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Efficiency of the Memory Polynomial Model in Realizing Digital Twins for Gait Assessment

Javier Conte Alcaraz*, Sanam Moghaddamnia†, Martin Fuhrwerk* and Jürgen Peissig*
*Institute of Communications Technology †Department of Electrical Engineering
*Leibniz Universität Hannover †Türkisch-Deutsche Universität

***Abstract*—One of the key issues of multi-sensory digital healthcare and therapy is the reliability and user compliance of the applied sensor system. In the context of digital gait analysis and rehabilitation, different technologies have been proposed allowing objective gait assessment and precise quantification of the rehabilitation progress using Inertial Measurement Unit (IMU) platforms. However, this depends largely on the estimation accuracy of the kinematics (body joint angles). This paper presents the concept of a digital equivalent based on the Memory Polynomial Model (MPM) to reduce the number of IMUs needed for the measurements and to simulate the physical mechanism of lower body joint angles based on acceleration data. The MPM parameter estimation is based on the Least Square (LS) approach and is performed using accelerometer records of non-pathological gait patterns. The Normalized Mean Square Error (NMSE) is used to evaluate the performance of the model. According to the results an NMSE of -20 dB is achieved, which indicates the great potential of applying the MPM to develop a digital twin. That kind of twin can serve as a prototype of the physical counterpart to improve the wearability of the sensor system and to reduce physically induced measurement errors as well.**

***Index Terms*—Gait rehabilitation, Nonlinear time-varying modeling, IMU, Multi-sensor integration, Digital twin, Machine learning**

I. Introduction

Wearable devices such as accelerometers, gyroscopes and magnetometers or a combination of them have been widely used in gait analysis and monitoring of physical activity [1], [2]. Nevertheless, the application of Wearable Technology (WT) in gait analysis is not limited to gait event detection and the calculation of spatiotemporal features, but include investigations on the stability and variability of normal and abnormal gait [3], [4] as well as the classification of various types of gait patterns [5]. Modeling gait patterns and gait phase recognition has attracted great attention in recent years [6], [7]. As WT products such as smartphones, fitness trackers, smartwatches and IMUs become cheaper, it becomes possible to use them in field-based applications. In this application it is desirable to use a small number of simply structured sensor modules at non-intrusive body locations and to determine the kinematics of other target locations using estimations techniques. This enables the derivation of digital counterparts which reduces the required amount of the data measurements. Building digital counterparts helps to increase the user acceptance and reduce error-proneness associated with measurement systems.

Behavior modeling approaches have been successfully utilized in the telecommunication industry to detect and equalize nonlinear effects induced by high power amplifiers [8]. In this paper, we propose the concept of the segment to segment modeling to design task-specific digital twins for reliable and user-friendly gait therapy applications. The digital equivalent can replace the physical counterpart (see Fig. 1) and requires no special knowledge of the physical structure of the human biomechanics, which in the case of the human movement is quite complex [9]. Therefore, we investigate the efficiency of the MPM in simulating the physical mechanism of lower body joint angles and its applicability as digital twin for gait kinematic analysis. To this end, we evaluate the performance of modeling different joint angles by means of NMSE based on signals of an IMU located at the feet.

The paper is organized as follows. In Section II, the modeling approach and the estimation methods used to determine the model parameters are described. Section III provides an overview on the sensor system and measured data. The signal processing process applied to raw acceleration signals are explained in Section IV. In Section V, the performance of the MPM is evaluated and discussed. Finally, the main conclusion of this work is presented in Section VI.

II. Modeling Approach

Modeling is the process of representing situations or phenomena as a set of mathematical equations. Mainly, there are physical and behavioral based modeling approaches. A physical model requires knowledge of the internal system construction, its elements and the theoretical rules describing the interactions between them [10]. A behavioral model does not require any prior knowledge and is built from the system input and output measurements. In this paper, the behavioral modeling approach is investigated. The model selection is carried out using criteria such as accuracy, computational complexity and the method used to estimate the model parameters. The

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most comprehensive form of a nonlinear system with memory is described by the Volterra series, which is a sum of multidimensional convolutions [11]. The Volterra model is suitable for modeling dynamic nonlinear behavior and provides high accuracy, however at the cost of very high computational complexity [12]. Among various nonlinear models with memory proposed in the literature, the MPM with moderate complexity and high accuracy is a widely-used behavioral model, particularly in the field of telecommunications [13].

