

Image Processing for Passivity Based Visual Motion Observer



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Outline

- Motivation
- Background
 - Visual Motion Observer
- Progress : Feature Information
- Feature Velocities
- Conclusion and Feature Works



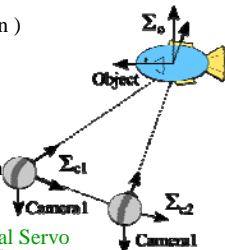
Motivation

How Animals Realize Real(External) World?

There are many methods to know real world.
- Vision - Sound - Sonic wave etc.

Then, they must be aware of real world.

- One approach (Vision)
- Stereo vision
- Two eyes are used to see object at 3D
- Reconstruction of an object pose from geometry relation



Position based Visual Servo



Motivation

- One approach (Vision)
- Stereo vision
- Two eyes are used to see object at 3D
- Shape is important

A question

All animals have stereo vision?
Some animals not always can see using two eyes

- Another approach (Vision)
- An eye is used to realize external world information
- Motion is important

One visual Sensor is used to estimate target motion

Visual Motion Observer (VMO)[4]



Background

Visual Sensor

Now: Camera sensor (visual information)

Advantages

- Rich information
- Easy understanding

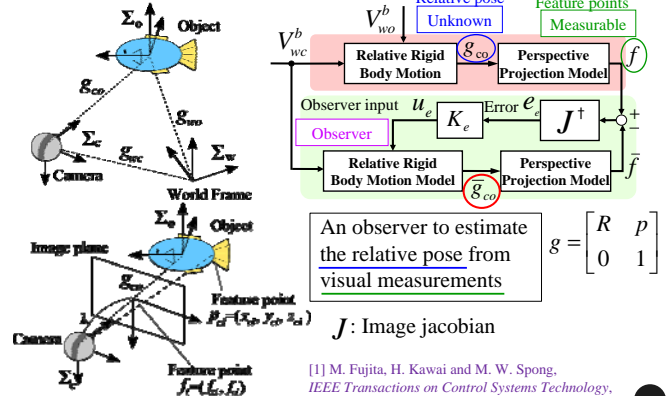
Application

- Target tracking
- Monitoring



Background

Visual Motion Observer (VMO)[4]



Passivity-based Visual Motion Observer [4]

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Lemma : Passivity

If $V_{wo}^b = 0$, then the visual feedback system satisfies

$$\int_0^T -u_e^T v_e d\tau \geq -\beta_c, \quad \forall T > 0$$

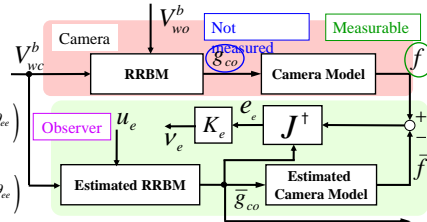
where v_e is defined as $v_e = K_e e_e$ and β_c is positive scalar.

Proof :

Use energy function

$$V = \frac{1}{2} \|p_{ec}\|^2 + \frac{1}{2} \text{tr}(I - e^{\hat{\theta}_{ec}})$$

$$(R_{ec} = e^{\hat{\theta}_{ec}})$$



[1] M. Fujita, H. Kawai and M. W. Spong, "Passivity-based Dynamic Visual Feedback Control for Three Dimensional Target Tracking: Stability and L2-gain Performance Analysis," *IEEE Transactions on Control Systems Technology*, Vol. 15, No.1, pp. 40-52, 2007.

