Masca: A Flexible Sleep Mask for Rapid Eye Movement (REM) Detection and Electrical Muscle Stimulation (EMS) Intervention

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***Abstract*—Masca is a low-cost, low-power sleep mask for Rapid Eye Movement (REM) sleep detection outside of the laboratory. Masca adapts to the human body, detecting eyelid motion using a comfortable, affordable device for sleep staging and actuation. Mental activity in REM sleep is crucial for long-term-potentiation of learning and memory. Tracking and influencing of REM sleep mentation opens up doors to augmentation of memory and learning: a future in which the content and consolidation of cognition in sleep is rendered controllable by wearable electronics. We show here that Masca offers reliable detection of head and eye movement, offering a new sleep wearable for interfacing with the REM dream state. In addition we report on using Masca to detect and intervene in REM: We show that electrical muscle stimulation during REM sleep can serve as a new modality for interfacing with sleep and influencing dream content.**

***Index Terms*—sleep, dream, interface, sensors**

I. Introduction

A. What Sleep States are

We spend 50,000 hours dreaming during our lifetimes, yet have no reliable way to capture or direct thought during sleep [1]. Sleep stage detection is the first step to interfacing with cognition in sleep, yet there exists no comfortable, conformable, low cost, low power Rapid Eye Movement (REM) sleep detection wearables. This means the processes underlying extraction of salience, the dreams mitigating post-traumatic stress, and the long-lasting neuronal changes after novel learning lie outside of our control. Capture and direction of REM sleep content, where dreams are most vivid, is a holy grail for the augmentation of memory and learning: Dream activity in REM, specifically, contributes to long-term-potentiation of learning, memory, and traumas. Sleep neuroscience has shown augmentation of each of these processes is possible in the laboratory. Yet tracking of REM, and interfacing with tracked dreams, has been extremely difficult to translate outside of laboratory contexts.

REM is one of 4 main types of phasic sleep stages humans pass through nightly. Rapid Eye Movement (REM) Sleep, Light Non-Rapid Eye Movement (NREM) Sleep, Deep NREM Sleep, and Sleep Onset cycle in 90 minute periods throughout the night, each reliably separable by electroencephalogram analysis. Throughout the night these cycles offer myriad cognitive benefits [2]. Post-learning sleep has been shown to improve memory performance, insight generation, motor skills, and much more: The building blocks of learning and creativity are formed in the furnace of sleep [3].

Our nightly descent into sleep creates brain-states demonstrably tailored for the rehearsal and consolidation of learning and memory, yet specific sleep stages have distinct benefits and thus offer distinct opportunities for cognitive enhancements. Audio cues which are tied to an aversive stimulus and presented during REM sleep, called targeted memory reactivation (TMR), enhance performance on previously learned skills, whereas cueing during NREM sleep impairs them [4]. For traumatic situations where forgetting is optimal, auditory cueing of conditioned fear stimuli during NREM but not REM show selective impairments of fear memory purple2017. Protocols like TMR illustrate the importance of specific sleep staging for the directed enhancement or impairment of memory consolidation.

B. Why we care about Dream Content

The occurrence of NREM or REM sleep alone are not the whole picture: Recent converging evidence points to the influential role of sleep thought content, namely dreams, mediating beneficial outcomes of each sleep stage [5]. Dream content often plainly reflects recently encoded memory, with novel learning experiences being a particularly strong driver of dream content, suggesting a role of dreaming in learning new information [5].

Recent research suggests a central role of dream content in post-sleep cognitive outcomes. Fiss et. al (1977) show that after reading a short story, participants who report dreams related to the story exhibit superior recall for the text the following morning [6]. Wamsley et. al (2010) show that improved performance on a virtual navigation task is strongly associated with occurrence of task-related dream imagery during an intervening afternoon nap, yet task-related thoughts during wakefulness do not similarly improve performance. This driving role of dream content has been found for creative insight generation as well as spatial navigation and memory consolidation [7]. REM dream content has even been shown to predict remission from Depression and PTSD after traumatic events [8].

Multiple studies have shown that manipulation of dream content is feasible, though not entirely reliable or predictable, through manipulation of sleep environment, pre-sleep, and in-sleep exposure or delivery of smell, audio or somatosensory stimulation [9]. If an uncomplicated and effective sleep interface for detection and influence of dreams can be devised, the cognitive causal role of this sleep mentation can be taken advantage of [1].

C. Why REM, and how sleep researchers detect it with PSG

With the goal of interfacing with sleep mentation it makes particular sense to focus on REM sleep, as it has been classically regarded as the source of apex dreams, those which are most vivid and can be most reliably recalled [**?**]. Primarily, any REM sleep interface must be an effective REM detector. Classically, the detection of sleep stages has been done via polysomnography (PSG), a combination of activity sensors including brain (EEG), eye (EOG), muscle (EMG), heart (ECG), breath and pulse oximetry. Yet PSG is rife with problems: The amalgam of sensors creates a device which is cumbersome and prohibitively expensive [**?**]. And even with so many concurrent sensors the detection of sleep stages remains more of an art than a science, as signals often disagree–REM sleep related changes in heart-rate variability from predominantly parasympathetic to sympathetic states, for instance, can occur up to 15 minutes prior to the EEG-defined onset of REM sleep [10].

Fig. 1. Polysomnography, a common type of sleep study. Polysomnography is expensive and requires a plethora of sensors resulting in an uncomfortable sleeping condition.

