Eléments de robustesse aux défauts de capteurs pour les véhicules (aériens) autonomes

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ONERA
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retour sur innovation

Laboratoire COPERNIC (ONERA Palaiseau)

Commande et Perception pour la Navigation autonome et la Coopération

- Une équipe pluridisciplinaire intégrée
  - 5 ingénieurs en traitement d'image et modélisation
  - 4 ingénieurs en commande et estimation
- Thèmes de recherche
  - Estimation d'état basée vision
  - Modélisation d'environnement pour la navigation autonome
  - Synthèse de lois de guidage et de navigation
  - Asservissement visuel
  - Guidage coopératif
  - Détection et localisation de défauts, reconfiguration
  - Adéquation algorithmes / architectures de calcul
- Cadre applicatif
  - Environnement encombré sans infrastructure d'aide à la localisation (GPS, Wifi, Marqueurs, . . .)

Moyens d'essai et de validation

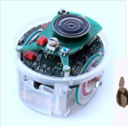
- Une volière avec motion capture
- Des plateformes robotiques (robots mobiles et drones) équipées de capteurs (dont caméras) et calculateurs embarqués

Asctec Pelican (x2)

Robotnik Summit XL (x1)

Kobuki TurtleBot 2 (x1)

EPFL ePuck (x6)



Asctec Firefly (x1)

Parrot ArDrone (x8)

Travaux présentés

- Localisation de source par une flotte de véhicules
  - Recherche en formation du maximum d'un champ
  - Détection de défauts de capteurs au sein de la flotte
  - Reconfiguration de la formation
- Navigation autonome en milieu intérieur encombré
  - Boucle intégrée localisation basée vision + guidage
  - Fusion multi-capteurs et détection de défauts
  - Résultats expérimentaux

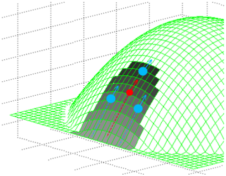
Section 1

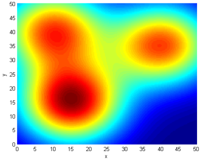
Détection de défauts de capteurs dans une flotte de véhicules

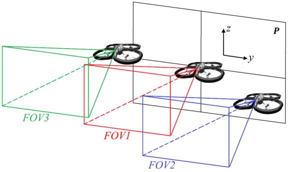
Context

Source location and surveillance missions

- Forest fire source location
- Chemical or gas leaks
- Surveillance of large areas or search and rescue







Interest for multi-vehicle systems (MVS)

- Mission repartition
- Robustness to faults or agent loss

Field maximization with a MVS

Goal

→ Find the global maximum of an initially unknown spatial field

Means

→ Multi-vehicle system (MVS)
→ Each vehicle measures the field value at its position

Constraints

→ Accurately locate field maximum
→ Take into account vehicle dynamics
→ Avoid collisions between vehicles
→ Limit the number of measurements

Arthur Kahn, Reconfigurable cooperative control for extremum seeking, PhD Thesis, Université Paris-Saclay, 2015

Assumptions

Consider some unknown, continuous, and time-invariant scalar field

$$\phi : \mathbf{x} \in \mathscr{D} \subset \mathbb{R}^2 \to \phi(\mathbf{x}) \in \mathbb{R}$$

to be maximized using N identical mobile agents with dynamics

$$M\ddot{\mathbf{x}}_i + C(\mathbf{x}_i, \dot{\mathbf{x}}_i)\dot{\mathbf{x}}_i = \mathbf{u}_i,$$

and measurement equation at $\mathbf{x}_i$

$$y(\mathbf{x}_i) = \phi(\mathbf{x}_i) + n_i(\eta_i),$$

n_i measurement noise and η_i the i-th sensor state

- $\eta_i = 0$ nominal sensor
- $\eta_i = 1$ faulty sensor (bias or modified variance)

Problem statement

- N identical vehicles with lossless synchronized communication
- Communication radius R defines agent i neighbourhood

$$\mathcal{N}_i(t) = \{j \mid \|\mathbf{x}_i(t) - \mathbf{x}_j(t)\| \leqslant R\}.$$

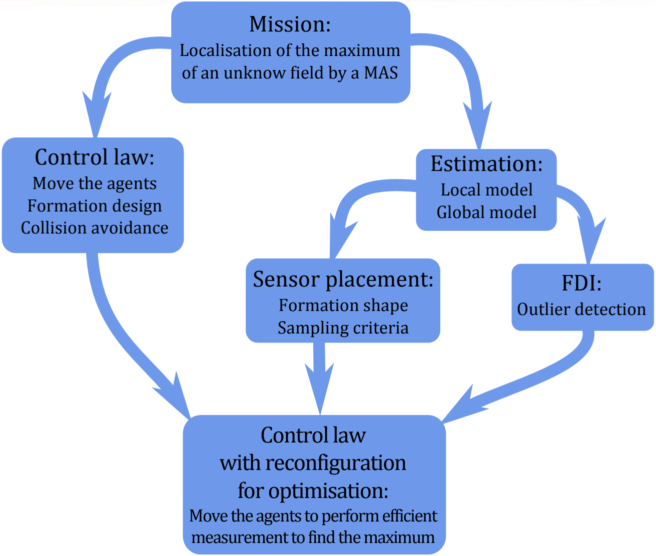
- Available information at time t_k for agent i

$$\mathcal{S}_i(t_k) = \bigcup_{\ell=0}^{k} \{[y_j(t_\ell), \mathbf{x}_j(t_\ell)] \mid j \in \mathcal{N}_i(t_\ell) \cap \mathcal{M}(t_\ell)\}.$$

