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Comparison between Classical and Intelligent Identification Systems for Classification of Gait Events

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Abstract: Gait event detection is important for diagnosis and evaluation. This is a challenging endeavor due to subjectivity, high amount of data, among other problems. ANFIS (Artificial Neural Fuzzy Inference Systems), ARX (Autoregressive Models with Exogenous Variables), OE (Output Error models), NARX (Nonlinear Autoregressive Models with Exogenous Variables) and models based on NN (neural networks) were developed in order to detect gait events without the problems mentioned. The objective was to compare developed models' performance and determinate the most suitable model for gait events detection. Knee joint angle, heel foot switch and toe foot switch during normal walking in a treadmill were collected from a healthy volunteer. Gait events were classified by three experts in human motion. Experts' mean classification was obtained and all models were trained and tested with the collected data and experts' mean classification. Fit percentage was obtained to evaluate models performance. Fit percentages were: ANFIS: 79.49%, ARX: 68.8%, OE: 71.39%, NARX: 88.59%, NNARX: 67.66%, NNRARX: 68.25% and NNARMAX: 54.71%. NARX had the best performance for gait events classification. For ARX and OE, previous filtering is needed. NN's models showed the best performance for high frequency components. ANFIS and NARX were able to integrate criteria from three experts for gait analysis. NARX and ANFIS are suitable for gait event identification. Test with additional subjects is needed.

Keywords: Gait analysis, biomechanics, system identification.

1. Introduction

Since walking is a pattern of motion, diagnosis of the patient's difficulties depends on an accurate description of the actions occurring at each joint. Traditionally, the method used for such description has been observed the patients gait. While performing the observation in a systematic manner results in more agreement among observers, there still is disagreement on details. An alternate approach is quantitated documentation of the person's performance with reliable instrumentation that provides a permanent record of fact [1]. However, the analysis of quantitative data has been a challenging endeavour [2]. The high amount of data, nonlinear dependencies, inter-subject and intra-subject variability, among others, are typical problems when motion analysis is performed. These complexities are compounded by long recording times in gait laboratories, and increasing patient populations result in late diagnosis, leading to an increased risk of disorder progression and further complications [3].

CI (Computational Intelligence) is a fusion of learning mechanisms and computing, specifically suited for powerful decision systems capable of interpreting and processing large volumes of data [3]. ANFIS (Artificial Neural Fuzzy Inference Systems), ARX (Autoregressive Models with Exogenous Variables), NARX (Nonlinear Autoregressive Models with Exogenous Variables) and OE (Output Error models) are four of many techniques that can be used for pattern recognition, therefore, are suitable for gait analysis. With CI, it is possible to model a biomechanical system by learning data relationships between inputs and outputs possibly corrupted by

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external noise; this system could represent a discriminator between gait disorders, a predictor of gait succession, etc. [3].

The present work reports a comparison of performance between ANFIS, ARX, OE, NARX and Artificial Neural Networks for classification of gait events during normal walking.

1.1 ANFIS

ANFIS are a combination of a Fuzzy Inference System with a neural network. This kind of systems take the advantage of adaptability and learning of the neural networks, and they also use inference linguistic rules (*if-then* type) of fuzzy logic [4].

With ANFIS is possible to build functional adaptive networks equivalents to fuzzy systems like Mamdani or Sugeno; for Sugeno systems, the adaptable network is built like shown in Fig. 1.

As proposed by Jang [5], these types of networks have different kinds of neurons. The circular neurons on Fig. 1 represent fixed nods, and the square neurons are adaptive nods; the last have a series of variable parameters, while the others do not. On the first layer all nods are square. These nods contain the membership functions corresponding to the Sugeno System Fuzzyfication. The parameters involved to these neurons modify the shape and location of the functions. Their outputs are the membership values of each input (*X* and *Y* in this case) for each membership function (*A1, B1, A2* and *B2*). This is represented by:

$$O_i^1 = \mu_{A_i}(X) \qquad (1)$$

where, $\boldsymbol{i}$ is the number of nods in the first layer (in this case $\boldsymbol{i}$ = 1, 2, 3, 4) and μ_{A_i} is the membership function labeled as $\boldsymbol{A_i}$ where $\boldsymbol{X}$ (the input) is evaluated. On the second layer, every nod is fixed. Those nods contain the *MIN* function, with which the output obtained is the minimal membership value calculated by the fuzzyfication on the previous layer; each nod in this layer represents an *if-then* type of rule. This way, each nod on the second layer is represented as follows:

$$W_i = \mu_{A_i}(X)\mu_{B_i}(Y)\,;\; i = 1, 2 \qquad (2)$$

where, W_i is obtained by the *MIN* operation between the result of the evaluation of *X* and *Y* in the membership functions μ_{A_i} and μ_{B_i} respectively. As in the second layer, the third is formed by fixed nods. This layer normalizes the firing strengths. The equation of each nod is:

$$\overline{W_i} = \frac{W_i}{W_1 + W_2}\,;\; i = 1, 2 \qquad (3)$$

On the fourth layer are the output functions or defuzzyfication functions of the Sugeno system. These functions depend on the parameters of the equations, which are the coefficients of the output functions. So, in case of linear functions the corresponding equations would be:

$$f_1 = p_1 X + q_1 Y + r_1 \qquad (4)$$

The parameters that define the function are $\boldsymbol{p_1}$, $\boldsymbol{q_1}$ and $\boldsymbol{r_1}$. These fourth layer outputs turn in to inputs of the fifth and last layers, which have only one fixed neuron, containing the sum function to complete the defuzzyfication.

