2.2 Technical challenges - Sensor design

The major technical challenges in the adoption of wearables are as follows:

1. The success of wearables depends on the ability to **connect** them seamlessly in a body-worn network. This means the meta-wearable framework must have the ability to route the signals and power between desired points in the structure. The ***interconnection process*** for creating such junctions in textile materials has been manual to-date. The concept of textillography to automate interconnections during the fabric manufacturing process has been proposed. An automated process that can provide precise, rugged, and flexible interconnections will help facilitate mass production and also lower the costs associated with wearables.
2. In the event of damage to the data buses in the ***meta-wearable framework***, the "failure" in the network must be recognized and ***alternate "data paths***" must be established in the fabric to maintain the integrity of the network by taking advantage of the redundant data buses in the fabric. Preliminary work on the concept of "soft" interconnects has resulted in a programmable network in a fabric that enables real-time routing that can be configured on the fly.
3. Currently, the so-called "t-connectors" and button snaps are being used for connecting sensors and processors to the meta-wearable. There is therefore the need for a ***common interface*** similar to the RJ-11 jack for telephones for ***connecting these sensors and processors to the meta-wearable*** so that general-purpose sensors and devices can be developed, thereby reducing their cost.
4. Many wearables, especially for health monitoring and gaming, are affected by **motion artifacts**. These artifacts can impact the accuracy of the results. There is therefore the need for in-depth studies to develop **robust signal processing algorithms** and systems to ensure the quality of the data generated by the wearables.
5. Current conductive fibers meet the basic needs of first-generation **textile wearables**. However, **new materials** are needed with copper's conductivity and the properties of cotton, polyester, or nylon. These materials should also

be available in large quantities. Research is needed to develop fibers that can also retain their conducting properties after repeated laundering.

6. Today's wearables are powered by ***lithium-ion rechargeable batteries***, which is another limiting factor in the adoption of the technologies due to the ***rigidity of the battery*** in relation to the flexible nature of the wearables, a key desired attribute of wearables shown in Figure 2.

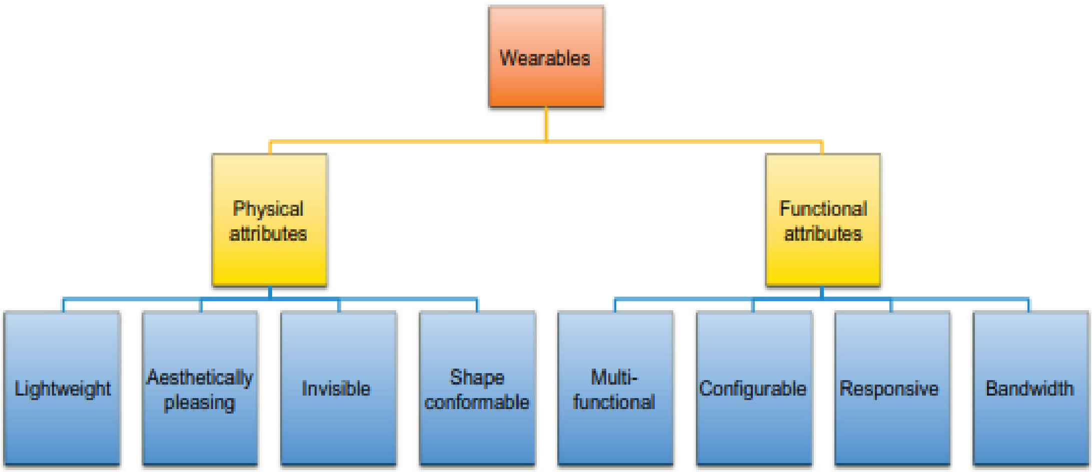

FIGURE 2 Key attributes of wearables.

This bottleneck is being addressed by research on two fronts, piezoelectric-based energy-harvesting systems and flexible textile battery, respectively. A textile battery, developed using a ***woven polyester fabric as a substrate***, has exhibited comparable electrochemical performance to those of conventional metal foil-based cells even under severe folding, unfolding motions simulating actual wearing conditions. The 13 mAh battery retained 91.8% of its original capacity after 5,500 deep folding, unfolding cycles. The researchers also successfully integrated the ***flexible textile battery with lightweight solar cells on the battery pouch*** to enable convenient solar-charging capabilities.

