A Survey on Automated Inventory Tracking Systems

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***Abstract*—Inventory tracking and monitoring is one of the most time-consuming tasks in maintaining a large product or commodity-based facility. Using computer vision techniques to track inventory in these facilities has a great potential because it tries to minimize manual labor, execution time and ensures safety in working facilities. There exist number of solutions which use state of the art computer vision methods and other technologies to track inventory in different warehouses as each man-made scenarios in large warehouse differ from one another. Also, a fully generalized method which applies to all categories of warehouses is still not been outlined. In this paper, we surveyed the computer vision techniques applied in the field of inventory tracking. While surveying, the need for a well-structured documentation that compares the features and different techniques in automated inventory tracking was felt. This work will offer the future developers to understand all the challenges that are associated with this topic and hopefully guide them to find a generalized computer vision-based solution for automated inventory tracking.**

***Keywords*—automated inventory Tracking System (AITS), computer vision, image processing, machine vision**

I. Introduction

A warehouse is a place where large quantities of products are stored. Accurately locating any object in such a large space is a very challenging task [1]. In recent years, there have been numerous works in the area of computer vision and its applications in various applications, including but not limited to the analysis of medical images, interpretation of satellite images, industrial inspection, the guidance of robots, detection of road signs and traffic situations, which has ultimately led to the development of autonomous cars [2]. However, not many works have been done in the domain of retail environments or inventory warehouses to detect product objects and their classifications [2]. Still, the workers manually keep track of the products in an inventory by scanning each product's bar code. Often heavy machinery is used to deploy products, which is not ideal to ensure a safe working environment for manual human labor as one case study from The Occupational Safety and Health Administration's (OSHA) accident database reveals that among 158 forklift operation-related accidents 63.41% times, someone was hit by a forklift when in motion [3].

Tracking inventory is directly associated with supply chain systems. Statistics show that 60% of the final cost of a product is due to the different aspects of this supply chain [4]. In a survey on computer vision approaches for the automatic identification of products in retail stores, the challenges, features, and results of different methods of detecting products in retail stores are presented [5]. The survey outlined multiple approaches that had been used in detecting products in retail stores using machine vision. It discusses and compares the performances of these methods as well as their main key features. Our work differs from this work in multiple viewpoints as we have tried not to limit this survey only to retail stores but to include all recent approaches, which try to find a solution to track inventories in all different scenarios. This study will help future researchers to find a generalized solution to develop an Automated Inventory Tracking System (AITS).

We have structured the survey into several steps. The first section discusses the process of acquiring relevant articles that we are going to discuss and analyze in the upcoming sections. The second section tries to generalize the research questions proposed in all those articles and outlines the challenges in Automated Inventory Tracking Systems. The third section compares their features and results. In the last section, we have concluded our analysis and discussed the future possibilities of the AITS.

II. Search Process

We have explored several database platforms to select our research articles. Date restriction has been applied to ensure that our survey covers only the recent works in the field of AITS. The platforms we have explored in this process are: "Google Scholar", "ScienceDirect", "ACM Digital Library" and "IEEE Explore".

The initial screening process was dependent on going through the title and abstract of each work. After that a full text review was done to select the work for our remaining analysis and discussion. The keywords that we have repeatedly used are "Inventory tracking", "Computer vision", "Product detection", "Object detection", "Large-scale Tracking", "Deep Learning", "Product Identification", "CNN", "Monitoring", "QRcode", "Barcode", and "Neural Network."

III. Research Questions and Challenges

A. Research Questions

A survey should start with some important questions that should be clearly defined [6]. It is also the most critical part of a systematic review, as asking the right questions can sometimes be difficult [6]. In our survey's scope there are numerous questions that should be answered first before diving deep into the technical aspects. These questions are mentioned in Table 1.

Table 1. Research questions

Question 1	What are the challenges while developing an Automated Inventory Tracking System?
Question 2	Which approaches should be adopted in developing an AITS?
Question 3	What are the main components and techniques of an AITS?
Question 4	Which hardware model is best suited in designing an AITS?

