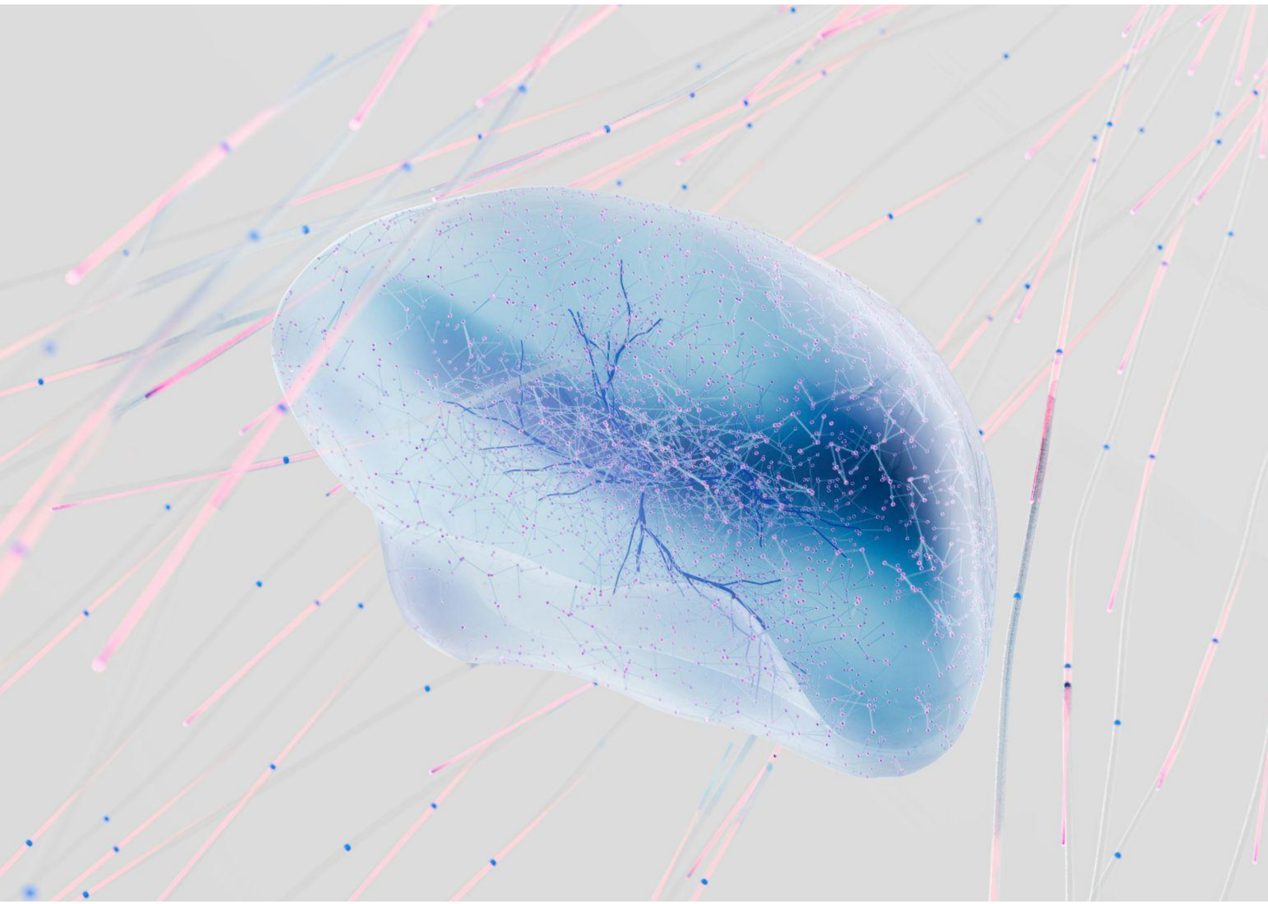
08.26.2024



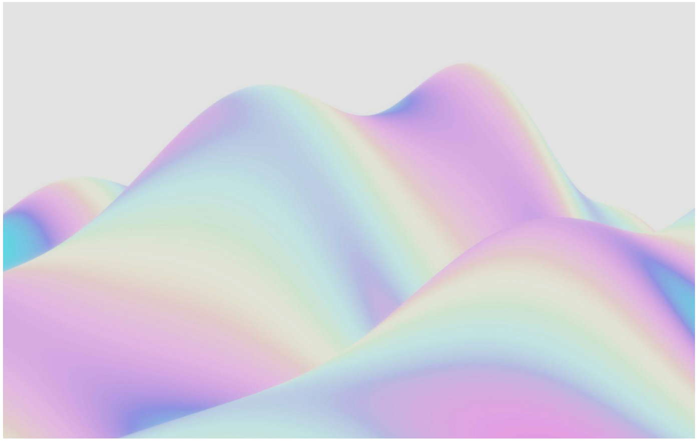
Telepathic Technologies White Paper

TELEPATHIC
Technologies

CONTENT

Abstract

Telepathic Technologies is building small, portable neuroimaging sensors and systems that can be integrated into existing technology stacks to enable wearable interfaces that can directly respond to, and interact with, the user's brain. Our system gives wearable designers access to their user's thinking at a level that is impossible to achieve with other physiological sensors. There is more discussion of these sensors' specific capabilities in the Use-cases section of this document, but their access to the user's brain enables a vast array of possibilities. These capabilities, including mental communication and mental control of devices, are so powerful that they can revolutionize how users interact with the world around them.



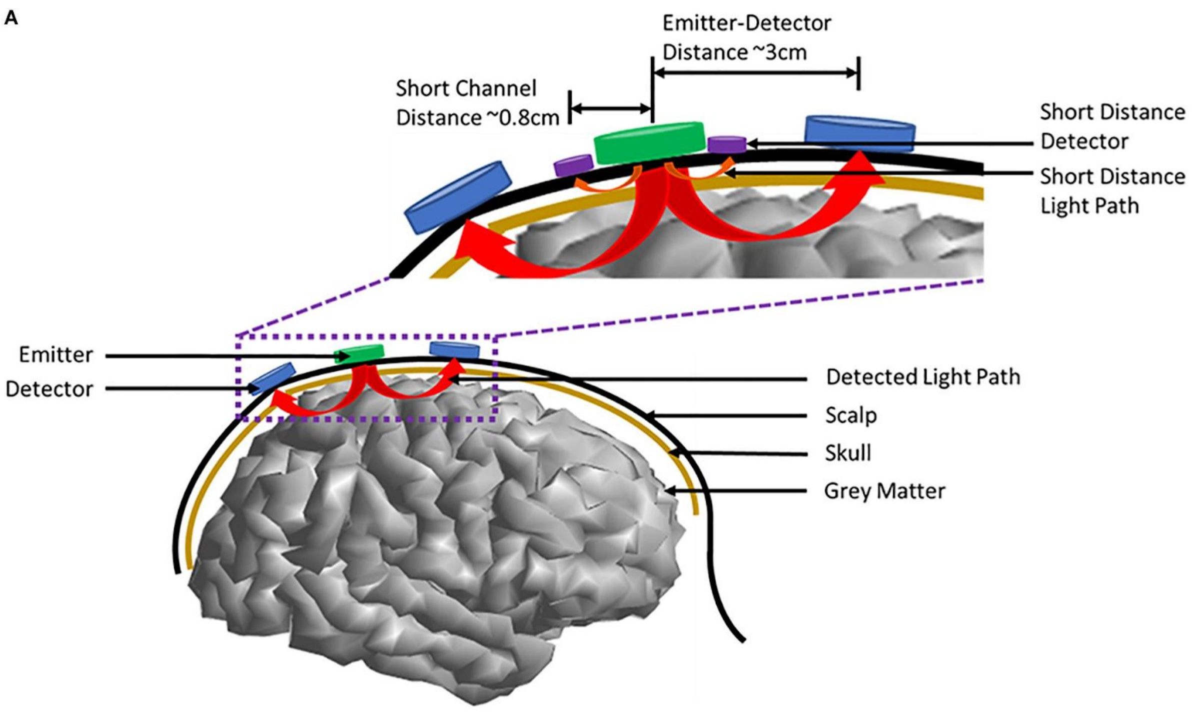
Technical Background

Our technology, fundamentally, is a brain-computer interface (BCI). BCIs have been an active research area in the human-computer interaction subfield of computer science for decades, but recent advances in machine learning have dramatically expanded their capabilities. The field of BCIs has been utilizing neuroimaging methods to give interface builders an insight into the workings of the brain since the 1970s [1]. Still, AI has revolutionized our ability to interpret these signals. These neuroimaging devices were initially designed for medical professionals but have also been a powerful tool to help neuroscientists to learn about the brain. The underlying sensors haven't changed much since they were first invented in the 20th century, but only recently has AI advanced to the point where it can accurately use these signals. For example, recent work in fMRI (functional Magnetic Resonance Imaging) has successfully reconstructed viewed images from a subject's brain data alone [2]. The hardware used here is neither new nor revolutionary, but combined with modern generative AI techniques, stable diffusion in this case, researchers could do something incredible with it. This is among the first research studies that have used neuroimaging to extract complex information from a user's brain, but there have been several other examples since.

