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TOPICAL REVIEW

# Modeling Nonlinear Dynamics in Human–Machine Interaction

**ADRIANO SCIBILIA**[1,2], **NICOLA PEDROCCHI**[1], **AND LUIGI FORTUNA**[2], **(Fellow, IEEE)**
[1]Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing (STIIMA), National Research Council of Italy (CNR), 20133 Milan, Italy
[2]Department of Electrical Electronic and Computer Engineering, University of Catania, 95131 Catania, Italy

Corresponding author: Adriano Scibilia (adriano.scibilia@stiima.cnr.it)

**ABSTRACT** In Human–Machine interaction, the possibility of increasing the intelligence and adaptability of the controlled plant by imitating human control behavior has been an objective of many research efforts in the last decades. From classical control-theory human control models to modern machine learning, neural networks, and reinforcement learning paradigms, the common denominator is the effort to model complex nonlinear dynamics typical of human activity. However, these approaches are very different, and finding a guiding line is challenging. This review investigates state-of-the-art techniques from the perspective of human control modeling, considering the different physiological districts involved as the starting point. The focus is mainly directed toward nonlinear dynamical system modeling, which constitutes the main challenge in this field. In the end, transport systems are presented as a technological scenario in which the discussed techniques are mainly applied.

**INDEX TERMS** Human–machine interaction, human-in-the-loop, decision making, human control modeling, machine learning.

## I. INTRODUCTION

In any system characterized by a close human-machine physical interaction, providing controlled elements with the ability to identify and understand what the human operator is doing, is crucial to increase efficacy and safety. While this is an ability that humans naturally learn over time, machines need to be explicitly trained on how to do this. Such recognition problem is heightened by the dissimilarities between humans and controlled plants from a mental, computational, and physical point of view. These differences imply that, when faced with the uncertainty of the real world, machines cannot always count on humans to behave as expected and cannot always easily anticipate how they will react to an unexpected event [1]. One way this challenge can be addressed is by equipping machines with explicit models of their human teammates. Many different techniques are used to model human cognition and behavior, spanning different timescales and levels.

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As detailed in [2], the first approaches in this research field aimed at identifying the linear human control models while keeping the focus on the background physiological processes. Pilot models when controlling an aircraft were vastly investigated both in the frequency domain and using optimal control strategies, successfully describing unwanted Spatial Disorientation scenarios or pilot's limitations and internal feedback loops. These techniques are the basis for model-based human-in-the-loop control frameworks in intelligent transport systems, robotics [3], and many other domains.

Despite the successes, such models lack in representing nonlinearities typical of human control behavior, especially when facing high-complexity scenarios. McRuer and Hess described the evidence of a pulsive behavior of the pilot when the demanded task is too complex, leading to the formulation of Dual Loop control models. They describe human bimodal control behavior, focusing on the error compensation (typical of classical crossover theory) and visual rate sensing (used in pursuit tasks with predictable inputs) [4]. The dual-channel structure proved to be more suitable for capturing nonlinear dynamics in the pilot system during the information processing stage, represented by thresholds and saturation elements, which were used for describing phenomena like Pilot Induced Oscillations (PIO) [5] or Spatial Disorientation (SD) [6].

In such a modeling technique, the human is considered a controller, an element part of the control loop (Human-in-the-loop control). Its sensing elements and muscle actuators' dynamics are related to the external stimuli, the executed task, and the controlled element. While executing a specific task, the human subject tries to optimize its behavior to achieve its goal while reducing efforts. If the difficulty increases, nonlinear dynamics is increasingly observable. Neuromuscular dynamics can be considered one of the primary physiological sources of nonlinearity in human control action. Modeling techniques in this context are often based on optimal control theory, trying to identify the system's objective function that the human tries to optimize while executing a specific motion.

Aside from classical model-based approaches, a deeper focus on information processing and learning abilities is necessary to have a complete overview of the human as a controller. Different modeling and data-driven approaches have been proposed with this goal in many research efforts, even resulting in a combination of them. The model proposed by Xu and Wu [7], for example, studied the origin of nonlinear PIO proposing a multi-loop human pilot model during a multi-axis control task. Here, the pilot's ability to sense a changing situation, being based on experience and judgment, is represented by a fuzzy logic control element, able to modulate his strategy and, indirectly, the system input/output characteristics (through the variation of model parameters). Apart from multi-loop models, fuzzy logic techniques have been used in association with other nonlinear system modeling approaches and control techniques in order to deal with uncertainties in the external environment [8] or in model parameters tuning [9]. For instance, Fuzzy systems and Artificial Neural Networks (ANN) have been successfully used in hybrid models in the past for human operator tuning [10] or parameter optimization of the controlled plant [11]. The spread of such kind of hybrid models led to the development of neuro-fuzzy systems, which will be discussed in detail in Section V-C.

Due to their simple mathematical structure and low computational cost when implemented, ANNs have been successfully used in the presence of unstructured data in learning, classification, and prediction algorithms in computer vision [12], autonomous driving [13], medical [14], [15], bio-informatics [16], industrial [17] and rehabilitation [18], [19] robotics.

In human-machine interaction, however, it may be important to capture temporal relationships between raw data in order to identify the system model accurately. Special kinds of ANNs, such as RNN [20], [21] and LSTM [22], are very common for this purpose, thanks to their internal loops between the hidden layers, which in the case of LSTM allows capturing even long-term temporal relations. Further details on these two architectures will be given in Section VI, as well as another data-driven approach, such as Reinforcement Learning, useful to model human decision-making and the generation of its internal goal.

Classical supervised, unsupervised, and semi-supervised learning methods are introduced to represent how a ''human controller'' creates a strategy to achieve a long-term goal, passing through several intermediate steps. There is a vast variety of practical applications exploiting such techniques [23], [24], [25], [26]. Remarkably, the optimal control theory modeled the human control action by identifying its internal cost function to minimize, similar to the reinforcement learning approach. Indeed, in such a case, the human decision-making process is modeled by describing its objective function, which is maximized by the subject during its actions.

The mentioned modeling techniques, from the classical control theory based to the modern data-driven approaches, have succeeded in representing a different aspect of the human control strategy when interacting with a machine. Application scenarios such as intelligent transport systems or human-robot collaboration offered many examples of modeling and control techniques which has been developed by combining two or more of these approaches.

## II. PAPER CONTRIBUTION

The investigations of human nonlinear dynamics when controlling a machine are so diversified that finding a common point between them is difficult. This work aims to give a structured overview of the existing techniques, focusing on the underlying physical and physiological human processes.

This human-centered review of the existing efforts will highlight the strengths and limitations of the presented techniques in their effort to model the intrinsic nonlinear dynamics in the human-machine system. Such nonlinearities will be referred to as spatial and temporal variables of functionals which are identifiable within the human physiological control districts involved in sensing and information processing, but also deriving from the interaction with controlled element dynamics and/or the external environment [27]. With respect to the existing review works relative to each research field, this effort will help find a guiding line between more traditional control modeling techniques and modern learning algorithms.

