Framework to analyze virtual communication channels to overcome communication fatigue in digital human mediation

Shreya Vairava Subramanian
sv523@cam.ac.uk
Department of Computer Science and Technology
University of Cambridge
United Kingdom

Abstract

Communication Fatigue occurs due to physical and mental exhaustion caused by overwhelming influx of messages through virtual messaging applications like Whats App, Telegram, Slack, Facebook Messenger, Instagram Chats and so on. To overcome this condition, the paper proposes a model to optimize these virtual messaging applications that filters relevant messages to prioritize communication.

1 Introduction

With technological advancements, social media is growing exponentially, thereby creating an enormous influence upon users. Beginning with electronic mail developed in 1970 leading up to threads developed in 2023, there have been various virtual communication channels regulating inflow and outflow of communication from one user to another [1]. On an average, there is a million communication occuring per day [2]. This creates an array of issues such as choice paralysis which is the inability to choose one option from a range of such options [3]. This leads to information overloading caused by multiple incoming comunications [4]. Eventually, this causes an intense burnout leading to communication fatigue which psychologically, is an important health concern.

2 Motivation

Virtual communication has become an integral part of an individual personal as well as professional lives. In the professional front, the advancement of technology has driven the rise in moving to online platforms for business communications [5]. Especially, during COVID - 19, the need to shift to digital mode without working physically in offices has increased the time spent by an average human in communicating online [6]. It was also in this period that physical interactions were not encouraged forcing humans to communicate with their beloved ones online. During these times, the emergence and reliance on virtual comunication channels rose [7]. This created a sense of monotonicity giving no options for any other forms of communication other than sitting in front of a laptop. Thus, the exhaustion that occurs through over - reliance on such channels have given birth to communication fatigue [8]. It has become imperative to address this concern as online communications have transformed the way we live today [9]. The main goal of this project is to address communication fatigue through affective artifical intelligence in which an intelligent system will be designed in which emotional cues will be monitored during virtual interactions to adjust the style of communication necessary to overcome fatigue.

3 Methodology

The first step is to collect the dataset related to virtual communication channels. Facial Expression data will be collected during interactions via web cameras where facial landmarks such as eyes, eyebrows along with facial action units such as smiling, frowning, laughing will be analyzed as a part of emotion recognition. For this, the datasets that will be used are :

(1) FER 2013 - A dataset that contains around 35,000 labelled samples of facial expression data captured during virtual interactions [10]
(2) AffectNet - A dataset that contains around 1 million facial images captured during online online communications [11]
(3) EmoReact - A dataset that constitutes an array of facial expressions captured during virtual comunications [12]

The next step is to collect speech data through audio used for communicating online. In this type, data from audio will be collected to analyze pitch, timbre, tone and speaking rate to determine the indicators of disinterest like frustration or stress. The datasets specifically used would be :

(1) EmoDB (Berlin) - A dataset that contains audio data spanned across 10 different emotions in German language [13]
(2) Toronto Speech - A dataset containing speech recordings spanned across different emotions [14]
(3) Ryerson Audio - Visual Database - A dataset containing emotional speech recordings in order to deterine which conversations would be the most engaging for the user to focus and what to avoid [15]

The next step is to collect interaction data through video conferencing platforms like talking conversations to analyze the frequency of verbal and non - verbal cues, response delays, interaction lengths and the rate of participation in discussions. The dataset to be used are :

(1) The AVEC 2023 - A dataset that contains audio and visual recordings of online interactions inclusing affective states [16]
(2) INTERACT - A dataset that focuses on casual virtual conversations taking place between humans in order to study the engagement levels and level of interest/disinterest in communicating with another user [17]

The second phase would be the data pre - processing and feature extraction procedure. In data pre - processing, the first step as mentioned above would be facial expression recognition during virtual interactions. In order to identify the regions of interest in the face, detection algorithms like Haar - Cascade algorithms [18] would be used to localize and analyze the images. The next step would be image normalization in which the image would be cropped to focus mainly on the facial aspects for any movements. Landmark detection algorithms such as OpenCV [19] would be used to track the facial movements and their geometry. A commonly used architecture like the Convolutional Neural Networks (CNNs) [20] can be employed to classify the emotions from these features.This can indicate expressions indicative of fatigue such as yawning, drooping etc.

