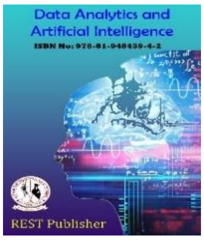
Data Analytics and Artificial Intelligence
Vol: 3(7), 2023
REST Publisher; ISBN: 978-81-948459-4-2
Website: http://restpublisher.com/book-series/daai/



Emotion Recognition Using Wireless Signals

S. Rekha
Adhiyamaan college of engineering (Autonomous), Hosur, Tamilnadu, India.
*Corresponding Author Email: rekha.s.mca2022@adhiyamaan.in

Abstract: *This paper demonstrates a new technology that can infer a person's emotions from RF signals reflected off his body. EQ-Radio transmits an RF signal and analyzes its reflections off a person's body to recognize his emotional state (happy, sad, etc.). The key enabler underlying EQ-Radio is a new algorithm for extracting the individual heartbeats from the wireless signal at an accuracy comparable to on-body ECG monitors. The resulting beats are then used to compute emotion-dependent features which feed a machine-learning emotion classifier. We describe the design and implementation of EQ-Radio, and demonstrate through a user study that its emotion recognition accuracy is on par with stateof-the-art emotion recognition systems that require a person to be hooked to an ECG monitor.*

1. INTRODUCTION

Emotion recognition is an emerging field that has attracted much interest from both the industry and the research community. Itis motivated by a simple vision: Can we build machines that sense our emotions? If we can, such machines would enable smart homes that react to our moods and adjust thelighting or music accordingly. Movie makers would have better tools to evaluate user experience. Advertisers would learn customer reaction immediately. Computerswould automatically detect symptoms of depression, anxiety, and bipolar disorder, allowing early response to such conditions. In this paper, we introduce a new method foremotion recognition that achieves the best ofboth worlds –i.e., it directly measures the interaction of emotions and physiological signals, but does not require the user to carrysensors on his body. Our design uses RF signals to sense emotions. Specifically, RF signals reflect off the human body and get modulated with bodily movements. Recent research has shown that such RF reflections can be used to measure a person's breathing and average heart rate without body contact.

2. EQ-RADIO OVERVIEW

EQ-Radio is an emotion recognition systemthat relies purely on wireless signals. It operates by transmitting an RF signal and capturing its reflections off a person's body.It then analyzes these reflections to infer theperson's emotional state. It classifies the person's emotional state according to the known arousal-valence model into one of four basic emotions : anger, sadness, joy, and pleasure (i.e., contentment). EQ-Radio's system architecture consists of three components that operate in a pipelinedmanner, as shown in Fig An FMCW radio, which transmits RF signals and captures their reflections off aperson's body. A beat extraction algorithm, which takes the captured reflections as input and returnsa series of signal segments that correspond to the person's individual heartbeats. An emotion-classification subsystem, which computes emotion-relevant featuresfrom the captured physiological signals – i.e., the person's breathing pattern and heartbeats – and uses these features to recognize the person's emotional state.

