PIKL: Embedded Software for Real-Time Pickleball Analytics

A Technical Report submitted to the Department of Computer Science

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

Oscar Laurence Lauth

Spring, 2025

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Briana Morrison, Department of Computer Science

PIKL: Embedded Software for Real-Time Pickleball Analytics

CS4991 Capstone Report, 2025

Oscar Laurence Lauth
Computer Science
The University of Virginia
School of Engineering and Applied Science
Charlottesville, Virginia USA
whd7zb@virginia.edu

ABSTRACT
Pickleball as a sport continues to grow in popularity, creating a demand for a smart tool to help serious players enhance their game. This motivates the creation of a smart pickleball paddle, the PIKL, equipped with sensors to provide real-time feedback on metrics such as impact location, swing speed, and stroke classification. Such a device demands a robust embedded software system that can handle sensor data collection, signal processing, and wireless transmission. The software runs on a microcontroller and is implemented with Zephyr, a Real Time Operating System (RTOS). Key components of the embedded software include sensor data acquisition through an analog-to-digital converter (ADC) as well as over inter-integrated circuit (I2C), shot data processing algorithms, and Bluetooth Low Energy (BLE) pairing and transmission. The final software system consistently detects pickleball shot impacts on the paddle face, accurately calculates metrics such as swing speed and stroke classification and reliably transmits this data in real time to a connected user device. Future work could include expanding stroke classification to cover overheads, volleys, and dinks, as well as tuning swing speed estimation using ground truth data.

1. INTRODUCTION
In recent years, pickleball has surged in popularity, becoming the fastest-growing sport in the United States (USA Pickleball, 2025). Several factors drive this rapid growth, including ease of play, health benefits and an addictive nature (DeMelo, 2022). Underpinning the pickleball craze is the rise of a competitive scene with millions of viewers and year-round tournaments (USA Pickleball, 2025). This influx of serious players eager to improve their game creates a demand for performance-enhancing technologies.

For more established sports, data-driven training tools have become essential for athletes (Frevel, et al., 2022). However, as a relatively new sport, pickleball lacks these sophisticated technologies. This technological gap presents an opportunity to develop PIKL, a smart pickleball paddle that provides real-time data analytics on swing speed, stroke classification, impact location, and impact force. The project seeks to fill this void in pickleball and offer experienced players a smart paddle to enhance their game.

2. RELATED WORKS
New technologies are emerging in the pickleball space, with a few existing competitors. One such product, the Kill-Shot Pro, is a pickleball paddle that incorporates a sensor panel over the paddle face that detects whether a player has hit the central sweet spot. (Kill-Shot Pro, 2024). The sweet spot, located in the center of the paddle, is the ideal area to make contact with the ball, providing maximum shot consistency and control (VanOs, 2024). Although the sweet spot is valuable for players to track, the Kill-Shot Pro's design has several limitations. For one, it only measures this single metric, whether the sweet spot was hit, limiting the feedback available to players. Furthermore, the panel's placement obstructs the paddle face, detracting from a natural playing experience. The PIKL addresses these limitations by offering a wide range of performance analytics, including impact location, impact force, swing speed, and

stroke classification. Additionally, by embedding the piezoelectric sensors in the edges of the paddle and building off a USA Pickleball Association (USAPA)-approved paddle, the PIKL preserves the authentic feel of a traditional pickleball paddle. Evaluating existing products like the Kill-Shot Pro helped identify valuable features, such as sweet spot tracking, while also highlighting areas for improvement in pickleball technology, ultimately shaping the design and functionality of the PIKL.

One of the most challenging aspects of the embedded software was implementing an ADC capable of sampling fast enough to capture ball-paddle impacts across multiple channels for the piezoelectric sensors. The microcontroller used in this project is the Particle Argon, powered by an nRF52840 System-on-Chip (SoC) from Nordic Semiconductor. This SoC provides BLE capabilities and serves as the platform for the embedded software. The PIKL's early ADC implementations relied on Zephyr's ADC libraries and software timers. However, these approaches proved insufficient for the required sampling speed and multi-channel operation. Thus, to improve performance, it became necessary to leverage the SoC's hardware more effectively. A particularly useful reference from Nordic's online Developer Academy (Nordic Semiconductor, 2024) provided guidance on using Nordic's nrfx drivers and proprietary hardware features of the SoC such as Programmable Peripheral Interconnect (PPI) to implement high-speed sampling. This reference significantly informed the ADC implementation, shaping how the system efficiently collects and processes samples from the piezoelectric sensors.

3. PROJECT DESIGN

A block diagram of the entire embedded software design is shown below in Figure 1.