The next step would be to perform speech analysis. In order to understand the rate of engagement in conversation, speech analysis can be performed to capture the tone, pitch, timbre etc. When people get tired during a conversation, their speech tends to become slower, less expressive and monotonous. A person having communication fatigue will have irregular pitch, meaning the pitch would vary anywhere from lower to higher without any consistency [21]. Another sign of communication fatigue observed during virtual interaction is reduction in speech rate [22]. Fatigued users tend to speak slowly with longer pauses during such interactions. Such fatigue - related aspects can be observed for analysis using speech emotion recognition models like a neural network.

Prosodic features, including rhythm, stress, and intonation of speech are extensively used to assess the physiological and psychological state, including fatigue [23]. As fatigue sets in, vocal production mechanisms are affected, producing some changes in these features. An example to showcase, a fatigued individual might exhibit a lower pitch, reduced intensity, and slower speaking rate [24]. These changes arise from decreased muscle control and reduced respiratory effort, which could affect the fundamental frequency, amplitude, and timing of speech signals.

By analyzing prosodic features like pitch, energy, and speaking rate,fatigue in communication can be detected. A decrease in pitch can indicate vocal fatigue. Similarly, lower energy levels, reflected in decrease in loudness and speech intensity, can be a sign of exhaustion. Furthermore, a slower speaking rate with longer pauses also suggests the possibility of communication fatigue. By combining these features and establishing thresholds,patterns that display signs of communication fatigue can be detected.

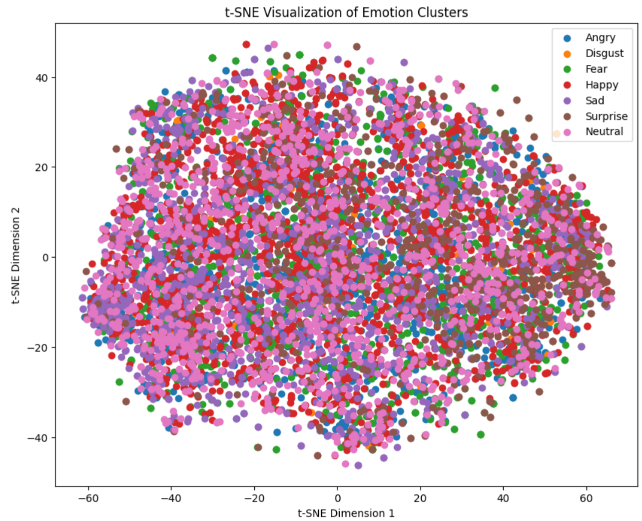

Figure 1: Distribution of Emotion Clusters

4 Results

The facial expression recognition was performed during virtual interactions in which facial expressions were analyzed.

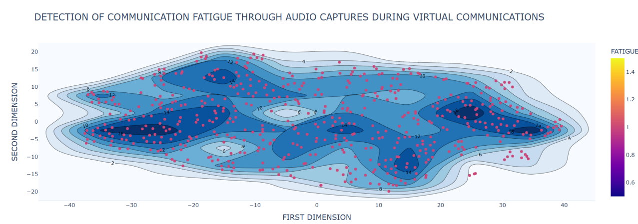

Figure 2: Detection of communication fatigue through audio captured during virtual communications

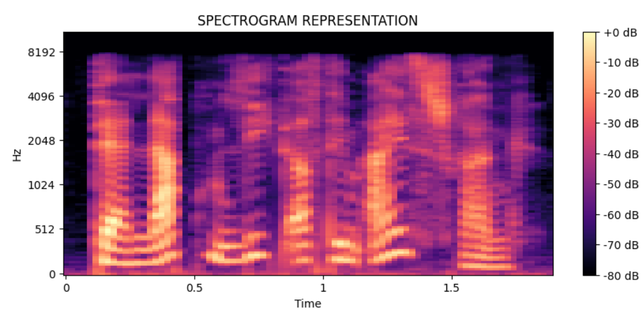

Figure 3: Spectrogram representation of audio communications

It can be found that that the highly used emotion during such virtual interactions tend to have a neutral impact on the user. Using the FER 2013 dataset, the distribution of emotion clusters through facial expression and it's movements were identified. Similarly, with audio captured during virtual voice interactions, the level of fatigue was detected using the prosodic features such as pitch, energy and speaking rate. Figure 3 indicates the spectrogram representation of a particular audio file. Figure 2 indicates the level of communication fatigue detected from the audio data. Figure 4, 5, 6 indicates how specific features like pitch, energy and speaking rates influence the production of communication fatigue during such virtual voice interactions.

