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 finger print* 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.

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 finger Print' (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) , 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.

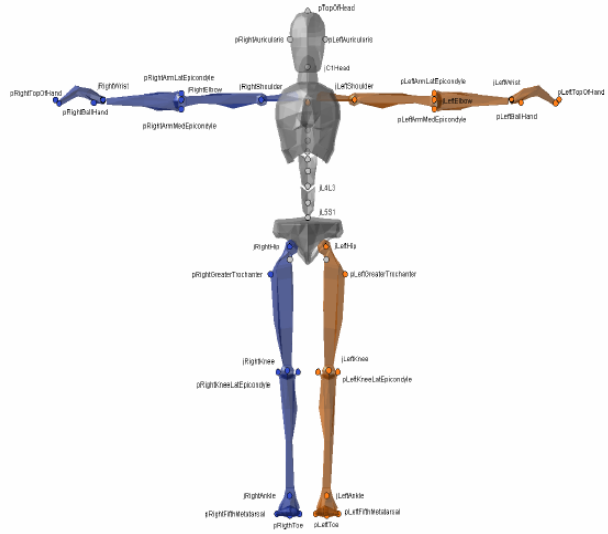

Figure 1. Anatomical Landmarks for the Moven® suit.

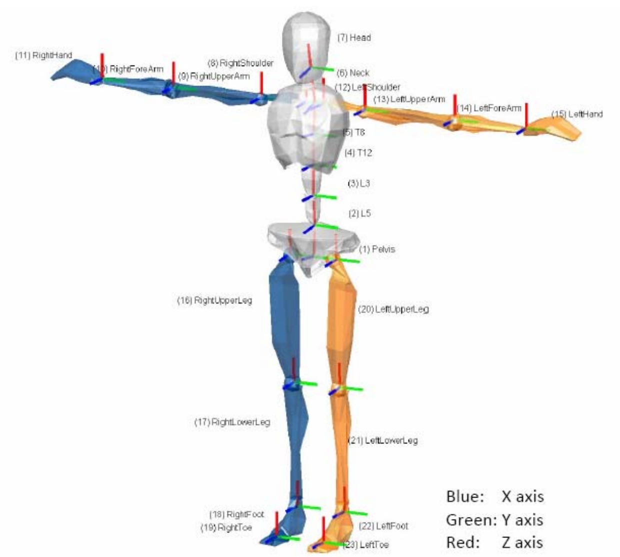

Figure 2. Body Segments defined in the Moven® suit.

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.

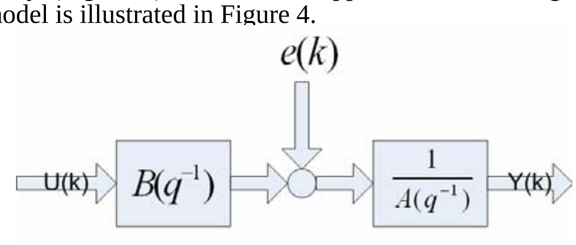

Figure 3. ARX Model.

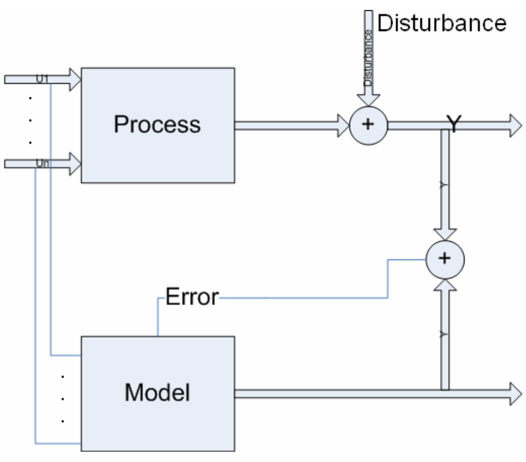

Figure 4. System Identification.

