Abstract— Gait event detection is important for diagnosis and evaluation. This is a challenging endeavor that can be addressed with Computational Intelligence (CI). Four different CI models were developed and compared. Spatio-temporal parameters during normal walking in a treadmill were collected from a healthy volunteer. Gait events were classified by three experts in human motion. All identification systems were trained and tested with the collected data and experts’ mean classification. Fit percentage was obtained to evaluate models performance. Nonlinear Autoregressive Models with Exogenous Variables (NARX) had the best performance for gait events classification with a fit percentage of 88.59%. High frequency components were the main source of error for classical models. NARX was able to integrate criteria from the three experts for gait event detection. NARX models are suitable for gait event identification. Future work will include implementation of supervisory systems and additional data.

Keywords: Gait Analysis, Biomechanics, System Identification

I. 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 to carefully observe the patient’s 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 increases risk of disorder progression and further complications [3].

Computational Intelligence (CI) is a fusion of learning mechanisms and computing, specifically suited for powerful decision systems capable of interpreting and processing large volumes of data [3]. Autoregressive Models with Exogenous Variables (ARX), Nonlinear Autoregressive Models with Exogenous Variables (NARX) and models based on Neural Networks with ARX regression vector (NNARX) are three of many techniques that can be used for pattern recognition and, therefore, are suitable for gait analysis. Those three models in particular share the main structure so this would allow a straight comparison between the systems. With CI, it is possible to model a biomechanical system by learning data relationships between inputs and outputs possibly corrupted by 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 ARX, NARX and NNARX for classification of gait events during normal walking.

A. ARX

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

\[ y(t) + a_1 y(t - 1) + \cdots + a_m y(t - m) = b_0 u(t) + b_1 u(t - 1) + \cdots + b_n u(y - n) + e(t) \]  (1)

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 1 can be re-written:

\[ y(t)(1 + a_1 q^{-1} + \cdots + a_m q^{-m}) = u(t)(b_0 + b_1 q^{-1} + \cdots + b_n q^{-n}) + e(t) \]  (2)

From equation 2, polynomials \( A(q^{-1}) \) and \( B(q^{-1}) \) are defined as:

\[ A(q^{-1}) = 1 + a_1 q^{-1} + \cdots + a_m q^{-m} \]

\[ B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_n q^{-n} \]
\[ B(q^{-1}) = b_0 + b_1 q^{-1} + \cdots + b_n q^{-n} \]

For SISO systems, \( A(q^{-1}) \) and \( B(q^{-1}) \) are polynomials, while for MIMO systems, they are polynomial matrices (one polynomial per input or output). Finally, ARX model structure considers systems described by:

\[
y(t) = A^{-1}(q^{-1})B(q^{-1})u(t) + A^{-1}(q^{-1})e(t)
\]

And the model structure, in predictor form, takes the form:

\[
\hat{y}(t|\theta) = B(q^{-1})u(t) + [1 - A(q^{-1})]y(t)
\]

In conclusion, model identification using ARX is reduced to find the correct coefficients of polynomial matrices \( A(q^{-1}) \) and \( B(q^{-1}) \). 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.

\[
\frac{1}{N} \sum_{t=1}^{N} \|y(t) - \hat{y}(t)\|^2
\]

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 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].

### C. NARX

Nonlinear Autoregressive Models with Exogenous Variables are a powerful class of nonlinear dynamical models used in many applications [4]. 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 [5]. 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:

\[
y(t) = f(y(t-1), y(t-2), \ldots, y(t-m), u(t-1), u(t-2), \ldots, u(t-n)) + e(t)
\]

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 [6].

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 [5]. Although NARX models have proved to be a powerful approach to identification of nonlinear phenomena [4 - 7], as far as the authors know, no gait events detection with NARX have been reported.

### II. 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 (Figure 2). All data was collected at the Human Motion Analysis Laboratory at the National Rehabilitation Institute (INR) in Mexico City.

As for ARX models, no gait events detection with NNARX have been reported as far as the authors know.
Figure 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 foot (heel and toe).

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 and knee angular velocity (knee angle’s first forward difference) and knee angular acceleration (knee angular velocity’s first forward difference). The identified phases where: Initial Contact (IC), Loading Response (LR), Mid Stance (MS), Terminal Stance/Pre-Swing (TSPSw), Initial Swing (ISw), Mid Swing (MSw) and Terminal Swing (TSw). 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 estimation and validation. The experts’ mean classification is shown on Figure 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 estimation. The last 15 strides were used for model validation.

For ARX 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 zeros was 29 for knee angle input, 29 for heel foot switch input and 29 for toe foot switch input; also, a \textit{dead time} of 7 was selected for knee angle and 9 for both foot switches. For the NARX model, the orders of the function

\[ y(t) = f(y(t-1), y(t-2), ..., y(t-m), u(t-n_k), u(t-n_k-1), ..., u(t-n_k-n_b-1)) \]

where: \( m=1, n_k\text{nee}=4, n_k\text{heel}=3, n_k\text{ toe}=1, n_b\text{nee}=2, n_b\text{ heel}=1, n_b\text{ toe}=1.\)

As for the neural networks, in all the cases a 2 layers network was used and training was made using Levenberg-Marquardt method.

For NNARX model, the hidden layer was formed by 8 \textit{tanh} units and one \textit{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.

