THEME ARTICLE: BIO-SENSING

Characterization and Feasibility of Wearable Spectroscopic Tracking of Nutrition Biomarkers

Tarek Hamid, Elizabeth C. Courtney, Patricia Flores, Jane Byun, Afsaneh Doryab, Sibylle Kranz, and Amanda Watson, *University of Virginia, Charlottesville, VA, 22903, USA*

Disorders related to nutrition and metabolism remain a critical public health challenge globally, affecting a significant portion of the population. While traditional calorie tracking methods help monitor dietary intake, they do not capture how the body synthesizes and metabolizes nutrients, and are often inaccurate, cumbersome, and inconvenient. Wearable biosensing technologies present a promising avenue for more precise, noninvasive monitoring of nutritional intake, providing individuals with real-time feedback to improve their dietary habits. In this study, we explore the feasibility of using an off-the-shelf wearable device to track nutrients in the blood. Utilizing a multiwavelength optical sensor covering a range of wavelengths in the visible spectrum, we compare the device's ability to measure spectral absorption profiles of various nutritional molecules relative to a spectrophotometer. Through advanced signal processing and statistical techniques, we are able to successfully recover molecular signatures from the wearable device relative to the spectrophotometer. Our results demonstrate the potential of wearable biosensing technology to track nutritional intake, offering a new tool for effectively managing nutritional disorders through real-time monitoring.

Nutritional status is essential for maintaining health and supporting vital physiological functions. A balanced diet, rich in both macronutrients and micronutrients, is crucial for promoting overall well-being. Macronutrients—carbohydrates, proteins, and fats—serve as the body's primary energy sources and support vital processes, such as energy metabolism, hormone production, and muscle maintenance; achieving the proper balance of these macronutrients is vital for sustaining health and well-being. However, despite the well-known importance of proper nutrition, modern dietary patterns often lead to significant imbalances, contributing to widespread public health issues.[1] The World Health Organization has recently identified nutrition-based disorders, such as obesity and malnutrition, as one of the top health concerns globally.[2] Furthermore, many leading causes of mortality, including diabetes and heart disease, are closely linked to poor dietary habits and can be managed through proper nutrition. The increasing consumption of processed foods has further exacerbated these health risks, contributing to the rise of chronic diseases and metabolic disorders.[1] While dietary intake refers to the nutrients consumed through food, metabolism determines how these nutrients are absorbed, processed, utilized, and stored in the body, meaning that intake alone does not fully capture an individual's nutritional status. Therefore, understanding and accurately monitoring nutritional status in the body is a critical step toward managing diet and preventing diet-related diseases.

Current tools for managing nutritional status are fairly limited and often suffer from issues related to accuracy, usability, and convenience. The most common method of assessing dietary intake to measure

Digital Object Identifier 10.1109/MPRV.2025.3575254

the type and level of provision of nutrients, such as food diaries or logging apps, relies heavily on self-reporting, which is prone to errors due to inaccurate portion estimation, incomplete food databases, and variability in food preparation as well as reporting bias. Current commercial wearable devices, while increasingly popular for tracking fitness and basic health metrics, are largely focused on general activity and caloric expenditure, rather than providing detailed insights on nutritional status. Furthermore, these tools often require manual input from users, adding to the inconvenience and increasing the likelihood of incomplete or inaccurate data. Other approaches, such as nutrient analysis kits or laboratory testing, while more precise, are costly, time-consuming, and impractical for daily use, and they only provide a single snapshot of nutritional status, which may not be sufficient for tracking daily fluctuations and long-term dietary patterns.[3] Critically, these methods are limited to dietary intake and do not capture nutrient levels available in the body, which varies greatly between individuals and is dependent on the digestion, absorption, and metabolism (nutrient kinetics) of dietary nutrients. Metabolites—small molecules that result from the biochemical processing of food—serve as direct indicators of nutritional status, reflecting how the body absorbs, utilizes, and stores nutrients. However, tracking metabolites in real time remains challenging, as current techniques rely on blood or urine sampling, requiring invasive collection and laboratory analysis. This limitation underscores the need for noninvasive technologies that can continuously monitor metabolic responses, providing a more accurate and dynamic understanding of nutrition. These noninvasive techniques can expand access to real-time nutritional tracking, where current methods are limited to research and medical settings due to high cost. Furthermore, they can be convenient to wear in everyday life in smartwatch form-factors, enabling continuous monitoring for the population at large, especially those who are at risk for diet-related diseases.

Recent advances in optical wearable technology have demonstrated the potential to continuously and noninvasively monitor nutrient content.[4] However, current commercial devices remain limited in providing detailed insights into calorie consumption, let alone tracking specific body nutrient content. Developing a wearable device capable of nutrient monitoring could offer numerous benefits. First, it could provide individuals with continuous feedback on their nutritional status, enabling more informed decision-making and promoting healthier habits. This personalized insight into circulating levels of carbohydrates, proteins, and fats could empower users to adjust their behaviors to meet specific health goals, whether for weight management, athletic performance, or general health improvement. Second, such a device could aid healthcare providers in monitoring patients with metabolic conditions, such as diabetes, cardiovascular disease, or other metabolic disorders. Continuous tracking of nutrient status would offer an objective assessment of a patient's metabolic state, facilitating more precise interventions and personalized treatment plans.

In this article, we assess the feasibility of using an off-the-shelf wearable device to quantify nutrient content in the body. We use a spectrometer combined with a laser-driven tunable light source to accurately measure the optical signatures of eight common nutrients and their metabolites. Next, we replicate these measurements by integrating Lumos,[5] a commercial multiwavelength optical wearable device, with the spectrometer, using Lumos as the light source. Finally, we evaluate Lumos independently—without the spectrometer—to see if it can reliably detect the same nutrient signatures and metabolites based on its own measurements, comparing these results to the spectrometer's baseline readings. Overall, our contributions can be summarized as follows.

1) *Nutrient Characterization in Wearables:* We provide a detailed analysis of eight common nutrients and their metabolites using a spectrometer in the visible spectrum and a corresponding wearable device using the same spectral sensing range. We show similar readings between the benchtop spectroscopy setup and the Lumos device across all tested nutrients and their metabolites.
2) *Molecular Signal Recovery:* We develop and implement a data pipeline that reconstructs the underlying molecular spectral signatures using the lower fidelity wearable signal, achieving less than 5% error across all molecules.

