Change Point Detection for Time Series: Application on Human Gait Anomaly Detection

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Abstract—It remains a significant challenge to detect abnormalities in time-series data where even small deviations can be masked by strong periodic patterns. Here, this is addressed by showing how a signal preprocessing method can be performed with known targets. An open- source gait-cycle dataset containing a known out- of- place event camouflaged as a periodic motion was employed for this study to compare the performance of change point detection algorithms in detecting a change on the raw signal and on the signal processed with the Fourier Transform. Analysis on raw signal evidence that conventional detection algorithms are not robust enough to separate the natural periodicity of the signal from the actual anomalous behaviour, leading to a very low detection rate. Yet after use of a Fast Fourier Transform (FFT) to remove the dominant frequencies present in the normal gait pattern, a further analysis produced significantly improved results. There was an explicit amplification of the signature of the anomaly by the preprocessing step with a standard detection algorithm (Pelt) able to detect it with much higher accuracy as well as a much higher F1 score. We conclude that given periodic time-series sensor data, a special preprocessing step is a necessary element in a successful anomaly detection pipeline, which would otherwise transform a non-working detection to a robust and trustworthy result.

Index Terms—Time-Series Analysis, Anomaly Detection, Change Point Detection, Signal Processing, Fourier Transform, FFT, Data Preprocessing, Gait Analysis.

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Contents

1. INTRODUCTION

Anomaly detection on temporal data has been a fundamental task in contemporary data analytics and is essential for a wide range of application domains including but not limited to healthcare, finance, and industrial process monitoring. In this process, rare and surprising patterns and deviations in a sequence of datapoints are recognized. Synapse Neurological and locomotion healthy adults' activation (e.g., right leg to the right or left while walking). In healthcare, with particular emphasis on human movement science, Gait Analysis utilizes time-series data concerning an individual's movement to yield deep insights into an individual's both healthy and pathological status. Characteristics of gait are specified by parameters such as step length, step frequency, walking speed, and ground reaction forces, and an abnormal value of these parameters may be used for early diagnosis of neurodegeneration (such as Parkinson's disease) or an increase in the risk of a fall among the elderly [14]. Thus, accurate quality of detection of gait anomalies is an important instrument for clinical diagnosis, patient monitoring, preventive healthcare approaches [4].

1.1 Anomaly Detection and Change Point Detection (CPD)

One of the most successful techniques for performing such a task is Time Series Anomaly Detection (TSAD) known as "Change Point Detection (CPD)", whose aim is to detect specific time moments in which the behavior of the time series—i.e., mean, variance, frequency spectrum, etc.—exhibits a sharp variation from its normal state [2]. From a mathematical point of view, considering a time series, $X = x_1, x_2, \dots, x_n$, the CPD problem is that of finding a collection of change points $(\tau_1, \tau_2, \dots \tau_n)$ that partitions the series in regions with partition. This segmentation can often be obtained by a cost function minimization such as the log-likelihood or the least squares. In gait monitoring, the CPD's contribution is to not only detect abnormalities, but also in estimating when events occur and, if necessary, to inform clinicians about the specific moment their intervention would be effective (e.g., whether the abnormal step was due to a stumble, the stumble itself) [23].

However, applying data-driven CPD to gait has been difficult because human walking is inherently periodic. Walk results in a periodic signal with gait cycles that happen regularly in time, and heel-strike and toe-off events produce evident peaks and valleys on the time-domain signal. These cycles are seen as a strong (sometimes the highest) periodicity in the frequency spectrum (typically around 1 to 2 Hz). Such rhythmic structure can obscure the delicate, unsteady gait signatures of genuine anomalies such as an unexpected change in speed or a lopsided step [1]. Hence, CPD algorithms can erroneously identify natural gait variations as change points (false positives) and fail to detect true anomalies (false negatives). This "masking effect" thus represents a fundamental problem in the analysis of rhythmic biomechanical data and inhibits an application of classical CPD approaches [19].

1.2 Proposed Approach: A Two-Stage Solution

We propose and validate in this study a two-step approach for handling mask recordings in rhythmic gait data. We apply the claim on datasets of the "170_UCR_Anomaly_gait-Hunt1". To the best of our knowledge, no work has attempted to identify anomaly unbidirectionally in any kind of dataset and our approach provides insight into the anomaly contribution of each instance in the datasets. This set covers a long period of normal gait (from index 18,500 to 33,070) followed by one single apparent anomaly (from index 33,070 to 33,180). It is clearly distinguishable between normal and abnormal behaviour makes it well suited to evaluate the performance of CPD algorithms.

1.2.1 Stage 1: Signal Filtering with Fast Fourier Transform

In order to reduce the masking effect, the first stage applies the Fast Fourier Transform (FFT), which is a popularly used method of signal processing transforming the time series data to the frequency domain, leading to periodicity components analysis [18]. In mathematical terms, for a discrete time series x[n] where (indicating convolution) and (indicating the delta impulse function):

$$X[k] = \sum_{n=0}^{N-1} x[n]e^{-i2\pi kn/N}$$

where N is the size of the data, k is the frequency index, and X[k] is the frequency spectrum. For gait signals, the major frequencies representing the healthy stride cycles (e.g., 1-2 Hz) are extracted via FFT. These removal frequencies are next eliminated using the band-stop filter, producing a "Residual Signal" which is predominantly not rhythmic, thus allowing easily visible anomalous segments [21]. This residual signal is a cleaner basis on which CPD methods could be applied.

1.2.2 Stage 2: Application of Diverse CPD Methods

In the second stage, a variety of CPD methods are applied to the filtered residual signal. These methods were selected to represent a broad spectrum of computational approaches and statistical assumptions:

- Exact Methods: The Pruned Exact Linear Time (PELT) algorithm utilizes dynamic programming to detect change points, offering optimal segmentation with a linear time complexity of O(n) [13].
- Approximate Methods: Binary Segmentation (BinSeg) recursively splits the series into segments, with a complexity of O(nlogn). Bottom-Up starts with small segments and merges them, while Window-based methods use a sliding window to detect local changes [2].
- Parametric and Non-parametric: L2 norm based approaches observe to the change of the sum of squared residuals of the predicted value from the observed value while the KernelCPD exploits the kernels to provide a flexible, distribution free detection [5].
- Classical Methods: Cumulative Sum (CUSUM): CUSUM is a change detection method used in statistical process control, which aggregates deviations inorder to detect change points [16].

1.3 Experimental Findings and Contributions

Preliminary results on using this CPD-based method on unfiltered raw gait data demonstrated the masking effect. But the anomaly was correctly extracted by the same means applied to the FFT-filtered residual signal. This finding confirms the effectiveness of the two-stage method for solving the masking issue in rhythmic biomechanical data [9].

The key novelty of this work is in improving anomaly detection in rhythmic gait data for more robust results for purposes such as continuous health monitoring and fall prevention.

2. LITERATURE REVIEW

This chapter surveys the general Change Point Detection (CPD) literature, emphasizing the methods and considerations that are directly relevant for this work, with its specific problems related to the use of rhythmic time-series, such as gait.

2.1 Foundations of Change Point Detection

If errors in the normal operation of the industrial process are those that are outside of normal behavior, the Change-Point Detection (CPD) approach has been proposed to determine discontinuous points, in time, where the statistical properties (such as mean, variance, or distribution) of the signal significantly change from their expected values [2]. In this paper, we consider the offline setting, where we analyse the entire historical data set to detect all change points, leading to a segmentation of the signal into statistically homogeneous segments [21].

Current CPD formulates the problem as a model selection problem and aims at minimising a penalised cost function:

$$\min\left(\mathrm{V(T)} + \mathrm{pen(T)}\right)$$

Here V (T) is the cost of a segmentation T, and the penalty term textpen(T) avoids overfitting by penalizing the model complexity ie the number of change points [7, 21]. This framework changes the question asked, from “Is there a change? Emphasizing the question from "what is the simplest model that describes the data?"

2.2 A Taxonomy of CPD Algorithms

CPD algorithm can be divided into three components: the cost function, the search strategy and the penalty. We adapt two of these techniques which have been developed in the python package ruptures [20].