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B. Challenges

Tracing and tracking technologies have gained much attention in recent years because of their potential to improve production systems and supply chains [7]. This improvement in the production system can result in a much improved operational management on a factory level [7]. However, given the diversity of the scenarios in different production and supply chains, some challenges are inevitable in outlining a general and universal tracking system that can apply to all these production and supply chains. This diversity can be well understood in Table 2.

Table 2. Diversity of AITS application areas

Application Area	References	Application Area Percentages
Small Areas: Retail stores, Vending machines, Stock Room	[1, 2, 5, 8]	23.5%
Library	[9]	5.9%
Large scale Inventory: Aircraft, Motor parts	[10–12]	17.6%
RoRo port terminals	[13]	5.9%
Warehouses	[14–20]	41.1%
Industry 4.0	[21]	5.9%

The challenges in generalizing lie in not only the domain of application areas but also in acquiring data, their technical approaches. It is understandable as each work has been designed to fulfill their objectives in forming their own AITS. However, the barrier in doing public research is more substantial in terms of accessing dataset, as producers are not as open to publishing their product information in the format of data [2].

IV. Related Works

A. Deep Learning Based Solutions

A deep learning-based method was proposed to detect objects in a densely packed scenario [7]. The dataset they used was "SKU-110K." Their proposed method introduced the Jaccard Index, which measures the quality of the detection boxes [7]. Where determining ends and beginnings of an object while minimizing the overlaps of the bounding boxes is a challenge, this paper proposes a method which includes learning the Jaccard index with a soft Intersection over Union (Soft-IoU) network layer with valuable information explaining how detections can be represented as a *Mixture of Gaussians* (MoG), reflecting their locations and their Soft-IoU scores. The Expectation-Maximizing (EM) is then used to cluster the Gaussians into groups [8].

The authors have also compared the results with previous works related to dense object detection. Two benchmark methods of counting LPN counting and IEP counting were used. The previous methods that were used by others are Faster Region based Convolutional Neural Network (R-CNN), You Only Look Once (YOLO) and One-Look Regression [8].

This work is the improvement of the existing model to the field of modern object detection in a densely packed scenario [8]. Though it has achieved better results than the previous models, object detection in this niche field is still challenging, as the accuracy is not near perfect.

In the scope of solving the problem of inventory tracking and detecting free space, this work offers some contributions, although it does not give us the general solution that we are looking for. This is because the model has only been tested on some selected datasets that have a similar type of scenarios in warehouses. We can detect all the objects in an image with this model, but it does not give us any insight into the usable free space that could be used for restocking, which is also an integral part of inventory management.

A quick inventory framework was proposed for library inventory tracking. The proposed model's accuracy and recall rate reached above 99% with a precision rate close to 100% on 1D/2D barcode books [9].

For 1D barcode European Article Numbers (EAN) code, Code 39, Code 128 and Codabar were preferred [9]. For 2D barcode, Data Matrix code was suggested. The barcodes were used as tags stuck on the back of each book, which then were captured as photos or short videos by mobile devices.

For implementation, a framework was developed, which had an independent algorithm server and offered Application Program Interfaces (API) to external application server [9]. The independent server was used to feature learning and training, and user interaction was done through the application server [9].

The test samples had 10 bookshelves with 2,137 books [9]. 10 separate inventory tests were performed on those 10 bookshelves. Compared to previous Radio Frequency Identification (RFID) technology, this framework was 35% faster using deep neural networks [9].

B. Computer Vision Based Software Solutions

A software solution of Intelligent Process Automation (IPA) was proposed, using a computer vision pipeline to locate, detect, and manage inventory logistics using label information of the images from warehouses [10]. This solution was exclusively designed to meet the needs of Mercedes-Benz U.S. International (MBUSI) [10].

The dataset was created by MBUSI engineers from the Mercedes Logistics Center (MLC), which includes 136 annotated images(4K) and 6 video clips (93 seconds of 1920x1080) [10]. Each image in this dataset included two labels: Vehicle part information labels and Bay location labels [10]. The part information label had multiple barcodes, which encoded various information such as bin serial numbers, part numbers, quantity, supplier, packaging, etc. The locations of the warehouses were encoded in the Bay location label barcodes [10].

