Providing Multi-Perspective Event Coverage in Wireless Multimedia Sensor Networks

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Abstract—The increasing availability of low-cost battery-operated wireless cameras motivated the deployment of large-scale Wireless Multimedia Sensor Networks (WMSNs) which can be leveraged for gathering disparate views of events from multiple perspectives. Such multi-perspective coverage not only provides better visual knowledge about the events but also helps prevent occlusions in many critical applications. Different than traditional k-coverage in Wireless Sensor Networks (WSNs), multi-perspective coverage computation considers the orientation of cameras in addition to their locations. In this paper, we first introduce a new metric which can measure multi-perspective coverage for a particular region from a given number of perspectives. Using this metric, we then propose camera placement techniques based on binary integer programming and heuristics to achieve full multi-perspective coverage with the least camera count. Finally, to be used as a baseline, we come up with a formula which can analytically compute the multi-perspective coverage for a given network of randomly placed cameras in a certain region. We evaluated the performance of these camera placement approaches (e.g., integer programming, heuristic and random) in terms of coverage and number of cameras needed under different number of perspectives.

I. INTRODUCTION

The integration of multimedia event monitoring systems (e.g., remote surveillance and habitat monitoring systems) with wireless sensor networks (WSNs) has started to receive attention primarily due to increasing availability of low-cost battery-operated wireless cameras [1][2][3]. Such networks, referred to as wireless multimedia sensor networks (WMSNs) [4][5][6][7], deploy a certain number of image and video cameras in conjunction with a large number of scalar sensors (i.e., temperature, motion, light, etc.) and can collect and process multimedia data. Each camera in a WMSN has a certain field-of-view (FoV) and Depth-of-View (DoV) which are the angle and the distance respectively where the camera can capture an accurate image/video. Typical applications of WMSNs include multimedia surveillance, habitat monitoring, intrusion detection, and health care delivery [4].

WMSNs can enhance the quality and performance of current multimedia event monitoring systems in several ways including data collection and aggregation, autonomous operation, coverage and quality of service [4]. For instance, with the reducing cost of wireless cameras, it is possible to deploy image/video cameras in large numbers under WMSNs which provides the opportunity to take image or video of an occurring event from multiple disparate viewpoints (i.e., perspectives) [4]. The perspective is the direction of the cameras with respect to the center of the event. For instance, a camera can be recording from north while another one can be recording from south, providing two different perspectives. Such a situation is not possible under traditional multimedia systems where the number of cameras is limited due to their costs and deployment inconvenience.

Capturing an event from multiple perspectives can be useful in many applications such as remote surveillance of and habitat monitoring in forests/underwater. In such applications, having such a feature can have a substantial impact on the quality of criminal investigations and research on animal behavior due to the following benefits: 1) Object classification and recognition quality can be improved significantly. For instance, in human classification in the presence of animals or other vehicles, the clear advantage of multiple cameras (e.g., one looking from the top and others from different sides) is the ability to classify humans with much higher degree of confidence by assessment of their geometrical properties [8]; 2) The effect of possible occlusions that exist in the environment is eliminated. In this way, the quality of human/animal tracking can also be significantly improved; and 3) 3-D video generation can be facilitated with multiple camera views.

Traditionally, coverage in multimedia surveillance systems and even in current WMSNs were assessed by computing the total FoV area of the cameras with respect to the total area of the monitored region. In such systems, FoV area for a camera can be from any perspectives among 360°. Given this interpretation of coverage, current systems strive to provide full coverage of a monitored region from any perspectives with the least number of cameras [9][10][11]. However, this does not address the needs of aforementioned applications which may have a requirement to capture events from multiple perspectives. To the best of our knowledge, currently there are no multimedia surveillance/monitoring systems which consider the issue of ω-perspective coverage where ω represents the number of perspectives. We will refer it as ω-pC hereafter. We believe that ω-pC is an important feature that needs to be provided in WMSNs. This paper is the first to study:

1) How to define a metric for assessing ω-pC where ω > 1?
2) Given a WMSN topology, how to determine $\omega$-pC for a given $\omega$ value and camera count?
3) How to place camera sensors in order to provide 100% $\omega$-pC of the monitored region with the least camera count?