The rest of this article is organized as follows. The "Background and Related Work" section provides background information on nutrients in the body, their corresponding metabolites, and prior efforts to characterize and quantify them for nutritional tracking. The "Experimental Study" section outlines the experimental setup used for assessing nutrients with both the spectrometer and the wearable device. The "Results" section presents an evaluation of the spectral readings obtained, along with the algorithm used to extract signals from the wearable device.

The "Discussion and Future Work" section discusses these results and their implications in real-world applications. Finally, the "Conclusion" section concludes this article.

BACKGROUND AND RELATED WORK

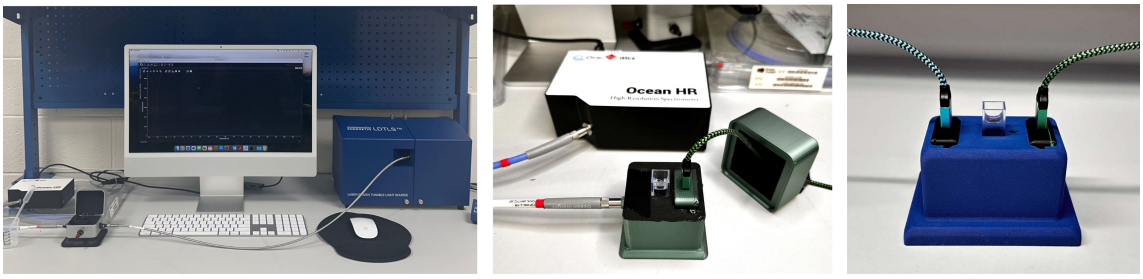
Carbohydrates, proteins, and fats are the primary sources of energy and essential components for numerous physiological functions. Carbohydrates, typically ingested as sugars and starches, are the body's preferred energy source due to their efficient metabolism. Proteins, made up of amino acids, are fundamental for tissue growth, repair, and the production of enzymes and hormones, while lipids, or fats, are crucial for energy storage, forming cell membranes, and regulating signaling pathways. Together, these three macronutrients groups govern key processes, such as energy levels, satiety, and metabolic balance.[1]

The byproducts of carbohydrate, protein, and fat metabolism dictate what can be sensed in the blood. Carbohydrates are broken down into glucose, a monosaccharide that provides immediate energy for the body. Proteins are digested into amino acids, such as tryptophan and tyrosine, which are used for tissue repair and hormone production, or converted into glucose or fatty acids for energy when needed. Fats, primarily in the form of triglycerides, are metabolized into fatty acids and glycerol, and dietary cholesterol is absorbed and used in cell membranes and hormone production. All three macronutrients can be converted into fatty acids and stored in adipose tissue for future energy needs, when energy intake exceeds energy expenditure. When glucose is scarce, such as during fasting, fatty acids are further broken down in the liver to produce ketone bodies, such as acetoacetate, hydroxybutyrate, and acetone. Lipoproteins play a key role in fat transport and metabolism. Low-density lipoprotein (LDL) carries cholesterol from the liver to tissues for cellular functions, while very-low-density lipoprotein (VLDL) transports triglycerides. Conversely, high-density lipoprotein (HDL) helps remove excess cholesterol from the bloodstream, returning it to the liver for excretion.[1] These metabolites, which travel through the bloodstream, provide critical insights into the body's metabolic processes, energy balance, and disease risk, but monitoring of these molecules over longer periods and in real time remains a significant challenge.

Conventional methods for monitoring nutritional status have long relied on self-reporting techniques, such as food diaries. These approaches require users to manually record their food consumption, often by estimating portion sizes and nutritional content, or by tediously weighing food before consumption and using nutrition labels. While widely adopted by those looking to manage their diet, these methods suffer from significant limitations: 1) self-reported dietary intake is prone to substantial inaccuracies, 2) food databases that allow users to select food and their nutrition content conveniently are often incomplete or inaccurate, and 3) there lies a cognitive burden of consistent logging, which may decrease adherence over time. In addition, the retrospective nature of these tools fails to provide real-time feedback, limiting their effectiveness in guiding immediate dietary choices.[3,6] More precise methods, such as doubly labeled water techniques, which measure energy expenditure through urine collection samples, or dietary recalls conducted by trained professionals, while more accurate, are impractical for daily use due to their cost, time-intensity, and the need for specialized expertise.[6] These limitations underscore the need for more objective and user-friendly approaches to nutritional monitoring.

Recent advances in wearable biosensing technologies have shown promise for monitoring various nutritional biomarkers by analyzing biofluids—excess levels in sweat, metabolic markers in saliva and tears, and real-time measurements from interstitial fluid (ISF)—to provide assessments of an individual's nutritional status. Devices, such as epidermal tattoo biosensors for sweat vitamin C levels,[7] microneedle-based sensors for glucose and lactate in ISF,[8] and tear-based biosensors for vitamins and alcohol,[9] have demonstrated the feasibility of noninvasive biochemical sensing. However, while these technologies provide valuable insights into specific micronutrients, they do not offer direct measurements of macronutrient metabolism in a continuous, noninvasive manner. The challenge remains in developing a sensor that can track how metabolites of carbohydrates, proteins, and fats are affected by dietary intake without relying on external food logging or biochemical sampling. Currently, the only wearable sensor capable of directly measuring a macronutrient is continuous glucose monitoring (CGM) systems, which track glucose levels in ISF. However, CGMs are limited to monitoring carbohydrate metabolism and do not provide information on protein or fat intake, especially in nonfasted states.[4]

Existing wearable nutrition monitoring technologies have largely focused on estimating caloric intake and expenditure rather than tracking macronutrient metabolism. Recent studies using wrist-worn wearable



(a) (b) (c)

FIGURE 1. Three configurations utilized for spectroscopic analysis of nutrition biomarkers. 3D printed structures were built to house the Lumos device for conditions 2 and 3. (a) Spectrometer and LDTLS. (b) Spectrometer and lumos. (c) Lumos and lumos.

devices have leveraged proxies, such as heart rate variability, physical activity tracking, and interstitial glucose fluctuations, to infer dietary intake rather than directly measuring the presence of macronutrients in the body. Dimitratos et al.[10] evaluated a wrist-worn device designed to estimate daily caloric intake and found a mean bias of -105 kcal/day, indicating variability in accuracy, while van den Brink et al.[11] demonstrated that combining continuous glucose monitoring with activity tracking could detect eating moments with an accuracy of 92.3% in training datasets . Although such methods provide useful estimations, their reliance on indirect proxies limits their ability to quantify metabolite concentrations in the blood in a physiologically meaningful way.

