ARTIFICIAL INTELLIGENCE DEVELOPMENT IN SENSORS AND COMPUTER VISION FOR HEALTH CARE AND AUTOMATION APPLICATION

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Artificial Intelligence Development in Sensors and Computer Vision for Health Care and Automation Application

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FOREWORD

The book titled " Artificial Intelligence Development in Sensors and Computer Vision for Health Care and Automation Application" is an essential resource for anyone who wants a thorough understanding of the significant impact of artificial intelligence (AI) in electronics, specifically in sensor technology, computer vision, and machine learning. It provides comprehensive insights into the transformative role of AI in these areas, making it a valuable asset in the rapidly evolving area of AI. I wholeheartedly recommend this book for its insightful exploration of cutting-edge technologies and their applications.

In this well-organized research, Dr. Minh Long Hoang successfully leads readers through an illuminating exploration that encompasses subjects ranging from inertial measurement unit (IMU) sensors to light detection and ranging (lidar) and radio detection and ranging (radar). Through the lens of machine learning models, the author demonstrates how IMU data can be utilized for diverse purposes, such as process optimization, risk prevention, fault diagnosis, and human activity recognition. The integration of lidar and radar sensors into self-driving cars and AI robotic systems adds an extra layer of depth to the discussion, providing real-world examples of how these technologies are reshaping our future.

Moreover, the exploration of computer vision is equally captivating, focusing on image recognition, motion tracking, and object classification. The book also introduces robust AI algorithms like convolutional neural networks (CNN) and you only look once (YOLO), showcasing their applications in healthcare and automated vehicle control. Additionally, the book sheds light on the role of deep learning in human pose estimation (HPE) for rehabilitation support and also examines the uncertainty of deep neural network (DNN) predictions, particularly in IMU data.

The concluding chapter seamlessly ties together the comprehension gained from the earlier discussions, exploring the incorporation of machine learning into augmented reality (AR) within the automotive industry. It highlights the significant potential of AI in enhancing the design process, manufacturing, and customer experience in the automotive sector.

Overall, this book is highly recommended for professionals, researchers, and students seeking a comprehensive and up-to-date knowledge of the symbiotic relationship between AI, sensors, and computer vision. The book not only demystifies complex concepts but also inspires readers to explore the limitless possibilities that arise at the intersection of these transformative technologies.

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PREFACE

Nowadays, artificial intelligence is playing an essential role in electronics, which demands potential innovations to enhance the performance and quality of digital applications. This book focuses on sensor technology and computer vision, where machine learning (ML) and deep learning (DL) are able to utilize input data and images for prediction, classification, and data visualization.

The initial chapters discuss the indepth research on data utilization in AI from various sensors, especially IMU (Inertial Measurement Unit), light detection and ranging (lidar), and radio detection and ranging (radar). IMU sensor is a common and powerful sensor providing motion data from accelerometers, gyroscopes, and magnetometers. With MEMS (Micro-electromechanical Systems) technology, the IMU sensors are compacted in a small size, with lower power consumption and high-quality factors. ML models handle these IMU data for process optimization, risk prevention, product improvement, fault diagnosis, human activity recognition, and automation. Furthermore, IMU data can be combined with Lidar and radar sensors to detect objects and navigate their surroundings in self-driving cars and AI robotic systems to avoid obstacles or pick up the demanded items. In addition, reinforcement learning algorithms play an important role in self-driving robots, together with simultaneous localization and mapping (SLAM) technology for high-resolution 3D maps of the environment.

On the other hand, computer vision has been developed for image recognition, motion tracking, and object classification. Many electronic devices can implement robust AI algorithms, such as convolutional neural networks (CNN), you only look once (YOLO), *etc.*, to support healthcare and automated vehicle control. Moreover, deep learning also provides solutions for human pose estimation (HPE), which evaluates human posture to support people in rehabilitation.

After deep analysis and research on classification and computer vision, ML regression can be taken into account in terms of prediction uncertainty. The aim is to examine the uncertainty of deep neural network (DNN) prediction, specifically in MEMS IMU data in this case. From this study, we are able to have a profound view of ML applications for high-technology sensors.

The last chapter discusses the incorporation of ML into augmented reality (AR) in the automotive industry. AR adopts the existing real-world environment and transfers virtual information to the top, practically enhancing the car industry in terms of the design process, manufacturing, and customer experience. The techniques discussed in previous chapters will be linked to this part *via* AI applications in AR, such as object recognition, SLAM, HPE, gesture recognition, and DL models.

Based on the above contents, this book includes the following chapters:

1. Current State, Challenges, and Data Processing of AI in Sensors and Computer Vision.
2. Human Activity Recognition and Health Monitoring by Machine Learning Based on IMU Sensors
3. Reinforcement Learning in Robot Automation by Q-learning.
4. Deep Learning Techniques for Visual Simultaneous Localization and Mapping Optimization in Autonomous Robot

5. Deep Learning in Object Detection for the Autonomous Car
6. Human Pose Estimation for Rehabilitation by Computer Vision
7. Prediction Uncertainty of Deep Neural Network in Orientation Angles from IMU Sensors
8. Machine Learning in Augmentation Reality for Automotive Industry.

This book depicts the input data processing, AI model structure, training process, model test/validation, and final performance of the whole system in use. After reading this book, readers will comprehend the working principles, pros, and cons of AI technology in the highly trending topics of the scientific field.

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CHAPTER 1

Current State, Challenges, and Data Processing of AI in Sensors and Computer Vision

Abstract: The first chapter of the book explores the transformative applications of artificial intelligence (AI) in sensor technology and computer vision, focusing on human activity recognition, health monitoring, medical imaging, and autonomous vehicles within the automotive industry. It highlights the substantial advancements AI brings to these fields, particularly emphasizing the roles of machine learning (ML) and deep learning (DL), a subset of ML. In the field of human activity recognition and health monitoring, AI's ability to enhance accuracy and efficiency is thoroughly examined. The discussion extends to medical imaging, where ML and DL techniques significantly improve diagnostic processes and patient outcomes. The chapter also delves into the automotive industry, showcasing AI's impact on enabling self-driving cars and optimizing manufacturing processes. Each section provides detailed insights into the potential capabilities of ML and DL, illustrating AI's role as a game-changer that revolutionizes traditional methods. The narrative underscores the transformative power of these technologies, driving innovation and creating new opportunities across various domains. Additionally, the chapter addresses the challenges faced in the construction and operation of ML models. It analyzes difficulties such as data quality issues, computational resource demands, and algorithmic training complexities, offering a balanced perspective on the promises and hurdles of AI deployment. The chapter concludes with an in-depth discussion on sensor data collection and processing and case studies to demonstrate AI applications in real life. This section covers methodologies for gathering high-quality sensor data, pre-processing techniques, and integrating this data into AI frameworks, setting the stage for understanding AI's profound impact and technical intricacies.

Keywords: AI, Computer vision, Machine learning, Sensors.

