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Location Based QR Calibration Code Utilizing Wi-Fi Fingerprinting Technique

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ABSTRACT

This paper depicts on incorporated localization algorithm using Wi-Fi fingerprinting for indoor positioning. The principle commitment of this work is the improvement of indoor positioning accuracy even fluctuation in RSSI which triggers variety of positioning error. Diverse of Wi-Fi chipset used on different devices make a single localization accuracy become worst. A few layers of Wi-Fi positioning is proposed, which depend on deterministic methods and iterative Bayesian estimation, which design together with calibration point to improve accuracy along the path movement in building. Each cycle of algorithm, localization region is utilized starting on calibration point. Here, calibration point is replaced by QR code which are located on certain part of building. The outcomes show that the algorithm help improves the estimation accuracy even in a few situations like diverse of Wi-Fi chipsets. The error dissemination shows an accomplishment of up to 70% or location error contrasted with the essential deterministic method of just 48%.

Key words: indoor positioning, localization, wireless positioning, Wi-Fi fingerprinting

1. INTRODUCTION

The well-known positioning and navigation system of GPS has empowered development of many application for outdoor based services. Indoor positioning is one of the fields that caught intention of researcher in wireless positioning. Indoor positioning system has enabled the range of many new applications for indoor location based-services (ILBS) such as indoor navigation, asset tracking, building security, and context-aware advertisement. For several reason, getting user location in building is a huge challenge. This is due to non-line-of-sight (NLOS) condition between satellite signal and inside building. In worst condition, the satellite signal is totally block by obstacle hence make localization impossible.

Because of this, the act of the satellite as transmitter need to be replaced by another option. One of popular option is Wi-Fi based positioning system which is almost available on each building or office. Nevertheless, the chosen of Wi-Fi as positioning system have several shortcomings. One of the most challenging part is the fluctuation of the RSSI signals emitted from access points. The heavy fluctuations of RSSI make it difficult to get accurate return of user location. To make it worse, the heterogeneity of Wi-Fi chipset on devices make the location estimation dissimilar on each device. Beside utilizing Wi-Fi, some reaseacher use Bluetooth Low Energy (BLE) beacon for indoor positioning [1]. Even though the BLE can improve the user accuracy, the drawback is the range of the beacon is just 10 meters where you need a large number of BLE beacon in large building.

Several Wi-Fi based positioning technologies have been discussed such triangulation, fingerprinting and others. In term of accuracy, Wi-Fi fingerprinting techniques return less error in location estimation compare to triangulation [2][3].However, it required labour extensive during offline signal mapping for the whole site building. The fingerprinting map must be altogether re-developed when there are changing to Wi-Fi passages (APs). The changing of surrounding such as furnishing, dividers also have the impact of RSSI on each point. Another challenge is the different sensitivity level of Wi-Fi chipset in market. This led to different reading in RSSI, hence lead to different location accuracy.

As referenced previously, the utilization of QR code in Wi-Fi localization has been proposed by different researchers [4][5][6]. Though, the features of an area estimation calculation and calibration are very isolated from the earliest starting point. A calibration point just tells the framework the right or real position of a user at a specific calibration position; from that point onward, the positioning calculation begins to continue the capacity of Wi-Fi unique fingerprint positioning without recalling the last point.

To improve the accuracy of the Wi-Fi unique fingerprint algorithm, the proposed algorithm consolidates the two most dominant in positioning, which are signal-based positioning and vision-based positioning [7]. Most of the present devices coordinate different sorts of sensors [8], in this way using these sensors may improve area precision. The main kinds of positioning are signal-based positioning, Wi-Fi unique fingerprinting, and vision-based positioning which uses a vision sensor. In this work, calibration point using QR code is proposed with matching algorithm for indoor positioning.

Numerous scientists [9],[10],[11] have demonstrated that under perfect conditions where there are sufficient passages (APs), a simple design of building geometry and strategic AP locations, K-NN will return less location error which could be under 5 meters. For indoor localization, an area location sweep higher than 5 meters will have a huge effect area on different rooms. This is a colossal test for indoor positioning contrasted with outdoor positioning.

Beside tracking user, this solution can be utilized in other field like advance transportation/asset management system as suggested by WN Hussein et al [12].Another, the solution of Wi-Fi fingerprinting technique can be combine as data fusion to vision based positioning as elaborate in [13].

2. INTEGRATED WI-FI FINGERPRINT

The test territory was set up on an academic building, as appeared in Figure 1. In real circumstance, there are some factors that are out of hand, for example:

- Number of access points (APs)
- Location of access points (APs)
- Geometry of the building.

