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Nonlinear Target Tracking for Threat Detection Using RSSI and Optical Fusion

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Abstract**—**Video surveillance data analysis plays a key role in homeland security where non-linear target tracking through distributed camera systems is often necessary. However, such a tracking problem poses a grand challenge because the subject of interest can be lost through obscuration. In this paper, we propose a novel approach to solving the track obscuration problem by fusing optical measurements and Received-Signal-Strength-Indicator (RSSI) techniques. While the RSSI of wireless sensing systems is coordinated to allow for continuous tracking, a distributed camera system is applied to track a target in its line of sight. The video and RSSI measurements are fused to enhance the location estimate accuracy of the studied target. Our real-world experiments demonstrate the applicability and accuracy of the proposed approach.

Keywords: Information Fusion, DDDAS, RSSI, target tracking

I. INTRODUCTION

Video surveillance has been widely used in a variety of places like airports, malls, libraries, and city streets. Such surveillance plays an important role in homeland security. For example, in 2013, the Transportation Security Administration (TSA) reported that 1,813 firearms were discovered in carry-on bags throughout the United States with which 81% of them were loaded [1]. Among the detection model with carry-on items, the TSA also regulates how their agents determine and track individuals in the security check process through their Screening of Passengers by Observation Technique (SPOT) program [2]. Under the SPOT program, if an agent determines that a passenger proposes a potential threat, then the information is relayed to other TSA agents and a track begins. Video tracking in airports and urban areas are becoming more apparent with the recent academic developments [3,4] and industry solutions of Lockheed Martin's BlipTrack system [5] and Apple's iBeacon technology [6]. Under the approach of Blipsystem, the location and walking patterns of passengers are determined in addition to the congestion rate of a particular area. The track is based on signals projected from Wi-Fi or Bluetooth enabled mobile devices on each passenger, but lacks an identification link. Apple's iBeacon technology utilizes passenger's bluetooth-enabled mobile device. Identification is also drawn from the mobile device, but does not retain the detection of the passenger when the device is misplaced or lost.

A. Video Tracking

Target tracking through distributed camera systems is fundamental in video surveillance and it presents a grand challenge in maintaining the identification and directionality of the target as expressed by Lipton, *et al* [7]. Many approaches have been researched to address the directionality and maintenance of the tracking system including track-to-track fusion [8]. A major challenge in tracking systems through cameras is when the target of interest moves outside of the field-of-view(FOV) [9], [10], and [11] due to obscurity. To maintain video tracking, researchers have mainly suggested two approaches.

- Estimation techniques such as nonlinear Kalman filters [12] and unscented filters [13] have been used to retain the track of the target of interest. However, such tracking may be very inaccurate when the target of interest is an intruder.
- Wi-Fi enabled device tracking is also proposed to track the target of interest. However, Wi-Fi tracking poses a challenge as environmental factors can distort the signal strength. These influences create ambiguous results which ultimately lead to inaccurate locations.

To improve the target tracking accuracy of the target of interest, researchers have applied information fusion to a track-to-track concept by combining tracking and identification [14]. For example, in 802.11 wireless (or Wi-Fi) tracking, a common metric used to locate a Wi-Fi enabled device is through the measurements of Received-Signal-Strength-Indicator (RSSI) [15]. The RSSI measurements are drawn from the attenuation of the propagation path between two devices [16]. From communication theory, if the transmit power is known, then the attenuation can be calculated by taking the difference of the received power from transmitted power [17]. Under the 802.11 protocol design, beacons can be obtained when an adapter is set to promiscuous mode and the values are extracted using radio tap headers [18]. To geolocate wireless devices, many aspects of interference are needed to obtain a precise measurement. Common areas of variable transmission include: *multi-path fading* [19], *indoor shadowing* [20], *angulation*, *offset*, *lateration*, and *trilateration*. These variables also include other aspects such as time of arrival (TOA) [16]. In combination, these categories can be used to refine the tracking measurement of RSSI by reducing the influences of interference and environmental factors. In order for us to refine the tracking metric, optical tracking using video cameras are applied to measure the uncertainty of Wi-Fi location.