- Define a strategy to find efficiently (time, measurements)

$$\mathbf{x}_M = \arg\max_{\mathbf{x} \in D} \{\phi(\mathbf{x})\}$$

Topics addressed



Proposed (local) solution

1 Define iteratively vehicle sampling positions

2 Model computation from measurements

3 Move vehicles with collision avoidance

Proposed (local) solution

1 Define iteratively vehicle sampling positions	Optimal sensor placement
2 Model computation from measurements	Local linear model
3 Move vehicles with collision avoidance	Formation control

Local approach

"Gradient climbing" algorithm (*Ögren 2004, Cortes 2009*)

1. Vehicles are kept in a close formation
2. Vehicles measure the field value at their positions and broadcast
3. Cooperative gradient estimation from measurements
4. Computation of formation motion along gradient direction

Contributions

- Cooperative weighted least-square estimation with local model
- Outlier detection: adaptive threshold related to cooperative estimation model
- Optimal sensor placement with faulty sensors (Fisher information matrix)
- Fleet control: vehicle formation motion and reconfiguration

Field modeling

Locally, spatial field ϕ can be written

$$\phi_i(\mathbf{x}) = \phi\left(\widehat{\mathbf{x}}_i^k\right) + \left(\mathbf{x} - \widehat{\mathbf{x}}_i^k\right)^{\mathsf{T}} \nabla\phi\left(\widehat{\mathbf{x}}_i^k\right) + \frac{1}{2}\left(\mathbf{x} - \widehat{\mathbf{x}}_i^k\right)^{\mathsf{T}} \nabla^2\phi(\chi_i)\left(\mathbf{x} - \widehat{\mathbf{x}}_i^k\right).$$

Parameter vector $\alpha_i^k = \begin{pmatrix} \phi\left(\widehat{\mathbf{x}}_i^k\right) \\ \nabla\phi\left(\widehat{\mathbf{x}}_i^k\right) \end{pmatrix}$ to be estimated

Local linear model

$$\overline{\phi}_i(\mathbf{x}) = \phi\left(\widehat{\mathbf{x}}_i^k\right) + \left(\mathbf{x} - \widehat{\mathbf{x}}_i^k\right)^{\mathsf{T}} \nabla\phi\left(\widehat{\mathbf{x}}_i^k\right),$$

with modeling error $e_i(\mathbf{x}) = \phi_i(\mathbf{x}) - \overline{\phi}_i(\mathbf{x})$

Weighted least-squares

Measurement of vehicle j

$$y_j(t_k) = \begin{pmatrix} 1 & \left(\mathbf{x}_j(t_k) - \widehat{\mathbf{x}}_i^k\right)^{\mathsf{T}} \end{pmatrix} \alpha_i^k + e_i(\mathbf{x}_j(t_k)) + n_j(t_k)\,.$$

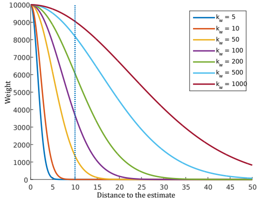
Vehicle i collects all measurements from $\mathscr{N}_i(t_k)$

$$\mathbf{y}_{i,k} = \overline{\mathbf{R}}_{i,k}\alpha_i^k + \mathbf{n}_{i,k} + \mathbf{e}_{i,k}$$

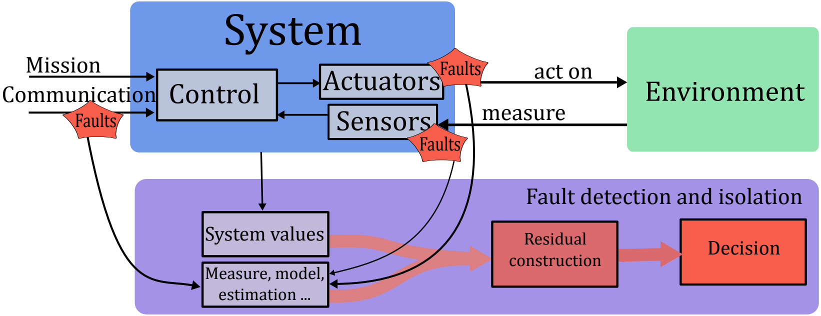
Weight matrix $\mathbf{W}_{i,k} =$

$$\operatorname{diag}\left(\sigma_{\eta_1(t_k)}^{-2} \exp\left(\frac{-\|\mathbf{x}_1(t_k) - \widehat{\mathbf{x}}_i^k\|_2^2}{k_{\mathrm{w}}}\right), \ldots,\ \sigma_{\eta_N(t_k)}^{-2} \exp\left(\frac{-\|\mathbf{x}_N(t_k) - \widehat{\mathbf{x}}_i^k\|_2^2}{k_{\mathrm{w}}}\right)\right)$$

$$\widehat{\alpha}_i^k = \left(\overline{\mathbf{R}}_{i,k}^{\mathsf{T}} \mathbf{W}_{i,k} \overline{\mathbf{R}}_{i,k}\right)^{-1} \overline{\mathbf{R}}_{i,k}^{\mathsf{T}} \mathbf{W}_{i,k} \mathbf{y}_{i,k}$$



