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U-Net Neural Network for Heartbeat Detection in Ballistocardiography

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***Abstract*—Monitoring vital signs of neonates can be harmful and lead to developmental troubles. Ballistocardiography, a contactless heart rate monitoring method, has the potential to reduce this monitoring pain. However, signal processing is uneasy due to noise, inherent physiological variability and artifacts (e.g. respiratory amplitude modulation and body position shifts). We propose a new heartbeat detection method using deeplearning to learn this variability. A U-Net model takes thirty-second-long records as inputs and acts like a non-linear filter. For each record, it outputs the samples probabilities of belonging to IJK segments. A heartbeat detection algorithm finally detects heartbeats from those segments, based on a distance criterion. The U-Net has been trained on 30 healthy subjects and tested on 10 healthy subjects, from 8 to 74 years old. Heartbeats have been detected with 92% precision and 80% recall, with possible optimization in the future to achieve better performance.**

Keywords—ballistocardiography, U-Net, heartbeat detection, contactless monitoring

I. Introduction

Ballistocardiography is a non-intrusive monitoring method for cardiac activity. It was invented at the end of the 19th century but supplanted by the first electrocardiographs, improving precision and robustness at that time. Today, with new sensor technologies and digital signal processing, this technology is gaining renewed interest. Ballistocardiography's principle relies on measuring ballistic forces [1]: during ventricular systole, blood is ejected from the left ventricle through the aortic arch, generating a pulsed cardiac ballistic force that slightly strains the bedding and the bed frame on which the patient is lying or sitting. This mechanical phenomenon allows cardiac monitoring through contactless measurements of a pressure variation, e.g. strain gauge, or a deformation, e.g. accelerometers, of the patient bed or mattress. A ballistocardiogram (BCG) is a record of this mechanical phenomenon characterized by H to N peaks or fiducial points. Figure 1 illustrates a BCG and annotates the I, J and K peaks, or IJK complex, of a heartbeat. In this paper, the heartbeat reference is the J peak.

Due to the mechanical focus of the sensors, respiratory and motor activities are often recorded along the ballistocardiogram, which gives valuable information on the overall physiological state of the individual.

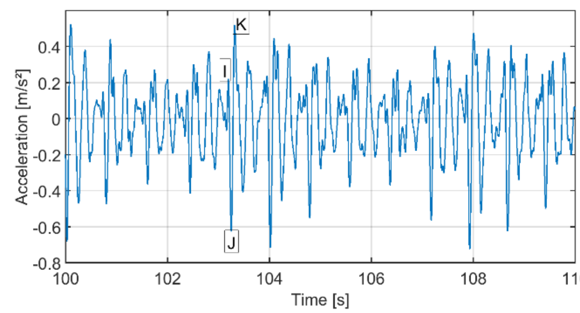

Figure 1. Example of a typical adult ballistocardiogram.

This monitoring technology has many applications in the medical field. As it is contactless and low-cost, it is adapted for long term and home surveillance of cardiovascular diseases. Heart failure and sleep apnea may be prevented in geriatrics [2,3]. For children in hospital, the physiological state (cardiac and respiratory activities) is usually evaluated by electrocardiography (ECG) and photoplethysmography (PPG). The former uses electrodes on the thorax and on the limb's extremities; the latter uses pulse oximetry probes that tweak either a finger or a toe. Monitoring children is difficult because of their high spontaneous mobility that leads to repetitive artifacts and false alarms. Moreover, electrodes peel off the epidermis and pulse oximetry probes can regularly detach from the finger or toe. Several factors are involved: the child twitches and pulls the probes, the electrode adhesive is worn or the nursing staff could not properly set up the electrodes. Children pain, which may be monitored by heart rate variability [4] or infrared thermography [5], affects the neuro-motor and cognitive development especially for preterm neonates [6]. Finally, the actual equipment is expensive to install and maintain; it must be changed or replaced several times during hospitalization and frequently in the same day. Consequently, a non-intrusive apparatus would represent a major progress to detect children heartbeats in a harmless way.

However, a BCG signal is generally affected by noise such as respiratory, movement artifacts and hardware limitation. Few studies [7] focus on pediatric ballistocardiography, where BCG signals are noisier. Compared to adults, the BCG signal amplitude of a 3 kg infant is about 30 times lower due to low weight and low cardiac contractile force [8]. Moreover, the amplitude and time variabilities of the IJK complex, illustrated at Figure 2, make it difficult to rely on ECG heartbeat detection algorithm such as the Pan-Tompkins dual threshold algorithm [9].