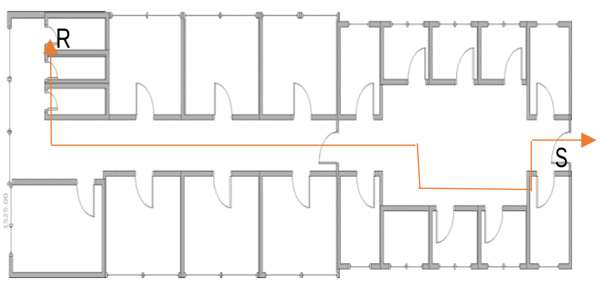

Figure 1: Path movement from point R to S in radio map development

Much of the time, a higher number of access points accessible, is useful for localization as many signal strength RSSIs can be collected from all APs. This will marginally lessen the positioning errors. Some of the studies or experiment utilizing positioning algorithm approach under good environment where the areas of APs were in strategic locations. For instance, in a single room there are up to four APs can be discovered which help to distinguish the strength degrees of Wi-Fi signals, henceforth improving localization. It is totally different condition on the site survey, there were just a couple of APs accessible close to the zone, so it was a gigantic test to perform localization. The field test zone comprises of a thin corridor and a rectangular region. In some places, RSSI must be recognized from a single AP although in other sections it was extremely difficult to distinguish the degree of RSSI. These would add to enormous localization errors.

2.1. Indoor Positioning

Bayesian estimation is one of the techniques that incorporate the earlier data on the situation and consolidate it with evidence from the sample data. Deterministic techniques provide fair positioning precision, as depicted in the previous area. The Wi-Fi module collect RSSI data from the APsduring the online process at each test point site. The more SSI collected, the higher accuracy of the approximate location.

The more RSSI information gathered, the better the estimated location precision. On the other hand, changes in RSSI readings convert into variances in user position, and despite the fact that more information are gathered that does not ensure the enhancements in location accuracy. One explanation is that each RSSI estimation is independent from the next estimation in a deterministic methodology, and some significant information isn't used to improve localization. Rather than applying basic normal estimation, the Bayesian estimation approach thinks about other crucial information, for example, state and observation conditions which are beneficial to improve localization. The Bayes rule can be composed as [14]:

$$p(s|x)=\frac{p(s|x).p(s)}{p(x)} \quad (1)$$

where x is observation in this situation is RSSI,s is state area, p(s│x) is a posterior estimate of state, and p(x│s) is the probability of RSSI's given state condition. For normal distribution the function is given by:

$$p(x)=\frac{1}{\sigma\sqrt{2\pi}}e^{(-\frac{(x-\mu)^2}{2\sigma^2})} (2)$$

mean of $p(x|s)$ is s, $\mu = s$

$$p(x|s)=\frac{1}{\sigma\sqrt{2\pi}}e^{(-\frac{(x-s)^2}{2\sigma^2})} (3)$$

where x is the observation or RSSI and s is the location itself. Multivariate Gaussian distribution was used as the location in two dimensions. The density function of multivariate Gaussian distribution is given by:

$$p(x_1, \ldots, x_k) = \frac{e^{\left(-\frac{1}{2}(x-\mu)^T\Sigma^{-1}(x-\mu)\right)}}{\sqrt{(2\pi)^k|\Sigma|}} (4)$$

where x is a k-dimensional vector, $\sum$ is a covariance matrix, and $|\Sigma|$ is the determinant of the covariance matrix.

By applying Bayesian techniques with basic deterministic algorithm, each cycle of calculation will consider the likelihood of previous location. This algorithm then matches together with calibration point that will be place in area of high potential error location. This will correct to the actual user location and continue with fresh recalculating location estimation. Each cycle, localization region is determined to predict the next possible user location. The localization region is control by mapping matrix table on next RP's location. Furthermore, the combine algorithm with calibration point help to prevent the accumulated error due to wrong possibility localization region.

