MODELLING APPROACH BASED ON ARTIFICIAL NEURAL NETWORKS APPLIED TO BIOMECHANICS OF PARATHLETES SWIMMERS

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Abstract. *The objective of this paper is to consider possible improvements that can benefit disabled swimmers (parathletes) to gain competitive advantage by studying the biomechanics involved in the sport and considering the help of simulations systems. Regarding the technological assistance, the relevance and aid computational models provide are asserted and a complete description of the choiced software tool to conduct the analysis of swimming techniques, SWUMSUIT, which was developed in Tokyo Technological Institute in Japan, is provided. On the other hand, the artificial neural network paradigm, which is a non-linear black box model, seems to be a useful alternative for modeling the complex systems. Due to their simple topological structure and universal approximation ability, the radial basis neural networks (RBF-NNs) have been widely used in pattern recognition. In this context, this paper presents a RBF-NN approach is applied to modeling of a parathlete swimmer swims breastroke style using biomechanics data generated by the SWUMSUIT.*

Keywords*: biomechanics, artificial neural networks, modeling, swimming.*

1. INTRODUCTION

Kinesiology is the scholarly study of human movement, and biomechanics is one of the many academic subdisciplines of kinesiology. Biomechanics in kinesiology involves the precise description of human movement and the study of the causes of human movement (Knudson, 2007). Biomechanics is deeply rooted throughout scientific history and has been influenced by the research work of early mathematicians, engineers, physicists, biologists, and physicians. Not one of these disciplines can claim sole responsibility for maturing biomechanics to its current state; rather, it has been a conglomeration and integration of these disciplines, involving the application of mathematics, physical principles, and engineering methodologies, that has been responsible for its advancement (Peterson and Bronzino, 2008).

Sports biomechanics is the application of physics and mechanics to the human body during sport. In such a technical sport such as swimming, it plays a very important part. The study of human swimming propulsion is one of the most complex areas of interest in sport biomechanics. Over the past decades research in swimming biomechanics has evolved from the observation subject’s kinematics to a basic flow dynamics approach.

Human swimming performance is poor when compared to species whose habitat is aquatic. A maximum swimming speed of approximately 2 m/s represents only about 16% of the maximum unaided speed attained on land. One obvious reason for this speed difference is the higher resistance one encounters when moving through water (Toussaint et al., 2004). The swimmers performance is determined by the ability to generate propulsive forces while reducing the resistance to forward motion.

The analysis of swimming continues to be challenging compared to many other sport activities due to the fact that swimming is performed at the interface of two media. However, methods of kinematics and kinetics modeling, measurement of velocity and force, and analyzing motion have advanced greatly in recent years due to improvement in technology as well as application of scientific approaches. Examples are presented in papers such as Yanai et al. (1996), Tella et al. (2008), Zaïdi et al. (2008), Callaway et al. (2009), Zaïdi et al. (2010), Barbosa et al. (2010), among others.

In recent years, artificial neural networks (ANNs) has been employed, quite frequently, as a promising tool in many areas, such as pattern recognition, function approximation, system identification, and time series forecasting for supporting the modeling of complex systems, which incorporate multiple parameters or variables. ANNs models are known as black-box models which are mainly identified using input-output data (Coelho et al., 2009). Recently, ANNs due to their strong learning capabilities have been proposed also for applications in swimming field. Examples are the approaches presented in Silva et al. (2007) and Rejman and Ochmann (2007).

Among different kinds of ANNs, the radial basis function neural networks (RBF-NNs) are widely used in time series analysis and pattern classification problems. The RBF-NNs are capable of fast learning using few hidden units for any input are also local approximators, i.e., construct local approximations to non-linear input-output mapping. RBF-NNs, as a special class of single hidden-layer feedforward ANNs, have been proved to be universal approximators (Hartman et al., 1990). This means that provided that the RBF-NN structure is sufficiently large, any continuous function can be approximated within an arbitrary accuracy by carefully choosing the parameters of the network.

