled way of setting the intensity of an aerobic training compared to the classical way of interpreting heart rate variability for the setting of the work load.

3. FUZZY MODULE DESIGN

One way of describing the fuzzy logic is that computing is performed using words rather than numbers. Subsequently, fuzzy decision making is using sentences rather than equations, giving the algorithm a more natural feel by incorporating *if-then* clauses. Thus, the idea behind fuzzy reasoning is using such rules.

The corresponding fuzzy sets allow for descriptions (with high degrees of uncertainty) of states and/or objects through partial membership to the considered set, as opposed to crisp data, for which an all or nothing approach is the norm. In fuzzy logic, the gradual transition between the *is-part-of* and *is-not-part-of* descriptors is shaped by a membership functions (MFs) that offer flexibility in modelling linguistic expressions such as "wind velocity is mild".

This is one of the most common representations of knowledge in working professionals. The resulting abstraction of information allows for uncertainty compensation, adaptive reasoning, unaccounted disturbances and so on, which ultimately translates into *fuzziness* (vagueness, imprecision).

A fuzzy *if-then* rule has the form:

$$\text{IF } x \text{ is A, THEN } y \text{ is B,} \tag{3.1}$$

where A and B are linguistic variables defined by fuzzy sets (and their corresponding membership functions) on two universes of discourse X and Y, respectively (Patrascu et al., 2014). The antecedent is the first part of the rule (after IF), whereas the consequence is the second part (after THEN).

Using a series of fuzzy *if-then* rules, known as a rulebase, the reasoning mechanism of the decision making module can be described. For example, the fuzzy rules could employ the relationship between input variables (heart rate and heart rate variability) and output variables (suggested adjustment of the training intensity) in a manner that is both meaningful and explicit.

An advantage of using fuzzy logic in such applications is that all rules are being evaluated in parallel, which means that more than one rule can be active for any input variation. Therefore, the final decision is a combination of possible decisions for each group or pair of inputs with various degrees of contribution.

The decision making module has a Mamdani type structure (Figure 1) with a MIN-MAX inference mechanism. The inputs are: (a) the difference "HRV" between the previously measured reference R-R interval of the subject and the R-R interval of the last training session, and (b) the variation "WHR" of work heart rate of the last two sessions.

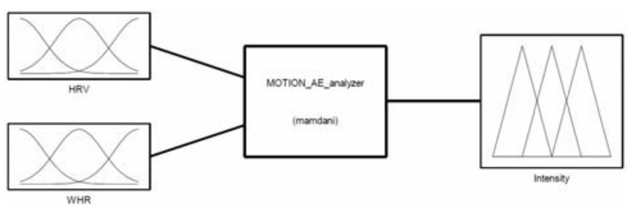

Figure 1. Fuzzy decision making module.

Table 1: Module rulebase

HRV / WHR	VLNeg	LNeg	SNeg	Z	SPos	LPos	VLPos
W Large N	Small Inc	NoVar	NoVar	NoVar	VLarge Dec	VLarge Dec	VLarge Dec
W Small N	Small Inc	Small Inc	NoVar	NoVar	Large Dec	Large Dec	VLarge Dec
W Zero	Large Inc	Large Inc	Small Inc	NoVar	Small Dec	Large Dec	Large Dec
W Small P	VLarge Inc	Large Inc	Large Inc	NoVar	NoVar	Small Dec	Small Dec
W Large P	VLarge Inc	VLarge Inc	VLarge Inc	NoVar	NoVar	NoVar	Small Dec

The output is "Intensity", representing the suggested increase or decrease of the next session's training intensity (as a percentage of the previous session's training intensity (Patrascu et al., 2015)). All three signals are defined over normalized [-1, 1] discourse intervals and have been scaled by suitable factors in order to preserve numeric compatibility.

