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Comparison of phonendoscopic signal reconstruction techniques for pattern analysis cardiac acoustics

Comparación de técnicas de reconstrucción de señales fonendoscópicas para el análisis de patrones acústicos cardíacos

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Abstract: This study evaluates the effectiveness of different techniques of statistical reconstruction of phonocardiographic signals in comparison with classical processing techniques. The problem statement addresses the stadistical signal reconstruction limitations and the advantages of statistical signal reconstruction techniques. The aim is to determine the precision and classic usefulness of these techniques in term of the signal clarity using the SNR and CF, as well as how to explore its potential for broader integration into clinical practice. The methodology includes a comparative analysis of the reconstructed data using statistical techniques and processed using relevant processing techniques, focusing on signal clarity of the signal and the feasibility of its implementation. The results show a SNR in PCA 17.41 dB compared to the mean SNR in traditional techniques 0.575 dB & a mean CF in PCA 10.948 mV compared to CF average in traditional techniques 10,880 mV, can offer improvements in signal clarity, with advantages in term of cost and accessibility. The conclusions suggest that, the statistical reconstruction techniques have the potential to improve signal quality when combined with other processing techniques. This study provides a critical on the applicability of statistical reconstruction techniques of phonocardiographic signals and their role in improving cardiovascular care.

Keywords: PCA (Principal Component Analysis), Fourier Transform, Heart Sounds, Phonocardiographic Signals, Digital signal processing.

Resumen: Este estudio evalúa la efectividad de diferentes técnicas de reconstrucción estadística de señales fonocardiografíca en comparación con técnicas clásicas de procesamiento. Se presenta el planteamiento del problema abordando las limitaciones actuales y las posibles ventajas de las técnicas de reconstrucción estadística de señales. El objetivo principal es determinar la precisión y utilidad clínica de estas técnicas en cuanto a la claridad de la señal a través del SNR y CF, así como explorar su potencial para una integración más amplia en la práctica clínica. La metodología empleada incluye un análisis comparativo de datos reconstruidos mediante técnicas estadísticas y procesados mediante técnicas de procesamiento relevantes, enfocándose en la claridad de la señal y la viabilidad de su implementación. Los resultados indican que ciertas técnicas de reconstrucción estadística pueden ofrecer mejoras en la claridad de la señal, con un SNR medio en PCA 17.41 dB comparado con el SNR medio en técnicas tradicionales 0.575 dB & un CF medio en PCA 10.948 mV comparado con el CF medio en técnicas tradicionales 10.880 mV. Las conclusiones sugieren que, a pesar de sus limitaciones, las técnicas de reconstrucción estadística tienen el potencial de mejorar la calidad de la señal cuando se utilizan junto con otras técnicas de procesamiento. Este estudio aporta una evaluación crítica sobre la aplicabilidad de las técnicas de reconstrucción estadística de señales fono cardiográficas y su papel en la mejora de la atención cardiovascular.

Palabras clave: PCA (Análisis de Componentes Principales), Transformada de Fourier, Ruidos Cardiacos, Señales Fonocardiografícas, Procesamiento Digital de señales.

1. INTRODUCTION

Cardiovascular diseases continue to be one of the main health concerns worldwide, as they carry a high incidence of morbidity and mortality. Faced with this challenge, various technologies have been developed aimed at improving both the evaluation and treatment of these conditions. Among these innovations, the phonocardiogram has emerged as a key tool for capturing heart sounds. However, the correct interpretation of phonocardiograms can be affected by the presence of noise and the inherent variability in the signals [18].

To address these problems, advanced applications have been developed that use sophisticated technologies to process phonocardiograms with greater accuracy. These applications allow the signals to be adjusted and cleaned using frequency filters, thus facilitating the combination of electrical signals from the heart with the sounds of the cardiac cycle at different auscultation points.

Tools like Matlab have been crucial in this context, since they allow handling large volumes of data and applying complex digital processing techniques. As a result, the use of these technologies has significantly improved the interpretation and classification of cardiac anomalies, allowing for more effective and timely diagnosis [6]. Despite these advances, significant challenges related to the quality and interpretation of stethoscope signals remain. Current techniques face problems such as noise in signals and difficulty in accurately identifying relevant patterns. In this sense, the present research proposes an innovative approach focused on the comparison between statistical reconstruction techniques of phonocardiographic signals and processing techniques. While current techniques focus on digital processing to improve signal resolution, the study seeks to evaluate how statistical reconstruction techniques can offer improvements in the clarity of phonocardiographic signals compared to conventional processing techniques [31].

