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# A photoplethysmography-based system for talking detection in bedridden patients

Erick Javier Argüello-Prada *, María Alejandra Dávalos Cantín, Juan Camilo Victoria

*Programa de Bioingeniería, Facultad de Ingeniería, Universidad Santiago de Cali, Calle 5 # 62-00 Barrio Pampalinda, Santiago de Cali, Valle del Cauca – Colombia, Código Postal: 760032, Cali, Colombia*

A R T I C L E I N F O

*Keywords:*
Talking detection
Speech events
Photoplethysmography
Bedridden patients
Effect size-based feature selection

A B S T R A C T

*Background and objectives:* Verbal interaction may help bedridden patients to manage or prevent frustration, anxiety, and depression caused by the restrictions they find when performing daily living activities. In this regard, automatic monitoring of how long and often bedridden patients talk could help to identify who is at risk. A considerable body of work has focused on using sensing devices to capture and quantify speech events. However, such approaches may raise privacy concerns and produce discomfort. This study introduces a non-invasive, easy-to-deploy, and privacy-protective system based on photoplethysmography (PPG) to detect talking in bedridden patients.

*Method:* Raw finger PPG signals were acquired from 36 participants who were lying in a bed for six minutes within which they were allowed to talk. We averaged six features extracted from PPG records and investigated statistically significant differences and effect sizes between silence and talking periods. Features showing statistically significant differences and moderate-to-high effect sizes were normalized to train a single perceptron and a binomial logistic regression.

*Results:* The absolute amplitude, the pulse amplitude, and the interpulse interval of PPG waveforms decreased significantly with talking and showed moderate-to-high effect sizes. Using the abovementioned features, the perceptron and the logistic regression achieved classification accuracies of 88.89% and 94.12%, respectively.

*Conclusions:* Results showed that it is possible to detect speech events in individuals with restricted mobility by tracking changes in the PPG signal's contour. Future work should aim to discriminate talking-driven effects on PPG signals during physical activity and establish validation criteria for correctly identifying speech events.

## 1. Introduction

In many cases, patients have to remain bedridden for extended periods. Under such circumstances, daily life activities like dressing or walking to the toilet cannot be performed independently. This lack of personal control imposed by bed confinement may have negative psychological effects on patients, their relatives, and even their caregivers [1–3]. On the other hand, social interaction has been regarded as a predictor of decreased morbidity and mortality, and its positive influence on well-being has been well documented [4]. In an attempt to contribute to the prevention or management of frustration, anxiety, and depression in bedridden patients, several strategies focused on facilitating social interaction have been adopted. In this regard, monitoring the social activity of bedridden patients plays a fundamental role.

Given that verbal communication is a key component of social interaction, several methods have been developed to monitor how long and how often individuals talk to each other. Traditional approaches include the utilization of questionnaires through which subjects can report their interactions. However, people often forget those with whom and how long they communicate. In this sense, there is a need for novel approaches able to avoid or reduce recall failures and subjectivity bias of surveys. A considerable body of work has mainly focused on using microphone-based or camera-based systems to capture and quantify speech events [5–8]. Although promising in terms of accuracy, such systems give rise to several issues. First, environmental noise and sources other than the voice of the monitored subject may interfere. Second, the awareness of being recorded may influence people's social interaction patterns. Third, the recording technique must be privacy-sensitive to discard any information that might be deemed as private to the users and, in turn, preserve data useful for analysis. In an attempt

* Corresponding author.
*E-mail address:* erick.arguello00@usc.edu.co (E.J. Argüello-Prada).

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to provide an alternative that does not raise privacy concerns, several efforts have aimed to detect talking events by capturing physical or physiological manifestations of speech. For instance, Matic and colleagues [9] developed an accelerometer-based talking detection system that senses the phonation-caused vibrations at the chest level. Other approaches involve detecting changes in the respiratory pattern by using inductive plethysmography sensors [10–12]. Still, wearing these sensors over extended periods may produce discomfort and attract undesirable social attention to the monitored subject.