7. The seamless integration of wearables in healthcare settings and for remote monitoring faces the challenge of ensuring compatibility with existing wireless technologies and established ***operational protocols*** in those settings.

Strategies and solutions must be developed to address this important aspect to help the adoption of wearables for remote monitoring.

8. The challenges associated with **protection of individual privacy, data security**, and other social aspects of the acceptance of wearables must be addressed because the wearables are collecting personal information. The electronics and communications industry in collaboration with privacy protection organizations must develop appropriate protocols that will identify proper technology and public policy solutions to further the free acceptance and use of wearables.

9. The supply chains for textiles/clothing and electronics are significantly different. Apparel manufacturing is a labor-intensive operation whereas electronics manufacturing is highly automated. Consequently, the production rates are much higher in electronics manufacturing. ***The apparel industry*** is not as precise in terms of topology and interfaces between the different components when compared to the electronics industry whose operating paradigm is precision. Thus, the ***differences between these manufacturing paradigms must be addressed*** for the widespread adoption of **textile-based meta wearables** for the various applications

10. Finally, the same wearable may be used in a ***range of environmental conditions*** indoors to outdoors which may include disaster zones involving high temperatures (e.g., fire) and hazardous materials. Therefore, they should be designed to function effectively and seamlessly in a wide range of ambient environments.

Designing wearable sensors involves several technical challenges across multiple domains, including hardware, software, and human factors.

Some of the major challenges are Listed below:

1. Power Consumption & Energy Efficiency

❖ Wearable sensors must be energy-efficient to prolong battery life.

- Trade-offs between data sampling rates, wireless communication, and processing must be optimized.
- Energy harvesting (solar, kinetic, or thermal) is still limited in efficiency.

2. Sensor Accuracy & Calibration

- Small size constraints may limit sensor accuracy.
- Variability in sensor readings due to environmental conditions (e.g., temperature, humidity).
- Need for regular calibration to maintain precision over time.

3. Miniaturization & Form Factor

- Sensors must be small, lightweight, and unobtrusive.
- Flexible and stretchable electronics are still in early development.
- Integration with clothing or accessories without compromising function or aesthetics.

4. Wireless Communication & Connectivity

- Bluetooth, Wi-Fi, and other wireless protocols must be optimized for low power.
- Data transmission should be reliable in different environments.
- Bandwidth constraints may limit real-time data streaming.

5. Data Processing & Storage

- Edge computing vs. cloud processing trade-offs.
- Real-time processing of large datasets with minimal latency.
- Secure and efficient storage of health or biometric data.

6. Biocompatibility & Comfort

- Materials must be skin-friendly, breathable, and hypoallergenic.
- Long-term use may cause irritation or discomfort.
- Ergonomics must be considered for continuous wearability.

7. Environmental & Mechanical Durability

- Wearables must withstand sweat, water, dust, and physical impacts.
- Stretchable and flexible electronics are prone to wear and tear.
- Reliability over long-term use is a challenge.

8. Security & Privacy Concerns

- Biometric and health data need robust encryption.
- Wireless transmission is vulnerable to hacking or data breaches.
- Compliance with regulations like GDPR and HIPAA.

9. Cost & Scalability

- High-quality sensors can be expensive.
- Mass production challenges in maintaining accuracy and reliability.
- Cost vs. performance trade-offs for consumer and medical markets.

10. User Adoption & Experience

- User acceptance depends on aesthetics, comfort, and ease of use.
- Complexity in setting up and maintaining devices.
- Psychological resistance to continuous monitoring or tracking.

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2.3 Technical challenges – Signal Acquisition

The nonidealities/Challenges in biopotential measurements can be due to:

i. Electrostatic Interference

ii. Biopotential Electrodes

iii. Instrumentation Amplifier

2.3.1 Electrostatic Interference (ESI) in Wearable Devices:

Electrostatic interference (ESI) is a significant challenge in the design and operation of wearable devices. It occurs when static charges accumulate on the device or the human body, leading to unwanted electrical discharges that can corrupt the signals acquired by the device's sensors.