Optical tracking through video cameras have been extensively researched and examined for decades such as Lipton *et al*. [7]. It is commonly known that a three dimension space is examined in multiple planes—image plane and world plane. Tracking under the world plane is drawn using the fundamental camera techniques of matrixes and ratios. World coordinates position the target to the three-dimension space and can be extrapolated using the camera focal length. In many situations, when a target becomes obscured and outside the FOV or line- of-sight (LOS), estimation techniques are drawn in aims to correct the tracking path and to retain the correct measurement. This paper focuses on information fusion of wireless and video information fusion to improve tracking and reduce faults.

B. Information Fusion Systems

Information fusion is a common technique to reduce the uncertainty of raw data sets and provide situation awareness [21]. It is given that both tracking in RSSI and optical tracking have various strengths and limitation against security threats, bad weather, and complex environments. Information fusion has been used to reduce measurement uncertainty, and through the researched model, both can complement one another to enhance tracking.

Combining models, measurements, and software approaches is a concept of the Dynamic Data-Driven Applications Systems (DDDAS) [22,23] as shown in Figure 1. DDDAS examples include video surveillance using cameras [24], unmanned air vehicles [25], and private networks [26]. DDDAS is consistent with information fusion as demonstrated for object assessment [27], situation assessment [28], sensor management [29], and user refinement [30]. Here, the RSSI and optical fusion is motivated by the DDDAS measurement component.

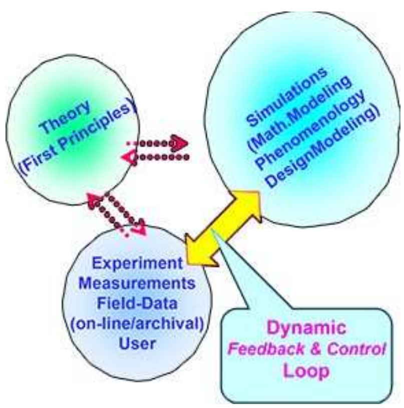

Fig. 1. DDDAS Concept [22]

In this paper, we propose a novel approach to solving the above non-linear tracking problem for threat detection by using optical fusion and Wi-Fi techniques. While the RSSI of wireless sensing systems is processed to allow continuous tracking, a distributed camera system is applied to track a target at its line of sight. We will demonstrate how to fuse two types of measurements together to improve the location estimate quality of the target of interest. We test the proposed approach in a real-world environment - the w-iLab.t test of iMinds [31]. Our experiment results have demonstrated that optical fusion and Wi-Fi techniques can complement each other very well and the proposed approach is applicable to real-world non-linear tracking for threat detection.

The rest of this paper is organized as follows. Section II gives the background and definition of this research problem. Section III outlines the methodology we propose for solving this research problem, Section IV presents our experimental methodologies and results. Section V discussed extensions of possibly expanding our proposed approach and experiments in the previous sections. Finally, Section VI concludes and presents future work.

II. Background and Research Problem Definition

Video surveillance systems have been widely installed and used in a variety of important places such as military bases, airports, streets, malls, train stations, and school buildings for homeland security guarantees. However, as shown in Figure 2, a camera can only observe a line of sight in a scene and many spots may not be monitored by cameras. Meanwhile, RSSI has been the ability to track a target not in the LOS. However, RSSI tracking techniques are not accurate due to wireless interference, refraction, diffraction, and scattering. Multipath fading is a known challenge when examining methods to reduce interference [32]. In wireless communication, refraction, diffraction, and scattering are common impacts to wireless propagation that leads to multipath fading [33]. We have seen this impact in our experiments when the distance of two given devices increases linearly. The propagation pattern reflects a non-linear approach [16]. As a result, the target tracking is lost and the accuracy becomes skewed. In one approach to correct the interference given from multipath fading, previous research studies [19] indicated that by either moving the physical location of the devices or changing the carrier frequency of the wireless communication enhances the precision of RSSI. This approach provides some forms of track improvement, but outlines issues when interference occurs. Although the paper refers to using 802.15.4 as their main component and 802.11 Wi-Fi traffic being a main problem for interference due to transmission, this paper will utilize Wi-Fi frequencies as the propose method for RSSI tracking.

