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Fusion of Security Camera and RSS Fingerprinting for Indoor Multi-Person Tracking

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Abstract— In this paper the fusion of data from a network of security cameras and RSS fingerprint observations are combined to facilitate the simultaneous tracking of multiple persons inside indoor environments. An objective of the developed algorithm is to utilize existing building infrastructure namely the networks of security cameras and WiFi access points. Additionally minimal initial and maintenance calibration is required as crowdsourcing of the fingerprint mapping and self-calibrating camera processing is an integral component of the algorithm. Experimental results are given that demonstrate the accuracy, robustness and adaptability of the developed tracking algorithm.

Keywords— indoor navigation; camera tracking; WiFi crowdsourcing; computer vision; fingerprinting

I. INTRODUCTION

Currently there is significant interest in the development of robust location based services (LBS) for indoor or campus type environments. This technology enables a plethora of emerging security applications including tracking employees and potential intruders within a secured environment such as an airport complex, large corporate offices, or product development facilities. Other applications are related to tracking assets such as the locations of mobile hospital equipment or wheelchairs. In addition, as mobile robotics continues to become increasingly integrated into public buildings, there is great motivation to assist the robot's navigational processing by supplying information regarding the location and activity of people inside the building [9].

Accuracy and robustness of indoor asset and person tracking based on RF wireless signaling alone is typically poor due to multipath distortion, excess attenuation and the difficulty of providing accurate time synchronization [12][19]. For this reason other sensors are used to provide a diversity of observables related to an object's location. GNSS signals are rarely considered for indoor applications as they are extremely weak and suffer the same multipath distortion effects as wireless data communication signals. MEMS based inertial sensors are of significance as they have become inexpensive and much more accurate during the past decade. However, they are still subject to moderate levels of drift and bias that

are difficult to compensate for [1]. Trajectory estimation of a mobile device based on dead reckoning requires tactical grade IMU's (inertial measurement units) which are typically bulky and prohibitively expensive in the context of consumer mobile devices. However, IMU sensors can still provide useful observables in support of asset and person tracking when used in conjunction with other sensors.

Computer vision (CV) processing based on wall mounted security cameras (SCs) as well as cameras integrated into the mobile device have been developed over the past decade for tracking moving objects as well as providing ego-motion estimation of the mobile camera [8]. While mobile ego-motion CV processing can be very effective in self-localization of the mobile device, it generally consumes too much battery power to be of practical use. CV developed for multi-person tracking with security cameras has also been developed over the past decade with significant progress [2][4][18]. However, a problem remains with CV based location in that object identification generally remains as an ill posed problem [6][7][14][15][17]. That is, while a general object can be aptly tracked with CV, the positive identification and abstraction of biometric attributes from video frames is difficult.

In this paper a novel network based object location, trajectory and identity estimation algorithm is proposed and described with preliminary experimental results. This algorithm is denoted as MOLTIE (Multi Object Location Trajectory and Identity Estimator). The MOLTIE system fuses SC CV processing with sensor data from each mobile device located within in the tracking environment. These mobile sensors are primarily the RSS of Bluetooth (BT) and WiFi wireless data signals, inertial sensors based on a MEMS IMU and also a barometer. In this paper the mobile wireless transceiver with associated sensors is denoted as MW (Mobile Wireless).

A feature of MOLTIE is that it requires minimal calibration. The initial calibration of the SCs is based on existing feature points in the building map (BM) that are visible to the camera in its FOV (field of view). Ongoing CV calibration is based on tracking these feature points when observable. Also, the RSS fingerprinting is based on spatially

smoothed radio maps which are generated from crowd sourced data captured from objects moving through the camera's FOV.

In the MOLTIE system, signals from the SCs are pre-processed which involves frame grabbing from each camera source, resizing the images, generating grey scale images and performing all of the necessary background differencing to isolate the moving foreground. Standard mixture of Gaussian (MoG) modeling of the background is applied to estimate the foreground pixels [5][13][16]. The processed frames are sent to MOLTIE which performs the object detection processing resulting in CV objects (CVOs) that are tracked. Likewise the sensors of the MW are read and some pre-processing is performed to minimize the wireless data transmission required. Location of the MW is estimated based on using pre-surveyed or crowd sourced radio maps generated from standard fingerprinting techniques [10]. The result is MW objects (MWOs) which are tracked. MOLTIE then considers the trajectory fragments of the CVOs and MWOs and determines the probabilities of association. This pairwise probability of association (PoA) between a CVO and MWO varies dynamically based on accumulated likelihood. The set of CVOs, MWOs and PoAs are then inputs to an overarching Bayesian probabilistic graph algorithm that establishes the overall history of the objects and the identities of these objects which is ultimately expressed statistically. This Bayesian processing is beyond the scope of the present paper. The processing of CVOs and MWOs differs from previously reported multi-object tracking algorithms as in [20], which also combines CV and WiFi but the association is implicitly applied with the intent that the WiFi observables assist the CV processing in connecting CV estimated tracklets. In MOLTIE, CVOs and MWOs are explicitly distinct objects.