2.3.2 Sources of ESI in Wearable Devices:

❒ **Triboelectric Effect:** Friction between materials (like clothing and the device) can generate static charges.

❒ **Human Body:** The human body itself can accumulate static charges due to activities like walking on carpets or removing synthetic clothing.

❒ **Environmental Factors:** Dry air and certain weather conditions can increase the likelihood of static charge buildup.

2.3.3. Impact of ESI on Wearable Devices

- **Signal Distortion:** ESI can introduce noise and artifacts into the acquired signals, making it difficult to extract accurate data.
- **Data Loss:** In severe cases, ESI can cause temporary or permanent data loss.
- **Device Damage:** Large electrostatic discharges can damage the sensitive electronics within the wearable device.

2.3.4. Technical Challenges of Biopotential Electrodes in signal acquisition in wearable devices:

Biopotential electrodes play a critical role in signal acquisition for wearable devices, but they face several technical challenges that impact their performance, reliability, and user comfort. Here are some of the key challenges.

1. Skin-Electrode Interface Issues:

- **Contact impedance variations**: Variability in skin properties, sweat, and motion artifacts lead to inconsistent impedance, affecting signal quality.
- **Signal degradation due to skin preparation**: Dry electrodes struggle with high impedance, often requiring skin preparation (e.g., abrasion or gels), which is not practical for long-term wearable applications.
- **Electrode polarization**: Some materials exhibit polarization effects, introducing DC drift and reducing signal fidelity.

2. Weak Signal Strength:

- **Biological Signals Are Low Amplitude**: Signals like ECG (microvolts) and EEG (nanovolts) require high sensitivity for detection.
- **Signal Attenuation**: Layers of skin, muscle, and fat can attenuate signals, affecting their accuracy.
- **Low Signal-to-Noise Ratio (SNR)**: Weak signals are more susceptible to interference, requiring advanced filtering techniques.

3. Motion Artifacts and Environmental Noise

- **Motion-induced artifacts**: Movement causes mechanical shifts, changing the contact impedance and introducing noise into the signal.
- **External electromagnetic interference (EMI)**: Wearable devices operate in environments with high EMI (e.g., from power lines, Wi-Fi), which can corrupt signals.

- **Baseline wander**: Breathing and body movements lead to slow signal drifts, affecting ECG and EEG measurements.

4. Power and Energy Consumption

- **Low power signal amplification**: High-quality biopotential signals require low-noise, high-gain amplification while maintaining low power consumption.
- **Continuous monitoring challenges**: Prolonged operation in battery-powered wearables demands efficient signal processing and low-energy transmission (e.g., Bluetooth Low Energy).
- **High Power Consumption of Sensors**: Continuous monitoring and signal amplification can drain the battery quickly.
- **Energy-Efficient Signal Processing**: On-device processing needs to be optimized to reduce power usage.
- **Trade-off Between Sampling Rate & Power Consumption**: Higher sampling rates improve signal quality but consume more power.

5. Signal Processing Challenges

- **Artifact reduction algorithms**: Effective filtering and adaptive signal processing are needed to compensate for noise, motion artifacts, and drift.
- **Machine learning for noise rejection**: AI-based denoising techniques are being explored but require computational efficiency for wearable implementation.

6. Miniaturization and Sensor Placement Issues:

- **Electronics miniaturization**: Wearables require compact, lightweight electrodes and signal acquisition circuits without compromising performance.
- **Flexible and stretchable electrodes**: Rigid electrodes cause discomfort and poor contact, necessitating the development of flexible materials that conform to body movement.
- **Wireless transmission**: Real-time signal acquisition requires robust and low-latency wireless communication with minimal data loss.

- **Size vs. Performance Trade-Off**: Miniaturized sensors may have lower sensitivity or limited processing capability.
- **Optimal Placement on the Body**: Different body locations yield varying signal quality (e.g., wrist-based PPG vs. chest-based ECG).
- **Movement-Induced Misalignment**: Sensors may shift or detach due to body motion, reducing data reliability.

