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Application of fuzzy NARX to human gait modelling and identification

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Abstract
A new modelling and classification approach for human gait is proposed. Body movements are obtained using a sensor suit recording inertial signals that are subsequently modelled on a humanoid frame with 23 degrees of freedom (DOF). Measured signals include position, velocity, acceleration, orientation, angular velocity and angular acceleration. The identification and modelling method segments the stream of non-linear movement data on the basis of the features extracted from the sensor signals. A model is then created for the movement of every individual. This model is used as a dynamic fingerprint for that specific individual. In the future stages of the work, the proposed approach will be further developed to include identification of various gestures and emotional manners as well as the identity of an individual. Furthermore, the feasibility of generating the identified behaviours in a humanoid robot will be explored. The approach is described and the characteristics of the algorithm are presented. The results obtained so far are reported and conclusions are drawn.

Keywords
fuzzy, narx, human, gait, application, modelling, identification

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1 Introduction

The human mind can derive rich and varied information from the characteristics of an individual’s movements or walk. Studies carried out in psychology confirm this observation. The aim of this study is to emulate this ability through machine intelligence. The focus of this paper is the development of a ‘Dynamic fingerprint’ (DFP) or a ‘Dynamic Signature’ derived for each individual based on characteristics of their body motion and gait.

Identification of an individual based on his/her biometric information has long been desirable for various applications and at the same time a challenge to achieve. Various methods have been developed in response to this need including fingerprints and iris identification. Such methods have proved to be partially reliable.

Human gait has been a popular field of research for over a century. Marey E.J [E-J Marey, 1895] studied the human gait as early as 1895 by attaching white tapes to the limbs of an individual, dressed in black body stocking. Cutting et al. [Cutting et al., 1978] introduced a biomechanical invariant for gait. Richardson and Johnston [Richardson and Johnston, 2005] used different participants to demonstrate the feasibility of recognition of a particular person among a group. Previous studies have shown that pattern of body movement can be adequate for identification of an individual [Berry and Misovich, 1994; Baron and Misovich, 1993]. Mounting incandescent bulbs to the joints in order to study the gait, a technique called cyclography, was implemented by Bernstein (1967).

Jaraba et al. [Jaraba et al, 2002] used a feature called centre of the control points and neural networks for individual recognition. Based on two experiments, [Stevenage et al., 1999] concluded that human visual system and brain is sophisticated enough to identify six participants based on their gait under normal and adverse viewing conditions. Cattin et al [Cattin et al., 2001] used three force plates to measure the ground reaction force and a CCD camera in order to identify a human being. Collins et al [Collins et al., 2002] applied template matching between some selected frames. Lee and Grimson [Lee and Grimson, 2002] fitted 7 ellipses to 7 regions of the body perpendicular to the direction of walk based on the canonical view of a walking person and used their locations, orientations, and aspect ratio as classification features. Ekinci [Ekinci, 2006] used distance vectors and principal component analysis (PCA) for dimension reduction and individual identification. Human movement is a non-linear process which could be modeled using non-linear black box modelling techniques. In a related approach Sherwood et al. [Sherwood et al., 2008] used four linear and nonlinear methods FIR (Finite Impulse Response), IIR (Infinite impulse response), Kalman Filter (KF), and Artificial Neural Network (ANN).

The aim of this study is to develop a ‘dynamic fingerprint’ (DFP) or a ‘dynamic signature’ derived for each individual based on characteristics of their body motion and gait.
Impulse Response), NARX and FTDNN (Focused Time Delay Neural Network) to build a model of a knee movement with 6 outputs (reaction forces and torques).

Franken and Veltink [Franken and Veltink, 1993] identified the dynamics of the knee - joint freely swinging lower leg system of paraplegic patients. Previdi and Carpanzano [Previdi and Carpanzano, 2003] studied feedback control of the knee – joint movement in paraplegic patients who have recovered partial functionality of muscles through Functional Electrical Simulation (FES). They used a polynomial NARX model for direct I/O controller and a standard LQ regulator has been defined as the starting point for designing a nonlinear gain scheduling controller.