These location labels are usually found on the rail of the stacks where the part boxes are kept, whereas the part information barcodes are usually on the front of the boxes. They also had designed an automated system that can take high resolution pictures and video of individual boxes and their corresponding location bar codes [10].

A 5-step pipeline was adapted for their process of extracting data and integrating this data into a central database from the natural images [10]. These steps included Label Localization, Label Preprocessing, Data Recognition, Information Classification and Database Integration. All the values reported in their paper were run on a 2.6 GHz 6-core Intel Core i7 (75-9750H) processor [10].

For object detection, which is effective for label localization, a fine-tuned version of YOLOv4 was used as well as Single-Shot multibox Detection (SSD) MobileNetV2 model [10]. The annotation tool labelImg was used to annotate the dataset [10]. After annotating the images, the results were then converted to YOLO and TensorFlow TFRecord format [10]. Canny edge detection and Hough Transformation techniques were performed on the slanted images for the purpose of preprocessing the images. For decoding the barcodes, the two most popular libraries, ZBar and ZXing, were applied [10]. The authors implied that only the Location barcodes results were acceptable using these two libraries [10].

The authors have successfully outlined a pipeline that gives an overall idea of how the problem should be tackled. Although the dataset was custom made and appropriate for the solution of inventory tracking in the Mercedes-Benz warehouse, a generalized solution needs to be developed for the implementation of inventory tracking in all commercial fields.

C. Indoor Navigation Based Solutions

An onboard solution was proposed for vision-based localization in global coordinates [14]. In contrast to a traditional approach where Light Detection and Ranging (LIDAR) sensor is used, they focused on the vision-based solution for the localization and navigation problem [14]. For identifying of the inventory here barcodes were also used instead of RFID tags [14].

Their main objective of their proposed solution was to achieve precise navigation in indoor scenarios [14]. This paper is related to our survey in a number of ways. One, it finds a novel way to track inventory using drones. Two, they had used a vision-based model, which utilizes the inventory images to track the products in a warehouse. Their proposed solution opens a new and appropriate door to the field of autonomous and vision-based inventory tracking in future times.

An on-board odometry sensor's odometry was fused to model-based visual localization estimates in their solution for navigation [14]. Global Navigation System Satellite (GNSS) was applied when experimenting with outdoor scenarios [14]. Low resolution images captured by the odometry sensor were utilized for localization.

Preprocessing previously captured images, a reference model was generated using a Structure from Motion approach. During the time of operation, the real time images were localized against this reference model. Scale Invariant Feature Transform (SIFT) features are extracted and matched against this model's features. They sped up the process using only the nearby reference cameras of the model. Further complexities and speeding up process were gained by exploiting tree-based feature matching and GPU-based feature extraction in their solution.

A 3-point algorithm was utilized for determining the current camera pose as the matched features lead to 2D-3D correspondences. The on-board sensors data was used to estimate the drift of the drone with respect to the reference model. The computational complexity of the process was very low, and it was done on-board. The drift was estimated through a mean calculation over the latest 6 seconds of time-synchronized camera poses and corresponding odometry data. Outliers from the model-based visual localization were filtered using Random sample consensus (RANSAC).

The proposed method enabled the compensation of the odometry sensor drift and achieved cm-precise localization. Here, like the previous paper's approach, ZXing open-source library was used to decode the barcodes of the inventory products [14].

For the experiment and result analysis, their equipment included a DJI M-100 equipped with a DJI Guidance sensing system for visual odometry that replaced GNSS while indoors and a Matrix Vision BlueFox3-M1100g (10 Mpx) with a 50mm focal length lens for barcode reading. The onboard processing was done on the MJI Manifold (NVIDIA Jetson TK1) [14].

They distributed 15 inventory tags with barcodes on the flight area and performed 5 flights. The inventory drone prototype was able to decode 73 out of 75 barcodes successfully. The achieved positioning accuracy of the barcodes in 3D in these flights has a standard deviation of 1.92 cm [14].

