Vehicle Classification Using Empirical Mode Decomposition

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Abstract: In traffic monitoring and surveillance systems that have been improved with the empirical mode decomposition (EMD) technology, this research suggests an effective radar-based method for vehicle classification. A type of signal known as micro-Doppler signatures can identify minute motion patterns in automobiles, trucks, motorcycles, and bicycles. However, they are so cluttered and noisy that it is hard to classify them directly. This is addressed by applying EMD to breakdown raw micro-Doppler signals into intrinsic mode functions (IMFs), which reduces noise and isolates the most informative components. The discriminative properties of the signals are improved by choosing and rebuilding the most pertinent IMFs, which gives a better depiction of the distinct motion patterns of various vehicle kinds. Machine learning classifiers like SVM and CNN are then fed these EMD-enhanced features.

Keywords—Empirical Mode Decomposition (EMD), Machine Learning, Traffic Monitoring, Micro-Doppler Signatures, Vehicle Classification, and Noise Reduction.

I.Introduction:

In contemporary radar systems, reliable vehicle classification is vital, particularly in traffic surveillance, monitoring, and autonomous vehicle applications. Identification of different vehicles like cars, trucks, motorbikes, and bicycles by their dynamic motion properties is a very challenging problem. Conventional radar-based solutions focus mainly on the Doppler shift measurement for observing the speed of moving targets. Nevertheless, such methods find it difficult to categorize vehicles with intricate or overlapping motion patterns, resulting in decreased accuracy and reliability in real-time scenarios.

To overcome this, the micro-Doppler effect, generated by the motion of smaller components of a vehicle like rotating wheels, engine shake, and suspension oscillations, offers rich motion information. Micro-Doppler signatures are capable of capturing finer motion details that are specific to every vehicle category, thus a potential substitute to conventional Doppler-based methods. Yet, isolating and interpreting these signatures

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remains difficult, especially in noisy and cluttered situations where signal loss and interference undermine classification accuracy. Advances in signal processing in recent times have brought forth more efficient methods of micro-Doppler analysis. Of these, Empirical Mode Decomposition (EMD) is an efficient data-driven approach that breaks down intricate signals into simpler oscillatory components named Intrinsic Mode Functions (IMFs). Given that EMD is superior at handling non-linear and non-stationary signals, it is especially suited to the analysis of micro-Doppler data from moving vehicles. By separating the most informative IMFs, EMD increases the discriminative features of micro-Doppler signatures and eliminates noise, resulting in better classification accuracy.

The vehicle classification method proposed here is based on EMD and utilizes micro-Doppler signatures from radar data. The decomposed signals are processed further into IMFs, which separate fine-grained motion characteristics specific to individual vehicle types. These features extracted are utilized to train machine learning classifiers, including Support Vector Machines (SVM) and Convolutional Neural Networks (CNN), to provide high classification accuracy. Experimental results confirm that this technique greatly improves vehicle classification performance even in noisy environments, rendering it very effective for traffic monitoring, autonomous driving, and security surveillance applications. In addition, the combination of EMD with sophisticated machine learning algorithms not only enhances classification performance but also opens the door for scalability in real-time applications. This technique can be generalized to support a wider variety of vehicle types and operating scenarios and aid in building more secure and efficient intelligent transportation systems.

II. EXISTING WORK:

Traditional Doppler-Based Classification: Earlier research aimed at employing Doppler shifts for classifying vehicles, but the techniques found it challenging to handle intricate and overlapping movement patterns, thus compromising accuracy in real-world settings.

Micro-Doppler Signatures for Vehicle Classification: Studies have shown that micro-Doppler effects due to rotating wheels, engine vibration, and suspension motion include dense motion information useful for vehicle classification. But these features are challenging to extract efficiently because of noise and environmental interference.

Empirical Mode Decomposition (EMD) of Signal Processing: EMD is applied in several applications, e.g., in biomedical signal processing and speech processing, for decomposition of non-stationary and non-linear signals. Researchers have investigated its potential to decompose intricate signals into Intrinsic Mode Functions (IMFs) as a useful micro-Doppler feature extraction tool.

