Robust and Energy-efficient PPG-based Heart-Rate Monitoring

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Abstract—A wrist-worn PPG sensor coupled with a lightweight algorithm can run on a MCU to enable non-invasive and comfortable monitoring, but ensuring robust PPG-based heart-rate monitoring in the presence of motion artifacts is still an open challenge. Recent state-of-the-art algorithms combine PPG and inertial signals to mitigate the effect of motion artifacts. However, these approaches suffer from limited generality. Moreover, their deployment on MCU-based edge nodes has not been investigated. In this work, we tackle both the aforementioned problems by proposing the use of hardware-friendly Temporal Convolutional Networks (TCN) for PPG-based heart estimation. Starting from a single “seed” TCN, we leverage an automatic Neural Architecture Search (NAS) approach to derive a rich family of models. Among them, we obtain a TCN that outperforms the previous state-of-the-art on the largest PPG dataset available (PPGDalia), achieving a Mean Absolute Error (MAE) of just 3.84 Beats Per Minute (BPM). Furthermore, we tested also a set of smaller yet still accurate (MAE of 5.64 - 6.29 BPM) networks that can be deployed on a commercial MCU (STM32L4) which require as few as 5k parameters and reach a latency of 17.1 ms consuming just 0.21 mJ per inference.

I. INTRODUCTION

Wrist-worn devices equipped with sensors, such as wristbands and smartwatches, enable a comfortable monitoring of vital signs, hence they are becoming increasingly popular in personalized health care and medical IoT applications [1]. Health rate (HR) is one of the most critical indexes to monitor, both for activity tracking and for clinical purposes. First generation HR-monitoring devices were based on a simple 1-3 leads ECG, connected through a chest strip, which, however, is uncomfortable or even impossible to wear in certain conditions. Recently, the optimization and miniaturization of photoplethysmogram (PPG) sensors has allowed to integrate HR and blood oxygenation (SPO2) monitoring in smaller, less invasive and cheaper devices [2]. A PPG sensor consists of one or more LEDs that continuously emit light to the skin and a photodiode that measures variations of light intensity caused by blood flow, which depends on the heart rate. A major limitation of PPG based HR estimation is represented by motion artifacts (MA) caused by variations of sensor pressure on the skin or ambient light leaking in the gap between the photodiode and the wrist. Moreover, blood flow can vary considerably depending on the type of physical activity, contributing to a less precise light absorption measurement, and hence HR estimate [3].

Several approaches have been proposed in literature [4], [5] to tackle these limitations, by cancelling/reducing the noise caused by MAs on the PPG signal before using it to compute the HR of subjects. However, these methods require an extensive hand-tuning of parameters for the target dataset, leading to difficulties in generalizing over many subjects and over different activities. Until now, limited attention has been given to deep learning approaches, despite the promising generalization results shown in [3], [6]. Moreover, none of the state-of-the-art algorithms (neither classic or deep learning ones) have been yet deployed on a MCU of the class found in wrist-worn edge devices.

In this paper, we propose a collection of TCNs for HR estimation based on raw PPG and acceleration data, called TimePPG. All TCNs are derived automatically from a single seed architecture using a NAS tool [7], and form a Pareto frontier in the accuracy vs complexity space, from which designers can select a model based on the available computing resources. In particular, we analyze in detail three TCNs from the TimePPG family. The best performing model, BestMAE, achieves a MAE of 5.30 BPM on the popular PPGDalia dataset, and includes ≈ 232k trainable parameters. Coupling this TCN with simple post-processing and fine-tuning steps, we further reduce the MAE to 3.84 BPM, outperforming the current (more complex) state-of-the-art algorithms [5]. At the other extreme, the smallest model in TimePPG, BestSize, uses only 5k parameters while still reaching an acceptable MAE of 6.29 BPM. Finally, as a compromise between the former two, we analyze BestMCU, i.e. the largest network that fits the memory of a popular MCU by STM, the STM32L476, which achieves a MAE of 5.64 BPM with 41.7k parameters. When deployed on the MCU, BestMCU consumes 5.17 mJ per inference, with a latency of 427 ms. BestSize reduces both metrics by 25×, reducing energy to 0.21 mJ and latency to 17.1 ms.