In this process, the output is influenced by disturbance, which is assumed to be white discrete noise. Accordingly, the model is represented by Eq.1 [Sohlberg, 2004]:

$$y(k)+a_1 y(k-1)+\ldots+a_{na} y(k-na)=b_1 u(k-1)+\ldots+b_{nb} u(k-nb) + e(k) \qquad \text{Eq.1}$$

By using the shift operator q^{-1}, the model is reformulated in the following compact form:

$$A(q^{-1})y(k)=B(q^{-1})u(k)+e(k) \qquad \text{Eq.2}$$

Where A and B are the model parameters and should be estimated, e is the disturbance, na is the number of past output terms and nb is the number of the past input values used to predict the current output. The parameters na and nb determine the order of the polynomials. The polynomials $A(q^{-1})$ and $B(q^{-1})$ are defined by Eq.3:

$$A(q^{-1})=1+a_1 q^{-1}+\ldots+a_{na} q^{-na}$$
$$B(q^{-1})=b_1 q^{-1}+\ldots+b_{nb} q^{-nb} \qquad \text{Eq.3}$$

Another way of representing Eq.1 is by introducing the linear regression model which is formulated as a product of two vectors $\varphi^T(k)$ and θ as Eq.4 and Eq.5:

$$y(k)=\varphi^T(k).\theta+e(k) \qquad \text{Eq.4}$$

$$\varphi^T(k)=[-y(k-1)\ldots y(k-na) \quad u(k-1)\ldots u(k-nb)]$$
$$\theta=[a_1\ldots a_{na} \quad b_1\ldots b_{nb}]^T \qquad \text{Eq.5}$$

The vector $\varphi^T(k)$ is the regression vector, which consists of input/output measurements and vector θ 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:

$$y(k)=f(y(k-1),\ldots,f(y-na),u(k-1),\ldots,u(k-nb)) + e(k) \qquad \text{Eq.6}$$

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:

$$y(k)=f[\varphi^T(k),\theta]+e(k) \qquad \text{Eq.7}$$

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

$$R_i: \text{IF } u_1=A_{i1} \text{ AND} \ldots \text{AND } u_P=A_{iP} \text{ THEN}$$
$$y=f_i(u_1,u_2,\ldots,u_P) \qquad \text{Eq. 8}$$

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:

$$\hat{y}=\frac{\sum_{i=1}^{M} f_i(u)\mu_i(u)}{\sum_{i=1}^{M}\mu_i(u)} \qquad \text{Eq.9}$$

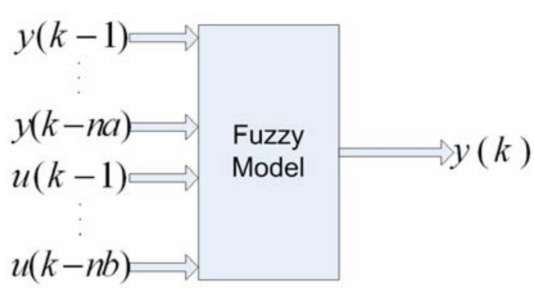

Figure 5. Fuzzy ARX Model.

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 : IF $y(k) = A_{i1}$ AND … $y(k-na) = A_{ina}$ AND $u(k) = B_{i1}$ AND… $u(k) = B_{inb}$ THEN

$$y_i(k+1) = a_{i1}y(k) + ... + a_{ina}y(k-na) + b_{i1}u(k) + ... + b_{inb}u(k-nb)$$

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

$$\hat{y}(k+1) = \sum_{i=1}^{k} \beta_i \hat{y}_i(k+1)$$

$$\beta_i = \frac{\prod_{j=1}^{na} \mu_{Aij}[\varphi(k)]}{\sum_{k=1}^{nj} [\prod_{j=1}^{na} \mu_{Aij}[\varphi(k)]]} \qquad \text{Eq.10}$$

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.

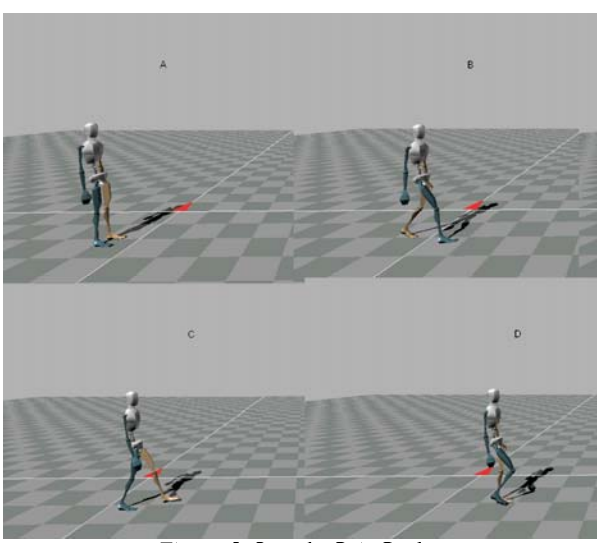

Figure 6. Sample Gait Cycle.