An essential distinction in BCI research is between non-invasive and invasive forms of neuroimaging. A large portion of modern BCI research is conducted using either fMRI or invasive BCI implants. fMRI is technically non-invasive, but it is non-portable so it shares some of the downsides of invasive neuroimaging methods. This is because invasive BCIs tend to have significantly better signal quality than non-invasive neuroimaging methods. This signal quality results from these methods having more access to brain signals as they don't need to deal with scalp-related noise.

In contrast, portable and non-invasive neuroimaging methods, like EEG (electroencephalogram), are far more convenient but provide much more noisy data than the alternative. Given the extraordinary risk (neurosurgery) associated with installing invasive BCIs, we feel that non-invasive neuroimaging solutions are much more practical for broad usage. Given that, we have chosen to focus on use cases that are rudimentary enough to use non-invasive neuroimaging but still significant enough to provide value to our users. Hopefully, non-invasive neuroimaging methods will continue to advance and enable new use cases, but we believe they can be instrumental even at their current level of development.

Though various neuroimaging methods are available to researchers today, we decided to focus on a more rarely used methodology called fNIRS (functional Near InfraRed Spectroscopy). fNIRS has not been studied, and other neuroimaging methods, like EEG or fMRI, have some significant advantages. fNIRS works by shining near-infrared light from detectors on the scalp into the brain itself. The skull is transparent with respect to near-infrared light, so it can shine right through it, but deoxygenated hemoglobin is not. Rather, near-infrared light is generally absorbed by hemoglobin in the blood [3]. Given this, and by tracking how much of this near-infrared light reaches detectors placed on the scalp, we can estimate the levels of oxygenated blood in different regions of the user's brain. Analyzing this data through machine learning enables us to learn about the inner workings of the user's brain in near real-time. We chose fNIRS over EEG for essentially three reasons. The first is that the fNIRS signal carries valuable spatial information about the brain's activity because it physically shines light into the brain itself. In contrast, EEG sensors listen for electrical signals on the scalp but don't provide any information about those electrical signals' location within the brain. The third reason is that fNIRS tends to be more robust to motion artifacts in its data than EEG [4]. This is a critical feature for us as we primarily want to install these sensors on wearable devices. Finally, we chose fNIRS because it has, so far, shown more incredible promise than EEG for extracting highly complex signals from the brain, like language.



Chen, W.-L., Wagner, J., Heugel, N., Sugar, J., Lee, Y.-W., Conant, L., ... Whelan, H. T. (2020). Functional Near-Infrared Spectroscopy and Its Clinical Application in the Field of Neuroscience: Advances and Future Directions. Frontiers in Neuroscience, 14 Figure 1. Retrieved from https://www.frontiersin.org/journals/neuroscience/articles/10.3389/fnins.2020.00724

In research contexts, fNIRS has been used to track a variety of psychological phenomena, including emotions [5], mental workload [6], stress [7], and even imagined speech. Machine learning connects the data obtained by fNIRS to the desired psychological phenomena via an experiment meant to induce the particular phenomena of interest. fNIRS is mainly used in experiments like this or other medical-related use cases and is primarily manufactured as research-grade hardware. The parts and even open-source versions of the system's design are readily available online.

Technical Description

Software

Our software stack is almost entirely written in Python. Some of its specific functions are described below.

- **Pre-processing (this is the first step following data collection)**
  - Convert from raw data to optical density
  - Use the Beer-Lambert law to convert from optical density to changes in blood oxygenation.
  - Motion artifact detection & removal
    - Take the short channels' data (channels with a lower-than-normal distance from each other; these are used to measure scalp-related noise), and use regression to remove its impact from the data.
  - Extrapolation of bad sensors
    - Sensors with a poor connection to the scalp give noisy data, so we replace their data with an extrapolation based on the data from other nearby sensors.
  - Bandpass filter
    - Filter out frequencies that are unlikely to contain brain signals
- **Machine Learning (this step takes place after preprocessing)**
  - Models built with PyTorch, SKLearn, Numpy, and TSAI.