Specific digital signal processing algorithms have been developed for detecting heartbeats, beat-to-beat heart rate and heart rate variability (HRV) in BCG signals using time domain or time-frequency domain methods [10]. Recently, a template matching algorithm [11] was developed using dynamic time warping to consider the IJK complex variability and the signal noise. Even if the overall sensitivity and positive predictivity were high (95.6 % and 96.8 % respectively) on a ten healthy adults database, those performances can still be improved as they fall below 90 % in the noisiest case. Moreover, the heartbeat template is automatically re-trained for every record, which produces errors in case of bad training.

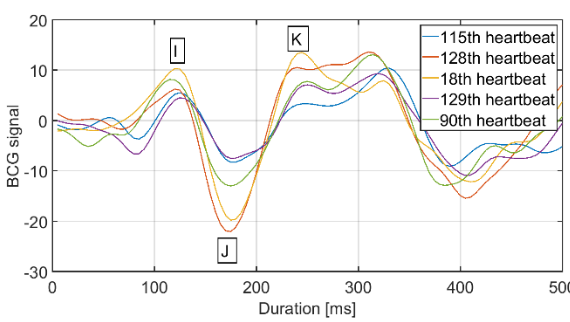

Figure 2. Variability of heartbeats.

Neural networks have been used to detect and classify heartbeats and fiducial points in ECG signals [12]. Convolutional neural networks have been applied to detect IJK segments in BCG, with a rather low accuracy of 88% [13]. U-Net, a recent deep learning architecture, has achieved impressive results for ECG delineation [14], with up to 99.9% F1 score for QRS segmentation and a small dataset. This method is applied to BCG heartbeat detection in this paper.

In this context, we introduce a new method to segment IJK complexes and detect heartbeats in BCG based on a U-Net model. The remaining of this paper is organized as follows: Section 2 presents the materials and Section 3 details the proposed method before results in Section 4. Finally, Section 5 concludes this study.

II. Materials

The acquisition setup and the recruitment process are detailed in this section.

A. Acquisition setup

The bed used for this experimentation is constituted of a slatted solid pine wood Ikea® Sniglar infant home bed and a firm latex polyurethane Tediber® Tedi mattress of 70x140 cm dimensions. The bed is equipped with a sensor, placed on top and 5 cm away of the mattress side, as shown in Figure 3. This sensor is based on a Murata SCA100T-D02 two-dimensional analog accelerometer with an output noise density as low as 14 $\mu g/\sqrt{Hz}$. The sensor is embedded in an ABS plastic case and linked with a shielded cable to a Biopac MP36R acquisition unit for AC coupling, amplification and power. The analogue output is AC coupled, anti-aliasing filtered and 100 times amplified before digitization at 1 kHz. The BCG is measured in the left-right bed direction. Signals are anti-alias filtered and downsampled to 200 Hz.

Figure 3. Setup of the BCG sensor on the mattress.

B. Volunteers recruitment process

Volunteers were recruited on the “La Science Infuse” week of the Cité des Sciences et de l’Industrie, which aims at vulgarizing science to the public. Children were originally targeted for this study, with parental consent; however, accompaniers and adult visitors were also willing to take part in the study. The authors found interesting to recruit them in order to compare adults with children BCG in further physiological studies.

Volunteers were asked to lie down and quiet in supine position for 35 seconds. For subjects taller than 140 cm, the bed size was not totally appropriate, and legs were uncomfortably out of the bed. That did not seem to alter the quality of the recording, as long as the subjects were still.

The I, J and K fiducial points of the BCG signals were automatically labelled using the DTW template matching algorithm [11], manually checked by two experts and adjusted if necessary.

In total, 336 subjects were recorded; however, many records were discarded because signals were polluted by motion artifacts as children had difficulties in concentrating not to move or talk, and because IJK complexes could not be labelled in time. In this study, 40 subjects are included, with ages ranging from 8 to 74.

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III. Methods

In this section, the architecture and settings of the U-Net neural network are detailed, then the heartbeat detection algorithm.

