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Chapter 10: Programmable Hardware Platforms for IoT-Driven Healthcare: Microprocessors, Microcontrollers, and FPGAs

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Abstract: The Internet of Medical Things (IoMT) has completely boosted the world of modern healthcare. Indeed, it has offer new opportunity for continuous monitoring and taken into account early clinical decision based on concrete evidence. These are in essence enabled by programmable hardware platforms: microprocessors, microcontrollers, and FPGAs, each with its own advantages in performance, energy efficiency, and deterministic behavior. The present chapter compares and contrasts these programmable hardware platforms, applied to various healthcare scenarios that range from medical imaging, wearable and implantable devices, and AI-assisted diagnostics to safety-critical control systems. Microprocessors provide high computational throughput needed by data-intensive imaging and machine learning applications. Microcontrollers make long-term, energy-efficient operation possible on small-sized, patient-centric devices. FPGAs allow the very low latency and simultaneous processing of many biomedical channels, such as ultrasound beamforming and brain–computer interfaces. Thus, this chapter presents the guiding principles on how to choose between these platforms, points out the merits of hybrid architectures, and emphasizes the proper matching between hardware resources and clinical or operational needs. All these together provide a roadmap for designing efficient, reliable, and scalable IoT-enabled healthcare systems.

Keywords: Internet of Medical Things (IoMT), IoT Healthcare, Microprocessors (MPUs), Microcontrollers (MCUs), Field-Programmable Gate Arrays (FPGAs), Healthcare.

1 Introduction

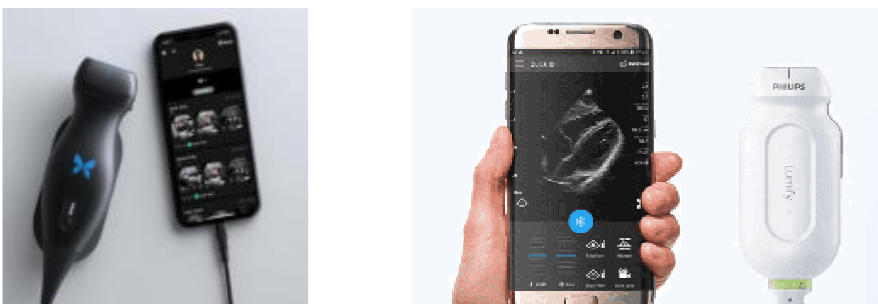
The evolution of medical care greatly depends on advances in hardware technologies. Supplied by analog circuitry, the first implanted pacemakers are smart and cloud-connected, wearables for medical innovation. They have continuously driven by the capabilities of underlying computational platforms. However, hardware is no longer performed in isolation but forms a connected variety of intelligent devices, and thus is specially seen in the IoMT applications. As an example, from the patient's wrist to the hospital server room, platforms continually acquire, process, and transmit health data in real-time (Bello et al., 2014; Huang et al., 2023).

This evolution has opened the way for an important change: from reactive, clinic-centered care to proactive. As well as personalized and distributed healthcare. Sensors, processors, and radio frequency (RF) communication modules enable the continuous monitoring of vital signs. Examples of vital signs are heart rate, glucose levels, and respiration rate. Instruments like CGMs (Olczuk et al., 2018), smart ECG patches (Lee et al., 2016), and portable ultrasound systems (Qiu et al., 2017) demonstrate how IoT-enabled hardware has expanded the spread and openness of modern medicine.

Three programmable hardware platforms: MPUs, MCUs, and FPGAs lying to bring a unique strength to healthcare applications. They are the core of this progress, while their integration defines key parameters including efficiency, reliability, and the performance of connected medical systems. This chapter discusses the architectural characteristics, application domains, and design trade-offs of these platforms in IoT-driven healthcare in view of edge intelligence, secure data flow, and heterogeneous system design.

2. IoT Healthcare with Microprocessor based systems.

Microprocessors work as high-performance engines of data-intensive applications. Multi-core architectures, rich peripheral interfaces, and compatibility with full operating systems like Linux, Android, and Windows IoT position microprocessors at the heart of various medical imaging, telemedicine, and AI-driven diagnostics (Khan et al., 2021). Advanced MPUs such as ARM Cortex-A series, Intel Xeon Scalable, and AMD EPYC deliver multi-gigaflop computing power, allowing real-time reconstruction of CT and MRI images and swift deep learning inference for tumor detection.



