Modeling and Control of Trust in Human and Robot Collaborative Manufacturing

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Abstract

Human and robot collaboration on the factory floor has opened a new realm of manufacturing in real-world settings. In such applications, human and robot work with each other as coworkers and human robot interaction (HRI) plays a critical role on the overall system performance. In particular, human's trust to robot determines the degree of autonomy of the robots and hence task efficiency and workload. In this paper, we use the difference between human performance and robot performance to develop a time series trust model. The human performance model is inspired by the muscle fatigue and recovery dynamics that capture the fatigue level of human body when performing repetitive kinesthetic tasks, which are typical types of human motions in manufacturing. The robot performance can be controlled in three different modes: manually by the human coworker, autonomously through robust intelligence algorithms, or collaboratively by the combination of manual and autonomous modes. In the collaborative mode, the robot performance is controlled autonomously unless the human coworker decides to take over and controls it manually. We illustrate the proposed models and control schemes using a simple numerical example by simulating human performance in a typical 9-hour work day and implementing the mentioned different modes to control the robot performance. The average trust and workload are compared among manual, autonomous, and collaborative modes. The collaborative mode is shown to have higher average trust with moderate workload.

1 Introduction

Human and robot collaborative manufacturing opens up a new realm of industrial mass production where humans and robots are co-workers (Charalambous 2013). In general, the key questions of human robot interaction addressed human factors engineering, artificial intelligence, robotics, psychology, design and implementation (Karwowski and Rahimi 2003). In manufacturing applications, a human worker and a peer human-friendly robot (for example, Rethink Baxter) collaborate with each other to manufacture customized products (Goodrich and Schultz 2007) and increase the overall system performance (Shi et al. 2012). For example, a skilled human worker can collaborate with a heavy duty robot to perform an assembly operation. In such applications, although the objective of human and robot collaboration is to improve productivity, improper human-robot interaction (HRI) may cause counter effects such as misuse of machine and/or safety issues. Hence, there arises a need for investigating the HRI in advanced manufacturing. These then motivate the current paper. In particular, because the trust of human to robot will directly affect the degree of autonomy of the industrial robot which is related to the efficiency of manufacturing processes, trust is a critical element in HRI. In this paper, we adopt the concept of trust among people and utilize it for HRI in automation (Lee and See 2004). However, relationships between people are different from HRI. This discrepancy brings about a need for investigating empirical and theoretical considerations for adopting trust in human coworkers as a model of trust in HRI (Lee and See 2004). Inspired by previous works (Moray, Inagaki, and Itoh 2000; Lewandowsky, Mundy, and Tan 2000), (Lee and Moray 1992), we propose a time series model for human to robot trust in a collaborative human-robot task in performance. Our model uses the difference between human performance and robot performance. This model is inspired by the fact that when a human worker observes a discrepancy between his/her performance and what he/she expects from the robot partner, his/her trust to the robot decreases accordingly. When the robot performance matches human expectation, the human's trust to robot increases. Therefore, we will consider both human and robot performance in the trust model. To model the performance of a human worker of doing a repetitive kinesthetic task, which is typical in manufacturing, we adopt the muscle fatigue and recovery model (Fayazi et al. 2013). This model shows how the performance of the human worker changes as his/her muscles gradually get tired or recovered. The robot performance depends on the speed of the robot for doing a specific task and its value is among a set of fixed numbers between zero and maximum speed of the robot. Next, we design control schemes to switch between manual and autonomous modes in order to increase the trust of the human to the robot. Since the performance of human worker changes during the working shift, his/her expectation from the partner robot changes over time accordingly. Therefore, the human to robot trust can be controlled by adjusting the robot performance according to what the operator desires. To do so, three approaches are available. One way is to increase or decrease the robot performance based on manual corrective requests that the human worker sends to the robot controller. Another way is to autonomously predict the human requests at different moments and adjust the robot performance without sending any corrective request. The latter approach can be achieved by a robust intelligence algorithm which tries to learn the pattern of the requests of the human operator as he/she collaborates with the robot over time. In this paper, we use the artificial neural networks as the robust intelligence algorithms which are a powerful tool in pattern recognition (Mehrotra, Mohan, and Ranka 1997). The last way is to use a control scheme to adjust the robot performance using both autonomous approach and manual approach interchangeably. In this collaborative mode, we use the robust intelligence algorithms to control the robot performance similar to the autonomous mode. However, the human worker can adjust the robot performance at the times that the robust intelligence fails to mimic the human pattern in adjusting the robot performance. We will show that the collaborative mode results in moderate workload with higher trust level.

