AI-Powered Real-Time Gait Detection Using LiDAR for Healthcare Monitoring

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Abstract. Leveraging the advanced capabilities of AI, real-time detection of gait anomalies through LiDAR technology is revolutionizing healthcare monitoring. This innovative approach enables precise and immediate assessment of patients' walking patterns, highlighting deviations that may indicate underlying health issues. By utilizing the detailed spatial mapping of LiDAR sensors, healthcare professionals can better understand an individual's mobility, allowing for timely interventions and personalized care strategies. This integration of cutting-edge technology promises to enhance patient outcomes by enabling more proactive and informed healthcare decisions.

Keywords: LiDAR, Internet of Things (IoT), Real-Time Healthcare Monitoring, Gait Anomaly Detection, Elderly Fall Risk, Smart Health Systems

1 Introduction to LiDAR in Healthcare

Light Detection and Ranging (LiDAR) technology, originally applied in autonomous driving and geographical surveying, is now gaining recognition for its transformative potential in the healthcare sector. Its ability to deliver precise, non-intrusive environmental mapping and motion tracking introduces innovative solutions to persistent challenges in patient monitoring, activity recognition, and the objective assessment of functional impairments such as gait abnormalities.

This chapter presents a comprehensive overview of LiDAR's application in healthcare. It begins by exploring the fundamental principles of LiDAR, the different system types, and the components that enable its functionality. It then discusses key advantages—particularly its privacy-preserving nature, accuracy, and non-intrusiveness—highlighting why LiDAR is uniquely suited to healthcare environments. The goal is to establish a foundational understanding of how LiDAR can support real-time, continuous monitoring of patients while enhancing clinical insights through quantitative, spatially rich data.

Chapter Scope and Objectives This chapter aims to provide a comprehensive and in-depth overview of the application of Light Detection and Ranging (LiDAR) technology in the domain of real-time healthcare monitoring, with a particular emphasis on its utility for the detection and analysis of gait anomalies.

N. K. Suryadevara (ed.), *Proceedings of the IoT AND LiDAR Technologies in Healthcare Workshop (ILTH 2024)*, Atlantis Highlights in Intelligent Systems 14,
https://doi.org/10.2991/978-94-6463-784-7_9

The primary objectives of this chapter are:

- To elucidate the fundamental principles of LiDAR technology, including its operational mechanisms, the different types of LiDAR systems (e.g., 2D vs. 3D, discrete return vs. full waveform), and their key constituent components, providing a solid technological foundation for understanding its healthcare applications.
- To critically examine the advantages that LiDAR offers for healthcare monitoring, such as its inherent privacy-preserving nature, high accuracy in spatial measurement, and non-intrusive operational characteristics, comparing these with alternative monitoring technologies.
- To discuss methods for LiDAR data acquisition in healthcare settings, including sensor calibration techniques crucial for indoor monitoring, and the role of software frameworks like the Robot Operating System (ROS) and libraries such as Open3D in processing and visualising LiDAR data.
- To explore the application of LiDAR in real-time patient activity recognition and fall detection systems, including common algorithmic approaches and performance considerations.

By addressing these objectives, this chapter seeks to equip researchers, clinicians, engineers, and students with a thorough understanding of the current state, capabilities, challenges, and future directions of LiDAR technology in enhancing healthcare monitoring and enabling objective, quantitative assessment of gait.

2 Overview of LiDAR Technology: Principles, Types, and Components

Understanding the core operational framework of LiDAR is essential before delving into its specific healthcare applications. This section outlines the fundamental principles governing LiDAR, differentiates between its various system types, and identifies the key components that enable its functionality [1].

