

# Bayesian online changepoint detection to improve transparency in human-machine interaction systems

メタデータ	言語: eng 出版者: 公開日: 2017-10-03 キーワード (Ja): キーワード (En): 作成者: メールアドレス: 所属:
URL	<a href="https://doi.org/10.24517/00008081">https://doi.org/10.24517/00008081</a>

This work is licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 3.0 International License.



# Bayesian Online Changepoint Detection to Improve Transparency in Human-Machine Interaction Systems

Hon Fai Lau and Shigeru Yamamoto

**Abstract**—This paper discusses a way to improve transparency in human-machine interaction systems when no force sensors are available for both the human and the machine. In most cases, position-error based control with fixed proportional-derivative (PD) controllers provides poor transparency. We resolve this issue by utilizing a gain switching method, switching them to be high or low values in response to estimated force changes at the slave environment. Since the slave-environment forces change abruptly in real time, it is difficult to set the precise value of the threshold for these gain switching decisions. Moreover, the threshold value has to be observed and tuned in advance to utilize the gain switching approach. Thus, we adopt Bayesian online changepoint detection to detect the abrupt slave environment change. This changepoint detection is based on the Bayes' theorem which is typically used in probability and statistics applications to generate the posterior distribution of unknown parameters given both data and prior distribution. We then show experimental results which demonstrate the Bayesian online changepoint detection has the ability to discriminate both free motion and hard contact. Additionally, we incorporate the online changepoint detection in our proposed gain switching controller and show the superiority of our proposed controller via experiment.

## I. INTRODUCTION

The continued development of human-machine interaction systems to accomplish difficult, dangerous, or delicate tasks cooperatively grows even more imperative as this technology moves into wider use in more varied fields. A typical example of a human-machine interaction system in wide use now is bilateral teleoperation. This is an interactive control between humans and robots and which consists of master and slave sub-robots in different environments. In [1], Hokayem and Spong investigated recent control theoretical approaches on teleoperation problems.

In such control schemes, force feedback is critical to achieve the goal of transparency which allows the human to experience the external force from the slave machine in different environments. Lawrence has defined the impedance matching to achieve this transparency in [2]. Due to changes in the environment, Hannaford [3], Yokokohji and Yoshikawa [4] specified the kinesthetic feedback between the human and the environment from the ideal behavior.

In human-machine systems, force sensors play important roles in improving the performance of transparency; however, most of these systems do not use force sensors either on the

human or the machine due to excessive cost. In [5], Raju, Verghese and Sheridan have suggested a position-position architecture which alternative to the force feedback architecture in the bilateral teleoperation. Position-position architecture is mainly controlled by the gain switching approach that was recently discussed by Ni and Wang [6] and [7]. However, the gain switching decisions are based on the threshold value from the estimated changes in slave environment which has to be observed and tuned in advance.

Recently, Takimoto and Yamamoto [8], [9], [10] have suggested an operator-support controller to improve the manual manipulation in human-machine systems. Their controller can support the human while operating an unstable object.

To continue their research, we formulated a two-port network to analyze the stability and performance of their controller in [11]. However, we were not able to complete the closed loop system and provide any physical output to the human. We believe that force feedback can help to perform a task more time effectively and more reliably. In this paper, we are interested to resolve these issues to successfully use teleoperation control architecture in representing human-machine interaction since it is part of the human-machine interaction field. Teleoperation control architecture which extends the human capability to accomplish tasks remotely by providing the human with similar feelings as a human who would perform the tasks directly. The master manipulator which is involved for the human to operate and its commands to the slave which is performing the actual tasks. For our problem setting, a human imposes a force on the master manipulator which converts it to the displacement commands for the slave manipulator. At the slave side, different circumstances (environments) consist of both free motion and hard contact situations. Hence, we introduce the technique of observing the estimated slave-environment force for both situations. We then use the estimated forces to reflect the displacement back to the master manipulator as the reaction forces to the human. Most previous studies considered gain switching as switching high or low gains to the slave manipulator. Its rules are based on a boundary value from estimated impedance changes between the free motion and the hard contact situation. The issue is to have the knowledge of the boundary value based on the experimental results. Furthermore, these results are not consistent due to the hardware mechanics. To resolve this issue, we utilize the Bayes' theorem to identify the changepoint when estimated force has significantly change when free motion changes to hard contact. The Bayes' theorem, in contrast to other classical statistics, not only utilizes means and variances,

