

Visual Feedback Attitude Synchronization: Tracking Performance Analysis



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Introduction

Mobile Sensor Network

A network consisting of multiple mobile sensors or robots with sensing devices

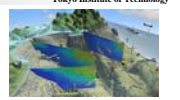
Network: Performance or **Robustness** against failures
Mobile: Dynamical environments

Applications

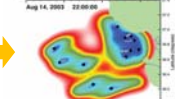
- Environmental Monitoring
- Search
- Exploration and Mapping
- Management System of Infrastructure



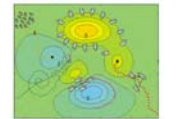
Oceanic Pollution



Environmental Monitoring



Ocean Sampling



Cooperative Control

Operation of Mobile Sensor Network

Each sensor is required to act **cooperatively** using only **limited** information.

➔ **Cooperative Control**



Introduction

Cooperative Control of Robotic Network

A distributed control strategy using only local information so that the robotic network achieves specified tasks

Cooperative Control Problems for Mobile Sensor Network

↓ formulated as

Pose Coordination Problems

Attitude Synchronization

To lead all agents' attitudes to a common one by utilizing distributed control strategies

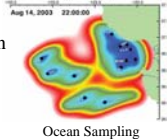
Available Information

Only Visual Information: each agent has **vision**

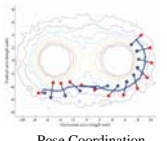
Objective of Our Work

To **present** vision-based attitude synchronization control laws for robotic networks in 3-dimensional space, **prove** the convergence mathematically and **analyze** the performance.

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Ocean Sampling



Pose Coordination



Outline

- Introduction
- **Visual Robotic Network**
 - Rigid Body Motion
 - Visibility Structure
 - Measured Output
- Visual Feedback Attitude Synchronization
- Tracking Performance
- Simulation
- Conclusion and Future Works



Visual Robotic Network: Rigid Body Motion

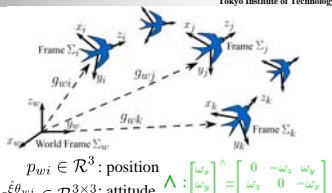
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Kinematics of Rigid Bodies

Pose $(p_{wi}, e^{\xi_{wi}}) \in SE(3)$

$$g_{wi} = \begin{bmatrix} e^{\xi_{wi}} & p_{wi} \\ 0 & 1 \end{bmatrix} \in \mathcal{R}^{4 \times 4}$$

Exponential Coordinate for Rotation
 $\xi_{wi} \in \mathcal{R}^3$: rotation axis
 $\theta_{wi} \in \mathcal{R}$: rotation angle



$p_{wi} \in \mathcal{R}^3$: position
 $e^{\xi_{wi}} \in \mathcal{R}^{3 \times 3}$: attitude $\wedge: \begin{bmatrix} \omega_x \\ \omega_y \\ \omega_z \end{bmatrix} \wedge = \begin{bmatrix} 0 & -\omega_z & \omega_y \\ \omega_z & 0 & -\omega_x \\ -\omega_y & \omega_x & 0 \end{bmatrix}$

Body Velocity **Common** $(v_{wi}^b = v_{wj}^b \forall i, j)$

$$V_{wi}^b = \begin{bmatrix} v_{wi}^b \\ \omega_{wi}^b \end{bmatrix} \in \mathcal{R}^6 \quad \dot{V}_{wi}^b = \begin{bmatrix} \dot{v}_{wi}^b \\ \dot{\omega}_{wi}^b \end{bmatrix} \in \mathcal{R}^{4 \times 4} \quad v_{wi}^b \in \mathcal{R}^3: \text{linear velocity} \\ \omega_{wi}^b \in \mathcal{R}^3: \text{angular velocity}$$

