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Preface

A large international conference on Advances in Engineering Technologies and Physical Science was held in Hong Kong, March 14–16, 2018, under the International MultiConference of Engineers and Computer Scientists 2018 (IMECS 2018). The IMECS 2018 is organized by the International Association of Engineers (IAENG). IAENG is a non-profit international association for the engineers and the computer scientists, which was founded originally in 1968 and has been undergoing rapid expansions in recent few years. The IMECS conference serves as a good platform for the engineering community to meet with each other and to exchange ideas. The conference has also struck a balance between theoretical and application development. The conference committees have been formed with over three hundred committee members who are mainly research center heads, faculty deans, department heads, professors, and research scientists from over 30 countries with the full committee list available at our conference Web site (http://www.iaeng.org/IMECS2018/committee.html). The conference is truly an international meeting with a high level of participation from many countries. The response that we have received for the conference is excellent. There have been more than 600 manuscript submissions for the IMECS 2018. All submitted papers have gone through the peer review, and the overall acceptance rate is 50.16%.

This volume contains 28 revised and extended research articles written by prominent researchers participating in the conference. Topics covered include electrical engineering, communications systems, engineering mathematics, and industrial applications. The book offers the state of the art of tremendous advances in engineering technologies and physical science and applications, and also serves as an excellent reference work for researchers and graduate students working with/on engineering technologies and physical science and applications.

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An Ensemble Kalman Filtering Approach for Discrete-Time Inverse Optimal Control Problems

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Abstract. Solving the inverse optimal control problem for discrete-time nonlinear systems requires the construction of a stabilizing feedback control law based on a control Lyapunov function (CLF). However, there are few systematic approaches available for defining appropriate CLFs. We propose a method that utilizes nonlinear Bayesian filtering to parameterize a quadratic CLF. In particular, we use the ensemble Kalman filter (EnKF) to estimate parameters used in defining the CLF within the control loop of the inverse optimal control problem formulation. Using the EnKF in this setting provides a natural link between uncertainty quantification and optimal design and control, as well as a novel and intuitive way to find the one control out of an ensemble that stabilizes the system the fastest. Results of the EnKF CLF procedure are demonstrated on both a linear and nonlinear test problem.

Keywords: Bayesian inference · Control Lyapunov function · Ensemble Kalman filter · Inverse optimal control · Nonlinear filtering · Stabilizing feedback control

1 Introduction

The aim of optimal control [7, 21] is to determine a control law for a given system that minimizes a cost functional relating the state and control variables. For a linear dynamical system with the associated cost functional that is quadratic in the state and control, the optimal control is a linear state feedback law where the control gain is obtained by solving a differential/algebraic Riccati equation [2]. The widespread applicability of this linear-quadratic regulator (LQR) problem is a consequence of the successful development of robust and efficient algorithms for solving the Riccati equation. However, for a nonlinear dynamical system, the optimal state feedback control law is described in terms of the solution to the Hamilton-Jacobi-Bellman (HJB) equation, which is very difficult to solve analytically for general nonlinear systems [14, 20]. This has led to many computational methods proposed in the literature to obtain an approximate solution to
the HJB equation as well as to obtain a suboptimal feedback control for general nonlin-
er dynamical systems (see, e.g., [6] and the references therein). An alternate approach
is to find a stabilizing feedback control law first, then establish that it optimizes a spec-
ified cost functional – this is known as the inverse optimal control problem.

Solving the inverse optimal control problem for discrete-time nonlinear systems
requires the construction of a stabilizing feedback control law based on a control Lyap-
unov function (CLF). However, there are few systematic approaches available for
defining appropriate CLFs. Available methods parameterize quadratic CLFs using a
recursive speed-gradient algorithm [17], particle swarm optimization [19] or, more
recently, the extended Kalman filter [1].

This work develops a novel approach employing nonlinear Bayesian filtering
methodology to parameterize a quadratic CLF. In particular, we use the ensemble
Kalman filter (EnKF) to estimate the parameters used in defining the CLF within the
control loop of the inverse optimal control problem. Using the EnKF in this setting pro-
vides a natural link between uncertainty quantification and optimal design and control,
as well as an intuitive way to find the one control out of an ensemble that drives the
system to zero the fastest. For preliminary results of this work, we refer the interested
reader to [5].

In the Bayesian framework, unknown parameters are modeled as random variables
with probability density functions representing distributions of possible values. The
EnKF is a nonlinear Bayesian filter which uses ensemble statistics in combination with
the classical Kalman filter equations for state and parameter estimation [3,8,10]. The
EnKF has been employed in many settings, including weather prediction [12,15] and
mathematical biology [3,4]. To the authors’ knowledge, this is the first proposed use
of the EnKF in inverse optimal control problems. The novelty of using the EnKF in
this setting allows us to generate an ensemble of control laws, from which we can then
select the control law that drives the system to zero the fastest. While the nonlinear
problem has no guarantee of a unique control, we use the control ensemble to find the
best solution starting from a prior distribution of possible controls.

The paper is organized as follows. We review the main ideas behind optimal control
and inverse optimal control in Sect. 2 and nonlinear Bayesian filtering and the EnKF in
Sect. 3. In Sect. 4, we describe the application of the EnKF to parametrizing the CLF
for inverse optimal control problem. The results in Sect. 5 demonstrate the effectiveness
of the EnKF CLF procedure on both a linear and nonlinear test problem. We conclude
in Sect. 6.

2 Optimal and Inverse Optimal Control

In this section we describe the optimal control problem and inverse optimal control
problem for discrete-time nonlinear systems, using similar notation to that in [1,18]. For
details on feedback control methodology for nonlinear dynamic systems, see, e.g., [6].

