THEORETICAL MODELLING OF EFFICIENT TRAJECTORY-BASED MOVING OBJECT TRACKING

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ABSTRACT *Wireless Sensor Network (WSN) has been the base for numerous surveillance applications to monitor indoor and outdoor environment. Object detection and tracking play a crucial role in regards to the usefulness of those surveillance applications. Proper analysis of object tracking process helps in providing a comprehensive understanding of the object behavior. However, object and tracking is challenging due to several aspects of the moving object such as complex motion, complex action development over time, complex shape, and loss of information. Although most of object tracking system were proposed based on the intuition that the object has usually smooth motion with no unexpected changes, it is practically impossible. Therefore, it is important to correctly model object's appearance representation, motion, and shape for proper tracking. This paper focuses on the modeling the dynamics spatiotemporal trajectory of a moving object in two dimensional space. A detailed theoretical modelling of efficient trajectory-based moving object tracking concept is presented in this paper. It provides a proper analysis of object tracking process that can helps in offering a comprehensive understanding of the object movement.*

Keywords Wireless Sensor Network (WSN); Sensing Field Coverage, Object Detection; Moving Object Tracking

1 INTRODUCTION

Wireless sensor networks (WSN) has been utilized in several domains for monitoring purposes. Currently, cities and buildings including houses, schools, hospitals, and shopping malls are monitored by different surveillance applications for which advanced cameras and computing stations are used [1]. The availability of powerful computing devices and low cost with high quality cameras had paved the way for more research that has been focusing on object detection, and tracking; where object recognition, localization, motion detection, tracking, and behavior understanding are of concern. The measurements of the monitoring and observations can significantly help in accurate localization of the object, organization of the tracking group, classification of the moving object behavior [2,3]. Object detection and tracking mechanisms play an important role in regards to the effectiveness of the surveillance applications [4,5] . Object detection concerns identifying and localizing the emergence of an object in the monitoring area; while object tracking is the process of discovering and estimating the course of the moving object over a specific time period. The movement of the object may occur in spatial disjoint locations. Proper analysis of object tracking process helps in providing a comprehensive understanding of the object behavior. However, object and tracking is challenging due to several aspects of the moving object such as complex motion, complex action development over time, complex shape, and loss of information. Although most of object tracking system were proposed based on the intuition that the object has usually smooth motion with no unexpected changes, it is practically impossible. Therefore, it is important to correctly model object's appearance representation, motion, and shape for proper tracking [6,7].

This paper focuses on the modeling the dynamics spatiotemporal trajectory of a moving object in two dimensions (x, y). The rest of the paper is organized as follows: Section 2 presents the background and some of the common research works on object tracking. The contributions of this paper are presented in Sections 3-7 where the modelling of sensing field coverage, object location discovery, sensor deployment, and sensing quality are respectively presented. Finally, Section 8 concludes the research presented in this paper and suggests some future research directions.

2 BACKGROUND

Generally, in tracking applications that are based on surveillance cameras, the object tracking is done through different important steps including object representation, feature selection, detection, and to end with object tracking [8]. As the moving object can be represented as a set of points, it can also be represented as basic geometric shapes such as circle, rectangle, ellipse etc. The appearance representations can be combined with the geometric shape representation to track a moving object. Probability densities and active multi-view and appearance models are among the common object appearance representations. Feature selection is another important step in object tracking. Some of the commonly Features used in the feature selection steps including texture, color, gradient, edges, optical flow etc. Object detection mechanism in most of the tracking applications is required in every frame of the video, where point detectors, background subtraction, and segmentation are usually used. Once the object is detected tracking process would start to create the object movement path with respect to time according to the object location in every frame. In the literature, there several approaches for tracking a moving object; considering main principle elements such as object extraction, recognition, and tracking where the decisions are done according to the object activities. Based on the representation, moving object tracking is classifies into three classes, namely point, kernel, and Silhouette tracking methods [9]. In this section, some of the common approaches that have been the basis for further research works. Traditionally, Kalman Filter technique is used for point tracking. The research works in [10,11,12,13] were proposed based on Kalman Filter. They have aimed at improving the tracking quality and time efficiency in processing certain frames in the video, where points in the noisy images are tracked. However, their limitation is that the variables are distributed using Gaussian distribution and not efficient for tracking in high density environment. Dual–Tree and Daub Complex Wavelet transform [14,15], in addition to multiple cues fusion-based algorithm [16], were proposed for kernel tracking. Although they are good in terms of directional selectivity and shape matching in regard to the emergence of disappearance of objects, nonetheless, the tracking is not efficient as the object detection rate is low. Also the assumption that the object shape and size should not be changed in sequential frames, make them not feasible practically. Research works presented in [17,18,19,20] were proposed for Silhouette tracking where Silhouette is extracted from a detected moving objects by shape matching. Although these solutions are less sensitive to the variations of the object appearance, however, in the presence of noise, features are affected significantly, and that a hybrid tracking with additional features to support silhouette tracking are needed in order to achieve very good tracking results. Even though camera-based systems provide complementary benefits, however, frame rate of the cameras can cause a bottleneck. Also, such system would not be efficient in several indoor and outdoor environment conditions such as fog, fire, smock, rain, to name a few. Therefore, the work presented in this paper considers the use of binary event sensor to achieve efficient tracking.