When sleep scoring clinicians must use personal judgment to determine sleep states in the face of such contradictions, unreliability is introduced, and yet automatic sleep scoring of PSG has proved extremely difficult [11]. Further, PSG creates an uncomfortable sleeping situation because it is tethered to the laboratory setting and requires extensive adhesion of sensors to the body. This causes demonstrably different sleep than that experienced at home and causes confounding incorporation of thoughts and feelings about sleeping under surveillance into dream content [12] [13].

D. Why NightCap (Success, clinically relevant signal, accuracy, first night effect, but changes sleep)

To overcome the intense labor and capital costs of PSG, as well as bring sleep neuroscience beyond the disruptive influence of laboratory observation, an inexpensive home-based sleep monitoring system is necessary. Two main strategies have been attempted in the past, namely building portable PSGs or devices which track solely body movement. The first has proved far too expensive, and the second far too unreliable [14]. In the 1990s, Harvard Medical School pioneered the development of a device which mitigated both difficulties, called the Nightcap [14]. This headworn device uses eye movement and head movement data gathered from custom, adhesive piezoelectric sensors stuck to the eyelid of each subject and a multipolar mercury switch worn on the head. Taken together these signals can be used to distinguish wake, NREM and REM sleep. These signals are sensitive to the varied types of muscular atonia and unique eye movement frequencies exhibited in specific sleep stages. Binary classification (yes/no) detection of body and eye movement were fed into a Nightcap state machine for sleep, automatically classifying sleep stage based on sensor thresholds each minute.

Nightcap-derived values for sleep latency, REM latency, wake time, NREM time, and REM time calculated showed no significant differences from those derived from polysomnography ajilore1995. The Nightcap identified sleep states correctly in 87% of 1-min epochs as compared to PSG, coming quite close to the 95% interrater reliability seen with PSG analysis. Further, the Nightcap reduced per-night cost of sleep monitoring by 10x, as it can be used without any supervising personnel and requires fewer disposable sensors than PSG.

The Nightcap offered a simpler, cheaper sleep staging tool and opened up opportunities for mobile sleep science and longitudinal diagnosis of sleep-related symptomatology at home. It demonstrated sensitivity to clinically relevant changes in sleep quality, enabling diagnosis outside of the laboratory with increased ecological validity. Yet it remained limited in many ways: The device remained wired and required a bulky amplification circuit, neither of which is ideal for sleeping settings. The wearable was mounted on the forehead, an unnatural location for sleepworn devices, making uptake with high compliance at scale difficult. Crucially, the device relied on custom, disposable, adhesive piezoelectric sensors which were stuck to the eyelid of each subject and thresholded for binary classification of eye movements. Though the Nightcap was a leap forward for sleep science in its time, the cost and comfort of such sensors was a major limiting factor in the uptake of such devices inside and outside the research laboratory.

E. Our device (First night effect, conformable, cheap)

Our device, Masca, takes on these device design challenges to modernize the Nightcap and push beyond the limitations of forehead worn, wired, disposable sensing. Harvard Professor Robert Stickgold, a leader on the original Nightcap work, has

Fig. 2. A Nightcap system being worn.

been kind enough to lend us original Nightcap devices, and advise us as we build a newer version.

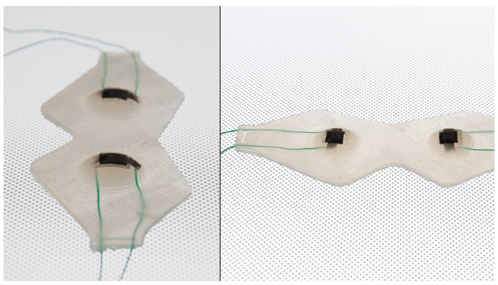

Fig. 3. Masca final prototype.

We use piezoresistive fabric sensors to detect eye movement, which offer increased sensitivity and conformability over the original Nightcap sensors. We make use of this increased sensitivity to detect eye movements without adhesion to the eyelid, improving comfort and ease of use. As these sensors are robust and do not require adhesion, we improve the device from a disposable to a reusable sensor design. We embed these in a silicone eye mask, a form factor which both improves sleep comfort for many and offers a natural material interaction with the eyelid. We place our amplifiers onto a custom built, miniaturized printed circuit board (PCB) which fits onto the eye mask, eliminating the need for a bulky electrical box. We add an inertial measurement unit (IMU) onto the PCB design, such that a forehead worn device is not needed to detect head movement. We also offer a software setup to detect body movement via a standard laptop webcam, as loss of muscle tone in REM sleep reduces movement output, if researchers desire data on whole body movement. We transmit data on eye, body and head movement wirelessly, using Bluetooth Low Energy communication from the Masca PCB, eliminating the need for wires in bed. We hope these improvements in comfort, conformability, reusability, communication, and cost make Masca a reliable sleep tracker and interface that everyone can use.