The paper is structured as follows, in Section III discusses the Dual loop control model, giving an overview of the human controller when interacting with a controlled machine. Section IV investigates the nonlinear muscular dynamics models. Then in Section V, the focus will be directed toward modeling techniques particularly useful for representing human information processing stages. Then machine learning efforts to model the human decision-making process are investigated in Section VI. Lastly, in Section VII, practical examples of human-machine schemes in which the described

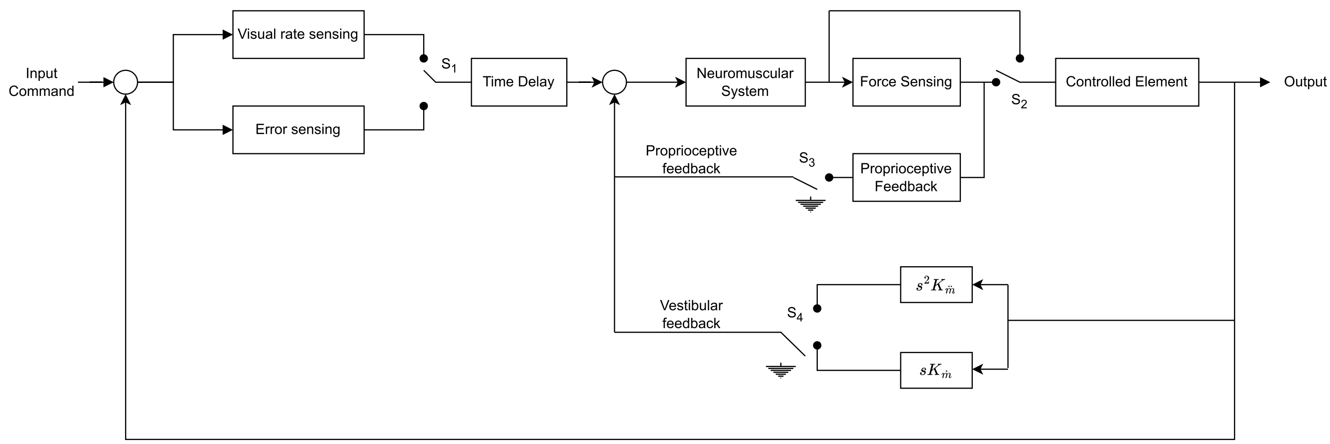


**FIGURE 1. Dual model of the human operator in a compensatory task.**

techniques are applied to model complex nonlinear dynamics are considered.

## III. DUAL LOOP CONTROL

In the last decades of the last century, Hess investigated human control strategies when interacting with a machine, resulting in his first "structural model" [28]. After the first linear version, Hess noted that often human operators' control strategies resulted in pulsive behavior, which was not linked to any feature of classical linear models. In [29], the pulsive behavior was linked to McRuer's quasi-linear model hypothesis in the frequency-domain context. The assumption was that when faced with a demanding task combined with the controlled element's high-order dynamics, the human operator avoids the computational effort and reduces the number of parameters by using a less computationally-demanding nonlinear strategy rather than a linear one.

The above assumption was applied to the early version of the Hess model, resulting in the Dual Model depicted in Figure 1. Such a model resulted from an effort to link the hypothesis behind the crossover theory with the optimal control approach.

The described nonlinear factor results in the various switching elements in Figure 1. The first one (S1) allows selecting error or error rate tracking and is supposed to operate in unison with S2, which enables or disables the proprioceptive feedback loop. The physiological reason behind this is that after a triggering event, the pilot control strategy regresses to simple tracking behavior, where the error rate is controlled without the help of proprioceptive feedback. Right after the two described sensing channels, there is a time delay element due to the information processing occurring in the central nervous system, present right before the neuromuscular actuation and internal feedback stages.

Moreover, switch S3 allows modeling both displacement and force sensing inceptors. Ultimately, S4 allows using vestibular rate or acceleration inputs for control, with gain elements dependent on the perceived velocity $K_{\dot{m}}$ or acceleration $K_{\ddot{m}}$ [30]. Ultimately, only neuromuscular and proprioceptive elements need parametrization, lowering the model complexity level. The neuromuscular block is often represented using second-order dynamics [31].

The neuromuscular force output is sensed and transformed into an estimation of the output rate of the controlled element using an internal model of its dynamics. This process is done by the proprioceptive system, which can be described in the Laplace domain using the following equation:

$$H_{\mathrm{ps}}(s) = \begin{cases} K_{\mathrm{ps}}(s+a) \\ K_{\mathrm{ps}} \\ \dfrac{K_{\mathrm{ps}}}{(s+a)}, \end{cases} \tag{1}$$

where $s$ is the Laplace variable in the complex plane, and $a \in \mathbb{R}$. In other words, the proprioceptive system transfer function $H_{\mathrm{ps}}$ can be defined, depending on the controlled element dynamics, as a derivative term multiplied by a gain element $K_{\mathrm{ps}}$ (first case), through a simple proportional relationship (second case); or as integration (third case). If we indicate the controlled element transfer function as $H_C$, the proprioceptive system's dynamics would be chosen in order to satisfy the following relationship around the crossover frequency:

$$H_{\mathrm{ps}}(s) \propto sH_C(s). \tag{2}$$

This concept well represents the operator's adaptability to external dynamics. This human's internal representation of machine dynamics expresses the hypothesis behind the crossover model and is equivalent to the Kalman estimator in the optimal control model [32].

The last case of Equation 1, in which the inner loop feedback signal is generated by integrating the force applied to the controlled element, is the one in which the effect of the pulsive control behavior on the time integrability of the human is more evident. In fact, the integration of a pulsive input signal can be approximated by

$$Y_{ps} = \sum_{i=1}^{n} A_i \Delta T_i, \tag{3}$$

being $A_i$ and $\Delta T_i$ the equivalent calculated amplitude and time duration of the ith pulse, and $Y_{ps}$ the resulting proprioceptive output signal. The computational burden of such an operation, if compared to integration over time, is significantly lower. In order to represent the discussed pulsive control effect on the inner loop feedback in the most simple and realistic way, the following logic is can be added before the neuromuscular system dynamics:

$$\begin{aligned} \frac{d\hat{q}}{dt} &= 0 \quad \text{if} \quad |\frac{dq}{dt}| < \alpha \\ \hat{q} &= \beta q \quad \text{if} \quad |\frac{dq}{dt}| \geq \alpha. \end{aligned} \tag{4}$$

where $q$ and $\hat{q}$ represent input and output variables, respectively, $\alpha$ and $\beta$ are the only parameters that must be tuned to reproduce pulsive behavior. The dependence of the model on just two parameters allows it to avoid its over-parametrization and simplifies its adaptability to experimental data. Basically, the action of this nonlinear element causes the output $\hat{q}$ to remain constant until a sufficiently rapid change in the input $q$ occurs.