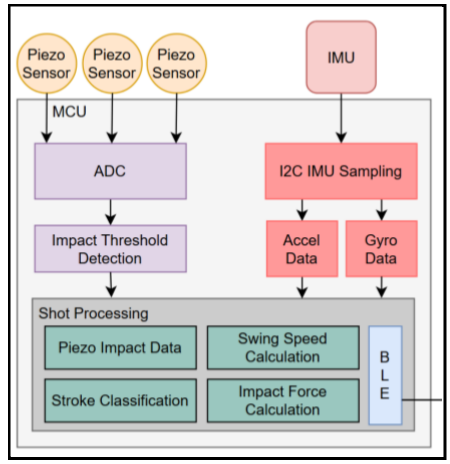

Figure 1. Embedded Software Diagram

3.1 ADC

The first embedded sub-component to analyze is the ADC. The outputs from the three piezoelectric amplifier circuits are analog voltages and must be converted with an ADC to be represented in the digital microcontroller unit (MCU). Thus, each piezo sensor circuit is connected to an ADC input channel on the MCU. From sensor testing, the fastest pickleball impact duration was approximately 334 µs or ~2.98 kHz as read by the piezo sensor/circuit. Based on Nyquist's sampling theorem, the ADC must sample at a rate exceeding 5.96 kHz (167 µs intervals) to ensure no impacts are missed and that a good representation of the impact's signal is captured. Furthermore, since three piezo sensors are used to estimate impact location, the ADC implementation must support rapid sampling across multiple channels. To meet these requirements, the software employs a double-buffered direct memory access (DMA) approach with programmable peripheral interconnect (PPI) and a hardware timer. PPI enables peripherals to interact directly without CPU intervention, optimizing efficiency. A hardware timer triggers periodic ADC sampling via PPI, storing data in a buffer. Once filled with 150 samples, DMA switches to a second buffer, ensuring uninterrupted data collection while the CPU processes the first buffer. During processing, each sample is checked against a 1.5V impact threshold. If exceeded, shot processing begins. This setup supports up to six channels at over 8 kHz, enabling high-speed, multi-channel data acquisition.

3.2 IMU

The next embedded sub-component is the 6-axis inertial measurement unit (IMU) sensor, which is used to sense motion and derive critical statistics such as swing speed, impact force classification, and stroke classification. The IMU, specifically the ISM330DHCX chip, includes a 3-axis accelerometer and a 3-axis gyroscope. The output data rate of 104 Hz for the IMU was chosen based on testing that showed an average swing lasts less than a second. With 104 samples per second, per axis, this provides sufficient resolution to capture the motion dynamics of a swing. To accurately interpret the IMU's measurements, it is essential to define its reference frame in the context of the paddle. The IMU is mounted inside the handle of the paddle, with its axes aligned as shown in Figure 2 below.

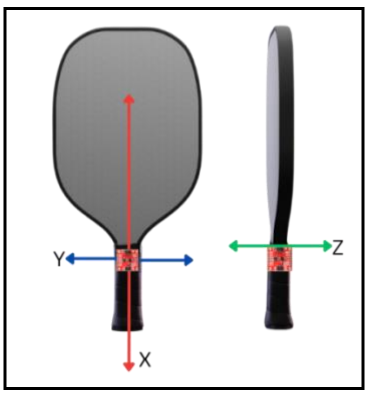

Figure 2. IMU Reference Frame Axes

The IMU communicates with the MCU via I2C. To synchronize data acquisition, a hardware timer generates periodic interrupts at 104 Hz, matching the sensors' output data rate. The timer interrupt handler submits a work item to the system work queue to read IMU samples. This design offloads the more time-intensive I2C data-fetching process to the main thread, preventing it from blocking BLE transmissions or other critical CPU tasks. The work handler uses the Zephyr sensor API to fetch accelerometer and gyroscope data, storing the results in circular buffers. These circular buffers store the most recent 85 samples, automatically overwriting older data when full. This ensures that, when a shot is detected, the accelerometer and gyroscope buffers contain the most recent swing data, ready for analysis.

3.3 Processing

Once the ADC code indicates that an impact has occurred, a work item is submitted to the system work queue to initiate shot processing. To calculate the first metric, swing speed, three different methods are used, each with its own trade-offs and considerations. Method one utilizes numerical integration of the z-axis acceleration, as this will yield the z-axis velocity vector pointing directly out of the paddle face. The second method relies on the large, inward centripetal acceleration along the x-axis induced during a swing. From the equation for centripetal acceleration, the tangential velocity, which equates to the velocity pointing out of the paddle face, can be derived. The final method utilizes the peak y-axis angular velocity from the gyroscope during a swing. This angular velocity is multiplied with an approximated swing radius to yield the linear velocity of the paddle.

