Remote Livestream-based Stress Assessment in Telehealth Services

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***Abstract*—Remote assessment of stress is a critical component of IoT telehealth services. However, despite extensive research into stress detection, there remains a crucial gap in establishing a standardized stress scale, particularly using remote, noninvasive methods. We present a framework for remote stress assessment using video-based physiological monitoring. The proposed system architecture includes video acquisition using RGB cameras, sampling, preprocessing to remedy motion and lighting artifacts, and physiological inference by independent component analysis to extract stress-related biomarkers including remote photoplethysmography (rPPG) and respiratory biomarkers. The framework aims to provide a standardized scale for acute stress assessment, offering a better understanding of stress levels in remote interactions, including therapy sessions, with future research directions for integrating computer-assisted psychotherapists who can effectively communicate with patients.**

I. Introduction

Stress assessment is a pressing need in progressive healthcare systems, especially after the significant increase in stress-related diseases such as anxiety, depression, and disability. Minor daily stressors have long-term implications on mental health and well-being [1]. Stress significantly exacerbates several diseases, including cardiovascular, autoimmune diseases, asthma, and depression, and weakens immunity against infections. Over 25% of Canadians rank their daily stress as high-to severe, and 75% of short-term disability claims in Canada are caused by mental disorders related to stress, which costs employers about 20 billion dollars per year [2].

Stress is psychological and physical strain triggered by physical, emotional, social, and cognitive stimuli that disrupt the homeostasis balance of the individual, activating a stress response to cope with the stressor. Stress can be prolonged (chronic stress) or short-term (acute stress). Acute stress response involves the activation of the Autonomic Nervous System (ANS), hypothalamic-pituitary-adrenal (HPA) axis, and immune system [3].

Common methods to measure stress responses include self-report questionnaires or physiological measurements like Heart Rate Variability (HRV) and electrodermal Activity (EDA) [4]. While wearables such as wristbands are commonly used for physiological biomarker assessment, Visual Contactless Physiological Monitoring (VCPM) offers a promising alternative. VCPM is an innovative technology that utilizes videos to measure vital signs by analyzing the change in intensity of three RGB colors in each pixel. It is a rapidly developing field and at this moment, it can effectively measure photoplethysmography signal (PPG), heart rate (HR), blood pressure (BP), respiratory rate (RR), and oxygen saturation (SpO2) [5] which are known biomarkers to indicate stress. Remote sensing enables monitoring stress in many scenarios using everyday devices like phones or computer cameras, without the need for specialized equipment.

There is a critical need for establishing a standardized stress scale in tele-health services. While many studies view stress detection as a classification issue (i.e. low or high), few studies explore stress level measurement. For example, Garzon-Rey *et al* [6] introduced a novel method using psychometric tests and biochemical variables, however these cannot be measured by non-invasive techniques. Arza *et al* [7] proposed a scale based on wearable sensors, but not all physiological parameters are considered, especially remote vital signs.

II. System architecture

We propose a system to measure stress on a uniform scale, using non-invasive remote sensing methods. The overall model is depicted in figure 1 and detailed herein.

A. Video Acquisition

Visible spectrum RGB digital cameras, covering from 380 to 700 nm frequencies, are utilized to capture live videos for the stressed person. Webcams, digital photography cameras, cameras in cell phones, or any smart device can be considered an RGB imager. The images and videos from those devices are optimized to offer better visual clarity to the human eye. A common practice is to position a laptop or tablet's frontal camera approximately 1 meter away from the subject to ensure recording breathing-related movements [8].

B. Video Sampling and Prepossessing

We adopt a sampling model of 30 frames per second (fps) with a resolution of 640 × 480 pixels per frame to optimally capture the intensity of vascular variations. The face is selected as the region of interest (ROI) due to its rich vascular network, which is sensitive to changes in blood volume and oxygenation levels [9]. To mitigate motion artifacts, face ROIs are tracked

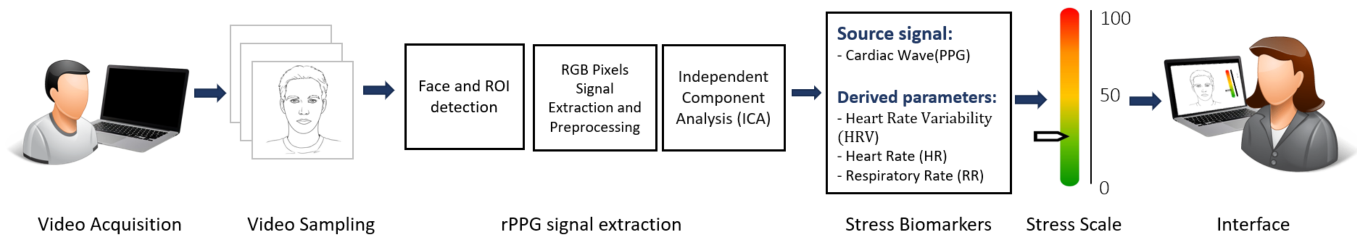

Fig. 1. Framework to assess and manage stress remotely

using the KLT algorithm to adjust for subject motion. To address lighting variations, an adaptive color difference operation is performed between raw rPPG signals in green and red channels. An adaptive bandpass filter is then designed based on the estimated HR frequency to remove motion and noise artifacts while preserving HR-related frequencies to dynamically adjust parameters based on HR estimation [10].

C. Physiological Biomarker Signals Extraction

We adopt an image processing model-based approach, independent component analysis (ICA), to extract PPG signals. ICA extracts PPG signals by separating cardiovascular pulse wave signals from mixed signals obtained from RGB color sensors on the facial region. It assumes linear mixtures of underlying source signals and aims to find a demixing matrix to estimate the source signals. By maximizing non-Gaussianity measures like kurtosis, ICA identifies independent sources, including the PPG waveform, amidst noise and artifacts, providing an estimate of the cardiovascular pulse wave [11].

D. Stress Biomarkers and Derived Parameters

Various stress biomarkers can be derived from remote PPG signals. The typical HR can be inferred by applying temporal filtering to rPPG signal. Then, to derive HRV, the inter-beat interval is computed from the filtered rPPG signal. To calculate the detrended HRV, the HRV signal is subtracted from the HR curve to extract the fluctuation. Finally, spectral analysis is employed on detrended HRV to estimate the RR [12]. Studies have shown that PPG, HRV, HR, and RR can be utilized as reliable biomarkers for stress assessment [4].

E. Stress Scale

Once remote biomarkers are estimated, they contribute to formulating a standard scale equation for acute stress, providing a scale from 0 to 100. Utilizing a stress scale with a wider range, instead of just two or three levels, enhances sensitivity to changes in stress states in real-life scenarios, facilitating quicker responses and more effective interactions. The user interface app serves as a plugin interface for online meeting applications, enabling real-time stress monitoring during virtual interactions.

III. Conclusions

The proposed framework for remote stress assessment encompasses an end-to-end service for tele-health users. Using physiological biomarkers derived from video feeds, we present a model for superimposing stress-level indicators on live-stream videos of users. The proposed system architecture integrates video acquisition, preprocessing, and physiological biomarkers extraction to estimate stress levels on a standardized scale. This framework offers a practical solution for real-time stress monitoring in various applications, extending to remote therapy, first-responders, and hazardous work environments. Future directions may involve exploring the integration of stress monitoring with computer-assisted psychotherapy for more autonomous and effective communication with patients.

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