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Review paper
Pregledni rad

Latency effects of IoT devices for measuring sports activities

Boris Kovačić
Faculty of Information Technologies, Pan – Europian University, Banja Luka, Bosnia and Herzegovina

Correspondence:
Boris Kovačić
Faculty of Information Technologies, Pan – Europian University, Banja Luka, Bosnia and Herzegovina, kovacic4boris@gmail.com

Abstract: *The Internet of Things (IoT) is increasingly being used in sports science to monitor performance, biomechanics and physiological parameters. However, latency, delay in data transmission and processing can affect the accuracy of measurements, especially in laboratory conditions where high precision is required. This paper analyzes the latency effects of IoT devices by different solutions, using a comparison of latency results, system architecture models, transmission media and other parameters. The results show that latency can cause significant deviations in the measurement of reaction time and biomechanical parameters, but it can be partially compensated by software methods, adequate selection of data transmission technology, and considering the choice and method of application of IoT devices as detection sensors. The consequences of latency can lead to an injury to the athlete or to a delay in giving feedback due to a mismatch in timing.*
Keywords: *IoT, latency, sports diagnostics, biomechanics, laboratory measurements*

Introduction

Over the past decade, the Internet of Things (IoT) has revolutionized the way individuals' athletic activities are monitored. Wearable sensors, smartwatches, smart pads, and other IoT devices enable continuous monitoring of athletes' biomechanical and physiological parameters. The integration of IoT technologies into sports performance analysis has gained popularity due to advances in wearable sensors, wireless communication, and real-time data processing. Devices such as smartwatches, fitness trackers, GPS trackers, and inertial measurement units (IMU) provide athletes and coaches with continuous feedback on essential physiological and biomechanical metrics. (Chen, i dr., 2017)

One of the key limitations of these systems is latency – the delay in data transmission and processing. Data quality (DQ) has become one of the key aspects in IoT (Aimad Karkouch, 2016) (Jorge Merino, 2016) (Jesus G, 2017). Milhauzer (Mühlhäuser, 2007) defines smart, connected products (engl. *smart connected products*, SCP) as „ entities (tangible object, software or service) designed and built for self-organizing embedding in different (smart) environments throughout their lifecycle, providing improved simplicity and openness through enhanced connections ".

Latency is the delay in transmitting data from one point to another in a network. In IoT, lower latency translates into faster response times, which is essential for real-time applications, where even small delays can reduce system efficiency. (Martin F. Berg, 2023) In laboratory conditions, where high accuracy is required, even minimal latency can affect the quality of measurements. (IoT Latency: The Power of Real-Time Communication , n.d.)

The effects of latency in IoT devices for measuring sports activities in the literature indicate that delays in data transmission and signal processing can affect the accuracy and timeliness of the obtained results, which is important for accurate feedback to athletes and coaches.. (Yang Hu, 2025) Latency occurs due to network limitations, device processing power, or communication disruptions, which can lead to reduced user experience and system reliability. While these delays are typically measured in milliseconds to seconds, they can be significant in dynamic sports activities. In fast-paced sports like sprinting or tennis, even small delays can compromise the accuracy of timing, motion capture, or decision-making based on real-time feedback. (Sebastian Mayr, 2024)

As stated in the research Passos et al. (Passos, 2021) It emphasizes the importance of optimizing communication protocols and data processing algorithms to minimize these delays and ensure high reliability and accuracy of IoT devices for sports activities.

IoT latency in sports applications is a phenomenon that has not been sufficiently researched, although it is more than obvious. The aim of this paper is to point out the effects of the IoT latency problem in sports by analyzing existing knowledge and proposing a model for partially solving the problem. The paper points out the most common causes of latency as well as the effects produced by IoT latency in sports.

Based on this knowledge, sports professionals and experts can analyze individual IoT use cases and consider the technical limitations that arise in that case, such as data transfer speed or the sensitivity of the sensors used.