- Cost functions: The parametric costs, such as the L2-norm (sum of squarederrors), can effectively learn mean shifts given Gaussian assumptions. Non-parametric costs are inherently more flexible and they do indeed map data into a high-dimensional feature space to detect changes in the full probability distribution, they are thus suitable for complex data where distributional assumption cannotbe precisely stated [5].
- Search Methods: Exact methods such as the Pruned Exact Linear Time (PELT) algorithm employ a pruning rule to achieve such an optimal average-case linear complexity O(n), which the PELT algorithm does, and is considered as a modern gold standard [13]. Approximate approaches sacrifice accuracy for efficiency. Binary Segmentation (BinSeg) is a top-down recursive greedy approach of O(nlogn) complexity [2].

2.3 Challenges in Applying CPD to Rhythmic Data

Carrying out CPD of biomechanical data, such as human gait, is challenging due to the characteristics of the signal.

- The "Masking Effect": The most problematic effect to account for is that of the powerful,periodic nature of the normal gait cycle. Conventional CPD algorithms may mistake natural peaks and troughs in walking as change points (false positives). In contrast, the large amplitude of this rhythm may obscure or "mask" small, true abnormalities, resulting in non-detection (false-negatives) [17, 19].
- Autocorrelation and non-stationarity: Gait data are often strongly serially autocorrelated and such autocorrelation can introduce spurious structure and trigger alarms in methods that assume independence [17]. Also, the slow motion-induced variation of features changes the piecewise-stationary assumption of most CPD [2].

2.4 Signal Pre-processing to Enhance Detection

Because of these difficulties, it is necessary to have a pre-processing stage. For these applications, the FFT canbe very useful, since it decomposes a signal in its frequency components, and may be used to determine which dominant frequencies characterize a rhythmic pattern [15]. A more attractive two-stage method is suggested in this study:

- Determine and subtract the frequency ranges ofthe regular stride rhythm using FFT.
- In the second step, apply CPD methods to the resulting "residual" signal, from which the masking effect of the periodicity has been diminished, and thereby improve the signal-to-noise ratio for the anomaly of interest [9].

2.5 Ethical Considerations in Gait Analysis

There are profound ethical responsibilities associated with evaluation of data on human movement. The privacy issue of constant monitoring by wearable sensors is also a matter of concern about sensing [12]. Biometric data for gait should be collected in such a way to ensure the security of data and clear informed consent so as not to be misused or exploited for other applications (i.e. as part of 'function creep') [6]. Also, models trained on biased datasets can amplify inequalities [3]. Lastly, there are marked clinical and social implications from both false positives (generating unwarranted fears and further testing) and false negatives (delaying potentially life-saving treatment) [11].

3. METHODOLOGY AND KEY CONCEPTS

The theoretical basis of this study will be provided in this chapter. It describes the CPD algorithms at a high level, and the cost functions they use, the metrics used for performance evaluation, signal processing techniques for preprocessing.

3.1 Change Point Detection Algorithms

CPD aims to detect time points on a sequence of ordered data at which statistical characteristics change. We use several algorithms from the via ruptures Python library [20].

- Pelt (Pruned Exact Linear Time): An exact and efficient search algorithm; Pelt will determine the optimal partition which minimizes a cost function and do so in linear time [13].
- BinSeg (Binary Segmentation) The widely used heuristic method for computing change points recursively. It is an approximation and is not guaranteed to detect the globally optimal change point set [20].
- Window: This approach uses a fixed-size sliding window to test statistical propertiesbetween twohalves of the window in order to identify anomalies.
- BottomUp: This approach first performs a finetuned segmentation and then merges the pair of adjacent segment that are statistically most similar.
- KernelCPD: A non-parametric method that can detect changes in the entireprobability distribution of asignal based on a kernel function [5].].

3.2 Cost Functions

The cost functions measure the "fit" of a hypothesized segment.

- L2 (Euclidean): It is used to identify changes in the mean of a signal by taking the sum of squares differences.
- Normal (Gaussian): This function supposes the data in each segment is normally distributed and it looks for changes of mean and standard deviation.
- Rank: A non-parametric, outlier-robust cost that is evaluated on the ranks of the signal values.

3.3 Performance Evaluation Metrics

In order to assess performance in an unbiased manner, the following standard classification metrics were employed:

- TP (True Positive): A Change Point detected inside the GT Anomaly window.
- False Positive (FP): The detected CP is outside the window containing the ground truth.
- FN (False Negative): Not detecting the change point in the ground truth window.
- Precision: Determines accuracy of detections: Precision=TP/(TP+FP).
- Recall (Sensitivity): The proportion of true change points that have been identified: Recall=TP/(TP+FN).
- F1-Score: The harmonic mean of Precision and Recall, assures that both Precision and Recall to be included, if we only have either Precision or Recall, then this is known as a balanced measure:

$$F1 - Score = 2\,\frac{Precision\ x\ Recall}{Precision + Recall}$$

3.4 Signal Preprocessing: The Fourier Transform

Fast Fourier Transform (FFT) decomposes signal from time domain to its component frequencies [18]. In the present study, the signal was filtered using the FFT:

1. The signal segment was subjected to the FFT.
2. The FFT_FILTER_TOP_K found the top K frequencies with the largest magnitude (the dominant repeating patterns).
3. We zeroed out the top K frequency components.
4. The filtered time-domain signal was reconstructed using the Inverse Fast Fourier Transform (iFFT).

This is intended to help eliminate the "noise" of the natural gait cycle, and boost the signal-to-noise level of the hidden anomaly [9, 10].

4. EXPERIMENTAL ANALYSIS

This part shows each step of the application of the above methods to the gait data set. For each iteration we detail the goal we wanted to achieve, the steps we performed and observations made.

4.1. Step 1: Initial Data Exploration

Purpose: To comprehend the basic statistical features as well as the graphic aspects of the raw gait signal, before applying any change point detection.

Procedure: The full dataset (170_UCR_Anomaly_gaitHunt1_18500_33070_33180. txt) was loaded. Descriptive statistics comprised tabulation, mean, standard deviation, minimum/maximum, and quartiles. The whole signal was then plotted to see its structure by eye.

```
--- Basic Statistics for 170_UCR_Anomaly_gaitHunt1_18500_33070_33180.txt ---
              Signal
count  64000.000000
mean    -718.665491
std      875.262129
min    -1951.000000
25%    -1812.000000
50%     -254.000000
75%       36.000000
max      425.733330
```

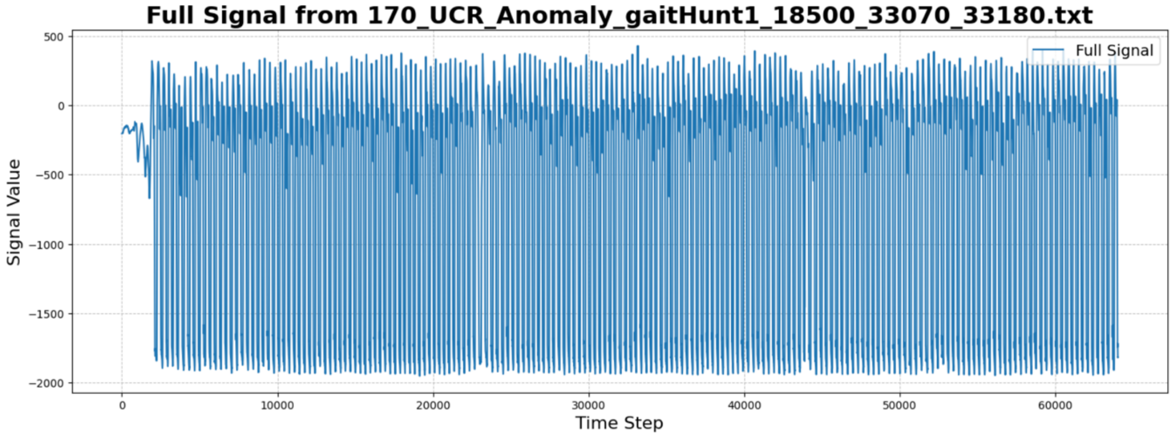

Figure 1: Statistical summary and visual inspection of the raw gait signal.

Results & Discussion: The descriptive statistics table and the signal plot offer quantitative and qualitative canvas for the dataset.

- Stats Summary: The signal is 64,000 samples in length. The high standard deviation (875.26) indicates a high variability of the signal's amplitude. One of the things we should take notice is the difference in the average (-718.67) and and the median. This imbalance suggests that the distribution of the data is distorted, but the majority of the information is attributable to the large negative values, which sink the mean.
- Visual assessment: We can be used to draw the full signal to visualize it (see Fig.1) which is readily apparent of its most salient feature: clear and stable periodicity. The signal shows an evident succession of the wave-like gait patterns. This recurrence "normal" behaviour makes it extremely difficult to detect change points, since the intrinsic oscillations of the signal may easily be confused with abnormal changes.

