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Human state digital twin architecture for physiology constrained adaptive robotic autonomy

Jaganathan Nirmaladevi[1], S. Saranya[2], Nidhi Mishra[3], Fazal Noorbasha[4], Manoharan Kavitha[5]
[1]Department of Information Technology, KGiSL Institute of Technology, Coimbatore, India
[2]Department of Electronics and Communication Engineering, Panimalar Engineering College, Poonamallee, Tamil Nadu, India
[3]Department of Computer Science and IT, Kalinga University, Chhattisgarh, India
[4]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Vaddeswaram, Guntur (District), Andhra Pradesh, India
[5]Department of Department of Electronics and Communication Engineering, Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Saveetha University, Chennai, India

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ABSTRACT

Time-dependent human cognitive and physical conditions should be considered in adaptive autonomy in collaborative robotics to ensure safety, performance, and operator comfort. But most of the current methods depend on heuristic levels of workload or individual physiological measures and fail to combine human-state estimation with the control structure. This paper suggests a human state digital twin (HSDT) framework of physiological-constrained adaptive robotic autonomy. This framework is a combination of multimodal physiological measures of electrocardiography-based heart-rate variability, electromyography, electrodermal activity, and task context to predict latent human states such as cognitive workload, fatigue, and stress. These estimates are included in a twin-constrained adaptive autonomy controller, which varies the control authority of the robot in real time. The simulated collaborative manipulation situation is tested in the proposed framework in different workload and fatigue conditions. It has demonstrated better tracking performance, less torque ripple, reduced operator stress indicators and less torque ripple. The paper presents a controlled and reconfigurable physiology-aware adaptive autonomy control architecture and a robotics-based digital twin control design framework of human-aware control design.

Corresponding Author:

Jaganathan Nirmaladevi
Department of Information Technology, KGiSL Institute of Technology
Coimbatore, India
Email: mkseee2007@outlook.com

1. INTRODUCTION

The new needs of collaborative robotics demand control architectures, which are able to cope with the changing cognitive, physical and physiological conditions of the human operator in real time. Fatigue, stress, workload, and task complexity have a major impact on human performance in industrial, assistive, and shared-workspace applications that directly impact the safety, efficiency, and the quality of interaction of a system. Conventional approaches to human-robot teaming are often based on the classic approaches of fixed safety margins, heuristic workload limits or pre-established levels of assistance, which do not work well in managing nonlinear and time-varying human factors. Recent developments in physiological sensing have shown that it is possible to improve the awareness between operators and states in their interaction [1]. Also, explainable and adaptive artificial intelligence is advancing with the focus on the need to have structured state-aware decision systems, but little has been done on how to directly incorporate them into robotic control laws [2]. Besides, recent control oriented embedded architectures emphasize the importance of having closely coupled estimation and control systems as opposed to viewing them as independent processes [3]. The paper proposes a human state digital twin (HSDT) implemented into the adaptive robotic control.

Earlier studies have done research on multimodal signal processing and data-driven modeling systems which are human centric systems [4]. Distributed intelligence methods have also been able to deal with issues involving dealing with heterogeneous physiological data [5]. The multimodal sensing techniques used jointly also illustrate the ability to garner meaningful information out of the complex signals [6]. Higher levels of physiological modelling have also been suggested in enhancing accuracy of human-state estimations [7]. But these are more of an approach to analyze data and to infer rather than integrate real-time control. The most important aspect in robotics is not where meaningful features are extracted out of physiological signals but rather how this information can be directly incorporated into control architectures which directly affect the behavior of the system. Recently, a new technology has been developed that is called digital twin and could become the new promising paradigm of modeling dynamic interactions between physical systems, human operators and environments. Specifically, human digital twins offer well-structured computationally represented operator behavior and physiological state, which can be used to enhance safety and ergonomics of collaborative systems [8]. Meanwhile, the trend of smart system design is toward transparency, reliability, and interpretability of the decision-making process in the context of human-related data [9]. Intelligent human-centered systems have also emphasized the significance of developing a robust and trust-aware system design [10]. The adaptive and context-aware systems of robotics are developing towards autonomy systems that not only react to the task demands, but also react to the condition of the operator [11].

One of the biggest shortcomings of current methods is that physiological sensing is generally utilized as a monitoring tool or to conduct offline analysis instead of being a part of closed-loop control systems. Even though developed learning structures have proved to be very robust in patterns that can be identified in the intricate physiological data [13], such models are hardly ever employed as inputs to control laws. A few studies have considered multimodal physiological learning [14], whereas others considered data-based human-state modelling [15]. Besides, physiological monitoring systems have also been created based on real-time signal interpretation systems [16]. Nevertheless, these methods do not directly incorporate physiological estimates in the adaptive control processes, which means that they cannot be conveniently applied in real-time robots.

Recent advances in human digital twin models accentuate continuous representation of operator condition and contextual interaction model [17]. The design of knowledge-based systems also emphasizes the need to make decisions in an organized manner in adaptive systems [18]. Responsive and human-aware control mechanisms have also been shown to be beneficial in adaptive automation approaches in robotics [19]. Secondly, the studies on system coordination and distributed intelligence emphasize that there has to be stable and interpretable decision-making structures [20]. Trust modeling techniques also help give the concept of reliability in human-centric systems greater weight [21]. Such adaptive architectures have also been proposed to have benchmarking methodologies [22]. The research on the spatiotemporal modeling and dynamic behavior analysis points to the significance of time-varying human movement, as well as physiological variability [23]. This is especially applicable in collaborative robotics where fatigue, stress and motor intent directly impact the quality of interactions and system safety. The studies of human-conscious control and soft robotic interaction also emphasize the necessity of the adaptive control mechanisms taking into consideration human comfort and physical state [24]. Also, systems based on robotics with human focus are becoming more in need of models which can be adjusted to the variations of the operator performance [25]. The fact that sensitivity-aware and fairness-aware modeling approaches suggest the relevance of responsiveness to the changes in human-state information also speaks in favor of the importance of the latter [26]. In addition, real-time processing of physiological signals is made possible by low-latency computational frameworks and this is essential in adaptive autonomy to dynamic environments [27]. The real-time processing architectures are also efficient to add the concept of physiological sensing into the control systems [28]. Recent studies in human-robot collaboration also confirms that workload, autonomy, robot speed, and complexity of the environment all impact the quality, safety, and comfort of the interaction [29], [30]. Human-centric digital twin studies also demonstrate that digital twins of humans can enable more context-aware and adaptive human-machine collaboration [31]. Further, reinforcement learning and task-load adjustment methods have been shown to enhance human-robot collaboration by adapting robot actions based on physiological and performance measures [32]. The most recent review of mental workload in collaborative tasks stresses that workload assessment is a critical aspect of cobot systems [33]. However, research on robotic teleoperation also demonstrates that physiological measures could be insufficient and need to be complemented by performance measures for reliable workload prediction [34]. Human-in-the-loop optimization also underlines the need for an adaptive robotic system which learns from the particular responses of the human user as opposed to the fixed controller tuning [35]. These recent advances highlight the need for the proposed HSDT-based TCAA approach, where physiological estimation and monitoring is not considered as a stand-alone output but is integrated with autonomy allocation and robotic control. Although these developments are made, there are still a number of research gaps. To begin with, there are few formal parametric models of human physiological state that are directly incorporated into the control laws of robots. Second, in closed-loop systems real-time estimates of the physiological state are rarely applied as dynamic constraints in the allocation of autonomy. Third, unity of assessment schemes of physiology-constrained adaptive autonomy is lacking especially in measurement of performance tracking, seamless change of authority and safety conscious control behavior. To overcome the difficulties, this paper suggests a human state digital twin (HSDT)-inspired twin-constrained adaptive autonomy (TCAA) model, where multimodal physiological cues are directly incorporated into the control of a robot. The proposed framework makes use of electromyography (EMG), electrodermal activity (EDA) and heart-rate variability (HRV) to predict in real-time latent human states including cognitive workload, fatigue, and stress. These estimates are integrated into an autonomy allocation mechanism which is a closed-loop and dynamically modulates the control authority between the human operator and the robot. The research problem that is to be discussed in this work is to ascertain whether direct application of the real-time estimation of latent human physiological states can be directly integrated into the control laws of robots with the aim of enhancing the safety, tracking performance and smoothness of the interaction in collaborative systems. The main contributions of this paper are as follows:

- A coordinated HSDT system of real-time multimodal estimation of the cognitive workload, fatigue, and stress.
- A physiology-constrained adaptive autonomy control architecture that provides estimates of human-state directly into control authority allocation.
- A TCAA model that allows easy and interpretable based transitions between human and robot control.
- A validation framework based on simulation showing enhancement of the accuracy tracking, smoothness of the torque and stability at different workload conditions.

The proposed method will further take the field of adaptive autonomy a step beyond monitoring-based systems by adding physiological state estimation to closed-loop control, bringing the concept of the next-generation collaborative robotics to a completely unified human-aware control paradigm. The suggested framework is specifically applicable in industry collaborative robots, assistive, and human-focused automation landscapes.

2. PROPOSED METHOD

2.1. Overall system architecture

The proposed design is based on TCAA architecture, according to which HSDT constantly adjusts the robot control authority assignment. The general system architecture is shown in Figure 1.

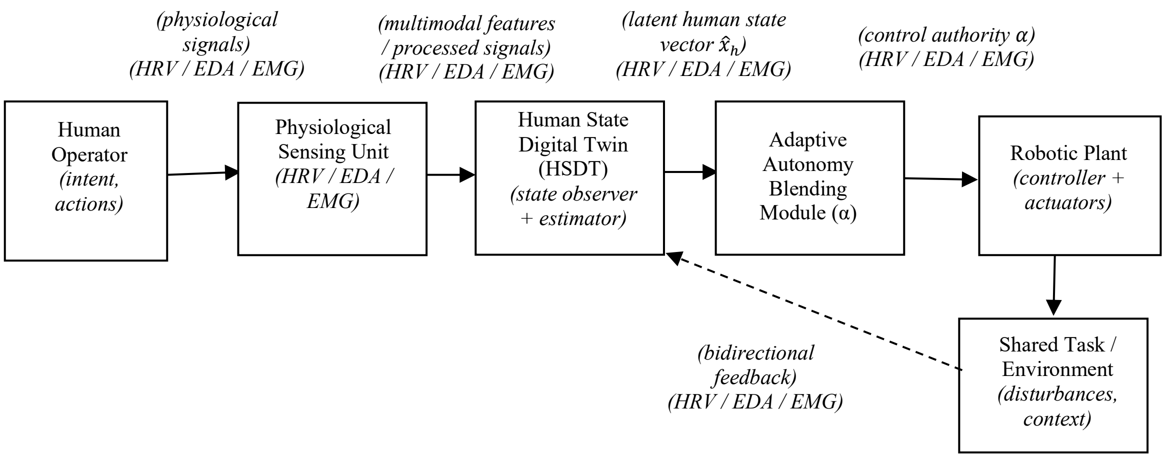

Figure 1. Overall architecture of the twin-constrained adaptive autonomy framework

The framework consists of five basic modules, namely: i) multimodal physiological sensing, ii) human state estimation, iii) autonomy blending controller, iv) robot dynamic control layer and

v) bidirectional feedback. Physiologic indicators such as electromyography (EMG), electrodermal activity (EDA), and heart-rate variability (HRV) are measured with a frequency f_s. Such signals are preprocessed and transformed into a latent human state vector $x_h \in \mathbb{R}^n$, which is a cognitive workload, fatigue, and stress. The state-space dynamic of the robot plant is provided as:

$$\dot{x}_r = f(x_r, u), y = h(x_r)$$

In this case, $x_r \in \mathbb{R}^n$ represents the state of the robot, $u \in \mathbb{R}^m$ denotes the control input, and $y \in \mathbb{R}^p$ represents the observable output. A, B and C are the state, input and output matrices of linearized representation of the robot dynamics. The input of the human operator u_h is added to the autonomous controller input u_a with an adaptive autonomy coefficient $\alpha \in [0,1]$ such that:

$$u = \alpha(x_h)u_a + (1 - \alpha(x_h))u_h$$

This shared-control formulation u_h represents the human command input, u_a represents the autonomous controller output and α is the degree of control authority allocated to each. The larger the value of α the greater the power given to the autonomous controller; the smaller the value of α, the larger the portion of control left in the hands of the human operator. Dynamic computation of the coefficient of blending is:

$$\alpha(x_h) = \sigma(W^T x_h + b)$$

In this W is a learned weighting vector, b is a scalar bias value, and $\sigma(\cdot)$ is a constrained sigmoid activation function that thwarts smooth and continuous switches between low and high autonomy levels.

3. METHOD

3.1. Human state digital twin modeling

HSDT modeling pipeline as shown in Figure 2 is a transformation of physiological measurements to a dynamically estimated human-state latent state to be used in adaptive robotic control. The HSDT is intended to give a mathematically consistent and real time model of cognitive load, fatigue, and stress computationally, using multimodal bio signal representations, and resilient to measurement noise and nonlinear physiological processes. Physiological measurements in the proposed framework are represented as multimodal cues EMG, EDA and photoplethysmography/electrocardiography (PPG/ECG)-measured heart-rate-variability (HRV) features. A band-pass filter of 20-450 Hz was used to filter the EMG signals in order to eliminate motion artifacts and high-frequency noise. To maintain slow sympathetic response components linked with stress and arousal, EDA signals were low-pass filtered. The extract of HRV features based on the ECG/PPG-derived inter-beat intervals was performed through conventional time-domain and frequency-domain measures. The estimator was run at 100 Hz and the robot control loop was run at 1 kHz to guarantee compatibility between physiological estimation and control execution in real-time.

These signals represent variations in operator state under changing workload conditions, and are processed in the framework. Digital band-pass filter is used to eliminate motion artifacts, baseline drift and high frequency noise. The standard difference equation is the means to obtain the filtered signal:

$$x_f[k] = \sum_{i=0}^{N} a_i\, x[k-i] - \sum_{j=1}^{M} b_j\, y[k-j]$$

In this case, $x[k]$ is the input signal, $x_f[k]$ is the filtered output, a_i and b_j are filter coefficients and N and M are the feedforward and feedback order of the filter respectively. The filter parameters are chosen depending on physiological signal bandwidths (*e.g.* 20-450 Hz of EMG and 0.04-0.4 Hz of HRV components). The z-domain stability and causality is provided by normal pole-zero analysis. After the signal conditioning we extract features so as to come up with the meaningful physiological descriptors of latent human states. The features that are extracted are root-mean-square (RMS) EMG amplitude (symbolizing muscular effort), skin conductance level (SCL) (symbolizing sympathetic nervous activity) and HRV spectral components, *i.e.* low-frequency (LF) and high-frequency (HF) power. These characteristics are put together into an observation vector:

$$z[k] = [\mathrm{RMS}_{EMG}, \mathrm{SCL}, \mathrm{HRV}_{LF}, \mathrm{HRV}_{HF}, \dots]^T$$

A nonlinear representation of fatigue and internal cognitive states which the observation vector can provide is partially observable. The latent state cannot be measured as physiological processes are nonlinear and correlated over time and therefore cannot be determined directly as a result of instantaneous measurements. Thus, a recursive state estimation model is used. A Kalman filter that is extended (EKF) is taken to predict the latent human state vector $\hat{x}_h$, that can be a cognitive load index, fatigue level, stress index, and neuromuscular activation state. The nonlinear state-space model is a discrete-time model in the form:

$$x_h[k+1] = Fx_h[k] + w[k]$$
$$z[k] = Hx_h[k] + v[k]$$

The observation-latent human states relationship is nonlinear and partially observable. As there are no instantaneous indicators of cognitive load, fatigue, and stress, a recursive state estimation method is employed.

