A feasibility study of an eyewear prototype for detecting head-ECG

M. Rossi[1], A.C. Palmisciano[1], A. Farabbi[1], N. Antonello[2], D. Trojaniello[2], T. Ongarello[2], P. Cerveri[1,3] and L. Mainardi[1]

[1] *Department of Electronics, Information, and Bioengineering, Politecnico di Milano, Milan, Italy*

[2] *EssilorLuxottica Smart Eyewear Lab, EssilorLuxottica, 20133 Milan, Italy*

[3] *Department of Industrial and Information Engineering, University of Pavia, 27100 Pavia, Italy*

***Abstract*—Advancements in wearable technology allowed the measurement of electrocardiogram (ECG) from unconventional locations. This work investigates the feasibility of a single-lead head-ECG using a novel eyewear prototype with three strategically placed dry electrodes. The quality of the recorded ECG signals and the derived heart rate variability (HRV) indexes are compared to standard lead I torso-ECG acquisitions with the subject completely still (baseline) and during a talking task. Twenty subjects (10 male), aged 26.85±3.60 years, participated in the study. Each participant underwent a 6-minute recording session while wearing the eyewear device, divided into 3-minute baseline and 3-minute talking phases. The head-based ECG was evaluated in terms of signal quality, and the derived RR features were compared to those obtained from gold-standard thorax ECG. During the baseline phase, head-based ECG recordings were generally of good quality, with HRV metrics highly correlated ($R > 0.9$) with those obtained from the chest. In the talking phase, a slight decrease in signal quality was observed. The linear relationship ($R > 0.8$) between head–based and chest ECG HRV features remained acceptable, with a small degradation of the HRV metrics while maintaining good HR estimates. This study demonstrates the feasibility of recording a head-ECG signal using an eyewear-based setup, which can benefit fields such as the monitoring of patients with cardiac conditions.**

***Keywords*—Eyewear-ECG, cardiac monitoring, heart rate variability**

I. INTRODUCTION

The electrocardiogram (ECG) is a crucial diagnostic tool for heart health monitoring, traditionally recorded from the torso using multiple electrodes. Recent advancements in wearable technology have enabled ECG acquisition from unconventional locations like the wrist [1] and head [2]. While wrist-worn smartwatches effectively replicate lead I ECG [3], head-based ECG measurements present significant challenges. Firstly, the use of dry electrodes, necessary for wearable devices, introduces skin-electrode interface issues [4]. Secondly, low amplitude voltages are recorded by head-ECG, typically ranging between 10 and 50 µV [5] and are substantially lower when compared to torso-ECG voltages which generally are in the magnitude of 1 mV. This difference is caused by the limited flow of cardiac dipole currents through the head which requires a careful selection of electrodes placement and materials. Previous studies explored various head locations, including the ear canal [6], mastoid [7, 8], and forehead [9]. Ear-based approaches, for example by means of earplugs, demonstrated promising results, especially with electrodes placed between the ear and the neck resulting in high signal-to-noise ratios (SNR) [6]. Mastoid-based measurements, often integrated into hearing aids or headsets [10], showed good signal-to-noise ratios and captured characteristic ECG waveforms, particularly R-peaks [8]. However, literature studies agree on the fact that differential electrodes placed bilaterally on the head (cross-ear ECG) produce low-amplitude signals. Higher SNRs can be obtained by moving one of the electrodes to a body region on the neck or below [6]. This work investigates the feasibility of recording a single-lead ECG on the head using a novel eyewear prototype with three strategically placed dry electrodes. The study aimed to assess the quality of the recorded ECG signals and derived heart-rate variability (HRV) indexes by comparing them to synchronous standard lead I torso-ECG acquisitions with the subject completely still and during simple daily life activities such as talking.

II. MATERIAL AND METHODS

A. Device Description

The eyewear device (patent pending) incorporated three dry electrodes (Fig.1). The *"finger electrode"* was positioned on the left temple, the *"head electrode"* was placed internally on the temple tip, and the *"reference electrode"* was located on the nose bridge. The ECG lead was derived by computing the differential voltage between the finger and head electrodes, referenced to the nose bridge. The electrodes were designed as flexible sheets made of a conductive elastomer for easy attachment [11]. The finger electrode had a 1 cm^2 surface