II. BACKGROUND AND RELATED WORKS

A. Temporal Convolutional Networks

TCNs are a class of 1D-Convolutional Neural Networks (CNNs), whose peculiarity is in the use of causality and dilation in convolutional layers [8], [9]. Causality constrains the convolution output \( y_t \) to depend only on inputs \( x_t \) with \( t \leq t \), whereas dilation is a fixed gap \( d \) inserted between input samples processed by the convolution, thus increasing its time receptive field without requiring more parameters. A convolutional layer in a TCN implements the following function:

\[
y_t^m = \sum_{i=0}^{K-1} \sum_{l=0}^{C_{in}-1} x_{t-dl}^i \cdot W_{i}^m
\]  

(1)

where \( x \) and \( y \) are the input and output feature maps, \( t \) and \( m \) the output time-step and channel respectively, \( W \) the filter weights, \( C_{in} \) the number of input channels, \( d \) the dilation

Published as a conference paper at the IEEE 2021 ISCAS Conference (https://doi.org/10.1109/ISCAS51556.2021.9401282)
factor, and K the filter size. In the original paper [8], TCNs were proposed as fully-convolutional architectures, but modern embodiments also include other common layers such as pooling and linear ones [10], [11].

B. State-of-the-art in PPG-based HR monitoring

HR monitoring through wrist-PPG is a relative new task, which both industry and researchers are exploring. The seminal work of [2] paved the way to algorithmic exploration in the field, releasing the first open-access dataset (the 12-subject SPC), and proposing a three-stage algorithm based on signal decomposition, spectrum estimation and spectral peak tracking (TROIKA), which achieves an average MAE of 2.34 BPM on SPC. Later, [4] improved TROIKA using the spectral difference with the acceleration spectrum to clean the PPG signal from Motion Artifacts (MAs), reducing the error to 1.28 BPM. With the same goal, the authors of [12] applied Singular Value Decomposition to the acceleration data to extrapolate periodic MAs. Followed by some iterations of the Iterative Method with Adaptive Thresholding (IMAT), this method reduced the MAE to 1.25 BPM. Two approaches used Wiener filtering [13], [14] to clean PPG signals with accelerometer data, reaching a MAE of 0.99 BPM. Lastly, the complex five-steps pipeline called SpaMA [15], further reduced the MAE on this dataset to 0.89 BPM. More recently, [5] presented a time-domain algorithm which achieves 4.6 BPM of MAE on the larger PPGDalia dataset with a 5-steps pipeline of light linear transformations, outperforming SpaMa [15] and the CNN presented in [3] on these data, but performing worse on the smaller SPC. On the most challenging PPGDalia dataset, [5] is the SoA algorithm and thus used as a comparison in this work.

All aforementioned approaches share the common problem of including an high number of free hyper-parameters, which are not automatically learned, but hand-tuned to maximize performance, leading to an overfitting of the test dataset. For instance, the authors of [3] have shown that the state-of-the-art results of [15], [16] on the SPC dataset, cannot be reproduced when cross-validation is used for optimizing hyper-parameters on the same dataset, leading to a MAE increase of 1.64-11.77 BPM. Further, they saw a degradation of up to 19.18 BPM MAE of classical approaches developed for SPC on the PPGDalia dataset, demonstrating that classical approaches hardly generalize over many subjects.

In recent years, researchers have tried to address this limitation with data-driven deep learning algorithms. The works of [6], [17] achieve comparable results to the ones of the classical methods, applying a CNN to frequency data and a CNN+LSTM (Long-Short Term Memory) to time data, respectively. In [3], the authors present a CNN architecture which outperforms two classical methods [15], [16] on PPGDalia. Despite these promising results, however, the deep learning architectures proposed in literature are still too complex to be embedded in a MCU-based wearable device. For instance, the best architecture presented in [3], based on a CNN ensembler, has 60M float32 parameters, while CorNet, a CNN+LSTM model, has 260k float32 parameters and requires 21.1 million operations.