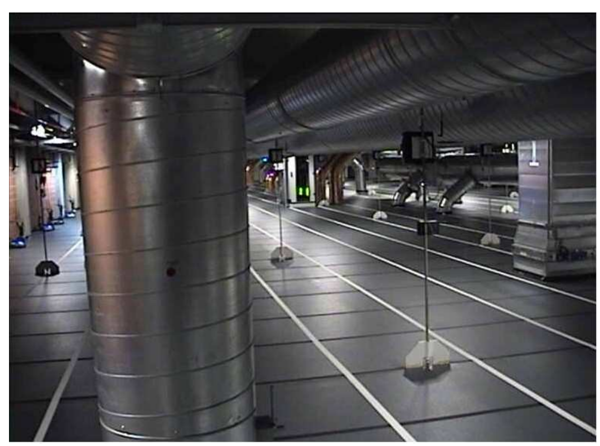

Fig. 2. Testbed Target Actual Path with Sensor Configuration

Our research problem is to nonlinearly track a target through distributed camera systems and Wi-Fi communications system accurately and efficiently for threat detection. Precisely speaking, as shown in Figure 2 (a topology view is given in Figure 3), we aim to track a target through video surveillance and Wi-Fi systems where camera observations are obscured. Specifically, how can we effectively fuse video tracking and Wi-Fi measurements together so as to obtain precise target tracking? In what follows, we first present the approach for solving the non-linear tracking problem and then give our evaluation of the proposed approach through the field experiments on the w-ilab.t testbed of iMinds [31].

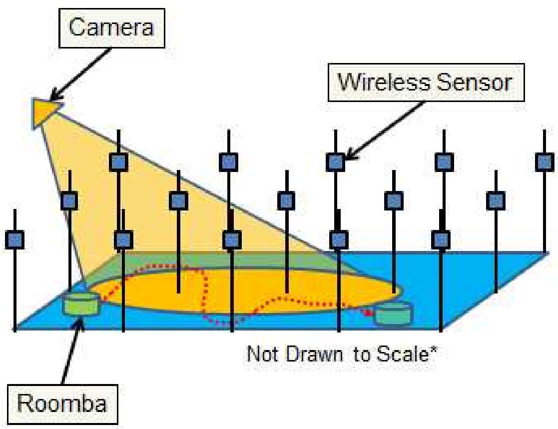

Fig. 3. Topology Design and Layout.

III. Research Methodology for Solving The Non-Linear Tracking Problem

In this research, we propose a novel fused approach where video surveillance measurements and Wi-Fi communication measurements to predict the location of a target. We applied our Wireless-Optical Fusion (WiOF) approach using Global Environment for Network Innovations (GENI) as one of the main resources to the examination of this fusion method.

A. Global Environment for Network Innovations

In order to establish a tracking metric for our fusion method, we employed the iMinds w-iLab.t testbed [31] for our study. We first give our experimental and data analysis methodology in this section and then discuss our experimental setup and results in Section IV.

In order to express the logical view of our experiment, Figure 3 depicts experimental testbed where cameras and sensor are installed to track an interested target that may be considered as a potential threat in the real-world scenario, such as in the airport and urban centers [1,2,34,35,36]. Under the design of the testbed environment, wireless sensors were positioned at a fixed distance of 6 meters by 3.6 meters in a grid formation over the span of a $1080m^2$ room in our experiments. The wireless sensors used in this testbed were embedded PCs using two Wi-Fi antennas. The target for this research was a moving robot with a predetermined path using a mounted Wi-Fi antenna and sensors to maintain a path. The path was designated based on the design structure of the testbed. Pan-Tilt-Zoom (PTZ) video cameras were also readily available for use to facilitate the optical portion of this research, and were placed in random locations. Lastly, the testbed utilizes piping and ventilation from the building's heating and cooling system to create an ambiguous environment for interference in addition to obscurity from the camera's point-of-view (POV). The topology entails multiple nodes and a post processing server to track the target - detailed as follows.

