Optimal Camera Configuration for Large-Scale Motion Capture Systems

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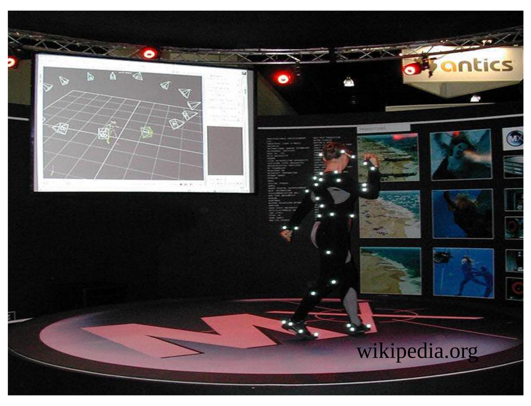
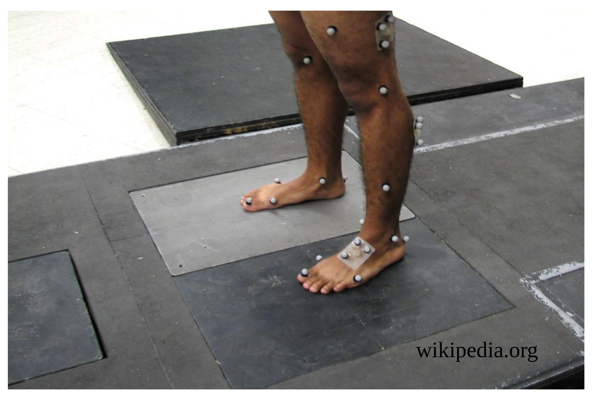
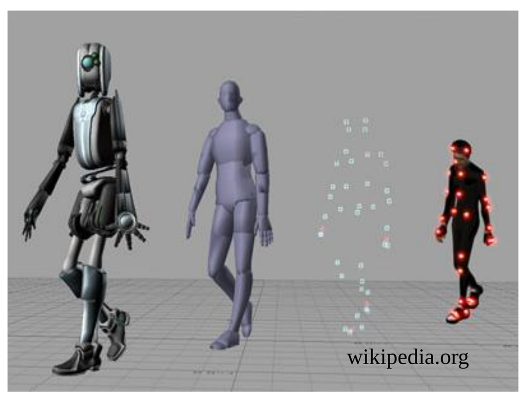
Optimal Camera Configuration

- A great deal of prior works exists where the field of view, working volume, focus, visibility, resolution and occlusion are considered for formulations[1]
- Most earlier studies discretize the space with grids to formulate the model[2],Which are in NP-hard including greedy heuristics, semi-definite programming, and simulated annealing [3]
- Relevant for many applications







Current research:

- how to formulate the problem and how to approximate the optimum.
- be vulnerable to occlusions from either static or dynamic objects.
- **Drawback:** NP-hard complexity for the objective, occlusion percentage is high.

Proposed Solution

- maximizing the coverage with the occlusion culling factor.
- We have built a new binary integer programming model incorporating occlusion culling factors, where the scene representation, camera model, visibility analysis, and geometric and optical constraints on sensor location are considered.

Formulation of the Objective:

$$\underset{x',y',z',\varphi}{\arg\text{Max}} \quad \sum_{x=1}^{n_x}\sum_{y=1}^{n_y}\sum_{z=1}^{n_z} \lambda g_{xyz}$$

$$\text{s.t.} \quad \sum_{x',y',z'} c_{x'y'z',\varphi,i} \geq 1, \quad 1 - t_{xyz} \leq c_{x'y'z',\varphi,i} + g_{xyz} \leq 1 + t_{xyz},$$

$$\sum_{x=1}^{n_x}\sum_{y=1}^{n_y}\sum_{z=1}^{n_z} t_{xyz} \geq M, \quad \sum_{i=1}^{M} c_i \cdot L_i \leq C_c, \quad l_{i_{\min}} \leq \kappa \leq l_{i_{\max}},$$

$$x'_{\min} \leq x' \leq x'_{\max}, \quad y'_{\min} \leq y' \leq y'_{\max}, \quad z'_{\min} \leq z' \leq z'_{\max},$$

$$\left|\frac{x-x'}{z-z'}\right| \leq \tan\left(\frac{\alpha}{2}\right), \quad \left|\frac{y-y'}{z-z'}\right| \leq \tan\left(\frac{\beta}{2}\right),$$

