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Adaptation of the Human-Machine Interface to the Human Skill and Dynamic Characteristics

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Abstract: Human Adaptive Mechatronics (HAM) considers operator's individual skills and preferences. Operator's performance is time-varying and stochastic. Modifying the static parameters of the Human-Machine Interface (HMI) the human operator's skill level and dynamic characteristics can be passively adapted. Knowledge-based approach is applied to change the machine parameters. This leads to a novel Skill Adaptive Control (SAC), which is described in the paper. A trolley crane system is simulated to test how operators can benefit of SAC. Four operators were using the system.

Keywords: Adaptation, fuzzy inference system, human adaptive mechatronics, human-machine interface, knowledge-based system, skill evaluation,

1. INTRODUCTION

Despite the trend of increasing automation degree in control systems, human operators are still needed in applications such as aviation and surgery, or machines used in remote mining, forestry, construction, and agriculture, just to name a few.

Traditionally, the human-machine systems are designed so that the machine is "constant" for every operator. Human Adaptive Mechatronics (HAM) approach, on the other hand, focuses on individual design, taking into account the skill differences and preferences of the operators (Suzuki et al., 2005; Harashima and Suzuki, 2006; Suzuki, 2010; Tervo, et al., 2010; Tervo and Koivo, 2010; Suzuki et al., 2013).

In general, human performance is time-varying and stochastic. In addition, the human operator adapts to the changes in the Human-Machine Interface (HMI) and he/she also learns while repeating similar tasks several times. Therefore, the tuning of the HMI should be done little-by-little. That is, once the skill/performance for the current settings has been evaluated, the optimal parameters for the HMI can be determined.

In this paper passive adaptation of the human operator's skill level and dynamic characteristics is realized by modifying the static parameters of HMI. Passive adaptation refers to a property, where the machine adapts itself to the human operator's skill level or control characteristics, but does not actively intervene to the human operator's control signal (in contrast to the active adaptation). There are only few examples of implemented passive adaptation systems in the literature, which can be interpreted as relevant for the scope of this paper. For teleoperation, robust control tuning based on the human frequency response estimation is proposed by Rauhala and Koivo (2001). The human frequency response is estimated based on several executions of a given task. Then robust control tuning techniques are applied for designing the control law for teleoperation. Adaptation of the strength of the assistance given by an assistance system based on the human skill level is described by Yoneda et al. (1999). The assist control force is calculated based on the human control model.

In this paper a knowledge-based approach is applied to change the machine parameters. The human model/skill evaluation is based on the statistical learning model concept discussed in (Palmroth, L. et al., 2009). The task is repeated and the statistical learner model evaluates the average performance of the human operator using the statistical distribution of data gathered. Fuzzy Inference System (FIS) is then used to determine the best possible HMI parameters. The procedure leads to a novel Skill Adaptive Control (SAC) algorithm. Mathematical model of the operator is not needed.

The power of the SAC algorithm is shown in an experiment, where a crane-like system is operated by four operators. For the test subjects the algorithm converged towards a value where the task performance is rather constant.

The paper is organized as follows. Section 2 gives a general description of the HMI adaptation system. Section 3 presents knowledge-based or heuristic methods, such as Fuzzy Inference Systems (FISs), which are used to adapt the HMI with respect to the human skill and dynamic characteristics. In Section 4 the Skill Adaptive Control (SAC) algorithm is developed. Section 5 presents the experimental setup and results of the SAC algorithm, when four operators are carrying the task.

2. DESCRIPTION OF THE HMI ADAPTATION SYSTEM

The idea of the HMI adaptation is to make changes in the control interface to better suit the operator's current skill level. The objective in the tuning is to prevent the unwanted phenomenon, such as oscillation due to the insufficient skill level of a human operator. Simultaneously the aim is to maximize the overall long term performance of the system. In a typical industrial system, such as a gantry crane, the HMI adaptation includes the phases shown in Fig.1. The structure shown in the figure is based on the framework for intelligent coaching of machine operators (Palmroth, L. et al., 2009).

