Integration of Mobile RFID and Inertial Measurement for Indoor Tracking of Forklifts Moving Containers

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Abstract. Described are the motivation and a method for combining readings of RFID tags placed in static locations in a plant environment using a mobile reader attached to a forklift and inertial measurements of the motion of the forklift to track its position and ultimately the positions of containers it moves within the plant. Strengths and limitations of RFID-based and inertial-based methods are presented along with an algorithm for postprocessing and combining the readings of each. The accuracy of the resulting position estimates are shown to be on the same order as the accuracy of RFID reader range variation.

1 Introduction

Desire for real-time visibility of inventory and assets across the supply chain is driving fast adoption of advanced information technology for location tracking. Location information eliminates the need for non-value added inventory search activities and creates a foundation to further optimize the operational efficiency of business units [1]. While the integration of RFID, GPS, and wireless communication is already common for the logistics industry to track products in routes between supply chain sites [2], tracking within indoor environments such as plants and warehouses is still a challenging problem.

Advancements in RFID technology have facilitated locating tagged assets indoors [3]. In particular, the field of Real Time Locating Systems (RTLS) is rapidly growing, primarily employing active RFID. Existing RTLS solutions differ in operating frequency, methods, granularity, accuracy, and the resulting cost of infrastructure and operation. Despite significant development, RTLS is presently prohibitive for commodity item tracking due to the substantial cost of active RFID and is typically employed only for tracking personnel and expensive resources.

Tracking commodity inventory or containers is usually accomplished using passive RFID and fixed readers operating at "choke points", providing zoning location of a given inventory item. For a large area, the infrastructure cost can be very high, and often fixed readers are installed only at shipping and receiving doors, providing inventory information but not location. The recent introduction of forklift-

Fodor M., Gusikhin O., Tseng E. and Wang W. (2009).
Integration of Mobile RFID and Inertial Measurement for Indoor Tracking of Forklifts Moving Containers.
In *Proceedings of the 3rd International Workshop on Intelligent Vehicle Controls & Intelligent Transportation Systems*, pages 120-129

mounted mobile RFID readers [4] addresses the problem of limited visibility into inventory locations associated with choke points. In this case the locations of the inventory items can be recorded from the location of the RFID reader at the point of unloading. Provided that these items will be moved using only vehicles equipped with the reader and the location of the reader is known, this method can offer relatively reliable location records. A number of different approaches have been proposed for localization of mobile readers. In addition to the RFID-based RTLS mentioned above [5, 6], other technologies include Wi-Fi, Ultrasonic, and Infrared. Often these network-centric approaches are hampered by the need for a substantial initial investment in infrastructure to ensure the required coverage and accuracy. An alternative approach relies on sensors and instrumentation installed on the delivery vehicle to track its location.

There is a substantial body of knowledge related to vehicle-centric localization methods developed within the field of robotics [7] and successfully applied in industrial settings [8]. The most common approaches are dead reckoning and the use of landmarks. Dead reckoning is a method of finding the relative position of a mobile device from a previous known position using inertial measurements or odometry. Challenges with this method include the need to know the original position and the accumulation of errors requiring continuous resetting of position using other sensors. Landmark-based localization determines the absolute position of the device through the recognition of predetermined distinct natural or artificial features of the environment. Artificial landmarks are location reference markers attached to walls, ceiling, or floor that can be easily recognized by vehicle-mounted instrumentation and can be relatively inexpensive to install. Examples include special visual patterns [9], infrared light-emitting diodes [10], and RFID tags [11-13].

Although both dead reckoning and landmark-based methods are error-prone, fusion of the two can result in relatively reliable localization. Several localization methods have been proposed that deal with uncertainty of the measurement data and provide data fusion from different noisy sources such as dead reckoning and landmarks. The Kalman Filter is a widely used method to compensate for noise and is applicable to the localization problem [14]. Monte-Carlo or Particle Filter localization [15] and fuzzy logic [16] have also been considered. In this paper we present an algorithm for the fusion of RFID-based localization and inertial measurement to obtain an accurate location of a delivery vehicle (forklift). With the forklift already equipped with a mobile RFID reader, it is logical to consider the use of passive RFID labels to create static location references in the environment. Since the application considered does not require instantaneous knowledge of an asset's location, the data from both inertial measurements and RFID are fused using post-processing.

This paper describes the automotive part stamping environment and the need for container tracking. Passive RFID and inertial-based localization are then presented with strengths and weaknesses of each individually. The synergistic fusion of the two methods is shown to eliminate the weaknesses of each and is further improved by post-processing. The data fusion algorithm is then described, followed by conclusions.