Model-based fault detection scheme



Problem characteristics

- Local model shared by vehicles
- Spatially-varying modeling error

Fault detection

Faulty sensor of vehicle i : $y_i = \phi(\mathbf{x}_i) + n_i(\eta_i) + d$

Detection residual $r_i = \hat{\phi}_i(\mathbf{x}_i) - y_i$

Adaptive threshold for residual analysis

$$|r_i| < k_{\mathrm{FDI}} \sqrt{\sigma_0^2 \left(1 + \mathbf{h}_i \mathbf{h}_i^T - 2\mathbf{h}_i[i]\right) + \mathbf{h}_i^T \mathbf{U}_i \mathbf{h}_i}$$

Takes into account measurement noise, sensor locations and modeling error

For fault isolation:

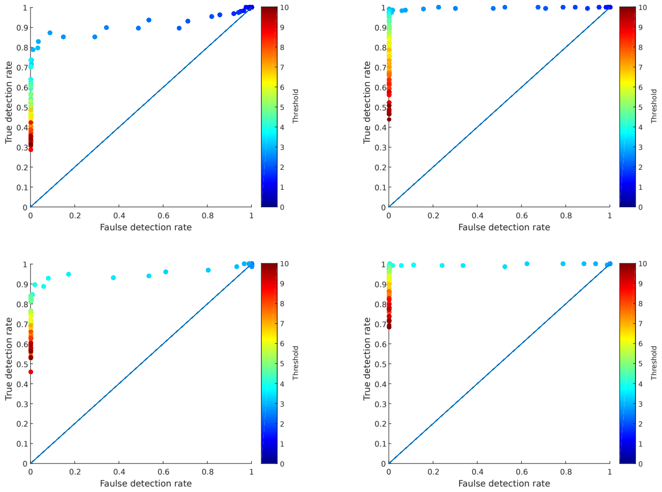
- For each vehicle, bank of N residuals r_{ij} excluding the j-th measurement
- Consensus between vehicles to identify the faulty sensors

Fault detection results

$d = 3$ $d = 5$

$N = 7$

$N = 15$



Optimal sensor placement

Find sensor locations (and associated formation shapes) that

- minimise estimate variance and modeling error influence
- take into account different sensor variances (faults)

Minimise a function of estimation error covariance matrix

$$\widehat{\boldsymbol{\Sigma}}_{\alpha_i^{k+1}} = \left(\overline{\mathbf{R}}_{i,k+1}^{\mathsf{T}} \mathbf{W}_{i,k+1} \overline{\mathbf{R}}_{i,k+1}\right)^{-1}$$

under collision avoidance constraint $\|\mathbf{x}_i - \mathbf{x}_j\|_2^2 \geqslant R_{\text{safety}}^2, \ \forall \{i,j\}, j > i$

Several optimal design criteria *(Walter & Pronzato 1987)*

Optimal sensor placement

T-optimal solution

$$\left(\mathbf{x}_1\left(t_{k+1}\right)\ldots\mathbf{x}_N\left(t_{k+1}\right)\right) = \arg\max_{\left(\mathbf{x}_1,\ldots,\mathbf{x}_N\right)} \mathrm{tr}\left(\overline{\mathbf{R}}_{i,k+1}^{\mathsf{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right)$$

$$\text{s.t. } \left\|\mathbf{x}_i - \mathbf{x}_j\right\|_2^2 \geqslant R_{\text{safety}}^2,\ \forall\{i,j\}, j > i.$$

Optimal sensor placement

T-optimal solution

$$(\mathbf{x}_1(t_{k+1})\ldots\mathbf{x}_N(t_{k+1})) = \arg\max_{(\mathbf{x}_1,\ldots,\mathbf{x}_N)} \operatorname{tr}\left(\overline{\mathbf{R}}_{i,k+1}^{\mathrm{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right)$$

$$\text{s.t. } \|\mathbf{x}_i - \mathbf{x}_j\|_2^2 \geqslant R_{\text{safety}}^2,\ \forall\{i,j\}, j>i.$$

Lagrangian $\mathscr{L} = \operatorname{tr}\left(\overline{\mathbf{R}}_{i,k+1}^{\mathrm{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right) + \sum_{j>i}\mu_{ij}\left(\|\mathbf{x}_i - \mathbf{x}_j\|_2^2 - R_{\text{safety}}^2\right)$