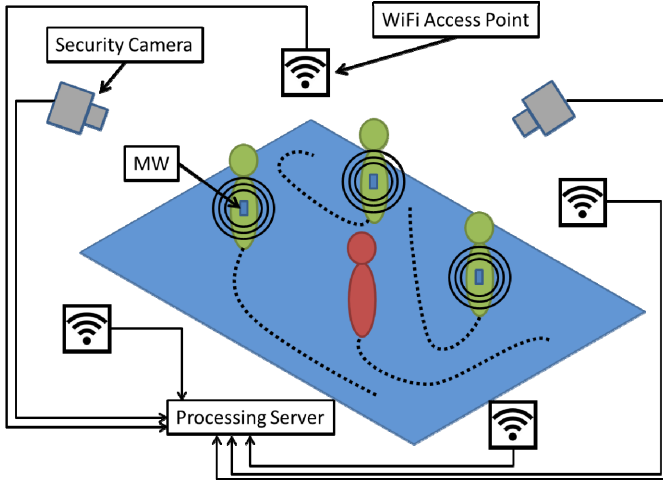


Figure 1 MOLTIE system

To further describe the operation of MOLTIE consider a scenario such as a corporate building where employees carry badges outfitted with a small wireless receiver that scans for WiFi signals and also contains an IMU sensor. Let us consider the scenario presented in Figure 1, where four people are walking through a building environment that is monitored by two SCs and four WiFi access points.

Three people (colored green) are employees each carrying a MW, while the person (colored red) is an intruder who does not carry a MW. The data from each MW is sent through WiFi to the processing server along with the processed CV data. MOLTIE will use this incoming information to establish the PoA between the CVOs and the MWOs. As the tracking progresses MOLTIE will identify which individual is not carrying a MW and raise an appropriate security threat flag.

The architecture for transmit-only employee badges is essentially the same as the MW device of Figure 1 with the exception that it contains a Bluetooth (BT) beacon that periodically issues advertising bursts that are received and demodulated by BT gateway receivers at fixed locations throughout the building. SCs within the building track people objects as they move throughout the hallways, lobbies and office areas. MOLTIE would reside in a server where the CV and MW signals are collected for central network processing. The CV component of MOLTIE detects potential person objects and tracks them as they walk through the facility. However, the CVO does not provide a unique identification of the object but is limited to easily abstracted attributes such as height, velocity, heading and color. In idealized conditions such attributes may be extended to human and face recognition but this is typically not reliable based on the SC quality and installation.

The MW processing of the MOLTIE attempts to locate the MW transceiver based on the RSS measurements and the IMU data. The trajectory estimate of the MW is then compared with the estimated trajectories of the CV tracked objects. Strong trajectory correlations of a pair of CV and MW objects indicate a higher PoA. Likewise if the pair of estimated CVO and MWO trajectories show only weak or negligible correlation then the PoA will be set very low. Hence the association of the CVOs and MWOs is probabilistically captured by the array of PoA values output from MOLTIE which ultimately identifies the employees in the current application example.

In typical indoor campus building scenarios, the CV processing results in a cluster of fragment trajectories that need to be associated into an overall CVO trajectory. In typical installations the SC FOVs are overlapping such that trajectory clusters from a plurality of camera outputs are combined. Robust association of these sets of CV generated trajectory fragments remains as an open research problem with current methods being heuristic and subject to frequent confusion especially as the number of moving objects in the scene increases. Notwithstanding, the CV processing of MOLTIE is reasonably robust for scenes with minimal occlusion but busy scenes are still problematic. However, this lack of robustness is anticipated by the higher level processing of MOLTIE as it is statistically based and uses soft decisions. This is a necessary mechanism for reliably recovering from CV related trajectory association errors.

