

METHODOLOGY FOR PEAK DETECTION USING THE MATRIX REPRESENTATION OF SIGNALS

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RESUMEN.

Este trabajo presenta una metodología para la detección de picos mediante la representación matricial de señales, aplicable a cualquier tipo de señal, como las de radar, biomédicas, electromagnéticas, entre otras. Este enfoque se destaca por su rapidez, baja complejidad computacional y por eliminar la necesidad de cálculos de umbrales de nivel. Además, procesa eficazmente señales con y sin zonas planas alrededor de los picos, siendo ideal para sistemas embebidos con limitaciones de memoria y potencia de cálculo limitada. La metodología se valida utilizando señales fotoplethysmográficas (PPG) para detectar picos sistólicos en 54 sujetos de tres bases de datos, cubriendo 188,419 picos etiquetados. La comparación de los picos detectados con las etiquetas mostró una Tasa de Falsos Positivos (*FDR*) promedio de 0.8027%, una Sensibilidad (*SE*) de 99.6786% y una Predicción Positiva (*+P*) de 99.5225%. Los indicadores de rendimiento computacional confirman la alta eficiencia del método, con una complejidad aproximada de $O(n)$.

Palabras Clave: Detección de picos, fotoplethysmografía, procesamiento de señales.

ABSTRACT.

This work presents a methodology for peak detection using matrix representation of signals, applicable to any type of signal, including those from radar, biomedical, electromagnetic, and other sources. This approach is distinguished by its rapid processing speed, minimal computational complexity, and the elimination of the necessity for level threshold calculations. Furthermore, it effectively handles signals with and without flat zones around the peaks, making it well-suited for embedded systems with memory constraints and limited computational resources. The methodology is validated using photoplethysmographic (PPG) signals to detect systolic peaks in 54 subjects from three databases, encompassing 188,419 labeled peaks. A comparison of the detected peaks with the labels revealed an average False Detection Rate (*FDR*) of 0.8027%, a sensitivity (*SE*) of 99.6786%, and a positive prediction (*+P*) of 99.5225%. The computational performance indicators substantiate the high efficiency of the method, with an approximate complexity of $O(n)$. **Keywords:** Peak detection, photoplethysmography, signal processing.

1. INTRODUCTION.

Photoplethysmography (PPG) is an optical technique used to measure changes in blood volume within the body. Accurate

PPG measurements are crucial for the early detection of cardiovascular diseases (CVD) [1]. A typical PPG signal (see Figure 2, dotted line) exhibits a systolic peak resulting from ventricular contraction, a diastolic peak indicating ventricular relaxation, and a dicrotic notch marking the closure of the aortic valve [2].

Several methods for detecting systolic peaks in PPG signals have been reported [1], [2], [3], [4], [5], [6], [7], [8]. In [1], a Matlab method is developed that increments a counter when the amplitude of the signal at an initial position is less than that at the next position, capturing the rising behavior before the systolic peak. To identify a peak, the count must exceed an adjustable threshold based on the sampling frequency of the PPG signal. This method is called MMPD. The ADT method described in [4] is considered the gold standard for systolic peak detection [1], [7], [9]. It consists of an adaptive threshold detection and a peak correction method. The initial threshold decreases with a constant slope until the amplitude of the PPG signal exceeds it, then follows the signal to its maximum value and defines a new threshold. The second part avoids the detecting of false peaks by defining a time interval after a peak has been found. This method is also implemented in Matlab.

Gradient-type methods [5], [6], [7], [8] use the first derivative of PPG signals. In [5], level thresholds are calculated using the average of segmented PPG amplitudes, identifying samples where the first derivative is zero. Systolic peaks occur where the zero crossing follows a maximum inflection. The method in [6] accumulates positive derivatives within a time window, dependent on the sampling frequency and identifies a systolic peak when the accumulation exceeds a baseline threshold. Methods using level thresholds [3], [5], [6] are sensitive to changes in amplitude and sampling frequency, a drawback noted in [8]. The FDPPG method in [8] uses the area under the curve of a signal derived from the cube of the derivate of the PPG signal. This work has the limitation of requiring the sampling frequency but has the advantage of being a fast method among the gradient methods and does not use level thresholds.