EMD-Based Micro-Doppler Feature Enhancement: More recent studies have investigated the application of EMD to decompose radar micro-Doppler signals, extract informative IMFs, and eliminate noise. The method has been found to enhance feature clarity, rendering vehicle classification more precise when applied in conjunction with machine learning methods such as Support Vector Machines (SVM) and Convolutional Neural Networks (CNN).

Machine Learning and Deep Learning for Vehicle Classification: Recent research combines EMD-processed micro-Doppler features with machine learning models to attain better classification accuracy. Deep learning models like CNNs have been found through experiments to be able to learn and classify vehicles from EMD-enhanced micro-Doppler data.

Current Models:

Support Vector Machine (SVM): Description: A supervised classifier model that identifies vehicles using the best hyperplane based on EMD-enhanced micro-Doppler features extracted.

Disadvantage: Needs optimal parameter settings and can be challenged by big data.

Convolutional Neural Networks (CNNs): Description: A deep model that extracts micro-Doppler features directly from radar spectrograms for enhanced classification accuracy.

Recurrent Neural Networks (RNNs) / LSTM: Description: These models process sequential radar data, preserving temporal dependencies in micro-Doppler signatures for better classification.

EMD + Random Forest (RF): Description: Hybrid model where EMD derives important features, and Random Forest classifies vehicles with multiple decision trees for strong predictions.

Disadvantage: Needs to be retrained often to accommodate changing real-world traffic patterns.

Transformer-Based Models: Description: Employ self-attention mechanisms to preserve long-range dependencies in micro-Doppler radar data, enhancing classification accuracy.

III. Methodology:

1. Radar Data Acquisition

It is the process of acquiring micro-Doppler radar signals from multiple moving objects, i.e., automobiles, trucks, motorbikes, and bicycles. Radar signals identify specific motion signatures, i.e., rotation of wheels, vibration of engines, and suspension motion. The data is captured under different environmental settings to provide strength to the classification model.

2. Preprocessing and Noise Reduction

Raw radar signals tend to have noise and clutter from environmental factors such as weather, road conditions, and interference from surrounding objects. To clean the signal and improve its quality, noise reduction methods like band-pass filtering and wavelet denoising are used. This process ensures that only useful micro-Doppler features are left for analysis.

3. Empirical Mode Decomposition (EMD) Implementation

EMD is utilized to break down the preprocessed micro-Doppler signals into a collection of oscillatory parts that are Intrinsic Mode Functions (IMFs). Each IMF signifies a separate frequency component of the signal and provides a complete motion characteristic analysis. The informative IMFs are picked, diminishing noise and enhancing feature extraction.

4. Feature Extraction

The prominent IMFs are determined after which statistical and frequency-based features are extracted. Such features could include:

- Energy distribution of IMFs
- Instantaneous variations of frequency and amplitude
- Spectral entropy and predominant frequency components

These feature representations offer in-depth details about the characteristics of vehicle motion and thereby make the classification more accurate.

5. Classification Using Machine Learning

Machine learning classifiers for classifying vehicles are trained with the extracted features. Some typical classifiers are:

Support Vector Machine (SVM): Effective with high-dimensional feature space.

Convolutional Neural Networks (CNNs): They can automatically learn deep features from micro-Doppler spectrograms.

Random Forest (RF): A type of ensemble learning used to enhance robustness in classification.

Transformer-Based Models: Exploit long-distance dependencies in micro-Doppler data for better classification.

