Drone Technology for Efficient Warehouse Product Localization

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Abstract: This paper presents a novel drone-based strategy for enhancing stock-monitoring systems, specifically focusing on the accurate localization of products within defined areas. Traditional localization techniques, which are often reliant on technologies such as RFID or precision positioning systems, face substantial limitations in terms of accuracy and operational efficiency. To address these issues, we introduce an advanced relative positioning system, uniquely designed to identify and accurately position steel bars relative to each other in an outdoor warehouse environment. The developed approach significantly improves localization precision and speed over conventional methods. Our analysis includes an evaluation of the system's performance, demonstrating advancements in self-localization capabilities. Results indicate a marked enhancement in the accuracy and efficiency of stock monitoring, showcasing the system's potential applicability to a diverse range of products and environments.

1 INTRODUCTION

Ensuring accurate product tracking within industrial environments is important for real-time inventory management and operational efficiency. This paper presents a novel approach highlighting the evolution of product positioning methodologies by using computing relative position. In our specific scenario, we deal with stacks of steel bars located outdoors, each stack is identifiable by a unique marker (See Figure 1). These steel bars undergo movement facilitated by forklifts equipped with powerful magnets, leading to positional shifts and interference. The dynamic nature of this environment needs constant human intervention for manual scanning, resulting in significant time consumption.

Several technologies are used for products tracking in industry. Radio-Frequency Identification (RFID), known for its non-line-of-sight data transmission capabilities, has been a pioneer, enabling efficient product tracking within diverse environments (Konsynski and Smith, 2003). However, challenges arise in environments that are in metal or with interference, leading to inaccuracies (Curtin et al., 2007).

Similarly, bar-code systems and QR codes (de Seta, 2023), offer cost-effective solutions but need direct line-of-sight, posing labor-intensive challenges in expansive settings. Advanced systems such as Real-Time Location Systems (RTLS) and GPS-based tracking have been investigated for outdoor or large-scale settings (Rácz-Szabó et al., 2020), however they often lack the precision demanded by industrial standards. Traditional methods are effective, however when dealing with outdoor environments, the efficiency is reduced. The integration of unmanned aerial vehicles (UAVs) into warehouse management is a solution for outdoor storage and product tracking practices. The authors in (Cristiani et al., 2020) explore a multi-robot system using micro-drones with embedded cameras, drastically reducing warehouse management time by using drones' capacity in navigating indoor shelves and aisles.

Similarly, the work in (Malang et al., 2023) offers an exhaustive review of UAV utilization in warehouse management, identifying key factors influencing drone use and showing their potential applications

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Figure 1: Illustration of the products position with QRcode tags.

in inventory management, intra-logistics, and surveillance in smart warehouses.

However, a critical challenge persists in ensuring uninterrupted drone tracking and accurate product position inference. Existing techniques often rely on fixed infrastructure or external markers, unsuitable for agile and rapidly changing environments like outdoor storage yards or manufacturing facilities, as explained in our case.

In this paper, we present a novel system for relative positioning utilizing images captured by drones. This system represents a fundamental change in product positioning, as it calculates item locations relative to one another, rather than depending on fixed points or external infrastructure. By doing so, it establishes a precise mechanism to automatically identify products' locations for autonomous warehouse management operations. Our method offers an increased accuracy and efficiency within complex industrial environments. Specifically for environments such as warehouses and manufacturing floors, where conventional systems often fall short in providing accurate and reliable information, our approach stands out for its adaptability without the need for exterior markers or infrastructure and shows a outstanding performance.

The remainder of this paper is organized as follows: Section 2 reviews the related work on system positioning. Section 3 describes the proposed framework, as well as the main concepts involved in this work. Implementation and empirical results of the proposed system are detailed in Section 4, while Section 5 summarizes our contributions and sketches some of our future perspectives.

2 STATE OF THE ART

The PILOT system, as detailed in (Famili et al., 2023), is an in indoor drone localization through its utilization of Time of Arrival (ToA) analysis of ultrasound signals. This approach tackles the complexity of indoor environments, such as the multi-path fading. Moreover, the integration of Frequency Hopping Spread Spectrum (FHSS) technology showcases innovative strategies to enhance location estimation accuracy, although specific precision metrics are not explicitly outlined in the literature.