2 Background

The automotive stamping plant is a first tier supplier providing major components for the vehicle body including doors, fenders, roofs, etc. The stamping plant supplies parts to assembly plants and service facilities using truck or rail transportation. In general, the stamping process consists of blanking, die press, and assembly/welding operations. At the end of the press or assembly operations the parts are placed into metal racks that are used to store and transfer them between stamping operations and customers. Containers hold 8 to several hundred parts each and are unique to each part. Typically, the size of the racks range between 4 to 12 feet in length, 3 to 7 feet in width, 4 to 8 feet in height, and weigh up to 5000 lb when loaded. There are over 20,000 racks in any given plant, and for each given part type there is a limited rack fleet. It is important to closely monitor the flow of racks within the plant and between the plant and the customer's site. If the empty racks are not received back from the customer on time or are held at the repair area, there may be an insufficient number of racks to support production, resulting in non-optimal production batch sizes or hampering the ability of the plant to satisfy customer demand. Each rack is tagged with a passive RFID label, and fixed readers at shipping doors monitor rack flow between the plant and its customers. However, more granular tracking using fixed readers would require a substantial investment in infrastructure as a typical stamping facility is over 1,000,000 square feet.

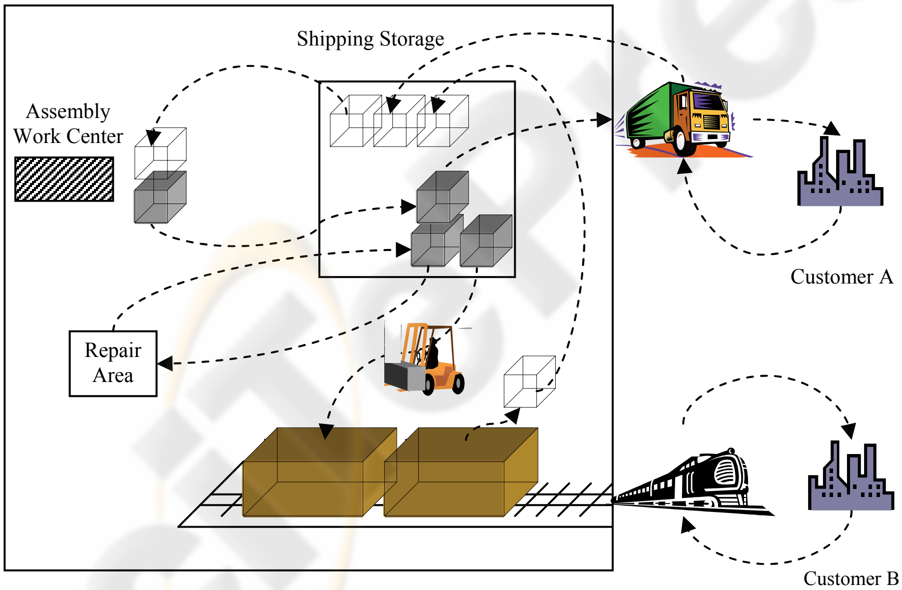

Fig. 1. Schematic of the flow of racks associated with the given work center.

The racks are handled by forklifts which move between the end of manufacturing lines and storage areas, to and from trucks and rail cars, or to and from a repair area. Figure 1 illustrates the rack flow within a typical stamping facility and associated with a given set of parts produced by an assembly-welding operation (work center). The forklift transfers the racks with parts from the work center to the dedicated shipping storage area and brings empty racks back to the work center. These parts can then be loaded onto trucks or rail cars. If there are quality concerns regarding the parts stored in the shipping area, the forklift may move these parts into a repair area and then back. A typical stamping facility employs 40 forklifts, and each forklift is equipped with a wireless terminal that can exchange data with a back office computer.

The many benefits of knowing the specific location and status of racks (full, empty, or in repair) include saving time for material handling personnel locating inventory and reducing downtime caused by unavailability of racks. In addition, when parts are quarantined due to quality concerns, location information can reduce the number of racks that are pulled from inventory. Location and status information can also facilitate a first-in-first-out (FIFO) inventory control system, improve inventory turnover rate, reduce the potential for obsolete parts, and improve material flow and space utilization.

