Review of neural modelling on cardiovascular rehabilitation active processes by using cycloergometers

Gorka Miñano[1 [ORCID](✉)], Mikel Larrea[2 [ORCID]], and Eloy Irigoyen[2 [ORCID]]

Department of System Engineering and Automation, University of the Basque Country (UPV/EHU), Alda, Urquijo s/n, E-48013 Bilbao, Vizcaya, Spain

Abstract. This work gathers important developments carried out in a specific area of the Biomedical Engineering which applies advanced models based on Artificial Neural Networks to improve Cardiovascular Rehabilitation (CR) processes by using Cycloergometers. This work presents an updated revision of proposals, focusing on different problems involved in CR and considering features and requirements nowadays taken into account during their modelling processes. Furthermore, the signals analysed in these models are studied and presented below. Among them, a review of solutions applied to CR processes, focused on Computational Intelligence are cited.

Keywords: Cardiovascular Rehabilitation, Computational Intelligence, Modelling

1 Introduction

Moderate and aerobic physical exercise is an essential part of the rehabilitation in people with cardiovascular problems [15, 9]. The treatments of cardiovascular pathologies need to combine different medical techniques as pharmacological or surgery treatments, diet changes, and physical activity [8]. The cost-benefit ratio of Cardiovascular Rehabilitation processes is very promising, considering each one of the factors involved in the selected treatment[39].

This physical activity consists of preconfigured exercises that must be correctly adapted to each patient, and it must be done under control to generate a clear and secure benefit [17]. This is considered more critical in patients with a cardiovascular advanced disease, or after suffering an intense attack, such as heart attacks [26]. Nowadays, rehabilitation processes are also considered for old people, in order to improve their quality of life. This kind of processes have their specific characteristics and problems [30]. The use of training machines joined with cardiovascular monitoring systems allows to do exercise under control and in a highly accurate manner. Between this group of machines, the cycloergometers are the least traumatic devices, allowing to practise exercise to people with whatever physical condition. The benefits obtained using these devices overtake simple and classical recovery processes of a cardiovascular disease, improving besides the general physical state of patients, adding a very low damage risk too [2]. Cycloergometers are devices based on cycling pedal movement. In many cases, they can be adapted, in order to be more accessible to the physical condition of patients.

The monitoring of the evolution of these exercises, in general, is based on the response of the electrical cardiovascular system. Often, it is only necessary to measure a basic unit, as the heart rate (beating per second), to detect the cardiovascular system's workload [9, 16, 44], as well as some possible cardiovascular problems [20, 19, 13, 29, 6]. Cardiac rhythm measurements provide us additional information, which is necessary for rehabilitation processes in patients who have serious or advanced illnesses [11]. In addition, these allow to find correlation between physical and psychological activities [32, 4], as well as a more detailed analysis of the physical performance [34]. Sometimes, more advanced and deeper electric signal analysis is used (e.g. like with electrocardiograms) during physical exercises or effort tests in a cycloergometer, in order to detect a disease [1]. In several cases, breath in/out gas, circulatory pressure or even chemistry tests of different biological processes involved in, are measured [12]. In most of the rehabilitation cases, the cardiac rhythm measurement is enough for specialised medical staff, to decide about the correct execution of the prescribed exercise [15].

The modelling of the cardiovascular system response, measured in the context of an exercise answer which is executed with an ergometer, is a useful tool for both to help medical staff to correctly control the exercise, and to be the basic starting point that is necessary to make an automatic exercise correctly. In this regard, there are many references dealing with this issue as the work by Mutijarsa et all where they create the relationship between pedalling cadence and cardiac beating [27], or others as Yuchi and Xiao where they develop a predictive model of cardiac beating based on physical activity [47, 46].

In this article, we discuss different methods, which nowadays have been applied to modelling of the cardiovascular system response. Among them, we focus on systems based on Computational Intelligence techniques. The purpose of this study is to reinforce an investigation line, in which we suggest the use of a model based on Neural Networks to reproduce a nonlinear NARX system [18], in order to so solve the problem of complex modelling, looking for improvements in future research lines and applications.