Control Input

$(:= g_{wi}^{-1} \dot{g}_{wi})$

Rigid Body Motion

$$\dot{g}_{wi} = g_{wi} \dot{V}_{wi}^b \quad (1) \quad \left(\begin{array}{l} \text{Relative Rigid Body Motion} \\ V_{ij}^b := (g_{ij}^{-1} \dot{g}_{ij})^b = -\text{Ad}_{(g_{ij}^{-1})} V_{wi}^b + V_{wj}^b \\ \text{coordi. trans. from } \Sigma_{wi} \text{ to } \Sigma_{wj} \\ (2) \end{array} \right) \text{Ad}_{(g_{ij}^{-1})} \in \mathcal{R}^{6 \times 6}$$

$g_{ij} := g_{wi}^{-1} g_{wj} = (p_{ij}, e^{\xi_{ij}})$: pose of rigid body j relative to body i



Visual Robotic Network: Visibility Structure and Measured Output

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Visibility Structure among Rigid Bodies

Rigid Body Set **Visibility Set**

$$\mathcal{V} := \{1, \dots, n\} \quad \mathcal{E} \subset \mathcal{V} \times \mathcal{V} \quad ((j, i) \in \mathcal{E}: \text{body } j \text{ is visible from body } i)$$

Visible Bodies

$$\mathcal{N}_i := \{j \in \mathcal{V} \mid (j, i) \in \mathcal{E}\} \quad (3)$$

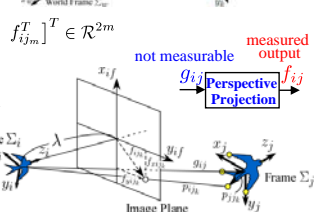
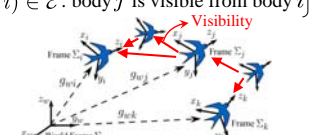
Measured Output

$$f_i = (f_{ij})_{j \in \mathcal{N}_i} \quad (4) \quad f_{ij} := [f_{ij1}^T \dots f_{ijm}^T]^T \in \mathcal{R}^{2m}$$

Vision Model (Perspective Projection)

$$f_{ijk} = \frac{\lambda_i}{z_{ijk}} \begin{bmatrix} x_{ijk} \\ y_{ijk} \end{bmatrix} \in \mathcal{R}^2 \quad \lambda_i \in \mathcal{R}: \text{focal length} \\ k \in \{1, \dots, m\}$$

$$p_{ijk} = \begin{bmatrix} x_{ijk} \\ y_{ijk} \\ z_{ijk} \end{bmatrix}: \text{position of } k \text{th feature point of body } j \text{ relative to body } i$$





Visual Robotic Network

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Visual Robotic Network Σ

n Rigid Bodies

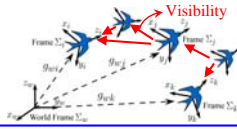
$$\dot{g}_{wi} = g_{wi} \hat{V}_{wi}^b, i \in \mathcal{V} \quad (1)$$

Measured Output

$$f_i = (f_{ij})_{j \in \mathcal{N}_i}, i \in \mathcal{V} \quad (4)$$

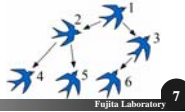
Visibility Structure

$$\mathcal{N}_i := \{j \in \mathcal{V} \mid (j, i) \in \mathcal{E}\}, i \in \mathcal{V} \quad (3)$$



Assumption 1 (Leader-following Type Visibility Structure)

- there exists a leader which has no visible body ($\mathcal{N}_1 = \emptyset$) $\Rightarrow G := (\mathcal{V}, \mathcal{E})$: Graph
- the other bodies have a fixed visible body ($|\mathcal{N}_i| = 1$, and \mathcal{N}_i is fixed $\forall i \in \mathcal{V} \setminus \{1\}$) \bullet Graph: Directed Spanning Tree
- there exists a visibility path from each body to the leader ($\forall i \in \mathcal{V} \setminus \{1\}$, $\exists v_1, \dots, v_r \in \mathcal{V}$ s.t. $v_1 = 1, v_r = i$ (v_k, v_{k+1}) $\in \mathcal{E} \forall k \in \{1, \dots, r-1\}$)



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7



Outline

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- Introduction
- Visual Robotic Network
- Visual Feedback Attitude Synchronization
 - Definition of Visual Feedback Attitude Synchronization
 - Visual Feedback Attitude Synchronization Law
 - Convergence Analysis
- Tracking Performance
- Simulation
- Conclusion and Future Works