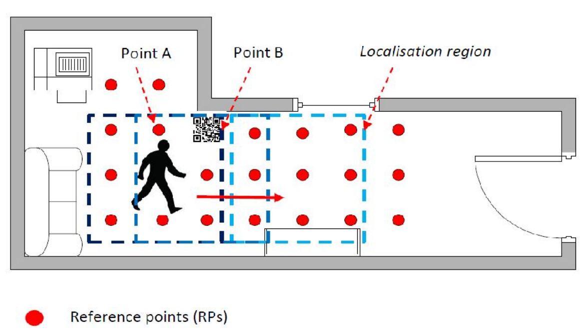

Figure 2: Example of building geometry and localization region with QR calibration

In first scenario the client is at point A as shown in Figure 2 At this evaluated area, the position could be based on location estimation algorithm and there is possibility of error. When there is error in positioning estimation, that's mean the next defining localization region will not accurate as needed. When the user walk to next location B, there is a QR calibration point. User can scan the QR code and current location information can be retrieved. This will update two information to the positioning algorithm which, the exact user location and update new localization region.

Next, the user will shift to another closest reference point which is yet in the correct localization region. EWKNN is then executed to estimate the initial user location. At that point, iterative Bayesian estimation analyze the underlying position evaluated by EWKNN with each and every reference point in the localization area. The estimation will be a highest likelihood for each reference point's area.

2.2. Integrated Positioning Algorithm

The highest likelihood point might be the closest area of the user's position. If there is error in the calculation of position estimation, it is still low as calculation just in the correct localization region. This is the way by which the algorithm works flawlessly with QR code for alignment. Figure 3 shows the flow algorithm for the enhanced Wi-Fi fingerprinting with QR calibration.

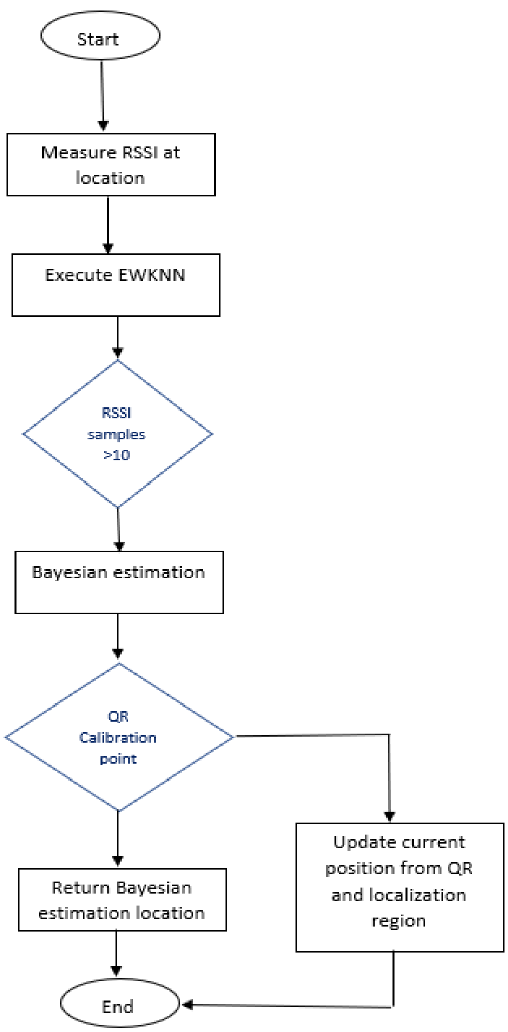

Figure 3: Flowchart of integrated positioning algorithm with QR calibration

3. RESULT AND DISCUSSION

The RSSI information are gathered on each RP location that have been distinguish before. Figure 4 shows the recorded RSSI from all APs accessible at one of RP's area. From this figure, it is undoubtedly show that the RSSI from each APs heavily fluctuates especially at 2.4GHz frequency band. The combination of each RSSI make the yield from the basic K-NN on gigantic error location.

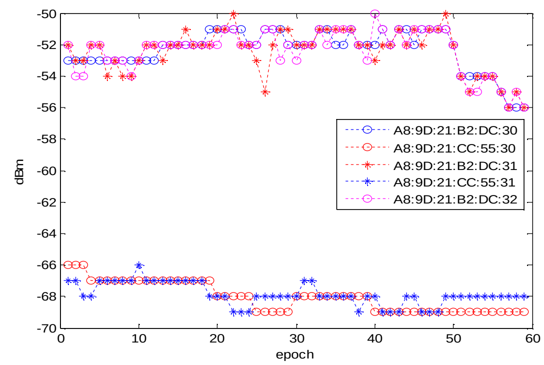

Figure 4: RSSI reading from one of RP location

The results demonstrating the error appropriation along the way movement for the algorithm are portrayed. A correlation has been made with a deterministic K-NN calculation as this is fundamental and prominently utilized in Wi-Fi fingerprinting [15], [16], [17].