Two solutions for $\mu_{ij} = 0$ (inactive constraints),

$$\mathbf{x}_i(t_{k+1}) = \widehat{\mathbf{x}}_i^{k+1} \qquad \left\|\mathbf{x}_i(t_{k+1}) - \widehat{\mathbf{x}}_i^{k+1}\right\|_2^2 = k_{\mathrm{w}} - 1$$

Optimal sensor placement

D-optimal solution

$$\left(\mathbf{x}_1\left(t_{k+1}\right)\ldots\mathbf{x}_N\left(t_{k+1}\right)\right)=\arg\max_{\left(\mathbf{x}_1,\ldots,\mathbf{x}_N\right)}\det\left(\overline{\mathbf{R}}_{i,k+1}^{\mathsf{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right)$$

$$\text{s.t. } \left\|\mathbf{x}_i-\mathbf{x}_j\right\|_2^2\geqslant R_{\text{safety}}^2,\ \forall\{i,j\},j>i.$$

Optimal sensor placement

D-optimal solution

$$(\mathbf{x}_1(t_{k+1})\dots\mathbf{x}_N(t_{k+1})) = \arg\max_{(\mathbf{x}_1,\dots,\mathbf{x}_N)} \det\left(\overline{\mathbf{R}}_{i,k+1}^{\mathsf{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right)$$

$$\text{s.t. } \|\mathbf{x}_i - \mathbf{x}_j\|_2^2 \geqslant R_{\text{safety}}^2,\ \forall\{i,j\}, j > i.$$

Lagrangian $\mathscr{L} = \det\left(\overline{\mathbf{R}}_{i,k+1}^{\mathsf{T}}\mathbf{W}_{i,k+1}\overline{\mathbf{R}}_{i,k+1}\right) + \sum_{j>i}\mu_{ij}\left(\|\mathbf{x}_i - \mathbf{x}_j\|_2^2 - R_{\text{safety}}^2\right)$

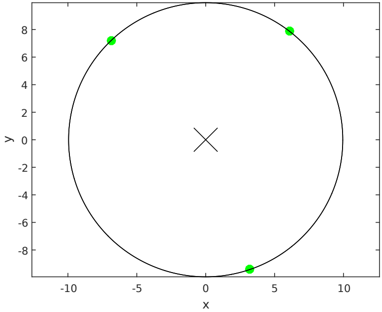
Two solutions for $\mu_{ij} = 0$ (inactive constraints),

$$\mathbf{x}_i(t_{k+1}) = \widehat{\mathbf{x}}_i^{k+1} \qquad \left\|\mathbf{x}_i(t_{k+1}) - \widehat{\mathbf{x}}_i^{k+1}\right\|_2^2 = \frac{2k_w}{3}$$

Numerical solutions

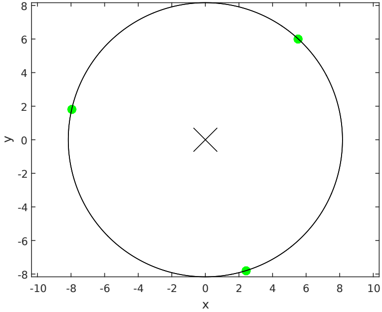
$N = 3$ agents, no faulty agent

T-optimal



$$\text{radius} = \sqrt{k_w - 1}$$

D-optimal

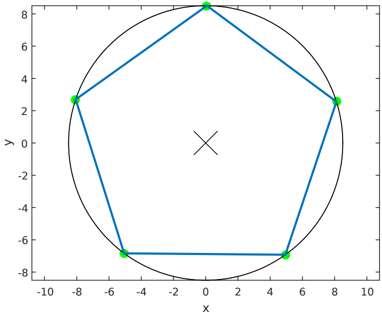


$$\text{radius} = \sqrt{\frac{2k_w}{3}}$$

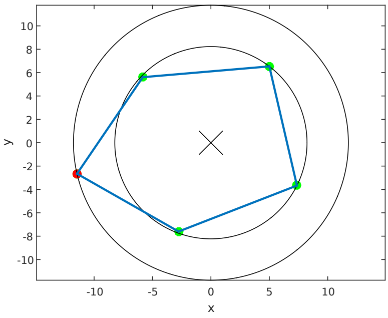
Numerical solutions

$N = 5$ agents, D-optimal placement

No fault



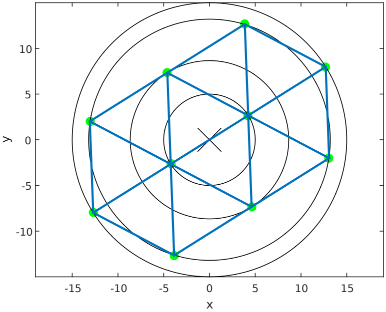
1 faulty agent



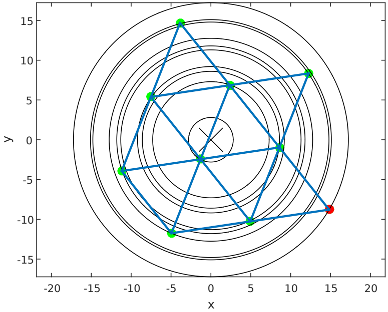
Numerical solutions

$N = 10$ agents, D-optimal placement

No fault



1 faulty agent



Numerical solutions

Conclusion on T-optimal and D-optimal sensor placement

- All vehicles should be located on a circle with inactive constraints
- A faulty agent is placed further from the fleet, due to estimation weight