Optical spectroscopy presents an alternative approach by enabling direct measurement of biochemical signatures in the body without requiring biofluid extraction. Spectroscopy has been widely used in food science for macronutrient content analysis, leveraging near-infrared (NIR) wavelengths for compositional assessments,[4] but its application in wearable, noninvasive nutritional status sensing remains largely unexplored. By leveraging spectroscopic techniques in the visible and NIR spectrum, we aim to develop a noninvasive method for continuous monitoring of carbohydrate, protein, and fat metabolism. This work builds upon existing biosensing approaches while introducing a novel optical-based technique that does not rely on biofluid sampling, addressing the limitations of current technologies.

EXPERIMENTAL STUDY

To explore the feasibility of tracking nutritional status using wearable spectroscopy, we designed a laboratory experiment where we tested a total of eight dietary molecules and their corresponding metabolites in the body: glucose, HDL, LDL, VLDL, tryptophan, tyrosine, ethyl acetoacetate, and acetone. The selection of these molecules was guided by several key factors. First, these molecules represent important indicators of the body's metabolic pathways for carbohydrates, proteins, and fats: glucose is the primary energy source derived from carbohydrate metabolism, tryptophan and tyrosine are critical amino acids in the blood, and ethyl acetoacetate and acetone are ketone bodies produced during fat metabolism. In addition, HDL, LDL, and VLDL are important lipoproteins that transport lipids. Second, the availability of pure samples for testing was an important consideration. Finally, molecular properties, such as size and structure, were a key determinant; tyrosine and tryptophan are among the larger amino acids, which can aid in easier detection in the visible spectrum.

We employed three data collection systems: one using a commercial spectrophotometer with a tunable laser light source to provide a baseline measurement for eventual signal recovery, one replacing the light source with a wearable device to assess the baseline noise of the wearable, and one using the wearable device independently to evaluate its feasibility. We also discuss the signal processing techniques we used to recover the signal, effectively matching the lower fidelity wearable data with the higher fidelity spectrometer data. This approach allowed us to confirm our ability to measure and recover the spectral profile of the underlying biomarker itself, rather than an analog or correlate. This is crucial for on-body scenarios where multiple confounding factors could affect the signal, and where various molecules with overlapping absorption spectra could be present.

Experimental Setup

The experimental setup is illustrated in Figure 1. Spectroscopic measurements were collected for

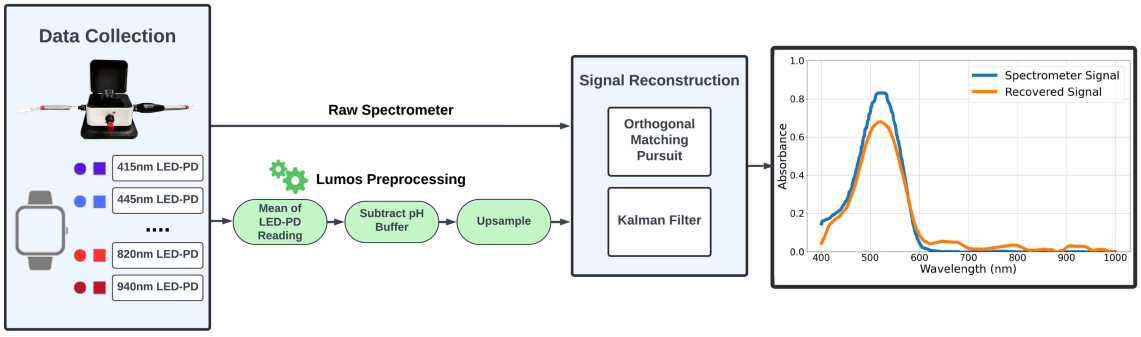


FIGURE 2. Pipeline for data processing and signal reconstruction to match spectrometer and Lumos signals.

various molecules under three conditions: using a commercial spectrometer with a tunable light source [see Figure 1(a)], using an off-the-shelf wearable device as the light source with the spectrometer [see Figure 1(b)], and using two sets of the same wearable device, one as the light source and the other as the detector [see Figure 1(c)].

Our setup utilized two key components for spectroscopic analysis: the Ocean Optics HR6 spectrometer[12] and the Lumos wearable device.[5] The HR6 spectrometer served as our primary tool for spectral characterization, analysis, and ground-truth measurement. The Hamamatsu Laser Driven Tunable LightSource (LDTLS)[13] was used as the light source for the spectrometer setup. To minimize environmental interference, all experimental conditions were conducted with covered setups. All solutions were prepared in a 7.4 pH buffer solution as a baseline, the normal pH of blood, with volumes ranging from 100 to 2000 μL. All measurements were conducted across a wavelength range of 400–1100 nm. Lumos,[5] a commercial wearable device, uses 10 LEDs and nine photodiodes (PDs) distributed across the visible spectrum, covering a spectral range of 400–1000 nm. The device is highly flexible, capable of adapting to various form-factors. Lumos operates by capturing each PD response during a single LED's operation, resulting in 90 measurements per cycle (10 LEDs $\times$ 9 PDs). For this feasibility study, we intentionally slowed the sampling rate of Lumos to cycle through all LEDs and PDs over 7 s, ensuring stable and accurate readings, although the device is capable of much faster operation.

Data Processing and Signal Recovery

Figure 2 outlines the pipeline for data processing and signal recovery from the Lumos wearable system. First, signals from each LED–PD pair on the Lumos device are averaged over the course of a single measurement (approximately 7 s). These data are then subtracted by the mean readings of the pH buffer from the same LED–PD pair, and then upsampled to match the spectrometer's sampling rate using cubic spline interpolation. After upsampling, the underlying molecular signature is recovered using signal recovery techniques. Signal recovery is important in this pipeline because the Lumos system, while capable of measuring molecular absorption, inherently produces signals with lower fidelity compared to a laboratory-grade spectrometer and light source. This is due to factors, such as lower resolution, sensor noise, and reduced light intensity, that make it challenging to interpret the raw data, especially for molecules with lower absorption values in the visible spectrum. Advanced signal processing techniques can be employed to help recover this underlying signal.