B. Topology Setup and Design

As mentioned above, the topology for this research entails the use of GENI [37] as the main focus for experiments. Under the scope of the research, the topology is represented and shown in Figure 4.

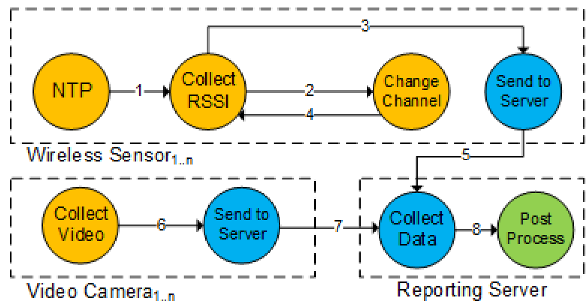

Fig. 4. Logic Design and Layout.

Each wireless sensor is synchronized with network time protocol (NTP) to ensure that the tracking metric is consistent throughout the various readings in regards to time. Once time has been synchronized, each wireless sensor and video camera begins with the data collection process. To facilitate the wireless reading, *Aircrack-ng* [38] was used to sense and collect wireless data in promiscuous mode as represented by 2 and 4 in Figure 4. Prior to the channel being changed, the previously collected data is transmitted to the server in the format of "Epoch Time : MAC-Address : Reading." Simultaneously, the video camera collects a recording of the targeted area and transmits the information to a reporting server as represented by arrows 6 and 7 in Figure 4. Once the data has been collected, post processing of the information is assessed as represented in arrow 8 in Figure 4. As denoted, wireless tracking outlines a significant portion of the research and therefore needs to be assessed to ensure track accuracy.

C. Wireless Tracking Localization Problem

In order for us to track the target under the scheme of RSSI, data was collected and reported to a server for post processing. As mentioned, data being transmitted to the server is in the format of "Epoch Time : MAC-Address : Reading" where "Epoch Time" is collected from the system time, the MAC-Address represents the targeted wireless device, and "Reading" is the RSSI value measured in dBm. Tracking calculations were measured using a localization equation [39] and [40] as represented in the following equation:

$$2(x_i - x_{i+1})\,x + 2(y_i - y_{i+1})\,y - (d^2_{i+1} - d^2_i)$$

$$= (x^2_i - x^2_{i+1}) + (y^2_i - y^2_{i+1}) \quad (1)$$

where three sensors with the strongest readings of RSSI in each target area are used for wireless tracking, and they are referred to Sensor i, with $i = 1, 2, 3$. Three readings were used based on triangulation and that additional sensor measurements increase the position error. The various techniques to improve the accuracy were based on the previous research done by Pu *et al*. [16]. In order for us to track multiple devices within an area, wireless beacons are collected when each wireless adapter is placed in a promiscuous mode. While in the promiscuous mode, the wireless sensor cycles through each 802.11 wireless channel using deterministic or stochastic methods. This allows for the detection of both associated and unassociated wireless devices within a given area. When a wireless device becomes associated to a network, detection is difficult to achieve if the sensor is not on the same channel frequency. By cycling through each channel, the adapter can collect a wider scope of devices within a given area. The rate of the cycle is determined at a fixed interval in either microsleep (miliseconds) or sleep (seconds). To calculate the location of the device, an Euclidean space is determined. Under the design of the Euclidean distance, it is shown that interference is not factored when measuring RSSI. In doing so, we applied various techniques drawn by previous work [39] to locate the target. Specifically, each sensor will produce an over determined system in regards to the localization problem. This over determined system is estimated using a least squares method and graphed for analysis. Once wireless tracking is achieved, optical tracking is included for the fusion model.

D. Optical Tracking Projection Transformation

Under the scope of optical tracking in video, there are numerous methods reported. It is understood that each technique has its own limitation, such as a particle filter [41]. Under the design of the wilab.t testbed, the provided PTZ cameras can be remotely connected and captured for processing. In the camera design, the angle and location is predetermined prior to experimental analysis, which includes areas that are outside the field of view (FOV). Marking tape outlines a 1 meter by 1 meter grid system as represented in Figure 5 per design of the testbed.