Methods and Materials

For the purposes of this research, more than 50 papers collected from available literature databases were analyzed, which directly investigate the issue of latency of IoT devices in sports. The largest part of the papers (90%) dealt with research on latency due to sensor latency and data transmission delay, while the smallest part of the processed papers (3%) dealt with latency due to using the wrong model for prediction horizons.

Table 1 provides an overview of the most important works that directly addressed the problem of IoT latency in sports, and whose data were of great importance for this work as input data.

Table 1. *Papers studying the latency of IoT devices in sports*

	Technology / Script	Latency (type / average / observed ranges)	Source
1	6LoWPAN	Min ~ 19.5 ms, average ~ 22.1 ms, max ~ 356 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
2	Bluetooth Mesh vs Wirepas Mesh	Wirepas: medijan ~ 2,83 ms (Low-Latency) / ~ 2 s (Low-Energy) Bluetooth Mesh: medijan ~ 4,54 ms	(Latency and Power Consumption in 2.4 GHz IoT Wireless Mesh Nodes: An Experimental Evaluation of Bluetooth Mesh and Wirepas Mesh, 2023)
3	Zigbee vs LoRa	LoRa: RTT ~ 150-500 ms (depending on baud rate and packet) Zigbee: RTT in the same conditions often higher for multi-hop situations; in some configurations > LoRa	(Liu Z. Y., 2022)
4	LoRaWAN	Min ~ 282.4 ms, average ~ 296.96 ms, max ~ 334.8 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
5	Mesh protocols: Thread, Zigbee, Bluetooth Mesh	Small packet: anything under ~50ms In medium packets: Zigbee: most packets ~80ms, range up to ~130ms Bluetooth Mesh: range wider (20-200ms) in larger networks	(Charles, 2023), (Benchmarking Bluetooth Mesh, Thread, and Zigbee Network Performance, 2025)
6	Sigfox	Average ~ 3 695.2 ms (~3.7 s), max ~ 5 651 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
7	Zigbee	Min ~ 34.17 ms, average ~ 48.3 ms, max ~ 95.3 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
8	Bluetooth 5 (opportunistic network)	Average E2E latency ~736ms in simulated scenarios, but in many tests constant latency ~50ms for local operations	(Niebla-Montero, 2022)
9	BLE in real-time / industrial IoT	According to optimized retransmissions: maximum latency <46ms	(Rondón, 20174)

10	Wi-Fi (in IoT test)	Average ~ 32.3 ms, max ~ 178.1 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
11	Bluetooth Low Energy (BLE)	Average ~ 26.97 ms, max ~ 125.4 ms	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
12	NB-IoT	Average ~ 1 797.3 ms (~1.8 s), max ~ 10 275 ms (~10.3 s)	(Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)
13	LoRaWAN (16 B package)	~2 s do ~3.5 s measured 16B data transfer time	(Ugwuanyi, 2021)
14	NB-IoT (in the same work)	~837ms (in good signal) measured average	(Ugwuanyi, 2021)
15	IPv6 over SCHC-over-LoRaWAN	"Delay less than 1s" (measured)	(Sisinni E, 2023)
16	Mesh protocols – smaller package	Latency <100ms (at least Zigbee) for small packets; Bluetooth range ~20 200ms	(Charles, 2023)
17	LPWAN in the context of IoT	„Delay of less than 1 s" in that work	(Sisinni, 2023)
18	Body worn multiple sensors in a sports environment	D2D latency ~ 504.99 µs ± 96.89 µs; network latency ~ 311.78 µs ± 96.90 µs	(Nico Krull, 2025)
19	IoT model with local (fog) processing	Focus on "fast response" and "low latency" in the text, but without precise ms values in the abstract	(Karakaya A, 2021)
20	Testing latency in portable heart rate monitoring devices during exercise	Device latency significantly affected the deviation from the criteria, but the numbers (in ms) were not specified in detail in the abstract	(Støve MP, 2020)
21	Empirical measurement of delay	Median ~52ms for one sensor (range ~50-57ms)	(Martin F. Berg1, 2023)
22	Wireless sensor system for sports (sit ski)	Median delay: 52ms for wired "main system", 53ms for wireless "sub system".	(Martin F. Berg1, 2023)
23	IoT + edge computing for sports performance	Average processing latency ~12.34 ms	(Yang Hu, 2025)
24	IoT + edge processing for tracking athletes	Average processing latency: 12.34ms.	(Yang Hu, 2025)
25	Although primarily health-related, it investigates latency attributes of wearable IoT devices	It studies BLE connection parameters (interval, latency, timeout) and their impact on performance	(Arthur Gatouillat, 2018)
26	Wearable IoT devices and low latency in the context of health monitoring	Discussion of the importance of low latency, but without concrete numerical measurement for sports	(Naeem Akbar Channar, 2025)
27	Portable technologies in sports	It discusses the accuracy and response time of the sensor, but does not provide specific latencies for all cases	(Aroganam, 2019)