Two separate techniques were used for signal recovery: Kalman filtering[14] and compressed sensing recovery using orthogonal matching pursuit (OMP).[15] Other algorithms, such as blind source separation[16] and various adaptive filters,[17] were also computed, but were outperformed by the aforementioned models. The following algorithms were chosen as they each offer unique advantages in signal processing and corresponding signal reconstruction.

1) *Kalman Filtering:* Known for its ability to estimate states of a system from noisy measurements, it operates by predicting the current state based on previous estimates and then correcting this prediction using new measurements, making it effective for tracking and predicting spectroscopic signals over time.
2) *Orthogonal Matching Pursuit:* It is an approach that allows for efficient signal reconstruction from sparse measurements. It works by iteratively selecting the most correlated basis vectors with the signal and solving a least-squares

problem to estimate signal coefficients. This is ideal for recovering high-resolution spectral information from the limited number of wavelengths sampled by the Lumos device.

Each algorithm was evaluated on its ability to closely match the original spectrometer signal using peak position error and spectral correlation, two spectroscopy-specific techniques that provide insights into the quality of spectral reconstruction. Peak position error quantifies the accuracy of identifying specific molecular signatures by measuring the difference in wavelength between corresponding peaks in the recovered and original spectra. This metric is particularly important for correctly identifying and quantifying individual components of the spectral waveform that correspond to high absorbance regions. Spectral correlation assesses the overall similarity in shape and pattern between the recovered and original spectra, offering a comprehensive measure of how well the algorithm preserves the spectral profile across the entire wavelength range. This is computed by calculating the Pearson correlation[18] between the two signals. Mean absolute error is also used to provide additional contextual information on the reconstructed signal strength. Together, these metrics provide a robust evaluation of both the precision in identifying specific spectral features and the overall fidelity of the reconstructed signal to the original spectrometer output.

RESULTS

Comparative Measurements Across Conditions

The figures above illustrate the spectral results for each molecule under the three experimental conditions: the spectrometer measurement, the spectrometer with the Lumos light source, and the Lumos wearable independently. The Lumos wearable produces analog-to-digital converter (ADC) counts, which correspond to the intensity of light detected by the device's PD after it reflects off the user's skin. The ADC converts the analog voltage signal generated by the light sensor (based on the intensity of the reflected light) into a digital value, which represents the magnitude of the reflected signal. Spectrometer measurements were referenced against public spectral databases[19,20] to confirm results. The spectrometer data were collected with approximately a 0.5 nm step size, for a total of more than 2000 data points per reading. Each Lumos data reading was averaged over 7 s for each LED–PD, for a total of nine data points per reading. For Lumos-spectrometer readings, there appears to be a 760 nm peak identified for all molecules, which we attribute to reflection artifacts from the experimental setup housing rather than molecular absorption features. We expect this to be remedied in future studies with improved housing design.

a) *Glucose:* For glucose [see Figure 3(a)], absorption spectra in the 500–550 nm region are clearly visible across all three experimental setups. Both the Lumos-spectrometer and Lumos setups replicate the spectrometer's glucose absorption peaks with high signal fidelity. Although the Lumos plot appears phase-shifted relative to the spectrometer data, this can be explained by the Gaussian spectral distribution of the LED emission and PD responses. The Lumos LEDs and PDs do not operate at a single wavelength but instead over a range; this range may be a contributor to the observed phase shift when compared to the fixed-wavelength spectrometer measurement.
b) *HDL:* The HDL absorption spectra [see Figure 3(b)] show clear features across all three setups, with a distinct peak at 450 nm and sustained absorption throughout the visible spectrum. However, both the Lumos-spectrometer and Lumos experiments demonstrated significantly higher noise levels, especially beyond 600 nm. Despite this noise, Lumos captures the characteristic HDL signature with reasonable fidelity.
c) *LDL:* Similar to HDL, the LDL absorption spectra [see Figure 3(c)] are most prominent in the 400–550 nm region. The spectrometer with the wearable captures a similar absorption feature, although there is some variation in the signal magnitude. The fully wearable solution shows a recognizable LDL profile with more noise.
d) *VLDL:* VLDL absorption spectra [see Figure 3(d)] are also concentrated primarily around the 400–500 nm range. The spectrometer with the wearable light source captures these features with a reduction in overall signal amplitude. The characteristic LDL signature is captured by the wearable, albeit at a lower intensity and with some observed phase shifts.
e) *Acetone and Ethyl Acetoacetate:* Acetone absorption values [see Figure 4(a)] were also very low for the visible spectrum; Lumos shows an identifiable peak in the NIR region, suggesting potential for NIR sensing. Similar to acetone, ethyl acetoacetate [see Figure 4(b)] shows low