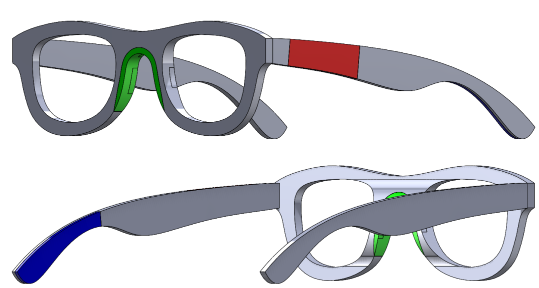


Fig. 1: CAD design of the eyeglass frame. Finger electrode (red), head electrode (blue), reference electrode (green).

area, while the larger head electrode (approximately 4 cm^2) aimed to maximize contact and mitigate signal interference from head shape and hair. This configuration leveraged the signal amplification achieved by measuring heart potentials at two distant points, similar to approaches used in some hearables [6], but eliminated the need for external wires by integrating all electronics within the eyewear frame. The ECG was acquired with 512Hz of sampling frequency using a MAX30003 biopotential amplifier (Analog Devices) front-end, an STM32 microcontroller (STMicroelectronics), and a Bluetooth low energy (BLE) module for the data transmission.

B. Protocol Description and Data Cohort

Twenty subjects (10 male), aged 26.85±3.60 years, participated in the study. Subject recruitment and data collection adhered to the experimental protocol (Opinion 46/2023, dated December 18^{th}, 2023), approved by the Politecnico di Milano Ethical Committee. Each participant underwent a 6-minute recording session while wearing the eye-frame, divided into 3-minute phases referred to as *baseline* and *talking*. During these sessions, subjects sat in front of a screen and maintained finger contact with the external electrode for Head-ECG (ECG_H) recording. Participants were exposed to a neutral stimulus (a gray screen) throughout the protocol. The *baseline* phase involved resting, while the *talking* phase required reading the first chapter of "Harry Potter and the Philosopher's Stone" displayed on the screen which caused a slight head movement. For the reference measurements, Thorax-ECG (ECG_T) was simultaneously recorded using a ProComp Infiniti System (Thought Technology Ltd., Canada) with a sampling frequency of 2048 Hz, employing standard wet Ag/AgCl electrodes in a Lead I configuration. Software-based triggering ensured synchronization between ECG_H and ECG_T recordings.

C. Data preprocessing

The ECG signals were processed using common methods to enhance the signal's content and remove unwanted artifacts. This preprocessing included the following steps: i) a band-pass ($0.5 - 45$ Hz), 4^{th}–order Butterworth filter was used to remove high and low-frequency noise and a baseline drift while preserving the essential ECG components; ii) a notch filter was used to remove the powerline interference at 50 Hz and iii) the ECG_T recording was downsampled to 512 Hz to match the sampling rate of ECG_H.

D. ECG Quality Assessment

To assess ECG signal quality, four indices were computed and evaluated according to thresholds found in the literature [12, 13]:

- kSQI: quantifies signal kurtosis, measuring its sharpness relative to a Gaussian distribution.
- pSQI: Calculates the ratio of ECG power spectral density within the 5-15 Hz band (primarily QRS) to that within the 5-40 Hz band. Higher ratios indicate a stronger QRS signal relative to noise.
- hosSQI: Combines skewness and kurtosis information.
- cSQI: calculates the ratio of the empirical standard deviation to the mean of the RR series. This index normalizes RR interval variability and helps identify potential noise-related R-peak detection errors.

The quality of each ECG acquisition was evaluated by combining these four indices using the criteria outlined in Table I.

TABLE I: Quality index thresholds and overall quality classification. mu and σ represent the mean and standard deviation of the ECG signal, respectively. $\hat{\mu}$ and $\hat{\sigma}$ represent the empirical standard deviation and mean of the RR series. N_o, N_u, and N_s represent the number of indices classifying the ECG recording as *optimal*, *unqualified*, and *suspicious*, respectively.

Quality Index	Thresholds
$kSQI = \frac{E[(x-\mu_x)]^4}{\sigma_x^4}$	Optimal if $kSQI > 5$ Unqualified if $kSQI \leq 5$
$pSQI = \frac{\int_5^{15} P(f)df}{\int_5^{40} P(f)df}$	Optimal if $0.5 < pSQI < 0.8$ Suspicious if $0.4 < pSQI < 0.5$ Unqualified if $pSQI < 0.4$ or $pSQI > 0.8$
$hosSQI = \lvert\frac{E[x-\mu]^3}{\sigma^3}\rvert\frac{kSQI}{5}$	Optimal if $hosSQI > 0.8$ Suspicious if $0.5 < hosSQI \leq 0.8$ Unqualified if $hosSQI \leq 0.5$
$cSQI = \frac{\hat{\sigma}_{RR}}{\hat{\mu}_{RR}}$	Optimal if $cSQI < 0.45$ Suspicious if $0.45 \geq cSQI \leq 0.64$ Unqualified if $cSQI > 0.64$
Overall	Excellent if $N_o > 3$ & $N_u = 0$ Unacceptable if $N_u \geq 3$ or $N_u = 2$ & $N_s \geq 1$ or $N_u = 1$ & &$N_s \geq 2$ Acceptable if not any of the previous cases