INTRODUCTION

Recently, the integration of AI [1 - 4] with sensors has completely changed the potential of many industries. Sensors collect massive volumes of physical world data, and AI algorithms can process this data to derive insightful conclusions and make prompt judgments. For instance, in the manufacturing industry, sensors and AI might provide predictive maintenance by spotting irregularities in the behavior of the machinery and foreseeing probable failures.

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Computer vision [5, 6] is a subfield of AI that is primarily concerned with endowing machines with the capacity to analyze and understand visual information derived from their surroundings. This technology has found utility in various industries, including healthcare (specifically in medical image analysis), automotive (particularly in the development of autonomous vehicles), retail (specifically in the establishment of cashier-less stores), agriculture (specifically in crop monitoring), and other sectors. AI-enabled computer vision algorithms have the capability to discern objects, patterns, and contextual information inside images and videos.

ML IN HUMAN ACTIVITY RECOGNITION AND HEALTH MONITORING

The potential for ML applications in human activity identification [6, 7] to reveal information about a person's behavior, health, and well-being has given these applications much relevance. ML and DL [8, 9] are essential for recognizing human activities for the following reasons:

• Accuracy and Precision: ML and DL algorithms can recognize various human behaviors with high degrees of accuracy. Since they can distinguish between various activities that have comparable sensor signals, identification is more accurate and dependable.

• Human actions can be complicated and entail many phases or variants. These complex patterns may be recognized by ML algorithms, which can then adjust to various activity circumstances.

• Real-Time Monitoring: Systems that can recognize ML activities may analyze data in real time, enabling quick feedback and action. Applications, including sports training, rehabilitation, and emergency response, can all benefit from this.

• Customization: ML algorithms may be trained to detect user-specific activity patterns, personalizing and adapting the recognition process to each user's requirements and habits.

• Health and Well-being: Wearable technology and smartphones with activity detection capabilities may track daily activities, workout regimens, sleep habits, and more. People can use this information to guide better lifestyle decisions and enhance their general well-being.

• Care for the Elderly: ML-based activity recognition is necessary for remote supervision of older people who live alone. Caregivers and family members can ensure seniors' safety by being informed of any odd or possibly hazardous actions.

• Fall Detection: It is essential for the care of older people that ML algorithms be able to identify the patterns connected to falls. Early diagnosis of falls can result in quicker medical intervention and better results.

• Physical Rehabilitation: Activity identification and DL coupled can assist patients in recuperating from accidents or operations and create individualized rehabilitation regimens. It guarantees that workouts are carried out correctly and track progress. The Human Pose Estimation [10] technique has been used widely in rehabilitation to monitor whether the patient moves correctly.

• Safety at Work: ML-powered activity recognition can track employees' movements and behaviors in commercial settings to spot possible risks and avert mishaps.

• Sports and fitness: ML-based activity detection is helpful in tracking fitness and training in sports. Athletes may get feedback on their performance, monitor their development, and make data-driven adjustments.

Overall, ML applications in human activity identification offer a wide variety of advantages, from strengthening many sectors and research domains to improving personal health and safety. The capability to identify human activity reliably and effectively has the potential to change how we engage with technology, keep track of our actions, and enhance our general quality of life.

In wearable technology, ML and DL have ushered in a new era of innovation. These cutting-edge techniques are crucial in transforming straightforward wearables into intelligent companions that adapt to our wants, monitor our health, and improve our general well-being as technology integrates seamlessly into every aspect of our lives. ML is unlocking the potential for wearables to track physical activity, predict health outcomes, offer individualized recommendations, and enable new levels of user interaction and engagement. These technologies have the capability to efficiently process and interpret extensive quantities of data that are gathered by sensors that are integrated within these devices. The integration of wearable technologies and advanced artificial intelligence is revolutionizing our interactions with the surrounding environment.

ML IN AUTONOMOUS VEHICLES

The automobile industry is seeing a sharp increase in demand for AI-powered computer vision systems. Autonomous cars rely on cameras and sensors to navigate, understand their environment, and make split-second decisions. These systems require real-time detection of pedestrians, other cars, traffic signs, and ba-

CHAPTER 2

Human Activity Recognition and Health Monitoring by Machine Learning Based on IMU Sensors

Abstract: The study of human activity recognition (HAR) holds significant importance within wearable technology and ubiquitous computing, driven by the increasing ubiquity of inertial measurement unit (IMU) sensors embedded in devices like smartphones, smartwatches, and fitness trackers. The effective classification and recognition of human actions are crucial for various applications, including health monitoring, fitness tracking, and personalized user experiences. This study comprehensively examines the advancements in HAR by applying machine learning (ML) methodologies to data collected from IMU sensors. We explore seven powerful ML algorithms that have been pivotal in transforming raw sensor data into actionable insights for activity classification. These algorithms include decision trees, random forests, support vector machines (SVM), k-nearest neighbors (KNN), artificial neural networks (ANN), convolutional neural networks (CNN), and long short-term memory networks (LSTM). Each algorithm is assessed based on its ability to accurately process and classify various human activities, highlighting their strengths and limitations in different scenarios. Moreover, the study delves into the critical role of evaluation metrics and the confusion matrix in validating the performance of these ML models. Metrics such as accuracy, precision, recall, F1 score, and specificity are examined to provide a holistic view of the model's efficacy. The confusion matrix is emphasized as a tool for understanding the true positive, false positive, true negative, and false negative rates, offering insights into the practical performance of the models in real-world applications. Through this detailed investigation, we aim to shed light on the current state of HAR and the potential future directions for research and development in this dynamic field.

Keywords: Machine learning, Human activity recognition, IMU sensors.

INTRODUCTION

The introduction of wearable technology, and more specifically, the incorporation of inertial measurement unit (IMU) sensors [1 - 3], has ushered in a new era in health monitoring. These high-tech sensors have become indispensable additions to wearable gadgets that are able to monitor and understand human motion in all its forms. They often include accelerometers, gyroscopes, and magnetometers.

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Wearables with inertial measurement units have been essential in delivering real-time information regarding physical activities and their effect on individual users, carers, and healthcare professionals.

The capacity to track and evaluate exercise is crucial in an age when chronic illnesses and sedentary lifestyles present major health issues. IMU sensors concealed inside wearable devices have successfully recorded fine-grained information about motion [4, 5]. Magnetometers [6, 7] offer context by sensing the Earth's magnetic field, whereas accelerometers measure and quantify linear acceleration [8, 9]. A gyroscope provides angular velocities of the concerned object [10, 11]. These three sensors work together to provide complete data of a person's motion, which improves recognition and categorization.

The use of IMU technology for human activity identification has significant implications for fitness and wellness tracking. Wearable technology provides unique insights into one's activity and lifestyle by analyzing subtle movements like walking, running, stair climbing, and even complicated ones like yoga postures. People can keep tabs on their fitness progress using this data-driven method, and doctors may create individualized plans to help patients with chronic diseases. Also, by incorporating IMU sensors into health monitoring wearables, abnormalities in activity levels that may indicate a change in health state may be spotted before they become serious [12].