2.1 LiDAR Principles LiDAR is an active remote sensing technology that functions by emitting pulses of laser light and measuring the properties of the light that is scattered and reflected back to the sensor. The fundamental principle involves calculating the distance to an object by precisely timing the two-way travel of a laser pulse from its emission to its return after reflecting off a target surface. This time-of-flight (TOF) measurement, combined with the known speed of light, allows for highly accurate distance determination. The active nature of LiDAR, meaning it generates its own illumination source (the laser), distinguishes it from passive optical sensors like cameras. This characteristic allows LiDAR to operate effectively in a variety of lighting conditions, including complete darkness, which is a significant advantage for continuous, 24/7 patient monitoring in healthcare environments where ambient light levels can vary considerably. The data collected by a LiDAR sensor typically forms a ‘point cloud’, which is a three-dimensional dataset representing the spatial coordinates of the points where the laser pulses have reflected off surfaces in the environment.

LiDAR sensors generate data in the form of a "point cloud"—a dense 3D dataset composed of the spatial coordinates of reflected points in the environment. These point clouds can be used to model a patient's posture, movement, or interaction with surroundings.

2.2 Types of LiDAR Systems LiDAR systems can be categorised based on several characteristics, including the way they record returns and their dimensionality [2].

Discrete Return vs. Full Waveform Discrete Return LiDAR systems identify and record distinct, individual points corresponding to the peaks in the energy of the reflected laser pulse. A single emitted laser pulse can generate multiple returns if it encounters several reflective surfaces at different distances along its path (e.g., foliage at different heights, or in a healthcare context, a patient's arm partially obscuring their torso). These systems might record between one to over eleven such discrete returns per pulse. This type is generally simpler to process and is effective for identifying distinct surfaces and object boundaries. Full Waveform LiDAR systems, in contrast, capture the entire distribution of the returned light energy for each pulse, rather than just discrete peaks. This results in a more complex dataset that contains richer information about the nature of the reflecting surfaces and the medium through which the pulse travelled. While processing full waveform data is more computationally intensive, it can offer advantages in applications requiring detailed analysis of target structure or penetration through semi-transparent media. In healthcare, this could potentially translate to more detailed information about patient posture or interaction with occluding objects like blankets.

2D vs. 3D LiDAR 2D LiDAR sensors typically scan their surroundings in a single plane, either horizontally or vertically, using a rotating mirror or sensor assembly. This produces a two-dimensional cross-section of the environment. 2D LiDAR is often employed in robotics for navigation and obstacle avoidance, and has been used in simpler gait analysis setups, primarily for tracking leg or ankle movements within that plane. These systems are generally more affordable and computationally less demanding than their 3D counterparts.

3D LiDAR sensors capture data across three dimensions, generating a comprehensive 3D point cloud of the environment. This is achieved by using multiple laser beams or by employing more complex scanning mechanisms that cover both horizontal and vertical fields of view. 3D LiDAR provides a much richer and more detailed representation of the scene, which is essential for applications requiring complete spatial awareness, such as complex activity recognition, detailed gait analysis in unconstrained environments, and fall detection in cluttered spaces. The choice between 2D and 3D LiDAR in healthcare depends on the specific application's requirements for data richness, coverage, processing capabilities, and cost. While 2D LiDAR may suffice for tracking specific limb movements in a constrained path, 3D LiDAR is generally preferred for comprehensive environmental understanding and monitoring complex human behaviours.

2.3 Key Components of LiDAR Systems A typical LiDAR unit includes the following:

- **Laser Source:** Emits controlled pulses of light, often in the infrared spectrum. The characteristics of the laser (e.g., wavelength, pulse repetition rate) influence the sensor's range, accuracy, and eye safety.
- **Scanner and Optics:** Directs the laser pulses towards the target area and collects the reflected light.
- **Photodetector and Receiver:** Detects the returning light pulses and converts them into electrical signals. The sensitivity and response time of the detector are crucial for accuracy.
- **Positioning and Orientation Systems:** For mobile LiDAR applications or even static systems requiring precise georeferencing, a Global Positioning System (GPS) is used to determine the sensor's absolute X, Y, Z location, and an Inertial Measurement Unit (IMU) provides data on the sensor's orientation (roll, pitch, and yaw). In indoor healthcare settings where GPS signals are unreliable, alternative local positioning systems and high-precision IMUs become critical for accurate point cloud generation and registration. For instance, the Unitree L1 LiDAR, a compact 4D (3D spatial + intensity/time) sensor, incorporates an IMU with a 3-axis accelerometer and 3-axis gyroscope, supporting a push frequency of 250Hz, which is vital for its applications in robotics and potentially for dynamic healthcare monitoring scenarios. The IMU data helps to correct for any movement or vibration of the sensor platform, ensuring the geometric accuracy of the resulting point cloud.