In general terms, the contribution of this paper is to consider possible improvements that can benefit disabled swimmers (parathletes) to gain competitive advantage by studying the biomechanics involved in the swimming considering aspects related to stroke, kick, body positioning and breathing. At the end, it brings into account the influence of the athlete disabilities. Regarding the technological assistance, the computational modeling approach of swimming techniques proposed in this paper is based on a RBF-NN using data generated by the software tool called Swimming hUman Model with GUI (Graphical User Interface) as a free software "Swumsuit" (Nakashima et al., 2004; Nakashima et al., 2007; Nakashima, 2007) is provided. In the paper, the inputs and the outputs obtained by the SWUMSUIT are scrutinized and features explained. Furthermore, the modelling methodology to apply the RBF-NN is described and the results presented. Finally, summing up the research, conclusions of the importance of computer aided systems helping the development of sports are considered and the limitations of this paper and future works perspectives are discussed.

The remainder of the paper is organized as follows: section 2 presents the fundamentals of biomechanics and swimming biomechanics. Section 3 describes the RBF-NN approach. Sections 4 and 5 describe the case study using SWUMSUIT and modeling results, respectively. Finally, section 6 presents the conclusions.

2. FUNDAMENTALS OF BIOMECHANICS AND SWIMMING BIOMECHANICS

Biomechanics has been defined as the study of the movement of living things using the science of mechanics (Hatze, 1974). Mechanics is a branch of physics that is concerned with the description of motion and how forces create motion. Forces acting on living things can create motion, be a healthy stimulus for growth and development, or overload tissues, causing injury. Biomechanics provides conceptual and mathematical tools that are necessary for understanding how living things move and how kinesiology professionals might improve movement or make movement safer.

The applications of biomechanics to human movement can be classified into two main areas: the improvement of performance and the reduction or treatment of injury. Human movement performance can be enhanced many ways. Effective movement involves anatomical factors, neuromuscular skills, physiological capacities, and psychological/cognitive abilities. Most kinesiology professionals prescribe technique changes and give instructions that allow a person to improve performance. Biomechanics is most useful in improving performance in sports or activities where technique is the dominant factor rather than physical structure or physiological capacity. Since biomechanics is essentially the science of movement technique, biomechanics is the main contributor to one of the most important skills of kinesiology professionals: the qualitative analysis of human movement (Knudson and Morrison, 2002). The quantitative analysis of data involves the measurement of biomechanical variables and usually requires a computer to do the numerical calculations performed.

Sport science plays a very important part in the performance of a swimmer. In terms of application of biomechanics in swimming, with the availability of computerized equipment, video technologies, and automated diagnostics, better information from swimming science has become possible; today, sports science can provide critical information that can lead to improved performances.

The goal of competitive swimming is to travel the event distance as fast as possible. The identification of the parameters that predict swimming performances is one of the main aims of the swimming "science" community. Indeed, it is consensual that biomechanical and energetic variables linked with effects of speed, active drag, energy cost and breathing are determinant for performance in the swimming in combination of skill acquisition and conditioning exercises in competitive swimming programs.

Fast swimming in the pool requires maximizing the efficiencies with which the human body can move through a liquid medium. A multitude of factors can affect the ability to swim fast as well as the final outcome. Biomechanics are the present tools used by sports scientists to determine which factors are important to fast swimming and, subsequently, to determine how the swimmer may maximize these factors to improve performance. In general, by applying physics/biomechanics equations to different strokes we will be able to find the most efficient stroke techniques, thus, decreasing the swimmers' times.

On other hand, paralympic swimming is an adaptation of the sport of swimming for athletes with disabilities. Swimmers are classified according to the type and extent of their disability. The classification system allows swimmers to compete against others with a similar level of function. Swimmers with physical disabilities are allocated a category between 1 and 10, with 1 corresponding to the most severe types of disability. Physical disabilities of Paralympic swimmers include single or multiple limb loss (through birth defects and/or amputation), cerebral palsy, spinal cord injuries (leading to paralysis or disability in limb coordination), dwarfism, and disabilities which impair the use of joints. Blind and visually impaired swimmers compete within separate categories, being allocated to categories 11, 12 or 13. Category 11 corresponds to totally blind swimmers, while competitors in category 13 have severe but not total visual impairment. Swimmers with mental disabilities compete in category 14 (BBC, 2008).