We start by defining a novel metric which is used to determine the $\omega$-pC weight for a particular point with a given set of cameras. This weight will then be used to determine $\omega$-pC percentage for a particular region.

Secondly, using the new metric defined above, we come up with a formula to analytically calculate the $\omega$-pC of a particular region under a given arbitrary WMSN topology. Specifically, we consider $n$ cameras randomly deployed in an area of interest and then compute the $\omega$-pC of the area based on the inclusion-exclusion principle.

Finally, using the proposed metric, we propose camera placement mechanisms to achieve full $\omega$-pC of a monitored region which is the main goal of this paper. To this end, we first propose a binary integer programming (BIP) solution to determine the least number of cameras required to provide almost full $\omega$-pC (i.e., close to 100%) given that such a solution would require running on some discrete placement and control points. While increasing the number of such points increases $\omega$-pC towards 100%, BIP will take much longer times. Therefore, as an alternative, we also propose a heuristic approach for providing full $\omega$-pC while minimizing the number of cameras used. We illustrate how the heuristic works with smaller values of $\omega$ and discuss on how it can be extended to work for different $\omega$ values.

We have implemented the placement approaches based on BIP and our heuristic. As another baseline, we used random placement for which the coverage was computed using our analytical formula. We compared their performance in terms of $\omega$-pC and camera count. The results show that our proposed placement techniques surely outperforms random placement. Moreover, we observed that with the addition of 15% extra cameras with respect to BIP solution, our heuristic can guarantee full $\omega$-pC.

This paper is organized as follows. Next section provides the related work. Section III outlines the assumptions and introduce our new metric which incorporates the idea of $\omega$-pC of a region. We compute the expected $\omega$-pC of randomly placed cameras in Section IV. In Section V, we describe our proposed camera placement techniques for achieving $\omega$-pC. Section VI includes the experimental evaluation of the proposed approaches. Finally, in Section VII we will conclude the paper by stating our findings and possible future extensions.

II. RELATED WORK

A. Coverage in WMSNs

Coverage problems in WMSNs have not received much attention given the fact that they can be modeled through the well-known art gallery problem [12]. Once the FoV of the cameras are known, art gallery problem can be used to determine the least number of nodes and their locations in order to provide 100% coverage of a monitored region. It has been shown in [12] that the problem can be solved in polynomial time in two dimensional (2-D) environments. However, earlier works in WMSNs considered only any-perspective coverage (i.e., as long as the area is covered, the perspective does not matter) for such placement. Our problem in this paper is different in the sense that we consider multiple perspectives when deploying the cameras.

Due to FoV shape, coverage in WMSNs has been considered as a special case of WSN coverage which is a well studied area. The solutions for both 1-coverage and $k$-coverage where a point should be under the sensing range of $k$ sensors have been proposed for WSNs [13]. For instance, [14] has chosen a series of placement and coverage points for placing the sensors and providing coverage respectively. A binary integer programming solution has then been proposed which finds the minimum number of sensors required to provide full $k$-coverage of the selected points. This strategy has been adopted to WMSNs with a FoV instead of a circular sensing range. The only difference was in setting up the program since a different check must be made based on the FoV coverage instead of simply checking sensing range. In [15] and [16], the authors have examined the solutions produced by linear programs and made extensions by considering other constraints such as connectivity besides coverage. In [9], maximal breach has been computed for a target which corresponds to worst-case camera coverage. Ercan et al., have investigated the camera placement problem in a room for minimizing the localization of a point via multiple cameras [17]. Finally, [18] has explored the coverage of a region that contains occlusions with varying number of cameras using smaller FoVs. As opposed to these efforts, in this paper, we focus on multi-perspective coverage and thus these solutions cannot be applied.

B. Multi-perspective Coverage

There are only a few works that deal with multiple perspectives in wired/wireless multi-camera networks. For instance, the work in [19] has examined how multiple perspectives of an environment will increase the ability of tracking a mobile object indoors. The paper has also focused on the presence of occlusions and how to deal with this problem while doing object tracking. Our work is different in the sense that we focus on camera placement to guarantee full multi-perspective coverage of a region as opposed to assessing the improvement on the quality of object tracking when multiple perspective views are available. Nonetheless, these works could complement each other since placements using our metric could provide the desired multi-perspective coverage to achieve object tracking.