2 Cardiovascular Rehabilitation with Cycloergometer

2.1 What is a cycloergometer and how does it work?

A cycloergometer is a physical exercising machine that simulates the effort that has to be made in a real bicycle [33, 31]. Exercise intensity can be controlled by the change of torque, which is introduced by putting resistance upon the spin of pedals or changing spinning frequency (revolutions per minute, RPM). Both parameters combined, the intensity and the torque, provide the mechanical power produced by the patient. Modern cycloergometers have an electromagnetic brake torque which allows changing torque with an electronic system.

The torque values that can be reached change according to the system velocity, although the cycloergometer allows to regulate the brake torque in such a way that different work-power schedules could be configured with respect to any patient, ranging from light aerobic profiles to anaerobic ones. The range of work revolutions goes from 30 RPM to 120 RPM, being typical medium values those inside the range between 60 and 80 RPM. Cycloergometer has included a cardiac rhythm sensor as well. With these devices, both mechanical effort signals and cardiac rhythm are tested with a frequency of one value per minute.

In order to accurately control a specific rehabilitation exercise, it is necessary to configure precisely the system settings and to maintain the supervision of work revolutions parameter, as well as the mechanical power generated. According to the physiological features of patients and to the objectives to aim into an exercise, the maximum and minimum limits are fixed, as well as the different periods of working and resting time.

In [34, 4, 32, 11] the cardiac rhythm evolution is proposed as the parameter for the Cardiovascular rehabilitation exercises and monitoring the physiological status of the patient.

2.2 Cardiovascular Rehabilitation using a Cycloergometer

In general, any rehabilitation process consists in a succession of physical efforts and relaxing periods. These processes have a variable length and intensity which will make the patient gets exercise. The main objective of these rehabilitation processes is to obtain a progressive and effective improvement of the patient cardiovascular system, carried out without putting the life of the person at risk [23].

A cardiovascular rehabilitation process on a cycloergometer consists in a planned and spaced on time session, in which there are some aims to set or cardiac rhythms to achieve. The work of Hernandez et al, according to the presented results, establishes that a detailed monitoring of the patient during the exercise, combined with a set of standardisation in cardiovascular rehabilitation processes, makes these processes perform better, based on the efficiency shown in their results [17].

Parameters calculation of rehabilitation process is made through the history of every patient and the observations obtained from consecutive performances. Based on that, the measure of the cardiovascular behaviour of each patient, together with the cycloergometer registers of mechanical efforts, have therefore a huge relevance, as mentioned by Conconi in [7]. In Fig. 1 the Conconi test registered on a cycloergometer is presented. This figure shows the Heart rate and revolutions per minute and also the power Watts, generated by the patient during the exercise.

There is a method very used that allows obtaining improvements in the treatment of patients with cardiovascular problems. This method sets a previously established profile of cardiovascular effort, logically according to cardiovascular rhythm of the patient. During the exercise, the cycloergometer will control and adapt the exercise intensity level, in order to fit the cardiac rhythm of the patient to the profile configured at the beginning of this exercise

As previously mentioned, the mechanical intensity of physical exercise on a cycloergometer depends on work revolutions and the brake torque produced by the machine. Each patient requires a different intensity of work to achieve a pre-established cardiovascular rhythm and in turn, the relation between RPM and torque