The first step is intent recognition. This can be performed using several methods. One that has been particularly successful with working machines is based on Hidden Markov Model (HMM) work cycle modeling (Aulanko and Tervo, 2009; 2010). In this paper the intent represents the objective of the work and the associated task sequence to be performed to accomplish the objective.

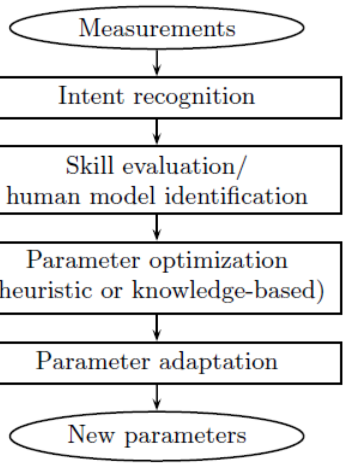

Fig. 1. A flowchart of the phases in a general HMI adaptation system.

Once the intent of the operator has been recognized, the objective of the work is known. The next step is to evaluate or model the task execution. This step is called skill evaluation. Skill evaluation in this paper is based on the statistical learning model concept. In principle, the task performance is evaluated using a Generalized Extreme Value (GEV) distribution (Kotz and Nadarajah, 2000) for each performance variable describing human skill. The statistical learner model evaluates the average performance of the human operator using the cumulative GEV distribution. The higher the cumulative GEV score is, the higher skill evaluation results are obtained. The parameters of the GEV distribution can be updated adaptively after each task execution to improve the skill evaluation.

After the skill evaluation, the next phase in the human skill adaptive HMI is to determine whether the HMI parameters are optimal for the operator's skill level or not. This can be done using analytic methods (Tervo and Koivo, 2010) or knowledge-based methods. This paper focuses on the latter.

In the knowledge-based approach, the parameter optimization is done an expert system which performs reasoning about the suitability of the current parameter setup ξ based on the skill evaluation results $\mathbf{Z}$

$$\xi^{*} = \text{HeuristicOptimization}(\mathbf{Z}, \xi), \qquad (1)$$

where "HeuristicOptimization" is for example a Fuzzy Inference System described in Section 4. This approach is feasible especially, when no accurate, mathematical human model is available.

In parameter adaptation phase the parameters in vector ξ^{*} are used to define a new parameter setup. The method of adaptation depends on the application. One can use, for example an iterative learning rule to update the parameter setup of the machine. However, the adaptation should be slow enough so that the usability of the system would not suffer. The concept of Just Noticeable Differences can be used to determine the maximum allowable change in the parameters (Igarashi, 2009).

The human skill adaptive HMI system can be seen as a block diagram shown in Fig. 2. The human controller tries to control the system based on the desired states (the intent) and the measured states (the observations given by the human senses). The human operator has a skill level, which can be evaluated based on the recognized intent, measured states, and the control actions the operator introduced. It is assumed that the HMI is parameterized so that the properties of the machine can be set up to correspond the operator's skill level. The parameter setup might include for example the sensitivity of the movements, the maximum allowable speed for different movements, and the configuration of the rate limiters (ramps) designed to smoothen the accelerations of the controlled elements.

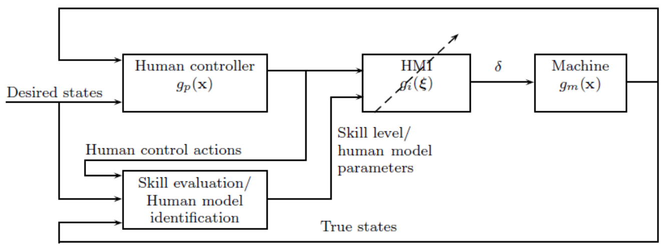

Fig. 2. Block diagram of the HMI adaptation system. The human operator controls the machine by using the control levers and buttons in the HMI. These are recorded in the machine's database. In the figure, δ describes human control commands.