3 Inertial Tracking

Inertial measurement of motion involves the use of linear accelerometers and/or rotational rate sensors whose signals are mathematically integrated to produce speed and position estimates. These sensors are deployed in a wide array of applications including air, space, and ground vehicles as well as various consumer electronic systems. In each application, the orientation or dynamic motion state of the vehicle or device is of interest. Automotive applications include anti-lock braking, traction control, yaw and roll stability controls. Typical sensor sets for ground vehicles measure longitudinal and lateral vehicle accelerations and yaw rate, with roll rate seeing wider use now in roll mitigation systems. In automotive applications, vehicle wheel speed sensors and GPS may also be added.

A general-purpose method for tracking a system in two-dimensional space involves combining longitudinal and lateral accelerations and yaw rate. Yaw rate $\dot{\psi}$ (see Figure 2 for signal and axis definitions) is integrated to provide yaw angle or heading:

$$\psi(t) = \psi_0 + \int_0^t \dot{\psi}\, dt . \tag{1}$$

Vehicle-fixed longitudinal (x-axis) and lateral (y-axis) accelerations, a_x and a_y respectively, are then combined with heading and yaw rate to give velocities in the fixed frame of reference (with respect to inertial ground):

$$V_x(t) = V_{x,0} + \int_0^t \left[a_x \cos(\psi) - a_y \sin(\psi) - \dot{\psi} V_y \right] dt , \tag{2}$$

$$V_y(t) = V_{y,0} + \int_0^t \left[a_y \cos(\psi) + a_x \sin(\psi) + \dot{\psi} V_x \right] dt . \tag{3}$$

Finally, these inertial velocities are integrated to give positions in the inertial frame:

$$X(t) = X_0 + \int_0^t V_x \, dt \, , \tag{4}$$

$$Y(t) = Y_0 + \int_0^t V_y \, dt \, . \tag{5}$$

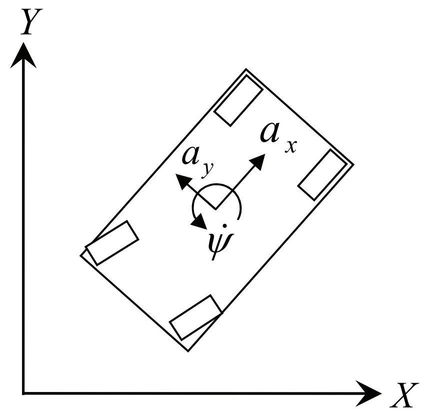

Fig. 2. IMU signals and axes.

Because the sensor measurements are prone to offset and noise errors, this double-integrating process results in error accumulation, limiting the time and distance over which this process provides acceptable results. These limitations can be mitigated to some degree by including kinematic constraints on the integration process which are imposed by the vehicle itself. For instance, the forward speed, yaw rate, and lateral acceleration of a wheeled vehicle are coupled directly as long as the vehicle moves without sliding its wheels (a good assumption for heavy, factory floor forklifts). Additionally, vehicle states such as speeds and rotational rates are bounded by the vehicle operating envelope. The inertial tracking method benefits from a continuous stream of data from the sensors, resulting in uninterrupted, fine-grained position information. However, to anchor the path calculation in absolute space, the position, heading, and velocity of the vehicle at the initiation of tracking (X_0, Y_0, $V_{x,0}$, $V_{y,0}$, and ψ_0) must be known by some other means. For this reason, in addition to the drift problem, inertial tracking alone is not completely suitable for forklift tracking.

4 RFID Grid Tracking

Unlike inertial tracking that drifts and has no inherent connection to absolute space, RFID tags used as a tracking system can be physically connected to the operating environment itself. RFID as a static positioning system requires the use of both tags as well as a reading device that receives their identification information. The tags are either attached at various fixed and known locations in the plant environment and detected with a reader attached to the forklift, or they are deployed on the forklift and read with a plurality of stationary readers. The former approach is advantageous as it also facilitates the detection of the tagged and tracked inventory (racks). If the location tags are deployed in a fine enough mesh within the plant environment, forklift tracking can be accomplished using this method alone. However, despite their low cost, passive RFID tags must still be installed, cataloged, and maintained and are subject to damage in the hostile plant environment where suitable safe installation locations may be few and far between. For example, a typical stamping plant may have support columns, the only suitable installation location for tags, separated by 40 feet or more.

There are other inaccuracies as well. Because the tags can be read at a distance from a range of orientations, the exact location of the reading device attached to the tracked vehicle is not known when communication is acquired with a tag. Therefore, the static RFID tag location signal has some position error since the passing reading device can only be assumed to be located within some expected range (10 to 15 feet) of the energized tag. Additionally, there may be time when the tracked vehicle is not in range of any tag or where a tag is damaged and inoperative. Thus the RFID tracking method, while attached to inertial space, is nevertheless somewhat inaccurate, discrete in nature, and intermittent.