(a) (b)

Fig. 10.1 (a) Butterfly iQ+, and (b) Philips Lumify ultrasound imaging system.

In portable systems such as the Butterfly iQ ultrasound device (see Fig. 10.1), ARM-based SoCs integrate DSPs and GPUs to perform beamforming and visualization while simultaneously managing wireless connectivity and user interface functions (Rittenhouse et al., 2024; Rubegni et al., 2024). Fig. 10.1 illustrates a Philips Lumify. A portable ultrasound compatible with Android operating system. It uses an AI-based workflow integration in mobile clinical settings. As well, an MPU-based platform for high-throughput imaging (Perez-Sanchez et al., 2024).

Elsewhere imaging, MPU platforms enable consumer-grade diagnostics. Fig. 10.2 shows an AliveCor KardiaMobile, an FDA-cleared portable ECG device based on AI inference classifying arrhythmias and embedded processor to acquire and process ECG data in real time, (Girvin et al., 2023). For instance, in hospital settings to deliver sub-second 3D reconstructions, GE Healthcare's Revolution CT scanner uses multi-core Intel Xeon processors. This device reduces patient scanning time and radiation dosage while maintaining diagnostic precision (Kaga et al., 2023).

Fig. 10.2 AliveCor KardiaMobile.

Achieving up to 100× energy efficiency gains over general-purpose cores, these processors are habitually complemented with their counterpart NPUs or GPUs; This combination is beneficial to offload AI inference tasks, such as arrhythmia classification (Stark et al., 2025), or lung anomaly detection (Malia et al., 2024), Despite their power consumption, MPUs need a deterministic real-time control due to cache unpredictability. As well as branch prediction and operating system scheduling overhead. In safety-critical applications such as ventilators or infusion pumps, these non-deterministic behaviors can compromise reliability (Paul et al., 2025). To improve their vulnerability, engineering recommends RTOSes (Eliasz et al., 2024), hypervisors (Szefer et al., 2012), or partition time-critical tasks onto dedicated cores (Chang et al., 2007).

The MPU-based systems and their software setup are very complex. Usually, it involves a very long lines of code across operating systems, drivers, and middle-ware, leading to difficult and hard certification under standards. (e.g. IEC 62304) (Heidenreich, 2014). This makes MPUs less suitable for standalone life-critical implants but highly effective in gateway devices, diagnostic platforms, and hospital servers where computational intensity and connectivity outweigh timing constraints.

Mainly in wearable or handheld form factors, effective thermal and power management are also supreme. As example, we cite techniques such as heterogeneous computing, dynamic voltage (DV), and frequency scaling (FS) (Ali et al., 2024). Passive cooling ensures also continued performance without compromising device ergonomics or battery life (Mahajan et al., 2006).

3. Edge Healthcare IoT Microcontroller Solutions.

Microcontrollers represent the backbone of both wearable and implantable IoT devices. They are designed and optimized for ultra-low power consumption. Unlike general-purpose processors, due to deterministic timing and direct interfacing of sensors, MCUs claim efficient pipelines, multiple low-power operational modes, and integrated analog peripherals. This enhancement enables these optimized processors to run for months or even years on small batteries capacity.

A key architectural feature setting MCUs apart is their Harvard architecture, as explained by Bunting (1985), which decouples paths for instruction and data memory, granting predictable execution cycles-a requirement necessary in bio-signal sampling and actuator control. Integrated high-resolution ADCs, PGAs, and low-noise signal conditioning circuits reduce system complexity and improve signal integrity when measuring weak physiological signals such as ECG or EEG.

Fig. 10.3 Example of a commercial CGM system that uses Nordic's nRF52832 SoC.

For instance, the Nordic nRF52832 MCU merges an ARM Cortex-M4 core with BLE in CGM systems for continuous glucose sensing, local pre-processing, and secure wireless transmission to smartphones or insulin pumps in real time (Xiong et al., 2024;

Cai et al., 2025). Such devices can operate for up to a week using a coin-cell battery, thanks to sleep currents of merely 5 μA. A leading commercial example, Dexcom G7 CGM depends on microcontrollers for ultra-low-power bio-signal acquisition and real-time glucose data streaming directly to patient smartphones (Garg et al., 2022). Fig. 10.3 shows an example of a commercial CGM system. Similarly, MCUs are also integrated into the Omnipod Insulin Pump shown in Fig. 10.4 to provide precise dosage control with safety monitoring and wireless communication towards glucose sensors, thus supporting recent developments in the field of closed-loop "artificial pancreas" systems (Kudva et al., 2020).