The rest of this paper is organized as follows. In Section 2, we present the model of human-to-robot trust. Then, in Section 3 we show how the performance of human worker changes by time as his/her muscles get tired or recovered. In Section 4, the artificial neural network is defined for learning the desired robot performance adjusted by the human worker. In Section 5 we show how the control scheme work. In section 6 the results for the simulation of a numerical example of a typical work day in manufacturing are shown. Finally, conclusions are made in section 7.

2 Trust Model

In this section, we introduce a time series model for the human trust dynamics. This model shows how a human worker trusts his/her robot partner, when they are collaborating simultaneously in a manufacturing task. To clarify the manufacturing application, let us start with an example. Consider the case when a skilled human worker collaborates with a heavy duty robot to do an operation, such as inserting screws into parts or welding, on a heavy product. In this case, the robot picks up the product and then holds it still in different positions and orientations so that the human operator can easily perform a series of specific operations on the product. Therefore, as the performance of the human worker varies during the working hours, a constant performance of the robot causes troubles to the human worker when he/she feels that the robot is working faster or slower than what he/she expects. At those moments, the trust of operator to the robot drops. To recover the trust, the robot performance should be adjustable so that the human worker feels comfortable in collaborating with the robot. Therefore, when defining the trust model, we assume that the dynamic of human trust is a function of human performance, P_H, and robot performance P_R. The human performance is a function of accumulated workload which can be described by the level of fatigue of human body in general and will be discussed in more details in Section 3. The robot performance, P_R, is related to the speed of the robot for doing a certain task. The value of P_R is between 0, when the robot does not work, and 1, when the robot works at its highest performance. Also, it can only takes multiple values of a fixed real number, c, which is the constant number for the increment or decrement of the robot performance. In other words,

$$P_R \in \{(i-1)c\} \quad i = 1, \cdots, i_f, \quad i_f = \frac{1+c}{c}. \qquad (1)$$

As mentioned in Section 1, the robot performance can be adjusted in three modes, manually, autonomously, or collaboratively. In the manual mode, the robot performance is adjustable by the human worker by sending corrective requests to the robot. In the autonomous mode, the robot seeks to learn and predict the manual corrective requests that the human worker sends to the robot controller through robust intelligence algorithms. In the collaborative mode, the robot performance can be controlled both manually and autonomously in different times of the day. More details of the robust intelligence algorithms will be discussed in Section 4. Intuitively, the dynamics of trust depend on the difference between the mentioned human and robot performances. In other words, when the human worker does not feel any considerable difference in the performances, his/her trust increases, and otherwise the trust starts to decrease. With this mindset, we propose the following model for the dynamics of human worker's trust to robot

$$\begin{aligned} T(k) = AT(k-1) - B_1 \left| P_H(k) - P_R(k) \right| \\ -B_2 \left| P_H(k-1) - P_R(k-1) \right| + R. \quad (2) \end{aligned}$$

We use k to indicate the time step, A, B_1 and B_2 are positive constants and R is the trust recover/regeneration rate that can be estimated using experimental data. As long as there is a considerable difference between the human and robot performances, the trust will decrease regardless of which one is greater than other. In contrast, if there is no considerable difference between the performances over some time, here from $k-1$ to k, the trust will increase. We will design control schemes to maximize human trust to robot in Section 4

3 Human Performance Dynamics

In this section, we model the dynamics of human performance when performing a physical labour in the manufacturing environment. In such scenarios, a human worker usually performs repetitive kinesthetic tasks and his/her performance can be related to the fatigue level of the human muscles while doing the task. Therefore, we adopt the muscle fatigue and recovery model proposed in (Ma et al. 2010) and (Fayazi et al. 2013) for our human performance model. Such a model, explains how a muscle or group of muscles get fatigued or recovered during performing physical tasks. We assume that the higher the fatigue level is the lower the performance would be. We assign the maximum value of the human performance to occur at the situation when he/she is not subjected to any fatigue, and the minimum value when he/she is experiencing the maximum level of fatigue(4). We first present the muscle fatigue and recovery model and then develop the human performance model based on the muscle fatigue and recovery model.