Sensor placement to minimize modeling error

- Be as close as possible to estimation position

Formation characteristics

- T-optimal $\rightarrow$ concentric circles
- D-optimal $\rightarrow$ *compact* formation around estimation position with active constraints

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A. Kahn, J. Marzat, H. Piet-Lahanier, M. Kieffer, Cooperative estimation with outlier detection and fleet reconfiguration for multi-agent systems, IFAC Workshop on Multi-Vehicule Systems 2015

Cooperative guidance law

- Manage vehicle motions to respect sensor placement
- Locate field maximum

A virtual point $\widehat{\mathbf{x}}^k$ is used in a two-layer control law

- High-level control
  - Move the virtual point to track the field maximum
- Low-level control
  - Keep the agents in formation around the virtual point
  - Avoid collisions between vehicles

High-level control

Gradient climbing of estimation position $\widehat{\mathbf{x}}^k$

$$\widehat{\mathbf{x}}^{k+1} = \widehat{\mathbf{x}}^k + \lambda^k \widehat{\nabla\phi}\left(\widehat{\mathbf{x}}^k\right) / \left\|\widehat{\nabla\phi}\left(\widehat{\mathbf{x}}^k\right)\right\|_2 .$$

$\widehat{\mathbf{x}}^k$ can be proven to converge to maximum for concave fields

Decentralized computation of estimation position is possible with incomplete communication graph

J. Marzat, A. Kahn, H. Piet-Lahanier Cooperative guidance of Lego Mindstorms NXT mobile robots, 11th International Conference on Informatics in Control, Automation and Robotics, Vienne Autriche, 2014

Low-level control

Vehicle dynamics

$$M\ddot{\mathbf{x}}_i(t) + C\left(\mathbf{x}_i(t), \dot{\mathbf{x}}_i(t)\right)\dot{\mathbf{x}}_i(t) = \mathbf{u}_i(t)$$

Proposed control law (similar to *Cheah, 2009*)

$$\begin{aligned}\mathbf{u}_i(t) =& M\ddot{\widehat{\mathbf{x}}}_i(t) + C(\mathbf{x}_i(t), \dot{\mathbf{x}}_i(t))\dot{\mathbf{x}}_i(t) - k_1\left(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}_i(t)\right)\\ &+ 2k_2\sum_{j=1}^{N}(\mathbf{x}_i(t) - \mathbf{x}_j(t))\exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\\ &- k_3^i(\eta_i, t)(\mathbf{x}_i(t) - \widehat{\mathbf{x}}_i(t)),\end{aligned}$$

Control stability

Candidate Lyapunov function $V(\mathbf{X}(t))$

$$V(\mathbf{X}(t)) = \frac{1}{2}\sum_{i=1}^{N}\Bigg[(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t))^T M(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t)) + (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))^T k_3^i(\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t)) + k_2\sum_{j=1}^{N}\exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\Bigg]$$

Control stability

Candidate Lyapunov function $V(\mathbf{X}(t))$

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$$+ (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))^T k_3^i(\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))$$
$$+ k_2\sum_{j=1}^{N}\exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\Bigg]$$

Speed control term

Control stability

Candidate Lyapunov function $V(\mathbf{X}(t))$

$$V(\mathbf{X}(t)) = \frac{1}{2}\sum_{i=1}^{N}\Bigg[(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t))^T M(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t))$$
$$+ (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))^T k_3^i (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))$$
$$+ k_2 \sum_{j=1}^{N} \exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\Bigg]$$

Position control term

Control stability

Candidate Lyapunov function $V(\mathbf{X}(t))$

$$V(\mathbf{X}(t)) = \frac{1}{2}\sum_{i=1}^{N}\Bigg[(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t))^T M(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t)) + (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))^T k_3^i(\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t)) + k_2\sum_{j=1}^{N}\exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\Bigg]$$

Collision avoidance term

Control stability

Candidate Lyapunov function $V(\mathbf{X}(t))$

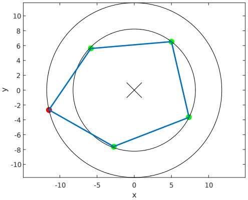
$$V(\mathbf{X}(t)) = \frac{1}{2}\sum_{i=1}^{N}\Bigg[(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t))^T M(\dot{\mathbf{x}}_i(t) - \dot{\widehat{\mathbf{x}}}(t)) + (\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t))^T k_3^i(\mathbf{x}_i(t) - \widehat{\mathbf{x}}(t)) + k_2\sum_{j=1}^{N}\exp\left(-\frac{(\mathbf{x}_i(t) - \mathbf{x}_j(t))^T(\mathbf{x}_i(t) - \mathbf{x}_j(t))}{q}\right)\Bigg]$$