H. F. Lau is with Graduate School of Natural Science and Technology, Kanazawa University, Kakuma-machi, Kanazawa, Ishikawa, 920-1192 JAPAN. ericlau@mccos.ec.t.kanazawa-u.ac.jp

S. Yamamoto is with Faculty of Electrical and Computer Engineering, Kanazawa University, Kakuma-machi, Kanazawa, Ishikawa, 920-1192 JAPAN. shigeru@t.kanazawa-u.ac.jp

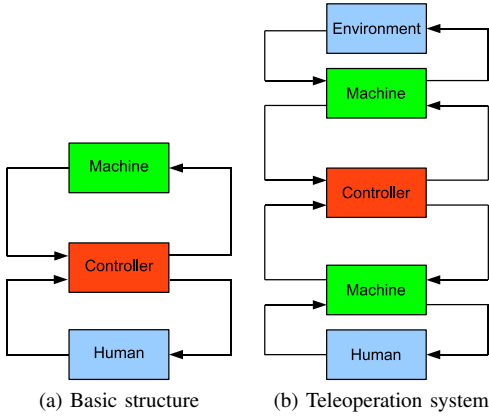


Fig. 1: Human-machine interaction systems.

but additionally some prior distribution. In [12], Adams and Mackay discussed the length of the “run” which determines the changepoint in the data stream. Thus, we utilize their approach to our problem formulation to distinguish different situations while the human is operating the machine by the changepoint which is applied to our proposed gain switching controllers to improve transparency.

## II. HUMAN-MACHINE INTERACTION SYSTEMS

Human-machine interaction systems where human and machines work cooperatively to perform tasks are used in many different fields. Examples range from humans driving a car to performing robot-assisted surgery. The basic architecture can be shown in Fig. 1(a). The main goal of this system is to design the controllers to support both the human and the machine and allow them to perform tasks easier and more effectively. In general, both the human’s input commands to the machine, and the machine’s output to the human are both fed through the controller. We believe that such feedback from the machine which the human can feel, can improve the overall performance of the system.

## III. TELEOPERATION CONTROL ARCHITECTURE

In this section, we consider a teleoperation system which consists of a master device, a slave device and a communication channel which controls the transfer of force and velocity information in representing HMI systems since it is part of the HMI field as shown in Fig. 1(b). We wish to route a virtual feedback force to the human without force sensors to improve the transparency between the human and any remote tasks. A human operator controls the master device while the environment is manipulated by the slave device as shown in Fig. 2. In teleoperation systems, the human operates and receives feedback from the slave in any environment. We assume that the master and slave dynamics is given by

$$M_m \ddot{x}_m = f_m + f_h, \quad (1)$$

$$M_s \ddot{x}_s = f_s - f_e, \quad (2)$$

where  $x$ ,  $f$  and  $M$  are the positions, the input forces and the inertia. The subscript “ $m$ ”, “ $s$ ”, “ $h$ ” and “ $e$ ” denote “master”, “slave”, “human” and “environment” indexes, respectively.

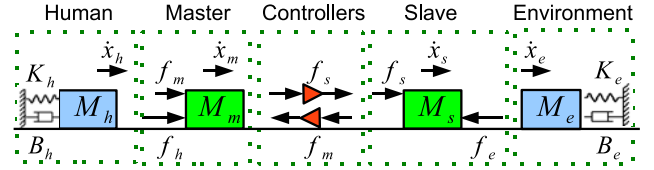


Fig. 2: Model of a teleoperation system.

In particular,  $f_h$  and  $f_e$  correspond to the external forces exerted by the human and the reflection force from the environment or object, respectively. In addition, the equation of motion of the environment or object is assumed to be described as

$$f_e = B_e \dot{x}_s + K_e x_s, \quad (3)$$

where  $B_e$  and  $K_e$  are the mechanical impedance parameters of the environment or object.

## IV. TRANSPARENCY IN TELEOPERATION

In any teleoperation systems, the essential goal is to provide a faithful transmission of velocities or positions and forces between the master and the slave to couple the human as closely as possible to the any remote tasks. We assume that the master and the slave have the identical dynamics. In that case, the perfect transparency behavior as the human would be able to feel the directly interacting forces with the remote task by manipulating the master can be described as

$$f_m = -f_e \text{ and } f_s = f_h. \quad (4)$$

When there is contact with the object, the slave’s velocity  $\dot{x}_s$  and the environment force  $f_e$  are not independent. They are related by the slave environment impedance  $Z_e$  as