3. KNOWLEDGE-BASED APPROACH FOR HMI ADAPTATION

Knowledge-based or heuristic methods, such as Fuzzy Inference Systems, can be used to adapt the HMI with respect to the human skill and dynamic characteristics. This approach is useful, when no accurate human model is available. In this case, the adaptation is based on similar reasoning as in the Intelligent Coaching System (ICS) structure (Palmroth, L. et al., 2009). Here, FISs are used to tune the HMI parameters, because they provide convenient means to imitate the reasoning of a human expert. The theoretical foundation of the fuzzy logic and FISs has been well established, see for example (Zadeh, 1965; Kandel, 1991; Yen and Langari, 1999). There exist widely used tools available to design and implement FISs.

When tuning purely the sensitivity δ (or the gain *k*) of the HMI, the reasoning system becomes very simple. Consider a Sugeno-type FIS (Yen and Langari, 1999), where the inputs are the probability of high performance (PrHighPerformance), the current gain of the HMI (CurrentGain), and the information whether the operator uses the full control range available to perform the task (FullControlUse). The FullControlUse can be defined as

$$\text{FullControlUse} = \frac{\max_t |\delta(t)|}{\delta_{max}}, \tag{2}$$

where δ is the control signal and δ_{max} is the maximum available control signal.

The first input describes the probability to obtain high performance with respect to any performance or skill index. The index value can be interpreted as probability, because the skill indices are scaled using the statistical learner model described by Palmroth et al. (2009). The output of the FIS is GainSuggestion, which describes whether the gain *k* of the HMI should be increased, decreased or kept constant. The output has then three constant membership functions: DECREASE (value -1), OK (value 0), and INCREASE (value 1). Assume a two-level partition for each input variable (LOW and HIGH), where the membership functions can be of any type. Now, the knowledge-based tuning can be realized simply by using the following rule base:

1. If (PrHighPerformance is not HIGH) and (CurrentGain is not LOW) then (GainSuggestion is DECREASE)
2. If (PrHighPerformance is not HIGH) and (CurrentGain is not HIGH) and (FullControlUse is HIGH) then (GainSuggestion is INCREASE)
3. If (PrHighPerformance is HIGH) then (GainSuggestion is OK)

The aim of the first rule is to decrease the gain *k*, if the low performance is due to too high a gain value. The second rule increases the gain, if the low performance is due to too low a gain value. In addition, it is required that the operator uses full control range until the gain is increased. This requirement is made, because if full controls are not used, the operator could increase the performance by using a larger control lever motions. If the performance is already at a high level, no modifications for the current HMI are needed.

The defuzzification of the FIS is performed using the weighted sum method, because it does not normalize the sum of the outputs to unity. If a new data point does not fit to the rule base well, all outputs obtain low weights. The better the data point fits to the FIS rule base, the higher the confidence of the decision and thus the higher changes in the gain can be allowed.

By using the knowledge-based approach, the suggestion how the gain *k* of the HMI should be modified during the n^{th} trial, is given by

$$\Delta k_n = \alpha k_n FIS(\mathbf{Z}, k_n), \tag{3}$$

where $\mathbf{Z}$ is the vector containing the inputs for the FIS and $0 \le \alpha \le 1$. The parameters more suitable for the current performance level of the operator are obtained using

$$k_n^* = k_n + \Delta k_n, \tag{4}$$

In (3), the FIS gives values in between -1 and 1, which can be interpreted as the *relative change* in the gain during the n^{th} trial. When multiplied with the current value k_n, the *absolute change* is obtained. The scalar α can be used to control the parameter adjustment.

4. SKILL ADAPTIVE CONTROL (SAC) ALGORITHM

The tuning method proposed above finds the parameters of the HMI, which are suitable for the current dynamics of the human operator with respect to the tuning criteria. However, the human operator adapts to the change in the machine's dynamics as well as to the change in the HMI. Thus, the solution given by the tuning method cannot be considered global. That is, if the parameters of the HMI are changed, the human adapts himself/herself to the changed system. As a result, the human operator's dynamics changes and the HMI parameters may not anymore fulfill the design criteria. Therefore, a recursive approach called Skill Adaptive Control (SAC) algorithm is developed. The idea is that the solution for the HMI tuning problem given by the tuning method is used only as a direction to which the parameters should be changed. The magnitude of the parameter change depends on the amount of the improvement to be achieved due to the change.

