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An Effective Model for Human Cognitive Performance within a Human-Robot Collaboration Framework

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Abstract— **With advances in technologies, robots can be employed in collaboration with human for completing the shared objective(s). This paper proposes a novel time-variant human cognitive performance modeling approach for human-robot collaborative actions. The proposed model considers human cognitive performance as a function of human cognitive workload, robot performance, and human physical performance. Novel about the proposed model is its ability to relate human cognitive workload and the task complexity to a utilization factor which is functionally correlated with the robot's mistake probability. The developed model is validated via a simulation environment and confirms that if the task complexity or the robot's mistake probability increases, human cognitive performance reduces over time.**

I. INTRODUCTION

The rapid developments in robotic technologies have laid the grounds for the use of robots to develop a variety of applications based on human-robot interactions. These applications range from manufacturing, packaging, health care, warehouse management, and cybersecurity, to their economic impacts on future developments and intellectual, cognitive skills, such as decision-making [1]–[5]. It is not far that humans and robots will collaborate at the workspace to achieve common goal(s) to improve the efficiency in handling the shared tasks in a human-friendly and secure work environment. The integration of human decision making into a human-robot collaboration (HRC) framework minimizes the chances of deviations in job handling from the expected/desired behaviors through conceptual coordination against the involved uncertainties [6]–[10].

In an HRC framework, both physical and decision-making activities are shared among the human(s) and the robot(s). Several approaches for the development of an HRC framework based on the physical performance of the human operators have been proposed in the literature [11]–[13]. Among these are the verbal and non-verbal human-agent autonomy [14], [15], integrated physical collision avoidance systems [16], trust-based collaborative frameworks for critical decision-making [17], avoidance of faults, and unnecessary shutdowns [18], [19]. An HRC framework can also be used for enabling remote control of task execution using perception-based methodologies, such as Attention Guided Imitation Learning (AGIL), numerical potential field algorithm [20], [21]. The electroencephalogram (EEG) signals have been used as direct inputs to model an active Brain-Computer Interaction (BCI) to control robot operation in [22]–[28]. A practical HRC framework should provide intuitive information about the performance of the human-robot collaboration that is not possible by considering physical performance only. Human cognitive performance should also be taken into account for the improvement in HRC. Cognitive science has the potential in the decision-making/thought process for HRC [11]. Techniques involving the cognitive responses to humanoids in HRC frameworks have been used to develop an understanding of security, autonomy, the performance of the robots, and cognitive trust in their operation over time. For example in [29], [30], a Dynamic Bayesian Network (DBN) approach has been used to implement a cognitive task allocation methodology. In [11], the authors have proposed a linear relationship between human cognitive performance and robot performance, but no mathematical relationship has been considered to address the effects of task complexity and human utilization on cognitive performance.

This research proposes a novel time-variant mathematical model for an effective human cognitive performance model within an HRC framework. It considers human cognitive performance as a function of human cognitive workload, robot-added workload, and human physical workload. The human cognitive workload is formulated in terms of maximum and minimum bounds of cognitive workload, human utilization factor, and the complexity of tasks. Human utilization has been quantified and directly related to the robot's mistake probability that defines the robot performance. The proposed model considers the cognitive workload as the dominant factor in quantifying human cognitive performance. Further, the developed model takes into account the effect of human physical and robot performances on human cognitive performance. Simulation results and performance analysis have been provided for a real-life scenario in the manufacturing industry. Besides, the effect of change of robot performance on human cognitive performance is investigated.

The organization of the remaining parts of this research work is as follows. Human-robot collaboration setting is discussed in Section II. In Section III, the proposed human performance model has been presented, and human physical

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performance model and cognitive workload model have been provided. The simulation scenario for the implementation of the proposed model along with its performance analysis have been presented in Section IV. Finally, the concluding remarks are provided in Section V.