This study presents a methodology based on the gradient method for the precise identification of peaks. The methodology is simple and robust, as it does not require level threshold calculations and works with signals with and without flat zones around peaks. This is crucial for memory-constrained embedded systems with limited processing power. The method is successfully tested on PPG signals from the CapnoBase IEEE TBME RR Benchmark Database [10], the MIT-BIH Polysomnographic Database [11], and the MIMIC-III Database [12], [13]. The CapnoBase database contains ECG and PPG signals from patients undergoing elective surgery or routine anesthesia. The MIT-BIH database contains recordings of various physiological signals during sleep, including PPG. The MIMIC-III database contains measurements from intensive care patients. All of these databases are freely available. Using the reference systolic peak values documented in the databases together with the values obtained by the proposed method, Sensitivity (SE), Positive Prediction ($+P$), and False Detection Rate (FDR) are calculated. These metrics are compared with results of the ADT [4], MMPD [1], and FDPPG [8] methods. In addition, the computational performance metrics are measured for each method, including evaluation of execution time and RAM usage. The proposed method shows an average speed up of 13.909 times over ADT, 7.0158 times over MMPD, and 16.8982 times over FDPPG, making it the optimal choice for peak detection.

2. PROPOSED METHODOLOGY.

The methodology consists of four stages: (1) preprocessing of PPG signals, (2) formation of a matrix T , (3) obtaining the vector of signs, and (4) peak identification. All steps are implemented in Python 3. Figure 1 illustrates the flowchart of the proposed methodology. Here, $f[n]$ represents the pre-processed PPG signal, n denotes the signal samples, T is the matrix obtained by multiplying the matrix representation of the PPG signals with a transformation matrix, V_s is the sign vector, and “peak” refers to the peaks detected by the method.

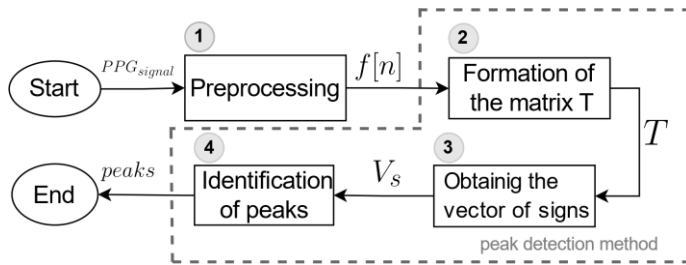


Figure 1. Flowchart of the proposed methodology

2.1. Preprocessing.

In this stage, a one-dimensional Gaussian filter with a standard deviation of 13 is applied. The standard deviation determines the degree of smoothing, which allows the smoothing of the diastolic peak and dicrotic notch, as shown in Figure 2.

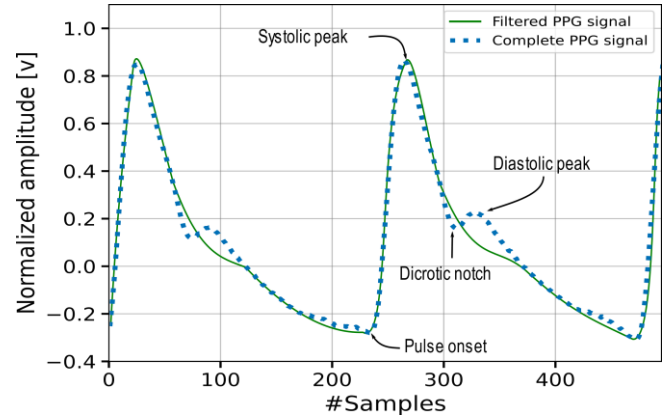


Figure 2. The dotted line represents the preprocessed PPG signal, while the solid line indicates the original PPG signal.

The Gaussian filter can be applied to the PPG signal using the convolution process [14], as shown in equation (1),

$$f = S_{ppg} * G, \quad (1)$$

where G is the one-dimensional Gaussian kernel, created in Python 3 with the command $G = \text{Gaussian1DKernel}(\text{stddev}=13)$ from the Astropy library; S_{ppg} is the PPG signal obtained from various databases; and $*$ is the convolution operator. The f signal must be adjusted to compensate for the phase shift introduced by the filter. This can be done by calculating the maximum delay for the cross-correlation [15].

2.2. Formation of the Matrix T.

In this stage, a matrix T is calculated as follows,

$$T = \begin{bmatrix} f[1] & f[2] & f[3] \\ f[2] & f[3] & f[4] \\ \vdots & \vdots & \vdots \\ f[n-3] & f[n-2] & f[n-1] \\ f[n-2] & f[n-1] & f[n] \end{bmatrix} \cdot \begin{bmatrix} -1 & 0 \\ 1 & -1 \\ 1 & 1 \end{bmatrix}, \quad (2)$$

where $f[n]$ is the n -th sample of the pre-processed PPG signal.