Control law can be proven to be Lyapunov stable

A. Kahn, J. Marzat, H. Piet-Lahanier, M. Kieffer, Cooperative estimation with outlier detection and fleet reconfiguration for multi-agent systems, IFAC Workshop on Multi-Vehicule Systems, Gênes Italie, 2015

Reconfiguration

Optimal sensor placement $\rightarrow$ desired formation shape

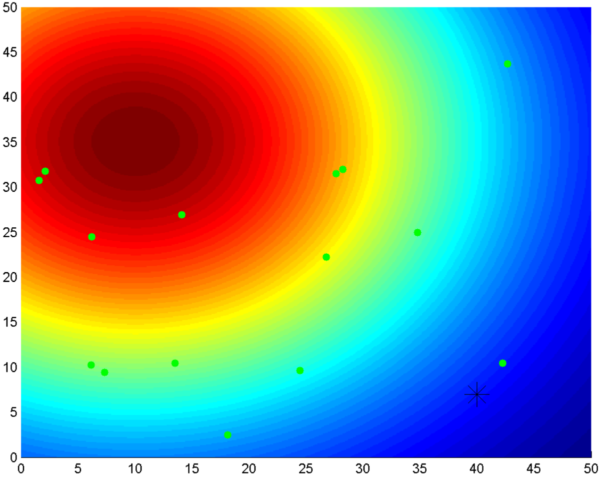


Faulty agent i $\rightarrow$ modified control law

$$k_3^i(\eta_i = 0) > k_3^i(\eta_i = 1)$$

Faulty agents are "pushed" far from the formation center

Local approach: complete loop simulation



Section 2

Robustesse aux défauts de capteurs sur plateformes expérimentales

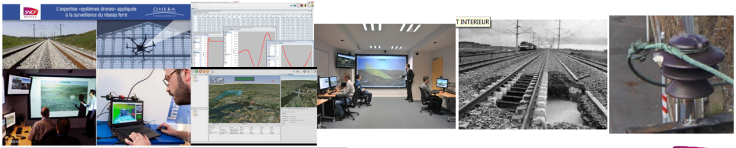
Navigation autonome à base de vision

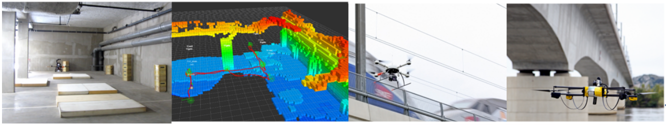
Partenariat Recherche Industrie SNCF Réseau – ONERA

- Indoor : inspection d'infrastructures
- Outdoor : suivi de linéaire, ouvrages d'art

Expérimentations drones sur sites SNCF pour preuve de concept

Chantier indoor : localisation et reconstruction d'environnement à base de vision, algorithmes de guidage pour navigation autonome





SNCF RÉSEAU

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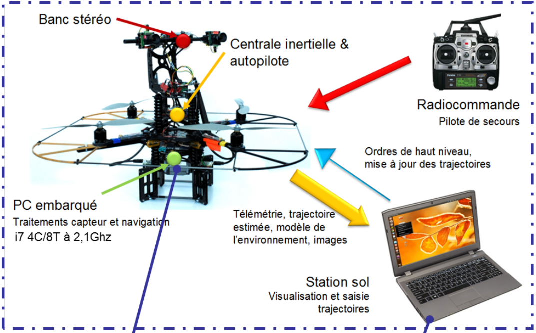
Plateforme expérimentale

Boucle complètement embarquée => robustesse à la perte de la liaison de données avec la station sol



Décollage et Atterrissage automatiques

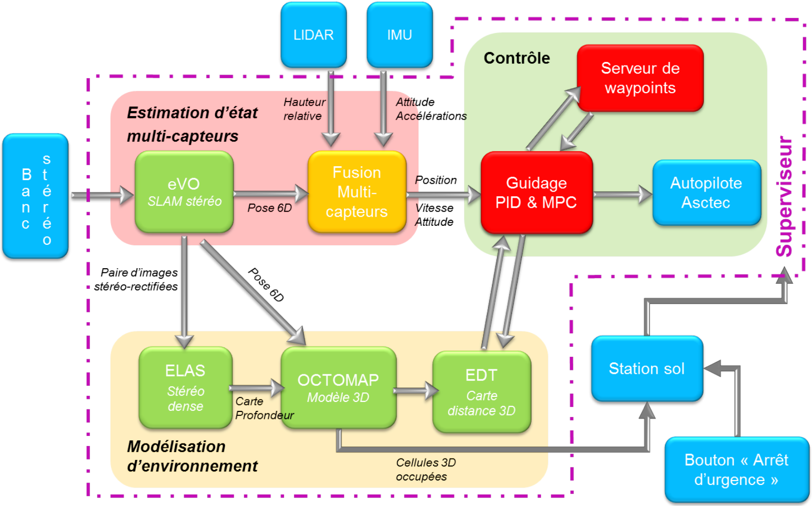
LIDAR

Mesure d'« altitude »