II. HUMAN-ROBOT COLLABORATION SETTING

Consider a human-robot collaboration (HRC) scenario, where a human and a robot are collaborating to perform a shared task. In this HRC setting, the robot can be utilized to perform repeated routine work while human intelligence can handle more complex tasks such as decision-making. For example, the human operator can supervise the robot to complete the assigned tasks by guiding the robot via cognitive signals and helping the robot by physically changing the object orientation appropriately so the robot can pick the object easily. The robot performs the task based on instructions received from the human in the form of cognitive signals. The more the robot can perform a task successfully, the less human supervision is required. Conversely, if the robot mistake rate increases, more assistance from the human operator is needed. Fig. 1 shows a symbolic diagram for an HRC setting, in which a robot transfers heavy objects from the source conveyor belt to the destination (packaging) conveyor belt. The human operator supervises the robot and observes (takes feedback from) the robot's actions, the source where the robot has to pick objects, and the destination where the robot delivers objectives for packaging. If the robot commits a mistake in picking/placing the objects from/in wrong conveyors, the human operator sends the robot corrective cognitive signals (e.g., in the form of push-button, vocal, or EEG signals) to correct its actions and guide it for successful completion of the task. Once the object is available on the destination conveyor, the human operator controls the conveyor to transfer it out of the workspace. Robot performance is measured in terms of its capability to accommodate a human operator's instruction(s). Therefore, the robot performance has a significant impact on the human cognitive workload during the collaboration between the human operator and a robot. The robot performance, $R_P(t)$, for a given time instant t depends on its success in the completion of tasks, which can be modeled as:

$$R_P(t) = R_{P,max} - \frac{S_R(t-1) - (1 - P_{mR})D_R(t-1)}{S_R(t-1)} \quad (1)$$

where $R_{P,max}$ is the maximum value of the robot performance, P_{mR} is the robot's mistake probability, $S_R(t-1)$ is the source rate (the feeding rate of source conveyor) and $D_R(t-1)$ is the delivery rate (percentage of items being handled by the robot and put on the destination conveyor) at the preceding time instant.

III. HUMAN PERFORMANCE MODELING

In this section, we model human performance. In particular, we provide a model for human cognitive performance, which indicates its cognitive capability to perform

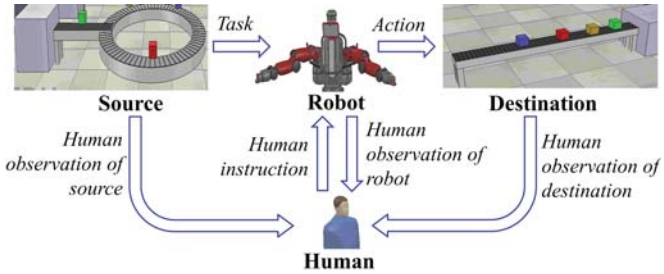


Fig. 1: A human-robot collaboration (HRC) setting.

the mental work [11]. A human's cognitive performance is at a maximum when it is subjected to a minimum workload, no fatigue, and maximum robot performance. On the other hand, human performance will be minimum when the human is experiencing maximum workload and fatigue level, and minimum robot performance. If the robot did not perform the immediate preceding task satisfactorily, the human operator instructs it to make a correction. The interactions between human and robot increase human utilization factor and cognitive workload.

A. Human Physical Performance Model

A human's physical performance can be related to the muscular contraction and expansion system and can be tied to the fatigue level of the muscles and their recovery. The fatigue and recovery models of muscles affect the human physical performance that can be modeled as [11]:

$$P_P(t) = \frac{F_{max,iso}(t) - F_{th}}{MVC - F_{th}} \quad (2)$$

where $P_P(t)$ is the human physical performance at time instant t and F_{th} stands for the threshold force which is calculated at the equilibrium point where the fatigue and the recovery balance out each other. $F_{max,iso}(t)$ stands for the maximum value of isometric force. The isometric force, $F_{iso}(t)$, is generated when the human muscles apply force but the length of muscles does not change [11]. *Maximum Voluntary Contraction (MVC)* stands for the maximum value of isometric force that one can produce at rest or the initial state (at zero-level of fatigue) [11]. Clearly, $F_{max,iso}(t)$ decreases over time due to muscle fatigue. Adopted from [11]–[13], we use the following first-order Euler approximation to represent the dynamic calculation of the maximum isometric force:

$$F_{max,iso}(t) = F_{max,iso}(t-1) - C_f F_{max,iso}(t-1)\frac{F(t-1)}{MVC} + C_r(MVC - F_{max,iso}(t-1)) \quad (3)$$

where C_f and C_r stand for the fatigue and recovery constants, respectively, and $F(t)$ denotes the real-time applied force that reduces over time due to increase in fatigue levels.

