NanoBioElectronics Laboratory
Ben-Gurion University of the Negev

Intelligent Microelectrodes Array for Hydroxyurea Quantification in Whole Blood

Matan Aroosh[1], Rajendra P. Shukla[1], Russell E. Ware[2], Alexander A. Vinks[2], and Hadar Ben-Yoav[1,*]

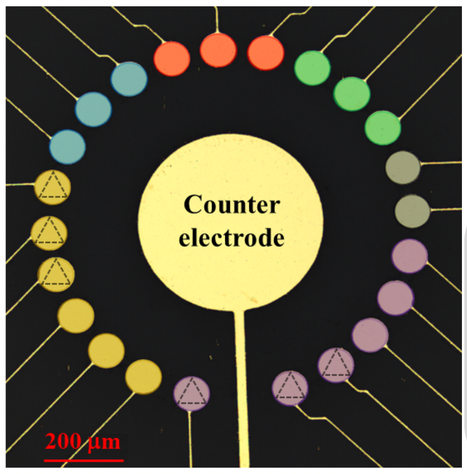
[1]Nanobioelectronics Laboratory (NBEL), Department of Biomedical Engineering, Ben-Gurion University of the Negev, Beer Sheva, Israel. [2]Cincinnati Children's Hospital Medical Center, Cincinnati, Ohio, USA

Introduction

Sickle cell disease is a common inherited blood disorder that leads to major morbidity and early mortality. It is caused by a genetic disorder that affects the beta-hemoglobin gene that leads to faulty hemoglobin protein function. The highest prevalence of sickle cell disease is observed in Africa and India and many affected children die before the age of 5 due to lack of proper diagnosis and treatment [1]. Hydroxyurea (HU) has been found as an efficient medication for sickle cell disease. The typical dosage optimization is weight-based with stepwise escalation. However, this kind of process takes several months to achieve [2]. The common analytical techniques for HU detection in blood are high-performance liquid chromatography and nuclear magnetic resonance that are expensive tools and require technical expertise [3]. **Here, we aim** at creating a simple, robust, low-cost, and accurate point-of-care testing device for HU blood quantification based on an innovative intelligent microelectrodes array and by using partial least square regression (PLSR) model for chemometrics analysis.

Methodology

Microfabrication of Modified Multi-Microelectrode Array



Microelectrode legend:

- R-GO
- Chitosan
- $WS2_a$
- $WS2_b$
- $MoS2_a$
- $MoS2_b$
- Bare
- Ag\AgCl [Ref]

Electrodeposition of 2D electrocatalytic materials:

- Different partial selectivity & cross-reactivity.
- Fast electron-transfer kinetics
- Durable (up to 20% strain)
- Low power requirements

Artificial Intelligent Architecture for Chemometrics Application

Signal preprocessing

Signal Smoothing
Using Moving Average filter

Smart Merging
Resulting in one representative signal for each modification

Signal Normalization
Maximum current normalization for peak detection

Electrochemical peaks Detection

Baseline Removal
Using Small-Window Moving Average- Based algorithm (**SWiMA**) for baseline estimation.[4]

Peak Detection
Insert the normalized signals to smart peak finder function with adaptations to electrochemical signals

PLSR Regression model

Feature Extraction

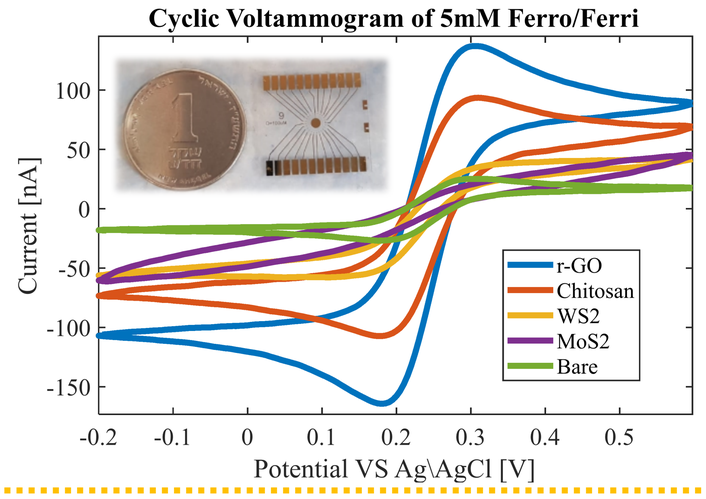
Peak Smart Selection
Auto adjustment of the extracted electrochemical peaks resulting same number of valuable peaks from every electrochemical signal

Single Representation Transform
Using the following transformation:

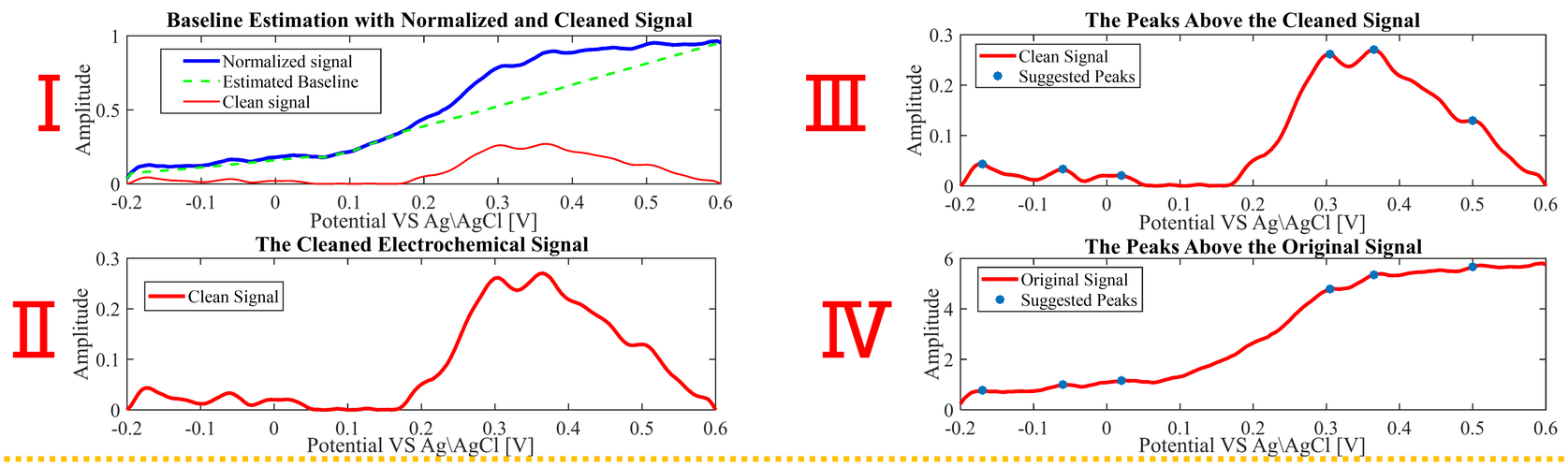
$$Feature = tg\left(\frac{I_p}{E_p}\right) \times \sqrt{{I_p}^2 + {E_p}^2}$$

Results

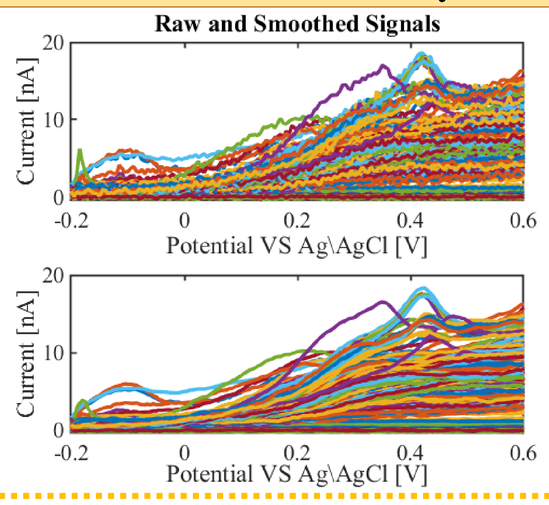
Microelectrodes Modification Validation



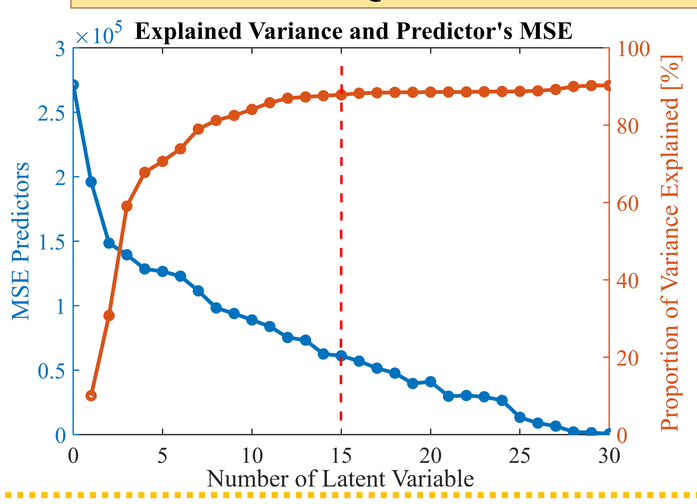
Peak Detection Visualization



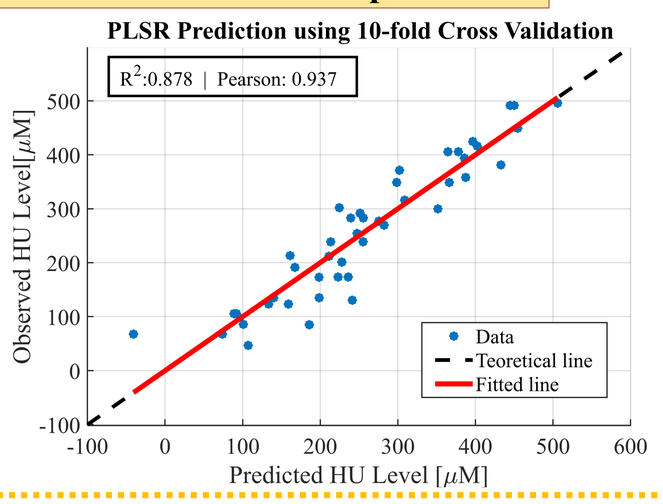
Differential Pulse Voltammetry Recording



PLSR HU Quantification Model of 50 Sickle Cell Disease Patients' Blood Samples



Using 15 latent variable and 10-fold Cross validation



Conclusions

- The optimized PLSR model using 50 children with sickle cell disease blood samples generates model with R^2 of 0.878 and Pearson correlation of 0.937 with 10- fold cross validation method.
- More data samples needed for test evaluation; the current test yielded a correlation of 0.102

Acknowledgement

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References

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* Corresponding author: Dr. Hadar Ben-Yoav. Email: benyoav@bgu.ac.il