Pulsive control as a result of the "ease of integrability" principle, as hypothesized by Hess, found a physiological interpretation in [33]. In particular, while proportional and derivative control feedback can be actuated using direct sensing organs, such as muscle spindles and Golgi tendon organs, integral control does not have similar sensing input sources and requires higher-level cognition in the central nervous system [29]. Consequently, when performing acceleration control, the human operator tends to generate a pulsive force rather than a continuous one to facilitate the integration process, being the computational cost of the latter much higher. Different explanations of the same phenomena are possible, being, for example, linked to energy saving strategy when the required force peak value is low enough.

## IV. NEUROMUSCULAR DYNAMICS

The latter consideration suggests the importance of neuromuscular actuation mechanisms as a source of nonlinearity in the human controller. Several dynamical system modeling approaches of the neuromuscular system have been proposed in the literature, starting from simple state-space descriptions [34]. Neuromuscular dynamics are typically nonlinear; for instance, we consider the model of a human limb, and its characteristics can be described in state-space form as

$$\begin{aligned} \mathbf{x}_{t+1} &= f(\mathbf{x}_t, t, \mathbf{u}) + \omega(t) \\ \mathbf{y}_{t+1} &= h(\mathbf{x}_t, t) + \epsilon(t). \end{aligned} \tag{5}$$

where $\mathbf{x}$ is the state vector representing two angles and two angular velocities, $\mathbf{u}$ is the control input corresponding to the two applied joint torques, $\omega$ is the process noise, while $\epsilon$ the observation noise. The general solution adopted in this nonlinear problem has been to linearize the nonlinear dynamics around a specific operating point, or a series of active topics, in state space. The resulting linear time-varying dynamics can be used only in a small interval around the operating point; in the case of the above example, neglecting the noise terms would be equivalent to

$$\begin{aligned} \mathbf{x}_{t+1} &= \mathbf{A}_t\mathbf{x}_t + \mathbf{B}_t\mathbf{u}_t \\ \mathbf{y}_{t+1} &= \mathbf{H}_t\mathbf{x}_t. \end{aligned} \tag{6}$$

Here, A is the state transition matrix and B the control transition matrix, while H represents the output measurement matrix.

Most control-theory-based neuromuscular modeling approaches aim to find the correct series of control inputs $u_1 \dots u_T$, corresponding to muscle forces and joint torques, which will make the system execute the desired trajectory in the time horizon $t = T$. Such a control system is an open loop; thus, if susceptible to disturbances, the controller would fail to reach the desired state, not sensing any state change. Moreover, the direct measurement of trajectories in state space can be problematic in high-dimensional systems, where part of the state may not be directly observable.

To overcome such shortcomings, optimal control approaches have been proposed [35], [36], where the dynamical system is controlled by optimizing an objective function. According to optimal control theory, the controller can directly access output and state variables or estimate their values to implement an optimal control law to maximize the system's performance. A general mathematical expression of the objective function to optimize to achieve this goal is

$$J(\mathbf{x}) = \min_{\mathbf{u}} \left( \phi(\mathbf{x}_{t_N}) + \int_{t_0}^{\infty} q(\mathbf{x}) + \frac{1}{2}\mathbf{u}^T\mathbf{R}\mathbf{u} \quad dt \right). \tag{7}$$

The system states are $u$ and $x$, the control torques, forces, or neural commands, and $x$, often expressed as joint angles, velocities, or muscle activation. Moreover, $\phi$ is the cost term dependent on the state, describing how a given target was reached. At the same time, $q$ is a state-dependent cost term considered over the whole time horizon $t_N$, and $u^T Ru$ is the cost dependent on the control input (also considered over the time horizon $t_N$). The velocity value and the control effort used to perform a given trajectory can be good examples of the last two mentioned cost terms in a practical application.

Optimal control approaches for adapting classical linear techniques, such as Linear Quadratic Gaussian Regulator (LQG), have been proposed for nonlinear dynamics typical of muscles and multi-body limbs. In [37], an Iterative Linear Quadratic Regulator (ILQR) was introduced based on linearizing nonlinear muscular dynamics. An advantage of this approach is that it does not need any predefined target trajectory in the state space to work. ILQR method was also extended in [38] for nonlinear stochastic systems characterized by state-dependent and control-dependent noise. Here, the ILQR technique permitted the description of the nonlinear relation between muscle force, fiber length, and contraction velocity. Further developments led to the use of Extended Kalman Filters (EKF) in systems where there is additive noise in sensory feedback loops [39], [40].

## V. INFORMATION PROCESSING AND DECISION-MAKING

The discussed models helped describe the human-machine system dynamics in a control-theory fashion. The involved physiological districts, sensing, and actuation systems were put in relation, considering the human as an element of the control loop, and the nonlinear dynamics present in motion command actuation and feedback were put in evidence. However, to understand how human beings act as a controller when interacting with a controlled machine, a deep focus on the information processing stage is crucial to understand how its central nervous system integrates pieces of information to make decisions, learn, and generate commands.

### A. FUZZY CONTROL MODELS

Processes such as human decision-making, inference, and judgment are challenging to characterize precisely. A modeling technique specifically meant to capture this concept is Fuzzy control modeling. If we represent a human controller as a fuzzy subsystem, the core of its control model would be described by the fuzzy rules it will set. Specifically, fuzzy rules describe the human decision-making process starting from formulating a hypothesis and successively mapping the fuzzy set from an input to an output space [41]. Such a mapping process can be defined as the "fuzzification process," while the reverse transformation will be called the "defuzzification." The physiological equivalent of this process is when the neuromuscular system receives an abstract decision from the central nervous system and consequently emits a force to the controlled device/machine. Fuzzy logic control models have been used to represent various human control activities in many research works, achieving good results in overcoming the limitation of approaches relying on a strict categorical division, especially in classification problems. In [42], fuzzy logic classification was used to represent radiologists' reasoning and decision-making process when recognizing breast cancer types from the analysis of medical images. While in [43], a fuzzy architecture was implemented for malware detection and classification in IoT applications. In the aeronautic domain, fuzzy control is suitable for developing a mental model of the pilot during a flight activity [44], [45], primarily referring to a compensatory type of sub-tasks [46]. The fuzzy logic control model was applied to study changes in simulated activity fidelity in aircraft control and Dynamic Multi-attribute Decision Making (DMADM) applications [47]. Additionally, fuzzy control theory was used for the safety evaluation of landing operations considering aircraft [48], [49] and rotorcraft [50]. However, the computational efficiency of fuzzy control systems is limited in cases in which a vast number of rules is present [51]. Moreover, it can be challenging to determine the rules when their number is high, and subjective model tuning will make its validation more challenging.