E. RR–features

RR-interval series were extracted from both ECG_H and ECG_T by identifying consecutive R peaks with the methods provided by the NeuroKit2 Python package [14] and calculating the time intervals between them. Based on these RR series, the following heart rate variability (HRV) features were extracted [15]: heart rate (HR), standard deviation of RR intervals (SDNN), root mean square of successive RR interval differences (RMSSD), percentage of successive RR interval differences $>$ 50 ms (pNN50), balance between sympathetic and parasympathetic nervous system activity calculated as the ratio of low-frequency (0.08-0.14 Hz) to high-frequency (0.2-0.45 Hz) power (LF/HF).

These HRV parameters are crucial for assessing cardiac function and autonomic nervous system regulation, providing valuable insights into cardiovascular health and physiological responses to various stimuli.

III. RESULTS

ECG signals recorded with the eyewear device (ECG_H) were compared to gold-standard chest ECG (lead I, ECG_T) in

TABLE II: Signal quality index for the baseline phase. The table presents median values with interquartile range (IQR) and the proportion of optimal (Opt), suspicious (Susp), and unqualified (Unq) signals.

		Median (IQR)	Opt	Susp	Unq
kSQI	ECG_T	14.19 (7.31)	90%	0%	10%
	ECG_H	9.49 (7.77)	75%	0%	25%
pSQI	ECG_T	0.64 (0.10)	90%	5%	5%
	ECG_H	0.65 (0.12)	95%	0%	5%
hosSQI	ECG_T	9.29 (8.51)	90%	5%	5%
	ECG_H	2.75 (6.09)	80%	15%	5%
cSQI	ECG_T	0.06 (0.03)	100%	0%	0%
	ECG_H	0.06 (0.03)	100%	0%	0%

TABLE III: Signal quality index for the talking phase. The table presents median values with interquartile range (IQR) and the proportion of optimal (Opt), suspicious (Susp), and unqualified (Unq) signals.

		Median (IQR)	Opt	Susp	Unq
kSQI	ECG_T	13.70 (8.18)	85%	0%	15%
	ECG_H	5.79 (11.43)	65%	0%	35%
pSQI	ECG_T	0.63 (0.10)	85%	10%	5%
	ECG_H	0.66 (0.10)	90%	5%	5%
hosSQI	ECG_T	9.01 (8.84)	95%	0%	5%
	ECG_H	1.97 (4.58)	60%	5%	35%
cSQI	ECG_T	0.08 (0.02)	100%	0%	0%
	ECG_H	0.08 (0.01)	100%	0%	0%

terms of signal quality and RR features. Table II and Table III illustrate the distribution of signal quality index (SQI) values during the baseline and talking sessions respectively. In the first phase, both ECG_H and ECG_T primarily exhibited optimal quality, with few instances classified as suspicious or unqualified. However, the proportion of non-optimal quality recordings increased during the talking phase. Table IV summarizes the overall signal quality. While most recordings were classified as excellent for both systems (80% for ECG_T and 65% for ECG_H in the baseline phase), a slight decrease in performance was observed during the talking phase, with only one ECG_H recording classified as unacceptable. The higher proportion of non-optimal ECG_H recordings likely resulted from the unconventional recording method and occasional instability in electrode-skin contact due to variations in head sizes and movements. Fig. 2 shows a strong linear relationship between RR features extracted from the ECG_H and ECG_T recordings during the baseline phase, indicating good agreement. This relationship slightly weakened during the talking phase. Table V presents the Pearson correlation coefficients, demonstrating significant correlation ($p-value < 0.01$) and strong linear relationships ($R > 0.9$) between most RR metrics extracted from ECG_H and ECG_T.

