ECG Signal Extraction from Intensive Care Unit Monitor Videos

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ECG Signal Extraction from Intensive Care Unit Monitor Videos

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Abstract— **Computer Vision (CV) application benefits the health area, notably in its applications for assistive technologies and objective and in-depth analysis of biomedical images. However, there are currently no CV resources that innovate by collecting patients' vital signs directly from the ICU (Intensive Care Unit) medical equipment panel. Thus, the present work goal was to extract the electrocardiogram (ECG) signal from ICU monitors. The approach consisted of transforming ECG monitor signals into one-dimensional digital signals by segmenting them into frames, then extracting the segmentation's upper contour. We used nine heart monitor screen recordings (videos) available on YouTube as a database. The segmentation results validate using the Dice coefficient. Two frames of every recording were validated, generating 18 validations and an average Dice of 90.02 ± 5.74. We concluded that the approach proposed can extract ECG images from videos of Intensive Care Unit monitors and transform them into a signal in the time domain. It can help future ECG assessments, via computation vision, regarding the changes in heart rhythm (arrhythmias). It can also help circumvent limitations to access the ECG in Intensive Care Units by using, for example, a simple video camera, such as those of cell phones, close to the monitor. Such an innovative approach, in turn, would allow obtaining and transmitting the signals to the computer that will be responsible for its analysis.**

Keywords— **ECG signal, segmentation, image processing, Intensive Care Unit monitor.**

I. Introduction

Computer vision (CV) is a technology that seeks to emulate human vision to automate image analysis, obtain high precision in this process and save time [1]. CV application benefits the health area, notably in its applications for assistive technologies and objective and in-depth analysis of biomedical images [2]. CV is also applicable to intensive care units [3], Homecare, and telemedicine [4], avoiding using storage devices, such as hard disks or memory cards.

Some of these demands may involve programming with a high level of complexity and high technology for the use of CV, which makes its implementation in the daily routine of a hospital or clinic unfeasible. Developing systems that demand processing in personal computers is highly indicated for these cases.

Currently, no CV resources innovate by allowing, for example, the visual inspection, reading, and interpretation of the patient's vital signs from the medical equipment panel itself. That would help, for example, collect information from the electrocardiogram (ECG), the pressure curve, and the oxygen saturation value of patients on Intensive Care Unit (ICU) monitors.

Concerning precisely the ECG signal, the first challenge in seeking its interpretation is to be able to extract it correctly from the ICU monitor screen. That is precisely the objective of this work. Specifically, as a first step in using CV for ECG analysis in medical equipment panels, this work intends to develop a computational tool based on the segmentation technique that extracts the ECG image and its amplitude and time scale from videos recorded from ICU monitor screens.

II. Methods

The general goal is to extract ECG images from ICU monitors to be turned into a signal (over time). The idea is that the turned ECG could be understood and treated as the ECG signal itself.

The database used contains nine heart monitor screen recordings available on YouTube. The following criteria were applied to choose the videos with the help of a physician:

1) The ECG signal should be shown in green color (ICU's monitors normally use this color to show the ECG signal);

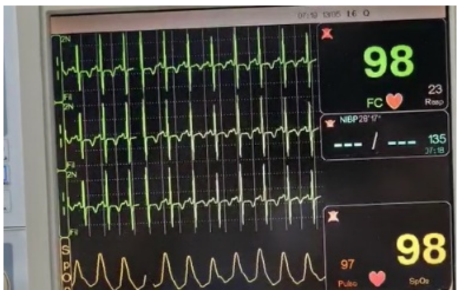
2) The ECG signal should not contain grids, that is, vertical and horizontal reference marks;

3) The camera used for filming should remain practically static or move little during recording;

4) The camera used for filming should be close to the monitor to allow clear visualization of the ECG signal, but at least 1 meter away to avoid electromagnetic interference [5].

Fig. 1 presents some examples of videos rejected for this project as they did not meet at least one of those criteria.

After choosing the videos to compose the database, the frame processing to extract the ECG signal started. All processing performs in MATLAB version 2018a. The first step consisted of transforming each video into a set of images to separate their frames. In the first frame of each video, a window containing only the ECG signal is selected manually, as shown in Fig 2.



(a)

(b)

(c)

Fig. 1. Examples of videos rejected for the study. (a) The screen contains grids; (b) and (c) the monitor is far from the camera.

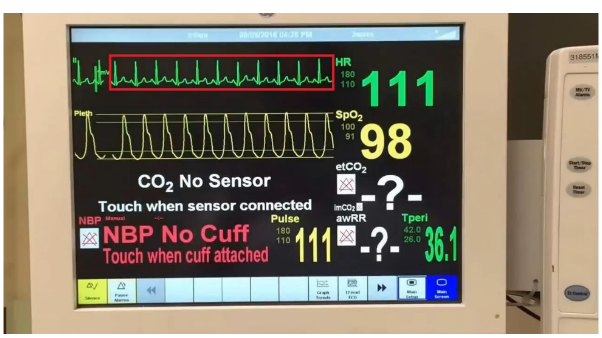


Fig. 2. Example of window selection (red outline) containing only the ECG signal at the first frame of each video.