The rulebase (see table 1) of the module is comprised of 35 rules that generate an output mapped over 7 membership functions (MFs), whereas the two inputs are each defined using 7, and 5 MFs respectively. Thus, for each input and output variable, the chosen linguistic terms are:

(a) Input "HRV" has 7 MFs (Figure 2) coded with VLNeg (very large negative), LNeg (large negative), SNeg (small negative), Z (zero), SPos (small positive), LPos (large positive), and VLPos (very large positive).

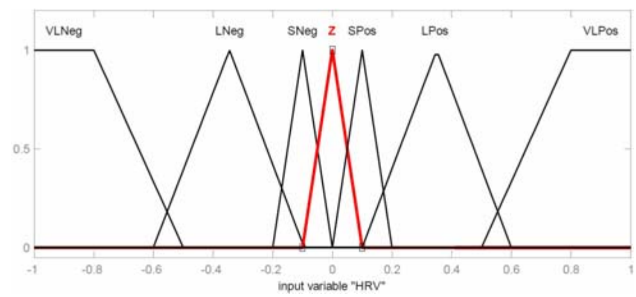

Figure 2. Input "HRV" of the fuzzy module.

(b) Input "WHR" has 5 MFs (Figure 3) coded with WLargeN (large negative), WSmallN (small negative), WZero (zero), WSmallP (small positive), and WLargeP (large positive).

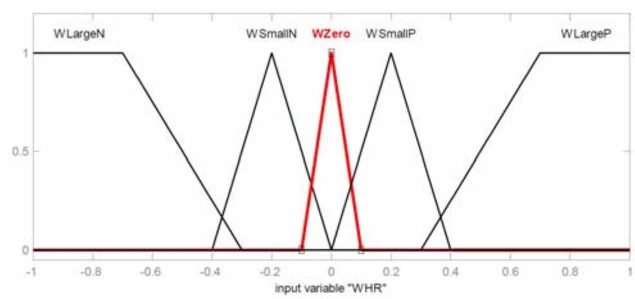

Figure 3. Input "WHR" of the fuzzy module

(c) Output "Intensity" has 7 MFs (Figure 4) coded with VLargeDec (very large decrease), LargeDec (large decrease), SmallDec (small decrease), NoVar (no variation), SmallInc (small increase), LargeInc (large increase), and VLargeInc (very large increase). For defuzzification of the output variable, a mean of maximum method has been chosen.

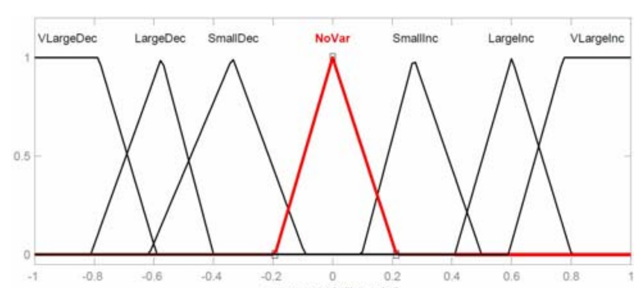

Figure 4. Output "Intensity" of the fuzzy module

In order to simulate and validate the module, a Matlab implementation "Training Intensity Analyzer" has been obtained (Figure 5). Using the resulting application, for each of the input variables, the operator needs to input two values: the "Reference R-R Interval", the "R-R Interval Before Session", the "Work Heart Rate Two Sessions Ago" and the "Work Heart Rate Last Session". Pressing the "Calculate" button returns the "Recommended Training Intensity", that suggest an increase or decrease of the intensity for the next training session, and by how much.