### B. ARTIFICIAL NEURAL NETWORKS

For nonlinear dynamical system modeling, Artificial Neural Networks have grown significantly in many research activities in the last years due to their flexibility and ability to imitate human learning, and decision-making. Moreover, when building a model from unstructured data, ANNs proved to be useful to build a reduced low-order model [52] and for their classification capability [53]. Artificial Neural Networks are composed of a linear combination of fundamental units (i.e., neurons), which can provide a linear transformation from the input data $x$ to output $y$ through several intermediate hidden layers. Each ANN scheme can vary significantly if the input vector dimension is known. The user usually chooses the dimensionality of the hidden and output layers. The input-output relationship of a single-layer neural structure with $m$ inputs (being $m$ a positive integer greater than 1) and single output would be, in the linear case:

$$y = \sum_{i=1}^{m} \mathbf{x}_i \mathbf{w}_i + q. \tag{8}$$

where variable $\mathbf{x}_i (i \in (1, 2, \ldots, m))$ represents the input signal of the model, $y$ represents the output signal, $\mathbf{w}_i (i \in (1, 2, \ldots, m))$ is the weight of each input signal and $q$ is the threshold of the activation function $f$. Nonlinear activation functions can be used to represent a wider range of dynamics. The more general definition of an ANN constituted by M layers, providing a nonlinear mapping between input and output data, would be:

$$\mathbf{y} = f_M(\mathbf{A_M}, \ldots, f_2(\mathbf{A_2}, f_1(\mathbf{A_1}, \mathbf{x})) \ldots). \tag{9}$$

Here, the $A_M$ to $A_1$ matrices contain the weight coefficients $w_i$ that map each variable from one layer to the next. The weights are chosen to fit the function:

$$\operatorname{argmin}_{\mathbf{A_j}} (f_n(\mathbf{A_n}, \ldots f_2(\mathbf{A_2}, f_1(\mathbf{A_1}, \mathbf{x}))) + \lambda g(\mathbf{A_j})). \tag{10}$$

Human behavior and information processing representation are based on the weights of neural networks. Such modeling technique is advantageous in aeronautical applications, for example, when mapping pilot control in research works where extensive data to process are available [54]. In [55], ANN and quasi-linear approaches are confronted in a two-axis tracking task, verifying neural network accuracy in describing nonlinear pilot behavior in aircraft control. In [56], an adaptive neural network controller is used by combining the trained network and a proportional-integral controller in an attempt to find a model-based method for control determination of unknown dynamics.

### C. NEURO-FUZZY SYSTEMS

Generally, neuro-fuzzy systems can be defined as all the modeling techniques involving artificial neural networks and fuzzy logic. These techniques can be categorized into three classes, depending on the combination of the two elements [57]:

- Cooperative neuro-fuzzy systems
- Concurrent neuro-fuzzy systems
- Hybrid neuro-fuzzy systems

In a cooperative system, the neural component is only present in an initial phase and determines the blocks composing the subsequent fuzzy system using training data. After this stage, only the fuzzy system will be executed.

In concurrent systems, on the other hand, the neural and the fuzzy components work simultaneously. This means that the information is pre-processed by one of the two components and then given in input to the other.

The most promising and utilized models belong to the hybrid systems category. A hybrid neuro-fuzzy system can be imagined as a fuzzy system in which parameters, such as fuzzy sets and fuzzy rules, are determined using a learning algorithm inspired by the neural network theory. Such a neuro-fuzzy system can be entirely created starting from measured input-output data without the *a-priori* knowledge needed to develop fuzzy rules with the traditional approach.

An example of a commonly used model of this type is the Adaptive-Network-Based Fuzzy Inference System (ANFIS), which was proposed for the first time in 1993 [58]. Its structure is composed of five layers. The first hidden layer maps the input variable relative to each membership function. The output layer calculates the global output as the summation of all the signals coming in the input. In particular, input membership function parameters are determined using back-propagation learning algorithms, and the least mean square method is used to determine the consequent parameters. The first advantage is to show both characteristics of neural networks and fuzzy logic, comprising if-then statements more suitable for human-like decision-making logic. In addition, its structure is not a black box, as in the case of neural networks, and therefore can be more easily debugged and improved. Moreover, it has smaller parameters to be determined to provide faster training without loss of generality [59]. The such model recently found diverse domains of application aside from human-machine interaction, such as electric distribution systems [60], [61], speech recognition [62], and economics [63]. In [64], the ANFIS model was used for human fall detection in comparison with other neuro-fuzzy techniques, such as the Local Linear Model Trees (LOLIMOT) model [65].

In LOLIMOT models, each neuron is a local linear model (LLM) and an associated validity function that determines the region of validity of the LLM. The normalized validity functions form a partition of unity for any model input z are:

$$\sum_{i=1}^{M} \phi_i(\mathbf{z}) = 1. \tag{11}$$

While the output of each LLM is calculated as follows:

$$\hat{\mathbf{y}} = \sum_{i=1}^{M} (\omega_{i,0} + \omega_{i,1}x_1 + \ldots + \omega_{i,nx}x_{nx})\phi_i(\mathbf{z}), \tag{12}$$

where $\mathbf{x} = [x_1, x_2, \ldots, x_{nx}]^T$. Here, the local linear models depend on $\mathbf{x}$, while the validity functions depend on $\mathbf{z}$ and are typically chosen as normalized Gaussian. The overall LOLIMOT network output is computed as a weighted sum of the LLMs outputs, where the $\phi_i(0)$ can be interpreted as the operating point-dependent weighting factors. The network interpolation between different LLMs is performed with the validity functions, where weights $w_{i,j}$ are linear network parameters. Again, LOLIMOT models were used in various domains of application, such as transportation [66], medicine [67], complex systems [68] and identification of time-variant nonlinear dynamics [69].

A dual fuzzy neural networks (DFNNs) model constituted by two equal neural networks has been used to simulate the physical nervous system in [70]. The advantage of dual fuzzy neural networks (DFNNs) is related to their close similitude to functioning and flexibility typical of humans. As in the case of ANNs, DFNNs can choose a suitable nonlinear mapping of input/output features through an iterative learning phase, in which neuron weights are updated. Such a model was implemented to simulate the relationship between the control signal and human perceived input [71]. Its performances were evaluated to provide insight into the pilot's decision-making process [72]. Moreover, [73] proposed a risk evaluation procedure founded on ANNs with the fuzzy control approach.

Even though in the Neuro-fuzzy model, neural networks and fuzzy logic are integrated, its drawback is to increase the computation and tuning time potentially. Besides, the experimental validation of the obtained model parameters may be tricky.

## VI. DATA-DRIVEN APPROACHES

Data-driven approaches have attracted more and more attention in recent years in various application scenarios in nonlinear dynamical system modeling and identification [74]. In human-machine interaction, learning processes starting from unstructured data using different types of Artificial neural networks (ANN) have been used for their processing classification by imitating human learning capability and decision-making, often combined with other learning algorithms, as we will discuss later in this section. A widely used type of network is the Convolutional Neural Network (CNN), traditionally used for capturing spatial relations in data, valid for applications with robust image processing, which are very common in human-robot collaboration [75] or autonomous system navigation [76].