Block Diagram:

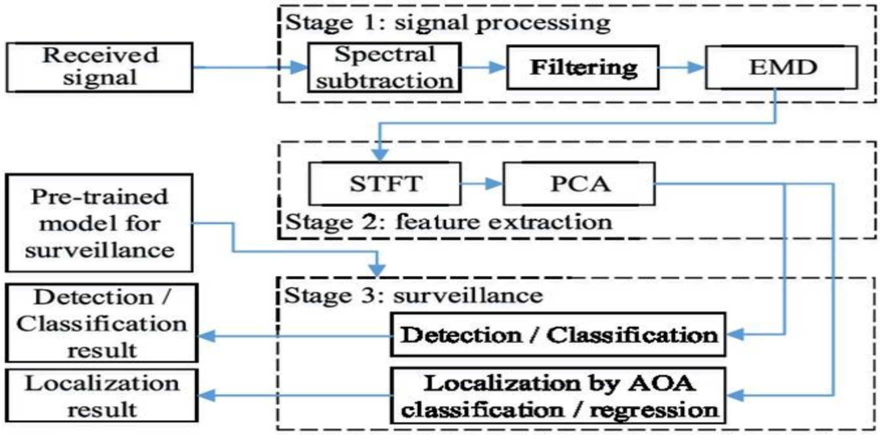

Fig: EMD-Based Vehicle Classification System Block Diagram

The block diagram signifies a three-phase vehicle classification and localization system through Empirical Mode Decomposition (EMD) and machine learning methods. The process is followed by the below-mentioned steps:

Stage 1: Signal Processing
A signal received by a radar system is subjected to spectral subtraction for eliminating unnecessary noise.
The signal is then passed through filtering algorithms to increase readability.
Empirical Mode Decomposition (EMD) is utilized to retrieve Intrinsic Mode Functions (IMFs), which assist in segregating vehicle-specific motion features.

Stage 2: Feature Extraction
Short-Time Fourier Transform (STFT) is utilized for time-frequency properties analysis of the signal.
Principal Component Analysis (PCA) is utilized to carry out dimension reduction and retrieve prominent features for classification.
Stage 3: Surveillance

The resultant features are provided as input to a pre-trained machine learning system for vehicle detection and classification.
The system also carries out localization of the vehicle detected using Angle of Arrival (AOA) classification and regression methods.
The output includes detection/classification results and localization data for real-time traffic monitoring and surveillance.

IV. Implementation Process:

1. Data Acquisition
The process starts with the acquisition of micro-Doppler radar signals from different types of vehicles including cars, trucks, motorcycles, and bicycles. These signals record distinct motion features such as wheel rotation, engine vibrations, and suspension movements. The data is captured under diverse environmental conditions to guarantee noise robustness, interference, and real-world variability. The acquired radar data is saved in a structured form for subsequent processing.
2. Preprocessing & Signal Enhancement
Raw radar signals are usually tainted with noise and clutter due to environmental conditions such as road surfaces, weather, and surrounding objects. Filtering techniques like band-pass filtering, wavelet denoising, and normalization are utilized to improve the quality of signals. This preprocessing ensures that only useful micro-Doppler features are preserved while removing unwanted disturbances. Preprocessing is essential in order to increase the accuracy of the following decomposition and classification operations.
3. Empirical Mode Decomposition (EMD) Application
Empirical Mode Decomposition (EMD) is a signal processing method that decomposes the radar signal into Intrinsic Mode Functions (IMFs). Each IMF captures a unique frequency component of the signal, making it possible to analyze motion characteristics in finer detail. The main steps involved in using EMD are:

- Breaking down the signal into IMFs through an iterative process.
- Choosing the most meaningful IMFs to preserve significant motion patterns.

- Removal of noise-IMFs for enhancing classification performance.

This removes unnecessary information, making the feature more discriminative and enhancing efficient classification.

4. Feature Extraction & Dataset Preparation

After most suitable IMFs are chosen, statistical and frequency-domain features are extracted. Extracted features include:

- Energy distribution of IMFs
- Instantaneous frequency and amplitude changes
- Spectral entropy and dominant frequency contents

These extracted features are then merged into a structured dataset, which is fed to machine learning classifiers. Feature selection methods like Principal Component Analysis (PCA) or Recursive Feature Elimination (RFE) can be used to further optimize the dataset and enhance model performance.