The proposed approach includes the implementation of statistical reconstruction techniques, such as Principal Component Analysis (PCA), to reduce the dimensionality of the signals and highlight significant patterns. In addition, digital treatment will be applied to eliminate noise and improve the clarity of the signals, ensuring that their fundamental characteristics are preserved. On the other hand, the Fourier transform will be used to analyze the frequency composition of the signals, adjusting the reconstruction and correcting distortions precisely [6].

The need to improve the diagnosis of cardiovascular diseases is, without a doubt, a global priority. The recent publication of the HEARTS Compendium of Essential Clinical Tools 2023 in the Americas, promoted by PAHO, highlights the importance of improving the management of cardiovascular risk and hypertension in primary health care [51]. This compendium presents tools designed for accurate blood pressure measurement, hypertension diagnosis, and treatment adjustment, thereby providing a significant opportunity to reduce deaths associated with cardiovascular disease through a more effective approach to prevention and treatment.

However, the development of quantitative techniques and advanced methods for the analysis of heart sounds has the potential to significantly improve the accuracy and reliability of this diagnostic method. Therefore, the implementation of a digital processing system that uses advanced algorithms, such as Principal Component Analysis (PCA) and Fourier Transform, can overcome these limitations and offer a more accurate and effective tool for the detection of cardiac anomalies. This approach not only addresses complications related to the subjective interpretation of the phonocardiographic signal, but also provides a viable solution in situations where other diagnostic modalities, such as electrocardiogram, are not practical, for example, in patients with burns or amputations [4].

Where the use of phonocardiography (PCG) as a fundamental technique in the analysis of cardiac signals, allows the sounds produced by the heart to be recorded graphically and quantitatively. These sounds, generated during the mechanical movements and electrical events of the cardiac cycle, provide key information for the detection of abnormalities [4]. PCG, in combination with other diagnostic methods, facilitates the accurate evaluation of heart sounds and murmurs, which is crucial for obtaining a reliable diagnosis in the clinical setting. Its ability to capture and analyze heart sounds in relation to cycle events, such as contraction and relaxation of the cardiac chambers, makes it an essential tool for improving cardiovascular diagnosis.

Among the signals captured by PCG, heart sounds play a key role in the identification of cardiac problems. These sounds fall into two categories: systolic and diastolic sounds. The first heart sound (S1), associated with the closure of the mitral and tricuspid valves, and the second sound (S2), produced by the closure of the aortic and pulmonary valves, are the main sounds that reflect the contraction and relaxation phases of the heart. heart. Furthermore, diastolic sounds, such as the third sound (S3) and the fourth sound (S4), provide information about ventricular filling, being useful in detecting abnormalities that affect cardiac function [5]. The precise identification of these sounds, together with the analysis of their frequency and duration [Table 1], is essential to improve the interpretation of phonocardiographic signals and increase the effectiveness in the detection of cardiac pathologies.

***Table 1:** Heart Sounds - Duration & Frequency [3]*

Noise	Duration [s]	Frequency [Hz]
S1	0.1 - 0.12	20 - 150
S2	0.08 - 0.14	50 - 60
S3	0.04 - 0.05	20 - 50
S4	0.04 - 0.05	< 25

Which leads to the process of analysis of phonocardiographic signals, dimensionality reduction and extraction of relevant information being key aspects to improve the clarity and precision of the signals. Principal Component Analysis (PCA) plays a fundamental role in this context, allowing a set of correlated variables to be transformed into a smaller set of uncorrelated variables, called principal components, that preserve most of the original information. The process begins by subtracting the means from the signals to center the data around zero, eliminating possible biases that may interfere with the analysis [20]. Then, the covariance matrix is calculated, which measures how the different characteristics of the signal vary jointly.

From the covariance matrix, the eigenvectors and eigenvalues are obtained, which allow the principal components to be identified. The largest eigenvalues indicate the components that retain the greatest amount of relevant information. By selecting these principal components, it is possible to significantly reduce the amount of data to be processed without losing important information [14]. This facilitates the improvement of the clarity of the phonocardiographic signals, reducing the noise present and ensuring that the most important characteristics are kept intact, which in turn contributes to a more precise and effective analysis of the cardiac signals.