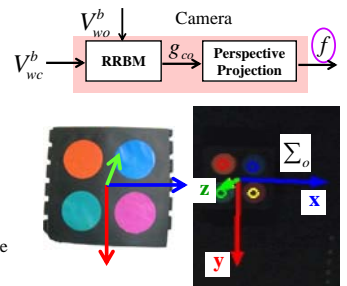
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Topics : Feature Points

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Previous Feature Points

Multiple point features on a known object are given.[1]



Feature Points

- Colored circles (four color)
- Feature points on a plane
- Extraction algorithm
- Extraction of each colored circle

Weak Points

- Difficulty of color variation
- Weakness against change of brightness
- Problem about Occlusion

Reconsideration

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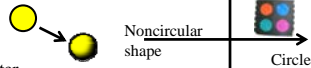
Topics : Feature Points

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Reconsideration about Feature Points

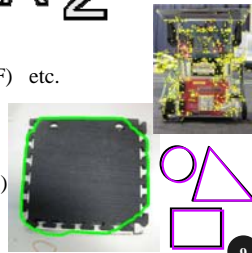
● Addition of feature points

- 3D feature points
Example : the control of quad copter
- Letters (ex. Alphabets, Numbers)



● Extraction from target object

- Point based Methods
- Speeded-Up Robust Features(SURF) etc.
- Edge based Methods
- Shape based Methods
- Snake (Detection of object's shape)
- Extraction of contours
- etc.



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Result : Movie

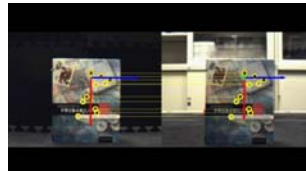
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Face Detection

Ball Features



Speeded-Up Robust Features



Snake and Optical Flow
Sorry!
There are no movies to watch

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Good Points and Weak Points

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Method	Extraction Difficulty	Extraction Time[ms]	Implementation to VMO	Accuracy of VMO
Ball Features	△	60	※Finished	△
Snake	△~×	Over 200	In review	(△~×)
SURF	○~△	124~40	Finished	△
Face Detection	○~△	100~80	To be prepared	(△)
Optical Flow	○~×	100~80	To be prepared	(△)
Colored Circle	○~△	60	Finished	○~△

Note : Self review

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Topics : Optical Flow

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Optical Flow

Optical flow is a reliable approximation to two-dimensional image motion

Estimation of the displacement field between two sequence images

It is similar to a human eye



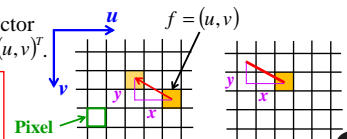
Detail

Extraction of a pixel displacement in a image sequence

Then, the difference is calculated

The value of a difference vector is movement of a pixel $f = (u, v)^T$.

$$\dot{f} = \frac{d}{dt} f = (\dot{u}, \dot{v})^T = \begin{pmatrix} \dot{x} \\ \dot{y} \end{pmatrix}$$



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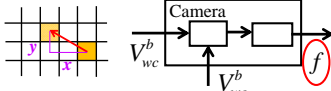
Application to Visual Motion Observer

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Phase Lead Compensation

Optical flow : Extraction of a pixel displacement in a image sequence

$$\dot{f} = \frac{d}{dt} f = (\dot{u}, \dot{v})^T = (x, y)^T$$

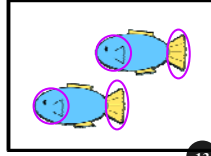


We can use feature points position f and their velocity \dot{f}

This leads to **phase lead compensation**

Problem in these days

- Image processing time is long : over 100ms
- Same problem occur[8]
- Consideration about particular area
- Miss calculation because of extraction miss
- Feature works



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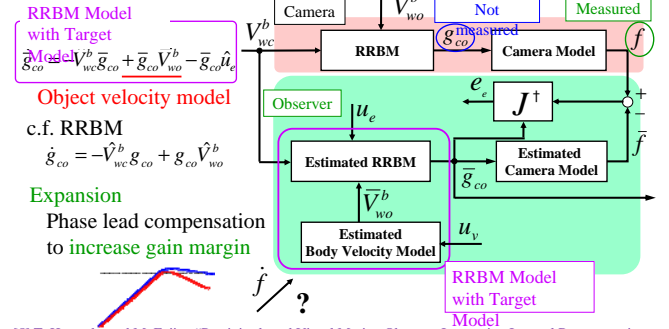
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3D Target Motion Model

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VMO Integrating Internal Representation of 3D Target Motion Model [5]



[5] T. Hatanaka and M. Fujita, "Passivity-based Visual Motion Observer Integrating Internal Representation of 3D Target Object Motion," *Proc. of the 2012 American Control Conference*, Montreal, Canada, 2012.