Fig. 10.4 Commercial insulin pump therapy from Omnipod.

Traditional cardiac implantables leverage lockstep-redundant MCUs with hardware watchdogs to ensure millisecond-accurate pacing and fail-safe operational lifetimes well in excess of ten years. For example, the energy-efficient microcontroller employed in the Medtronic Micra leadless pacemaker enabled over a decade of operation within a very small form factor (El-Chami et al., 2019). In consumer health, Apple Watch and Fitbit Sense use MCUs for continuous SpO_2 monitoring, heart-rate variability analysis, and motion-based activity tracking to enable wearable-grade MCUs for multimodal health sensing with low battery drain (Hajj-Boutros et al., 2023).

Fig. 10.5 Leadless Pacemaker.

Wearable health monitors use MCUs with DSP instructions to enable on-device analysis of heart rate variability, motion activity, and SpO_2, thus preserving battery life and enhancing privacy by reducing the transmission of raw data. Examples include those shown in Fig. 10.6. These systems are further optimized by designers using event-driven architectures-in which the MCU stays in deep sleep until awakened by a sensor interrupt-adaptive sampling, in which the acquisition frequency is changed based on the detected activity level-and sensor fusion, which merges inputs from multiple sensors to eliminate redundancy and prolong battery life.

DMA controllers perform the data transfer process without loading the CPU, and they do this to provide easy transfer of bio-signal data between peripherals and memory. As claimed by Recio et al. (2007), multi-channel, simultaneous sampling allows synchronized acquisition from multiple ECG or EEG leads, enabling diagnosis accuracy. Reliability and security are also catered for within the hardware: watchdog timers recover from software stalls; redundant sensing provides data integrity; and secure bootloaders with encrypted firmware updates protect against unauthorized modifications, maintaining compliance with medical cybersecurity standards.

Fig. 10.6 Example of wearable health technology.

4. FPGA-Based Implementations in Connected Healthcare

FPGAs, which occupy a unique niche, as illustrated in Fig 10.7, are offering massive parallelism, deterministic latency, and hardware-level reconfigurability. Unlike fixed-function processors, an FPGA can implement, for example, custom digital circuits tailored to specific biomedical algorithms that the designers are interested in. These are ideal for applications requiring real-time processing of large datasets where precision up to microseconds is important.

In medical imaging, these devices speed up the most computationally intensive parts of the workload, such as filtered back-projection in computerized tomography (CT) and iterative reconstruction in magnetic resonance imaging (MRI), which have reported speedups of 50–100× over CPU-based systems (Inam et al., 2020; Yadav et al., 2025). In ultrasound, they can perform delay-and-sum beamforming over 128 or more transducer elements, reconstructing frames in real time with very low latency. Commercially, Siemens MRI systems employ FPGA accelerators for real-time iterative reconstruction and artifact suppression, thus allowing for higher-resolution imaging while reducing patient scan times (Düppenbecker et al., 2016).

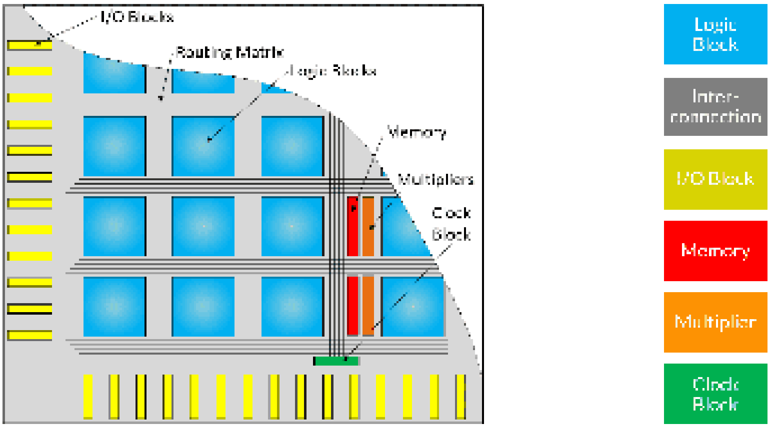


Fig. 10.7 Typical ressources of a FPGA.