In outdoor environments, the fusion of the Global Navigation Satellite System (GNSS) with compass-based systems, as highlighted by Flavia et al. in (Causa and Fasano, 2021), has markedly enhanced autonomous drone navigation. Although GNSS-based approaches have gained precision improvements, they may still lack in accuracy for locating products stored in densely packed piles.

The employment of stereo vision techniques for indoor drone control, as elucidated by Anand et al. in (George et al., 2023), represents a significant stride in indoor positioning systems. This method emphasizes 3D reconstruction through drone-mounted cameras, boasting high positional accuracy, especially in aligning the drone's yaw rotation with the virtual camera. However, precise precision figures remain absent from existing summaries.

Other approaches, such as Sensor Fusion, integrate ultrasound, LIDAR Time of Flight (ToF) rangefinders, visual odometers, and Ultra-Wide Band (UWB) positioning (Xu et al., 2018), promising approximately 5 cm accuracy during flight.

Furthermore, UWB Sensing for Indoor Precision introduces a system employing impulse-radio ultra-wideband (IR-UWB) two-way ranging (TWR), achieving high precision and interference resilience. With a reported standard deviation of 1.2 cm for single-measurement TWR in semi-closed environments, it holds particular significance for demanding indoor applications.

Building upon these advancements, this paper introduces a new approach for autonomous warehouse management, focusing on accurately identifying the relative positions of products items in dynamic outdoor environments. By combining drone-based image capture with a high-speed processing algorithm supported by a trustworthiness score, this system ensures precise identification of each item's location. Additionally, it provides a user-friendly visualization interface to facilitate product localization in outdoor warehouses.

3 PRODUCTS POSITIONING AND TRUSTWORTHINESS SYSTEM FRAMEWORK

In this paper, we present a framework designed to detect and position products utilizing an embedded camera on a drone, augmented with a trustworthiness scoring mechanism. Figure 2 illustrates the utilization of this framework in a smart outdoor warehouse environment.

- **Drone Integration**: The framework uses information coming form a drone equipped with a camera to gather visual data for product detection and localization at predefined waypoints within the warehouse.

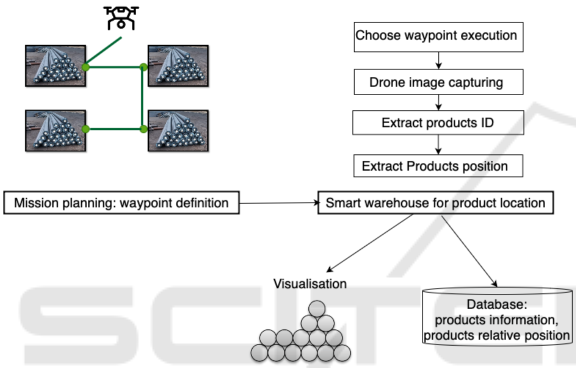

Figure 2: Schematic representation of the developed system in operation within a smart outdoor warehouse.

- **Smart Outdoor Warehouse Operation**: Upon capturing visual data, the framework extracts product IDs from each image, represented by QR codes (see Figure 1). Then, it computes relative product positions and assigns trustworthiness scores based on contextual information. These data are then stored in the database for further analysis and visualization.
- **Database Management**: The framework's database contains comprehensive product information, including unique IDs (QR codes), compositions, dimensions, and relative positions (e.g., left, right, top, down).
- **Products Location Visualization**: An intuitive interface is developed to update product locations and facilitate visualization, ensuring seamless integration with existing warehouse management and Enterprise Resource Planning (ERP) tools to optimize picking products.

Additionally, the framework provides open interfaces for easy integration into existing warehouse management and ERP systems, thereby offering a valuable tool for production and distribution planning. It contributes to resource optimization and enhances industrial processes.

The subsequent subsection details the algorithm for determining relative product positions, followed by an explanation of the trustworthiness scoring computation.

3.1 Relative Product Position

This subsection focuses on determining the relative positions of products within captured images. It involves detecting the IDs of existing products in each image and computing their relative positions. The framework defines eight possible relations between products: up, down, left, right, up-right, up-left, down-right, and down-left. These relations allow for understanding the spatial arrangement of products within the images. The algorithm employed for this task involves computing the central position of detected corners from QR codes and determining the relative positions based on the computed coordinates.