For the modeling of muscle fatigue and recovery, we introduce a model for isometric force generation, i.e. when the muscles do not move but they apply force. When a muscle applies some force for an amount of time, the maximum isometric force that one can produce, $F_{max,iso}(k)$, decreases. The dynamic model of fatigue for $F_{max,iso}(k)$ is a function of the time, initial maximum isometric force one can generate at rest, called Maximum Voluntary Contraction (MVC), and real-time applied force $F(k)$ (Ma et al. 2009). On the other hand, when the muscle does not apply any force, it get recovered. The recovery process is also a function of the time and MVC (Ma et al. 2010). Based on (Liu, Brown, and Yue 2002), when the muscles fibers work, some of them become fatigued and some recover. That is to say, fatigue and recovery occur simultaneously (Ma et al. 2010). Note that the above mentioned works consider the continuous dynamics. However, according to the setup in this paper, we cannot adjust the robot performance in a continuous fashion since the robot performance remains constant for a fixed time period. Therefore the corresponding human performance should also be described in a discrete time setting. We use the discretized version of the combined fatigue and recovery model in (Fayazi et al. 2013) using the first-order Euler approximation

$$\begin{aligned} F_{max,iso}(k) = &F_{max,iso}(k-1) \\ &-C_f F_{max,iso}(k-1)\frac{F(k-1)}{MVC} \\ &+C_r(MVC - F_{max,iso}(k-1)), \end{aligned} \quad (3)$$

where C_f is the fatigue constant and C_r is the recovery constant, having different values for each person. Equation (3) is for isometric muscle contraction and if the human worker exerts the maximum force all the time, i.e. $F(k-1) = F_{max,iso}(k-1)$, has an equilibrium point at which the fatigue and recovery balance out. This point is the lowest limit (threshold) of the $F_{max,iso}(k)$. This threshold force, F_{th}, can be calculated by assuming that $F_{max,iso}(k) = F_{max,iso}(k-1)$ at the threshold and its value is

$$F_{th} = MVC\frac{C_r}{2C_f}(-1 + \sqrt{1 + \frac{4C_f}{C_r}}). \quad (4)$$

Theoretically, at the threshold force, the fatigue and recovery occur at the same rate and one can generate this threshold force for a long time. Since the fatigue and recovery model predicts the human muscle status related to workload during manufacture performance, this model can be used to measure the performance of a human worker. Hence, similar to what is proposed in (Fayazi et al. 2013) in order to describe the state of fatigue, we propose the following performance model for human, P_H

$$P_H(k) = \frac{F_{max,iso}(k) - F_{th}}{MVC - F_{th}}. \quad (5)$$

Note that in Equation (5), $F_{max,iso}$ varies between the minimum value F_{th} and the maximum value MVC, therefore it is a normalized value between 0 and 1. The maximum value MVC, is assumed when the human operator starts the task, i.e. $F_{iso,max}(k=0) = MVC$. Equation (5) indicates the maximum performance, $P_H = 1$, the minimum value of the human performance, $P_H = 0$, when the recovery and the fatigue countervail each other.

Remark 1 *The threshold force, F_{th}, is the minimum value of $F_{max,iso}$. So the forces below F_{th} are not theoretically achievable.*

Remark 2 *For a working group of muscles, there is a linear relationship between the dynamic force and the corresponding velocity of applying force (Fayazi et al. 2013). One can propose the following relation between the maximum isometric force, $F_{max,iso}$, and the maximum dynamic force, $F_{max,d}$ (Fayazi et al. 2013)*

$$F_{max,d}(k) = F_{max,iso}(k)(1 - \frac{v(k)}{v_{max}}), \quad (6)$$

where $v(k)$ indicates the speed of the human motion. v_{max} is the maximum achievable speed of the human motion. Since $F_{max,d}(k)$ can vary between 0 and $F_{max,iso}(k)$ at every time step k based on the $v(k)$, it is not a proper measure for evaluating the human performance. Therefore, in Equation (5), we use the maximum isometric force, $F_{max,iso}(k)$ governed by the dynamics in Equation (3), instead of the maximum dynamic force, $F_{max,d}$.

