Time-Frequency Analysis of Sympathetic Skin Response Signals for Detection of Peripheral Neuropathy Using Machine Learning Techniques

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***Abstract*—Peripheral neuropathy (PN) is a prevalent neurological disorder affecting the peripheral nerves, leading to sensory and motor dysfunction. Early diagnosis is crucial to prevent severe consequences like amputations and ulcers. This paper proposes a method for detecting PN using Sympathetic Skin Response (SSR) signals, analyzed through time-frequency (TF) methods: Short-Time Fourier Transform (STFT), Smoothed Pseudo-Wigner-Ville Distribution (SPWVD), and Choi-Williams Distribution (CWD). The features extracted from these TF representations are then used in conjunction with machine learning classifiers, including Support Vector Machine (SVM), k-Nearest Neighbors (KNN), and Naive Bayes (NB), to classify individuals as healthy or affected by PN. Experimental results show that the SVM classifier, particularly when using SPWVD features, provides the highest classification accuracy and area under the curve (AUC). This study demonstrates the potential of combining time-frequency analysis with machine learning to improve the diagnosis of PN, offering a non-invasive and effective approach for early detection and intervention.**

***Index Terms*—Peripheral Neuropathy (PN), Polyneuropathy (PNP), time-frequency analysis, Short Time Fourier Transform (STFT), Sympathetic Skin Response (SSR), machine learning, classification, Smoothed Pseudo-Wigner-Ville Distribution (SPWVD), Choi-Williams Distribution (CWD)**

I. INTRODUCTION

Peripheral Neuropathy (PN), also known as Polyneuropathy (PNP), is a of the most common neurological syndrome characterized by widespread, bilateral, and relatively symmetric disturbances of the peripheral nerves, both sensory and motor, often accompanied by impaired autonomic function [1].

PN encompass a wide spectrum of etiologies, which can be classified based on fiber size (small or large), fiber type (somatic motor, somatic sensory, or autonomic), pattern of injury (axonal or demyelinating), distribution (length-dependent or length-independent), and onset pattern (acute, subacute, or chronic). Common causes include diabetes, vitamin B12 deficiency, alcohol use, monoclonal gammopathy of undetermined significance (MGUS), and hereditary forms such as Charcot–Marie–Tooth disease (CMT). These conditions most frequently manifest in a length-dependent pattern [2].

In fact, the PN can lead to a variety of issues in the lower limbs, including numbness, burning, pinprick feeling, and discomfort.In severe situations, the PN can cause ulcers and amputations. It is estimated that 40 to 60 million diabetics suffer with lower limb issues caused by PN, with one lower limb amputated every 30 seconds. Accurate identification of PN is critical for effective treatment and avoiding serious consequences. Many studies and diagnostic approaches have been established, but no particular data is provided, and opposing diagnosing criteria are available in a different region of the world [3].

In the opening iteration, the researchers used several methods to identify the presence or not of PN.

- Corneal Confocal Microscopy Image (CCMI)
- muscle electromyography (EMG) and ground reaction forces (GRF) during gait
- Enerve conduction studies (NCS)

Regretfully, information about the small fibers is not provided by the methods mentioned in the preceding paragraph.

Sympathetic Skin Response (SSR) Signals are multi-component and non-stationary by nature [4]. Therefore, using time-frequency (TF) analysis is crucial to properly describing these signals [4]. Their multi-component structure can be accurately represented when the right TF analysis approach is chosen. In this study, the SSR signals corresponding to the PN states are analyzed using three TF techniques: Smoothed pseudo-Wigner-Ville distribution (SPWVD), Choi-Williams distribution (CWD) and short-time Fourier transform (STFT).