In this model, continuous-time fatigue and recovery processes are used to represent the dynamic evolution of the maximum isometric force. It can be verified in Eq. 3 that fatigue increases when muscles continuously apply the force. On the other hand, when no force is used or if the applied force is relatively small, the muscles will recover, i.e., $MVC - F_{max,iso}(t-1)$ will be increased.

$F_{max,iso}(t)$ is maximum when the human operator starts the task, i.e. $F_{max,iso}(t=0) = MVC$. Therefore, based on Eq. 2, $P_P(t=0) = 1$ at the beginning when $F_{max,iso}(t=0) = MVC$ [11], but then it reduces to zero when $F_{max,iso} = F_{th}$. Further, it can be verified that in Eq. 2, the isometric force is affected by the fatigue level. Higher fatigue levels result in lower isometric force, which in turn will reduce the overall human performance values.

B. Human Cognitive Workload Model

The cognitive workload refers to the amount of mental work to be performed in a given period. A human operator's performance degrades for high cognitive workloads and/or while handling complex tasks. During the inactive mode (when no cognitive work is performed), the human operator's cognitive performance level gradually increases. This recovery process can improve the cognitive performance up to the Optimum Level of Arousal (OLA) point [11], [31], [32]. Here, we model the human operator's cognitive workload for a given time, $C_w(t)$, as a function of the complexity of the task(s) to be performed and the human operator's utilization factor as:

$$\begin{aligned} C_W(t) =& (C_{W,max} - C_{W,min})(\frac{u(t)}{1-C(t)})^{1-C(t)} \\ & (\frac{1-u(t)}{C(t)})^{C(t)} + C_{W,min} \end{aligned} \tag{4}$$

where $C_{W,min}$ and $C_{W,max}$ are the minimum and maximum cognitive workloads respectively, which may vary from person to person, depending on the individual's capabilities to handle the tasks. $C(t)$ is the complexity of the task (a relative value between 0 to 1) being handled at time t and $u(t)$ is the human operator's utilization factor which can be captured as:

$$u(t) = u(t-1) + \triangle u(t) \tag{5}$$

where $\triangle u(t)$ stands for the change in the utilization factor which is a function of the robot's mistake probability for a given time as:

$$\triangle\, u(t) = \frac{P_{mR}(t) - u(t-1)}{\tau} \tag{6}$$

where τ is a positive integer number representing the time constant. In other words, τ is the time that the human operator takes to respond to the changes in the robot's mistake probability, thereafter the effect of changes in robot's mistake probability appears in human operator utilization factor.

Remark 1. If the human operator is doing the same task all the time, then the value of $C(t)$ will be a constant number, otherwise its value changes depending on the complexity of the task being handled at each time instant.

Remark 2. In the proposed HRC framework, individual tasks are assumed to be independent events. Further, a task either can be failed by the robot, which requires human operator's intervention, or it will be successfully handled by the robot, which does not need the human operator to be utilized. This allows us to use a binomial form in Eq. 4 to describe the human cognitive workload based on successfully handled tasks and failed ones.

C. Human Cognitive Performance Model

Human(s) cognitive workload primarily impact(s) its cognitive performance. Further, human physical workload or the additional workload due to mistakes of the robot affect the cognitive performance of the robot as well. Incorporating all these factors, human cognitive performance, $C_P(t)$ for a given time, can be modeled as:

$$C_P(t) = C_{P,max} - \alpha C_w(t) - \beta H_w(t) - \gamma H_R(t) \tag{7}$$

where $C_{P,max}$ is the maximum cognitive performance for a given time, $H_w(t)$ is the human physical workload for a given time, $H_R(t)$ is the additional workload added due to mistakes of the robot, and α, β, and γ are positive real numbers with $\alpha + \beta + \gamma = 1$.