One of the closest work to ours has been reported in [20]. The author have considered the problem of providing circular coverage with sufficient resolution for a given object. The circular coverage has been defined as 360° coverage where cameras can sit randomly on a circle around an event and the union of their FoVs’ arcs fully covers the event (i.e., creates a circle). They have tried to select the cameras to minimize the image transmission cost to the sink. Our work is different
from this work in two ways. First, their 360° of coverage does not consider the perspective of cameras. Regardless of the camera locations, the area is considered fully covered as long as the union of FoVs’ arcs form a circle. In our work, we differentiate between different camera topologies that provide 360° coverage by checking their perspectives. Our ω-pC weight function is used for such differentiation and it quantifies how a particular topology is close to the topology with the desired perspectives. In a sense, our metric is more specific and flexible since it allows to specify the requested number of perspectives. Second, as opposed to [20], we do not study a camera selection problem in a randomly deployed camera network for a specific event. We focus on camera placement for the whole event area.

In [21], the authors have considered a 3-D environment where multiple cameras are located on the walls of a room. The goal is to provide an image of the room from any viewpoint requested by a user. This has been achieved by the aggregation of images from multiple cameras. The cameras have been assumed to be able to crop the images and send only the parts which can be combined at a central location to generate a new view. As opposed to an image processing approach, our goal is to provide initial camera topology to guarantee multi-perspective coverage and thus is different than this work.

III. A New Metric for Multi-Perspective Event Coverage

A. Preliminaries

A WMSN in our context is formed by a set of scalar sensors and multimedia sensors (e.g., Imote2 [22] and CmuCam3 [3]). While scalar sensors will detect the events, multimedia sensors are used to capture a video or image of the event whenever needed. We will refer the multimedia sensors as cameras hereafter. A sample WMSN is shown in Figure 1.

![Considered WMSN Model throughout the paper.](image)

Each camera in a WMSN has a certain field-of-view (FoV) \( s \) and Depth-of-View (DoV) \( d \) which are the angle and the distance respectively where the camera can capture an accurate image/video as seen in Figure 1. The cameras are assumed to have a fixed random position and orientation (i.e., the direction the camera faces) and they do not move. While the exact boundaries of the monitored area is known, the events (i.e., their location, shape and radius) are not known in advance and they are assumed to appear randomly within the monitored area.

The perspective of a camera refers to a direction from where we have a view of the event. Assuming a circle around an event, in the ideal case the perspectives should be evenly distributed along this circle in order to get diverse views of an event as seen in Figure 2b. Obviously, this may not always the case as seen in Figure 2a. Our proposed metric in this paper will quantify how close is the topology in Figure 2a to the ideal case in Figure 2b in terms of multi-perspective coverage.

![Fig. 2. (a) 3 cameras providing 3 similar perspectives. (b) 3 cameras with 3 diverse perspectives in the ideal case.](image)

B. Computation of ω-pC for a Region

In WMSNs, typically a region is considered covered if the FoV of any of the cameras is covering that region regardless of its orientation. However, when ω-pC is considered for the same region, we need to ensure that the same region is covered with \( \omega \) cameras, each of which is oriented with a different perspective. Note that this is different from the idea of \( k \)-coverage in WSNs [23] where a certain point should be under the sensing range of \( k \) different sensors. We propose to adopt this idea to WMSNs in a different way. While \( k \)-coverage can still be considered in WMSNs for fault-tolerance purposes, our goal is not to provide fault-tolerance in this paper. The main idea of ω-pC is to provide \( \omega \) different perspectives for viewing the events. Nonetheless, having multiple cameras for the same point from different views will still bring fault-tolerance.

