

以模糊類神經理論與混沌理論
構建高速公路事件偵測演算法

Freeway Incident Detection Algorithms:
Fuzzy-Neural-Based and Chaotic-Based Approaches

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摘要

安全與效率為運輸之重要課題，為降低事件造成之車流延滯、生命財物損害以及社會成本並提升運輸安全，因此本研究主要目的在於構建自動事件偵測系統，目前自動事件偵測多數共同問題為：算法績效往往取決於演算法的門檻值設定、車流狀況（中、高流量有較佳之偵測率）與兩相鄰偵測器之距離；部分演算法不具有移轉性，應用於不同時間或地點時，演算法之參數與門檻值必須重新校估與驗證；輸入資料來源與品質受限於偵測器型式。

為有效處理上述不確定性，本研究嘗試加入適當模糊推論規則於類神經網路中，而成為一模糊類神經網路系統，擷取類神經網路自我學習與高容錯能力的特性，透過模糊隸屬函數將網路各層間傳遞之明確數值改為模糊隸屬度，並結合模糊推論規則，依照各車流參數之影響程度推論出事件發生與否，模糊類神經之網路參數（模糊系統參數與門檻值、鍵結權重）均透過訓練而自動學習適當值，因此可避免在建構系統時，主觀設定其激發函數參數值與推論規則門檻值所引發之問題。綜合而論，模糊類神經網路之優點是網路鍵結權重、激發函數之參數、模糊推論規則之門檻值設定均由學習訓練過程而得，可避免人為主觀設定之誤差，且透過適當的訓練過程將有較佳的移轉性。此外，為有效適應於不同車流狀況，本研究發展滾動式學習法則，經由收集即時的交通資訊，並反複訓練網路參數，以期使模糊類神經之網路參數更能符合當前車流特性，進而提升偵測績效。而實際上，複雜的車流動態具有不確定、非線性的特性，因此本研究亦嘗試構建混沌診斷系統，利用混沌車流參數之變化（包含最大里亞譜諾夫指數、相關維度、相對複雜度、相關時間、赫式指標等），來判斷交通事件是否發生。

由離線測試結果分析得知，滾動式模糊類神經網路比模糊類神經網路有較佳之偵測績效；而混沌異常診斷系統具有最高的偵測正確率，但同時也付出最高的誤報率之代價。然而，三種不同之事件偵測系統其離線測試分析均顯示具有即時事件偵測之可行性。此外，未來研究方向亦可朝向整合滾動式模糊類神經網路與混沌異常診斷系統，利用混沌異常診斷的高偵測正確率先行偵測事件發生，在輔以滾動式模糊類神經網路進行再次確認，以降低整體誤報率。

關鍵詞：事件偵測、模糊類神經網路、模糊推論、滾動式學習過程、混沌診斷



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Abstract

Safety and efficiency is the most important issue in transportation. To reduce traffic flow delay, damage to life and properties and social cost, and to increase efficiency and safety in transportation system, this research focuses on non-recurring congestion and develops the automatic incident detection algorithm. Existent automatic incident detection algorithms may encounter one or some of the following difficulties: the detection performance is subject to the settings of algorithm threshold, traffic flow condition (medium and heavy traffic flows normally have higher detection rate) and the distance between two adjacent detectors; Most detection algorithms are not transferable in that parameters and thresholds of an algorithm must be recalibrated and revalidated to be valid for different locations or times; Quantity and quality of traffic flow data is subject to detector types.

In dealing with the uncertain contexts, both neural networks and fuzzy inference have been proven as powerful tools. The FNN approaches have the advantages of learning capability to avoid subjectively setting of the parameters and possessing high fault tolerance due to the distributed memory of parameters separately stored on each link of the network. To capture the change in traffic dynamics through network training, this study presumes that the rolling-trained procedure in FNN might be imperative in augmenting the incident detection performance. Thus, the present research attempts to develop a rolling-trained fuzzy neural network (RTFNN) approach for freeway incident detection. Its underlying logic is to establish a proper fuzzy neural network and then adaptively adjust the network parameters using the most up-to-date traffic data in response to the prevailing traffic conditions so as to improve the detection performance over the conventional FNN approach. In practice, the complexity of traffic dynamics is

characterized with uncertain and nonlinear nature. The chaos abnormality diagnosis algorithm proposed in this paper attempts to use the change in chaotic traffic parameters, including largest Lyapunov exponent, capacity dimension, correlation dimension, relative Lz complexity, Kolmogorov entropy, delay time, and Hurst exponent to examine the existence of traffic incident.

The RTFNN approach was found to have the highest potential, compared with FNN approach, to achieve a better incident detection performance. The Chaotic diagnosis approach performed the best detection rate, which covering low flow condition to heavy flow condition, but it also suffered the worst false alarm rate. However, all the tests results have indicated the feasibility of attaining the real-time automatic incident detection using the fuzzy-neural-based approaches and chaotic diagnosis approach. Furthermore, these approaches are promising and, in expectation, can be integrated into the hybrid incident detection algorithm with chaotic-based approach, which has the capability of identification, for initial diagnosis and with fuzzy-neural-based, which has the capability of classification, for confirmation of incidents in future exploration.

Keywords: Incident detection, Fuzzy neural network, Fuzzy inference, Rolling-trained procedure, Chaotic diagnosis



CONTENT

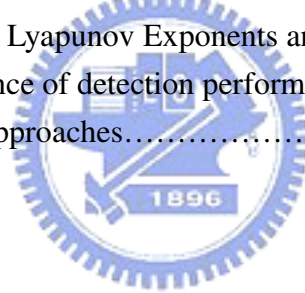
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