DESIGN OF A MULTI-SCALE FLIGHT PARAMETER DATA ANOMALY DETECTION ALGORITHM

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ABSTRACT

Anomaly detection in flight parameter time-series data is crucial for aircraft operation. While the DCdetector model excels at detecting long-duration anomalies with its dual-attention contrastive structure, it underperforms for short-duration anomalies. This paper proposes two multi-scale optimized models based on DCdetector: a multi-scale segmentation model and a multi-scale concatenation model. The segmentation model divides input data into multiple scales using pooling layers for separate feature extraction, while the concatenation model merges multi-scale features before processing. Experiments on flight datasets show both models improve short-duration anomaly detection without compromising long-duration anomaly performance.

METHODOLOGY

Fig 1 presents the architecture of our multi-scale segmentation model based on DCdetector. The key innovation is a multi-scale feature extraction mechanism where input time-series data undergoes multi-scale downsampling through varying pooling windows, generating subsequences at different temporal resolutions, enabling simultaneous capture of macro trends and micro anomalies.
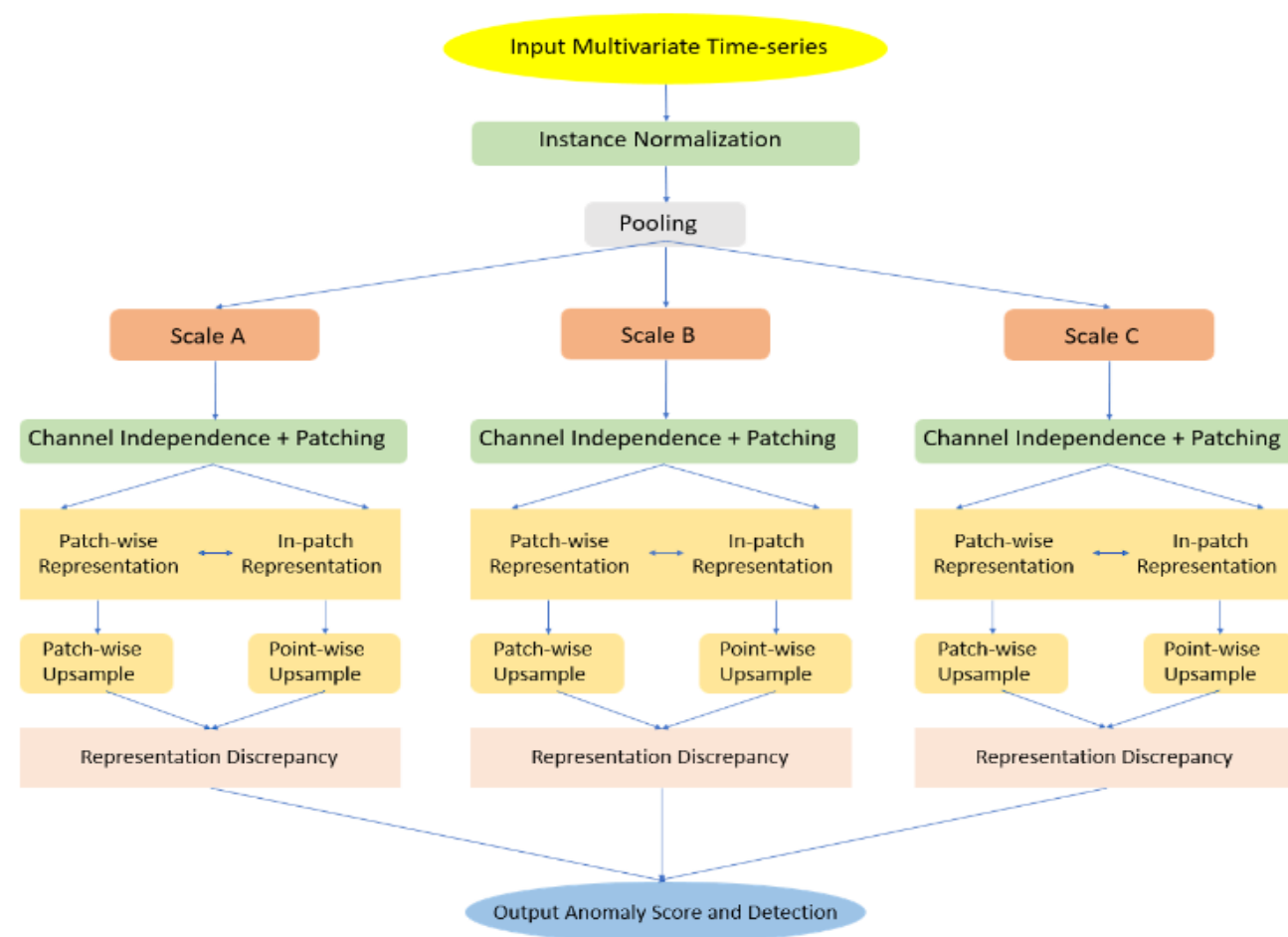