3. MODELLING APPROACH BASED ON RBF-NN

The RBF-NN is a three-layer feed-forward network that generally uses a linear transfer function for the output units and a nonlinear transfer function (normally the radially symmetrical Gaussian function) as an activation function in the hidden layer. Its input layer simply consists of the source nodes connected by weighted connections to the hidden layer and the net input to a hidden unit is a distance measure between the input presented at the input layer and the point represented by the hidden unit. The nonlinear transfer function (Gaussian function) is applied to the net input to produce a radial function of the distance. The output units implement a weighted sum of the hidden unit outputs, i.e., a linear combination of the basis functions. In other words, the RBF-NN model can be viewed as a realization of a sequence of two mappings. The first is a nonlinear mapping of the input data via the basis functions and the second is a linear mapping of the basis function outputs (i.e., nonlinearly transformed inputs) via the weights to the model output.

For a RBF-NN, the adjustable parameters are the centers, widths, and output weights. The basic structure of the RBF-NN used in the present paper is shown in Fig. 1, which illustrates the relationship between the *m*-dimensional input vector $\boldsymbol{x}\in\Re^m$ and the *n*-dimensional output vector $\boldsymbol{y}\in\Re^n$, $f:\boldsymbol{x}\rightarrow\boldsymbol{y}$. If this mapping is viewed as a function in the input space, learning can be seen as a function approximation problem. According to this point of view, learning is equivalent to finding a surface in a multidimensional space that provides the best fit to the training data.

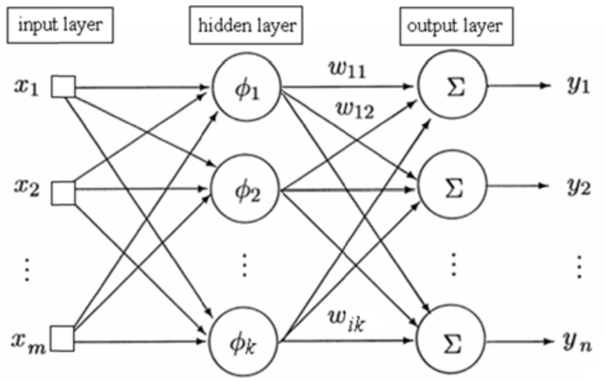


Fig. 1. Structure of the RBF-NN.

The nodes within each layer are fully connected to the previous layer. The input nodes (activation) are directly connected to the hidden layer neurons. There have been a number of popular choices for the basis function ϕ_j at the hidden layer of RBF-NNs. The most common choice is a Gaussian function. In this paper, the output of the *j*-th hidden neuron using the symmetrical Gaussian function can be written as

$$\phi_j(\boldsymbol{x}) = \exp\left\{-\frac{\left\|\boldsymbol{x}-\boldsymbol{\mu}_j\right\|^2}{\sigma_j^2}\right\} \tag{1}$$

where $\|\cdot\|$ is a norm on the input space, $\boldsymbol{x} = (x_1, x_2, ..., x_m)^{\mathrm{T}}$ is the input vector, $\boldsymbol{\mu}_j$ is the center vector (prototype vector), and $\boldsymbol{\sigma}_j$ is the radius width (spread or width of the radial basis function) of the *j*-th hidden node. The output layer represents the outputs of the RBF-NN, and each output node is a linear combination of the *k* radial basis functions of hidden nodes:

$$y_i = \sum_{j=1}^{k} w_{ij}\cdot\phi_j(\boldsymbol{x}) \tag{2}$$

where w_{ij} is the synaptic weight connecting hidden neuron *j* to output neuron *k* and *m* is the number of the hidden layer neurons.

In this paper, the RBF-NN training is aimed at adjusting Gaussian basis function centers, spread parameters, and weights to result in minimum sum-squared error for all the output units among all the patterns. A key problem by using the RBF-NN approach is about how to choose the optimum initial values of the following three parameters: the output weights, the centers and widths of the hidden unit. The RBF-NN evaluated in this paper employs a training method based on self-organizing maps (SOM) (Kohonen, 2001) proposed by Pucciarelli and Soares (2008). This paper investigates the potential of applying the RBF-NN architecture using a training method based on self-organizing maps proposed by Pucciarelli and Soares (2008) to modeling of a parathlete swimmer swims breastroke style using biomechanics data generated by the Swumsuit.

4. DESCRIPTION OF SWUMSUIT

SWUMSUIT is a simulation model for a self-propelled swimmer, which can represent the dynamics of the whole body and which has the potential to be a widely used tool for the analysis of various mechanical problems in human swimming (Nakashima et al., 2007). In this model, the fluid force is considered as simplified modeled force, and the equations of motion of the self-propelled swimmer's body in the translational and rotational directions are solved by the time integration.