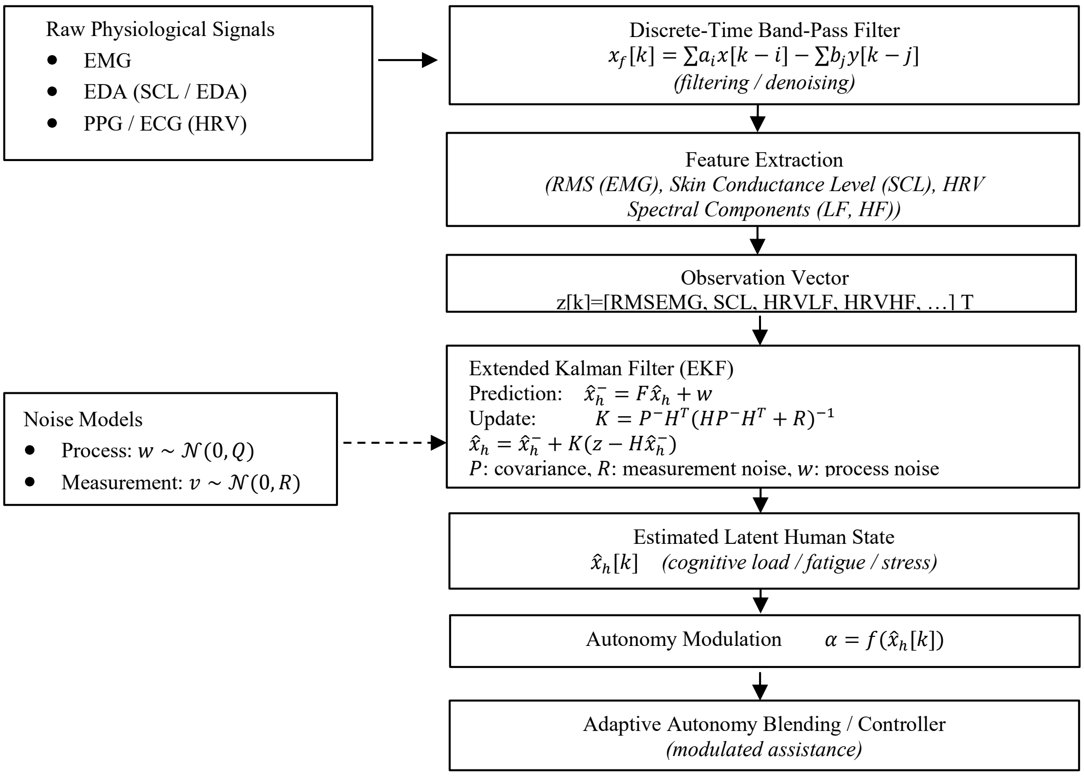

Figure 2. Human state digital twin signal processing and estimation framework

The estimation of the latent human state vector $\hat{x}_h$ that reflects cognitive workload, fatigue level, stress index, and neuromuscular activation is done through the use of an Extended Kalman filter (EKF). The EKF is chosen since the latent human state is nonlinear, partially observable and recursively evolves based on noisy physiological measurements. EKF is less computationally complex than particle filters, so it can be used in real-time autonomy modulation. Compared to a standard Kalman filter, the EKF is an effective way to model nonlinear dependencies between physiological variables and latent variables like workload, fatigue and stress. The nonlinear state space model can be put in discrete-time terms as:

$$x_h[k+1] = Fx_h[k] + w[k]$$
$$z[k] = Hx_h[k] + v[k]$$

In this case, F denotes the state transition matrix, H is the observation matrix, $w[k] \sim \mathcal{N}(0,Q)$, and $v[k] \sim \mathcal{N}(0,R)$ denote process and measurement noise respectively with covariance matrices Q and R respectively. EKF takes place in two recursions. In the prediction step:

$$\hat{x}_h^- = F\hat{x}_h$$
$$P^- = FPF^T + Q$$

where P is the state covariance matrix which is the uncertainty in estimation. In update step Kalman gain is calculated as:

$$K = P^- H^T (HP^- H^T + R)^{-1}$$

The state estimate is given by:

$$\hat{x}_h = \hat{x}_h^- + K(z - H\hat{x}_h^-)$$

and the covariance update is given as:

$$P = (I - KH)P^-$$

This recursive estimation makes it possible to keep on updating the latent human state with the availability of new observations. The covariance matrix P can be used to give a measure of the confidence of estimations, which can be included in safety-conscious autonomy constraints. The observability matrix will be assessed as:

$$O = \begin{bmatrix} H \\ HF \\ HF^2 \\ \vdots \end{bmatrix}$$

To make a tradeoff between responsiveness and noise suppression additional tuning methods like expectation-maximization (EM) or innovation covariance matching can be used. The autonomy blending coefficient is directly modulated using the estimation of the latent state $\hat{x}_h$. The autonomy modulation is determined as:

$$\alpha[k] = \alpha_{min} + (\alpha_{max} - \alpha_{min})\, \sigma(\beta^T \hat{x}_h[k])$$

The bounded sigmoid mapping provides that $0 \leq \alpha(t) \leq 1$, and avoids discontinuous human and robot control. The derivative of the sigmoid function is limited, so the rate of change of autonomy is smooth, thus minimizing sudden changes in torques and enhancing the stability of closed-loop interaction. In this $\sigma(\cdot)$ a bounded sigmoid function and β is a learned weighting vector that is used to map human conditions to levels of autonomy. The autonomy coefficient is found to be high under high cognitive load or fatigue and allows increased robotic assistance. In more loose conditions, authority of human control is underlined. HSDT modeling framework offers the following main properties: i) continuous estimation of human state over time, ii) robustness to sensor noise and signal variability, iii) mathematically consistent state-space representation, and iv) direct integration into closed-loop adaptive control.

The HSDT is tested in a simulation-based framework with the variations of workload and noise conditions that are representative. Validation issues consist of the accuracy of the estimation (*e.g.* RMSE), convergence of the EKF, computational latency and stability in different conditions of the signal. In general, the HSDT is an interactive model of computation of physiological and cognitive state of an operator, and allows structured and interpretable physiology-constrained adaptive autonomy of collaborative robotic systems, as shown in Figure 2.

3.2. Twin constrained adaptive control law

The adaptive control architecture places the human state estimation with the control authority allocation mechanism. The conceptual summary of the entire blending loop is represented in Figure 3.