Consider the discrete-time affine nonlinear system

\[ x_{k+1} = f(x_k) + g(x_k)u_k, \quad x_0 = x(0), \]

where \( x_k \in \mathbb{R}^n \) is the state of the system at time \( k \), \( u_k \in \mathbb{R}^m \) is the control input at time \( k \),
and \( f : \mathbb{R}^n \to \mathbb{R}^n \) and \( g : \mathbb{R}^n \to \mathbb{R}^{n \times m} \) are smooth mappings with \( f(0) = 0 \) and \( g(x_k) \neq 0 \).
for all $x_k \neq 0$. The nonlinear optimal control problem is to determine a control law $u_k$ that minimizes the associated cost functional

$$V(x_k) = \sum_{n=k}^{\infty} \left( L(x_n) + u_n^T E u_n \right), \tag{2}$$

where $V : \mathbb{R}^n \rightarrow \mathbb{R}_+$ has $V(0) = 0$, $L : \mathbb{R}^n \rightarrow \mathbb{R}_+$ is positive semidefinite, and $E$ is a real, symmetric positive definite $m \times m$ weighting matrix. The boundary condition $V(0) = 0$ is necessary so that $V(x_k)$ can be used as a CLF. The cost functional (2) can be rewritten as

$$V(x_k) = L(x_k) + u_k^T E u_k + V(x_{k+1}). \tag{3}$$

For an infinite horizon control problem, the time-invariant function $V^*(x_k)$ satisfies the discrete-time Bellman equation

$$V^*(x_k) = \min_{u_k} \left\{ L(x_k) + u_k^T E u_k + V^*(x_{k+1}) \right\}. \tag{4}$$

Taking the gradient of (4) with respect to $u_k$ yields the optimal control

$$u_k^* = -\frac{1}{2} E^{-1} g^T(x_k) \frac{\partial V^*(x_{k+1})}{\partial x_{k+1}} \tag{5}$$

which, when substituted into (3), yields the discrete-time Hamilton-Jacobi-Bellman (HJB) equation

$$V^*(x_k) = L(x_k) + V^*(x_{k+1}) + \frac{1}{4} \frac{\partial V^*(x_{k+1})}{\partial x_{k+1}} g(x_k) E^{-1} g^T(x_k) \frac{\partial V(x_{k+1})}{\partial x_{k+1}}. \tag{6}$$

Since solving the discrete-time HJB Eq. (6) is very difficult for general nonlinear systems, an alternative approach is to consider the inverse optimal control problem. In inverse optimal control, the first step is to construct a stabilizing feedback control law, then to establish that the control law optimizes a given cost functional. By definition, the control law

$$u_k^* = -\frac{1}{2} E^{-1} g^T(x_k) \frac{\partial V^*(x_{k+1})}{\partial x_{k+1}} \tag{7}$$

is inverse optimal if it satisfies the following two criteria [18]:

1. It achieves (global) exponential stability of the equilibrium point $x_k = 0$ for the system (1).
2. It minimizes the defined cost functional (2), for which $L(x_k) = -\nabla$ with

$$\nabla := V(x_{k+1}) - V(x_k) + u_k^{*T} E u_k^* \leq 0, \tag{8}$$

where $V(x_k)$ is positive definite.

The inverse optimal control is, therefore, characterized by function $V(x_k)$. A control law satisfying the above definition can be defined using a quadratic control Lyapunov function (CLF) of the form

$$V(x_k) = \frac{1}{2} x_k^T P x_k, \tag{9}$$
where the matrix $P \in \mathbb{R}^{n \times n}$ is symmetric positive definite (i.e., $P = P^T > 0$). Once an appropriate CLF (9) has been selected, the state feedback control law (7) becomes

$$u_k^* = -\frac{1}{2} \left( E + \frac{1}{2} g^T(x_k)Pg(x_k) \right)^{-1} g^T(x_k)Pf(x_k).$$

(10)

It is noted that since $E$ and $g^T(x_k)Pg(x_k)$ are symmetric positive definite matrices, the inverse matrix in the optimal feedback control law (10) is guaranteed to exist. Therefore, the problem at hand is to select an appropriate matrix $P$ to achieve stability and minimize a meaningful cost function.

As noted in the introduction, currently proposed methods to estimate the entries of the matrix $P$ in the CLF (9) include a recursive speed-gradient algorithm [17], particle swarm optimization [18], and, more recently, use of the extended Kalman filter [1]. In this work, we propose use of nonlinear Bayesian filtering techniques, in particular the EnKF, to estimate the entries of the matrix $P$ from a distribution of possible values, which allows us to find the best control out of an ensemble.

3 Nonlinear Bayesian Filtering and the EnKF

We approach the solution to the inverse optimal control problem from the Bayesian statistical framework, using nonlinear Bayesian filtering methodology to parameterize the quadratic CLF. In the Bayesian framework, the quantities of interest (such as the system states or parameters) are treated as random variables with probability distributions, and their joint posterior density is assembled using Bayes’ theorem. In particular, if $x$ denotes the states of a system and $y$ some partial, noisy system observations, then Bayes’ theorem gives

$$\pi(x \mid y) \propto \pi(y \mid x)\pi(x),$$

(11)

where the likelihood function $\pi(y \mid x)$ indicates how likely it is that the data $y$ are observed if the state values were known and the prior distribution $\pi(x)$ encodes any known information on the states before taking the data into account.