On occasion, simple scenarios involving isolated and unobstructed CV objects in which the PoA can be justified to be high, present themselves. This is an opportunity for the MOLTIE system to do maintenance calibration of the RSS

radio maps by crowd sourcing based on the MW observables received from such isolated objects. It is well published that the accuracy of location estimation of MWOs based on fingerprinting is highly dependent on the quality of the radio maps. Radio maps depend on many factors including the orientation of antennas, location of access points, placement of the MW receiver on the object, crowdedness as humans are good absorbers in the frequency range of wireless devices, location of furniture and so forth. Each is a source of variability that implies that radio maps become outdated and need constant updating. Ongoing manual surveying is not a viable solution as it is expensive to perform. Instead MOLTIE relies on continual crowd sourced updates whenever there is an opportunity. Such an opportunity arises whenever a CVO is isolated and associated with an MWO. Assuming frequent opportunities for crowd sourcing, the radio maps can accommodate many of the variants that affect RSS. Furthermore as MOLTIE fuses the CV, IMU and RSS observables, it has some measure of the orientation and placement of the MW device which is utilized in refining the radio maps. Ongoing calibrations of the camera intrinsics and extrinsics can be done based on unobstructed view of the building features and relating these to a static building map. Furthermore, interesting constraints such as the object height being approximately constant as the object moves provides constraints applicable to calibrating camera intrinsics. Ongoing calibration of SCs is necessary as the camera pans and zooms.

One of the anticipated applications of MOLTIE is intruder detection in a large corporate office, airport or other secure facility wherein the primary objective is that of isolating person objects without employee badge identification rather than only tracking legitimate employees. As such the intruder would be indistinguishable from regular employees as a CVO but he would not be associated with a MWO. Hence the MOLTIE system can notify building security authorities of this potential breach.

The focus of this paper is the MOLTIE algorithm which will be described in section II. In section III a description of the crowd sourcing will be given. Section IV presents experimental results of the initial MOLTIE system and section V, discussion and conclusions.

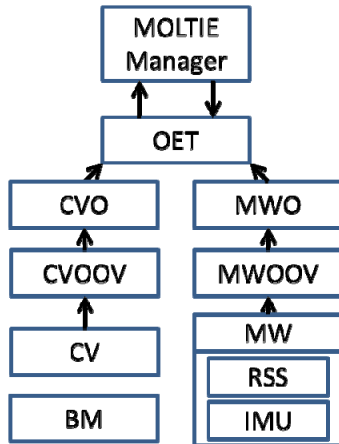


Figure 2 High level structure of MOLTIE

II. MOLTIE ALGORITHM

The overall structure of the MOLTIE algorithm is given in Figure 2. At the top level is the MOLTIE Manager which is based on a Bayesian probabilistic graph algorithm that is beyond the scope of the present paper. The next block down is the Object Event Tracker (OET). The input to the OET is the detected current set of CVOs and MWOs. These objects are then paired based on the correlation of the trajectories and a matrix of PoA coefficients is produced. The rest of the system level block diagram of Figure 2 is best explained from the bottom up. BM is the building map which includes all of the static and semi-static information regarding the building. It contains the construction geometry (walls, stairs, doors etc), the material type and colors, floor surface (carpet or tile), furniture location and so forth. The BM also contains the crowd sourced RMs of all the WiFi access points and BT gateways. The BM is available to all of the processing blocks. The SCs connect to the CV processing block which does the blob tracking in the image views and determines the cluster of blob tracks that are associated with each CVO in the SC's FOV. As eluded to earlier this is a difficult task that is further complicated by having to correlate clusters across SCs that have overlapping FOVs. The CVOs are regarded as probabilistic which necessitates soft decision processing in the higher level blocks.

The CVO Orthographic View (CVOOV) block uses the blob trajectories and events, and maps these from the image plane of the camera to an orthographic floor view or world frame. This is based on the perspective mapping of the SC [3]. There is one CVOOV for every CVO identified and tracked. In this block the object dynamics are accounted for such as a state variable vector of displacement, heading angle and velocity. The output of the CVOOV is the CVO in the world frame represented as a probability density function (PDF) that is conditioned on the CV observables from all the SCs.

In the MW block, the IMU, RSS and barometer sensor observables are used to estimate a location and trajectory of the MW. This estimation is based on the likelihood of the estimated trajectory with the IMU and RSS observations. The RSS is correlated with the RM for the specific WiFi or BT signal. The maximum likelihood trajectory forms the MWO which is then sent to the OET introduced earlier. In a multi-object tracking scenario there will be a number of MWOs each of which is tracked in a separate MWOOV. As with the CVOOV the outcome is a pdf conditioned on all of the MW sensor observables.