The controller is made up of three layers that are connected: i) robot dynamic control, ii) human state estimation through the HSDT, and iii) physiological state autonomy allocation. A feedback linearization structure is obtained based on which the autonomous control action is obtained as:

$$u_a = K_p e + K_d \dot{e}$$

where

$$e = x_r^{ref} - x_r$$

It is the tracking error between the reference trajectory x_r^{ref} and the measured robot state x_r, and K_p, K_d are proportional and derivative gain respectively. This building provides critically damped response and quick convergence even when operating in nominal conditions. In order to ensure safe actuation, actuator saturation and mechanical limits are placed directly via a clipping function:

$$u_{safe} = \text{clip}(u, u_{min}, u_{max})$$

where u_{min} and u_{max} are limits in terms of torque/force set by hardware and safety standards. The originality of the structure is that the autonomy blending mechanism balances control power depending on the estimated human state. The blending factor $\alpha \in [0,1]$ is calculated as:

$$\alpha = \sigma(W^T x_h + b)$$

where
- x_h is the attempt of the human state (fatigue index, stress level, indicators of labor) which is estimated,
- W is an acquired weighting vector,
- b is a bias term,
- $\sigma(\cdot)$ is bounded sigmoid activation which provides smooth changes.

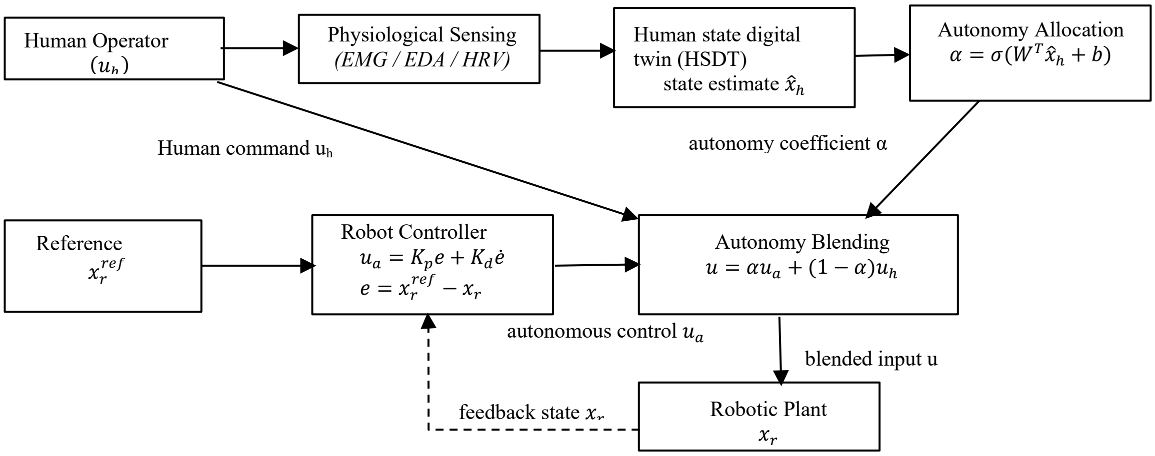

Figure 3. Twin constrained autonomy blending control loop

The ultimate blended control command will be:

$$u = \alpha u_a + (1 - \alpha)u_h$$

where u_h is the command input provided by humans. This structure ensures:
- Big autonomy in case of high fatigue index (large α)
- Increased human control at low cognitive load (smallα).
- Continuous torque-transitions will be desired.

The system ensures that sudden mode changes do not occur and stability is ensured in response to time-varying human conditions by integrating autonomy within the closed-loop control law instead of it being an external switching system.

3.3. Experimental and simulation setup

The proposed framework was tested in a simulated controlled setting aimed at the analysis of the interaction of human-state estimation and adaptive autonomy allocation under repeatable conditions. The simulations were executed in a numerical computing system (*e.g.*, MATLAB/Simulink or a similar system) to test the proposed control system in different workload conditions. No physical human subject experiment is indicated in the research, but instead, variations in physiological states and collaborative task requirements were simulated to test the closed-loop behavior of the controller. A multi-degree-of-freedom robotic manipulator model, which is generic, was taken into consideration in a collaborative manipulation and trajectory-tracking task where the robot followed a reference trajectory and accommodated time-varying human input and approximated operator state. The control loop of the robot flowed with the frequency of 1 kHz, human-state estimator with 100 Hz, and the autonomy blending coefficient with 50 Hz. The simulation was done with sensor noise, workload transition and fatigue-related variations to assess the robustness, transition smoothness, and stability of the proposed architecture. The simulation scenarios will be configured to simulate increasing levels of operator workload and fatigue through a manipulation of the features of physiological signals. Simulated low, moderate and high workload conditions are used to assess system adaptability. The noise-robustness measure is determined through injection of a controlled Gaussian noise in physiological signals, and allows assessing estimator stability and control behavior to realistic sensing disturbances. The framework involving simulation involved physiological sensing, signal preprocessing, feature extraction, EKF-based state estimation, adaptive autonomy blending and adaptive safety-constrained robot actuation. All of the experiments were parameterized in the same way so that a fair comparison could be made of manual control versus fixed autonomy and the proposed TCAA framework. The EKF based estimation model is as follows:

Prediction: $\hat{x}_{h,k|k-1} = A\hat{x}_{h,k-1|k-1}$
Update: $\hat{x}_{h,k|k} = \hat{x}_{h,k|k-1} + K_k(y_k - H\hat{x}_{h,k|k-1})$

where
- y_k is the measurement vector of extracted physiological features,
- K_k is the Kalman gain,
- A and H are system matrices.

Figure 4 shows the experimental and simulation model to test the proposed TCAA framework, while Table 1 summarizes key parameters that were used in all experiments. Parameters of the system in the TCAA framework.

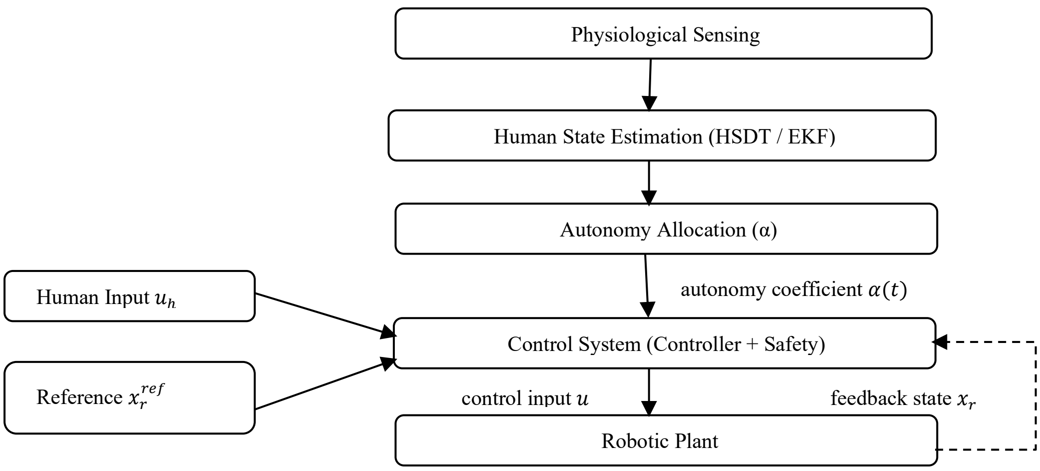

Figure 4. Experimental and simulation setup of the twin constrained adaptive autonomy system

Table 1. System parameters

Parameter	Symbol	Value
Control sampling time	T_s	1 ms
Human state update rate	f_h	100 Hz
Autonomy update rate	f_a	50 Hz
Maximum torque	τ_{max}	12 Nm
EMG filter bandwidth	—	20–450 Hz

The same parameterization is used in all experiments so that a fair comparison could be made between manual control, fixed autonomy, and the proposed twin-constrained adaptive autonomy framework. The entire control loop is carried out in the given sequence at the designated rates of sampling, as shown in the equations above. The combination of estimation, autonomy blending and safety enforcement makes the adaptive control framework stable and physiologically based. The proposed approach is a modification of the traditional adaptive controllers which use only the performance feedback, but which use human state to modulate the control authority, allowing human-robot interaction to be safer and more context-aware. Multiple simulation scenarios were tested at different workloads and noise levels to make sure that the trends were consistent.