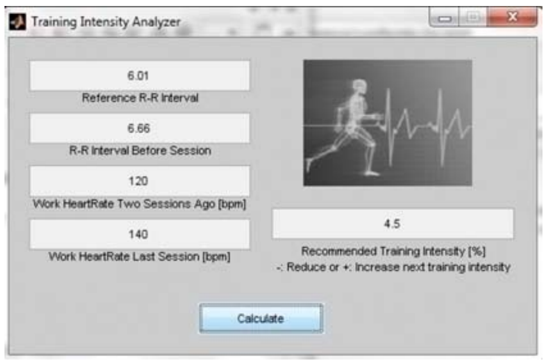

Figure 5. Training Intensity Analyzer

4. THE MOTION-AE APPLICATION

The MOTION-AE application has been implemented on a smartphone with an Android OS. The specifications of the smartphone are: Processor ARM Cortex-A9, Dual core, 1400Hz, 1Gb RAM. The application has been developed using the code editor Android Studio for Android 4.4 KitKat version.

The analysis of the problem at hand in the previous sections leads to the definition of a series of functional requirements for the software application:

- REQ.1. The application should be able to generate suggested training intensities for the next training session based on previous training sessions data, therefore the application should incorporate a decision making algorithm and have access to a database.
- REQ.2. The application should be able to receive user input and communicate its suggestions to the user, therefore the application should have an easy to use comprehensive graphical user interface (GUI).
- REQ.3. The suggested training intensity adjustment should take into account user physiology and R-R interval data, should account for uncertainties in data and/or user physical characteristics, and should incorporate empirical knowledge (as this is the only type of knowledge available in the respective medical and sports fields pertinent to the problem of aerobic endurance training).
- REQ.4. The maintenance of the software application needs to be supported by a technician.

The main features of the proposed application are presented in table 2. Several categories of stakeholders are also described in table 2. The main beneficiaries of the system are users that access the mobile application (for example trainees or trainers). The secondary beneficiaries are sports goods providers (sensor producers or retailers) and different software providers (maintenance, data base storage, etc.). Table 3 lists the actors that interact with the software application.

Table 2: Main features of the MOTION-AE application

Feature	Description	Actors	Cross-Ref
Compute intensity adjustment	Fuzzy Module makes a decision of how the next session's training intensity should be adjusted based on user's current state and previous training sessions. This feature includes Evaluate data, Inference, and Generate decision.	Fuzzy Module	REQ.3
Display intensity adjustment	GUI displays the suggested training intensity adjustment	GUI	REQ.1 REQ.2
Prepare computation	User inputs data in order to request a training intensity adjustment according to the user's current physical state.	User	REQ.1 REQ.2
Store data	Database receives and stores data.	Database	REQ.1
Send data	GUI sends data to Database for storage.	GUI	REQ.1
Evaluate data	Fuzzy Module uses fuzzification to translate quantitative raw data into information for the inference.	Fuzzy Module	REQ.3
Inference	Fuzzy Module runs MIN-MAX inference in order to obtain a decision.	Fuzzy Module	REQ.3
Generate decision	Fuzzy Module uses defuzzification to translate its decision into a quantitative adjustment of training intensity.	Fuzzy Module	REQ.3
Maintain system	Technician performs maintenance operations on the system.	Maintenance	REQ.4

Table 3: Actors and interactions

Main elements	Aim	Interacts with
User	Requests next training session intensity adjustment	GUI
GUI	Mediates interactions between the user and the fuzzy module	User
Fuzzy Module	Computes next training sessions intensity adjustment	GUI Database
Maintenance	Software application maintenance	Fuzzy Module GUI
Database	Stores previous training sessions data	Fuzzy Module GUI

Through the Graphical User Interface (GUI) module (Figure 6) the user introduces the crisp values of recorded data: "Reference R-R Interval", "R-R Interval Before Session", "Work Heart Rate Two Sessions Ago", and "Work Heart Rate Last Session". The input and output variables of MOTION-AE have the same membership functions as in the case of the Training Intensity Analyzer presented in the previous section (Figures 2 through 4).