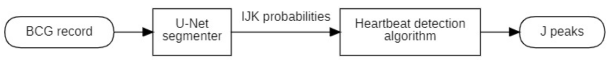

Figure 4. Pseudo algorithm of the methods.

A. U-Net architecture

The role of the neural network is to take BCG records as inputs and find for every record sample its probability of belonging to IJK class or not.

The neural network for segmenting the records is based on a U-Net architecture [15], with two symmetric paths and monodimensionnal inputs.

On the left side of Figure 5, the contraction path or encoder finds what information is present in the record. It is constituted of row repetitions, where one row includes two sequential convolution layers ($kernel\_size = 9$, $strides = 1$ and same padding), with batch normalization and ReLU activation. Six-teen filters are used for the first convolution layers. Each row is followed by a MaxPooling layer which downsamples the data with $pool\_size = 2$, and the filter numbers of the convolution layers in the rows are doubled.

On the right side, the role of the expanding path or decoder is to localize this information in the record. It is constituted of row repetitions, where one row includes two sequential convolution layers ($kernel\_size = 9$, $strides = 1$ and same padding), with batch normalization and ReLU activation. Each row is preceded by a concatenation layer, fed by:

- a transposed convolution layer (with $kernel\_size = 8$, $strides = 2$ and same padding) following the previous row,
- the output of the corresponding encoded row.

In the expanding path, the number of filters of the convolution layers are divided by two, row after row.

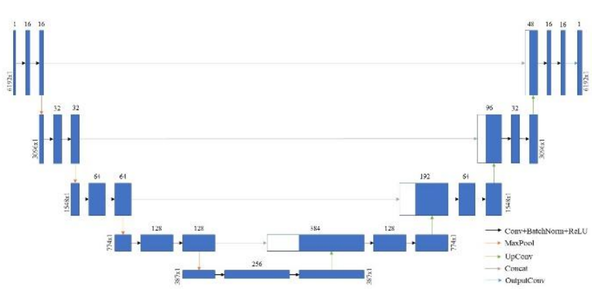

Figure 5. Neural network architecture.

In this architecture, the input length must be multiples of two power the number of downsampling steps, e.g. 16. BCG records are thus shortened to 6192 samples which approximately corresponds to 30 seconds long records. In the end, i.e. on the top right side of Figure 5, a convolution layer (one filter, $kernel\_size = 1$, $strides = 1$ and valid padding) and a sigmoid activation function are used to find the probability of belonging to class IJK or not.

This neural network is trained using a binary entropy loss and an Adam optimizer, which is a stochastic gradient descent algorithm based on adaptive estimates of first and lower-order moments [16]. The training set includes 30 random BCG records from the 40 selected records of the database; models are trained 50 times over the training set. This process is repeated 30 times, and the model that produces the best test F1 score is kept.

B. Heartbeat detection algorithm

The most obvious algorithm to detect heartbeats from the output of the previously defined U-Net model is to segment IJK in the records as the samples where this class probability is the greater, then find the index of the most extreme value, i.e. maximum or minimum depending of the convention. This ideal algorithm makes the strong assumption that IJK segments are well distinguished in BCG records by the neural network, which may not always be the case because of noise.

A more robust approach is designed, where peaks in the neural network outputs are detected even if their height (IJK probability) are lower than 0.5. Those samples have higher probabilities than their neighbors to be part of IJK segments. Samples in the half-height width regions of the peaks are classified as IJK segments, and J peaks, i.e. heartbeats reference, are detected as IJK segments global extrema. A minimal distance criterion for the peak finding algorithm is added to prevent non physiological effects, e.g. resting heart rates higher than 120 beats per minute for healthy adults.

IV. Results

The U-Net performance for IJK segmentation can be evaluated separately from the overall heartbeat detection algorithm. Indeed, IJK segmentation is only an intermediate step for the heartbeat detection algorithm.

A. U-Net

In order to see if the neural network has not been overfitted, the loss curve along epochs is examined.