2.3. Obtaining the vector of signs.

In this stage, the sign vector V_s of size $(n-2, 1)$ is calculated by multiplying the first column by the second column of the matrix T , as shown in equation (3).

$$V_s[k] = T[k, 1] \cdot T[k, 2] \quad \forall k \mid k = \{1, 2, 3, 4, \dots, n-2\} \quad (3)$$

Negative values and zeros in V_s represent critical points for identifying signal peaks. The basic principle of the method is to locate the sample where the first derivative changes from positive to negative. For a systolic peak at position k , the

preceding sample, represented by $T[k, 1]$, has a positive value (indicating an increasing trend), and the following sample, represented by $T[k, 2]$, has a negative value (indicating a decreasing trend). The product $T[k, 1] \cdot T[k, 2]$ yields a negative value, which is why negative values are sought in the vector V_s .

It is true that a pulse onset (or trough) also produces a negative value in V_s . Because $T[k, 1]$ would have a negative value and $T[k, 2]$ a positive value, resulting in a negative product $T[k, 1] \cdot T[k, 2]$. Conditionals are used in step 4 to distinguish between a systolic peak and a pulse onset, focusing on identifying the locations of the systolic peaks. In addition, zeros in V_s are of particular interest as they represent peaks with flat zones.

2.4. Identification of peaks.

In this stage, the negative values and zeros present in the vector V_s are analyzed. Negative values correspond to well-defined peaks or trough, as shown in Figure 3. A well-defined peak is identified at the k -th sample when $V_s[k] < 0$, and additionally, $T[k, 1] > 0$ and $T[k + 2, 1] < 0$. Zeros mean flat zones. A flat zone is identified when $m \geq 2$, where m is the number of consecutive samples with $V_s = 0$. If a zero is found within a flat zone, subsequent zeros are ignored to create a new data set with a well-defined peak at position k' . The peak position is the first zero, as shown in Figure 3. A critical point at position k' is considered a peak if $V_s[k'] = \dots = V_s[k' + (m - 1)] = V_s[k' + m] = 0$, and additionally, $T[k', 1] > 0$ and $T[(k' + m) + 2, 1] < 0$.

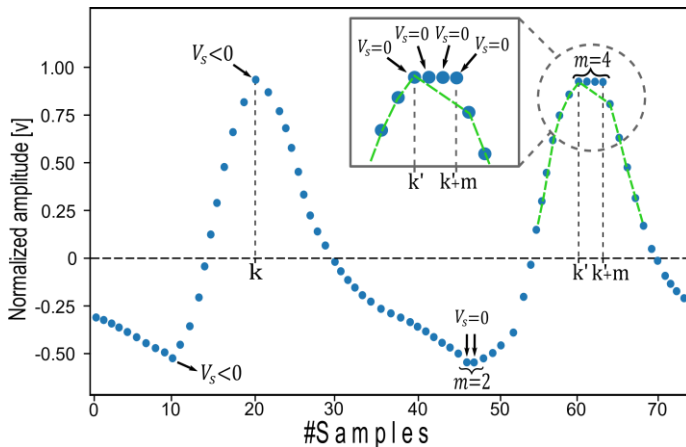


Figure 3. Filtered PPG signal with a well-defined peak and a flat zone.

3. RESULTS AND ANALYSIS OF RESULTS.

The open access databases selected to evaluate the proposed method are CapnoBase IEEE TBME RR Benchmark [10], MIT-BIH Polysomnographic Database [11], and MIMIC Database [12], [13]. These databases provide expert-determined

labels for systolic peaks that serve as references for the calculation of validation metrics. This section presents the validation and computational performance metrics of the proposed method and compares it with the MMPD method [1], the FDPPG method [8], and the ADT method [4]. For a fair comparison, all methods are implemented in Python 3 and executed on the same computer.

3.1. Validation metrics.

The systolic peak detection methods are evaluated using the Sensitivity (SE), Positive Prediction ($+P$), and Failed Detection Rate (FDR) metrics, as shown in the following equations:

$$SE = 100 \cdot \left(\frac{TP}{TP + FN} \right), \quad (4)$$

$$+P = 100 \cdot \left(\frac{TP}{TP + FP} \right), \quad (5)$$

$$FDR = 100 \cdot \left(\frac{FN + FP}{TP} \right), \quad (6)$$

where TP are the correctly detected peaks, FN are undetected peaks, and FP are peaks detected in error.