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Addition of feature velocities

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Perspective Projection (Pinhole Camera Model)

$$\begin{bmatrix} f_{xi} \\ f_{yi} \end{bmatrix} = \frac{\lambda}{z_{ci}} \begin{bmatrix} x_{ci} \\ y_{ci} \end{bmatrix}$$

Previous work[4]

$$\frac{d}{dt} \begin{bmatrix} f_{xi} \\ f_{yi} \end{bmatrix} = \frac{\lambda}{z_{ci}} \begin{bmatrix} \dot{x}_{ci} - \dot{z}_{ci} \frac{x_{ci}}{z_{ci}} \\ \dot{y}_{ci} - \dot{z}_{ci} \frac{y_{ci}}{z_{ci}} \end{bmatrix}$$

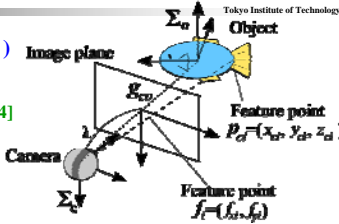


Image Jacobian with Time Differential Form

$$\begin{bmatrix} \dot{f}_{xi} \\ \dot{f}_{yi} \end{bmatrix} = f(p_{ci}, \dot{p}_{ci}) = \begin{bmatrix} \frac{\partial f}{\partial x_{ci}} & \frac{\partial f}{\partial y_{ci}} & \dots & \frac{\partial f}{\partial z_{ci}} \end{bmatrix} \begin{bmatrix} p_{ci} - \bar{p}_{ci} \\ \dot{p}_{ci} - \dot{\bar{p}}_{ci} \end{bmatrix}$$

Previous work[7]

Next, Derivative $\dot{p}_{ci} - \dot{\bar{p}}_{ci}$

$$\begin{bmatrix} \dot{f}_{ei} \\ \dot{f}_{ei} \end{bmatrix} = \begin{bmatrix} \dot{f}_i - \dot{\bar{f}}_i \\ \dot{f}_i - \dot{\bar{f}}_i \end{bmatrix} \rightarrow J^+ e_e$$

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Addition of feature velocities

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The Relation between the Actual Feature Point and the Estimated One

$$p_{ci} - \bar{p}_{ci} = \begin{bmatrix} \bar{R}_{co} & -\bar{R}_{co}(\bar{R}_{co} p_{ci})^\wedge \end{bmatrix} \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \end{bmatrix}$$

$$\begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix}^\wedge = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix}$$

$$f_i - \bar{f}_i = \begin{bmatrix} \frac{\lambda}{z_{ci}} & 0 & -\frac{\lambda \bar{x}_{ci}}{z_{ci}^2} \\ 0 & \frac{\lambda}{z_{ci}} & -\frac{\lambda \bar{y}_{ci}}{z_{ci}^2} \end{bmatrix} (p_{ci} - \bar{p}_{ci})$$

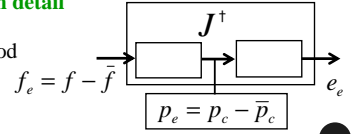
$$\text{Estimated Error Vector } e_e = \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \end{bmatrix}$$

$$p_{ee} = \bar{R}_{co}(p - \bar{p})$$

$$e_R(R_{ee}) = \frac{1}{2}(R_{ee} - R_{ee}^T)^\vee$$

Previous work[4] in detail

I consider same numerical method to calculate $\dot{p}_{ci} - \dot{\bar{p}}_{ci}$



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Addition of Feature Velocities

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$$\text{Body velocity of the target object : } V_{wo} = \begin{bmatrix} \omega & v \\ 0 & 0 \end{bmatrix} \quad \text{Observer Input : } u_e = \begin{bmatrix} \hat{\omega} & \hat{v} \\ 0 & 0 \end{bmatrix}$$