Photoplethysmography (PPG) is a simple and low-cost technique by which it is possible to acquire clinically relevant information about the human body [13]. This technique uses a light source and photodetector to capture the wave-like motion of the blood through the vessels. When the light source illuminates the tissue, the photodetector converts the variations in reflected or transmitted light intensity resulting from blood flow into an electrical signal, known as the PPG signal. Previous work has shown that speech events may increase sympathetic and parasympathetic activity [14]. In turn, talking-induced elevation in sympathetic tone can elevate heart rate (HR) and reduce peripheral circulation, as reported by earlier studies [15,16]. Based on the above-mentioned limitations of current alternatives for automated monitoring of verbal interaction, and given that bedside monitors include pulse-oximetry probes that can be easily attached to the patient's finger, the present study aims to propose a novel PPG-based system to detect talking events in bedridden patients. The advantages of this novel approach include its privacy-protective nature and easy-to-deploy character.

## 2. Methods

### 2.1. Subjects

We included thirty-six participants (19 male and 17 female) with ages ranging from 20 to 54 years (mean $\pm$ SD age of 24.54 $\pm$ 6.80 years). All volunteers signed an informed consent form before participation, and none had known cardiovascular or respiratory diseases. The study protocol was approved by the Ethics Committee of the Engineering Faculty of the Universidad Santiago de Cali, Colombia (registry code 052).

### 2.2. Signals' acquisition and preprocessing

We used a reflective PPG sensor consisting of a light-emitting diode (IRL80A, OSRAM Opto Semiconductors) and an NPN phototransistor (LPT80A, OSRAM Opto Semiconductors). The IRL80A is a gallium arsenide infrared emitting diode whose peak emission is at 950 nm, thereby matching the maximum photosensitivity wavelength of the LPT80A phototransistor. PPG sensor output was band-pass filtered with a cut-off frequency from 0.5 to 10 Hz and recorded at 100 Hz with a microprocessor-based data acquisition system. After digitalization, raw PPG signals were transmitted to a computer Laptop (Intel Core i3-3217U CPU at 1.8 GHz; 4 GB of memory) for offline processing.

### 2.3. Experimental protocol

The experiment lasted 6 min, and it was composed of three phases: (1) baseline phase, (2) talking phase, and (3) recovery phase. Each phase lasted 2 min, and the participants were lying in a bed during the procedure with the PPG sensor clipped on the index finger. We also asked them to maintain their posture to simulate bed confinement status. Volunteers remained silent during the baseline (B) and recovery (R) phases. In the talking phase (T), they talked continuously about what they did last week.

### 2.4. Signals' processing and statistical analysis

Raw finger PPG signals were digitally filtered with a finite impulse response (FIR) band-pass filter (0.5–10 Hz) to reduce high-frequency contamination. We computed the PPG features listed in Table 1 by extracting the amplitude and temporal location of signals' peaks and troughs (see Fig. 1). To obtain peaks and troughs information, we implemented an optimized version of the method described in [17], which has proven to provide accurate interpulse information when the signal amplitude is highly variable. The algorithm identifies the systolic rising edge preceding the pulse by verifying that the amplitude of the current sample is higher than that of the previous one. A counter increases by one until the condition is unsatisfied (i.e., the slope sign changes from positive to negative). If the counter reaches or exceeds a certain threshold, then the upslope may correspond to a new pulse. Conversely, if the counter does not reach the threshold, that upslope is ignored, and the counter resets.

Averages of feature values over each 2-min segment (baseline, talking, and recovery) were calculated for each participant and entered into a Microsoft Excel spreadsheet. Then we examined the distribution of the differences between baseline and interventions (i.e., baseline-talking and baseline-recovery) by using a Kolmogorov-Smirnoff test with the Lilliefors correction. Statistically significant differences between pairwise comparisons were assessed using a paired $t$-test or Wilcoxon signed-rank test, as appropriate. A $p$-value $< 0.05$ was regarded as statistically significant. We computed effect sizes by dividing the difference mean by the average of the standard deviations, as recommended in [18]. All the signal processing was performed in Matlab (The Mathworks Inc., Natick, USA), and the statistical analysis was conducted using R statistical software [19]. Fig. 2 outlines the PPG-derived feature computation and averaging preceding the statistical analysis.