More than just collecting data, integrating IMU sensors into health monitoring requires cutting-edge data processing methods and ML algorithms [13 - 20]. Wearables produce massive amounts of motion data, and it is difficult to derive valuable insights from this raw data. Extraction of useful metrics like step counts, distance walked, energy consumption, and posture evaluation is made possible by signal processing techniques combined with sophisticated algorithms. By converting these measures into objective health indicators, we may better understand the relationship between one's exercise routine and health.

This study shows how the ML model can be implemented to track human activity like sitting, walking, sleeping, *etc.*, based on acceleration, angular velocities, and magnetic field. The IMU data is captured by the wearable device and then sent to the ML models *via* the MQTT broker using Wi-Fi connectivity with the assistance of the Internet of Things (IoT) technology [21]. Subsequently, ML predictions are sent to the IoT dashboards, enabling family members or medical professionals to monitor health data, as illustrated in Fig. (**1**).

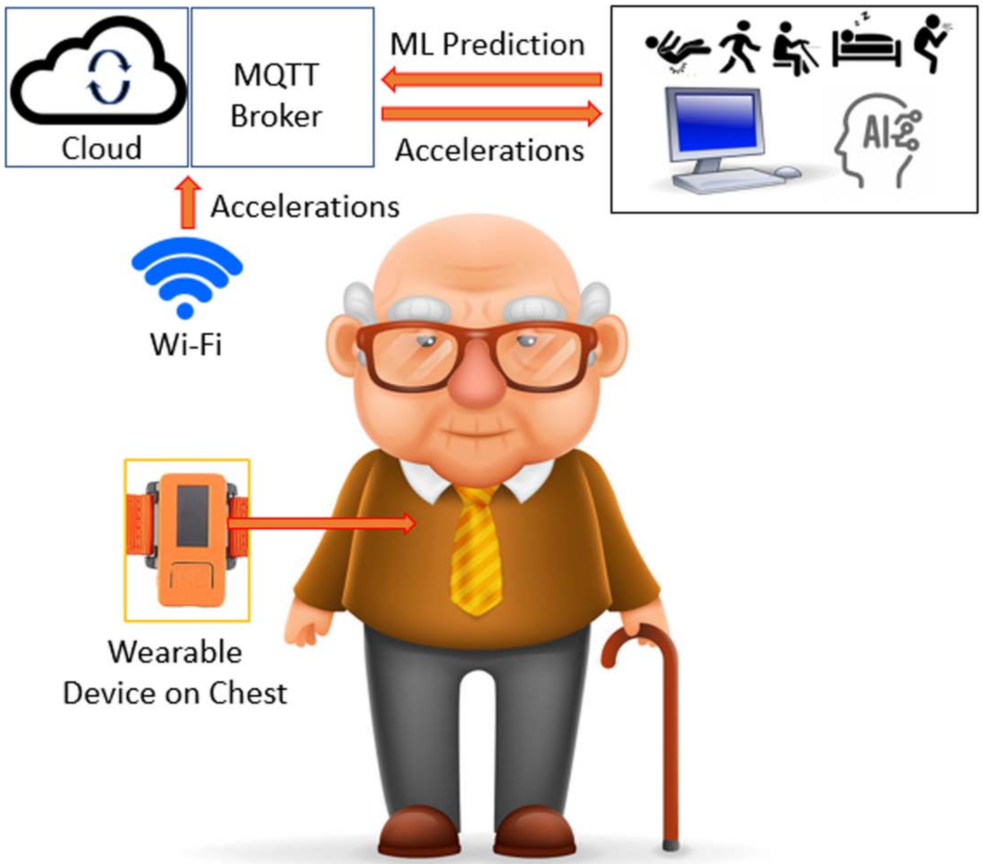

Fig. (1). Working operation.

DATA ACQUISITION AND INPUT FEATURES

The IMU sensor is embedded into a wearable device on the chest or arm. Each motion leads to a variation of sensor data, which is fed into the training process of the ML model.

The triaxial accelerometer (Xacc, Yacc, Zacc), triaxial gyroscope (Xω, Yω, Zω), and triaxial magnetometer (Xm, Ym, Zm) data are acquired and saved to the text file for training. Each sensor includes data from the Xaxis, Yaxis, and Zaxis. Therefore, there are mainly about 12 ML model input features, as shown in Table **1**. The input number can vary for each research study. It is also possible to use only an accelerometer without a gyroscope or magnetometer in various applications. In addition, from these data, other features may be calculated to generate new feature input, such as the acceleration normalization:

CHAPTER 3

Reinforcement Learning in Robot Automation by Q-learning

Abstract: This chapter demonstrates the pivotal role of reinforcement learning (RL), specifically employing the Q-learning algorithm, in enhancing the capabilities of autonomous mobile robots (AMRs) for transportation tasks. The focus is on enabling the robot to learn and execute two critical tasks autonomously. The first task involves the robot learning the optimal path to transport an object from its current location to a specified destination. The second task requires the robot to adeptly avoid obstacles encountered along the way, ensuring safe and efficient navigation. The robot is equipped with advanced sensors, including light detection and ranging (Lidar) and inertial measurement unit (IMU) sensors, to accomplish these tasks. The Lidar sensor provides detailed scanning of the surrounding environment, allowing the robot to detect and map obstacles, while the IMU sensors aid in precise positioning and movement tracking. These sensory inputs are crucial for the robot to understand its environment and make informed decisions accurately. The chapter elucidates the working principles of the Q-learning algorithm, a model-free RL technique that enables the robot to learn optimal actions through trial-and-error interactions with its environment. The training process involves the robot being rewarded for successful task completion and penalized for undesirable actions, gradually refining its policy to maximize cumulative rewards. Through detailed explanations and practical demonstrations, this research showcases how Q-learning facilitates the robot's learning process, enabling it to master the tasks of path planning and obstacle avoidance. The insights gained from this study highlight the potential of RL in advancing the autonomy and efficiency of mobile robots in transportation and other applications, paving the way for further innovations in the field.

Keywords: Autonomous mobile robot, Q-learning, Reinforcement learning.

INTRODUCTION

In the field of autonomous mobile robots [1 - 3], it has always been a challenge to make smart systems that can move through complicated environments, avoid obstacles, and achieve the goal. The integration of Q-learning [4, 5], a robust algorithm of reinforcement learning method, with advanced sensor technologies like LiDAR and IMU, is one of the most promising solutions that has come up in recent years. This combination of AI and sensor data allows autonomous mobile

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robots to learn, adapt, and make smart choices in real time. This lets them move through complex situations, avoid obstacles, and complete mission-critical tasks.

As a subset of reinforcement learning, Q-learning is a good way to teach self-driving mobile robots how to act best by learning how they interact with their surroundings. In this case, the robot's environment is the physical place it works in and the data it gets from its LiDAR and IMU sensors about what it sees and hears. LiDAR sensors provide a precise, high-resolution 3D map of the environment with the SLAM (Simultaneous Localization and Mapping) technique [6 - 10], which lets the robot know where items and obstacles are in space. At the same time, IMU sensors give important information about the robot's direction, speed, and acceleration, which makes it easier to control and plan its movements.