4 Robust Intelligence

As mentioned in Sections 1 and 2, there are three modes to control the robot performance, i.e., through manual control by the human worker, through autonomous control by robust intelligence algorithms, or through collaborative control of both manual and autonomous modes. Robust intelligence algorithms will learn the expected robot performance by the human worker over the course of working shift. The result of the learning algorithms can be used to predict the desired robot performance so that the human worker does not necessarily need to adjust it manually. We use the artificial neural network for this purpose. This section depicts the method of using neural networks for the robust intelligence part of this problem.

Neural Network Controller for The Robot Performance

The applications of artificial neural networks in function approximation, pattern recognition and other nonlinear mappings are widely known (Mehrotra, Mohan, and Ranka 1997). The function approximation capability of neural networks gives rise to several applications in control engineering such as black box model identification, adaptive inverse control and model predictive control (Hagan and Demuth 1999). The goal of using neural network in this problem is to have an autonomous control system for adjusting the performance of robot during the work day which is a black box model identification. This control system is designed so that it reduces the worker's task load for adjusting the performance of robot manually. To do so, a neural network with proper method of training and also some training data are required.

One way of training the neural network to achieve this goal is to mimic the behaviour of the worker in adjusting the performance of the robot during the work day. This behaviour results in a desirable pattern for the performance of robot when collaborating with the coworker. Therefore, when collecting the training data, the worker collaborates with the robot in the manual adjustment mode which is explained in detail in section 5. In this data set, the particular day, month and time of the work is used as the input to the neural network and the performance of robot is used as the desired output of the neural network. Note that when collecting data, we only need to store the information of the moments that the worker does not do correction to the robot performance. In other words, these moments are the ones that the worker is satisfied with a specific performance of robot.

The neural network used in this paper is shown in Figure 1. This network consists of an input layer, a hidden layer and an output layer of neurons which form a Perceptron artificial neural network. This type of neural network has the capability of approximating many nonlinear functions (Hagan and Demuth 1999). In the neural network used in this paper, two different activation functions are utilized for the hidden layer and the output layer respectively. The activation functions determine the output of the neurons in each layer as a function of the weighted sum of the inputs to that layer. The activation function of the hidden layer is a tangent sigmoid function as follows

$$\text{tansig}(x_{py}) = \frac{e^{x_{py}} - e^{-x_{py}}}{e^{x_{py}} + e^{-x_{py}}}, \tag{7}$$

where x_{py} is the input for the tangent sigmoid function. The output of this function is in $(-1, 1)$ region. In the neural network shown in Figure 1, this variable is defined as $x_{py} = W_{py}\mathbf{p}$ where W_{py} represents the weights of the neural network that connect the input layer $\mathbf{p}$ to the hidden layer $\mathbf{y} = \text{tansig}(W_{py}\mathbf{p})$. The activation function for the output layer is chosen to be the linear function according to the following

$$\text{purelin}(x_{yo}) = x_{yo}, \tag{8}$$

where $x_{yo} = W_{yo}\mathbf{y}$ for the output layer, W_{yo} are the weights of the neural network that connect the hidden layer to the output layer. Once enough data is collected for such a neural network, the Error Backpropagation training algorithm (Hagan and Demuth 1999) is used to train the neural network. This algorithm is a gradient decent based optimization algorithm for minimizing the mean squared estimation error of the neural network. It can be used for training whether single layer or multi-layer neural networks. A well trained neural network is able to do a nonlinear mapping from the input data set to the output data set. The details of implementing such a neural network for determining the robot performance in the autonomous and collaborative modes are explained in section 5.