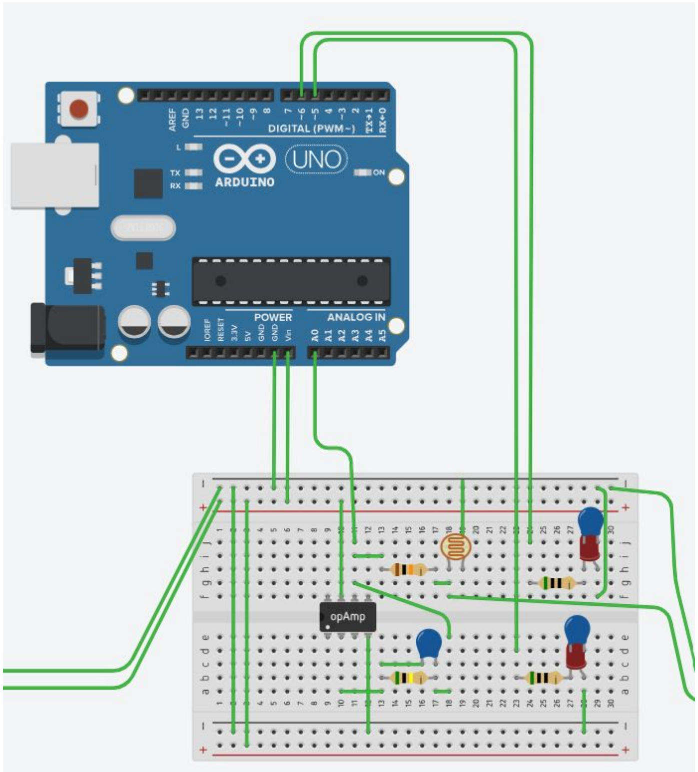
Hardware

Our hardware is currently under development, so the exact details are changing frequently, but the essential elements have not changed very much. These essential elements are: several light emitters that shine light into the subject's brain, some light detectors that detect how much light returns to the scalp, and a few integrated circuits for driving the LEDs and amplifying the signals from the detectors. These elements are controlled and driven by an Arduino included in the design.

This hardware was initially inspired by open-source fNIRS specifications [8], but we have changed the design dramatically.

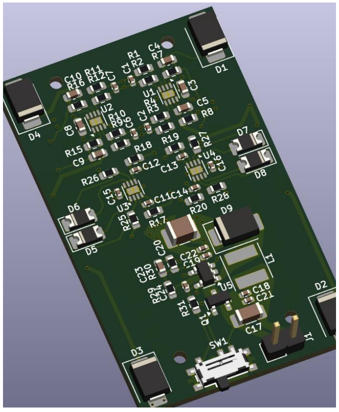
- **Components**
  - Various resistors
  - Various capacitors
  - 741 Operational Amplifier integrated circuit
  - 740nm LED & 850nm LED
  - 900nm photodiode (900nm diode can detect our wavelengths of interest)
  - Arduino to handle the firmware-level code

