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Designing of dynamic Kalman filter for prediction of mean arterial blood pressure

Ujjwal Manikya Nath[a,*], Chanchal Dey[b], Rajani K. Mudi[c]

[a] *Jorhat Engineering College, Jorhat, Assam-785007, India*
[b] *University of Calcutta, Kolkata- 700009, India*
[c] *Jadavpur University, Salt Lake campus, Kolkata- 700098, India*

Abstract

Presently high blood pressure or hypertension is a global heath issue. Anti-hypertension vasodilator drug are usually injected to the patient body to regulate the mean arterial blood pressure (MABP) within prescribed limit. For long term treatment, it is quite essential to estimate the prospective behaviour of MABP based on its previous data as well as present drug infusion for a subject. So, development of an appropriate MABP model for a patient with hypertension is an upcoming area of research in bio-medical engineering. Here, in the reported work, a dynamic Kalman filter is designed for estimation of the future value of the MABP where the Kalman gain is a function of instantaneous behaviour of the MABP model in relation to the drug diffusion. The main contribution of the proposed work is to get enhanced performance compared to conventional technique with the help of variable Kalman gain instead of fixed value. During simulation study, three types of MABP models are considered to justify our proposed work i.e. for sensitive, normal, and insensitive patients.

Keywords: Kalman filter; state estimation; dynamic Kalman filter; mean arterial blood pressure model

* Corresponding author. Tel.: +91-93332-23528;
E-mail address: um.nath@yahoo.com

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1. Introduction

Hypertension is the medical terminology of high blood pressure which is a very common ailment of our today's stressful daily life, affecting people of any age group [1]. It can lead to severe complications and increases the risk of heart disease, cardiac arrest, and even death [2]. Blood pressure (BP) [3] is the pressure exerted by the blood against the arterial walls. It is an important parameter to ascertain healthiness of the overall physiological behaviour of a human body. Functioning of heart as well as flexibility of blood vessels (arteries) are the key factors towards maintaining the healthy value of blood pressure. It is a vital parameter because it delivers oxygen, nutrients, white blood cells, antibodies for immunity, and hormones such as insulin etc. to the various organs of human body. Moreover, blood pressure (BP) regulation is extremely essential to avoid unwanted medical emergencies as well as to restrict blood loss during surgery.

Sodium Nitroprusside (SNP) is an anti-hypertension vasodilator drug which is considered to be a powerful medication to lower mean arterial blood pressure (MABP) [4]. However, to adjust the appropriate dose of SNP it is also essential to estimate the future value of MABP for a patient based on drug infusion. In [5], Kalman filter (KF) and fuzzy logic based controller is used to track the desired value of MABP. Other blood pressure control schemes are found in [6-10]. Here, in the reported work, we will try to predict the future behavior of MABP for three different patient models [6-7] i.e. for sensitive, normal and insensitive class based on past and present drug infusion data [11]. Here, Kalman filter (KF) [12-14] plays two important roles, initially it helps to estimate the future state and subsequently update the predicted state if there is any mismatch between actual model response and predicted response. Hence, the proposed work is based on dynamic Kalman filter methodology where Kalman gain will vary based on present process operating condition instead of fixed Kalman gain. In the reported work Kalman gain is a function of mismatch between actual model response and corrected output.

Rest of the paper is organized as follow – in section 2, discussion is provided on mean arterial blood pressure estimation. Subsequently, in section 3, discussions are presented about designing of Kalman filter. Proposed work is reported in section 4 and simulation study is given in section 5. At the end conclusion is presented in section 6.

2. Mean arterial blood pressure

In biomedical engineering control-oriented modeling for drug delivery problems is quite complex, dynamic and challenging in nature. In tune with system modeling, dynamic model of patient's response to the SNP infusion based on correlation analysis with pseudo-random binary signal (PRBS) is reported by Slate [11]. Input-output behavior due to the effect of SNP on MABP for a patient is modeled as given by Eqn. (1) and corresponding block diagram representation is shown in Fig. 1.

$$\frac{\Delta P(s)}{I(s)} = \frac{Ke^{-T_i s}(1+\alpha e^{-T_c s})}{\tau s+} \tag{1}$$

Where $\Delta P(s)$ = Change in MABP (mmHg),

$I(s)$ = Infusion rate of drug (ml/h),

K = Sensitivity of the patient to the drug (mmHg/(ml/h)),

α = Recirculation coefficient (dimension less),

T_i = Initial transport delay (sec),

T_c = Recirculation transport delay (sec),

τ = Time constant (sec).