The simulation model SWUMSUIT is designed to solve the six degrees-of-freedom absolute movement of the whole human body as one rigid body, using the inputs of the human body geometry and relative joint motion. Therefore, the swimming speed, roll, pitch and yaw motions, propulsive efficiency, joint torques and so on are computed as the output data.

In SWUMSUIT, the relative body motion as the joint angles is given for the human body, which is modeled as rigid link segments. The absolute motion of the whole body is computed considering the unsteady fluid force acting on the human body. The human body is represented by a series of 21 truncated elliptical cone segments. With respect to the fluid force, the inertial force due to the added mass of the fluid, the drag force in the normal and tangential directions, and buoyancy are taken into account. In order to compute the inertial force due to the added mass and the drag forces in the normal and tangential directions, fluid force coefficients are invoked. These coefficients have been determined by an experiment in which a model of a human limb was flapped in the water, measuring its motion and fluid force (Nakashima et al., 2004; Nakashima et al., 2007; Nakashima, 2007). A block diagram and main window of SWUMSUIT are presented in Figs. 2 and 3, respectively.

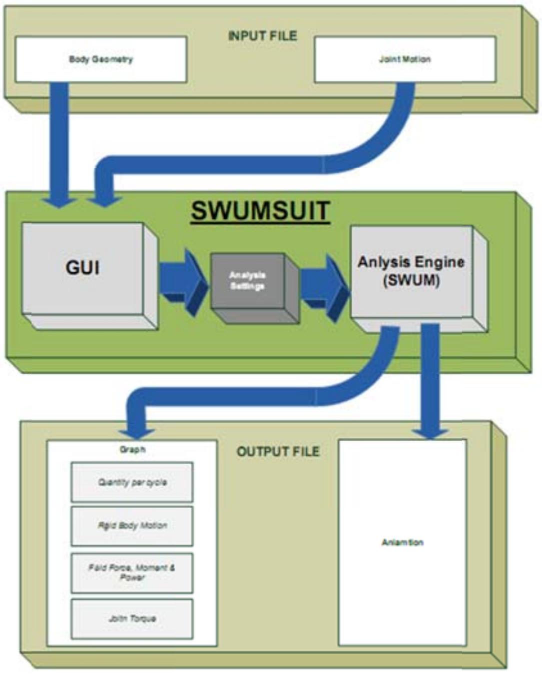
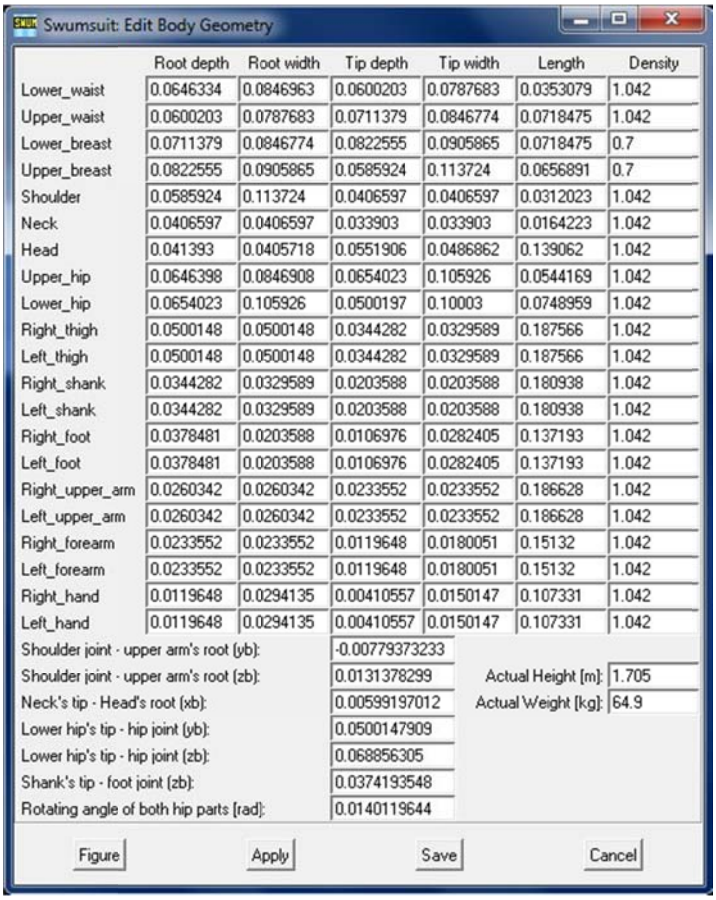


Fig. 2. Block diagram of SWUMSUIT.