F. EMS + Control as first use case

As a pilot use case for Masca, we aim to demonstrate initial feasibility of dream influencing via a new sensory stimulation modality, transcutaneous electrical muscle stimulation. We propose a revamping of Nielsen et. al (1993), in which somatosensory stimulation of the legs via leg-worn pressure cuffs showed demonstrable limb-specific changes in kinesthetic dream content [9]. Visual-kinesthetic synesthesia, direct incorporation of pressure and squeezing sensations, and increased bodily bizarreness in dreams were each observed nielsen1993. Earlier research had demonstrated a tie between muscular activity and mentation during sleep–EMG activity in the zygomaticus, the smiling muscle, had been shown to be correlated with both positive dreamed affect and dreamed communication–but Nielsens work was pioneering in its use of this tie as an instigator, rather than correlate, of dream content [**?**]. Professor Nielsen has been kind enough to offer advice on our current experimental design.

We propose use of transcutaneous electrical muscle stimulation (EMS) in place of pressure cuffs, as EMS offers more flexibility in terms of body placement and more specificity in terms of sensations generated. Further, EMS during sleep has already been shown to be a valid, feasible method for decades to effectively relieve sleep apnea symptoms [15]. Lastly, EMS opens up doors to fascinating new research questions on dream incorporation, as there is fMRI evidence to suggest electrically stimulated muscle movements are interpreted as self-generated rather than exogenous, possibly making this methodology markedly different than classical dream stimulation via audio or scent [16].

The controlled incorporation of outer stimulus into dreams has been a primary challenge for dream direction, as relay of much sensorimotor information from the the thalamus to cerebral cortex is cut off in sleep by thalamo-cortical sensory gating [17]. Research on gating mechanisms for ones own muscle movement during sleep is sparse. Thus direct EMS in REM, if proven effective, offers both insight into a new research question about the extent of thalamic gating of motor movement and a new modality for dream direction in the REM state.

G. Mission: Make sleep science relevant again

The crucial role of sleep in healthy consolidation and integration of learning, memory and emotion in the human brain has been established clearly by sleep neuroscience [18]. Furthermore, researchers in the laboratory have demonstrated the ability to restore and augment these processes, whether through targeted memory reactivation, dream direction, or audio entertainment. The main limitation factors on the democratization of this science and the spread of these beneficial protocols is the cost and accessibility of sleep laboratory equipment. The Nightcap made great strides towards this goal, yet was limited by available sensor technology. Masca hopes to build on this work, offering a form factor with contemporary sensing and communication technology built for cheap, comfortable sleep interfacing in the laboratory and the home.

II. Methods

A. Sensor Design and Fabrication

Here we explain the design and fabrication of Masca, our low-cost, comfortable wearable designed for REM sleep stage detection. We developed two types of soft sensors designed for detecting eye movements. The design criteria were: (i) ease of fabrication for fast-prototyping and large manufacturing, (ii) deformability and conformability to the skin for maximum comfort, and (iii) high sensitivity to detect strain or pressure due to eye movements during REM.

1) Triboelectric sensor: The first attempt at fabricating a sensor for the sleep mask operates based on the triboelectric effect. Triboelectric nanogenerators (TENG) are a class of devices that can produce electricity from mechanical energy through a combination of electrostatic induction and contact electrification due to friction between different materials. During its regular contact, as the TENG is compressed and separated to and from the skin, electrons travel from the skin to the silicone rubber surface and vice versa [19]. The induction of charges results in a successive flow of positive and negative currents and voltages. This principle allows us to harvest energy from biomechanical motions through TENG. We designed a self-powered sleep mask to gather energy from eye movements and detect them simultaneously.

To fabricate the triboelectric sensor, we first 3D-printed a custom injection mold with the Formlabs Form 2 printer. The mold or scaffold consists of two detachable parts that together make a 2 mm diameter cylinder. A conductive thread was positioned on the center of the cylinder while fast-cure silicone (Ecoflex 00-35) was injected. After curing, the two-part scaffold is dismantled to reveal a conductive thread encapsulated with a silicone layer. We tested this TENG-thread device by connecting it to a load with high-value resistance (1 MOhm) in order to observe the voltage generated on the load. The TENG-thread device can successfully detect the presence of touch and pressure of the finger. However, the current prototype is too bulky and uncomfortable to be worn as a sleep mask. A miniaturization effort needs to be further conducted through precision engineering and fabrication in order to develop a smaller-scale TENG device that not only is comfortable and seamless, but also has a high sensitivity for REM detection [20].

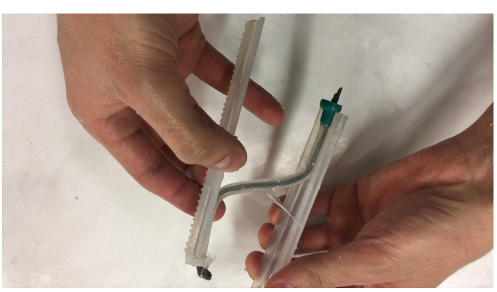

Fig. 4. Fabrication process of triboelectric nanogenerator thread.

2) Piezoresistive sensor: For the fabrication of our final sensor, we then prioritized a second approach, which explores the piezoresistive effect of smart fabric coated with conductive materials for pressure sensing. The pressure-sensing element is a 5x5 mm multi-layer structure made out of piezoresistive fabric in between two conductive fabrics. The piezoresistive fabric is a knit fabric coated with PPy, a conductive polymer in concentration that gives surface resistivity of 20 KOhm/sq. Since it is piezoresistive, the resistance of this fabric sensor changes in correlation to the applied force [21]. Similar to how an FSR works, a higher pressure compresses the conducting molecules coated onto the fabric. These molecules then form a network with each other, allowing more current to flow and reducing the resistance around the area in contact. Therefore, the larger the force area and the stronger the force are, since these networks can be approximated in parallel with each other, the lower its total resistance. We observed that smaller active area gives higher sensitivity for detecting lower pressure from eye movements due to its smaller contact area.

