学校编码：10384

学号：23220131153375

厦门大学

硕 士 学 位 论 文

贝叶斯故障诊断方法的改进及其应用研究

Research on Improvement and Applications for Bayesian Fault Diagnosis

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专业名称：工程硕士(控制工程)

答辩日期：2016年5月

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摘　要

控制回路故障检测与诊断有助于保证生产过程的安全和高效、降低维护费用和减少停机时间。贝叶斯诊断是控制回路监测的概率化诊断框架，它能够综合多个监测器技术，以构建诊断系统进而作出最优决策。然而，工业过程控制回路诊断中存在许多不同的实际情况，严重制约了贝叶斯诊断的性能。本文重点从数据降维、似然估计等方面研究改进贝叶斯诊断性能的方法，提出了基于优化直方图估计的证据离散化方法、基于线性判别分析的特征提取与降维以及平均移动似然估计方法。通过仿真系统、工业基准数据和工业规模系统的仿真实验，验证了所提方法的有效性。论文主要包含以下几个方面的工作：

(1)综述了现有的贝叶斯诊断方法及其研究现状，系统介绍了控制回路贝叶斯诊断的基本原理。

(2)针对贝叶斯诊断中证据的“维数灾难”问题，研究了三种典型的降维方法，它们分别是无监督降维、有监督降维、基于独立性降维的典型代表。

(3)针对贝叶斯诊断中似然估计的精度问题，研究了三种典型的似然估计方法，它们分别是离散似然估计方法、连续似然估计方法的典型代表，以及为了更好地结合先验知识，所提出的平均移动似然估计方法。

(4)针对证据离散化造成信息损失的问题、“维数灾难”问题、贝叶斯诊断无法有效结合先验知识的问题，分别提出了三种特定条件下的贝叶斯诊断解决方案：基于优化直方图估计和主成分分析的诊断、基于线性判别分析和核密度估计的诊断、基于平均移动似然估计结合先验知识的诊断。

关键词：故障检测与诊断；数据驱动；贝叶斯诊断；特征提取；似然估计

Abstract

The purpose of control loop detection and diagnosis is to ensure the safety and efficacy of the production process, reduce maintenance costs and downtime. Bayesian diagnosis is a probabilistic diagnosis framework of control loop monitoring, which can combine multiple monitor technology to build a diagnosis system and make an optimal decision. However, there are many different situations in the control loop diagnosis for industrial process. The performance of Bayesian diagnosis is severely restricted. In this paper, we focus on the improved method of Bayesian diagnosis to enhance the diagnostic performance through dimension reduction and likelihood estimation, which proposed the evidence discretization method based on histogram estimation optimization, the feature extraction and dimension reduction based on linear discriminant analysis and the averaged shifted likelihood estimation method. Simulated system, bench scale system and industrial scale system verify the effectiveness of the proposed method. The major work of this thesis includes:

(1)A review of the existing methods and the research status for Bayesian diagnosis is made, the basic principle of Bayesian diagnosis is introduced in this paper.

(2)Accounting for the problem of "Curse of dimensionality" in Bayesian diagnosis, three typical dimension reduction methods are studied, which are the typical representative of unsupervised dimensionality reduction, supervised dimensionality reduction and independence based dimensionality reduction.

(3)Accounting for the problem of likelihood estimation accuracy for Bayesian diagnosis, three kinds of typical likelihood estimation method are studied, which are typical representative of discrete likelihood estimation method and continuous likelihood estimation method. In order to better integrate the prior knowledge, we proposed averaged shift likelihood estimation method.

(4)Accounting for information loss of evidence discretization, "Curse of Dimensionality" problem, Bayesian diagnosis can not be effectively combined with prior knowledge. Three specific solutions of Bayesian diagnosis are put forward: diagnosis base on principal component analysis and optimal histogram, diagnosis base on linear discriminant analysis and kernel density estimation, diagnosis base on averaged shifted likelihood estimation and prior knowledge.

Keywords: Fault detection and diagnosis; Data-driven; Bayesian diagnosis; Feature extraction; Likelihood estimation

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