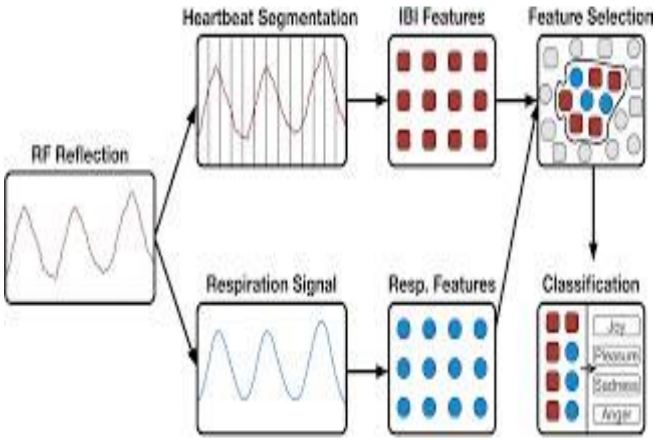


FIGURE 1. EQ-Radio Overview

3. CAPTURING THE RF SIGNAL

EQ-Radio operates on RF reflections off thehuman body. To capture such reflections, EQ-Radio uses a radar technique called Frequency Modulated Carrier Waves (FMCW) [5]. There is a significant literatureon FMCW radios and their use for obtainingan RF signal that is modulated by breathing and heartbeats [7, 11, 49]. We refer the reader to [7] for a detailed description of such methods, and summarize below the basic information relevant to this paper. Theradio transmits a low power signal and measures its reflection time. It separates RF reflections from different objects/bodies intobuckets based on their reflection time. It then eliminates reflections from static objects which do not change across time andzooms in on human reflections. It focuses ontime periods when the person is quasi-static.It then looks at the phase of the RF wave which is related to the traveled distance as follows [58]: $\varphi(t) = 2\pi\ d(t)\ \lambda$, where $\varphi(t)$ is the phase of the signal, λ is the wavelength, d(t) is the traveled distance, and t is the timevariable. The variations in the phase correspond to the compound displacement caused by chest expansion and contraction due to breathing, and body vibration due to heartbeats.2 The phase of the RF signal is illustrated in the top graph in Fig. 1. The envelop shows the chest displacements as the inhale-exhale process. The small dents are due to minute skin vibrations associated with blood pulsing. EQ-Radio operates on this phase signal.

4. BEAT EXTRACTION ALGORITHM

Recall that a person’s emotions are correlated with small variations in her/his heartbeat intervals; hence, to recognize emotions, EQ-Radio needs to extract these intervals from the RF phase signal describedabove. The main challenge in extracting heartbeat intervals is that the morphology ofheartbeats in the reflected RF signals is unknown. Said differently, EQ-Radio does not know how these beats look like in the reflected RF signals. Specifically, these beats result in distance variations in the reflected signals, but the measured displacement depends on numerous factors including the person’s body and her exact posture with respect to EQ-Radio’s antennas. This is in contrast to ECG signals where the morphology of heartbeats has a known expected shape, and simple peak detection algorithms can extract the beat-to- eat intervals. However, because we do not know the morphology of these heartbeats in RF a priori, we cannot determine when a heartbeat starts and when it ends, and hence we cannot obtain the intervals of each beat. In essence, this becomes a chicken-and-egg problem: if we know the morphology of the heartbeat, that would help us in segmenting the signal; on the other hand, if we have a segmentation of the reflected signal, we can use it to recover the morphology of the human heartbeat. This problem is exacerbated by two additional factors. First, the reflected signal is noisy; second, the chest displacement due to breathing is ordersof magnitude higher than the heartbeat displacements. In other words, we are operating in a low SINR (signal-to- interference-and-noise) regime, where “interference” results from the chest displacement due to breathing. To address these challenges, EQ-Radio first processes the RF signal to mitigate the interference from breathing. It then formulates and solves an optimization problem to recover the beat-to-beat intervals. The optimization formulation neither assumes nor relies on perfect separation of the respiration effect.

5. EMOTION CLASSIFICATION

After EQ-Radio recovers individual heartbeats from RF reflections, it uses the heartbeat sequence along with the breathingsignal to recognize the person's emotions. Below, we describe the emotion model which EQ-Radio adopts, and we elaborate on its approach for feature extraction and classification.

2D Emotion Model: EQ-Radio adopts a 2D emotion model whose axes are valence and arousal; thismodel serves as the most common approach for categorizing human emotions in past literature. The model classifies between four basic emotionalstates: Sadness (negative valence and negative arousal), Anger (negative valence and positive arousal), Pleasure (positive valence and negative arousal),and Joy (positive valence and positive arousal).

Feature Extraction:

EQ-Radio extracts features from both the heartbeat sequence and the respiration signal. There is a large literature on extracting emotion-dependent features from human heartbeats , where past techniques use on-body sensors. These features can be divided into time-domain analysis, frequency-domain analysis, time frequency analysis, Poincare plot , Sample Entropy , and Detrend Fluctuation Analysis . EQ- Radio extracts 27 features from IBI sequences as listed in Table 1. These particular features were chosen in accordance with the results in [34]. We referthe reader to for a detailed explanation of these features. EQ-Radio also employs respiration features. To extract the irregularity of breathing, EQ-Radio first identifies each breathing cycle by peak detection after low pass filtering. Since past work that studies breathing features recommends time-domain features , EQ- Radio extracts the time-domain features in the first row of Table 1.