Bayesian filtering methods rely on the use of discrete-time stochastic equations describing the model states and observations to sequentially update the joint posterior density. Assuming a time discretization $t_k, k = 0, 1, \ldots, T$, with the observations $y_k$ occurring possibly in a subset of the discrete time instances (where $y_k = \emptyset$ if there is no observation at $t_k$), we can write an evolution-observation model for the stochastic state estimation problem using discrete-time Markov models. The state evolution Equation

$$X_{k+1} = F(X_k) + V_{k+1}, \quad V_{k+1} \sim \mathcal{N}(0, Q_{k+1}),$$

(12)

where $F$ is a known propagation model and $V_{k+1}$ is an innovation process, computes the forward time propagation of the state variables, while the observation equation

$$Y_{k+1} = G(X_{k+1}) + W_{k+1}, \quad W_{k+1} \sim \mathcal{N}(0, R_{k+1}),$$

(13)

where $G$ is a known operator and $W_{k+1}$ is the observation noise, predicts the observation at time $t_{k+1}$ based on the current state (and parameter) values.
Letting $D_k = \{y_1, y_2, \ldots, y_k\}$ denote the set of observations up to time $t_k$, the stochastic evolution-observation model allows us to sequentially update the posterior distribution $\pi(x_k \mid D_k)$ using a two-step, predictor-corrector-type scheme:

$$\pi(x_k \mid D_k) \rightarrow \pi(x_{k+1} \mid D_k) \rightarrow \pi(x_{k+1} \mid D_{k+1})$$

(14)

The first step (the prediction step) employs the state evolution Eq. (12) to predict the values of the states at time $t_{k+1}$ without knowledge of the data. The second step (the analysis step or observation update) then uses the observation Eq. (13) to correct the prediction by taking into account the data at time $t_{k+1}$. If there is no data observed at $t_{k+1}$, then $D_{k+1} = D_k$ and the prediction density $\pi(x_{k+1} \mid D_k)$ is equivalent to the posterior $\pi(x_{k+1} \mid D_{k+1})$. Starting with a prior density $\pi(x_0 \mid D_0)$, $D_0 = \emptyset$, this updating scheme is repeated until the final posterior density is obtained when $k = T$.

### 3.1 Ensemble Kalman Filter

As noted in the introduction, the ensemble Kalman (EnKF) filter is a nonlinear Bayesian filter that uses ensemble statistics in combination with the classical Kalman filter equations to accommodate nonlinear models [8,10]. While there are versions of the EnKF that perform joint state and parameter estimation [3,11], for our purposes we need only consider the standard EnKF for state estimation, which will be adapted in the following section for the inverse optimal control problem. To avoid confusion with the states of the control system (1), here we denote the states in the filter as $a_k$, $k = 0, \ldots, T$, as opposed to the typical $x_k$ notation. The EnKF algorithm for state estimation is outlined as follows.

Assume the current density $\pi(a_k \mid D_k)$ at time $t_k$ is represented in terms of a discrete ensemble of size $N$, denoted as

$$\mathcal{S}_{k|k} = \{(a_{1|k}), (a_{2|k}), \ldots, (a_{N|k})\}.$$ (15)

In the prediction step, the states at time $t_{k+1}$ are predicted using the state evolution Eq. (12) to form a state prediction ensemble, given by

$$a_{k+1|k}^j = F(a_{k|k}) + v_{k+1}^j, \quad j = 1, \ldots, N,$$ (16)

where $v_{k+1}^j \sim \mathcal{N}(0, Q_{k+1})$ represents error in the model prediction. Ensemble statistics yield the prediction ensemble mean

$$\bar{a}_{k+1|k} = \frac{1}{N} \sum_{j=1}^{N} a_{k+1|k}^j$$ (17)

and prediction ensemble covariance matrix

$$\Gamma_{k+1|k} = \frac{1}{N-1} \sum_{j=1}^{N} (a_{k+1|k}^j - \bar{a}_{k+1|k})(a_{k+1|k}^j - \bar{a}_{k+1|k})^T.$$ (18)
When an observation $y_{k+1}$ arrives, an artificial observation ensemble is generated around the true observation, such that

$$y^j_{k+1} = y_{k+1} + w^j_{k+1}, \quad j = 1, \ldots, N, \quad (19)$$

where $w^j_{k+1} \sim \mathcal{N}(0, R_{k+1})$ represents the observation error. The observation ensemble is compared to the observation model predictions

$$\hat{y}^j_{k+1} = G(a^j_{k+1|k}), \quad j = 1, \ldots, N, \quad (20)$$

which are computed using the observation function $G$ as defined in (13). The posterior ensemble at time $t_{k+1}$ is then computed by

$$a^j_{k+1|k+1} = a^j_{k+1|k} + K_{k+1}(y^j_{k+1} - \hat{y}^j_{k+1}) \quad (21)$$

for each $j = 1, \ldots, N$, where the Kalman gain $K_{k+1}$ is defined as

$$K_{k+1} = \Sigma_{k+1}^{\hat{y}y}(\Sigma_{k+1}^{\hat{y}\hat{y}} + R_{k+1})^{-1}. \quad (22)$$

In the Kalman gain formula (22), $\Sigma_{k+1}^{\hat{y}y}$ denotes the cross covariance of the state predictions $a^j_{k+1|k}$ and observation predictions $\hat{y}^j_{k+1}$, $\Sigma_{k+1}^{\hat{y}\hat{y}}$ the forecast error covariance of the observation prediction ensemble, and $R_{k+1}$ the observation noise covariance. This formulation of the Kalman gain straightforwardly allows for nonlinear observations, as opposed to the more familiar formula for linear observation models [16]. Use of the artificial observation ensemble (19) ensures that the resulting posterior ensemble in (21) does not have too low a variance [8]. The posterior means and covariances for the states are then computed using posterior ensemble statistics, and the process repeats.