$$f_e = Z_e \dot{x}_s. \quad (5)$$

If the human can feel as if they are performing the task directly, the human’s force on the master  $f_h$  and the master’s velocity  $\dot{x}_m$  or position  $x_m$  should satisfy that  $f_h = f_e$  and  $\dot{x}_m = \dot{x}_s$  or  $x_m = x_s$ . It is especially important to transmit any change in the impedance of the environment to the human in the teleoperation system. In other words, by defining the transmitted impedance  $Z_t$  seen by the human as

$$f_h = Z_t \dot{x}_m. \quad (6)$$

The objective is to make the transmitted impedance  $Z_t$  mimics the impedance of the environment  $Z_e$  such as

$$Z_t = Z_e. \quad (7)$$

A hybrid matrix is an alternative way to describe the teleoperation system. The matrix relates  $(\dot{x}_m, \dot{x}_s)$  and  $(f_h, f_e)$  in the hybrid notation

$$\begin{bmatrix} f_h(s) \\ -\dot{x}_s(s) \end{bmatrix} = \begin{bmatrix} h_{11}(s) & h_{12}(s) \\ h_{21}(s) & h_{22}(s) \end{bmatrix} \begin{bmatrix} \dot{x}_m(s) \\ f_e(s) \end{bmatrix}. \quad (8)$$

When the teleoperation system ideally has the perfect transparency with minimal distortion, the hybrid matrix can be written as

$$H_{ideal}(s) = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}. \quad (9)$$

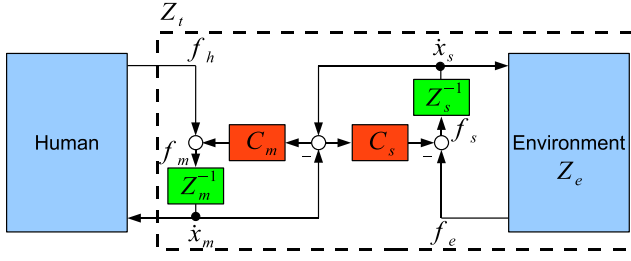


Fig. 3: Position-position architecture.

## V. HYBRID REPRESENTATION IN POSITION-ERROR BASED CONTROL

In the teleoperation architecture which does not use any force sensors on the master or slave manipulators, we adopt a position-error based (PEB) control system as shown in Fig. 3. In the figure,  $Z_m$  and  $Z_s$  represent the impedance of the master and the slave manipulators, i.e.,

$$f_m = Z_m(s)\dot{x}_m, \quad (10)$$

$$f_s = Z_s(s)\dot{x}_s. \quad (11)$$

Moreover,  $C_m(s)$  and  $C_s(s)$  are the controllers for the master and the slave which can be designed as

$$C_m(s) = (k_{d_m}s + k_{p_m})/s, \quad (12)$$

$$C_s(s) = (k_{d_s}s + k_{p_s})/s. \quad (13)$$

where  $k_{p_m}, k_{d_m}, k_{p_s}, k_{d_s}$  are the proportional and derivative gains of the master and the slave (the subscript “ $p$ ” and “ $d$ ” represent the proportional and derivative gain, respectively). In Fig. 3, the inputs of  $C_m(s)$  and  $C_s(s)$  controllers are the master and the slave velocities. Hence, by integrating both velocities by their zero pole, they can be regarded as the proportional-derivative controllers in position-error based architecture. Then, the master and the slave control inputs  $f_m$  and  $f_s$  are given by

$$f_m = C_m(\dot{x}_s - \dot{x}_m) + f_h, \quad (14)$$

$$f_s = C_s(\dot{x}_m - \dot{x}_s) - f_e. \quad (15)$$

From the above equations, we obtain a hybrid representation as

$$\begin{bmatrix} f_h(s) \\ -\dot{x}_s(s) \end{bmatrix} = \begin{bmatrix} Z_m + \frac{C_m Z_s}{Z_s + C_s} & \frac{C_m}{Z_s + C_s} \\ \frac{C_s}{Z_s + C_s} & 1 \end{bmatrix} \begin{bmatrix} \dot{x}_m(s) \\ f_e(s) \end{bmatrix}. \quad (16)$$

## VI. DESIGN OF CONTROLLERS TO IMPROVE TRANSPARENCY

In this paper, we consider the environment of the system in two different cases: (i) the human and the slave machine are moving freely without touching any obstacles, i.e.,  $Z_e = 0$ , (ii) the slave machine is in a hard contact situation such that the human is not able to move the master device, i.e.,  $Z_e = \infty$ .