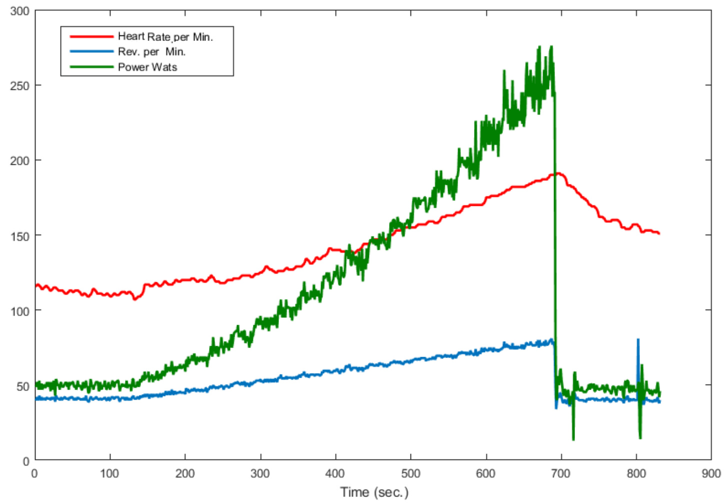

Fig. 1. Example of a cardio training on a cycloergometer

becomes different through the time [10, 40, 15, 21]. Fig. 2 shows the data from a typical cardio-training session.
The function that fits the cardiovascular rhythm of a patient and the mechanical effort developed is extremely non-linear. Moreover, this function changes along the time and it is different for each person. Other aspects that affect this function over time are, among the most important: the history of each patient; the environmental situation; patient daily diet; and other kind of physical efforts not controlled. This means that it is necessary to achieve a precise and safe control system to perform an exercise accurately, effectively and safely. The control system is usually not automatic, being operated by specialised medical staff. Without a precise control of the exercise, it is possible to endanger the life of patients or not achieve the expected improvements [17, 40]. For all these reasons, the accurate performance of a system model of the system composed by the cycloergometer and the person who needs a cardiovascular exercise under control has an enormous importance.

2.3 Analysis and system proposal to be modelled

Most of the works developed in this research area reproduce models of the binomial cycloergometer-patient based on Perceptron Neural Networks or non-linear mathematical models including autoregressive exogenous inputs. Preliminary results show the possibility to model that binomial system in healthy people, through sessions made using the Conconi test and performing different cardiovascular training in a commercial cycloergometer [18, 25]. These models adjust the relationship between the cycloergometer Power input (Watts) and the Heart Rate (beats per minute) of a person performing the exercise. These models correctly performs when they

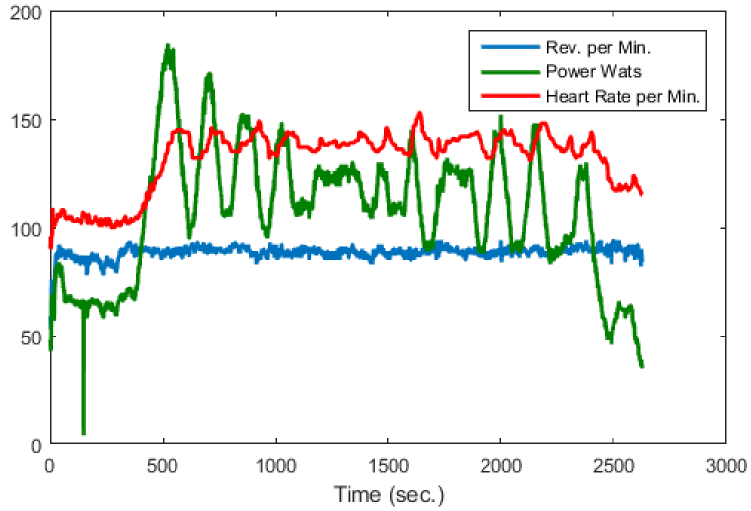

Fig. 2. Example of a cardio-training on a cycloergometer

are tested with series of samples in which ranges or workload are similar. Although, these are limited when they are applied to work ranges with variations. In the following section an initial and brief compilation of works that pretend to improve the mentioned models is presented. All this works are related to the area of the Computational Intelligence.

3 Proposed Methodologies to Cardiovascular System Modelling

In the last years, there have been several attempts to progress within different lines of research to obtain a better knowledge of the human cardiovascular system, in order to face the challenge of explaining about how it works and to be able to face different illnesses. For that purpose, it is not necessary to collect a big amount of signals from different sources and exercise conditions, to understand and analyse the cardiovascular history of a patient. With the selection of an appropriate set of parameters, it is possible to obtain a model of the cardiovascular system that performs accurately, as the references presented below establish.