However, for the study of nonlinear dynamics introduced by the human into the system during its control activity, aspects such as its temporal delay [77], or temporal relations in general within the given data series, might be more

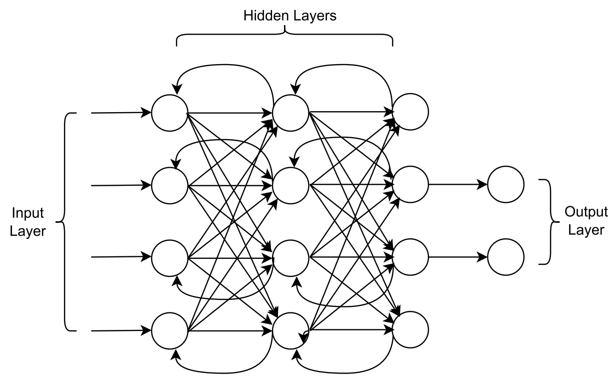


**FIGURE 2. General structure of a Recurrent Neural Network and its internal feedbacks.**

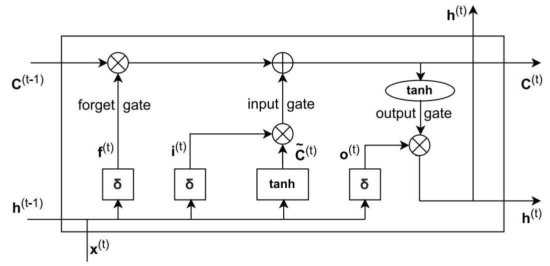


**FIGURE 3. Internal structure of an LSTM unit [80].**

relevant. Recurrent neural networks (RNNs) are the primary ANNs suitable for processing time series and other sequential data types. RNNs can extract a sequence's contextual information by defining the mutual dependencies between various time stamps. As shown from the scheme represented in Figure 2, standard RNN is composed of numerous successive recurrent layers and has a lot of feedforward and feedback connections in the time direction, allowing it to sequentially model its layers to map a sequence with other sequences. This makes it a good choice for dynamic system identification and control.

Concerning its structure, an RNN can be defined as an extension of feedforward ANN with internal loops in hidden layers. The activation of the state of a recurrent hidden layer at each time instant is dependent on that of the previous one. At a given time frame, each non-input unit computes the current activation as the nonlinear function of the weighted sum of all the activation of every connected unit [78]. They have been successfully applied in natural language processing (NLP), image captioning, speech recognition, and other fields. In [79], the authors investigated the approximation capability of continuous-time RNNs to the time-invariant dynamical systems. They proved that such network performances for approximating any finite time trajectory of a time-variant system were high. However, despite its suitability to model temporal variations present in the input, depending only on the current information and the previous output, a standard RNN may encounter difficulties when it comes to capturing long-term dependencies of time sequences.

To overcome this limit, a popular type of RNN which was proposed in a lot of research works is the Long Short-Term Memory network (LSTM), An LSTM network is a modified RNN, mainly designed to improve its ability to capture long-term relationships by avoiding premature gradient disappearance in error back-propagation algorithms through time.

LSTM is composed of a combination of units, representing internal structure in Figure 3. Each unit simultaneously receives an input vector $\mathbf{x}^{(t)}$ and the state of the hidden layer in the previous time instant $\mathbf{h}^{(t-1)}$ and updates, as output information, the cell state $\mathbf{C}^{(t)}$ and the current state of the hidden layer $\mathbf{h}^{(t)}$. This operation is done through three embedded layers in each LSTM unit: the input, output, and forget gates. The three gates have different roles and work in coordination: the forget gate $\mathbf{f}^{(t)}$ determines the probability that certain information has to be canceled from the cell state vector; the input gate $\mathbf{i}^{(t)}$ identify the new information to be stored, while the output gate $\mathbf{o}^{(t)}$ controls the output of the current hidden state $\mathbf{h}^{(t)}$. Translated into mathematical expressions, LSTM unit operations are the following:

$$\begin{aligned}
\mathbf{f}^{(t)} &= \sigma(\mathbf{W_f}\mathbf{h}^{(t-1)} + \mathbf{U_f}\mathbf{x}^{(t)} + \mathbf{b_f}) \\
\mathbf{i}^{(t)} &= \sigma(\mathbf{W_i}\mathbf{h}^{(t-1)} + \mathbf{U_i}\mathbf{x}^{(t)} + \mathbf{b_i}) \\
\tilde{\mathbf{C}}^{(t)} &= \tanh(\mathbf{W_C}\mathbf{h}^{(t-1)} + \mathbf{U_C}\mathbf{x}^{(t)} + \mathbf{b_C}) \\
\mathbf{C}^{(t)} &= \mathbf{C}^{(t-1)} \odot \mathbf{f}^{(t)} + \mathbf{i}^{(t)} \odot \tilde{\mathbf{C}}^{(t)} \\
\mathbf{o}^{(t)} &= \sigma(\mathbf{W_o}\mathbf{h}^{(t-1)} + \mathbf{U_o}\mathbf{x}^{(t)} + \mathbf{b_o}) \\
\mathbf{h}^{(t)} &= \mathbf{o}^{(t)} \odot \tanh(\mathbf{C}^{(t)}). \qquad (13)
\end{aligned}$$

where $\mathbf{W}$, $\mathbf{U}$, and $\mathbf{b}$ represent respectively the recurrent matrix, input weight matrix, and bias vector, $\sigma$ and *tanh* are sigmoid and hyperbolic tangent functions, and $\odot$ represent the element-wise Hadamard product.

Yeo and Melnyk [81] implemented LSTM networks to build a simulation model of noisy nonlinear dynamical systems using experimental data. Their goal was to identify the best fit of the probability density function of a given stochastic process and to represent the underlying nonlinear dynamics. Chen et al. [80] used LSTM networks to learn the characteristics of strongly nonlinear external dynamics of Van der Pol and Lorenz systems.

As said, neural networks used for unstructured learning have increased their potential by combining them with other learning algorithms. The most promising technology in this sense is Reinforcement Learning.

Unlike supervised and unsupervised learning, reinforcement learning has arisen as the third kind of machine learning paradigm. Using computational Reinforcement Learning algorithms allowed us to quantitatively describe several previously abstract concepts in neuroscience, cognitive, and behavioral science [82].

As detailed in [83], reinforcement learning (RL) can rely on Markov Decision Processes as a learning framework in which a learning agent interacts with an external environment and perceives its state, choose its actions to maximize a numerical reward function. The reward function is a simple numerical value for each time stamp, which can increase or decrease by one unit in the future due to the agent's actions. Therefore, the goal to maximize the reward function can be translated into maximizing the expected value of the cumulative sum of the scalar reward signal. Being defined from external information acquired from the environment through sensory inputs (in the case of a human operator), the goal to achieve is always defined outside the learning agent. In the case of a human being, that means that the learning agent can be defined as only the subsystem deputed to process the external inputs to define a control strategy (i.e., the central nervous system). The sensory subsystems can be considered part of the environment. In real-world complex situations in which humans are confronted with a challenging task, their duty is to derive efficient representations of the environment from high-dimensional sensory inputs and use them to generalize past experience and be able to use it in new situations [84]. If we consider an episodic task in which the agent-environment interaction can be decomposed into sub-sequences of repeated interactions, there is also a final time step, T. In this case, for a given timestamp $t$, the reward function to maximize is:

$$G_t = \sum_{k=0}^{T-t-1} \gamma^k R_{t-k-1}. \tag{14}$$

where $\gamma$, being $0 \leq \gamma \leq 1$, is the discount rate. This parameter determines the present value of future rewards. When $\gamma$ is close to zero, the weight of immediate rewards is higher and mostly taken into account by the agent; as it approaches 1, the goal takes future reward values more strongly weighted. If we have a continuous interaction in which there are neither definable intermediate steps nor a known final time frame, the above equation can be rewritten with $T = \infty$.