IV. DISCUSSION

The results for the baseline phase demonstrated that head-based ECG recordings were generally of good quality, with HRV metrics highly correlated with those obtained from the chest ECG. Signal quality analysis revealed that the majority of recordings from both setups were classified as "Excellent" or "Barely Acceptable", with no "Unacceptable" recordings. A higher proportion of recordings were classified as "Barely Acceptable" compared to the chest ECG (35% vs. 20%), likely due to the challenging nature of recording ECG signals far from the heart. Specifically, variations in head shape could lead to unstable electrode-skin contact, requiring manual adjustments by participants. Despite these limitations, the strong correlation ($R > 0.9$) between HRV indices extracted from head-based ECG and chest ECG during the baseline phase is particularly noteworthy. These findings support the effectiveness of measuring ECG between the head and a point below the neck, achieving high-amplitude signals and the potential for reliable RR series and associated HRV parameters estimation in resting conditions. In contrast, cross-ear ECG methods, commonly used in hearables and headsets, often suffer from low signal amplitudes (20-50 μV), making them susceptible to interference from noise sources such as eye movements and muscle activity (reaching hundreds of μV) [6]. During the talking phase, both head-based and chest ECG recordings exhibited a slight degradation in signal quality, with a higher proportion of "Barely Acceptable" and one "Unacceptable" recording for the head-based system. The correlation analysis shows that the linear relationship between HRV features from head-based and chest ECG remains good ($R > 0.8$), although with lower values of R for all parameters except HR. This behavior can be attributed to artifacts introduced by subtle movements during speech. Some limitations of the present work deserve comments. Firstly, the use of a single-size frame may not optimally fit all head shapes, potentially impacting electrode-skin contact stability. Secondly, the experiments were conducted in a controlled environment with limited subject movement, which may not fully reflect real-world conditions. Finally, this study provides only a preliminary agreement analysis. Future research should address these limitations by developing more adaptable frame designs, conducting experiments in more realistic settings, enrolling a larger experimental population, and performing a more in-depth agreement analysis. Further analyses should also investigate whether the ECG recorded from the head preserves the details of the different phases of the cardiac cycle.

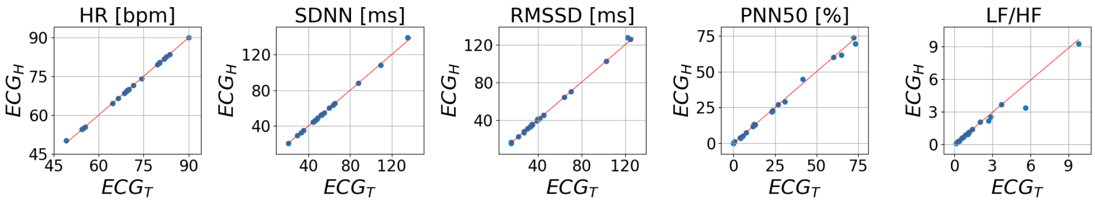
TABLE IV: Classification of ECG quality indices.

		Excellent	Barely Acceptable	Unacceptable
Baseline	ECG_T	16 (80%)	4 (20%)	0 (0%)
	ECG_H	13 (65%)	7 (35%)	0 (0%)
Talking	ECG_T	14 (70%)	6 (30%)	0 (0%)
	ECG_H	11 (55%)	8 (40%)	1 (5%)

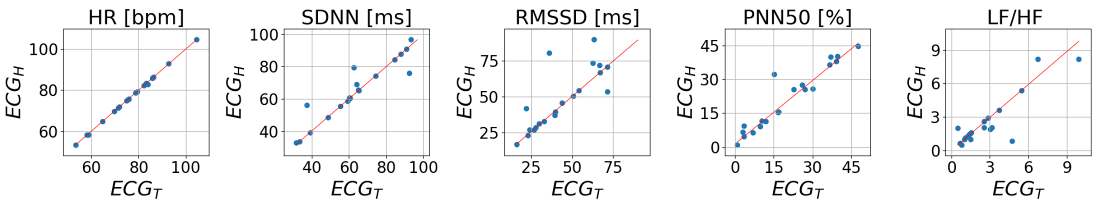
TABLE V: The Pearson correlation coefficient (R) between RR metrics calculated from ECG_T and ECG_H data. All statistical metrics indicated a significance level with a p-value less than 0.05.

	HR	SDNN	RMSSD	PNN50	LF/HF
Baseline	1.00	1.00	0.99	0.99	0.98
Talking	1.00	0.93	0.80	0.95	0.88

This study demonstrated the feasibility of recording ECG signals using electrodes positioned on the head. An eyewear-based ECG setup produced high-quality signals, with heart rate variability parameters closely matching those of standard



(a) Baseline



(b) Talking

Fig. 2: RR features scatter plots.

ECG, indicating its potential for long-term, unobtrusive monitoring. Such a system could benefit preventive healthcare, early cardiac abnormality detection, and effortless, on-demand monitoring available at any time for patients with heart conditions.

ACKNOWLEDGEMENTS

This work was carried out in the EssilorLuxottica Smart Eyewear Lab, a Joint Research Center between EssilorLuxottica and Politecnico di Milano.