Algorithm 1 takes as input the positions of two points ($pos1$ and $pos2$) and an optional *threshold* value. The *threshold* represents the sensor error. It computes the relative direction between these two points based on their coordinates. It extracts the x and y coordinates of $pos1$ and $pos2$. It calculates the differences in x and y coordinates between $pos1$ and $pos2$, storing them in variables dx and dy. Then, it checks if both $|dx|$ and $|dy|$ are less than the threshold. If so, sets direction to 'same', indicating that the points are at the same position. If $|dx| > |dy|$, compares the sign of dx. If dx is positive, sets direction to 'right'; otherwise, sets it to 'left'. If $|dy|$ exceeds the threshold, appends the direction with 'down' if dy is positive, or 'up' if dy is negative and vise-versa. Finally, the algorithm returns the computed 'direction´ as the relative position between pos1 and pos2.

By accurately determining the relative positions of products, the framework facilitates tasks such as inventory management and product localization in industrial settings.

3.2 Trust-Ability Computation

This subsection discusses the computation of trust relationships among products based on their relative positions. Trust relationships are essential for minimizing errors in the identification and localization processes. The framework defines a "directed trust graph´´ where nodes represent product IDs and edges represent trust relationships between products' relative positions. The directed trust graph $G =$

Algorithm 1: determine_relation.

```
Input: pos1, pos2, threshold=10
x1, y1 ← pos1
x2, y2 ← pos2
dx, dy ← x2 − x1, y2 − y1
direction ← None
if |dx|¡threshold and |dy|¡threshold then
    direction ← 'same'
else if |dx| > |dy| then
    if dx > 0 then
        direction ← 'right'
        if |dy| > threshold then
            direction ← 'right-' + (dy > 0 'down' else 'up')
        end if
    else
        direction ← 'left'
        if |dy| threshold then
            direction ← 'left-' + (dy > 0 'down' else 'up')
        end if
    end if
else
    if |dx| > threshold then
        if dx > 0 then
            direction ← 'right'
        else
            direction ← 'left'
        end if
    else
        if dy > 0 then
            direction ← 'down'
        else
            direction ← 'up'
        end if
    end if
end if
Return direction
```

(V,E,R,ϕ), where node set V represents product ID and edge set E represents trust relationships among products' relative position. The trust graph enumerates different types of trust relationships R. The mapping function $\phi : E \implies R$ maps the observed edges to trust relationship types, so each edge strictly corresponds to a specific trust relationship. Moreover, the trustworthiness varies for different application domains.

In our case, the trust relations between nodes have eight types, i.e., R = {left, right, up, down, up-left, down-left, up-right, down-right}. Other scenarios or applications can require a different number of relations, and the trust-ability graph would automatically adapt.

Trust Evaluation. The trust evaluation task is to predict the unobserved trust relationships in a trust graph G. Specifically, given a trust graph $G = (V,E,R,\phi)$, the goal is to trust more cumulative information that are coming from the other direction. For example if a node A is telling that B is on my right and that B is saying that A is on my left, the trust value is highly increased. Note that trust relationships are directed, and the trust relationship from node u to node v is not equal to the relationship from node v to node u, but it allows to increase the trust-ability in case that they express the same semantic of relation.

Figure 3 shows an instance of trust-ability computation for node A. Initially, all relations of node A are portrayed in Figure 3(a), each starting with a trust-ability score of zero (including Right, Up-right, Right, Down-right, Down, Down-left, Left, and Up-left).

In Figure 3(b), let's consider the computed relation being Up-right with node B, resulting in an increment of one to the trust-ability score for the Up-right edge of A. Now, suppose the subsequent computed relation for node A indicates that B is to its Right. Following the same process, the trust-ability score of the Right relation of node A increases by 1. Consequently, both relations, Up-right and Right, pertaining to node A exhibit identical trust-ability scores of one for the same node B.