The next metric, paddle impact location, is computed by averaging the ten ADC voltage values on each piezo sensor after impact. With these averages, a triangulation is computed to find the weighted midpoint coordinates of where the ball hit the paddle face. Next, the impact force metric is trivially calculated by multiplying the z-axis acceleration at impact with the measured mass of the paddle (0.4 kg) as force is equal to mass times acceleration. Lastly, to classify strokes as forehand or backhand, the computed swing velocity is used alongside the y-axis acceleration at the point of impact. Since the y-axis is perpendicular to the handle, flipping the paddle from a forehand to backhand position causes the sign of the y-axis acceleration (a_y) to flip. However, because the paddle has two sides, an additional variable is needed to account for the player rotating the paddle and striking with a different face. Therefore, the sign of the estimated swing velocity (from either method 1 or 3) is used to determine which side of the paddle was used for the hit. The classification logic is shown in Table 2 below.

Table 1. Stroke Classification Logic

Swing Velocity	y-axis Acceleration	Classified Stroke
$v_{swing} > 0$	$a_y > 0$	Backhand
$v_{swing} > 0$	$a_y < 0$	Forehand
$v_{swing} < 0$	$a_y > 0$	Backhand
$v_{swing} < 0$	$a_y < 0$	Forehand

Once shot processing is complete, the four computed metrics are transmitted to the connected user device via BLE notifications. Each metric is assigned a unique characteristic identifier within a custom BLE Generic Attribute service.

4. RESULTS

The embedded software functions as required. All shots are consistently detected by the ADC implementation and BLE transmissions are reliable and rapid, giving a real-time feedback experience. Furthermore, the accuracy of the four pickleball metrics provided by the system is measured. Without a radar gun, the swing speed could only be evaluated for relative, and not absolute or grounded accuracy. However, testing showed accurate relative swing speed reports. Next, the impact location accuracy was shown to be 70% accurate across all regions of the paddle face. The stroke classification feature was then tested and achieved an overall accuracy of 76.7%, with 86.7% forehand accuracy and 66.7% backhand accuracy. Lastly, the classification of soft, hard, and medium hits from the impact force metric showed 83.3% accuracy. These results show the embedded software system is able to estimate the four key pickleball metrics to a high degree of accuracy.

5. CONCLUSION

The PIKL successfully delivers a suite of performance metrics, including impact location detection, stroke classification, swing speed estimation, and impact force measurement. These metrics are calculated with a high degree of accuracy and are stored for post-match analysis, providing players with meaningful insights into their performance. As pickleball's popularity continues to rise, the PIKL smart paddle offers substantial value to dedicated players and professionals seeking to better understand and improve their game.

6. FUTURE WORK

As a prototype, the PIKL is a success. However, there are still numerous areas for future improvement. For one, more reliable swing speed estimation using ground truth data. Currently, the PIKL estimates swing speed using a median filter on three different swing speed calculations. This method is effective in providing reliable and reasonable estimations of swing speed, but it is not reinforced with ground truth swing speed data. To improve the swing speed estimator, the actual speed of the swing could be measured using a radar gun and compared to the IMU measurements. This comparison can help to calibrate the IMU and the data processing code. Additionally, this ground truth data could be used to tune speed estimation and could even be incorporated into a supervised learning algorithm such as linear regression for more accurate measurements.

7. ACKNOWLEDGEMENTS

Special thanks to my capstone group members, Jiseoung Kim, Kemper Siever, and Wilmot Westreicher who worked hard to help build the PIKL. Additional thanks to Professor Adam Barnes for advising on the project.

REFERENCES

DeMelo, J. (2022, September 3). Why is pickleball so popular? *The New York Times.* https://www.nytimes.com/2022/09/03/well/move/pickleball-popular-sport.html

Frevel, N., Beiderbeck, D., & Schmidt, S. (2022). The impact of technology on sports: A prospective study. *Technological Forecasting and Social Change*, *182*, 121838. https://doi.org/10.1016/j.techfore.2022.121838

Kill-Shot Pro. (2024). Pickleball training tool—Kill-shot pro smart pickleball paddle. Kill-Shot Pro. https://killshotpro.com/

Nordic Semiconductor. (2024). .*Exercise 3: Interfacing with ADC using nrfx drivers and TIMER/PPI*. Nordic Developer Academy. https://academy.nordicsemi.com/courses/nrf-connect-sdk-intermediate/lessons/lesson-6-analog-to-digital-converter-adc/topic/exercise-3-interfacing-with-adc-using-nrfx-drivers-and-timer-ppi/

USA Pickleball. (2025). Pickleball Annual Growth Report—USA Pickleball. https://usapickleball.org/about-us/organizational-docs/pickleball-annual-growth-report

VanOs, D. (2024, February 2). What is the sweet spot on a pickleball paddle? Selkirk Sport. https://www.selkirk.com/blogs/paddles-and-product-education/what-is-the-sweet-spot-on-a-pickleball-paddle