For simplicity, the following assumptions are made for realizing the SAC algorithm. It is assumed that the operator performs K trials of a well-defined control task. Moreover, the task the operator executes is the same in the trials, and the system dynamics remain constant. Thus, the plan of the operator is known beforehand. After performing K trials, the operator's skills are evaluated using a knowledge-based method using (1). Finally the parameters of the true HMI are adapted to better suit the operator's current skill level. By using the new parameters, K trials are performed again and so forth.

Once the optimal parameters for the current dynamics/skills of the human operator have been found, the parameters need to be adjusted so that the future performance is maximized. The parameters are adjusted by using the following iterative adaptation rule

$$\xi(i+1) = \max(\min(\xi(i) + \gamma(\xi^*(i) - \xi(i)), \xi_{\min}(i)) \qquad (5)$$

where γ ($0 \leq \gamma \leq 1$) is the learning rate, i is the iteration index, and $(\xi_{\min}, \xi_{\max})$ are the minimum and the maximum allowed values for the parameters. In the knowledge-based approach, too small a K enables high variation of the average performance and thus variance in the decision of the reasoning system.

The proposed implementation of the SAC can be put in an algorithmic form as follows:

1. *Initialization*: Set $i = 1$ and the initial values of $\xi(1)$.
2. *Data gathering*: Perform K trials of a given task.
3. *Identification/evaluation*: Evaluate the performance with respect to the chosen criterion and update the associated GEV distributions.
4. *Optimization*: Solve (1) to obtain the optimal system parameters $\xi^*(i)$ for the current operator dynamics.
5. *Adaptation*: Adjust the current system parameters to better suit the operator's skill level by using (5).
6. *Termination*: Set $i \to i+1$ and go back to step 2. Alternatively, the algorithm can be terminated if a predefined stopping criterion is fulfilled.

It is worthwhile to mention that updating the parameters of the statistical learning model in step 3 leads to a self-tuning system.

5. EXPERIMENTAL SETUP AND RESULTS

In order to test the SAC algorithm, a trolley crane simulator is set up. The simulator was developed in Tervo (2010) and Tervo and Koivo (2010) to test the concept of human skill adaptive control. In the simulator, the dynamics of the trolley crane system are simulated in Simulink and the visualization is done with Matlab.

The structure of the trolley crane system is shown in Fig. 3. The rope is assumed to be stiff and its mass is assumed to be zero. The trolley can be moved in a horizontal direction by introducing the control force *F*. The trolley is assumed to be affected by linear friction force proportional to the velocity of the trolley.

Mathematical model of the trolley crane system becomes

$$\begin{cases} (M+m)\ddot{z} + b\dot{z} + mL\cos(\phi)\ddot{\phi} + mL\sin(\phi)\dot{\phi}^2 = F \\ mL\cos(\phi)\ddot{z} + mL^2\ddot{\phi} + mgL\sin(\phi) = 0 \end{cases} \qquad (5)$$

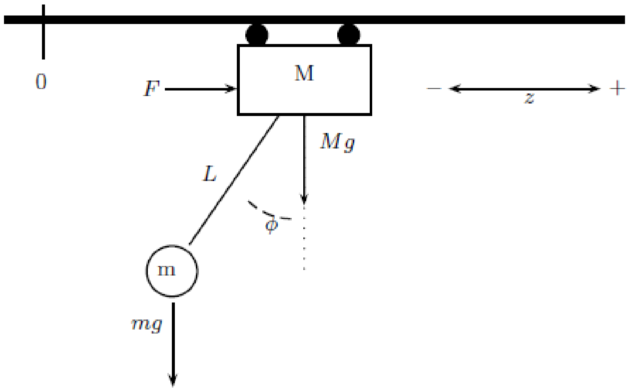

Fig. 3. A free-body diagram of the trolley crane system. A load with weight m is connected to a trolley with weight M via a rope. The position in the horizontal direction is denoted by z, the length of the rope by L, and the rope angle by ϕ. Control force is *F*. The friction coefficient is *b*.