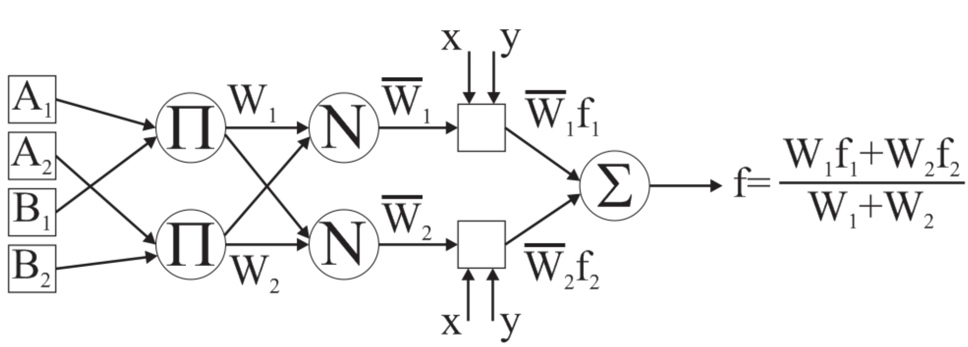

Fig. 1 ANFIS equivalent of a Sugeno fuzzy system.

The learning process of the system consists on finding the right values of the adaptive nodes to obtain the desirable output of a certain input. This parameters, as mentioned before are of two types: (1) The defining parameters of the membership functions, such as form and location (parameters of the premises); (2) The parameters defining the output functions (the polynomial coefficients), or the consequences.

For system identification, it must be chosen a model within a group of models which equals the best on the dynamic and static characteristics of the system to identify. The basic principle of identification depends on a group of parameters θ, changing the problem of identification to a problem of parameters estimation.

Fuzzy systems can be used to identify non-linear systems, but the rules and design of the membership functions depend on the designer, dropping the precision of the model. Auto adjusting neural networks can also be used; however, the networks could get trapped in local minimums in a long period of training [4]. ANFIS combine the virtues of both, neural networks and fuzzy logic, avoiding the mentioned inconveniences, making them an attractive option for non-linear systems identification.

Fuzzy Logic Systems have been used for gait events detection in order to emulate muscle activation patterns during FES (functional electrical stimulation) gait [6, 7]. Both authors reported that Fuzzy Logic Systems are suitable for gait events detection and have good performance in comparison with classification using a look-up table [6] and threshold detection method [7]. Some other authors have used ANFIS for gait analysis [8, 9]. Jonic et al. compared ANFIS performance for generate rules to control locomotion versus multilayer perceptron with Levenberg-Marquardt modification of backpropagation learning algorithm and a combination of an entropy minimization type of inductive learning; ANFIS gave the most explicit, comprehensible and fewer rules of classification using ground reaction forces, hip acceleration, knee and hip joint angles and the angle between the trunk and the horizontal as the system inputs [8]. Lauer and colleagues found that ANFIS is capable to detect seven phases of gait with a high degree of accuracy and repeatability using electromyography as system input [9].

1.2 ARX and OE

Autoregressive Models with Exogenous Variables and Output Error Models are linear parametric models based on the next system representation:

$$y(t) + a_1 y(t-1) + \cdots + a_m y(t-m) = b_1 u(t-1) + \cdots + b_n u(y-n) + e(t) \quad (5)$$

where, $y(t)$ are the system outputs at time t, $u(t)$ are the system inputs at time t and $e(t)$ are the system error signals (such as noise, disturbances, etc) at time t. $a_i, i = 1,2, \ldots, m$ are adjustable parameters related with the system outputs and $b_i, i = 1,2, \ldots, n$ are adjustable parameters related with the system inputs. Using q as a shift operator (where $q^{-i}x(t) = x(t-i)$), equation (5) can be re-written:

$$y(t)(1 + a_1 q^{-1} + \cdots + a_m q^{-m}) = u(t)(b_1 q^{-1} + \cdots + b_n q^{-n}) + e(t) \quad (6)$$

From equation (6), polynomials $A(q)$ and $B(q)$ are defined as:

$$A(q) = 1 + a_1 q^{-1} + \cdots + a_m q^{-m} \quad (7)$$

$$B(q) = b_1 q^{-1} + \cdots + b_n q^{-n} \quad (8)$$

For SISO systems, $A(q)$ and $B(q)$ are polynomials, while for MIMO systems, they are polynomial matrices (one polynomial per input or output). Finally, ARX model structure is given by:

$$y(t) = A^{-1}(q)B(q)u(t) + A^{-1}(q)e(t) \quad (9)$$

In conclusion, model identification using ARX is reduced to find the correct coefficients of polynomial matrices $A(q)$ and $B(q)$. This can be done using least squares method in order to minimize the error between the actual system output and the model output as shown in the next equation.

$$\frac{1}{N}\sum_{t=1}^{N} \|y(t) - \hat{y}(t)\|^2 \quad (10)$$

where, $y(t)$ is the system output and $\hat{y}(t)$ is the model output. In the same way, OE model structure has the next form:

$$y(t) = F^{-1}(q)B(q)u(t) \quad (11)$$

As can be seen, OE model has a simpler structure than ARX model, which makes its implementation easier. The first step when identification with linear parametric models is being used is to choose a correct model structure considering accuracy and complexity.

Autoregressive models have been barely used for gait analysis, including a few attempts of the design of postural stability criterion, capture of shape deformations in gait, modeling of energy transfers during normal walking, and design of falls detection systems [3]. No gait events detection with ARX or OE have been reported as far as the authors know, although autoregressive models have shown to be capable of linearly separate different gait patterns better than other methods such as statistical descriptor or wavelet decomposition [3].

1.3 NARX

Nonlinear Autoregressive Models with Exogenous Variables are a powerful class of nonlinear dynamical models used in many applications [10]. They constitute nonlinear extensions of the conventional linear ARX models. NARX models offer a number of advantages, including accuracy and compactness of representation, physical significance, and direct correspondence between the NARX and the physical system parameters [11]. The NARX model is based on the linear ARX model, which is commonly used in time-series modeling. Defining equation for the NARX model is as follows:

$$y(t) = f\big(y(t-1), y(t-2), \dots, y(t-m), u(t-1), u(t-2), \dots, u(t-n)\big) + e(t) \quad (12)$$

where the next value of the dependent output signal y(t) is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal [12].

Tafazoli et al. used NARX models for identification of neuromuscular system in combination with ARX models, in which ARX gets the linear part of the system and the NARX picks up the nonlinearities. The combined method showed a better performance than ARX and NARX separately due to ability of combined model structure to model nonlinear dynamical systems [11]. Although NARX models have proved to be a powerful approach to identification of nonlinear phenomena [10-13], as far as the authors know, no gait events detection with NARX have been reported.