7. Multi-Sensor Integration Challenges:

- **Synchronization Issues**: Combining signals from multiple sensors (e.g., accelerometer + ECG) requires precise synchronization.
- **Data Fusion Complexity**: Integrating different signal types (electrical, optical, mechanical) to improve accuracy is computationally challenging.
- **Cross-Talk Between Sensors**: Sensors placed close to each other may interfere with each other's signals.

8. Real-Time Data Processing Challenges:

- **Latency Issues**: Processing and transmitting data in real-time is challenging for low-power devices.
- **Computational Complexity**: Advanced signal filtering, feature extraction, and machine learning algorithms require significant processing power.
- **Edge vs. Cloud Computing**: Deciding where to process data (on-device vs. cloud) affects latency and efficiency.

Signal acquisition in wearable sensors presents several technical challenges that affect the accuracy, reliability, and efficiency of data collection. These challenges arise due to factors such as sensor placement, environmental interference, power constraints, and user movement. Below are the key challenges:

9. Temperature & Environmental Variability

- **Temperature-Induced Drift**: Sensor performance may degrade due to temperature changes affecting electrical properties.

- **Humidity & Sweat Interference**: Moisture can alter skin-electrode impedance and cause signal degradation.
- **Pressure Sensitivity**: Changes in pressure (e.g., tightness of a wristband) can affect optical sensors like PPG.

10. Standardization & Calibration Issues

- **Need for Frequent Calibration**: Over time, wearable sensors may drift, so they need recalibration to maintain accuracy.
- **Lack of Standardization**: Different manufacturers use varying protocols, making interoperability difficult.
- **Variability Among Users**: Differences in skin type, physiology, and body movement patterns affect signal quality.

2.3.5 Technical challenges of Instrumentation Amplifier in signal acquisition in wearable devices:

1. DC Offset and Drift Issues:

- **Electrode-skin interface polarization** creates **DC offsets**, which can saturate the IA.
- **Temperature variations** cause **offset drift**, affecting signal accuracy.
- **Long-term stability** of low-noise IAs is essential for continuous monitoring.

2. Bandwidth and Gain Design Challenges:

Wearables require **precise gain control** and **optimized bandwidth** to capture various biopotential signals:

- ECG: **0.05–150 Hz**, requiring low-frequency noise suppression.
- EEG: **0.1–100 Hz**, needing ultra-low noise performance.
- EMG: **10–500 Hz**, requiring high dynamic range.

3. Common-Mode Noise and Interference:

- Wearable devices are highly susceptible to **electromagnetic interference (EMI)** from mains power (50/60 Hz) and wireless signals (Wi-Fi, Bluetooth, cellular).

- Motion artifacts and electrode impedance mismatches introduce **common-mode noise**, which is difficult to suppress completely.

4. Signal Processing:

- The signal acquired by the INA needs to be processed to extract the relevant information. This can be challenging, as the signal may be noisy or contain artifacts.
- Signal processing techniques like filtering, averaging, and artifact removal are used to improve signal quality.

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2.4 Sampling frequency for reduced energy consumption

Reducing energy consumption in wearable devices while maintaining functionality often involves optimizing the **sampling frequency** of sensors.

2.4.1 Some factors to be considered for optimal sampling frequency:

1. Adaptive Sampling:

Instead of using a constant high-frequency sampling rate, adapt it based on user activity:

- **Event-driven sampling:** Increase sampling only when significant movement or changes are detected.
- **Context-aware sampling:** Lower frequency during low-activity periods (e.g., sleep mode).
- **Hierarchical sampling:** Use a low-power sensor (e.g., accelerometer) to trigger high-power sensors (e.g., ECG, gyroscope) when needed.

2. Optimal Sampling Rates for Different Sensors:

Typical sampling rates (which can be reduced for power savings):

- **Accelerometer:** 10–50 Hz (high-motion activities) → Can drop to <10 Hz for idle states.
- **Gyroscope:** 20–100 Hz → Reduce in low-motion scenarios.
- **Heart Rate (PPG/ECG):** 10–500 Hz → Reduce during rest, increase during exercise.
- **Temperature:** 0.1–1 Hz → Can be sampled even less frequently.
- **Environmental sensors:** ~1 Hz or lower, depending on need.

