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Experiments in Incremental Online Identification of Fuzzy Models of Finger Dynamics

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Abstract. This paper suggests a set of evolving *Takagi-Sugeno-Kang* (TSK) fuzzy models that characterize the finger dynamics of the human hand in the framework of *myoelectric* (ME) control of prosthetic hands. The fuzzy models represent the reference models in ME-based control systems. The fuzzy model outputs are the finger angles, namely the midcarpal joint angles. Starting with the ME signals obtained from eight ME sensors, which are used as fuzzy model inputs, different numbers of additional model inputs obtained from past inputs and/or outputs are considered. The structure and parameters of the fuzzy models are evolved by an incremental online identification algorithm. The evolving TSK fuzzy models for three out of five fingers are tested against the experimental data and compared. The experimental results highlight that the proposed fuzzy models are consistent with both training and validation data.

1. Introduction

The development of myoelectric (ME)-based control systems for prosthetic hands include several approaches pointed out in [1]: on-off control, proportional control, direct control, finite state machine control, pattern recognition-based control, posture control, and regression control. All these approaches are considered in the model-based control design framework, which requires accurate human hand modeling. The human hand in this context is a Multi Input-Multi Output (MIMO) nonlinear dynamical system, with the inputs represented by the ME signals considered as control signals and the outputs represented by the finger angles.

Some recent results on ME-based control systems include filtering and classification of ME signals in terms of machine learning techniques with popular applications dealing with neural networks (NNs) and fuzzy logic [2–13]. Consistent surveys on the use of ME signals in rehabilitation and bio-inspired robots are given in [1, 3, 4, 6]. Some of these recent applications treat the NN-based control of robotic hands [2], the prediction of the muscle force using wavelet NNs [5], the prediction of handgrip force from ME signals by extreme learning machines [12], the classification of ME signals by NN tree combined with the maximal Lyapunov exponent [7], nonlinear autoregressive with exogenous inputs (NARX) recurrent dynamic NNs and evolving Takagi-Sugeno-Kang (TSK) fuzzy models using ME signals obtained from five ME sensors placed on human subject's arm [9, 10], and fuzzy bionic hand control [11, 13].

Two system architectures for prosthetic hand ME-based control systems are suggested in [14] and [15] aiming the implementation ideas given in [16] and suggesting evolving fuzzy models [14] and variable structure recurrent NNs [15]. With this regard, the models that characterize the human hand dynamics, *i.e.*, the finger dynamics, play the role of reference models in ME-based control systems. The inputs of this nonlinear system are the ME signals obtained from eight sensors placed on human subject's arm, and the outputs are the flexion percentages that correspond to the midcarpal joint angles. For the sake of simplicity the flexion percentages are referred to in the sequel as flex percentages and finger angles.

The concept of evolving fuzzy (rule-based) controllers was proposed by P. Angelov back in 2001 and further developed in his later works [17–22]. These controllers employ evolving TSK fuzzy models, which are characterized by computing the rule bases by a learning process, *i.e.*, by continuous online rule base learning. Some recent papers with illustrative results on evolving fuzzy models are [23–30]. The TSK or Mamdany fuzzy models are developed by evolving the model structure and parameters in terms of online identification algorithms. The adding mechanism [28] in the structure of online identification algorithms plays an important role because it adds new local models or removes them, which gives the evolving structure and parameters.

This paper is built upon our papers on evolving TSK fuzzy models [9, 14, 26, 30] and nonlinear NARX recurrent dynamic NN models [10, 15], and develops a set of evolving TSK fuzzy models of the midcarpal joint angles in the framework of human hand dynamics. For the sake of simplicity only the models for three finger angles are given, namely for the first one (thumb), the third one (middle finger) and fifth one (pinky).

This paper is organized as follows: the main implementation details of the online identification algorithm are described in the next section. Aspects concerning the development of evolving TSK fuzzy models and experimental results are given in Section 3. A performance comparison is included. The conclusions are highlighted in Section 4.

2. Online identification algorithm

The online identification algorithm is implemented using the theory adapted from [31] and supported by the eFS Lab software developed by A. Dourado and his team and described in [32] and [33]. The flowchart of the incremental online identification algorithm is presented in Fig. 1. This algorithm is organized in terms of the following steps also described in our recent papers highlighted in the References section:

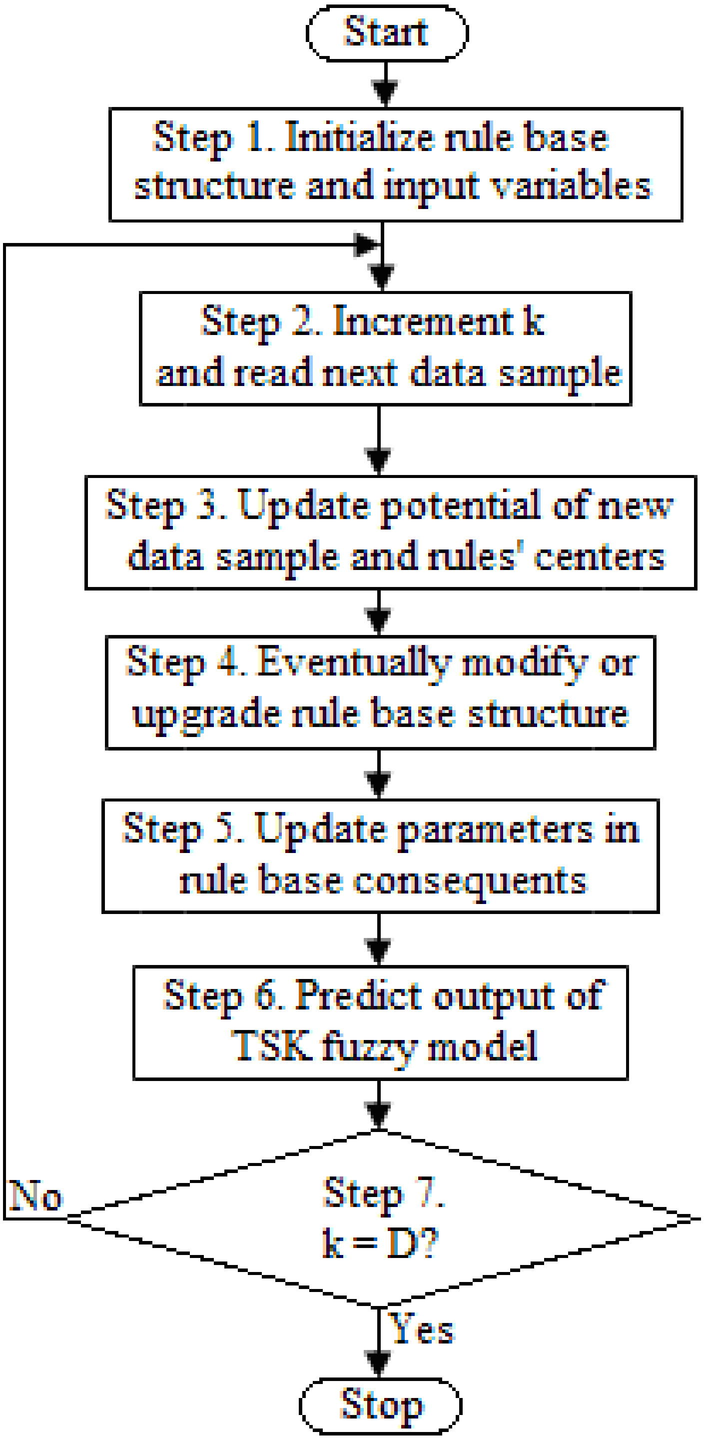

Fig. 1. Flowchart of incremental online identification algorithm [30].

Step 1. The rule base structure is initialized in terms of setting all parameters of the rule antecedents such that to contain just one rule, $n_R = 1$, where n_R is the number of rules. The subtractive clustering is next applied to compute the parameters of the evolving TSK fuzzy models using the first data point $\mathbf{p}_1$. The general expression of the data point **p** at the discrete time step k (which is also the index of the current sample) is $\mathbf{p}_k$, which belongs to the input-output data set $\{p_k|k = 1...D\} \subset R^{n+1}$

$$\begin{aligned} &\mathbf{p}_k = [p_k^1 \; p_k^2 \; \dots p_k^{n+1}]^T \\ &\mathbf{p} = [\mathbf{z}^T \; y]^T = [z_1 \; z_2 \; \dots z_n \; y_1]^T = [p^1 \; p^2 \; \dots p^n \; p^{n+1}] \end{aligned} \tag{1}$$

where D is the number of input-output data points or data points or data samples or samples, **z** is the input vector, and T stands for matrix transposition. The rule base of TSK fuzzy models with affine rule consequents is

$$Rule\; i : IF\; z_1 \;\text{IS} LT_{i1} \; AND \dots AND z_n \;\text{IS} LT_{in} \; THEN y_l^i = a_{i0} + a_{il} z_1 + \dots + a_{i0} + a_{il} z_n, i = 1 \dots n_R \tag{2}$$

where $z_j, \; j = 1 \dots n$, are the input (or scheduling) variables, n is the number of input variables, $LT_{ij}, i = 1 \dots n_R, j = 1 \dots n$, are the input linguistic terms, y_l^i is the output of the local model in the rule consequent of the rule $i, i = 1 \dots n_R$ and $a_{i\chi}, i = 1 \dots n_R, \chi = 0 \dots n$, are the parameters in the rule consequents.

Using the algebraic product t-norm as an AND operator and the weighted average defuzzification method in TSK fuzzy model structure, the expression of TSK fuzzy model output y_l is

$$y_l = \frac{\sum_{i=1}^{n_R} \tau_i y_l^i}{\sum_{i=1}^{n_R} \tau_i} = \sum_{i=1}^{n_R} \lambda_i y_l^i, \; y_l^i = [1 \; \mathbf{z}^T]\pi, \; \lambda_i = \frac{\tau_i}{\sum_{i=1}^{n_R} \tau_i}, \; i = 1 \dots n_R \tag{3}$$

where the firing degree of the rule i and the normalized firing degree of this rule are $\tau_i(\mathbf{z})$ and λ_i, respectively, and the parameter vector of the rule i is $\pi_i, i = 1 \dots n_R$. Regarding the rule i, the firing degree is

$$\tau(\mathbf{z}) = AND(\mu_{i1}(z_1), \mu_{i2}(z_2), \dots, \mu_{in}(z_n)) = \mu_{i1}(z_1) \cdot \mu_{i2}(z_2) \cdot \; \dots \; \cdot \mu_{in}(z_n), \; i = 1 \dots n_R \tag{4}$$

and the parameter vector is

$$\pi_i = [a_{i0} \; a_{i1} \; a_{i2 \; \dots \; a_{in}}]^T, i = 1 \dots n_R \tag{5}$$