REFERENCES

[1] Marc Strik, Sylvain Ploux, Daniel Weigel, Joske van der Zande, Anouk Velraeds, Hugo-Pierre Racine, F. Daniel Ramirez, Michel Haïssaguerre, and Pierre Bordachar. The use of smartwatch electrocardiogram beyond arrhythmia detection. *Trends in Cardiovascular Medicine*, 34(3):174–180, 2024.

[2] Tobias Röddiger, Christopher Clarke, Paula Breitling, Tim Schneegans, Haibin Zhao, Hans Gellersen, and Michael Beigl. Sensing with earables: A systematic literature review and taxonomy of phenomena. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 6(3):1–57, September 2022.

[3] Mathieu Nasarre, Marc Strik, Francisco Daniel Ramirez, Samuel Buliard, Hugo Marchand, Saer Abu-Alrub, Sylvain Ploux, Michel Haïssaguerre, and Pierre Bordachar. Using a smartwatch electrocardiogram to detect abnormalities associated with sudden cardiac arrest in young adults. *EP Europace*, 24(3):406–412, 09 2021.

[4] Hyeonseok Kim, Eugene Kim, Chanyeong Choi, and Woon-Hong Yeo. Advances in Soft and Dry Electrodes for Wearable Health Monitoring Devices. *Micromachines*, 13(4):629, apr 2022.

[5] Wilhelm von Rosenberg, Theerasak Chanwimalueang, Valentin Goverdovsky, Nicholas S. Peters, Christos Papavassiliou, and Danilo P. Mandic. Hearables: feasibility of recording cardiac rhythms from head and in-ear locations. *Royal Society Open Science*, 4(11):171214, November 2017.

[6] Patrick van der Heijden, Camille Gilbert, Samira Jafari, and Mattia Alberto Lucchini. Multi-Channel Soft Dry Electrodes for Electrocardiography Acquisition in the Ear Region. *Sensors 2024, Vol. 24, Page 420*, 24(2):420, jan 2024.

[7] Bruno Gil, Salzitsa Anastasova, and Guang Yang. A smart wireless ear-worn device for cardiovascular and sweat parameter monitoring during physical exercise: Design and performance results. *Sensors*, 19(7):1616, April 2019.

[8] Saygun Guler, Ata Golparvar, Ozberk Ozturk, and Murat Kaya Yapici. Ear Electrocardiography With Soft Graphene Textiles for Hearable Applications. *IEEE Sensors Letters*, 6(9):1–4, sep 2022.

[9] Wilhelm Von Rosenberg, Theerasak Chanwimalueang, Valentin Goverdovsky, David Looney, David Sharp, and Danilo P. Mandic. Smart Helmet: Wearable Multichannel ECG and EEG. *IEEE Journal of Translational Engineering in Health and Medicine*, 4:1–11, 2016.

[10] David Da He, Eric S. Winokur, and Charles G. Sodini. An ear-worn vital signs monitor. *IEEE Transactions on Biomedical Engineering*, 62(11):2547–2552, November 2015.

[11] Yun-Hsuan Chen, Maaike De Beeck, Luc Vanderheyden, Evelien Carrette, Vojkan Mihajlović, Kris Vanstreels, Bernard Grundlehner, Stefanie Gadeyne, Paul Boon, and Chris Van Hoof. Soft, comfortable polymer dry electrodes for high quality ecg and eeg recording. *Sensors*, 14(12):23758–23780, December 2014.

[12] Zhidong Zhao and Yefei Zhang. SQI Quality Evaluation Mechanism of Single-Lead ECG Signal Based on Simple Heuristic Fusion and Fuzzy Comprehensive Evaluation. *Frontiers in Physiology*, 9, June 2018.

[13] M. Nardelli, A. Lanata, G. Valenza, M. Felici, P. Baragli, and E.P. Scilingo. A tool for the real-time evaluation of ECG signal quality and activity: Application to submaximal treadmill test in horses. *Biomedical Signal Processing and Control*, 56:101666, February 2020.

[14] Dominique Makowski, Tam Pham, Zen J. Lau, Jan C. Brammer, François Lespinasse, Hung Pham, Christopher Schölzel, and S. H. Annabel Chen. NeuroKit2: A python toolbox for neurophysiological signal processing. *Behavior Research Methods*, 53(4):1689–1696, feb 2021.

[15] Fred Shaffer and J. P. Ginsberg. An overview of heart rate variability metrics and norms. *Frontiers in Public Health*, 5, September 2017.