This first foray indicates the importance of being able to discriminate a true non-periodic anomaly from the intrinsic, dominant cyclical features of the signal in any viable anomaly-detection method.

4.2. Step 2: Change Point Detection on Raw Signal

Objective: To determine a raw score for the selected change point detection algorithms when applied directly to the segment of the raw signal containing the anomalous structure.

Procedure: The segmentof the signal from time step 32,000 to 35,000. We thereafter applied each of the eight settings under consideration in Section 3.1 in detecting CPs within the segment. For each algorithm the quality metrics (Precision, Recall, F1-Score) were computed and a plot where the detected change points were overlaid on the signal were plotted.

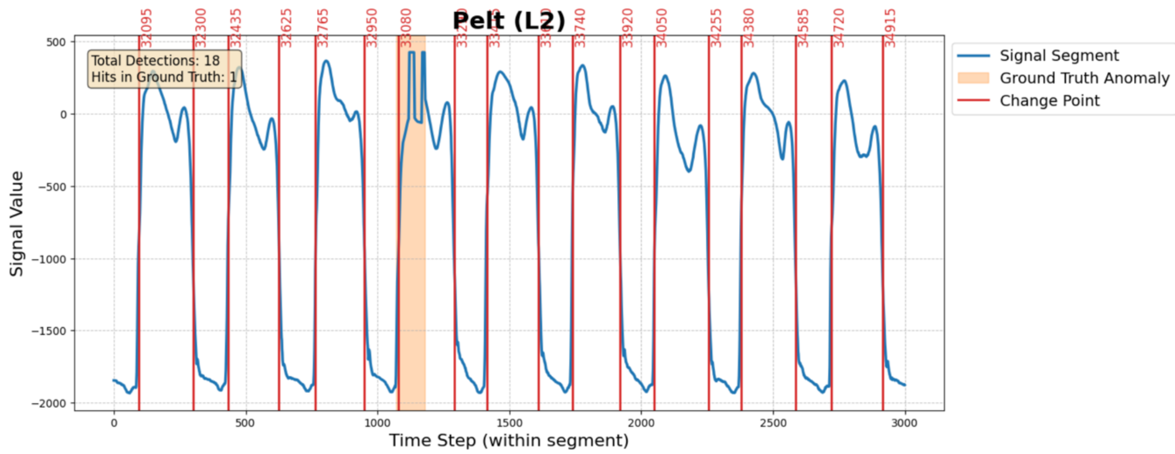

Figure 2: Detection results for Pelt (L2) on the raw signal.

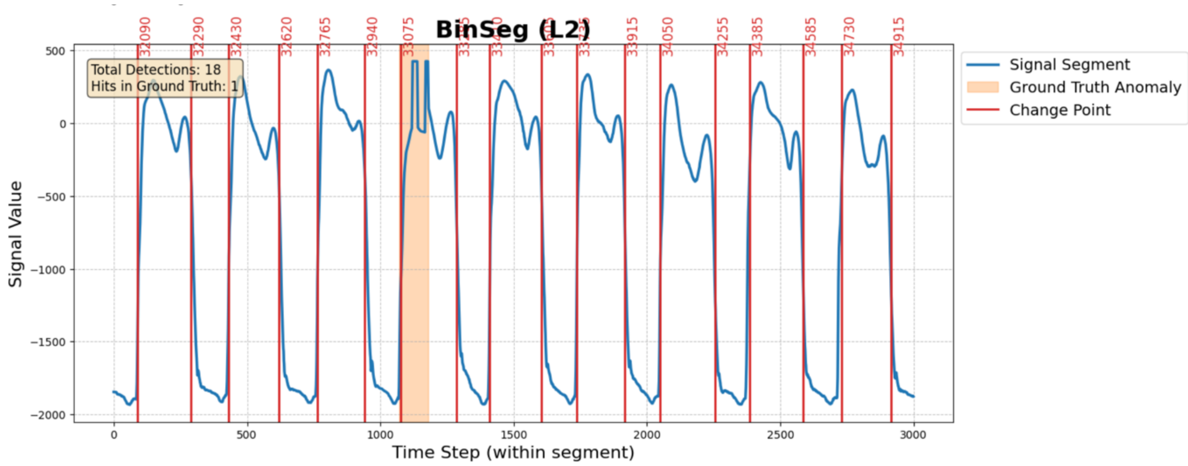

Figure 3: Detection results for BinSeg (L2) on the raw signal.

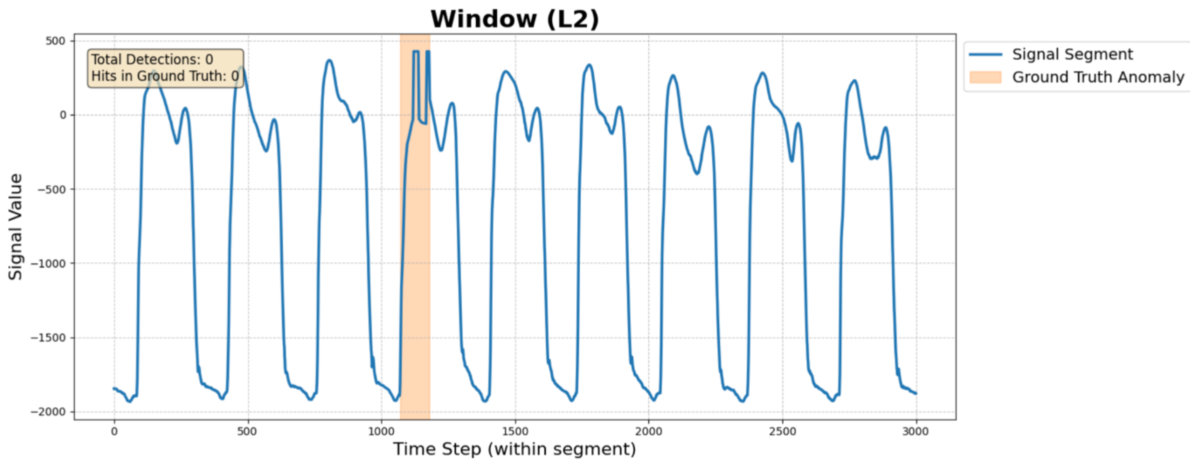

Figure 4: Detection results for Window (L2) on the raw signal.

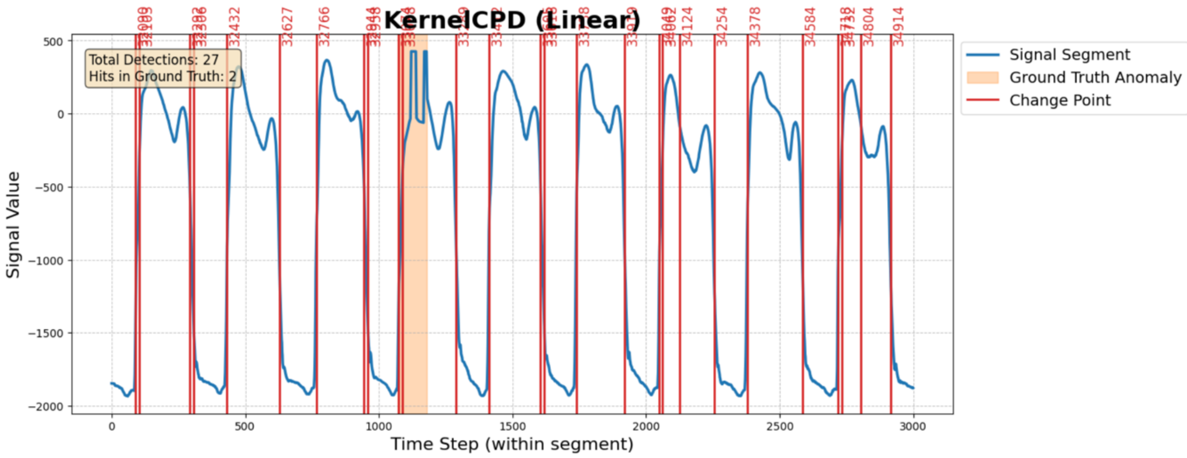

Figure 5: Detection results for KernelCPD (Linear) on the raw signal.