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.

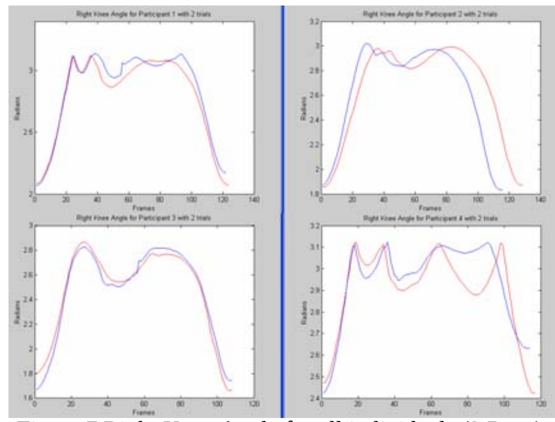
Figure 7.Right Knee Angle for all individuals (2 Reps).

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.

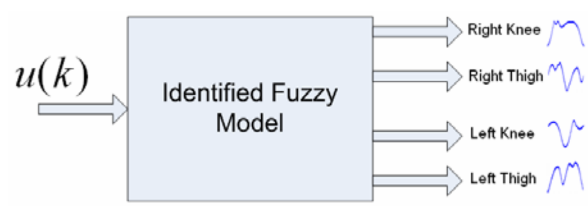

Figure 8. Identified Fuzzy Model.

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.

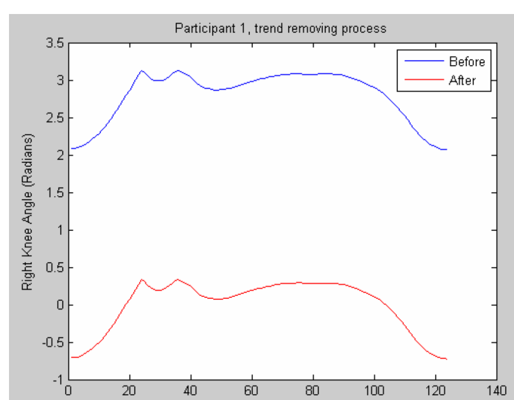

Figure 9. Trend and Mean Removal.

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:

$$VAF = 100\%.[1 - \frac{\mathrm{var}(y_1 - y_2)}{\mathrm{var}(y_1)}] \qquad \text{Eq.11}$$

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.

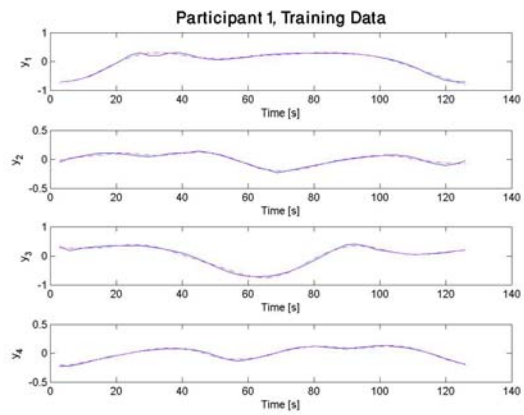

Figure 10. Model Output Comparison for Real outputs (Participant 1, training data).

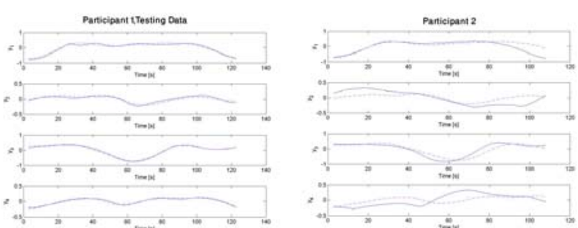

Figure 11. Model Output Comparison for Real outputs (Participant 1, validation data & Participant 2).

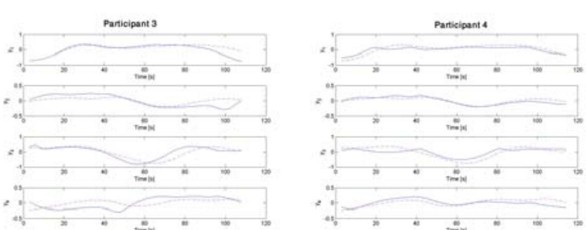

Figure 12. Model Output Comparison for Real outputs (Participant 3 & Participant 4).