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8



Visual Feedback Attitude Synchronization

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Definition: Visual Feedback Attitude Synchronization

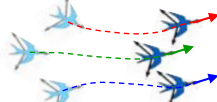
A visual robotic network Σ is said to achieve visual feedback attitude synchronization, if

$$\begin{cases} v_{wi}^b = v_{wj}^b \\ \lim_{t \rightarrow \infty} \phi(e^{-\xi \theta_{wi}} e^{\xi \theta_{wj}}) = 0, \forall i, j \in \mathcal{V} \end{cases} \quad (5)$$

Energy Function of Rotation

$$\phi(e^{\xi \theta_{wi}}) := \frac{1}{2} \text{tr}(I_3 - e^{\xi \theta_{wi}}) \geq 0 \quad (\phi(e^{\xi \theta_{wi}}) = 0 \Leftrightarrow e^{\xi \theta_{wi}} = I_3)$$

- Attitude Synchronization
- All rigid bodies' linear velocity is the same
 - All attitudes asymptotically converge to a common value



[7] Y. Igarashi, T. Hatanaka, M. Fujita and M. W. Spong, "Passivity-based Attitude Synchronization in SE(3)," *IEEE Trans. on Control System Technology*, Vol. 17, No. 5, pp. 1119-1134, 2009.

9



Visual Feedback Attitude Synchronization Law

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Visual Feedback Attitude Synchronization Law

$$k_{ij}, k_{eij} > 0 \in \mathcal{R}$$

$$\begin{cases} v_{wi}^b = v \\ \omega_{wi}^b = k_{ij} \text{sk}(e^{\xi \tilde{\theta}_{ij}})^{\vee} \\ \tilde{V}_{ij}^b := (\tilde{g}_{ij}^{-1} \tilde{g}_{ij})^{\vee} = -\text{Ad}_{(\tilde{g}_{ij}^{-1})} V_{wi}^b + u_{ij} \\ u_{ij} = k_{eij} \begin{bmatrix} p_{eij} + \frac{1}{k_{eij}} e^{\xi \theta_{eij}} v_{wi}^b \\ \text{sk}(e^{\xi \theta_{eij}})^{\vee} - \text{sk}(e^{\xi \tilde{\theta}_{ij}})^{\vee} \end{bmatrix} \end{cases} \quad (7)$$

$v \in \mathcal{R}^3$: common body linear velocity

\mathcal{N}_i : visible bodies

Visual Observer to estimate relative pose of neighbors [10]

$$j \in \mathcal{N}_i, i \in \mathcal{V}$$

Estimated Pose

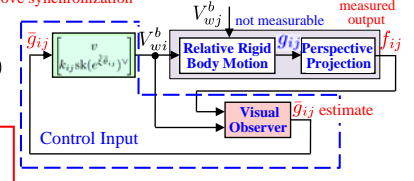
$$\tilde{g}_{ij} = (\tilde{p}_{ij}, e^{\xi \tilde{\theta}_{ij}})$$

Estimation Error

$$g_{eij} = \tilde{g}_{ij}^{-1} g_{ij} = (p_{eij}, e^{\xi \theta_{eij}})$$

$$g_{eij} = I_4 \Rightarrow \tilde{g}_{ij} = g_{ij}$$

cancel term of velocity input to prove synchronization



Input (7): calculated only by measured output f_{ij}

[10] M. Fujita, H. Kawai and M. W. Spong, *IEEE Trans. on Control System Technology*, Vol. 15, No. 1, pp. 40-52, 2007.

