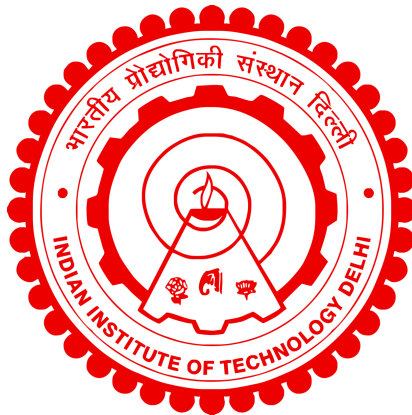


ON APPLICATIONS OF QUICKEST CHANGE DETECTION

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DEPARTMENT OF ELECTRICAL ENGINEERING

INDIAN INSTITUTE OF TECHNOLOGY DELHI

MARCH 2026

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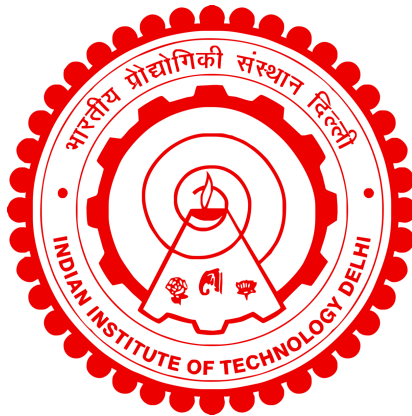
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Department of Electrical Engineering

Submitted

in partial fulfillment of the requirements of the degree of Doctor of Philosophy

to the



**INDIAN INSTITUTE OF TECHNOLOGY
DELHI**

MARCH 2026

Dedicated to

My MOTHER

Certificate

This is to certify that the thesis entitled “**On Applications of Quickest Change Detection**”, submitted by **Mr. Saqib Abbas Baba** to the Indian Institute of Technology Delhi, for the award of the degree of **Doctor of Philosophy** in Electrical Engineering, is a record of the original, bona fide research work carried out by him under our supervision and guidance. The thesis has reached the standards fulfilling the requirements of the regulations related to the award of the degree.

The results contained in this thesis have not been submitted in part or in full to any other University or Institute for the award of any degree or diploma to the best of our knowledge.

Prof. Arpan Chattopadhyay

Department of Electrical Engineering,
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Abstract

The rapid evolution of interconnected systems in modern industrial and cyber-physical domains has heightened the need for efficient and robust techniques to detect and respond to abrupt changes, anomalies, or attacks. Quickest Change Detection (QCD) provides a statistical framework for identifying such changes in real time, where a decision maker observes a sequence of random variables, and a change occurs at an unknown point, altering their distribution. The objective is to detect this change as *quickly* as possible while maintaining acceptable false alarm rates. This thesis advances QCD methodologies with applications in distributed networks, remote state estimation, multi-sensor systems, UAV-based surveillance, and adversarial inference.

The first contribution integrates QCD with UAV-based sensing to monitor abrupt changes at spatially separated locations. We propose the Location-Switching and Change Detection (LS-CD) algorithm, which couples location-switching heuristics with CUSUM-like methods to minimize detection delay under energy constraints. We derive performance guarantees, including tight bounds on WADD and ARL2FA; in particular, we establish a novel asymptotic upper bound on ARL2FA. These results quantify trade-offs between accuracy, energy consumption, and switching strategies.

We also introduces the novel concept of inverse QCD which is an instance of inverse cognition where a cognitive target infers the stopping time of a radar that employs Bayesian QCD. Using particle filtering, we develop methods to estimate the radar's stopping time, defined as the instant when the radar concludes that the target has entered its sensing region. This inverse-cognition perspective bridges QCD theory with cognitive radar applications, enabling adversarial inference and decision-making in dynamic environments.