The physical parameters of the trolley crane used in the simulator experiment are given in Table 1. A linearized model of (5) was also used.

Table 1. Physical parameters of the trolley crane model

Description	Symbol	Value
Load mass	m	2.00 kg
Trolley mass	M	1.00 kg
Rope length	L	1.00 m
Trolley friction coefficient	b	1.00 $\frac{\mathrm{Ns}}{\mathrm{m}}$

The objective of the experiment is to tune the gain *k* (that is, sensitivity δ) of the control interface using the SAC algorithm. In the task, the objective was to transfer the cart from initial point (−0.75 m) to the terminal point (0.75 m) and then dampen the swinging of the load. The initial values for $\dot{z}$, ϕ, and $\dot{\phi}$ were zero. The task was defined to be finished, when the cart position is close enough to the terminal point (a predefined threshold), and the values of cart speed, rope angle, and angular velocity were under predefined thresholds. During the experiment, the values of z, $\dot{z}$, ϕ, and $\dot{\phi}$ were recorded into a file. In addition, the values of the operator's control signal δ were recorded into the same file. In the identification, only the signals of δ and z were used, because the industrial cranes do not have rope angle ϕ measurement available.

The starting time of the task was randomized so that the human operator could not see the simulation visualization until a random time interval was passed. In this way the human operator delay from perception to action can be estimated accurately. For simplicity, the rope length was kept constant during the task execution. For each experiment, the human operator performed the task 150 times, having unlimited rest time after each 10 trials. Every second of the trials was chosen for training data, and the rest for validation data. Thus, the training and the validation data sets consisted of 75 trials of the task. The data from the training and the validation sets were averaged. The effect of learning was not considered because the human operator had practiced the task over 100 times before the data were recorded.

The SAC algorithm is run by four operators, who knew the purpose of the experiment. The first operator, OP1 performed the SAC iteration starting from a very low initial value of gain k_n (k_n = 0.6) as well as from a high initial value (k_n = 8). The other operators OP2, OP3 and OP4 performed the iteration starting only from low initial value (k_n = 0.6). Operator OP1 is a very experienced on this task. Operator OP2 is a beginner, with the least amount of practice. Operators OP3 and OP4 are rather experienced but with less training than OP1.

Since the knowledge-based approach is heuristic, it cannot be guaranteed that the resulting parameters are optimal. However, sometimes the knowledge-based method is the only option. The first task in the knowledge-based approach is to define the performance (or skill) index. In this case, the overshoot percentage was chosen

$$\mathrm{PO} = 100\left(\frac{max_t\, z(t)}{z(T)} - 1\right), \qquad (6)$$

where $z(t)$ is the cart position and T is the task execution time. The overshoot percentage was scaled into a "skill index" by using the statistical learner model approach. In practice, this is done by fitting a GEV distribution for the average PO values (average of each and the GEV probability density distribution are shown in Fig. 4 (on the left). As can be seen, the fit is not perfect but on the other hand, there were only 150 data points available (30 samples per subject). The right hand side plot in the figure is the complement cumulative distribution of the fitted GEV, which is used to obtain the normalized skill index value.

GEV generalized extreme value distribution

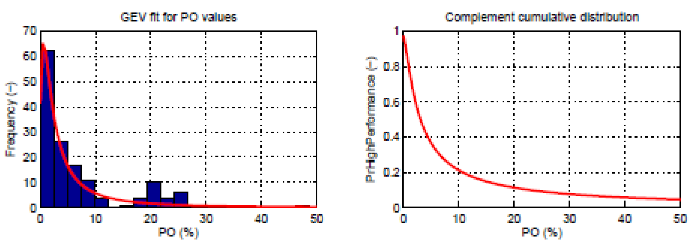

Fig. 4. The performance/skill evaluation using to the over-shoot percentage and GEV.