10



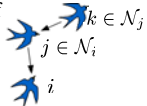
Visual Feedback Attitude Synchronization

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Theorem 1: Visual Feedback Attitude Synchronization

Suppose the leader does not rotate ($\omega_{w1}^b = 0$). Then, a visual robotic network Σ with control law (7) and Assumption 1 achieves visual feedback attitude synchronization if

$$\begin{cases} k_{jk} < \frac{2k_{ij}k_{eij}}{k_{ij} + k_{eij}}, k \in \mathcal{N}_j, j \in \mathcal{N}_i, i \in \mathcal{V}_q \\ k_{jk} < \frac{2k_{ij}k_{eij}}{k_{ij} + 2k_{eij}}, k \in \mathcal{N}_j, j \in \mathcal{N}_i, i \in \mathcal{V}_r \end{cases} \quad (10)$$



$$\mathcal{V}_q := \{i \in \mathcal{V} \mid i \notin \mathcal{N}_j \forall j \in \mathcal{V}\}, \mathcal{V}_r := \{i \in \mathcal{V} \setminus \{1\} \mid \exists j \in \mathcal{V}, i \in \mathcal{N}_j\}$$

Gain condition (10) implies that if the backward rigid bodies move fast, then visual feedback attitude synchronization is achieved.

Sketch of Proof

Lyapunov Function Candidate: $q_i = \{1, 2, \dots\}$

$$U := \sum_{i=2}^n \sum_{j \in \mathcal{N}_i} q_i \left(\phi(e^{\xi \tilde{\theta}_{ij}}) + \frac{1}{2} \|p_{eij}\|_2^2 + \phi(e^{\xi \theta_{eij}}) \right) \geq 0 \Rightarrow \text{Lyapunov Argument (Asymptotic Stability)}$$

Control Estimation

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11



Outline

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- Introduction
- Visual Robotic Network
- Visual Feedback Attitude Synchronization
 - Tracking Performance
 - Tracking Performance based on Input-to-state Stability
 - Tracking Performance based on \mathcal{L}_2 -gain Performance
 - Simulation
- Conclusion and Future Works

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12



Tracking Performance Analysis

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Theorem 1: $\omega_{w1}^b = 0$

➔ For a rotating leader ($\omega_{w1}^b \neq 0$), is there sufficient tracking performance?

Evaluate attitude errors regarding the leader's angular velocity as an external disturbance

x_e : All rigid bodies' control and estimation errors

Qualitative Evaluation: Input-to-state Stability

For any bounded input, the state will be bounded

$$\|x_e(t)\|_2 \leq \beta(\|x_0\|_2, t) + \alpha(\|\omega_{w1}^b\|_{\mathcal{L}_\infty}), \forall t \geq 0 \quad \alpha(\cdot) \in \mathcal{K}, \beta(\cdot, \cdot) \in \mathcal{KL}$$

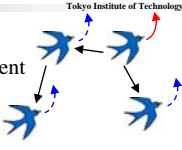
Quantitative Evaluation: \mathcal{L}_2 -gain Performance Analysis

For any energy bounded input, the output will be bounded

$$\|x_e\|_{\mathcal{L}_2} \leq \gamma \|\omega_{w1}^b\|_{\mathcal{L}_2} + \delta \quad \gamma, \delta \geq 0$$

H. K. Khalil, *Nonlinear Systems*, Third Edition, Prentice Hall, 2002.

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Tracking Performance Analysis based on ISS

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Theorem 2: Tracking Performance based on ISS

Suppose the leader rotates ($\omega_{w1}^b \neq 0$) and Assumption 1 is satisfied.

If $|\bar{\theta}_{ij}(0)| < \frac{\pi}{2}$, $|\theta_{eij}(0)| < \frac{\pi}{2}$, $j \in \mathcal{N}_i$, $i \in \mathcal{V}$ and for any positive scalars ϵ_i , ϵ'_i ($\epsilon'_i > \epsilon_i$), inequality (12) is satisfied, then there exists class- \mathcal{K} function $\beta(\cdot, \cdot)$ and class- \mathcal{K} function $\alpha(\cdot)$ satisfying inequality (13).

$$\begin{cases} k_{eij} > \epsilon_i \\ \frac{k_{eij}(k_{ij} - \epsilon_i)}{k_{ij} + k_{eij} - \epsilon_i} > \epsilon'_i, \quad j \in \mathcal{N}_i, \quad i \in \mathcal{V}, \end{cases} \quad (12)$$

$$\|x_e(t)\|_2 \leq \beta(\|x_e(0), t\|_2) + \alpha(\|\omega_{w1}^b\|_{\mathcal{L}_\infty}). \quad (13)$$