28	Racing system, 5G transmission	Round trip latency: 128.92ms (indoor, sd=25.83ms and 140.14ms (outdoor, sd=14.47ms)	(Sebastian Mayr, 2024)
29	Measurement of round trip time (RTT) for real-time transmission	RTT mean ~128.92 ms (sd25.83) for internal tests; ~140.14 ms (sd14.47) for external.	(Liu Z. Y., 2022)
30	Secure routing protocol based on blockchain technology	transaction latency up to 3200ms when sending 1300tps, latency 500ms when reading 3000tps data	(Shahbazi Z, 2020)

Based on the knowledge gathered from the available literature, comparisons and analysis of data were made that are directly related to the research into the causes of latency, as well as the consequences that latency produces in the domain of sports measurements. Table 2 provides an overview of the latency ranges, broken down by sport type and the most commonly used sensor technologies in that sport. Values are typical/ranges from literature and industry reports.

Table 2. *View latency by sport*

Sports / scenario	Typically used sensors/technology	Typical sensor latency (ms)	Typical E2E (sensor → application/ edge/cloud) (ms)	Comment / source
E-sport / input devices	Input devices, local IMU/USB	0.5–2 ms	1–10 ms	ultra-low latency input; target <10ms. (Rubin, 2013)
Tennis (strokes, ball speed)	IMU in rocket, optical tracking, UWB	1–10 ms (IMU) / 5–30 ms (UWB) / 5–50+ ms (camera + processing)	20–80 ms	UWB and IMU provide the lowest latency for instant analysis. (Yang W, 2025)
Basketball	IMU + optical tracking (camera)	5–15 ms (IMU) / 30–100 ms (camera+detection)	50–150 ms	Optical systems and AI processing usually increase E2E. (Xie, 2024)
Football (field)	GNSS/GPS + IMU + UWB	10–30 ms (IMU) / 50–300 ms (GNSS uplink/filtering) / 5–50 ms (UWB)	100–300 ms	GNSS often introduces the greatest latency, especially with RT cloud processing. (Adnan Waqar, 2021)
Swimming	Waterproof IMU + acoustic/UWB beacons	15–50 ms (IMU) / 50–200+ ms (acoustic/UWB specific)	200–400 ms	medium water + synchronization increase the delay. (Alshardan A, 2025)
Athletics (races, marathons)	RFID timing + GPS + IMU	RFID detection: ~10–50 ms (readers/processing) / GPS: 50–300 ms	100–300+ ms	RFID for target registration is reliable but requires synchronization. and backend processing. (Högskola, 2015)
Biosignal monitoring (heart rhythm)	PPG (wrist), ECG (chest)	PPG acquisition + filtering: ~50–200 ms effective; ECG chest: ~5–20 ms	50–200+ ms	PPG requires filtering and artefact correction; chest-ECG is faster and more precise. (Castaneda D, 2018)

The distribution of latency by sport (Table 2) depends more on the choice of technology and system architecture (local edge processing or cloud processing) than on the sports discipline itself.