Table 1 shows the results for the different databases. For the CapnoBase database, PPG signals from 16 subjects with 10,993 labeled peaks are evaluated at a sampling rate of 300 Hz. For the MIT-BIH database, signals from 15 subjects with 50,006 labeled peaks at a sampling rate of 250 Hz are considered. Finally, for the MIMIC database, signals from 23 subjects with 127,420 labeled peaks at a sampling rate of 125 Hz are analyzed. This study evaluates 54 subjects with 188,419 peaks in the CapnoBase IEEE TBME RR Benchmark Database, the MIT-BIH Polysomnographic Database, and the MIMIC Database. This exceeds the scope of previous studies such as [4] with 22,622 labeled systolic peaks; [16] with 8,567; [17] with 17,442; [8] with 23,767; [18] with 87,236; [3] with 15,708; and [19] with 15,710.

It is important to note that optimal efficiency for a peak detection method is achieved when SE and $+P$ values are close to 100% and FDR values are close to 0%. The results show that, on average, across the different databases, the FDR is 2.5904%, 1.9777%, 0.8202%, and 0.8027% for the MMPD, ADT, FDPPG, and the proposed method, respectively. The SE values are 97.8186%, 98.3849%, 99.7021%, and 99.6786% for MMPD, ADT, FDPPG, and the proposed method, respectively. Meanwhile, the $+P$ values are 99.7019%, 99.6926%, 99.4816%, and 99.5225% for MMPD, ADT, FDPPG, and the proposed method, respectively. These results demonstrate that

the proposed method can accurately detect systolic peaks in PPG signals.

Table 1. Validation metric results for the four peak detection methods.

Database	Method	TP	FN	FP	Sensitivity	+P (%)	FDR (%)
Capnobase	MMPD	10952	41	43	99.627	99.6089	0.7670
	ADT	10922	71	40	99.3541	99.6351	1.0163
	FDPPG	10957	36	55	99.6725	99.5005	0.8305
	Proposed	10953	40	46	99.6361	99.5818	0.7852
MIT-BIH	MMPD	49688	318	91	99.3641	99.8172	0.8231
	ADT	49851	155	128	99.6900	99.7439	0.5677
	FDPPG	49927	79	369	99.8420	99.2663	0.8973
	Proposed	49922	84	350	99.8320	99.3038	0.8694
MIMIC	MMPD	120367	7053	387	94.4648	99.6795	6.1811
	ADT	122464	4956	370	96.1105	99.6988	4.3490
	FDPPG	126900	520	410	99.5919	99.6780	0.7329
	Proposed	126869	551	405	99.5676	99.6818	0.7535

3.2. Computational performance metrics.

Systolic peak detection methods are evaluated based on execution time and RAM consumption. Figure 4 shows how much memory is used for PPG signal recordings from 15,312 to 612,500 samples. The figure shows that the ADT and FDPPG methods use more RAM than the others, while the proposed method memory consumption is comparable to that of the MMPD method. Specifically, the ADT method exhibits the highest consumption, peaking at 112.0168 MB, followed by the FDPPG method at 97.0117 MB, the proposed method at 92.9898 MB, and the MMPD method at 91.1567 MB for a signal with 612,500 samples.

Figure 5 displays the execution time plotted against the number of samples, demonstrating that the proposed method outperforms the speed of the ADT, FDPPG, and MMPD methods. All methods exhibit computational complexity of approximately $O(n)$, indicating that their execution time increases linearly with the number of samples in the PPG signal. Figure 5 reveals varying slopes of the straight lines representing each method. Linear regression analysis from samples 122,500 to 1,102,500 identifies the slope for each method: ADT at 244.22 ms, MMPD at 126.28 ms, FDPPG at 300.47 ms, and the proposed method at 16.70 ms. These results demonstrate that the proposed method is significantly faster than existing methods in the literature. For instance, with a signal of 490,000 samples, the proposed method performs 13.8136 times faster than the ADT method, 7.0722 times faster than the MMPD method, and 17.5654 times faster than the

FDPPG method. On average, across all samples, the proposed method is 13.9090 times faster than the ADT method, 7.0158 times faster than the MMPD method, and 16.8982 times faster than the FDPPG method.