2. GENERAL OBJECTIVE

Develop a system for characterizing phonendoscopic signals using digital processing methods and analysis of principal components subject to performance indicators.

2.1. Specific Objectives

- Search and collect information from recognized databases on phonocardiographic signals of the four valves of the heart: pulmonary valve, tricuspid valve, aortic valve and mitral valve.
- Perform signal processing, including normalization and evaluation of performance indicators such as Signal-to-Noise Ratio (SNR) and Crest Factor (CF).
- Evaluate the results obtained using the paired T test, analyzing the statistical differences in the SNR and CF metrics before and after the preprocessing of the cardiographic phono signals.

3. MATERIALS AND METHODS

3.1. Initial Filtering

The process to characterize the phonocardiographic (PCG) signal begins with the application of the average or moving average filter. This filter is essential for smoothing the signal and reducing high frequency noise. By statistically averaging the signal values over a given time interval, the averaging filter helps eliminate abrupt variations and unwanted artifacts by taking the average of every N consecutive samples of the waveform. [19].

$$y_s(i) = \frac{1}{2N+1}\left(y(i+N) + \sum_{k=1}^{N} y(i-k)\right) \quad (1)$$

Equation (1) defines: ys(i) as the smoothed signal; y(i+N) as the value of the original signal at i + N; and (i − k) as the previous N values of the signal; and N as the number of samples used for smoothing.

Once the averaging filter is applied, the signal envelope is obtained. This step is critical as it highlights amplitude variations over time, facilitating the identification of relevant components in the PCG. The envelope acts as a guide to identify key moments in heart sounds [10].

$$s(t) = \frac{1}{\pi}\int \frac{s(\tau)}{t-\tau}d\tau \quad (2)$$

Equation (2) defines: s(t) as the resulting function; s(τ) as the original function; t as the current time; and τ as the integration variable in the time interval.

Subsequently, a Hanning window is applied for the aortic and pulmonary valve of 10 samples, while for the tricuspid and mitral valve of 110, which optimizes signal filtering and improves the smoothing of transitions for the first 7000 signal data. This type of filtering minimizes the spectral leakage effect, which is vital to obtain a cleaner analysis of the signal characteristics [10].

$$\omega(n) = 0{,}5\left(1 - cos\left(2\pi\frac{n}{N}\right)\right), 0 \leq \eta \leq N \quad (3)$$

Equation (3) defines: w(n) as the window value; N as the total size of the window; and n as the window index.

A 5th order bandpass filter is then implemented to isolate the frequencies of interest within the PCG (20 Hz - 20,000 Hz). This filter allows only the specific frequencies associated with heart sounds to pass through, eliminating components that are not relevant to the analysis [11].

$$H(z) = k\frac{\frac{1}{Q}\frac{s}{\omega_0}}{\left(\frac{s}{\omega_o}\right)^2 + \frac{1}{Q}\frac{s}{\omega_0} + 1} \quad (4)$$

Equation (4) defines: H(z) as the transfer function; k as the gain constant; s as the complex variable; ω0 as the resonance frequency; and Q as the quality factor.

To eliminate external interference, a Notch filter is used that specializes in removing mains frequency noise (60 Hz). This step seeks to improve signal quality and ensure that heart sounds are analyzed without external distractions [40].

$$H(s) = k\frac{\left(\frac{s}{\omega_o}\right)^2 + 1}{\left(\frac{s}{\omega_o}\right)^2 + \frac{1}{Q}\frac{s}{\omega_0} + 1} \quad (5)$$

Equation (5) describes the following: H(s) is the transfer function; H0 is the profit; s is the complex variable; ω0 is the resonance frequency; and Q is the quality factor.

3.2. Principal Component Analysis

To begin, 212 recordings are selected from the CirCor DigiScope Phonocardiogram Dataset, a recognized database. These signals are subjected to a digital treatment that includes noise elimination using filters explained in section III-A, normalization to ensure data consistency, and segmentation into relevant components for detailed analysis [19]. This treatment prepares signals for accurate evaluation of processing techniques.

Next, PCA is used as the main tool to evaluate the effectiveness of the applied techniques. This technique allows reducing the dimensionality of the data, highlighting the most relevant characteristics for the analysis and facilitating the comparison of techniques in terms of their ability to reduce noise and improve signal quality [2]. In parallel, a systematic comparison of current methodologies is carried out, considering their ability to face the technical and practical challenges associated with the interpretation of phonocardiographic signals. To do this, quantitative and qualitative metrics are used to evaluate the performance of these techniques and formulate proposals to overcome the identified limitations [48].

