Mechatronics 53 (2018) 140–151

Contents lists available at ScienceDirect

Mechatronics

journal homepage: www.elsevier.com/locate/mechatronics

Improved model based fault detection technique and application to humanoid robots

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ARTICLE INFO

Keywords:
Extended Kalman filter (EKF)
State estimation
Optimized EWMA
Fault detection (FD)
Multiscale representation
Humanoid robot (HR) systems

ABSTRACT

One of the issue of significant interest for robotics is the fault detection, specifically when we have application in risky circumstances. Robotic systems required a capacity to efficiently identify and endure some defects so that they can keep achieving the required tasks while avoiding instantaneous repairing process. Consequently, we aim in this work to propose a systematic approach for state estimation and fault detection technique to enhance the operation of humanoid robots (HR) systems using an extended Kalman filter (EKF)-based multiscale optimized exponentially weighted moving average chart (MS-OEWMA). The objectives of this work are sixfold: (1) apply EKF technique to estimate the state variables in HR systems. The EKF is among the most popular nonlinear state estimation methods; (2) use dynamical multiscale representation for obtaining accurate settled characteristics; (3) propose a new optimized EWMA (OEWMA) based on the best selection of both smoothing parameter (λ) and control width L; (4) combine the advantages of state estimation technique with MS-OEWMA chart to improve the monitoring of HR systems; (5) investigate the effect of fault types (change in variance and mean in shift) and fault sizes on the monitoring performances; (6) validate the developed technique using two robot models: inverted pendulum and five-bar linkage. The detection results are evaluated using three fault detection metrics: missed detection rate (MDR), false alarm rate (FAR) and out-of-control average run length (ARL_1).

1. Introduction

The use of humanoid robotics become increasing investigation domain for many technical fields. The good understanding of the human body dynamics will lead to the creation of a robust model of humanoid robotics. Humanoid robots are used frequently to assist old and sick people as well as doing a hazardous task. They are also suitable for other industrial applications especially in the automotive as they can run devices and equipment intended for human operator despite the sophistication inherited to some cases. The first humanoid robot developed in the world was WABOT-1 by Waseda University, Tokyo. The term humanoid refers to a character or an appearance resembling that of a human while in robotics, it indicates robots with the ability to coordinate, collaborate, learn, communicate and interact physically [1]. Human-Robot collaboration becomes more significant in numerous fields and that relation has a tendency of coexistence. Some researchers talk about circumstances where robots have to take initiatives [2]. In such interactive context, safety and robustness becomes a major subject [3]. The monitoring system for detection of abnormal performance has a crucial role to ensure the good performance of any system and to guarantee acceptable and safe working behavior [4–8]. Finding irregular response in the system is useful in bounding turbulence and keeping robust operation [9]. We can explain the fault as a form of an allowed of mistaken behavior that produces process malfunction without satisfying the desired goal [10,11]. In order to keep a safe and reliable process, a detection system is needed [12–16]. Fault detection is essential to observe the continuity of good functioning of the system under typical circumstances for ensuring safety [4,5]. Identifying faults in the process is used for limiting process animality and maintain it safe and reliable [8,9].

Basically, fault detection techniques are categorized into two main groups: data-based techniques [17–21] and model-based techniques [22–28]. Model-based group is depending generally upon system dynamic structure. Thus, the selected measurements are compared with

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https://doi.org/10.1016/j.mechatronics.2018.06.006
Received 14 January 2018; Received in revised form 7 June 2018; Accepted 12 June 2018
0957-4158/

mathematical model under fault-free conditions. The difference between measured and expected non-faulty values (called the residuals) is utilized to indicate fault occurrence or not. State estimation is necessary for non-measurable quantities before being able to apply monitoring. Practically, estimating these variables is challenging because it requires several experimental procedures. Hence, developing and applying technique capable of estimating these important variables is advantageous. Various estimators were developed for estimating state variables. In [29], an extended kalman filter (EKF) technique is developed by inertial sensors or leg configuration sensors in order to estimate state of robot locomotion. In the papers [30,31], the authors have designed a sliding model estimators for a 5-link biped robot to estimate the absolute orientation of the torso. A model-based state estimation using a planar Spring-Loaded Inverted Pendulum (SLIP) dynamic model has been developed in [32]. In [33], an effective solution for state estimation based on multiple model adaptive estimation has been proposed. Bae and Oh [34], have proposed a new Kalman filter-based approach for humanoid robot state estimation, by considering the correlation between the state and disturbance in the estimation phase.