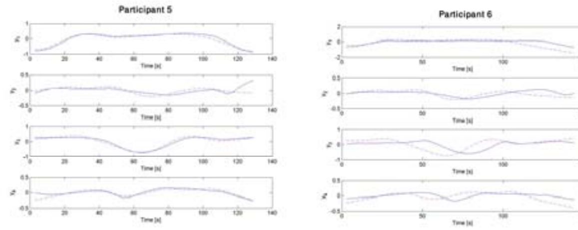

Figure 13. Model Output Comparison for Real outputs (Participant 5 & Participant 6).

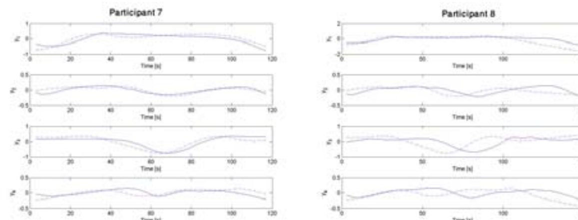

Figure 14. Model Output Comparison for Real outputs (Participant 7 & Participant 8).

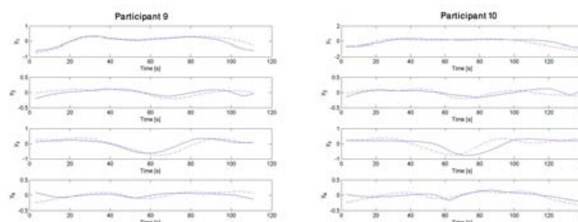

Figure 15. Model Output Comparison for Real outputs (Participant 9 & Participant 10).

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

Participant	Right Knee	Right Thigh	Left Knee	Left Thigh
Participant 1 (Training Data)	98.8033	95.7635	98.9169	98.4401
Participant 1 (Testing Data)	96.1989	84.1697	98.5555	94.7711
Participant 2	58.3022	43.0108	79.6113	14.3635
Participant 3	64.6287	45.0586	66.3889	11.0427
Participant 4	42.0717	74.7742	11.4654	0.3312
Participant 5	95.575	-18.9101	94.1211	68.541
Participant 6	-102.7485	-26.8916	-94.9383	-210.3939
Participant 7	69.9385	58.0533	70.2446	-35.0546
Participant 8	-73.9943	-32.2634	-94.2602	-158.0598
Participant 9	75.1333	-2.6918	66.6822	-293.4986
Participant 10	54.1964	-3.214	32.5261	11.5929

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:

Participant	Total VAF/Person
Participant 1 (Training Data)	97.9810%
Participant 1 (Testing Data)	93.4238%
Participant 2	48.8220%
Participant 3	46.7797%
Participant 4	32.1606%
Participant 5	59.83%
Participant 6	-108.7431%
Participant 7	40.7955%
Participant 8	-89.6444%
Participant 9	-38.5937%
Participant 10	23.7754%

Table 2.Total Average of VAF (%) Per Person for all outputs.

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:

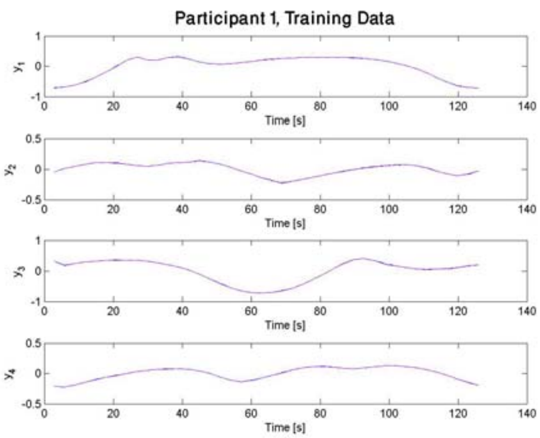

Figure 16. Model Output Comparison for Real outputs (Participant 1, training data).

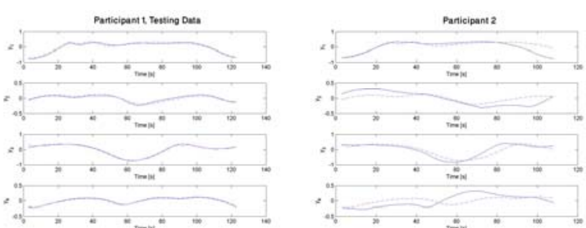

Figure 17. Model Output Comparison for Real outputs (Participant 1, Testing data & Participant 2).