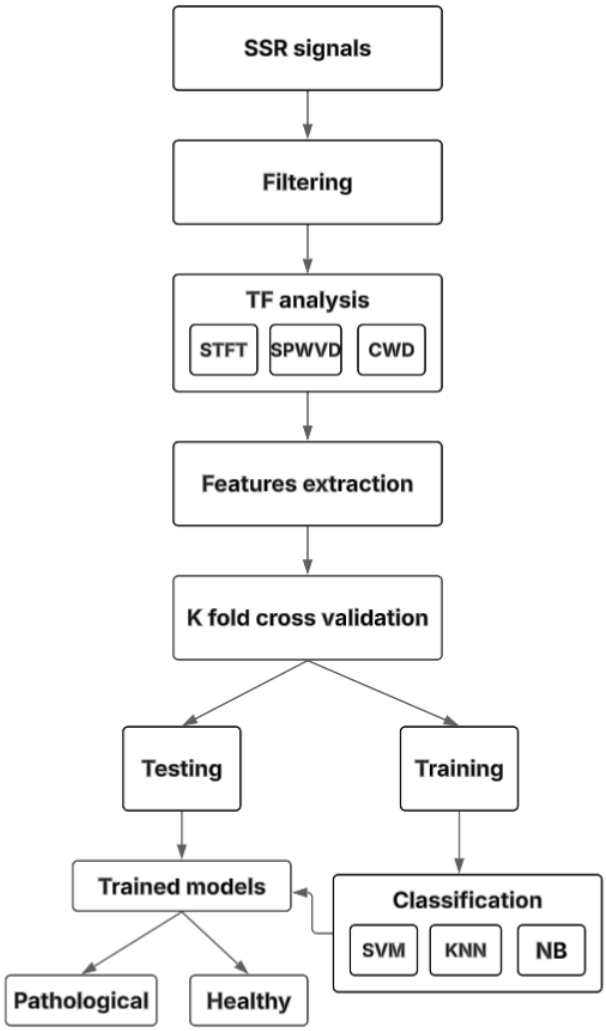


Fig. 1: Pipeline for the proposed method.

The proposed method consists of three main steps: signal filtering, feature extraction, and anomaly classification using a statistical test combined with machine learning techniques.

The remainder of the paper is organized as follows:

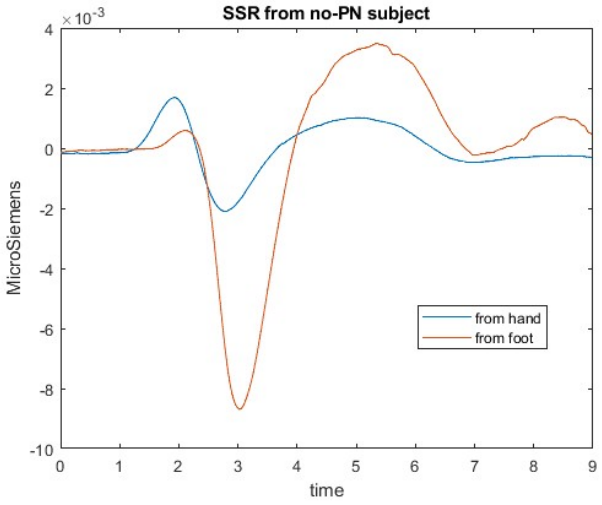
- **Section 2** presents the methodology, including the database description, feature extraction techniques, and classification approach.
- **Section 3** describes the experimental results obtained using the proposed method.
- **Section 4** provides a discussion of the results and conclusion.

II. METHODS

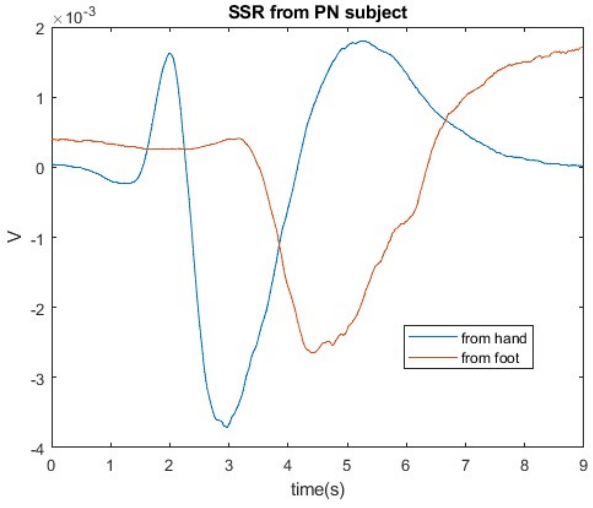
The proposed study comprised four steps: filreting, TF analysis, extraction of features, classification of pathological subject or not states in SSR signal. Fig.1shows the pipeline for the proposed method.

A. *Data-Base*

We used a database of 141 SSR forms from persons ages 25 to 72 (mean = 48.5, SD = 23.5), 36 of whom did not have PNP, and 105 of whom did. Both the hand and the foot simultaneously recorded SSR data, and measurements were taken on the right and left in turn. However, each acquisition is recreated five times in order to improve our database. As a result, each subject will complete 20 SSRs in total. For nine seconds, the signal was continuously captured while being sampled at 200 Hz. Thus, there are 1800 points in each SSR vector.In fact, [fig:2]Figure2 illustrates an example of typical examples of SSR data recorded from healthy and damaged subjects, the upper graph [fig:2]Figure 2-a) shows the SSR data recorded from the subjects that don't have PNP and the bottom graph [fig:3]Figure 2-b) shows the SSR data recorded from the subjects that have PNP.



