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マイクロデバイスによるリアルタイム脳波信号解析による てんかん発作の予知

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Forecasting epileptic seizure by real-time EEG signal analysis by a micro-device

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本研究の目的は、脳波信号をリアルタイムで正常（N）、発作前（P）、発作（S）に分類できるマイクロデバイスを開発することである。このために、Si MEMS 共振器上に物理的リザーバー・コンピューティング（PRC）法を実装することを提案する。我々は提案する MEMS デバイスの製作に成功し、PRC 実装の為の実験セットアップを開発した。予備的な結果では、N/S 分類で 97％の精度、N/P 分類で 77％の精度が得られた。我々は、この結果が将来、発作予測装置の製作に貢献することを期待している。

We aim to develop a micro-device capable of classifying EEG signals into Normal (N), Pre-seizure (P), and Seizure (S) categories in real-time. We propose to implement physical reservoir computing (PRC) method on Si MEMS resonators to achieve this goal. We successfully created the proposed MEMS devices and developed an experimental setup for PRC implementation. Preliminary results suggest ～97% accuracy in N/S classification and ～77% accuracy in N/P classification. Further improvement can be achieved by increasing nonlinear response, optimizing hyper-parameters, and collecting personalized training-data. We expect the results will contribute to making a seizure-forecasting device in the future.

1. 研究内容

1.1 Introduction

Epilepsy is a chronic disease of the central nervous system that causes sudden lack of consciousness and convulsive seizure potentially leading to severe accidental injuries or death. Seizures are caused by synchronized firing of neurons, which manifest as a change in the electrical activity (brain-wave) of the brain observed in electroencephalogram (EEG) recordings (Fig. 1). The change in the EEG from 'Normal' state to 'Seizure' state is reported to happen gradually over several minutes[1]. This gives an opportunity to forecast an impending seizure so that the patients and caregivers can take timely caution to avoid injuries. To contribute to this purpose, we aim to develop a micro-scale device that can process EEG signals in real-time and classify them into 'Normal' (N), 'Pre-seizure' (P), and 'Seizure' (S) categories (Fig. 1)[2]. We employ a hardware-based artificial intelligence technique called 'Physical Reservoir Computing' (PRC) using a microelectromechanical system (MEMS) resonator to achieve this goal. The main benefit of this approach is that the resulting devices are portable, energy efficiency, requires low training-cost for fast real-time

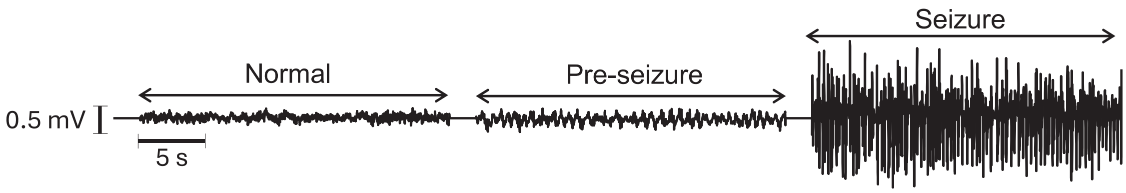

Figure 1: Electroencephalograms (EEG) corresponding to 'Normal', 'Pre-seizure', and 'Seizure' states: data from the Pompeu Fabra university's database (artefact-removed) [2]. Normal and pre-seizure signals are collected topically while seizure signals are acquired intracranially.

processing that does not need access to cloud or internet. Accurate classification between Normal/Seizure signals (N/S classification) can facilitate a Seizure-detection system, while accurate classification between Normal/Pre-seizure signals (N/P classification) can allow a Seizure-forecasting system. We successfully developed the proposed PRC system and preliminary analysis suggests N/S classification accuracy ~97% and N/P classification accuracy ~77%. We present further discussion on PRC implementation, classification results, and discussion on potential improvement.

1.2 Methods

1.2.1 Reservoir computing (RC)

A time-domain signal (V_{in}) is nonlinearly transformed (V_{out}): $V_{out}(t_n) = \mathcal{F}([\alpha_{in} \cdot V_{in}(t_n) + \alpha_{fb} \cdot$ V_out$(t_{n-1})])$, where the subscript 'n' on time (t) represents the n-th segment of the input/ output signal, α_{in} and α_{fb} are scale-factors applied to the input and the feedback (in this work, $\alpha_{fb} = 0$), and $\mathcal{F}$ represents a nonlinear function. $V_{out}(t_n)$ segments are divided in l time-intervals of length θ and each interval is used to construct an element (x_i) of the reservoir state vector (X). Then, for a typical classification task, X is mapped to a desired reservoir output (b) assigned for a given class of the input signal, $b = W_{out}X$, where the elements of the W_{out} vector are optimized during a training phase. Only W_{out} requires training, which gives RC its reputation as a low-cost training algorithm.