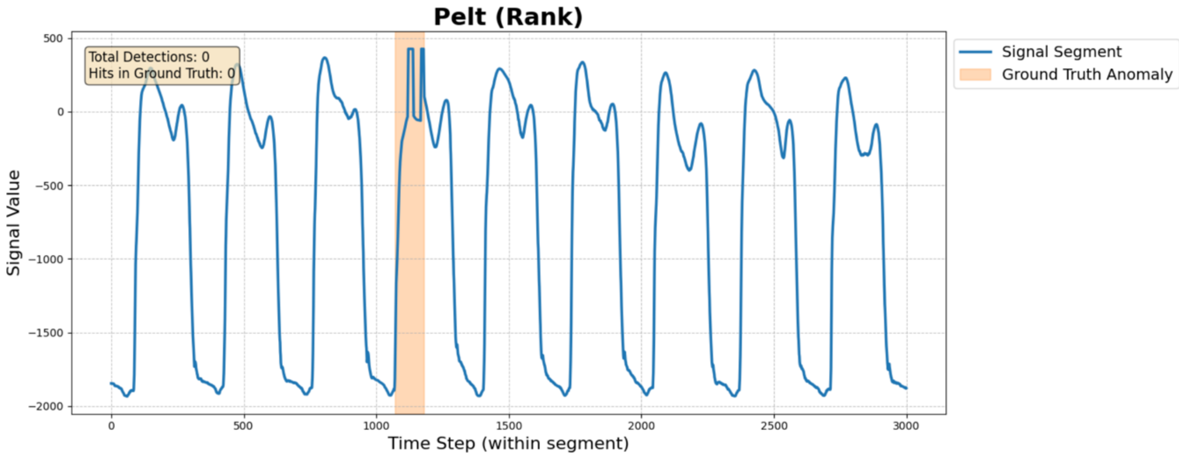

Figure 6: Detection results for Pelt (Rank) on the raw signal.

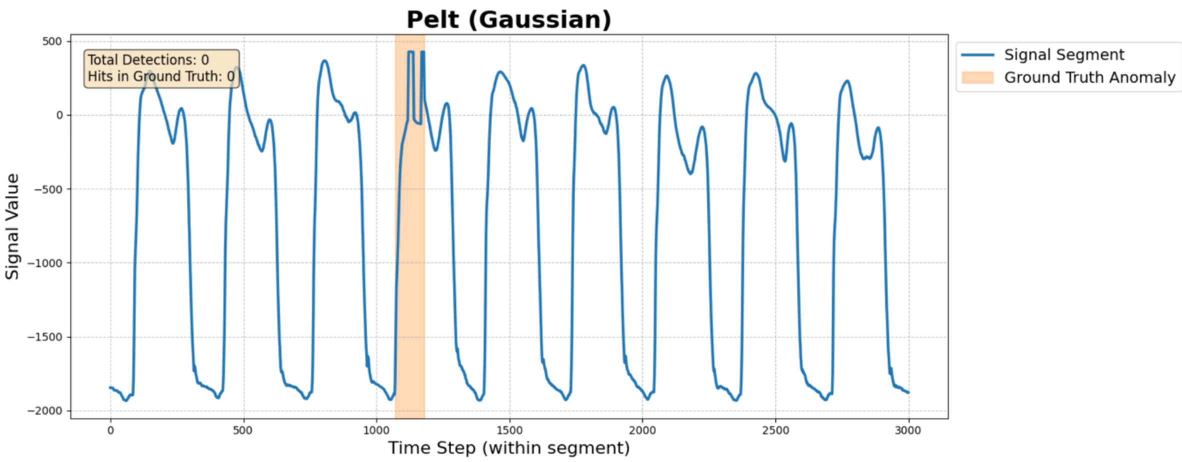

Figure 7: Detection results for Pelt (Gaussian) on the raw signal.

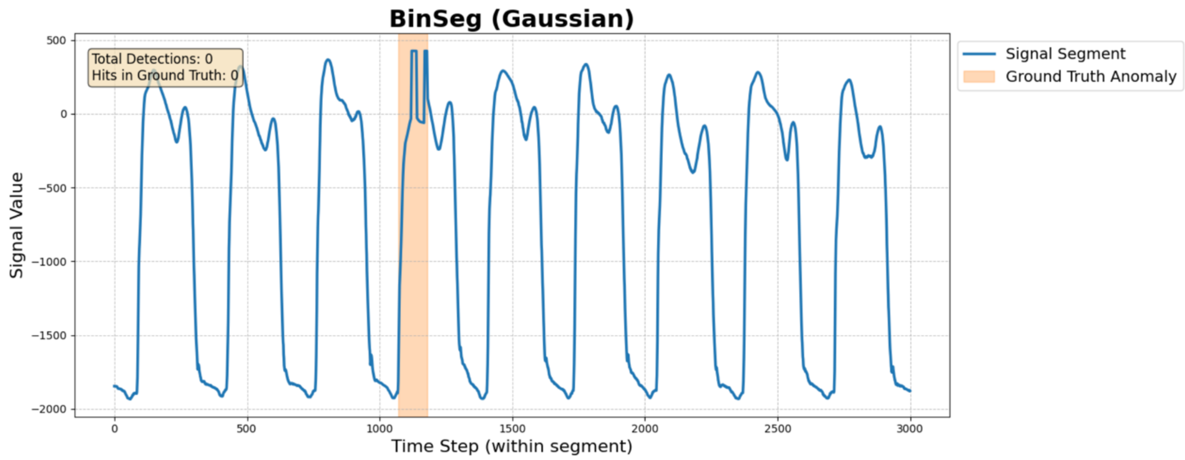

Figure 8: Detection results for BinSeg (Gaussian) on the raw signal.

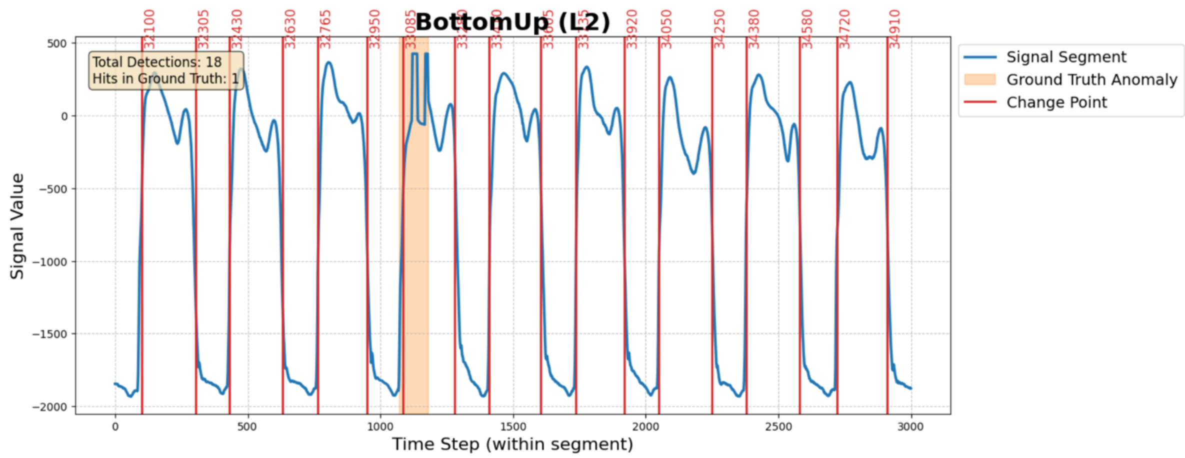

Figure 9: Detection results for BottomUp (L2) on the raw signal.

--- PERFORMANCE REPORT (WITHOUT FOURIER FILTERING) ---

	Precision	Recall	F1-Score	Detections	Hits in GT
Pelt (L2)	5.56%	100.00%	0.105	18	1
BinSeg (L2)	5.56%	100.00%	0.105	18	1
Window (L2)	0.00%	0.00%	0.000	0	0
KernelCPD (Linear)	7.41%	100.00%	0.138	27	2
Pelt (Rank)	0.00%	0.00%	0.000	0	0
Pelt (Gaussian)	0.00%	0.00%	0.000	0	0
BinSeg (Gaussian)	0.00%	0.00%	0.000	0	0
BottomUp (L2)	5.56%	100.00%	0.105	18	1

Figure 10: Performance report of all algorithms on the raw signal without Fourier Filtering.

The evidence certainly tells an important story. The L2-based cost algorithms (Pelt, BinSeg, BottomUp) and the KernelCPD algorithm also successfully reached 100% Recalls, but due to precision being very very low (i.e 7.41% in the worst case, 5.56% in the best case), they performed very poorly.

