Earloop: Enhancing Communication Dynamics with Real-Time Feedback for Healthier Conversations

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1 Abstract

In the wake of the COVID-19 pandemic, the shift to remote and hybrid work has highlighted the loss of subtle, non-verbal cues essential for effective communication. These cues, often missed in virtual and in-person settings, lead to misunderstandings, weaker interactions, and reduced productivity. Studies have shown the importance of non-verbal cues for effective communication and team productivity [1][2]. To address this, we developed "Earloop," an intelligent wearable device providing instant feedback on behavioral metrics. Using advanced sensors and algorithms, Earloop processes and displays real-time data through an intuitive interface, allowing users to monitor and adjust their communication patterns. Earloop's goal is to significantly improve interpersonal connections, thus creating a more connected and productive work environment in our post-pandemic world [3]. The system being developed to implement this change is shown in Fig. 1.

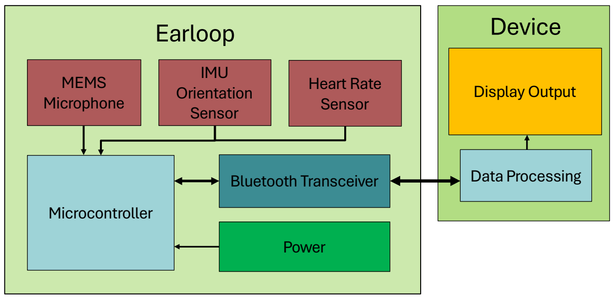

Fig. 1: Flow chart of operation for proposed behavioral metric monitoring and analysis system.

2 Research Challenge

The main challenges this research aims to overcome is providing a real-time feedback system without disrupting daily activities [6] as well as fitting everyone's communication styles, as these vary widely among individuals[4]. These communication styles vary from subtle verbal and non-verbal behavioral cues such as head movements/nods, gaze direction, talk-time and facing-time (time spent facing other people). Additionally, developing an unobtrusive, wearable device that accurately detects these behavioral cues is challenging given currently available sensors in the market [5].

References

[1] J. A. Burgoon, L. K. Guerrero, and K. Floyd, Nonverbal Communication, 1st ed. Routledge, 2021.
[2] A. Mehrabian, Silent Messages: Implicit Communication of Emotions and Attitudes, 2nd ed. Wadsworth, 2007.
[3] S. K. Wiederhold, "Connecting through technology during COVID-19," International Journal of Environmental Research and Public Health, vol. 17, no. 23, pp. 1-10, 2020.
[4] J. S. Goodwin, "Challenges in wearable technology for real-time feedback," IEEE Pervasive Computing, vol. 19, no. 1, pp. 21-27, 2020.
[5] S. T. Murphy, C. R. Zajonc, "The development of individual communication styles: A longitudinal study," Journal of Personality and Social Psychology, vol. 64, no. 5, pp. 787-796, 1993.
[6] A. Pentland, Honest Signals: How They Shape Our World, MIT Press, 2008.

3 Design Methods and Results

3.1 Inertial Measurement Unit

The Earloop uses the BNO055 IMU (Inertial Measurement Unit) shown in Fig. 2 to perform all tasks pertaining to direction, orientation and acceleration. Each device calibrates its location by looking at two fixed points with a set distance, then uses trigonometric functions and identities to determine each device's specific location, as shown in Fig. 3.

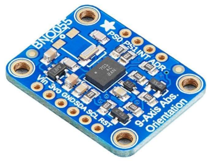

Fig. 2: BNO055 Inertial Measurement Unit used in Earloop.

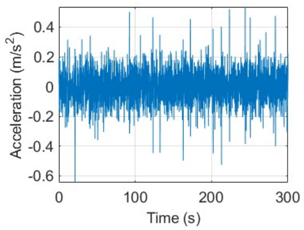

Fig. 4: Raw vertical head movement data.

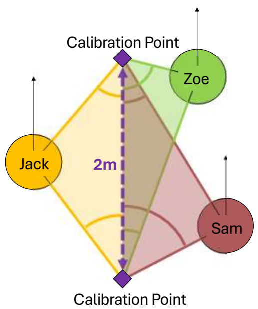

Fig. 3: Top-down geometric layout to determine user positions and face angles.

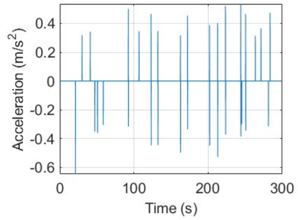

Fig. 5: Filtered signal to only display peaks and troughs.

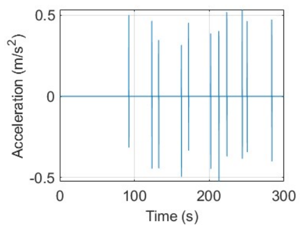

Fig. 6: Plot showing only detected head nods.

Using a MATLAB script to processes raw data, head nods can be detected. Fig. 4 shows the raw data, along with noise and fluctuations. Fig. 5 filters the data to display only significant peaks and troughs, highlighting major acceleration changes. Finally, Fig. 6 detects head nods by showing peaks followed by troughs within a short window, emphasizing rapid upward and downward movements.

3.2 Microphone

The Earloop uses the MAX4466 MEMS Microphone as shown in Fig. 7 to perform any audio processing. The talk time for each user is derived from the equation shown in EQ1, where the total number of samples will be split into separate frames.

$A(t) = Audio\ Signal$
$N = Samples\ per\ Frame$
$M = Threshold\ Count\ for\ Speech$
$T = Amplitude\ Threshold$
$T(t) = Talk\ Time$

$$T(t) = \sum_{i=0}^{N} \begin{cases} 1\ if\ \left(\sum_{j=0}^{M} A(t+j) > T\right) > M \\ 0\ otherwise \end{cases}$$

EQ. 1: Equation for determining talk-time per user.

Fig. 7: MAX4466 MEMS Microphone used in Earloop

3.3 Display Output

Upon calculating the talk-time for each user, the data is fed to a central system. The system then processes the data and displays as a graphic as shown in Fig. 8

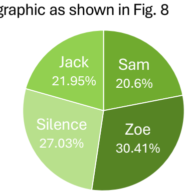

Fig. 8: Graphical output for total talk-time for each user during a conversation.

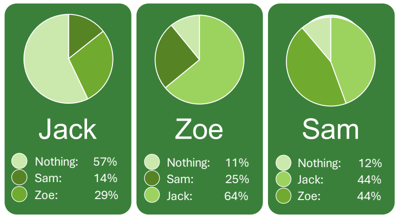

Fig. 9: Graphical output of Facing-Time for each user

Once all of the positions for each user is set, the system will start recording how long each user faces another user (or nothing). This duration is saved and displayed on the User Interface as shown by the graphic in Fig. 9.

3.4 Conclusion

The Earloop device demonstrates significant potential in enhancing communication dynamics through real-time feedback on behavioral metrics. By accurately detecting talk time, verbal utterances, and head movements, Earloop provides valuable insights into individual communication patterns, addressing the need for non-disruptive, personalized social aids in both virtual and in-person settings. The integration of microsensors allows for precise data collection and analysis, enhancing interactions and productivity. Moving forward, we plan to use machine learning to better predict user behavior, improve device comfort, and expand the system to recognize a broader range of non-verbal cues through collection of data from Heart Rate sensors and other microsensors as well. Long-term studies will validate its impact on societal communication and pose as a vital tool in fostering healthy work environments to teaching social skills in a rapidly growing virtual and interconnected world.