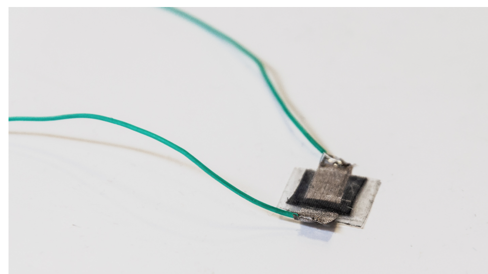

Fig. 5. Piezoresistive fabric pressure sensor with its interconnects.

3) Mask design: Next, we integrated the two textile-based soft pressure sensors for both eyes with conductive threads or flexible stranded wires. After that, they were attached to a 3D-printed, customized mold designed for a sleep mask. The design involves a bump structure that goes towards the eye to ensure that the soft pressure sensors conformably presses against the eyelids to sensitively detect eye motions. Silicone (Ecoflex 00-35) was chosen as the material for casting for its fast curing time and high conformability. The soft pressure sensors embedded in a silicone bath were then cured, peeled off, and connected to the hardware system for sensor read-out and wireless transmission.

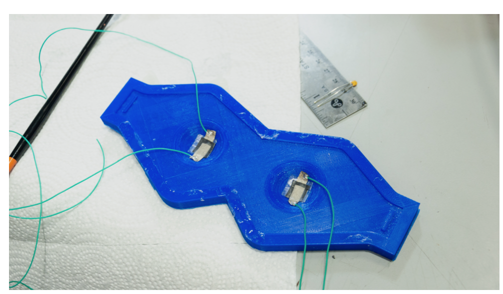

Fig. 6. 3D-printed sleep mask mold for casting silicone.

B. Hardware

1) System design and fabrication: We designed a double-sided PCB (Printed Circuit Board) using Autodesk Eagle, which was fabricated in-house using a Modela MDX-20 3-axis CNC machine. The board was shaped using a 1/32 end mill for holes and edges, 1/64 for the roughing pass, and the 1/100 for the finishing pass. To handle logic and networking we used an RFDuino (RFD22301) module, a Nordic nRF51 microcontroller with integrated Bluetooth based on the ARM Cortex-M0 core. This microcontroller has 128kb of Flash and 8kb of RAM. The typical supply voltage is 3V.

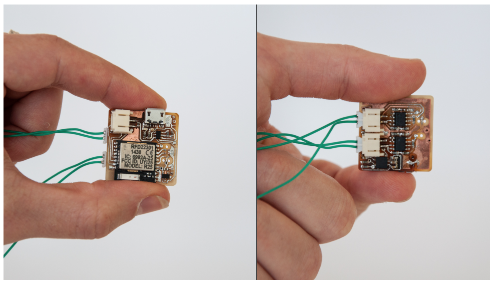

Fig. 7. Final PCB front and back view.

To sense head movement, we used a 6-axis Inertial Measurement Unit (IMU) MPU6050 that combines a 3-axis micromachined microelectromechanical systems (MEMS) accelerometer, 3-axis MEMS gyroscope, and a Digital Motion Processor (DMP). We interfaced with the IMU through the I2C bus.

2) Piezoresistive sensor interfacing: In order to sensitively detect the lower range of force exerted by the eyelids during REM and eliminate intrinsic noise, we designed our own filter and amplifier circuit. As shown in Figure 8, the soft pressure sensor hardware interface consists of four stages: potential divider, buffer, low-pass filter (LPF), and non-inverting amplifier stage. We used a double operational amplifier (TLV2374) because of its single supply and rail-to-rail input and output features. The two piezoresistive fabric sensors had different electrical properties as they were not identical, so we had to use different resistor values to achieve an adequately calibrated baseline and amplification.

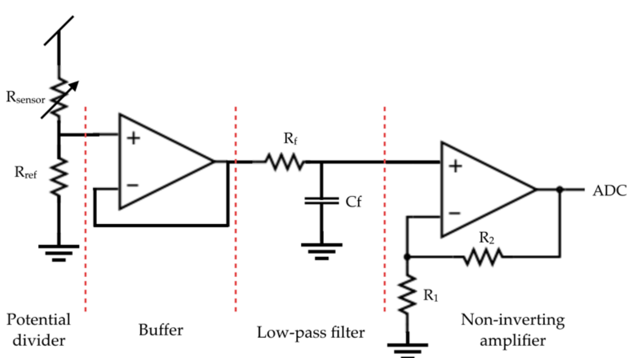

Fig. 8. Piezoresistive sensor interface circuit.