The increasing availability of compact, relatively low-cost, and high-performance LiDAR units, such as the Unitree L1 , is a significant factor driving their adoption in new fields, including healthcare research and development. These advancements make the deployment of LiDAR systems in hospitals, clinics, or home-care environments more economically and practically viable than in the past, when LiDAR was often associated with bulky and expensive equipment [3].

2.4 Advantages of LiDAR for Healthcare Monitoring LiDAR technology presents several key advantages that make it particularly well-suited for healthcare monitoring applications, distinguishing it from other sensing modalities like cameras or wearable sensors [5].

Privacy Preservation One of the most significant benefits of LiDAR in healthcare is its inherent capacity for privacy preservation. Unlike traditional camera-based systems that capture detailed visual images, LiDAR primarily generates point clouds representing depth and spatial information. These point clouds do not typically include identifiable Red, Green, and Blue (RGB) colour data that could reveal facial features or other explicit personal details. This characteristic makes LiDAR a more suitable option for continuous monitoring in privacy-sensitive environments such as patient rooms, bathrooms, or long-term care facilities, where constant visual surveillance would be ethically problematic and poorly accepted by patients. While the 3D data can still be used to reconstruct human forms and recognise activities, the absence of explicit imagery offers a higher degree of privacy compared to video. Nevertheless, it is important to acknowledge that the "degree" of privacy is not absolute; detailed 3D models of human movement can still be perceived as intrusive if not managed with strict ethical oversight and robust data governance protocols. The focus remains on monitoring movement and posture for safety and health assessment rather than identification through visual appearance.

Accuracy LiDAR systems are renowned for their ability to provide highly precise distance measurements and generate detailed, metrically accurate 3D maps of their surroundings. This accuracy is crucial for healthcare applications such as tracking the precise movements of a patient, measuring gait parameters with high fidelity, detecting subtle changes in posture indicative of a potential fall, or accurately mapping a patient's room to identify obstacles and assess environmental safety. The direct measurement of distances via time-of-flight, independent of ambient lighting conditions, contributes to the robustness and reliability of LiDAR data.

Non-Intrusiveness LiDAR technology facilitates non-intrusive patient monitoring. Systems can be installed in the environment (e.g., mounted on walls or ceilings) to monitor individuals without requiring them to wear any sensors or devices. This contrasts sharply with wearable sensor-based approaches, which can suffer from issues such as patient non-compliance (e.g., forgetting to wear the device or finding it uncomfortable), battery life limitations, or the device itself altering the patient's natural behaviour. By being unobtrusive, LiDAR allows for the collection of more naturalistic data on a patient's activities and gait patterns over extended periods, which can be more representative of their true functional status and health condition. This is particularly beneficial for continuous monitoring of elderly individuals or patients with chronic conditions in their own homes or in care facilities.

These advantages collectively position LiDAR as a compelling technology for a new generation of healthcare monitoring systems that aim to be effective, respectful of patient dignity, and capable of providing objective, quantitative data for clinical assessment and intervention.

2.5 Eye Safety Considerations: IEC 60825-1 A critical aspect of deploying any laser-based technology, including LiDAR, in environments with human presence, especially in healthcare settings, is ensuring eye safety. LiDAR systems operate by emitting laser radiation, and exposure to this radiation can pose a risk to the human eye if not properly managed. Consequently, adherence to internationally recognised safety standards is paramount.

The primary standard governing laser safety is IEC 60825-1, "Safety of laser products – Part 1: Equipment classification and requirements" [4]. This standard classifies laser products into different hazard classes based on their potential to cause harm, particularly to the eyes and skin. The classification depends on factors such as the laser's wavelength, power output, and beam characteristics.