A. Model Description and Identification

Due to the advantages in terms of performance and complexity, the MPM is seen as a promising approach in realizing digital twins for gait kinematic analysis. The mathematical description of the model is given by

$$\hat{y}(n) = \sum_{k=1}^{K}\sum_{q=0}^{Q} a_{kq}x(n-q)|x(n-q)|^{k-1}, \qquad (1)$$

where Q and K are the memory depth and nonlinearity order, respectively. $x(n)$ and $\hat{y}(n)$ are the discrete-time model input and output signals, respectively. The model coefficients are a_{kq}. Fig. 1 illustrates the system concept in which the MPM is used. In most telecommunication high power amplifier models, only the odd-order nonlinear terms are calculated, because the even-order terms are usually outside of the operational bandwidth [12]. Currently few studies have been conducted in biosignal processing using MPM [14]. Therefore, either all, even or odd-terms are analyzed to determine the optimal values for K and Q (see Fig. 2 and Fig. 3). The MPM is linear in its coefficients and can be identified using the LS technique [15]. The easiest way to implement the LS algorithm is to use the vector presentation as follows:

$$\mathbf{y} = X\mathbf{a} \qquad (2)$$

where

$$\mathbf{y} = [y(0)\ y(1)\ \dots y(N-1)]^T \qquad (3)$$

$$\mathbf{a} = [a_{10}\dots a_{K0},\, a_{11}\dots a_{K1},\, \dots,\, a_{1Q}\dots a_{KQ}]^T \qquad (4)$$

$$X = \begin{bmatrix} x_{1,0}(0) & x_{1,1}(0) & \cdots & x_{K,Q}(0) \\ \vdots & \vdots & \ddots & \vdots \\ x_{1,0}(N-1) & x_{1,1}(N-1) & \cdots & x_{K,Q}(N-1) \end{bmatrix} \qquad (5)$$

with

$$x_{k,q}(n) = x(n-q)|x(n-q)|^{k-1}. \qquad (6)$$

Thus, the MPM coefficients $\mathbf{a}$ can be calculated using the LS solution for real valued signals given by

$$\mathbf{a} = (X^TX)^{-1}X^T\mathbf{y}, \qquad (7)$$

where $(\cdot)^{-1}$ represents matrix inversion.

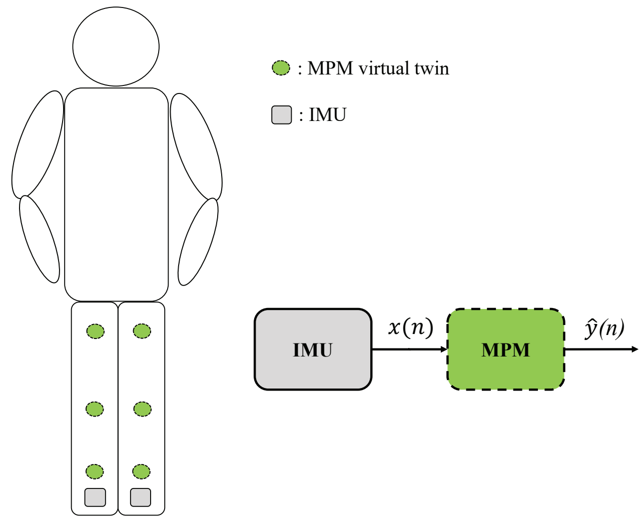

Fig. 1. System concept – accelerometer data $x(n)$ recorded at the feet is used to simulate the joint angle $\hat{y}(n)$ of lower limbs.

B. Performance

Accuracy in modeling is a major requirement in digital twin realization, and thus it is of essential importance to use sound criteria to assess the model performance. A very common criterion in time domain is the NMSE given by

$$\text{NMSE (dB)} = 10\,\log_{10}\left(\frac{\sum_{n=0}^{N-1}|y(n)-\hat{y}(n)|^2}{\sum_{n=0}^{N-1}|y(n)|^2}\right), \qquad (8)$$

where $\hat{y}(n)$ and $y(n)$ are the estimated output of the model and the reference signal, respectively [16]. N is the length of the signal. In this paper, the reference signals used to validate the model are the lower limbs joint angles (hip, knee and ankle).