3 MODELING OF THE SENSING FIELD COVERAGE

For the purpose of efficient sensing coverage that satisfies the requirements of the monitoring applications, the modeling of the network can be described as follows: The sensing field includes m binary homogeneous sensor nodes (with r_i sensing range and fixed R transmission range) and it is divided into trajectories that are formed by the intersection of the sensing ranges (coverage) of each sensor node as shown in Figure 1. Each sensor is placed at distance d_i from a reference point p_r, that is $d_i(s_i, p_r)$. The sensing field model can be described by $(n + 1)$-tuple $(n, P_0, \ldots, P_{n-1})$, where n is the number of trajectories (paths) in the sensing field, P_i denotes the width of the ith trajectory where $i = 0, 1, 2, \ldots, n - 1$. Based on node deployment, the width of trajectories is equal for all $i = 0, 1, \ldots, n - 1$, such that $P_i \leq r_i$. The moving object would definitely fall in one of the trajectories. Once an object O is detected, the sensor nodes notifies the base station directly; thus, data aggregation and routing are not assumed. Having n trajectories and m sensor nodes with fixed r_i sensing range placed $d_i$away from a reference point p_r, then, the following property holds: $P_i < r_i < d_i(s_i, p_r)$.

4 LOCATION DISCOVERY

The object detection model utilized in this research is based on the sensing accuracy probability described in[21], which is as follows:

The sensing probability to accurately detect an object is:

(1) $P(S_i) = \lambda\delta^{-(K*d(s_i, p))a}$

where:

- λ is the detection accuracy parameter that indicates the maximum probability with which the object O is certainly detected by sensor node i, such that $0 < \lambda \leq 1$; that is, when $d(i, p) = 0$, then $\lambda = 1$.
- δ and K indicate the vertical and the horizontal location parameters respectively, where $\delta > 1$ and $K > 0$. A probability distribution can be formed based on reference point (a point that is used to define a location of another point) that is can be defined by $(d_r(s_i, p_r), P_r(S_i))$. It means that when an object o appears at $d_r(s_i, p_r)$ distance away from a sensor node i, the probability with which the object is detected is $P_r(S_i)$. Hence, making $Kd_r(s_i, p_r) = 1$, would result in $P_r(S_i) = \lambda\delta^{-1}$, which help in selecting a reference point $(d_r(s_i, p_r), P_r(S_i))$.by determining the location parameters according to Equations (2) and (3) below:

(2) $\delta = \lambda(P_r(S_i))^{-1}$

(3) $K = d_r(s_i, p_r)^{-1}$

- α is a positive parameter ($\alpha > 0$) that indicates the sharp (or smooth) decrease of the sensing probability, from λ to 0, with respect to $d(s_i, p)$. If it is required to designate that at specified distance $d^{'}(s_i, p)$, the accuracy sensing probability is $P^{'}(S_i)$, theα should be set as follows:

(4) $\alpha = \log d_{K*d^{'}(i, p)} \log_{\delta}((\lambda)/(P^{'}(S_i)))$

where $d^{'}(s_i, p)$ must be greater than $d_r(s_i, p_r)$, and $P^{'}(S_i)$ must be less than $P_r(S_i)$, and vice versa.