Other monitoring techniques that are based on models [23], are used to detect the faults in process such as the generalized likelihood ratio test (GLRT) [24], exponentially weighted moving average (EWMA) charts [25], Shewhart charts [26] and CUSUM charts [35]. Regarding data-based fault detection problem, several techniques have been developed in literature [36,37]. For example, in [36], Christensen et al. proposed an enhanced fault detection approach based on fault injection and learning using autonomous robots. In [37], two approaches to fault detection in robotic swarm systems are developed by combining advantages of univariate PCA and statistical process control charts. Also, virtual viscoelastic control model is used for the circle formation of the robot swarm.

In the current work, we develop a new fault detection technique that combines the benefits of exponentially weighted moving average (EWMA), EKF and multiscale representation. The following objectives will be sought. First, to deal with scenarios where a process model is available, the EKF method will be applied to estimate the nonlinear state variables and predict the behavior of humanoid robots (HR) systems. Second, an improved chart-based EWMA will be developed to enhance the monitoring of HR systems. The EWMA chart showed good detection enhancement with respect to Shewhart, GLRT and CUSUM chart in cases of small and moderate faults. However, the detection quality of EWMA needs to have relatively good information about the changed parameters (smoothing parameter (λ) and control width L). Thus, an optimized EWMA (OEWMA) based on the best selection of smoothing parameter (λ) and control width (L) will be developed to enhance the monitoring performances of the classical EWMA chart. Nevertheless, the efficiency of any monitoring technique depends on the quality of the available process data. Practical measurements are usually altered with noise that hides the significant changes in the data and reduces the performance of the applied fault detection techniques. Multiscale representation of data is a powerful data analysis and feature extraction tool which was successfully applied for filtering, modeling, state estimation, fault detection, and others. Thus, combining the advantages of multiscale representation with those of optimized EWMA should provide even further improvements in fault detection (FD). To do that, Multiscale optimized EWMA (MS-OEWMA) is proposed for FD in HRS. Therefore, in the current work, we develop a new fault detection technique that combines the advantages of EKF and MS-OEWMA, in which, the detection chart MS-OEWMA is applied to the residuals computed using the EKF. The advantages of EKF-based MS-OEWMA method are threefold: (i) in optimized EWMA, the two parameters (L and λ) are optimized in order to reduce the false alarm rate (FAR) and missed detection rate (MDR); (ii) the dynamical multiscale representation is proposed to extract accurate deterministic features and decorrelate autocorrelated measurements; (iii) MS-OEWMA chart is able to detect smaller fault shifts in the mean/variances and enhance the monitoring in HR systems. The results demonstrate the effectiveness of the MS-OEWMA chart over the EWMA chart in terms of FAR and MDR and both of them outperform the shewhart chart.

The current paper is organized as follows Section 2 presents the description of the developed EKF-based MS-OEWMA approach. In Section 3, the performance of the proposed technique is demonstrated using two simulated examples, linear inverted pendulum and five-bar linkage models. Finally, the conclusions are presented in Section 4.