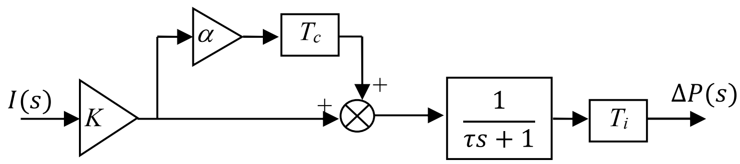


Fig. 1 Block diagram representation of MABP model for a patient.

Values of all the parameters for three different subjects [6-7] are listed in Table 1. It is to note that model parameters are not identical for all type of patient. These values are well approximated and actually they vary from person to person.

Table 1. Parameters value of patient's model

Parameter	Sensitive	Normal	Insensitive
K	-9	-0.7143	-0.1786
α	0	0.4	0.4
T_i	20	30	60
T_c	30	45	75
τ	30	40	60

A disturbance signal is introduced shown in Fig. 2 as suggested in [6-7].

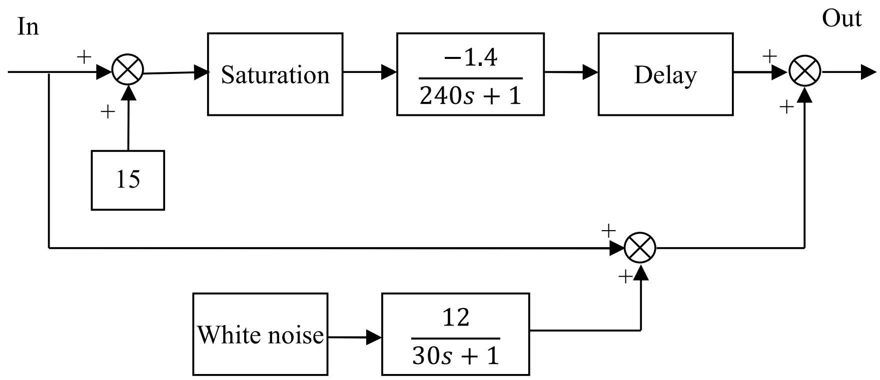


Fig. 2 Block diagram representation of process model with disturbance.

The transfer function as given by Eqn. (1) is computed after substituting the values as listed in Table 1. However, the transfer function model also can be realized with the help of *state space* model as given by Eqn. (2)

$$\dot{x} = Ax + Bu \text{ and } y = Cx, \tag{2}$$

where x is the state variable and u is the input excitation. A is dynamic system matrix, B is input matrix, and C is output matrix.

3. Designing of Kalman filter

Kalman filter (KF) [12-14] is based on *predictor-corrector* algorithm for solving numerical problems as shown in Fig. 3. KF estimates the *state* by using feedback control while filter estimates the process state and subsequently obtains feedback in the form of (noisy) measurements. Moreover, the mathematical relations for Kalman filter fall into two groups: *prediction* equations and *measurement update* equations. The *prediction* equations are responsible for projecting forward the current state and error covariance provides the *priori* estimates for the next time step. The *measurement update* equations are responsible for feedback i.e. for incorporating a new measurement into the *priori* estimate to obtain an improved *posteriori* estimate.

The *prediction state* is based on Eqns. (3) and (4) and Eqns. (5)-(7) are concerned with *measurement update* state. The first task during the measurement update is to estimate the Kalman gain (K_K) by Eqn. (5). The subsequent step is to measure the process output to obtain y_k, and then to generate the *corrected* state estimate by incorporating the measurement data as given in Eqn. (5). The final step is to obtain a *corrected* error covariance estimate from Eqn. (7). After each time sample and measurement update pair, the estimation process is repeated with the previous *corrected* estimates used to project or predict the new *prediction state*. This recursive nature is one of the very lucrative features of Kalman filter.