As mention earlier, for a sensing accuracy model that is based on a fixed radius, a sensor node would definitely sense any object appears within its sensing radius, such that:

(5) $P(S_i) = \begin{cases} 1, & d(s_i, p) < r \\ 0, & otherwise \end{cases}$

Sensing field (SF) is coverage of a WSN at any point i (p_i) is defined as the probability of a sensor detecting the object at that point.

(6) $SF(p_i) = 1 - \prod(1 - P(S_i))$

where $SF(p_i)$ is the sensing coverage at specific location (p_i), and $P(S_i)$ is the sensing probability of sensor node i at p_i of the sensing field.

Sensing field coverage $Cov(SF, p_i)$ is that the sensing field SF is the efficient sensing measures at a at specific location (p_i) from all sensor nodes in the field. If there are n sensor nodes, the total contribution of detection functions of each node, which reflects the coverage of sensing field at point p_i, is:

(7) $Cov(SF, p_i) = \sum_1^n(s_i, p_i)$

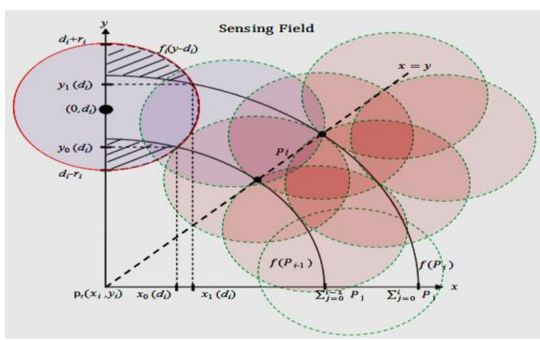

Figure 1 Modeling of the Sensing Field Coverage

5 SENSOR PLACEMENT

An optimal sensing coverage with respect to the sensor position within the sensing field SF can be defined such that a maximum sensing coverage and maximum detection probability are obtained.

Let the posItion of a sensor s_i be at distance d_i from the angle θ of a reference point p_r, then for SF coverage model

$(n, P_0, \ldots, P_{n-1})$ with r_i representing the sensing range of s_i positioned within d_r, and that $(1)/(2)(P_i + r_i) \le r_i \le \sqrt{(2)}(\sum_{j=0}^{i} P_j)$, the optimal sensing coverage would be achieved if location l_i of s_i with respect to the distance of the reference point $d_i(s_i, p_r)$, for all $i = 0, 1, \ldots, n-1$, meet the following condition:

(8) $l_i = \begin{cases} \sqrt{(((P_i)^2 - (r_i)^2)/(3))}, & ((P_i)/(2)) \le r_i \le P_i \\ \sqrt{((P_i)^2 - (r_i)^2)}, & (P_i) < r_i \le \sqrt{(2)}(P_i) \end{cases}$

Let s_i be positioned at point $(0, d_i)$, where $d_i \ge 0$. Considering the trajectory P_i depicted in Figure 1, Proving Lemma (1) can be done by determining the position of a sensor s_i that can maximize the sensing coverage.

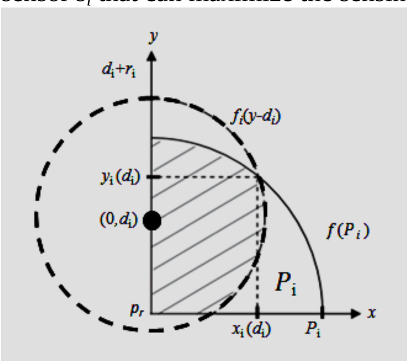

Figure 2 Optimal sensor position in the trajectory P_i

Assume there are two circles represented by equations (9) and (10) as follows:

(9) $x^2 + y^2 = P_i^2$

(10) $x^2 + (y - d_i)^2 = r_i^2$

Where the first one that includes P_i, and the sesond one includes the semicircle of the sensing coverage. Solving for x in (9) gives:

(11) $x^2 = P_i^2 - y^2$

By subsituting (11) in (10), it will give:

(12) $y_i(d_i) = ((P_i)^2 + (d_i)^2 - (r_i)^2) / 2d_i$

Solving for P_i, $y_i(d_i)$ axis would be resulted of the intersection point $(x_i(d_i), y_i(d_i))$ of the two circles.