1.4 Neural Networks

ARX, OE, and other model structures can be trained as neural networks do. The estimation problem of matrices *A(q)*, *B(q)* and *F(q)*, which define the model structure, is addressed as a estimation of the network's weights. Thus, regardless the model structure (ARX, OE, NARMAX, etc), neural networks can be developed for systems identification. This represents an attractive solution, since neural networks have good performances at learning nonlinear relationships from a set of data. ARX and OE models structures were presented on subsection B, ARMAX structure is as follows:

$$y(t) = A^{-1}(q)B(q)u(t) + A^{-1}(q)C(q)e(t) \quad (13)$$

C(q) is defined as *A(q)* ad *B(q)* are:

$$C(q) = 1 + c_1 q^{-1} + \cdots + c_k q^{-k} \quad (14)$$

Therefore, for an ARMAX model, the coefficients that will be estimated through the neural network training will be [$a_1, \dots, a_m, b_1, \dots, b_n, \dots, c_1, \dots, c_k$].

2. Methods

It was asked to a healthy volunteer to walk on a treadmill at a constant self-selected pace for one minute. Knee joint angle was measured with a twin axis goniometer SG150 (Biometrics Ltd, UK). Only knee flexion-extension data was recorded from goniometer. Additionally, heel contact and toe off were detected with two foot switches placed on volunteer's footwear, one at the heel and one at the toe (Fig. 2). All data was collected at the Human Motion

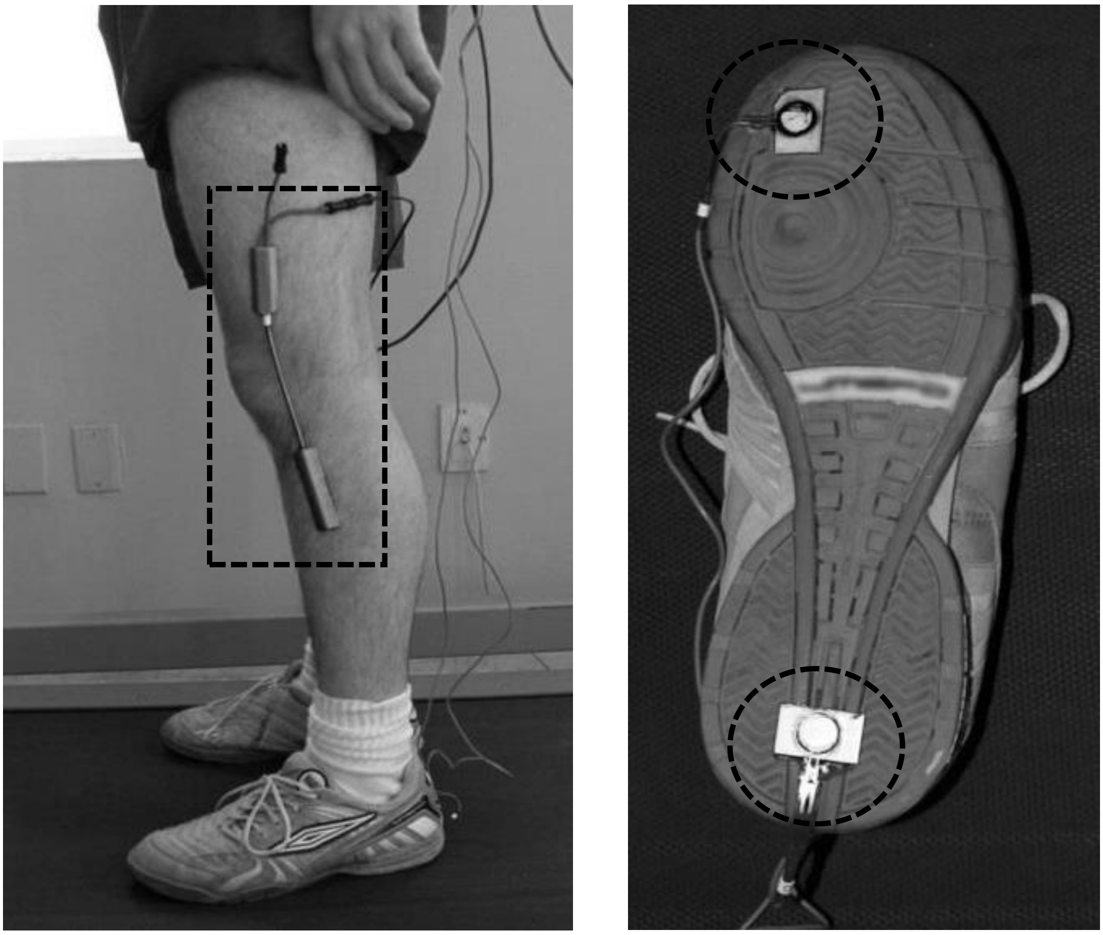

Fig. 2 Sensors for gait data collection. Picture on left shows the goniometer placed on volunteer's leg in order to measure knee's flexion/extension angle. Picture on right shows both foot switches placed on volunteer's footwear (heel and toe).

Analysis Laboratory at the National Rehabilitation Institute (INR) in Mexico City.

Twenty five strides at constant velocity were considered for model identification and testing. Initial and final steps were not used due to the inherent acceleration and deceleration at those moments. All strides were identified by initial contact (heel foot switch transition from "inactive status" to "active status") and cut from one initial contact to subsequent initial contact. Once separated, every stride was normalized in terms of gait cycle percentage. All data processing and identification was done using Matlab v7.4.0 (The MathWorks, Inc., USA).

For every stride, seven gait phases were identified by three motion analysis experts at INR using the collected data, knee angular velocity (knee angle's first forward difference) and knee angular acceleration (knee angular velocity's first forward difference). The identified phases were: IC (Initial Contact), LR (Loading Response), MS (Mid Stance), TSPSw (Terminal Stance/Pre-Swing), ISw (Initial Swing), MSw (Mid Swing) and TSw (Terminal Swing). A numeric value was assigned for every phase: 1-IC, 2-LR, 3-MS, 4-TSPSw, 5-ISw, 6-MSw, 7-TSw. The mean of the experts' gait phase classification was obtained and used for the model training/estimation and validation. The experts' mean classification is shown on Fig. 3.