This high recall with low precision is a clear result of a large number of false positives. It was visually observed in the plots generated for those algorithms. Change points are identified in both the anomaly region and also the rest of the signal in general, at the maximum and minimum point of the regular gait cycles commonly.

The L2 cost is also susceptible to translation of the signal mean. The intrinsic periodicity of the gait signal results in non-stop and abrupt mean shifts throughout the wave. Such thresholds were properly identified by the algorithms to respond to these shifts, but the algorithm was not able to distinguish between the shift from a "normal" cycle, and the shift which represented the "anomaly" cycle.

Also a few algorithms (Window, Pelt (Rank), and the Gaussian ones) did not work at all, with zero change points detected. This reflects a structural incompatibility between their underlying assumptions and the data. For example, the structure of a signal is not piecewise Gaussian distributed, so the variant of the Pelt (Gaussian) and BinSeg (Gaussian) are not appropriate.

In summary, this preliminary work shows that the MA (strong) periodic signal in the raw signal serves as a Type II error, that is, simply a noise and smooth the direct anomaly detection impossible. It requires some preprocessing step to suppress the periodic noise and to enhance the signature of the anomaly.

4.3. Step 3: Signal Preprocessing with Fourier Transform

Objective: The aim is to reject the major periodic components from the signal segment and thus to enhance the signal-to-noise ratio so that the non-periodic anomaly becomes more observable.

Method: The Fast Fourier transformation (FFT) is performed on the signal excerpt (timelag 32,000 to 35,000). The magnitude spectrum of the resulting signal was then plotted. The FFT_FILTER_TOP_K=60 option identified and removed the 60 frequencies with the largest magnitude. Finally, the signal was reconstructed with the inverse FFT, and a comparison plot was rendered with the original signal segment superimposed on the new, filtered segment.

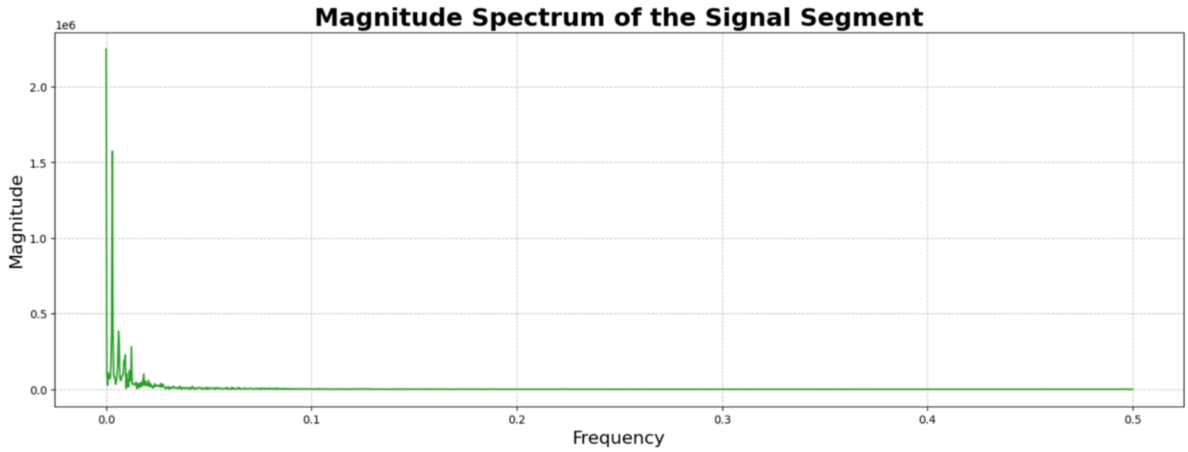

Figure 11: Magnitude Spectrum of the Signal Segment.

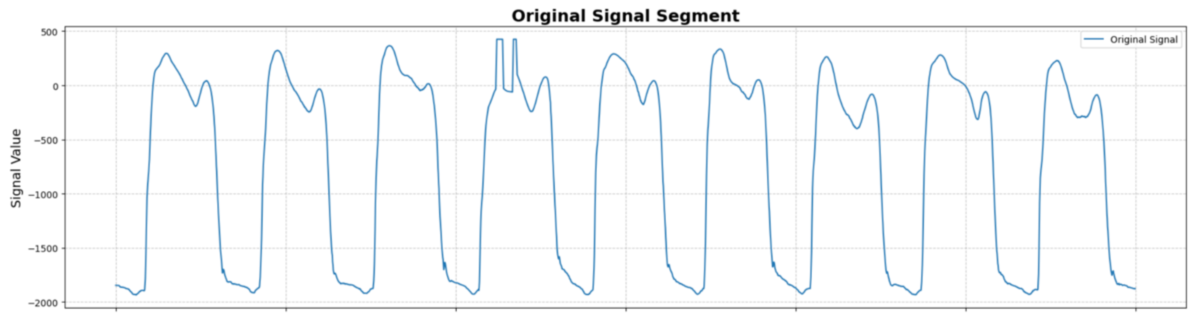

Figure 12: Signal segment before Fourier Filtering.

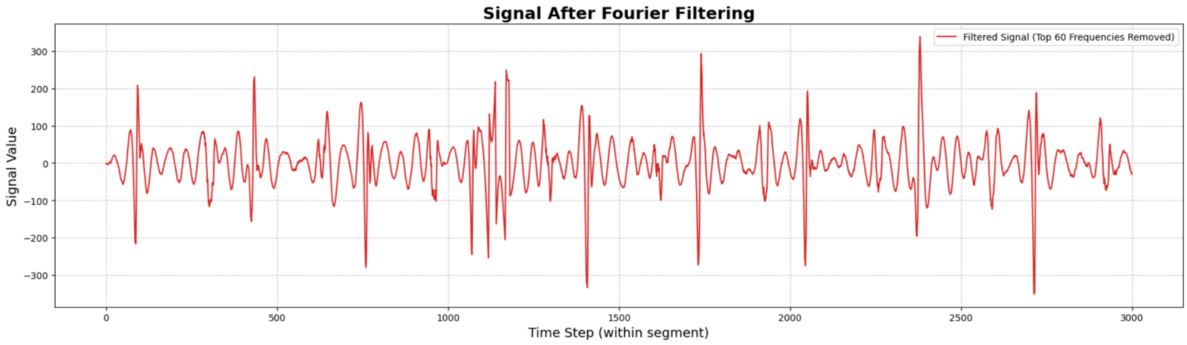

Figure 13: Signal segment after Fourier Filtering.

Results and Discussion: Figure 7 illustrates the complex t-a plot after application of the FFT and further filtering. These plots are important because they show how the signal has been conditionned for the second round of analysis.

- Magnitude Spectrum Analysis: The first plot shows the signal's frequency content. The plot is dominated by a systematic series of sharp, high-absorbtion spikes at the low end of the frequency scale. These spikes are the mathematical equivalent of the strong, periodic wave pattern encountered in the time-domain signal. They are the dominant ones that make up normal gait. Rest of the (the spectrum) is a low-level ("noise") "floor" including non-periodic contributions, where the anomaly is assumed to be located.
- Signal Filtering Comparison: The bottom figure compares raw signals before and after filtering.
  - The Top Panel Original Signal is exactly what we simulated: we have large, cyclical waves that are the obstacle that was direct detection.
  - The Filtered Signal (bottom panel) describes the output after the top 60 components were subtracted. This is a drastic change: the broad waves are gone, and the signal is now a flatter sequence concentrated around zero.

This successful conversion is the crux of the preprocessing approach. Once the “normal” periodic changes can be accounted is this an inaudible change previously catered for by a small deviation on a large waveform, in this new context it may now suddenly appear as a much larger statistical change compared-with the now stable baseline. The signal is now prepared for a more faithful study.

4.4. Step 4: Change Point Detection on Filtered Signal

Objectives: To use the same set of change point detector algorithms on the newly filtered signal and examine whether preprocessing results in an enhancement of the detection accuracy.

Procedure: The filtered signal segment was transformed with the eight algorithm settings. Similarly to Step 2, the metrics (Precision, Recall, F1-Score) for each algorithm were computed, along with plots displaying the new batch of detected change points.