The fuzzification module converts the received data into fuzzy values and determines the degree to which they belong to each of the appropriate fuzzy sets via membership functions. MOTION-AE uses triangular-shaped membership functions:

$$\mu_{x_i}(v) = \begin{cases} \dfrac{v-a}{b-a}, v \in [a,b) \\ \dfrac{c-v}{c-b}, v \in [b,c] \end{cases}, \tag{4.1}$$

where: v is the crisp value of the x_i input variable ($i \in \{\mathrm{HRV}, \mathrm{WHR}\}$ in this case); $\mu_x(v)$ is the membership degree evaluated for the membership function in v; a, b, and c are scalar parameters that shape the membership function (a and c locate the base of the triangle, while b locates the peak on the $[a, c]$ universe of discourse for the x variable).

Figure 6. MOTION-AE Application GUI

Given the mappings of input variables onto membership functions, the inference mechanism uses a set of rules:

$$\text{IF } x_{HRV} \text{ is A AND } x_{WHR} \text{ is B THEN } y \text{ is C}, \tag{4.2}$$

where y is the computed output (specifically the "Intensity" variable), while A, B, and C are linguistic instances of the three i/o variables.

The antecedent of the rule has more than one part, thus the fuzzy operator AND is applied (minimum criterion between the membership degrees of the input variables). This operation is known as antecedent evaluation (Figure 8), and it is implemented using the MIN fuzzy operator:

$$Ant_j(v) = \min_{j=1:n}(\mu_{HRV}(v), \mu_{WHR}(v)), \tag{4.3}$$

where n is the total number of rules (7x5).

The consequence is obtained via aggregation of the fuzzy sets that represent the result of each rule using the MAX fuzzy operator:

$$y(v) = \max_{j=1:n}(Ant_j(v)), \tag{4.4}$$

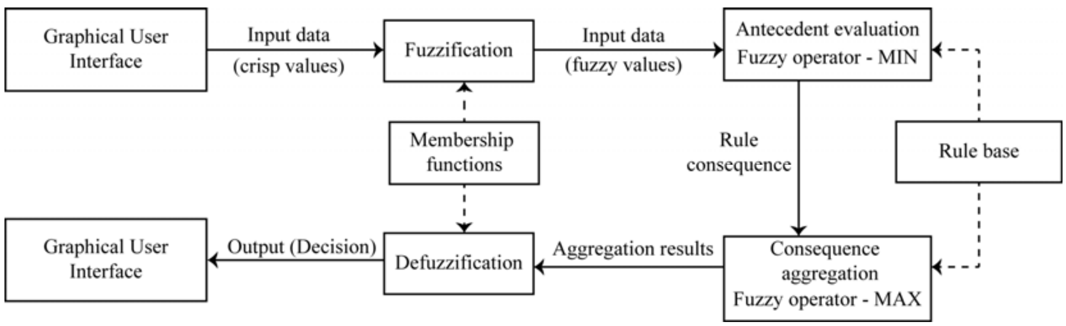

Figure 7. MOTION-AE Fuzzy Module - GUI interaction diagram

The defuzzification module (Figure 7) converts the aggregate output *y(v)* into a corresponding crisp value, which suggests the user how to change the intensity of the next training session (increase/decrease and by how much) in order to obtain optimal results for aerobic training, and it is displayed on the Graphical User Interface.

The defuzzification method used for calculating the suggested intensity variation of the training is Mean of Maximum (MoM). Even if, for defuzzification, Centre of Gravity (CoG) is the most common method used, MoM has been selected, mainly for being computationally cheaper than CoG.

For the MoM method, the largest $Ant_j(v)$ value is first identified, followed by computing the mean of its projection on the discourse universe of the output y. In the CoG method, the area under all the $Ant_j(v)$ values is first calculated, followed by finding the centre of area under the resulting curve, which is more computationally taxing.