For bio-signal processing, FPGAs simultaneously filter and detect the QRS waveforms in the noise while processing several channels of ECG or EEG signals (Jameil et al., 2022; Hook et al., 2024). The motion and power-line interference in electrically noisy environments are well suppressed through adaptive filters, like those using the LMS algorithm, implemented in hardware. This approach is used in experimental closed-loop epilepsy monitoring systems, wherein FPGAs detect seizure onsets and trigger neural stimulation in real time (Zhou et al., 2023).

For instance, FPGAs are highly important in neural interfacing systems, be they BCIs or neuro-prosthetics. They process several neural channels in parallel, carrying out spike detection, sorting, and feature extraction on chip at the edge. This enables closed-loop systems to provide responsible electrical stimulation within sub-millisecond latency, thus allowing naturalistic motor control in prosthetic limbs. A popular application can be seen in Fig. 10.8: the recent development of platforms like the Neuralink brain implant prototype involves FPGA-based solutions to support high-bandwidth neural data streaming and real-time signal classification (Shaima et al., 2024).

Their reconfigurability enables the decoding algorithms to be updated over time, without exchanging implanted hardware, which supports long-term adaptability as neuroscience advances. The usage of resources in medical design should be effectively optimized in FPGAs. Fig. 10.9 illustrates a typical hardware structure of an FPGA applied in medical and healthcare development. The logic elements realize customized control logic and arithmetic units; DSP blocks accelerate convolution, correlation, and spectral analysis; block RAM stores filter coefficients, interim data, and patient-specific parameters and minimizes access to slower off-chip memory; and high-speed transceivers support Gigabit serial links to imaging detectors, sensor arrays, and hospital networks.

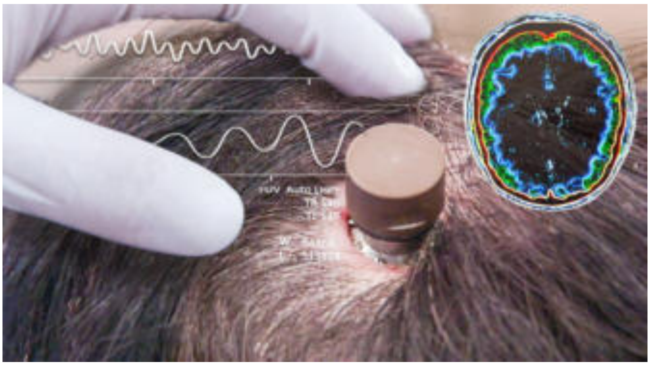


Fig. 10.8 Neurallink brain chip.

In hybrid FPGA-processor SoCs, like Xilinx Zynq UltraScale+, the cache-coherent interconnect allows the ARM processors to share data with the FPGA fabric seamlessly for runtime acceleration. Such a co-design methodology brings together the flexibility of software and the performance of hardware for next-generation diagnostic and monitoring platforms (Yadav et al., 2025). Robotic surgical platforms, such as the da Vinci Surgical System, use FPGA-based modules that provide deterministic motion control of robotic arms and haptic feedback, which rely on microsecond accuracy for safe human-machine interaction (Douissard et al., 2019).

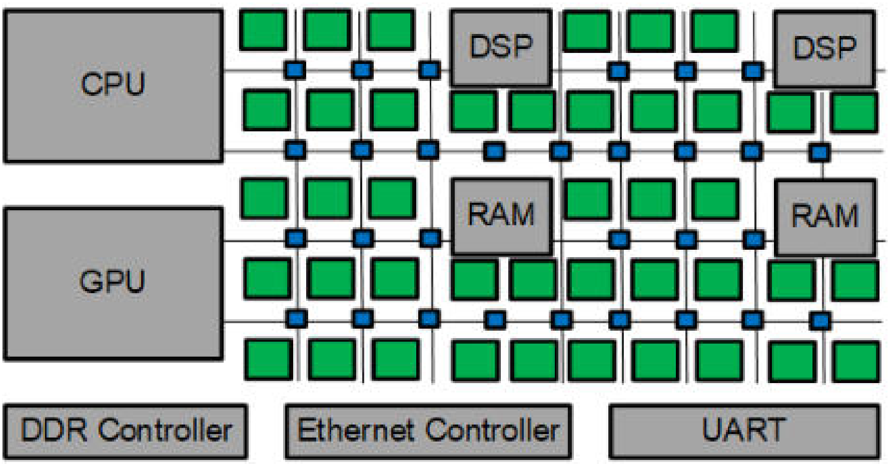


Fig. 10.9 FPGA in medical and healthcare applications.