Identification with all models was done using three inputs: knee angle, heel foot switch and toe foot switch; and one output: gait phase.

The first ten strides were used for training and estimation. The last 15 strides were used for model validation.

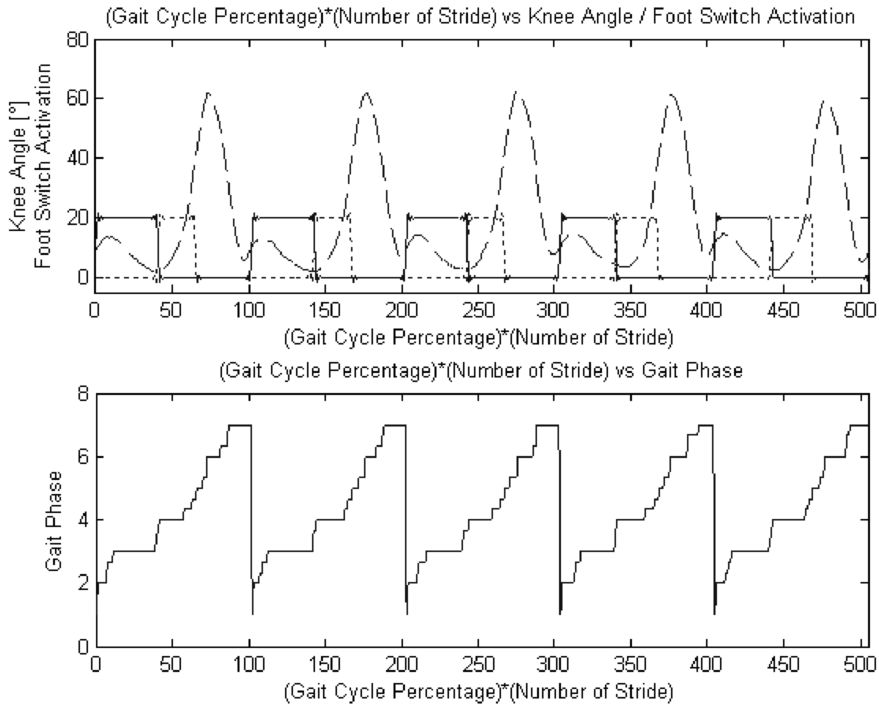

Fig. 3 Five consecutive resampled strides. On upper graph, knee angle (dashed line), heel foot switch (solid line) and toe foot switch (dotted line) is shown, while in lower graph, the corresponding experts' mean gait phase classification.

ANFIS fuzzyfication was made using Matlab's Fuzzy Toolbox, with the following settings: eight Gaussian membership functions for knee angle input, and three Gaussian membership functions for both, heel foot switch input and toe foot switch input, constant output, hybrid optimization method, error tolerance of 0.001 and 80 epochs. ANFIS model was tested with Matlab's Simulink.

For ARX, OE and NARX identification, the model was estimated using least squares for error minimization. For ARX, the number of poles used for the estimated model was 5, while the number of zeroes was 29 for knee angle input, 29 for heel foot switch input and 29 for toe foot switch input; also, a *dead time* of 7 was selected for knee angle and 9 for both foot switches. As for OE, the number of zeroes selected was 5 for knee angle, 6 for heel foot switch and 7 for toe foot switch; the number of poles was 7 for knee angle, 8 for heel foot switch and 9 for toe foot switch; finally, a *dead time* of 3 was selected for knee angle and for heel foot switch, while 4 was selected for toe foot switch. For the NARX model, the orders of the function:

$$y(t) = f\big(y(t-1), y(t-2), \dots, y(t-m), u(t-n_k), u(t-n_k-1), \dots, u(t-n_k-n_b-1)\big) \qquad (15)$$

where, m=1, nk_{knee}=4, nk_{heel}=3, nk_{toe}=1, nb_{knee}=2, nb_{heel}=1, nb_{toe}=1. As for the neural networks, in all the cases a two layers network was used and training was made using Levenberg-Marquardt method.

For NNARX model, the hidden layer was formed by eight *tanh* units and one *tanh* unit in the output layer. The number of past inputs and past outputs used was one for each variable (knee angle, heel foot switch, toe foot switch, and gait phase), as well as the time delay. NNARX training was delimitated to 500 maximum iterations, and a weight decay of 1e-3. NNRARX model had the same structure than the NNARX model; however, the training parameters were 1 iteration, and 1e-3 for weight decay, the initial weights matrices were fixed for optimal performance. For NNARMAX model, the hidden layer was formed by seven *tanh* units and one *tanh* unit in the output layer. The number of past inputs, past outputs and past residuals used was one for each variable, the time delay was one for the knee angle and two for heel foot switch and for toe foot switch. The maximum iterations for training was 200 and the weight decay was 1e-3. Also, a moving average filter of 4 delays window was used at the output of the neural network.

Comparison between estimated models outputs and the real system output was made with a fit percentage, obtained by:

$$fit = 100 \times 1 - \frac{\|out_{real} - out_{model}\|}{\|out_{real} - mean\,(out_{real})\|} \tag{16}$$

where, out_{real} is the validation data and out_{model} is the model output. Fit percentage was also calculated between each expert classification and experts' mean.

3. Results

Fit percentage between each expert classification and experts' mean is shown in Table1.

ANFIS model used 72 *if-then* rules to perform the classification; Fig. 4 shows the phase gait estimated by ANFIS model and the phase gait determined by the experts. Fit percentage for ANFIS model was 79.49%. ARX output compared versus experts' classification is shown on Fig. 5. Fit percentage for ARX model was 68.8%. Fit percentage for OE model was 71.39% and is shown on Fig. 6. Fit percentage for NARX model was 88.59% (Fig. 7). Figs. 8-10 show NNARX (67.66% fit percentage), NNRARX (68.25% fit percentage) and NNARMAX (54.71% fit percentage) output classifications versus experts' mean.