In our work, we try to reflect how using advanced computing models it is possible to easily reproduce the behaviour of a cardiovascular system, based principally on the pre-selected parameters. We will present how to identify and classify cardiovascular systems, taking into account different goals in researching. The methods proposed by several authors are based on classification techniques, transformation techniques to adapt the information to meaningful variables, and time series techniques to fit a function to the evolution of the system. The research work that we have performed relies on this last technique. Anyway, we find interesting to review current developments in the rest of categories.

3.1 Classification systems

The models obtained with this technique generate a result that puts in value and shows useful information coming from data sets which were previously measured systematically. This method is very common in different clinic tests because it allows analysing big volume of data based on learning models. The work of Burghardt and Ajtai suggests to use Neuronal and Bayesian Networks, in order to classify different genotypes and their possible influence on cardiovascular illnesses. This work analyses standard databases related to these illnesses. [3]. Weng et al set out a comparison of four learning machines (random forest, logistic regression, gradient boosting machines, neural network), that from a statistical data set of a population group they estimate the probability of suffering a cardiovascular illness.[43]. Choi et al present a comparative study of different computational models, such an Artificial Neuronal Network (ANN), that from statistical database of patients calculate the risk of suffering a heart attack within a period of time between 12 and 18 months.[5]. Rashid proposes an expert system based on ANNs in order to prematurely detect different cardiovascular problems, taking into account statistical databases [36].

3.2 Transforming Information

The information obtained from the behaviour of the cardiovascular system is usually very extensive. Thus, it is essential to transform the information obtained into another parameters' set that will be easier to process or analyse. In this way, Guillermo et al propose a system combining ANNs and transformed wavelets to detect murmurs in electrocardiogram (ECG) signals.[14]. Acharya and collaborators suggest to detect heart arrhythmia based on ANN models that are trained from different ECG signals divided in segments [1]. In the work of Li et al, a different technique which compress the ECG signals measuring from each patient, is used. This system is designed to transmit to a control unit the most relevant information, in order to make easier the tracing of the cardiovascular system evolution of a patient [22]

3.3 Cardiovascular System Modelling by Time Series

Other kind of works process and analyse ECG signals, using temporal slide windows, to find abnormalities into the cardiovascular system. Rius et al propose a regression model to compare multivariable electrocardiographical strokes in order to detect arrhythmia during the exercise of physical training.[37]. In other work, Rajpurkar presents an ANN to detect arrhythmia in portable ECG machines. [35].

From the point of view of Time Series, these are a set of sequential data obtained from the response of a system. In the context of rehabilitation exercises or cardiovascular training, they are a fundamental tool for the control. Nowadays, there are several proposals that develop intelligent control systems by using advanced models extracting from time series processing. Vieira et al propose a personal cardiovascular rehabilitation system based on Expert Systems that makes use of a Kinect device.[42]. On the other hand, Myers proposes the use of ANN for heart problem detection during the training or cardiovascular tests [28]. Instead, Mutijarsa proposes a system based on ANN to model and predict the cardiovascular response when pedalling on a bicycle [27]. Moreover, the work of Song proposes a model to control the load of a training based on the results obtained previously. [41]. Otherwise, Xiao and Yuchi carry out a study in which they propose an ANN model based on time series, testing different ANN topologies and input signals. They use bicycles among other training devices[45, 44, 46, 47]. Finally, the work of Savioli et al proposes an analysis with Deep Learning techniques in pedalling system [38].

4 Conclusions

The collection of references presented in this work shows that, nowadays, there are different open frontiers to overcome and study, with respect to accurately design and control cardiovascular rehabilitation processes of patients suffering heart problems. This is a very promising field, since many new proposals are currently appearing, as the work presented by Ldwing et al [24].