3. Duty Cycling & Data Fusion

- **Duty cycling:** Turn sensors on/off periodically rather than continuous operation.
- **Data fusion:** Combine low-power sensors to estimate states and reduce reliance on power-hungry sensors.

4. Edge Processing & Compression:

- Perform basic data processing locally to reduce transmission energy costs.
- Use efficient compression algorithms to reduce data size before transmission.

2.4.2 Optimal Sampling Frequencies:

Wearable devices, particularly those used for health monitoring, require careful consideration of sampling frequency to optimize both performance and energy consumption. The sampling frequency determines how often data is collected from sensors, directly impacting battery life and data management needs.

Heart Rate Monitoring:

Research indicates that the optimal sampling rate for wrist-worn optical sensors, which are commonly used for heart rate (HR) and heart rate variability (HRV) monitoring, ranges from 21 Hz to 64 Hz. Specifically, a rate of 64 Hz is recommended for comprehensive HR and HRV metrics, while rates as low as 32 Hz can maintain sufficient accuracy for many applications, reducing data storage needs by half. For less precision-sensitive applications, a sampling rate of 21 Hz may be acceptable.

Energy-Efficient Human Activity Recognition:

In the context of human activity recognition, a lower sampling frequency can significantly reduce energy consumption. However, this reduction must be balanced against the potential loss of accuracy in recognizing activities. A careful analysis is needed to determine the lowest effective sampling rate that still meets accuracy requirements.

General Recommendations:

A common guideline across various studies emphasizes that while high sampling rates may enhance signal quality, they also lead to increased power consumption. Therefore, it is advisable to adopt the lowest possible sampling frequency that still fulfills the application's requirements. This approach not only conserves battery life but also minimizes data management challenges.

Trade-offs in Sampling Frequency

Battery Life vs. Data Quality: Higher sampling frequencies can lead to quicker battery depletion, necessitating more frequent charging or larger batteries that may compromise device portability.

Data Storage Requirements: Lowering the sampling rate can significantly decrease the volume of data generated, which is crucial for devices that continuously monitor health metrics.

2.4.3. General guide for various sensors commonly used in wearables:

1. Motion Sensors (Accelerometer, Gyroscope, Magnetometer)

Sensor Type	Activity Level	Recommended Sampling Frequency
Accelerometer	Low-motion (sleep, rest)	1–10 Hz
	Walking, daily activity	10–50 Hz
	High-motion (sports, falls)	50–200 Hz
Gyroscope	Low-motion	10–20 Hz
	High-motion (sports, VR)	50–200 Hz
Magnetometer	Orientation tracking	10–50 Hz

💡 **Power-saving tip:** Use an accelerometer to detect motion and activate the gyroscope only when needed.

2. Physiological Sensors (Heart Rate, ECG, PPG, SpO_2, EEG, EMG)

Sensor Type	Use Case	Recommended Sampling Frequency
Heart Rate (PPG/ECG)	Resting HR	10–25 Hz
	Exercise monitoring	100–500 Hz

Sensor Type	Use Case	Recommended Sampling Frequency
SpO_2 (Oxygen Saturation)	Continuous monitoring	1–10 Hz
EEG (Brain Activity)	Sleep monitoring	100–250 Hz
EMG (Muscle Activity)	Gesture detection	500–2,000 Hz

💡 **Power-saving tip:** Use lower sampling rates during rest and increase during activity.

3. Environmental Sensors (Temperature, Humidity, Gas, Pressure)

Sensor Type	Use Case	Recommended Sampling Frequency
Temperature	Skin/body monitoring	0.1–1 Hz
Humidity	Comfort monitoring	0.1–1 Hz
Barometer (Pressure)	Altitude tracking	1–10 Hz

💡 **Power-saving tip:** These sensors can sample at low frequencies since changes occur slowly.