Potential divider: The first stage of the sensor interface hardware is the potential divider circuit. This circuit is built to transform a change in resistance given by the soft pressure sensor to a change in voltage (Equation 1). The reference resistor is chosen to be significantly lower than the offset to bring the close to the zero level. This ensures that the voltage baseline is low and that signal amplification would not dramatically reach the voltage rail limit. As REM occurs, the low pressure exerted from the eye movements reduces the resistance of R_{sensor} and results in the small increase of V_{pot}.

$$V_{pot} = V_{cc} \frac{R_{ref}}{R_{ref} + R_{sensor}} (1)$$

Buffer and low-pass filter: The buffer or voltage follower circuit acts as a separator between the low-pass filter and potential divider. It copies the voltage from the non-inverting input to the output (Equation 2). This minimizes the loading effects from the potential divider that could influence the response of the LPF by providing a low source impedance. The passive LPF consists of R_f and C_f elements with low cut-off frequency of 5 Hz (Equation 3). The filter eliminates various noise sources; for example, from AC main hum, environments, to high-frequency vibrations and passes through DC signal, which is the frequency of operation (Equation 4).

$$V_{buf} = V_{pot} (2)$$

$$f_c = \frac{1}{2\pi R_f C_f} (3)$$

$$V_{lpf} = V_{buf} \frac{1}{\sqrt{1 + (\omega R_f C_f)^2}} (4)$$

Amplifier: Finally, to enable the detection of low-pressure signals, a non-inverting amplifier is also designed in the circuit. We chose the non-inverting configuration to easily tune the gain of the amplifier and avoid the use of negative supply. As shown in Equation 5 below, by experimenting with R1 and R2 values, we can tune the voltage output given by the sensor based on the pressure sensitivity and maximum rail output. We designed an amplifier circuit with a gain of around 50 to amplify mV range of input signal to a maximum of 3.3 V output The amplification is fulfilled before the signal is fed to the Analog-to-Digital Converter (ADC) input of a microprocessor for digitization and further processing.

$$V_{ADC} = V_{lpf} (1 + \frac{R_2}{R_1}) (5)$$

3) Power analysis: For powering the board we use a 3.7V 350mA LiPo battery. To provide a constant voltage of 3.3V for the microcontroller and piezoresistive eye movement sensors, we used a 150mA Low-Noise LDO (Low-Dropout) Regulator (MIC5205). The RFduino draws a maximum of 15mA, and the accelerometer and gyroscope operate at a current of 0.5mA and 3.6mA respectively. The estimated total current draw is 19.1mA, enabling our device to run for for 18.3 hours with the aforementioned battery capacity. A LiPo charge management controller (MCP73831) is used to recharge the battery by powering the board with a USB micro. A red and green LED are used to indicate the charging and done state.

4) System programming: To save space on the PCB, we used a Tag-Connect No Legs 6-pin Cable fitted with a 6-pin 0.1 pitch ribbon connector. The spring loaded connector pins combined with the three alignment pins provide a reliable temporary connection to the board utilizing a very small footprint (3.1 x 6.2 mm) on the board. To program the board, we used the RFduino USB shield (RFD22121).

C. Software

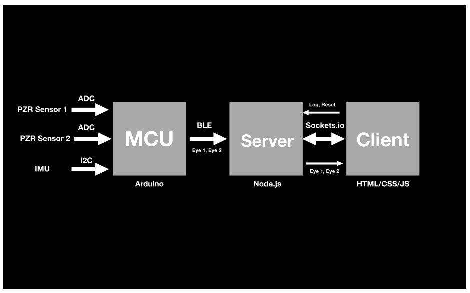

Fig. 9. Masca software architecture.

1) Embedded: In order to detect the subtle eye vibrations during REM, we are relying on the variations in mechanical pressure the eyelids apply to the sensor on the eye mask. The pressure variations produce a change in the resistance that we use to detect when the eyes are moving.

The software system is composed of 3 submodules: embedded, server, and client. For the embedded software, in an early prototype, to validate the ability to detect eye movements, we used a textile sleep mask with the custom flexible piezoresistive sensors we designed sewn with conductive thread. To detect the eye movement, we connected the eyelid sensors to a voltage divider circuit and used an Arduino Uno microcontroller to read the output values. Next, we conducted several pilots to test data collection.

For the final version of Masca, the embedded software is written in Arduino language, which is basically a set of C/C++ functions. For sensing eye movements, the Analog to Digital Conversion (ADC) is used to measure the amplified signal of the piezoresistive sensors. To ensure an accurate ADC reading, an analogRead is performed to set the MUX to a particular eye pins ADC channel but the result is discarded as it can sometimes be garbage when switching between channels. A delay of 1 millisecond is used to ensure that the appropriate registers are set, and then the actual analogRead is used to read the voltage fluctuations caused by pressure on the piezoresistive sensor.

Example:

$$\begin{aligned} &\text{edaReading = analogRead(edaPin);} \\ &\text{delay(1);} \\ &\text{edaReading = analogRead(edaPin);} \end{aligned} \tag{1}$$

To filter the signal, an alpha-beta low-pass filter was implemented to smooth the data. Using trial and error, we converged to an alpha value of 0.85.

$$\text{value = value + } \alpha \text{ (input - value)}$$

We read the new signal values, filter them, and send them to the server via BLE (Bluetooth Low Energy). There is a delay of 8 milliseconds at the end of each loop, summing up to 10ms when adding the two 1 millisecond delays performed when reading the piezoresistive sensor values from the ADC. This enables a transmission frequency of 100Hz, significantly faster than eye movements during REM (10Hz) [22].

For the final design we could not communicate with the IMU due to a hardware communication problem. To overcome this, we implemented movement detection using a webcam and OpenCV. To support the idea that larger fluctuations in the signal represent REM, we cross-validated the experiment with video analysis of body movement during sleep. We recorded still images of a sleeping subject every 10 seconds using a webcam triggered by a custom Python script during a sleep trial and compared frames to get a measure of movement. Next, the images were processed by computing the sum over each pixel-wise differences in the grayscale images collected using Numpy in Python. This computed the L1 norm between sequential images. This leads to spikes in magnitude during sleep. Figure 10 shows a graph depicting these image difference values over time with the eye sensor readings over time.