Camera (fixed)

$$p_{ci} = g_{co} p_{oi} \rightarrow \frac{d}{dt} p_{ci} = \dot{g}_{co} p_{oi} = g_{co} \hat{V}_{wo} \begin{bmatrix} p_{oi} \\ 1 \end{bmatrix} = R_{co} \hat{\omega} p_{oi} + R_{co} v$$

$$(\because \dot{g}_{co} = -v_{wc} \dot{g}_{co} + g_{co} \hat{V}_{wo} = g_{co} \hat{V}_{wo})$$

Camera model (fixed)

$$\bar{p}_{ci} = \bar{g}_{co} p_{oi} \rightarrow \frac{d}{dt} \bar{p}_{ci} = \dot{\bar{g}}_{co} p_{oi} = \bar{g}_{co} \hat{u}_e \begin{bmatrix} p_{oi} \\ 1 \end{bmatrix} = \bar{R}_{co} \hat{\omega} p_{oi} + \bar{R}_{co} \hat{v}$$

$$(\because \dot{\bar{g}}_{co} = -v_{wc} \dot{\bar{g}}_{co} + \bar{g}_{co} \hat{u}_e = g_{co} \hat{V}_{wo})$$

From these equations,

$$\dot{p}_{ci} - \dot{\bar{p}}_{ci} = R_{co} \hat{\omega} p_{oi} + R_{co} v - (\bar{R}_{co} \hat{\omega} p_{oi} + \bar{R}_{co} \hat{v}) \quad \text{Eliminate actual rotation}$$

$$= \bar{R}_{co} \{ (R_{ee} \hat{\omega} - I) p_{oi} + R_{ee} v - \hat{v} \} \quad (\because R_{ee} = \bar{R}_{co}^{-1} R_{co})$$

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Addition of Feature Velocities

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$$\dot{p}_{ci} - \dot{\bar{p}}_{ci} = \bar{R}_{co} \{ (R_{ee} \hat{\omega} - I) p_{oi} + R_{ee} v - \hat{v} \}$$

$$= \bar{R}_{co} \{ (R_{ee} \hat{\omega} - \hat{\omega} R_{ee}) p_{oi} + \hat{\omega} R_{ee} p_{oi} - p_{oi} + (R_{ee} v - \hat{v} - \hat{\omega} p_{ee}) + \hat{\omega} p_{ee} \}$$

Kinematic Model of Estimation Error

$$\hat{V}_{ee} = -\hat{u}_e g_{ee} + g_{ee} \hat{V}_{wo} = -\begin{bmatrix} \hat{\omega} & \hat{v} \\ 0 & 0 \end{bmatrix} \begin{bmatrix} R_{ee} & p_{ee} \\ 0 & 1 \end{bmatrix} + \begin{bmatrix} R_{ee} & p_{ee} \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{\omega} & v \\ 0 & 0 \end{bmatrix}$$

$$\Rightarrow \begin{cases} v_{ee} = -\hat{\omega} p_{ee} - \hat{v} + R_{ee} v \\ \omega_{ee} = -\hat{\omega} R_{ee} + R_{ee} \hat{\omega} \end{cases} \quad \left(V_{ee} = \begin{bmatrix} \omega_{ee} & v_{ee} \\ 0 & 0 \end{bmatrix} \right)$$

v_{ee} and ω_{ee} seem to be variables \Rightarrow Add to estimation error

$$\text{c.f. } e_e = \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \end{bmatrix}$$

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Addition of Feature Velocities