$y_i(d_i)$ can also be obtained by subtracting the two circles equations while expanding to achive a linear equation for $x_i(d_i)$ and $yi_0(d_i)$. The linear equation is the equation of the line that passes through the intersection points when the two circles intersect. Let $f(d_i)$ represents shaded area shown in Figure 2, such that:

(13) $f(d_i) = \int_i^{y_i(d)} f_i(y - d_i)\, dy + \int_{yi(di)}^{P} {}_i f_{Pi}(y)\, dy$

(14) $f(d_i) = \int_{-di}^{y_i(d)}{}_i^{-d} {}_i f_i(y)\, dy + \int_{yi(di)}^{P} {}_i f_{Pi}(y)\, dy$

While $f_i(y)$ and $f_{Pi}(y)$ are both contineous functions, their antiderivatives can be $F_i(y)$ and $F_{Pi}(y)$ respectively; therefore, $f(d_i)$ can be written as:

(15)

$f(d_i) = F_i(y_i(d_i) - d_i) - F_i(-d_i) + F_{Pi}(P) - F_{Pi}(y_i(d_i))$

The first derivative of $f(d_i)$represents the slope of the tangent line at the function. It can also be written as:

(16)

$f'(d_i) = f_i(y_i(d_i) - d_i)((d(y_i(d_i))/(dd_i) - 1) + f_i(-d_i) - f_{Pi}(y_i(d_i))((d(y_i(d_i))/(dd_i))$

(17) $f'(d_i) = f_i(-d_i) - f_i(y_i(d_i) - d_i)$

Equation (16) holds as $x_i(d_i) = f_{Pi}(y_i(d_i)) = f_i(y_i(d_i) - d_i)$.

It is obvious that $f'(d_i) = 0$ implies that $f'(d_i) = \sqrt{(((P_i)^2 - (r_i)^2) / 3)}$ when $(P_i)/(2) \le r_i \le P_i$, or $\sqrt{((P_i)^2 - (r_i)^2)}$ when $P_i < r_i \le \sqrt{(2)}P_i$. Thus, Lemma (1) can be further proven by the the second derivative of $f(d_i)$, where $f''(d_i) < 0$.

6 Sensing Quality

For a sensing field model $(n, P_0, \ldots, P_{n-1})$, the sensing coverage of a sensor $s_i$with a sensing range r_i(such that $(1)/(2)P_i \le r_i \le \sqrt{(2)}(\sum_{j=0}^{i} P_j)$, *for* $i = 0, 1, \ldots, n-1)$, that is beyond the width $P_i$where object O moves can be minimized if the optimal placement of s_i at distance d_i away from the reference point p_r meets the following condition:

(18)

$d_i = \sqrt{(((\sum_{j=0}^{i-1} P_j)^2 + (\sum_{j=0}^{i} P_j)^2 - 2(r_i)^2) / 2)}$

The shaded area in Figure 1 represented by $f(d_i)$, where $i \ge 1$, can be given as follows:

(19) $f(d_i) = \int_{y1(di)}^{d_i + r} {}_i f_i(y - d_i)\, dy - \int_{y1(di)}^{\sum_{j=0}^{iP}} {}_j f_{Pi}(y)\, dy + \int_{di-r}^{y_0(d)} {}_i f_i(y - d_i)\, dy + \int_{y0(di)}^{\sum_{j=0}^{i-1P}} f_{Pi-i}(y)\, dy$

(20) $f(d_i) = \int_{y1(di)-di}^{r} {}_i f_i(y)\, dy - \int_{y1(di)}^{\sum_{j=0}^{iP}} {}_j f_{Pi}(y)\, dy + \int_{-ri}^{y_0(d)} {}_i f_i(y)\, dy + \int_{y0(di)}^{\sum_{j=0}^{i-1P}} {}_j f_{Pi-i}(y)\, dy$

where

(21) $f_i(y) = \sqrt{((r_i)^2 - (y)^2)}$

(22) $f_{Pi-1}(y) = \sqrt{((\sum_{j=0}^{i-1} P_j)^2 - (y)^2)}$

(23) $y_0(d_i) = ((\sum_{j=0}^{i-1} P_j)^2 + (d_i)^2 - (r_i)^2)/(2d_i)$

(24) $y_1(d_i) = ((\sum_{j=0}^{i} P_j)^2 + (d_i)^2 - (r_i)^2)/(2d_i)$

Let the antiderivatives of $f_i(y)$, $f_{Pi}(y)$, and $f_{Pi-1}(y)$ represented by $F_i(y)$, $F_{Pi}(y)$, and $F_{Pi-1}(y)$ respectively; hence, $f(P_i)$ can be expressed as follows:

(25) $f(d_i) = \mathrm{Fi}(r_i) - F_i(y_1(d_i) - d_i) - F_{Pi}(\sum_{j=0}^{i} P_j) + F_i(y_0(d_i) - d_i) - F_i(-r_i) + F_{Pi-1}(\sum_{j=0}^{i-1} P_j) + F_{Pi}(y_1(d_i)) - F_{Pi-1}((y_1(d_i))$

The first derivative of $f(d_i)$ is:

(26) $f'(d_i) = (dF_i(r_i))/(d(r_i))(d(r_i))/(d(d_i)) - (dF_i(y_1(d_i) - d_i))/(d(y_1(d_i) - d_i))(d(y_1(d_i) - d_i))/(d(d_i)) - (dF_{Pi}(\sum_{j=0}^{i} P_j))/(d(\sum_{j=0}^{i} P_j))(d(\sum_{j=0}^{i} P_j))/(d(d_i)) - (dF_i(-r_i))/(d(-r_i))(d(-r_i))/(d(d_i)) + (dF_{Pi-1}(\sum_{j=0}^{i-1} P_j))/(d(\sum_{j=0}^{i-1} P_j))(d(\sum_{j=0}^{i-1} P_j))/(d(d_i)) + (dF_{Pi}(y_1(d_i) - d_i))/(d(y_1(d_i))(dy_1(d_i))/(d(d_i)) - (dF_{Pi-1}(y_0(d_i) - d_i))/(d(y_0(d_i))(dy_0(d_i))/(d(d_i))$

(27) $f'(d_i) = (f_{Pi}(y_1(d_i) - f_i(y_1(d_i) - d_i)(dy_1(d_i))/(d(d_i)) + f_i(y_0(d_i) - d_i) - f_{Pi-1}(y_0(d_i)))(dy_0(d_i))/(d(d_i)) + f_i(y_1(d_i) - d_i) - f_i(y_0(d_i) - d_i)$

(28) $f'(d_i) = f_i(y_1(d_i) - d_i) - f_i(y_0(d_i) - d_i)$

It is clear that Equation (28) holds as

(29) $f_i(y_1(d_i) - d_i) = f_{Pi}(y_1(d_i)) = x_2(d_i)$

and

(30) $f_i(y_0(d_i) - d_i) = f_{Pi-1}(y_0(d_i)) = x_1(d_i)$

Therefore, Lemma 2 is proven as $f'(d_i) = 0$ results in that $d_i = \sqrt{(((\sum_{j=0}^{i-1} P_j)^2 + (\sum_{j=0}^{i} P_j)^2 - 2(r_i)^2) / 2)}$.

For a sensing field model $(n, P_0, \ldots, P_{n-1})$, with a fixed trajectory width P_i and a fixed distance d_i of sensor s_i position from the reference point p_r, having the sensor sensing range

r_i, the number of sensors m' that efficiently sense the object O in P_i is:

(31) $m' = [(\pi/4)/(2cos^{-1}(((d_i)^2 + (\sum_{j=0}^{i} P_j)^2 - (r)^2)/(2d_i(\sum_{j=0}^{i} P_j)))]$ for $i = 0, 1, \ldots, n-1$

Assume that there are two neighboring sensors positioned in the trajectory P_i as shown in Figure 3.

The maximum sensing coverage in the trajectory P_i can be achieved if there is no gap between coverage areas of those sensors. The maximum allowed angle θ of the two neighboring, which maximize the sensing coverage can be derived using Cosine law as follows:

(32) $(r_i)^2 = (d_i)^2 + (\sum_{j=0}^{i} P_j)^2 - 2d_i(\sum_{j=0}^{i} P_j)cos(\theta)$

Thus,

(33) $\theta_i = ((d_i)^2 + (\sum_{j=0}^{i} P_j)^2 - (r_i)^2)/(2d_i(\sum_{j=0}^{i} P_j))$

By taking that the first quadrant of unit circle, the angel at $p_r(x_0, y_0)$ is 45°. Hence, the number of sensors required for maximizing the sensing coverage in the trajectory P_i is $m'_{P_i} = [(\pi/4)/(2cos^{-1}(((d_i)^2 + (\sum_{j=0}^{i} P_j)^2 - (r_i)^2)/(2d_i(\sum_{j=0}^{i} P_j))))]$ for all $i = 0, 1, \ldots, n-1$.