The following parameters specific to the incremental online identification algorithm are initialized according to the recommendations given in [31]:

$$\hat{\theta}_1 = [(\pi_1^T)_1 \; (\pi_2^T)_1 \dots (\pi_{n_R}^T)_1]^T = [0 \; 0 \dots 0]^T, \; \mathbf{C}_1 = \Omega \mathbf{I}, r_s = 0.4, \; k = 1, n_R = 1, \; z_1^* = z_k, \; P_1(\mathbf{p}_1^*) = 1 \tag{6}$$

where $C_k \in R^{n_R(n+1) \times n_R(n+1)}$ is the fuzzy covariance matrix related to the clusters, **I** is the $n_R(N+1)^{th}$ order identity matrix, $\Omega = \text{const}, \Omega > 0$ is a relatively large number, $\hat{\theta}_k$ is an estimation of the parameter vector in the rule consequents at time k, and $r_s, r_s > 0$ is the spread of all Gaussian input membership functions $\mu_{ij}, i = 1 \dots n_R, j = 1 \dots n$ of the fuzzy sets afferent to the input linguistic terms LT_{ij}

$$\mu_{ij}(z_j) = e^{-\frac{4(z_j - z_{ij}^*)^2}{r_s^2}}, \ i = 1 \dots n_R, \ j = 1 \dots n \tag{7}$$

$z_{ij}^* \ \ i = 1 \dots n_R, \ j = 1 \dots n$, are the membership function centers, $\mathbf{p}_1^*$ in (7) is the first cluster center, $\mathbf{z}_1^*$ is the center of the rule 1 and also the projection of $\mathbf{p}_1^*$ on the axis $\mathbf{z}$ in terms of (2), and $P_1(\mathbf{p}_1^*)$ is the potential of $\mathbf{p}_1^*$.

Step 2. The data sample index k is incremented, namely replaced with $k+1$, and the next data sample $\mathbf{p}_k$ that belongs to the input-output data set $\{\mathbf{p}_k | k = 1 \dots D\} \subset R_{n+1}$ is read.

Step 3. The potential of each new data sample $P_k(\mathbf{p}_k)$ and the potentials of the centers $P_k(\mathbf{p}_\eta^*)$ of existing rules (clusters) with the index η are recursively updated according to these formulas for which no explanation is given as follows to ensure a reasonable length of this section but a reference to [31] is outlined:

$$\begin{aligned}
&P_k(\mathbf{P}_K) = \frac{k-1}{(k-1)(\vartheta_k + 1) + \sigma_k - 2\upsilon_k} \\
&\vartheta_k = \sum_{j=1}^{n+1} (p_k^j)^2, \sigma_k = \sum_{j=1}^{n+1} \sum_{l=1}^{k-1} (p_l^j)^2, \upsilon_k = \sum_{j=1}^{n+1} (p_k^j \sum_{l=1}^{k-1} p_l^j) \\
&P_k(\mathbf{p}_\eta^*) = \frac{(k-1) P_{k-1}(\mathbf{p}_\eta^*)}{k - 2 + P_{k-1}(\mathbf{p}_\eta^*) + P_{k-1}(\mathbf{p}_\eta^*) \sum_{j=1}^{n+1} (d_{k(k-1)}^j)^2}
\end{aligned} \tag{8}$$

Step 4. The possible modification or upgrade of the rule base structure is carried out by means of the potential of the new data in comparison with that of the existing rules' centers. The rule base structure is modified if certain conditions outlined in [31] are fulfilled.

Step 5. The parameters in the rule consequents are updated using either the Recursive Least Squares (RLS) algorithm or the weighted Recursive Least Squares (wRLS) algorithm. These updates result in the updated vectors $\hat{\theta}_k$ (an estimation of the parameters in the rule consequents at the discrete time step k) and $\mathbf{C}_k, \ k = 2 \dots D$.

Some details on RLS will be given as follows. However, the details on wRLS are not included here as they would lead to the corresponding extension of the manuscript. The global objective function used in case of RLS is

$$J_G(\theta) = \sum_{k=1}^{D} (y_k - \psi_k^T \theta)^2, \psi_k^T = [\lambda_1(z_k)[1 \ \ z_k^T] \ \ \lambda_2(z_k)[1 \ \ z_k^T] \ \dots \ \lambda_{nR}(z_K)[1 \ \ z_k^T]] \tag{9}$$

where z_k is the input vector z at the discrete time step k. The minimization of the objective function $J_G(\theta)$ can be achieved by the RLS algorithm referred to also as the Kalman filter and characterized by the recurrent equations

$$\begin{aligned}
&\hat{\theta}_k = \hat{\theta}_{k-1} + C_k \psi_{k-1} (y_k - \psi_{k-1}^T \hat{\theta}_{K-1}) \\
&C_k = C_{k-1} - \frac{C_{k-1} \psi_{k-1} \psi_{k-1}^T C_{k-1}}{1 + \psi_{k-1}^T C_{k-1} \psi_{k-1}}, \ k = 2 \dots D
\end{aligned} \tag{10}$$

with the initial conditions specified in (6). A locally weighted objective function instead of that global one given in (9) is minimized by the wRLS algorithm. The wRLS algorithm is characterized by different equations to those given in (10), and details are given in [31].

Step 6. The output of the evolving Takagi-Sugeno-Kang fuzzy model at the next discrete time step $k+1$ is predicted and expressed as $\hat{y}_{k+1}$:

$$\hat{y}_{k+1} = \psi_k^T \hat{\theta}_k \tag{11}$$

with the general notations (applied to any element of the data set)

$$y = \psi^T \theta,\ \theta = [\pi_1^T\ \ \pi_2^T\ \ \dots\ \pi_{n_R}^T]^T,\ \psi^T = [\lambda_1[1\ z^T]\ \ \lambda_2[1\ z^T]\ \ \dots\ \lambda_{n_R}[1\ z^T]] \tag{12}$$

Step 7. The algorithm continues with step 2 until all data points of the input-output data set $\{p_k | k = 1 \dots D\}$ are read.