Besides Q-learning, there are other reinforcement learning techniques. Policy gradient [11] methods, such as reinforcement, directly parameterize and optimize the policy using gradient ascent. These methods are advantageous in continuous action spaces, making them well-suited for tasks like robotic control requiring precise movements. Q-learning evaluates and improves the policy indirectly, while policy gradient methods offer a more direct approach, potentially leading to faster convergence in complex environments. In addition, actor-criticism algorithms [12] combine the benefits of both Q-learning and policy gradient methods by maintaining two separate models: the actor (policy) and the critic (value function). The actor updates the policy based on feedback from the critic, which evaluates the action taken by the actor. This synergy allows actor-critic methods to balance exploration and exploitation effectively, making them highly effective in dynamic and uncertain robotic environments.

Nevertheless, Q-learning has its own pros over other reinforcement learning (RL) in robot automation. Q-learning is straightforward and requires less computational resources than more complex RL techniques. This simplicity makes it an attractive choice for robotic applications where computational power may be limited or where quick deployment is needed. This method is a model-free algorithm, meaning it does not require a model of the environment's dynamics. This point is beneficial in robotic automation, where environmental modeling can be complex or infeasible. Q-learning is capable of acquiring knowledge directly from interactions with the environment, which allows it to be flexible and suitable for a wide range of robotic activities. As an off-policy algorithm, Q-learning can learn the optimal policy independently of the robot's actions during training, allowing it to use data from exploratory actions more effectively and helps in environments where it is necessary to explore different actions to discover the best strategies.

Additionally, Q-learning is particularly effective for tasks with discrete action spaces, such as grid-based navigation or simple manipulation tasks. Robots operating in environments where the actions can be discretized benefit from Q-learning's straightforward approach to learning optimal policies without the complexities involved in continuous action spaces. Moreover, Q-learning's theoretical foundation provides guarantees of convergence to the optimal policy, giving sufficient exploration and appropriate learning rate decay. This robustness is valuable in robot automation, where the reliability and stability of the learning algorithm are crucial for consistent performance.

Combining Q-learning with advanced sensing technology makes it possible for mobile robots to improve themselves independently. Robots can try different paths, determine the results of their actions, and learn from their mistakes to make good decisions in the real world. Such systems can teach not only how to get to predetermined places but also how to get there in the safest and most efficient way possible by changing their behavior as the environment changes. This chapter will examine the integration process that enables robots to acquire the capacity to navigate toward desired destinations while effectively avoiding impediments encountered along their trajectory. In this exploration, we will examine the fundamental principles underlying Q-Learning, the importance of LiDAR and IMU sensors, and the practical implications of this technology in contemporary robotics. The research provides a better idea of how Q-Learning makes it possible for independent mobile robots to navigate the world around them with accuracy and flexibility.

This chapter is organized as follows: the first part is about the Q-learning description. The next part depicts the actual learning process of the robot to reach the desired goal in a mapping location and avoid the obstacle on that path by Q-learning. Finally, the overview and conclusion are discussed in the last part.

Q-LEARNING WORKING PRINCIPLE

Q-learning is an algorithm that operates model-free, relying solely on observed data rather than explicit knowledge of the environment. It is a value-based approach, meaning that it estimates the value of each state-action pair based on the expected cumulative reward. Furthermore, Q-learning is an off-policy method, as it updates its value estimates using the maximum value of the next state-action pair, regardless of the policy being followed. By iteratively updating the Q-values, Q-learning aims to determine the optimal sequence of actions to be taken by an agent given its present state. The letter “Q” is an abbreviation that represents the term “quality”. The concept of quality pertains to the extent of value an activity possesses in optimizing future benefits.

CHAPTER 4

Deep Learning Techniques for Visual Simultaneous Localization and Mapping Optimization in Autonomous Robots

Abstract: In the previous chapter, we explored the application of reinforcement learning to autonomous robots, focusing on the indoor maps constructed using the Simultaneous Localization and Mapping (SLAM) technique. Visual SLAM (VSLAM) is highlighted as a cost-effective SLAM system that leverages 3D vision to execute location and mapping functions without limitations on distance detection range. VSLAM can also incorporate inertial measurement unit (IMU) measurements to enhance the accuracy of the device's pose estimation, particularly in scenarios where visual data alone is insufficient, such as during rapid movements or temporary visual obstructions. This chapter shifts the focus to integrating deep learning (DL) with VSLAM to boost its accuracy and performance. DL can significantly enhance VSLAM by providing semantic understanding, object detection, and loop closure detection, improving the system's overall situational awareness. We delve into six DL models that are pivotal in advancing VSLAM capabilities: Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Neural Networks (NNs), Graph Convolutional Networks (GCNs), Message Passing Neural Networks (MPNNs), and Graph Isomorphism Networks (GINs). Each of these models offers unique advantages for VSLAM. CNNs are adept at processing visual information and extracting spatial features, while LSTMs excel in handling temporal dependencies, making them suitable for dynamic environments. NNs provide a flexible framework for various learning tasks, and GCNs effectively capture spatial relationships in graph-structured data. MPNNs and GINs enhance the ability to process and analyze complex graph-based data, improving the robot's understanding of its environment. This chapter provides a comprehensive overview of how these DL models can be integrated with VSLAM to achieve more robust and efficient autonomous navigation. Through detailed explanations and practical examples, we illustrate the potential of combining DL with VSLAM to advance the field of autonomous robotics.

Keywords: Autonomous robot, Convolutional neural network, Graph convolutional network, Graph isomorphism network, Long short-term memory network, Message passing neural networks, Neural networks, VSLAM.

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INTRODUCTION

Visual simultaneous localization and mapping (VSLAM) [1 - 4] is a cutting-edge technology in the robot sector, which is the process of determining the position and orientation of a camera relative to its environs while simultaneously mapping the environment. VSLAM relies primarily on cameras, but it can also integrate additional sensors, such as IMUs or LIDAR, for enhanced accuracy and robustness. Cameras provide visual data that can be utilized to create a 3D model of the environment. DL techniques have been integrated into various aspects of VSLAM to improve its robustness and performance [5, 6]. The DL can support VSLAM to operate more reliably and effectively in a wide range of real-world scenarios. It enables robots to navigate and interact with their surroundings with a high degree of accuracy and autonomy. Chapter 6 describes six DL methods that are effectively utilized in VSLAM to enhance its function. These are convolutional neural networks (CNN) [7 - 9], long short-term memory (LSTM) [10, 11], neural networks [12], graph neural networks (GNN) [13, 14], message passing neural networks (MPNN) [15, 16] and graph isomorphism network (GIN) [17 - 19]. The architecture of these techniques will be demonstrated along with their essential roles in VSLAM [20].