The human will feel interaction forces while operating the slave in both environments through the transmitted impedance  $Z_t$  which can be derived from (16) as

$$Z_t = \frac{f_h}{\dot{x}_m} = \frac{h_{11} + (h_{11}h_{22} - h_{12}h_{21})Z_e}{1 + h_{22}Z_e}. \quad (17)$$

In the first case where both the human and the slave can move freely, first from (17) with  $Z_e(s) \rightarrow 0$ , we obtain

$$Z_t \rightarrow h_{11} = Z_m + \frac{C_m Z_s}{Z_s + C_s}. \quad (18)$$

To achieve (7), i.e.,  $Z_t = Z_e = 0$ , we assume there are intervening impedances [4], which are the sum of both the master impedance  $Z_m$  and the environment impedance, and are transmitted back to the human. Consequently, we can take account of  $C_m Z_s / (Z_s + C_s) \rightarrow 0$  by adjusting  $C_m$  to have low gains and  $C_s$  to have high gains. This results in the system having a superior position tracking performance between the slave and human during free interactive motions.

In the second case where the human and the slave do not move freely due to obstacles blocking the slave, i.e.,  $Z_e(s) \rightarrow \infty$ ,

$$Z_t \rightarrow h_{11} - \frac{h_{12}h_{21}}{h_{22}} = Z_m + \frac{C_m(Z_s + C_s)}{Z_s + C_s} \quad (19)$$

which indicates that  $C_m$  has to be adjusted to have high gains and  $C_s$  has to be adjusted to have low gains to achieve (7) in hard contact situations, i.e.,  $Z_t = Z_e = \infty$ .

## VII. GAIN SWITCHING APPROACH BASED ON ESTIMATED SLAVE-ENVIRONMENT FORCE

As we mentioned in the previous section for the two cases, free motion and hard contact, we need to change  $C_m$  and  $C_s$ . One way is to use gain switching controller which switches to high value or low value according to the estimated interaction forces  $\hat{f}_e$  compared to the threshold value such as the controller’s gains for the free motion case

$$\begin{cases} C_m \text{ to have low gains} \\ C_s \text{ to have high gains} \end{cases} \text{ if } \hat{f}_e < \text{threshold} \quad (20)$$

and for hard contact motion case

$$\begin{cases} C_m \text{ to have high gains} \\ C_s \text{ to have low gains} \end{cases} \text{ if } \hat{f}_e \geq \text{threshold}. \quad (21)$$

The estimated slave-environment force is given by

$$\hat{f}_e(t) = a_1 x_s(t) + a_2 x_s(t-1) + a_3 x_s(t-2) \quad (22)$$

where

$$a_1 = \frac{\hat{M} + \hat{B}T + \hat{K}T^2}{T^2}, a_2 = -\frac{(2\hat{M} + \hat{B}T)}{T^2}, a_3 = \frac{\hat{M}}{T^2}.$$

and the values of  $\hat{M}$ ,  $\hat{B}$ ,  $\hat{K}$  are estimated by using the extended recursive least square method.

### VIII. BAYES' THEOREM

In contrast to frequentist approaches to changepoint detection, most Bayesian approaches offer offline changepoint detectors. To detect in real time human-machine interaction, we adopt a Bayesian online changepoint detection (BOCPD) method. This method is based on the Bayes' theorem which allows us to make some inferences for event  $\theta$  from observed data  $y$ . In other words, we can draw the posterior probability  $P(\theta|y)$  of  $\theta$  given  $y$  is

$$P(\theta|y) = \frac{P(\theta, y)}{P(y)} = \frac{P(y|\theta)P(\theta)}{P(y)} \quad (23)$$

where  $P(\theta)$  is the prior probability of  $\theta$  that was inferred before new  $y$  became available;  $P(y|\theta)$  is the conditional probability of  $y$  if  $\theta$  is true which is also called a likelihood function;  $P(y)$  is the marginal probability of  $y$  which is called normalizing constant.