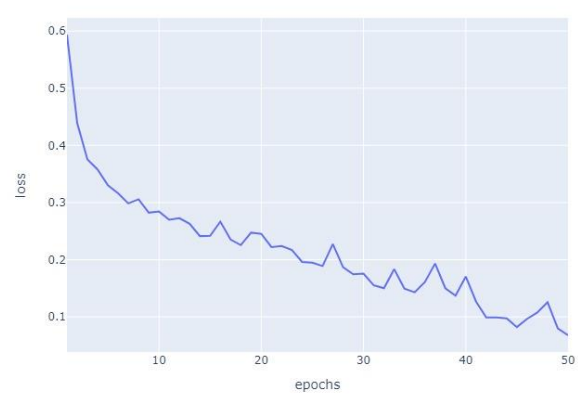

Figure 6. Binary entropy losses after epochs of training for IJK segmentation by the U-Net.

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The precision-recall curve also gives useful hints about the U-Net ability to segment IJK. Those performance are illustrated at Figure 6 and Figure 7 respectively. Typical trends of these curves are observed. The F1 score for IJK segmentation with the U-Net approximately equals 95%. Definition of recall (or sensitivity), precision (or positive predictive value) and F1 score statistics are reminded below in Equation 1, Equation 2 and Equation 3, where TP, FP and FN stand for true positives, false positive and false negative respectively.

$$recall = \frac{TP}{TP+FN} \quad \text{Equation 1}$$

$$precision = \frac{TP}{TP+FP} \quad \text{Equation 2}$$

$$F1score = \frac{2.recall.precision}{recall+precision} \quad \text{Equation 3}$$

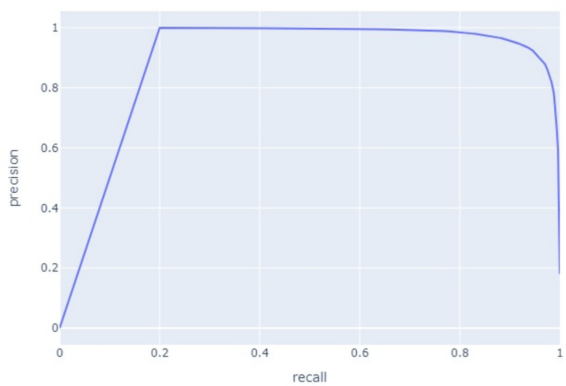

Figure 7. Precision-recall curve for IJK segmentation by trained the U-Net.

B. Heartbeat detection performance

The most important performance values are the heartbeat detection rates, in terms of precision and recall. An error tolerance of 150 ms on the location of heartbeats is added.

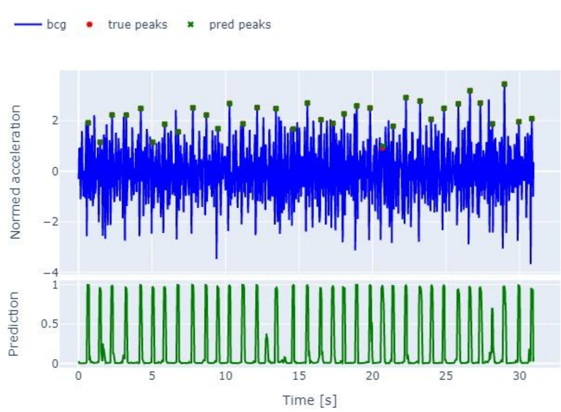

Figure 8. Example of BCG signal (blue line) with the U-Net output IJK prediction probability (green line), the true J peaks (red dot) and the heartbeat detection algorithm predicted J peaks (green cross).

Figure 8 illustrates, on a testing record, the IJK probability of each sample, and the predicted labels by the heartbeat detection algorithm. The mean heart rate error is another performance index, based on the comparison of linear interpolations of true and predicted heart rate series. It is defined in Equation 4, where HR_{true_i} and $HR_{predicted_i}$ stand respectively for the ith sample of the linear interpolated true heart rate and predicted heart rate series; L=6192 is the number of samples in one BCG record.

$$HRerror = \frac{1}{L}\sum_{i=0}^{L}\left|HR_{true_i} - HR_{predicted_i}\right| \quad \text{Equation 4}$$

The performances of the heartbeat detection algorithm based on U-Net IJK segmentation, are reported in Table 1.

Table 1. Statistics and HR error

set	precision	recall	F1 score	Mean HR error
test	92.1 %	80.9 %	85.7 %	5.7 bpm
train	94.2 %	92.6 %	92.9 %	3.1 bpm

V. Discussion

This paper introduced a new way to detect heartbeats in ballistocardiography that learns the heart rate physiological periodicity and heartbeats variabilities. U-Net is relevant for this task, as it allows an intermediate segmentation step that helps to detect heartbeat in further steps. The performances of this model are good, and it can be optimized using data augmentation and hyper parameters optimization. Multi-class segmentation, based on the other fiducial points present in BCG, must also be investigated.