The processing of the CVOOV and MWOOV is based on the two step update Bayesian processing which results in the posterior probability of the state variables associated with the tracked objects conditioned on all of the observations available up till the present time. For simplicity of explanation only the displacement state variables will be considered. However, the velocity and heading state variables are generally additionally required for an effective dynamics model. At the completion of an update cycle, the MMSE (Minimum Mean Square Error) estimate of the state variables

is calculated as the mean of this updated posterior distribution. Consequently the Bayesian update consists of the following two steps:

Probability diffusion - The CVO or MWO has various parameters that govern its dynamic motion which is a function of the state variables estimated from the previous update cycle. The diffusion probability kernel is computed accordingly and convolved with the posterior probability of the output of the previous update cycle. Let s_t represent the state variable vector where the subscript t denotes the time update index. Let $p(s_{t-1})$ represent the posterior probability of the state variable vector conditioned on the complete set of observations up to the time $t-1$. Furthermore define $p(s_t | s_{t-1}, u_k)$ as the kernel of the diffusion probability that is tantamount to the transition probability between the states of s_{t-1} and s_t conditioned on any deterministic update component u_k . The predicted state probability for update t is denoted as $\bar{p}(s_t)$ and is then given as the general vector convolution as

$$\bar{p}(s_t) = \int p(s_t | s_{t-1}, u_k) p(s_{t-1}) ds_{t-1}$$

It should be noted that $p(s_t | s_{t-1}, u_k)$ is specifically dependent on the BM and forbids transition probability through object impenetrable walls or into forbidden areas where it is impossible for the object to be located.

Correction with measurements - During the update time interval of $t-1$ to t , there is a set of observation events that are then accounted for. In the CVOOV, this is the set of blob attributes estimated from one or more of the SCs. If the blob track in the image has terminated then there is no CV update. Likewise for the MWOOV there will be a set of RSS and IMU sensor observations. These observations are sporadic as they are sourced by a scanner or BT gateway that often misses transmissions. Also many WiFi and BT packet transmissions will be lost due to low signal level and packet collisions. Hence the reception of MW sensor observations is not necessarily reliable. Regardless, the set of available CV or MW observations is denoted as z_t . The likelihood of z_t based on the state vector s_t is determined individually for the CV and the MW and is denoted in general as the conditional probability of $p(z_t | s_t)$. This is applied as the second Bayesian update step resulting in the posterior PDF for the current update step which is expressed as

$$p(s_t | z) = \eta p(z_t | s_t) \bar{p}(s_t)$$

where η is a normalizing constant such that $p(s_t | z)$ integrates to unity.

The generalized Bayesian two step update is applied individually to each CV blob cluster detected in the CVOOV

based on the assumption that it represents an underlying physical object. As the identity of this object is unknown then the update dynamics are rather generic. If an outcome of the CV processing is for instance, human detection, then the update dynamics can be refined to account for this information. Likewise, the two step Bayesian is applied to each individual MW in the MWOOV. In general the update modeling is generic as we do not know the eventual association of the MWO and CVO. However, in the example of the MW being employee badges, there will be an association with a human physical object of high probability and therefore the state variable update can be based on human dynamics models.

III. RSS CROWDSOURCING

An enabling component of MOLTIE is the RSS crowd sourcing utility that builds up the radio maps (RMs). As the accumulation of measurements over time will be large, the RM can be created with extra variables in addition to the two floor level displacement variables. Such additional variables could be the orientation of the person and placement of the MW device on the person or robot object. When there is a single isolated CV object then the position estimation is simple and is highly accuracy. This is illustrated by the example output in Figure 3 from the processing of a SC frame to detect a single CVO person object. Generally MoG processing is necessary to exclude the shadows from the bounding box. The result is a bounding box that accurately marks the location of the feet contact with the floor surface and the top of the head. RSS readings from the MW device are then filtered and interpolated into the grid based RM.

