NecX: Enabling Gesture Control Using the Neck

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ABSTRACT
On-body sensing has been extensively explored by researches in the past decade. In this work, we present NecX, using neck as an input device. The system exploits surface Electromyography (sEMG) to detect the intensity of neck muscle. Our system captures the conducted current flowing through our sensor when the muscle is stressed, and uses the signal variations to identify a neck gesture. In our current prototype, we designed 5 neck gestures including rotation and tilt, etc. To evaluate the system, we conducted a controlled user study and collected data from 2 users, presenting an average classification accuracy of 94.1%. Furthermore, we implemented a real-time system to apply NecX in the gaming control.

Author Keywords
Neck; EMG; sensing; hands-free

ACM Classification Keywords
H.5.m. Information interfaces and presentation: Miscellaneous.

General Terms
Human Factors; Design.

INTRODUCTION AND RELATED WORK

Neck is one of such part of our body densely packing tons of information. It is the neural pass of the body; it can move, give vocal data and provide heart rate information. We envision a device that can tap on this information and result in novel input technique while it can also keep a track on health status. The interaction can be fast enough as compared to that of a smartphone, enabling hands-free interaction with the phone while both of hands are not accessible. In addition, it is possible to use this wearable device for health sensing, for example, monitoring the tiredness, heart rate or even muscle stress. It can take many forms, such by being part of the clothing collar or in a form of a pendant. We also plan to focus on providing accessibility to special people who cannot move lower part of their body or people aging with disabilities.

In this project, we introduce NecX, a novel input device enabling health monitoring and hands-free interaction. Our system uses surface Electromyography (sEMG) to achieve such capabilities. When muscle is stressed, a current issues from the motor unit flows through and actuates the muscle. By attaching electrode pads to the target muscle (in our case, on both side of neck), the current will be conducted through the pads and picked by our sensor board. Our algorithm captures these signal variations when the muscle is in action and uses it for gesture detection and classification.

Figure 1: NecX detects and classifies 3 neck gestures using EMG sensing.

sEMG sensing has been explored in previous research for sensing muscle emotion. Since EMG signal is extremely sensitive to nuance muscle movement, such sEMG sensing via facial muscle can distinguish the emotional state with minor movements or even no visible representation [1]. Researchers also explored muscle-computer interfaces (MCI) using neck motions. The sEMG sensing via forearm muscle [2] activity explores gesture of five fingers. The work can distinguish different position and pressure, as well as tapping and lifting of fingers. Wu *et al*. built a real-time surface EMG sensing system of detecting neck and shoulder movement [3]. Similarly, Zhang *et al.* uses sEMG sensing to identify tongue muscle activity and can differentiate six tongue gestures while the lower face and neck is resting [4]. Rofouei *et al.* developed a non-invasive, wearable neck-cuff system to monitoring the quality of sleep. Others developed a wearable master device for the disabled who has spinal injury with very limited mobility control below their neck [6].

In NecX, we target on both normal users and people with disabilities. We expect this wearable device can be used as a health monitoring tool and a hands-free input device (see Figure 1). This device is capable of capturing the user's heart rate and detecting muscle stress even when the head and neck is stationary; by simply perform a neck gestures, the user is able to pick up a call or change the volume of the songs while keeping the phone in the pocket. Different from the previous study, we used only 2 channels of sEMG data to enable such functions. We believe reducing the number of channels can enhance flexibility in designing a new form

factor and also reduce the power consumption for a longer battery life.

THEORY OF OPERATION

The electrical signals of Surface Electromyography (sEMG) are produced with muscle activations. The observation of signals is shown as voltage changes with electrodes attached on the skin of users..The sEMG signal is acquired through differential amplification, which would stabilize the output signal, and filter noise. The range of sEMG usually varies from 5 Hz to 250 Hz; however, the real time experiment suggests 65 – 180 Hz as cut-off frequency to avoid strong DC noise at 60 Hz.

The best electrodes used for measuring sEMG is pre-gelled Ag – AgCl (Sliver / Sliver Chloride) electrodes due to its low impedance and high stability [8]. In order to obtain the best performance, its placement must satisfy some requirements. As shown in Fig 2, it should be placed between the motor unit and the tedious insertion, along the longitudinal midline of the muscle [7]. Secondly, the positive lead and negative lead should be separate with 1 ~ 2cm. Finally, the reference electrodes should be placed at a neutral muscle different from the EMG detecting surface with bipolar configuration. Surface Electromyography (sEMG) is used for evaluation and recording surface electrical activity caused by skeletal muscles.