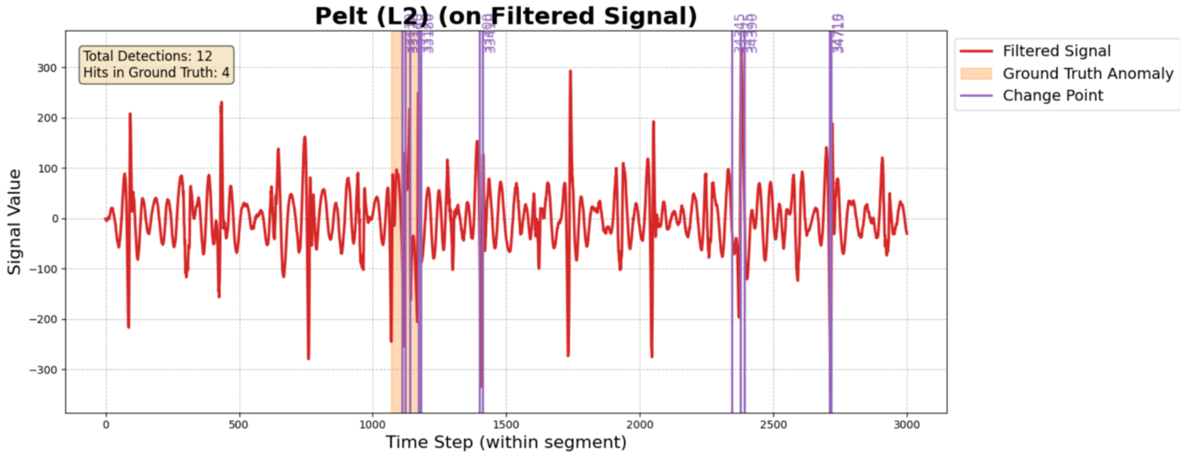

Figure 14: Detection results for Pelt (L2) on the filtered signal.

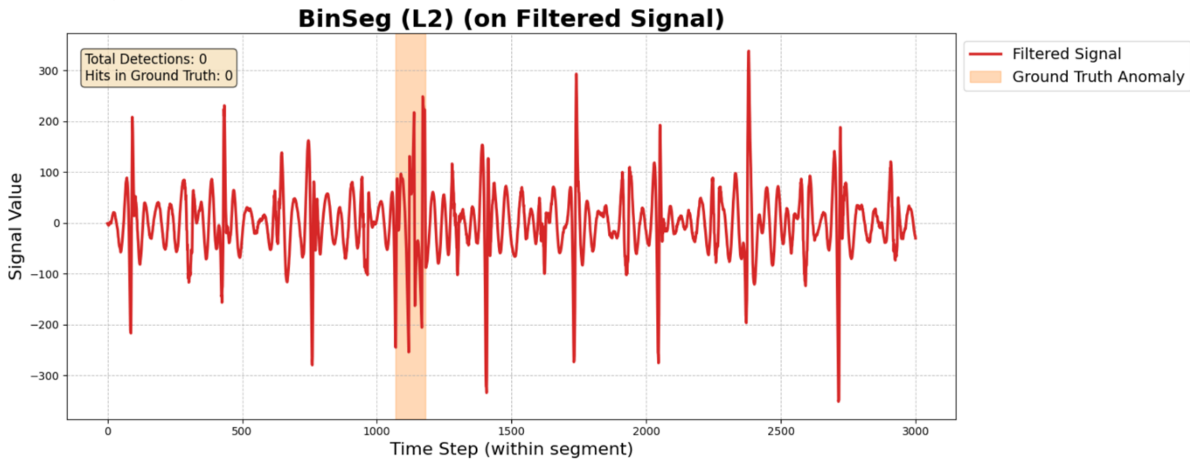

Figure 15: Detection results for BinSeg (L2) on the filtered signal.

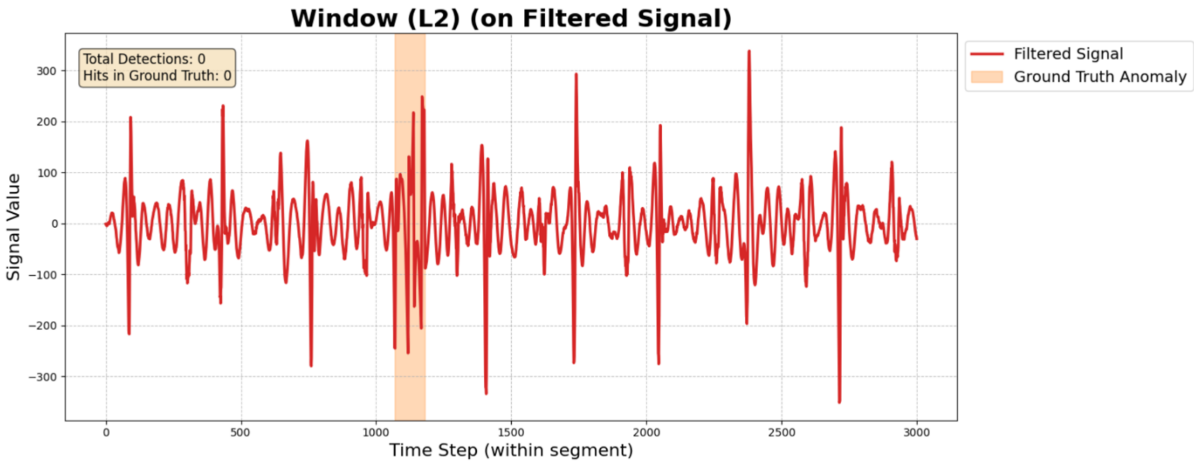

Figure 16: Detection results for Window (L2) on the filtered signal.

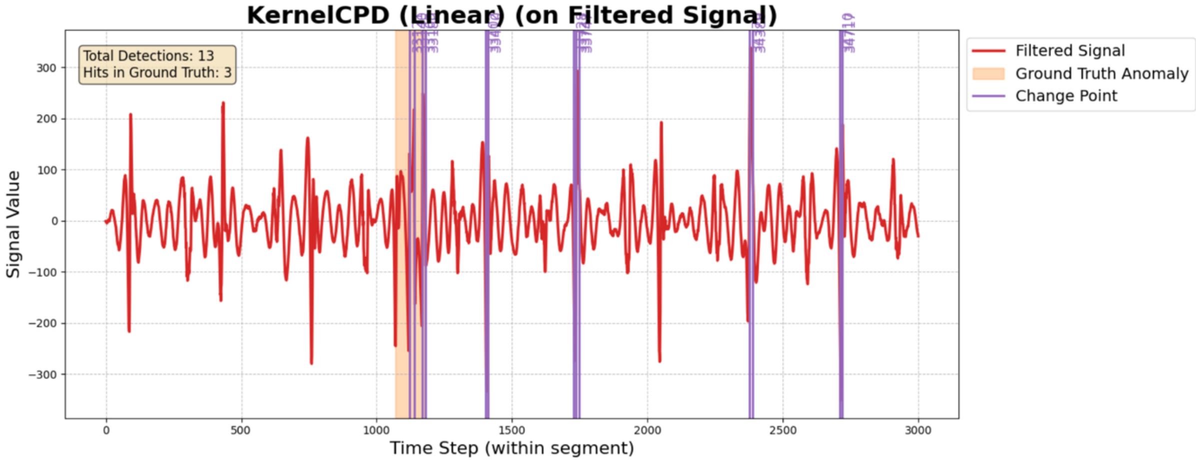

Figure 17: Detection results for KernelCPD (Linear) on the filtered signal.

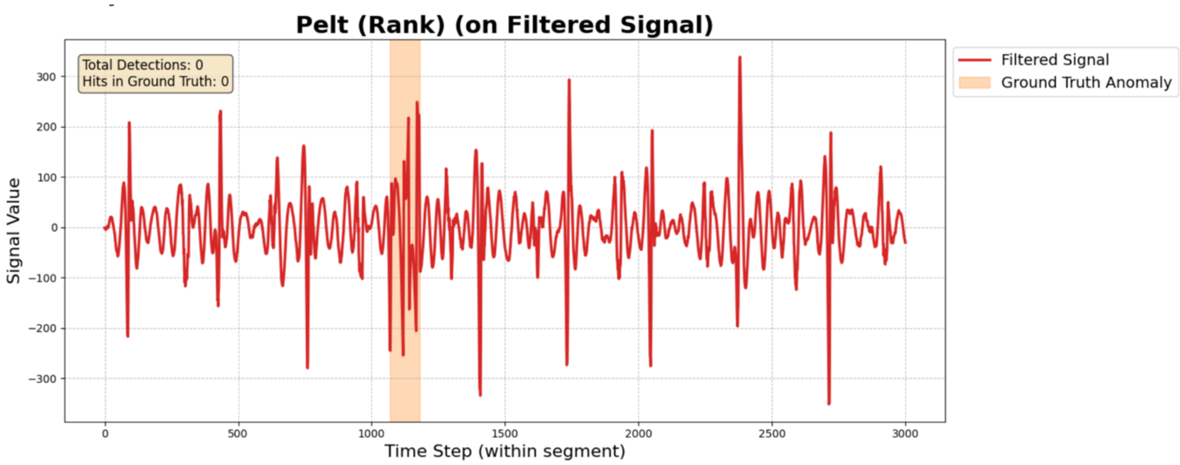

Figure 18: Detection results for Pelt (Rank) on the filtered signal.