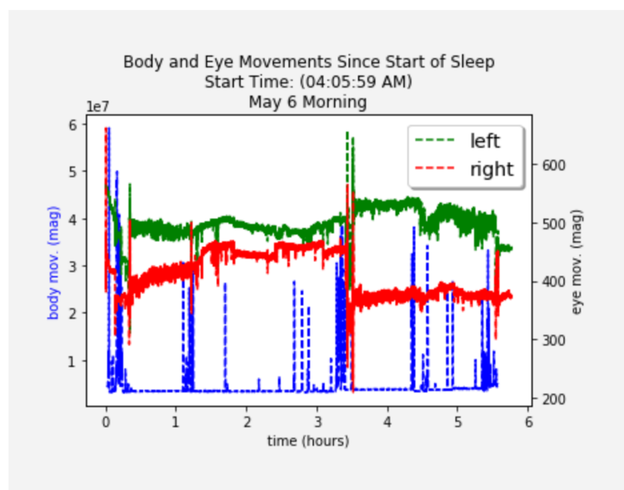

Fig. 10. Body and eye movements in one night are plotted here. Consecutive images from a standard USB webcam were compared to obtain body movement magnitudes. The left and right sensor readings are 10-bit analog values reported by the piezoresistive sensors (at 10 HZ) embedded in the sleep mask. The large spike around 3.5 hours corresponds to a brief disruption of sleep.

2) Server: The back-end is written using Node.js (), a cross-platform JavaScript run-time environment that executes JavaScript code server-side. To receive the data sent from the embedded system, Noble () is used, a Node.js BLE (Bluetooth Low Energy) central module.

In order to detect the subtle eye vibrations during REM, we are relying on the variations in mechanical pressure the eyelids apply to the sensor on the eye mask. The pressure variations produce a change in the resistance that we use to detect when the eyes are moving. To detect eye movements, a double threshold filter and a refractory period of inactivation is employed. The lower threshold filters out signal noise, identifying significant pressure changes that could indicate eye movements. The upper threshold filters out major pressure changes caused by eyelid movements and other unwanted artifacts. If the resistance change is within this range, the value is classified as an eye movement. Given that there are can be around 3 of eye movements per second, a refractory period of inactivation of 300 milliseconds is implemented to reject false positives such as double activations. The number of eye movements per minute is also calculated.

The server communicates with the client using socket.IO (), a real-time bidirectional event-based communication framework. This enables the server to listen for user input events such as toggling logging and performing reset. Activating logging timestamps and logs piezoresistive eye sensor values, classified eye movements, and number of eye movements per minute. Regardless of whether logging is activated or not, the three aforementioned values are sent to the client side for the user to visualize. The server also listens for the reset user event to zero all the counters, a function useful when calibrating and testing.

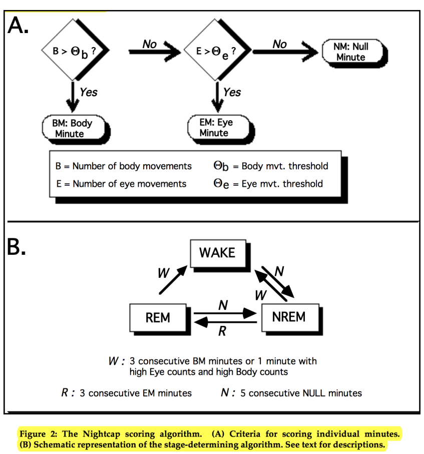

Fig. 11. The sleep stage FSM used for Stickgold's Nightcap.

3) FSM rebuild: In Stickgolds Sleep State Machine, detailed above (Figure 11), each minute during the sleep cycle is classified as a body minute, eye minute, or null minute and sleep stages are automatically classified based on movements per minute. We implemented this setup as a Python program () with signal processing based on our sensor thresholds. Although we didn't have enough experimental data to test all its functionality, the Python FSM is implemented in code and runs. This Python program was used to collect all of the data shown in Figure 11. The FSM has been further tested on heavily synthetic data, but more testing is necessary and more details are available at the GitHub repo.

In future work we plan to integrate this FSM into the software back-end and BLE data transmissions discussed earlier, allowing for wireless sleep stage classification on a per minute basis. With the advances in machine learning, we expect we will achieve superior accuracy compared to the Nightcap.

4) Graphical User Interface (Client): The user interface (UI) is a web application written in JavaScript, leveraging jQuery for interacting with the DOM, and client-side socket.IO to communicate back and forth with the server. The client listens for the streaming of the two piezoresistive eye movement sensor values and plots the data in real-time using D3.js (). Every time the server detects an eye movement, a socket event is emitted and a the UI displays the result. The client also receives the number of eye movements per second and displays it to aid the experimenter in judging whether the participant is in REM or NREM. The UI allows for input fields to specify the user, group, gender and age, information which is logged into a CSV file when logging is started. There are two buttons for the experimenter to interact with the system, one for toggling logging on and off, and one for resetting all the eye movement counters. Clicking these buttons emit socket events for the server to listen and perform the appropriate action. Jade is used as the template engine instead of raw HTML.

