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（博士課程）
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論 文 要 旨

THESIS SUMMARY

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要旨（英文 800 語程度）
Thesis Summary（approx.800 English Words ）

This dissertation proposes optimization-based methods for estimating time-varying signals over dynamic graph topologies by leveraging graph signal processing and proximal splitting techniques. With the increasing demand for sophisticated data analysis across various applications, the importance of effective data collection and utilization has undergone significant transformation. Extracting meaningful information from collected data is crucial for enhancing conventional analyses and enabling unprecedented data utilization.

Time-varying signal processing focuses on extracting temporal relationships within data, while graph signal processing leverages spatial relationships by interpreting data points as nodes in a graph. By combining these techniques, time-varying graph signal processing has emerged as a promising framework for handling data that can be represented as time-varying graph signals, with applications in environmental monitoring, traffic optimization, finance, and more.

While data-driven methods—particularly those based on machine learning—are increasingly common for handling complex data structures, they have notable drawbacks. They often require large amounts of training data, which may be infeasible in domains like environmental monitoring, where data collection is expensive. Additionally, their black-box nature can limit transparency and interpretability.

To address these challenges, we focus on an optimization-based approach suitable for limited time-varying graph signal data—one that does not require extensive training datasets and maintains high interpretability. Conventional optimization-based methods for time-varying graph signal processing have primarily assumed static graph topologies. However, in applications involving mobile sensor networks—such as sensor-equipped drones or vehicles—it is more realistic to assume that the network topology changes over time.

Accordingly, this dissertation proposes time-varying graph signal estimation methods over dynamic graph topologies using proximal splitting techniques. We demonstrate the effectiveness of dynamic graph assumptions over static ones in both physical and nonphysical sensing domains, namely environmental monitoring and finance.

In Chapter 3, we introduce a time-varying graph signal recovery method capable of handling graph signals corrupted by various types of noise. With advancements in mobile devices equipped with high-quality sensors, using networks of such devices for sensing has become practical. Consequently, methods to recover such signals from various types of noise and corruption have become increasingly important. Upon considering network signal recovery, we leverage graph signal processing to effectively utilize the information inherent in the network topology. Unlike conventional methods that assume static graphs, we consider dynamic network topologies, which are more appropriate for mobile device networks. Our proposed method effectively leverages the network's dynamics by formulating an optimization problem under the assumption that the graph is time-varying. In addition to leveraging priors in the vertex domain, we also utilize priors in the temporal domain to enhance recovery performance. The proposed formulation can handle Gaussian noise, sparse noise, and missing values, making the method highly robust to corruption. We then solve the problem using a primal-splitting-based algorithm. We evaluate the proposed method on both a synthetic dataset and a real-world dataset to show the effectiveness of dynamic graph representations over static graph representations in time-varying graph signal recovery.

In Chapter 4, we propose a sparse index tracking method that leverages market graphs to reduce investment risk. Financial indices like the S&P 500 and NASDAQ 100 are known for their stable growth and are attractive investment targets. However, investing directly in an index requires distributing capital across all its constituent assets, and the true weighting schemes used by index providers are often unknown. Investors must, therefore, construct their own portfolios to track the performance

of the target index. Ideally, the portfolio should be sparse to reduce transaction costs. Conventional methods impose sparsity using L1-norm regularizations, but these methods lack the ability to precisely control the number of nonzero weights in the portfolio. We introduce a sparse index tracking method based on an L0-norm constraint, allowing easy control of the number of nonzero weights by adjusting a single parameter. Furthermore, to mitigate risks associated with concentrated investments, we impose market graph neutrality in our formulation to diversify the investment. We represent relationships among assets using a market graph and apply graph clustering to partition them into groups. Our tracking method distributes capital across all groups, effectively dispersing investments and helping investors avoid the risks of concentrated portfolios. By reconstructing the groups frequently, we effectively capture the dynamics of the market graph in our method.

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