Figure 5 shows the distributions of average RSSI reading from four available MAC addresses (APs) on each RP position during offline phase (blue colour) on Qualcomm WiFI chipset and online phase (green colour) on Broadcom Wi-Fi chipset. Based on RSSI distribution, it is clearly show the different level of RSSI measure using both Wi-Fi chipset (Broadcom and Qualcomm). This suggest that different Wi-Fi chipset have different sensitivity level. Due to this, the vertical red dotted line indicates the position of the RP, which return the highest position error estimation based on K-NN. The horizontal red dotted line indicate that in term of distance, the RSSI measurement from four APs (-55dBm, -55dBm, -66dBm and -68dBm) is closer to other offline RSSI measurement. Because of this factor, deterministic algorithms appear to pick up the wrong nearest distance, as the nearest pattern can be found elsewhere in RP. To handle this weakness, the information of last positioning need to take into account and Bayesian technique can be combine to get better localization.

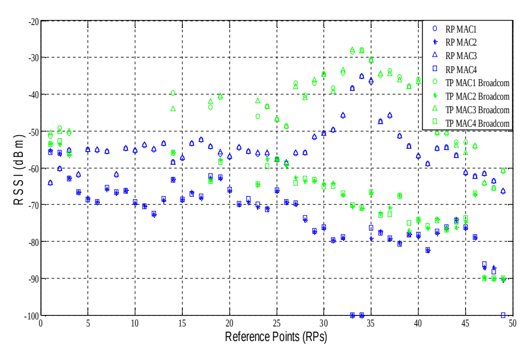

Figure 5: .Distribution RSSI reading from all APs

3.1. Position R to S with Qualcomm Atheros

This area, some portion of the reproduction results for various calculations are introduced on every development course. Figure 6 portrays an examination of calculations between K-NN, K-NN with Kalman filter and EWKNN with Bayesian estimation with alignment point. The deterministic method that was utilized, EWKNN, is incorporated with iterative Bayesian estimation and is more dependable than the other two calculations. It gives less blunder spikes and keeps the mistake dissemination underneath 5 meters on every cycle.

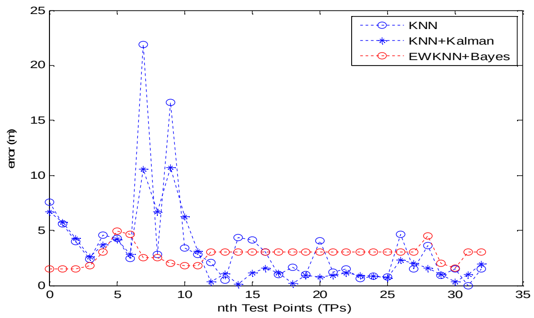

Figure 6: EWKNN with Bayesian estimation, K-NN and K-NN with Kalman Filter, without QR calibration point.

Figure 6, it can be seen that errors begin to increment significantly from points 5 to 10 onwards. Thusly, it has been chosen to set QR alignment at point 5, where before the errors outperform the 5-meter limit. Figure 7 delineates the outcomes for similar algorithms with a QR calibration adjustment. Location data on QR code promptly diminishes the errors level to zero and improves the precision from point 5 toward point 8. Contrasted with traditional K-NN calculation, QR alignment just improves the point where the QR code is located, while at different TPs it just gives similar outcomes.

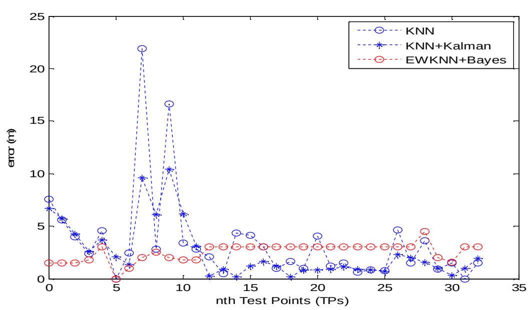

Figure 7: The error pattern on QR calibration (at point5) forvarious algorithms.

3.2Position R to S with Broadcom

Figure 8 delineates the errors distribution from point R toward point S with a Broadcom Wi-Fi chipset. As observed, from TPs 1 to 20, there is great accuracy for each algorithm. Nevertheless, after point 20, the error become obvious and take shots up to 30 meters for the K-NN. Similar pattern applies for the other algorithms. Presently the region of errors distribution is past 5 meters. To avoid error rising steeply, QR calibration is placed in that region with high potential errors, as appeared in Fig. 8.