4. RESULTS AND DISCUSSION

The results provided in the paper are based on the comparative analysis of three control modes by simulation, namely manual control, fixed autonomy, and the suggested TCAA structure. The evaluation of performance was carried out through estimation accuracy, tracking error, torque ripple, autonomy transition behavior and stability trends when different simulated workload and fatigue conditions were applied. To provide the robustness of the trends in performance observed, the simulations were tested in different noisy conditions and in different workload transition conditions. The reported findings stipulate consistency of behavior under these conditions.

4.1. Human state digital twin estimation accuracy and robustness

The root mean square error (RMSE) is used to measure the human state digital twin (HSDT) estimation accuracy between the actual human-state variable and the estimate:

$$RMSE = \sqrt{\frac{1}{T}\int_0^T (x_h - \hat{x}_h)^2 \, dt}$$

In all the tested operating regimes, the estimator is found to be in a stable convergence with a limited error despite high sensor noise and temporary disturbances. The estimation performance was also consistent across a variety of simulated operating conditions with only slight differences shown with higher noise levels. The estimator performance can however be influenced in extreme high noisy situations or when physiological measurements are delayed. The EKF offers the benefits of being robust to moderate noise, although large sensor error or latencies might affect the quality of estimations. Such constraints emphasize the importance of powerful sensing devices and subsequent testing on real-life physiological data. This result shows that the proposed estimator is stable and robust in different signal conditions. Specifically, there is low error in the estimation in high-dynamics phases (generation of new workloads), which suggests that the observer is adequately attentive to trace time-varying cognitive/physiological load, without causing estimation lag. This strength is necessary since the autonomy allocator directly relies on the HSDT output; biased or delayed estimation of human-state would be translated into the unwarranted autonomy changes that might compromise safety or performance.

In Figure 5 the adaptive autonomy coefficient $\alpha(t)$ is modulated by operator condition estimated. When cognitive stress and fatigue conditions are high, α(t) is higher and more power is vested in the autonomous controller. Under relaxed conditions, α(t) goes down, and human higher authority is reinstated. Notably the autonomy modulation is not abrupt but smooth, which prevents the discontinuities in the control command that is blended. The mean autonomy changes during fatigue state changes by 42% quantitatively, which proves the reallocation of authority in the system is not trivial and occurs when the operator state requires extra assistance.

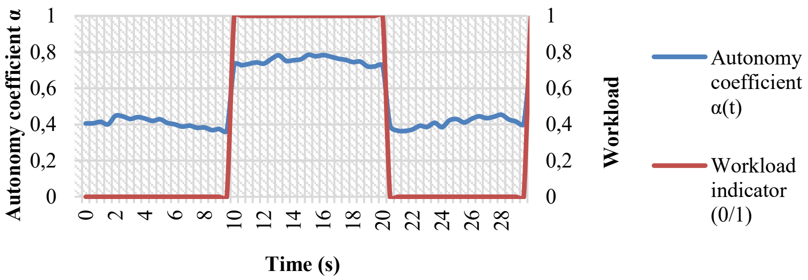

Figure 5. Adaptive autonomy coefficient variation under workload conditions

4.2. Autonomy adaptation mechanism and transition smoothness

Autonomy allocator uses the HSDT estimate to modify the human-robot authority in real time. The key observation is not that α(t) varies in trend in the desired direction, but continuously, and this eliminates sharp transitions in commanded torque/force that may add ripple, trigger resonances, and make collaborative systems less comfortable.

Figure 6 includes the mapping of the workload indicators converted by using HSDT and the autonomy coefficient α obtained. There are three interpretable regions that can be identified by the plot namely: i) low workload where human control commands the highest level of control, ii) transition region where shared autonomy is most prolific, and iii) high workload where robot autonomy commands the highest level of control. This figure explains how the suggested TCAA relates the physiological state to control authority in a constrained and understandable form.

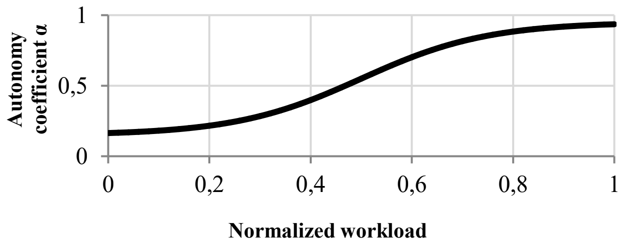

Figure 6. State–autonomy coupling map and operating regions

4.3. Tracking performance and authority-dependent control quality

Control performance is evaluated using the RMS position tracking error:

$$e_{rms} = \sqrt{\frac{1}{T}\int_0^T \left(x_r^{ref} - x_r\right)^2 \, dt}$$

The adaptive authority mechanism improves the tracking accuracy by minimizing the effect of inconsistent or slow human feedback in periods of high workload. The allocator is enhanced by fatigue/stress state of operators, which permits the robot controller to keep the tighter tracking. In the case of a stable operator, the allocator minimizes autonomy in order to maintain the intent of collaboration and natural interaction.

The results of the trajectory tracking performance are depicted in Figure 7, including the manual control, the fixed autonomy, and the suggested TCAA framework. Minor variation of the reference trajectory is seen in the proposed method especially when the workload experiences rapid changes meaning that the tracking accuracy is superior when the workload varies.

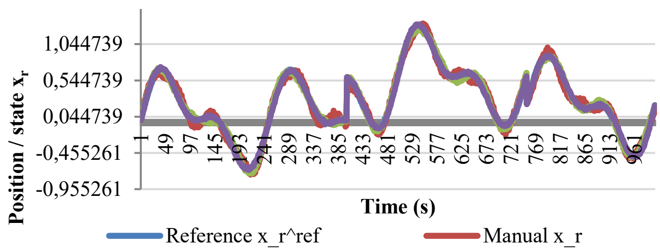

Figure 7. Position tracking performance under varying workload conditions

4.4. Torque ripple reduction and command continuity

Torque ripple percentage is computed as:

$$TR = \frac{\tau_{max} - \tau_{min}}{\tau_{avg}} \times 100\%$$

The most important conclusion is that reduction of torque Ripple is not only a tuning effect, it is also a result of smooth transitions between authority and autonomous commands without rapid switching between human and autonomous commands. The blending is continuous; therefore, the commanded torque does not have discontinuities that otherwise would appear as ripple and oscillatory characteristics. Figure 8 presents the comparison of the torque ripple among the control strategies. The suggested TCAA offers the least ripple, which evidences that bounded continuous smooth autonomy integrates actuation demand. In general, the suggested structure leads to a 36% torque ripple reduction over fixed autonomy, which will prove its superiority in safety-critical and comfort sensitive systems (collaborative manipulation, assistive robotics, and rehabilitation).