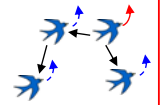
Control Error Vector: $e_{cij} = \text{sk}(e^{\hat{\xi}\bar{\theta}_{ij}})^\vee$

Estimation Error Vector: $e_{ij} = \begin{bmatrix} p_{eij} \\ \text{sk}(e^{\hat{\xi}\theta_{eij}})^\vee \end{bmatrix}$ Error Vector: $e_{ceij} = \begin{bmatrix} e_{cij} \\ e_{ij} \end{bmatrix}$

x_e : Stack Vector of e_{ceij} , $j \in \mathcal{N}_i$, $i \in \mathcal{V}$

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Tracking Performance Analysis based on ISS

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Proof

Step 1: 2 rigid bodies

Energy Function: $U_2 := \phi(e^{\hat{\xi}\bar{\theta}_{21}}) + \frac{1}{2}\|p_{e21}\|_2^2 + \phi(e^{\hat{\xi}\theta_{e21}})$

Time Derivative of U_2

$$\dot{U}_2 = -e_{ce21}^T Q_{21} e_{ce21} + e_{e21}^T \omega_{w1}^b \quad Q_{21} := \begin{bmatrix} (k_{21} + k_{e21})I_3 & -k_{e21}\bar{I} \\ -k_{e21}\bar{I}^T & k_{e21}I_6 \end{bmatrix} \in \mathcal{R}^{9 \times 9}$$

Here,

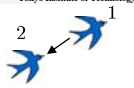
$$\dot{e}_{e21}^T \omega_{w1}^b = -\frac{\gamma_2}{2} \left\| \omega_{w1}^b - \frac{1}{\gamma_2} e_{e21} \right\|_2^2 + \frac{\gamma_2}{2} \|\omega_{w1}^b\|_2^2 + \frac{1}{2\gamma_2} \|e_{e21}\|_2^2 \leq 0$$

Thus, for any positive scalar ϵ ,

$$\begin{aligned} \dot{U}_2 &\leq -e_{ce21}^T Q_{21} e_{ce21} + \frac{\gamma_2}{2} \|\omega_{w1}^b\|_2^2 + e_{e21}^T W_2 e_{ce21} + \epsilon \|e_{ce21}\|_2^2 - \epsilon \|e_{ce21}\|_2^2 \\ &= -e_{ce21}^T P_2 e_{ce21} + \frac{\gamma_2}{2} \|\omega_{w1}^b\|_2^2 - \epsilon \|e_{ce21}\|_2^2 \\ &\quad (P_2 := Q_{21} - W_2 - \epsilon I_9) \end{aligned}$$

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Tracking Performance Analysis based on ISS

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$$\begin{aligned} \dot{U}_2 &\leq -e_{ce21}^T P_2 e_{ce21} + \frac{\gamma_2}{2} \|\omega_{w1}^b\|_2^2 - \epsilon \|e_{ce21}\|_2^2 \\ &\leq 0 \quad \left[\text{Gain Condition (12): } \epsilon' = \frac{1}{2\gamma_2} + \epsilon \right] \\ &\leq \frac{\gamma_2}{2} \|\omega_{w1}^b\|_2^2 - \epsilon \|e_{ce21}\|_2^2 \end{aligned}$$

Integrating from 0 to T yields

$$\frac{U_2(T) - U_2(0)}{\geq 0} \leq \frac{\gamma_2}{2} \int_0^T \|\omega_{w1}^b\|_2^2 dt - \epsilon \int_0^T \|e_{ce21}\|_2^2 dt$$

Thus,

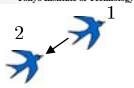
$$\int_0^T \|e_{ce21}(t)\|_2^2 dt \leq \frac{1}{\epsilon} U_2(0) + \frac{\gamma_2}{2\epsilon} \int_0^T \|\omega_{w1}^b(t)\|_2^2 dt$$

Here, if $|\bar{\theta}_{21}(0)| < \frac{\pi}{2}$, $|\theta_{e21}(0)| < \frac{\pi}{2}$, $j \in \mathcal{N}_i$, $i \in \mathcal{V}$

$$U_2(0) \leq \|e_{ce21}(0)\|_2^2 \quad (\text{Refer to the resume})$$

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Tracking Performance Analysis based on ISS