Since the direction is very crucial in providing ω-pC, we first introduce a weight metric which can assess how close a camera is to the desired orientation. This metric is then used to define ω-pC percentage. We used the notation in Table I in defining the new metrics.

| \( \omega \) | Number of perspectives |
| \( X \) | Set of cameras in use |
| \( \theta_i \) | Orientation of each camera sensor \( i \in X \) |
| \( s_i \) | Sector of camera \( i \) |
| \( A(\cdot) \) | Area function |

TABLE I

Notation for ω-pC Definition

Fig. 1. Considered WMSN Model throughout the paper.
Definition 1. $\omega$-pC Weight ($\omega$-pCW) for Point p:
Let us assume that a point $p$ is covered by a set of $X$ cameras with intersecting FoVs. Consider a unit disk which we refer to as Perspective Disk (PD) with $|X|$ sectors such that each sector $s_i$ has the direction $\theta_i$ and has an arc width of $\frac{2\pi}{|X|}$. Then, $\omega$-pCW for $p$ denoted as $\omega$-pCW($p, X$) will be:

$$\omega$-pCW($p, X$) = A(\bigcup_{i \in X}(s_i))$$

This is illustrated in Figure 3a with $\omega = 2, 3, 4$. In this figure, the colored region is covered by all three cameras numbered 1, 2, and 3 from various perspectives. Any point picked in this region would have the same $\omega$-pCW since the camera orientations ($\theta$) are same for all the points. The $\omega$-pCW associated with a particular point in this region can be calculated by finding the ratio of combined area of their corresponding sectors in PD to the total area of the PD (i.e., 1) for different $\omega$ values as shown in Figure 3b,c,d. For instance, for $\omega = 2$, the sectors of width $\frac{2\pi}{2} = 180^\circ$ are overlapping and fully covering the PD. Therefore, the 2-pCW for a point in this region will be 1. However, when $\omega = 3$, the sectors are of width $\frac{2\pi}{3} = 120^\circ$ and thus they cannot fully cover the PD. This is also valid for $\omega = 4$ where each sector is of width $\frac{2\pi}{4} = 90^\circ$. Therefore, 3-pCW and 4-pCW for a point in this region will be less than 1.

Note that $\omega$-pCW will be a value between 0 and 1. One can achieve a $\omega$-pCW of 1 by having $|X| = \omega$ and each $i \in X$ will be oriented such that the $\theta_i$s are distributed equally around the PD and there is no overlap among the $s_i$s as this will fully cover the PD with sectors (see Figures 4, 5 and 6). Cameras with nearly the same orientation will contain a lot of overlap of the sectors within the PD and these overlaps will result in no improved multi-perspective coverage.

For an arbitrary region $r$ which is under FoV of a set of $X$ cameras, this is defined as the weighted area of region assuming that each point $p$ picked in $r$ has the same $\omega$-pCW($p, X$). Denoted as $\omega$-pC($r, X$), it can be computed as follows:

$$\omega$-pC($r, X$) = A(r) \times \omega$-pCW($p, X$)

where $A(r)$ denotes the area of region $r$ and $p \in r$. Note that even if a region $r$ is covered by multiple cameras at the same time, this does not directly provide full $\omega$-pC since the orientations of the cameras also need to be considered. A $\omega$-pCW of 1 is required for providing full $\omega$-pC since $\omega$-pC in that case will simply be the normal area of the region.

IV. $\omega$-pC FOR RANDOMLY DEPLOYED WMSNs

In this section, we will turn our attention to randomly deployed WMSNs. These are the networks where camera placement is done arbitrarily. We provide a formula for computing $\omega$-pC for such networks.

A. Computation of Expected $\omega$-pC

The expected $k$-coverage has been studied in WSNs [24] to determine the number of sensors necessary for achieving a certain level of coverage in a particular area of interest. Similarly, using our new metric, we determine an expected $\omega$-pC of a region covered by randomly deployed WMSN based on the number of cameras used ($n$), the proportion of the area of a camera sensor’s FoV to the total area of the region ($a$), and the $\omega$ value. Such a mathematical formulation not only gives an idea of how many cameras would be needed to provide a certain $\omega$-pC in case of random deployment but can also be used as a baseline for comparing with manual placement approaches that will be discussed next.