### 4 EnKF CLF Procedure for Inverse Optimal Control

To apply the EnKF to the inverse optimal control problem, we treat the entries of the symmetric positive definite $P$ defining the quadratic CLF in (9) as the states of the filter and apply the following updating procedure to find the control that drives the system to zero the fastest. At time $k$, assume a discrete ensemble of $P$ matrices

$$P^j_{k|k} = \begin{bmatrix} P^j_{1,1} & \cdots & P^j_{1,n} \\ \vdots & \ddots & \vdots \\ P^j_{1,n} & \cdots & P^j_{n,n} \end{bmatrix} \in \mathbb{R}^{n \times n}, \quad j = 1, \ldots, N, \quad (23)$$

where each matrix $P^j_{k|k}$ is symmetric positive definite. Using symmetry to our advantage, we need only update the upper triangular entries of the $P$ matrices, which we place into the vectors

$$p^j_{k|k} = \begin{bmatrix} P^j_{1,1} \\ \vdots \\ P^j_{1,n} \\ \vdots \\ P^j_{n,n} \end{bmatrix} \in \mathbb{R}^{\hat{n}}, \quad \hat{n} = \frac{n(n+1)}{2}. \quad (24)$$
As in the prediction step of the filter, we generate a prediction ensemble
\[ p_{k+1|k}^j = p_{k|k}^j + v_{k+1}^j, \quad v_{k+1}^j \sim \mathcal{N}(0, Q), \tag{25} \]
where here the propagation function in Eq. (16) is multiplication by the \( \hat{\mathbf{n}} \times \hat{\mathbf{n}} \) identity matrix and the covariance of the innovation term \( v_{k+1}^j \) is some constant matrix \( Q \). Prediction ensemble statistics can be computed as in (17)–(18), however they are not needed for the remaining computations.

Reformulating the prediction ensemble vectors \( \{p_{k+1|k}^j\}_{j=1}^N \), we can compute the corresponding predicted controls, states, and root mean square error (RMSE) values for each ensemble member using the following formulas. The predicted controls are given by
\[ u_{k+1|k}^j = -\frac{1}{2} \left( \mathbf{E} + \frac{1}{2} g^T(x_{k|k}^j)p_{k+1|k}^jg(x_{k|k}^j) \right)^{-1} g^T(x_{k|k}^j)p_{k+1|k}^jf(x_{k|k}^j) \tag{26} \]
as in (10) for each \( j = 1, \ldots, N \), which are then used to generate the state prediction ensemble
\[ x_{k+1|k}^j = f(x_{k|k}^j) + g(x_{k|k}^j)u_{k+1|k}^j, \quad j = 1, \ldots, N, \tag{27} \]
as in the nonlinear system (1).

For the analysis step of the filter, we interpret as “observations” the RMSE values of the states as we drive them to zero. Since the aim is to find a control that drives the RMSE to zero, we treat RMSE = 0 as the true “observation” and generate an observation of the states as we drive them to zero. Since the aim is to find a control that drives the system to zero the fastest, we can stop when the minimum \( \text{RMSE} \) is found, based on some prescribed stopping criterion. In particular, if we want to find the control that drives the system to zero the fastest, we can stop when the minimum RMSE of all ensemble members is less than some prescribed tolerance. We refer to this process as the EnKF CLF procedure, and the resulting EnKF CLF corresponds to the control law with minimum RMSE that stops the algorithm, i.e. drives the system to zero the fastest.

\[ \text{RMSE}_{\text{obs}}^j = w_{k+1}^j, \quad w_{k+1}^j \sim \mathcal{N}(0, R). \tag{28} \]

We then compare the “observed” RMSEs to the RMSEs of the predicted states, given by
\[ \text{RMSE}_{k+1|k}^j = \sqrt{\left(\frac{x_{k+1|k}^j}{n}\right)^2 + \left(\frac{x_{k+1|k}^j}{n}\right)^2 + \cdots + \left(\frac{x_{k+1|k}^j}{n}\right)^2} \tag{29} \]
and compute the posterior ensemble as in (21) using the formula
\[ p_{k+1|k}^j = p_{k+1|k}^j + \mathcal{K}_{k+1}(\text{RMSE}_{\text{obs}}^j - \text{RMSE}_{k+1|k}^j), \tag{30} \]
where the Kalman gain is defined as in (22) with \( \sum_{k+1}^{\text{yy}} \) denoting the cross covariance of the predictions \( p_{k+1|k}^j \) and RMSE predictions \( \text{RMSE}_{k+1|k}^j \), \( \sum_{k+1}^{\text{yy}} \) the forecast error covariance of the RMSE prediction ensemble, and \( R \) the observation noise covariance. Posterior control law, state, and RMSE ensembles can be computed after reformulating the posterior ensemble of entry vectors \( \{p_{k+1|k}^j\}_{j=1}^N \) into their corresponding matrices \( \{p_{k+1|k}^j\}_{j=1}^N \), and ensemble statistics can be computed.

This process is repeated for each successive time step until an appropriate control is found, based on some prescribed stopping criterion. In particular, if we want to find the control that drives the system to zero the fastest, we can stop when the minimum RMSE of all ensemble members is less than some prescribed tolerance. We refer to this process as the EnKF CLF procedure, and the resulting EnKF CLF corresponds to the control law with minimum RMSE that stops the algorithm, i.e. drives the system to zero the fastest.
5 Results

We illustrate the effectiveness of the proposed EnKF CLF method on two numerical examples, one involving a linear system and the other a nonlinear system.