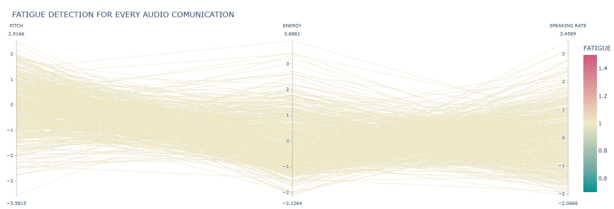

Figure 4: Division of prosodic features on communication fatigue detection

Category	Number of Files
Total Files	535
Files Indicating Fatigue	126
Files Not Indicating Fatigue	409

Table 1: Summary of Files Analyzed for Fatigue

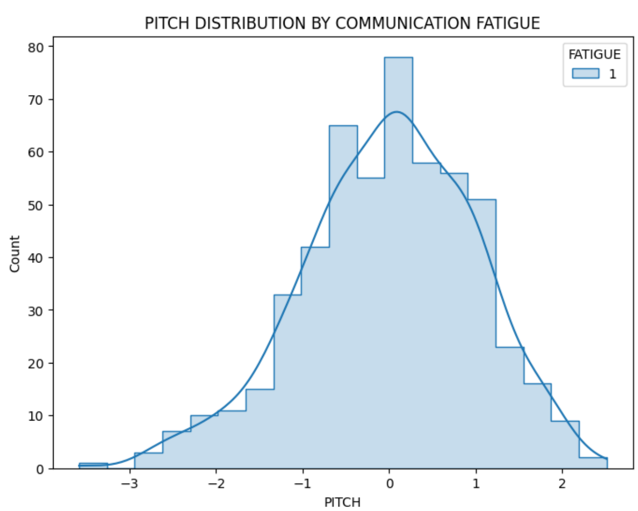

Figure 5: Effect of Pitch on Fatigue

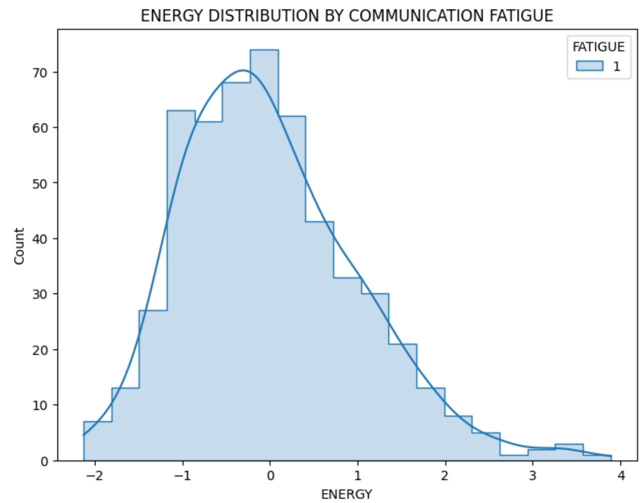

Figure 6: Effect of Energy on Fatigue

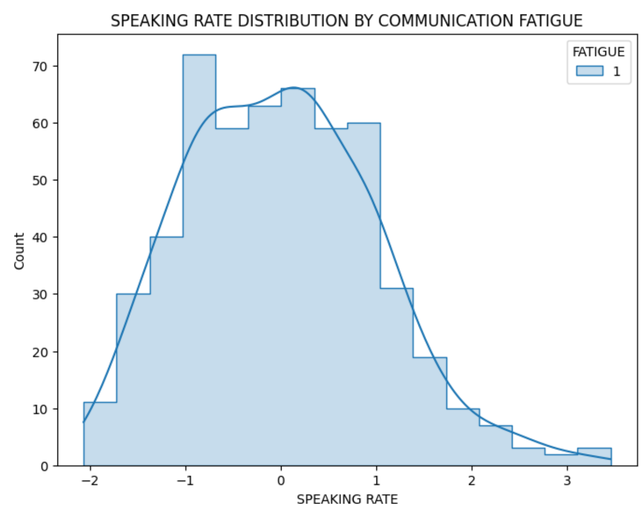

Figure 7: Effect of Speaking Rate on Fatigue

5 Conclusion

Thus, it can be found from the analysis that a total of 126 audio files captured during virtual interactions displayed signs of communication fatigue whereas a total of 409 indicated no signs of comunication fatigue. Thus, 23.55% indicated comunication fatigue during audios captured through virtual interactions.

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