Fig. 1. Multi-scale segmentation model.

The enhanced multi-scale concatenation model (Fig. 2) extends the segmentation model by introducing cross-scale feature fusion. After multi-scale decomposition and dual-branch feature extraction, it concatenates all scale features with original representations for joint processing through dual-attention and difference representation modules.
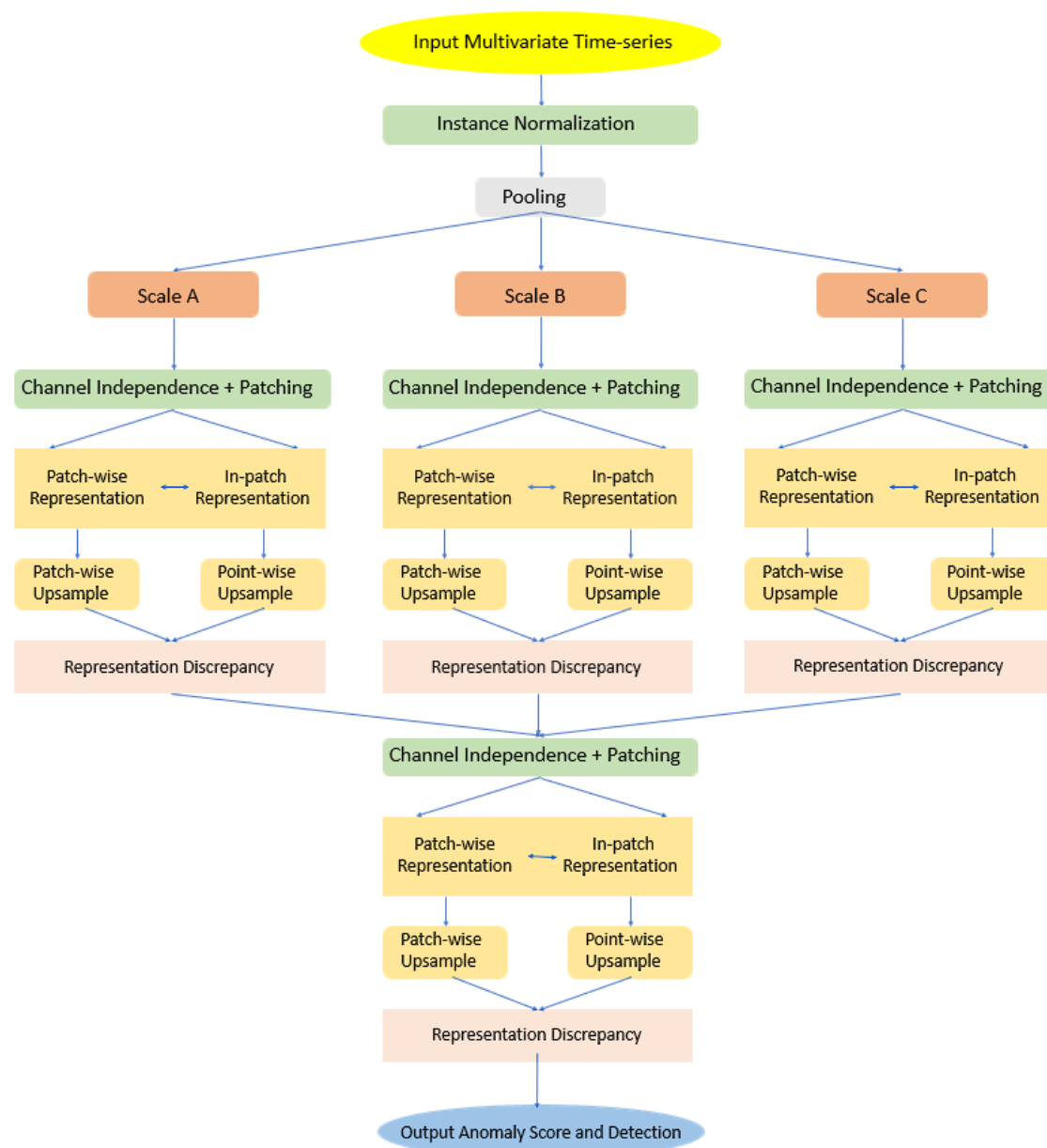