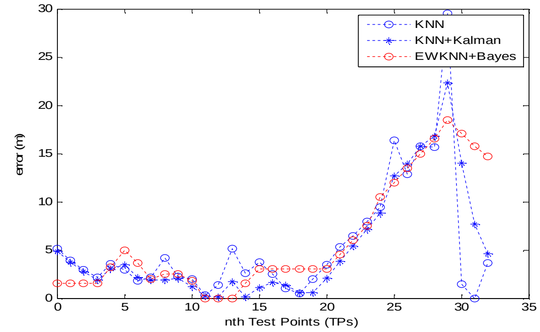

Figure 8 : EWKNN with Bayesian estimation, K-NN and K-NN with a Kalman filter, without the QR calibration

The QR calibration point at TP 25 aides toward bring down errors to zero. Past that point, K-NN and K-NN + Kalman filter remain the same as before, however they go up radically at 30 meters. Though, an alternate impact on EWKNN+Bayes is seen when the errors results go up drastically, where the growth in errors can be controlled within 10 meters. After that point, the errors fall steadily while the outcomes for K-NN show a descending pattern and shown on following Figure 9.

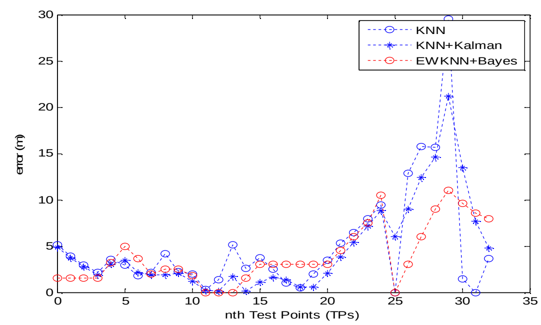

Figure 9: The error pattern on QR calibration (point 25) on different algorithms.

3.3Position S to R with Qualcomm Atheros

Both Figure 10 and 11 show a similar pattern in errors dissemination. The errors soar substantially from point 18 toward point 25 and afterward plunge discernibly towards the last TPs. QR calibration at point 25 gives better outcomes for EWKNN with Bayesian estimation contrasted with the other two algorithms.

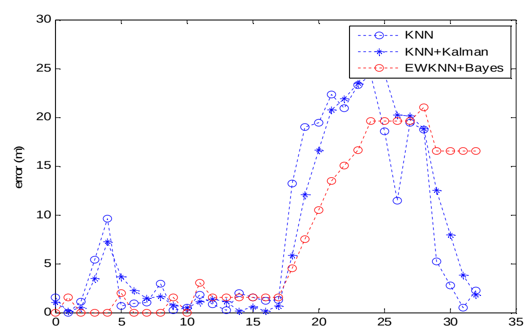

Figure 10: EWKNN with Bayesian estimation, K-NN and K-NN with Kalman Filter, without the QR calibration.

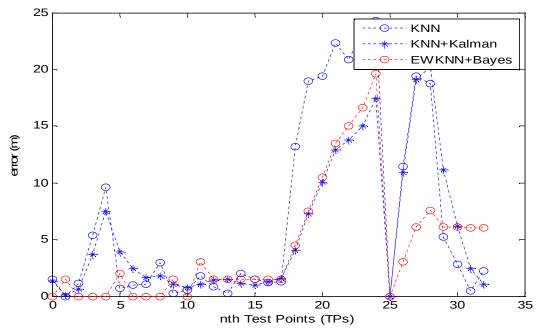

Figure 11: The error pattern on QR calibration (at point 25) on three different algorithms.

3.4Position S to R with Broadcom

Both Figure12 and 13 show unique pattern that have not been seen previously. For K-NN algorithm there is an area of critical errors from point 3 toward point 12. Meanwhile, the proposed algorithm shows predictable errors at 4 meters in this area. At the point when calibration point at TP 5 was scan as appeared in Figure 12, the estimation was at the actual position that has accuracy 100% until TP 16. This happens soon after adjustment of the location error while basic deterministic shows the descending pattern. The descending pattern implies the estimation of user position gets close to the real user position. For EWKNN-Bayesian estimation, which uses the region of the confinement territory each cycle of localisation, return high precision for user's position. From TP 5 to TP 16, zero errors recorder within this range as appeared in Figure 12.