By using the Bayes' theorem, we can draw some relations between the posterior and the prior.

$$P(\theta|y) \propto P(y|\theta)P(\theta) = \text{Likelihood} \cdot \text{Prior}. \quad (24)$$

### IX. BAYESIAN ONLINE CHANGEPOINT DETECTION FOR SLAVE-ENVIRONMENT

Our goal is to partition the free motion and hard contact situation segments from a set of data  $y_1, y_2, \dots, y_t$ , which is denoted by  $y_{1:t}$ . The delineations between segments are called the changepoints. To determine these segments, we use the run length method suggested by [12], which is based on the Bayes' theorem under the assumption that changepoints occur by a stochastic process, the data are i.i.d. between changepoints, and the parameters are independent across the changepoints. When the changepoint has occurred if the run length  $r_t$  drop to zero; otherwise, the run length is increased by one. In the method, to find the marginal predictive distribution we integrate over the posterior distribution  $P(r_t|y_{1:t})$  on the current run length as

$$P(y_{t+1}|y_{1:t}) = \sum_{r_t} P(y_{t+1}|r_t, y_t^{(r)})P(r_t|y_{1:t}) \quad (25)$$

where  $y_t^{(r)}$  represents the set of data  $y$  is associated with run length  $r_t$ . Furthermore, to find  $P(r_t, y_{1:t})$ , we estimate the run length distribution  $P(r_{ti}|y_{1:t})$  for  $i = 1, 2, \dots, t$  of run length  $r_t$ . For each time step  $t$ , the run length distribution contains  $i$ -elements of probabilities such that  $\sum_{i=1}^t r_{ti} = 1$ .

By maximizing each run length distribution, we can determine that the changepoint has occurred if  $r_t = 0$  when the element of  $i = t$  of the run length distribution has the highest probability; otherwise, conclude that it has not occurred and increment run length as  $r_t = r_{t-1} + 1$ . The run length distribution can be denoted as

$$P(r_{ti}|y_{1:t}) = \frac{P(r_{ti}, y_{1:t})}{\sum_{r_{ti}} P(r_{ti}, y_{1:t})}. \quad (26)$$

When we denote the joint distribution  $P(r_{ti}, y_{1:t})$  of the run length  $r_t$  at time  $t$  and the observed data  $y_{1:t}$  as  $\phi_t$

( $:= P(r_{ti}, y_{1:t})$ ), it can be updated online recursively as

$$\begin{aligned} \phi_t &= P(r_{ti}, y_{1:t}) = P(y|r)P(r) \\ &= \sum_{r_{(t-1)i}} P(r_{ti}, y_t|r_{(t-1)i}, y_{1:t-1})P(r_{(t-1)i}, y_{1:t-1}) \\ &= \sum_{r_{(t-1)i}} \underbrace{P(r_{ti}|r_{(t-1)i})}_{\text{Changepoint prior}} \underbrace{P(y_t|r_{(t-1)i}, y_t^r)}_{\text{Likelihood}} \phi_{t-1} \end{aligned} \quad (27)$$

Notice that the conditional prior on  $P(r_{ti}|r_{(t-1)i})$  is computed as a growth function such that  $r_t = r_{t-1} + 1$  or a changepoint function such that the changepoint has occurred  $r_t = 0$ . Moreover, the conditional of the posterior distribution and the joint distribution is restated as  $P(r_{ti}|y_{1:t}) \propto \phi_t$ .

The online changepoint detection algorithm is given as follows (in the algorithm,  $t-1$  and  $t+1$  mean just previous time and next time, respectively).

*Algorithm 1:* (Online changepoint detection algorithm)

1. Initialize mean  $\mu_{t-1}$ , variance  $\sigma_{t-1}^2$ , degree of freedom  $\nu_{t-1}$  and the run length distribution  $P(r_{(t-1)i}) = 1$ .
2. **while** (new data  $y_t$  is available) **do**
3. Compute the Gaussian prediction function by the student's t-distribution

$$\begin{aligned} \zeta_t &= P(y_t|\mu_t, \sigma_t^2, \nu_t) \\ &= \frac{\Gamma(\frac{\nu_t+1}{2})}{\sqrt{\nu_t\pi\sigma_t^2}\Gamma(\frac{\nu_t}{2})} \left(1 + \frac{(y_t - \mu_t)^2}{(\nu_t + \sigma_t^2)}\right)^{-\frac{\nu_t+1}{2}} \end{aligned} \quad (28)$$

where  $\Gamma$  is the gamma function.

4. For  $i = 1$  to  $t-1$ , compute growth probabilities

$$P(r_{ti}, y_{1:t}) = P(r_{(t-1)i}, y_{1:t-1})\zeta_t(1 - H) \quad (29)$$

where we assume that the hazard function  $H = \lambda^{-1}$  and  $\lambda$  is a timescale parameter.