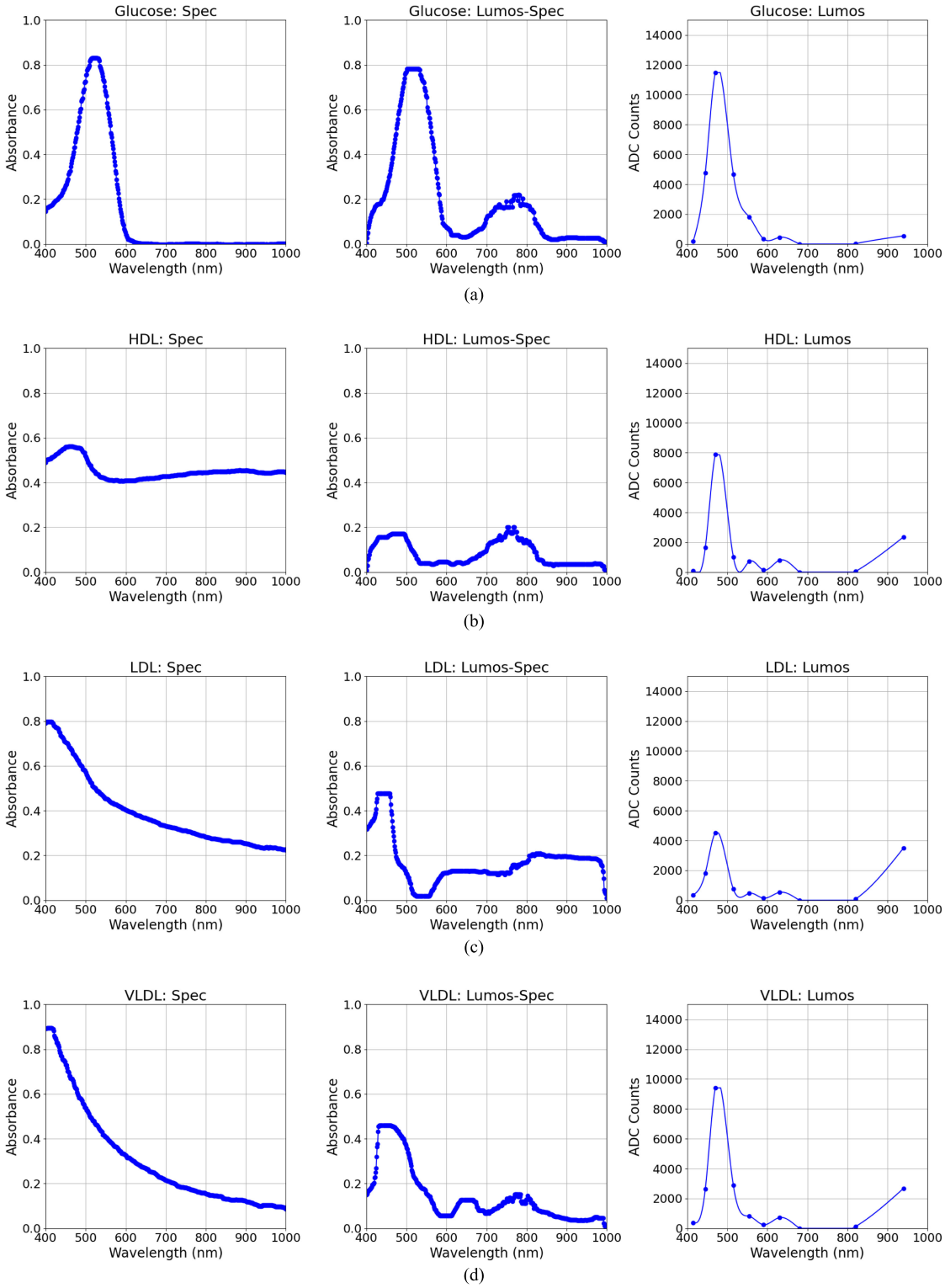


FIGURE 3. Comparative measurements for glucose, HDL, LDL, and VLDL across three experimental conditions. (a) Glucose measurements. (b) HDL measurements. (c) LDL measurements. (d) VLDL measurements.

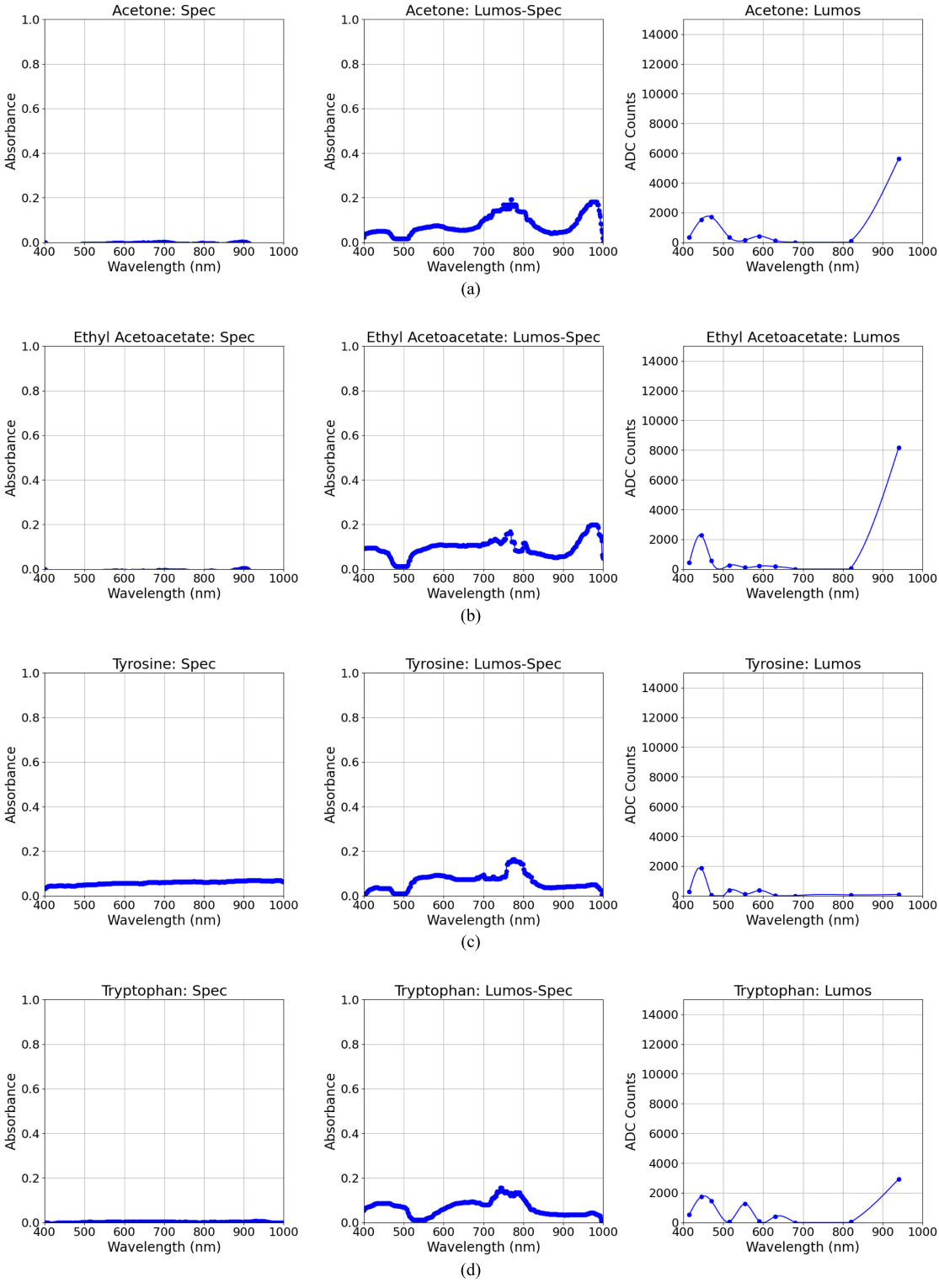


FIGURE 4. Comparative measurements for acetone, ethyl acetoacetate, tyrosine, and tryptophan across three experimental conditions. (a) Acetone measurements. (b) Ethyl acetoacetate measurements. (c) Tyrosine measurements. (d) Tryptophan measurements.