Prediction state

$$x_k|_{predict} = Ax_{k-1} + Bu_k \tag{3}$$

$$P_k|_{predict} = AP_{k-1}A' + Q \tag{4}$$

Update state

$$K_k = \frac{P_k|_{predict}C'}{CP_k|_{predict}C' + R} \tag{5}$$

$$x_k|_{corrected} = x_k|_{predict} + K_k\left(y_k - Cx_k|_{predict}\right) \tag{6}$$

$$P_k|_{corrected} = (I - K_kC)P_k|_{predict} \tag{7}$$

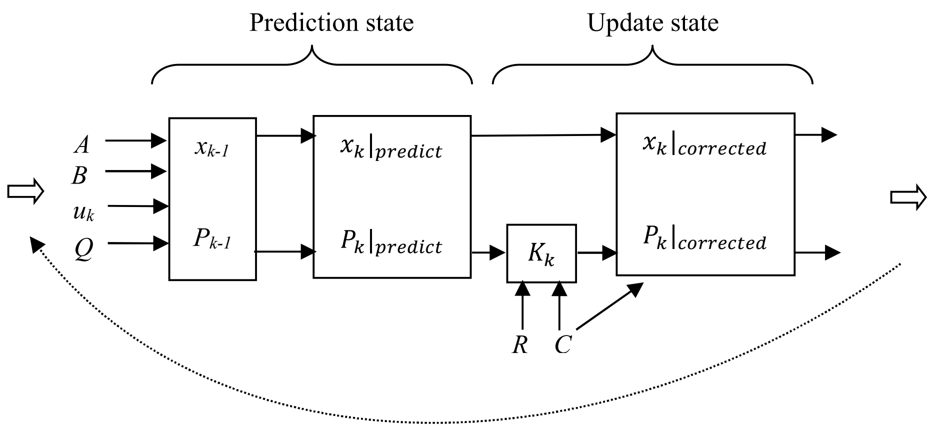


Fig. 3 Basic block diagram of Kalman filter.

During realization of the filter, each of the measurement error covariance matrix and the process noise (Q) need to be measured prior to operation of the filter. Sometimes a very poor model can be used simply by injecting enough uncertainty via the selection of Q. Certainly in this case one would expect that the measurements of the process would be reliable. The measurement noise covariance (R) is also considered during the measurement updated state.

4. Proposed dynamic Kalman filter

In the proposed case, a dynamic Kalman filter is illustrated where Kalman gain (K_K) is modified by a factor (γ). γ is calculated based on the Eqn. (8) and the proposed Kalman gain ($K_k|_{proposed}$) is given by Eqn. (9).

$$\gamma = |measurement - y_k|_{corrected}|, \tag{8}$$

$$K_k|_{proposed} = (\gamma + 1)\frac{P_k|_{predict}C'}{CP_k|_{predict}C' + R}. \tag{9}$$

Fig. 4 shows the proposed Kalman filter with dynamic gain for MABP estimation. One extra feedback loop is incorporated in the Fig. 4 to provide the dynamic nature of the KF behaviour. The factor γ is based on difference between actual measurement and corrected output ($y_k|_{corrected}|$) of the KF.

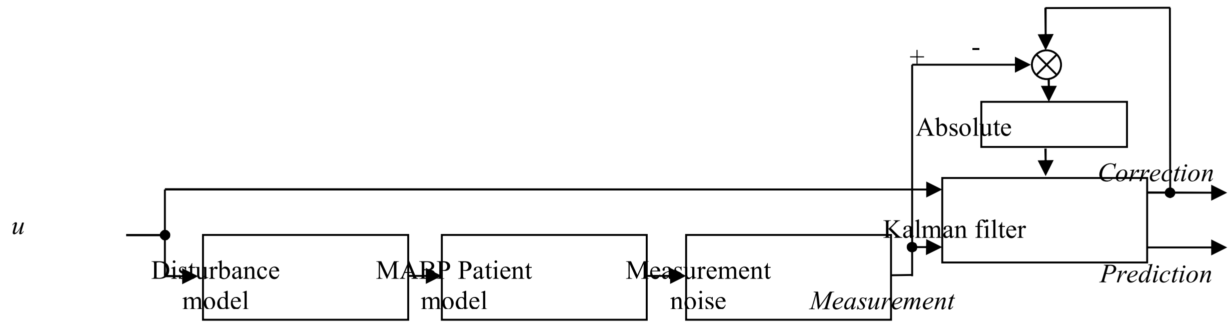


Fig. 4 Proposed dynamic Kalman filter for MABP estimation.