5 Control Scheme

In this section we explain the details of implementation of the three different methods for adjusting the robot performance. In all of these modes we assume that the human worker works with the following pattern. He/She starts to

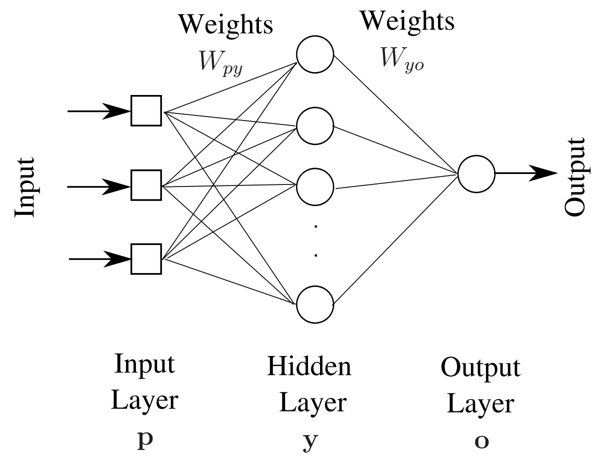

Figure 1: The structure of neural network used for learning the robot performance

work at 8 AM and ends at 17 PM. There is an approximately one hour lunch break around noon. Also there are two shorter breaks (15 to 20 minutes) in mid-morning and mid-afternoon (around 10 AM and 15 PM, respectively). During such a workday, based on the Equation (5) the human performance decreases from the beginning of the day through the end of the day, except for the break times or the lunch time when the human performance recovers. Due to these changes in the human performance, there are three methods for adjusting the robot performance according to the human worker needs. These methods are as follows.

Manual Mode

For this mode, a human-sensitivity based approach is adopted to simulate how the human coworker adjusts the robot performance according to Equation (1). Most of the time performance of the robot does not match the human performance exactly. However if the difference between these two performances exceeds some certain value, then the human worker would feel the significance and send some corrective commands to change the robot performance to match with his/her performance. We define this value as human sensitivity, H_S. With this setting, when the human worker decides to adjust the robot performance we obtain

$$P_R(k+1) = u_H(k), \tag{9}$$

where $u_H(k)$ represents the manual control. According to the Equation (9), the human worker adjusts the robot performance for the next time step. When he/she does not change the robot performance, we have $P_R(k+1) = P_R(k)$.

Autonomous Mode

Based on the explanations in Section 4, to train the neural network, we simulate and collect the corresponding data for the human-robot interaction of a particular worker for a period of 4 months. According to the data, as in Figure 1, we have 3 inputs to the artificial neural network, namely month, day and time of the day, and one output which is the performance of the robot. The number of hidden layer neurons are chosen to be 15 and the Error Backpropagation training algorithm is used to train the neural network. After training the neural network, it will predict the desirable robot performance based on the specific time data. With this setting we have

$$P_R(k+1) = u_{RI}(k), \tag{10}$$

where $u_{RI}(k)$ represents the autonomous control calculated by the neural network for the next time step. The neural network is the only source of robot performance adjustment in this mode and thus it is used at each time step whether it generates a new command or the similar command as the previous step.

Collaborative Mode

The autonomous mode reduces the human workload through the use of robust intelligence algorithms. However, the manual mode offers more accurate control mode since the human worker knows what robot performance suits his/her needs at a moment and uses the accurate value of the human performance. In collaborative mode, the human has the ability to change the robot performance whenever he/she wants and meanwhile he/she can benefit from the autonomous mode. Therefore, we can describe the process of controlling the robot performance by the following equation

$$P_R(k+1) = I(k)u_H(k) + (1 - I(k))u_{RI}(k), \tag{11}$$

where $u_H(k)$ and $u_{RI}(k)$ are as in Equations (9-10) respectively, and $I(k)$ is an index function such that

$$I(k) = \begin{cases} 1 & \text{manual control} \\ 0 & \text{otherwise} \end{cases}$$

In this setting, the robot performance at the next time step is determined whether by the human commands or the predictions of the robust intelligence algorithms. The results of utilizing this scheme are presented in Section 6.