### 2.5. Classification models and validation

Features showing statistically significant differences between baseline and talking phases, as well as moderate or high effect sizes, were normalized by calculating the percentage of change from their baseline averages for each participant, which expresses as:

$$\%change = 100 \times \frac{Intervention\ \ average - Baseline\ \ average}{Baseline\ \ average}, \tag{1}$$

where intervention averages correspond to the mean values computed from the talking and recovery phases. A single perceptron and a binomial logistic regression were trained with the baseline-talking and baseline-recovery normalized differences, which were labeled as 0 and 1, representing "talking" and "silence" segments, respectively. We assessed each model's performance using the leave-one-subject-out cross-validation (LOSOCV) strategy, in which one sample is separated from the data and used as a test subject. Five well-known metrics were chosen for performance assessment: precision, sensitivity, specificity, F1-score, and accuracy (see equations 2–6):

**Table 1**
The six PPG–derived features considered for this study.

| Notation | Description | Feature |
|---|---|---|
| $f_1(i)$ | The absolute amplitude of the $i$-th pulse | $y_{pk}(i)$ |
| $f_2(i)$ | The amplitude of the $i$-th pulse | $y_{pk}(i) - y_{tr}(i)$ |
| $f_3(i)$ | The time difference between adjacent peaks | $t_{pk}(i+1) - t_{pk}(i)$ |
| $f_4(i)$ | The amplitude difference between adjacent peaks | $y_{pk}(i+1) - y_{pk}(i)$ |
| $f_5(i)$ | The amplitude difference between adjacent troughs | $y_{tr}(i+1) - y_{tr}(i)$ |
| $f_6(i)$ | The area of the $i$-th pulse | $[y_{pk}(i) - y_{tr}(i)] \times [t_{tr}(i+1) - t_{tr}(i)]$ |

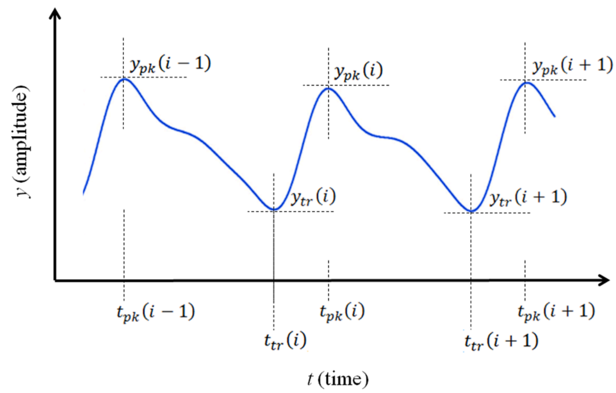


**Fig. 1.** A typical PPG signal showing the fiducial points to define the five features considered for this study. Whereas $y_{pk}(i)$ and $y_{tr}(i)$ represent the amplitude of the peak and the trough of the *i*-th PPG pulse, $t_{pk}(i)$ and $t_{tr}(i)$ represent the time at which the peak and the trough occur, respectively.

$$Precision = 100 \times \frac{TP}{(TP + FP)}, \tag{2}$$

$$Sensitivity = 100 \times \frac{TP}{(TP + FN)}, \tag{3}$$

$$Specificity = 100 \times \frac{TN}{(TN + FP)}, \tag{4}$$

$$F1\_score = 100 \times \frac{TP}{\left(TP + \frac{1}{2}(FP + FN)\right)}, \tag{5}$$

$$Accuracy = 100 \times \frac{(TP + TN)}{(TP + TN + FP + FN)}. \tag{6}$$

A true positive (TP) occurs when a "talking" segment is correctly labeled as such by the model, whereas a true negative (TN) occurs when a "silence" segment is labeled as such. If a "talking" segment is labeled as a "silence" segment, it will count as a false negative (FN). Likewise, If a "silence" segment is labeled as a "talking" segment, it will count as a