The aim of this work is to develop an algorithm imitating human identification process by deploying kinematic properties of movement of an individual (position, velocity, and acceleration) and determining his/her identity. The recognition process is based on a sequence of motions. Nonlinear black box approach is used to model the dynamics of the input - output data and identify the relationship between them. A Nonlinear Autoregressive eXogenous (NARX) model using fuzzy logic is defined using the input data. Due to its non-linear characteristics, the NARX model can easily be used in the future deployment of the approach in robotics. The developed system can be also used in surveillance applications to identify criminals concealing their identity through changes to their physical appearance (haircut, aging, and plastic surgery).

The data used in the study is obtained using a sensor suit Moven® developed by Xsens [Xsens Technologies, 2008]. The inertial signals are measured and inferred through an inverse kinematic model of the human body with 23 degrees of freedom (DOF) model across the human body. The signals include position, velocity, acceleration, orientation, angular velocity and angular acceleration.

In this stage of study, the focus is on recognizing the characteristics of walk. A set of motion primitives is extracted from the captured data as the basis of the identification algorithm. The methodologies developed will be later applied to other human movements such as hand gestures. The paper reports on the work carried out so far. The data obtained from various candidates is analyzed to extract candidate motion primitives. In parallel to using the DFP for identification, the model can also be used to obtain further information about certain individuals, for example whether they are carrying a hidden artifact under their cloths. Caso et al [Caso et al., 2006] used hand movements to find the impact of deception and suspicion.

The paper is organized as follows. In Section 2 data acquisition is described. Section 3 covers the nonlinear black box modelling using fuzzy logic. In Section 4 experimental results using the models are presented, and finally the conclusion of the paper is presented in Section 5.

2 Data Acquisition Process

Data is being acquired using an inertial movement suit, Moven®, which provides data on 23 different segments of the body kinematics such as position, orientation, velocity, acceleration, angular velocity and angular acceleration as shown in Figure 1 and Figure 2.

In capturing human body motion, no external emitters or cameras are required. As explained by [Roetenberg et al., 2007], mechanical trackers use goniometers which are worn by the user to provide joint angle data to kinematics algorithms for determining body posture. Full 6 DOF tracking of the body segments is achieved using connected inertial sensor modules. The body segment orientation, position, velocity, acceleration, angular velocity and angular acceleration are also estimated using this method. The kinematics data is saved in an MVNX file format which is read and used, using an intermediate program coded in MATLAB.

Using the extracted features, a DFP can be generated for each individual. The DFP is used to identify the individual or detect departure from his/her expected pattern of behaviour. Using this comparison, it is possible to find the smoothness or stiffness of the movement and find out if the person is concealing an object. In order to recognize identity of an individual, different measurements will be made to extract the unique DFP for that individual. The data produced by the suit consists of kinematics information associated with 23 segments of
the body. The position, velocity, acceleration data for each segment will be then analyzed and a set of feature of derived including stride length (relative to height), type of walk, body movements, foot movements, arm swing, knee’s angle, thigh’s angle, centre of the gravity, smoothness and stiffness of the movements.

3 Modelling and Identification

A black box approach based on Autoregressive exogenous model (ARX) is deployed in this process to identify the relationship between input and output of the system under study (Figure 3). The overall approach for building the model is illustrated in Figure 4.

\[
A(q^{-1}) = 1 + a_1 q^{-1} + \ldots + a_{na} q^{-na} \\
B(q^{-1}) = b_1 q^{-1} + \ldots + b_{nb} q^{-nb} \tag{Eq.3}
\]

Another way of representing Eq.1 is by introducing the linear regression model which is formulated as a product of two vectors \( \phi'(k) \) and \( \Theta \) as Eq.4 and Eq.5:

\[
y(k) = \phi'^T(k) \Theta + e(k) \tag{Eq.4}
\]

\[
\phi'(k) = [-y(k-1), \ldots, -y(k-na), u(k-1), \ldots, u(k-nb)]
\]

\[
\Theta = [a_{na}, b_1, \ldots, b_{nb}]^T \tag{Eq.5}
\]

The vector \( \phi'(k) \) is the regression vector, which consists of input/output measurements and vector \( \Theta \) is the parameter vector of unknown parameters.