6 Simulation

In this section, we present a numerical example by using MATLAB R2012a software for three different control schemes described in previous sections. This example shows (i) how the human trust evolves according to the discrepancy between the human and the robot performance; and (ii) how the workload of the human worker changes. The human performance dynamics (5) described in Section 3 are simulated for a typical 9 hour workday starting at 8 AM. In the simulation we shift the time origin to 8, i.e. we use $k' = k - 8$ instead of k in all of the equations. For a fixed repetitive task we assume that the external force applied by the human worker is constant. So, we use a constant value for the external force, i.e., $F(k) = \frac{MVC}{4}$. The maximum value for both human performance and robot performance is 1, i.e. $P_{H,max} = 1$ and $P_{R,max} = 1$. The human worker is assumed to start with P_H between $[0.95, 1]$. The robot is assumed to start with the maximum performance, $P_{R,max}$. The break time pattern are as described in the beginning of the Section 5. The results for each of the three control schemes are as follows.

Manual Mode

According to the explanations in Section 5, we assume that human sensitivity is $H_S = 0.05$. The results of this simulation is shown in Figure 2. As can be seen in this figure, when time passes, the performance of the human worker decreases. However, since the robot performance does not change, the difference between the human performance and the robot performance increases and thus the trust of human to robot decreases. Therefore, when the human performance decreases during the time interval 8 AM to 10 AM, the human worker sends some corrective commands to decrease the robot performance so that the robot performance matches his/her performance. After that, the human worker takes a break for a while and so the robot performance is also set to be zero. We use the same trend for the rest of the day with breaks at 12 PM and 15 PM, respectively. In this section, we simulate the human-robot interaction and investigate how the trust is affected by this interaction. In other words, once the human and the robot performance were determined, we can compute the human trust to robot in the collaboration task and apply the control scheme discussed later in Section 5 to increase the trust. As can be seen in Figure 2, the human worker starts his/her work at 8 AM, as time passes the value for trust increases since the difference between human and robot performance is low but it decreases when this difference becomes higher. After sending the corrective commands by the human worker it increases again but it decreases as the difference between performances increases. The trust value does not change during the breaks.

Autonomous Mode

According to the explanations in Section 5, we use the neural network for adjusting the robot performance autonomously. The results of this simulation are shown in Figure 3. As can be seen in this figure, the autonomous mode adjusts the robot performance properly most of the times. For the autonomous mode, the trust level has a similar trend as in the manual mode except for the end of the break times, when the neural network cannot predict the desired robot performance accurately. This leads to a sudden momentarily drop of trust due to a temporary significant difference between the human performance and the robot performance adjusted by the autonomous mode.

Collaborative Mode

For simulation of this method, we use the same configuration of the manual and autonomous control modes described in this section. Then we combine them as described in Section 5 to obtain the collaborative mode. The results are shown in Figure 4. System starts to work in the autonomous mode at the start of the workday. After sometime, if the robot performance does not match the human performance, the value of trust decreases. In contrast to the autonomous mode, the human worker can switch to the manual mode by sending some corrective commands. Since the difference between the robot performance and the human performance is very low right after the system switches to manual mode, the

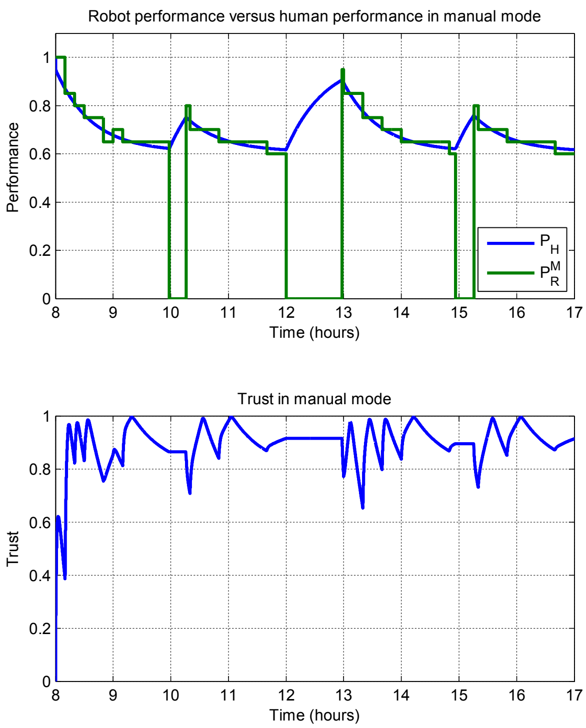

Figure 2: Evolutions of human performance P_H, robot performance P_{RM} under manual mode, and trust T.