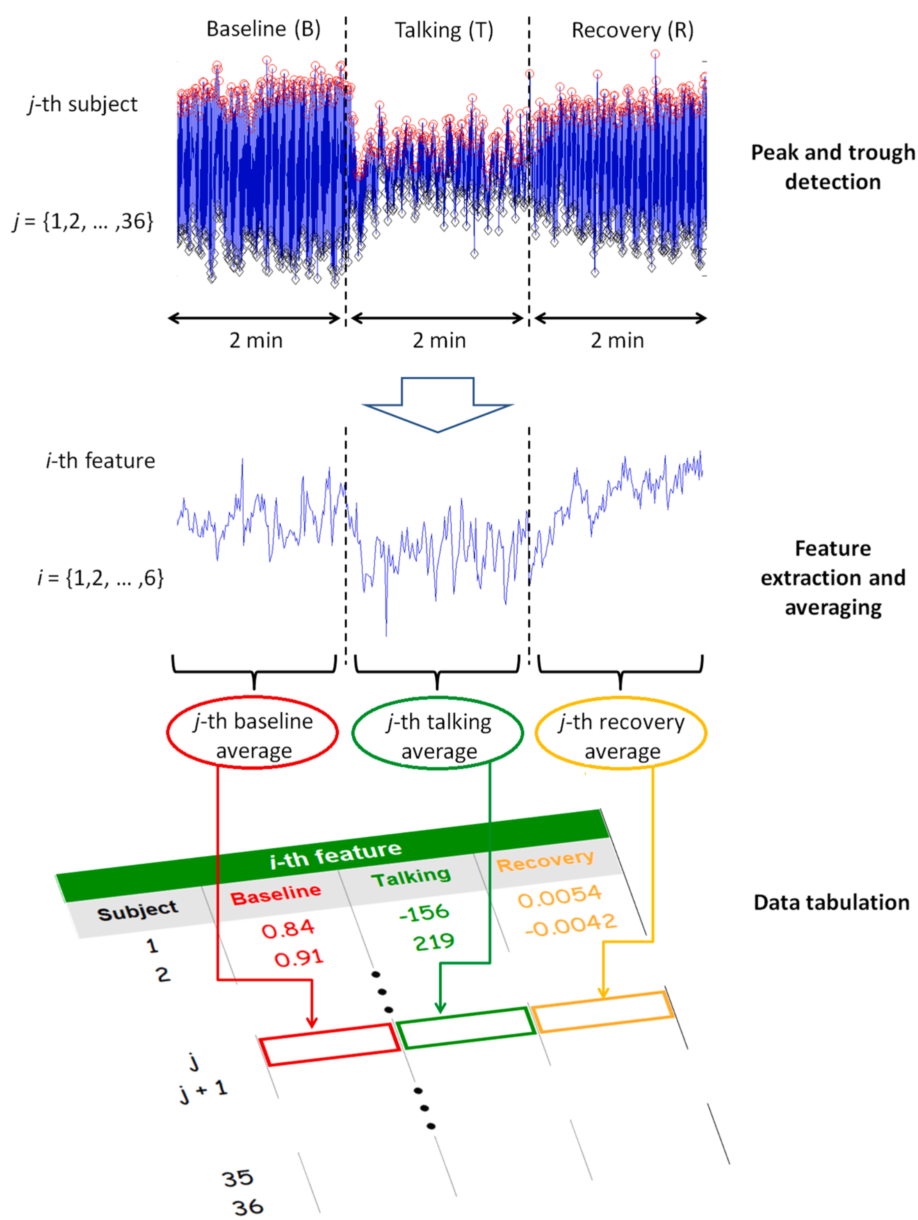


**Fig. 2.** Graphical summary of feature computation and averaging.

false positive (FP).

### 2.6. Online implementation

The classifier showing the best performance was implemented in another MATLAB code for real-time detection of speech events. As shown in Fig. 3, PPG-derived features are computed pulse-by-pulse, and averages over the first 30 s are set as baselines. Once a peak-trough pair is detected, the result is held until the next detection. The classifier takes the percentages of change as inputs, and the decision on whether or not the subject is talking is made by a hard-limiter function.

We used a KY037 sound sensor as ground truth for talking detection. One subject was instructed to lie down in the same bed used during the experimental phase and keep quiet during the initial 30 s. After that, the subject was asked to talk for five minutes.

## 3. Results

According to the results of the Kolmogorov-Smirnoff test, differences or paired data had a normal distribution for all the six features computed from the 36 PPG recordings. Paired *t*-test revealed a statistically significant effect of talking on features 1, 2, 3, and 6, while no significant differences were found between baseline and recovery averaged values.