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

\[ \text{Fit} = \frac{\sum (y(t) - \hat{y}(t))^2}{\sum (y(t) - \bar{y})^2} \]

where \( \bar{y} \) is the mean of the outputs. The fit is expressed in percentage.
where \( out_{\text{real}} \) is the validation data and \( out_{\text{model}} \) is the model output. Fit percentage was also calculated between each expert classification and experts’ mean.

### III. Results

Fit percentage between each expert classification and experts’ mean is shown in Table 1.

**Table 1** Fit percentage between experts classification and experts’ mean

<table>
<thead>
<tr>
<th>Fit Percentage</th>
<th>Experts’ Mean</th>
<th>Expert 1</th>
<th>Expert 2</th>
<th>Expert 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Experts’ Mean</td>
<td>87.03%</td>
<td>83.60%</td>
<td>88.56%</td>
<td></td>
</tr>
<tr>
<td>Expert 1</td>
<td>87.03%</td>
<td>81.98%</td>
<td>74.73%</td>
<td></td>
</tr>
<tr>
<td>Expert 2</td>
<td>83.60%</td>
<td>73.11%</td>
<td>81.98%</td>
<td></td>
</tr>
<tr>
<td>Expert 3</td>
<td>88.56%</td>
<td>81.98%</td>
<td>74.73%</td>
<td></td>
</tr>
</tbody>
</table>

Fit percentage for all models versus experts’ mean is shown on Table 2. NARX output compared versus experts’ classification is shown on Figure 4 as an example of the classification achieved with the models developed.

**Table 2** Fit percentage for all models versus experts’ mean

<table>
<thead>
<tr>
<th>Model used</th>
<th>Fit percentage [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>ARX</td>
<td>68.8</td>
</tr>
<tr>
<td>NARX</td>
<td>88.59</td>
</tr>
<tr>
<td>NNARX</td>
<td>67.66</td>
</tr>
</tbody>
</table>

All models had 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. NNARX shows 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 NARX model since this was the model with the best global fit percentage. The results are shown in Table 3.

**Table 3** Individual stride’s fit percentage for NARX model versus experts’ mean

<table>
<thead>
<tr>
<th>Stride</th>
<th>Mean [%]</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>87.745</td>
</tr>
<tr>
<td>2</td>
<td>88.262</td>
</tr>
<tr>
<td>3</td>
<td>88.685</td>
</tr>
<tr>
<td>4</td>
<td>88.913</td>
</tr>
<tr>
<td>5</td>
<td>89.099</td>
</tr>
<tr>
<td>6</td>
<td>88.942</td>
</tr>
<tr>
<td>7</td>
<td>89.493</td>
</tr>
<tr>
<td>8</td>
<td>88.864</td>
</tr>
<tr>
<td>9</td>
<td>88.618</td>
</tr>
<tr>
<td>10</td>
<td>89.441</td>
</tr>
<tr>
<td>11</td>
<td>88.976</td>
</tr>
<tr>
<td>12</td>
<td>88.661</td>
</tr>
<tr>
<td>13</td>
<td>88.585</td>
</tr>
<tr>
<td>14</td>
<td>88.899</td>
</tr>
</tbody>
</table>

### IV. Discussion

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 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 on Table 1. 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 NARX and the experts' mean (88.59%), this suggest that NARX models 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 NARX model (shown on Table 3) is, in some cases, higher than 87%. Nevertheless, is important to say that even when there were differences between experts’ evaluations, the mean was used for training and validation since the results of the model identification was not affected by such differences. This made simpler the estimation process. Also 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.

NARX had better performance than ARX and NNARX (79.49%, 88.59% and 68.8% fit percentage respectively). It is known that high frequency components might be challenging for ARX 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 might be useful for different evaluations or biomechanics applications that don’t have to deal with high frequency components. Despite ARX models had lower accuracy than NARX, it must be said, it 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 [8]. However, in this work, results with NNARX didn’t show better performances than those obtained with classical models (ARX and NARX). This might be because, even if the estimation problem is addressed with NN’s, the model structure still is based on a ARX model. It is important to observe that, even though NN’s models didn’t show better performances than linear models, the conflict regions of the signal that were found for identification with a linear model (the corners of the square signal), didn’t seem to represent a major problem for the NNARX model. In fact, the high frequency changes of the signal were well followed by the NNARX model. It is interesting to observe that NNARX model 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.

In comparison with gait events classification reported using Artificial Neural Fuzzy Identification Systems (ANFIS) 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) [9], which is lower than the accuracy obtained with the NARX system developed (88.59%), also, one of the problems for the real time implementation was the number of rules contained by the fuzzy gait phase detector (210 rules were required). Using a same idea than 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 the NARX model 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 Kuen used the data from two legs), but the number of rules obtained by Kuen was at least 100 [10]. 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, correct detection percentage is also better with our NARX system, and the number of sensors used 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 don’t have high frequency components as high as in gait event detection, and that is why ANFIS have such a good performance [11]. The NARX system developed showed that even with high frequency components in the output, it can be used for gait events classification, while Jonic’s system showed that ANFIS is highly accurate for identification of systems with relatively low frequency components.

Lauer et al also used a supervisory control system (SCS)
systems, additional data for training/estimation, and gathering criteria from more experts.

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References