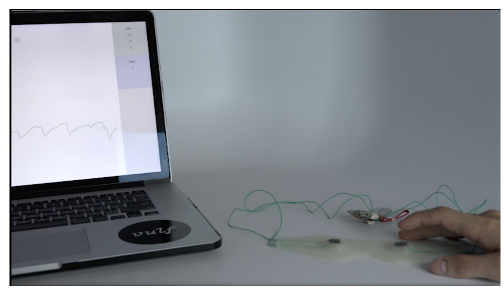

Fig. 12. Demonstration of Masca real-time UI.

D. Pilot experimental methods

At the beginning of the study, all subjects (n=3) were given a consent form to sign. Subjects lay down on a couch within a sound-dampened room. Afterwards, the devices used in the study were explained to them: a comfortable sleep mask which uses conductive and piezoresistive fabrics to detect eye movements, and an FDA approved electrical muscle stimulator device for pain relief via muscle actuation with a maximum voltage and current of 70 V and 0.72 mA respectively. Participants were outfitted with both devices to test comfort, and each underwent a muscle actuation demonstration to ensure no discomfort. Stimulation site was the lower leg, with EMS pads placed 3 inches apart on the upper and lower Gastroncnemius calf muscle. Participants confirmed experience of muscle contraction. Participants were then instructed to fall asleep.

Our experimental design built off of Nielsen (1995). On stimulation trials, the EMS was actuated according to the following schedule: after at least 5 minutes of REM sleep in the first REM period, and 5 minutes in the second REM period. REM was defined as minutes in which eye movements exceeded 10 eye movements per minute [22]. After each

Fig. 13. A subject wearing Masca during sleep.

stimulation trial, participants were asked to 1) lie quietly for 30 seconds and remember the preceding dream, 2) report the entire dream, 3) report any apparent body experiences or awareness of the EMS during the dream 4) describe their level of comfort with the system. After the first stimulation trial, participants were asked to fall back asleep after issuing a dream report. After the second, they were fully awakened.

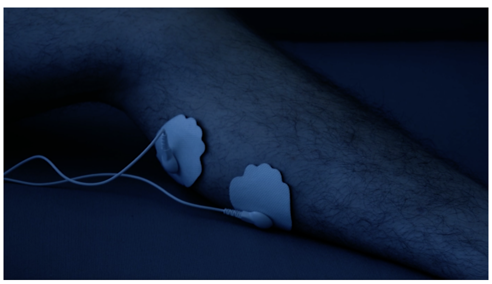

Fig. 14. EMS electrodes attached on a subject's leg.

On control trials, EMS was initiated during NREM rather than REM, but participants were awakened according to the same schedule for the experimental conditions and asked the same questions. Each subject underwent only one round of sleep, whether they were in the experimental or control group. After each subject was finished, the eye mask and stimulation pads were cleaned with isopropryl alcohol. The experimental procedure has been reviewed and validated by MITs Committee on the Use of Humans as Experimental Subjects (COUHES).

E. Dream report rating methods

All questions were adapted from Nielsen (1995). The order of NREM vs REM trial dream reports was independently rated by two condition blind judges. The following rating categories were used:

Did the participant report a dream? If no, end Rating. If yes, continue:

1) EMS Pads. Does the participant refer to the EMS pads (or similar object) as being on the leg? (y/n) Which leg? (right/left/both/neither)
2) Leg Sensation. Apart from references to pads, does the participant refer to any discrete sensations in/of the foot or leg? (y/n) Which foot or leg? (right/left/both/neither)
3) Leg Activity. Apart from references to the pads, how intense is activity of the feet or legs? (1 = not at all 4 = moderate, 7 = extreme)
4) Reality Quality. Does the participant say that any part of the dream seemed real or as if they were awake? (y/n)
5) Gravity Themes. Does the participant refer to a heightened or unusual sense of gravity (e.g., heaviness, floating, flying, spinning, etc.)? (y/n)
6) Gravity Themes. Does the participant refer to a heightened or unusual sense of gravity (e.g., heaviness, floating, flying, spinning, etc.)? (y/n) .
7) Bodily Bizarreness. Overall, how unusual or bizarre is the bodily involvement in this dream? (1 = not at all, 4 = moderate, 7 = extreme)
8) Laboratory Incorporation. Does the participant refer to any parts of the sleep laboratory or its equipment, the experimenter or technicians, or the experimental procedures? (y/n)

F. Results

G. Dream recall and incorporation

Two condition blind raters compared transcriptions of dream reports gathered from trials of stimulation in REM (Subject 1) and NREM (Subject 2). Both raters noted that Subject 2 failed to recall a dream on 2 separate wakeups following stimulation in NREM (QA). Both raters confirmed 0 references to legs or leg sensation (Q2), 0 reality quality (Q4), and 0 bodily bizarreness (Q7) in NREM.

Both raters noted that Subject 1 successfully recalled a dream on 2 separate wakeups following stimulation in REM (QA). Both raters confirmed references to legs or leg sensation (Q2) in both dreams (mean intensity 1/7 for Dream 1 SD 0, mean intensity 6.5/7 SD +/-.5) on dream 2). Both raters confirmed reality quality in both dreams (Q4). Raters disagreed on rating of bodily bizarreness on Dream 2, with a mean rating of 4/7 and SD +/- 3, and as such this question was discarded from analyses (Q7). Subject 3 failed to fall asleep, and as such was excluded from analysis.