It can be seen, from Fig. 4 to Fig. 10, that all models have the biggest error where the high frequency elements are present (at the corners of the squared signal), being ARX model the most affected by this high frequency components. The second error region for ANFIS models is located between the fifth and the sixth gait phase (Initial Swing and Mid Swing). It could be because the angle values during these phases are in the same range, and additional data from foot switches is not available since the leg is not supported on the ground; then, the system cannot identify if the angle is increasing or decreasing with the input information. Angular velocity would help the system to recognize the difference between these two phases. NNARX and NNRARX show an error region at the seventh gait phase, perhaps due to the abrupt changes between phases 7 and 1, making impossible to the neural network to follow them as fast as other models.

Model fit percentage for every stride was calculated in order to evaluate the model's performance in individual cycles. This was done only for ANFIS and NARX models since those were the models with the best global fit percentage. The results are shown in Table 2.

4. Discussion and Conclusion

Gait events classification is a complex task that requires experience and knowledge from the evaluator. Even when the evaluator has both experience and knowledge, it can be hard to identify gait phases using only a limited amount of data and without looking at the subject performing the test. The three experts that participated in this experiment expressed the difficulty to evaluate the gait cycles; in fact, it took about an hour for each expert to classify the gait events of the 25 cycles. Also, the experts asked for more information such as angular velocity and angular acceleration in order to make the classification. It is also important to notice that gait evaluation, even with the help of technology (in this case foot switches and

Table1 Fit percentage between experts classification and experts' mean.

Fit percentage	Experts' mean	Expert 1	Expert 2	Expert 3
Experts' mean		87.03%	83.60%	88.56%
Expert 1	87.03%		73.11%	81.98%
Expert 2	83.60%	73.11%		74.73%
Expert 3	88.56%	81.98%	74.73%	

Table 2 Individual stride's fit percentage for ANFIS and NARX models versus experts' mean.

Stride	Mean [%] ANFIS	Mean [%] NARX
1	83.357	87.745
2	81.969	88.262
3	80.929	88.685
4	79.160	88.913
5	76.629	89.099
6	72.342	88.942
7	74.920	89.493
8	77.130	88.864
9	80.155	88.618
10	78.712	89.441
11	80.647	88.976
12	80.107	88.661
13	81.605	88.585
14	84.509	88.889

goniometer), is affected by subjectivity, since it is performed by a human. Criteria and chosen references might vary between the evaluators, resulting in a variation between experts' classification shown in Table1. However, it doesn't mean that any of the three experts made a wrong evaluation, but that the gait classification made by human observers might be slightly different between them. Actually, the fit percentage between expert 2 and the other experts (73.11% and 74.73%) is minor than the fit percentage between ANFIS and the experts' mean (79.49%) and NARX (88.59%), this suggests that ANFIS and NARX are suitable for gait event classification, since the difference of the classification made with the models and the experts' mean classification is comparable with the difference that could be found between the evaluations made by experts. Even more, fit percentage for individual strides evaluated with ANFIS model (shown on Table 2) is, in some cases, higher than 80%, and higher than 87% for all strides classified by NARX model. Nevertheless, it is important to say that even when there were differences between experts' evaluations, the mean that used for training and validation since the results of the model identification was not affected by such differences. This made the training/estimation process simpler. Also it is important to consider that all models tested, only used three inputs for gait events detection, while the experts needed two additional inputs (angular velocity and acceleration), it means that the developed identification systems can differentiate gait events with fewer inputs than the experts.

ANFIS and NARX had better performance than ARX and OE (79.49%, 88.59%, 68.8% and 71.39% fit percentages respectively). It is known that high frequency components might be challenging for ARX and OE models since they are linear models, and that is why it is commonly recommended to perform a low-pass filtering before estimation. However, for this case, filtering could affect the evaluation of the gait events, since there would be a slope between phases (instead the abrupt changes between them that dictate the end of a phase and the beginning of the next phase) that would make difficult to determine which phase corresponds to a particular set of inputs. Still, ARX and OE might be useful for different evaluations or biomechanics applications that don't have to deal with high frequency components. Despite ARX and OE models had lower accuracy than ANFIS and NARX, it must be said that linear models had fair enough performance and could be used for applications where the obtained fit percentages are tolerated. However, nonlinear models, such as NARX showed a better performance for identification of this particular system. This was expected due to the complexity of the output of the system, which presents abrupt changes between gait phases and a cyclic behavior.

Neural networks are suitable for treatment of nonlinear relationships; therefore it would be expected to obtain favorable results using these algorithms in order to identify nonlinear systems [14]. However, in this work, results with NN's didn't show better performances than those obtained with linear models (ARX and OE). This might be because, even if the estimation problem is addressed with NN's, the model structure still is linear. It is important to observe that,