5. Compute changepoint probabilities

$$P(r_{tt}, y_{1:t}) = \sum_{i=1}^{t-1} \frac{P(r_{ti}, y_{1:t})}{\lambda - 1}. \quad (30)$$

6. Compute run length distribution

$$P(r_{ti}|y_{1:t}) = \frac{P(r_{ti}, y_{1:t})}{P(y_{1:t})} = \frac{P(r_{ti}, y_{1:t})}{\sum_{i=1}^t P(r_{ti}, y_{1:t})}. \quad (31)$$

7. Update the mean  $\mu$ , the variance  $\sigma^2$  and the degrees of freedom  $\nu$  as

$$\begin{aligned} \mu_{t+1} &= \frac{\kappa\mu_t + y_t}{\kappa + 1} \\ \sigma_{t+1}^2 &= \frac{1}{\nu_t} \left[ (\kappa + 1) + \frac{1}{2}(y_t - \mu_t)^2 \right] \\ \nu_{t+1} &= \nu_t + \delta \end{aligned} \quad (32)$$

where  $\kappa$  and  $\delta$  are constant values.

8. If

$$t = \arg \max_i P(r_{ti}|y_{1:t}). \quad (33)$$

then changepoint has occurred and reset run length as  $r_t = 0$ . If not, increment  $r_t = r_{t-1} + 1$ .

9. **end while**

## X. GAIN SWITCHING APPROACH BASED ON BAYESIAN ONLINE CHANGEPOINT DETECTION

In this section, we investigate an alternative way to design the gain switching controller based on the Bayesian online changepoint detection. We follow the procedure to estimate the unknown changepoint such as the transition from the free motion to the hard contact, and vice versa. We are able to detect changepoint values to conduct our hypotheses in both free motion and hard contact regions when the run length drops to zero; however, we need to determine whether the changes from the free motion to the hard contact, or vice versa in the teleoperation system. To resolve this issue, we use the Euclidean distance function between the master and the slave positions at two different times which is given by

$$d_t(x_m, x_s) = \frac{1}{t} \sum_{k=0}^t \|x_m(k) - x_s(k)\|^2. \quad (34)$$

In addition, we make hypothesis as

$$\begin{aligned} H_0 : r_t = 0 \text{ and } d_t(x_m, x_s) < d_{t-1}(x_m, x_s) \\ H_1 : r_t = 0 \text{ and } d_t(x_m, x_s) \geq d_{t-1}(x_m, x_s), \end{aligned} \quad (35)$$

then we either accept the hypothesis  $H_0$  (free motion) or reject it and conclude that the hypothesis  $H_1$  (hard contact) is substantiated. For instance, we wish to establish an assertion that  $d_t < d_{t-1}$  when a changepoint occurs. This is the hypothesis  $H_0$ , and the negation of this assertion is taken to be the hypothesis  $H_1$ .

Hence, the proposed BOCPD-based gain switching approach for (12) and (13) is suggested as

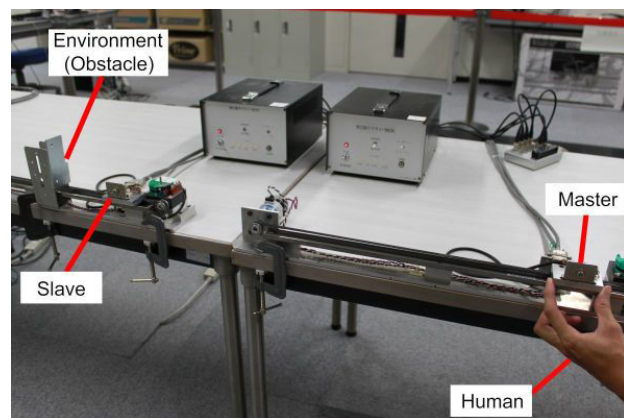
$$\begin{aligned} H_0 : \begin{cases} k_{p_m} \text{ to be low, } k_{d_m} \text{ to be low} \\ k_{p_s} \text{ to be high, } k_{d_s} \text{ to be high} \end{cases} \\ H_1 : \begin{cases} k_{p_m} \text{ to be high, } k_{d_m} \text{ to be high} \\ k_{p_s} \text{ to be low, } k_{d_s} \text{ to be low.} \end{cases} \end{aligned} \quad (36)$$

## XI. EXPERIMENTAL RESULTS

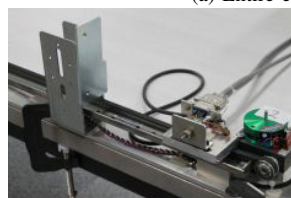
In this section, we consider a two-motor system to depict the teleoperation control architecture as shown in Fig. 4. In our two-motor system, humans hold the master motor device to operate the slave motor device. During the manipulation, any obstacle can be placed next to the slave motor device to create a hard contact situation.