H. Subjective report

All subjects reported minor discomfort with the pressure of the eyemask. Quotes on the subjective dream experience from Subject 1 (REM stimulation) follow:

Was like a beach...just looking at them, the rocks...I can see my feet...I had a small image of running in a field. And then feeling the grass hit on my feet.

I didn't get any dreams until I started feeling the device. Yeah it was cool, at some point you can anticipate the increase of the, you know, da-da-da-da-da-da (*the shock*) and then once it started to get stronger you kind of will be waiting for like boom this is the peak and then at the peak you get an image. I enjoyed that stimulation you know. That felt internal. So, it's internal because it made me compile a sound but not hear a sound. When I was explaining to you guys about the pattern and how it's evolving I made a sound. Kind of. Imagine

Subject 1 (REM Stim)	Dream Recall Y/N	Leg Y/N (mean/7, SD)	Reality	Bizarreness
Wakeup 1	Y	Y (1, +/- 0)	Y	1, +/- 0
Wakeup 2	Y	Y (6.5, +/- .5)	Y	4, +/- 3

Subject 2 (NREM Stim)	Dream Recall Y/N	Leg Y/N (mean/7, SD)	Reality	Bizarreness
Wakeup 1	N	n/a	n/a	n/a
Wakeup 2	N	n/a	n/a	n/a

Fig. 15. Subjective report results.

a sound turns into something. That something is what that (stimulation) turns into.

III. Discussion

Most importantly, results support our hypothesis of EMS stimulation incorporation into REM sleep dreams, with clear focus on the stimulated leg in dream plot and dream sensation. This result is novel, as EMS has not previously been used, to our knowledge, for dream direction. These results are in line with past literature showing exogenous somatosensory stimuli from pressure cuffs can be amplified and elaborated into apparent sensory determinants of dream content [9]. Subjective report offers support of earlier research suggesting EMS stimuli are interpreted as self-generated rather than exogenous [16]. Moreover, results illustrate how such determinants are frequently associated with an especially vivid reality quality during the dream [9]. Results are also in line with previous work demonstrating reduced dream recall in NREM vs REM sleep, lending credence to our REM tracking form factor [23]. Observed lower intensity incorporation into REM period 1 vs 2 is in line with literature demonstrating increasing intensity of dreams in deeper REM cycles, perhaps explaining why Nielsen (1993) did not perform wakeups after REM period 1 [23].

IV. Future device design work

In the future, we would like to outsource the PCB through an industrial manufacturer, making it much easier to attain a clean connection and overcome the problems given by the CNC machine and soldering of miniaturized components (such as IMU6050). To improve the power efficiency and operation lifetime of our hardware, a buck-boost converter with battery level detection will also be integrated into the system. We also plan to improve the reliability and reproducibility of the soft piezoresistive pressure sensors, by laser cutting the fabric elements and incorporating a very thin mesh layer to normalize their resistance baseline.

In future work, we are also interested in detecting not only eye motion, but also the motion's direction. This can be done by incorporating multiple soft pressure sensors around the eye region and other sensing modalities, such as EOG, into a single comfortable smart sleep mask. In order to further improve the weight and comfortability of this mask, we plan to fabricate a flexible form-factor of the current PCB that can be embedded in silicone simultaneously with the soft pressure sensors. Finally, due to the straightforward fabrication process and materials used in this project, we plan to fabricate and distribute the REM sleep mask on a large-scale. Incorporated with our OpenSleep platform, this would further support the accessibility of our technology and enable the collection of ’big data’ of sleep stage sensing and the profound impact of dream content manipulation to a large audience.

V. Future experimental methods

In future experiments, after initial validation of the tracking efficacy and comfort of Masca in pilot testing, we will do a separate control comparison with a larger subject n. Experimental trials using Gastronemicus EMS stimulation in REM will be compared to control trials of no (sham) stimulation in REM with wakeups in REM following Nielsen (1993). Our pilot methods served primarily to validate REM vs. NREM detection and introduce the possibility of using EMS to influence REM content. Future experiments make use of this validated tracking and serve to elucidate whether this REM influencing capability stems from stimulation or simply device placement on a limb. The order of sham vs. stimulation trial dream reports will be scrambled and independently rated by two condition blind judges to compare sham vs. EMS stimulation dream reports with the same rating method used in pilot testing. The experimental procedure has also been reviewed and validated by MITs Committee on the Use of Humans as Experimental Subjects (COUHES).

VI. Conclusions

Fig. 16. Full prototype of Masca integrated with PCB.

Our aim with Masca is twofold: to offer a new form factor for REM detection, and to demonstrate a pilot use of this interface for a new form of dream direction using EMS. Our results offer initial evidence that dream content is influenced in identifiable ways by electrical muscle stimulation of the limbs, using a more compact and affordable system for REM detection than has existed in the past. Developing a compact REM detection and intervention device can enable a full range of applications to interface with our dreams, translating sleep neuroscience outside of the laboratory: Memory augmentation, motor learning amplification, traumatic nightmare reduction, lucid dream provocation, dream recall increase, dream theme inception, and more nuanced quantified self for sleep are all within reach with such a device. Masca brings us one step closer to a future in which unconscious cognition in sleep is rendered controllable via conformable electronics, allowing at-home sleep sensing and actuation of dream content.

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