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Thus,

$$\int_0^T \|e_{ce21}(t)\|_2^2 dt \leq \frac{1}{\epsilon} \|e_{ce21}(0)\|_2^2 + \frac{\gamma_2}{2\epsilon} \int_0^T \|\omega_{w1}^b(t)\|_2^2 dt$$

From [16, pp. 95, Theorem 1], we get the following from ISS definition

$$\|e_{ce21}(t)\|_2 \leq \beta_2(\|e_{ce21}(0), t\|_2) + \alpha_2(\|\omega_{w1}^b\|_{\mathcal{L}_\infty}) \quad \alpha_2(\cdot) \in \mathcal{K}, \beta_2(\cdot, \cdot) \in \mathcal{KL}$$

Step 2: Chain Type Visibility Structure (m Rigid Bodies)

Using the ISS property:

Cascade connection of ISS systems is also ISS

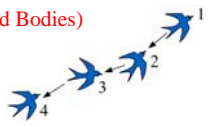
We get the following from ISS definition

$$\|x_{em}(t)\|_2 \leq \beta_m(\|x_{em}(0), t\|_2) + \alpha_m(\|\omega_{w1}^b\|_{\mathcal{L}_\infty}) \quad \alpha_m(\cdot) \in \mathcal{K}, \beta_m(\cdot, \cdot) \in \mathcal{KL}$$



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Tracking Performance Analysis based on ISS

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Step 3: Multiple Chain Type Visibility Structures (Assumption 1)

For each Σ_{colci} , $i \in \mathcal{V}_q$, we get the following

$$\|x_{ei}(t)\|_2 \leq \beta_i(\|x_{ei}(0), t\|_2) + \alpha_i(\|\omega_{w1}^b\|_{\mathcal{L}_\infty}), \quad i \in \mathcal{V}_q$$

$$\alpha_i(\cdot) \in \mathcal{K}, \beta_i(\cdot, \cdot) \in \mathcal{KL}$$

For $\|\cdot\|_2$, $\beta_i(\cdot, \cdot)$, the followings is satisfied

$$\|x_{ei}\|_2 \leq \|x_{ei}\|_2 + \|x_{ej}\|_2$$

$$\beta_i(\|x_{ei}\|_2, \cdot) + \beta_j(\|x_{ej}\|_2, \cdot) \leq \beta_i \left(\begin{bmatrix} x_{ei} \\ x_{ej} \end{bmatrix}, \cdot \right) + \beta_j \left(\begin{bmatrix} x_{ei} \\ x_{ej} \end{bmatrix}, \cdot \right)$$

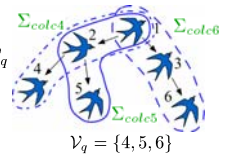
Thus, summation of the above inequality for $i \in \mathcal{V}_q$ yields

$$\|x_e(t)\|_2 \leq \sum_{i \in \mathcal{V}_q} \beta_i(\|x_e(0), t\|_2) + \sum_{i \in \mathcal{V}_q} \alpha_i(\|\omega_{w1}^b\|_{\mathcal{L}_\infty})$$

$$\beta := \sum_{i \in \mathcal{V}_q} \beta_i, \quad \alpha := \sum_{i \in \mathcal{V}_q} \alpha_i \quad \Rightarrow \text{Inequality (13)}$$

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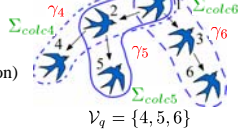
Tracking Performance Analysis based on \mathcal{L}_2 -gain Performance

Assumption 1 \Rightarrow Multiple Chain Type Visibility Structures

For each Σ_{colci} , $i \in \mathcal{V}_q$

Real Symmetric Matrix: $P_i \in \mathcal{R}^{9(n_i-1) \times 9(n_i-1)}$
(refer to the resume for the definition)
 n_i : number of bodies of Σ_{colci}

Identifier: $\{1, 2, \dots, n_i\}$

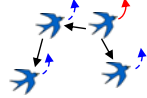


Theorem 3: Tracking Performance based on \mathcal{L}_2 -gain Performance

Suppose the leader rotates ($\omega_{w1}^b \neq 0$) and Assumption 1 is satisfied.