Next, we extend QCD to multi-sensor networks operating over lossy wireless communication links. The research derives a CUSUM algorithm and considers the complexities introduced by multiple heterogeneous sensors, each with distinct observation distributions. A sensor scheduling algorithm is introduced as a heuristic to address challenges of sensor heterogeneity, communication delays, and data loss. By

balancing observation freshness with information content, this work demonstrates the efficacy of tailored QCD algorithms in reducing detection delays across varying queue disciplines and network conditions.

Finally we address the detection of false data injection (FDI) attacks in distributed networks without a fusion center. Leveraging Kalman Consensus Information Filters (KCIF) for process tracking, we propose Bayesian and non-Bayesian QCD algorithms to identify and localize attacks at individual nodes in a graph-based sensor network. These algorithms, designed to account for non-i.i.d. observations, demonstrate significant improvements in detection delay and false alarm trade-offs. This is followed by another close contribution that investigates FDI detection in remote state estimation scenarios involving multiple sensors transmitting observations to a central estimator. While our contributions to this work were selective, it employs a Markov Decision Process (MDP) framework to design optimal Bayesian QCD algorithms for non-i.i.d. innovation sequences post-change and proposes generalized CUSUM-based methods for adversarial attack strategies, yielding substantial performance gains in detection accuracy.

Through theoretical analyses, algorithmic innovations, and extensive numerical simulations, this thesis provides a comprehensive framework for advancing QCD methodologies in diverse applications. The findings underscore the importance of QCD in enhancing security, reliability, and efficiency within modern sensing and decision-making systems.

सारांश

आधुनिक औद्योगिक तथा साइबर-भौतिक क्षेत्रों में परस्पर जुड़ी प्रणालियों के तीव्र विकास ने अचानक परिवर्तनों, विसंगतियों तथा हमलों का शीघ्र पता लगाने और उनके प्रति त्वरित प्रतिक्रिया देने हेतु कुशल एवं सुदृढ़ तकनीकों की आवश्यकता को बढ़ा दिया है। Quickest Change Detection (QCD) वास्तविक समय में ऐसे परिवर्तनों की पहचान के लिए एक सांख्यिकीय ढाँचा प्रदान करता है, जिसमें निर्णयकर्ता यादृच्छिक चरों के अनुक्रम का अवलोकन करता है तथा एक अज्ञात समय पर परिवर्तन होकर उनके वितरण को बदल देता है। उद्देश्य यह है कि स्वीकार्य झूठे अलार्म की दरों को बनाए रखते हुए परिवर्तन का पता यथासंभव शीघ्र लगाया जाए। यह शोध-प्रबंध वितरित नेटवर्क, दूरस्थ अवस्था आकलन, बहु-संसार प्रणालियाँ, UAV-आधारित निगरानी, तथा प्रतिकूल अनुमान जैसे अनुप्रयोगों के लिए QCD पद्धतियों को आगे बढ़ाता है।

पहला योगदान स्थानिक रूप से पृथक स्थानों पर होने वाले अचानक परिवर्तनों की निगरानी हेतु UAV-आधारित सेंसिंग के साथ QCD का एकीकरण करता है। हम Location-Switching and Change Detection (LS-CD) एल्गोरिदम प्रस्तावित करते हैं, जो ऊर्जा-सीमाओं के अंतर्गत पता लगाने में देरी को न्यूनतम करने के लिए लोकेशन-स्विचिंग ह्यूरिस्टिक्स को CUSUM-सदृश विधियों के साथ युग्मित करता है। हम प्रदर्शन-गारंटियाँ प्राप्त करते हैं, जिनमें WADD तथा ARL2FA पर कसी हुई सीमाएँ सम्मिलित हैं; विशेषतः, हम ARL2FA के लिए एक नवीन एसिम्प्टोटिक ऊपरी सीमा स्थापित करते हैं। ये परिणाम सटीकता, ऊर्जा-व्यय तथा स्विचिंग रणनीतियों के बीच संतुलन को स्पष्ट रूप से दर्शाते हैं।