Finally, to evaluate the effectiveness of the techniques, indicators such as the Signal-to-Noise Ratio (SNR) and the Crest Factor (CF) are used. The SNR measures the clarity of the signal compared to the background noise, while the crest factor evaluates the jitter in the data [42]. These indicators are essential to ensure the statistical validity and quality of signal processing, reflecting how advanced techniques can improve the clarity of phonocardiographic signals and facilitate more accurate analysis.

3.3. Indicators

3.3.1. Signal-to-Noise Ratio (SNR)

$$\mathrm{SNR} = 10\log\left(\frac{\text{Signal strength}}{\text{noise potential}}\right) \quad \textbf{(6)}$$

The first indicator, the Signal-to-Noise Ratio (SNR), is a fundamental measure that allows us to understand how much of the signal of interest is present compared to the accompanying noise. In essence, it helps us discern how clear the message we want to extract from our data is amidst the unwanted "noise." A high SNR indicates that the signal is clearly distinguishable from noise, while a low SNR suggests that noise may be dominating the signal, making it difficult to accurately interpret [9]:

3.3.2. Crest factor in the frequency domain

The crest factor in the frequency domain seeks to evaluate how the power of a signal is distributed across the frequency spectrum. Specifically, it measures the relationship between the maximum value of the power spectral density (PSD) and the RMS. This indicator allows you to identify the presence of significant peaks in the signal compared to the average level, providing information about the intensity of high-frequency components or transients present in the signal. [13]:

$$\mathrm{CF} = 10\log\left(\frac{\text{Maximum Absolute value}}{\text{RMS value}}\right) \quad (7)$$

3.3.3. Paired t-test

The paired t test, also called dependent, compares the mean of a group at two different times or under two similar conditions to check if there are significant variations that are not due to chance. For example, if two related data sets are analyzed, this test evaluates whether the observed differences between the two are large enough to be considered important. The assumptions of this test include normality of the dependent variable, independence of observations, and that groups are consistently paired [1].

$$t = \frac{\sum d}{\sqrt{\left(\frac{n(\sum d^2) - (\sum d^2)}{n-1}\right)}} \quad (8)$$

3.4. Sample Description

In this study, existing data were taken from a database where the population was made up of pediatric subjects, that is, children and adolescents aged between 0 and 21 years. Participants were selected in general medical screening campaigns carried out in the northeast of Brazil, a specific region that provides a particular sociodemographic context to the sample. The average age of the participants was 6.1 years, with a standard deviation of 4.3 years, indicating a majority of young children, although the range spanned from newborns to young adults. This phonocardiographic data set was obtained from the CirCor DigiScope Phonocardiogram Dataset, a well-known database used for the analysis of cardiac signals using processing techniques [52].

Following this line, current research focuses on the capacity of two specific methods: Principal Component Analysis (PCA) and digital filtering [20]. The main objective is to compare how each of these approaches approaches the reconstruction of phonocardiographic signals, analyzing not only the structure of the signals, but also the patterns that can be revealed through each technique.

To carry out this comparison, a systematic methodology was designed. A sample of 212 recordings was selected from a total of 5272, for a confidence level of 95\% and a margin of error of 6.61\%, which allowed a representative analysis of cardiac activity in the population studied [52].

4. RESULTS

This section presents the results of the analysis of the phonocardiographic signals corresponding to the four heart valves: aortic, mitral, pulmonary and tricuspid. These results were obtained through the application of advanced digital processing techniques and Principal Component Analysis (PCA).

We will begin with comparisons of the original phonocardiographic signals, with filtering, and the signals treated by PCA and filtering. These visualizations illustrate improvements in signal clarity and stability, highlighting the effectiveness of the methods applied in optimizing the acoustic analysis of each valve.

Subsequently, tables will be presented that summarize the statistical indicators, such as the signal-to-noise ratio (SNR) and the Crest Factor (CF), obtained from the signals of each valve, both before and after the application of PCA. These indicators quantify the improvements observed and are essential to validate the effectiveness of the methodologies used in the study. Additionally, the results of the paired T test, which evaluates the statistical significance of differences in the indicators, will be included, providing solid support for the findings.