Fig. 3. Main window of SWUMSUIT.

There are in SWUMSUIT a window to edit swimmer geometry (see Fig. 4), other window to modify the joint motion (see Fig. 5), and another to visualize the body geometry (see Fig. 6).



	Root depth	Root width	Tip depth	Tip width	Length	Density
Lower_waist	0.0646334	0.0846963	0.0600203	0.0787683	0.0353079	1.042
Upper_waist	0.0600203	0.0787683	0.0711379	0.0846774	0.0718475	1.042
Lower_breast	0.0711379	0.0846774	0.0822555	0.0905865	0.0718475	0.7
Upper_breast	0.0822555	0.0905865	0.0585924	0.113724	0.0656891	0.7
Shoulder	0.0585924	0.113724	0.0406597	0.0406597	0.0312023	1.042
Neck	0.0406597	0.0406597	0.033903	0.033903	0.0164223	1.042
Head	0.041393	0.0405718	0.0551906	0.0486862	0.139062	1.042
Upper_hip	0.0646398	0.0846908	0.0654023	0.105926	0.0544169	1.042
Lower_hip	0.0654023	0.105926	0.0500197	0.10003	0.0748959	1.042
Right_thigh	0.0500148	0.0500148	0.0344282	0.0329589	0.187566	1.042
Left_thigh	0.0500148	0.0500148	0.0344282	0.0329589	0.187566	1.042
Right_shank	0.0344282	0.0329589	0.0203588	0.0203588	0.180938	1.042
Left_shank	0.0344282	0.0329589	0.0203588	0.0203588	0.180938	1.042
Right_foot	0.0378481	0.0203588	0.0106976	0.0282405	0.137193	1.042
Left_foot	0.0378481	0.0203588	0.0106976	0.0282405	0.137193	1.042
Right_upper_arm	0.0260342	0.0260342	0.0233552	0.0233552	0.186628	1.042
Left_upper_arm	0.0260342	0.0260342	0.0233552	0.0233552	0.186628	1.042
Right_forearm	0.0233552	0.0233552	0.0119648	0.0180051	0.15132	1.042
Left_forearm	0.0233552	0.0233552	0.0119648	0.0180051	0.15132	1.042
Right_hand	0.0119648	0.0294135	0.00410557	0.0150147	0.107331	1.042
Left_hand	0.0119648	0.0294135	0.00410557	0.0150147	0.107331	1.042

Fig. 4. Window to edit swimmer geometry in SWUMSUIT.

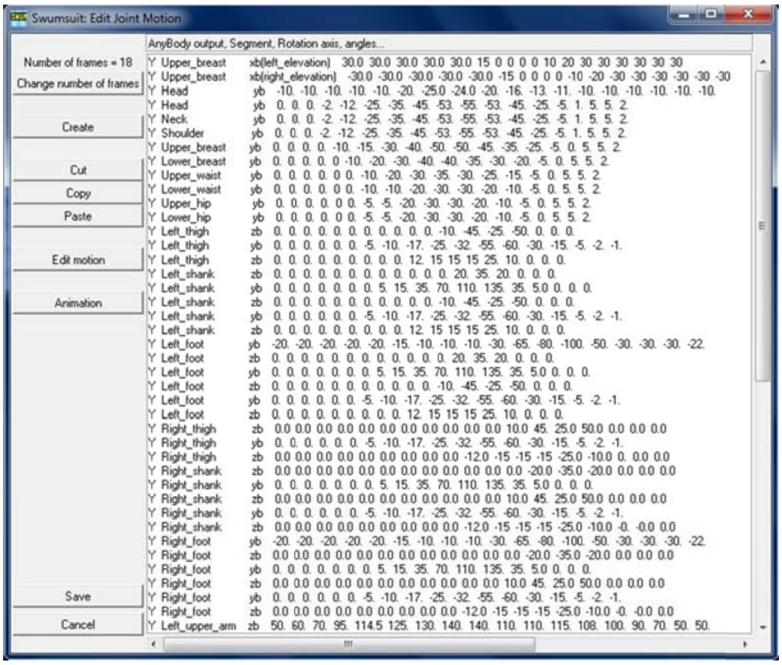


Fig. 5. Window to modify the joint motion in SWUMSUIT.