Continuing, let's imagine that in another computation, B concludes that A is positioned to its left (as depicted in Figure 3(d)). Consequently, A updates its trust-ability score to double, now standing at two, while simultaneously decreasing the trust-ability score of the Up-right link with B by one. At this point, the maintained relation between A and B is Right with a trust-ability of two.

Upon completion of this process for all relations of node A, only one relation includes node B: the relation with the highest trust-ability score is selected to determine the link.

The final generated graph is a connected graph (see Algorithm 2).

The algorithm for trust-ability computation evaluates trust relationships based on observed edges in the trust graph, considering factors such as product IDs, relative positions, and trust scores. By computing trust relationships, the framework enhances the reliability of product localization and warehouse management systems.

3.3 Video Capture Loop and Trust-Ability Score

This subsection describes the operational execution of the framework's video capture process and the

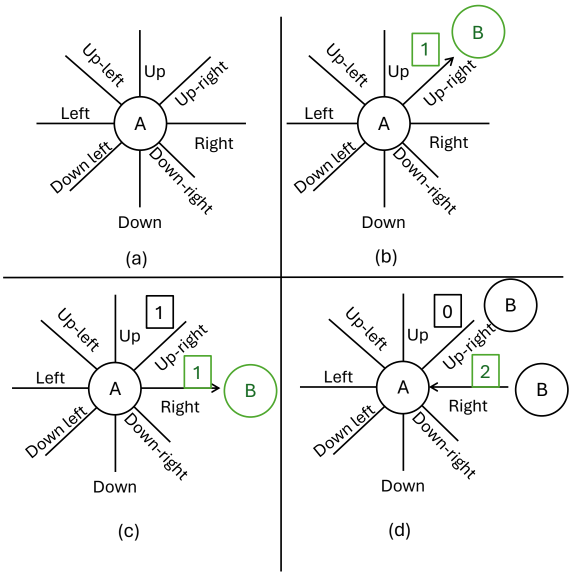

Figure 3: Illustration of an example of trust-ability update.

Algorithm 2: Trust-ability Computation.

```
function COMPUTE TRUST-ABILITY(all_relationships)
    combined_trust ← {}
    for all relation in all_relationships do
        qr_id ← relation['qr_id']
        neighbor_id ← relation['neighbor_id']
        trust ← relation['trust']
        inverse_rel ← inverse_relation(relation['relation'])
        key ← (min(qr_id, neighbor_id), max(qr_id, neighbor_id))
        if key not in combined_trust then
            combined_trust[key] ← {'trust' : 0, 'relations' : []}
        end if
        combined_trust[key]['trust'] += trust
    end for
    return bound_trust(combined_trust)
end function
```

computation of trust-ability scores in real-time. The video capture loop continuously captures frames from a drone-mounted camera, pre-processes them to enhance QR code visibility, and detects QR codes within the frames. For each pair of detected QR codes, the framework computes their relative positions and trust scores based on the computed relations. It visualizes the trust graph, incorporating both positions and trust scores, to provide a comprehensive understanding of spatial interactions between products. By performing these tasks in real-time, the framework enables efficient monitoring and management of products in industrial environments, enhancing productivity and accuracy in inventory-related tasks.

Algorithm 3: Video Capture Loop and trust-ability score.

```
while drone is operational do
    Capture video frame
    if frame is not empty then
        preprocessed_frame ← preprocess_image(frame)
        corners, data ← detect_qr_codes(preprocessed_frame)
        for all QR codes (corner_i, qr_id_i) do
            pos_i ← get_position(corner_i)
            for all QR codes (corner_j, qr_id_j) do
                pos_j ← get_position(corner_j)
                relation ← determine_relation(pos_i, pos_j)
                trust ← compute_trust(qr_id_i, qr_id_j, relation, frame)
                visualize_graph_trust(graph, pos)
            end for
        end for
    end if
end while
```

4 EXPERIMENTAL RESULTS

In our experiments, we used a drone equipped with a camera to capture real-time videos in two types of scenarios: indoor and outdoor warehouse environments. The drone was flown over waypoints, capturing video sequences from which QR codes were extracted. To pre-process the captured frames, we utilized the *preprocess_image()* function (see Algorithm 3), which converted the RGB images to grayscale and applied adaptive thresholding to enhance the visibility of the QR codes. Subsequently, the *detect_qr_codes()* function was employed to identify QR codes within each frame, returning their relative positions and the contents of the information (ID). Then, a directed graph was generated based on the detected relations, and a trust-ability score was computed.