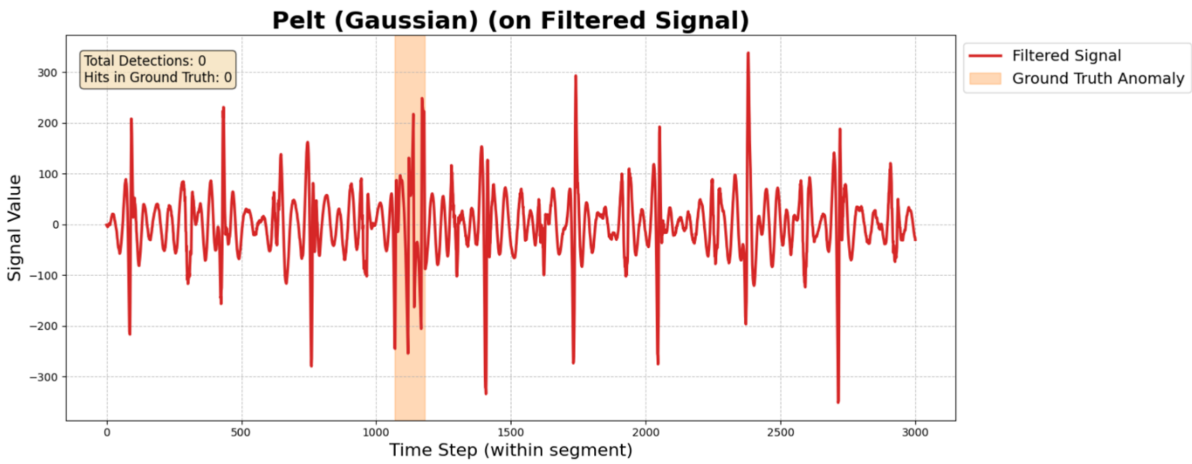

Figure 19: Detection results for Pelt (Gaussian) on the filtered signal.

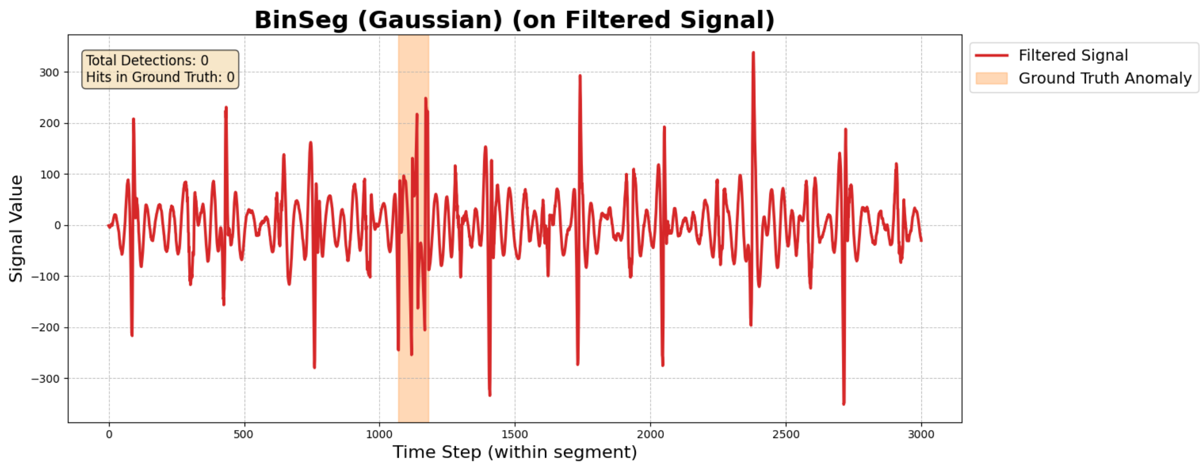

Figure 20: Detection results for BinSeg (Gaussian) on the filtered signal.

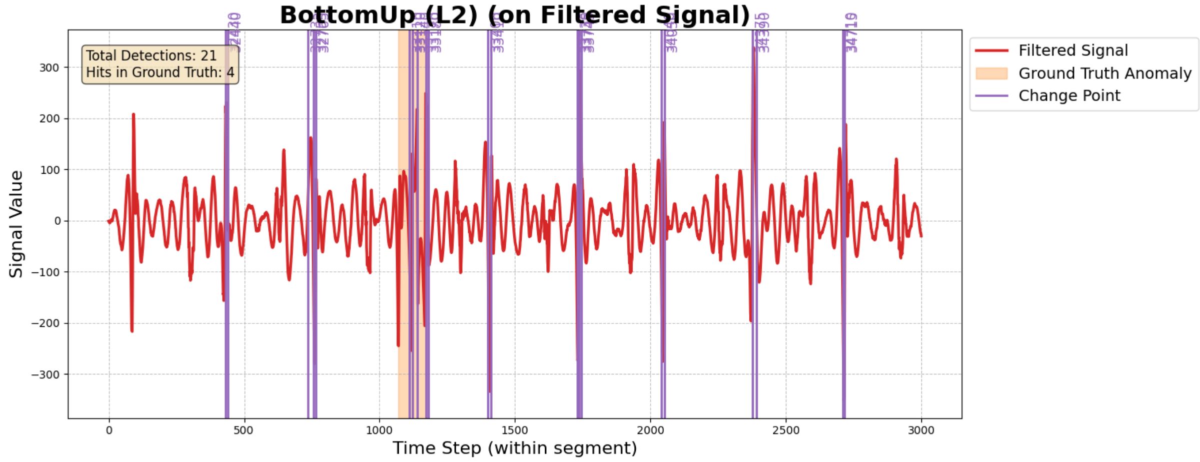

Figure 21: Detection results for BottomUp (L2) on the filtered signal.

--- PERFORMANCE REPORT (WITH FOURIER FILTERING) ---

	Precision	Recall	F1-Score	Detections	Hits in GT
Pelt (L2)	33.33%	100.00%	0.500	12	4
BinSeg (L2)	0.00%	0.00%	0.000	0	0
Window (L2)	0.00%	0.00%	0.000	0	0
KernelCPD (Linear)	23.08%	100.00%	0.375	13	3
Pelt (Rank)	0.00%	0.00%	0.000	0	0
Pelt (Gaussian)	0.00%	0.00%	0.000	0	0
BinSeg (Gaussian)	0.00%	0.00%	0.000	0	0
BottomUp (L2)	19.05%	100.00%	0.320	21	4

Figure 22: Final performance report for all algorithms on the FFT-filtered signal, detailing Precision, Recall, and F1-Score metrics.

Interpretation: The Pelt (L2) algorithm had highest performance as a model. The F1-Score increased from 0.105 to 0.500, almost five times as many folds. This dramatic change was achieved by a significant increase of Precision from 5.56% to 33.33%. This hapened because the number of false positives was greatly reduced: the overall number of detections for Pelt (L2) was reduced from 18 to 12.

The success of this approach is illustrated by the plot for Pelt (L2) applied to the filtered signal. The change points detected are now tightly packed inside of the shaded ground truth anomaly region.

Most of the points where the algorithm gets it wrong in "normal" (but now flat) part of the signal, are missed for the recounstruction of raw signals.

We also observe a change in the number of Hits in GT (true positives) for both Pelt (L2) and BottomUp (L2) from 1 to 4. This suggests that algorithms were able to detect more than a single structure change within the anomaly, once the periodic noise was taken off.

All of the models that have failed failed in the previous cases (Window, Rank and Gaussian) and failed again, reinforcing their inability to address this type of data. Interestingly, BinSeg (L2), which did find some significant changepoints in the raw data, failed on the filtered signal. This indicates that when the anomaly was more obvious, BinSeg's heuristic approximate search works best, but as the anomalous behavior starts to become more subtle, we can see that BinSeg's performance drops off, showing the gain of Pelt's exact search over cleaned data.