The selected window was applied to cut all video frames, as the processing is applied considering only the select region in all the videos. Therefore, just the ECG signal is segmented. The processing consisted of segmenting the image recorded on the ECG monitor to transform it into an ECG signal (time-domain). As for considering the RGB system color, all frames were split into R (red), G (green), and B (blue) components, and just the G component was used in the processing, as the ECG depicts in green color in all videos used. Thus, the green component pixels were selected in the range 100 – 255, generating a binary mask, where pixels in this range are white, and the others are black. The next step was to fill small holes that remained at the segmentation using a morphological closing operation with a circular structuring element of radius 1. The result of this process is approximately the ECG signal image segmented. To obtain the ECG signal amplitude, we extracted the upper contour of the segmentation. All columns of the segmented image were scanned from top to bottom, and the first white pixel found was selected. The result is the ECG signal, as exemplified in Fig. 3.

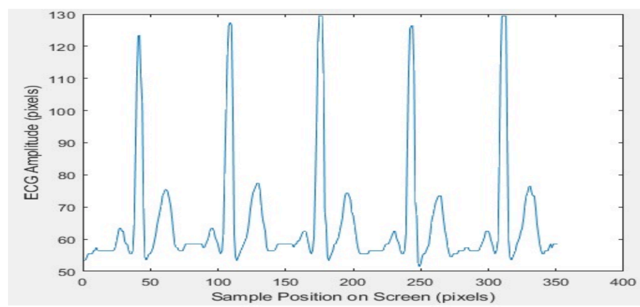


Fig. 3. ECG signal extracted from the segmented image.

The ECG amplitude scale (1 mV) stands directly in a vertical bar on the screen, and the ECG horizontal length conventionally represents 6 seconds (Fig. 4). Accordingly, the number of pixels of those elements determines the ECG scale in millivolts and seconds.

Fig. 4. Elements in the ECG image used to determine the amplitude and time scale of the signal.

The validation considered the ECG signal segmentation results. For this, we use the Dice coefficient, which compares them to Gold Standards by Eq. 1.

$$Dice(A,B) = 2 * \frac{|A \cap B|}{|A| + |B|} \tag{1}$$

The dice express the similarity between two regions (A and B). It varies from 0 to 1, with values close to 1 indicating the highest similarity between the regions. This work presented the Dice results on a scale from 0 to 100. Two Gold Standards were generated for each video, referring to the first and last frames. Thus, 18 images were validated. The Gold Standards were generated using the Gimp software by manually contouring the ECG signal by an ECG specialist, as shown in Fig. 5.

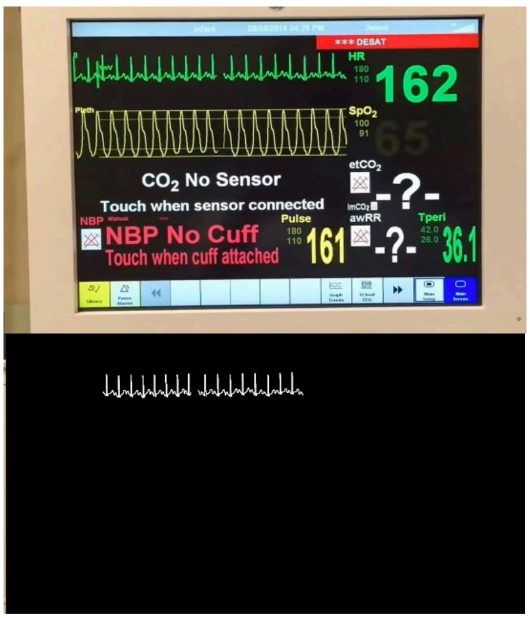


Fig. 5. Example of frame and Gold Standard manually generated for segmentation validation.

III. RESULTS AND DISCUSSION

In this work, the approach chosen to transform ECG signals displayed on ICU monitors into one-dimensional digital signals consisted of segmenting them into frames and extracting the segmentation's upper contour. Such an approach helps provide a remote ECG assessment via computer vision.

After segmenting the ECG signals, the results were validated using the Dice coefficient. The database contained nine videos, and two frames of each recording were validated, generating 18 validations and an average Dice of 90.02 ± 5.74. The Dice results appear in the boxplot of Fig. 6.

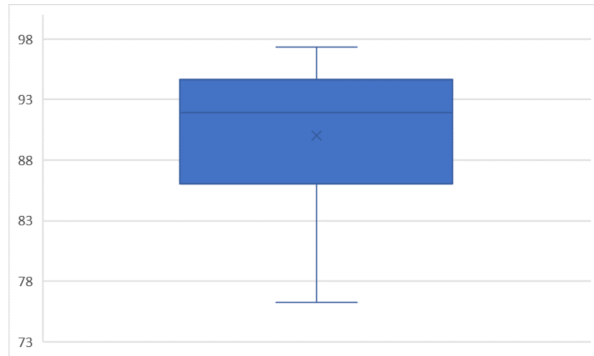


Fig. 6. Boxplot Dice coefficients result from the validation of the ECG signal segmentation.