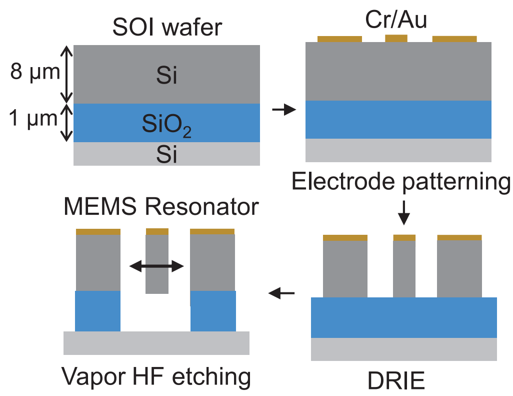

Figure 2: Schematic illustration of the fabrication steps implemented for creating the MEMS resonator devices from SOI wafers.

1.2.2 Device fabrication method

Devices are fabricated using silicon-on-insulator (SOI) wafers with 8 μm thick, p-type, single-crystal Si device layer, ~1 μm thick SiO_2 layer, and ~400 μm thick Si handle layer. First, Cr/Au metal thin-film (~100 nm) electrodes are deposited on the device layer. Then, device areas are patterned using photoresist (OFPR) and etched by deep reactive-ion-etching (DRIE). For these two steps, UV photolithography method is used using Cr photomasks fabricated by a direct-laser-writing instrument. Finally, the resonator structures are released by vapor-HF etching of the SiO_2 layer.

1.2.3 PRC implementation strategy

For implementing RC via a physical system

(PRC), which in our case is a MEMS resonator, the dynamics of the physical system perform the task of nonlinear transformation ($\mathcal{F}$) of the input electrical signal (V_{EEG}). Real-time electrical EEG signals are created (from pre-recoded data taken from real patients[2]) using an arbitrary function generator (AWG, Moku-Go). Signals are pre-processed and amplified using a custom-made non-inverting amplifier and introduced to the resonator as a dc-bias voltage (V_{dc}). An ac signal (V_{ac}) from a lock-in amplifier is introduced to the actuation electrode. The resulting electrical signal corresponding to the motion ($y(t)$) of the micro-resonator is captured by the capacitive detector, amplified by a trans-impedance amplifier (TIA) (Fig. 3A) and detected by the lock-in amplifier. The output signal is essentially related to the solution of the duffing equation: $m\ddot{y} + b\dot{y} + ky + \alpha y^3 = F_0(V_{EEG}) \cos \omega t$, where m, k, α are the effective mass, linear-stiffness, and cubic-stiffness of the resonator, b is the effective damping coefficient, $F_0(V_{EEG})$ is the amplitude of the periodic ($2\pi/\omega$) electrostatic driving force. Then, reservoir states are determined from the output signal (Fig. 3B-C).

1.3. Results

1.3.1 Device fabrication and characterization

MEMS resonator devices with integrated electrostatic actuators and capacitive detection electrodes are successfully fabricated with the method illustrated in Fig. 2. Scanning-electron-micrographs (SEM) of a fabricated device is shown in Fig. 3B. Resonators are ~300 μm long, ~1 μm wide (height ~8 μm) and oscillates in in-plane, fundamental flexural mode. Devices are characterized inside a vacuum chamber (~1 Pa). Typical frequency response (forward-sweep) is shown in Fig. 4, which shows a hardening-type cubic nonlinearity.

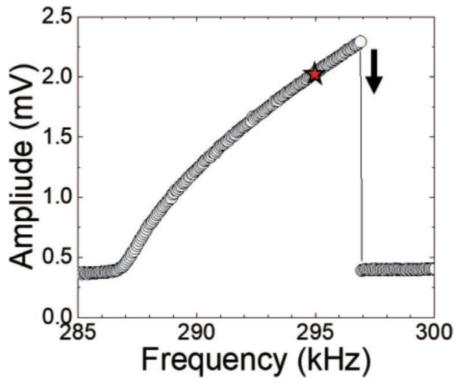

Figure 4: Frequency response of a MEMS resonator device during a forward frequency-sweep showing hardening typed cubic nonlinear behavior.