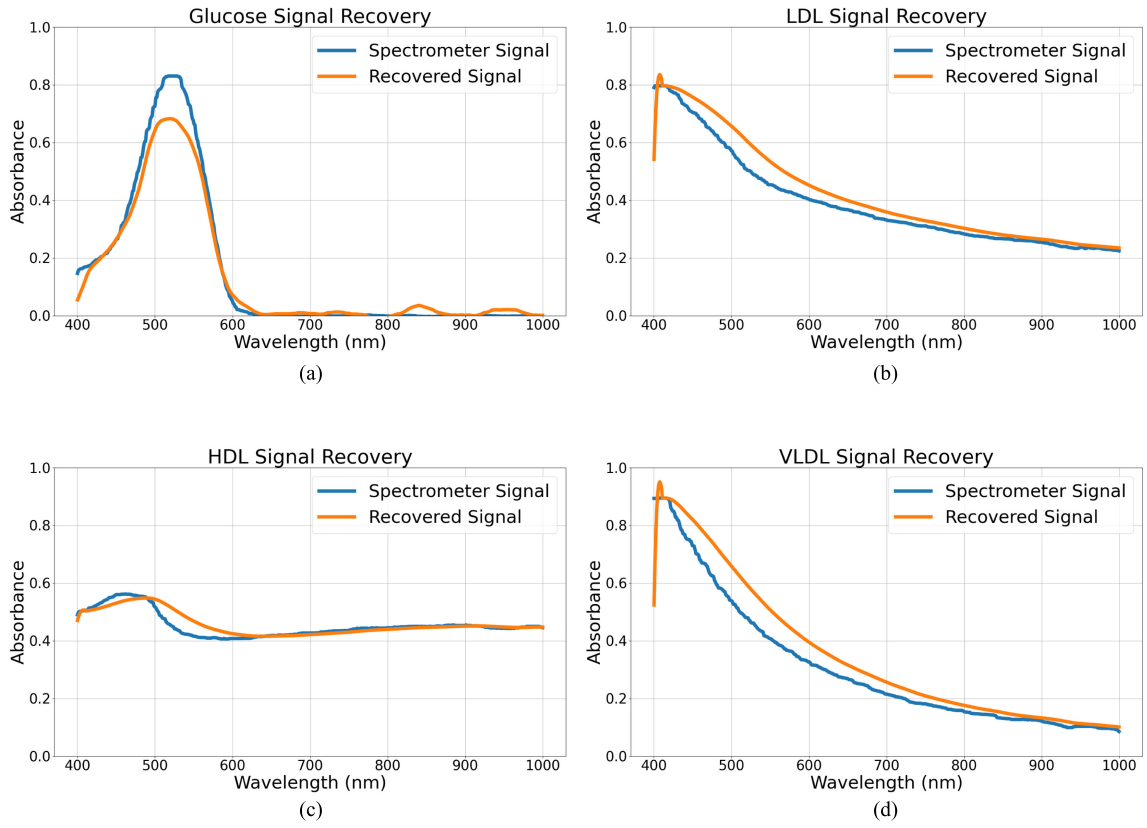


FIGURE 5. Plots of Lumos signal recovery for (a) glucose, (b) LDL, (c) HDL, and (d) VLDL. All plots show a strong ability to recover the original spectrometer signal using the referenced algorithms. (a) Signal recovery of glucose using OMP. (b) Signal recovery of LDL using Kalman filtering. (c) Signal recovery of HDL using Kalman filtering. (d) Signal recovery of VLDL using Kalman filtering.

to zero absorption in the visible spectrum, with an identifiable peak in the Lumos configuration in the NIR spectrum.

f) *Tyrosine:* The tyrosine absorption spectra [see Figure 4(c)] across all three conditions exhibit lower overall absorbance compared to previous molecules. The spectrometer provides a clear baseline with minimal absorbance peaks. The spectrometer with the wearable light source captures some additional variation in the 600–700 nm region, which can be attributed to noise. The fully wearable setup demonstrates higher noise and very low signal detection. Overall, the data suggest that tyrosine may be more challenging to measure using the wearable in this configuration.

g) *Tryptophan:* Similar to tyrosine, all configurations show low signal detection for tryptophan [see Figure 4(d)], with a varying amount of noise detected in the wearable–spectrometer setup and the wearable independently. There is a slight peak in the 950 nm LED for tryptophan in the Lumos configuration, which may suggest promise in detecting this molecule using NIR sensors.

Lumos Signal Recovery

Signal recovery techniques were applied to glucose, HDL, LDL, and VLDL signals from Lumos to recover the underlying spectral signal relative to each molecule. These molecules were chosen as they showed clear absorption characteristics in the visible spectrum using the spectrometer that could be recovered using signal processing techniques. The most performant algorithm for each of the aforementioned macronutrients is shown in Figure 5.

Peak position error, spectral correlation, and mean absolute error metrics for raw data relative to the Kalman and OMP recovered signals are given in Table 1 for each molecule. Both models showed the ability to accurately reconstruct the spectrometer signal from the underlying Lumos data with high fidelity, with low peak position error and high correlation, and a marked improvement relative to using the raw Lumos data.

TABLE 1. Comparison of raw signal versus kalman and OMP-Recovered signal performance for different molecules using peak position error (PPE), spectral correlation (corr), and mean absolute error (MAE).