III. Time PPG

Fig. 1 shows the complete flow proposed in this work. As anticipated, we use an automatic tool to explore the space of possible TCN architectures for PPG-based HR monitoring. As a starting point for this exploration we use TEMPONet [11], a TCN which shows impressive results in other bio-signals analysis tasks, originally developed for EMG-based gesture recognition. TEMPONet includes a modular feature extractor, composed of 3 convolutional blocks, each with two dilated convolutions, 1 strided convolution and 1 pooling layer. The output channels in each block are 32, 64, and 128 respectively. The feature extractor is followed by a classifier composed of 3 linear layers, contributing to almost half (200k) of the total network parameters. All layers use ReLU activations and batch normalization [18]. Further details on the network are omitted for sake of space, and can be found in [11].

To adapt TEMPONet to our task, we modify the input layer to match the target dataset, described in detail in Section IV. The network takes as input raw sensor data generated by a PPG-sensor and a tri-axial accelerometer. Samples are gathered at 32 Hz and fed to the model in sliding windows of 8 s with an overlap of 75 %, resulting in a 256×4 input matrix. We also remove the final classification layer, replacing it with a single neuron for regression, and use a LogCosh loss for training.

A. Design Space Exploration

NAS methods are the natural tools for automatically exploring novel NN architectures for a given task, acting on hyper-parameters such as the number and type of layers, the number of convolution filters, etc [19]. However, standard NAS approaches

Fig. 2. Ground truth and prediction of a well tracked patient (S7) and of the worst one (S5). Values above 140 BPM are not well estimated by our algorithm.
require an enormous number of training iterations and are optimized for large-scale computer vision tasks, leading to oversized networks for simpler tasks. Therefore, in this work we resort to MorphNet [7] a new NAS algorithm which slightly reduces the search space using a seed network (TEMPONet in our case) in exchange for a dramatic reduction in complexity.

MorphNet limits the optimization to the number of channels in each layer, and learns an optimal architecture which retains as much as possible the initial performance of the network, while reducing either its memory footprint, the number of required Multiply-and-Accumulate (MAC) operations, or a combination. This is obtained with a two-step algorithm: first, the network size is reduced by applying group Lasso [20], a sparsifying regularizer which forces entire filter channels to small magnitude values. At the end of this phase, all channels whose magnitude is inferior to a threshold are eliminated. Since compression is associated with an obvious performance penalty, MorphNet alternates it with an expansion step, in which the number of channels in all layers is uniformly up-scaled by a constant. Two regularizers are introduced in the original paper, to guide the alternates it with an expansion step, in which the number of channels in all layers is uniformly up-scaled by a constant. Two regularizers are introduced in the original paper, to guide the

Fig. 3. TimePPG results in the MAE vs. memory and MAE vs. MACs planes.

While miss-predicting intervals of time of S5 with HR > 140 BPM (lower part of the figure).

We claim that this is indeed just an effect of the scarcity of data, and not a limitation of our models. To demonstrate it, in one of our experiments we apply an additional fine-tuning step to our trained TCNs. Specifically, we fine-tune on the initial portion of data (25%) relative to the patient under exam, with a low learning rate, freezing the weights of the first convolutional block. We then compute the MAE on the remaining 75% of data. Note that this step is hardly reproducible in the field, since collecting ground truth data for fine-tuning is hard. However, it mimics the effect of a larger dataset which would include data similar to those of a given test subject.