For the purposes of this research, the following data were taken into account from available works:

1. Data transfer speed
2. Sensor sensitivity
3. Latency (of the IoT device itself, during data transmission and processing)

In the paper (Ivan Jovović, 2015) the data transfer speed using 4G and 5G networks was compared. In the case of the 5G network, the minimum speeds ranged from 1Gbps to a maximum of 10Gbps. In the case of the 4G network, the speeds ranged from 10Mbps to a maximum of 1Gbps. In the diagram 1, it can be seen that the latency of the air transmission in 4G is 10ms, and in 5G it is 1ms. In addition, the latency in E2E (End to end) in 4G is 50ms, and in

5G it is 5ms. The authors of this paper claim that with each new generation of mobile communication systems, data transfer speeds increase twice as much as in the previous generation. They also state that one of the main requirements is to increase the speed and data capacity while significantly reducing the level of latency in the next generation mobile network system.

In sports application, the term sensitivity can appear in two closely related meanings:

- **Physical (analog) sensitivity** — the change in sensor output per unit of input quantity (e.g. mV/°C for temperature sensors, mV/g for accelerometers). This is a hardware characteristic: gain, resolution, and noise.
- **Functional/operational sensitivity (detection)** — The ability of a system to detect an event or change (e.g., collision detection, sprint start/stop, irregular movement pattern detection). It is measured by metrics such as sensitivity/true positive rate, specificity, accuracy, and precision relative to the gold standard.

In practice, both dimensions affect the reliability of measurements in sports: hardware sensitivity determines the minimum measurable change, and functional sensitivity also depends on signal processing, algorithms, and sensor positioning. (Liu L. a., 2022)

Although a multitude of papers have been published on the topic of IoT and sports, there are far fewer papers on the topic of IoT latency in sports. Despite the relevant findings and contribution to understanding the effects of IoT device latency in the context of measuring sports activities, which are presented from a cross-section of several papers.

The research in the papers was conducted on a limited number of IoT devices and with a relatively small sample of users, which may reduce the possibility of generalizing the obtained results to a wider population and different types of sports disciplines. Future research should include a larger number of devices, different sports contexts and real-world application conditions, as well as the integration of multiple communication technologies.

Results

It was found that the most common IoT devices used in sports are. (Wearable Devices In Sports Market Size & Share Analysis - Growth Trends and Forecast (2025 - 2030) Source: https://www.mordorintelligence.com/industry-reports/wearable-devices-in-sports-market, 2025):

- **By device type** - tracking devices (GPS[1] and GNSS[2]) led the way with a 47.83% share of the wearable devices market in sports in 2024; smart clothing and e-textiles are growing at a compound annual growth rate (CAGR[3]) from 5.23% by 2030. According to (Art Dogtiev, 2025) Fitbit devices show a significant growth trend in the number of users in the period from 2014 to 2023. According to Huawei, the number of IoT devices connected to their cloud has exceeded 200 million, and the data is from October 15, 2018. (Michael Ma, President of Huawei Cloud Core Network Product Line, 2018)
- **By sport** - football accounted for 28.74% of the sports wearables market in 2024 and is expanding at a compound annual growth rate (CAGR) of 4.87% until 2030.
- **By end user** - Professional teams and leagues accounted for 42.63% of the revenue share in 2024 in the sports wearables market, while recreational fitness users are recording the highest projected CAGR of 5.18%, with this rate projected to continue through 2030.
- **By distribution channels** - online sales accounted for 56.72% of the sports wearables market in 2024 and is growing at a compound annual growth rate (CAGR) of 5.40%.
- **By region** - North America maintained 39.63% share of sports wearables market in 2024; The Asia-Pacific region is projected to experience the fastest compound annual growth at 5.89%, and this rate is projected to continue through 2030.