There are always some noises existing that cannot be avoided [8]. One is ambient noise, like radiated EMI surrounding users with frequency of 50 – 60 Hz. The other is transducer noise, like different impedance between the skin and electrode sensors. Some other issues usually occur with measuring surface EMG. For example, a neck gesture may displace the activated muscle away from the skin where the electrodes are attached. This may cause the inconsistency in EMG signal.

Some other issues usually occur with measuring sEMG. It evolves consistency in impedance, which is critical for the reliability of sEMG measurements. Another issue comes up with different kind of bio-signals of users such as ECG (heart rate), EEG (brain), EOG (eye), which appears as periodic noise to sEMG signal [9].

SYSTEM IMPLEMENTATION DETAILS

Figure 3 shows the system architecture and data flow. The system first identifies an event of muscle movement, and then extracts features for gesture recognition. In this section, we will detail the hardware design and the algorithms for gesture detection and classification.

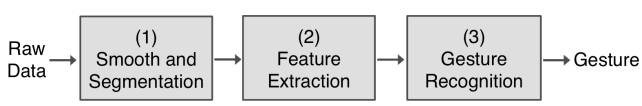

Figure 3: System architecture and data flow. The raw data was first smoothed to remove noise. After the system identifies a segment of muscle movement, it feeds into our classifier for gesture classification.

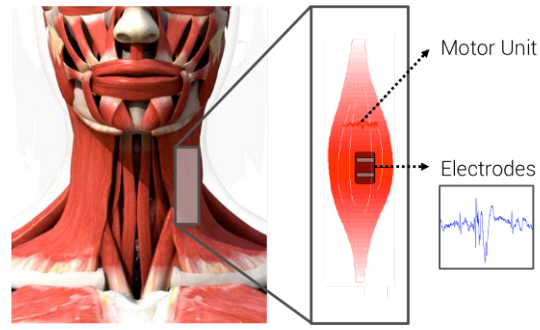

Figure 2: Electrodes setup for measuring sEMG. To get the best measurements, the electrodes should be placed at the center between the motor unit and tedious insertion.

Hardware

To measure the sEMG on the neck, we use the OLIMEXINO-328 and two SHIELD-EKG-EMG boards, each of which collects sEMG data from one side of the neck (see Fig 4). Electrode pads are attached on the user's neck; the red pad (positive) and black pad (negative) are instrumented on the side of neck and white pad (ground) is attached on the back of the neck. Instrumenting the white pad behind the neck (i.e., at a neutral position) can reduce ambient noise. The Olimex-328 is an Arduino-based motherboard and has a 10-bit ADC on board. We sample the analog data at 256 Hz, which is sufficient for our use case as we expect a neck gesture should be relatively slow. Finally, the data are streamed to a laptop for gesture recognition through Bluetooth. To better understand the capability of Olimex-328, we simulated the circuit in MultiSim and verify that the board has a low pass filter with the cut-off frequency of 3.4 kHz (see Fig 6). We also designed a 3D-printing case for this prototype (Fig 5).

Neck Gesture Detection

As described earlier, any muscle movements on neck causes a current flowing through the electrode pads, which raises the output voltage from the Olimex-328 board. When muscle relaxes, the voltage drops to the baseline. Our first step is to identify signal variations, and to recognize an event of muscle excitation.

Figure 7 shows the process of gesture segmentation. We first smooth the raw data to remove noises. We next applied the 1st derivative on both channels, after which we took the

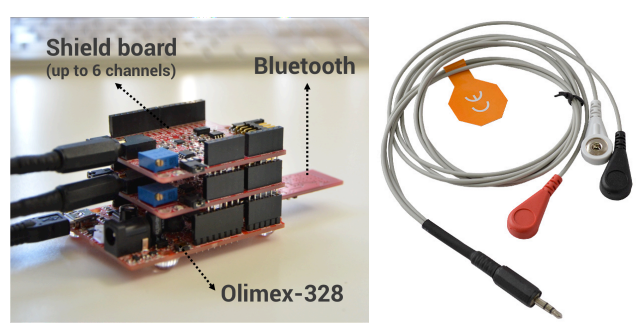

Figure 4: The sensor board (*left*) and lids (*right*).