4.1. Aortic valve

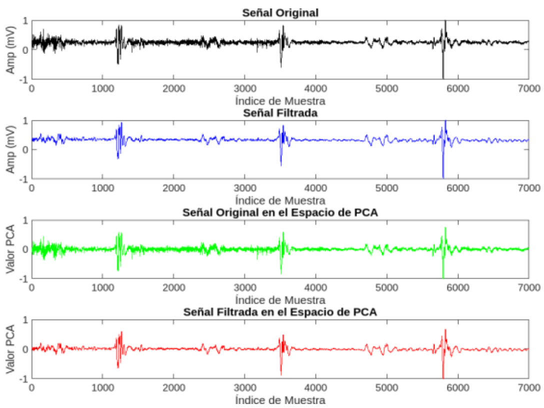

Fig. 1. *Aortic Valve - Principal Component Analysis*

[Fig 1] shows the principal component analysis of the phonocardiographic signals of the aortic valve. The original signal presents noise and a DC component, making the evaluation of valve function difficult. The filtered signal improves clarity by removing unwanted frequencies, while the PCA-processed signal allows for better representation of blood flow, essential for cardiovascular health.

Table 2: *Aortic valve - Crest Factor Effectiveness*

Aortic Valve sign			
	Crest Factor without PCA	**Crest Factor with PCA**	**Difference in the increase PCA**
Average	13.83 mV	13.89 mV	0.07 mV
Standard deriation	6.26 mV	6.22 mV	0.12 mV

T-Paired Test Aortic Valve Signal (CF)	
H Value	**P Value**
1	0.0817 %

Table 2 shows the Crest Factor values for the aortic valve signals, comparing the results before and after applying PCA. They demonstrate that there are improvements in CF, where the p-value of 0.0817% indicates that these differences are statistically significant, suggesting a notable impact of processing on signal quality.

Table 3: *Aortic valve – Effectiveness Signal – Noise Ratio*

Aortic Valve sign			
	Signal Noise Ratio Without PCA	**Signal Noise Ratio With PCA**	**Difference in the increase PCA**
Average	1.69 dB	15.58 dB	13.89 dB
Standard deriation	3.85 dB	4.29 dB	4.81 dB

T-Paired Test Aortic Valve (CF) Signal	
H Value	**P Value**
1	0%

Table 3 presents the Signal-Noise Ratio (SNR) values of the phonocardiographic signals of the aortic valve. A notable improvement in SNR is observed, with a p-value of 0% in the paired T-test, confirming that these improvements are statistically significant and evidence the effectiveness of the applied processing.

4.2. Mitral valve

[Figure 2] shows the principal component analysis of the mitral valve phonocardiographic signals. The original signal presents noise and a DC component, making the evaluation of valve function difficult. The filtered signal improves clarity by removing unwanted frequencies, while the PCA-processed signal allows for better representation of blood flow, essential for cardiovascular health.

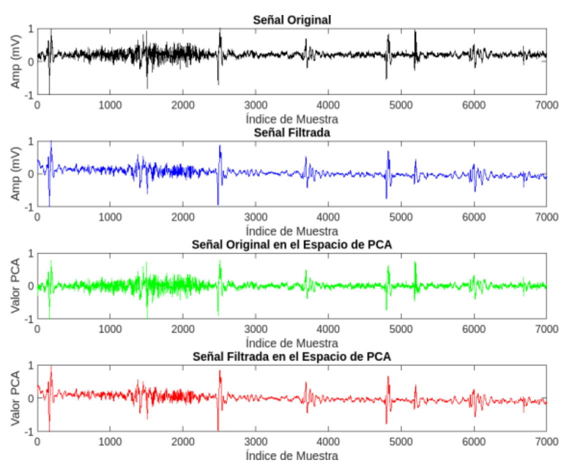

Fig. 2. *Mitral Valve - Principal Component Analysis*

Table 4: *Mitral Valve - Crest Factor Effectiveness*

Aortic Valve Sign			
	Crest Factor without PCA	**Crest Factor with PCA**	**Difference in the increase PCA**
Average	13.83 mV	13.89 mV	0.07 mV
Standard deriation	6.26 mV	6.22 mV	0.12 mV

T-Paired Test Aortic Valve Signal (CF)	
H Value	**P Value**
1	0.0817 %

Table 4 shows the values of the Crest Factor for the mitral valve signals, comparing the results before and after applying PCA. They demonstrate that there are improvements in CF, where the p-value of 0.38671% indicates that these differences are statistically significant, suggesting a notable impact of processing on signal quality.