2. Description of extended Kalman filter-based multiscale optimized EWMA method

2.1. Extended Kalman filter description

As the name indicates, EKF is an extended version of the Kalman filter (KF) [38,39]. EKF, which is considered the standard approach to solve state estimation problems, is selected because of the following three reasons. First, EKF is based on the linear dynamic nature of the process. Second, it can handle the nonlinearities in the process and observation models via linearization about the current mean and variance. Third, EKF performs the estimation recursively which makes the EKF as a suitable approach for inferring a large number of parameters from a limited number of observations. The complete derivation of the formulas used in the presented EKF can be found in [40]. Similar to KF, the state vector z_k is estimated via minimalizing a weighted covariance matrix of estimated error, i.e., $\mathbf{E}[(z_k - \hat{z}_k)\mathbf{M}(z_k - \hat{z}_k)^T]$, where $\mathbf{M}$ is a symmetric nonnegative definite weighting matrix. When all states are having same importance, $\mathbf{M}$ may assumed to be identity matrix, this reduces the covariance matrix to $\mathbf{P} = \mathbf{E}[(z_k - \hat{z}_k)(z_k - \hat{z}_k)^T]$. The minimizing equation may be written as follows:

$$\mathbf{J} = \frac{1}{2} Tr(\mathbf{E}[(z_k - \hat{z}_k)(z_k - \hat{z}_k)^T]). \tag{1}$$

To minimize the above objective function (1), EKF estimates the state vector by a two-step algorithm: prediction and estimation (or update), as explained below.

Prediction Step: First, one-step predictions of the augmented state vector and the measurement vector are computed using the previously estimated state vector and the nonlinear model, i.e.,

$$\hat{z}_{k|k-1} = \mathfrak{F}(\hat{z}_{k-1|k-1}, u_{k-1}), \; \hat{y}_{k|k-1} = \mathfrak{R}(\hat{z}_{k|k-1}, u_k). \tag{2}$$

*Estimation (Update) Step:*Next, an updated estimation for augmented state vector is computed after finding the measurement vector, y_k, as shown:

$$\begin{aligned} \mathbf{P}_{k|k-1} &= \mathbf{A}_{k-1}\mathbf{P}_{k-1|k-1} + \mathbf{G}_{k-1}\mathbf{Q}\mathbf{P}_{k-1}^T, \\ \mathbf{K}_k &= \mathbf{P}_{k|k-1}\mathbf{C}_k^T(\mathbf{C}_k\mathbf{P}_{k|k-1}\mathbf{C}_k^T + \mathbf{H}_k\mathbf{R}\mathbf{H}_k^T)^{-1}, \\ \mathbf{P}_{k|k} &= (I - \mathbf{K}_k\mathbf{C}_k)\mathbf{P}_{k|k-1}^T, \\ \hat{z}_{k|k} &= \hat{z}_{k|k-1} + \mathbf{K}_k(\hat{y}_{k|k-1} - y_k), \end{aligned} \tag{3}$$

where $\mathbf{A}_{k-1} \approx \frac{\partial \mathfrak{F}}{\partial z}\Big|_{\hat{z}_{k-1|k-1}}$, $\mathbf{C}_{k-1} \approx \frac{\partial \mathfrak{R}}{\partial z}\Big|_{\hat{z}_{k-1|k-1}}$, $\mathbf{G}_{k-1} \approx \frac{\partial \mathfrak{F}}{\partial \epsilon}|_{\epsilon_{k-1}}$ and $\mathbf{H}_k \approx \frac{\partial \mathfrak{R}}{\partial v}|_{v_k}$ represent the matrices of the linearized system model in each time step. The measurement residual (error) is given by:

$$R_k = z_k - \hat{z}_{k|k}. \tag{4}$$

2.2. Multiscale optimized EWMA chart

The classical EWMA chart (Z) can be computed as [41]:

$$Z_i = \lambda X_i + (1 - \lambda) Z_{i-1}, \quad i = 1, \ldots, N \tag{5}$$

where λ defines the smoothing parameter, X_i denotes the value of the $i - th$ individual observation. The initial value Z_0 is set equal to process in-control mean μ_0. The EWMA chart detects a fault in the process when Z_i exceeds its control limits (UCL; upper control limit while LCL; lower