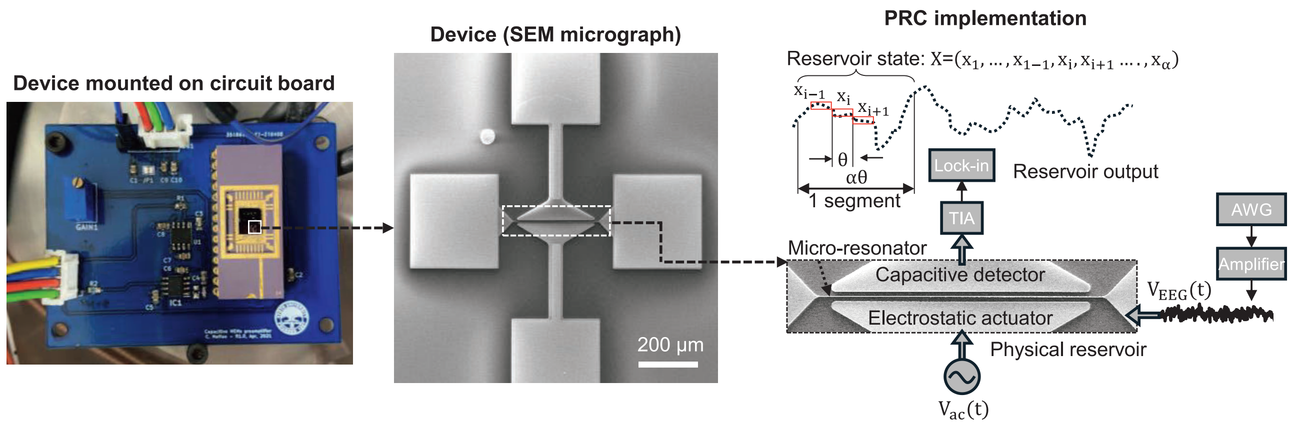

Figure 3: (A) Device on a circuit-board designed for electromechanical characterization, (B) SEM image of a Si MEMS resonator device, (c) Illustration of the PRC implementation strategy for EEG signal classification by the MEMS resonator device.

1.3.2 EEG classification

A total of 10 EEG samples from each of N, P, S categories are injected into the MEMS resonator (reservoir) and corresponding output signals are acquired (section 1.2.3). Output signals corresponding to each type of signal are split into 140 EEG segments and divided in 80:20 ratio for training and testing, respectively. After training the W_{out} vector with EEG segments in the training-set, the task is to correctly identify the type of the EEG-segments in the test-set (Fig. 5A-B). We perform a 5-fold cross-validation to avoid train-test selection-bias and estimate the average classification accuracy. Preliminary analysis suggests that between N and S type signals a classification accuracy of ~97% can be achieved. However, between N and P type signals, classification accuracy is about 77%. We found that the classification accuracy significantly depends on the choice of hyperparameters, such as θ, and Ridge-parameter (λ) as shown in the heatmaps of Fig. 5C-D.

1.4 Discussion

It is worth noting that high classification accuracy between N and S is expected due to large differences in 'amplitudes' of these signals. However, N and P signals having comparable