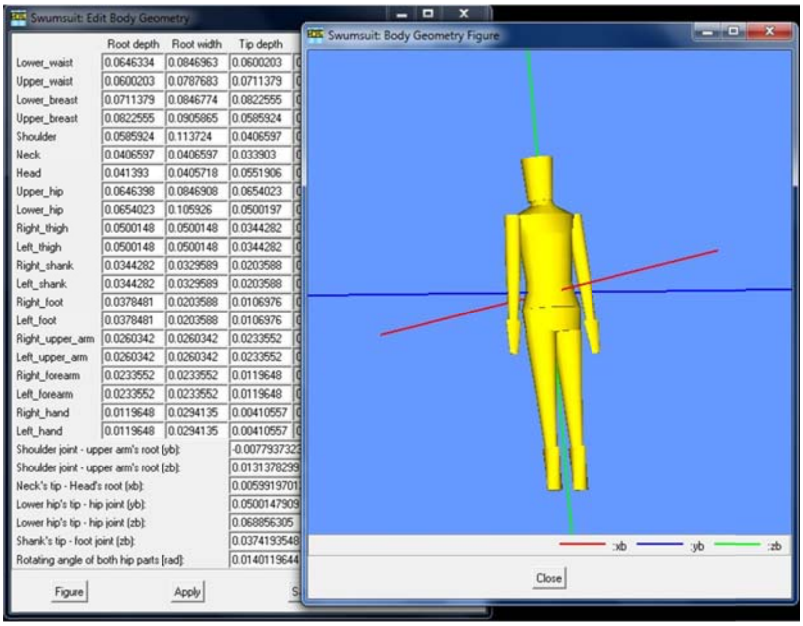


Fig. 6. Window to visualize the body geometry in SWUMSUIT.

5. RESULTS OF MODELLING USING RBF-NN AND SWUMSUIT

The case study evaluated in this paper was of breaststroke style of a parathlete swimmer (see Figs. 7 and 8). The file generated by SWUMSUIT for 18 frames of joint motions employed 732 samples. Fig. 7 presents a comparison of geometry of an athlete and a parathlete using SWUMSUIT.

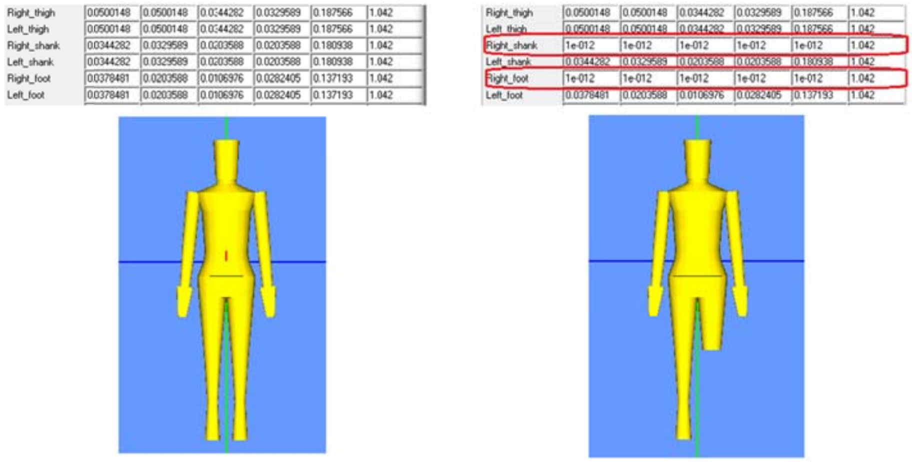


Fig. 7. Comparison of geometry of an athlete and a parathlete using Swumsuit.

After a post-processing task, it was adopted 67 input vectors and 27 output vectors for RBF-NN's application based on relevancy of generated data by SWUMSUIT. It was adopted the variables of stroke speed, propulsion efficiency in relation for the force of tangential and normal drags, and torque of right and left ankles of 3 rotation axis. An example of stroke speed of breaststroke style is presented in the Fig. 9. The adopted setups of RBF-NN are presented in Table 1. The results are presented in Table 2. The stroke velocity estimated by setup #5 (best result in terms of mean squared error index, see details in Table 2) of RBF-NN is showed in Fig. 10.