Now the inputs for the parameter adaptation FIS in (3) can be defined as PrHighPerformance (Overshoot-based index), CurrentGain $k_n(i)$, and FullControlUse (2). The operator-wise values for PO, as well as the corresponding skill index PrHighPerformance, and the other inputs of the parameter adaptation FIS are shown in Fig. 5.

The input membership functions of the FIS are shown in Fig. 6. Note that the third input (FullControlIse) is in practice binary-valued. The suggestion with respect to the current gain value are computed using (3), with $\alpha = 0.12$.

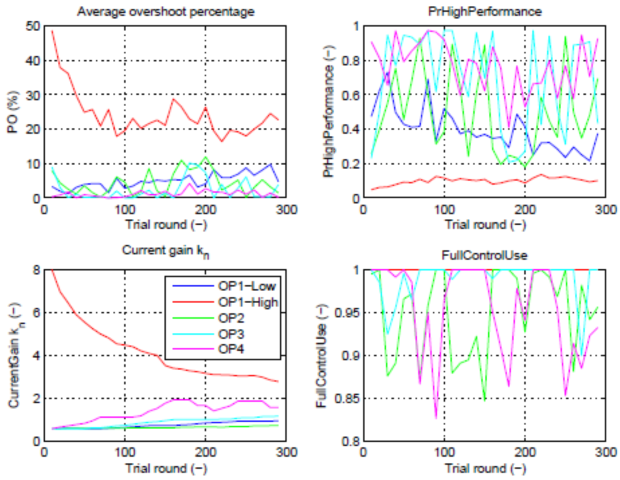

Fig. 5. The overshoot percentage (PO), the performance evaluation index (PrHighPerformance) according to the scale shown in Fig. 5, the current value of the gain k_n, and FullControlUse.

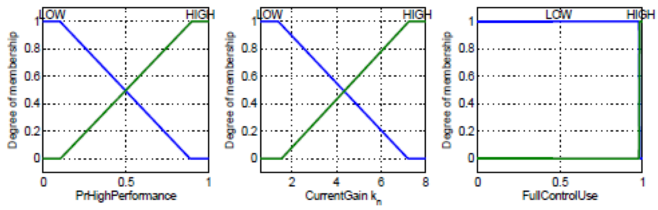

Fig. 6. The input membership functions of the parameter adaptation FIS.

Looking at PO and gain k_n in Fig. 5 (left-hand side), one can see clear evidence of convergence, especially in gain. Recall that in knowledge-based approach one cannot expect a clean global optimum.

5. CONCLUSIONS

A knowledge-based approach for the HMI adaptation system for machine work is proposed. The method exploits the skill evaluation and the current parameter in a FIS, which performs reasoning whether the current parameters are suitable or not.

In order to adapt the system to the human operator's dynamic characteristics, the Skill Adaptive Control (SAC) algorithm is proposed. The algorithm consists on data gathering, modeling, optimization and adaptation steps. Basically the data gathering is done by letting the human operator to perform the task several times, after which the rest of the steps are taken. Then the algorithm starts again from the beginning. The SAC algorithm is implemented in a trolley crane simulator, and an experiment involving several operators is performed.

The knowledge-based approach is based only on statistical performance evaluation and heuristic rules. Thus, it cannot be guaranteed that the human operation would fulfill any closed-loop performance criteria after parameter adjustment.

Although the results obtained in the trolley crane experiment are promising, before the implementation of the method in a real-life system, the usability challenges should considered. In general, a significant challenge in the development of the human adaptive systems is to keep the system "familiar" for the human operator. Even the human adaptive system should (at least to some extent) fulfill the basic principles for the direct manipulation systems such as predictability, overall controllability and transparency. The usability issues are left for future research.

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