5. TESTS AND RESULTS

For the testing and validation of the MOTION-AE application, 4 subjects have been chosen, all female, with ages between 21 and 23 years old. For this, some precise measurements of the heart rate variability are required. The latter ones also imply the need for a controlled protocol of calculating the HRV's reference (see Section 2 for details):

- the value of the HRV for one specific day has to be recording first thing in the morning before eating
- the subjects were not allowed to drink coffee or consume alcohol during the 3 weeks experiment (1 week before the actual recordings started)
- the subjects with a reverse day-night schedule would have performed the same measurements as if they had the same day-night program
- for each measurement there have been taken 3 recordings, at 5 minutes apart, out of which the lowest value of the HRV of the 3 values is kept
- this recording process is performed for the next 10 days
- at the end of the 10th day, the value of the reference can be calculated by subtracting the standard deviation of the values from their mean
- after the reference is established, 3 more days of recordings need to be performed.

Moreover, the second variable needed to test the application, the work heart rate, also requires a specific protocol for the necessary recordings (details in Section 2):

- before starting the training session, the subject had 5 minutes in which to accustom themselves to the heart rate (HR) sensor due to the need to start from an individual value of the base heart rate
- during the training session the heart rate is to be recorded continuously without pausing the monitor
- each break or pause in the training session is noted in an observations chart
- the start value and the end value of the HR during an exercise is also noted, and so is the exact time at which it started and ended
- at the end of the training session the subject also has a 5 minutes de-acclimation period
- the work heart rate is computed as an average of the heart rate values during the training session, as it reflects the intensity of the training session

The subjects R-R intervals and heart rates of the training sessions during 13 days have been recorded, as 10 entries are necessary to determine the Reference R-R Interval, while the extra 3 have been used for validating the application.

The MOTION-AE application has been used on two of the subjects (A and B), whereas the data from the other two subjects (C and D) has been used for comparing the app with the classical interpretation of the heart rate variability. First, the Reference R-R Interval of the four subjects has been obtained (table 4) (Barkhuus and Polichar, 2011; Bekker et al., 2010). After the reference was obtained the actual experiment could start.

Table 4: Reference R-R Interval for the four subjects

	Subj. A	Subj. B	Subj. C	Subj. D

	Subj. A	Subj. B	Subj. C	Subj. D
Day 1	5.77	5.66	6.01	5.12
Day 2	6.05	5.40	5.89	5.15
Day 3	6.32	5.12	5.80	5.22
Day 4	6.67	5.90	5.99	5.30
Day 5	6.71	5.34	6.10	5.40
Day 6	6.65	5.70	6.15	5.39
Day 7	6.32	5.55	6.00	5.19
Day 8	6.10	5.41	6.14	5.64
Day 9	6.79	5.30	5.88	5.29
Day 10	6.13	5.10	5.94	5.25
Average	6.35	5.45	5.99	5.30
Standard Deviation	0.34	0.26	0.12	0.15
Reference	*6.01*	*5.19*	*5.87*	*5.14*

On the next three days the authors have done the following calculations: first, they have calculated the new reference for each day taking in consideration the previous data and then applied the MOTION-AE application on the training program of the first two subjects while still utilizing the classical method for the other two subjects.

To determine whether or not the application had the desired effect of gradual increase of intensity and not jumping into overtraining due to fatigue the authors have observed the work heart rate evolution for all the subjects during the three test days.

For the two subjects for whom the application has not used to determine the next value of intensity, the classical HRV interpretation was used. This has a higher degree of subjectivity than our application due to the fact that it does not offer a percentage by which to increase or decrease the value of the load. This means that by using the classical HRV interpretation the trainer only gets a general idea of the trainee's fatigue level.

Table 5: Evolution of the R-R Interval and the Computed Reference R-R Interval

	Subj. A	Subj. B	Subj. C	Subj. D
Reference Before Day 11	6.01	5.19	5.87	5.14
R-R Interval Day 11	6.44	5.21	6.12	5.14
Reference Before Day 12	6.03	5.17	5.88	5.13
R-R Interval Day 12	6.39	5.30	5.40	5.31
Reference Before Day 13	6.05	5.17	5.75	5.14
R-R Interval Day 13	6.50	5.19	5.80	5.27

As can be seen in table 6, subjects A and B had a gradual increase in their work heart rate with low and few decreases, while the other two subjects had many relatively high variations. As stated in Section 1 of this paper, the need to objectively control the variation of the work heart rate during a long training schedule that span over many months is fundamental in maintaining the fatigue level in check. The fact that we managed to design an objective tool that allows us to control the intensity level of training for such a long period of time may be seen as a success in overcoming the subjective methodology described in Section 1.