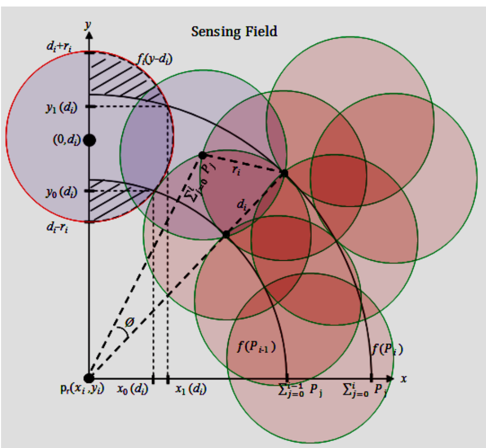

Figure 3 Angle θ between two sensors for maximum sensing coverage

7 TRACKING A MOVING OBJECT

Having describing the maximum sensing coverage in the sensing field, now tracking (Tr) of an object O moving on a trajectory P_i is defined as measure of how well it can be observed by the sensors over time. Assume that an object is moving in the sensing field SF from a specific location at point $p_1(t_0)$ to point $p_2(t_1)$ along a curve $c(t)$. Such movement can be defined as follows:

The *tracking* (Tr) of object O in the sensing field during the period of time interval $[t_0, t_1]$ along a curve $c(t)$ in the trajectory P_i is defined as:

(34) $Tr(c(t), t_0, t_1) = \int_{t0}^{t_1} Cov(SF, c(t))|(dc(t))/(dt)|dt$

such that if $c(t_i) = x(t_i), y(t_i)$, hence

$|(dc(t_i))/(dt)|dt = \sqrt{(((dx(t_i))/(dt))^2 + ((dy(t_i))/(dt))^2)}$

Assume there is a sensor s_i located at (x_i, y_i) where is probability sensing function at point $p_i(x'_i, y'_i)$ is defined as

(35) $P(s_i(x_i, y_i), p_i(x'_i, y'_i)) = (1)/(d_i(s_i, p_i)) = (1)/(\sqrt{((x'_i - x_i)^2 + (y'_i - y_i)^2)})$

Assume there is an object O is travelling from point $p_1(1, 0)$ to point $p_2(x_i, y_i)$.

If $p_2 = (0, 1)$, then (cos πt/2, sin πt/2) would represent the minimum path, and the tracking over that path is $Tr = (1)/(2)\pi$.

Making lines from the position where s_i is located at (x_i, y_i), which intersect x-axis where the object is detected at $p_i(x'_i, y'_i)$, and with angle θ_i, where $0 < \theta_1 < \cdots < \theta_i < \theta_{i+1} < \cdots < \theta_n = \pi/2$. Obviously, from $p_1(1, 0)$ to $p_2 = (0, 1)$, the moving object O would pass over every line orderly and one time only. Approximating the trajectory between the points $p_i(x_i, y_i)$ and $p_{i+1}(x_i, y_i)$ where the lines intersect, and making perpendicular line to the trajectory line where the intersection point is $v_i(x_i, y_i)$, will results in having two angles $\varphi_i$and φ_i, respectively. It can be One can verified that tracking the object from $p_i(x_i, y_i)$ to $v_i(x_i, y_i)$ along the trajectory line is

(36)

$Tr = \int_0^{d_i(s_i, p_i)\sin\varphi_i}(1)/(\sqrt{((d_i(s_i, p_i))^2\varphi_i + x_i^2)})dx = \ln(1 + \sin\varphi_i)/(\cos\varphi_i)$

where $d_i(s_i, p_i)$ is the distance from the location of the sensor s_i to the point p_i. Thus, tracking the movement from $p_i(x_i, y_i)$ to $p_{i+1}(x_i, y_i)$ will be:

(37) $Tr = \ln(1 + \sin\varphi_i)/(\cos\varphi_i) + (1 + \sin\varphi_i)/(\cos\varphi_i)$

Note that $\varphi_i + \varphi_i = \theta_{i+1} - \theta_i$ where the tracking path is minimized; and $\varphi_i = \varphi_i$ means that $d_i(s_i, p_i)=d_{i+1}(s_i, p_{i+1})$, and also if $n \rightarrow \infty$and that the stop point for the moving object is $p_2 = (0, 1)$, hence, represented by the quarter circle with radius 1 and centered at $p_i = (0, 0)$, the minimum length of the trajectory from $p_1(1, 0)$ to $p_2 = (0, 1)$ can be defined as $(\cos(\pi t/2), \sin(\pi t/2))$ for $0 \le t \le 1$. Therefore,

(38) $Tr = \int_0^1(\sqrt{(\cos^2(\pi t/2) + \sin^2(\pi t/2))})^{-1} * \sqrt{((\pi/2 \cos(\pi t/2))^2 + (-\pi/2 \sin(\pi t/2))^2)} dt = (1)/(2)\pi$

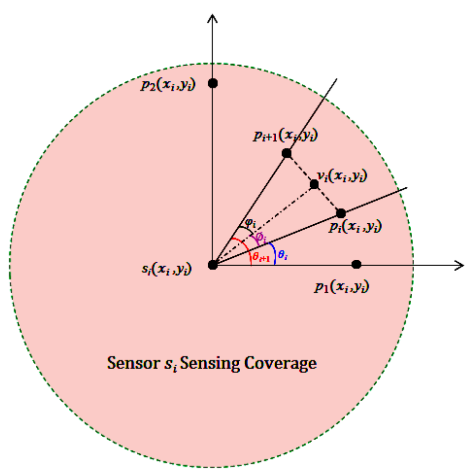

Figure 4 Tracking object moving from $p_1(x_i, y_i)$ to $p_2(x_i, y_i)$

8 CONCLUSION AND FUTURE WORK

This paper considers the utilization of Wireless Sensor Networks (WSNs) for monitoring a moving object and how efficient a tracking of an object can be. The research in this paper presented a theoretical modelling of an efficient moving object tracking based on the trajectory of the object movement. A thorough analysis of object tracking process has been presented where tracking is defined as measure of how well it can be observed by the sensors over time, while considering:

- Sensing field coverage where the monitoring area is divided into trajectories that are formed by the intersection of the sensing ranges (coverage) of each sensor node.
- Object location discovery according to the probability of the sensing accuracy of a sensor.
- Sensor deployment where maximum sensing coverage and maximum detection probability can be obtained.
- Sensing quality where the number of sensors required for maximizing the sensing coverage in the trajectory is computed.

A comprehensive understanding of tracking the object movement can be realized based on the theoretical concept provided. In relation to that, future work would go on in several directions:

- The exploration of some concept such as Scalar field, Vector field, Partial derivatives, Schwarz' theorem, Divergence, Curl, and Laplacian to acquire useful information such as position, direction, and velocity of the moving object.
- The utilization of binary bit information for approximating and tracking the multiple moving objects using binary wireless sensor network, where a base station can estimate the object location and movement in a region that includes the sensors detecting the object, by using the bit vector of the reported sensed data.
- The implementation of the presented modelling in simulated environment to validate the efficiency of the applications that would utilize the concept, where clustering communication paradigm is used for reporting the sensed data to a base station.

REFERENCES

1) L Becker and Ph Russ. Evaluation of joint angle accuracy using markerless silhouette based tracking and hybrid tracking against traditional marker tracking. Poster für Mas- terarbeit bei Simi Reality Motion Systems GmbH und der Otto-von-Guericke-Universität Magdeburg, 2015.

2) A. Delprado and R. Eaton. A statistical approach to silhouette tracking. In 2013 6th International Congress on Image and Signal Processing (CISP), volume 2, pages 657_663, Dec 2013.

3) P.K. Gangwar, Y. Singh, and V. Mohindru. An energy efficient zone-based clustering approach for target detection in wireless sensor networks. In Recent Advances and Inno- vations in Engineering (ICRAIE), 2014, pages 1_7, May 2014.