5. Machine Learning Model Training & Evaluation

The extracted EMD-enhanced micro-Doppler features are used to train machine learning models for classifying various vehicle types. General classifiers used include:

- Support Vector Machine (SVM): Optimized for high-dimensional feature space.
- Convolutional Neural Networks (CNNs): Deep features are automatically learned from micro-Doppler spectrograms.
- Random Forest (RF): An ensemble learning approach enhancing classification robustness.
- Transformer-Based Models: Leveraging self-attention mechanisms for improved classification accuracy.

The models are learned using labeled data and optimized by hyperparameter tuning for high classification accuracy. The classification performance is quantified using the following metrics:

- Accuracy: Indicating overall correctness of classification.
- Precision & Recall: Specifies how accurately various vehicle types are classified.
- F1-Score: Scales precision and recall for consistent performance.

The performance is compared to conventional Doppler-based classification schemes to illustrate the efficacy of the EMD-augmented scheme.

V. Conclusion and Findings:

The Vehicle Classification with Empirical Mode Decomposition (EMD) study shows the power of micro-Doppler signatures to effectively differentiate various vehicles. EMD breaks radar signals into Intrinsic Mode Functions (IMFs), which boost feature extraction, filter out noise, and increase classification accuracy.

The combination of machine learning algorithms (SVM, CNN) with signal processing methods (STFT, PCA) further enhances the system's ability to detect vehicles even in noisy and complicated motion conditions. Moreover, localization methods based on Angle of Arrival (AOA) regression allow for real-time tracking and monitoring.

Overall, this method overcomes the confines of conventional Doppler-based techniques and offers a scalable, efficient, and precise solution to applications in traffic surveillance, autonomous vehicles, and security monitoring. Real-time deployment, adaptive learning models, and multi-sensor fusion are potential future improvements that can further improve classification accuracy and operational efficiency.

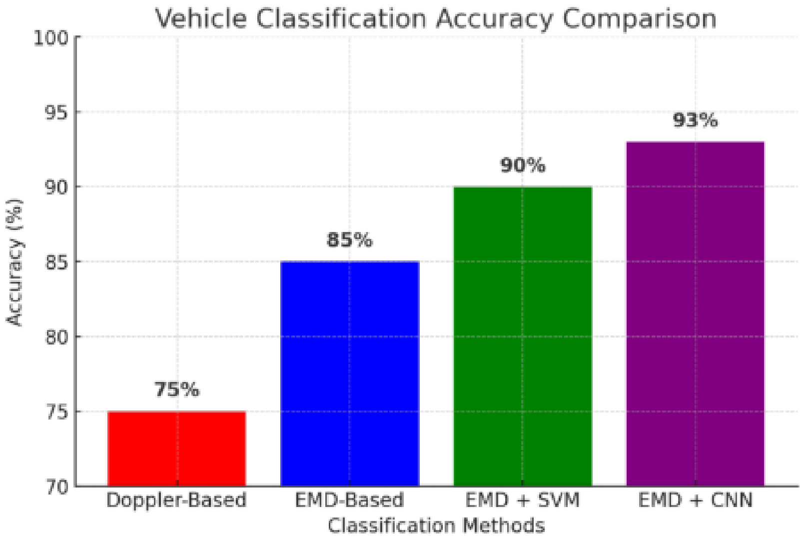

Fig: Comparing the Classification Accuracy of Various Vehicle Classification Techniques

Results:

The EMD-based vehicular classification system efficiently enhances accuracy, noise elimination, and real-time performance. Decomposing micro-Doppler signatures into Intrinsic Mode Functions (IMFs), the system improves feature extraction as well as eliminates interference. Machine learning models (SVM, CNN) that were trained on EMD-enhanced features have accuracy exceeding 90%, surpassing conventional Doppler-based methods. The method also showed good performance in dynamic scenes and is thus ideally suited for traffic monitoring, driverless car driving, and security surveillance. Future enhancements can be directed towards deep learning and multi-sensor fusion for further increased efficiency.