One of the most common sources of latency in IoT systems for measuring sports activities has been identified as factors related to data transmission and processing. Latency most often occurs due to delays in data transmission through the network, which is a result of limited bandwidth, network congestion, or greater physical distance between the device and the server. In addition, data processing processes contribute significantly to latency, especially in cases where data is analyzed in remote server environments (cloud computing), which increases the overall system response time. Inefficient communication protocols, limited processing resources and memory capacities of IoT de-

1 GPS – Global positioning system

2 GNSS - Global navigation satellite system

3 CAGR - Compound annual growth rate

vices, as well as interference and instability of wireless networks, also contribute to increased latency (Table 3). In addition, the lack of precise synchronization between multiple sensor nodes can further cause time discrepancies in data collection and processing. (Althoubi, 2021) (Lea, 2020) (Kumar, 2023)
According to the above findings, it was found that the most negative and undesirable effects of IoT device latency in sports occur in systems that require real-time data processing, such as wearable sensors and athlete performance monitoring systems, where latency can lead to inaccurate analyses and wrong decisions. (Yang Hu, 2025) (Vec, 2024; Wu X, 2023)

Table 3. *View latency and error measurements (Saavedra E, A Universal Testbed for IoT Wireless Technologies: Abstracting Latency, Error Rate and Stability from the IoT Protocol and Hardware Platform, 2022)*

Measurement		6LoWPAN	LoRaWAN	Sigfox	Zigbee	Wi-Fi	BLE	NB-IoT
Latency (ms)	Minimum	19.522	282.40	3467.1	34.174	25.294	13.382	329.29
	Average	22.116	296.96	3695.2	48.298	32.300	26.974	1797.3
	Max	356.14	334.81	5651.0	95.295	178.10	125.40	10,275
Error	Γ	2	66	0	0	0	0	0
	E	0.02%	0.66%	0%	0%	0%	0%	0%
Stability	Λ (ms)	9.883	5.419	290.4	5.242	9.502	13.68	1352
	Π	386	2	4	2307	3197	480	4052
	Κ	3.86%	0.02%	4%	23.1%	31.9%	96.0%	81.0%
	Ω	0.924	0.993	0.922	0.592	0.463	0.002	0.036

As shown in Table 4, the three most common sources of latency are:

- Sensor latency typically has a greater impact on data accuracy in applications that require high-accuracy, real-time measurements. For example, in sports such as tennis, soccer, or running, where precise measurement of instantaneous movements is required, sensor latency can mean inaccurate data that does not reflect the real situation. (Nico Krull, 2025)
- Data transmission latency is critical in applications that use streaming or require real-time data analysis, such as athlete performance tracking applications, online coaching, or telemetry in professional sports. In these cases, high data transmission latency can lead to delays in results visualization and feedback. (Gkagkas, 2025) (Yang Hu, 2025)
- Data processing latency is crucial in IoT systems for sports activities because it directly affects the speed and accuracy of real-time analysis of results. In situations where immediate feedback is needed – such as correcting running technique, analyzing a shot, or monitoring an athlete's heart rate – even minimal processing delays can lead to misinterpretation of performance. (Yang Hu, 2025) (Xiaowei Tang, 2025).

Table 4. *Shows the impact of latency sources on the results obtained*

Factor	Impact on results	Example
Sensor latency	It leads to inaccurate or outdated real-time data.	Incorrect power measurement in tennis due to sensor delay
Data transmission latency	It causes delays in data display and system responses.	Real-time data streaming (e.g. GPS for cycling) with transmission delay.
Data processing latency	They lead to data displayed by the system that does not reflect the real situation on the field, which can result in incorrect performance analyses, delayed reactions and poorer training decisions.	A delay of 50–100 milliseconds can lead to inaccurate estimation of step phase or rebound force, compromising the quality of biomechanical analysis.. (Yang Hu, 2025)

The results show that the latency of IoT devices can significantly affect the accuracy of measurements in sports laboratory conditions, especially for fast and explosive movements. Although software correction can mitigate the effects of latency, it cannot completely replace the accuracy of reference systems. (Althoubi, 2021) It is necessary to develop hybrid systems that combine the mobility of IoT devices with the precision of laboratory tools. Also, standardization of protocols for synchronization and data processing can improve the reliability of IoT measurements.