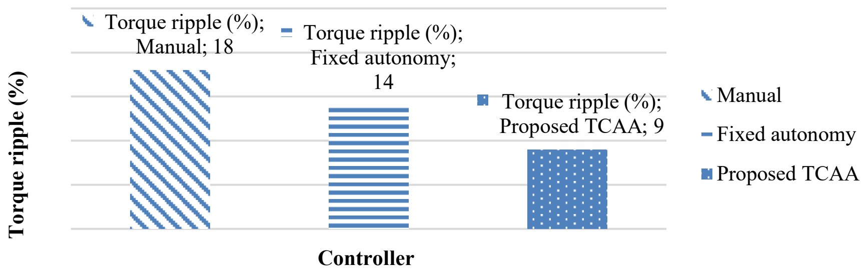

Figure 8. Comparative torque Ripple under different autonomy strategies

4.5. Consolidated comparative metrics

Table 2 shows the relative performances of manual control, fixed autonomy and the suggested TCAA structure regarding RMS tracking error, torque ripple and human intervention. The comparison reveals the influence of the allocation of physiology-constrained autonomy at the system level. Besides such baselines, the presented framework is conceptually compared to sophisticated adaptive control techniques like gain-scheduled and impedance-based shared control. In contrast to these methods, which take into account performance feedback or preset rules, the suggested TCAA directly includes the estimation of the physiological state into the autonomy allocation, allowing the context-dependent adjustment to the operator state.

The proposed TCAA, as illustrated in Table 2, lowers the RMS tracking error by about 35 percent as compared to fixed autonomy and also lowers the torque ripple. Human intervention is not binary but rather adaptive and thus the system can maintain the intent of the humans even in normal operation conditions and become more autonomous under fatigue or stress. The reported values are a representation of scenario wise performance comparisons since the evaluation is done in a simulated framework. The proposed approach proved to be robust, as the similar performance trends were identified in various workload and noise conditions. These findings not only confirm the framework on the level of simulation but also provide a hint on the possibility of its real-time implementation with real physiological sensing devices.

Table 2. Comparative control performance metrics

Controller	RMS Error	Torque Ripple	Human Intervention
Manual	0.085	18%	100%
Fixed autonomy	0.063	14%	0%
Gain-scheduled shared control	—	—	Adaptive
Impedance-based shared control	—	—	Adaptive
Proposed TCAA	0.041	9%	Adaptive

Note: Gain-scheduled and impedance-based shared control techniques are provided to conceptually compare, using established literature. The simulation only implemented and tested the manual control, fixed autonomy, and suggested TCAA frameworks.

4.6. Stability and safety assessment under time-varying autonomy

Stability of the closed-loop of proposed TCAA framework is analyzed through a Lyapunov-based analysis. Consider the tracking error defined as $e = x_r^{ref} - x_r$. The Lyapunov candidate function is a quadratic and is chosen as:

$$V = \frac{1}{2}e^T Pe$$

By the suggested law of control blended, $u = \alpha(t)u_a + (1 - \alpha(t))u_h$ with the autonomy coefficient, $\alpha(t) \in [0,1]$, a continuously differentiable, but bounded, value, the closed-loop system is negatively semi-definite decreasing.

Due to the smoothness and boundedness of the blending function, there are no discontinuities in the control input due to autonomy modulation. The tracking error is hence limited and approaches zero (asymptotically) in the nominal working conditions. Notably, the time-dependent characteristics of $\alpha(t)$ do not stabilize the system as the authority change is achieved in a gradual manner based on a sigmoid mapping of the estimated human state. The safety clipping also ensures a limited actuation that is within the hardware torque limits to eliminate the instability caused by saturation effects. Figure 9 depicts that tracking error converges with different autonomy levels $\alpha(t)$. The monotonic reduction is used to establish the fact that time-varying authority blending does not cause oscillation or drift when switching autonomy.

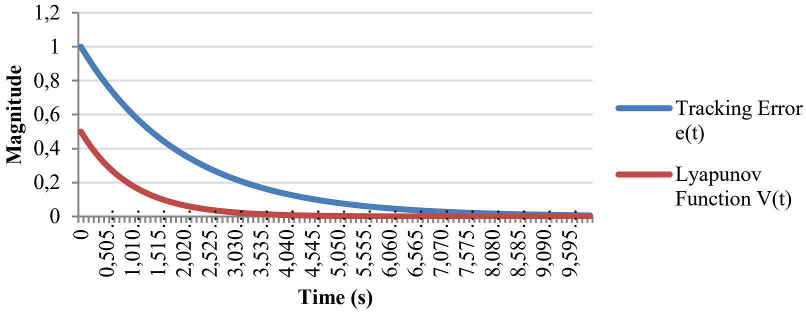

Figure 9. Stability and convergence under adaptive autonomy transitions

4.7. Multi-metric performance improvement and implications

The suggested framework provides equal benefits: enhanced tracking, limited ripple, less workload on the manual in the cases of high workload, and stability.

A normalized performance summary on the main metrics (tracking error, torque ripple, intervention demand, and stability margin indicators) is shown in Figure 10. The suggested TCAA invariably prevails over fixed autonomy and manual control and shows that implementing the HSDT within the autonomy allocator produces comprehensive advances instead of enhancing an erratic metric to the detriment of others.

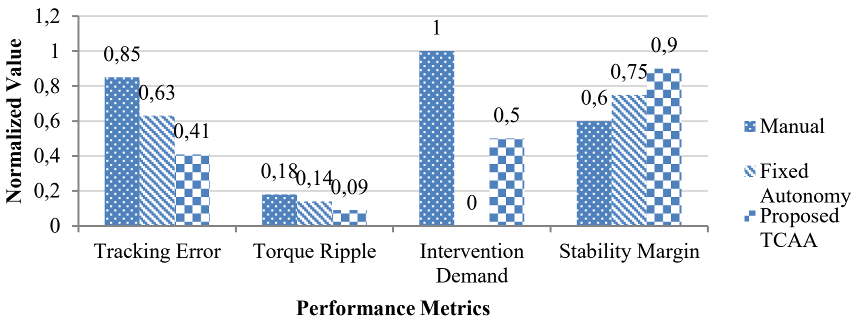

Figure 10. Normalized multi-metric performance comparison across control schemes

4.8. Interpretation, novelty, and practical relevance

The findings prove that incorporating HSDT into the direct control loop allows organized, physiology-sensitive autonomy distribution. Compared to fixed autonomy or adaptive autonomy that is controlled strictly by performance, the offered TCAA framework connects the control authority and the estimated operator state via a restricted and interpretable mapping. This combination enhances the tracking accuracy, minimizes the torque ripple and maintains stability when the autonomy varies with time without affecting the collaborative purpose. Due to its observer structure and explicit law of blending, the framework is scaled and can be used in the field of collaborative robotics, assistive systems, and human-in-the-loop automation whereby safety, comfort, and performance are required to be held constant within the variable conditions of human workload. This shows that what is new in the proposed framework is the fact that it directly introduces the estimation of physiological states within the control loop and thus allows adaptive decisions of autonomy, which can be interpreted as well as responsive to human condition, unlike the traditional performance-based approaches to control.