Sécurité dans espace grande dimension

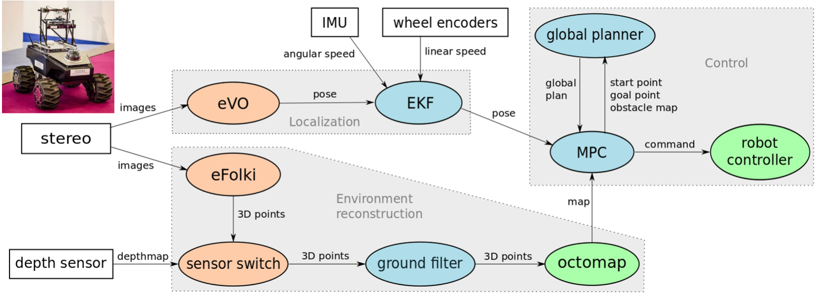
Arrêt d'urgence couplé à un superviseur de mission

Perception et commande : architecture intégrée



Perception et commande : architecture intégrée

Boucle similaire embarquée sur robot mobile Robotnik Summit XL

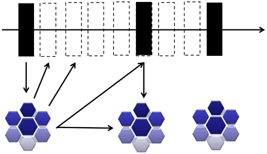


H. Roggeman, J. Marzat, M. Sanfourche, A. Plyer, Embedded vision-based localization and model predictive control for autonomous exploration, IROS Vicomor 2014

J. Marzat, J. Moras, A. Plyer, A. Eudes, P. Morin, Vision-based localization, mapping and control for autonomous MAV : EuRoC challenge results, ODAS 2015

Localisation basée vision : eVO

- Carte 3D d'amers appariés (stéréo) => pose de la caméra
- Mise à jour par mécanisme d'images-clés (nombre d'amers)



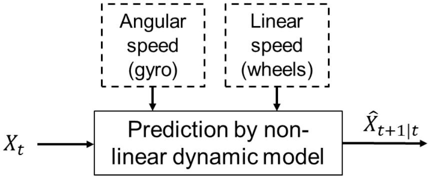
Incertitudes liées à la vision

→ Besoin de fusion multi-capteurs et détection d'anomalies

- Robot mobile : eVO + encodeurs roues + IMU
- Drone : eVO + IMU + lidar

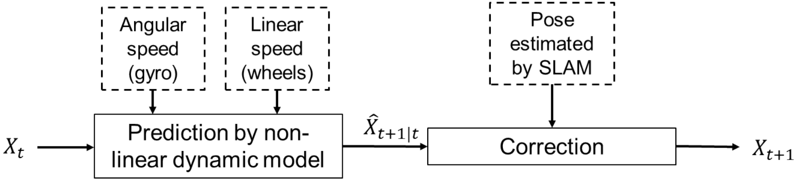
M. Sanfourche, V. Vittori, G. Le Besnerais, eVO : a realtime embedded stereo odometry for MAV applications, IROS 2013

Fusion multi-capteurs

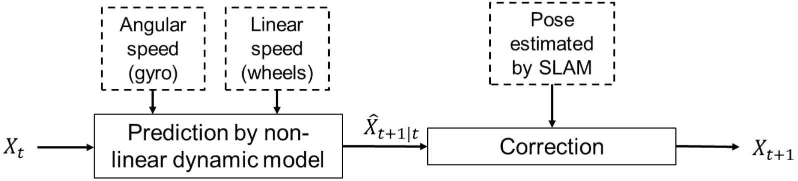


$$\begin{cases} \hat{x}_{t+1} = x_t + t_e v_t \cos\theta_t \\ \hat{y}_{t+1} = y_t + t_e v_t \sin\theta_t \\ \hat{\theta}_{t+1} = \theta_t + t_e \omega_t \end{cases}$$