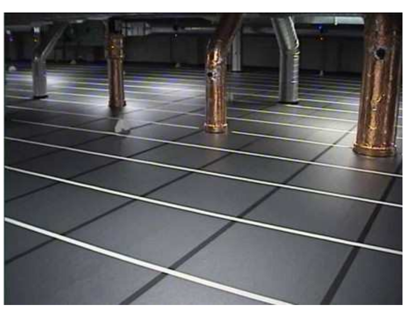

Fig. 4. Test Bed Floor Design as a Calibration Mechanism

These lines will be used as reference points to track the moving target. The implementation of the video tracking is designed in MATLAB and uses functions and toolboxes that are developed for tracking. Specifically, projective transformations are applied to the video feed to convert the 2D image coordinate to 3D world. This method was selected as a camera is unaware of the physical location of the target in regards to world coordinates. A transformation method is needed in relation to the focal length f of the camera. To fully facilitate the research model, information fusion is applied to the world coordinate values obtained from the video and RSSI tracking.

E. Track-to-Track Information Fusion

Information fusion using track-to-track concepts is the main focus of this research. Under the ideology of this design, world coordinates from both wireless and optical tracking are applied in a fused model to further enhance the positioning of the target. Under the logical approach of the WiOF model, optical tracking takes precedence over the wireless tracking due to environmental factors and other various influences as represented in Figure 6. The application of the WIOF approach reduces the uncertainty when a target is outside the FOV and retains the track if it renters the view. In Figure 6, two sources of inputs are fed into the fusion model with a conditional statement to verify if the target is out of the FOV. This approach was selected based on the condition that wireless has environmental influences that can be negligible in the target localization. The selected track is then applied to the tracking mechanism and filtered for final output. During the filtering step of the logic model, a nonlinear Kalman filter [12] will be applied to the position to remove the noise of the wireless metric measurements and enhance the accuracy of the target's position estimate.

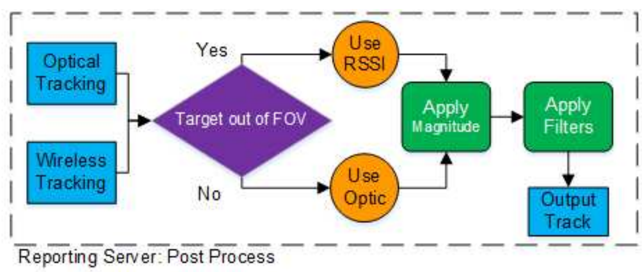

Fig. 6. Information Fusion Logic Model.

IV. Experiment Results

A. Wireless Calibration Metric

We began our experiments by finding the relationship between RSSI and distances that are less than 10 meters and then studied the relationship for the case of distance greater than 10 meters. These results are applicable to the two different calibration cases in real world.

In the initial approach of the WiOF tracking, a calibration phase was needed to measure the relationship of RSSI to a world coordinate space (distance). Under this calibration phase, the target was positioned at fixed locations between 6 meters to 30 meters away at 6 meter intervals. In the configuration, RSSI was measured at a rate of one second for duration of five minutes and fitted with a logarithmic function using a nonlinear least squares method. The fit is presented in Figure 7 and resulted in Equation (2) with a R^2 value of 0.9289.

$$r = -4.783 ln(x) - 40.271 \quad (2)$$

Within equation (2), r represents the input value of RSSI where $-100 < r < 0$ due to the design specification of the wireless adapter of each sensor and x represents the distance in meters. A limitation that was foreseen in the measurement of RSSI was the sampling method. It is noted that the wireless driver for each sensor would only evaluate RSSI to whole numbers (integers) and therefore—all measurements in this experiment in relation to RSSI would be presented as such. Under the preliminary calibration of wireless devices, it was discovered that the fitting application was not an effective method in regards to the localization technique for RSSI. Additional measurements were needed in the application to properly assess the relationship of RSSI to distance.