- Where $\lambda = P(\bigcup_{i=2}^{n} A_i)$, g_{xyz} is a binary variable representing if the grid point is covered by M cameras; $c_{x'y'z',\varphi,i}$ is a binary variable representing if the camera is deployed at (x',y',z') with orientation φ ; t_{xyz} denotes a binary variable at the grid (x,y,z) [4]. L_i denotes the price for the camera c_i, C_c denotes the total budget for the camera configurations. $l_{i_{\min}}$ and $l_{i_{\max}}$ are the minimum and maximum effective lengths of the i th camera. $\kappa = \frac{\|([x_i\ y_i\ z_i]^t - T)\cdot \mathbf{V}_o\|}{\|[x_i\ y_i\ z_i]^t - T\|\cdot\|\mathbf{V}_o\|}$, $\mathbf{V}_o$ is the direction of this point that is parallel to the optical axis. α and β denote the horizontal and the vertical FoV, respectively. n_x, n_y and n_z denote the number of grids in three directions, respectively. Our goal is to find the optimal x',y',z' and φ , to maximize the coverage of grid points x, y, z.

Greedy Heuristics with Riesz-Particle Scale

- Step 1: If $\lambda(x,y,z)_j$ =0, for any $j=1,2,...,n$, set $g(x,y,z)_j$=1 and remove all constraints in which $g(x,y,z)_j$ appears with a coefficient of 1.
- Step 2: If $\lambda(x,y,z)_j$ >0, for any $j=1,2,...,n$, and $g(x,y,z)_j$ does not appear with 1 as the coefficient in any of the remaining constants, set $g(x,y,z)_j$=0;
- Step 3: For each of remaining variables, determine $\frac{\lambda(x,y,z)_j}{|\mathfrak{L}_j|}$, where $|\mathfrak{L}_j|$ is the number of constraints in which $g(x,y,z)_j$ appears with the coefficient 1, select the variable k' for which $\frac{\lambda(x,y,z)_j}{|\mathfrak{L}_j|}$ is minimum, set $g(x,y,z)_{k'}$ =1 and remove all constants in which $g(x,y,z)_{k'}$ appears with the coefficient 1. Examine the resulting model.
- Step 4: If there are no more constraints, set all the remaining variables $g(x,y,z)_j$ to 0 and stop, otherwise go to step 1.
- Step 5: We maximize the use of overlapping by

$$\mathbb{P}' \leftarrow \arg\max \left|\bigcup_{i=1}^{M}\bigcup_{j=1}^{M}(\mathfrak{C}(i)+\mathfrak{C}(j)-\mathfrak{C}(i)\cup\mathfrak{C}(j))\right|,$$

Inspired by [5], we introduce the Riesz energy to discretize rectifiable submanifolds of interest $\Omega \subset \mathfrak{C}$ via particle interaction(for grid points), where only a few samples, called Riesz particles, are required to scale the cardinality of $\mathfrak{C}(i)$.

$$\min_{\mathbf{x_i},\mathbf{x_j}\in\Omega} \varepsilon_\beta(\Omega,N) = \min_{\mathbf{x_i},\mathbf{x_j}} \left\{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n} \frac{\omega(\mathbf{x_i},\mathbf{x_j})}{\|\mathbf{x_i}-\mathbf{x_j}\|^m}\right\}^{\frac{1}{m}},$$

$$\omega(\mathbf{x_i},\mathbf{x_j}) \propto e^{[\alpha'\cdot\gamma(\mathbf{x_i})\gamma(\mathbf{x_j})+\beta'\cdot\|\mathbf{x_i}-\mathbf{x_j}\|]^{-\frac{m}{2d}}}.$$

β' is the local discrepancy coefficient to balance off the local conflict with the distributed points for shor-range interactions, where $\gamma(\mathbf{x}) \propto -\ln f(\mathbf{x})$, $\alpha' = -1$.

To approximate the optimum, the procedure of a maximum overlapping coverage method is provided in Algorithm 1. where for each discretized subcover, we find the most use of the overlapping by $i \leftarrow \arg\max \frac{|\bigcup_{j=1}^{M}((S'\cap\mathfrak{C}(j))|}{|S'\cap\mathfrak{C}^*|}$, this will ensure that the current grid can be covered by as many cameras as possible. As the grid is sample-based, the cardinality of $\mathfrak{C}(i)$ has been large-scaled, then the time cost that can be measured by $\mathcal{O}(\sum_{i=1}^{M}|\mathfrak{C}(i)|)$ will be decreased greatly. The performance ratio H_k is the worst-case ratio of the size of the optimal configuration to the size of the approximate one with the largest overlap S.