For healthcare applications involving continuous or proximate patient monitoring, LiDAR systems are typically designed to meet the criteria for Class 1 laser products. According to IEC 60825-1, a Class 1 laser is considered safe under all conditions of normal use. This means that the maximum permissible exposure (MPE) – the level of laser radiation to which a person may be exposed without hazardous effect or adverse biological changes in the eye or skin – cannot be exceeded when viewing the laser with the naked eye or with the aid of typical magnifying optics (e.g., telescopes or microscopes, under specified conditions).

Many commercially available LiDAR sensors intended for applications involving human interaction, such as those used in robotics or consumer devices, are engineered to comply with Class 1 eye safety standards. For example, the Unitree L1 LiDAR is specified as meeting the IEC-60825 Class 1 eye safety level. Manufacturers achieve this through careful design choices, including the use of specific laser wavelengths (often in the near-infrared spectrum, which are less hazardous at lower power levels than visible lasers), controlling the laser power output, and managing the beam divergence and scanning mechanisms to ensure that the energy density at any point accessible to a person remains below the MPE limits for Class 1.

Compliance with such eye safety standards is a non-negotiable prerequisite for the ethical and widespread deployment of LiDAR technology in healthcare environments. It ensures that patients, caregivers, and any other individuals in the vicinity of the LiDAR system are not exposed to harmful levels of laser radiation. This is particularly important for vulnerable populations, such as elderly patients or individuals with cognitive impairments, who might inadvertently look directly at sensor emissions for extended periods. Regulatory bodies and institutional review boards typically require evidence of compliance with standards like IEC 60825-1 before approving the use of such devices in clinical studies or patient care settings. Therefore, selecting LiDAR systems that are certified as Class 1 eye-safe is a fundamental step in developing and implementing responsible LiDAR-based healthcare solutions.

3 Real-Time Healthcare Monitoring Using LiDAR

The capacity of LiDAR to provide accurate, non-intrusive, and privacy-conscious spatial data has catalysed its exploration in various real-time healthcare monitoring scenarios. From enhancing the safety and independence of elderly individuals in Ambient Assisted Living (AAL) environments to enabling sophisticated patient activity recognition and critical fall detection, LiDAR offers a powerful alternative or complement to traditional monitoring methods [6]. This section will examine these applications, detailing the techniques employed, the challenges encountered, and the software tools that facilitate the acquisition, processing, and visualisation of LiDAR data in healthcare contexts.

3.1 Applications in Ambient Assisted Living (AAL) Ambient Assisted Living (AAL) aims to create intelligent environments that support the daily lives, health, and safety of individuals, particularly older adults or those with chronic conditions, enabling them to live independently for longer. LiDAR technology is emerging as a significant enabler for AAL due to its ability to perform non-invasive and continuous monitoring [7]. The global demographic trend towards an ageing population, coupled with a shrinking workforce available for direct care, underscores the urgent need for technological solutions that can alleviate the burden on caregivers and traditional healthcare systems. LiDAR-based systems can contribute to this by automating aspects of observation and safety assurance within the home or care facility.

Key AAL applications of LiDAR include:

- **Activity Recognition:** Monitoring and identifying Activities of Daily Living (ADLs) such as walking, sitting, standing, sleeping, and potentially more complex behaviours like cooking or cleaning. Deviations from established routines can signal potential health issues or a decline in functional ability.
- **Gait Analysis:** Continuously assessing gait parameters to detect subtle changes that might indicate an increased risk of falls, the progression of a neurological condition, or the effectiveness of a rehabilitation programme.
- **Fall Detection:** Providing a reliable means of detecting falls, especially in unwitnessed situations, allowing for timely alerts to caregivers or emergency services. This is crucial as falls are a major cause of morbidity and mortality in older adults.
- **Occupancy Monitoring and Social Interaction:** Tracking the presence and movement of individuals within a space, which can be used to understand social engagement patterns or to ensure safety (e.g., detecting if a person has wandered off).
- **Environmental Mapping and Obstacle Detection:** Creating 3D maps of the living environment to identify potential hazards (e.g., clutter, poorly placed furniture) that could increase fall risk.