Molecule	Lumos			OMP			Kalman		
	PPE (%)	Corr	MAE	PPE (%)	Corr	MAE	PPE (%)	Corr	MAE
Glucose	5.80	0.66	0.17	1.60	0.99	0.05	5.00	0.87	0.07
LDL	21.23	−0.03	0.32	3.40	0.96	0.02	1.00	0.99	0.03
HDL	3.20	0.56	0.16	0.60	0.76	0.01	4.80	0.88	0.01
VLDL	13.20	0.32	0.24	2.80	0.97	0.04	0.60	0.99	0.05

Overall, our results demonstrate the feasibility of using a wearable multiwavelength optical sensor to detect and quantify key macronutrients, particularly glucose, HDL, LDL, and VLDL, with promising accuracy relative to traditional spectrometer measurements. However, the current setup showed limitations in capturing tyrosine, tryptophan, acetone, and ethyl acetoacetate, which exhibited low absorption profiles in the visible spectrum, and absorption observed in the NIR spectra for the Lumos device indicates that these molecules may be detected in this range. The Lumos device does have more sensing capabilities in the NIR spectra when compared to the spectrometer even if less accurate due to the sensing range of the PDs, which are not fixed-point but rather cover a range of the spectrum up to 1100 nm.

DISCUSSION AND FUTURE WORK

In this section, we discuss future work planned for wearable and noninvasive nutrient tracking. We begin by discussing limitations of the current experimental setup, our plans to test the Lumos system in vivo, and future considerations when considering such a system for real-time physiological tracking. Lastly, we explore various applications for this system.

Future Work

We plan to expand the spectral capabilities of the Lumos device to incorporate optical sensors operating in the NIR and infrared range (1000–2000 nm); this extended range has the potential to capture a broader array of nutrients, including those that were not tested in the present study. One of the key advantages of the Lumos device is its flexibility—it can be adapted to develop customized nutrition tracking systems by tuning the LED–PD array to match the spectral resolution of target molecules, such as glucose, HDL, LDL, and VLDL, where they can be more accurately detected.

While these initial results are promising, several challenges remain in translating this technology to practical, on-body use. First, our current study was conducted in vitro, and future work must address the complexities of in vivo measurements, including signal attenuation through skin and other tissues, motion artifacts, and environmental interferences. It is unclear if macronutrients can be measured or accurately estimated from a single site on the body, as the distribution and concentration of these molecules may vary across different tissues and regions. In addition, factors, such as blood flow, skin thickness, and local metabolic activity, could influence the reliability of measurements at certain sites, potentially leading to inconsistent or inaccurate readings. Future work should investigate whether multisite measurements or a combination of sensing modalities is necessary to obtain a more comprehensive assessment of nutritional status. Furthermore, many of these molecules have overlapping spectral signatures and are present in the body at relatively low concentrations, which may make commercial translation difficult. In-the-wild signal recovery of molecular signals may prove to be challenging. By leveraging machine learning algorithms on subject-specific data, we can enhance the accuracy of signal reconstruction in dynamic environments by accounting for variations in individual physiology and environmental noise. The combination of flexible hardware and adaptive software may enable highly personalized, continuous nutrition monitoring devices.

Future work must also consider differentiating between consumed macronutrient byproducts and those that are byproducts of catabolic processes in a fasted state. This distinction is critical as providing feedback to a potential user that macronutrient content is elevated, despite the user not consuming anything, may result in frustration and device distrust. For instance, individuals with a genetic predisposition to high production of LDL in the liver may be frustrated when LDL measurements do not decrease although no dietary cholesterol was consumed. The energy demands of

continuous optical sensing may also limit battery life, particularly if nutrition must be constantly monitored. An eating detection algorithm to facilitate corresponding nutrition detection may prove beneficial in this context. Eating detection has been thoroughly explored using wearable technology and has shown good promise.[21] Lastly, while the current system focuses purely on macronutrient tracking, it does not account for other physiological metrics, such as heart rate, body temperature, and hydration levels, which could enhance nutritional monitoring. Incorporating a multimodal approach with other available biomarkers may improve overall signal fidelity and detection accuracy.

Real-World Applications

The utility of a nutrient tracking device, if implemented correctly, cannot be overstated in the commercial sector. Such a device could provide real-time feedback to individuals about the effect of their dietary intake on nutrition status, empowering them to make healthier food choices and gain a better understanding of their metabolism to enhance overall performance. Consumers focused on fitness or weight management would benefit from more precise tracking, reducing reliance on manual logging or estimations. Insurance companies might also offer incentives for improved nutritional habits based on these data, creating a market where individuals are rewarded for healthier behaviors. However, ensuring data privacy would be paramount, as users would need to trust that their personal dietary information is secure.

In healthcare, continuous nutrition monitoring would have profound implications for managing chronic conditions, such as diabetes and cardiovascular disease. Dietary management for these conditions, which is often tedious or difficult, could be simplified through real-time monitoring, allowing patients and healthcare providers to personalize recommendations and track adherence. Healthcare professionals could remotely adjust treatment plans based on actual dietary intake, providing a more dynamic and responsive approach to care. The technology could also support preventative health efforts by identifying unhealthy dietary patterns early and offering corrective suggestions before conditions worsen. With the rise in popularity of bariatric surgery and GLP-1 receptor agonist drugs for weight loss, wearable continuous nutrition monitoring could also offer a noninvasive alternative for managing and tracking dietary intake in these cases. Continuous nutrition tracking could enable large-scale research studies that are currently not feasible, such as exploring the behavioral aspects of eating, studying metabolic processes in greater detail, and examining dietary patterns and their long-term impact on public health across different populations. This would enable new avenues of research for public health and nutrition science. The proposed approach offers a low-cost, noninvasive alternative to laboratory blood draws, enabling individuals to monitor nutrient levels over time without the burden of clinical visits.

CONCLUSION

Our findings demonstrate that wearable biosensing technology has the potential to track nutritional intake, providing a new tool for effectively managing nutritional disorders through real-time monitoring. By employing advanced signal processing techniques, we were able to retrieve the baseline spectral profile of glucose, HDL, LDL, and VLDL using the wearable device. Although there are current limitations, such as challenges in detecting certain molecules, our results underscore the significant potential of wearable biosensing technology for noninvasive nutritional monitoring. Future research will focus on expanding spectral capabilities, addressing in vivo measurement challenges, and utilizing advanced machine learning techniques to enhance detection accuracy.

ACKNOWLEDGMENTS

This work was supported by the University of Virginia Engineering Research Innovation Award.