CNN serves as the fundamental framework for several computer vision tasks within the domain of VSLAM. Deep learning models have a high level of proficiency in extracting features from visual input, hence facilitating the ability of robots to detect and identify objects, landmarks, and structures present in their environment. CNN is important in feature recognition and matching since it contributes significantly to achieving accurate localization and mapping.

LSTM is a specific kind of recurrent neural network (RNN) that demonstrates exceptional proficiency in the realm of sequential data processing. LSTM models are employed in visual simultaneous localization and mapping (VSLAM) to make predictions and monitor the robot's or camera's movement and orientation over a certain period. The comprehension of temporal aspects is of utmost importance in order to ensure precise localization while the system navigates its surroundings.

Neural networks in VSLAM encompass a wide range of architectures beyond CNNs and LSTMs. These networks may be utilized for various tasks, such as semantic segmentation, object detection, and loop closure detection. These visual data interpretations enhance the system's situational awareness by offering a more comprehensive comprehension of the information.

GNNs refer to a specific category of neural networks that have been designed to handle data formatted in the form of graphs effectively. This unique architecture makes GNNs particularly well-suited for capturing and representing the spatial connections between various entities and points of interest within a given environment. In VSLAM, GNNs are employed to improve the accuracy of the map and strengthen the alignment of features by including the geometric and topological characteristics of the environment.

Graph convolutional network (GCN) is a type of GNN used to process and understand data with graph-like structures. These networks can aid in loop closure detection by considering the graph's topological structure and identifying when a previously observed place is revisited.

MPNN refers to a distinct category of GNNs that have been specifically developed to facilitate the process of message transmission and information aggregation across nodes within a graph. Within the domain of VSLAM, MPNN plays a crucial role in enabling effective communication among various map components, including features, landmarks, and camera postures. This form of communication facilitates the process of enhancing the map and increasing the precision of localization.

GIN is a neural network architecture specifically designed to solve the graph isomorphism problem. GINs are a specific type of GNNs that have been designed and optimized to perform graph isomorphism tasks. In the context of VSLAM, GINs may be employed to detect loop closures and recognize previously visited areas within the map. This utilization enhances the system's capability to uphold a coherent and precise representation of the surrounding environment.

The utilization of neural network paradigms serves as the fundamental basis for contemporary VSLAM systems [20], facilitating the navigation, localization, and construction of detailed maps of the environment by robots and autonomous vehicles. The combination of deep learning with robotics demonstrates the collaborative potential of these two domains, resulting in significant progress in the areas of autonomous navigation and spatial comprehension.

Chapter 6 is organized as follows: the first part is about VSLAM architecture and the traditional methods for pose estimation. In the next part, CNN, LSTM, neural networks, GCN, MPNN, and GIN will be depicted, together with their advantages in VSLAM. The last part is the conclusion, which summarizes this chapter.

VSLAM ARCHITECTURE

VSLAM contains 5 main stages: Sensor data, visual odometry, backend optimization, loop closure, and map reconstruction, as shown in Fig. (**1**).

CHAPTER 5

Deep Learning in Object Detection for the Autonomous Car

Abstract: This chapter explores the practical application of artificial intelligence (AI) techniques in self-driving cars, mainly focusing on object recognition. Deep learning has emerged as a powerful tool for object detection, playing a crucial role in processing data from lidar, radar, and video cameras. These three technologies are essential components of autonomous vehicles, providing critical obstacle information that enables the automatic system to execute appropriate actions based on the received data. We delve into three advanced techniques that enhance object detection capabilities in autonomous cars: PointPillars for Lidar, Convolutional Neural Networks (CNNs) for radar, and You Only Look Once (YOLO) for video cameras. PointPillars is a state-o--the-art technique that efficiently processes lidar point cloud data to detect objects, offering high accuracy and real-time performance. This method transforms point cloud data into a structured format that is easier for neural networks to process, facilitating rapid and accurate object detection. For radar, Convolutional Neural Networks (CNNs) are employed to leverage their strength in processing grid-like data structures. CNNs can effectively handle the spatial information captured by radar sensors, enabling precise detection and classification of objects, even in challenging conditions such as poor visibility or adverse weather. In video camera applications, the YOLO (You Only Look Once) algorithm is utilized for its ability to detect and classify multiple objects within a single frame quickly. YOLO's real-time detection capability and high accuracy make it an ideal choice for video-based object detection in self-driving cars. This chapter provides a comprehensive overview of these cutting-edge deep learning techniques, demonstrating their pivotal role in advancing the object recognition capabilities of autonomous vehicles. Through detailed discussions and examples, we highlight how these methods contribute to the development of safer and more reliable self-driving car systems.

Keywords: Autonomous car, Camera, CNN, Lidar, Object detection, PointPillars, Radar, YOLO.

INTRODUCTION

Lidar [1 - 4], radar [5 - 8], and camera [9, 10] are three core equipment of self-driving cars because the autonomous car needs the “eyes” to be able to see the surrounding environment. Object identification makes the car comprehend the events around it, and then, the car system proceeds with action decisions like bra-

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king the car when another car suddenly crosses over or when other vehicles are in front of it at a close distance. Both lidar and radar can estimate the distance from the car to other obstacles. However, it is substantially important to know more accurately about the type of vehicle and acquire a profound view of the surrounding obstacles in autonomous driving mode. Deep learning is a powerful tool in computer vision, which possesses a high level of object recognition. In this chapter, we will discuss 3 deep learning methods: PointPillar in lidar [11, 12], CNN in radar [13, 14], and YOLO in camera [15 - 17].

PointPillars is an advanced deep learning framework that was developed explicitly to detect objects inside Lidar point cloud data. The PointPillars method aims to tackle the task of effectively handling and deriving valuable insights from the three-dimensional point cloud data produced by lidar sensors. PointPillars is a novel advancement in lidar-based object recognition, which utilizes deep neural networks to identify and classify objects inside a given scene accurately. PointPillars presents a distinct viewpoint by directly analyzing point clouds, which allows the model to effectively capture subtle characteristics and spatial connections within the three-dimensional (3D) environment, rendering it highly suitable for applications that need accurate and dependable item recognition. One notable advantage of PointPillars is its capacity to manage lidar data's inherent sparsity and irregularity effectively. The architectural design effectively arranges point clouds into structures resembling pillars, facilitating efficient feature extraction and representation learning. In addition, PointPillars demonstrates the ability to acquire and adjust to intricate patterns autonomously by employing deep learning methodologies. As a result, it exhibits versatility in a wide range of settings and surroundings.

CNN has emerged as a crucial tool in enhancing the capabilities of radar technology for autonomous vehicles. They provide a sophisticated approach to address the intricate issues associated with object recognition and perception in intricate driving scenarios. Radar, a vital sensor in autonomous vehicle systems, employs radio waves to detect and determine objects' existence and precise positioning. It is crucial in facilitating navigation, obstacle avoidance, and overall situational awareness. In the domain of radar technology for autonomous vehicles, CNN is utilized to extract significant characteristics and patterns from radar data. This enables precise and instantaneous identification of objects. The distinctive benefit of CNN is its capacity to acquire hierarchical representations of information autonomously. This feature enables the model to recognize the radar data's fine details and spatial correlations. The use of CNN in radar-based autonomy aims to tackle the intricate challenges related to diverse weather circumstances, the existence of many objects, and the requirement for resilient and adaptable detection techniques. CNN has the ability to utilize convolutional layers to collect and evaluate localized patterns within radar data effectively. This characteristic renders CNN very suitable for tasks involving identifying objects, such as people and bicyclists.