Additionally, we show experimental results which demonstrate the superiority of our proposed methods in comparison with other methods such as position-error based control and a gain switching approach based on estimated slave environment forces in both free motion and hard contact situations. The experimental results of position-error based controller is shown in Fig. 5. Obviously, the position tracking between the master and the slave is not performing well which illustrates the position-error based controller is providing poor transparency between the human and the environment.

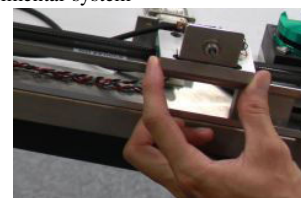
A gain switching controller decision based on the estimated force from the slave environment is as shown in Fig. 6. The improved position tracking of the master and the slave over the position-error based control as shown in Fig.



(a) Entire experimental system



(b) Slave manipulator



(c) Master manipulator

Fig. 4: Teleoperation in the two motor system used in the experiments.

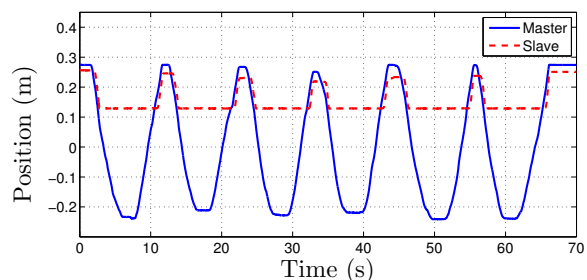


Fig. 5: Master and slave position by PEB control.

6(a). Prior to implementing the gain switching, we observed the estimated force which is about 12 when the slave is in contact with the obstacle. Hence, we establish this boundary value to the threshold value to decide whether the slave is in free motion or in hard contact. Nevertheless, the real time estimated force is bounding up and down along the threshold values because of the gain switching controllers shown in Fig. 6(b). The master's gain and the slave's gain switching high to low and low to high alternately can be noticed in Fig. 6(c). Consequently, the human can feel the hard contact by the resonating force transmitted to them instead of only a backward force to the human. Hence, the estimated force is not a optimum method for the gain switching controllers. Bayesian online changepoint detection method takes account of the estimated force to determine whether there are obstacles or not as shown in Fig. 6(d). However, it shows the Bayesian online changepoint detection failed to detect changes on both free motion and hard contact. The run length increases and drops alternately due to the fact that the estimated forces are too sensitive.

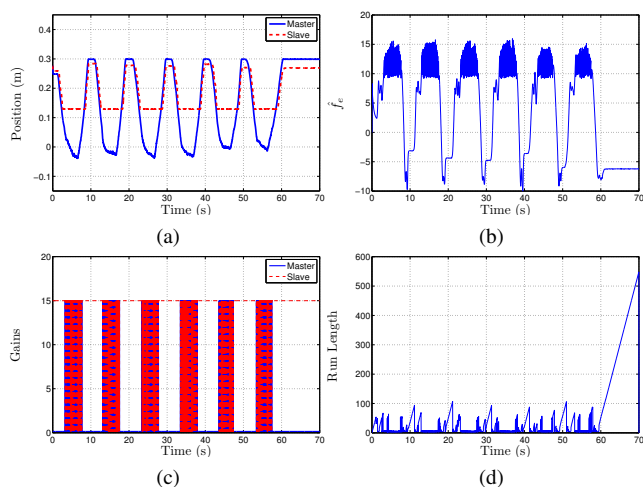


Fig. 6: Gain switching approach using estimated slave environment force (a) Master and slave position, (b) Estimated slave environment force, (c) Master's and Slave's controllers gain, (d) Run length.

Finally, our proposed gain switching controller based on Bayesian online changepoint detection is shown in Fig. 7. The transparency has the overall best improvement as illustrated by the position of the master and the slave shown in Fig. 7(a). In our proposed controller, instead of the estimated force, we utilize the Bayesian online changepoint detection to recognizing the changepoint from the Euclidean distance as shown in Fig. 7(b). As the slave is in hard contact, its value is increased. The gains of both the master and the slave have been switching appropriately in Fig. 7(c) because the results of run length drops when there are abrupt changes such as the transition from the free motion to the slave in the hard contact or the other way around is shown in Fig 7(d). Thus, our proposed gain switching controllers using Bayesian online changepoint detection can switch the master's gain to high for providing the feelings that the slave is hit by an obstacle, while the slave's gain is switched to low. Moreover, the slave also tracks the human motion when it is not disturbed by any obstacles during free motion. To improve transparency, we switch the master's gain as low as possible.