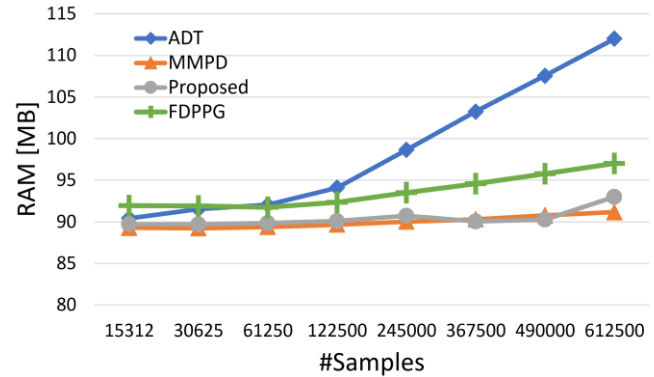


Figure 4. RAM consumption against the number of samples for the different methods.

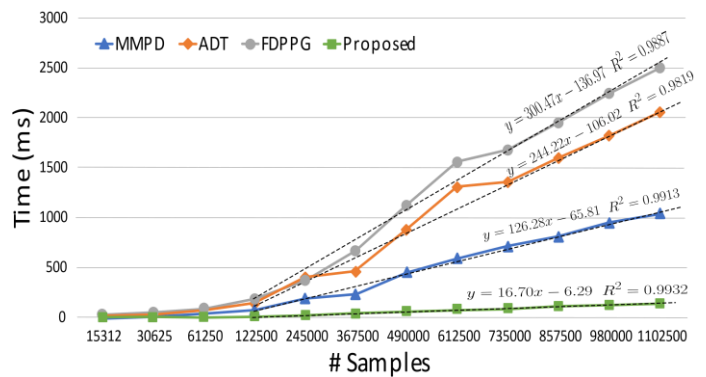


Figure 5. Execution time against the number of samples and their linear regression.

One of the key benefits of adopting the proposed methodology is its capacity to partition a PPG signal into multiple windows, while maintaining accuracy. This feature is particularly advantageous for parallel processing on Central Processing Units (CPUs) and Graphics Processing Units (GPUs).

Figure 6 depicts a segment of a PPG signal extracted from the MIT-BIH database, comprising 800 samples. The signal is partitioned into four windows, each comprising 200 samples, as indicated by the orange dotted lines. Subsequently, the peak detection methods are applied individually within each window. The results presented in Figure 6 demonstrate that threshold-based methods, such as MMPD and ADT, exhibit reduced accuracy when the signal is partitioned in proximity to systolic peaks, thereby limiting their practicality for parallel processing. Conversely, the FDPPG method accurately identifies the four systolic peaks; however, is occasionally produces false positives in proximity to signal transitions, most

notably at Sample 600 in Figure 6(c). In comparison, the proposed method accurately identifies all four peaks without generating false positives.

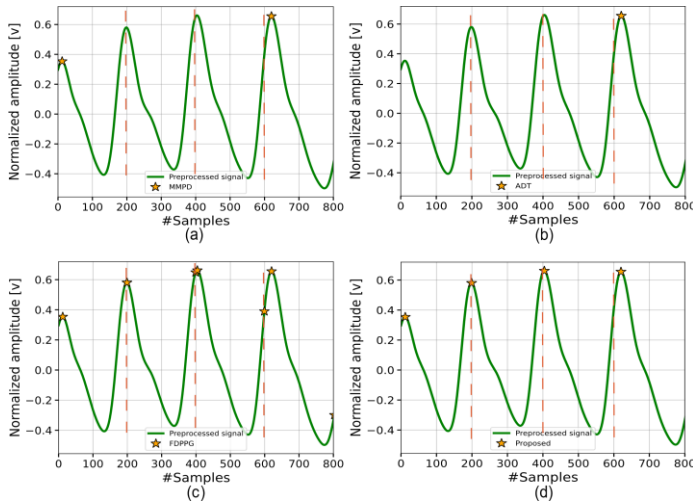


Figure 6. Verification of systolic peak detection by the methods when the PPG signal is partitioned. (a) MMPD method, (b) ADT method, (c) FDPPG method, and (d) proposed method.

Next, a new test is designed to evaluate the temporal performance and RAM consumption on a high sample density signal. This experiment implements a parallel processing approach on the CPU and explores six different scenarios. In the first scenario, the signal is segmented into two windows, each window containing half of the samples, and then processed by two parallel threads. This pattern is repeated in subsequent scenarios, with the number of windows and parallel threads gradually increasing to four, eight, ten, and twenty, respectively. The final scenario runs the signal without parallel processing and without partitioning.