IV. EXPERIMENTAL RESULTS

We evaluate our TimePPG models on the PPGDalia dataset [3], the largest publicly available dataset for PPG-based heart rate estimation. The dataset includes sensors’ data from a PPG-sensor and a 3D-accelerometer, together with golden HR values from 15 subject and a total of 37.5 hours of recording. We validate TimePPG models following the cross validation scheme proposed in [3]. We train all TCNs with an Adam optimizer (learning rate = 1e-3, weight decay = 5e-4), and a batch size of 128 over 500 epochs, with an early stop mechanism with patience of 20. All experiments are performed using Python 3.6, TensorFlow 1.14 [23] and the Nucleo-STM32L476RG evaluation board, with 128 kB of RAM, 1 MB Flash and an average power consumption of 12.1 mW at 80 MHz [24].

B. Post-Processing

Despite being accurate on average, fully data-driven models such as TCNs can sometimes make large errors, especially when inputs deviate significantly from the distributions seen during training. Fortunately, for HR monitoring, these errors can be easily filtered with a post-processing step, which removes predictions that are not compatible with human physiology. Specifically, we impose a limit on the maximum relative HR variation over time. To this end, we compare the latest TCN prediction with the mean of the previous N predictions: if the difference between the two is larger than a threshold \( th \), the predicted HR is clipped to mean ± threshold. We set N to 10 and \( th \) to 10% of the mean, identical for all patients.

C. Fine-Tuning

Deep learning benefits from large amounts of training data, unfortunately not yet available in datasets for PPG-based HR monitoring, which include < 20 patients. Therefore, subjects with particularly high/low HR are badly tracked by our TCNs, since their unique data distributions are not present elsewhere in the training set. To underline this effect, Fig. 2 showcases the accurate tracking on a patient with HR < 140 BPM (S7),
imposed by the target MCU; it requires 41.7k parameters, and 4M MACs and achieves a MAE of 5.64 BPM, i.e. a model compression of 5.6× w.r.t. BestMAE, with a MAE increase of just 0.34 BPM. BestSize is the smallest model found in our design space exploration, obtained using MorphNet’s flops regularizer with a strength of 1e-5 and a pruning threshold of 0.01. The model has just 5.09k parameters (46% compression) and less than 100k MACs, with a MAE of 6.29 BPM (0.99 increase). Section IV-C analyzes the execution metrics of the latter two TCNs on the STM32L476RG.

### B. TimePPG-BestMAE: state-of-the-art comparison

Table I compares our proposed BestMAE TCN with different state of the art methods, including both classical and deep learning approaches. We report the results of the TCN alone, as well as those obtained after the application of our proposed post-processing and with fine-tuning.

TimePPG outperforms previous deep learning approaches, such as the CNN from [3] and the Generative Adversarial Network (GAN)-based method reported in [26] (not in the table since individual subjects performance are not reported in the original paper), achieving a mean MAE of 5.3 BPM vs. 7.65 BPM (CNN) and 8.3 BPM (GAN). Further, our model has 230k parameters, i.e. 260× smaller than the CNN ensemble of [3].

Among classical algorithms, Schack2017 and SpaMaPlus are smaller than the CNN ensemble of [3].

### C. Embedded Deployment Results

Table II summarizes the results obtained deploying the previously described BestSize and BestMCU TCNs on the STM32L476RG. Specifically, we deploy both float32 and int8-quantized variants of each TCN. Unfortunately, the toolchain offered by STM to deploy neural network models on their MCUs, called X-CUBE-AI [27], does not support int8 quantization with dilation factors higher than 1. To cope with this limitation, we are obliged to use larger filters of size \( d \times (K - 1) + 1 \) and dilation 1 to maintain the original receptive field of the float models. This actually increases the number of parameters in the networks, resulting in a more complex network – 1.8× higher number of parameters and 2.7× more computation. Overall, the table shows that latency and energy consumption metrics obtained with our methodology starting from a single seed model span more than one order of magnitude. On one extreme, the float version of BestMCU achieves a mean MAE of 5.64 BPM with an energy consumption of 5.17 mJ and 427 ms of latency. Alternatively, we can use BestSize to lower the energy consumption to just 0.21 mJ and the latency to 17.1 ms at the cost of a higher MAE, 6.29 BPM.