III. Experimental Setup

In this study, 18 healthy participants (mean age: 22±4 years, height: 178±4 cm) from our faculty are considered. It is worth mentioning that the medical history of all participants shows no pathological findings or surgical intervention in the lower limbs. The data recording was performed via wireless IMUs from the company Shimmer with Bluetooth connected to a mobile Android tablet and the data processing was conducted in MATLAB. Only the 16 bit triaxial ±16 g accelerometer and ±2000 °/s gyroscope data with the sampling rate of 60 Hz are used for investigations. The IMU sensors were placed at the feet, lower legs, upper legs and the pelvis of the participants. The orientation of the sensor's axis was set arbitrary due to the signal processing techniques applied in Section IV. The IMUs were secured with tight tape to reduce motion artifacts. Each participant performed a walk test in forward and backward directions of around 15 m at a preferred velocity, and subsequently

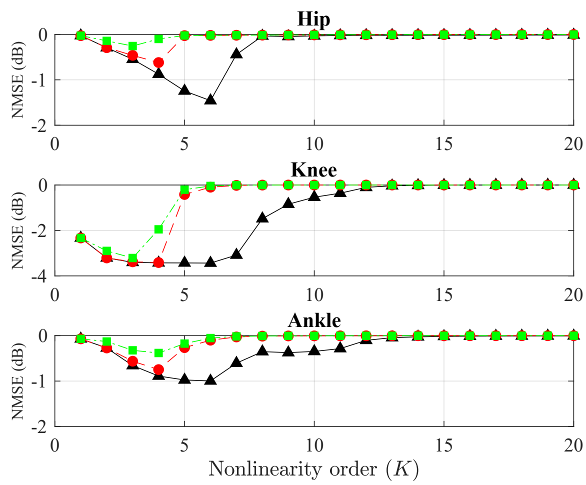

Fig. 2. Performance comparison of MPM for different nonlinearity orders K. Triangle markers represent the all-order terms. Circle markers represent the even-order terms. Square markers represent the odd-order terms. The optimal values can be found, where the NMSE is minimized.

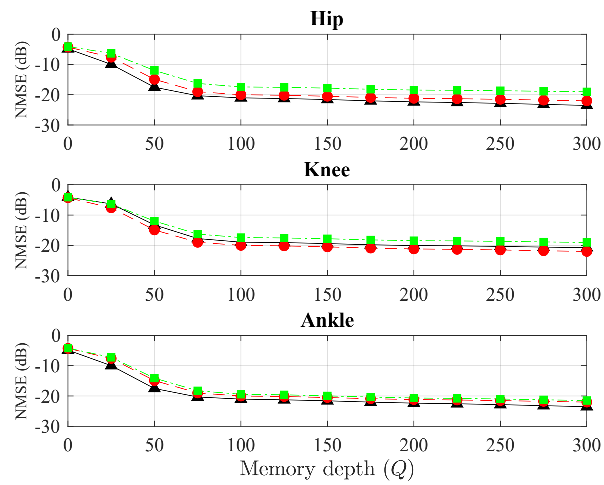

Fig. 3. Performance comparison of MPM for different values of the memory depth parameter Q using the optimal values of K (see Fig. 2). Triangle markers represent the all-order terms. Circle markers represent the even-order terms. Square markers represent the odd-order terms.

five walking trials. In order to avoid the effect of turn-arounds, the backward directions were excluded. Moreover, the first and last two gait cycles were removed prior to the signal processing step to avoid transient phenomena.

IV. Processing Nonlinear Dynamic Signals

The first attempt of realizing digital twins for gait rehabilitation is to determine kinematics (joint angles) of the lower limbs using only the accelerometer data of the IMUs placed at the feet. This includes also the signal processing steps described below.

The raw accelerometer data ($\mathbf{S} \in \mathbb{R}^{N\times 3}$) of relevance for gait analysis is contaminated with various noise factors such as motion artifacts, step impacts, sensor orientation and location related noises. In order to overcome this problem, the norm of the accelerometer signal is calculated and used as input for the MPM. This step is calculated by

$$x(n) = ||\mathbf{S}(n)||_2 = \sqrt{|\mathbf{S}_{n,1}|^2 + |\mathbf{S}_{n,2}|^2 + |\mathbf{S}_{n,3}|^2}\,, \quad \forall\, n \in N \tag{9}$$