4. Audio & Communication Sensors (Microphone, Bluetooth, GPS)

Sensor Type	Use Case	Recommended Sampling Frequency
Microphone	Voice detection	8–16 kHz
	Speech processing	16–44.1 kHz
Bluetooth	Data transmission	Event-driven
GPS	Location tracking	0.1–1 Hz (1 reading every few sec/min)

💡 **Power-saving tip:** Use **event-driven** GPS updates instead of continuous tracking.

2.4.4. Strategies to Optimize Power Consumption

1. **Adaptive Sampling:** Lower frequency when motion is low.
2. **Event-Triggered Sampling:** Only activate high-power sensors when needed.
3. **Duty Cycling:** Periodically turn off sensors when data isn't critical.
4. **Edge Processing:** Process data locally to minimize wireless transmission.

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2.5 Rejection of irrelevant information

In the context of wearable devices, rejecting irrelevant information is crucial for enhancing data quality and ensuring efficient processing. This process involves several strategies and techniques aimed at filtering out noise and non-essential data, thus improving the accuracy and reliability of the information collected.

Wearable devices collect vast amounts of data from multiple sensors, but **filtering out irrelevant information** is crucial to enhance accuracy, reduce power consumption, and improve user experience. Below are key techniques used for this purpose:

1. <u>Signal Processing Techniques</u>

Filtering raw sensor data helps remove unwanted noise and irrelevant signals.

❒ **Low-Pass & High-Pass Filters**

- **Low-pass filter**: Removes high-frequency noise (e.g., muscle artifacts in ECG).
- **High-pass filter**: Eliminates slow-changing drift (e.g., movement artifacts in PPG).

❒ **Band-Pass & Notch Filters**

- **Band-pass filter**: Isolates specific frequencies (e.g., EEG signals).
- **Notch filter**: Removes specific interference (e.g., 50/60 Hz power line noise).

2. <u>Adaptive & Context-Aware Sampling</u>

Reducing data collection when it's unnecessary can improve battery life.

❒ **Motion-Triggered Sampling**

- Use a **low-power accelerometer** to activate high-power sensors (ECG, gyroscope) only during movement.

❒ **Activity Recognition-Based Filtering**

- Reduce heart rate sampling during rest and increase during workouts.

- Ignore irrelevant motion patterns (e.g., minor hand tremors in gesture tracking).

❐ **Event-Driven Data Collection**

- **Sleep tracking**: Lower sampling rate during deep sleep.
- **Fall detection**: Store only high-impact acceleration changes.

3. <u>Data Fusion & Machine Learning</u>

Combining sensor data can enhance relevance while rejecting useless information.

❐ **Sensor Fusion**

- Merge accelerometer, gyroscope, and magnetometer data to improve motion accuracy.
- Combine heart rate (PPG) and motion data to eliminate motion artifacts.

❐ **AI & Machine Learning Filters**

- Train models to **ignore false positives** in step counting, fall detection, and ECG anomalies.
- Use deep learning to distinguish **real voice commands from background noise**.

4. <u>Edge Processing & Data Compression</u>

Processing data locally can prevent sending irrelevant data to the cloud.

❐ **Feature Extraction on Device**

- Only transmit key metrics (e.g., **average heart rate**, not raw PPG signals).

❐ **Compressed Data Storage**

- Store only significant deviations from normal trends.

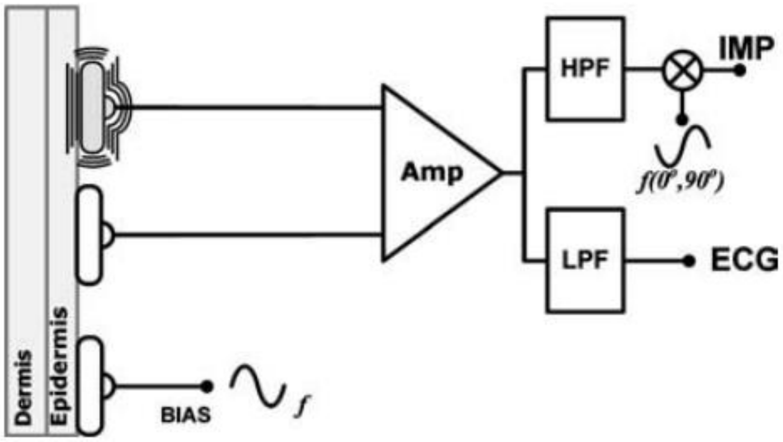
5. <u>User-Customized Data Filtering</u>

Let users **define thresholds** for relevant information:

❖ Adjust **step count sensitivity** to ignore minor movements.