Then, for any $k_{l(l-1)}, k_{el(l-1)}$, $l \in \{2, \dots, n_i\}$ and positive scalar γ_i , $i \in \mathcal{V}_q$ satisfying LMI $P_i > 0$, $i \in \mathcal{V}_q$, there exists a nonnegative scalar δ satisfying the following inequality.

$$\|x_e\|_{\mathcal{L}_2} \leq \gamma \|\omega_{w1}^b\|_{\mathcal{L}_2} + \delta, \quad \gamma := \sqrt{\sum_{i \in \mathcal{V}_q} \gamma_i}. \quad (14)$$



γ evaluate cont. and est. errors \Rightarrow Barometer of Tracking Performance

Proof of Theorem 3

Proof

For each Σ_{colci} , $i \in \mathcal{V}_q$

Energy Function: $U_i := \sum_{i=2}^{n_i} \left(\phi(e^{\hat{\delta}_i(i-1)}) + \frac{1}{2} \|p_{ei(i-1)}\|_2^2 + \phi(e^{\hat{\delta}_i(i-1)}) \right)$

Time Derivative of U_i

$$\begin{aligned} \dot{U}_i &= -x_{ei}^T P_i x_{ei} + \frac{\gamma_i}{2} \|\omega_{w1}^b\|_2^2 - \frac{1}{2} \|x_{ei}\|_2^2 - \frac{\gamma_i}{2} \left\| \omega_{w1}^b - \frac{1}{\gamma_i} x_{ei} \right\|_2^2 \\ &\leq 0 \\ &\leq \frac{\gamma_i}{2} \|\omega_{w1}^b\|_2^2 - \frac{1}{2} \|x_{ei}\|_2^2 \leq 0 \end{aligned}$$

Integrating from 0 to T yields

$$\underbrace{U_i(T) - U_i(0)}_{\geq 0} \leq \frac{\gamma_i}{2} \int_0^T \|\omega_{w1}^b\|_2^2 dt - \frac{1}{2} \int_0^T \|x_{ei}\|_2^2 dt$$



Proof of Theorem 3

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$$\underbrace{U_i(T) - U_i(0)}_{\geq 0} \leq \frac{\gamma_i}{2} \int_0^T \|\omega_{w1}^b\|_2^2 dt - \frac{1}{2} \int_0^T \|x_{ei}\|_2^2 dt$$

Summation of the above inequality for $i \in \mathcal{V}_q$ yields

$$-\sum_{i \in \mathcal{V}_q} U_i(0) \leq \sum_{i \in \mathcal{V}_q} \frac{\gamma_i}{2} \int_0^T \|\omega_{w1}^b(t)\|_2^2 dt - \frac{1}{2} \int_0^T \|x_e(t)\|_2^2 dt$$

$(\|a\|_2^2 + \|b\|_2^2 = \|a+b\|_2^2)$
Conservative

Extract the square root

$$\sqrt{\int_0^T \|x_e(t)\|_2^2 dt} \leq \sqrt{\sum_{i \in \mathcal{V}_q} \gamma_i \int_0^T \|\omega_{w1}^b(t)\|_2^2 dt} + \sqrt{2 \sum_{i \in \mathcal{V}_q} U_i(0)}$$

Thus, we get the following inequality

$$\|x_e\|_{\mathcal{L}_2} \leq \sqrt{\sum_{i \in \mathcal{V}_q} \gamma_i} \|\omega_{w1}^b\|_{\mathcal{L}_2} + \sqrt{2 \sum_{i \in \mathcal{V}_q} U_i(0)} \quad (\sqrt{a^2 + b^2} \leq a + b)$$

$$\gamma := \sqrt{\sum_{i \in \mathcal{V}_q} \gamma_i}, \quad \delta := \sqrt{2 \sum_{i \in \mathcal{V}_q} U_i(0)} \quad \Rightarrow \text{Inequality (14)}$$

