On-Device Multi-level Signal Quality Aware Compression for Energy-efficient Wearable PPG Sensing

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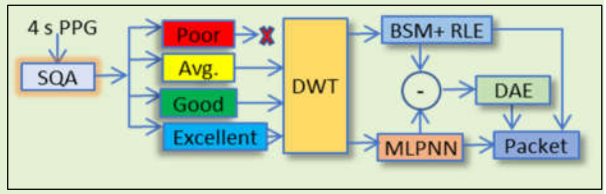

***Abstract*— On-device computing in biomedical sensors have become attractive towards developing wearable health monitoring systems. The challenge is to make a compromise between the latency and complexity in a resource constrained implementation. This paper describes an on-device implementation of multi-level signal quality aware and quality controlled compression (MSQQCC) that enhances the compression factor while preserving the clinical features in a wearable photoplethysmography (PPG) sensing application. The multi-level quality assessment (QA) provides three eligible PPG qualities, viz., 'excellent', 'good' and 'average', based on which corresponding upper limits are set for further compression using a discrete wavelet transform, while the 'corrupted' segments are discarded. A pretrained multilayer perceptron neural network provides the optimal quantization level of coefficients. The residual data is separately compressed using an autoencoder. MSQQCC was evaluated with 300 mins of PPG data from 3 public data sets and 110 mins of data collected at laboratory. The end-to-end pipeline was implemented in a standalone system with ARM Cortex A53 controller, requiring 35.51 KB of memory and 1.8s latency to process 4s PPG data. The on-device QA achieved 98.45 % overall accuracy (Ac), which outperforms published works on PPG QA. The mean deviation of PPG clinical features by 5 %, with overall CR and PRD were 40.85 and 2.52, which are superior than many published works. A real-time transmission over Bluetooth shows improvement of energy efficiency by a significant factor and 34% extended battery life for wearable PPG sensor. The results are encouraging for adoption of MSQQCC in wearable biomedical health monitoring.**

***Index Terms*— Compression, On-device, Photoplethysmography, Quality assessment, Wearable sensor.**

I. Introduction

WEARABLE health monitoring is gaining popularity day-by-day due to widespread use of low power biomedical sensors and embedded computing in smart watches and similar devices [1]. Photoplethysmography (PPG) is an automatic choice of sensor used in wearable gadgets due to its non-invasive (optical) sensing, low power requirement and deriving a pool of cardiovascular, hemodynamic, and respiratory parameters [2]. The primary challenges in wearable health monitoring are data reliability, secured sharing with proper management of high volume of data and energy efficiency of the battery powered sensing device. The paradigm of edge computing has enabled on-device analysis of data before further usage and sharing [3], thus making the sensor inherently 'intelligent'.

In wearable monitoring, the PPG data is corrupted with motion artifact (MA), and hence, signal quality assessment (SQA) may reduce the 'false positive' and 'false negative' cases of automated interpretation [4]. Currently, a plethora of research is available on PPG SQA, and the approaches are broadly classified under waveform morphology analysis ([5],[6],[7]) and signal quality index (SQI) with machine learning (ML) models ([8],[9],[10],[11],[12]) and deep learning-based approaches ([13],[14]). Most of the SQA techniques proposed binary classifier except [15] and [16]. The objective of multiclass PPG SQA is to identify the 'moderate' quality (neither excellent, nor too poor) segments which can be utilized for deriving basic physiological parameters, like heart rate [15]. Many of these methods use PPG beat-segmentation and then use a binary classifier to determine the pulse-wise quality by evaluating it in the time domain, frequency domain, or a combination of strategies. Moreover, methods exclusively based on correlation may only be partially successful in SQA under a few cardiac disorders. Non-segmenting approaches seem to offer a better solution ([17],[18]) in this regard. The methods based on SQI determine various quality index mainly based on pulse morphology and feed to a classifier for MA detection. The methods exclusively based on ML extract a group of features, often a combination of morphological, linear or nonlinear features followed by a supervised [15] or unsupervised [3] classifier for the MA corruption detection. In general, the accuracies (Ac) of these are higher than simple morphological features-based approaches, in particular, when multiclass detection is required. Dl-based approaches directly feed the raw data to a convolution architecture [13] for direct

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