The non-intrusive nature of LiDAR is particularly advantageous in AAL, as it respects the privacy and dignity of individuals in their personal living spaces, a factor that often limits the acceptability of camera-based monitoring. By providing objective data on physical function and behaviour, LiDAR-powered AAL systems can support personalised care, enable early detection of health problems, and ultimately enhance the quality of life and safety for vulnerable individuals.

3.2 Patient Activity Recognition: Techniques and Challenges Recognising patient activities in real-time is a cornerstone of proactive healthcare monitoring, enabling early detection of adverse events, assessment of functional status, and understanding behavioural patterns. LiDAR data, with its rich 3D spatial information, provides a robust basis for developing sophisticated activity recognition systems.

Techniques for LiDAR-based Human Activity Recognition (HAR) often involve several stages. Initially, the raw point cloud data is processed to segment and track individuals within the monitored environment. This may involve background subtraction to isolate moving objects, followed by clustering algorithms to group points belonging to each person. Once individuals are tracked, their posture, movement trajectories, and interactions with the environment can be analysed to infer activities. Some approaches convert the 3D point cloud data, or specific features derived from it (like intensity or reflectivity), into 2D image-like representations (e.g., bird's-eye view projections, intensity images) that can then be processed using established 2D Convolutional Neural Network (CNN) architectures. Alternatively, and increasingly, methods that directly process 3D point clouds using specialised deep learning architectures like PointNet or its variants are being employed to learn features indicative of different activities.

These models can capture complex geometric relationships and motion patterns directly from the 3D data.

- **Data Volume and Complexity:** LiDAR sensors can generate large volumes of point cloud data, especially 3D systems operating at high frame rates. Processing this data in real-time for activity recognition requires efficient algorithms and significant computational resources.
- **Annotation Scarcity:** Training supervised deep learning models for HAR requires large, accurately annotated datasets where specific activities are labelled in the LiDAR data. Creating such datasets is time-consuming, expensive, and requires domain expertise. The lack of diverse, publicly available LiDAR HAR datasets remains a significant bottleneck for research and development.
- **Segmentation and Tracking in Dynamic Environments:** Accurately segmenting individuals from the background and tracking them robustly, especially in cluttered or multi-occupant scenarios, can be challenging. Occlusions, similar appearances, and complex interactions can lead to tracking errors, which in turn affect activity recognition accuracy.
- **Nuance and Variability of Human Activities:** Human activities are inherently complex, variable, and context-dependent. Distinguishing between subtle variations of an activity or recognising novel activities not seen during training poses a considerable challenge for current models. Moving beyond simple posture detection (e.g., sitting, standing, walking) to understanding more nuanced interactions or abnormal behaviours requires more sophisticated reasoning capabilities.

Addressing these challenges is crucial for advancing the field of LiDAR-based HAR. Current research focuses on developing more efficient point cloud processing techniques, exploring unsupervised or semi-supervised learning methods to reduce reliance on labelled data, and designing more robust tracking and activity modelling algorithms.

Deep Learning Approaches (e.g., YOLOv5 for human detection) Deep learning has become a dominant approach for analysing LiDAR data in HAR, owing to its ability to automatically learn salient features from complex, high-dimensional inputs. A foundational step in many HAR systems is the accurate detection and tracking of humans within the LiDAR point cloud. Models like YOLOv5 (You Only Look Once version 5) [8], primarily known for object detection in 2D images, have been adapted for use with LiDAR data. This adaptation often involves transforming the 3D LiDAR data into a 2D representation, such as a bird's-eye view projection or an intensity/reflectivity map, which can then be fed into the YOLOv5 architecture. By training YOLOv5 on such LiDAR-derived images, it can learn to detect and localise humans in real-time.

Transfer learning is a particularly valuable strategy in this context, especially given the scarcity of large-scale labelled LiDAR datasets for human detection. By starting with a YOLOv5 model pre-trained on extensive 2D image datasets (like COCO), and then fine-tuning it on a smaller, specific LiDAR dataset, researchers can leverage the powerful feature extraction capabilities learned from the source domain. This approach can significantly reduce the amount of LiDAR-specific training data required and accelerate the development of accurate human detection models.