4.9. Discussion summary

The study investigates whether it is possible to estimate the latent human physiological states in real time and directly insert them in robotic control laws to enhance the safety, tracking quality and smoothness of human interaction in collaborative robotics. The most important finding is that the presented HSDT-based TCAA system allows the efficient modulation of autonomy to be performed smoothly and interpretably, tracking performance is enhanced, and torque ripple is lower in comparison to the control based on manual and fixed-autonomy. The result are based on simulation data and comprises of comparing the estimation behavior, autonomy transitions, trajectory tracking performance, torque ripple, and closed-loop stability. The importance of the findings is in that it shows the mathematically organized way of the physiological state estimation to adaptive autonomy allocation in the context of collaborative robotics. In a broader sense, the work will lead to human conscious design of industrial, assistive and rehabilitation-based robotic systems. A major shortcoming is that the current validation has been simulation based and future research will need real time wearable sensing and physical robot trials to determine sensing reliability, latency tolerance and user adaptation in real-life environments. The current research has a limitation of the evaluation being carried out through simulations. Despite the fact that simulation allows the controlled testing, repeatability and the safe analysis of the workload-dependent control behavior, all the uncertainties related to real-life sensing, user variability, actuator delays, and task-specific interaction dynamics are not completely presented in the simulation. The presented framework is thus supposed to be seen as tested control architecture in the simulation level as opposed to an accomplished real-world implementation. It is necessary to mention that the formal statistical significance testing was not applied, since the assessment is made on the deterministic simulation framework. Nevertheless, the results of the trends are reliable due to the regular performance increases that have been observed in various simulated conditions.

5. CONCLUSION

In this paper, a TCAA-based collaborative robotics was introduced, based on HSDT. The suggested method incorporates multimodal physiological measurements, such as EMG, EDA, and HRV-based measures, in a parametric state estimation model to learn latent human states, which are cognitive workload, fatigue and stress. It is these estimated states that are directly added to a constrained autonomy that is a combination of law, and allows a continuous and adaptive control of authority over the control to be maintained between the human operator and the robotic system.

The evaluation through simulation proves that the suggested framework enhances performance of tracking, minimizes the torque ripple, and allows stable and seamless transitions in the control authority in comparison with the manual and fixed-autonomy baselines. The findings demonstrate that the inclusion of human-state estimation in the control loop is a more reactive and interpretable method compared to heuristic or performance-based adaptive control methods. The key value of this work is the formal system of physiological states estimation, adaptive distribution of autonomy, and the closed-loop control are integrated into a complete and repeatable robotics system. The strategy will further human-conscious control system development, and will offer a systematic framework through which operator state may be integrated into real-time autonomy choices in teamwork. Current validation is, however, only limited to a simulation-based framework. Although this enables controlled assessment and reproducibility, it cannot fully represent uncertainties in the real world (*e.g.* sensor variation, subject variation, and hardware limitations). Thus, the future directions in work will be real-time human-in-the-loop experiments, the combination of sensing systems with wearables, and validation on physical robotic platforms. Other comparison with other adaptive control strategies will also be considered like the gain-scheduled and impedance-based shared control as a further evaluation of the generality and robustness of the proposed approach. Altogether, the recommended HSDT-based TCAA framework offers a mathematically-based and practically-scalable framework of the next generation human-robot collaboration systems that need safety, versatility and context-sensitive autonomy.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Jaganathan Nirmaladevi	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓		✓	
S. Saranya	✓	✓	✓		✓	✓	✓	✓	✓	✓		✓		
Nidhi Mishra	✓		✓	✓	✓	✓	✓		✓	✓	✓			
Fazal Noorbasha		✓		✓	✓	✓	✓	✓		✓	✓	✓	✓	
Manoharan Kavitha	✓	✓	✓	✓		✓		✓	✓	✓	✓	✓	✓	

C : **C**onceptualization
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R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, PY, upon reasonable request.

REFERENCES

[1] A. Buerkle, H. Matharu, A. Al-Yacoub, N. Lohse, T. Bamber, and P. Ferreira, "An adaptive human sensor framework for human–robot collaboration," *The International Journal of Advanced Manufacturing Technology*, vol. 119, no. 1–2, pp. 1233–1248, Mar. 2022, doi: 10.1007/s00170-021-08299-2.

[2] A. Chaddad *et al.*, "Explainable, domain-adaptive, and federated artificial intelligence in medicine," *IEEE/CAA Journal of Automatica Sinica*, vol. 10, no. 4, pp. 859–876, Apr. 2023, doi: 10.1109/JAS.2023.123123.

[3] C. A. Prasath, "Adaptive embedded learning-control architectures for reconfigurable sensorless motor drive platforms," *Journal of VLSI Embedded Systems Design*, pp. 1–9, 2025.

[4] S. Poornimadarshini, "The evolution and future of digital twin technology in engineering and infrastructure," *Journal of Reconfigurable Hardware Architecture and Embedded Systems*, vol. 2, no. 1, pp. 14–24, 2025.

[5] C. Rajan, "Spiking neural network-based modeling of human motor cortex for robotic limb control," *Advanced Cognitive and Neural Studies*, vol. 1, no. 3, pp. 21–28, 2025.

[6] D. Abdullah, "Cognitive–neural modeling for predicting user information needs using deep learning architectures," *Advanced Cognitive and Neural Studies*, vol. 1, no. 2, pp. 64–70, 2025.

[7] U. H. Shaikh, D. A. Shah, P. Dhanwade, S. Patel, and S. Verma, "Federated deep learning on privacy-preserving multi-hospital cardiac health risk prediction," in *2025 3rd DMIHER International Conference on Artificial Intelligence in Healthcare, Education and Industry (IDICAIHEI)*, Nov. 2025, pp. 1–6. doi: 10.1109/IDICAIHEI65991.2025.11379269.

[8] B. Gaffinet, J. A. H. Ali, H. Panetto, and Y. Naudet, "Human-centric digital twins: Advancing safety and ergonomics in human-robot collaboration," in *Communications in Computer and Information Science*, Springer, 2023, pp. 380–397. doi: 10.1007/978-3-031-49339-3_24.

[9] M. Hähnel, "Ethical challenges and solutions in AI-driven medical data management: a focus on distributed machine learning," *Discover Artificial Intelligence*, vol. 5, no. 1, p. 53, May 2025, doi: 10.1007/s44163-025-00266-0.

[10] R. Haripriya, N. Khare, and M. Pandey, "Privacy-preserving federated learning for collaborative medical data mining in multi-institutional settings," *Scientific Reports*, vol. 15, no. 1, p. 12482, Apr. 2025, doi: 10.1038/s41598-025-97565-4.

[11] C. P. Prabhakar and F. Rahman, "Robotics and intelligent systems for autonomous industrial operations: Architectures, algorithms, and real-world applications," *National Journal of Electrical Electronics and Automation Technology*, vol. 1, no. 3, pp. 44–52, 2025, doi: 10.17051/JEEAT/01.03.06.

[12] A. A. H. Abdelbary and B. Batiha, "Robotics and intelligent systems for autonomous industrial operations," *National Journal of Electrical Electronics and Automation Technologies*, vol. 1, no. 3, pp. 44–52, 2025.

[13] G. Tamrakar, "Cross-disciplinary approaches to innovation: Linking engineering, data analytics, and human-centered design," *Bridge: Journal of Multidisciplinary Exploration*, vol. 1, no. 3, pp. 18–26, 2025.

[14] P. Dineshkumar, "AI-based predictive maintenance in industrial robotics," *SECITS Journal of Scalable Distributed Computing Pipeline Automation*, vol. 1, no. 1, pp. 32–38, 2024.