हम inverse QCD की नई अवधारणा भी प्रस्तुत करते हैं, जो प्रतिलोम संज्ञान का एक उदाहरण है, जिसमें एक संज्ञानात्मक लक्ष्य उस रडार के रुकने के समय का अनुमान लगाता है जो Bayesian QCD का उपयोग करता है। पार्टिकल फिल्टरिंग के माध्यम से हम रडार के रुकने के समय का अनुमान लगाने की विधियाँ विकसित करते हैं, जिसे उस क्षण के रूप में परिभाषित किया जाता है जब रडार यह निष्कर्ष निकालता है कि लक्ष्य उसके सेंसिंग क्षेत्र में प्रवेश कर चुका है। यह दृष्टिकोण QCD सिद्धांत को संज्ञानात्मक रडार अनुप्रयोगों से जोड़ता है तथा गतिशील परिवेशों में प्रतिकूल अनुमान एवं निर्णय-निर्माण को सक्षम बनाता है।

इसके पश्चात, हम QCD को बहु-सेंसर नेटवर्कों तक विस्तारित करते हैं जो हानिप्रवण वायरलेस संचार लिंकों पर संचालित होते हैं। इस अध्ययन में एक CUSUM एल्गोरिदम विकसित किया गया है तथा अनेक विषम सेंसरों द्वारा उत्पन्न जटिलताओं पर विचार किया गया है, जिनके अवलोकन वितरण परस्पर भिन्न हैं। सेंसर-विषमता, संचार-विलंब तथा डेटा-हानि की चुनौतियों से निपटने हेतु एक सेंसर-शेड्यूलिंग रणनीति प्रस्तावित की गई है। अवलोकनों की समयबद्धता तथा सूचना-समृद्धि के बीच संतुलन स्थापित कर यह कार्य विभिन्न नेटवर्क स्थितियों में पता लगाने में देरी को प्रभावी रूप से कम करता है।

अंततः, हम बिना किसी संलयन केंद्र के वितरित नेटवर्कों में false data injection (FDI) हमलों का पता लगाने की समस्या का अध्ययन करते हैं। प्रक्रिया-ट्रैकिंग हेतु Kalman Consensus Information Filters (KCIF) का उपयोग करते हुए, हम ग्राफ-आधारित सेंसर नेटवर्क में व्यक्तिगत नोड्स पर हमलों की पहचान एवं स्थानीयकरण के लिए Bayesian तथा non-Bayesian QCD एल्गोरिदम प्रस्तावित करते हैं। non-i.i.d. अवलोकनों को ध्यान में रखकर डिज़ाइन किए गए ये एल्गोरिदम पता लगाने में देरी तथा झूठे अलार्म की दरों के बीच बेहतर संतुलन प्रदर्शित करते हैं। इसके अतिरिक्त, एक निकटवर्ती योगदान दूरस्थ अवस्था आकलन परिदृश्यों में FDI का अध्ययन करता है, जहाँ अनेक सेंसर अपने अवलोकन एक केंद्रीय अनुमानक को प्रेषित करते हैं। इस संदर्भ में Markov Decision Process (MDP) ढाँचे के माध्यम से परिवर्तन के पश्चात गैर-स्वतंत्र अवलोकन अनुक्रमों के लिए इष्टतम Bayesian QCD एल्गोरिदम तथा सामान्यीकृत CUSUM-आधारित विधियाँ विकसित की गई हैं, जिससे पता लगाने की सटीकता में उल्लेखनीय सुधार प्राप्त होता है।

सैद्धांतिक विश्लेषण, एल्गोरिदमिक नवाचार तथा व्यापक संख्यात्मक सिमुलेशनों के माध्यम से यह शोध-प्रबंध विविध अनुप्रयोगों में QCD पद्धतियों के उन्नयन हेतु एक समग्र ढाँचा प्रस्तुत करता है। निष्कर्ष आधुनिक सेंसिंग एवं निर्णय-निर्माण प्रणालियों में सुरक्षा, विश्वसनीयता तथा दक्षता बढ़ाने में QCD के महत्व को रेखांकित करते हैं।

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