First, we begin with Lemma 1 to establish the expected area of all space which are covered by exactly $k$ cameras assuming that a camera covers a portion of the total region denoted as $a$ (i.e., $a = A(FoV) / A(Region)$). Then in Lemma 2, we show how to compute the weight for the expected area. Using Lemma 1 and Lemma 2, the expected $\omega$-pC will be deduced in Theorem 3.

**Lemma 1.** Let $X^k \subseteq C$ be a subset of size $k$ of the total set of cameras $C$ where $|C| = n$. Let us assume that each camera is placed randomly and independently. Then, for all $X^k \subseteq C$, the expected ratio of the area covered by the intersection of all $k$ cameras (i.e., $\bigcap_{i \in X^k}(FoV_i)$) to the total area is $(\binom{n}{k})a^k(1-a)^{n-k}$.

**Proof:** Consider a particular $X^k = x_1, x_2, ..., x_k$, then the expected ratio of $A(X^k)$ to the total area of the region would be $a^k$. Note that $a^k$ is the expected area of the intersection of all $k$ cameras, thus this area does decrease as $k$ increases. However, we must exclude the area covered by the remaining $x_i \notin X^k$. The expected area ratio that these cameras do not cover is $(1-a)^{n-k}$ since there are $(n-k)$ $x_i$ that are not in $X^k$. Therefore, we can multiply these for a total area ratio of $a^k(1-a)^{n-k}$. However, we must consider this for all $X^k \subseteq C$. Since there are $\binom{n}{k}$ of these subsets $X^k$, then the final ratio
of $A(X^k)$ to the total area of the region is $\binom{n}{k} a^k (1-a)^{n-k}$.

**Lemma 2.** Given an $\omega$ value, the expected weight for a region covered by $k$ cameras with random orientations is $(1 - (1 - \frac{1}{\omega})^k)$.

*Proof:* Pick a random point within the PD, then the probability that this point is not covered by 1 randomly placed sector is $(1 - \frac{1}{\omega})$. Now, consider $k$ randomly placed sectors, the probability that this point is not covered by any sector would be $(1 - \frac{1}{\omega})^k$. Therefore, the probability that a point is covered by at least one of the sectors would be the complement (i.e., $(1 - (1 - \frac{1}{\omega})^k)$). The expected weight of the region covered by $k$ cameras will relate to this probability and be $(1 - (1 - \frac{1}{\omega})^k)$ as well.

**Theorem 3.** Given $n$ cameras being placed randomly with random orientations within an environment, $e$. Then, the total expected $\omega$-pC for the whole region ($\omega$-pC($e,n$)) will be equal to $\sum_{k=1}^{n} \binom{n}{k} a^k (1-a)^{n-k}(1 - (1 - \frac{1}{\omega})^k)$.

*Proof:* From Lemma 1 we know that the expected area covered by $k$ cameras is $\binom{n}{k} a^k (1-a)^{n-k}$. Also we know from Lemma 2 that the expected weight of a region covered by $k$ cameras is $(1 - (1 - \frac{1}{\omega})^k)$. Therefore, by the definition of $\omega$-pC, total coverage will be $\sum_{k=1}^{n} \binom{n}{k} a^k (1-a)^{n-k}(1 - (1 - \frac{1}{\omega})^k)$.

V. CAMERA PLACEMENT STRATEGIES FOR PROVIDING $\omega$-pC

In this section, we investigate centralized camera placement strategies which will strive to provide full $\omega$-pC while minimizing the number of cameras required.

A. Problem Definition

Our problem can be formally defined as follows: “Given $\omega$, a region of interest with known boundaries and cameras with same FoV, $s$, and DoV, $d$, determine the least number of cameras, their locations and orientations to provide 100% $\omega$-pC for the entire region”.

In WSNs, a similar problem to this problem is providing $k$-coverage for the considered region with sensors assuming that each sensor has a circular sensing range. This problem has been shown to be NP-Hard by a reduction to minimum-cost satisfiability problem in [14]. Our problem is a special case of this problem given that the orientations of the cameras should be considered when placing the cameras. To the best of our knowledge, there is no prior work which studied the problem of guaranteeing $\omega$-pC for a region based on the initial camera deployment. Given the infinite number of locations to place the cameras, we will follow the same approach as in [14] and discretize the problem to set up a binary integer programming (BIP) solution as explained next.