The human physical workload and the additional workload due to mistakes of the robot can be indirectly estimated from the human physical performance and the robot performance for a given time is as follows:

$$H_W(t) = P_{P,max} - P_P(t) \tag{8}$$

$$H_R(t) = R_{P,max} - R_P(t) \tag{9}$$

where $P_{p,max}$ and $R_{P,max}$ are the maximum human physical performance and robot's maximum performance, respectively. $P_P(t)$ and $R_P(t)$ have been derived in Eq. 2 and Eq. 1, respectively.

IV. ANALYZING THE HUMAN COGNITIVE PERFORMANCE WITHIN THE PROPOSED HRC SETTING

Consider a manufacturing workspace in which a human operator and a robot can collaboratively work to transfer the produced items as shown in Fig. 2. The source conveyor carries the incoming boxes to the workspace, and the destination conveyor moves the inspected items to the packaging area. The robot's task is to physically move the objects from source conveyor to packing conveyor based on the human's instructions. The human operator supervises and instructs the robot to complete its task correctly. The human operator is assumed to help the robot by physically changing the object orientation appropriately so the robot can pick the object easily. Also, the human operator is involved in (minimal) physical activity, such as regulating the speed of the destination conveyor, maintaining the logs, etc.

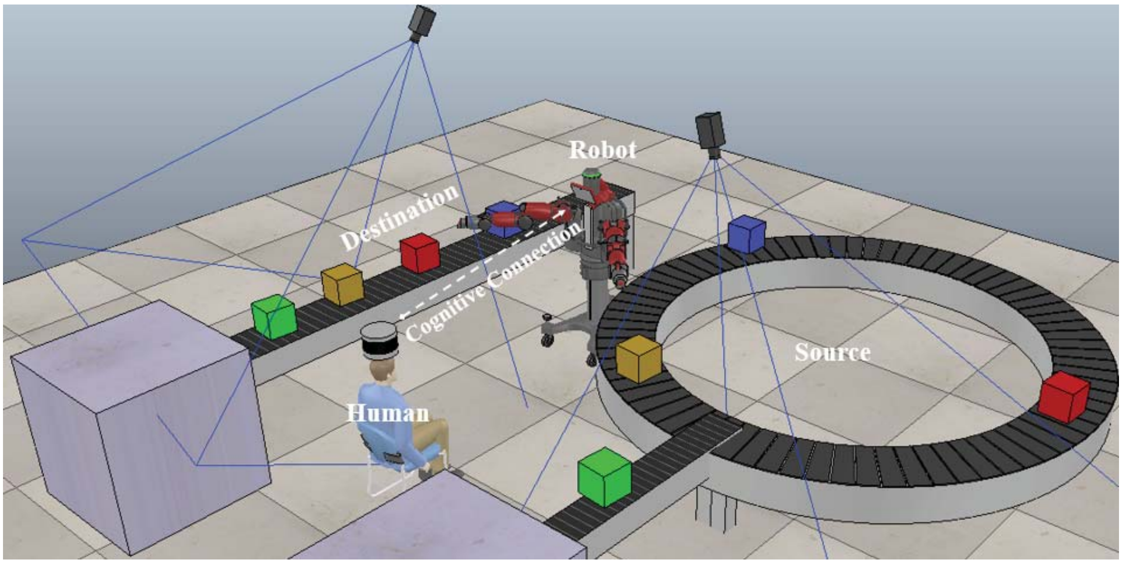


Fig. 2: A human-robot collaboration scenario: robot transfers heavy objects from the "source" conveyor belt to the "destination" conveyor belt, and the human operator guides the robot to successfully complete the task.