where $\mathbf{S}(n)$ is a row vector of the matrix $\mathbf{S}$. The signal $x(n)$ is then filtered using a Butterworth low-pass filter with a cutoff frequency of 7 Hz to reduce the high frequency components. Due to the dynamic gait pattern, the length of each gait cycle not only differs from one cycle to another, but also from one participant to another. To remove the person-related features walking speed and step period we need to normalize the gait cycles. Therefore, the gait cycle is detected using Zero Velocity Update (ZUPT) [17] detection algorithm to find the Heel Contacts (HCs) [18], [19]. Afterwards, gait cycle normalization can be performed by resampling the data to a cyclic length of 100 samples [20]. For the sake of clarity, the amplitude of the input and reference signals were not normalized. The data recorded in this study were used to define the left and right gait cycle independently for each side. The total amount of cycles for each participant was set to 50. The biomechanical signals used as references for this study are the lower body joint angles (hip, knee and ankle). To estimate above-mentioned joint angles, a sensor fusion technique based on a Kalman Filter (KF) is applied [21].

V. Evaluation Results

To assess the efficiency of the MPM in simulating the lower body joint angles, the MPM is implemented in MATLAB, followed by the estimation of the model parameters K and Q. The performance of the MPM is evaluated twofold: First, the system concept (see Fig. 1) is evaluated with the data from the 18 participants to proof the possibility of modeling the desired signals using the data from the accelerometer at the foot. Second, the generation of a model and its cross-validation using the NMSE is carried out to evaluate the MPM performance. Hereto the data from different participants are used to estimate the desired lower limb joint angle signals. In general, the nonlinearity order K and the memory depth Q have to be determined, respectively. The nonlinearity order delivering the minimum value of NMSE is used to determine the memory depth. Fig. 2 shows the MPM performance in terms of mean NMSE for all participants as a function of the nonlinearity order for hip, knee and

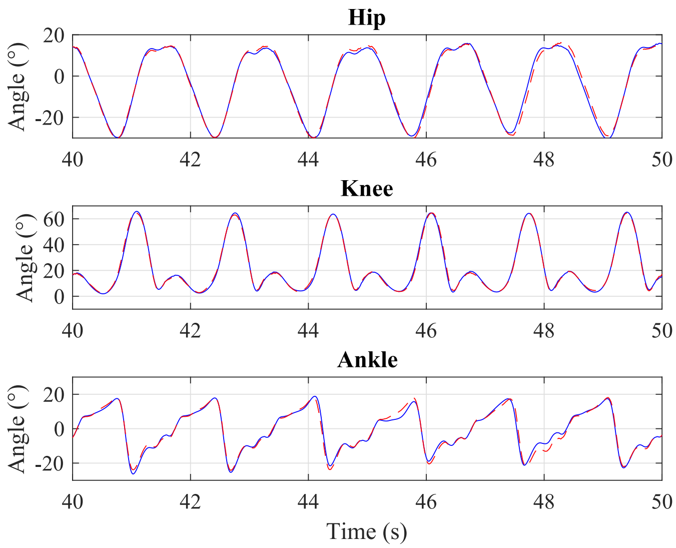

Fig. 4. Estimation of the joint angles using the MPM and the optimal values for K and Q. The blue solid line represents the reference signal. The red dashed line represents the estimation.

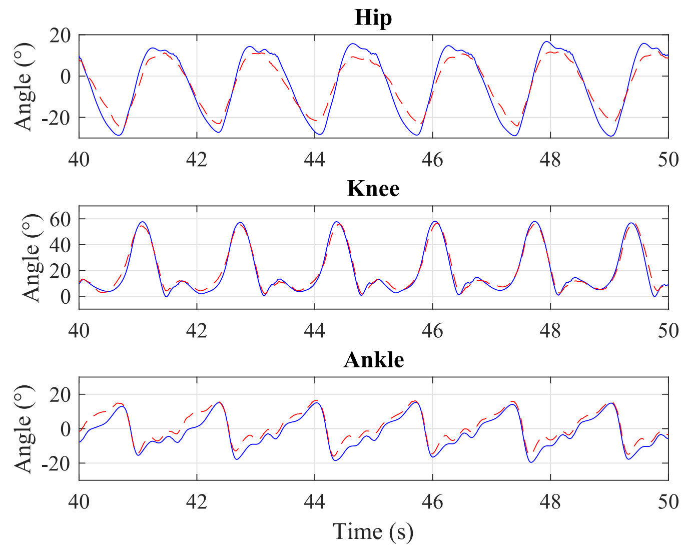

Fig. 5. Cross-validation estimation results of the joint angles using the proposed MPM and the optimal values for K and Q. The blue solid line represents the reference signal. The red dashed line represents the estimation.