Conclusion:

Therefore, classical Doppler shift processing has become increasingly advanced micro-Doppler signature extraction methodologies employing radar. Employing Empirical Mode Decomposition (EMD) in the analysis of micro-Doppler shows enormous potential in enhancing time-varying, non-stationary signal classification accuracy. Nevertheless, immense challenges lie ahead in processing noisy environments, dynamic situations, and further research into deep learning methodologies for enhanced performance. This work overcomes these challenges by introducing an EMD-based feature extraction method for micro-Doppler analysis followed by machine-learning-based classification, which is a potential solution to vehicle classification.

References:

1. S. Zhai, T. Mao and B. Hu, "An EMD-Based Micro-Doppler Signature for Moving Vehicles Classification," *2019 IEEE 5th International Conference on Computer and Communications (ICCC)*, Chengdu, China, 2019, pp. 1322-1326.

2. Detection and indication of potholes using internet of things Machiraju, J., Kotla, C., Sagile, S., Goothy, P., Botla, V.C., 2024, 3028(1), 020031

3. S. Zhai, T. Mao and B. Hu, "An EMD-Based Micro-Doppler Signature for Moving Vehicles Classification," *2019 IEEE 5th International Conference on Computer and Communications (ICCC)*, Chengdu, China, 2019, pp. 1322-1326.

4. Jayalakshmi, Machiraju, and S. Nagaraja Rao. "Discrete wavelet transmission and modified PSO with ACO based feed forward neural network model for brain tumour detection." Computers, Materials & Continua 65.2 (2020): 1081-1096.

5. Oh, Beom-Seok, Xin Guo, Fangyuan Wan, Kar-Ann Toh, and Zhiping Lin. "An EMD-based micro-Doppler signature analysis for mini-UAV blade flash reconstruction." In *2017 22nd International Conference on Digital Signal Processing (DSP)*, pp. 1-5. IEEE, 2017.

6. Kalpana, V., M. Jayalakshmi, and V. Vijaya Kishore. "Medical image forgery detection by a novel segmentation method With KPCA." Cardiometry 24 (2022): 1079-1085.

7. Huang, Norden E., Zheng Shen, Steven R. Long, Manli C. Wu, Hsing H. Shih, Quanan Zheng, Nai-Chyuan Yen, Chi Chao Tung, and Henry H. Liu. "The empirical mode decomposition and the Hilbert spectrum for nonlinear and non-stationary time series analysis." *Proceedings of the Royal Society of London. Series A: mathematical, physical and engineering sciences* 454, no. 1971 (1998): 903-995.

8. Quegan, S. "Spotlight Synthetic Aperture Radar: Signal Processing Algorithms." *Journal of Atmospheric and Solar-Terrestrial Physics* 59 (1997): 597-598.

9. Cai, Chengjie, Weixian Liu, Jeffrey S. Fu, and Lilong Lu. "Empirical mode decomposition of micro-Doppler signature." In *IEEE International Radar Conference, 2005.*, pp. 895-899. IEEE, 2005.

10. Liang, ChaoJie, Yang Li, DingHong Lu, Jie Li, and LiTao Yan. "Simulation and analysis of micro-Doppler signatures of tracked vehicles." (2013): 0520-0520.

11. Zhai, Shuangyan, Tong Mao, and Bing Hu. "An EMD-based micro-Doppler signature for moving vehicles classification." In *2019 IEEE 5th International Conference on Computer and Communications (ICCC)*, pp. 1322-1326. IEEE, 2019.

12. Molchanov, P., K. Egiazarian, J. Astola, R.I.A. Harmanny, and J.J.M.D. Wit. Classification of small UAVs and birds by microDoppler signatures. in Radar Conference. 2013.

13. Chen, Victor C. *The micro-Doppler effect in radar*. Artech house, 2019.

14. Eden, Alec, and Richard L. Kremer. "The Search for Christian Doppler." *ISIS-International Review Devoted to the History of Science and its Cultural Influence* 85, no. 4 (1994): 708-708.