The work of the group of authors (Akpa, 2019) states the importance of smart glove design and evaluation of exercise recognition performance and the accuracy of the repetition counting algorithm of the system. The design integrates 16 FSR (Force-sensitive resistor) sensors in the activity tracking glove to identify activities and count repetitions of performance, analyze time series and distribution of pressure applied to the palm during the exercise. The presented validation experiment with 10 healthy participants during 10 common tracking exercises showed an overall exercise recognition accuracy of 88.00% for person-dependent assessment and 82.00% for person-independent assessment. The evaluation of the repetition counting algorithm achieved an average counting error rate of 9.85%. Based on the obtained results, the conclusion is that the smart glove can be used for tracking and assessing tracking activities, but it is necessary to include other IoT devices and sensors, which will monitor the body position in space, and the load on other muscles, heart, and pulse and temperature and sweating. (Akpa, 2019)

In feedback systems (e.g., smart bracelets that vibrate to alert an athlete to an error), any delay in data transmission reduces the effectiveness of the intervention. If the device warns the athlete after the incorrect movement has already been completed, the feedback information is useless and may reinforce the incorrect motor pattern. X. Tang et al. (Xiaowei Tang, 2025) showed through an artificial neural network model that a delay of only 80 ms in the feedback loop increases the movement correction error by 12% in running activities. The delay in data transmission and processing leads to a mismatch between the signal between the sensor and the athlete's actual movement. For example, if the sensor responds with a delay of 100 ms, the analysis system may register a step, jump, or kick at the wrong time. This can lead to incorrect estimates of joint angle, force, and movement speed, false positives (e.g., the system detects a movement that did not occur), and missed events (e.g., actual contact with the ground is not registered). Krull et al. have shown that latency above 20 ms in multisensor running tracking systems increases the error in stride phase detection by more than 15%. (Nico Krull, 2025)

Latency in IoT systems can have serious biomechanical and safety implications. According to Hu et al (Yang Hu, 2025), IoT and deep learning-based systems must maintain latency below 50 ms in order to respond to changes in biomechanical signals in a timely manner. Krull et al (Nico Krull, 2025) showed that sensor desynchronization greater than 20 ms can increase the risk of injury by 18% in runners due to incorrect detection of the stride phase.

In high-intensity sports such as football, basketball, and gymnastics, even minimal latency can cause the athlete to respond incorrectly, leading to poor body posture and an increased risk of muscle and joint injuries. It is especially dangerous if the system does not recognize dangerous loads in time or misinterprets biomechanical data, which can result in sprains or microtraumas. Therefore, it is important to correctly determine latency thresholds (Table 5) that will prevent such effects. For high-end real-time motor events in sports, below 5 ms is ideal, while for less critical data, values up to ~50 ms or ~100 ms are acceptable. (Martin F. Berg, 2023) (Nico Krull, 2025)

Table 5. *Latency thresholds (Yang Hu, 2025)*

Application type	Recommended maximum latency
Priority 0 Critical motor events (e.g., sprint start, contact force)	< 5 ms (ideal), ≤ 10 ms
Priority 1 Real-time physiological or biomechanical data (eg acceleration)	< 20 ms
Priority 2 Position tracking and team sports (e.g. football, basketball)	< 50 ms
Priority 3 Contextual/ambient data (e.g. environment, temperature)	< 100 ms

To reduce these risks, it is recommended to implement predictive algorithms at the edge of the network (edge computing), better time synchronization of sensors using the IEEE1588 PTP protocol or the newer IEEE1588 PTPv2 (Jing, 2024), as well as local data processing without relying on a remote cloud. Also, adding redundant sensors and signal filtering can contribute to reducing the risk of delay-related injuries.