ankle angles for all the participants according to

$$\mathrm{NMSE}_{\mathrm{avg}}(\mathrm{dB}) = 10\log_{10}\left(\frac{1}{P}\sum_{p=1}^{P}\frac{\sum_{n=0}^{N-1}|y_p(n)-\hat{y}_p(n)|^2}{\sum_{n=0}^{N-1}|y_p(n)|^2}\right). \tag{10}$$

Here, $y_p(n)$ is the joint angle signal of the p-th participant and $\hat{y}_p(n)$ represents the modeled joint angle signal using the participant specific model. P is the number of investigated participants. This is achieved taking into account either all, even or odd-order terms. An optimal solution is given, where the NMSE is minimized. Having the nonlinearity order estimation, the memory depth of the MPM model is determined. Fig. 3 shows the results of mean NMSE vs. memory depth for hip, knee and ankle angles.

The NMSE results for the evaluation of the required memory depth Q show no minimum as for the estimation of the nonlinearity order K. Therefore, we select Q such that an NMSE of at least -20 dB is reached, which for the investigated signals relates to an absolute error of approximately 5° (4°, 6° and 4° for the joint hip, knee and ankle angles, respectively). Fig. 4 shows the estimation of the joint angles using the MPM and the optimal values for K and Q. It is seen that an NMSE of about -20 dB can be achieved for each joint angle at different values of order and memory depth. For ankle and hip angle modeling an order $K = 6$ and memory depth $Q = 75$ samples is sufficient to achieve the given accuracy, whereas this is achievable for the knee angle at $K = 6$ and $Q = 200$ as shown in Tab. I. These results show the polynomial's capacity to model joint signals.

TABLE I
Optimal parameters for the MPM of different joint angles based on an IMU located at one foot.

	K			Q		
	All	Even	Odd	All	Even	Odd
Hip	6	4	3	75	100	>300
Knee	6	4	3	200	100	>300
Ankle	6	4	4	75	100	150

For the evaluation of the MPM for the estimation of lower body joint angles, the cross-validation technique is applied. Cross-validation is normally used in machine learning to estimate the capability of a model on new data sets. For the cross-validation analysis the data is separated in subsets, namely, training and test. The procedure is often called ξ-fold cross-validation. In this part of the analysis, the value of ξ is set to 10 for the evaluation of the MPM. The training set is formed using the 70% of the data and the remaining 30% is allocated for the test set. The training and test sets contain data from different participants. Therefore, the test set is unseen data for the MPM. The results of the capability of MPM are depicted in Fig. 5. It can be seen, that the test set estimated and reference signals differ more significantly compared to the training set. The related estimation performance in terms of mean NMSE using the estimated coefficients $\mathbf{a}$ from the training set amounts about -12 dB, -15 dB and -7 dB for the hip, knee and ankle, respectively. The reason for the inferior NMSE results is the high dynamic nature of gait patterns on the one hand, and on the other, the limitations involved in data recording. On this basis, significant analysis on large data sets as well as different placements of IMU sensor to record accelerometer data is the subject of investigations in our future work.

VI. Conclusion

In this paper, the idea of memory polynomial modeling to simulate the physical mechanism of gait kinematics was presented. Therefore, the IMU sensors are used to record accelerometer data at the feet in order to model the hip, ankle and knee joint angles. Using gait cycle normalization and the LS estimation approach the MPM is identified and the optimal solution is obtained using the NMSE. The performance of the MPM in modeling the desired signals is verified and an NMSE of about -20 dB is achieved taking into account both even and odd orders. The MPM capability to estimate the desired signal using data from other participants was examined. The NMSE differs from one joint angle estimation to another and the performance is lower than the given NMSE in modeling. The initial work shows that the MPM has potential in building digital twins for gait rehabilitation; however further investigations need to be performed to improve the model accuracy. Thus, the focus of our future work is the improvement of the model performance using different sensor placements, pre-processing and estimation approaches followed by significant analysis on a larger data set.

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