5.1 Numerical Example: Linear System

For our first numerical example, we consider the discrete-time linear system

$$x_{k+1} = \begin{bmatrix} 0.9974 & 0.0539 \\ -0.1078 & 1.1591 \end{bmatrix} x_k + \begin{bmatrix} 0.0013 \\ 0.0539 \end{bmatrix} u_k$$  \hspace{1cm} (31)

with initial point $x_0 = [2, 1] \in \mathbb{R}^2$. The goal is to minimize the performance measure

$$J = \frac{1}{2} \sum_{k=0}^{N-1} \left[ 0.25(x_1)^2_k + 0.05(x_2)^2_k + 0.05u_k^2 \right]$$

as described in [13]. We set up the EnKF CLF estimator by letting

$$E = 0.05, \quad Q = q_0 I_2, \quad R = r_0,$$  \hspace{1cm} (32)

where $q_0 = 1 \times 10^{-4}$ and $r_0 = 1 \times 10^{-3}$. We generate uniform prior of size $N = 1,000$ ensemble members on the upper-triangular entries of the $P$ matrix with minimum value 0.05 and maximum value 0.2. We set the stopping criterion such that the filter stops when $\min(RMSE) < 1 \times 10^{-3}$ to find control that drives system to zero the fastest. After 103 steps, the procedure results in the following matrix $P$ defining the EnKF CLF:

$$P = \begin{bmatrix} 1.2429 & 1.7809 \\ 1.7809 & 2.7101 \end{bmatrix}$$  \hspace{1cm} (33)

where the estimated entries of $P$ are rounded to four decimal places.

Figure 1 shows the states $x_1$ and $x_2$ and control $u$ corresponding to the EnKF CLF, along with their respective ensemble means when the algorithm stops. After an initial transient, the control defined by this resulting CLF matches the expected control for the linear system (31) [13]. It can also be seen that, for this example, the ensemble mean curves for $x_1$, $x_2$, and $u$ all follow a similar pattern as those corresponding to the minimum RMSE.

5.2 Numerical Example: Nonlinear System

For our second numerical example, we consider the discrete-time nonlinear system

$$x_{k+1} = f(x_k) + g(x_k)u_k$$  \hspace{1cm} (34)

with initial point $x_0 = [2.5, -1] \in \mathbb{R}^2$, where

$$f(x_k) = \begin{bmatrix} 2x_{1,k} \sin(0.5x_{1,k}) + 0.1x_{2,k}^2 \\ 0.1x_{1,k}^2 + 1.8x_{2,k} \end{bmatrix}$$  \hspace{1cm} (35)
Fig. 1. The states $x_1$ and $x_2$ and control $u$ for the linear system (31) estimated using the EnKF CLF procedure. In each plot, the resulting EnKF CLF curves, generated using the CLF with $P$ matrix (33), are shown in solid red, and the corresponding ensemble means are shown in dashed blue.

and

$$g(x_k) = \begin{bmatrix} 0 \\ 2 + 0.1 \cos(x_{2,k}) \end{bmatrix}. \quad (36)$$

This system was also analyzed in [1]. Here we let

$$E = 1, \quad Q = q_0 I_2, \quad R = r_0 \quad (37)$$

with $q_0 = 1 \times 10^{-2}$ and $r_0 = 1 \times 10^{-3}$, and we generate a uniform prior ensemble of size $N = 1,000$ on the upper-triangular entries of $P$ with minimum value $0.05$ and maximum value $0.2$. We stop the algorithm when $\min(\text{RMSE}) < 1 \times 10^{-3}$. After 8 steps, the resulting matrix $P$ defining the CLF that drives the system to zero the fastest is given by

$$P = \begin{bmatrix} 0.2291 & 0.0288 \\ 0.0288 & 0.1799 \end{bmatrix} \quad (38)$$

where the estimated entries of $P$ are rounded to four decimal places.

Figure 2 shows the states $x_1$ and $x_2$ and control $u$ corresponding to the EnKF CLF, along with their respective ensemble means when the algorithm stops. Unlike the linear example, it is interesting to note that, for this nonlinear problem, the ensemble means do not follow similar behavior as the resulting EnKF CLF curves. The EnKF CLF procedure is able to find a CLF in the ensemble that drives the system to zero (to the
prescribed tolerance) in 8 iterations, despite the ensemble mean (and therefore some of the other ensemble members) diverging.

![Graphs showing the states $x_1$ and $x_2$ and control $u$ for the nonlinear system (34) estimated using the EnKF CLF procedure. In each plot, the resulting EnKF CLF curves, generated using the CLF with $P$ matrix (38), are shown in solid red, and the corresponding ensemble means are shown in dashed blue.]

**Fig. 2.** The states $x_1$ and $x_2$ and control $u$ for the nonlinear system (34) estimated using the EnKF CLF procedure. In each plot, the resulting EnKF CLF curves, generated using the CLF with $P$ matrix (38), are shown in solid red, and the corresponding ensemble means are shown in dashed blue.

### 6 Conclusion

In this work we present a novel approach using nonlinear Bayesian filtering, in particular the EnKF, to parameterize a quadratic CLF for inverse optimal control. We demonstrate the effectiveness of using the EnKF to estimate the upper-triangular entries of the symmetric positive definite matrix $P$ in (10) on both a linear and nonlinear example. Since the nonlinear problem does not guarantee a unique solution, the ensemble formulation allows us to find the control that stabilizes the system the fastest (i.e., using the least amount of steps).

Indeed, the numerical examples illustrate the usefulness of the EnKF CLF procedure in finding the one control out of an ensemble that drives the system to zero the fastest, even in cases where the ensemble mean may not. For the linear example described in Sect. 5.1, the ensemble mean curves for the system states and control shown in Fig. 1 follow a similar pattern as those corresponding to the minimum RMSE. This is not the case for the nonlinear example described in Sect. 5.2, where the ensemble means shown
in Fig. 2 diverge – despite this, the EnKF CLF procedure is still able to find a control law for the nonlinear system that drives the system to zero in a small number of iterations. In both of the numerical examples presented, we used ensembles of size $N = 1,000$ ensemble members. We note that while it is possible to find the expected control for the linear system (31) using a much smaller ensemble size (e.g., $N = 10$), decreasing the ensemble size makes it more difficult to find a control that will work in the nonlinear problem. In fact, while it is still possible to find a control that drives the system to zero using a smaller ensemble size, increasing the size of the ensemble gives more possible candidates for the EnKF CLF procedure to find a suitable control. For the presented numerical example, increasing the ensemble size from $N = 1,000$ to $N = 5,000$ increased the CPU time of running the algorithm by only half a second on a standard laptop computer.