References

1. Acharya, U.R., Fujita, H., Lih, O.S., Hagiwara, Y., Tan, J.H., Adam, M.: Automated detection of arrhythmias using different intervals of tachycardia ecg segments with convolutional neural network. Information Sciences **405**, 81–90 (sep 2017), http://adsabs.harvard.edu/abs/2018IEITI.101.1189X
2. Bouaziz, W., Schmitt, E., Kaltenbach, G., Geny, B., Vogel, T.: Health benefits of cycle ergometer training for older adults over 70: a review. European Review of Aging and Physical Activity **12**(1) (nov 2015)
3. Burghardt, T.P., Ajtai, K.: Neural/bayes network predictor for inheritable cardiac disease pathogenicity and phenotype. Journal of molecular and cellular cardiology **119**, 19–27 (2018)
4. Catai, A., Chacon-Mikahil, M., Martinelli, F., Forti, V., Silva, E., Golfetti, R., Martins, L., Szrajer, J., Wanderley, J., Lima-Filho, E., Milan, L., Marin-Neto, J., Maciel, B., Gallo-Junior, L.: Effects of aerobic exercise training on heart rate variability during wakefulness and sleep and cardiorespiratory responses of young and middle-aged healthy men. Brazilian Journal of Medical and Biological Research **35**(6), 741–752 (jun 2002). https://doi.org/10.1590/s0100-879x2002000600016
5. Choi, E., Schuetz, A., Stewart, W.F., Sun, J.: Using recurrent neural network models for early detection of heart failure onset. Journal of the American Medical Informatics Association p. ocw112 (aug 2016). https://doi.org/10.1093/jamia/ocw112
6. Cole, C.R., Blackstone, E.H., Pashkow, F.J., Snader, C.E., Lauer, M.S.: Heart-rate recovery immediately after exercise as a predictor of mortality. New England Journal of Medicine **341**(18), 1351–1357 (oct 1999). https://doi.org/10.1056/nejm199910283411804
7. Conconi, F., Ferrari, M., Ziglio, P.G., Droghetti, P., Codeca, L.: Determination of the anaerobic threshold by a noninvasive field test in runners. Journal of Applied Physiology **52**(4), 869–873 (apr 1982). https://doi.org/10.1152/jappl.1982.52.4.869