- Filter out **non-essential notifications** based on activity context.
- Enable **priority-based alerts** for health anomalies.

6. Example-1:



Schematic of a **bioimpedance measurement system** combined with an ECG (electrocardiogram) sensor.

- **BIAS signal:** A sinusoidal current at frequency fff is injected into the skin (dermis/epidermis), likely to measure bioimpedance (IMP).
- **Amp (Amplifier):** The signals are amplified before filtering.
- **HPF (High-Pass Filter):** Extracts high-frequency components, which are used for impedance (IMP) measurement.
- **LPF (Low-Pass Filter):** Extracts low-frequency components, which correspond to the ECG signal.
- **IMP Measurement:** There's a mixer or demodulator (shown with $f(0^0, 90^0)$ for extracting impedance-related information from the high-frequency signal.

Rejection of Irrelevant Information:

- **HPF and LPF are classic filters** used to separate signals of interest (ECG vs. IMP) and reject irrelevant information.
- The **demodulation step** (mixing with reference signals) helps isolate the desired impedance measurement from other noise.

Working:

- **ECG Acquisition:** Low-frequency components are passed through the LPF to capture the heart's electrical signals.
- **Impedance Measurement:** The high-frequency current injected into the body creates a modulated signal detected through impedance changes (e.g., due to blood flow). The HPF and mixer demodulate this to provide the IMP signal.

7. Example- 2: Sources of Irrelevant Information in EMG Signals

❒ **Motion Artifacts:** Caused by electrode movement, skin stretching, and external forces.

❒ **Power Line Interference:** 50/60 Hz noise from electrical sources.

❒ **Cross-Talk from Other Muscles:** Overlapping signals from nearby muscle groups.

❒ **Baseline Wandering:** Slow changes in signal due to sweat, skin-electrode impedance shifts.

❒ **Electrode Noise:** Poor contact with the skin leads to high impedance and unstable signals.

7.1 Filtering Techniques

❒ **High-Pass Filtering (HPF):**

- Removes low-frequency motion artifacts and baseline drift.
- Cutoff frequency: **10–20 Hz**.

❒ **Notch Filtering:**

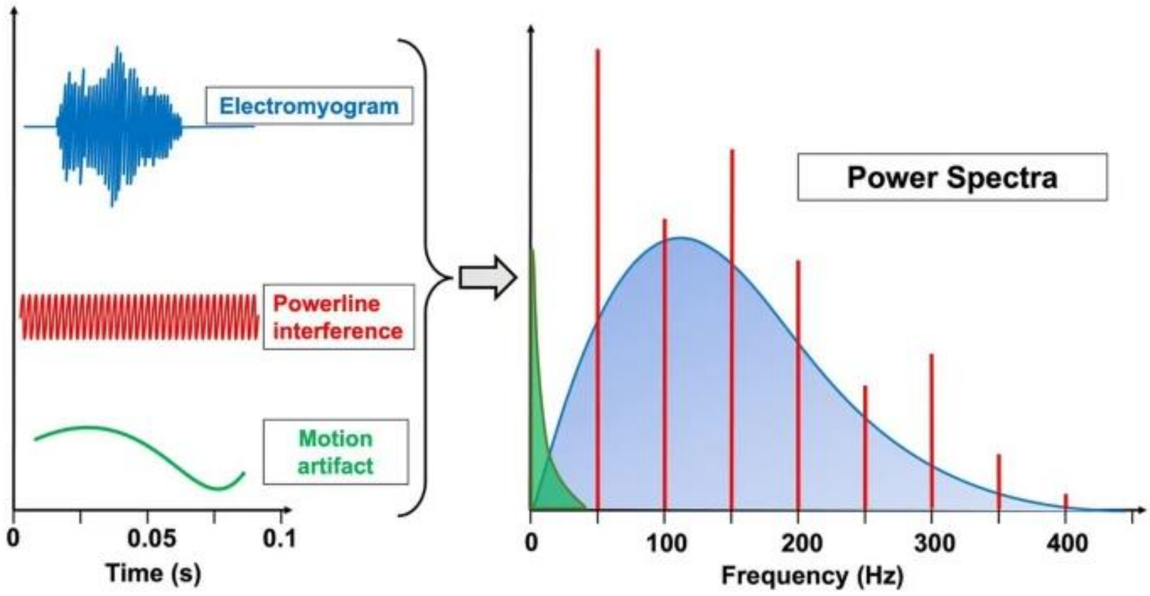
- Eliminates power line interference (50/60 Hz).