TABLE I: **Human Cognitive Performance Simulation Parameters**

Name & Symbol of Parameters	Value
Fatigue constant, C_f	10^{-4}
Recovery constant, C_r	2.4×10^{-4}
MVC	200
Minimum threshold force, F_{th}	151.9
Time constant, τ	10
Max cognitive workload, $C_{W,max}$	1
Min cognitive workload, $C_{W,min}$	0
Cognitive workload co-efficient, α	0.7
Physical workload co-efficient, β	0.1
Additional robot workload co-efficient, γ	0.2

To simulate this scenario, we use the derived set of equations from Eq. 1 to Eq. 9 in which the simulation parameters are chosen as summarized in Table I. Some of the parameters' values including C_f, C_r, MVC, and F_{th} are set similar to those in [11]. Since in human cognitive performance, the human cognitive workload is a dominant factor, in Eq. 7, the value of α is selected larger than the values for β and γ.

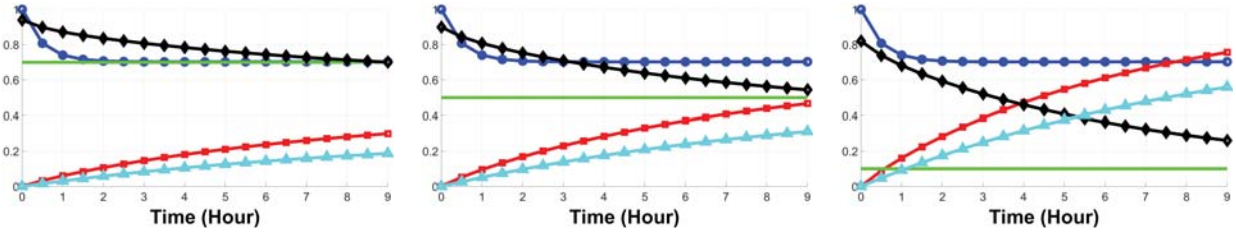
The simulation runs over an operating period of ten hours with the sample time of 30 minutes. The minimum level of human cognitive performance, $C_P(t)$, at any given hour is assumed to be more than 0.2, below which the human operator is considered to be incapable of performing the cognitive workload. In order to maintain simplicity, the robot's mistake probability has been assumed to be constant over time.

The simulations are performed using three different task complexity values, $C(t) = 0.1, 0.4$, and 0.7, each simulated for three different values of robot performance, $R_P(t) = 0.7, 0.5$, and 0.1. The simulation results are provided using three different task complexity values, $C(t) = 0.1, 0.4$ and 0.7 in Fig. 3, Fig. 4, and Fig. 5 respectively for each $R_P(t) = 0.7, 0.5$, and 0.1.

Analyzing the results of the three subplots in Fig. 3, it can be seen that for a fixed value of task complexity, the human cognitive performance, $C_P(t)$, decreases, while its utilization factor, $u(t)$, increases for decreasing values of robot performance, $R_P(t)$. For higher values of $R_P(t)$, higher values of $C_P(t)$ are observed, at the corresponding time instants. For example, in the case when $R_P(t) = 0.1$, the robot is making mistakes frequently and requires assistance from the human operator much often, resulting in lower values for $C_P(t)$ than those for the case when $R_P(t) = 0.7$, at the corresponding time instants. Similar trends are observed in the comparison of the three subplots in Fig. 4 and Fig. 5.

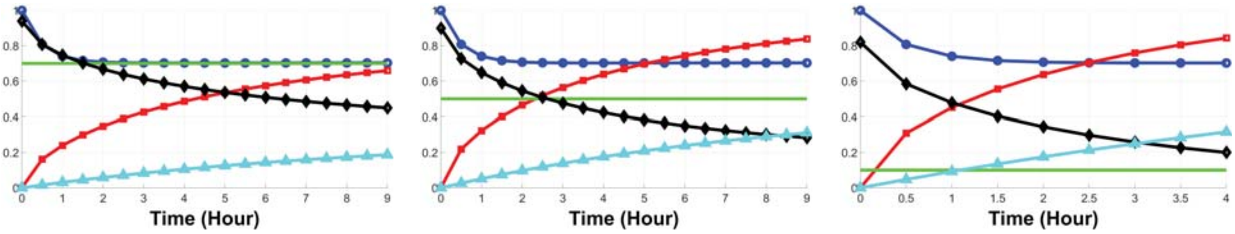
The impact of task complexity on the performance values can be analyzed by comparing the results in the subplots in Fig. 3a, Fig. 4a, and Fig. 5a for similar values of robot performance. The results reveal that for a fixed value of robot performance, the values for human cognitive performance, $C_P(t)$, decrease, while the utilization factor, $u(t)$, increases for increasing values of task complexity, $C(t)$. For lower values of $C(t)$, higher values of $C_P(t)$ are observed at the corresponding time instants. For example, in the case when $C(t) = 0.7$, the robot requires frequent instructions from the human operator, resulting in a lower value for $C_P(t)$ than the case when $C(t) = 0.1$ at the corresponding time instants. Similar trends are observed in the comparison of the other corresponding subplots shown in these figures, i.e., Fig. 3b, Fig. 4b and Fig. 5b as well as Fig. 3c, Fig. 4c and Fig. 5c.