While we used the EnKF as our filter of choice in this work, the proposed EnKF CLF procedure can be straightforwardly adapted for use with other nonlinear filtering schemes (such as particle filters) instead. Future work will explore modifying this procedure to accommodate different filters and will study if (and how) the choice of filter affects the number of iterations needed to find a CLF matching the prescribed criteria. We also plan to apply the EnKF CLF method to an optimal design and control application relating to HIV drug therapy, which has been alternatively approached using receding horizon control [9].

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References

Deep Learning Based Structural Health Monitoring Framework with Electromechanical Impedance Method

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Abstract. Electromechanical impedance (EMI) method is a popular structural health monitoring (SHM) technique for monitoring the integrity of a mechanical structure. The EMI method is highly sensitivity to small damage. However, it also has a well-known issue that an impedance signal can be changed by other ambient variations. It has introduced much difficulty in damage measurement with the index-based measurement methods, such as RMSD (Root Mean Square Deviation). In this article, we present our study on applying the deep learning technique to address this issue. An experimental setup was designed for applying the EMI method to monitor the integrity of a metallic structure. The damage classification process was carried out with a deep learning tool. This preliminary study has demonstrated very positive results with the testing configuration under different structural conditions.

Keywords: Deep convolutional neural networks · Deep learning · Electromechanical impedance (EMI) · Fault diagnosis · Structural health monitoring · Temperature variation

1 Introduction

STRUCTURAL health monitoring is a process to detect damage of an engineering structure with various engineering measurement techniques. The electromechanical impedance (EMI) method is one of the popular structural health monitoring (SHM) techniques for monitoring the integrity of a mechanical structure by examining the variations in the mechanical impedance of the structure. The variations in the mechanical impedance account the change in structural stiffness, damping and mass caused by the damage in the structure [1]. The EMI method is highly sensitivity to small damage. However, it also has a well-known issue that an impedance signal can be changed by other ambient variations, such as temperature, loading, sensor coupling etc. It causes the difficulty in damage assessment with the index-based measurement methods commonly used in SHM, such as RMSD (Root Mean Square Deviation), since the human operator is required to interpret a single varied index for assessing damage conditions.

Machine learning is considered as one of the solutions to tackle the difficulty of damage assessment in SHM, which provides the autonomous SHM with the supervised
learning. The deep learning has drawn huge amount of attention in the field of machine learning due to its superior performance in visual pattern recognition [2]. However, it has very limited reference in applying the deep learning technique in the SHM applications.

In this article, the application of the deep learning technique in SHM was studied. An experimental setup was designed for applying the EMI method to monitor the integrity of a metallic structure. A color bar notation has been proposed [3] to represent the resulted FRF (Frequency Responses Function) from the EMI measurement. The damage classification process has been carried out with a deep learning tool. This preliminary study has demonstrated a reliable measurement with the testing configuration under different structural conditions.

2 Electromechanical Impedance (EMI) Technique

The EMI technique is based on the mechanical impedance property of a mechanical structure. The integrity of a mechanical structure can be evaluated by monitoring the variations in mechanical impedance, which accounts the change in structural stiffness, damping and mass caused by the damage in the structure. The mechanical impedance can be measured by the piezoelectric principle, described as the electromechanical impedance (EMI) [4] method.

Under the EMI method, a piezoelectric device, PZT patches are pasted onto a structure specimen. An impedance analyzer will acquire its characteristic impedances over a frequency range. The FRF (Frequency Response Function) of the specimen will be created as illustrated in Fig. 1.

![Fig. 1. FRF (Frequency Response Function)](image)

In the EMI-based SHM, the key indicator of damage is the change in the real part of the impedance of the PZT patch [4]. The status of a structure can be assessed by monitoring the electrical impedance and comparing it to a baseline (the reference condition) measurement for a specified frequency range. One of the popular damage assessment techniques is the root mean square deviation (RMSD) [5]. The RMSD index is presented as follows:
\[ \text{RMSD} = \sum_{i=1}^{n} \sqrt{\frac{[\text{Re}(Z_{i,1}) - \text{Re}(Z_{i,2})]^2}{[\text{Re}(Z_{i,1})]^2}} \]

where RMSD represents the damage metric, \( Z_{i,1} \) is the impedance of the PZT measured in healthy conditions, and \( Z_{i,2} \) is the impedance for the comparison with the baseline measurement at frequency interval \( i \). As reported in a lot of literatures [1, 4], the reliability of the impedance-based method would be affected by the working environmental condition. The shift of impedance frequency spectrum will cause unreliable detection results, particularly when applying the ‘Root Mean Square Diation’ (RMSD) detection technique.

3 Issues of RMSD Technique

The structural variation was demonstrated with the bolt loosening detection application. Bolt loosening is caused by the loss of preloads due to repetitive external forces and vibrations. Pre-load monitoring is important to ensure the safety of component connections in the real engineering application [6], such as the assessment of a critical civil facility after severe natural hazards. Huge efforts have been spent on developing detection techniques of monitoring the loss of pre-load in real-time assessment, such as acoustic ultrasonic emission, magnetic field analysis, and X-ray analysis. Vibration-based damage identification technique was also investigated. Nevertheless, these methods either require sophisticated instruments or require an accurate modelling of the structure under investigation. They are not feasible for the implementation of real-time damage assessment system. On the other hand, the EMI technique offers following advantages [4] to tackle with the need of the pre-load monitoring problem.