3. Development of evolving Takagi-Sugeno-Kang fuzzy models and experimental results

All reference models (TSK fuzzy models in this paper) involved in the system architectures for prosthetic hand ME-based control systems are suggested [14, 15] actually use the same eight inputs that belong to the vector

$$[z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}]^T \tag{13}$$

where $z_{j,k}(b),\ 0b \leq z_k \leq 255b$, is the MES obtained as the output of the ME sensor j, $j = 1 \dots 8$, and the measuring unit stands for bit. The placement of the ME sensors on a human hand is illustrated in [14] and [15] because the same hardware support is used in this paper as well.

The outputs of all reference models are the finger angles $y_{l,k}$ (%) of the fingers l, $l = 1 \dots 5$, expressed as flexion percentages of finger closing between fully relaxed (0) and fully contracted (100), 0%$\leq y_{l,k} \leq 100\%$. The finger indices l are $l = 1$ for the thumb, $l = 2$ for the index finger, $l = 3$ for the middle finger, $l = 4$ for the ring finger, and $l = 4$ for the pinky.

The incremental online identification algorithm sketched in the previous section was applied to obtain the evolving TSK fuzzy models of finger dynamics. A part of the results for the thumb (or the first finger, $l = 1$), the middl e finger (or the third finger, $l = 3$) and the pinky (or the fifth finger, $l = 5$) and implementation details is presented as follows. The value of the parameter Ω in step 1 was set to $\Omega = 10000$, which proved to be sufficient to obtain very good and encouraging results.

The input vector given in (13) makes use of information from all ME sensors because of the need to model the effects of cross-couplings in the MIMO nonlinear dynamical system represented by the human hand. The dynamics is introduced as follows in the TSK fuzzy models in terms of inserting several past values of the outputs $y_{l,k},\ l \in \{1, 3, 5\}$, and/or inputs by appropriate shifting. The parameters in the rule consequents are updated in step 5 using either RLS or wRLS. This leads to 18 + 18 + 18 TSK fuzzy models with the inputs specified in Table 1, Table 2 and Table 3 for the first, third and fifth finger, respectively.

Table 1. Input vectors and estimation algorithms for estimation of rule consequents parameters of TSK fuzzy models of first finger

Model number	Input vector and optimization algorithm
1/2	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}]^T$, RLS/wRLS
3/4	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}]^T$, RLS/wRLS
5/6	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}$ $y_{4,k-1}\ y_{5,k-1}]^T$, RLS/wRLS
7/8	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{1,k-2}]^T$, RLS/wRLS
9/10	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}$ $y_{5,k-1}\ y_{1,k-2}]^T$, RLS/wRLS
11/12	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}]^T$, RLS/wRLS
13/14	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}]^T$, RLS/wRLS
15/16	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{1,k-2}]^T$, RLS/wRLS
17/18	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}]^T$, RLS/wRLS

Table 2. Input vectors and estimation algorithms for estimation of rule consequents parameters of TSK fuzzy models of third finger

Model number	Input vector and optimization algorithm
1/2	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}]^T$,RLS/wRLS
3/4	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{3,k-1}]^T$,RLS/wRLS
5/6	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}$ $y_{4,k-1}\ y_{5,k-1}]^T$, RLS/wRLS
7/8	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{3,k-1}\ y_{3,k-2}]^T$,RLS/wRLS
9/10	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}$ $y_{5,k-1}\ y_{3,k-2}]^T$, RLS/wRLS
11/12	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{3,k-1}]^T$, RLS/wRLS
13/14	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}]^T$,RLS/wRLS
15/16	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{3,k-1}\ y_{3,k-2}]^T$,RLS/wRLS
17/18	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}\ y_{3,k-2}]^T$, RLS/wRLS

Table 3. Input vectors and estimation algorithms for estimation of rule consequents parameters of TSK fuzzy models of fifth finger

Model number	Input vector and optimization algorithm
1/2	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}]^T$,RLS/wRLS
3/4	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{5,k-1}]^T$,RLS/wRLS
5/6	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}$ $y_{4,k-1}\ y_{5,k-1}]^T$, RLS/wRLS
7/8	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{5,k-1}\ y_{5,k-2}]^T$,RLS/wRLS
9/10	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}$ $y_{5,k-1}\ y_{5,k-2}]^T$, RLS/wRLS
11/12	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{5,k-1}]^T$, RLS/wRLS
13/14	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}]^T$,RLS/wRLS
15/16	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{5,k-1}\ y_{5,k-2}]^T$,RLS/wRLS
17/18	$z_k = [z_{1,k}\ z_{2,k}\ z_{3,k}\ z_{4,k}\ z_{5,k}\ z_{6,k}\ z_{7,k}\ z_{8,k}\ z_{1,k-1}\ z_{2,k-1}\ z_{3,k-1}\ z_{4,k-1}\ z_{5,k-1}$ $z_{6,k-1}\ z_{7,k-1}\ z_{8,k-1}\ y_{1,k-1}\ y_{2,k-1}\ y_{3,k-1}\ y_{4,k-1}\ y_{5,k-1}\ y_{5,k-2}]^T$, RLS/wRLS

The outputs of the evolving TSK fuzzy models are $y_{1,k}$ for the models of the first finger angle:

$$y_{1,k} = f(z_k) \tag{14}$$

$y_{3,k}$ for the TSK fuzzy models of the third finger angle:

$$y_{3,k} = g(z_k) \tag{15}$$

and $y_{5,k}$ for the TSK fuzzy models of the fifth finger angle:

$$y_{5,k} = h(z_k) \tag{16}$$

where f, g and h are the nonlinear input-output maps of the TSK fuzzy models. Using the information given in Tables 1 to 3, equations (14) to (16), the TSK fuzzy models developed in this paper can be viewed as NARX models. Since the human hand has more finger angles, as pointed out in Section 1, this paper develops models for midcarpal joint angles. More precisely, the outputs of TSK fuzzy models are the flexion percentages of fingers in terms of midcarpal joints.