8. (coordinador), J.A.V., Cosín, J., Maroto, J.M., Muñiz, J., Casasnovas, J.A., Plaza, I., Abadal, L.T.: Guías de práctica clínica de la sociedad española de cardiología en prevención cardiovascular y rehabilitación cardíaca. Revista Española de Cardiología **53**(8), 1095–1120 (jan 2000). https://doi.org/10.1016/s0300-8932(00)75211-0
9. Dibben, G.O., Dalal, H.M., Taylor, R.S., Doherty, P., Tang, L.H., Hillsdon, M.: Cardiac rehabilitation and physical activity: systematic review and meta-analysis. Heart **104**(17), 1394–1402 (apr 2018), http://adsabs.harvard.edu/abs/2011EnST...45.1761T
10. Dolan, L.B., Barry, D., Petrella, T., Davey, L., Minnes, A., Yantzi, A., Marzolini, S., Oh, P.: The cardiac rehabilitation model improves fitness, quality of life, and depression in breast cancer survivors. Journal of Cardiopulmonary Rehabilitation and Prevention: July 2018 - Volume 38 - Issue 4 - p 246–252 **38**, 246–252 (2018)
11. Fantoni, C., Raffa, S., Regoli, F., Giraldi, F., Rovere, M.T.L., Prentice, J., Pastori, F., Fratini, S., Salerno-Uriarte, J.A., Klein, H.U., Auricchio, A.: Cardiac resynchronization therapy improves heart rate profile and heart rate variability of patients with moderate to severe heart failure. Journal of the American College of Cardiology **46**(10), 093906 (nov 2005). https://doi.org/10.1016/j.jacc.2005.06.081, http://adsabs.harvard.edu/abs/2017Chaos..27i3906L
12. Farfán, Á., Guachun, X., Idrovo, J., Jaramillo, W., Wong, S.: Caracterización de series rr de pruebas de esfuerzo: Pre-condicionamiento isquémico. Maskana **8**, 373–378 (2017)
13. Fox, K., Borer, J.S., Camm, A.J., Danchin, N., Ferrari, R., Sendon, J.L.L., Steg, P.G., Tardif, J.C., Tavazzi, L., Tendera, M.: Resting heart rate in cardiovascular disease. Journal of the American College of Cardiology **50**(9), 823–830 (aug 2007). https://doi.org/10.1016/j.jacc.2007.04.079, + http://dx.doi.org/10.1016/j.jacc.2007.04.079
14. Guillermo, J.E., Castellanos, L.J.R., Sanchez, E.N., Alanis, A.Y.: Detection of heart murmurs based on radial wavelet neural network with kalman learning. Neurocomputing **164**, 307–317 (sep 2015). https://doi.org/10.1016/j.neucom.2014.12.059
15. Hansen, D., Dendale, P., Coninx, K., Vanhees, L., Piepoli, M.F., Niebauer, J., Cornelissen, V., Pedretti, R., Geurts, E., Ruiz, G.R., Corrà, U., Schmid, J.P., Greco, E., Davos, C.H., Edelmann, F., Abreu, A., Rauch, B., Ambrosetti, M., Braga, S.S., Barna, O., Beckers, P., Bussotti, M., Fagard, R., Faggiano, P., Garcia-Porrero, E., Kouidi, E., Lamotte, M., Neunhäuserer, D., Reibis, R., Spruit, M.A., Stettler, C., Takken, T., Tonoli, C., Vigorito, C., Völler, H., Doherty, P.: The european association of preventive cardiology exercise prescription in everyday practice and rehabilitative training (EXPERT) tool: A digital training and decision support system for optimized exercise prescription in cardiovascular disease. concept, definitions and construction methodology. European Journal of Preventive Cardiology **24**(10), 1017–1031 (apr 2017). https://doi.org/10.1177/2047487317702042
16. HASKELL, W.I.L.L.I.A.M.L., YEE, M.A.R.T.I.N.C., EVANS, A.N.T.H.O.N.Y., IRBY, P.A.M.E.L.A.J.: Simultaneous measurement of heart rate and body motion to quantitate physical activity. Medicine and science in sports and exercise **25**(1), 109—115 (January 1993). https://doi.org/10.1249/00005768-199301000-00015, http://europepmc.org/abstract/MED/8423743
17. Hernández CD, González MBM, M.P.A.F.E.P.P.N.: Protocolo de actuación de rehabilitación cardiovascular en pacientes con enfermedad coronaria aguda. Rev Cub de Med Fis y Rehab 2017; 9 (1) (2017)
18. Irigoyen, E., Miñano, G.: A NARX neural network model for enhancing cardiovascular rehabilitation therapies. Neurocomputing **109**, 9–15 (jun 2013). https://doi.org/10.1016/j.neucom.2012.07.031