D. RFID Based Solutions

For small and medium enterprises (SMEs) a passive RFID-based indoor inventory localization method was proposed for effectively tracking inventory in terms of the multi-stacking racking (MSR) [15]. This model uses reference tags and introduces a concept of calculating the distance between these reference tags and RFID reader. The study shows that the proposed system has a similar location awareness rate compared with existing active RFID-based methods, and the construction cost is relatively low, making it suitable for SMEs with limited resources for facility investment [15].

Table 3. Common properties and technologies used in different aits

Categories	Technologies	References	Application Areas
RFID Tags		[1, 12, 13, 21]	Retail store, warehouses, Industry 4.0
Barcode	1-D barcode	[9, 10, 16	Large scale inventory, Library
	2-D barcode	[1, 10, 11]	
Dataset	Images	[2, 9, 10, 17, 18]	Small areas, warehouses, large inventories,
	Video	[10]	
Barcode Decoder	Zbar	[10]	Large inventories and warehouses
	ZXing	[10, 11]	
Object Detection	CNN	[2], 9, 13]	Small areas, library, warehouses
	YOLOv4	[10]	
Navigation System	Global Navigation Satellite System (GNSS)	[11]	Warehouses

A portable XCODE IU9030 RFID reader with a frequency of 900 MHZ was used which has 2-3m recognition range [12].

The recognition rate of this reader is 10tags/sec. The air interface protocol supports EPC Class 1, Gen2, and ISO18000-6B. Their proposed algorithm was implemented by Visual C++. Their model considered an MSR of dimension 216cm in width and 144cm in length which consisted of two rows and three columns [15].

Their testing had two parts, reference tag recognition accuracy along with inventory location accuracy and evaluation of the accuracy of location identification by comparing the identified and actual locations of stock items [15].

Their result revealed that in case of the number of stock items equal or less than two and tag recognition interval set to one second or less, the recognition rate was 100%. Also, with a tag recognition interval set to 0.3 seconds and three or fewer items, the recognition rate was also 100% [15]. This eventually means that the recognition rate can be improved with a lower number of items or/and decreased interval [15].

Another RFID localization model was proposed which is based on phase, Received Signal Strength Indicator (RSSI), and readability [16]. The method is little affected by antenna tracking errors. The proposed method locates the tagged items on the racks laterally through pinpointing the minimum of the unwrapped phases, which had been unwrapped based on the hybrid Random Forest (RF) [16]. This method achieved 27.1cm mean lateral positioning accuracy and ordered the tagged items horizontally and vertically with more than 96.7% and 98% accuracy, respectively [16].

In the Table 3, we have showed the common properties and technologies that have been used in different AITS.

V. Conclusion

In large-scale inventory tracking, we need to track all the products that are in store. However, it is not the whole process of inventory tracking. There is also the need to get an estimation of the free space in the warehouse to order the next delivery. Also, for deployment of the delivery, we need to have a fair estimation of the free space in these large inventories or warehouses. Detection of free space or gap in the product-wise way is another dynamic, which until now has been explored very little in our AITS [5]. Although different warehouse houses different products, the empty spaces in the aisles or racks are similar in nature. They are not identical, but the shapes of the empty spaces around the boxes or products have some common properties. These common properties can be used to generate an algorithm that can detect free space in these densely packed product scenarios. Many computer vision techniques use Hough transformation to detect lines, squares, and circles in an image. This technique can be further modified to detect empty space depending on the shapes of the surrounding objects.

We are heading into a future where human manual labor is going to be replaced by machines and drones to avoid hazards in human lives in heavy lifting and inventory facilities. For inventory specification and inventory management, it is important to have at our disposal basic data (item number, name, designation), general characteristics, technological properties, material stock properties, economic and business characteristics [22]. The main objective of automated inventory tracking does not only give a solution for efficiency in these field, but rather it ensures that people have a safer working environment in these places. This survey's motivation and approaches aligns with this moto and outlines an autonomous generalized solution to this problem.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Md Munimul Hasan: Conceptualization, Methodology, Investigation, Writing - original draft preparation. Jiangjiang Liu: Supervision. All authors had approved the final version.

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