TABLE 1. Features used in EQ-Radio

Domain	Name
Time	Mean, Median, SDNN,**pNN50**, RMSSD, SDNNi, meanRate, *sdRate*, HRVTi, *TINN*.
Frequency	Welch PSD: **LF/HF**, peakLF, peakHF. Burg PSD: **LF/HF**, peakLF, peakHF. Lomb-Scargle PSD: **LF/HF**, peakLF, peakHF.
Poincaré	SD_1, $\mathbf{SD_2}$, $\mathbf{SD_2/SD_1}$.
Nonlinear	$\mathbf{SampEn}_1$, $\mathbf{SampEn}_2$, $\mathbf{DFA}_{all}$, DFA_1, DFA_2.

selected IBI features in **bold**;
selected respiration features in *italic*.

Table 1: **Features used in EQ-Radio.**

Handling Dependence: Physiological features differ from onesubject to another for the same emotional state. Further, those featurescould be different for the same subjecton different days. This is caused by multiple factors, including caffeine intake, sleep, and baseline mood of theday. In order to extract better features that are user-independent and day- independent, EQ-Radio incorporates abaseline emotional state: neutral. The idea is to leverage changes of physiological features instead of absolute values. Thus, EQ-Radio calibrates the computed features by subtracting for each feature its corresponding values calculated at the neutral state for a given person on a given day.

Feature Selection and Classification:As mentioned earlier, the literature has many features that relate IBI to emotions. Using all of those features with a limited amount of training data can lead to over-fitting. Selecting a set of features that is most relevant to emotions not only reduces the amount of data needed for training but also improves the classification accuracy onthe test data. EQ-Radio uses another class of feature selection mechanisms, namely embedded methods , this approach allows us to learn which features best contribute to the accuracyof the model while training the model. To do this, EQ-Radio uses l1-SVM which selects a subset of relevant features while training an SVM classifier. Table 1 shows the selected IBI and respiration features in bold anditalic respectively.

6. EVALUATION

In this section, we describe our implementation of EQ-Radio and its empirical performance with respect toextracting individual heartbeats and recognizing human emotional states. EQ-Radio versus ECG-based emotionrecognition In this section, we compare EQ-Radio'semotion classification accuracy with that of an ECG-based classifier. Note that both classifiers use the same set of features and decision making process. However, the ECG-based classifier uses heartbeat information directly extracted from the ECG monitor. In addition, we allow the ECG monitor to access the breathing signal from EQ-Radio and useEQ-Radio's breathing features. This mirrors today's emotion monitors which also use breathing data but require the subject to wear a chest band in order to extract that signal. The results in Table 2 show that EQ-Radio achieves comparable accuracy to emotion recognition systems that use on-body sensors.

TABLE 2. Comparison with the ECG-based Method

Method	Person-dependent	Person-independent
EQ-Radio	87%	72.3%
ECG-based	88.2%	73.2%

Table 2: **Comparison with the ECG-based Method.**

7. CONCLUSION

This paper presents a technology capable of recognizing a person's emotions by relying on wireless signals reflected off her/his body. We believe this marks an important step in the nascent field of emotion recognition. It also builds on a growing interest in the wireless systems' community in using RF signals for sensing, and as such, the work expands the scope of RF sensing to the domain of emotion recognition. Further, while this work has laid foundations for wireless emotion recognition, we envision that the accuracy of such systems will improve as wireless sensing technologies evolve and as the community incorporates moreadvanced machine learning mechanismsin the sensing process. We also believe that the implications of this work extendbeyond emotion recognition. Specifically, while we used the heartbeat extraction algorithm for determining the beatto-beat intervals and exploited these intervals for emotion recognition, our algorithm recovers the entire human heartbeat from RF, and the heartbeat displays a very rich morphology. We envision thatthis result paves way for exciting research on understanding the morphology of the heartbeat both in thecontext of emotion-recognition as well as in the context of non-invasive health monitoring and diagnosis.

REFERENCES

[1]. Microsoft project oxford emotion api. https://www.projectoxford.ai/emotion.
[2]. S. Jerritta, M. Murugappan, R. Nagarajan,and K. Wan. Physiological signals based human emotion
[3]. Mingmin Zhao, Fadel Adib, Dina KatabiMassachusetts Institute of Technology {mingmin, fadel, dk}@mit.edu