The average Dice coefficient of 90.02 reveals high similarity between the segmented region and Gold Standard and good performance of the proposed method in segmenting ECG signals depicted on cardiac monitor screens. The minimum Dice obtained was 76.27, but the segmentation result was excellent, as shown in Fig. 7.

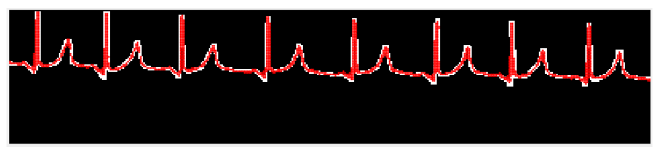


Fig.7. Gold Standard (white) and segmented signal (red). Scale not shown.

As shown in Figure 7, the segmented region was thinner than the Gold Standard, which impacted the Dice result. However, it is possible to verify that the ECG segmentation was correct. As the Gold Standards were drawn manually over the frames, they may be slightly different from the signals shown on the monitor, which introduces an error in the quantitative validation. That is a physical limitation of the professional who carried out the tracing; thus, it cannot be circumvented. Visual inspection confirms that the segmentation was correct despite of a smaller Dice.

After finishing the segmentations, the one-dimensional digital signal was generated by extracting the upper contour of the segmented ECG. That was mirrored on the horizontal axis. The results were plotted on the original frame for visual inspection, as exemplified in Figure 8. It is possible to verify that the proposed method accurately extracts the ECG signal from the frames. Therefore, that result indicates that computer vision can apply to transforming ECG signals displayed on the ICU monitor screen into one-dimensional digital signals (time-domain).

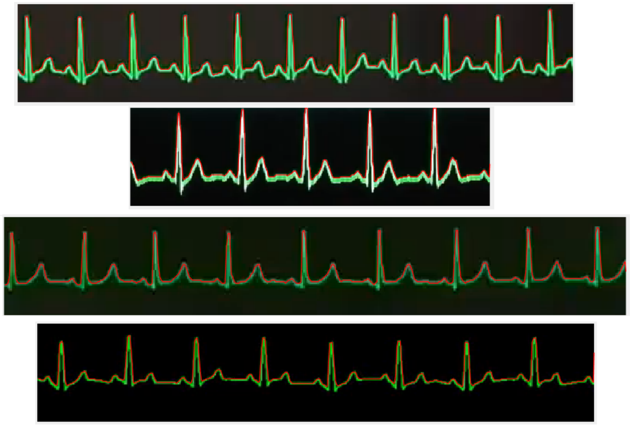


Fig. 8. ECG signals from cardiac monitors (green) and one-dimensional digital signals resulting from processing (red). Scale not shown.

The ECG temporal signals resulted from digital signal processing as the signal amplitude could convert from pixels to millivolts and the time scale convert from pixels to seconds. Additionally, the validation of the ECG signal relied on the Dice test and visual inspection.

One limitation of the method proposed in this work is that the segmentation of the ECG signal is impaired if there are other elements beyond the ECG in the selected window, such as grids, signal markings, and written warnings, as shown in Fig. 9. Thus, the window chosen must contain only the ECG signal. The green tones of the ECG signals can vary greatly depending on various factors, such as the heart monitor settings, quality of the device used to perform the recording, reflections on the monitor screen, and the ambient illumination where the monitor poses. Thus, to ensure adequate ECG signal segmentation from different videos, the method proposed in this work selects a wide range of colors in the G component (green). Due to that feature of the method, other elements in the window that are not green can be selected incorrectly, interfering with the final result.

Even though the tool still needs improvements, it may help ECG monitoring in ICUs as patients' signals can be visually monitored and sent as an ECG signal to a single computer to be processed. Thus, if an intercurrence detects in a patient, help can be much faster, as the program would warn out any possible abnormalities.

Monitoring and assessing ICU patients' vital signals, such as ECG, is crucial as it can provide continuous and noninvasive follow-up [6, 7]. As one would expect, many authors have proposed diversified approaches for it [8, 9, 10].

Fig. 9. Elements (green or not) present in the selected window (highlighted in red) that impair the ECG signal's segmentation.

However, to the best of our knowledge, using ICU monitor videos as a direct source of ECG signal is first described in the present work.

Other authors proposed extracting ECG signals from images [11,12]. However, they proposed extracting ECG signals from ECG recordings' images on paper. Therefore, that approach is not applicable in ICU monitor videos, as proposed in the present work.

IV. Conclusions

The present tool can extract ECG from videos of Intensive Care Unit (ICU) monitors and transform it into a time-domain ECG signal. It can help future ECG assessments, via computation vision, regarding pathological changes in the heart rhythm (arrhythmias).

It can also help circumvent limitations to access the ECG in ICU by using, for example, a simple video camera close to the monitor, such as those of cell phones. That approach, in turn, would allow obtaining and transmitting the signals to the computer responsible for ECG analysis.

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Conflict of interest

The authors declare that they have no conflict of interest.

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