□

Analysis of Gain Condition

3 Rigid Bodies $P_3 > 0$



$$P_3 = \begin{bmatrix} (k_{21} + k_{e21} - \frac{1}{2}) I_3 & 0 & Q_3 \{ S_3 - k_{e21} I_3 \} & 0 & 0 & -\frac{1}{2} k_{21} I_3 \\ 0 & (k_{21} - \frac{1}{2}) I_3 & 0 & 0 & 0 & 0 \\ -k_{e21} I_3 & 0 & (k_{e21} - \frac{1}{2} - \frac{1}{2\gamma^2}) I_3 & 0 & 0 & 0 \\ 0 & 0 & 0 & (k_{32} + k_{e32} - \frac{1}{2}) I_3 & 0 & -k_{e32} I_3 \\ 0 & 0 & 0 & 0 & (k_{32} - \frac{1}{2}) I_3 & 0 \\ -\frac{1}{2} k_{21} I_3 & 0 & S_3^T \{ R_3 \} & -k_{e32} I_3 & 0 & (k_{e32} - \frac{1}{2}) I_3 \end{bmatrix}$$

Affine on $k_{i(i-1)}, k_{ei(i-1)}$

Schur Complements

$x \in \mathcal{R}^m$, $Q(x) = Q(x)^T$, $R(x) = R(x)^T$ and $S(x)$ depend affinely on x .

$$\begin{bmatrix} Q(x) & S(x) \\ S(x)^T & R(x) \end{bmatrix} > 0 \Leftrightarrow \begin{cases} R(x) > 0 \\ Q(x) - S(x)R(x)^{-1}S(x)^T > 0 \\ \begin{cases} Q(x) > 0 \\ R(x) - S(x)Q(x)^{-1}S(x)^T > 0 \end{cases} \quad (*) \end{cases}$$

$$P_3 := \begin{bmatrix} Q_3(K_3) & S_3(K_3) \\ S_3(K_3)^T & R_3(K_3) \end{bmatrix}, \quad K_3 := [k_{21} \ k_{e21} \ k_{32} \ k_{e32}]^T \quad \Rightarrow (*)$$

S. Boyd, L. E. Ghaoui, E. Feron and V. Balakrishnan, *Linear Matrix Inequalities in System and Control Theory*, SIAM Studies in Applied Mathematics, Vol. 15, 1994

Analysis of Gain Condition

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$$P_3 > 0 \Leftrightarrow \begin{cases} k_{e21} > \frac{1}{2} \\ \gamma^2 \frac{2 \cdot 4k_{21}k_{e21} - 2k_{21} - 4k_{e21} + 1}{2k_{21} + 2k_{e21} - 1} > 1 \\ k_{e32} > \frac{1}{2} \\ k_{e32} - \frac{1}{2} - \frac{k_{21}^2}{4k_{21} + 4k_{e21} - 2} - \frac{2k_{32}^2}{2k_{32} + 2k_{e32} - 1} - \frac{2\gamma^2 k_{21}^2 k_{32}^2}{(2k_{21} + 2k_{e21} - 1)(\gamma^2(4k_{21}k_{e21} - 2k_{21} - 4k_{e21} + 1) - (2k_{21} + 2k_{e21} - 1))} > 0 \end{cases}$$

too complex

LMI Solutions

Minimize γ Condition: $k_{i(i-1)}, k_{ei(i-1)} < 10$

$$\begin{aligned} k_{21} &= 8.72, \quad k_{32} = 9.98 \\ k_{e21} &= 9.97, \quad k_{e32} = 9.98 \end{aligned} \quad \Rightarrow \|x_3\|_{\mathcal{L}_2} \leq 0.47 \|\omega_{w1}^b\|_{\mathcal{L}_2} + \sqrt{2U_3(0)} \quad (\gamma = 0.47)$$

Linear Matrix Inequality

$$P_i > 0$$

Gain condition or solvability has not found yet.

Outline

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- Introduction
- Visual Robotic Network
- Visual Feedback Attitude Synchronization
- Tracking Performance
- Simulation
- Conclusion and Future Works