Regarding the YOLO technique, an object recognition algorithm has been developed as a groundbreaking technology in camera-based perception for autonomous cars, making notable advancements. YOLO distinguishes itself in real-time and precise object detection by its distinctive and effective methodology for identifying and categorizing things inside camera photos. Cameras play a pivotal role as primary sensors in the domain of autonomous vehicles, enabling the acquisition of visual data pertaining to the vehicle's surrounding environment. One notable characteristic of YOLO is its capacity to do holistic image processing in a singular forward pass, therefore obviating the necessity for several iterations and substantially expediting the object recognition procedure. This characteristic renders YOLO compatible with autonomous driving situations' dynamic and real-time demands. The YOLO technique partitions the input picture into a grid and concurrently estimates bounding boxes and class probabilities for items included within each grid cell. The utilization of this particular method for object identification allows YOLO to attain remarkable computational efficiency without compromising its ability to accurately recognize various items, including individuals, automobiles, and traffic signs. The incorporation of YOLO into camera-based perception systems for autonomous vehicles solves the requirement for efficient and accurate object identification, which is a crucial factor in decision-making and navigation. The design of YOLO enables it to manage intricate landscapes, different lighting situations, and occlusions effectively, hence exhibiting resilience in a wide range of real-world driving circumstances. The utilization of YOLO in camera systems inside the realm of autonomous driving is playing a significant role in advancing more agile and adaptable automobiles. The rapid and precise processing of visual input by YOLO significantly improves the perception system, hence facilitating the development of autonomous driving that is both safer and more dependable.

The (Fig. **1**) illustrates the lidar, radar, and camera mounted on the autonomous car.

LIDAR

As demonstrated in Fig. (**1**), the lidar sensor is positioned above the car, and the point cloud data may include points corresponding to the vehicle's structure, such as those on the roof or hood. Knowledge of the vehicle's dimensions makes it possible to isolate and identify the places closest to it. The lidar data is saved in a 3D point cloud for each scan. The optimization of data processing through the

CHAPTER 6

Human Pose Estimation for Rehabilitation by Computer Vision

Abstract: Human pose estimation (HPE) is a valuable tool for rehabilitation, providing critical insights into the body's posture and movements. Both patients and therapists can significantly benefit from this technology, which enhances various aspects of the rehabilitation process by offering precise and real-time feedback on body mechanics. This research explores four well-known models in HPE: BlazePose, OpenPose, MoveNet, and OpenPifPaf. Each model is examined in detail, focusing on their architecture and working principles. BlazePose is renowned for its efficiency and accuracy, making it suitable for real-time performance applications. OpenPose is a comprehensive framework that detects multiple body parts, offering a detailed human posture analysis. MoveNet is designed for high-speed applications, providing quick and accurate pose estimation, while OpenPifPaf excels in producing precise keypoint detection, which is crucial for detailed posture analysis. The comparison between these models is demonstrated through practical cases of rehabilitation exercises. Since rehabilitation often requires exercises to be performed slowly and deliberately to ensure safety and effectiveness, this study emphasizes model accuracy over speed. We can assess the models in actual rehabilitation scenarios' reliability and suitability for different rehabilitation exercises. This research aims to provide a thorough understanding of how each HPE model operates and their respective strengths and limitations in rehabilitation. Through detailed analysis and real-world comparisons, we highlight the potential of HPE technology to improve rehabilitation outcomes by offering accurate, real-time feedback to both patients and therapists. This feature can lead to more effective rehabilitation programs tailored to the specific needs of individual patients.

Keywords: BlazePose, Computer vision, Human pose estimation, MoveNet, OpenPose, OpenPifPaf.

INTRODUCTION

Accurate evaluation of human posture and mobility is crucial in rehabilitation to improve therapeutic results and safeguard patients' health. Human pose estimation (HPE) [1 - 5] is a revolutionary technique that uses computer vision to analyze and understand the complex details of human posture and movement. The integration of HPE with rehabilitation techniques offers significant data on patient movements and creates an interactive link between healthcare professionals and

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their patients. This study explores the various uses of HPE in rehabilitation, providing insights into its capacity to transform the therapy field [6].

Gaining a comprehensive understanding of the complexities of human movement is crucial in the rehabilitation process, as therapists aim to customize therapies according to the specific requirements of each individual. HPE is essential in this situation, providing a non-invasive method of recording and assessing patients' body position and movements. This technology paradigm covers a range of models, each designed to interpret the intricacies of human motion. BlazePose [7 - 11], OpenPose [12, 13], MoveNet [14, 15], and OpenPifPaf [16] are notable models in this context, each having unique architectures and operating concepts.

In movement analysis, pose estimates can be applied to gait and joint mobility assessments. Pose estimation enables the examination of walking patterns and the detection of irregularities in gait. This information is vital for developing precise rehabilitation treatments for persons with walking disabilities. Through real-time monitoring of joint positions, therapists may evaluate the extent of movement and joint flexibility, facilitating the identification of constraints and monitoring of advancements in the rehabilitation process.

In addition, exercise monitoring and guidance are also significant functions provided by pose estimation. This estimation verifies if patients are executing workouts with precise techniques to avoid injuries and optimize the efficacy of rehabilitation activities. Patients can receive real-time feedback on their movements, helping them make adjustments and perform exercises more appropriately, which is particularly useful for home-based rehabilitation programs. By analyzing the pose data over time, therapists can tailor rehabilitation programs to address each individual's specific needs and progress. This personalized approach can lead to more effective outcomes. This technique generates valuable data on movement patterns and joint angles, providing insights into the effectiveness of different rehabilitation strategies and optimizing treatment plans.

This work aims to clarify the internal mechanics of these four popular HPE models, providing a thorough examination of their architectures and functioning mechanisms. By conducting a detailed and subtle analysis, our objective is to clearly outline the advantages and constraints of each model, especially rehabilitation activities. By focusing our investigation on actual rehabilitation situations, we aim to emphasize the practical consequences of these HPE models, clarifying how they might be utilized to improve therapeutic approaches. The subsequent conversation not only connects technology and healthcare but also envisions a future where human pose assessment becomes a fundamental part of rehabilitation techniques, helping both patients and therapists.

BLAZEPOSE

The prevailing benchmark for human body position is the COCO topology [17], with 17 landmarks distributed throughout the torso, arms, legs, and face. Nevertheless, the COCO keypoints identify the positions of the ankle and wrist points without including crucial details regarding the size and direction of the hands and feet. This absence of scale and orientation information hinders the usability of COCO keypoints in practical fitness domains. Adding more keypoints is essential for the utilization of domain-specific pose estimation models, such as those designed for hands, face, or feet.