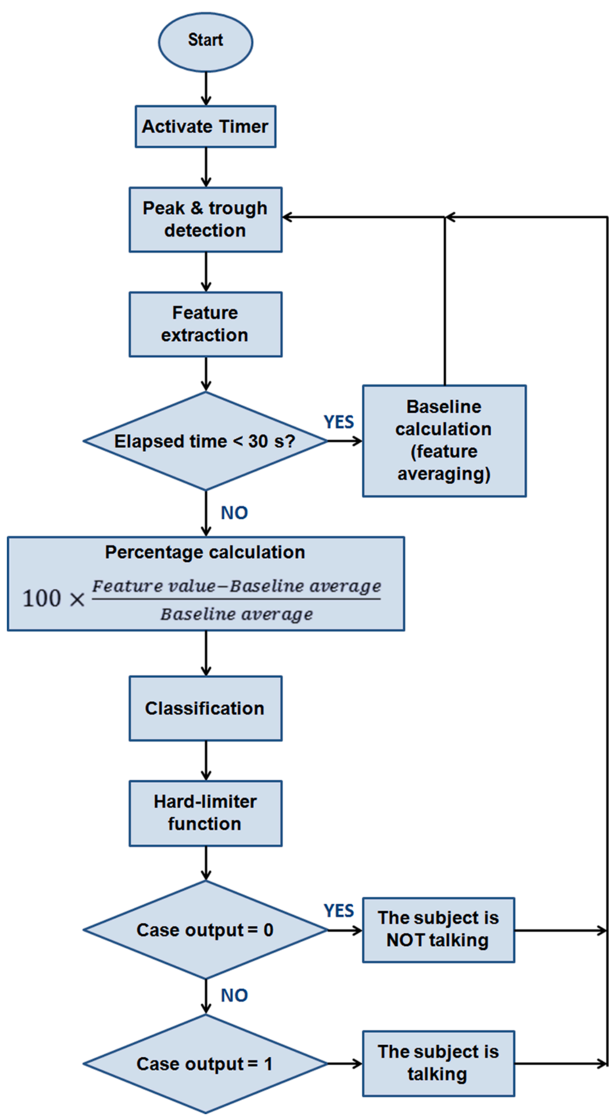


**Fig. 3.** Workflow for real-time detection of talking events.

As illustrated in Table 2, the pulse amplitude, the interval between adjacent pulses, and the product between the pulse amplitude and the interpulse interval, showed the largest effect sizes. Table 3 summarizes percentages of change from baseline during talking and recovery phases of the abovementioned features.

From Table 3, it can be seen that the binomial logistic regression model showed higher specificity, precision, and accuracy than that achieved by the perceptron. Each iteration yielded a specific combination of the β-coefficients of the independent variables (including the intercept), and by using a maximum-likelihood estimator to adjust the β-coefficients, we implemented the logistic regression as follows:

$$y = 5.31 - 2.78 \times f_2 - 2.88 \times f_3 + 2.62 \times f_6, \quad (7)$$

where the value of $y$ is taken by the hard-limiter function (see Fig. 3) and set 0 or 1 for silence and talking segments, respectively. Fig. 4 illustrates the result of the implementation.

## 4. Discussion

The non-invasive character of photoplethysmography (PPG), along with the fact that PPG signals are the result of very complex interactions between cardiac, respiratory, and autonomic functions [13], has opened up new possibilities in using PPG sensing technologies for remote monitoring of heart rate (HR) and other clinically relevant indexes related with cardiovascular condition [20,21]. In this study, we developed a PPG-based system for monitoring how long and often bedridden patients talk. Individuals who have to remain bedridden for a long term may find severe limitations in activities of daily living, which, in turn, could lead to feelings of loneliness, anxiety, and depression [2,22]. The good news is that those feelings can be prevented through several strategies facilitating social interaction. As healthcare resources are limited, it would be desirable to accurately and automatically identify patients with a low level of social interaction, which may help determine whether or not an intervention is necessary. Due to its non-invasive, easy-to-deploy, and privacy-protective nature, a system like the one we introduced could be more convenient than previous approaches aiming to detect speech events [5,12].