❒ **Low-Pass Filtering (LPF):**

- Removes high-frequency noise and external interference.
- Cutoff frequency: **450–500 Hz** (since EMG signals typically range from 10–500 Hz).

❒ **Band-Pass Filtering (BPF):**

- Allows only the EMG signal range (e.g., **20–450 Hz**) while filtering irrelevant noise.



Qualitative sketch of sEMG signal, powerline interference and motion artifacts in time and frequency domains.

Left Side (Time Domain Representation)

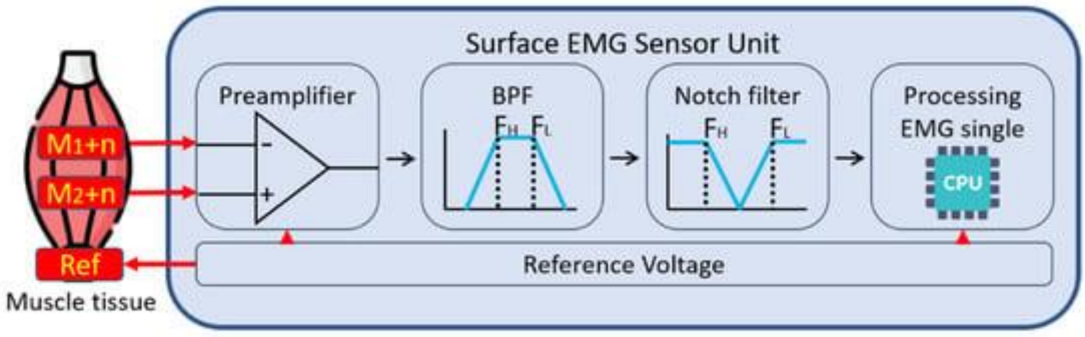
- **Electromyogram (EMG) Signal (Blue):** Represents the desired muscle activity.
- **Powerline Interference (Red):** A high-frequency sinusoidal noise (typically at **50/60 Hz**) caused by electrical sources.
- **Motion Artifact (Green):** A low-frequency distortion due to electrode movement and skin stretching.

Right Side (Frequency Domain - Power Spectra)

- **EMG Power Spectrum (Blue Area):** Shows the frequency distribution of the useful EMG signal (typically **20–450 Hz**).
- **Powerline Interference (Red Lines):** Sharp peaks at **50 Hz and its harmonics** (100 Hz, 150 Hz, etc.).
- **Motion Artifact (Green Area):** Dominates the **low-frequency range (0–20 Hz)**.

Rejection of Irrelevant Information?

- **Notch Filter (50/60 Hz)** – Removes powerline interference.
- **High-Pass Filter (Cutoff: 10–20 Hz)** – Eliminates motion artifacts.
- **Band-Pass Filter (20–450 Hz)** – Keeps relevant EMG signals.
- **Adaptive Noise Cancellation (ANC)** – Uses reference sensors (e.g., accelerometers) to remove movement-related noise.



Surface EMG measurement sensor block diagram

7.2 Hardware-Based Solutions for Reducing Irrelevant Information

- **Use High-Quality Electrodes:** Reduces motion artifacts and electrode noise.
- **Ensure Proper Skin Preparation:** Cleansing skin before placing electrodes minimizes impedance variations.
- **Optimize Electrode Placement:** Avoids cross-talk from unwanted muscles.
- **Shielding & Grounding:** Reduces power line interference from external devices.

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