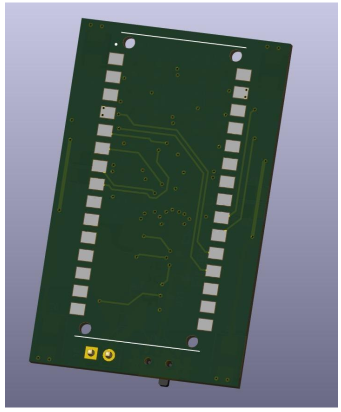
Version 1

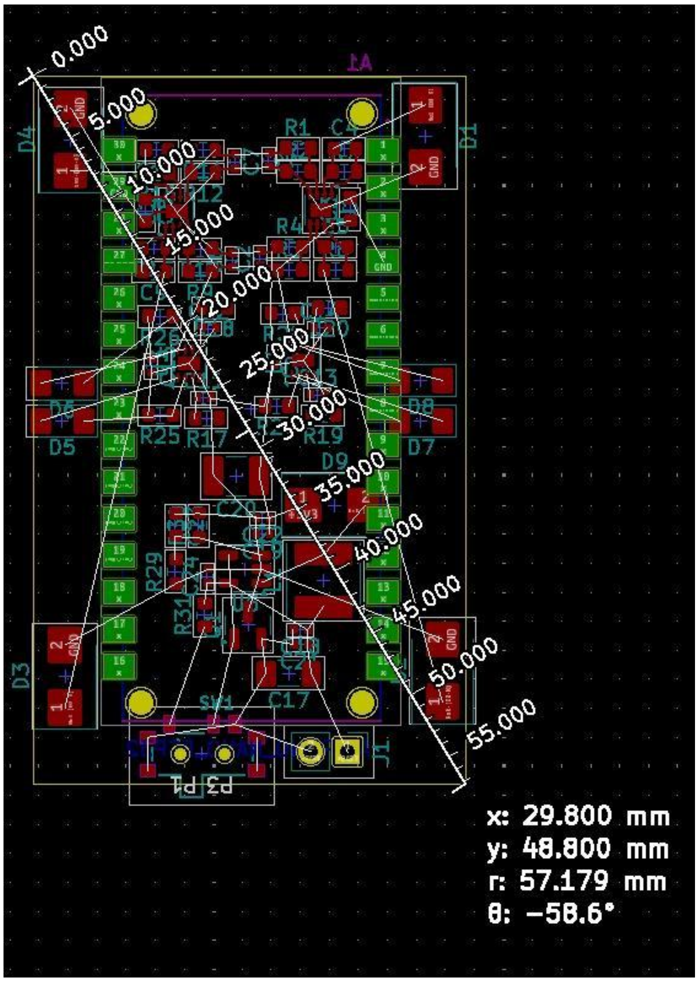


A breadboard-based implementation of our circuit. Included are two infrared light emitters in two different wavelengths and a photodiode for infrared light detection.

Version 2





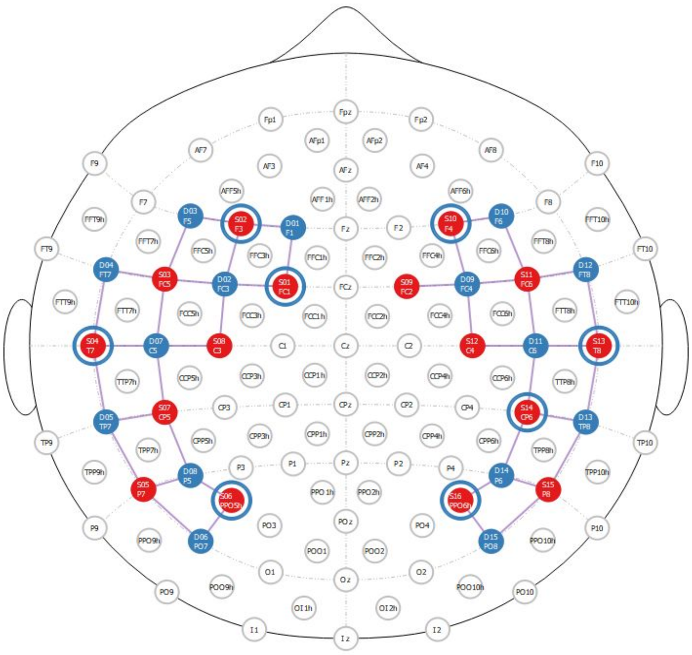


A miniature version of our hardware (sizes indicated below), printed onto a circuit board. It is both smaller and contains more data channels than the above breadboard version.

Experiments & Data Collection

We use simple experiments to gather data on our users' imagination of specific words while wearing fNIRS equipment.

- The sampling rate of fNIRS machine: 6.1 Hz
- Number of data channels: 100
  - Short channels: 16 (These channels are used solely for noise reduction)
  - Full channels: 84
- Wavelengths of interest: 760nm and 850nm
- Testing Vocabulary: “Bravo”, “Echo”, “Golf”, “Hotel”, “Kilo”, “November”, “Papa”, “Tango”, “Uniform”, “Whiskey”
- Location of sensors on head →
  - Red circles are sources
  - Blue circles are detectors



Use Cases

Our sensors could fit well into a number of different use cases and even enable use cases that simply would not be possible without them. Described below are a few potential use cases for our sensors that are both valuable and difficult to replicate using other technology.

