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Ph.D. Seminar Talk 1

Title: **Comparative Study of Dimensionality Reduction Techniques and Sensor Modalities for Wet Multi-Disc Clutch Fault Clustering**

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Date and Time: **06-04-2026 @ 4:00 PM**

Venue: **https://meet.google.com/kqd-bahy-fjc**

Abstract

use of dimensionality reduction (DR) techniques to process high-dimensional sensor data and identify fault patterns effectively. A comprehensive comparative study was conducted on six dimensionality reduction (DR) methods—Principal Component Analysis (PCA), Factor Analysis (FA), Canonical Correlation Analysis (CCA), Kernel PCA (KPCA), Local Tangent Space Alignment (LTSA), and t-distributed Stochastic Neighbor Embedding (t-SNE)—applied to multi-class wet clutch fault diagnosis. High-dimensional feature sets (113 features for encoders, 112 for paired accelerometers, 56 for pressure or current sensors) were extracted from four sensor modalities capturing clutch behavior. The DR techniques were evaluated on their ability to cluster seven fault conditions (healthy and various defect severities) into distinct groups in a 2D space. The results demonstrated that super vised CCA produced near-perfect class separation for all sensors, while the unsupervised t-SNE achieved similarly excellent clustering, especially for pressure and current signals. Nonlinear KPCA also significantly improved class reparability over linear PCA, though its clusters required nonlinear decision boundaries for classification. FA exhibited a unique dichotomy: it yielded 100% fault separation with some sensors (vibration, pressure, current) but failed for the encoder. LTSA showed mixed performance, successfully unfolding a fault manifold for encoder data (achieving ~ 92.8% clustering accuracy) but not for other sensors. These findings underscore that advanced DR methods can dramatically enhance fault pattern discernibility in high-dimensional data, with supervised and manifold-learning techniques outperforming classical linear projections. The study’s novel contribution lies in systematically comparing diverse DR approaches on a common fault diagnosis problem, highlighting each method’s strengths, limitations, and the influence of sensor characteristics on DR effectiveness.