Table 5: *Mitral Valve - Effectiveness Signal Noise Ratio*

Mitral Valve Signal			
	Signal Noise Ratio Without PCA	**Signal Noise Ratio With PCA**	**Difference in the increase GWP**
Average	-0.58 dB	18.98 dB	19.56 dB
Standard deriation	2.29 dB	5.89 dB	5.43 dB

T-Paired Test Mitral Valve Signal (SNR)	
H Value	**P Value**
1	0 %

Table 5 presents the Signal-Noise Ratio (SNR) values of the phonocardiographic signals of the mitral valve. A notable improvement in SNR is observed, with a p-value of 0% in the paired T-test, confirming that these improvements are statistically significant and evidence the effectiveness of the applied processing.

4.3. Pulmonary Valve

[Figure 3] shows the principal component analysis of the phonocardiographic signals of the pulmonary valve. The original signal presents noise and a DC component, making the evaluation of valve function difficult. The filtered signal improves clarity by removing unwanted frequencies, while the PCA-processed signal allows for better representation of blood flow, essential for cardiovascular health.

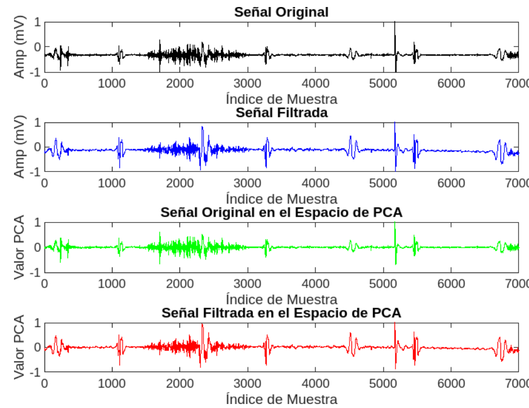

Fig. 3. *Pulmonary Valve - Principal Component Analysis*

Table 6: *Pulmonary Valve - Crest Factor Effectiveness*

Pulmonary Valve Signal			
	Crest Factor without PCA	**Crest Factor with PCA**	**Difference in the increase PCA**
Average	12.03 mV	12.07 mV	0.05 mV
Standard deriation	5.04 mV	5.04 mV	0.13 mV

T-Paired Test Pulmonary Valve Signal (CF)	
H Value	**P Value**
1	2.5276 %

Table 6 shows the Crest Factor values for the pulmonary valve signals, comparing the results before and after applying PCA. They demonstrate that there are improvements in CF, where the p-value of 2.5276% indicates that these differences are statistically significant, suggesting a notable impact of processing on signal quality.

Table 7: *Pulmonary Valve - Effectiveness Signal Noise Ratio*

Pulmonary Valve Signal			
	Signal Noise Ratio Without PCA	**Signal Noise Ratio With PCA**	**Difference in the increase GWP**
Average	2.01 dB	15.78 dB	13.58 dB
Standard deriation	3.93 dB	4.52 dB	5.25 dB

T-Paired Test Pulmonary Valve Signal (SNR)	
H Value	**P Value**
1	0 %

Table 7 presents the values of the Signal-Noise Ratio (SNR) of the phonocardiographic signals of the Pulmonary valve. A notable improvement in SNR is observed, with a p-value of 0% in the paired T-test, confirming that these improvements are statistically significant and evidence the effectiveness of the applied processing.

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4.4. Tricuspid valve

[Figure 4] shows the principal component analysis of the phonocardiographic signals of the tricuspid valve. The original signal presents noise and a DC component, making the evaluation of valve function difficult. The filtered signal improves clarity by removing unwanted frequencies, while the PCA-processed signal allows for better representation of blood flow, essential for cardiovascular health.