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Kinematic Model of Estimation Error

$$\begin{cases} v_{ee} = -\hat{\omega} p_{ee} - \bar{v} + R_{ee} v \\ \omega_{ee} = -\hat{\omega} R_{ee} + R_{ee} \hat{\omega} \end{cases} \left(v_{ee} = \begin{bmatrix} \omega_{ee} & v_{ee} \\ 0 & 0 \end{bmatrix} \right)$$

$$\begin{aligned} \dot{p}_{ci} - \dot{\bar{p}}_{ci} &= \bar{R}_{co} \left\{ \hat{\omega} p_{oi} + \hat{\omega} R_{ee} p_{oi} - \hat{\omega} p_{oi} + v_{ee} + \hat{\omega} p_{ee} \right\} \\ &\vdots \\ &= \bar{R}_{co} \left\{ \hat{\omega} p_{ee} - (\bar{R}_{co} p_{oi})^\wedge \hat{\omega} e_R(R_{ee}) + v_{ee} - \hat{p}_{oi} \omega_{ee} \right\} \end{aligned}$$

$$\therefore \dot{p}_{ci} - \dot{\bar{p}}_{ci} = \bar{R}_{co} \left[\hat{\omega} \quad -(\bar{R}_{co} p_{oi})^\wedge \hat{\omega} \quad I \quad -\hat{p}_{oi} \right] \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \\ v_{ee} \\ \omega_{ee} \end{bmatrix}$$

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Addition of Feature Velocities

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The Relation between Feature Points on Image Plane and Them in Space

$$\begin{bmatrix} f_{xi} \\ f_{yi} \\ \dot{f}_{xi} \\ \dot{f}_{yi} \end{bmatrix} = \begin{bmatrix} \frac{\partial f}{\partial x_{ci}} & \frac{\partial f}{\partial y_{ci}} & \dots & \frac{\partial f}{\partial z_{ci}} \end{bmatrix}_{x_{ci}=\bar{x}_{ci}, \dots, z_{ci}=\bar{z}_{ci}} \begin{bmatrix} p_{ci} - \bar{p}_{ci} \\ \dot{p}_{ci} - \dot{\bar{p}}_{ci} \end{bmatrix}$$

$$= \begin{bmatrix} \frac{\lambda}{\bar{z}_{ci}} & 0 & -\frac{\lambda \bar{x}_{ci}}{\bar{z}_{ci}^2} & 0 & 0 & 0 \\ 0 & \frac{\lambda}{\bar{z}_{ci}} & -\frac{\lambda \bar{y}_{ci}}{\bar{z}_{ci}^2} & 0 & 0 & 0 \\ -\frac{\lambda \dot{z}_{ci}}{\bar{z}_{ci}^2} & 0 & -\frac{\lambda \dot{x}_{ci}}{\bar{z}_{ci}^2} + \frac{2\lambda \dot{z}_{ci} \bar{x}_{ci}}{\bar{z}_{ci}^3} & \frac{\lambda}{\bar{z}_{ci}} & 0 & -\frac{\lambda \bar{x}_{ci}}{\bar{z}_{ci}^2} \\ 0 & -\frac{\lambda \dot{z}_{ci}}{\bar{z}_{ci}^2} & -\frac{\lambda \dot{y}_{ci}}{\bar{z}_{ci}^2} + \frac{2\lambda \dot{z}_{ci} \bar{y}_{ci}}{\bar{z}_{ci}^3} & 0 & \frac{\lambda}{\bar{z}_{ci}} & -\frac{\lambda \bar{y}_{ci}}{\bar{z}_{ci}^2} \end{bmatrix} \begin{bmatrix} p_{ci} - \bar{p}_{ci} \\ \dot{p}_{ci} - \dot{\bar{p}}_{ci} \end{bmatrix}$$

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Addition of Feature Velocities