19. Jouven, X., Empana, J.P., Schwartz, P.J., Desnos, M., Courbon, D., Ducimetière, P.: Heart-rate profile during exercise as a predictor of sudden death. New England Journal of Medicine **352**(19), 1951–1958 (may 2005). https://doi.org/10.1056/nejmoa043012
20. cheng Ming ZHOU ; zhen Wei ZHANG ; Hua ZHANG ; feng Jun CAI ; Jian HUANG, Y.H...: Research progress on application of exercise rehabilitation therapy in aged patients with hypertension. Chinese Journal of cardiovascular Rehabilitation Medicine 2017;26(6):667-669 (2017)
21. Keteyian, S.J., Kerrigan, D.J., Lewis, B., Ehrman, J.K., Brawner, C.A.: Exercise training workloads in cardiac rehabilitation are associated with clinical outcomes in patients with heart failure. American Heart Journal **204**, 76–82 (oct 2018)
22. Li, H.Y., Young, K.H., Lee, M.C.: Signal compression method based heart rate model estimation and pi control for cardiac rehabilitation with treadmill. 2018 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM) (2018)
23. Lucini, D., Milani, R.V., Costantino, G., Lavie, C.J., Porta, A., Pagani, M.: Effects of cardiac rehabilitation and exercise training on autonomic regulation in patients with coronary artery disease. American Heart Journal **143**(6), 977–983 (jun 2002). https://doi.org/10.1067/mhj.2002.123117
24. Ludwig, M., Hoffmann, K., Endler, S., Asteroth, A., Wiemeyer, J.: Measurement, prediction, and control of individual heart rate responses to exercise—basics and options for wearable devices. Frontiers in Physiology **9** (jun 2018). https://doi.org/10.3389/fphys.2018.00778
25. Minano, G., Irigoyen, E.: Computational intelligence techniques application to enhance controlled training for people with cardiovascular problems. Soft Computing Models in Industrial and Environmental Applications, 6th International Conference SOCO 2011 **17**, 611–619 (Sep 2011). https://doi.org/10.1007/978-3-642-19644-7_64, http://adsabs.harvard.edu/abs/2018IAWPL..17.1673K
26. Moraca, M., Burazor, I., Stevovic, S., Juricic, S., Stojkovic, S., Beleslin, B., Dikic, A.: 224effects of exercised - based cardiac rehabilitation after myocardial infarction with chronic total occlusions. should we pay attention? European Heart Journal **39**(suppl_1) (aug 2018)
27. Mutijarsa, K., Ichwan, M., Utami, D.B.: Heart rate prediction based on cycling cadence using feedforward neural network. In: 2016 International Conference on Computer, Control, Informatics and its Applications (IC3INA). IEEE (oct 2016). https://doi.org/10.1109/ic3ina.2016.7863026
28. Myers, J., de Souza, C.R., Borghi-Silva, A., Guazzi, M., Chase, P., Bensimhon, D., Peberdy, M.A., Ashley, E., West, E., Cahalin, L.P., Forman, D., Arena, R.: A neural network approach to predicting outcomes in heart failure using cardiopulmonary exercise testing. International Journal of Cardiology **171**(2), 265–269 (feb 2014). https://doi.org/https://doi.org/10.1016/j.ijcard.2013.12.031
29. Nishime, E.O.: Heart rate recovery and treadmill exercise score as predictors of mortality in patients referred for exercise ECG. JAMA **284**(11), 1392 (sep 2000). https://doi.org/10.1001/jama.284.11.1392
30. Oliveira, M.F., Santos, R.B., Trepa, M., Costa, R., Barreira, A., Fernandes, P., Magalhaes, S., Cabral, S., Torres, S.: Cardiac rehabilitation program for all: even after 80s? European Heart Journal **39**(suppl_1), A0.5-4-18 (aug 2018), http://adsabs.harvard.edu/abs/2018cosp...42E3797Z
31. Olsson, S.: Ergometer device (Nov 5 1974), uS Patent 3,845,756
32. Perini, R., Veicsteinas, A.: Heart rate variability and autonomic activity at rest and during exercise in various physiological conditions. European Journal of Applied Physiology **90**(3-4), 317–325 (oct 2003). https://doi.org/10.1007/s00421-003-0953-9