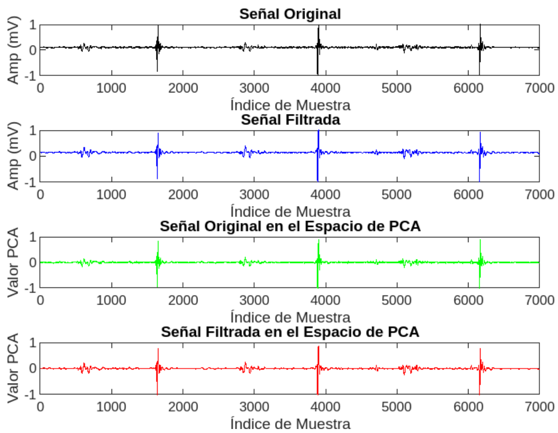

Fig. 4. *Tricuspid Valve - Principal Component Analysis*

Table 8: *Tricuspid Valve - Crest Factor Effectiveness*

Tricuspid valve sign			
	Crest Factor without PCA	**Crest Factor with PCA**	**Difference in the increase PCA**
Average	8.07 mV	8.15 mV	0.10 mV
Standard deriation	2.70 mV	2.78 mV	0.16 mV

T-Paired Test Tricuspid valve signal (CF)	
H Value	**P Value**
1	0.1181 %

Table 8 shows the Crest Factor values for the pulmonary valve signals, comparing the results before and after applying PCA. They demonstrate that there are improvements in CF, where the p-value of 0.1779% indicates that these differences are statistically significant, suggesting a notable impact of processing on signal quality.

Table 9: *Tricuspid Valve - Effectiveness Signal Noise Ratio*

Tricuspid valve sign			
	Signal Noise Ratio Without PCA	**Signal Noise Ratio With PCA**	**Difference in the increase GWP**
Average	-0.82 dB	19.30 dB	19.78 dB
Standard deriation	1.62 dB	5.25 dB	4.91 dB

T-Paired Test Tricuspid valve signal (SNR)	
H Value	**P Value**
1	0 %

Table 9 presents the Signal-Noise Ratio (SNR) values of the phonocardiographic signals of the tricuspid valve. A notable improvement in SNR is observed, with a p-value of 0% in the paired T-test, confirming that these improvements are statistically significant and evidence the effectiveness of the applied processing.

5. CONCLUSIONS

In this study, an analysis of phonocardiographic signals was carried out with the objective of evaluating the effectiveness of digital processing techniques and Principal Component Analysis (PCA). Throughout the research, the signal-to-noise ratio (SNR) and Crest Factor (CF) were significantly improved by eliminating unwanted components. Projecting the data onto the first principal component via PCA is critical because this component captures most of the variability in the data, meaning it represents the most significant characteristics of the signal. In contrast, the following principal components, although they may contain useful information, generally represent minor variations and may be more influenced by noise. This ability to focus on the most important variability not only improves accuracy in calculating signal quality indicators, but also simplifies analysis, making it easier to identify patterns in phonocardiography. These methodologies have high potential for application in clinical practice, where precision in the interpretation of cardiac data is essential.

The signals used in the analysis were extracted from the CirCor DigiScope Phonocardiogram Dataset, which contains recordings of phonocardiograms from patients with various cardiac conditions. The sample used in this study consisted of a representative subset of these recordings, selected to ensure that the signals covered a wide range of frequencies and variations in cardiac behavior. During the preprocessing phase, parameters such as the size of the smoothing window were adjusted, which was increased in some signals to stabilize them and improve their quality before processing.

Signal processing included the implementation of band-pass filters adjusted to capture the relevant heart rates, between 20 Hz and 20 kHz. A Butterworth filter was chosen because of its smooth, ripple-free frequency response, allowing a gradual

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transition between allowed and attenuated frequencies. This type of filter is especially effective in applications where preservation of the signal waveform is critical, such as in the case of phonocardiographic signals. The order of the Butterworth filter was adjusted to optimize the removal of unwanted frequencies; Higher filter order provides a sharper response in cutting off unwanted frequencies, allowing for more effective separation of useful signal components. However, too high an order can cause distortions and artifacts in the signal, negatively affecting its quality. Therefore, it is crucial to select the filter order in a way that maintains the integrity of the signal while improving its clarity.

The application of PCA was fundamental in this process, since it highlighted the most relevant characteristics of the cardiac signals and allowed the data to be projected effectively to calculate indicators such as SNR and CF. To validate the results obtained, the paired T test was used, which is a statistical tool that allows two sets of related data to be compared to determine if there are significant differences between them. This test is particularly suitable in the analysis of signals because it takes into account the variability within them, eliminating the effect of variability between subjects or conditions. By comparing signals before and after applying filtering and PCA techniques, the paired T test provides a robust way to assess whether improvements in SNR and CF are statistically significant, supporting the effectiveness of the methods used.

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