These models have been expanded to cover nonlinear identification and modelling using fuzzy technique. A nonlinear model is described by Eq.6:

\[
y(k) = f(y(k-1), \ldots, y(k-na), u(k-1), \ldots, u(k-nb)) + e(k) \tag{Eq.6}
\]

Where \( f() \) is a nonlinear function of the regression and parameter vectors, and \( na \) and \( nb \) are the system’s orders. Eq.6 can be also written in terms of regression and parameter vectors as Eq.7:

\[
y(k) = f[\phi'^T(k), \Theta] + e(k) \tag{Eq.7}
\]

As in [Nelles, 2001], Takagi and Sugeno proposed a new type of fuzzy system with rules as follows:

\[
R_i: \text{IF } u_1 = A_{i1} \text{ AND } \ldots \text{ AND } u_P = A_{iP} \text{ THEN } \]

\[
y = f_i(u_1, u_2, \ldots, u_P) \tag{Eq.8}
\]

If functions \( f_i() \) are trivially chosen as constants, a singleton fuzzy system is recovered which is called a zero-th order Takagi - Sugeno fuzzy system, since a constant can be seen as a zero-th order Taylor series expansion of a function \( f_i() \). The output of a Takagi - Sugeno fuzzy system can be calculated by Eq.9 and illustrated in Figure 5:

\[
y(k) = \sum_{i=1}^M \frac{\mu_i(u)}{\sum_{i=1}^M \mu_i(u)} f_i(u_1, u_2, \ldots, u_P) \tag{Eq.9}
\]

For a nonlinear model, we construct a model structure where the regression vector is the input to a nonlinear fuzzy logic system. The nonlinear ARX model is named NARX. By using Takagi – Sugeno rules, the
NARX model for rule i is given by:

\[ R_i : \text{IF } y(k) = A_{i1} \text{ AND } \ldots y(k-na) = A_{ina} \text{ AND } u(k) = B_{i1} \text{ AND} \ldots u(k) = B_{ina}, \text{ THEN} \]

\[ y_i(k+1) = a_{i1} y(k) + \ldots + a_{ina} y(k-na) + b_{i1} u(k) + \ldots + b_{ina} u(k-na) \]

The output of the fuzzy system is given in Eq.10:

\[ \hat{y}(k+1) = \frac{\sum_{i=1}^{k} \beta_i \hat{y}_i(k+1)}{\sum_{j=1}^{na} \prod_{j=1}^{na} \mu_{Aij} [\phi(k)]} \]

\[ \beta_i = \frac{\sum_{j=1}^{nj} \prod_{j=1}^{na} \mu_{Aij} [\phi(k)]}{\sum_{j=1}^{nj} \prod_{j=1}^{na} \mu_{Aij} [\phi(k)]} \]

Some researchers such as [Hatanaka et al., 2004] have optimized Takagi - Sugeno fuzzy by using Genetic algorithm in designing the membership functions.

The Fuzzy Modelling and Identification (FMID) toolbox has been used for construction and validation of various models [Babuska, 1998]. In order to automatically generate fuzzy models from measurements, a comprehensive methodology is implemented. Fuzzy clustering technique is employed to partition the available data into subsets characterized by a linear behavior. Based on the fuzzy partitions, a multivariable model of the Takagi - Sugeno type is constructed. The toolbox provides both modelling and simulation tools.

4 Experimental Results

The data produced by the Moven system is stored in rich detail within an MVNX (Moven Open XML format) file which contains 3D position, 3D orientation, 3D acceleration, 3D velocity, 3D angular rate and 3D angular acceleration of each segment in an XML format (ASCII). The orientation output is represented by quaternion formalism. In Figure 6, a sample walk of one of the participants is demonstrated where the arrow is the origin of space.