A univariate feature selection method based on the effect size yielded classification accuracies of 88.89 % and 94.12 % for a single perceptron and a binomial logistic regression, respectively. Both classifiers showed an F1-score of 81.92 % (single perceptron) and 94.12 % (logistic regression), which was greater than that achieved by Cámbara and colleagues [23], who implemented different Convolutional Neural Networks (CNN) architectures to detect speech events for authentication processes (F1-score = 64.7 ± 0.3, $n$ = 31). We finally implemented the

**Table 2**
Mean (standard deviation) values of the six features computed from PPG recordings. Larger effect sizes are highlighted in bold. Features 1, 2, 4, and 5 are expressed in volts, while features 3 and 6 are expressed in milliseconds and volts × milliseconds, respectively.

| Feature | Baseline (B) | Talking (T) | Recovery (R) | *p*-value | | Effect size (B – T) |
|---|---|---|---|---|---|---|
| | | | | B - T | B - R | |
| 1 | 2.81 (0.73) | 2.60 (0.77) | 2.79 (0.75) | < 0.001 | 0.9822 | 0.28 |
| 2 | 0.93 (0.38) | 0.66 (0.31) | 0.95 (0.37) | < 0.001 | 0.6364 | **0.77** |
| 3 | 0.81 (0.11) | 0.76 (0.09) | 0.80 (0.13) | < 0.001 | 0.3928 | **0.61** |
| 4 | −0.01 (0.00) | −0.03 (0.00) | −0.01 (0.00) | 0.6312 | 0.8671 | 0.14 |
| 5 | −0.01 (0.00) | 0.00 (0.00) | −0.02 (0.00) | 0.2065 | 0.7589 | 0.35 |
| 6 | 0.42 (0.17) | 0.28 (0.12) | 0.40 (0.18) | < 0.001 | 0.4363 | **0.97** |

**Table 3**
Classification results.

| Classifier | Precision | Sensitivity | Specificity | F1-Score | Accuracy |
|---|---|---|---|---|---|
| Single perceptron | 83.33 % | 97.22 % | 80.56 % | 81.92 % | 88.89 % |
| Binomial logistic regression | 94.12 % | 94.12 % | 94.12 % | 94.12 % | 94.12 % |

logistic regression because the consequences of being wrongly classified as socially isolated (i.e., a high false negative rate) are minimal compared to failing to spot a patient as socially active (i.e., a high false positive rate).

According to Table 2, the absolute amplitude, the pulse amplitude, and the interpulse interval of the PPG waveform decrease significantly with talking. Previous research has found that talking may increase sympathetic activity [14], which, in turn, elevates heart rate and causes vasoconstriction. Furthermore, several authors have reported that the psychological load during several stress-inducing tasks, such as reading, writing, and solving mathematical problems, is insufficient for activating the sympathetic when done in silence [14,15]. However, some stressful situations may also significantly enhance the sympathetic tone and, thus, provoke changes in the PPG contour similar to those driven by talking [24,25]. Likewise, motion artifacts may still be present and, thus, produce changes in PPG waveforms that may lead to false detections (see Fig. 4). In this sense, the respiratory pattern could provide more discriminating information for classification. Previous studies have reported that inhalation-exhalation ratios decrease during speech tasks, mainly due to vocalization causing individuals to expire more than when they keep quiet [10,11,26]. As respiration modulates blood volume pulse [27,28] it would be feasible to extract respiratory patterns and features from PPG signals. This information could be helpful to assess whether or not the above-mentioned changes are specific to talking. With regard to motion artifacts, talking-induced changes are likely to last more than artifact-induced changes [29], so one factor to consider for correctly identifying speech events could be the duration of the corresponding alert.

One novel aspect of this work is the utilization of not only statistically significant differences but also effect sizes for selecting the features that contribute to classification. Whereas the use of statistical significance for feature selection is well-documented [30,31], studies reporting the usefulness of the effect size in this matter are scarce [32]. On the other hand, researchers should be cautious when using statistical significance as a measure of separability since it depends on the sample size. A meaningless difference could become “significant” if the sample size is large enough, which is not the case for the effect size [33,34]. While statistical significance examines whether differences are likely due to chance, effect size indicates how relevant the differences are in a practical context (e.g., a class-separation problem). In this study, only three of the six PPG-derived features defined in Table 1 showed moderate-to-high effect sizes (see Table 2). As reproducibility depends on the statistical power and high effect sizes yield high statistical power [35], it becomes necessary to report whether the magnitude differences are not only significant but also meaningful.