To sum up, this step explicitly demonstrates that by filtering out the strongest periodical contributions the basic anomalous structure was unveiled and Pelt (L2) was able to get at it relatively well.

4.5. Step 5: Final Comparative Analysis

Objective: Build a final figure that shows all algorithms in the full run and filtered run, summarizing the general influence of the method.

Procedure: We created a bar chart to show the F1-Score of the 8 algorithms. For every algorithm there are two corresponding bars next to each other, of which the left one is the F1-Score of the raw signal and the right one the F1-Score of the filtered signal. This offers a visceral, strong visual summary of the whole experiment.

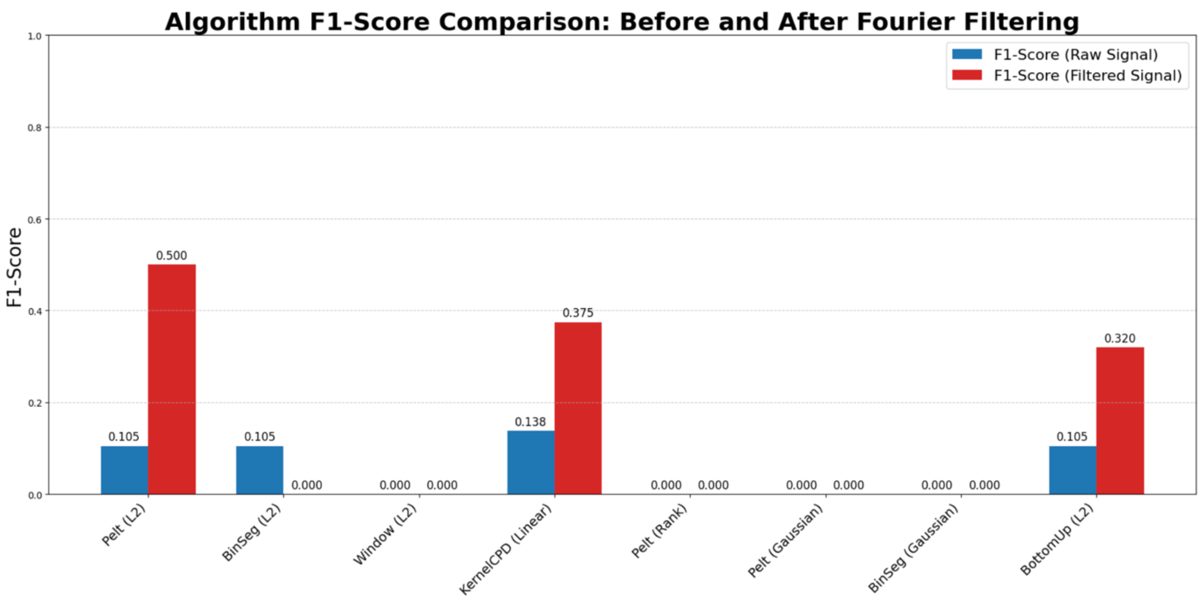

Figure 23: F1-Score Comparison Before and After Fourier Filtering.

- Final Technical Interpretation of the Comparison Graph This bar graph representsthe F 1-Scoreof the algorithm on the Raw Signal (blue bar) and on the Filtered Signal (orange bar). F1-Score is our primary measure that weighs tradeoff of finding the anomaly (Recall) and not sounding false alarms (Precision).
- The Hugeness of Filtering: First, let’s start with the obvious result: HUGE performance leaps as long as a method actually worked. For Pelt (L2), BottomUp (L2) and KernelCPD (Linear),

the orange bar is much longer than the blue one. Thus, this result is a clear evidence that our Fourier filtering preprocessing step was very successful. The problem has been reduced by us from impossible to one of tractability.

- Pelt (L2): The Unambiguously Best: The Pelt (L2) is shining in this table. Its F1. Score before filtering was a pathetic 0.105. Its F1-Score increased almost 5 times when filtered to 0.500. This turned the result from basically useless to genuinely useful. The explanation is technical: Pelt does an exact search and the L2 cost function is sensitive to the drift in the mean of the signal. With the removal of the large, oscillating waves, the anomaly was now the largest statistical change in the flattened signal, and the optimality of Pelt allowed it to exploit that simplicity to maximum advantage.
- The “Also-Improved” Tier: We also observe that BottomUp (L2) and KernelCPD (Linear) experienced larger increases, increasing their respective F1-Scores more than 2×. This also supports our hypothesis that methods which can be sensitive to changes in the signals structure can gain from elimination of the periodic "noise.
- The Non-Responding Algorithms: The graph clearly shows four algorithms (Window, Pelt (Rank) and both Gaussian models) falling into the lower right “corner” of the graph, meaning that they reached an F1-Score of 0 in both simulations. This is an important conclusion on its own. It says that their core beliefs just simply did not align at all with the nature of the data, preprocessing or no.

5. DISCUSSION

This experiment took on the task of detecting a weak anomaly from a time signal with strong dominant periodicity. The empirical findings are two stage and an obvious narrative is built around the importance of signal pre-processing in time-series analysis. This chapter considers these results and their implications more generally, as well as promising areas of future research.

5.1 The Failure of Direct Detection and the Necessity of Preprocessing

The first phase of the experiment which involved directly applying a range of CPD methods to the raw gait signal served as an important baseline. The results were clear: direct detection was out of the question. Algorithms that are tuned to mean-shifts (Pelt (L2), KernelCPD) had a recall = 100%, and very poor precision. This was again a consequence of the structure of the signal. Algorithms were properly identifying statistical change, but they were not able to tell whether the "normal" gait cycle was changing or the "abnormal" change occurred from the anomaly. The periodically nature of the signal became the dominant interreference which resulted an intolerable high false positive rate and made the model invalid in practice.

5.2 Fourier Filtering as a Key Enabler for Success

In the second leg of the analysis the importance of the customized preprocessing approach was evidenced. Through the FFT, the top 60 frequency components that are dominant in the signal were detected and suppressed, reducing the periodic "noise." The filtered signal that emerged had little baseline drift (stable close to zero) against which we could clearly see the anomaly.

Re-applying the detection algorithms to this cleaned the signal produced a substantial gain. The exact search method combined with the cost function designed to detect mean-shifts, i.e., the Pelt (L2) algorithm, clearly outperformed the other algorithms. The F1-Score increased from 0.105 to 0.500 by a factor of approximately 5. It was not just a matter of sensitivity, but a shift of regime from failed detection to successful detection.

5.3 Limitations and Avenues for Future Research

Although this paper has successfully shown one feasible approach, it is appropriate to recognise its limitations and point to future work [8].

1. Hyperparameter tuning: The results of the models were caused by the selected parameters used in this study. The penalty rate for the ruptures algorithms and the number of frequency to filter (TOP_K = 60) were set according to commonly used heuristics. The achieved F1-Score (0.500) in the end is much better, but not perfect. In addition, we are presented with a limited set of hyperparameters experimentally taken to their optimal values, and can further be searched for with a systematic hyperparameter optimization method so that the penalty value and K value can be further optimized to have a better trade-off between precision and recall.
2. Alternative Preprocessing Methods: Fourier filtering worked, is however not the only one. Future work could consider other advanced signal processing methods, e.g., Wavelet Transforms, that provide time-frequency localization and may be better-suited for capturing transient anomalies.
3. Generalization: The analysis was only carried out on single datasets from UCR archive. In order to demonstrate the generality of this approach, it should be applied to larger samples of time series including a variety of anomalies and periods.
4. Ensemble Learning: As different algorithms represented separate aspects of the change in hand, was possible to investigate an ensemble methodology. Summarizing the results of several algorithms (E.g., Pelt (L2) and KernelCPD) to a better and more accurate final detection [10].

6. CONCLUSION

The main take away message of this thesis is that a one-size-fits-all hole should be avoided in the case of time-series anomaly detection. The novelty of this study lies in a seemingly simple but perceptive intuition: one must make the data have salvo the structural properties, included and normalized. We pinpointed the hugest periodicity in the gait signal as the main barrier and adapted a specially crafted Fourier filtering method to erase such periodicity and converted an impossible-to-solve problem to a possible-to-solve problem. This almost 5 times increase in F1-Score of the Pelt (L2) algorithm after filtering clearly proves the effectiveness of our approach.

This work provides a case study that techniques for careful pre-processing are not an ancillary or preliminary nuisance but the very heart and soul of a successful time-series analysis. For academics and practitioners, alike it serves as another reminder that the largest gains in performance frequently comes not from using a more complex algorithm but from more intelligent data preparation.

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