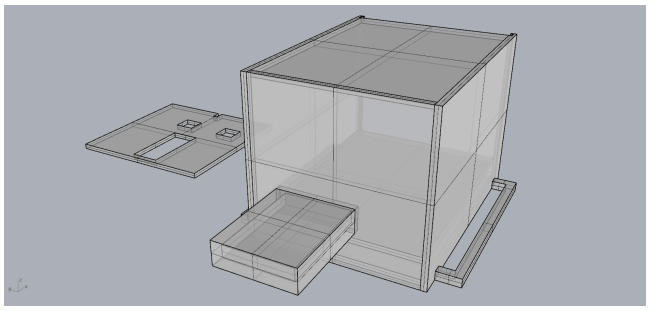

Figure 5: 3D printing case for NecX.

absolute value of both channels and summed them up (see the figure of *Total Variation* in Fig 7). To identify the data segment of a muscle movement, we next apply another 1st derivative on the curve and apply the thresholds on it (the figure of *1st Derivative* in Fig 7). The intersection of the curve and the threshold line (marked as *red* dots in Fig 7) represents the start and end of a muscle movement event, which shows as the green segment in Fig 7.

Festures for Neck Gesture Classification

After an event is detected, features are extracted from the recognized segment. We chose various features for gesture classification, including: (1) *Auto-correlation* of two channels, (2) *Cross-correlation* of channel 1 and 2, (3) *difference of the max values* between two channels (4) *difference of the min value* between two channels *(5)* difference of the max and min value in each channel, and (6) *total zero crossing counts* in both channels. Therefore, we build an 8-tuple feature vector for gesture classification.

EXPERIMENTAL PROCEDURE AND RESULTS

To evaluate the system, we conducted a small, controlled user study. We recruited two participants to perform five neck gestures: left rotate (LRotate), right rotate (RRotate), left tilt (LTilt), right tilt (RTilt) and up tilt (UTilt). Participants were asked to perform each gesture with 10 repetitions. The collected data were then processed using our algorithm for event detection and feature extraction. Once a muscle movement event is identified and the feature vector is built, the vector is fed into WEKA for gesture classification. We used the collected data to train a 5-class RFBNetwork model (i.e., each class representing one

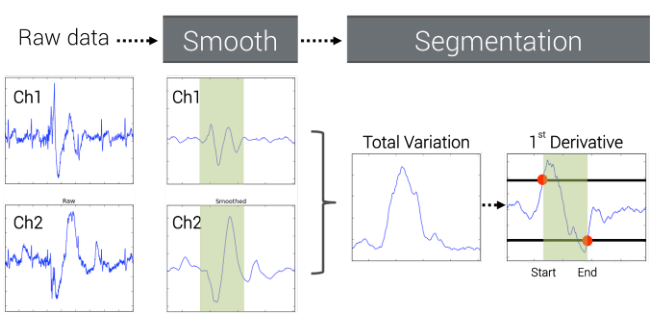

Figure 7: Segmentation algorithm. We applied the threshold (black lines) on the 1st Derivative curve and the intersections represent the start and end of a muscle event.

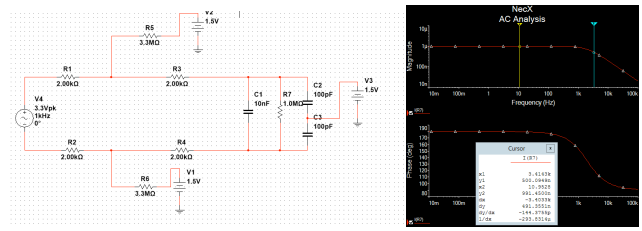

Figure 6: Schematic of the low-pass filter (*left*) and MultiSim simulation (*right*). The Olimex-328 board uses a low-pass filter with cut-off frequency of 3.4 kHz.

gesture). In WEKA, we perform 10-fold cross validation and obtained a classification accuracy of 94.1%. Figure 9 shows the confusion matrix.

Real-time Implementation

The offline analysis described above shows the feasibility of using NecX to detect and classify neck gestures; however, it is also important to demonstrate the ability for NecX to work in real-time. We therefore implemented a real-time version of our system and designed a few prototype applications. In order for NecX to run in real-time, we modify the classifier to enhance the robustness against any possible noise. In particular, we used 5 classifiers to perform the same gesture prediction at the same time, including Support Vector Machine (SVM), RFBNetwork, Decision Tree (LMT), BayesNetwork (BayesNet) and Nearest Neighbor (NNge). The final decision is determined by a majority vote from the predictions of these 5 classifiers. Figure 8 shows the process of leveraging this stacked classifier. In the video figure, we showed the on-the-fly neck gestures recognition and used NecX to play Tetris and to detect heart rate and muscle stress.