(a)



(b)

Fig. 2: Recorded SSR data:a)healthy subject (without PNP),b) subject with PNP

B. Filtring

The SSR signals were filtered with a moving average smoothing function of 500 ms . In fact, authors in [5] shown that this filtering is appropriate in terms of masking noises and retaining important signal components. However, the proposed filtering was used to eliminate high-frequency noise [6].

C. TF analysis Methods

the filtred SSR A is analysed by using three TF analysis techniques, namely STFT, SPWVD, and CWD.

1) STFT: is a time-frequency analysis technique used to examine how the frequency content of a signal evolves over time. By applying the Fourier transform to successive and overlapping time windows of the signal, STFT provides a two-dimensional representation showing both time and frequency information [7]. The mathematical representation of STFT of a signal is defined as:

$$\text{STFT}\{x(t)\}(t,\omega) = \int_{-\infty}^{\infty} x(\tau)\, w(\tau - t)\, e^{-j\omega\tau}\, d\tau \quad (1)$$

where $x(t)$ represents the SSR signal, $w(\tau - t)$ denotes the short-time window function with a sliding variable τ, and ω is the frequency component of the signal.

2) SPWVD: is a time-frequency representation that enhances the readability of the Wigner-Ville Distribution (WVD) by reducing cross-term interference. It applies smoothing functions in both time and frequency domains, providing a clearer and more accurate depiction of signal energy distribution over time and frequency [7].

$$\text{WVD}(t,f) = \int_{-\infty}^{+\infty} R_x(t,\tau)\, e^{-j2\pi f\tau}\, d\tau \quad (2)$$

Where $R_x(t,\tau)$ denotes the autocorrelation function. Even though WVD has high time and frequency resolution

$$\text{SPWVD}(t,f) = \iint h(t-\tau)\, g(f-\xi)\, \text{WVD}(\tau,\xi)\, d\tau\, d\xi \quad (3)$$

where g and $h(t)$ represent the time and frequency smoothing windows, respectively.

3) CWD: belonging to Cohen's class of distributions. It employs an exponential kernel function to effectively suppress cross-terms while preserving the time-frequency localization of signal components [7]. The kernel function used in the Choi–Williams Distribution (CWD) is of exponential form and is defined as:

$$\phi(\nu,\tau) = e^{-\frac{\nu^2\tau^2}{\sigma}}, \quad \sigma > 0 \quad (4)$$

The corresponding determining function $G(t,\tau)$ becomes:

$$G(t,\tau) = \sqrt{\frac{\sigma}{\pi}} \cdot \frac{1}{2\pi} \cdot e^{-\frac{\sigma t^2}{4\tau^2}} \quad (5)$$

Where, σ is a parameter that controls the degree of smoothing and governs cross-term suppression. The expression $(\tau - \nu)$ refers to the time–frequency plane in ambiguity domain analysis.

D. Features extraction

In the current study, the different features are used to extract the different properties of SSR signal. The extracted features with the corresponding mathematical formulation are shown in table I . where x is the SSR signal, N=1800 is the size of SSR signal.

TABLE I: Feature vector dimension

Features Name	Formula
Mean	$Mean = \frac{1}{N}\sum_{i=1}^{N} x_i$ (6)
Variance	$Var = \frac{1}{N}\sum_{i=1}^{N}(x_i - Mean)^2$ (7)
Skewness	$Ske = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i -)^3}{\left[\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \text{Mean})^2}\right]^3}$ (8)
Kurtosis	$\text{Kur} = \frac{\frac{1}{N}\sum_{i=1}^{N}(x_i - \text{Mean})^4}{\left[\sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \text{Mean})^2}\right]^2}$ (9)
Trimean	$\text{Tri} = \frac{Q_1 + 2Q_2 + Q_3}{4}$ (10)
Median	Mid $= Q_2$ (11) Q:quartile Q1 :first quartile Q3 :third quartile
Interquartile Range (IQR)	IQR $= Q_3 - Q_1$ (12)
Midhinge	Mid $= \frac{Q_1 + Q_3}{2}$ (13)
Signal Energy	SE $= \sum_i |x_i|^2$ (14)
Normalized Power	$P_1 = \frac{1}{P}\sum_f x_f^2$ (15) P: total Power