5 IMU and RFID Fusion

Combining the inertial (IMU) and static (RFID) tag data can reduce or eliminate the limitations associated with each individually. The inertial measurements provide continuous data that is potentially accurate enough to reasonably "connect the dots" between the sparse static tag data. Using the absolute position data from the RFID tags, offset errors in the IMU readings can be estimated and removed, resulting in improved positioning, and the IMU data integration can be initialized with static RFID location information to connect it to absolute space.

In the automotive stamping plant setting, the instantaneous location of a tracked vehicle is less important than an accurate estimate of the vehicle's path during a finished delivery as each event takes a few minutes or less. Therefore, the method proposed here assumes that inertial sensor data and static tag data will be collected and stored during an event. When the event ends, the data will be post-processed to determine the path of the delivery vehicle (especially its end points). Using data from the entire event provides a richer data set from which to calculate path, whereas attempting a continuous, immediate position estimate during the delivery event limits the calculations to data that has occurred in the past only and provides no real benefit as the post-processed data is timely enough (within a few seconds of the event ending) for the stamping environment.

6 Postprocessing using Best-Fit Optimization

The proposed computational method relies upon a recursive solution that makes repeated guesses of the initial vehicle position and IMU sensor offsets to attempt to minimize the error between the resulting IMU-based path estimate and the known locations of the static RFID position readings taken over that path. As the solution converges, RFID reader range information is employed to attempt to predict the RFID signal acquisition and loss locations to further improve solution fidelity. The full method is consists of the following 6 steps.

Step 1. Inertial (IMU) and static tag (RFID) data is collected during an inventory delivery event. Inertial data is collected continuously at a regular rate, typically 10 to 100 Hz. Static tag data consists of the time and ID number of each tag as communication with the tag is acquired and then lost.

Step 2. Upon completion of the delivery event (determined by observing acquisition and loss of inventory tag readings), the vehicle path is reconstructed solely from the inertial data by making vehicle initial state assumptions (X_0, Y_0, $V_{x,0}$, $V_{y,0}$, and ψ_0). Typically, these initial conditions are chosen based on information from the end of the previous delivery event.

Step 3. Using a best guess position for each RFID tag reading, one that represents the most likely average vehicle position while it is in communication range with the location tag, a path error calculation is made using the path constructed in Step 2:

$$E = \frac{1}{n}\sum_{1}^{n}\sqrt{\left[X(t_n) - X_{RFID,n}\right]^2 + \left[Y(t_n) - Y_{RFID,n}\right]^2}\ . \tag{6}$$

Here n is an index indicating the acquisition and loss events for the RFID tag readings, and $X(t_n)$ and $Y(t_n)$ give the position of the IMU integration calculation (Equations 1-5) at these RFID tag detection times. The best guess positions, $X_{RFID,n}$ and $Y_{RFID,n}$, are unique for each tag and are based on the position of the tag, the most likely vehicle path followed when in range of the tag, and the reader's expected communication range. These values can be cataloged during the tag's installation or constructed from data collected during system operation.

Step 4. The assumed vehicle initial state (first used in Step 2) is perturbed, and Steps 2 and 3 are repeated until these parameters converge to minimize the error calculated in Step 3. This iterative process can be conducted using any of a number of optimization algorithms such as Matlab's *fminsearch* function. The result of this step is the best match of the inertial sensor-based position to the best guess RFID tag positions used in Step 3.

Step 5. The result of Step 4 is used to calculate the most likely RFID tag acquisition and loss locations using detection range assumptions. At each time of acquisition or loss, the vehicle position (from Step 4) and tag location data are used to find the intersection of the estimated vehicle path with the locus of expected tag detection range points. This locus can be assumed to be circular, or more complex shapes can be used based on more detailed tag and reader information. These new acquisition/loss points establish a more likely vehicle path for further optimization of the vehicle initial conditions (X_0, Y_0, $V_{x,0}$, $V_{y,0}$, and ψ_0).

Step 6. Steps 3 and 4 are repeated using the new acquisition/loss positions produced in Step 5. These positions are updated with each iteration of the inertial data path optimization, and this step is repeated until the solution converges and each subsequent iteration produces a path prediction that is negligibly different from the iteration before.