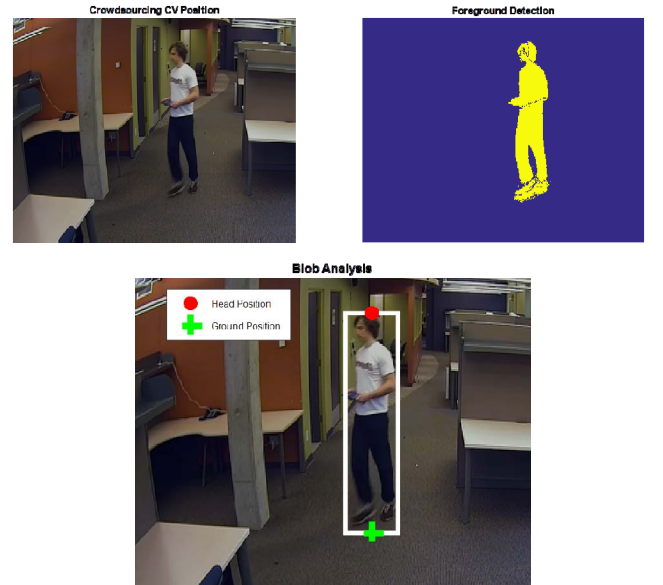


Figure 3 Top left, input frame with single person object for crowdsourcing. Top right, foreground detection using MoG. Bottom middle, blob analysis of person object including head position, ground touching point and bounding box.

Figure 4 shows the process of generating the RM. In this case the person used for crowdsourcing walked around a perimeter within an office floor. A set of five wall mounted SCs are used with the CV processing described which determines the locations in the CVOOV as shown by the red dots. The contour plot of the RM is shown. Note that this is interpolated based on a spatial Gaussian interpolation kernel over the set of grid points of the RM that are spaced every 0.25 meters. Figure 4 illustrates the RM as only partially complete as only observations along the perimeter path are included. Hence further measurements over the 2D floor space are required to complete the RM.



Figure 4 Crowdsourced RSS radio map

IV. EXPERIMENTAL RESULTS

The MOLTIE setup in the office environment is as shown in Figure 5 where the FOVs of the five SCs have been indicated along with the trajectory perimeter path. As evident, no single SC has ubiquitous coverage and therefore the set of SCs is used to provide uninterrupted coverage of the test perimeter around the inner offices. This is the truth trajectory as determined by manual analysis of the SC videos and relating these to surveyed markers on the floor.

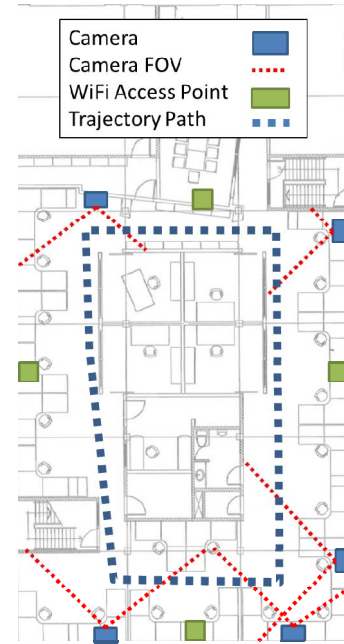


Figure 5 MOLTIE experimental testing environment

The raw data from the five SCs is sent to the Swann video recording box which compresses the images and acts as a server to host the currently available video frames. Using ffmpeg, video frames are streamed directly to the MOLTIE server. The MW device used for experimentation is an Android tablet that runs a WiFi scanning app and returns the associated RSS value for each access point observed. Additionally this app samples from the onboard sensors (IMU, barometer) and returns the values. As the sampling frequency for the sensors is considerably higher than that of the WiFi scanning (~ 50 Hz vs. ~ 1.5 Hz), pre-processing is done on the tablet prior to UDP transmission to the server. Currently MOLTIE is implemented in Matlab and time synchronization is achieved as the UDP packets from the tablet are time stamped as is the streaming video from the Swann video recording box.

An experiment was conducted where two people walked around the building environment with one of the people carrying the MW. The results from the CV tracking can be seen in Figure 6. This trajectory information was then used to construct a CVOOV for each of the objects. A dynamics model was used to update the prediction for each CVOOV over the course of the experiment duration. The data from the MW was used to construct a MWOOV that was also updated based on a dynamics model for the predicted motion of the MW.