E. Classification

At this stage of the study, we propose three machine learning techniques to classify SSR signals: Support Vector Machine (SVM), Bayesian Networks (BN), and k-Nearest Neighbors (KNN). To evaluate the proposed method, the performance of the proposed approach was evaluated using the area under the ROC curve and the performances metrics such as classification accuracy (Acc) and AUC the area under the ROC curve. The proposed approach is tested for reliability using the K-fold cross-validation technique with K=10.

$$\textbf{Acc(\%)} = \frac{TP + TN}{TP + TN + FP + FN} * 100 \quad (16)$$

- **TP (True Positive)**: PN signal is correctly classified,
- **TN (True Negative)**: Healthy signal is correctly classified.
- **FP (False Positive)**: Healthy signal is incorrectly classified
- **FN (False Negative)**: PN signal is incorrectly classified.

III. Results and discussion

This work outweighs the results obtained by other researchers which analyze and detect PNP diseases using others database that are depicted in table II .

TABLE II: Performance (F-m and AUC) of classifiers using different TFDs

Classifier	STFT		CWD		SPWVD	
	ACC	AUC	ACC	AUC	ACC	AUC
NB	56.00	49.80	46.13	45.10	46.42	48.50
KNN	46.90	46.90	53.73	51.70	61.64	61.00
SVM	56.84	51.70	61.17	69.20	78.74	81.00

The results obtained in this study show that time-frequency analysis techniques, particularly STFT, CWD, and SPWVD, can effectively analyze SSR signals to detect the presence of peripheral neuropathy (PN). Among the classifiers evaluated, Support Vector Machine (SVM) demonstrated the best performance across all three time-frequency distributions (TFDs), achieving the highest classification accuracy (Acc) and area under the curve (AUC). Specifically, the SVM classifier achieved 78.74% accuracy and 81.00 AUC using SPWVD, outperforming both k-Nearest Neighbors (KNN) and Naive Bayes (NB) classifiers.

The use of SPWVD, which provides a clearer representation of signal components by reducing cross-term interference, was the most effective TFD for classification. This aligns with previous studies suggesting that the use of advanced time-frequency distributions can improve classification performance, especially for non-stationary signals like SSR. While STFT and CWD also yielded reasonable results, the higher resolution and smoother representations offered by SPWVD contributed to better feature extraction and, consequently, more accurate classification.

The results demonstrate that time-frequency analysis can successfully differentiate between healthy subjects and those with PN. However, the relatively lower performance of KNN and NB classifiers highlights the importance of choosing the right classifier for time-frequency features. For example, SVM, which is known for its ability to handle high-dimensional data, provided significantly better results.

A comparison with prior studies on peripheral neuropathy detection reveals that the proposed method outperforms previous approaches in terms of classification accuracy. For instance, studies that used simpler techniques or different types of signal analysis achieved lower accuracies, underlining the advantages of time-frequency analysis combined with advanced machine learning techniques in diagnosing PN.

There are several factors that could be improved in future studies. First, increasing the diversity of the dataset, particularly with respect to different stages of neuropathy (e.g., mild, moderate, severe), could further refine classification performance. Additionally, exploring other feature extraction methods, such as incorporating morphological features or using deep learning techniques for automatic feature learning, could enhance model performance. Moreover, it would be interesting to examine the use of more advanced classification methods, such as deep neural networks, to automatically learn the most relevant features from raw SSR signals, which could lead to even higher diagnostic accuracy.

Overall, this study demonstrates the potential of time-frequency analysis and machine learning in the detection of peripheral neuropathy, with promising applications in clinical diagnostics and personalized treatment strategies. Future work will focus on enhancing classification methods and exploring the incorporation of more complex data sources to further improve detection accuracy and reliability.

IV. Conclusion

In order to detect the presence or absence of peripheral neuropathy (PN), which affects both small myelinated and unmyelinated nerve fibers, this work focuses on extracting relevant features from the recorded signals. These features aim to capture the underlying physiological alterations induced by PN. Time-frequency representations (such as STFT, WVD, and SPWVD) are employed to analyze non-stationary signal characteristics. From these distributions, meaningful features—such as energy distribution, entropy, statistical moments, and texture descriptors—are extracted and later used for classification or diagnostic purposes.

In Future studies can use a variety of characteristics, such as SSR signals morphologic data, to improve classification accuracy performance. However, PN data can be classified based on the level of the disease (mild, moderate or severe neuropathy). References

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