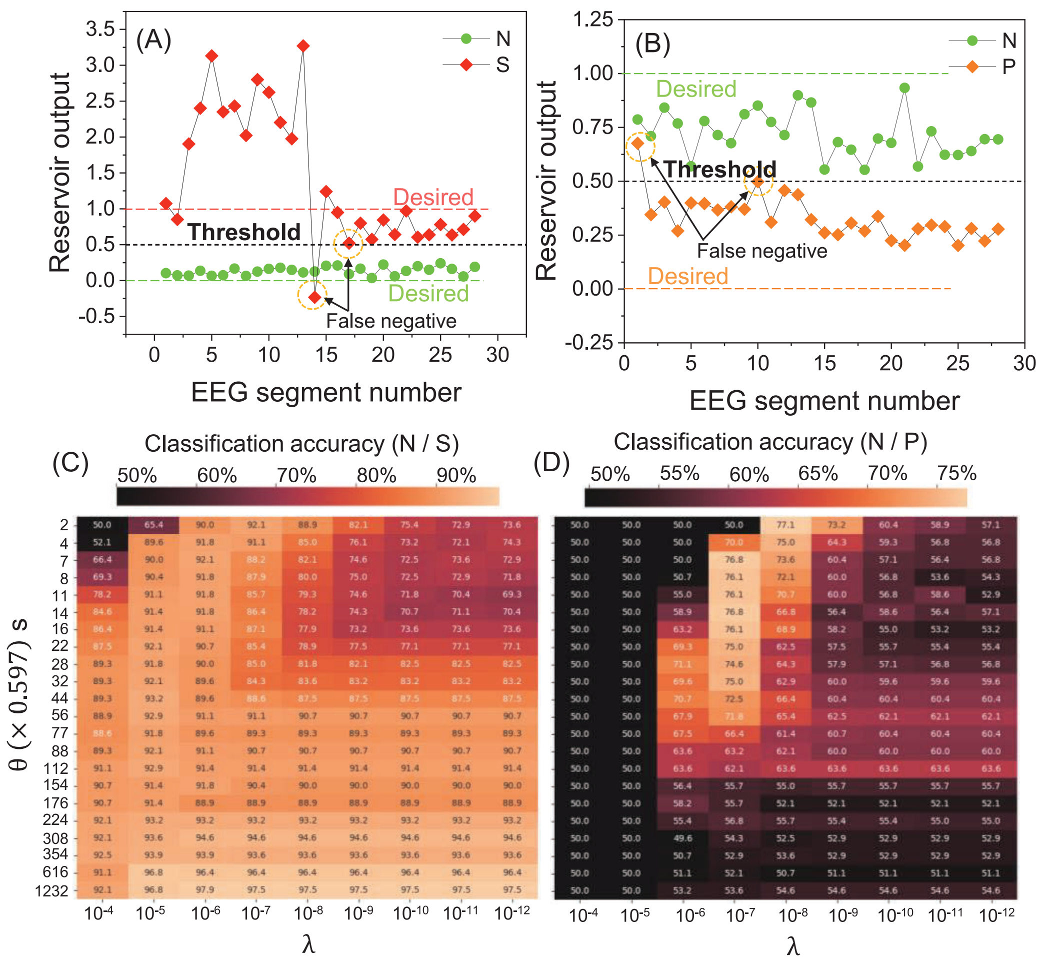

Figure 5: Results for (A) N/S and (B) N/P classification tasks, and heat-maps showing average classification accuracies for 5-fold cross-validation task corresponding to θ, λ variation for (C) N/S and (D) N/P classification.

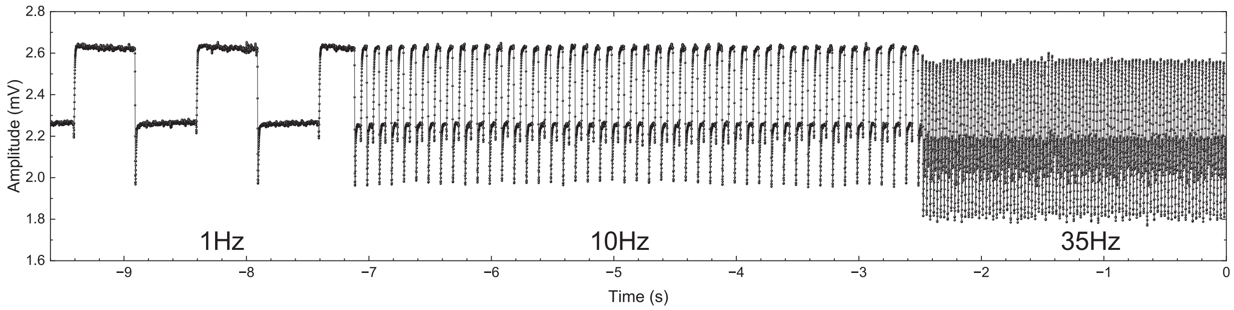

Figure 6: MEMS resonator's output signal corresponding to 1-0-1-0.... input bitstream (square-wave) at different frequencies. The output nearly (linearly) follows the input with over/undershoots and transient behavior.

amplitudes poses a tougher challenge. Although, the N/P classification can potentially be improved by further optimizing hyperparameters, we speculate that a potential cause for relatively low accuracy can be due to a lack of sufficient nonlinearity in the system. When a simple 1-0-1-0... bitstream is given as input (V_{dc}), we observed that the resonator's output nearly follows the input (with overshoot/undershoot) (Fig. 6). Thus, we believe increasing the nonlinearity of the system may lead to better N/P classification result. Implementing feedback (echo) in the system ($\alpha_{fb} \neq 0$) can also improve N/P classification. Also, we noticed (by visual inspection) significant qualitative variation in the EEG data (of same type) perhaps across different patients, which can make the N/P classification accuracy dip close to 50% (for Fig. 5D, P type data with similar qualitative features are considered). This indicates that collecting EEG data from individual patients for training may be required for effective N/P classification.

1.5 Conclusion

We developed a MEMS resonator-based PRC system for real-time EEG classification. Classification accuracy of ～97% is achieved in N/S classification, and an accuracy ～77% is achieved for N/P classification when P signals having similar qualitative features are considered. We believed, a more rigorous optimization of hyperparameters, increasing the nonlinearity in the system's response, and collecting personalized training data can improve classification accuracies.

References

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[2] R. G. Andrzejak et al., Phys. Rev. E 86, 046206 (2012)

2. 発表（研究成果の発表）

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