5. Simulation study

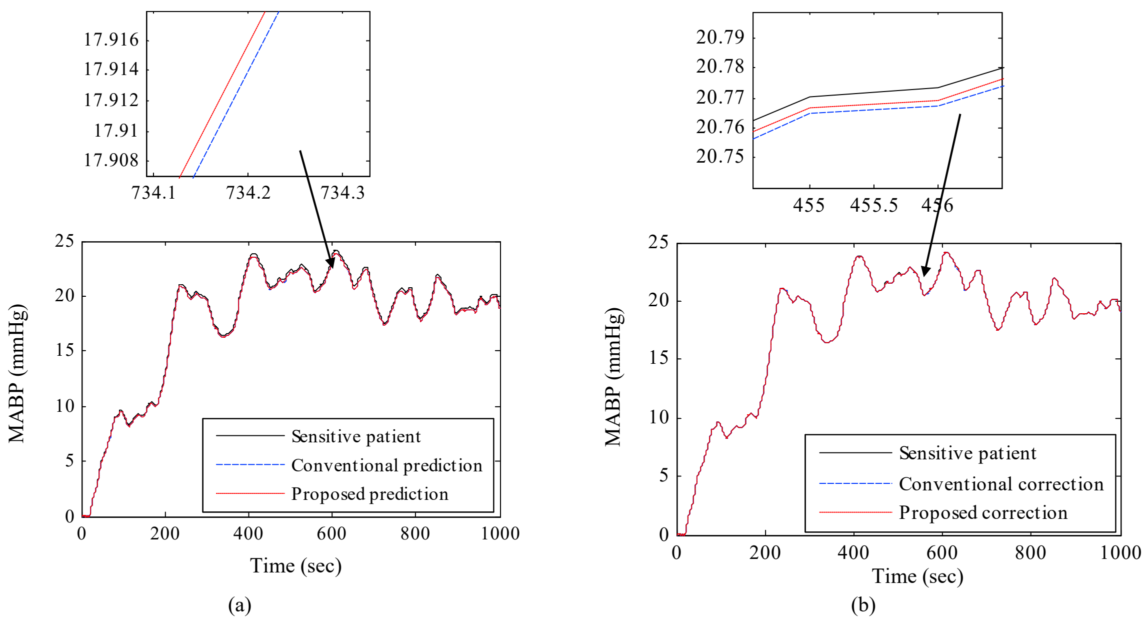
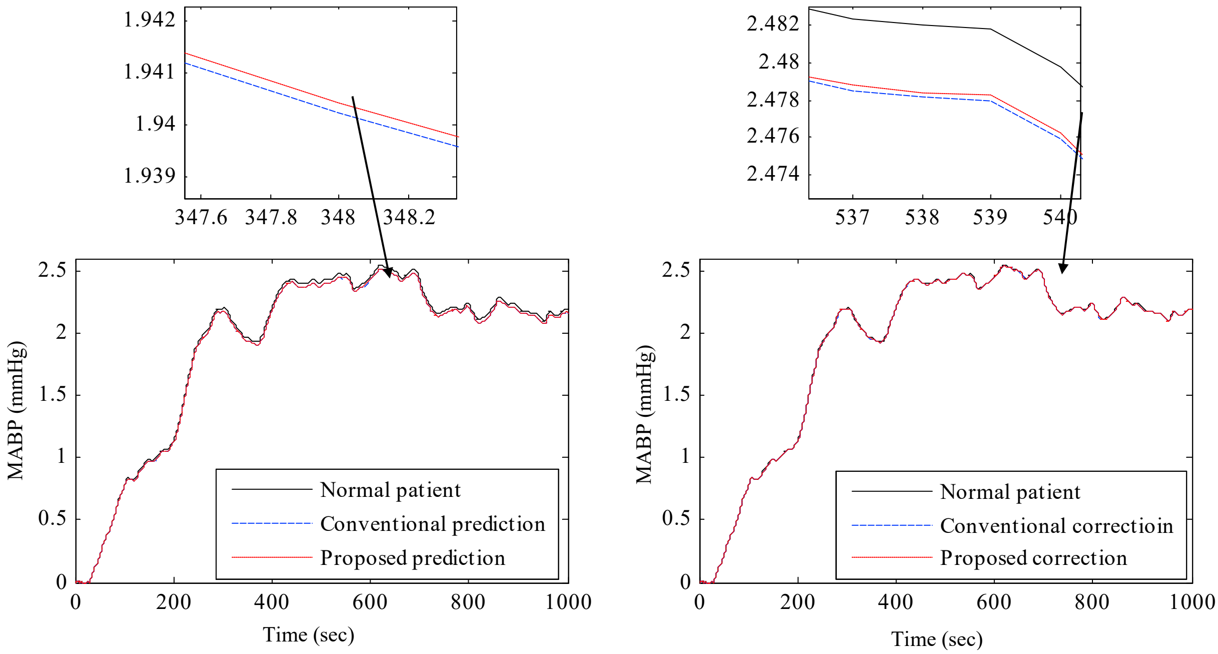
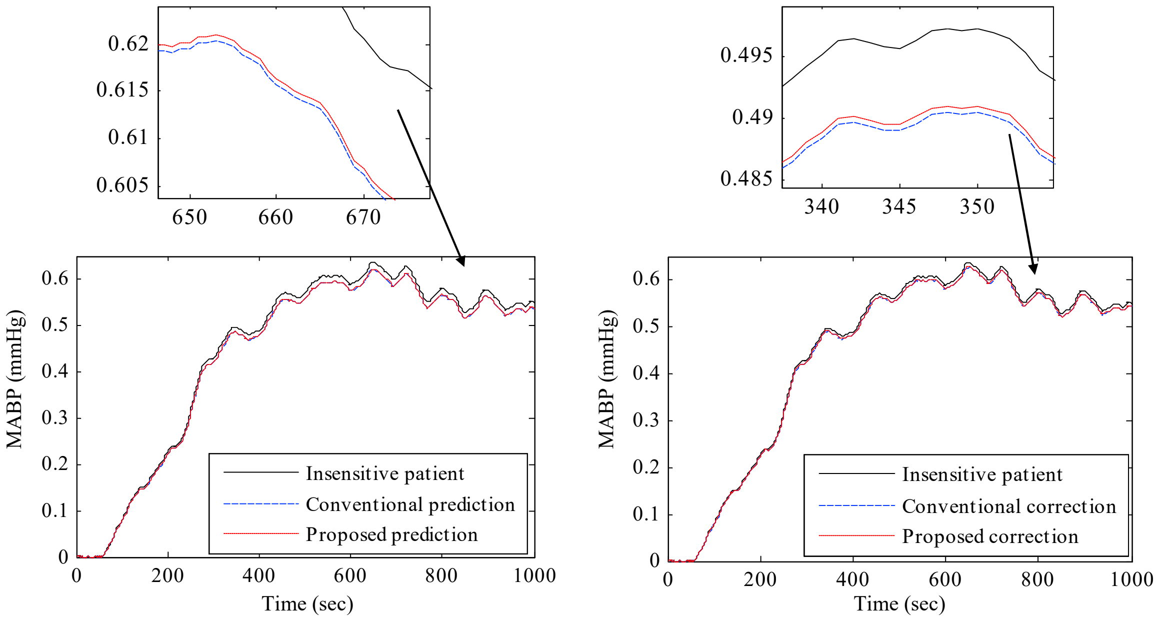