CHALLENGES

Although we showed the feasibility of using NecX in both the off-line analysis (accuracy of 94.1%), we actually encountered some difficulties in implementing the real-time system. The issues arouse from the hardware limitation. Since the electrode pads we used in the studies are pre-gelled, the pads become partially detached from the skin, which changes the perceived signals significantly. This means that the signal patterns are barely reproducible and therefore, the classification accuracy drops dramatically. To overcome this issue, we included a stacked classifier in the real-time implementation (Fig 8) on a smaller gesture set, including left rotate (LRotate), up tilt (UTilt) and shaking the head..

The original daughterboards SHIELD-EKG-EMG used in this project have shortage circuit issue with onboard ADC. When reference voltage (AREF) pin is connected, the temperature suddenly jumps from 20° C (68° F) to 50° C (122° F) within 1 second, which could potentially damage both chip and users. Also the reference voltage for boards is 3.3V, which is supposed to be 1.1V. Both issues proved the AREF pin is shorted. Thus we cut a wire on board, which fix the bug. With this modification, power

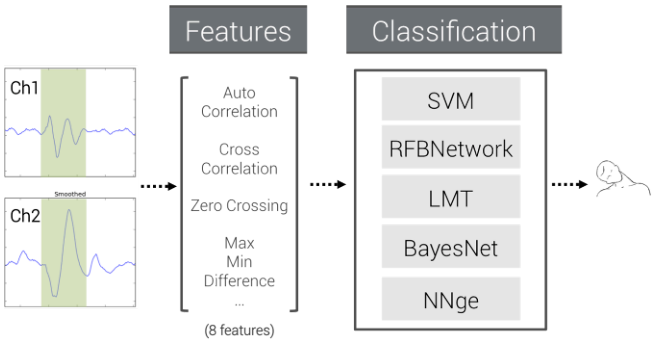

Figure 8: The stacked classifier for real-time gesture recognition. The prediction result is based on the majority vote from the outcomes of respective classifiers.

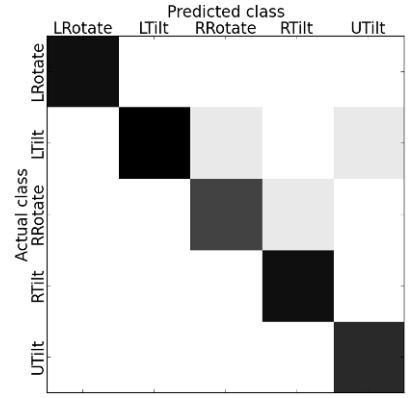

Figure 9: Confusion matrix of the classification result.

consumption is reduced to half of the originals, and twice battery life as benefit.

FUTURE WORK AND DISSCUSSION

In order to minimize the instrumentation overhead over the users, we only used 2 channels of sEMG data for gesture recognition. In addition, the electrode pads used in our prototype would partially detached from our skin, which change the signal and affect the classification result. Our next step is to adopt other electrodes such as those in [2] to mitigate these issues, and will use more channels to explore more gestures.

Our primary goal within this quarter is to enable gesture control using neck. The future work will aim at providing more bio-sensing capabilities such as heart rate monitoring, muscle stress detection and thirsty stage detection. Measuring ECG parallel to sEMG data could potentially enable use our system as a health monitoring tool.

Besides using NecX as an input device, it is also possible to provide haptic feedback to user whenever needed. For example, when the system detects a muscle stress around the user's neck, the system can vibrate the device, reminding users to change their neck position before any muscle injure occurs. We leave this as the future work.

CONCLUSION

In this work, we proposed a new wearable device, called *NecX*, using neck as the input. We leveraged sEMG sensing to enable neck gesture control. In particular, our algorithm can reliably recognize an event of muscle movement and presented the classification of 94.1% in a 5-class RFBNetwork model (i.e., each class representing a gesture). We also implement a real-time system that leverages a stacked classifier to show the feasibility of using our approach in gaming control. We envision such wearable device could be applied to, besides the gesture control presented in this paper, other health applications such as muscle stress detection and heart rate monitoring.

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