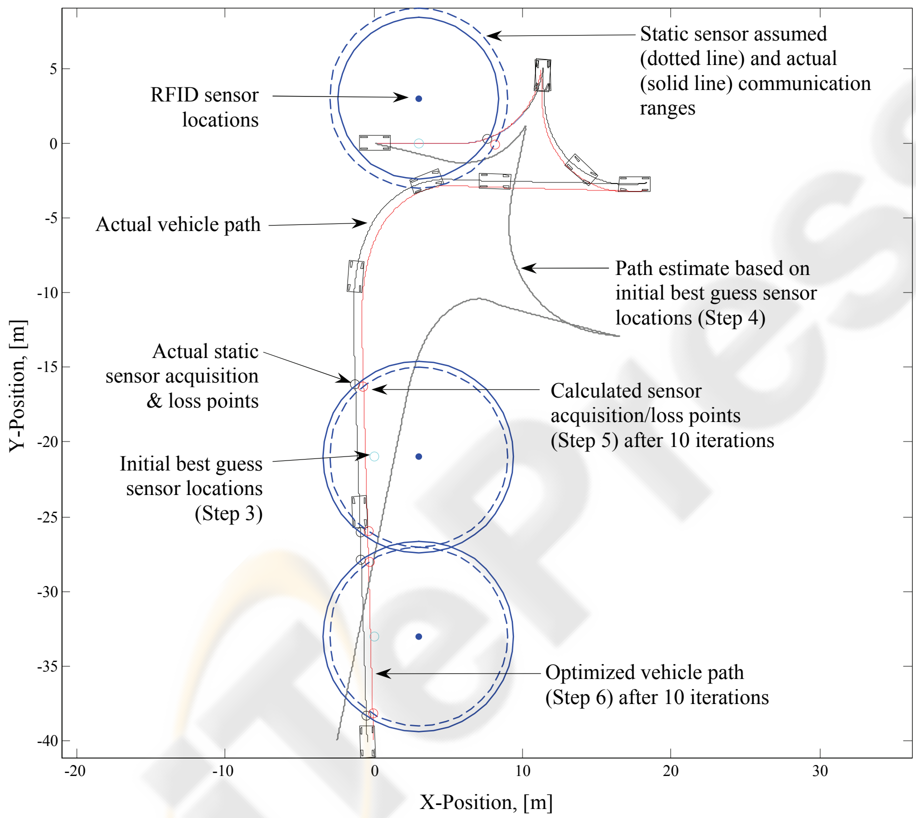

Fig. 3. Forklift path reconstruction showing actual forklift position evenly spaced in time, RFID antenna locations and ranges, initial path estimate, and final path estimate after ten iterations.

Figure 3 illustrates several of the aspects of the method described above. The actual path of the forklift is shown for a delivery event with forklift orientation superimposed at regular time intervals. Large solid circles surround the RFID location tags and depict their actual detection range, while the large dashed circles are the assumed reader ranges used in Step 5. The smaller circles located within the tag detection range are the initial best guess detection locations used in Step 3, and the half-tone line is the path resulting from the optimization using these points (result of Step 4). Shown also is the result of the 10th iteration of Step 6 using updated acquisition and loss points calculated in Step 5. Note the convergence of the optimized path toward the actual path from the Step 4 result to the Step 6 result.

The accuracy of the path reconstruction depends mostly on the accuracy of the assumed reader detection range as compared to the actual range. Note from the figure that the path error (the distance between the actual and final estimated path) is roughly the same size as the reader range variability. For a typical forklift-mounted RFID reader, this is 5 – 10 feet. Solution accuracy can be further improved by including inertial sensor offset errors that are optimized with the initial conditions.

7 Conclusions

Presented here is an effective method of indoor localization of forklift vehicles equipped with mobile RFID readers. The method is based on the fusion of inertial measurements with information from static RFID location tags. While each individual method alone is prone to substantial errors, fusion of the two can provide results of reasonable quality while minimizing the cost of implementation. The accuracy of the resulting location estimate depends on the spacing of the location tags throughout the plant as well as the variability of the RFID reader detection range. In practice it is possible to achieve an accuracy within 5-7 feet which is acceptable for the stamping plant problem.

The ultimate goal of this development is to determine and record the locations of the RFID tagged containers handled by a given forklift. Specifically, the described approach has been developed to track the rack locations for automotive stamping plants. While this paper has focused on the fusion of the inertial measurements with the static information from the RFID tag locations for the purpose of tracking the delivery vehicle, it should be noted that the full material tracking problem is more complex. In addition to location awareness, the pick-up and delivery event with its associated inventory must be identified by monitoring the stream of RFID tag readings seen by the mobile reader. This must be accomplished robustly despite delivery complexities such as moving stacks of racks where not all of the moved racks will be seen by the reader during the entirety of the delivery event.

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