The eight system inputs were generated in order to cover different ranges of magnitudes and frequencies and to capture various hand movements on a long time horizon of 434.91 s, namely 250 s for training plus and 184.91 s for validation, and outputs measured from the equipment. The evolution of the system inputs versus time is presented in Figs. 2 to 7, which include the input data for both training and validation.

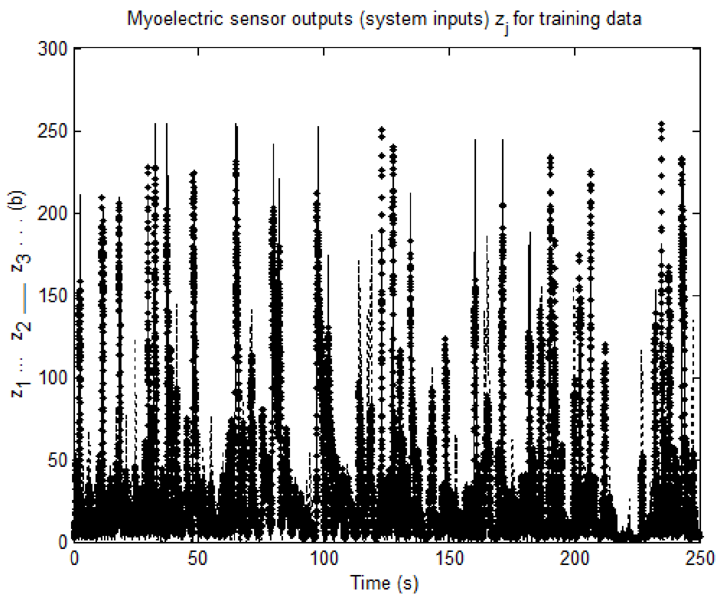

Fig. 2. System inputs $z_{1,k}$, $z_{2,k}$ and $z_{3,k}$ versus time for training data.

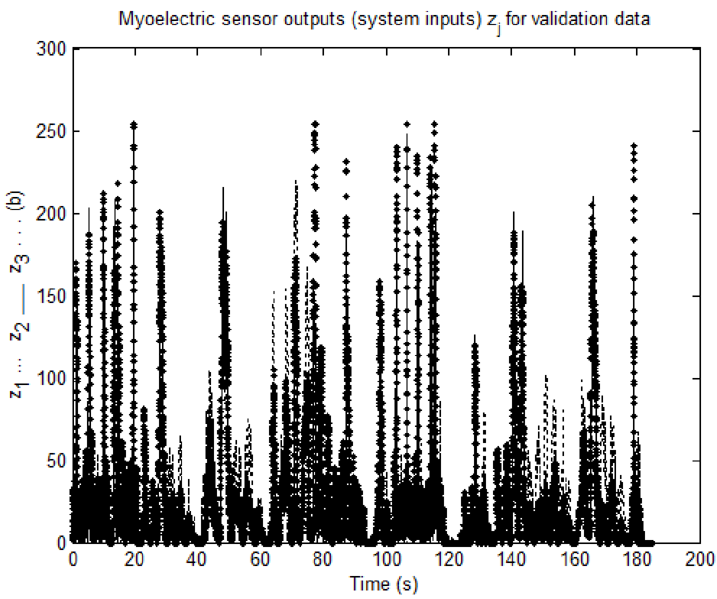

Fig. 3. System inputs $z_{1,k}$, $z_{2,k}$ and $z_{3,k}$ versus time for validation data.

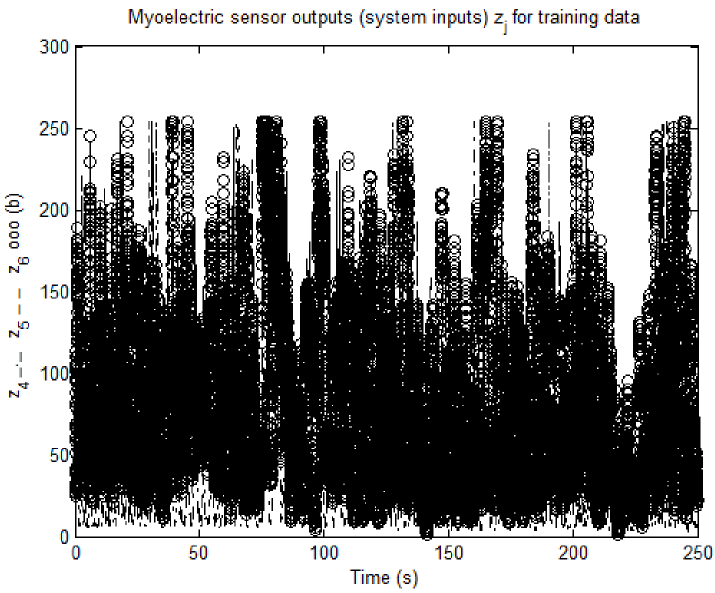

Fig. 4. System inputs $z_{4,k},\ z_{5,k}$ and $z_{6,k}$ versus time for training data.