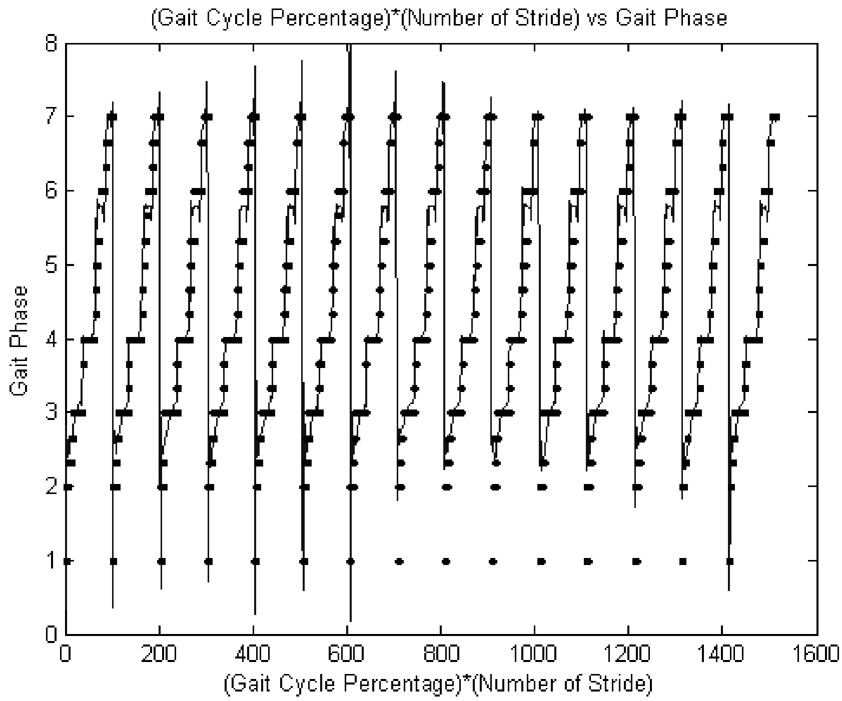

Fig. 4 Gait phase estimated by ANFIS. The solid line is the phase of gait estimated. The dotted line corresponds to the actual gait phases as determined by the experts. Fit percentage: 79.49%.

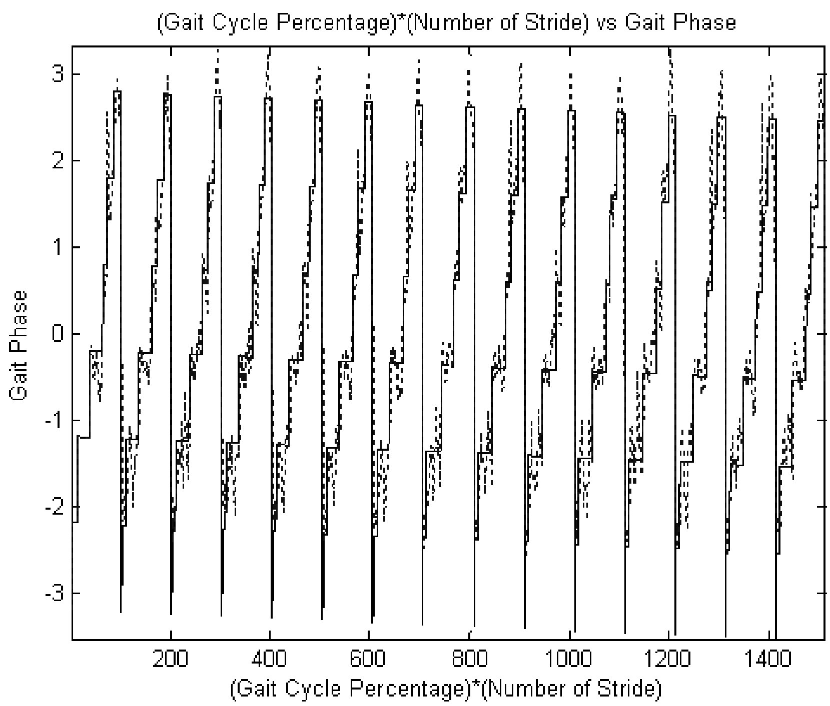

Fig. 5 Gait phase estimated by ARX. The dashed line is the phase of gait estimated. The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 68.8%.

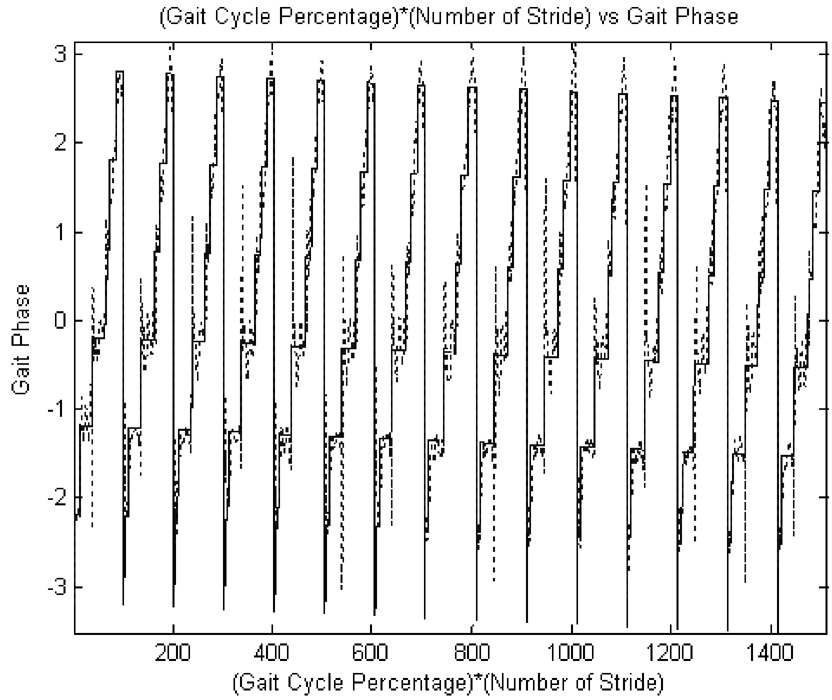

Fig. 6 Gait phase estimated by OE. The dashed line is the phase of gait estimated. The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 71.39%.

