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Neuromorphic respiration rate detection using convolutional neural networks

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Abstract: Ambient assisted living (AAL) technologies can significantly enhance autonomy for elderly and disabled individuals. A key challenge is balancing effective monitoring with privacy, as conventional cameras may be perceived as intrusive. Neuromorphic cameras offer a privacy-preserving alternative by sensing only changes in brightness rather than full image frames and operating at lower spatial resolution. This work investigates a non-invasive approach for estimating patients' respiration rate using neuromorphic cameras combined with convolutional neural networks.

I. Introduction

The concept of Ambient Assisted Living (AAL) encompasses different methods, systems and services designed to support individuals like the elderly and chronically ill in maintaining independence in their familiar environments. By making use of intelligent technologies and embedding them into everyday settings, AAL aims to reduce reliance on institutional care. A core aspect of AAL is the use of non-invasive and non-contact vital parameter detection as many patients might have problems with body worn sensors and active participation in regular measurements. Machine vision techniques like remote photoplethysmography which can be used to detect the heart rate, respiration rate and blood oxygenation mostly rely on high definition cameras which can feel intrusive to place in the home of the affected person. The technology of neuromorphic vision presents a novel way of handling machine vision as a neuromorphic camera does not capture frames with a global or rolling shutter but uses the changes in brightness for each pixel to generate events [1]. This has the effect that only movement within the field of view is visible and information like the setting, the face of a person or even the clothing they are wearing is not visible in the recording. Due to the high sensitivity to changes in light, neuromorphic cameras can also pick up small movement of the human body which is caused by vital functions like respiration or the heartbeat.

I.I. Related work

Previous studies have explored privacy-preserving sensing technologies for non-contact monitoring in Ambient Assisted Living environments, including the use of neuromorphic vision and LiDAR sensors for human detection and vital parameter estimation. Event-based cameras have been shown to capture subtle motion patterns related to physiological processes such as respiration and heart rate while avoiding the privacy concerns associated with frame-based imaging. Existing approaches have primarily relied on handcrafted signal processing methods or global event statistics. In contrast, the present work builds on these findings by applying deep learning techniques to directly learn spatiotemporal features from neuromorphic data, aiming to improve robustness and accuracy in respiration rate estimation.

II. Methodology

For this work, a dataset was used, which was generated in the past [2]. The set included 25 participants between the ages of 20 and 55, each of which participated in multiple measurements in resting state and after physical activity, producing 132 measurements. Data augmentation was used to increase the size of the dataset to 528 samples. The dataset was created using a neuromorphic camera from the manufacturer Inivation with a resolution of 640 by 480 pixels. The participants were sat in distances from 0.5 m to 1.5 m in front of the camera with the camera being aimed at the chest and neck region. The recordings were saved in the aedat4 format and data augmentation has been done by applying different layers of filtering to the data, therefore generating different levels of signal to noise ratio (SNR). The reference measurements were taken with an ADInstruments powerlab [3] and a respiration belt.

II.I. Neural Network

The dataset was used to train a neural network composed of multiple 1+2-dimensional convolutional neural network (CNN) layers, where the single dimension corresponds to convolution along the temporal axis and the remaining two dimensions represent spatial convolutions. This architecture enables efficient extraction of spatiotemporal features from event-based data [4]. The convolutional encoder consists of a sequence of temporally separable 3D convolutions with normalization and nonlinear activation functions, followed by pooling operations to obtain a compact feature representation. To further enhance temporal modeling, a two-layer bidirectional long short-term memory (LSTM) network with a hidden size of 64 was integrated, allowing the model to capture both short- and long-term temporal dependencies. The LSTM output is processed by a fully connected regression head to estimate the respiration rate. Figure 1 illustrates the overall network architecture and provides a visualization of the input data and feature processing stages.

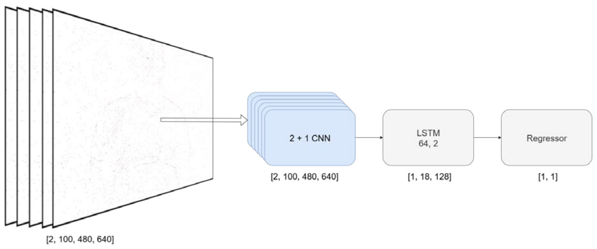

Figure 1: Visualization of the neural network

The network was trained using a Huber loss function to improve robustness against outliers, with an AdamW-based optimization strategy and an initial learning rate of 10^{-4}. Training was performed for up to 200 epochs using a learning rate scheduler based on the validation loss, and gradient clipping was applied to stabilize optimization. The dataset was divided into training, validation, and test sets using a 70–20–10 split, and all experiments were conducted on an NVIDIA A100 GPU.

III. Results and discussion

When evaluating the network on the test set, an overall MAE of 1.3 was achieved for all respiration rates between 8 and 28 rpm. The optimal distance for measuring the respiration rate with neuromorphic cameras was 0.5 m.

Table 1: MAE values for different distances.

Distance	Sample count	MAE
0.5 m	82	1.2117
1 m	38	1.6747
1.5 m	36	1.5984

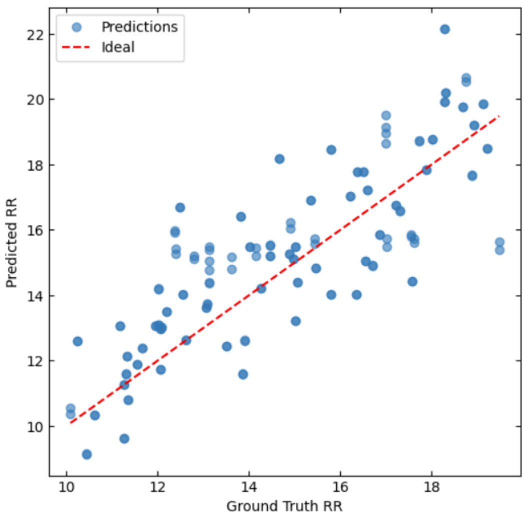

Figure 2: Respiration rate predicted by the neural net over ground truth respiration rate

For respiration rate values above 28 rpm the data was not sufficient to efficiently train the network. Therefore, these values are excluded from the test set. Fig. 2 shows the predicted respiration rates plotted over the ground truth measurements of the corresponding recordings.

The proposed approach is more robust to movement artifacts, compared to a previous work, which relied on the overall event count in the frame to predict the respiration rate [2].

IV. Conclusions

This work demonstrates the feasibility of non-contact respiration rate estimation using neuromorphic vision and deep learning, providing a privacy-preserving alternative to conventional camera-based approaches in Ambient Assisted Living environments. By combining 1+2-dimensional convolutional layers with an LSTM-based temporal model, the proposed network is able to effectively capture respiration-related spatiotemporal dynamics from event-based data. The achieved mean absolute error of 1.3 rpm across a wide range of respiration rates indicates competitive performance, particularly at shorter subject-to-camera distances, where signal quality is highest. Compared to prior methods relying on global event statistics, the presented approach shows improved robustness to movement artifacts, highlighting the advantage of learned spatiotemporal representations. Future work will focus on extending the dataset to higher respiration rates, improving performance at larger distances, and integrating the system into real-world AAL scenarios for long-term monitoring.

Author's statement

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