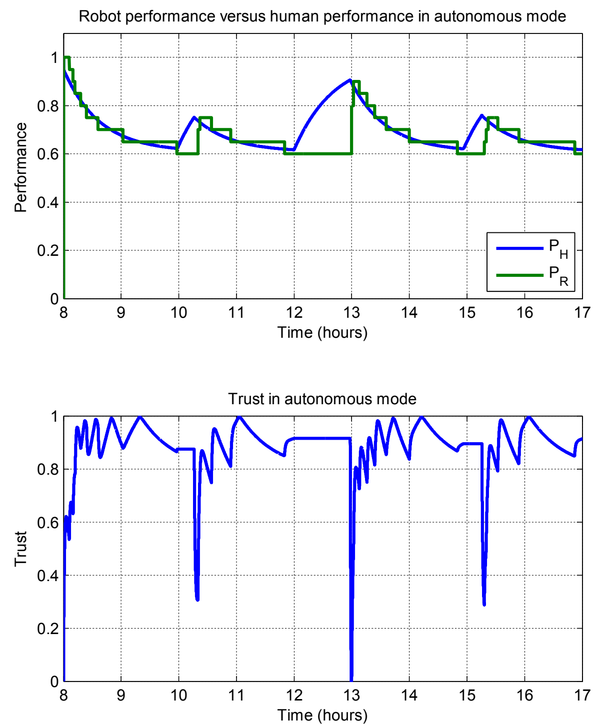

Figure 3: Evolutions of human performance P_H, robot performance P_{RA} under autonomous mode, and trust T in autonomous mode.

Table 1: Comparison between workload and average trust for manual, autonomous, and collaborative modes

	Manual	Autonomous	Collaborative
Workload	100	0	67.3
Average Trust	0.8965	0.8875	0.8988

robot performance remains constant in the manual mode for a fixed time period, 5 minutes. Then system switches back to the autonomous mode and remain in autonomous mode if no corrective commands are sent. Figure 4, shows the human and robot performances for the collaborative mode.

Comparison of Control Schemes

We can measure the human workload under the manual, autonomous, and collaborative mode. The workload for the manual mode is 100% since the human worker always changes the robot performance by himself/herself. Control workload under the autonomous system is 0% since the human worker does not change the robot performance at all. The amount of workload for the collaborative mode depends on the amount of time on which the system is in the manual mode. In our example this value is 67.3%. Moreover, for these three modes we can compare the average value of trust (see Table 1). It can be seen that in the autonomous mode, average trust value is 0.8875 which is lower than this value for manual mode, 0.8965 but it is a very high value. By using the collaborative mode, we can increase the trust while the workload is smaller than manual mode.

7 Conclusion

In this paper, we proposed a trust model of human coworker to his/her robot counterpart in a collaborative manufacturing task and used this model to determine the task efficiency and workload. The trust depends on the difference between human performance and robot performance. Since the tasks in manufacturing usually are repetitive kinesthetic tasks, we used the muscle fatigue and recovery model to capture the human performance. We used three methods to control the robot performance. These methods are manually by the human coworker, autonomously by robust intelligence, and collaboratively by using both manual and autonomous modes. For illustration, by using MATLAB software we simulated the human performance and robot performance and the corresponding trust during a typical work day when they do a certain manufacturing collaborative task. For the human performance we implemented the muscle fatigue and recovery model and we used the three mentioned modes to adjust the robot performance and we calculated the corresponding trust for each of these methods. We presented the workload and average trust for manual, autonomous and collaborative mode. It can be seen that the collaborative mode have higher average trust with moderate workload.