33. Pfleiderer, W., Arnold, F., Haussermann, R.: Ergometer with automatic load control system (Nov 29 1977), uS Patent 4,060,239
34. Pigozzi, F., PARISI, A.A.A., Di Salvo, V., SPATARO, L.D.L.A., Iellamo, F.: Effects of aerobic exercise training on 24 hr profile of heart rate variability in female athletes. J Sports Med Phys Fitness **2001141**, 101–7 (2001)
35. Rajpurkar, P., Hannun, A.Y., Haghpanahi, M., Bourn, C., Ng, A.Y.: Cardiologist-level arrhythmia detection with convolutional neural networks. arXiv preprint arXiv:1707.01836 (Jul 2017), http://adsabs.harvard.edu/abs/2017arXiv170701836R
36. Rashid, U.: ANN based expert system to predict disease in cardiac patients at initial stages. International Journal of E-Health and Medical Communications **6**(2), 1–9 (apr 2015). https://doi.org/10.4018/IJEHMC.2015040101, http://adsabs.harvard.edu/abs/2018arXiv181104290L
37. Rius-Suárez, M., Ilarraza-Lomelí, H., Franco-Ojeda, M., Rojano-Castillo, J., García-Saldivia, M., Cruz-Rivero, M.: Instrumento para la evaluación del riesgo de arritmias durante el entrenamiento no aeróbico en pacientes con enfermedad cardiovascular. Fisioterapia **39**(3), 108–115 (may 2017)
38. Savioli, N., Vieira, M.S., Lamata, P., Montana, G.: Automated segmentation on the entire cardiac cycle using a deep learning work-flow. arXiv e-prints (oct 2018), http://adsabs.harvard.edu/abs/2018arXiv180901015S
39. Shields, G.E., Wells, A., Doherty, P., Heagerty, A., Buck, D., Davies, L.M.: Cost-effectiveness of cardiac rehabilitation: a systematic review. Heart **104**(17), 1403–1410 (apr 2018)
40. Somanader, Deborah S.; Chessex, C.G.L.G.S.L.: Quality and variability of cardiovascular rehabilitation delivery. Journal of Cardiopulmonary Rehabilitation and Prevention **37**, 412–420 (2017)
41. Song, B., Becker, M., Gietzelt, M., Haux, R., Kohlmann, M., Schulze, M., Tegtbur, U., Wolf, K.H., Marschollek, M.: Feasibility study of a sensor-based autonomous load control exercise training system for copd patients. Journal of medical systems **39**(1), 150 (2015)
42. Vieira, Á., Gabriel, J., Melo, C., Machado, J.: Kinect system in home-based cardiovascular rehabilitation. Proceedings of the Institution of Mechanical Engineers, Part H: Journal of Engineering in Medicine **231**(1), 40–47 (dec 2016). https://doi.org/10.1177/0954411916679201
43. Weng, S.F., Reps, J., Kai, J., Garibaldi, J.M., Qureshi, N.: Can machine-learning improve cardiovascular risk prediction using routine clinical data? PLOS ONE **12**(4), 16-APRA16-134 (apr 2017), http://adsabs.harvard.edu/abs/2016apra.prop..134M
44. Xiao, F., Chen, Y., Yuchi, M., Ding, M., Jo, J.: Heart rate prediction model based on physical activities using evolutionary neural network. In: 2010 Fourth International Conference on Genetic and Evolutionary Computing. IEEE (dec 2010). https://doi.org/10.1109/icgec.2010.56
45. Xiao, F., Yuchi, M., yue Ding, M., Jo, J., Kim, J.H.: A multi-step heart rate prediction method based on physical activity using adams-bashforth technique. In: 2009 IEEE International Symposium on Computational Intelligence in Robotics and Automation - (CIRA). IEEE (dec 2009). https://doi.org/10.1109/cira.2009.5423181
46. Xiao, F., Yuchi, M., Ding, M., Jo, J.: A research of heart rate prediction model based on evolutionary neural network. In: 2011 International Conference on Intelligent Computation and Bio-Medical Instrumentation. IEEE (dec 2011). https://doi.org/10.1109/icbmi.2011.40
47. Yuchi, M., Jo, J.: Heart rate prediction based on physical activity using feedforwad neural network. In: 2008 International Conference on Convergence and Hybrid Information Technology. IEEE (2008). https://doi.org/10.1109/ichit.2008.175