– The technique is not based on any model, and thus can be easily applied to complex structures.
– The technique, because of high frequency, is very sensitive to local minor changes.

Therefore, an EMI-based pre-load monitoring system was setup to demonstrate the capability of the EMI technique (Fig. 2).

Fig. 2. Experimental structure for bolt pre-load monitoring
A specimen was designed to connect two steel plates. The change of the structural condition was artificially introduced by changing the pre-load condition, which was labelled with “Ok” (tight) and “Loose” (not firmly held). A piezoelectric patch (PZT sensor) was attached to the structure for monitoring the structural integrity. A professional impedance analyzer WK3260B as illustrated in following figure was used to get the impedance of the PZT patch over a typical frequency range (100 kHz–500 kHz). The measured data was acquired with a data logging software (Fig. 3).

![Fig. 3. Measurement equipment setup](image)

With the looseness of the bolt, the dominating frequency peak will shift according to the stiffness decrease [7] as illustrated in following figure (Fig. 4).

![Fig. 4. Illustration of Frequency Shift caused by the looseness of the bolt (base-line vs loosen bolt)](image)

We used a selected group of data (bolt in tightened condition) from the collected data set as the baseline for evaluation. The RMSD values were calculated over the whole frequency spectrum. By reviewing the calculated RMSD, it was found that there was a variation in the RMSD value for different measurements under the same loading condition as illustrated in Fig. 5. The variation may be contributed by the instrumentation condition or environmental condition. It is difficult for users to set a threshold
RMSD value for identifying the structural conditions (Ok/Loose), since the RMSD values for the “Ok” and “Loose” conditions are overlapped in some area.

In addition, one of well-known issues for the EMI technique is the alteration of impedance signal response caused by other ambient variations, such as temperature, sensor coupling etc. As investigated in Park’s research [4], the ambient temperature change will cause the shift of resonant frequencies as well as the magnitude change of the impedance signal response. Figure 6 illustrated the change of frequency response caused by ambient temperature from 19 °C to 29 °C and under the structural condition (bolt in tightened condition).

**Fig. 5.** RMSD result for different loading conditions

**Fig. 6.** Illustration of the frequency shift caused by ambient temperature (29 °C vs 19 °C – the baseline)
It causes a big problem to the metric-based damage assessment as illustrated in Fig. 7.

Researchers have proposed solutions to tackle with this problem [8, 9]. However, some method is limited to the temperature compensation without considering the structural condition change [8], some method is subjected to have study on the free PZTs before attached to the structure [9]. In conclusion, the proposed methods are either limited or difficult to execute.

4 Condition Classification with Deep Learning

Considering the difficulties encountered when using the RMSD approach, the Deep Learning [10] technique has been evaluated for applying to the classification of our damage detection experiment. Deep Learning is one of machine learning methods used in image recognition tasks. The deep learning process is divided into two phases. The first phase is the training phase. A large dataset is collected with the corresponding labels and is used to teach the machine learning process how to classify different groups of input data. A machine learning algorithm is adopted for summarizing the dataset into a training set. The training set will be utilized in the predication phase by the trained classifier. The deep learning technique uses multiple transformation steps to extract features from the model automatically. It is advantageous to adopt the deep learning technique in SHM applications since the prior knowledge of the structural model is not required.

Convolutional Neural Networks (CNNs) is one of deep learning architectures that has proven successful for image analysis [11]. Different models implementing CNNs have been proposed [12] to improve the image classification performance. The major differences among the different models are the number of layers and the interconnection structures.

Fig. 7. RMSD result for different loading conditions (with temperature variation)
To apply the deep learning technique, the condition classification is modelled as an image classification problem. One of the approaches is to visualize an FRF as a line-chart type image as illustrated in Fig. 1. The shape of the line-chart can be characterized to represent the EMI response of the structure. However, the effectiveness for visualizing the FRF in this approach is questionable. To preserve the details of the FRF, the required resolution should be higher than $1000 \times 1000$ pixels. This image size will make our model to be incompatible for most of popular CNN models, such as AlexNet, GoogLeNet [12], as shown in Table 1. It also increases the computational complexity even if we create our own CNN model. Furthermore, most of the space in the line-chart representing the FRF contains no information. A more suitable visual representation of the FRF should be used instead of the line-chart representation.

Table 1. Image size of some popular CNN models (10)

<table>
<thead>
<tr>
<th>CNNs models</th>
<th>LeNet-5</th>
<th>AlexNet</th>
<th>OverFeat</th>
<th>GoogLeNet</th>
<th>VGG-16</th>
</tr>
</thead>
<tbody>
<tr>
<td>Image size</td>
<td>28 × 28</td>
<td>227 × 227</td>
<td>231 × 231</td>
<td>224 × 224</td>
<td>224 × 224</td>
</tr>
</tbody>
</table>

Therefore, a color bar semantic as illustrated in Fig. 8 is proposed in the article [3] for applying the deep learning to the FRF-based problem. Under the color bar semantic, the vertical axis represents the frequency range. To align the color bar image with the requirement of the typical CNNs models, the horizontal axis should be extended to have the same number of data points as the vertical axis with same color intensity. Furthermore, this color bar semantic can be further extended to combine both the imaginary part and real part in the horizontal axis. It can maximize the information regarding the conditions of a structure with the active signature concept [13].

The value of the FRF is encoded with the RGB color scheme. A common “hot-to-cold” colormap as illustrated in Fig. 9 has been applied, where R, G, B are the color intensity for the red, green and blue components of the RGB color scheme. For example, the impedance value $800 \Omega$ for the range $\pm 900 \Omega$ is represented by $R = 1$, $G = 0.22$ and $B = 0$. 