4.1 Indoor Obtained Results

Figure 4 represents from top to down (1) one test environment, (2) the generated trust-ability graph and (3) the user interface for products details information.

The graph was annotated with trust scores, showcasing the level of confidence in each relationship. Trust scores were computed using the *compute_trust* function, taking into account neighbor relative position.

Table 1: Obtained results using different number of products in indoor environment.

Number of Products	Detected Products	Position Accuracy (%)	Trust-ability (max 5)
5	5	100	4
22	18	94	4
30	25	94	3.8
43	36	94	3.8
90	78	94	3.8

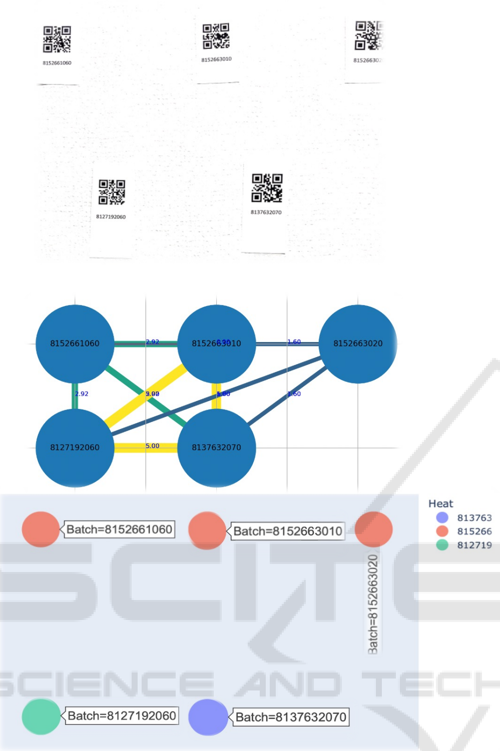

Figure 4: Representation of an example of products' image, the generated graph with the computed trust-ability score for each arrow and the warehouse user visualization.

Table 1 provides an overview of the performance metrics across different scenarios. The *Number of Products* column indicates the varying number of products present in the environment during each test. *Detected Products* column represents the number of detected QR codes.

Position Accuracy represents the products that are detected and located in the correct position within an error of 2 cm. More precisely, it represents the products that are correctly located from those that have been detected. Trust-ability is crucial for understanding the reliability of relationships inferred from the detected QR codes, which will be computed using Algorithm 2. We choose for our experiments that the trust-ability values range from 0 to 5, with higher scores indicating greater reliability.

The obtained indoor results show that more than 81% of the products where detected with an accuracy of positioning the products of not less than 94%. The trust-ability is higher than 3, which means that the majority of the relations between the nodes can be trusted.

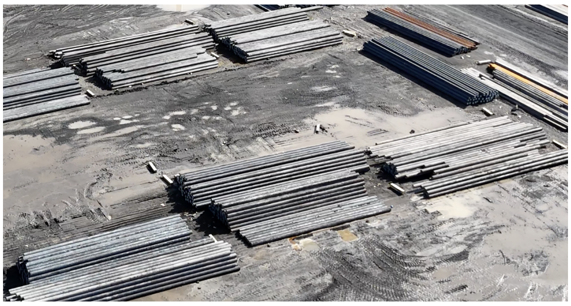

Figure 5: Top view of the outdoor testing environment.

4.2 Outdoor Obtained Results

Figure 5 illustrates the outdoor testing environment, showcasing the algorithm's real-world applicability.

The objective was to demonstrate the effectiveness of the proposed algorithm in locating products by detecting QR codes and positioning products within the captured frames in outdoor environment. Due to logistical constraints, the number of outdoor products is lower compared to the indoor products.

Table 2 provides an overview of the performance metrics across different scenarios.

We choose for our experiments that the trust-ability values range from 0 to 5, with higher scores indicating greater reliability. We need to mention that each line of one specific *Number of product* represents an average of all different perceived drone videos.