While the majority of posture detection methods utilize the COCO topology, which consists of 17 key points, the Blazepose detector is capable of predicting 33 important points for the human body, including the torso, arms, legs, and face, as shown in Fig. (**1**). It is imperative to incorporate additional crucial elements to achieve better results in future applications of domain-specific pose estimation models, such as those for hands, face, and feet. Each vital point is estimated using three degrees of freedom in addition to the visibility score. The blazing posture is a high-speed model that may be utilized for real-time applications, surpassing the precision of most current models.

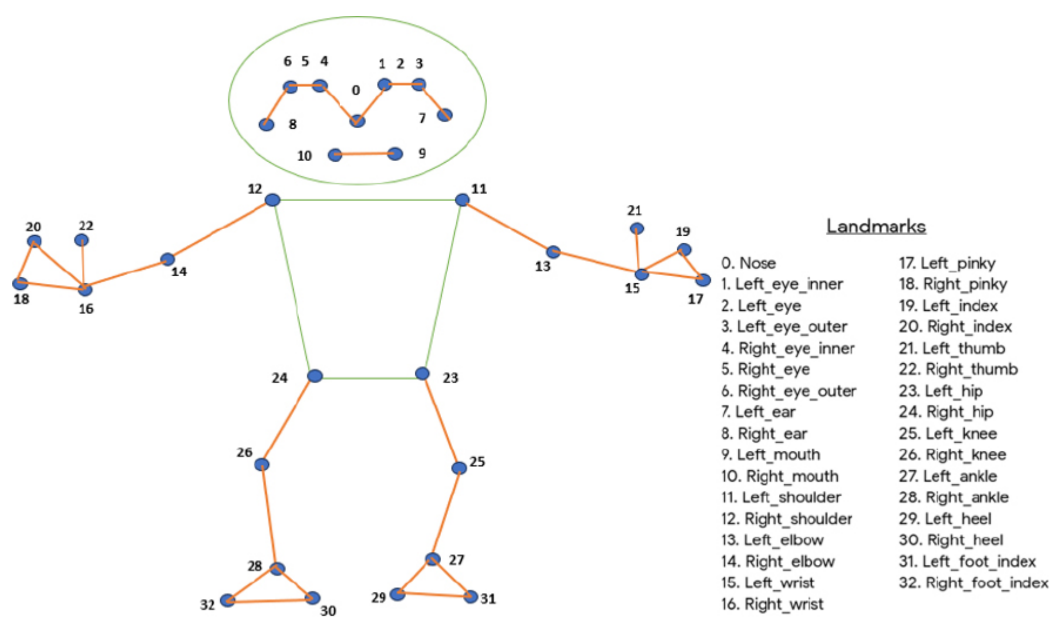

Fig. (1). Keypoints on the human body by BlazePose.

CHAPTER 7

Prediction Uncertainty of Deep Neural Network in Orientation Angles from IMU Sensors

Abstract: The chapter delves into how the Monte Carlo Dropout method is integrated into the neural network, enabling the network to estimate uncertainty by performing multiple forward passes during prediction. This technique allows for a probabilistic interpretation of the model's outputs, providing insight into the confidence levels associated with each prediction. Furthermore, the research examines the prediction uncertainties of Euler angles on the X, Y, and Z axes. The study aims to determine the deep learning model's confidence level for each orientation angle by analyzing these uncertainties. This point is particularly important in applications where precise orientation data is crucial, such as robotics, autonomous vehicles, and motion capture systems. The results are presented in a comparative format, highlighting the differences in uncertainty levels across the three axes. This comparison provides knowledge about the model's robustness and reliability in predicting orientation angles. The chapter underscores the importance of accounting for prediction uncertainty in neural networks, as it enhances the model's reliability and provides valuable information for decision-making processes. By providing a comprehensive analysis of uncertainty prediction in Inertial Measurement Unit (IMU) sensor data, this chapter contributes to the broader field of artificial intelligence (AI) by emphasizing the significance of uncertainty estimation in regression tasks. This approach not only improves model performance but also increases the trustworthiness of AI systems in various important applications.

Keywords: Deep neural network, IMU, Measurement, Monte Carlo dropout, Uncertainty.

INTRODUCTION

This chapter explores the field of regression, specifically addressing the complex job of predicting uncertainty for orientation angles obtained from inertial measurement unit (IMU) sensor data [1 - 5]. The dataset includes inputs from accelerometers, gyroscopes, and magnetometers.

Precise orientation angle prediction is of utmost relevance in several disciplines, such as robots and virtual reality, where exact spatial awareness is essential for optimal system performance. Traditional approaches for regression frequently fail to adequately account for the inherent uncertainty related to predicting orientation

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angles. This chapter aims to close this disparity using the Monte Carlo dropout approach in the functioning of neural networks [6 - 8], providing a resilient framework for measuring prediction uncertainty.

Our focus is specifically on predicting Euler angles, which are crucial for describing the orientation of an object in three-dimensional space. Our technique seeks to improve the accuracy of orientation angle predictions by utilizing IMU sensor data, which captures the dynamic interaction of acceleration, rotation, and magnetic forces. The Monte Carlo Dropout approach incorporates a random component into the deep neural network (DNN) [9 - 11], allowing for the examination of several potential results and, as a result, a more sophisticated comprehension of prediction uncertainty.

This investigation examines the uncertainty in predicting Euler angles along the X-Y-Z axis. This comprehensive research aims to elucidate the underlying confidence levels in the outputs of the deep learning model, offering valuable insights into the dependability of orientation predictions. This chapter studies uncertainty prediction for orientation angles, contributing to the broader discussion on using AI in spatial awareness. It expands the bounds of regression analysis into novel and essential domains.

MONTE CARLO DROPOUT

Monte Carlo dropout is a method that uses dropout in both a neural network's training and testing stages to approximate uncertainty. Dropout is a regularization method frequently employed during training to prevent overfitting by randomly deactivating (setting to zero) a portion of the units in a layer. Monte Carlo dropout expands on this concept by using dropout during the testing phase and calculating predictions' average and standard deviation over multiple stochastic forward passes.

• The mean prediction represents the average prediction across multiple Monte Carlo samples. Each element in the tensor corresponds to a specific value in the model's output.

• The standard deviation prediction represents the uncertainty or variability in predictions across the Monte Carlo samples.

Monte Carlo dropout is an important tool for estimating uncertainty in predictions generated by neural networks, which is applied to IMU data. IMU data can be noisy and subject to various sources of uncertainty, such as sensor noise and environmental conditions. Traditional neural networks might provide point estimates without capturing the uncertainty associated with predictions. Monte

Carlo dropout allows the neural network to produce a distribution of predictions rather than a single-point estimate. Running multiple stochastic forward passes with dropout during testing generates an ensemble of predictions that can be used to estimate uncertainty.