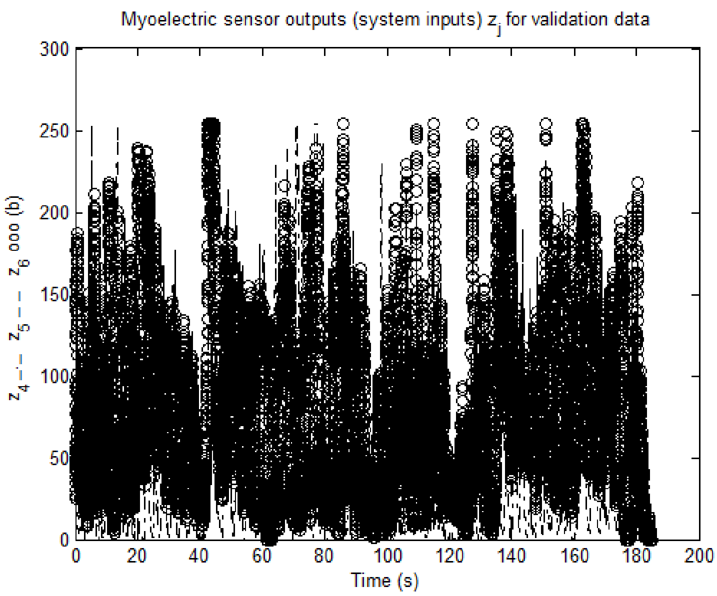

Fig. 5. System inputs $z_{4,k},\ z_{5,k}$ and $z_{6,k}$ versus time for validation data.

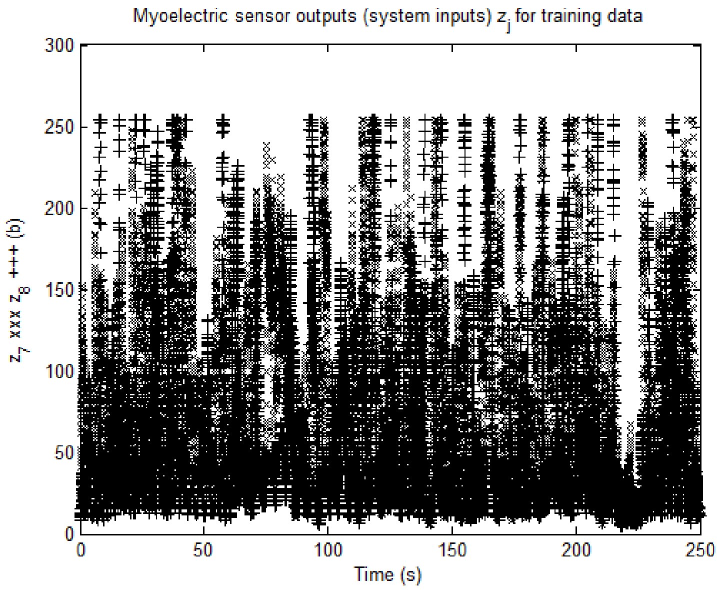

Fig. 6. System inputs $z_{7,k}$ and $z_{8,k}$ versus time for training data.

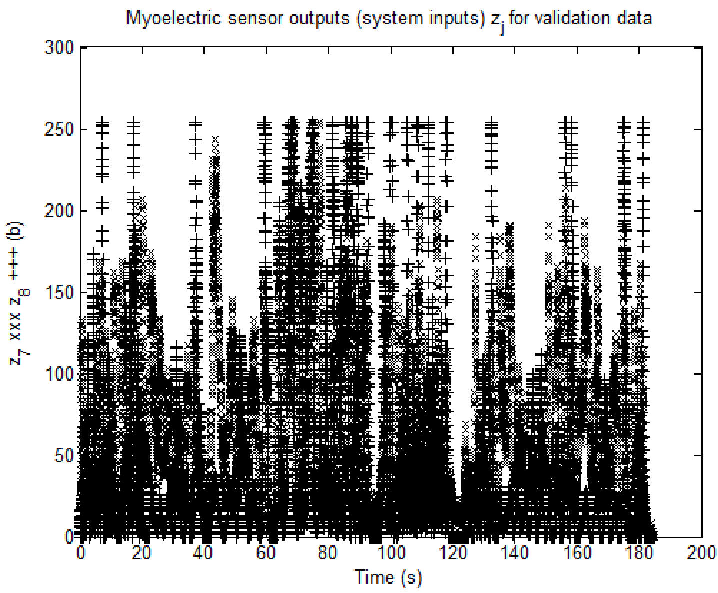

Fig. 7. System inputs $z_{7,k}$ and $z_{8,k}$ versus time for validation data.

Although no much information can be extracted from the graphs presented in Figs. 2 to 7, the idea is to illustrate the nature of the input values. This noisy nature of the signals, also mentioned in Section 1, is similar in all system inputs. Figs. 6 to 11 illustrate the inputs that correspond to the set of $D = 25000$ data points of the training data and the inputs of the other set of $D = 1891$

data points of the testing data. The real system output values will be presented along with the model outputs in the sequel. The past input and output values were actually obtained by shifting the training and validation data samples.

The TSK fuzzy models evolved to different numbers of rules. The parameter values of these models were obtained by the application of the incremental online identification algorithms for the models with the inputs described in Tables 1 to 3. The number of parameters and rules of the final evolved TSK fuzzy models are presented in Tables 4 to 6.