B. Binary Integer Programming Approach

For our BIP solution, we need to define a set of grid points for placing the cameras, $P$, and another set of grid points, $\Omega$, that need to be $\omega$-p covered. We will let $\Omega$ and $P$ be grid placements, and $\Omega$ will be placed over the region of interest. The set of orientations will be denoted as $\theta$.

We would like to note that when placing the grid of $P$ over the region of interest, it is difficult to get the $\omega$-pC of the points in the set $\Omega$ which lie on the edge of the monitored region. Therefore, the total area of the grid $P$ should be slightly larger (e.g., 1-5%) than that of the monitored region in order to achieve full $\omega$-pC over control points lying on the edge. In this case, more choices for camera placements will be available (i.e., more points in $P$). While the use of grid placements gives a uniform cover of the entire region of interest, our algorithm would also work with any other type of placement (e.g., random) as long as it converges.

In order for our BIP to be considered an accurate approximation of an optimal full $\omega$-pC, the set $\theta$ must be chosen such that $|\theta| = \omega$ and the orientations from $\theta$ should fill the $PD$. A covered $PD$ for $\omega = 2, 3, 4$ can be viewed in Figs 4, 5, and 6 respectively. In each case, the cameras are placed in such a way that their orientation vectors create sectors which do not overlap in the PD.
Each element of the variable $x$ corresponds to a particular placement point and an orientation. Therefore, every 1 in the vector $x$ will correspond to a position and orientation to place a camera. We also need a constant matrix $A$ with dimensions $|P \times \theta| \times |\Omega \times \theta|$, and the following entries.

$$ a_{ij} = \begin{cases} 1, & \text{if } j \in P \times \theta \text{ covers the control point from the correct orientation } i \in \Omega \times \theta \\ 0, & \text{else} \end{cases} $$

Let $b$ be a column vector of size $|\Omega \times \theta|$, and $c$ is a row vector of size $|P \times \theta|$. All of the entries in both $b$ and $c$ are equal to 1. With these variables, we can form the following BIP:

$$ \begin{align*} \min & \quad cx \\
\text{subject to} & \quad Ax \geq b \end{align*} $$

Basically the function $cx$ to be minimized is just the number of cameras that are being placed. Then, the constraint $Ax \geq b$ requires that each control point be covered by at least one camera from each orientation. The entire algorithm can be summarized as follows for a given region of interest and $\omega$ value:

1. Pick control points $\Omega$ within the region of interest
2. Pick placement points $P$
3. Set $|\theta| = \omega$
4. Generate $A$, $b$ and $c$ as mentioned above
5. Solve the BIP of minimizing $cx$ subject to $Ax \geq b$
6. Vector $x$ will determine how many cameras to place and where to place them

In such a BIP solution, full $\omega$-pC is not possible since we are restricted with the grid points to be covered rather than the whole region. The only improvement for coverage would be to increase the number of grid points as long as the used BIP solver can converge (come up with a solution) with large number of such points. However, achieving exactly 100% $\omega$-pC will still not be possible. Due to the inability to produce a truly optimal solution with the BIP method, we now introduce an alternative solution based on some heuristics.

**C. Heuristic Approach**

Our proposed heuristic can provide full $\omega$-pC of a region albeit it will not have any guarantees for the optimal camera count. The idea is based on optimal placement of $\omega$ cameras to fill the PD as shown in Figures 4, 5, 6. For instance, in Figure 4, cameras 1 and 2 create a square area which is 2-p covered since its corresponding PD is fully filled in. Perhaps a better example is when $\omega = 3$, since the intersection region would be an equilateral triangle if the FoV of each camera is $\frac{\pi}{3}$ as seen in Figure 5. Finally, Figure 6 shows optimal placement for $\omega = 4$ which creates the same shape as $\omega = 2$.