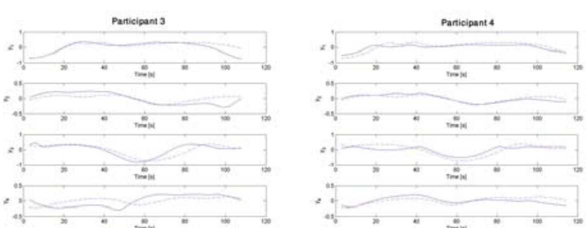

Figure 18. Model Output Comparison for Real outputs (Participant 3 & Participant 4).

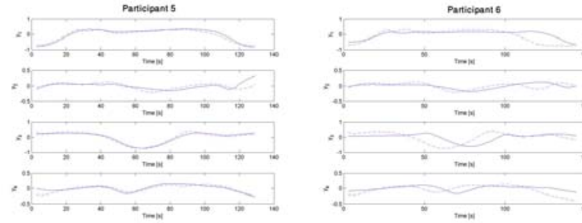

Figure 19. Model Output Comparison for Real outputs (Participant 5 & Participant 6).

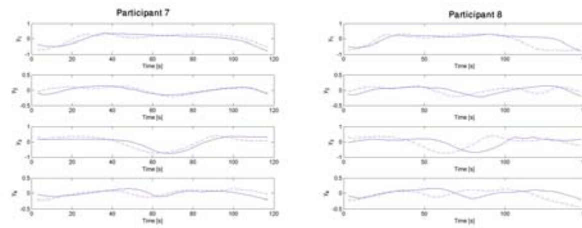

Figure 20. Model Output Comparison for Real outputs (Participant 7 & Participant 8).

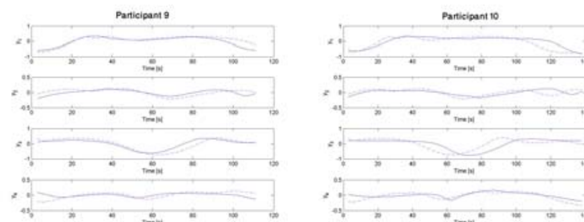

Figure 21. Model Output Comparison for Real outputs (Participant 9 & Participant 10).

The VAF for each output is shown in Table.3:

Participant	Right Knee	Right Thigh	Left Knee	Left Thigh
Participant 1 (Training Data)	99.9922	99.8765	99.9715	99.9824
Participant 1 (Testing Data)	97.4012	87.7668	98.7269	96.729
Participant 2	55.6938	43.8868	79.0866	13.261
Participant 3	61.7969	45.7262	65.2906	8.7962
Participant 4	37.6006	71.4811	10.4214	3.9531
Participant 5	94.9163	8.2166	94.3987	69.2864
Participant 6	-32.8898	-14.3595	-103.6705	-233.5192
Participant 7	68.8271	56.6473	69.1961	-33.2642
Participant 8	-1.2542	-16.7944	-98.954	-169.4062
Participant 9	71.7147	-9.4769	66.0751	-296.7491
Participant 10	60.1214	-14.9344	29.5635	7.0234

Table 3.VAF (%) for all outputs.

Participant	Total VAF/Person
Participant 1 (Training Data)	99.9556%
Participant 1 (Testing Data)	95.1560%
Participant 2	47.9821%
Participant 3	45.4025%
Participant 4	30.8641%
Participant 5	66.7045%
Participant 6	-96.1098%
Participant 7	40.3516%
Participant 8	-71.6022%
Participant 9	-42.1090%
Participant 10	20.4435%

Table 4.Total Average of VAF (%) Per Person 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 characters gait and other motions could more closely adhere to reality.

References

[E-J Marey, 1895] Centre Nationale d'Art Moderne, E-J Marey 1830/1904: La Photofraphie Du Movement Paris Centre Georges Pompidou, Musee national d'art moderne, Paris.

[Cutting et al.,1978] James E.Cutting, Dennis R.Proffitt, and Lynn T.Kozlowski. *A Biomechanical Invariant for Gait Perception*. Journal of Experimental Psychology: Human Perception and Performance 1978, Vol.4, No. 3, 357 – 372.