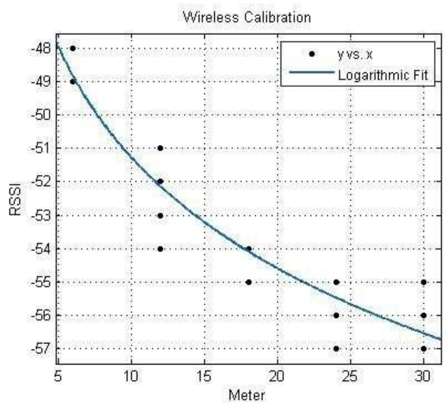

Fig. 7. Logarithmic Fit for Wireless Calibration Using Nonlinear Least Square

Under the second calibration attempt, the samples were taken at the closes possible distance of 0.152 meters up to the furthest distance of 54 meters. Samples were collected for duration of 10 minutes with variable angles and objects—such as copper piping and heating, ventilation, and air-condition (HVAC) units—to influence the measurement of RSSI. In Figure 8, a new fit is presented using a power fit with a non-linear least squares method.

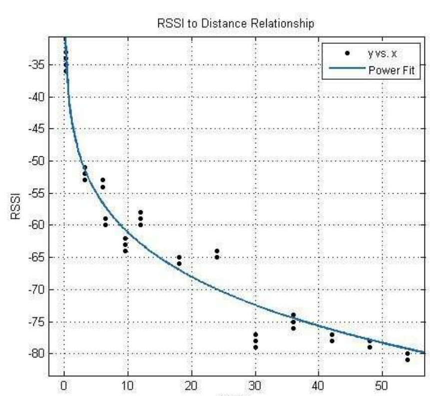

Fig. 8. Power Fit for Wireless Calibration Using Non-Linear Least Square

It was discovered that R^2 was measured to be 0.9513 and the fitting is shown in Equation (3).

$$r = -42.98x^{0.1534} \quad (3)$$

Under Equation (3), further investigations concluded that this calibration metric was reasonable as this additional calibration method was used. It was determined that the relationship of RSSI to distance was not reasonable as expressed in Section IV-D and that the technique drawn from Oguejiofor, *et al*. [42] also had the results for RSSI to distance relationship. Specifically, the relationship of RSSI to distance is heavily sensitive to environmental factors and the readings within 10 meters seem to be reasonable. However, our experiments have shown that Equation (3) provides much more accurate relationship of RSSI to the distance for the readings within 10 meters, compared to Equation (2) and the results in [42]. Thus, we will use Equation (3) for the relationship in the rest of the paper. Once the evaluation of RSSI to distance was determined, video calibration was needed in order to ensure its accuracy to fulfill the fusion model.

B. Optical Tracking Calibration Processes

For the calibration of each optical device, cameras were calibrated initially using static images as represented in Figure 8. As depicted in Figure 8, calibration was implemented using black and white tape that was set in the test bed configuration as indication points of world coordinates. The focal length f of the camera was collected from the manufacture's documentation, and the angle of the view was retrieved from the camera's software. As depicted, the calibration method presented a mean error rate of 0.70 pixels in regards to the accuracy of the optical tracking. In Figure 9, the coordinate system markers X and Y represents the projection of the camera in regards to the tracking location of the testbed. The green points of the calibration represent the detection locations of the gird lines in respect to the testbed while the red plus sign represents the calibrated position. It is shown that the aim of using the grid markings of the testbed as a calibration method was inconclusive within Matlab's cameraCalibrator tool, and therefore—manual calibration was needed.

Fig. 9. Camera Calibration Mechanism

C. *Manual Optical Tracking Calibration*

As the detection of the calibration function was inconclusive using the Matlab cameraCalibrator tool, a manual calibration was needed in order to ensure the effectiveness and accuracy of the optical tracking. It was known that the grid configuration of the testbed was established to be a 1 meter by 1 meter design and, therefore, it was reasonable to estimate the values needed to fulfill the projection transformation for optical tracking.

