Non-contact Video-based Respiratory Rate Monitoring using Hilbert Motion Magnification

Camilly Costa, Yuri Alencar, Gustavo Castro, Victor Cardoso, João Weyl and Moisés Silva.

***Abstract*— The objective of this study is to propose a fully automatic and contact-free method for the assessment of respiratory function based on user-grade RGB camera technology. The methodology revolves around the application of the Hilbert transform and dimensionality reduction algorithms applied exclusively to the temporal content of video measurements. Originally proposed to perform video-based modal analysis, this work demonstrates its applicability to monitoring respiratory rate in an automated fashion. The approach has the potential to be suited for mobile healthcare applications and telemedicine practices.**

***Keywords*— Non-contact Monitoring, Respiratory Rate, Motion Magnification.**

I. Introduction

Respiratory rate monitoring is crucial for evaluating patients health across diverse clinical scenarios, aiding in the detection of physiological fluctuations and pathological conditions. Rapid recognition of changes and anomalies facilitates timely interventions, particularly crucial in intensive care units and surgical procedures, where continuous respiratory monitoring can avert severe complications and enhance clinical outcomes [1].

Related works exist in this area [2], [3], offering distinct approaches to non-contact vital sign monitoring. In [2], an RGB-D camera system is utilized alongside advanced algorithmic techniques for real-time assessment of respiratory function without physical contact, leveraging depth information to accurately locate regions of interest on the user's body and track respiratory movements.

In contrast, this article evaluates an algorithm, originally designed for modal analysis, to perform respiratory tracking. This technique relies on the application of Hilbert transform and dimensionality reduction algorithms to the temporal content of video measurements, offering potential implications for mobile healthcare applications and telemedicine practices by providing a simpler and more accessible method for respiratory monitoring.

II. Proposed Method

The algorithm, illustrated in Figure 1, combines the Hilbert Transform, Principal Component Analysis (PCA), and Blind Source Separation (BSS) to analyze the pixel time-series of video measurements. It begins by transforming pixel intensity measurements into a representation of pixel displacement over time using the Hilbert Transform. This approach extracts real and imaginary parts of the analytical signal estimated from the video, providing motion information from the scene [4].

Next, PCA is applied to reduce the amount of data, aiming to identify significant eigenvalues corresponding to observable motion patterns in the scene. It is expected that the number of significant eigenvalues will be approximately equal to the number of observable spatial patterns in the scene [5]. Thus, the most important eigenvectors, corresponding to significant singular values, are retained to preserve essential information.

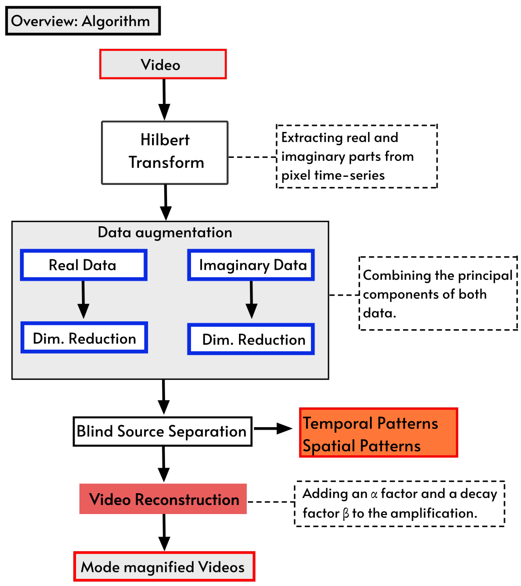

Fig. 1. Flowchart of the proposed video-based monitoring approach.

Subsequently, in the Blind Source Separation (BSS) stage, the temporal displacement series obtained from the principal components is used to generate motion patterns. The columns of the mixing matrix provided by BSS are utilized to expand these motion patterns to all frames in high spatial resolution using the projection matrix obtained from PCA step [6]. The resulting signal sources correspond to the temporal patterns of each mode of motion in the scene [7].

Finally, with the identified motion coordinates, the video can be reconstructed with the new data, allowing for a more in-depth analysis and understanding of motion patterns and dynamics present in the original scene. This integrated approach is particularly useful in applications such as computer vision, video processing, and motion analysis of videos depicting complex motion.