This heuristic for camera placement for a particular $\omega$ value can be applied as follows:

1. Find a polygon which $\omega$ cameras can fully cover with $\omega$-pC
2. Find a full cover of the region with these polygons
3. For each polygon, place $\omega$ cameras in the same spots that achieve full $\omega$-pC of the polygon

As an example, we pick $\omega = 1, 2, 3, 4$. We first simply fill the monitored region with either equilateral triangles ($\omega = 1, 3$) or squares ($\omega = 2, 4$).

![Fig. 7. Sample triangular placement for $\omega = 1$ (a) and for $\omega = 3$ (b) for a rectangular region.](image)

Then, cameras are placed at the corners of these shapes such that each shape would have $\omega$ cameras covering it. For instance, the coverage from equilateral triangles is shown in Figure 7 for a rectangular region. When $\omega = 1$, for every triangle, we will place one camera as shown in Figure 7a. When $\omega = 3$, we will place three cameras as shown in Figure 7b. This also requires that $s$ be fixed depending on the $\omega$ value (e.g., when $\omega = 1, 3$, $s$ is set to $\frac{\sqrt{3}}{2}$ to create equilateral triangles and when $\omega = 2, 4$, $s$ is set to $\frac{\sqrt{2}}{2}$ to create squares). In this way, every point in the monitored region will be guaranteed to have full $\omega$-pC. Then, the number of cameras required for a particular $\omega$ value can be found by the following function of $d$:

$$ f(d) = \begin{cases} \omega * \left[ \frac{2}{\sqrt{3}} \right] * \left[ \frac{\pi}{3} + 1 \right], & \text{if } \omega = 1, 3 \\
\omega * \left[ \frac{1}{\sqrt{2}} \right]^2, & \text{if } \omega = 2, 4 \end{cases} $$

This equation simply counts the number of triangles or squares needed to fill a square region of interest which is a unit square. For the triangle case ($\omega = 1, 3$), first there is a count of how many rows of triangles will be required which is $\left[ \frac{2}{\sqrt{3}} \right]$ since $\frac{\sqrt{3}}{2}$ is the height of a triangle. Then, the number of triangles per row can be calculated as $\left[ \frac{\pi}{3} + 1 \right]$ since at least one triangle must always be used and for every $\frac{\sqrt{3}}{2}$ of the region of interest another triangle must be added in order for that row to be fully covered. Multiplying the number of rows by the number of triangles per row will give us the result shown in the formula. The case of filling the region of interest with squares is more straightforward. The number of squares per row and number of rows are same due to the region of interest and the polygon also being square. Therefore, both of these values are simply $\left[ \frac{1}{\sqrt{2}} \right]$. The result can be obtained by squaring this value times $\omega$.

Note that our heuristic can be extended to work with other $\omega > 4$ as long as the created shapes are able to form regular tessellations. For instance, for $\omega = 5$ the shape will be a pentagon and for $\omega = 6$, the shape will be a hexagon. While hexagons can be packed together to cover an area, it is not
possible to do that for pentagons. We leave this as a future work.

VI. EXPERIMENTAL EVALUATION

A. Experiment Setup and Performance Metrics

We have evaluated the performance of BIP, our heuristic and random placement using MATLAB. MATLAB’s bintprog function was used for solving BIP [25]. For the implementation of the BIP, we have varied the size of the sets P and Ω which are the possible position of camera placements and control points respectively. While |P| varied from 81 to 225, |Ω| varied from 36 to 192, and then |θ| varied from 1 to 4. These values were chosen differently for each experiment in order to provide the best solution with a reasonable convergence time. In addition, the camera’s FoV was set to $\frac{2\pi}{\omega}$ (except for the case of $\omega = 1$ since the FoV would be a circle and thus we chose an arbitrary width of $\frac{2\pi}{\omega}$ in order to satisfy the setup conditions of the BIP. Finally, DoV was set appropriately such that the $a$ value would correlate to the area of the FoV. We have considered a region of interest which is a unit square to place the cameras.

The following metrics are used for assessing the performance of the proposed algorithms:

- $\omega$-pC Percentage: This is the ratio of $\omega$-p covered area to the area of the region of interest. Our aim is to provide full $\omega$-pC for the whole region meaning that $\omega$-pC percentage will be 1. We will use $\omega$-pC percentage and $pC$ interchangeably in this section.
- # of cameras: This metric shows the number of cameras used in placement when full $\omega$-pC is desired.