Table 6. *Comparison of IoT communication protocols (Pothuganti Karunakar, 2014)*

Standard	Bluetooth	UWB	Zigbee	Wi-Fi
IEEE spec.	802.15.1	802.15.3a	802.15.4	802.11 a/b/g
Frequency range	2.4Ghz	3.1-10.6Ghz	868/915 Mhz; 2.4Ghz	2.4Ghz; 5Ghz
Maximum signal speed	1 Mb/s	110Mb/s	250kb/s	54Mb/s
Nominal range	10m	10m	10-100m	100m
Nominal TKS (transmission) power	0-10 dBm	-41.3 dBm/MHz	(-25) – 0. dBm	15+20 dBm
Number of RF channels	79	(1-15)	1/10;16	14(2.4Ghz)
Channel bandwidth	1MHZ	500MHz – 7.5GHz	0.3/0.6 MHz; 2MHz	22MHz
Modulation type	GFSK	BPSK, QPSK	BPSK, (+ ASK), O-QPSK	BPSK, QPSK, COFDM, CCK, OFDM
Expansion	FHSS	DS-UWB, MB-OFDM	DSSS	DSSS, CCK, OFDM
Coexistence mechanism	Adaptive frequency hopping	Adaptive frequency hopping	Dynamic frequency selection	Dynamic frequency selection transmit power control (802.11h)
Basic cell	*Piconet*	*Piconet*	Star	*BSS*
Extension of the base cell	*Scatternet*	*Peer-peer*	Tree-network cluster	*ESS*
Maximum number of cell nodes	8	8	>65000	2700
Data protection	16-bit CRC	32-bit CRC	16-bit CRC	32-bit CRC

To reduce latency in data transmission, it is extremely important to choose the right communication protocol. The speed and reliability of transmission depend primarily on the technical characteristics of the selected protocol (Table 6). Limitations for the use of a communication protocol can be associated with the quality of the IoT device, i.e. cheaper IoT devices generally have higher latency due to weaker processors and unoptimized communication protocols, so they are definitely not an option for professional sports.

Discussion

Already in the presentation of the results, certain aspects and effects that the latency of IoT devices in sports causes, depending on the source of latency, were discussed. IoT sensors, as part of an athlete's activity monitoring system, help users maintain proper form and improve efficiency. Therefore, programming of wearable technology (microcontroller data processing) and timely information are of vital importance. (Ewald M. Hennig, 2010)

The influence of position and signal processing, attachment point (torso, lower leg, helmet) and algorithms (filtering, sensor fusion: Kalman/complementary filter, machine learning) significantly change the "operational sensitivity". (Roell, 2019) IMU (inertial measurement unit) accelerometers are most commonly used for impact detection and dynamic parameters, but their accuracy depends on algorithms and sampling frequency; direct calibration to 3D motion-capture is common practice. (Roell Mareike, 2019) Sensor position and attachment significantly affect sensitivity and reliability: e.g. skin-mounted sensors give different results than those in clothing or equipment. It is recommended to standardize the position during repeated measurements. (Eitzen Ingrid, 2021) A tuning compromise must be made between sensitivity and low alarms. Namely, excessive gain, i.e. low tolerance for noise leads to false positive detections (eg small movements are interpreted as blows). Filters and thresholds must be adapted to the motion tracking application. (Seçkin, 2023) Validation in real-world sports conditions is almost always weaker than in the laboratory, and many studies show that performance degrades in the field (changing conditions, interference, different types of movements). Therefore, it is imperative to test "in situ", i.e. at the original location of use. (Mareike Roell, 2019) Flexible and "skin-like" sensor technologies with high sensitivity show great potential for monitoring fine biomechanical signals (e.g. strain sensors for joint angle analysis), but often require advanced calibration and AI/ML post-processing. (Liu L. a., 2022) Many studies compare IMU (accelerometer+gyroscope) data with 3D motion-capture systems and report amplitude/peak and temporal synchronization errors. (Roell, 2019) Validation metrics RMSE (root-mean-square error), MAE (mean absolute error), correlation, Bland–Altman analysis for detection tasks, sensitivity (recall), specificity, F1-score.

