LOMORO: Long-term Monitoring of Dynamic Targets with Minimum Robotic Fleet under Resource Constraints

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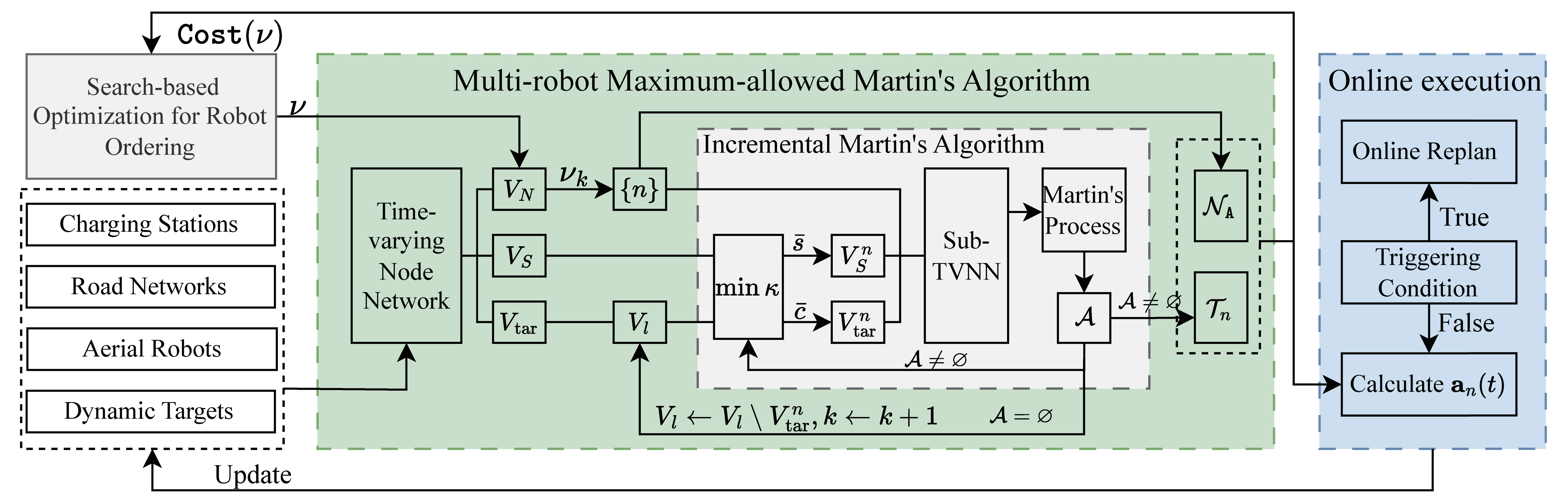
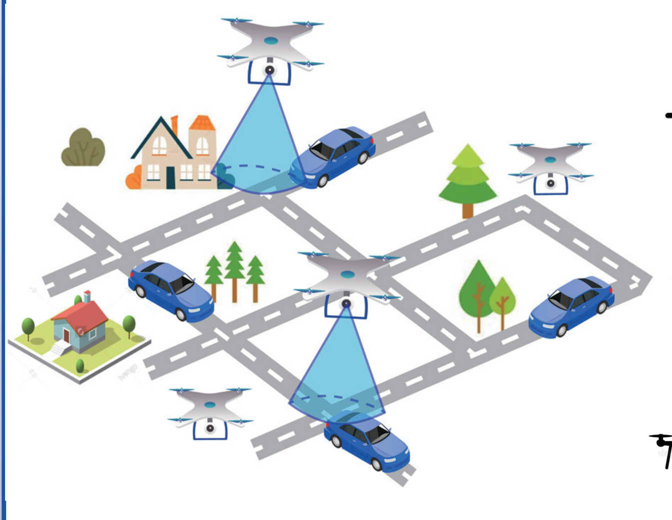
Overall Framework



Introduction



Long-term monitoring with ***limited resources***

Dynamic targets with undetermined trajectories

Minimum robotic fleet

Methods

Search-based Optimization for robot ordering

$$\texttt{Cost}(\nu) \triangleq \Big(|\mathcal{N}_{\mathbb{A}}(t)|, \max_{n\in\mathcal{N}_{\mathbb{A}}} T_{\boldsymbol{\tau}_n}, \sum_{n\in\mathcal{N}_{\mathbb{A}}} \Delta b_n\Big),$$