In order to examine the Dynamic Finger Print hypothesis, ten individuals (5 Males and 5 Females between 18 - 40) wearing the Moven suit, undertook four repetitions of a simple walking task. From these tasks, a range of some 3,210 cases of knee and thigh angles, across the ten individuals were collected and recorded. Features for an identification trial, right knee’s angle for four participants for 2 repetitions per each individual is shown in Figure 7. For this trial, the goal was to clearly identify an individual based on purely a combination of subtended angles at the knee and thigh by modelling the individual’s movement using fuzzy ARX model. The secondary goal is to find the similarities of walk between the participants.

One set of data has been used for modelling and two others for validation and testing of the generated models. The MATLAB toolbox has been used to approximate four signals of right knee, left knee angles, right thigh and left thigh angles. The model is presented in Figure 8.

Before feeding the data into the toolbox, the linear trends and mean have been removed from the data as shown in Figure 8 for the right knee angle of participant 1.
Before starting the modelling process, the fuzzy modelling variables are initialized. The number of clusters per output (number of rules) which will be used to partition the available data into subsets characterized by a linear behaviour is set to 5 and then increased to 15. The type of antecedent of the fuzzy model has been set to projected memberships. The variance account for each data set (VAF) that demonstrates percentage of matching to the generated model’s output, is considered as an evaluation parameter, and is calculated from Eq.11:

\[ VAF = 100\% \cdot \left[ 1 - \frac{\text{var}(y_1 - y_2)}{\text{var}(y_1)} \right] \]  

Eq.11

The VAF of two signals is 100%, if the two signals are identical. The VAF decreases if the two signals differ. The model is tested by both the training data and validation data. The outputs of the model having 5 clusters per output are shown in Figures 10-15.

![Figure 10. Model Output Comparison for Real outputs (Participant 1, training data).](image)

![Figure 11. Model Output Comparison for Real outputs (Participant 1, validation data & Participant 2).](image)

![Figure 12. Model Output Comparison for Real outputs (Participant 3 & Participant 4).](image)

![Figure 13. Model Output Comparison for Real outputs (Participant 5 & Participant 6).](image)

![Figure 14. Model Output Comparison for Real outputs (Participant 7 & Participant 8).](image)

![Figure 15. Model Output Comparison for Real outputs (Participant 9 & Participant 10).](image)

The VAF for each output is shown in Table.1:

<table>
<thead>
<tr>
<th>Participant</th>
<th>Right Knee</th>
<th>Right Thigh</th>
<th>Left Knee</th>
<th>Left Thigh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participant 1 (Training Data)</td>
<td>90.6552</td>
<td>95.0108</td>
<td>98.4626</td>
<td>94.6401</td>
</tr>
<tr>
<td>Participant 1 (Testing Data)</td>
<td>96.1609</td>
<td>94.1697</td>
<td>98.5555</td>
<td>94.7171</td>
</tr>
<tr>
<td>Participant 2</td>
<td>90.3022</td>
<td>93.0106</td>
<td>79.6133</td>
<td>14.3035</td>
</tr>
<tr>
<td>Participant 3</td>
<td>64.8587</td>
<td>45.6069</td>
<td>66.3686</td>
<td>11.6427</td>
</tr>
<tr>
<td>Participant 4</td>
<td>62.0717</td>
<td>74.7742</td>
<td>31.4656</td>
<td>1.9312</td>
</tr>
<tr>
<td>Participant 5</td>
<td>95.5756</td>
<td>79.5106</td>
<td>94.1211</td>
<td>68.5461</td>
</tr>
<tr>
<td>Participant 6</td>
<td>-123.7460</td>
<td>-20.6091</td>
<td>-64.9393</td>
<td>-210.3090</td>
</tr>
<tr>
<td>Participant 7</td>
<td>-89.0320</td>
<td>-89.0535</td>
<td>70.2446</td>
<td>-29.0546</td>
</tr>
<tr>
<td>Participant 8</td>
<td>-73.9643</td>
<td>-32.3634</td>
<td>-64.2802</td>
<td>-186.0898</td>
</tr>
<tr>
<td>Participant 9</td>
<td>75.1303</td>
<td>-9.6918</td>
<td>66.6822</td>
<td>-293.4966</td>
</tr>
<tr>
<td>Participant 10</td>
<td>-54.1564</td>
<td>-3.216</td>
<td>32.5261</td>
<td>11.6693</td>
</tr>
</tbody>
</table>

Table 1. VAF (%) for all outputs.