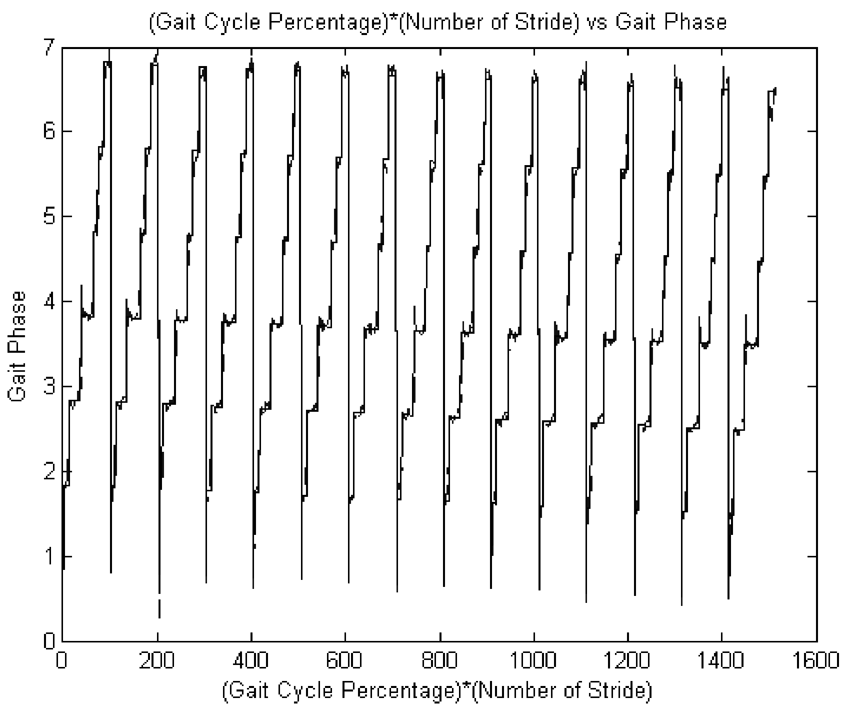

Fig. 7 Gait phase estimated by NARX. The dashed line is the phase of gait estimated. The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 88.59%.

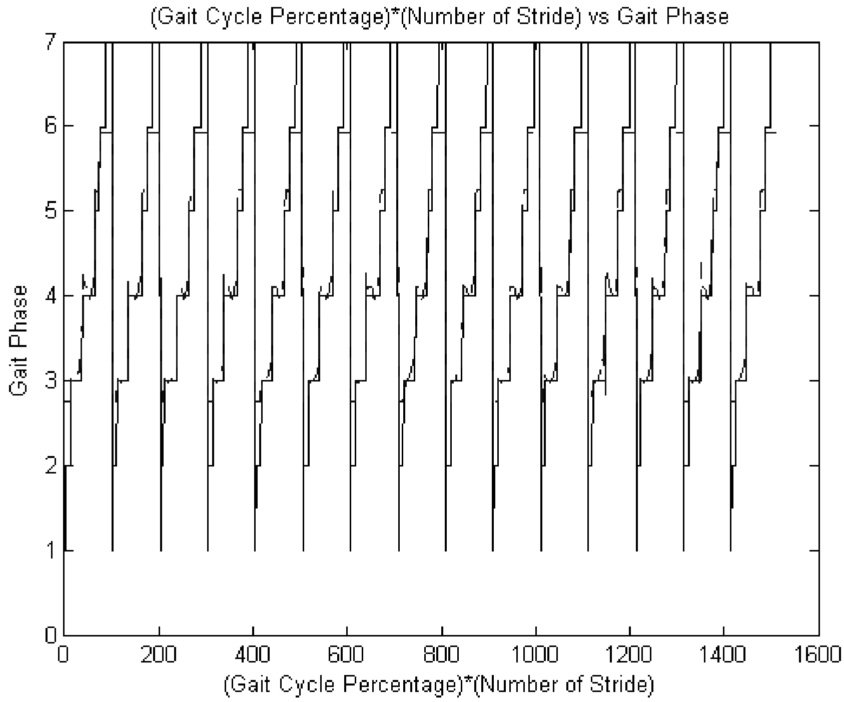

Fig. 8 Gait phase estimated by NNARX. The dashed line is the phase of gait estimated. The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 67.6652%.

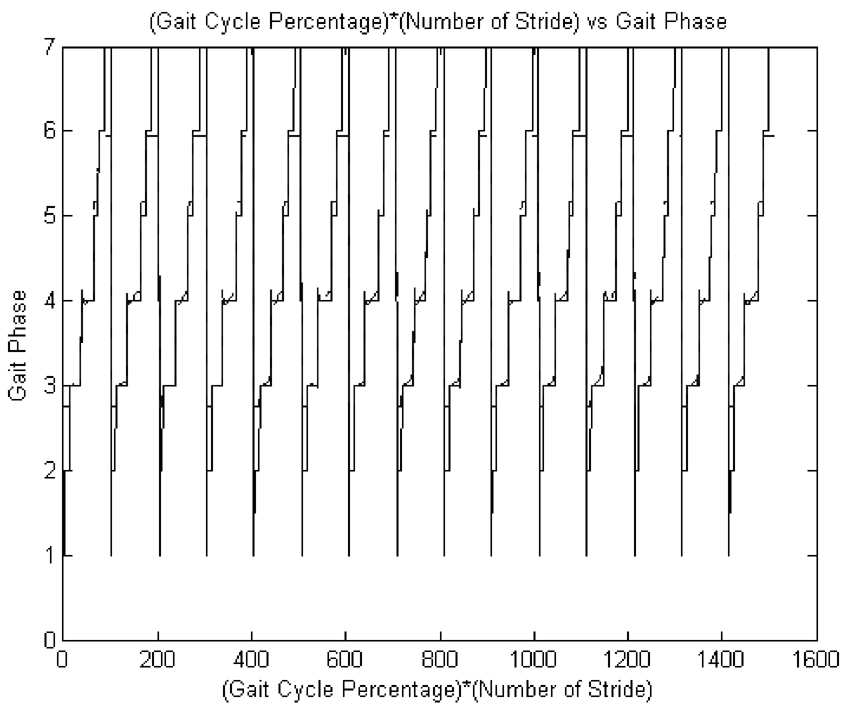

Fig. 9 Gait phase estimated by NNRARX. The dashed line is the phase of gait estimated. The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 68.2582%.