Time-Varying Node Network

$$\begin{aligned} &C^{(1)}(\bar{v},\bar{u}) = d(\mathbf{p}_{\bar{v}}(t),\mathbf{p}_{\bar{u}}(t))/v_n + T_0\cdot\mathbb{I}(\bar{v}\in V_{\text{tar}}),\\ &C^{(2)}(\bar{v},\bar{u}) = \gamma_n C^{(1)}(\bar{v},\bar{u}), \forall \bar{v}\in V\backslash V_S^{\text{dock}}, \bar{u}\in E_{\bar{v}},\\ &C^{(1)}(\bar{s}_0,\bar{s}_i) = -C^{(2)}(\bar{s}_0,\bar{s}_i)/\beta_s,\\ &C^{(2)}(\bar{s}_0,\bar{s}_i) = -b_n^{\max}\cdot i/N_s, \forall \bar{s}_0\in V_S^{\text{dock}}, \bar{s}_i\in E_{\bar{s}}, \end{aligned} \tag{7}$$

Algorithm 1: Multi-robot MAM

Input: $\mathcal{R},\mathcal{S},\mathcal{N},\mathcal{M}$, robot sequence ν
Output: $\mathcal{N}_{\mathbb{A}}(0)$ and $\mathcal{T}_n, \forall n\in\mathcal{N}_{\mathbb{A}}(0)$

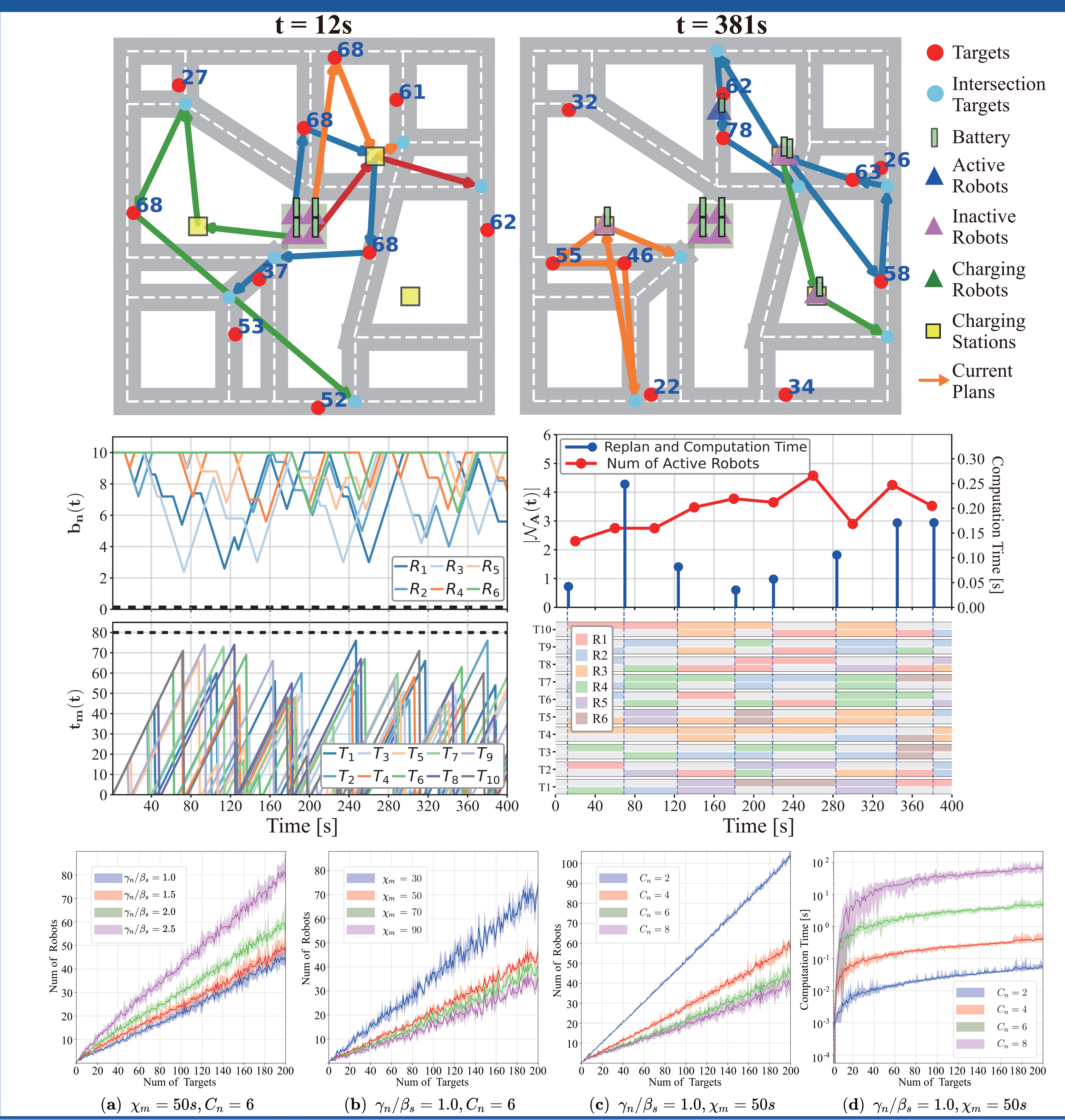
Construct $G=(V,E)$ using $\mathcal{R},\mathcal{S},\mathcal{N},\mathcal{M}$
Initialize $\mathcal{N}_{\mathbb{A}}(0)\leftarrow\varnothing$
Initialize targets-left set $V_l\leftarrow V_{\text{tar}}$
while V_l *is not empty* **do**
  Robot $n\leftarrow\alpha.\text{pop}()$
  $V_{\text{tar}}^n, \mathcal{T}_n \leftarrow$ Incremental-MA(V_l, n)
  if $\mathcal{T}_n\neq\varnothing$ **then**
    $V_l\leftarrow V_l\backslash V_{\text{tar}}^n$
    $\mathcal{N}_{\mathbb{A}}(0)\leftarrow\mathcal{N}_{\mathbb{A}}(0)\cup\{n\}$
Return $\mathcal{N}_{\mathbb{A}}(0), \mathcal{T}_n, \forall n\in\mathcal{N}_{\mathbb{A}}(0)$