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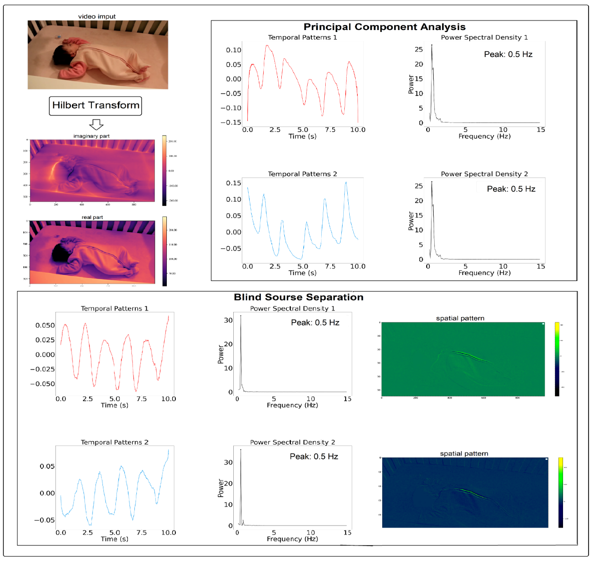

Fig. 2. Spatial patterns and temporal patterns recovered from the original video. Generated from applying BSS to PCA components.

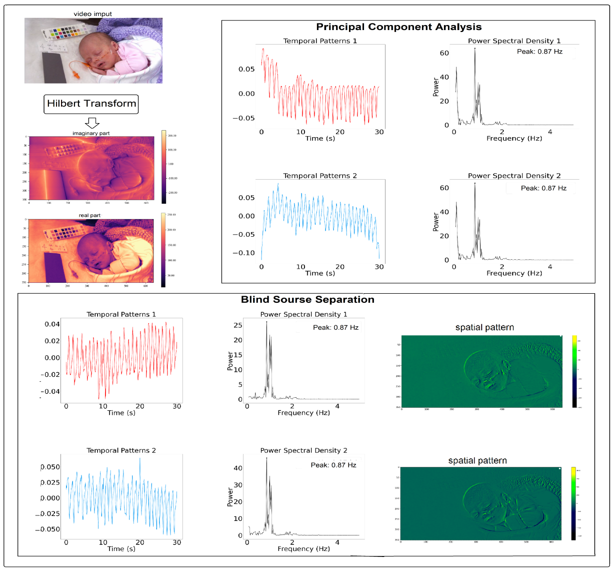

Fig. 3. Spatial patterns and temporal patterns recovered from the original video. Generated from applying BSS to PCA components.

III. Results and Analysis

In this experiment, video of infants under clinical observation were analyzed using the Power Spectral Density (PSD) to measure oscillations per second. This information was used to determine the respiratory rate and compare the results with expected values. The video used for this analysis is publicly available and is originally found in [8].

According to [9], The frequency represents the number of complete oscillations of a wave per second. The respiratory rate for adults at rest varies from 12 to 25 breaths per minute (0.233 to 0.416 Hz), while for newborns at rest, it ranges from 30 to 53 breaths per minute (0.5 to 0.883 Hz).

In Figures 2 and 3, a frequency of 0.5 Hz and 0.87 Hz were estimated, respectively. Based on these results, the respiratory rates were calculated as 30 breaths per minute for Figure 2 and 52 breaths per minute for Figure 3. These values fall within the expected range for infants aged 0 to 12 months. The respiratory rates of the infants in the videos, based on the results observed in the PSD graphs, were estimated using the following formula [9]:

$$RPM = 60f$$

Therefore, we can conclude that the method used to determine the respiratory rate is effective and consistent with clinical expectations for this age group. Additionally, the observation of oscillation modes evidencing thoracic movements reinforces the accuracy of the measurements taken.

IV. Conclusions

This study proposes an advanced and non-invasive technique for respiratory monitoring using video cameras and computer vision algorithms. The method enables the capture and analysis of thoracic movements associated with breathing, using Hilbert transform to calculate pixel-wise phase changes over time. The results demonstrated that the technique is capable to accurately measure respiratory rate, with values within the expected range for the studied age group, suggesting it could be applied in clinical and research settings, although still requiring additional testing and comparison with existing alternatives. Additionally, the approach can be easily automated, making it suitable for long-term monitoring in patients with respiratory issues.

V. Acknowledgements

It was supported by the Laboratory of Applied Electromagnetism (LEA) at the Federal University of Pará. Furthermore, the authors acknowledge that this study was financed in part by the Amazon Foundation to Support Studies and Research (FAPESPA), Grant agreement 050/2023. It was also financed by the São Paulo Research Foundation (FAPESP) with the support provided by grant 2022/10105-3, as well as the National Council for Scientific and Technological Development (CNPq). Additionally, the authors gratefully acknowledge the financial support provided by the Instituto Sustentabilidade da Amazônia com Ciência e Inovação (ISACI).

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