The values of the RMSE between the model outputs and the real-world system outputs (the human hand finger angles) $y_{dl,k}$, *i.e.*, the expected outputs, are also included in Tables 4 to 6, which include results for training and validation. The RMSE, considered as a global performance index, is defined as

$$RMSE = \sqrt{\frac{1}{D}\sum_{k=1}^{D}(y_{1,k} - y_{dl,k})^2},\ l \in \{1, 3, 5\} \tag{17}$$

where the real-world system outputs $y_{dl,k}$ were obtained by real-time measurements conducted on the human hand.

Table 4. Numbers of parameters, numbers of rules and RMSE for the TSK models of the first finger

Model number	Number of parameters	Number of rules n_R	RMSE on training data	RMSE on validation data
1	250	10	16.377	16.026
2	200	8	17.752	17.384
3	420	15	1.4707	1.579
4	252	9	8.1356	9.5275
5	960	24	1.3682	1.5262
6	960	24	1.4087	1.5403
7	310	10	1.0798	1.0931
8	248	8	17.638	9.2594
9	817	19	1.0198	1.0635
10	774	18	3.5721	7.8036
11	780	15	1.4236	1.5119
12	780	15	1.3845	1.6654
13	1216	19	1.3192	1.6224
14	1216	19	1.4042	1.5154
15	550	10	1.0515	1.0872
16	660	12	8.7746	8.5002
17	1273	19	1.0016	1.0583
18	1273	19	1.0332	1.0662

Table 5. Numbers of parameters, numbers of rules and RMSE for the TSK models of the third finger

Model number	Number of parameters	Number of rules n_R	RMSE on training data	RMSE on validation data
1	200	8	25.073	21.957
2	150	6	24.001	23.246
3	532	19	1.702	1.726
4	392	14	28.102	20.315
5	920	23	1.5023	1.5035
6	920	23	1.5758	1.5816
7	310	10	1.2027	1.1279
8	992	32	3.8509	1.1564
9	1075	25	1.1522	1.1213
10	1075	25	1.1876	1.138
11	624	12	1.6807	1.7218
12	416	8	18.275	22.693
13	1536	24	1.4487	1.4932
14	1536	24	1.5362	1.5641
15	990	18	1.1773	1.1478
16	1155	21	18.487	5.4116
17	1809	27	1.1546	1.1181
18	1809	27	1.1913	1.1346

Table 6. Numbers of parameters, numbers of rules and RMSE for the TSK models of the fifth finger

Model number	Number of parameters	Number of rules n_R	RMSE on training data	RMSE on validation data
1	325	13	24.27	22.993
2	225	9	24.262	23.896
3	392	14	1.3985	1.8051
4	476	17	33.76	9.8582
5	840	21	1.2554	1.3839
6	840	21	1.313	1.4304
7	837	27	1.1	1.1217
8	868	28	59.549	1.1422
9	903	21	1.0833	1.1293
10	903	21	1.1189	1.143
11	1768	34	1.3841	1.5153
12	1820	35	65.246	49.911
13	1344	21	1.2646	1.4063
14	1344	21	1.324	1.4434
15	1485	27	1.0919	1.1301
16	1485	27	1.5237	1.1599
17	1541	23	1.0654	1.1168
18	1541	23	1.0976	1.1251

As expected, the TSK fuzzy models and their performance depend on the number of input variables. Different model structures, *i.e.* different numbers of rules resulting in different number of identified parameters, are obtained for different input variables.

Tables 4 to 6 indicate that the validation performance is consistent with the training one in terms of RMSE. Tables 3 to 6 also show that the best first finger angle models are the TSK fuzzy models 7, 9, 15, 17 and 18, the best third finger angle models are the TSK fuzzy models 7, 9 and 17, and the best fifth finger angle models are the TSK fuzzy models 7, 9, 17 and 18. However, since the RMSE values obtained by these models are rather close and the further ME-based real-time control of the finger angles of the prosthetic hand is targeted, the models with a low number of parameters out of these three sets of models are recommended to be next used in the model-based fuzzy control designed. These models are the TSK fuzzy model 7 for the first finger, the TSK fuzzy model 7 for the third finger, and the TSK fuzzy model 7 for the fifth finger angle. A trade-off to performance and model complexity should be targeted.

A part of the real-time experimental results on the validation data set is exemplified in Figs. 8 to 10. The time responses of y_1 versus time of the TSK fuzzy model 7 and of the real-world system are illustrated in Fig. 8. The time responses of y_3 versus time of the TSK fuzzy model 7 and of the real-world system are presented in Fig. 9. The time responses of y_5 versus time of the TSK fuzzy model 7 and of the real-world system are presented in Fig. 10. This could be a methodological issue as we are checking/showing the performance of the models on validation data. But these models were selected as the best for modeling this validation data. So ideally their performance should be checked in new unseen test data.