4) U. Gosda, R. Weber, O. Michler, S. Zeisberg, and E. Mademann. Target tracking in wireless sensor networks by data fusion with video-based object detection. In Positioning Navigation and Communication (WPNC), 2013 10th Workshop on, pages 1_6, March 2013.

5) Min Huang, Gang Chen, Guo-feng Yang, and Rui Cao. An algorithm of the target detection and tracking of the video. Procedia Engineering, 29:2567_2571, 2012.

6) Hao Jiang, Jiannan Zhai, and J.O. Hallstrom. Flashtrack: A fast, in-network tracking system for sensor networks. In Distributed Computing in Sensor Systems (DCOSS), 2014 IEEE International Conference on, pages 51_58, May 2014.

7) X. Li, K. Wang, W. Wang, and Y. Li. A multiple object tracking method using kalman filter. In The 2010 IEEE International Conference on Information and Automation, pages 1862_1866, June 2010.

8) Daw-Tung Lin and Kuan-Yu Wu. Wide area object tracking using multiple cameras with mixed configuration of over-lapping and non-overlapping fov. International Journal of Multimedia and Ubiquitous Engineering, 11(3):239_248, 2016.

9) T. Luo, R. H. Y. Chung, and K. P. Chow. A novel object segmentation method for silhouette tracker in video surveillance application. In 2014 International Conference on Computational Science and Computational Intelligence, volume 1, pages 103_107, March 2014.

10) Khalid Jamal Jadaa. Object detection and localization using wireless sensor networks based on probabilistic model. Submitted to Al- Yarmouk Journal, ISSN: 20752954 (Online), 2017.

11) Sandeep Kumar Patel and Agya Mishra. Moving object tracking techniques: A critical review. Indian Journal of Computer Science and Engineering, 4(2):95_102, 2013.

12) Om Prakash, Manish Khare, Chandra Mani Sharma, and Alok K Singh. Moving object tracking in video sequences based on energy of daubechies complex wavelet transform. In National Conference on Communication Technologies & its impact on Next Generation Computing (CTNGC), 2012.

13) Cuijuan Shang, Guilin Chen, Chengchao Ji, and Chih-Yung Chang. An efficient target tracking mechanism for guaranteeing user-defined tracking quality in wsns. Sensors Journal, IEEE, 15(9):5258_5271, Sept 2015.

14) Roshan Singh, Ravindra Kumar Purwar, and Navin Rajpal. A better approach for object tracking using dual-tree complex wavelet transform. In Image Information Processing (ICIIP), 2011 International Conference on, pages 1_5. IEEE, 2011.

15) B. Stenger, P. R. S. Mendonca, and R. Cipolla. Model-Based Hand Tracking Using an Unscented Kalman Filter. In Proc. British Machine Vision Conference, volume I, volume 1, pages 63_72, 2001.

16) S. Vasuhi, M. Vijayakumar, and V. Vaidehi. Real time multiple human tracking using kalman filter. In 2015 3rd International Conference on Signal Processing, Communication and Networking (ICSCN), pages 1_6, March 2015.

17) Liang Wang, Tieniu Tan, Huazhong Ning, and Weiming Hu. Silhouette analysis-based gait recognition for human identification. IEEE Transactions on Pattern

Analysis and Machine Intelligence, 25(12):1505_1518, Dec 2003.

18) Chen Yan-yan, Chen Ning, Zhou Yu-yang, Wu Ke-han, and Zhang Wei-wei. Pedestrian detection and tracking for counting applications in metro station. Discrete dynamics in nature and society, 2014, 2014

19) Alper Yilmaz, Omar Javed, and Mubarak Shah. Object tracking: A survey. Acm computing surveys (CSUR), 38(4):13, 2006.

20) Abdul-Lateef Yussi_, Suet-Peng Yong, and Baharum B Baharudin. Parallel kalman filter- based multi-human tracking in surveillance video. In Computer and Information Sciences (ICCOINS), 2014 International Conference on, pages 1_6. IEEE, 2014.

21) X. Zhang, W. Hu, H. Bao, and S. Maybank. Robust head tracking based on multiple cues fusion in the kernel-bayesian framework. IEEE Transactions on Circuits and Systems for Video Technology, 23(7):1197_1208, July 2013.