Theorem 1 For $\max|\mathfrak{C}(i)| \leq k, i=1,2,...,M, M,k \in \mathbb{R}^+$ and for all sufficient large $n \gg k$,

$$\sum_{j=1}^{k}\left(\frac{1}{j}\right) \leq H_k \leq 1+\ln(k) \leq \sum_{j=1}^{k}\left(\frac{1}{j}\right)+\frac{1}{2}.$$

Algorithm 1: Set Covering for finding that subcover which has the maximum overlapping coverage

Input: Covered grid points g(x,y,z) by $\mathbb{P}'$, {g(x,y,z)} $\subset \mathfrak{G}, \mathbb{P}' \subset \mathbb{P}, \mathfrak{G}, \mathfrak{C} = \bigcup_{i=1}^{n}\mathfrak{C}(i)$.
Output: The position and orientation of the cameras: $\mathbb{P}'$.
$\mathbb{P}' \leftarrow \emptyset$;
$\mathfrak{C}^* \leftarrow \emptyset$;
while *{g(x,y,z)}C*&*$\mathfrak{G}$ **do**
  $\forall S' \in \mathfrak{C}, i \leftarrow \arg\max \frac{|\bigcup_{j=1}^{M}((S'\cap\mathfrak{C}(j))|}{|S'\cap\mathfrak{C}^*|}$;
  $\mathfrak{G} \leftarrow \mathfrak{G} \setminus \mathfrak{C}(i)$;
  $\mathfrak{C}^* \leftarrow \mathfrak{C}^* \cup \mathfrak{C}(i)$;
  $\mathbb{P}' \leftarrow \mathbb{P}' \cup \{P_{c_i}\}, P_{c_i} \in \mathbb{P}$;
end

Simulation and Results Analysis

- We use three types of cameras, Vantage 8, Vantage 5 and RTS 4000 in 15m*15m*3.7m. occupies a size of 50cm*50cm*32cm
- For the Riesz energy model, the parameters that we use are β' =4, m=40. The number of particles that are unique is 250 for each camera-based cluster, here we provide a 20-camera configuration, with 12 V8 cameras and 8 V5 cameras, $\alpha \in [-60°, 60°]$ and $\beta \in [25°, 35°]$.

Comparison of the Different Approaches

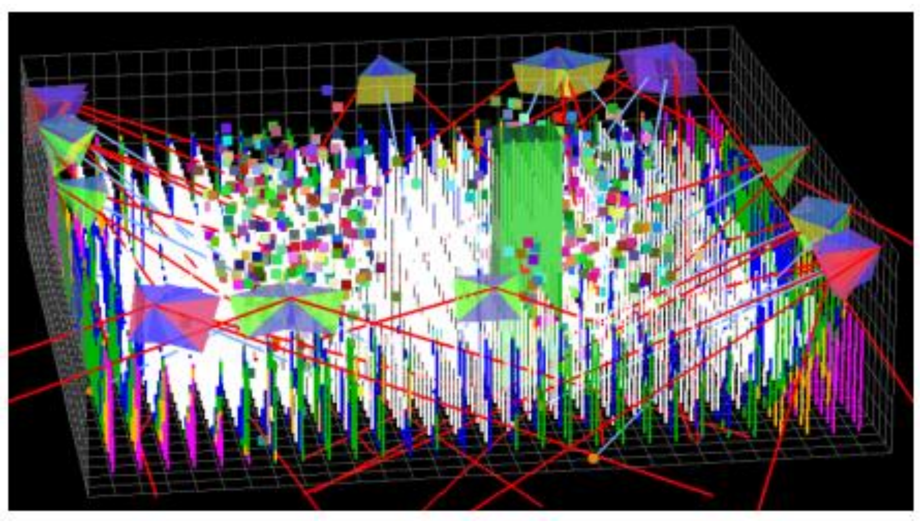


Figure 3: Camera Configuration with greedy algorithm[2]