In model confidence evaluation, Monte Carlo dropout can provide insights into the model's confidence in its predictions. If the predictions are consistent across different dropout samples, the model may be more confident in those predictions. On the other hand, if predictions vary widely, it indicates higher uncertainty.

It is essential to have a thorough knowledge of uncertainty for applications that heavily rely on IMU data for decision-making, such as navigation and robotics. Monte Carlo dropout may enhance decision-making by providing valuable information, and the degree of uncertainty can guide determining whether to rely on the forecasts or explore alternate alternatives.

In addition, the model trained with Monte Carlo dropout tends to be more robust, as it learns to make predictions in the presence of dropout-induced uncertainty during both training and testing phases.

In this work, the Monte Carlo dropout technique is applied to the IMU dataset from [12], which contains 12 features:

Sensor data:

• Acceleration on X-Y-Z axes (Acc_x, Acc_y, Acc_z).

• Angular velocities on X-Y-Z axes (Gyro_x, Gyro_y, Guro_z).

• Magnetic fields on X-Y-Z axes (Mag_x, Mag_y, Mag_z).

Orientation data (as illustrated in the figure):

• Euler angles on X-Y-Z axes (Euler_x, Euler_y, Euler_z).

Goals:

• Use deep learning to get prediction uncertainty of X-Y-Z Euler angles alternately from other input features. These angles are illustrated in Fig. (**1**).

• Check the relationship between 3 Euler angles in terms of uncertainty.

CHAPTER 8

Machine Learning in Augmented Reality for Automotive Industry

Abstract: The augmented reality (AR) field has experienced substantial progress in recent years, driven by breakthroughs in hardware, software, and computer vision techniques. Artificial intelligence (AI) integration has significantly enhanced AR, making it more accessible and expanding its practical applications across various industries, notably in automotive manufacturing. In this context, AR aids assembly processes by improving the efficiency and accuracy of assembly line workers. AR systems provide real-time guidance and feedback by incorporating object detection, tracking, and digital content overlay, increasing productivity and superior quality in automobile production. This chapter delves into the transformative role of AR in the automotive industry, highlighting its impact on the design process, manufacturing, and customer experience. Drawing on Machine Learning (ML) methodologies discussed in previous chapters, the chapter explores how AR technologies are employed to streamline complex assembly tasks, reduce human error, and enhance overall operational efficiency. The design process benefits from AR through enhanced visualization and prototyping, allowing for more precise and creative developments. In manufacturing, AR supports workers by overlaying critical information and instructions directly onto their field of view, facilitating faster and more accurate assembly operations. This real-time assistance boosts productivity and ensures that higher quality standards are met consistently. The chapter addresses the use of AR in enhancing the customer experience, from virtual showrooms to personalized, interactive user manuals, creating a more engaging and informative interaction with the product. By providing a comprehensive overview of AR's applications in the automotive sector, this chapter underscores the technology's potential to revolutionize industry practices. The integration of AI and AR not only enhances current manufacturing processes but also paves the way for innovative advancements in automotive design and customer engagement.

Keywords: Augmentation Reality, machine learning, AI, Automobile.

INTRODUCTION

The area of augmented reality (AR) [1 - 5] has experienced notable progress in recent years, propelled by considerable developments in hardware capabilities, software development, and advanced computer vision techniques. With the integration of AI, this revolutionary technology has become more readily

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available and has been widely utilized in several sectors. AR has become a crucial tool, especially in automobile production since it transforms conventional processes and promotes efficiency at all stages [6 - 8].

This chapter explores the crucial significance of AR in the automobile industry, specifically in design, production, and consumer experience. AR has become an essential resource in the automobile sector through the utilization of ML techniques [9, 10]. An important use of this technology is in assisting with assembly, dramatically improving the productivity and precision of assembly line workers in vehicle production [11 - 15]. This enhancement is accomplished by seamlessly integrating object recognition, tracking abilities, and overlaying digital material.

In the following sections, we will examine the many ways in which AR affects automotive processes. We will discuss its influence on the design phase, its role in improving manufacturing processes, and its capacity to enhance the customer experience. The interdependent connection between AR and ML approaches serves as the foundation of our investigation, revealing the complex ways in which these technologies work together to stimulate innovation and achieve exceptional results in the automotive field. This chapter seeks to offer a thorough comprehension of the synergistic relationship between AR and ML. It attempts to shed light on how AR is affecting the automobile manufacturing industry and provides practical insights to guide the way forward.

AUGMENTATION REALITY CONCEPT

AR technology merges the physical environment with computer-generated data or digital content, thereby increasing the user's experience. AR overlays digital features onto the actual world, enabling users to engage with both the physical and virtual surroundings concurrently. This technology seeks to offer a more engaging and immersive experience by combining computer-generated material with the user's environment.

AR systems offer instantaneous information and interactions, adapting dynamically to modifications in the user's surroundings. Augmented reality enriches the actual environment by including digital components like photos, films, 3D models, or text, which exist alongside and engage with tangible items. AR experiences may be accessed using a range of devices, such as smartphones, tablets, smart glasses, heads-up displays, and dedicated AR devices. Typically, AR utilizes computer vision technology to identify and monitor items in the physical environment, enabling precise positioning of digital products. Users have the ability to interact with AR features using gestures, touch, voice commands, or other input techniques, resulting in a more immersive and user-friendly experience. AR systems can utilize sensors and contextual data to adjust to the user's position, actions, and environment, delivering pertinent and contextually aware information. Furthermore, several AR experiences integrate head-tracking or positional tracking to adapt the viewpoint of digital material in accordance with the user's motions, resulting in a heightened sense of immersion and realism.

MACHINE LEARNING IN AR FOR CAR INDUSTRY

Car Design Process

As shown in Fig. (**1**), the automotive designer can use AR glasses to assess the visual appearance of a vehicle in the physical world prior to its construction by incorporating digital data into factual circumstances. Additionally, augmented reality is employed in design review processes, allowing for the evaluation of virtual prototypes of automotive components in terms of suitability and performance, eliminating the need for costly and time-consuming actual prototypes.

Fig. (1). Designer wears AR glasses for designing an automobile.

AR can speed up the design process by reducing the need for physical automotive prototypes. Thus, designers have the ability to display 3D models of their intended automobiles in real time to verify the proper functioning of various components. These AR functions work based on the following AI techniques:

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Dr. Minh Long Hoang received Ph.D. in 2022 from the University of Salerno, Italy. The project was a Nationally Operative Program (PON) of the European Union about "Industry 4.0 oriented enhancement of Inertial Platform performance". As part of this project, he collaborated with the Sensor System srl Company (Italy) and Baumer Company (Germany) as a researcher in the R&D departments in the field of inclinometers. In 2022, he started working on projects, such as organ-on-a-chip, sensor system in Internet of Things (IoT), digital lifelong prevention project and multiple machine Learning projects at the University of Parma as researcher and assistant professor. His research interests include inertial measurement unit (IMU) sensors, microelectromechanical systems (MEMS), real-time measurements, embedded systems, signal processing, machine learning and deep learning.