Fig. 5 Sensitive patient response due to conventional and proposed state for (a) prediction and (b) correction state.



(a) (b)

Fig. 6 Normal patient response due to conventional and proposed state for (a) prediction and (b) correction state.



(a) (b)

Fig. 7 Insensitive patient response due to conventional and proposed state for (a) prediction and (b) correction state.

For simulation study, MABP model is chosen which is classified into three different categories i.e. sensitive, normal and insensitive [6-7] model. Block diagram representation of the MABP model as given by Eqn. (1) is shown in Fig. 3 and values of the related parameters are listed in Table 1. Initially, state space model (Eqn. (2)) is computed based on the MABP model and KF is designed based on it. Here, for simulation study MATLAB SIMULINK tool is used. A negative unit step (-1 ml/h) is applied as input to the MABP model and corresponding responses are observed.

Simulation responses are shown in Figs. 5-7 for sensitive, normal, and insensitive model respectively. The zoomed view is also depicted for better visibility of the reported results. For quantitative estimation, integral absolute error (IAE) is calculated for both the conventional and proposed KF cases. Two sets of IAE values are calculated as given by Eqns. (10) and (11) and the values are listed in Table 2. In Eqn. (10), IAE_P is calculated based on the difference between model output and predicted output. However, difference between model output and corrected output is represented by IAE_C.

$$IAE_P = \sum |\text{Actual model output - Predicted output}|. \tag{10}$$

$$IAE_C = \sum |\text{ Actual mode output - Corrected output}|. \tag{11}$$

Figs. (5)-(7) as well as IAE_P and IAE_C values listed in Table 2 substantiate the superiority of our proposed technique. The reported scheme is capable to provide closer response than the conventional KF method as well as smaller IAE values indicates the superiority of our proposed technique. The graphical analysis of IAE_P and IAE_C are shown in Fig. (8) and Fig. (9) respectively. It is clearly visible from Figs. (8) and (9) that proposed scheme provides lesser IAE values compared to existing technique.