B. Experiment Results

1) Comparison of BIP and Heuristic Approach: We have picked different $\omega$ and $a$ values and compared the performance of BIP and our heuristic approach. The results of the experiments are shown in Figure 8. $\omega$-pC is always 1 for our heuristic since it can guarantee full coverage. However, $\omega$-pC varies for the BIP solution since the goal of this solution is to cover a finite number of control points in the monitored region. This means that a full $\omega$-pC is not always guaranteed. However, it provides a near full $\omega$-pC of the monitored region. The coverage values for BIP are shown separately using arrows in Figure 8. While our heuristic provides better $\omega$-pC compared to BIP solution, this comes at the expense of increased camera count as expected. Our heuristic solution requires approximately 15% more cameras than the BIP which remains fairly constant throughout each experiment. We also note that when $a$ is increased, FoV for each camera increases and covers more areas which in turn decreases the number of required cameras. However, the rate of increase in the camera count is more when $a$ is decreased indicating that large values of FoV should be selected for cameras if the total deployment cost is to be decreased.

2) Comparison with Randomly Placed Cameras: We have also assessed the $\omega$-pC of a randomly placed network for comparing with our BIP and heuristic approaches. We have simply applied the function that we derived in Theorem 3 which provides the expected $\omega$-pC of randomly placed cameras given the number of cameras, the $\omega$ and $a$ values. We would like to note that we have also simulated the random placement to help us validate the correctness of our formula in Theorem 3. We have observed that the results do converge to the formula when the number of trials is greater than 100. Therefore, we have tried 500 experiments for each of the evaluations. The results of the experiments are depicted in Figures 9 and 10. From these figures it is apparent that our solutions are achieving higher $\omega$-pC than random placement which is expected. The improvement in $\omega$-pC for our solutions are roughly 10% to 20% higher for each experiment which is very significant.

In terms of camera count, our heuristic requires significantly less cameras to provide full $\omega$-pC. For example, consider a scenario where $a = .1$ and $\omega = 1$. From Figure 10, one can see that it would require about 60 cameras to achieve full $\omega$-pC with random placement while it only took 18 cameras to achieve the same full coverage with our heuristic solution. Another important feature of Figures 9 and 10 is that they reaffirm our motivation for using $\omega$-pC within a WMSN. This
is because the $\omega$-pC values become more linear as $\omega$ increases. Given the cheap cost of cameras in WMSNs [22], it is wiser to add more cameras to the network since this will help increase $\omega$-pC significantly with the increasing values of $\omega$.

VII. CONCLUSION

WMSNs provide opportunities for taking multi-perspective image or video of the events which can improve the quality of many applications. In this paper, we have motivated the need for developing a multi-perspective coverage metric to be used for WMSNs instead of a standard FoV coverage. We have introduced a novel metric named $\omega$-pC for providing such multi-perspective coverage for a given point or region. Using this metric, we have derived the expected $\omega$-pC of randomly placed cameras. In order to guarantee full $\omega$-pC for a monitored region, we have presented camera placement mechanisms which will require the least number of cameras to be deployed in the monitored region. First, an optimal solution based on integer programming methods was presented. Since this approach does not guarantee full $\omega$-pC, we have also presented a heuristic approach to achieve full $\omega$-pC based on the shape created with the given $\omega$ value.

Our experimentation has shown that BIP solution cannot guarantee full $\omega$-pC even though it provides the least camera count. However, with a 15% increase in the camera count, our heuristic was able to provide 100% $\omega$-pC for different values of $\omega$. The experiments have also revealed that even with randomly placed cameras $\omega$-pC will increase significantly particularly with larger values of $\omega$. However, our centralized placement techniques always outperform random placement in terms of camera count. Finally, we have observed that in order to guarantee convergence in our BIP solution, the number of control and placement points should be decreased when larger values of $\omega$ are considered.

As a future work, we plan to extend our heuristic to work for arbitrary values of $\omega$. In addition, we plan to work on a distributed heuristic which can turn on the necessary cameras in a randomly deployed WMSN to provide the desired $\omega$-pC.

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