Using the projection equation as represented in (4), world coordinates (X, Y) were easily retrieved as necessary information. Under the equation, f represents the focal length of the lens, (x, y) represents the coordinate location on the image (video), and Z represented the known location between the camera and the environment (world). Once the optical calibration phase was deemed reasonable, the target was set afoot in the testbed for tracking [43]:

$$x = f \times \frac{X}{Z}, \qquad y = f \times \frac{Y}{Z} \tag{4}$$

To verify the feasibility of the optical tracking, a target was instructed to move to a fixed path within the testbed. Under Figure 10, a particle filter (PF) was applied to a video recording with a target in the FOV. It is demonstrated in Section IV-D, the effectiveness of the PF tracking method in regards to the calibration phase.

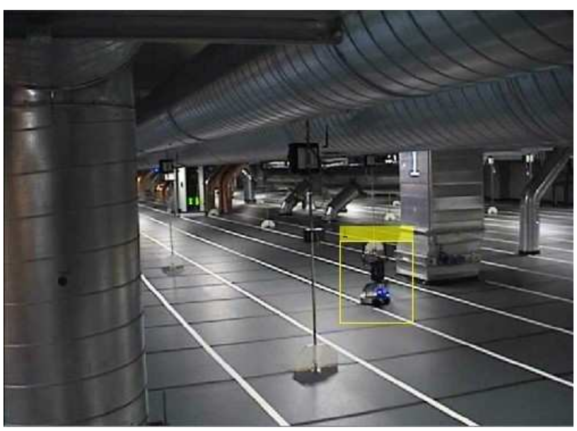

Fig. 9. Testbed Target Actual Path with the Sensor Configuration.

D. *Tracking Measurement*

In the initial measurement of each experiment, actual coordinate data was collected from the target per design of the testbed as represented in Figure 10. In Figure 10, multiple sensors are depicted in a grid-like formation, but per experimentation purposes—not all sensors were used. It is also depicted that a target is set in a particular path through various sensors, but this does not reflect all experiments in this paper. Under a preliminary experiment, three sensors were used at a fixed location in addition to a single camera. The target was instructed to move at a fixed path at a rate of 16cm/s to verify the measurements of both RSSI and optical tracking. Using optical tracking, Figure 11 demonstrates the particle filter applied to the video recording to track the target.

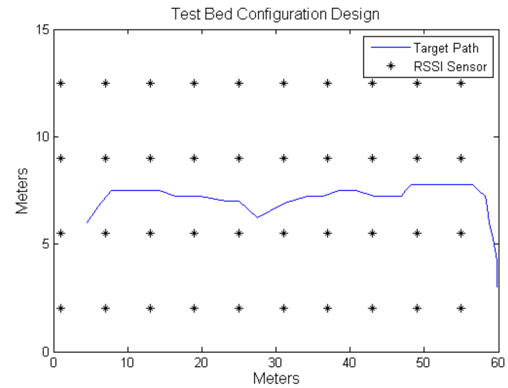

Fig. 11. Particle Filter Tracking.

E. *Fusion Tracking Model and Measurement*

Our proposed WiOF information fusion method performs track-to-track fusion of optical and RSSI data. RSSI tracking has been studied independently of optical systems for wireless sensor networks, typically for indoor settings [44, 45,46,47,48,49,50]. The WiOF method improves on RSSI or optical methods alone for robust tracking over camera occlusions or RSSI uncertainties.

Figure 12 depicts the results of our proposed approach. As shown, the tracks from Section IV-D were plotted on the graph together using our WiOF fusion method. As shown, a target enters an area and maintains a particular direction and movement over a period of time. The position was tracked using the RSSI, but the track was not accurate. Once the subject enters the camera's FOV, the tracking was then enhanced to precisely follow the target. When the target exits the fixed of view, the RSSI tracking is resumed.

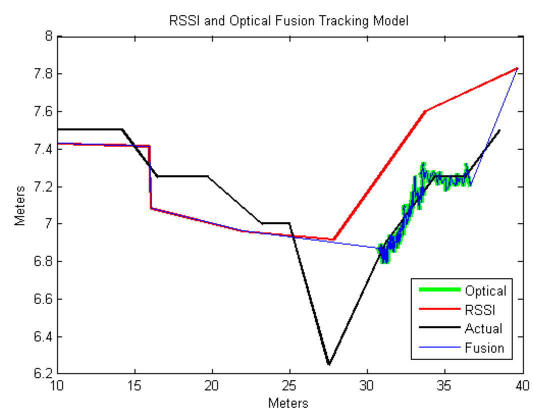

Fig. 12. RSSI and Optical Fusion Tracking Results.