Table 2 shows that the developed approach maintained a high level of accuracy in detecting QR codes even in outdoor environments. However, a small decrease in position accuracy was observed with an increasing number of products. This decrease can be attributed to factors such as increased complexity in distinguishing QR codes due to environmental factors like lighting variations, shadows, and potential occlusions.

Despite the decrease in accuracy with a greater number of product densities, the algorithm's robustness and adaptability in outdoor environments are

Table 2: Statistical obtained results using different number of products in outdoor environment.

Number of Products	Detected Products	Position Accuracy (%)	Trust-ability (max 5)
5	5	100	4
11	10	90	3.8
21	16.8	79	3.2

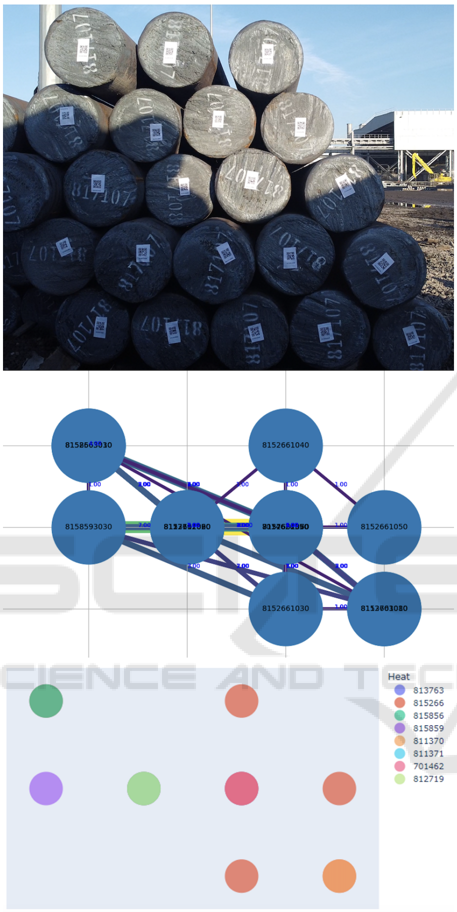

Figure 6: Representation of an example of products' image, the generated graph with the computed trust-ability score for each arrow and the warehouse user visualization.

promising.

The drone successfully continuously captured videos, and the algorithm demonstrated consistent performance in detecting and positioning QR codes without any external positioning system.

In conclusion, our experiments validated the effectiveness of the proposed algorithm, highlighting its application in product location for the warehouse where accurate QR code detection and relative product position help improve warehouse management.

5 CONCLUSION AND FUTURE WORK

In conclusion, this paper has addressed the important need for automating the monitoring of product positions within outdoor industrial environments, emphasizing the challenges and advancements in the field. The evolution of product positioning techniques has been explored, with a focus on overcoming limitations faced by traditional methods such as RFID, barcode systems, and GPS-based tracking.

The integration of unmanned aerial vehicles (UAVs) into warehouse management has been identified as a new generation solution for large-scale and outdoor environments.

Recognizing the challenges in continuous drone tracking and accurate product inference, this paper introduces a novel system of relative positioning using drone-captured images. This innovative approach calculates the location of products in relation to each other, revolutionizing traditional fixed-point and external infrastructure systems. Grounded in recent advancements in sensor technology and data processing algorithms, this method offers enhanced accuracy and efficiency, particularly suited for complex industrial environments like large (outdoor) warehouses and manufacturing floors.

The proposed framework has been detailed, emphasizing the use of embedded cameras in drones, a smart outdoor warehouse, a comprehensive database, and a product location visualization interface. The algorithm for relative product positioning, involving QR code detection and trust-ability graph computation, has been presented in detail.

Experimental results demonstrate the algorithm's effectiveness in indoor settings, showcasing its adaptability and robustness in various environments. For outdoor locations, the system also achieved a good accuracy in detecting products location.

In summary, this work contributes to the evolving landscape of industrial product positioning by presenting an innovative solution that uses drone technology and advanced algorithms. The proposed system has the potential to significantly enhance inventory management and operational workflows in diverse industrial settings. Future perspectives involve further refining the algorithm for a better detection, expanding the system's capabilities for other mission such as products stability, and exploring applications in other domains.

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