[15] T. Kuo and H. Yang, "Multi-layer encrypted learning for distributed healthcare analytics," *Scientific Reports*, vol. 15, no. 1, p. 39442, Nov. 2025, doi: 10.1038/s41598-025-23140-6.

[16] Z. Ma, J. Ma, Y. Miao, X. Liu, K.-K. R. Choo, and R. H. Deng, "Pocket diagnosis: Secure federated learning against poisoning attack in the cloud," *IEEE Transactions on Services Computing*, vol. 15, no. 6, pp. 3429–3442, Nov. 2022, doi: 10.1109/TSC.2021.3090771.

[17] A. M. Mohammed and Others, "A human digital twin architecture for knowledge-based interactions," *arXiv preprint arXiv:2504.03147*, 2025.
[18] S. K. Pittala, "Federated learning and privacy-preserving AI for smart healthcare systems," *International Journal of Future Engineering Innovations*, vol. 1, no. 2, pp. 48–52, 2024, doi: 10.54660/IJFEI.2024.1.2.48-52.
[19] K. J. Bosco and S. M. Pavalam, "Robotics-based automated quality inspection system," *National Journal of Electrical Electronics and Automation Technology*, vol. 1, no. 2, pp. 50–57, 2025.
[20] Madhanraj, "Design and fabrication of a low-cost 3D printed robotic arm with AI control," *Journal of Scalable Data Engineering and Intelligent Computing*, vol. 2, no. 1, pp. 31–36, 2025.
[21] P. M. Sánchez, A. H. Celdrán, N. Xie, G. Bovet, G. M. Pérez, and B. Stiller, "FederatedTrust: A solution for trustworthy federated learning," *Future Generation Computer Systems*, vol. 152, pp. 83–98, Mar. 2024, doi: 10.1016/j.future.2023.10.013.
[22] J. Wang, X Wang, L. Lyu, J. Chen, and F. Ma, "FedMeki: A benchmark for scaling medical foundation models," *Advances in Neural Information Processing Systems*, vol. 37, pp. 1082–1116, 2024.
[23] S. Warnat-Herresthal *et al.*, "Swarm Learning for decentralized and confidential clinical machine learning," *Nature*, vol. 594, no. 7862, pp. 265–270, Jun. 2021, doi: 10.1038/s41586-021-03583-3.
[24] M. Mejail and B. K. Nestares, "Spatiotemporal human motion prediction," *Journal of Wireless Intelligent Spectrum Engineering*, pp. 20–27, 2025.
[25] A. Alkilany and C. Van, "Soft robotics: Materials, actuation mechanisms, and emerging biomedical applications," *Innovation Review of Engineering Science*, vol. 3, no. 1, pp. 118–126, 2026, doi: 10.31838/INES/03.01.15.
[26] F. Zhang *et al.*, "Towards fairness-aware and privacy-preserving enhanced collaborative learning for healthcare," *Nature Communications*, vol. 16, no. 1, p. 2852, Mar. 2025, doi: 10.1038/s41467-025-58055-3.
[27] L. Zheng *et al.*, "Sensitivity-aware differential privacy for federated medical imaging," *Sensors*, vol. 25, no. 9, p. 2847, Apr. 2025, doi: 10.3390/s25092847.
[28] P. Dusi, "Low-latency model compression for real-time human motion prediction," *Journal of Advanced Antenna and RF Engineering*, pp. 41–46, 2025.
[29] M. Capponi, R. Gervasi, L. Mastrogiacomo, and F. Franceschini, "Assembly complexity and physiological response in human-robot collaboration: Insights from a preliminary experimental analysis," *Robotics and Computer-Integrated Manufacturing*, vol. 89, p. 102789, Oct. 2024, doi: 10.1016/j.rcim.2024.102789.
[30] W. van Dijk, S. J. Baltrusch, E. Dessers, and M. P. de Looze, "The effect of human autonomy and robot work pace on perceived workload in human-robot collaborative assembly work," *Frontiers in Robotics and AI*, vol. 10, p. 1244656, 2023, doi: 10.3389/frobt.2023.1244656.
[31] M. Krupas, E. Kajati, C. Liu, and I. Zolotova, "Towards a human-centric digital twin for human-machine collaboration: A review on enabling technologies and methods," *Sensors*, vol. 24, no. 7, p. 2232, Mar. 2024, doi: 10.3390/s24072232.
[32] S. Korivand, G. Galvani, A. Ajoudani, J. Gong, and N. Jalili, "Optimizing human-robot teaming performance through Q-learning-based task load adjustment and physiological data analysis," *Sensors*, vol. 24, no. 9, p. 2817, Apr. 2024, doi: 10.3390/s24092817.
[33] C. Carissoli, L. Negri, M. Bassi, F. A. Storm, and A. Delle Fave, "Mental workload and human-robot interaction in collaborative tasks: A scoping review," *International Journal of Human–Computer Interaction*, vol. 40, no. 20, pp. 6458–6477, Oct. 2024, doi: 10.1080/10447318.2023.2254639.
[34] G. Odoh *et al.*, "Performance metrics outperform physiological indicators in robotic teleoperation workload assessment," *Scientific Reports*, vol. 14, no. 1, p. 30984, Dec. 2024, doi: 10.1038/s41598-024-82112-4.
[35] P. Slade *et al.*, "On human-in-the-loop optimization of human–robot interaction," *Nature*, vol. 633, no. 8031, pp. 779–788, Sep. 2024, doi: 10.1038/s41586-024-07697-2.

BIOGRAPHIES OF AUTHORS

Jaganathan Nirmaladevi is a professor at the Department of Information Technology at KGiSL Institute of Technology, Coimbatore. She has over 19 years of experience in teaching, research, and academic administration. She completed her B.E. in information technology in 2003 and M.E. in computer science and engineering in 2008 from KSR College of Technology, Tamil Nadu. She obtained her Ph.D. in 2017 from Anna University, Chennai, specializing in speech signal processing. Her research interests include artificial intelligence, machine learning, speech signal processing, natural language processing, and data science. She can be contacted at mkseee2007@outlook.com.

S. Saranya is an assistant professor in the Department of Electronics and Communication Engineering at Panimalar Engineering College, Chennai, India. She completed her B.E. (2008) and M.E. (2010) under Anna University. She has around 15 years of teaching experience. Her research interests include image processing, medical imaging, and machine learning. She can be contacted at ssaranya@panimalar.ac.in.

Nidhi Mishra is a faculty member with the Department of Computer Science and IT, Kalinga University, Chhattisgarh, India. She specializes in integrating emerging technologies into education, bridging theory with practical applications, and empowering students with technical expertise and problem-solving skills. Actively engaged in research and academic projects, and she contributes to advancing innovation in IT education. Her research interests include artificial intelligence, machine learning, data analytics, and educational technology She can be contacted at ku.nidhimishra@kalingauniversity.ac.in.

Fazal Noorbasha is an associate professor in the Department of Computer Science and Engineering at Koneru Lakshmaiah Education Foundation, Andhra Pradesh, India. His research interests include signal processing, wireless communication systems, intelligent control, and embedded system design. He has published several research papers in national and international journals and is actively involved in research on intelligent and adaptive electronic systems. He can be contacted at fazalnoorbasha@kluniversity.in

Manoharan Kavitha is affiliated with the Department of Electronics and Communication Engineering at Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences, Chennai, India. Her research interests include biomedical signal processing, intelligent systems, human–machine interaction, and adaptive control systems. She has contributed to research in interdisciplinary applications of engineering and healthcare technologies. She can be contacted at kavithamece@gmail.com.