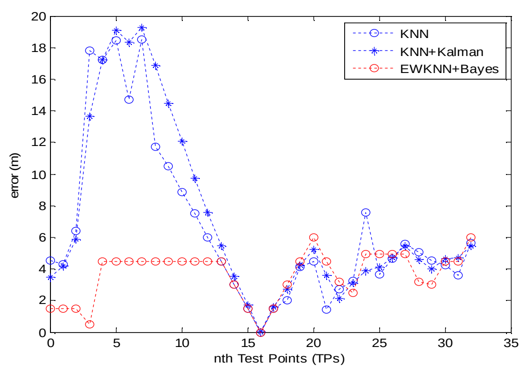

Figure 12: EWKNN with Bayesian estimation, K-NN and K-NN with Kalman Filter, without QR calibration

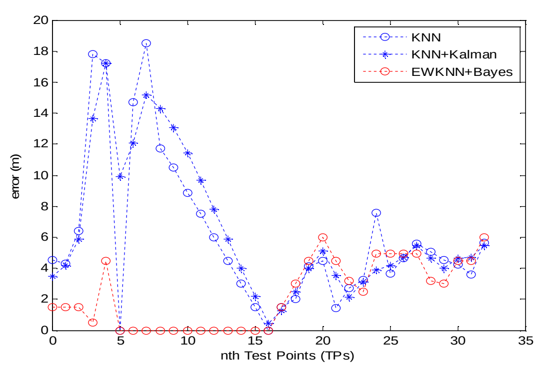

Figure 13: The error pattern QR calibration (at point 5) on three different algorithms

The outcomes on previous diagrams show that the area of QR calibration point is recommended to be in the locale of the high location error. Based on TPs area, the fact of the matter was followed on the design delineate show in Figure 13. Implementing this algorithm together with QR calibration point, the calibration area has been recognized instead of putting the QR code everywhere in the building.

The Figure14 shows the location of calibration point QR code that based on result experiment in this simulation that should be placed according to graphs from Figure 6 to Figure 13. Based on this location QR calibration points, the overall performance comparison between algorithm are compared as shown in Figure 15. Based on our experiment, when combined K-NN with QR calibration delivers of 48% location error for less than 5m. Then K-NN with additional Kalman filters utilizing the QR calibration point, this algorithm gives better in location error for 51% of the time. From the graphs it show that when QR calibration is implemented along the path with deterministic basic algorithm, the improvement increased by 3%. Implementation of integrated EWKNN, Bayesian estimation together with localization region, utilizing QR calibration point shows drastic improvement with location for 70% of the time of error less than 5m.

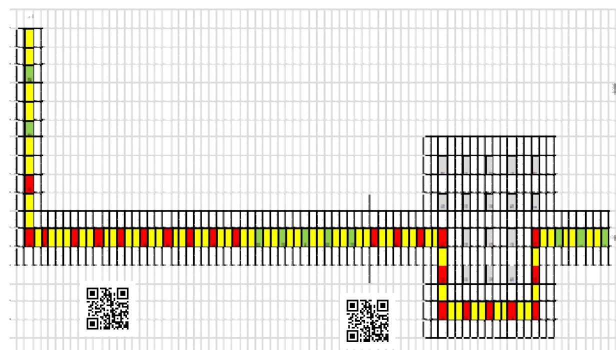

Figure 14 : Proposed position of QR code calibration in building based on results

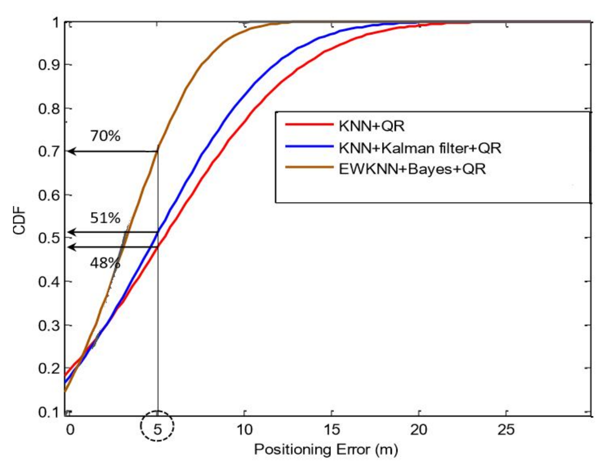

Figure 15: CDF on integrated algorithm

4. CONCLUSION

The comparison has been made between basic deterministic K-NN, K-NN combine with Kalman Filter, and EWKNN with Bayesian estimation. Based on distribution of error throughout the path of user from S to point R (vice versa), the location of calibration have been determined. From here, the design algorithm that fit with QR calibration point together with dynamic localization region have been proposed. Results show a significant improvement by almost 20% increment of accuracy of the time for error below 5 meters.

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