Fig. 2. Multi-scale concatenation model.

EXPERIMENTS

The DCdetector model demonstrates strong performance in detecting long-duration anomalies in flight data but fails to identify short-duration anomalies, as shown across multiple datasets. Table I presents the model's detection performance on unmodified UCR, UCR_AUG and MSL datasets, where average precision and recall rates represent means across all test sequences.

Table. I. Multi-scale segmentation model.

Dataset	Average Anomaly Length	Average Prediction Count	Average Precision	Average Recall Rate
UCR	460	697	64.13%	100%
UCR	10	212.66	0.56%	14.0%
UCR_AUG	2434.4	2407.73	91.22%	84.53%
UCR_AUG	10	207.26	2.13%	13.3%
MSL	7716	8285	92.17%	98.33%
MSL	10	665	0%	0%

The multi-scale partitioning model greatly improves short anomaly detection. Fig. 3 compares results between the original DCdetector (without multi-scale pooling) and the multi-scale partitioning model on the UCR_1 dataset, and Fig. 4 illustrates the detection results under varying pooling scale combinations
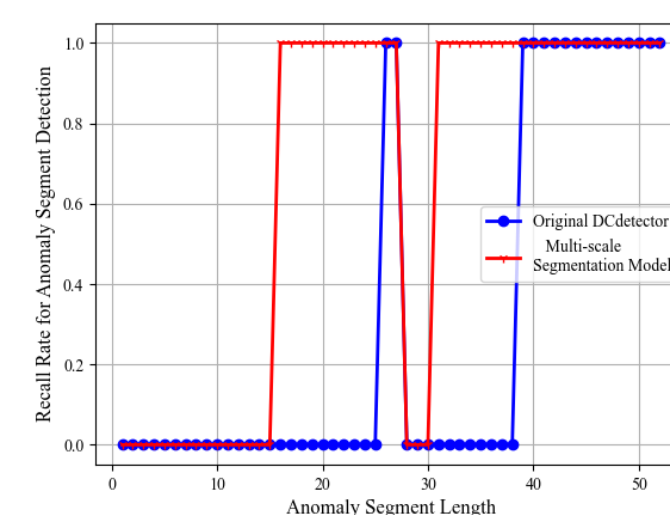