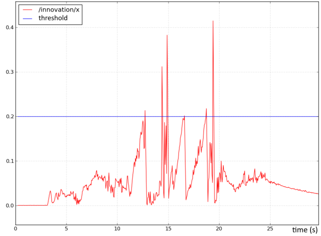
Fusion multi-capteurs

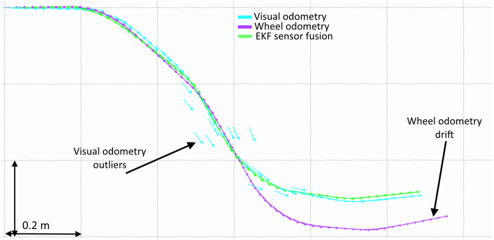


Fusion multi-capteurs



Test sur l'innovation (position), seuil fonction de la vitesse maximale





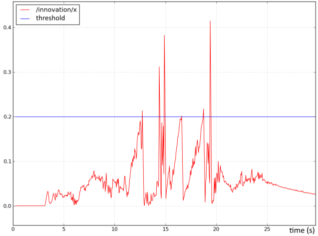
Fusion multi-capteurs

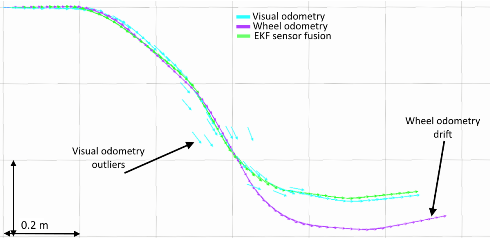
$$\begin{cases} \widehat{\boldsymbol{P}}(k+1) = \widehat{\boldsymbol{P}}(k) + \widehat{\boldsymbol{v}}(k+1)\ \delta t \\ \widehat{\boldsymbol{v}}(k+1) = \widehat{\boldsymbol{v}}(k) + (\boldsymbol{R}(k)\widehat{\boldsymbol{a}}_{\boldsymbol{IMU}} + \boldsymbol{g})\ \delta t \\ \boldsymbol{R}(k) = \boldsymbol{R}_{\boldsymbol{IMU}} \end{cases}$$

IMU :
acceleromètres
+ rotation

eVO : position

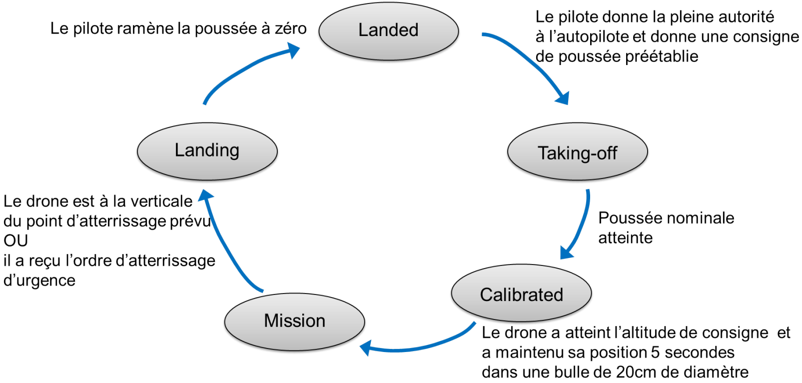
Test sur l'innovation (position), seuil fonction de la vitesse maximale





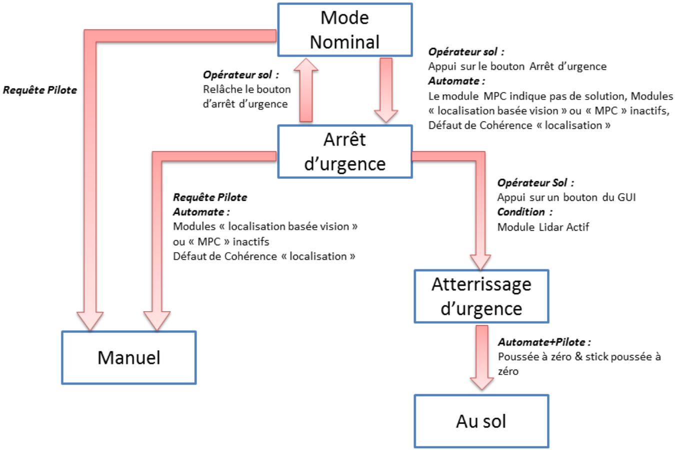
Stratégie de supervision

Une machine à état pour gérer tous les événements de mission

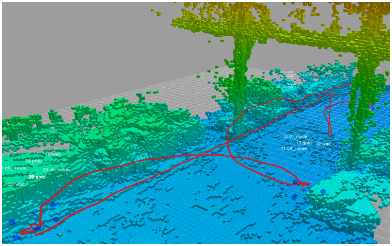


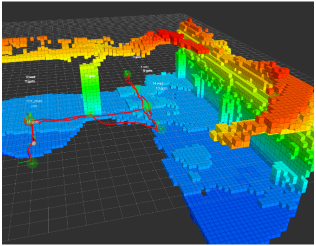
Stratégie de supervision

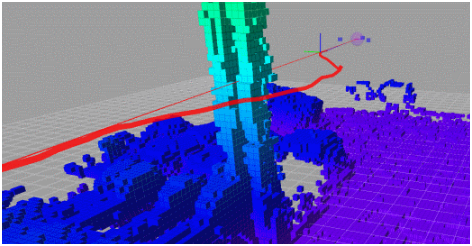
Une machine à état pour gérer tous les événements de mission



Résultats expérimentaux







Conclusions et perspectives

Localisation de source par une flotte de véhicules

- Estimation coopérative (modèle local) et placement optimal
- Détection et localisation de défauts de capteurs
- Commande de formation avec reconfiguration

Robustesse aux défauts de capteurs sur plateformes exp.

- Expérimentations en milieu industriel encombré
- Fusion multi-capteurs (vision et al.) avec détection d'anomalie
- Procédures de sécurité pour déploiement opérationnel

Perspectives

- Expérimentations à échelle réelle avec flottes de véhicules, incluant des fonctions de diagnostic et reconfiguration