This algorithm will be tested in controlled-environment database such as pediatric and neonatal intensive care units.

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References

[1] C-S. Kim, S. L. Ober, M. S. McMurtry, B. A. Finegan, O. T. Inan,and R. M. Hahn,“Ballistocardiogram: Mechanism and Potential for Unobtrusive Cardiovascular Health Monitoring”, *Nature Scientific Reports*, vol. 6, Aug. 2016, Art. No. 31297.

[2] Aydemir V. B., Fan J., Dowling S., Inan O. T., Rehg J. M. , Klein L., « Ballistocardiography for Ambulatory Detection and Prediction of Heart Failure Decompensation », Journal of Cardiac Failure, Volume 24, Issue 8, Supplement, Page S116, August 2018.

[3] Wang Z., Zhou X., Zhao W., Liu F., Ni H., Yu Z., « Assessing the severity of sleep apnea syndrome based on ballistocardiogram », PLoS One, 2017, Apr 26.

[4] B. M. Appelhans, and L. J. Luecken, "Heart rate variability and pain: Associations of two interrelated homeostatic processes", *Biological Psychology*, vol. 77, no. 2, pp 174-182, Feb. 2008.

[5] S. Brummelte, R. E. Grunau, V. Chau, K. J. Poskitt, R. Brant, J. Vinall, A. Gover, A. R. Synnes, and S. P. Miller, "Procedural pain and brain development in premature newborns," *Annals of Neurology*, vol. 71, no. 3, pp 385-396, Feb. 2012.

[6] A. Alalwani, Y. Chahir, B. Guillois, M. Molina, and F. Jouen, "Neonatal Pain Recognition using LBP descriptor and Wavelet Thresholding Technique", *IEEE International Conference on Multimedia Computing and Systems*, Apr. 2014.

[7] W. K. Lee, H. Yoon, D. W. Jung, S. H. Hwang, and K. S. Park, "Ballistocardiogram of baby during sleep", *37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society,* 2015.

[8] M. Erkinjuntti, K. Vaahtoranta, J. Alihanka, and P. Kero, "Use of the SCSB method for monitoring of respiration, body movements and ballistocardiogram in infants,"Early Human Development, vol. 9, pp 119-126, Feb. 1984.

[9] J. Pan, and W. J. Tompkins, "A Real-Time and QRS Detection Algorithm", IEEE Transactions on Biomedical Engineering vol. 32 pp. 230-236, 1985.

[10] O. T. Inan, P-F. Migeotte, K-S. Park, M. Etemadi, K.Tavakolian, R.Casanella, J.Zanetti, J. Tank, I.Funtova, G. K. Prisk, and M. DiRienzo, "Ballistocardiography and seismocardiography: A review of recent advances", IEEE Journal of Biomedical and Health Informatics, vol. 19, no. 4, pp. 1414-1427, Jul. 2015.

[11] G. Cathelain, B. Rivet, S. Achard, J. Bergounioux, and F. Jouen, "Dynamic Time Warping for heartbeat detection in ballistocardiography", Computing in Cardiology Conference, 2019.

[12] J. Camps, B. Rodriguez, and A. Minchole, "Deep Learning Based QRS Multilead Delineator in Electrocardiogram Signals", Computing in Cardiology Conference, 2018.

[13] Han Lu and Haihong Zhang and Zhiping Lin and Ng Soon Huat, "A Novel Deep Learning based Neural Network for Heartbeat Detection in Ballistocardiograph", 40th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 2018.

[14] Viktor Moskalenko , Nikolai Zolotykh(B) , and Grigory Osipov, "Deep Learning for ECG Segmentation", Neuroinformatics 2019: Advances in Neural Computation, Machine Learning, and Cognitive Research III, pp 246-254, 2019.

[15] O. Ronneberger, P. Fischer, and T. Brox, "U-Net: Convolutional Networks for Biomedical Image Segmentation", Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015, pp 234-241, 2015."

[16] D. P. Kingma, and J. Ba, "Adam: A Method for Stochastic Optimization", 3rd International Conference for Learning Representations, San Diego, 2015.