Note that these results could be improved by i) applying a quantization-aware training and ii) manually porting the network to the MCU implementing \( d > 1 \) with int8 filters. These steps would be objects of our future work. Despite these limitations, BestSize model result in a Flash occupation of just 8.07 KB, which could be very promising for the porting on commercial ultra-low-power wrist-worn devices, but with almost equal computation compared to the float32 model.

### V. Conclusions

The efficient execution of HR monitoring algorithms is a critical enabler for the personalized health care. In the direction of employing lightweight algorithms for HR, we have proposed a set of TCN regressors, all automatically derived from a single seed model using NAS. With our exploration, we spanned a wide range in all metrics, reaching as low as 3.84 BPM average MAE, 0.21 mJ of energy per inference and 8.07 KB of memory footprint, enabling the deployment of our models even to very tiny MCUs with small embedded flash memories.
REFERENCES

[1] A. S. Yeole and D. R. Kalbande, “Use of internet of things (iot) in healthcare: A survey,” in Proceedings of the ACM Symposium on Women in Research 2016, 2016, pp. 71–76.

[2] Z. Zhang, Z. Pi, and B. Liu, “Troika: A general framework for heart rate monitoring using wrist-type photoplethysmographic signals during intensive physical exercise,” IEEE Transactions on biomedical engineering, vol. 62, no. 2, pp. 522–531, 2014.

[3] A. Reiss, I. Indlekofer, P. Schmidt, and K. Van Laerhoven, “Deep ppg: Large-scale heart rate estimation with convolutional neural networks,” Sensors, vol. 19, no. 14, p. 3079, 2019.

[4] Z. Zhang, “Photoplethysmography-based heart rate monitoring in physical activities via joint sparse spectrum reconstruction,” IEEE Transactions on biomedical engineering, vol. 62, no. 8, pp. 1902–1910, 2015.

[5] N. Huang and N. Selvaraj, “Robust ppg-based ambulatory heart rate tracking algorithm,” in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020, pp. 5929–5934.

[6] D. Biswas, L. Eversen, M. Liu, M. Panwar, B.-E. Verhoef, S. Patki, C. H. Kim, A. Acharya, C. Van Hoof, M. Konijnenburg et al., “Cornet: Deep learning framework for ppg-based heart rate estimation and biometric identification in ambient environment,” IEEE transactions on biomedical circuits and systems, vol. 13, no. 2, pp. 282–291, 2019.

[7] A. Gordon, E. Eban, O. Nachum, B. Chen, H. Wu, T.-J. Yang, and E. Choi, “Morpheus: Fast & simple resource-constrained structure learning of deep networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 1586–1595.

[8] S. Bai, J. Z. Kolter, and V. Koltun, “An empirical evaluation of generic convolutional and recurrent networks for sequence modeling,” arXiv preprint arXiv:1803.01271, 2018.

[9] C. Lea, R. Vidal, A. Reiter, and G. D. Hager, “Temporal convolutional networks: A unified approach to action segmentation,” in European Conference on Computer Vision. Springer, 2016, pp. 47–54.

[10] L. Ren, Y. Liu, X. Wang, J. Lü, and M. J. Deen, “Cloud-edge based heart rate estimation and biometric identification in ambient environment,” IEEE transactions on biomedical engineering circuits and systems, vol. 13, no. 2, pp. 282–291, 2019.

[11] A. Gordon, E. Eban, O. Nachum, B. Chen, H. Wu, T.-J. Yang, and E. Choi, “Morpheus: Fast & simple resource-constrained structure learning of deep networks,” in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 1586–1595.

[12] A. Gruber and Y. LeCun, “Deep learning for signal processing,” in Proceedings of the IEEE, vol. 104, no. 1, pp. 84–125, 2016.

[13] A. Tenk, “Accurate heart rate monitoring during physical exercises using ppg,” IEEE Transactions on Biomedical Engineering, vol. 64, no. 9, pp. 2016–2024, 2017.