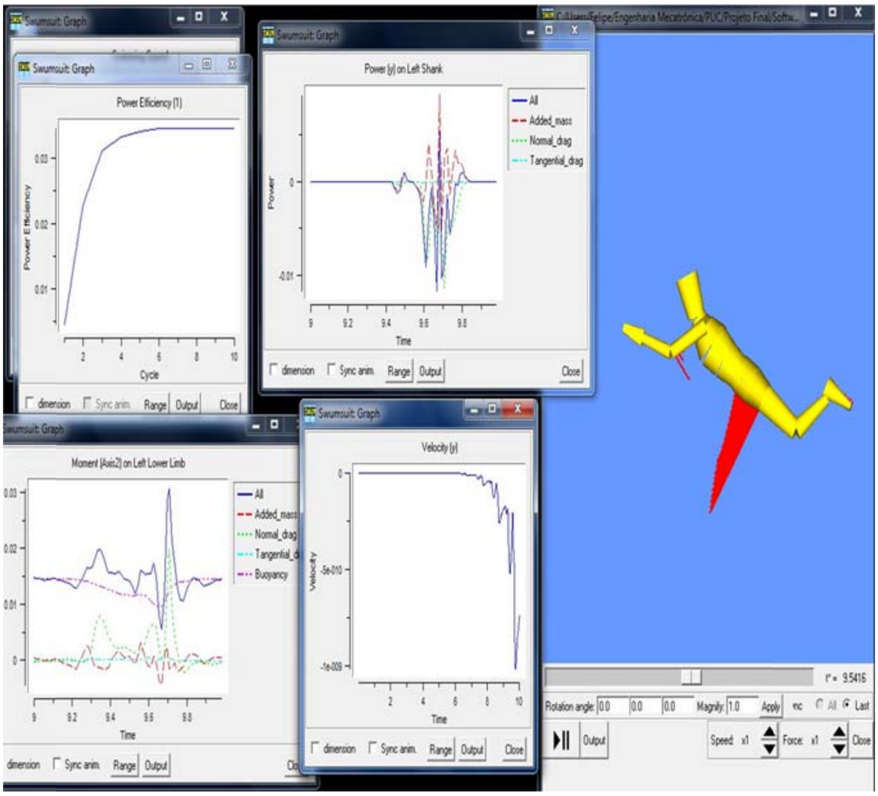


Fig. 8. Output and animation of swimmer.

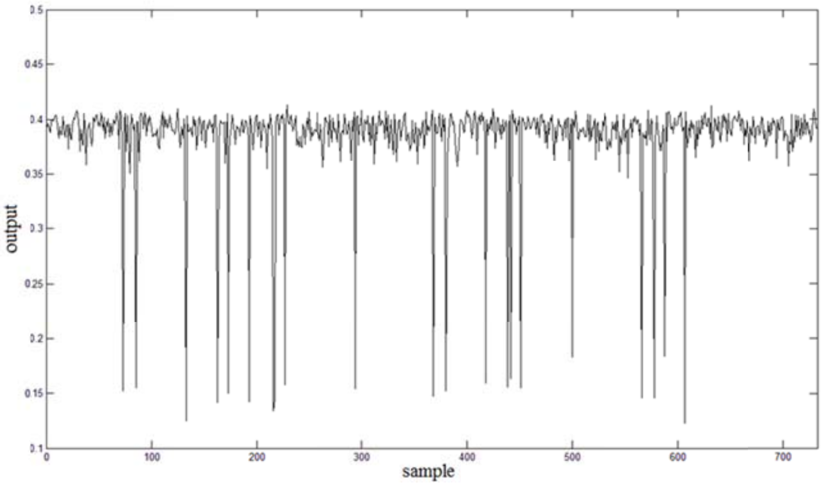


Fig. 9. Example of stroke speed of breaststroke.

Table 1. Parameters of RBF-NN using SOM.

Setup #	Dimension of Kohonen map	# maximum of epochs	dispersion of RBFs
1	[38,14]	2800	0.5
2	[45,18]	1440	1.0
3	[38,14]	1440	0.5
4	[67,27]	1440	0.2
5	[134,54]	520	0.5

Table 2. Results using RBF-NN using SOM.