Adaptation Systems

As a result of having access to the user’s brain, our system is well-positioned to detect when a user is pleased or displeased with their device and to intervene in response. For example, headphones with integrated fNIRS sensors could interpret increased stress/discomfort on the user's part as indicating that the volume is too high. Additionally, we can monitor the states a user is in when they lower the volume and, in the future, take adaptive actions. Headphones with this capability could reduce the volume until the stress is alleviated. In this way, our sensors could enable devices that can adapt to their user in real-time and act to make their user more comfortable. The result would be wearable devices that can act on their users' behalf without interrupting their user’s thought processes.

Command and Control

Another potential use-case of our system would be control. That is, using mental commands detected by our sensors to give commands to a device or another person. For example, a drone user could direct it to fly up by simply imagining the word “up” in their head while wearing a device equipped with our sensors. This capability empowers users to control devices, or even vehicles, without using their physical body. This is a potentially life-changing capability for paralyzed users, and would be highly convenient for anyone.

This capability would also allow the user’s devices to understand their desires better. For example, when a user wishes to turn their car to the right at an intersection, they use the muscles in their hands and arms to move the steering wheel clockwise. This action moves the vehicle to the right, but the car doesn’t understand the intentions underlying this action. This means your vehicle may move to the right, but the car still does not know that you’re turning right to get onto the next street. This is a fundamental problem with physical control interfaces – they can only convey an action, not the context. On the other hand, a brain-computer interface could read the desire to turn right in a user’s mind and their reasoning for doing so. This could enable the system to make more intelligent decisions regarding its user’s commands than without this context.

Bibliography

1. Kawala-Sterniuk, A., Browarska, N., Al-Bakri, A., Pelc, M., Zygarlicki, J., Sidikova, M., Martinek, R., & Gorzelanczyk, E. J. (2021). Summary of over Fifty Years with Brain-Computer Interfaces-A Review. Brain sciences, 11(1), 43. doi:10.3390/brainsci11010043

2. Takagi, Yu & Nishimoto, Shinji. (2022). High-resolution image reconstruction with latent diffusion models from human brain activity. 10.1101/2022.11.18.517004.

3. Pinti, P., Tachtsidis, I., Hamilton, A., Hirsch, J., Aichelburg, C., Gilbert, S., & Burgess, P. W. (2020). The present and future use of functional near-infrared spectroscopy (fNIRS) for cognitive neuroscience. Annals of the New York Academy of Sciences, 1464(1), 5–29. doi:10.1111/nyas.13948

4. Pinti, P., Scholkmann, F., Hamilton, A., Burgess, P., & Tachtsidis, I. (2019). Current Status and Issues Regarding Pre-processing of fNIRS Neuroimaging Data: An Investigation of Diverse Signal Filtering Methods Within a General Linear Model Framework. Frontiers in Human Neuroscience, 12. doi: 10.3389/fnhum.2018.00505

5. Si, X., He, H., Yu, J., & Ming, D. (2023). Cross-Subject Emotion Recognition Brain-Computer Interface Based on fNIRS and DBJNet. Cyborg and bionic systems (Washington, D.C.), 4, 0045. doi:10.34133/cbsystems.0045

6. Liang Wang, Zhe Huang, Ziyu Zhou, Devon McKeon, Giles Blaney, Michael C. Hughes, and Robert J.K. Jacob. 2021. Taming fNIRS-based BCI Input for Better Calibration and Broader Use. In The 34th Annual ACM Symposium on User Interface Software and Technology (UIST ’21), October 10–14, 2021, Virtual Event, USA. ACM, New York, NY, USA, 26 pages. doi:10.1145/3472749.3474743

7. Molina-Rodríguez, S., Hidalgo-Muñoz, A. R., Ibáñez-Ballesteros, J., & Tabernero, C. (2023). Stress estimation by the prefrontal cortex asymmetry: Study on fNIRS signals. Journal of affective disorders, 325, 151–157. doi:10.1016/j.jad.2023.01.018

8. Tsow, F., Kumar, A., Hosseini, S. M. H., & Bowden, A. (2021). A low-cost, wearable, do-it-yourself functional near-infrared spectroscopy (DIY-fNIRS) headband. HardwareX, 10. doi:10.1016/j.ohx.2021.e00204

TELEPATHIC
Technologies

Telepath Technologies, Inc, 1
Central Park W, New York,
NY, 10023.