Algorithm 2: Incremental Martin's Algorithm

Input: Target left set V_l, robot n
Output: $V_{\text{tar}}^n, \mathcal{T}_n$

Initialize $V_N^n\leftarrow\{\bar{n}\}, V_{\text{tar}}^n\leftarrow\varnothing, V_S^n\leftarrow\varnothing$
Initialize $L_{\bar{n},p}\leftarrow\{\}, L_{\bar{n},t}\leftarrow\{\}$
$l_0\leftarrow(\bar{n},\mathbf{R}_{l_0},\varnothing)$
$L_{\bar{n},t}\leftarrow L_{\bar{n},t}\cup\{l_0\}$
$\mathcal{T}_n\leftarrow\varnothing$
while V_l *is not empty* **do**
  $\bar{c}\leftarrow\arg\min_{\bar{v}\in V_l}\kappa(\bar{v},\bar{n})$
  $\bar{s}\leftarrow\arg\min_{\bar{s}\in V_S} d(\mathbf{z}_s,\mathbf{p}_{\bar{c}}(0))$
  $V_{\text{tar}}^n\leftarrow V_{\text{tar}}^n\cup\{\bar{c}\}, V_S^n\leftarrow V_S^n\cup\{\bar{s}\}$
  $L_{\bar{c},p}\leftarrow\{\}, L_{\bar{c},t}\leftarrow\{\}, L_{\bar{s},p}\leftarrow\{\}, L_{\bar{s},t}\leftarrow\{\}$
  Add a new dimension of 1 to $\hat{\mathbf{R}}_{l_{\bar{v}}}, \forall l_{\bar{v}}\in L_p^n\cup L_t^n$
  Propagate all nodes in L_p^n to $\bar{c}$ and $\bar{s}$
  $\mathcal{A}\leftarrow\text{MP}(G^n,L_p^n,L_t^n)$
  if $\mathcal{A}=\varnothing$ **then**
    $V_{\text{tar}}^n\leftarrow V_{\text{tar}}^n\backslash\{\bar{c}\}, V_S^n\leftarrow V_S^n\backslash\{\bar{s}\}$
    Break
  $\mathcal{T}_n\leftarrow\mathcal{A}$
Return $V_{\text{tar}}^n, \mathcal{T}_n$

Results



(a) $\chi_m = 50s, C_n = 6$ (b) $\gamma_n/\beta_s = 1.0, C_n = 6$ (c) $\gamma_n/\beta_s = 1.0, \chi_m = 50s$ (d) $\gamma_n/\beta_s = 1.0, \chi_m = 50s$

Conclusion

This work addresses the ***long-term monitoring*** of ***dynamic targets*** in a road network using a fleet of aerial robots with ***limited resources***. We propose a hierarchical approach that incrementally assigns targets, optimizes monitoring sequences and charging strategies, and adapts online to real time constraints. Our method ensures strict adherence to resource and monitoring constraints while ***minimizing the active fleet size***. Extensive simulations demonstrate its scal ability and effectiveness in deploying a small UAV fleet for large-scale target monitoring.