[Richardson and Johnston,2005] Michael J.Richardson and Lucy Johnston. *Person recognition from dynamic events: The kinematic specification of individual identity in walking style*. Journal of Nonverbal behavior, 29(1), Spring 2005 @ Springer Science + Business Media Inc.

[Berry and Misovich,1994] Diane S.Berry, Stephen J.Misovich. *Methodological Approaches to the study of social event perception*. Society for personality and social psychology, 1994.

[Baron and Misovich,1993] Reuben M.Baron, Stephen J. Misovich. *Dispositional Knowing From and ecological perspective*. Society for personality and social Psychology, 1993.

[Jaraba et al.,2002] J.Elias Herrero – Jaraba, Carlos Orrite – Urunueka, David Buldain, and Armando Roy – Yarza. *Human Recognition by gait analysis using neural networks*. Springer – Verlag Berlin Heidelberg 2002.

[Stevenage et al.,1999] Sarah V.Stevenage, Mark S.Nixon and Kate Vince. *Visual Analysis of gait as a cue to identity*. Applied cognitive psychology, 13: 513 – 526 (1999).

[Cattin et al.,2001] Philipppe C. Cattin, Daniel Zlantik, and Ruedi Borer. *Biometric System using Human Gait.* Institute of Robotics, Swiss Federal Institute of Technology (ETH) 2001.

[Collins et al.,2002] T.Collins, R. Gross, and J.Shi. *Silhouette – based human identification from body shape and gait.* International Conference on Automatic Face and Gesture Recognition, 2002.

[Lee and Grimson,2002] L.Lee and W.E.L. Grimson.*Gait analysis for recognition and classification*. IEEE Conference on Face and Gesture Recognition, 155 – 161 , 2002.

[Ekinci, 2006] Murat Ekinci. *A New approach for human identification using gait recognition*. Springer – Verlan Berlin Heidelberg 2006.

[Sherwood et al.,2008] Jesse Sherwood, Reza Derakhshani, Trent Guess.*A Comparative Study of Linear and Nonlinear Data - Driven Surrogate Models of Human Joints*.University of Missouri - Kansas City, 2008.

[Franken et al., 1993] Henry M. Franken, Peter H. Veltink, Member, IEEE, Roel Tijsmans, Henk Nijmeijer, Senior Member, IEEE, and Herman B. K. Boom, Associate Member, IEEE. *Identification of Passive Knee Joint and Shank Dynamics in Paraplegics Using Quadriceps Stimulation*. IEEE Transactions on Rehabiliation Engineering, VOL. I. NO. 3. Sep 1993.

[Previdi and Carpanzano,2003] Fabio Previdi and Emanuele Carpanzano. *Design of a Gain Scheduling Controller for Knee-Joint Angle Control by Using Functional Electrical Stimulation.* IEEE Transactions on Control Systems Technology, VOL. 11, NO. 3, May 2003.

[Xsens Technologies, 2008] Xsens Technologies B.V., Moven®, wireless inertial motion capture, www.xsens.com.

[Caso et al.,2006] Letizia Caso, Fridanna Maricchiolo, Marino Bonaiuto, Aldert Vrij, and Samantha Mann. *The impact of deception and suspicion on different hand movements*. Journal of Nonverbal behavior, 2006.

[Roetenberg et al.,2007] Daniel Roetenberg, Henk Luinge, and Per Slycke. *Moven: Full 6DOF Human Motion Tracking Using Miniature Inertial Sensors*. Xsen Technologies, December, 2007.

[Sohlberg, 2004] Bjorn Sohlberg. *Applied Modelling & Identification*. Dalarna University, Sweden.

[Nelles, 2001] Oilver Nelles. *Nonlinear System Identification*. Springer Verlan. Heidelberg.

[Hatanaka et al., 2004] Toshiharu Hatanaka, Yoshio Kawaguchi and Katsuji Uosaki. *Nonlinear System Identification Based on Evolutionary Fuzzy Modeling*.Department of Information and Physical Science,Osaka University, Japan, 0-7803-851 5-2/04 2004 IEEE.

[Babuska, 1998] Robert Babuska. *Fuzzy Modeling and Identification Toolbox For Use with Matlab*. Faculty of Information Technology and Systems,Delft University of Technology, The Netherlands.