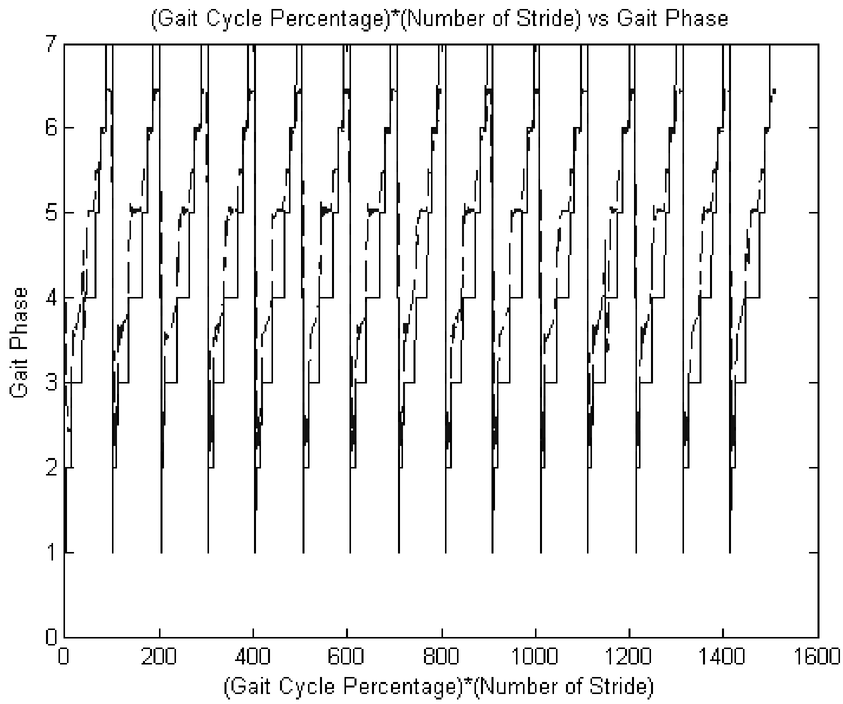

Fig. 10 Gait phase estimated by NNARMAX. The dashed line is the phase of gait estimated (with a moving average filter with 4 past inputs). The solid line corresponds to the actual gait phases as determined by the experts. Fit percentage: 54.7123%.

even though NN models did not show better performances than linear models, the conflict regions of the signal that were found for identification with linear models (the corners of the square signal), did not seem to represent a major problem for the NN models. In fact, the high frequency changes of the signal were well followed by the NNARX, NNRARX and NNARMAX models. It is interesting to observe that NN models had the best performance between sub phases 3, 4, 5 and 6; because of this, it is important to continue to explore the application of such models for the identification of gait phases, probably with a larger set of data.

Skelly et al. used a system divided in two levels, a lower level containing the fuzzy logic estimator and an upper level with a supervisor system; they reported an accuracy of 80% with the fuzzy logic estimator (before the supervisor system) [7], which is similar to the accuracy obtained with the ANFIS system developed (79.49%), however, one of the problems for the real time implementation was the number of rules contained by the fuzzy gait phase detector, Skelly's system had 210 rules, while ANFIS model developed has 72 rules. Using the same idea with Skelly of a two-level system, it could be used a second stage of processing in order to improve the system performance, such as saturation (since it is previously known that there are no phases higher than seven or lower than one) and rounding (which would help to make abrupt transitions between phases). It must be noticed that the number of inputs used by Skelly's system was eight (four per foot), while ANFIS developed here used only three, this could suggest that using more data (such as angular velocity) would improve performance and it will be still a lower number of sensors.

Kuen et al. used the same number of sensors that we used (except in one subject for which Kuenused the data from two legs), but the number of rules obtained by Kuen was at least 100 [6]. For Kuen's system, percentage of correct detection varies from more than 80% to less than 45%, and the best performance was obtained with the subject using six sensors. In comparison with our ANFIS system, correct detection percentage is similar, but the number of rules is smaller and the number of sensors used for a 79.79% fit percentage was only three at all times, being possible to obtain more information without placing more sensors on the subject.

Jonic's ANFIS system used four sensors and reported a cross correlation of 0.95 for muscle activity prediction and a 0.999 cross correlation for knee joint angle; these outputs do not have high frequency components as high as in gait event detection, and that is why ANFIS have such a good performance. The system developed shown that even with high frequency components in the output, ANFIS can be used and Jonic's system showed that ANFIS is highly accurate for identification of systems with relatively low frequency components.

Lauer et al. also used a SCS (supervisory control system) [9] as Skelly did [7], and reported a greater than 95% of accuracy. This shows that SCS's improve considerably the system's performance and marks part of the future work of this paper. It must be noticed that Lauer used electromyography signals as inputs, and it is necessary to retrain the system due to the variations in the placement of the surface recording electrodes and differences in skin impedance. These problems are not present with the sensors suggested in this work (goniometer and foot switches), however, there are some other problems to be solved such as the obstruction of the wires and the goniometer calibration.

To improve the NARX model performance a low pass filter might be used, since the major areas of error were located in the corners of the square signal, but it is important to consider that this could reduce the capability of the abrupt changes between sub phases that the NARX model reached.

It is also important to observe that the fit percentage for individual strides can reach 84% for ANFIS and 89% for NARX, since the identification system might be used as part of a control system in real time, this is the fit percentage that would affect the system performance.

The main achievement of the ANFIS and NARX model developed is that they made possible that the gait events classification considering more than one criteria, combining three different points of view from the experts. This is important since subjectivity is one of the most common problems in gait analysis in practice. The opportunity to create systems capable to include more than one opinion of the same problem enriches the gait evaluation system gathering the experience from different evaluators being this, the experience, the most important factor for gait evaluation in the clinical application of gait analysis. This suggests that it could be possible to create different systems capable to reunite the expertise of different evaluators in different areas of the clinical assessment, not only for gait event detection, but also for pathological patterns of motion, upper limb motion analysis, pattern recognition of daily living activities, making possible to evaluate motion outside the clinic, etc.

In conclusion, NARX model had the best performance. However, ARX and OE linear models could be used in applications without high frequency components. NNARX, NNRARX and NNARMAX are models that should be explored in the future because they showed a good performance in the middle sub phases of the gait, and the might achieve a better performance with a larger group of data and SCS. Also, ANFIS had a performance comparable with previously reported fuzzy systems, but it could be improved with supervisory systems and additional data. ANFIS' ability of generalization makes it an attractive system for gait events classification and it also should be explored in more depth. Individual stride fit percentage reached 89% of accuracy versus experts' mean. It was possible to train a system capable to consider the criteria of three different experts in human motion analysis.

Future work will include the incorporation of supervisory systems, additional data for training/estimation, and gathering criteria from more experts.

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