The output of each CVOOV is a PDF of the location of the two CVOs denoted as CVO_1 and CVO_2 . These PDFs are conditioned on all of the CV data accumulated during the trial. Likewise the output of the MWOOV is the PDF of the location state variables of the single MWO. However, there are two sets of RMs, one for a clockwise trajectory and one for a counter-clockwise trajectory. These are denoted as MWO_{CW} and MWO_{CCW} respectively. The pairwise matching of the CVOs and MWOs, calculated in the OET computes the

correspondence of the four pairs $\{CVO_1, MWO_{CW}\}$, $\{CVO_2, MWO_{CW}\}$, $\{CVO_1, MWO_{CCW}\}$ and $\{CVO_2, MWO_{CCW}\}$. The correspondence of these pairs is based on using the Kullback-Liebler distance (KLD) [21]. This is the expected value of the log of the ratio of the two candidate PDFs of each of the four pairs which can be directly calculated with the numerically grid based PDFs at the outputs of the CVOOVs and MWOOV. The result for the present trial is shown in Figure 7. As expected, the KLD grows rapidly for the mismatched case and slowly for the matched case. In the current trial the person associated with the MW device walked in a CCW direction. Note that the two matched cases (green and black dashed) are indistinguishable from the KLD perspective. This is of interest in that, in this case, the difference between the CW and CCW RMs is small. However, this is not true in general as the distance between the CW and CCW RMs results in an additional KLD decrement.



Figure 6 CV tracking results for two person scenario

Finally the PoA is calculated based on the KLD. This is computed using the ratio of the cumulative area under the KLD curves. The PoA begins at 0.5 as initially it is unknown which CVO is associated with the MWO. As the trial begins and the two persons separate then the PoA rises to

~ 0.95 . The PoA calculated in this manner based on the KLD is more of a heuristic metric and not an actual calculation of probability. However, in the trials completed thus far it appears to be of practical significance as it provides reasonable values for the CVO and MWO association. We are currently investigating a better theoretical basis for this metric.

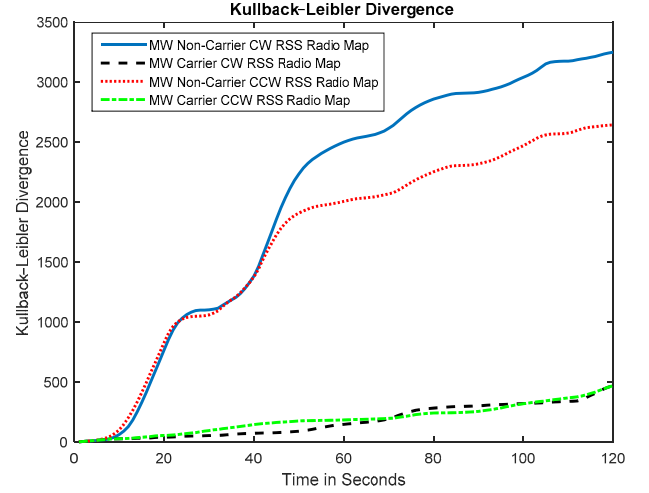


Figure 7 Outcome of pairwise Kullback-Leibler Distance

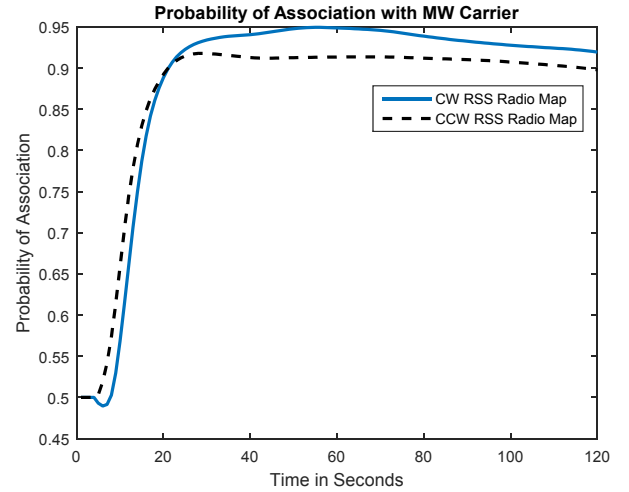


Figure 8 PoA calculated based on the KLD

V. DISCUSSION AND CONCLUSION

In this paper the framework of a novel object tracking system is given which is applicable to a wide range of LBS applications. Preliminary experimental results of employee tracking in an office environment are given proving the validity of the overall framework. By partitioning the CVOOV from the MWOOV the observables of the CV and MW processing are performed separately as they are independent sets of observations and combined probabilistically in the PoA metric calculation. In trials thus far, the processing appears robust however, there are challenges with interpreting the clusters of CV blob

trajectories for multi-person scenarios where frequent occlusion occurs. This is the subject of ongoing research.

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