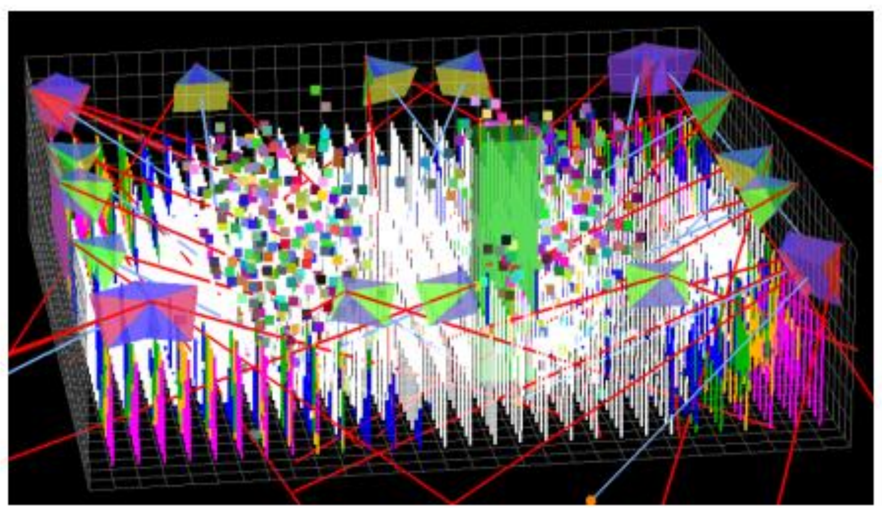


Figure 4: Camera Configuration with multiple objectives[6]

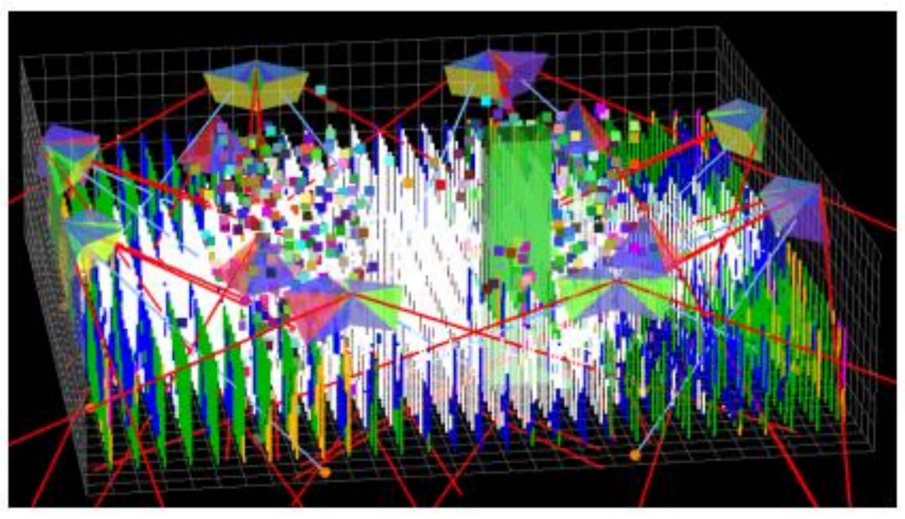


Figure 5: Camera configuration with our method

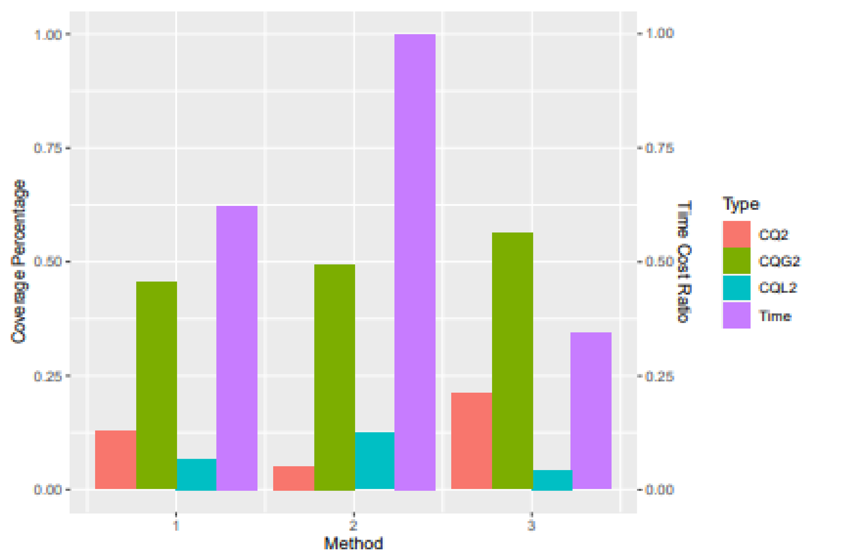


Figure 6: Static occlusion analysis for the greedy algorithm [2], multiple objectives method [6] and ours, respectively.

Approaches	Static Visibility	Dynamic Visibility	Total Penalty Score
Greedy algorithm [2]	88.44%	53.34%	173245495
Multiple objectives [6]	87.71%	73.71%	336689528
Ours	**95.67%**	**88.56%**	**36471524**

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[6] Chung-Hao Chen, Yi Yao, Wei-Wen Hsu, Andreas Koschan, and Mongi Abidi. Continuous camera placement using multiple objective optimisation process. IET Computer Vision, 9(3):340–353, 2015.