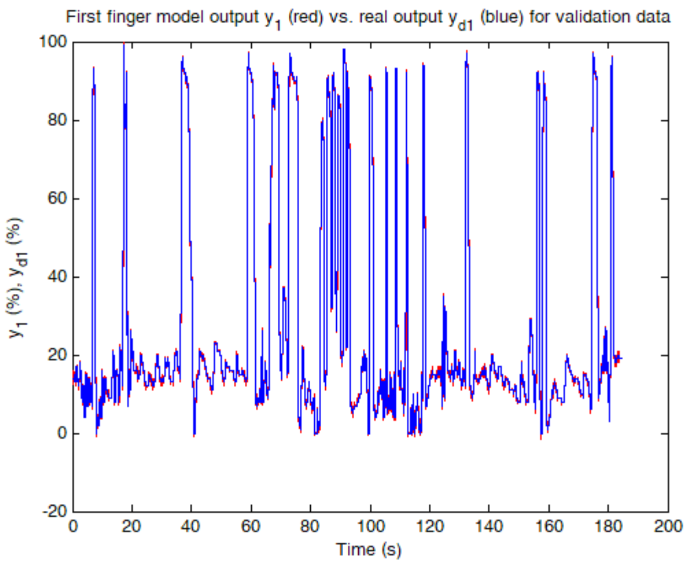

Fig. 8. Finger angle y_1 versus time of TSK fuzzy model 7 (red) and real-world system (blue) on validation data set.

The results given in Tables 4 to 6 point out that the best models were obtained for the TSK fuzzy models with the inputs considered in this paper, and there is no need to insert additional inputs in order to describe the finger dynamics. However, this has only been tested on 434.91 s, but more people and larger data sets could conclude in different results. Actually, it seems that past samples (–2) of the output of interest have increased the performance of the model significantly, so it might be that one or two extra past samples (–3, –4, . . .) increase the performance even more without increasing the number of parameters significantly. In addition, other fuzzy model structures [34–43] and optimization techniques inserted in the online identification algorithm [44–53] can lead to performance enhancement. The results also show that RLS leads to better performance compared to wRLS; however, the particular operating principle of wRLS has to be investigated on the basis of the results reported in [34]–[53] considering that the focus is next model-based control [34–36, 39, 41, 44–46, 50].

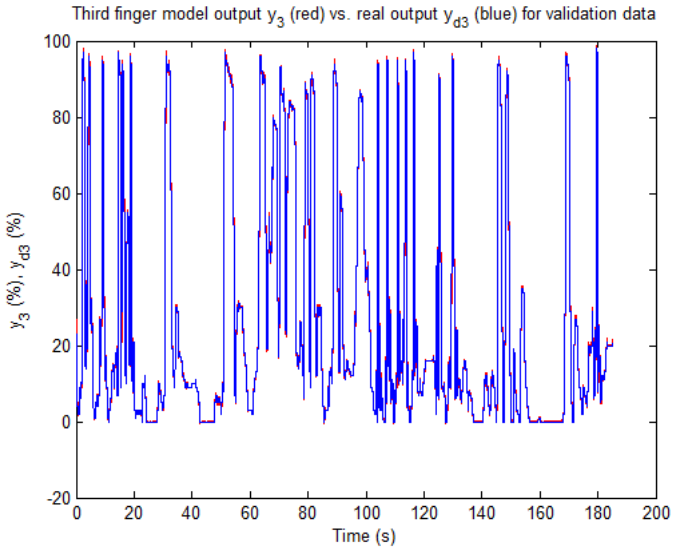

Fig. 9. Finger angle y_3 versus time of TSK fuzzy model 7 (red) and real-world system (blue) on validation data set.

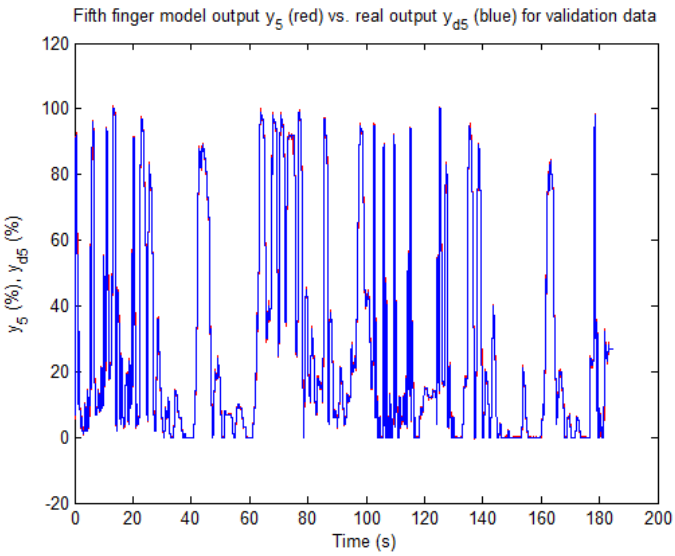

Fig. 10. Finger angle y_5 versus time of TSK fuzzy model 7 (red) and real-world system (blue) on validation data set.

As shown in [9] and [14] for the first finger, the TSK fuzzy models developed on the basis of the online identification algorithm given in Section 2 (in the two versions that include RLS or wRLS) outperform TSK models evolved by DENFIS, which is a representative online identification algorithm. In addition, the evolving TSK fuzzy models outperform NN models with a similar number of identified parameters.

4. Conclusions

This paper suggested a set of TSK fuzzy models to describe as accurate as possible the nonlinear dynamics specific to the midcarpal joint finger angles in the framework of ME-based control systems for of prosthetic hand fingers. The structure and parameters of TSK fuzzy models were computed by an incremental online identification algorithm.

The experimental results illustrate that past outputs (self) improve the performance, but not past inputs or past outputs of other fingers. The effects of cross-coupling are not shown because of the very good performance exhibited by the evolved TSK fuzzy models. The past inputs and past outputs of other fingers can be considered as well as additional fuzzy model inputs to improve the model performance, leading to different models with more rules and numbers of identified parameters, thus affecting the trade-off to performance and model complexity.

Future research will be focused on the development of more efficient fuzzy models of this nonlinear dynamic subsystem that belongs to ME-based control systems. Cost-effective models in terms of small number of parameters and computation time will be targeted.

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