REFERENCES

1. S. Espinosa-Salas and M. Gonzalez-Arias, *Nutrition: Macronutrient Intake, Imbalances, and Interventions*, in Ser. StatPearls [Internet]. Treasure Island, FL, USA: StatPearls Publishing, 2024. Accessed: Aug. 8, 2023.
2. World Health Organization, "Obesity and overweight," 2024. Accessed: Feb.7, 2025. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight
3. M. Rusin, E. Årsand, and G. Hartvigsen, "Functionalities and input methods for recording food intake: A systematic review," *Int. J. Med. Inform.*, vol. 82, no. 8, pp. 653–664, 2013.
4. J. R. Sempionatto, V. R.-V. Montiel, E. Vargas, H. Teymourian, and J. Wang, "Wearable and mobile sensors for personalized nutrition," *ACS Sensors*, vol. 6, no. 5, pp. 1745–1760, 2021.
5. A. Watson, C. Kendell, A. Lingamoorthy, I. Lee, and J. Weimer, "Lumos: An open-source device for wearable spectroscopy research," *Proc. ACM Interactive Mobile Wearable Ubiquitous Technol.*, vol. 6, no. 4, pp. 1–24, Jan. 2023.

6. National Research Council (US) Committee on Diet and Health, *Diet and Health: Implications for Reducing Chronic Disease Risk*. Washington, DC, USA: Nat. Academies Press, 1989.
7. J. R. Sempionatto et al., "Epidermal enzymatic biosensors for sweat vitamin C: Toward personalized nutrition," *ACS Sensors*, vol. 5, no. 6, pp. 1804–1813, 2020.
8. H. Teymourian et al., "Microneedle-based detection of ketone bodies along with glucose and lactate: Toward real-time continuous interstitial fluid monitoring of diabetic ketosis and ketoacidosis," *Anal. Chem.*, vol. 92, no. 2, pp. 2291–2300, Jan. 2020, doi: 10.1021/acs.analchem.9b05109.
9. J. R. Sempionatto et al., "Eyeglasses-based tear biosensing system: Non-invasive detection of alcohol, vitamins, and glucose," *Biosensors Bioelectronics*, vol. 137, pp. 161–170, Apr. 2019, doi: 10.1016/j.bios.2019.04.058.
10. S. M. Dimitratos, J. B. German, and S. E. Schaefer, "Wearable technology to quantify the nutritional intake of adults: Validation study," *JMIR mHealth uHealth*, vol. 8, no. 7, 2020, Art. no. e16405, doi: 10.2196/16405.
11. W. J. v. d. Brink, T. J. v. d. Broek, S. Palmisano, S. Wopereis, and I. M. d. Hoogh, "Digital biomarkers for personalized nutrition: Predicting meal moments and interstitial glucose with non-invasive, wearable technologies," *Nutrients*, vol. 14, no. 21, 2022, Art. no. 4465, doi: 10.3390/nu14214465.
12. O. Insight, "SR6 UV-VIS spectrometers." Accessed: May 1, 2025. [Online]. Available: https://www.oceaninsight.com/products/spectrometers/general-purpose-spectrometer/ocean-sr6-series-spectrometers/ocean-sr6-uv-vis-spectrometers/
13. Hamamatsu, "Laser driven tunable lightsource." Accessed: May 1, 2025. [Online]. Available: https://www.hamamatsu.com/us/en/product/light-and-radiation-sources.html
14. R. Kalman, "A new approach to linear filtering and prediction problems," *Trans. ASME–J. Basic Eng.*, vol. 82, no. 1, pp. 35–45, 1960.
15. J. Tropp and A. Gilbert, "Signal recovery from random measurements via orthogonal matching pursuit," *IEEE Trans. Inf. Theory*, vol. 53, no. 12, pp. 4655–4666, Dec. 2007.
16. A. Hyvärinen and E. Oja, "Independent component analysis: Algorithms and applications," *Neural Netw.*, vol. 13, no. 4/5, pp. 411–430, 2000.
17. S. Haykin, *Adaptive Filter Theory*, 5th ed. Upper Saddle River, NJ, USA: Pearson, 2008.
18. K. Pearson, "Note on regression and inheritance in the case of two parents," *Proc. Roy. Soc. London*, vol. 58, pp. 240–242, 1895.
19. M. Taniguchi, H. Du, and J. S. Lindsey, "PhotochemCAD 3: Diverse modules for photophysical calculations with access to multiple spectral databases," *Photochemistry Photobiol.*, vol. 94, pp. 277–289, 2018.
20. A. Noelle et al., "UV/VIS photochemistry database: Structure, content and applications," *J. Quantitative Spectrosc. Radiative Transfer*, vol. 253, 2020, Art. no. 107056.
21. B. M. Bell, R. Alam, and N. Alshurafa, "Automatic, wearable-based, in-field eating detection approaches for public health research: A scoping review," *npj Digit. Med.*, vol. 3, 2020, Art. no. 38, doi: 10.1038/s41746-020-0246-2.

TAREK HAMID is currently working toward a Ph.D. degree in electrical engineering at the University of Virginia, Charlottesville, VA, 22903, USA. He is the corresponding author of this article. Contact him at pve8nt@virginia.edu.

ELIZABETH C. COURTNEY is currently working toward an undergraduate degree in electrical engineering at the University of Virginia, Charlottesville, VA, 22903, USA. Contact her at xzy8ta@virginia.edu.

PATRICIA FLORES is currently working toward an undergraduate degree in electrical engineering at the University of Virginia, Charlottesville, VA, 22903, USA. Contact her at sjy7da@virginia.edu.

JANE BYUN is currently working toward an undergraduate degree in computer engineering at the University of Virginia, Charlottesville, VA, 22903, USA. Contact her at rjr5dn@virginia.edu.

AFSANEH DORYAB is an assistant professor at the Departments of Systems and Information Engineering and Computer Science, University of Virginia, Charlottesville, VA, 22903, USA. Contact her at ad4ks@virginia.edu.

SIBYLLE KRANZ is an associate professor at the Kinesiology Department, University of Virginia, Charlottesville, VA, 22903, USA. Contact her at sk4gd@virginia.edu.

AMANDA WATSON is an assistant professor at the Electrical Engineering Department, University of Virginia, Charlottesville, VA, 22903, USA. Contact her at aawatson@virginia.edu.