This situation can also be observed in table 5, that displays the value of the reference and R-R interval for all the subjects. Here it can be observed that by using our application the level of fatigue for the two subjects is kept in check and at a lower individual value, allowing for a more efficient training. As stated in Section 2 of this paper, there is a need for an objective tool that can reliably offer an interpretation of the heart rate variability. Due to the fact that using our application we were able to control the fatigue levels through constant adjustment by a certain percentage of the work load, we may have found an easy to use tool for both professional athletes or amateurs.

On the other hand, the two subjects that used the subjective interpretation of the HRV have their fatigue level almost at the limit or it varies considerably from one day to the next.

Table 6: Work heart rate for all the subjects during the 3 days testing period

	Subj. A	Subj. B	Subj. C	Subj. D
Day 11	120	120	130	122
Day 12	132	124	141	123
Day 13	150	136	129	139
Day 14	145	140	134	145

In order to analyze the computational correctness of the Android OS based fuzzy implementation (presented in Section 4) vs. the classical Matlab toolbox (presented in Section 3), random input values have been chosen and a comparative offset has been computed. Thus, we can ascertain the degree of reliability over the actual implementation of the fuzzy specific functions (fuzzification, inference, defuzzification), relative to the high degree of reliability that a powerful tool as Matlab provides. However, the Matlab engine is not optimized (or created) to run in a mass-available manner on mobile devices, and requires a great deal of computational resources. The results are shown in table 7, yielding an offset between 0.01% and 0.24% in fuzzy module output, which is acceptable, considering differences in processing power and computational precision.

Table 7: Comparative outputs between the Training Intensity Analyzer and MOTION-AE

Reference R-R Interval	R-R Interval Before Session	Work Heart Rate Two Sessions Ago [bpm]	Work Heart Rate Last Session [bpm]	Training Intensity Analyzer Output [%]	MOTION-AE Output [%]	Offset [%]
6.01	6.66	120	140	-24.6	-24.58	0.02
6.01	6.66	120	170	-25.5	-25.31	0.19
6.01	6.66	120	100	-10.5	-10.49	0.01
6.01	6.66	120	80	-10.2	-10.35	0.15
6.01	6.01	120	132	0.3	0.06	0.24

Reference R-R Interval	R-R Interval Before Session	Work Heart Rate Two Sessions Ago [bpm]	Work Heart Rate Last Session [bpm]	Training Intensity Analyzer Output [%]	MOTION-AE Output [%]	Offset [%]
6.01	6.3	120	132	-17.4	-17.45	0.05
6.01	5.7	120	132	8.1	8.32	0.21

6. CONCLUSIONS

The MOTION-AE mobile application enhances the performance of aerobic training by giving a more gradual and controlled way of setting the training intensity, compared to the classical interpretation of heart rate variability for setting the training work load.

The MOTION-AE app keeps track of previous exercise sessions and the performances achieved by the subject, offering trainers and coaches an objective instrument to be used in aerobic training programs.

The MOTION-AE application opens the path to an implementation into a larger control system for aerobic endurance training, by providing setpoints for heart rate control systems in the setting of specialized training sessions. By implementing a fuzzy decision making tool, the app thus ensures that uncertainties in measurements and the variation of the input parameters due to the individuals' physical characteristics are taken into account when computing the optimal intensity for the next training session.

Due to its portability as a mobile application and its low computational cost, MOTION-AE can successfully suggest training intensities even for everyday users that need help in improving their aerobic workouts.

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