Setup #	Mean Squared Error (MSE)	Correlation coefficient, R^2	time (hours) using Pentium IV
1	0.0146	0.8159	7.60
2	0.0126	0.8416	13.00
3	0.0136	0.8290	3.25
4	0.0109	0.8627	11.75
5	0.0031	0.9615	17.25

It is possible to verify by reported in Table 1 a directly proportional improvement between SOM size and the setups results as are these little influenced by the threshold of dispersion or by the number of iterations. However, for unaltered SOM dimensions (setups #1 and #3), fewer iterations achieved a superior performance with smooth detection of peaks and better adjusting to the system dynamics (see Table 2).

A map in SOM with the same dimensions of from inputs and outputs (setup #4) is capable of improving peak detections, pointing the RBF-NN variation detection capability and thus reducing the MSE index.

A larger map (setup #5 – two times inputs and outputs) further enhances the results needing even less iterations to achieve this goal, as shown in Table 2. Larger errors are observed in early training as the RBF-NN using SOM adapts itself to the dynamics. Due to its training characteristics, the increased dimensions of SOM lead to a large increase in computational cost of the algorithm. The dealt example required a larger scale map for the wide dispersion of data away from the peak values of central mass average, which were correctly detected only with great neurological capacity.

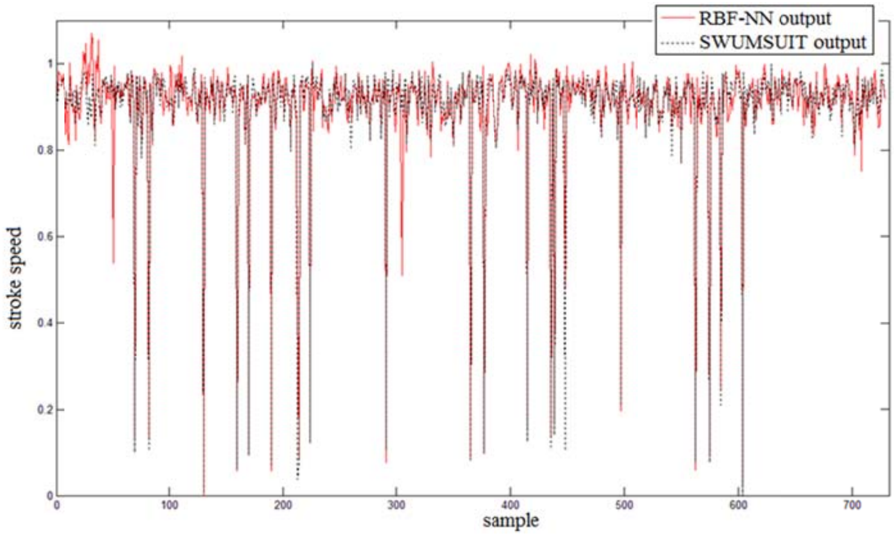


Fig. 10. Stroke velocity estimated by setup #5 of RBF-NN using SOM.

The biomechanical analysis is independent of time and generates a dispersed mass of data that may not be adequate to be represented by other NN techniques, except by the great grouping capabilities of SOM. The self-organizing map could, with increasing dimensions, create a reticulated neural structure large and specialized enough to be able to capture all the nuances and minimum variations of the input patterns. Later, a RBF-NN was applied to the simplified data, presenting no over fitting but its full capacity of generalization, outputting satisfactory results.

6. CONCLUSION

The ANN approach, which is a nonlinear black-box model, seems to be a useful alternative for modeling the complex systems. Due to their simple topological structure and universal approximation ability, RBF-NNs have been widely used in time-series prediction, pattern classification, and nonlinear system modeling. RBF-NNs form a different class of ANN which has certain advantages, including better approximation capabilities, simpler network structures and faster learning algorithms. In RBF neural networks the transformation from the input space to the space constructed by hidden layer is nonlinear, whereas the transformation from the space constructed by hidden layer to the output space is linear.

In this study, a RBF-NN model was successful applied to modeling of a parathlete swimmer swims breastroke style using biomechanics data generated by the SWUMSUIT. Further investigation about the improvements in RBF-NN design based on SOM using evolutionary algorithms and swarm intelligence approaches to applications in swimming field will be realized.

7. ACKNOWLEDGEMENTS

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9. RESPONSIBILITY NOTICE

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