Such modern development tools include HLS, which can automatically convert algorithms in C, C++, or OpenCL into optimized hardware. The barrier is lower for software-centric engineers and engineers who might have never worked on hardware design. This enhances system longevity through over-the-air reconfiguration, allowing updates to the signal processing pipelines or AI models in the field.

5. Platform Comparison and Selection Criteria

The design of health-care hardware necessarily makes trade-offs among computation throughput, power efficiency, determinism, development complexity, and cost. There is no single universally dominating platform; rather, the choice will depend on application domain and clinical needs.

5.1 Hardware Selection Guidelines for IoT Healthcare

The choice of hardware platform depends on a careful balancing between performance, power, latency, and connectivity. Table 10.1 enumerates recommended platforms for some key healthcare applications.

Table 10.1 Hardware platform selection by application domain.

Application	Recommended platforms	Key rationale
Medical Imaging (CT, MRI, Ultrasound)	MPU + GPU/FPGA	High throughput, real-time reconstruction
AI-Driven Diagnostics	MPU + NPU/FPGA	On-device inference, low-latency AI
Wearables & Implants (CGM, ECG Patch)	MCU (ultra-low-power)	Long battery life, sensor integration
Real-Time Control (Ventilators, Surgical Robots)	FPGA or RT-MCU	Deterministic latency, safety-critical response
Multi-Modal Monitoring Systems	Hybrid (MCU+FPGA+MPU)	Balance power, performance, and connectivity

5.2 Application-Specific Hardware Guidelines

Segmentation of the medical field entails choosing the right hardware platform through the alignment of architectural strengths of MPUs, MCUs, and FPGAs to the unique application demands. What works in one instance rarely works in another; instead, optimal performance and power efficiency with safety comes through context-aware hardware selection.

Computing platforms, particularly for high-throughput applications in medical imaging and AI-driven diagnostics, have to handle these large datasets with minimal latency. In such domains, it is often preferred to use microprocessors with integrated GPU or dedicated AI accelerators (e.g., NVIDIA Jetson, Google Edge TPU) for the execution of deep learning inference, image reconstruction, and real-time visualization. Alternatively, FPGAs might be very attractive when custom, low-latency pipelines are required (iterative CT reconstruction, real-time beamforming in ultrasound) where their parallel architecture offers much better energy efficiency and deterministic performance compared to general-purpose processors.

Energy efficiency is a top priority for battery-powered, wearable, or implantable devices. Ultra-low-power microcontrollers include deep sleep modes, integrated analog front-ends, and event-driven execution which represent the main design option for engineering. By consuming power in the microwatt range, these MCUs capably manage sensor interfacing, basic signal processing as well to data acquisition. For the moment, spike detection, multi-channel ECG filtering, provide a good trade-off between energy consumption and flexibility. The use of advanced SoC applications based on low-power FPGAs allow parallel bio-signal processing. We cite as an example of synthesizable processors: Lattice iCE40 and Intel Cyclone V.

For safety-critical real-time systems, fault resilience and deterministic response are preconditions in many applications (e.g. surgical robots, ventilators, or impla^{2}ntable neuro-stimulators…). In these applications, FPGAs and real-time microcontrollers (executing RTOS or others operating systems) are widely used because of their predictable timing behavior and low interrupt latency.

Conclusion

In this chapter, we have developed hardware dedicated for healthcare domain. Microprocessors, microcontrollers, and FPGAs each bring substantial value in such diverse applications. They serve different needs in diagnostics, monitoring, and therapies. MPUs offer ultra-high throughput for applications such as imaging and AI-driven diagnostics. MCUs provide ultra-low power operation critical to wearables and implants. FPGAs offer true parallelism, determinism, and very high channel counts essential for time-critical and multi-channel biomedical applications.

Significantly, there are no single platform universally governs across all use cases. Instead, optimum system design requires context-aware hardware selection and, increasingly, the integration of heterogeneous platforms. Hybrid solutions allow designers to take advantage of each of their strengths, achieving computationally powerful, yet energy-efficient solutions.

Besides advancing individual architectures, progress in the future will be critically linked to the development of methodologies and toolchains in design, as well as co-optimization at the level of hardware-software ecosystems, accelerating the deployment of dependable IoT-enabled healthcare technologies. Hardware platform choices and integration will continue to be a key driver in the innovation of healthcare.

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