As seen in the table, the largest values are produced from the data set of participant 1 based on the training data. The second largest VAF value belongs to the data set from participant 1 – the testing data. The rest of the outputs have smaller values and could be easily recognized. The advantage of this model is that comparison between different people’s gait would be possible. For instance, participant 2’s left knee is very close to the participant’s 1 left knee, or in total has a VAF of 48.822% against participant 2. The criteria for comparison and identification would be the total average of VAF/Person which is shown in Table.2:
According to the definition for VAF there can be negative values, so the smaller the value the more different the comparing signals will be. This can be significantly improved by increasing the number of clusters from 5 to 15, where in the subsequent model outputs can now be seen in Figures 16-21:

The VAF for each output is shown in Table 3:

<table>
<thead>
<tr>
<th>Participant</th>
<th>Right Knee</th>
<th>Right Thigh</th>
<th>Left Knee</th>
<th>Left Thigh</th>
</tr>
</thead>
<tbody>
<tr>
<td>Participant 1 (Training Data)</td>
<td>93.962%</td>
<td>99.971%</td>
<td>98.728%</td>
<td>98.728%</td>
</tr>
<tr>
<td>Participant 1 (Testing Data)</td>
<td>97.4012%</td>
<td>87.786%</td>
<td>98.728%</td>
<td>98.728%</td>
</tr>
<tr>
<td>Participant 2</td>
<td>95.659%</td>
<td>43.909%</td>
<td>79.978%</td>
<td>13.927%</td>
</tr>
<tr>
<td>Participant 3</td>
<td>64.796%</td>
<td>45.787%</td>
<td>65.247%</td>
<td>8.936%</td>
</tr>
<tr>
<td>Participant 4</td>
<td>87.606%</td>
<td>71.611%</td>
<td>19.421%</td>
<td>3.930%</td>
</tr>
<tr>
<td>Participant 5</td>
<td>94.516%</td>
<td>93.789%</td>
<td>94.391%</td>
<td>93.364%</td>
</tr>
<tr>
<td>Participant 6</td>
<td>62.868%</td>
<td>14.395%</td>
<td>63.805%</td>
<td>233.549%</td>
</tr>
<tr>
<td>Participant 7</td>
<td>88.627%</td>
<td>95.647%</td>
<td>89.156%</td>
<td>33.584%</td>
</tr>
<tr>
<td>Participant 8</td>
<td>-1.264%</td>
<td>-16.745%</td>
<td>-89.564%</td>
<td>-169.406%</td>
</tr>
<tr>
<td>Participant 9</td>
<td>71.147%</td>
<td>8.476%</td>
<td>65.275%</td>
<td>-256.781%</td>
</tr>
<tr>
<td>Participant 10</td>
<td>89.121%</td>
<td>-14.544%</td>
<td>94.569%</td>
<td>7.082%</td>
</tr>
</tbody>
</table>

Table 3. VAF (%) for all outputs.

According to this table, increasing the number of clusters increases the performance of the model. However, by increasing the clusters further up to 35, there does not
appear to be any significant changes in the outputs.

5 Conclusions

Takagi – Sugeno technique was deployed in this study to model the subtended angles at the knees and thighs produced during walk. The performance of the model was validated for different partition sizes of the input data. The model produced 95.156% matching for a cluster size of 15 in the input space. Such generated models could conceivably be utilized as reference models when teaching humanoid robots to imitate an individuals walking gait. Using these and additional features of an individual’s movements it is anticipated that further improvements for robust bipedal control and accurate modelling, identification and classification will be realised. Additional applications of DFP models will include their application in the area of animation where a character's gait and other motions could more closely adhere to reality.

References