References

Charalambous, G. 2013. Human-automation collaboration in manufacturing: Identifying key implementation factors. In *Contemporary Ergonomics and Human Factors 2013:*

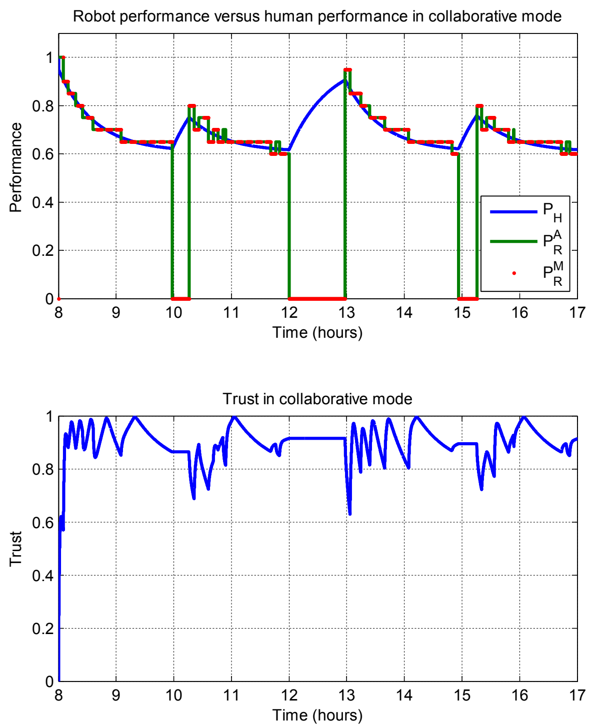

Figure 4: Evolutions of human performance P_H, robot performance P_R, and trust T in collaborative mode.

Proceedings of the International Conference on Ergonomics and Human Factors 2013, 59.

Fayazi, S.; Wan, N.; Lucich, S.; Vahidi, A.; and Mocko, G. 2013. Optimal pacing in a cycling time-trial considering cyclist's fatigue dynamics. In *American Control Conference (ACC), 2013*, 6442–6447.

Goodrich, M. A., and Schultz, A. C. 2007. Human-robot interaction: a survey. *Foundations and Trends in Human-Computer Interaction* 1(3):203–275.

Hagan, M., and Demuth, H. 1999. Neural networks for control. In *American Control Conference, 1999. Proceedings of the 1999*, volume 3, 1642–1656 vol.3.

Karwowski, W., and Rahimi, M., eds. 2003. *Human-Robot Interaction*. Taylor & Francis Inc.

Lee, J., and Moray, N. 1992. Trust, control strategies and allocation of function in human-machine systems. *Ergonomics* 35(10):1243–1270.

Lee, J. D., and See, K. A. 2004. Trust in automation: Designing for appropriate reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society* 46(1):50–80.

Lewandowsky, S.; Mundy, M.; and Tan, G. 2000. The dynamics of trust: comparing humans to automation. *Journal of Experimental Psychology: Applied* 6(2):104.

Liu, J. Z.; Brown, R. W.; and Yue, G. H. 2002. A dynamical model of muscle activation, fatigue, and recovery. *Biophysical Journal* 82(5):2344 – 2359.

Ma, L.; Chablat, D.; Bennis, F.; and Zhang, W. 2009. A new simple dynamic muscle fatigue model and its validation. *International Journal of Industrial Ergonomics* 39(1):211 – 220.

Ma, L.; Chablat, D.; Bennis, F.; Zhang, W.; and Guillaume, F. 2010. A new muscle fatigue and recovery model and its ergonomics application in human simulation. *Virtual and Physical Prototyping* 5(3):123–137.

Mehrotra, K.; Mohan, C. K.; and Ranka, S. 1997. *Elements of artificial neural networks*. MIT Press.

Moray, N.; Inagaki, T.; and Itoh, M. 2000. Adaptive automation, trust, and self-confidence in fault management of time-critical tasks. *Journal of Experimental Psychology: Applied* 6(1):44.

Shi, J.; Jimmerson, G.; Pearson, T.; and Menassa, R. 2012. Levels of human and robot collaboration for automotive manufacturing. In *Proceedings of the Workshop on Performance Metrics for Intelligent Systems*, PerMIS '12, 95–100. New York, NY, USA: ACM.