Reinforcement learning algorithms were extensively used in many research works relating to humans interacting with a machine, with many reward functions designed and more suitable for the different application scenarios. In [85], a Deep Deterministic Policy Gradient (DDPG) reinforcement learning algorithm is used to estimate human intentions in a human-robot interaction framework using EMG sensory inputs. At the same time, [86] integrated RL into the robot motion planning in a multi-robot collaborative manufacturing plant to implement human-in-the-loop control in teleoperated robots through augmented reality and digital twin techniques.

In the transport field, [87] adopted microscopic traffic simulation and reinforcement learning to implement the lane-changing strategy in connected and automated vehicles (CAVs). Reinforcement Learning has been successfully used with model-based techniques for systems identification in [88]. This was done to estimate the reward function from online data by acquiring and processing linear and nonlinear external dynamics. Mu et al. [89] used a reinforcement learning algorithm for partially non-modeled nonlinear systems, coupled with two neural networks, to implement an event-triggering dynamic strategy. In robotics, Deep Reinforcement Learning can be used for motion planning in cooperative applications with a human subject, learning how the human interacts with a specific environment and adaptively computing the best way to interact with him [90].

## VII. NONLINEAR DYNAMICS IN HUMAN-MACHINE SYSTEMS

The discussed modeling techniques and data-driven approaches have been successfully used for describing nonlinear dynamics in many application domains where humans interact with a controlled element.

Transport systems, for example, are a particularly relevant field of application for nonlinear dynamics modeling in human-machine interaction for what concerns the nonlinear dynamics deriving human decision-making, from the nonlinear nature of the controlled element and/or the system, and from human body physical coupling with the controlled system.

For what concerns the first point, connected and automated vehicle (CAVs) development has gained more and more attention from companies and research centers in the last few years. In studies dealing with automated lane changing, machine learning techniques were extensively used for human decision-making modeling and its use in automatic control strategies.

Let us consider the situation described by Figure 4, in which Vehicle 1 (V1) has to choose a lane-change strategy and is followed by vehicles 2,3, and 4. If we discretize the CAV travel as a series of time steps t, and $S_t$ are the state of the external environment at each step t, we would have that:

$$S_t = \{\tilde{a}_{1L}, \tilde{a}_{1R}, \tilde{a}_{2L}, \tilde{a}_{4R}, \tilde{a}_3, \tilde{\nu}_L, \tilde{\nu}_R, \tilde{\sigma}_L, \tilde{\sigma}_R\}(t). \tag{15}$$

Here, $\tilde{a}$ represents the acceleration difference of the considered vehicles (in the subscripts, numbers represent the vehicle and the letter the lane change direction) after V1 lane change; $\nu$ represents the mean acceleration difference between the central and the left or right lanes; $\sigma$ represents the difference between the standard deviations of the acceleration differences. From a learning agent perspective, these acceleration differences represent the gain obtained after a lane change. Therefore, the reward function could be formulated as follows:

$$R_t = a_1^{t+1}. \tag{16}$$

The subscript number stands for vehicle 1, and $t+1$ represents two consecutive simulation time stamps.

A lot of research efforts on this topic used simulation environments such as Matlab toolboxes [91], [92] to represent vehicles' behavior, or robotic toolkits using partially observable Markov decision processes (POMDPs), such as in [93]. A connected and automated vehicle does not rely on any external supervisor but must autonomously learn with a trial-and-error approach to decide when to make a lane change and

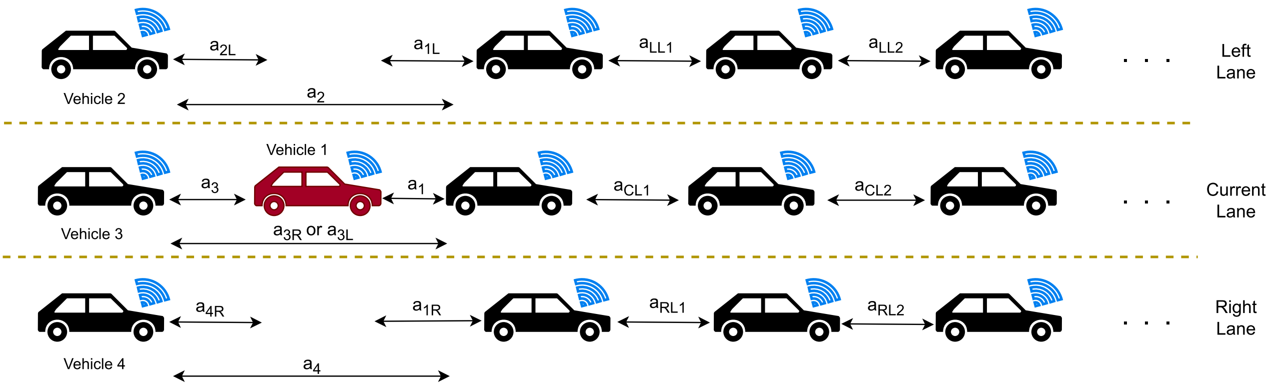


**FIGURE 4.** Connected Automated Vehicles represented in a lane-change scheme.

how to execute it. One of the most challenging aspects is that the vehicle must evaluate the long-term benefit of such an action and become farsighted in its strategy to maximize the travel's efficiency. For this challenge, reinforcement learning seems to be the preferential approach (as noticeable from its formulation described in the previous section). For instance, in a high-fidelity simulation environment, [94] used a deep reinforcement learning training program for car following. In [87], the authors also used reinforcement learning in a microscopic traffic simulation environment [95] calibrated using actual highway data. Li et al. [96] used an evolutionary learning approach for lane change tested in a highway simulation environment. The optimization problem objective is to maximize the velocity while minimizing the disruption to the following vehicle; if it is impossible to reach this goal in the current lane, a change-lane decision is taken. In this case, the reward $\mathbf{r_{i,t}}$ depends on the difference between desired velocity $\mathbf{v_d}$ and actual velocity $\mathbf{v_{i,t}}$ of the controlled vehicle and the acceleration of the following one ($\mathbf{a_{k,t}}$):

$$\mathbf{r_{i,t}} = -|\mathbf{v_{i,t}} - \mathbf{v_d}| + \mathbf{a_{k,t}}. \tag{17}$$

If the velocity difference overcomes a certain threshold, the lane is changed.

However, the lane change has not a time-driven structure but an event-driven one, described as a discrete dynamic process, which can be well represented as a Markov Decision Process. In [97], POMDPs were also used for an automatic lane change in long-distance road experimental trials using automated vehicles. Here, the decision-making process is modeled, referring not only to the controlled vehicle but also to the surrounding environment, inspired by the consideration that human drivers change their behavior when interacting. Reaction modeling is performed by measuring the temporal evolution of the vehicle state, including in it also a reaction and a deviation parameter.