Furthermore, it can be observed that in the subplots Fig.



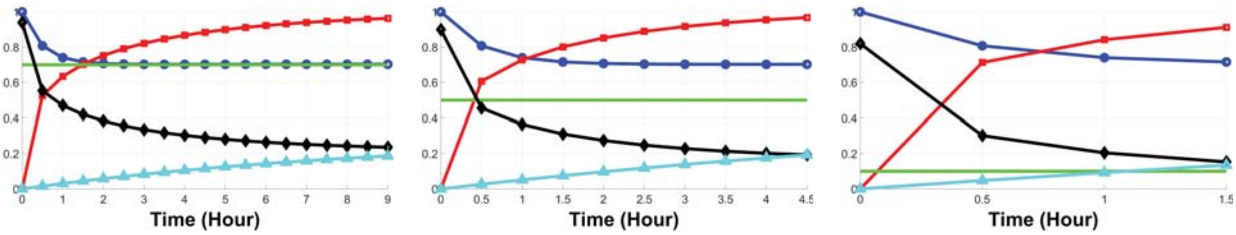
(a) Robot performance, $R_P(t)$ = 0.7 (b) Robot performance, $R_P(t)$ = 0.5 (c) Robot performance, $R_P(t)$ = 0.1

Fig. 3: The change of physical performance (●), cognitive workload (■), robot performance (—), cognitive performance (◆), and utilization factor (▲) are represented over time for the task complexity, $C(t)$ = 0.1



(a) Robot performance, $R_P(t)$ = 0.7 (b) Robot performance, $R_P(t)$ = 0.5 (c) Robot performance, $R_P(t)$ = 0.1

Fig. 4: The change of physical performance (●), cognitive workload (■), robot performance (—), cognitive performance (◆), and utilization factor (▲) are represented over time for the task complexity, $C(t)$ = 0.4



(a) Robot performance, $R_P(t)$ = 0.7 (b) Robot performance, $R_P(t)$ = 0.5 (c) Robot performance, $R_P(t)$ = 0.1

Fig. 5: The change of physical performance (●), cognitive workload (■), robot performance (—), cognitive performance (◆), and utilization factor (▲) are represented over time for the task complexity, $C(t)$ = 0.7.

4c, Fig. 5b and Fig. 5c, the maximum operating time t_{max} is less than the ninth hour. This is because the human operator's cognitive capabilities have exhausted already, i.e., the overall human cognitive performance values, $C_P(t)$, are below 0.2.

V. CONCLUSIONS

In this paper, a dynamical human cognitive performance model has been proposed for a Human-Robot Collaboration (HRC) framework. This model has been simulated for a shared task between a human operator and a robot. Simulation results have been used to validate the proposed collaboration model and analyze the effects of variations in the values of the involved parameters. A mathematical representation of human cognitive performance has been provided in terms of the associated human physical workload, robot added workload, and human cognitive workload. Also, the complexity of tasks at hand and the associated human utilization factor for different values of human capabilities have been considered to model the HRC framework.

Simulation results show that for a fixed complexity of the task, a decrease in robot performance increases human utilization factor and the associated cognitive workload, which in turn degrades the human cognitive performance. It has also been shown that human cognitive workload decreases as the robot performance improves. For fixed values of robot performance, the human utilization factor increases as the task complexity increases which in turn increases the human cognitive workload and degrades the human cognitive performance.

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