Fig. 3. Comparison With/Without Multi-scale Pooling Module
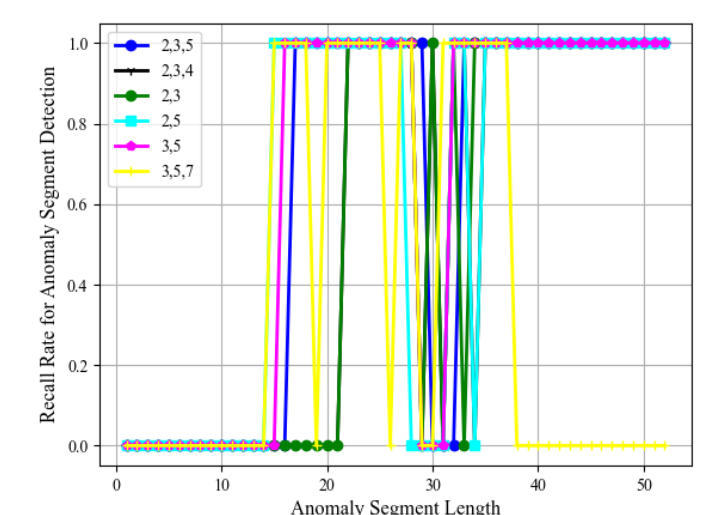

Fig. 4. Comparative Performance of Multi-scale Segmentation Model at Different Scales

Comparative experiments (Fig. 5) evaluate the multi-scale concatenation model against the partitioning model and original DCdetector on UCR_1 across varying anomaly lengths. Fig. 6 shows performance varying scale combinations
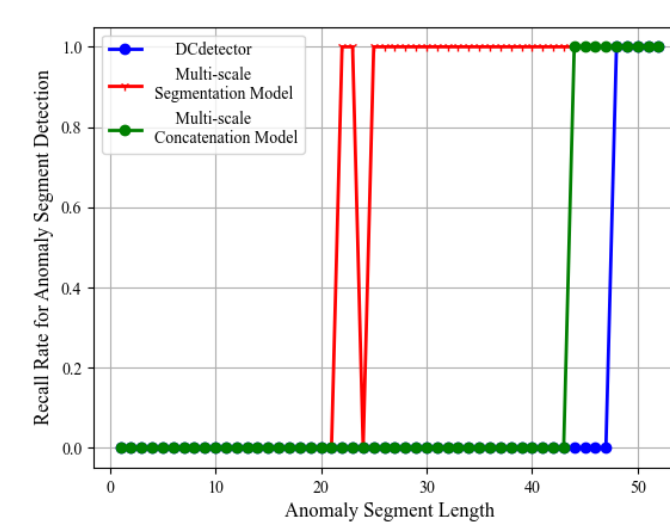

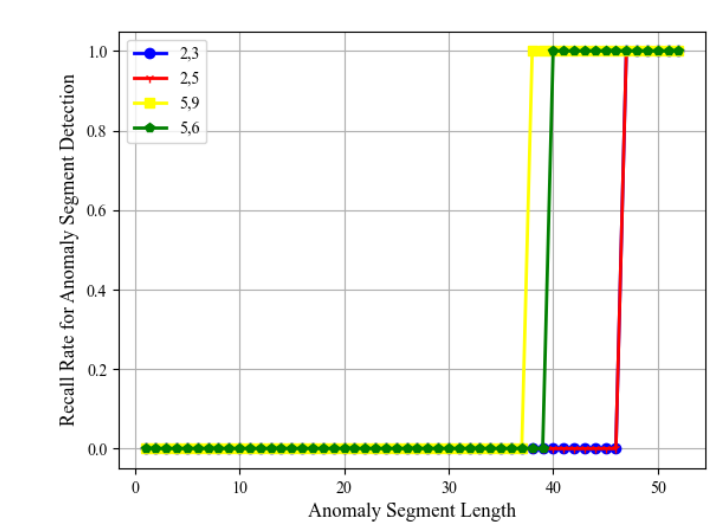Fig. 5. Comparative Performance of Different Anomaly Detection Models

Fig. 6. Comparative Performance of Multi-scale Concatenation Model at Different Scales

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