Figure 5 represent the differences between the traditional hidden goal method, which applies only to specific regions of interest, and the reactive method, which models the group of vehicles in general and their deviation.

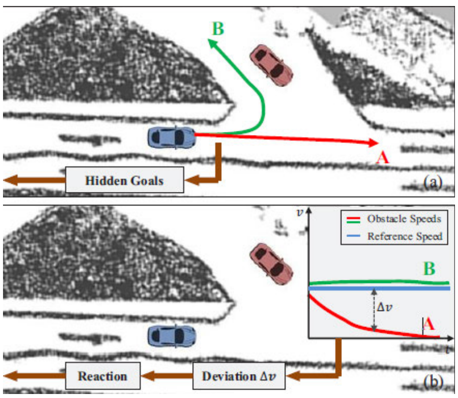


**FIGURE 5.** Motion intention estimation as explained in [97], using hidden goal (a) and reaction (b) methods.

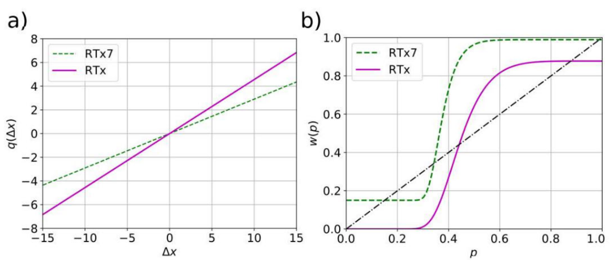


**FIGURE 6.** Modeling of regret biasing (a) and probability weighting (b) at a cognitive level as studied in [98].

A further aspect of human decision-making in a lane-changing application is related to risk propensity. In [98], the authors proposed a decision model that considered the driver's perception, reasoning, and emotions. Risk propensity considers two mental processes: regret biasing and probability weighting, corresponding to the emotional aspect and cognitive reasoning. Both functions' nonlinearity increases proportionally to the emotional bias and cognitive weighting. The proposed model was tested with a dataset from a naturalistic driving database. Figure 6 represents the obtained fitted functions without considering regret biasing and probability weighting (purple line) and with the two terms (green dashed line). Figure 6a represents the regret q-functions, which resulted in being linear, indicating the regret influence is not evident in all cases. On the other hand, Figure 6b shows a w-function divided into three intervals; in two of them, the function overweights the objective probability (dot-dashed line), indicating a general optimism and bent to take risks.

As said, aside from human decision-making representation, the source of nonlinearity in the human-machine complex may be related to the dynamics of the controlled element. If the human subject continuously controls such devices, this will raise an essential challenge concerning system modeling and control.

In cooperative teleoperated robotic systems, for instance, many nonlinear control approaches have been developed in order to deal with non-passive (and therefore unstable [99]) factors such as the uncertainty of the environment, the presence of variable communication delays, kinematics, and dynamics parametric uncertainty. Such kinds of systems have found vast applications in healthcare [100], space [101], and exploration in dangerous environments [102] and disaster scenarios [103]. Even if Linear control approaches have been successfully developed for robust stability achievement in the presence of uncertain system dynamics, nonlinear controllers proved to guarantee good stability and performance through the exploitation of special properties of nonlinear rigid body dynamics of primary and secondary manipulators [104].

In [105], nonlinear bilateral control of a teleoperation system with a flexible-link secondary manipulator is performed by designing a robust tip position tracking controller for the secondary manipulator. The desired trajectory is determined based on the primary's position signal, and a force controller for the primary robot, which should track the environmental force exerted on the secondary manipulator. While [106] proposes a control strategy able to establish position-position kinematic correspondence between primary and secondary by incorporating in the adaptive controller the models of operators, controlled robots, tools, and environment, as well as their parametric uncertainty. Further approaches, as in [107], enlarged this concept by mapping the human arm stiffness references in a bilateral teleoperation framework, building a ''teleimpedance control'', later extended with a semi-autonomous contact detection strategy in [108]. Moreover, another challenging aspect of bilateral teleoperation systems control is related to the presence of communication time delays, which may cause the system to degrade its performance and even result in unstable behavior. The time delays should therefore be considered in the design stage of the controller. In [109], this problem is faced by considering adaptive neural synchronization control of bilateral teleoperation systems with backlash-like hysteresis, one of the most important nonlinearities in robots. While in [110], a finite-time synchronization control method is proposed based on fuzzy approximation of system uncertainties.

Another example of highly nonlinear controlled systems interacting with an unknown external environment consists in multirotor remote control. Multirotor applications were carried out in several research activities, with practical applications like surveillance, photography, video-making, grasp or motion of an object, or military [111]. The equation of motion of a multirotor with a mass $m$ and inertia tensor $\mathbf{J}$ can be written as:

$$\begin{aligned} m\ddot{\mathbf{x}} &= -m\mathbf{g}\mathbf{e_3} + \mathbf{fRe_3} \\ \mathbf{R} &= \mathbf{R}\hat{\Omega} \\ \mathbf{J}\dot{\Omega} &= -\Omega \times \mathbf{J}\Omega + \boldsymbol{\tau}. \end{aligned} \tag{18}$$

where $\mathbf{f}$ and $\boldsymbol{\tau}$ are the force and torque inputs, $\mathbf{x}$ is the multirotor position with respect to the inertial frame, $\Omega = [p_B, q_b, r_B]^T$ is the angular velocity vector in the body frame, $\mathbf{g}$ is the gravity force, $\mathbf{e_3} = [0, 0, 1]^T$ and $\mathbf{R}$ is the transformation matrix from the body to an inertial frame.

Trajectory tracking control for such systems is not accessible due to its nonlinearity, under-actuation, and highly coupled states. Although simple linear controllers such as PID or LQR have been successfully proposed in the past [112], [113], [114], [115] for a limited number of non-agile movements, controllers using feedback linearization, backstepping or geometric control techniques are more suitable to handle with the nonlinearity of the system. Various types of Feedback Linearization (FL) techniques were used for multirotor, such as input-output and state-space linearizations [116] have been used for finding the rotor's dynamics linear approximation. In [117], FL performances were compared with an adaptive sliding mode control technique. While in [118] FL controller was combined with a Luenberger observer.

However, the rotorcraft nonlinearity cannot be eliminated if a modeling error is present in feedback linearization. Thus its stability is not guaranteed. Therefore, backstepping control strategies with sliding mode techniques have been increasingly used to overcome these problems, associated with sliding mode techniques in [119], [120], and [121]. When roll and pitch angles were high, such as in [122], and [123], the Lagrangian formulation was preferred, even at a higher computational cost. Xian et al. [124] proposed a different approach in which an energy-based passivity controller controlled a quadrotor with a suspended payload. Also, neural networks were used in multiagent trajectory tracking applications, such as in [125], where an online RNN-based controller enabled the formation of a multiagent system characterized by a leader-follower structure. Such a control strategy allowed each agent to have the same output even with a different number of inputs, facilitating the system task planning.