Table 2. Performance indices

Methods	Sensitive Patient		Normal Patient		Insensitive Patient	
	IAE_P	IAE_C	IAE_P	IAE_C	IAE_P	IAE_C
Conventional	182.14	4.99	21.82	2.89	10.34	5.98
Proposed	180.20	3.19	20.15	2.70	9.87	5.43

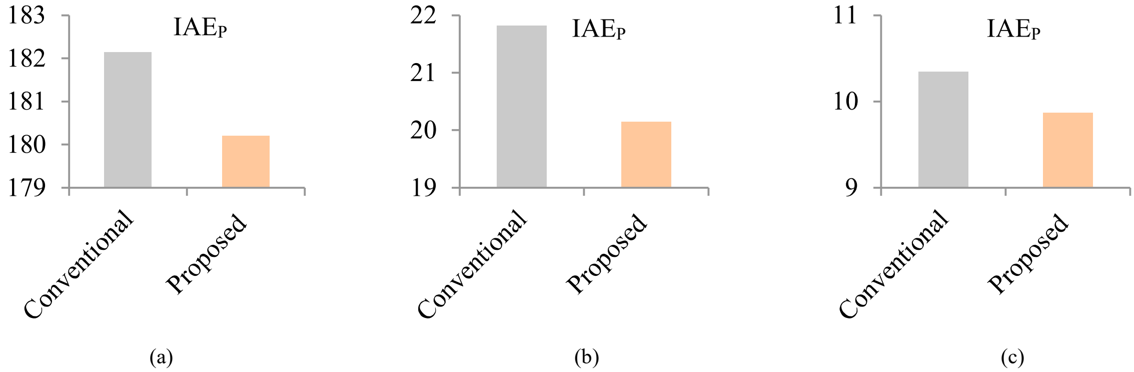
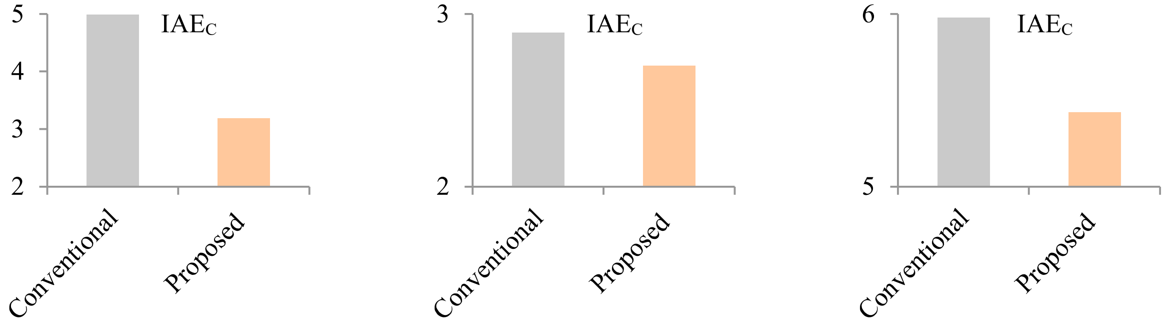


Fig. 8 Graphical analysis of IAE values of prediction error (IAE_P) for (a) sensitive patient (b) normal patient and (c) insensitive patient.



(a) (b) (c)

Fig. 9 Graphical analysis of IAE values of correction error (IAE_C) for (a) sensitive patient (b) normal patient and (c) insensitive patient.

6. Conclusion

In the reported work a dynamic Kalman filter is proposed and the performance is tested on three different mean arterial blood pressure (MABP) patient models – sensitive, normal and insensitive. The variable Kalman gain is the function of mismatch between actual model response and corrected output instead of fixed Kalman gain. From the simulation study, it is found that the proposed Kalman filter (KF) with dynamic gain is capable to provide better estimation compared to fixed Kalman gain with conventional strategies.

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