A running error analysis demonstrated that the video results were more accurate with the RSSI than video results alone.

V. Discussions

As denoted in Figure 12, the target entered the environment of the testbed at (10, 7.5) and continued its path to the end at (40, 7.8) where the actual location of the target is marked as "Actual" in Figure 12. As the target entered the perimeter of surveyed area, three wireless sensors with the strongest reading of RSSI were used to locate the target as denoted by the red line. As the target continues its projected movement, RSSI tracking continues as previously mentioned in Section III-B where either existing or newer wireless sensors with a stronger RSSI reading were used to track the target. As the target continues its movement throughout the surveyed area, there were some moments where the RSSI tracking was relatively close to the actual path. This track result never matched the exact position, but was relatively close. At the 25 meter marker on the *x*-axis, the target moves very irregular by a sudden movement to the right. Although the distance the target traveled on the *y*-axis was roughly 1 meter, the precision was not as accurate as hoped. Eventually, the target enters the FOV of the camera as denoted by the 30 meter marker on the *x*-axis. Optical tracking began its procedure to locate the target in addition to the RSSI tracking measurement. The target eventually left the FOV and continued for the remaining duration under RSSI tracking. It was depicted that the fusion model presented a novel approach to existing techniques.

Using the depicted line drawn from the fusion track (blue), the location of the target was reasonable as the tracking was relatively close to the actual path. Although there were situations where the target made abrupt movements that were not detected or noticed in the RSSI tracking metric (25,7.1), the optical portion of the fusion model allowed for precision when visible under the FOV. It is demonstrated that further improvement is needed in this WiOF fusion model.

It is apparent that the accuracy of the WiOF fusion method implementation presented some errors from the actual tracking path, but requires further improvement. Although the accuracy of the RSSI tracking measurement started relatively close to the actual path, it eventually drifts. Three wireless sensors were used to construct the RSSI tracking, but the rate of which the wireless sensor retrieves each value should be enhanced (quicken) to provide additional data points. Although each sensor cycled through 11 channels in the 2.4 GHz wireless spectrum to obtain all clients within an area—associated clients to the local Wi-Fi network would be believed to present different results that is more accurate.

VI. Conclusions and Future Work

In this paper, we have studied the problem of non-linear target tracking in video surveillance data analysis for homeland security. Such tracking is often done through distributed camera systems. However, such a tracking problem poses a challenge because the subject of interest is lost through obscurity. In this paper, we have suggested a novel approach to solving this problem by using optical fusion and RSSI techniques where wireless sensors are used to track an interested target as well with distributed camera systems. Specifically, in the proposed Wi-Fi-optical fusion approach, a distributed camera system is applied to track a target at its line of sight while the RSSI of wireless sensing systems allows continuous tracking. Furthermore, these two types of measurements have been fused together to estimate the location of the target. In order to evaluate our proposed approach, we have conducted the field experiments on the w-iLab.t testbed of iMinds at University of Ghent. We employed filtering techniques for removing the noises of measurements. Then, we examined the relationship between RSSI and distance. Finally, we have presented our evaluation of the proposed WiOF approach for estimating the location of an interested target. We have given a comparison of estimated locations with their actual ones. Our experimental results demonstrate the applicability and accuracy of the proposed WiOF approach.

In the future, we plan to conduct a series of sophisticated experiments for the evaluation of the WiOF approach and study the non-linear tracking problem for the case of networks under attacks. Using the measurements from the optical and wireless systems; we seek to add kinematic and geospatial modeling with software improvements using a cloud architecture [51] and cyber trust [52] to enhance the DDDAS concept for both single and multiple target tracking.

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The views and conclusions contained herein are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of Air Force Research Laboratory, NSF, or the U.S. Government.

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