Extensive research efforts were also directed through modeling unwanted human control behavior in transport systems, particularly to Rotorcraft-Pilot Coupling (RPC) [126]. For evaluating human-rotorcraft interaction in aspects such as comfort and handling qualities, some performed modeling efforts present in literature were directed towards studying the dynamical behavior of the human body. Understanding such body dynamics, in this case, the upper body is fundamental to identifying potentially dangerous nonlinearities in RPC. These approaches vary significantly and can be classified into two main categories, such as finite element models (FEM); and multibody dynamics (MBD) or lumped parameter models (LPM).

Lumped parameter models are composed of elementary mechanical subsystems, such as lumped masses and viscoelastic elements with linear or nonlinear properties. In the linear case, parameters are relatively easy to identify, with a low associated computational cost and can be easily tuned to fit the biomechanical characteristics of a specific subject. However, in LPM where nonlinear viscoelastic elements are used, the cost of identifying its characteristics may increase, depending on the applied force or displacement. In [127], the authors used a piecewise LPM as an analytical tool to perform a preliminary analysis of vehicle crashworthiness in order to reduce the time required to assemble and tune FEMs and perform a nonlinear finite element analysis in crash testing. In the proposed LPM, the spring and damping coefficients are defined as piecewise linear functions of input displacement and velocity. Lumped parameters nonlinear models are also present in works such as [128], in which a one-degree-of-freedom model was applied for analyzing human body dynamic response during a helicopter landing. In works such as [129], and [130], previous state-of-the-art linear models were optimized using a genetic algorithm to capture the nonlinear effects of passengers' dynamic response when subjected to vibrations.

In [131], a multibody model of the upper body was designed by connecting a model of the pilot's arms to a model of the spine. Such a spine model, as well as the scaling procedures, was used for studying seat-to-head transmissibility. This coupled spine-arms model can be used to evaluate the biodynamic response of the human operator in terms of involuntary motion induced on the control inceptors, including the related nonlinearities.

Finite element models have been successfully used in recent research to represent human body behavior during an impact, often in relation to injury risk prediction and vehicle safety. The Total Human Model for Safety (THUMS) is a famous finite element human body model intended for injury analysis [132]; it has been used in association with a model of a vehicle's internal structure, with the purpose of simulating human body kinematics in response to a large impact in a car crash. The geometries of the structurally complex human body parts, including the head, torso, ligaments, joints, and internal organs, are represented by finite element meshes, and their impact responses have been studied separately. Moreover, in relation to transport safety, within the context of the European project "Human model for safety two" (HUMOS2) [133] human body numerical body models were constructed in order to create a database able to represent the European population with high fidelity. Portions of HUMOS2 models have been used in many research efforts, such as [134] for which thoracic accidents and [135] for head injuries in motorcycle crashes. Another example of FEM used to provide kinematic and kinetic data of the human body in a computationally efficient way has been proposed in [136] by the Global Human Body Models Consortium (GHBMC).

## VIII. CONCLUSION

The presented modeling research efforts of nonlinear dynamics in human-machine interaction successfully captured many aspects of the human learning process, information processing, and control action. From the classical control-theory fashion of dual-loop control to the more recent machine-learning techniques, many advances have been made in identifying the sources of nonlinearity in human control behavior and in implementing models able to transfer such ability to the controlled machines. Modeling and data-driven techniques were presented in a human-centered way in order to show how they succeeded in representing different aspects of the human as a controller. For instance, the decision-making process directed toward achieving an internal goal is well described by reinforcement learning approaches, while optimal control models of the neuromuscular system or biodynamical models are most useful for nonlinear dynamics deriving from human body actuation districts or from its coupling with the controlled element. Moreover, data-driven techniques associated with control systems were analyzed in relation to nonlinearities that derive from the controlled element dynamics and/or the external environment. As proved by the discussed man-machine systems, the discussed algorithms can be combined to increase the level of autonomy and the usability of machines even in complex scenarios such as connected vehicles, automatic lane changes, teleoperation, or remote control of rotorcraft, This is done while acting in an environment surrounded by humans, with consequent potential issues regarding safety and adding unexpected physical interaction that requires a level of adaptability, which is typical of human beings and constitutes one of the reasons that motivated such modeling efforts. Despite the successes concerning classical control theory models discussed in the first sections, modern machine learning frameworks struggle to capture the physiological context relying upon the human learning process. Neural networks and algorithms based on reinforcement learning or optimal control paradigm still have almost a black-box approach to what concerns this aspect. Advances in understanding the human brain are still a challenge that motivates many research activities.

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**ADRIANO SCIBILIA** received the B.Sc. degree in electronic engineering from the University of Catania, in 2015, and the M.Sc. degree in biomedical engineering from Politecnico di Milano, in 2018. He is currently pursuing the Ph.D. degree with the University of Catania. From 2017 to 2018, he was a part of the Advanced Robotics Department, Italian Institute of Technology. Since 2018, he has been a Research Fellow with the Institute of Intelligent Industrial Technologies and Systems for Advanced Manufacturing, National Research Council of Italy. His research interests include physical human–robot interaction, safety in collaborative robotic systems, and modeling of human control behavior in human–machine interaction.

**NICOLA PEDROCCHI** received the M.Sc. degree in mechanical engineering from the University of Brescia, Brescia, Italy, in 2004, and the Ph.D. degree in applied mechanics and robotics, in 2008. From 2008 to 2011, he was a Research Assistant with the Institute of Industrial Technologies and Automation (STIIMA), National Research Council of Italy (CNR), where he is currently a Full Researcher, since 2011. Since 2015, he has also been coordinates the activity of the Robot Motion Control and Robotized Processes Laboratory, CNR-STIIMA. His research interests include control techniques for industrial manipulators in advanced applications requiring the interaction of robot-environment (e.g., technological tasks) or robot–human operator (e.g., workspace sharing and teach-by-demonstration). He is involved in research for accurate elastic modeling and dynamic calibration of industrial robots.

**LUIGI FORTUNA** (Fellow, IEEE) received the degree (cum laude) in electrical engineering from the University of Catania, Italy, in 1977. He was a Coordinator of the courses in electronic engineering and the Head of the Dipartimento di Ingegneria Elettrica Elettronica e dei Sistemi. From 2005 to 2012, he was the Dean of the Engineering Faculty. He also teaches automatic control and robust control. He is currently a Full Professor of system theory with the University of Catania. He has published more than 500 technical articles and 12 scientific books. His scientific research interests include robust control, nonlinear science and complexity, chaos, cellular neural networks, soft-computing strategies for control, robotics, micronanosensor and smart devices for control, and nanocellular neural networks modeling. He was the IEEE Circuits and Systems (CAS) Chairperson of the CNN Technical Committee, the IEEE CAS Distinguished Lecturer, from 2001 to 2002, and the IEEE Chairperson of the IEEE CAS Chapter Central-South Italy.

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