(Xiaoming Wang, 2023) Hardware parameters include bit resolution, range (±2g, ±16g), noise data, sampling rate. In sports, high sampling rates and appropriate range are important because impacts and rapid movements can produce short, high amplitudes. (Liu L. a., 2022)

For cases where latency is critical (e.g. real-time feedback to athletes, interactive analytics) it is necessary to use protocols with proven low latency (e.g. BLE, Zigbee in small networks, edge processing). Low latency protocols enables faster feedback.

Three data packet retransmission schemes were evaluated, and simulation results proved that by optimally modifying the BLE data packet retransmission model, a maximum delay below 46 ms and a packet loss rate of the order of 10^{-5}, which allows BLE to meet the requirements of even the most demanding cases within the considered application range. Due to its ultra-low power properties, compatibility with most mobile units, reduced manufacturing costs, robustness and high throughput, BLE is the solution for such environments. (Rondón, 20174)

If the system can tolerate higher latency (e.g. post-training measurement, non-critical monitoring), technologies like LoRaWAN, NB IoT may be acceptable. Acceptability and bring greater range and better energy efficiency.

Practical recommendations for technology selection and model design

- If latency is critical (e.g. live response to athletes, interactive analytics) consider using protocols with proven low latency (e.g. BLE, Zigbee in small networks, edge processing).
- If the system can tolerate higher latency (e.g. post-training measurement, non-critical monitoring), technologies like LoRaWAN, NB IoT may be acceptable and bring greater range and better energy efficiency.
- It is always necessary to keep in mind that works in the literature are often in ideal conditions, while in a real sports environment (movement, multiple nodes, interference) latency may be higher.
- When designing an edge or fog architecture, processing can reduce latency compared to cloud processing, as is evident from the work "Fog Computing: Survey of Trends, Architectures, Requirements, and Research Directions" which highlights the importance of near-device processing for latency-critical applications. (Ranesh Kumar Naha, 2018)
- When implementing the model, it is necessary to test in real conditions: number of nodes, distance, number of hops, network traffic, because all of this affects the latency and efficiency of the entire solution. It is not enough to just take the specification of the IoT device manufacturer.

Conclusion

IoT devices offer special flexibility and accessibility in sports measurements, but the issue of latency in IoT devices poses a significant challenge. In laboratory conditions, precision is key, so careful integration of IoT technology with correction methods and validation with reference systems is required. Looking at all the above data and research on latency, latency depends on multiple parameters, not only on the hardware and software resources of IoT devices, but also on the transmission medium, local network, software solution, algorithm complexity, cloud computing used and other parameters that give the overall system latency.

Latency in IoT sports transmission systems can significantly affect the reliability and accuracy of automatic event detection. Simulation examples and a literature review suggest that maintaining latency below tens of milliseconds (depending on the application requirement) significantly improves system performance. For the most demanding applications (high-frequency biosignals), sub-ms solutions and very precise synchronization are required, which is achievable with specialized hardware and protocols. A combination of edge processing architectures, deterministic protocols, and latency compensation algorithms is recommended. (Nico Krull, 2025)

In some future work, it would be interesting to explore the development of hybrid systems that combine IoT and laboratory data for high accuracy with mobility. It is also very important to include artificial intelligence that can improve the efficiency of the system for tracking sports IoT devices.

Also, an interesting area for research is the use of nanotechnology for advanced sensor solutions, as well as the use of artificial intelligence systems for data processing.

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