Several limitations can be found in the present study. First, only healthy individuals participated in the experiment, so further research is needed to examine the usefulness of the current results in clinical populations. Second, we used a locally-designed system for acquiring and processing PPG signals. Therefore, using proprietary equipment for these purposes may substantially alter the results. Third, parameters like the inflection point area ratio (IPA), the augmentation index (AI), and the stiffness index (SI) were overlooked. On the other hand, we decided to focus on general PPG waveform features that did not require the identification of the diastolic peak and the dicrotic notch, as they can hardly be detected in older adults’ records [36]. Finally, only short-term records were used for identifying differences between features’ mean values. Nevertheless, we considered the potential discomfort and physiological effects of remaining bedridden for extended periods, so we limited recording sessions to several minutes per subject.

## 5. Conclusion

Automatic monitoring of verbal interaction in bedridden patients may help to identify whether there is a risk of developing depression or anxiety, which, in turn, have been regarded as predictors of increased morbidity and mortality. The present study showed that it is possible to detect speech events in patients with bed confinement status by tracking changes in the absolute amplitude, the pulse amplitude, and the interpulse interval of the PPG waveform. Several two-class separation problems, like the one we just addressed, might be benefit from considering features showing not only statistically significant

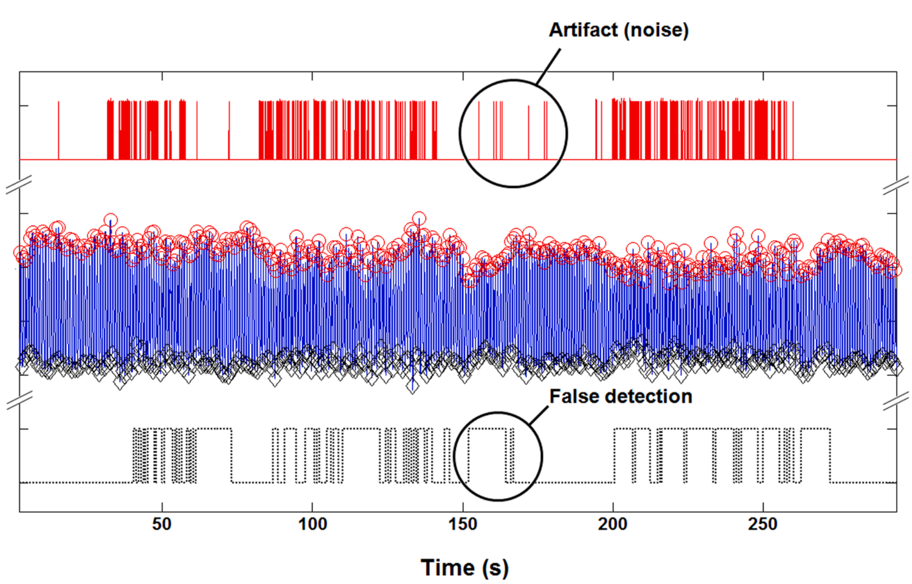


**Fig. 4.** Online implementation of the proposed system for talking detection. The solid red, the solid blue, and the black dotted lines indicate the audio signal, the PPG signal, and the system output, respectively. Detected peaks and troughs are labeled as red circles and black diamonds.

differences but also moderate-to-high effect sizes. However, changes in PPG-derived parameters caused by talking may not be observable during physical activity. In this sense, further research should aim to discriminate the effect of talking on the PPG contour during dynamically active periods and establish validation criteria for correctly identifying speech events.

## CRediT authorship contribution statement

**Dávalos Cantín:** Investigation, Methodology, Software, Validation, Writing - original draft, Writing - review and editing. **Victoria:** Data curation, Investigation, Methodology, Validation, Visualization, Writing - original draft, Writing - review and editing. **Argüello-Prada:** Conceptualization, Data curation, Investigation, Methodology, Writing - original draft, Writing - review and editing.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Data will be made available on request.

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