![Fig. 8. The FRF of the structure in color bar](image-url)
For the implementation of the proposed deep learning condition classification method, an interactive deep learning training system, DIGITS [14], has been adopted. The DIGITS provides an integrated environment for dataset preparation, the training network configuration and deployment, as well as the training set creation.

Another important consideration for setting up the training model is the network selection and configuration. Two standard networks, AlexNet and GoogLeNet [12] were evaluated. The model based on the AlexNet did not converge to the reasonable accuracy within appropriate iterations (epochs). As illustrated in Fig. 10, the final accuracy is around 50%.

On the other hand, the model based on the GoogLeNet demonstrates a very good performance in training stage with appropriate solver and parameter setting as shown in Fig. 11. The general difference between AlexNet and GoogLeNet is the number of layers. The numbers of layers for AlexNet and GoogLeNet are 8 and 22 respectively. The result demonstrates that increasing the complexity of CNN network has a favorable effect to this experiment.
5 Performance Evaluation for Different EMI Features

The EMI signature (the impedance) is a complex number. The damage detection can be assessed in theory according to the Reactance (X), Resistance (R), Susceptance (B) and Conductance (G), where

\[
\text{Impedance: } Z = R + jX, \\
\text{Admittance: } Y = G + jB \text{ and } Z = 1/Y
\]

However, it was reported that the real part of impedance (Resistance) should be used for the EMI assessment only, since the imaginary part of the impedance (Reactance) is temperature-sensitive and it is less related to the structural change [13]. In addition, some researchers have adopted the EM admittance signature (inverse of impedance) for damage detection [4, 13]. In this study, different EMI features, \(X\), \(R\), \(B\) and \(G\) are evaluated with the same data set to comment their detection performance using the proposed deep learning framework. Furthermore, the temperature variation issue is also addressed with the deep learning detection framework.

For the EMI features evaluation, 160 data from 801 samples were selected to create the training dataset (Table 2).

The classification accuracy results are summarized in the following table. The results demonstrate that the Resistance is the best EMI feature among the four features (Table 3).

Some more 241 sets of data were included in the data set with a heat up stage for the “Loose” condition as illustrated below. The performance of the system with the Resistance as the EMI feature is evaluated as follows (Table 4):
With the additional data and the shift of temperature in the “Loose” stage, the classification accuracy deteriorates with 92.4% (vs 100%) overall accuracy and 83.3% (vs 100%) accuracy for “Loose” condition (Table 5).

In order to improve the classification accuracy, the training set was updated (240 training data in total) to include the “heat up” stage data.

Table 2. Data sample for the EMI features evaluation test (Test#1)

<table>
<thead>
<tr>
<th>Loading condition</th>
<th>Samples</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Ok”</td>
<td>0–50</td>
<td></td>
</tr>
<tr>
<td>“Ok”</td>
<td>50–129</td>
<td>Training set</td>
</tr>
<tr>
<td>“Ok”</td>
<td>130–210</td>
<td></td>
</tr>
<tr>
<td>“Ok”</td>
<td>211–300</td>
<td>Heat up (Up to 31 °C)</td>
</tr>
<tr>
<td>“Ok”</td>
<td>301–500</td>
<td></td>
</tr>
<tr>
<td>“Loose”</td>
<td>501–549</td>
<td></td>
</tr>
<tr>
<td>“Loose”</td>
<td>550–629</td>
<td>Training set</td>
</tr>
<tr>
<td>“Loose”</td>
<td>630–800</td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Performance evaluation result for Test#1

<table>
<thead>
<tr>
<th>EMI features</th>
<th>Overall</th>
<th>“Ok”</th>
<th>“Loose”</th>
</tr>
</thead>
<tbody>
<tr>
<td>Reactance (X)</td>
<td>89.5%</td>
<td>88.0%</td>
<td>92.0%</td>
</tr>
<tr>
<td>Resistance (R)</td>
<td>100.0%</td>
<td>100%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Susceptance (B)</td>
<td>95.6%</td>
<td>93.0%</td>
<td>100.0%</td>
</tr>
<tr>
<td>Conductance (G)</td>
<td>92.5%</td>
<td>88.0%</td>
<td>100.0%</td>
</tr>
</tbody>
</table>

Table 4. Data sample for the temperature variation (Test#2)

<table>
<thead>
<tr>
<th>Loading condition</th>
<th>Samples</th>
<th>Remark</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Ok”</td>
<td>0–50</td>
<td></td>
</tr>
<tr>
<td>“Ok”</td>
<td>50–129</td>
<td>Training set</td>
</tr>
<tr>
<td>“Ok”</td>
<td>130–210</td>
<td></td>
</tr>
<tr>
<td>“Ok”</td>
<td>211–300</td>
<td>Heat up (Up to 31 °C)</td>
</tr>
<tr>
<td>“Ok”</td>
<td>301–500</td>
<td></td>
</tr>
<tr>
<td>“Loose”</td>
<td>501–549</td>
<td></td>
</tr>
<tr>
<td>“Loose”</td>
<td>550–629</td>
<td>Training set</td>
</tr>
<tr>
<td>“Loose”</td>
<td>630–800</td>
<td></td>
</tr>
<tr>
<td>New Data</td>
<td></td>
<td></td>
</tr>
<tr>
<td>“Loose”</td>
<td>851–970</td>
<td>Heat up (Up to 37 °C)</td>
</tr>
<tr>
<td>“Loose”</td>
<td>971–990</td>
<td></td>
</tr>
<tr>
<td>“Ok”</td>
<td>991–1091</td>
<td>Resume to “Ok” condition</td>
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