Beyond 2D adaptations, deep learning architectures designed to directly consume 3D point clouds, such as PointNet [9] and its derivatives (e.g., PointNet++ [10]), offer another avenue for HAR. PointNet can process raw point clouds to classify objects or segment scenes, making it applicable for identifying human presence or segmenting body parts for posture estimation and activity recognition. These models respect the permutation invariance of point sets and can learn local and global features directly from the 3D geometry, potentially capturing more nuanced information than 2D projections. The features learned by these networks can then be fed into temporal models like LSTMs or Transformers to recognise sequences of activities. The choice between 2D projection-based methods and direct 3D point cloud processing often involves a trade-off between computational efficiency and the richness of spatial information retained.

3.3 Fall Detection Systems: Algorithms and Performance Fall detection is one of the most critical applications of LiDAR in healthcare, particularly for elderly care and AAL [11]. Falls are a leading cause of injury and mortality among older adults, and rapid detection can significantly improve outcomes by ensuring timely assistance. LiDAR's ability to accurately capture 3D posture and movement without compromising privacy makes it an excellent candidate for robust fall detection systems. These systems can be particularly beneficial in private spaces like bathrooms, where camera-based monitoring is often unacceptable and where fall risks are high.

Algorithms for LiDAR-based fall detection typically work by monitoring the point cloud data for patterns indicative of a fall. This often involves:

- **Human Detection and Tracking:** Continuously identifying and tracking the person(s) within the LiDAR's field of view.
- **Posture Estimation:** Analysing the shape, height, and orientation of the point cloud cluster representing the person to estimate their posture (e.g., standing, sitting, lying). A sudden transition to a lying posture, especially if accompanied by a rapid change in vertical position, is a key indicator of a fall.
- **Motion Analysis:** Examining the velocity and acceleration derived from the tracked human's position. High downward velocity followed by a period of inactivity on the ground is characteristic of a fall.
- **Environmental Context:** Some advanced systems may incorporate information about the environment (e.g., proximity to furniture, floor level) to improve detection accuracy and reduce false alarms.

Many systems accumulate LiDAR points over short time windows (frames) and then analyse changes in the detected person's state across these frames. To enhance privacy and reduce communication latency, particularly for in-home systems, there is a trend towards edge-based processing. This involves using specialised hardware like Neural Processing Units (NPUs) integrated with the LiDAR sensor or a local hub to perform the fall detection computation locally, rather than sending raw point cloud data to the cloud. Such an approach ensures that potentially sensitive spatial data remains within the user's premises, and alerts can be generated more quickly.

The performance of fall detection systems is typically evaluated using metrics such as:

- **Sensitivity (Recall):** The proportion of actual falls that are correctly detected.
- **Specificity:** The proportion of non-fall events that are correctly identified as non-falls.
- **Accuracy:** The overall proportion of correct classifications (both falls and non-falls).
- **Precision:** The proportion of detected falls that are actual falls.
- **False Positive Rate (False Alarm Rate):** The proportion of non-fall events incorrectly identified as falls.
- **False Negative Rate:** The proportion of actual falls that are missed by the system.

A significant challenge in fall detection is accurately distinguishing genuine falls from other normal daily activities that might involve rapid movements or lying down, such as quickly sitting on a low chair, kneeling, or lying down on a bed or floor intentionally. Minimising false alarms is crucial for user acceptance and to prevent caregiver fatigue.

4 Conclusion

Research is ongoing to develop more sophisticated algorithms, often incorporating machine learning and deep learning, to improve the robustness and reliability of LiDAR-based fall detection across diverse individuals, activities, and environments. The use of multi-sensor datasets, including low-cost 8x8 LiDAR, is also being explored to create and evaluate advanced fall detection algorithms, with metrics like the instantaneous norm of the signal and temporal differences between frames showing promise in distinguishing fall and non-fall events.

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