The test uses an artificial PPG signal consisting of 245 million samples derived from successive replicas of a PPG signal extracted from the MIMIC database. In the proposed scenarios with parallel processing, the window sizes range from 122.5 million samples for two parallel threads to 12.25 million samples for twenty parallel threads. Figure 7 presents the results, showing that execution time decreases from 102.84 seconds with two parallel threads to 44.91 seconds with ten parallel threads. Although the methodology without parallel processing is inherently faster, it significantly increases RAM consumption, which peaks at 668.47 MB. For scenarios that require RAM consumption below 668.47 MB to efficiently process large signals, opting for execution with two or four parallel threads proves beneficial in reducing memory consumption.

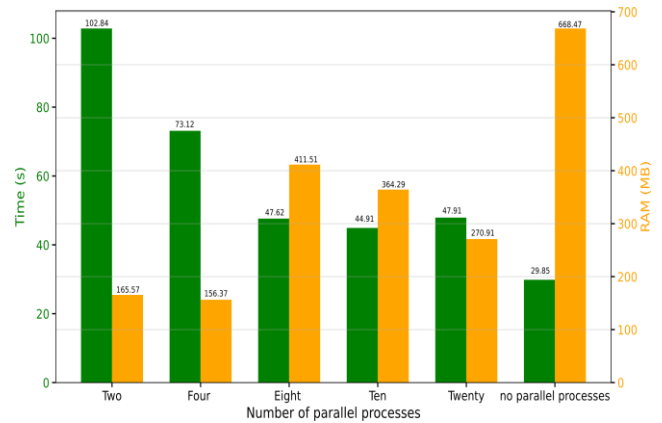


Figure 7. Results of execution time and RAM memory consumption for the proposed method applied to parallel data processing in CPU.

In the final testing phase, the relationship between the Gaussian filter and its effect on the PPG signal is explored by varying the sampling frequency. The effect of the Gaussian filter on the PPG signal varies depending on the sampling frequency. At lower sampling rates, the filter may become too long; while at higher sampling rates, the filter may need to be lengthened to effectively suppress the dicrotic notch. This variability leads to constraints on the filter size within the methodology.

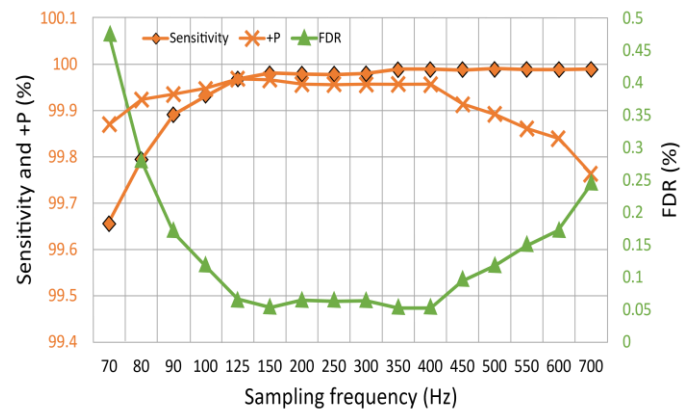


Figure 8. Sensitivity, +P, and FDR results within the 70 Hz to 700 Hz sample rate range.

Figure 8 illustrates the sensitivity, Positive Prediction (+P), and False Detection Rate (FDR) for a PPG signal extracted from the MIMIC database, sampled at 125 Hz and subsequently subjected to oversampling and downsampling to encompass frequencies from 70 Hz to 700 Hz. The results demonstrate that within this frequency range, the filter achieves optimal performance, with sensitivity and +P exceeding 99% and FDR below 0.5%. Outside this range, sensitivity and +P may decline below 99%, while FDR tends to increase, necessitating adjustments to the filter's standard deviation. It is noteworthy

that the peak detection method in stages 2, 3, and 4 operates independently of the sampling rate, ensuring consistent performance.

4. CONCLUSIONES.

This study presents a methodology for peak detection using a matrix representation. The effectiveness of this approach is validated by testing on PPG signals obtained from the CapnoBase IEEE TBME RR Benchmark Database, the MIT-BIH Polysomnographic Database, and the MIMIC-III Database, which include data from hospitalized patients.

The proposed method demonstrates exceptional performance: Sensitivity greater than 99%, Positive Prediction value greater than 99%, and a False Detection Rate less than 0.90%. It also shows reduced memory consumption compared to the ADT and FDPPG methods while comparable to the MMPD method. Execution time analysis showed that this method is the fastest reported, outperforming the ADT, FDPPG, and MMPD methods by 13.909, 16.8982, and 7.0158 times, respectively. This approach offers significant advantages for parallel processing, especially for signals with high sample density, making it a promising method for accurate peak detection.

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