[14] H. Chung, H. Lee, and J. Lee, “Finite state machine framework for instantaneous heart rate validation using wearable photoplethysmography during intense exercise,” IEEE journal of biomedical and health informatics, vol. 23, no. 4, pp. 1595–1606, 2018.

[15] S. Salehizadeh, D. Yao, B. Bolkovskiy, C. Cho, Y. Mendelson, and K. H. Chon, “A novel time-varying spectral filtering algorithm for reconstruction of motion artifact corrupted heart rate signals during intense physical activities using a wearable photoplethysmogram sensor,” Sensors, vol. 16, no. 1, p. 10, 2016.

[16] T. Schäck, M. Muma, and A. M. Zoubir, “Computationally efficient heart rate estimation during physical exercise using photoplethysmographic signals,” in 2017 25th European Signal Processing Conference (EUSIPCO). IEEE, 2017, pp. 2478–2481.

[17] X. Chang, G. Li, L. Tu, G. Xing, and T. Hao, “Deepehr: Accurate heart rate estimation from ppg signals based on deep learning,” in 2019 IEEE 16th International Conference on Mobile Ad Hoc and Sensor Systems (MASS), 2019, pp. 371–379.

[18] J. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” arXiv preprint arXiv:1502.03167, 2015.

[19] M. Tan, B. Chen, R. Pang, V. Vasudevan, M. Sandler, A. Howard, and Q. V. Le, “Mnasnet: Platform-aware neural architecture search for mobile,” in Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2019, pp. 2820–2828.

[20] M. Yuan and Y. Lin, “Model selection and estimation in regression with grouped variables,” Journal of the Royal Statistical Society: Series B (Statistical Methodology), vol. 68, no. 1, pp. 49–67, 2006.

[21] D. Jahier Pagliari, E. Macii, and M. Poncino, “Dynamic Bit-width Reconfiguration for Energy-Efficient Deep Learning Hardware,” in Proceedings of the International Symposium on Low Power Electronics and Design, ser. ISLPED ’18. ACM, 2018, pp. 47:1—47:6.

[22] D. Jahier Pagliari and M. Poncino, “Application-Driven Synthesis of Energy-Efficient Reconfigurable-Precision Operators,” in 2018 IEEE International Symposium on Circuits and Systems (ISCAS), 2018, pp. 1–5.

[23] M. Abadi, A. Agarwal, P. Barham, E. Brevdo, Z. Chen, C. Citro, G. S. Corrado, A. Davis, J. Dean, M. Devin, S. Ghemawat, I. Goodfellow, A. Harp, G. Irving, M. Isard, Y. Jia, R. Jozefowicz, L. Kaiser, M. Kudlur, J. Levenberg, D. Mané, R. Monga, S. Moore, D. Murray, C. Olah, M. Schuster, J. Shlens, B. Steiner, I. Sutskever, K. Talwar, P. Tucker, V. Vanhoucke, V. Vasudevan, F. Viégas, O. Vinyals, P. Warden, M. Wattenberg, M. Wicke, Y. Yu, and X. Zheng, “TensorFlow: Large-scale machine learning on heterogeneous systems,” 2015, software available from tensorflow.org. [Online]. Available: https://www.tensorflow.org/

[24] S. Microelectrometcs. Sm324746. [Online]. Available: https://www.st.com/resource/en/datasheet/stm32f476je.pdf

[25] M. Zhou and N. Selvaraj, “Heart rate monitoring using sparse spectral curve tracking,” in 2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC). IEEE, 2020, pp. 5347–5352.

[26] P. Sarkar and A. Etemad, “Cardiogan: Attentive generative adversarial network with dual discriminators for synthesis of ecg from ppg,” arXiv preprint arXiv:2010.00104, 2020.

[27] S. Microelectrometcs. (2017) X-cube-ai. [Online]. Available: https://www.st.com/en/embedded-software/x-cube-ai.html

Published as a conference paper at the IEEE 2021 ISCAS Conference (https://doi.org/10.1109/ISCAS51556.2021.9401282)