## XII. CONCLUSIONS

We showed how the transparency of human-machine interaction systems without force sensors can be improved in this paper. We first utilize the network representation in the teleoperation system which is an example of HMI systems to analyze its transparency. Moreover, several improvements to the gain switching approach, including Bayesian online changepoint detection, is investigated. This latter method, allows us to set the gain switching controllers without knowledge of the threshold values before the gain switching approach is performed. Experiments show that the Bayesian approach is superior to a regular gain switching approach as far as stability, performance and transparency.

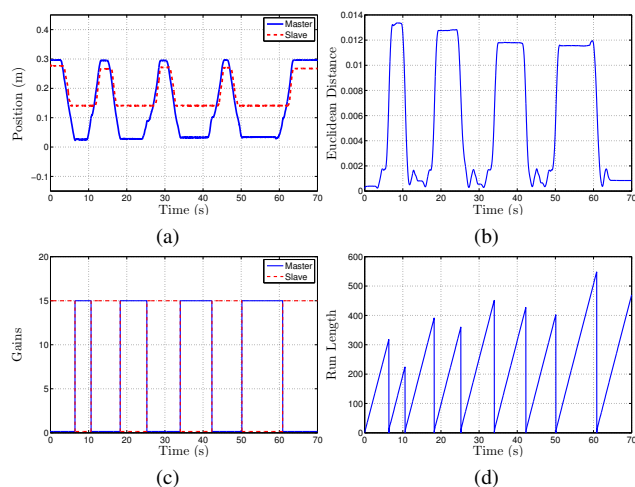


Fig. 7: Gain switching approach using Bayesian online changepoint detection (a) Master and slave position, (b) Euclidean distance, (c) Master's and Slave's controllers gain, (d) Run length.

## REFERENCES

- [1] P. F. Hokayem and M. W. Spong, "Bilateral teleoperation: An historical survey," *Automatica*, Vol. 42, Issue 12, pp. 2035-2057, December 2006.
- [2] D. A. Lawrence, "Stability and transparency in bilateral teleoperation," *IEEE Trans. Robotics and Automation*, Vol. 9, pp. 624-637, October 1993.
- [3] B. Hannaford, "A design framework for teleoperators with kinesthetic feedback," *IEEE Transactions on Robotics and Automation*, Vol. 5, pp. 426-434, 1989.
- [4] Y. Yokokohji and T. Yoshikawa, "Bilateral control of master-slave manipulators for ideal kinesthetic coupling-formulation and experiment," *IEEE Transactions on Robotics and Automation*, Vol. 10, Issue 5, pp. 605-620, October 1994.
- [5] G. J. Raju, G. C. Verghese, and T. B. Sheridan, "Design issues in 2-port network models of bilateral remote teleoperation," *Proceedings of the IEEE International Conference on Robotics and Automation*, pp. 1317-1321, 1989.
- [6] L. Ni and D. W. L. Wang, "A Gain-switching Control Scheme for Position-error-based Force-reflecting Teleoperation," *Haptic Interfaces for Virtual Environment and Teleoperator Systems*, pp. 239-246, 2002.
- [7] L. Ni and D. W. L. Wang, "A Gain-Switching Control Scheme for Position-Error-Based Bilateral Teleoperation: Contact Stability Analysis and Controller Design," *The International Journal of Robotics Research*, Vol. 23, No. 3, pp. 255-274, March 2004.
- [8] T. Takimoto and S. Yamamoto, "An active control method for oscillatory motions in human behavior," *SICE Annual Conference*, pp. 3195-3198, August 2005.
- [9] T. Takimoto, S. Yamamoto, and H. Oku, "Washout Control for Manual Operations," *European Control Conference*, TuC10.2, pp. 1561-1566, July 2007.
- [10] T. Takimoto, S. Yamamoto, and H. Oku, "Washout Control for Manual Operations," *IEEE Transactions on Control Systems Technology*, Vol. 16, No. 6, pp. 1169-1176, November 2008.
- [11] H. F. Lau and S. Yamamoto, "Network Interpretation of a Human-Machine Interaction System," *The 7th Asian Control Conference*, pp. 1491-1496, 2009.
- [12] R. P. Adams and D. J. MacKay, "Bayesian online changepoint detection," *Technical Report at University of Cambridge arXiv:0710.3742v1*, [stat.ML], 2007.