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Image Jacobian of the i th Feature Point

$$\begin{bmatrix} f_{xi} \\ f_{yi} \\ \dot{f}_{xi} \\ \dot{f}_{yi} \end{bmatrix} = \begin{bmatrix} \frac{\lambda}{\bar{z}_{ci}} & 0 & -\frac{\lambda \bar{x}_{ci}}{\bar{z}_{ci}^2} & 0 & 0 & 0 \\ 0 & \frac{\lambda}{\bar{z}_{ci}} & -\frac{\lambda \bar{y}_{ci}}{\bar{z}_{ci}^2} & 0 & 0 & 0 \\ -\frac{\lambda \dot{z}_{ci}}{\bar{z}_{ci}^2} & 0 & -\frac{\lambda \dot{x}_{ci}}{\bar{z}_{ci}^2} + \frac{2\lambda \dot{z}_{ci} \bar{x}_{ci}}{\bar{z}_{ci}^3} & \frac{\lambda}{\bar{z}_{ci}} & 0 & -\frac{\lambda \bar{x}_{ci}}{\bar{z}_{ci}^2} \\ 0 & -\frac{\lambda \dot{z}_{ci}}{\bar{z}_{ci}^2} & -\frac{\lambda \dot{y}_{ci}}{\bar{z}_{ci}^2} + \frac{2\lambda \dot{z}_{ci} \bar{y}_{ci}}{\bar{z}_{ci}^3} & 0 & \frac{\lambda}{\bar{z}_{ci}} & -\frac{\lambda \bar{y}_{ci}}{\bar{z}_{ci}^2} \end{bmatrix} \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \\ v_{ee} \\ \omega_{ee} \end{bmatrix} \quad J_i$$

$$\begin{bmatrix} I & -(\bar{R}_{co} p_{oi})^\wedge & 0 & 0 \\ \hat{\omega} & -(\bar{R}_{co} p_{oi})^\wedge \hat{\omega} & I & -\hat{p}_{oi} \end{bmatrix} \begin{bmatrix} \bar{R}_{co} & 0 & 0 & 0 \\ 0 & \bar{R}_{co} & 0 & 0 \\ 0 & 0 & \bar{R}_{co} & 0 \\ 0 & 0 & 0 & \bar{R}_{co} \end{bmatrix} \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \\ v_{ee} \\ \omega_{ee} \end{bmatrix}$$

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Image Jacobian with Feature Velocities

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Previous Work[4]

Passivity : ○

$$f_e = f - \bar{f} \xrightarrow{J^\dagger} e_e$$

$$e_e = \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \end{bmatrix}$$

Proof : Use energy function

$$V = \frac{1}{2} \|p_{ee}\|^2 + \frac{1}{2} \text{tr}(I - R_{ee})$$

Observer Input

$$u_e = -K(-e_e) = K e_e$$

This Work with Feature Velocities

Passivity : not proven yet

$$f_e = f - \bar{f} \xrightarrow{J'^\dagger} e'_e$$

$$\dot{f}_e = \dot{f} - \dot{\bar{f}} \xrightarrow{J'^\dagger} e'_e = \begin{bmatrix} p_{ee} \\ e_R(R_{ee}) \\ v_{ee} \\ \omega_{ee} \end{bmatrix}$$

Observer Input

Continued : Feature work

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Progress and Feature Works

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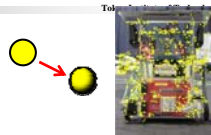
Progress

Reconsideration about feature points

- 3D feature points
- Speeded-Up Robust Features(SURF)

Consideration about optical flow

It continues to Yuta's bachelor thesis



Feature Works

- Exploration of image processing methods for VMO
 - Shape based
 - Points based
 - Time series based etc.
- Efficient analysis of image processing methods on VMO
- Robust feature points for VMO

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Thank you !

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References

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■ Vision and Internal Representation Model

- [1] D. Marr, "Vision: A Computational Investigation into Human Representation and Processing of Visual Information," New York, 1982.
- [2] J. Gray, "Consciousness: Creeping Up on the Hard Problem," Oxford University Press, 2004.
- [3] R. Sheldrake, "The Sense of Starting at: And Other Aspects of the Extended Mind," New York, Crown Publishers, 2003.

■ Visual Motion Observer

- [4] M. Fujita, H. Kawai and M. W. Spong, "Passivity-based Dynamic Visual Feedback Control for Three Dimensional Target Tracking: Stability and L2-gain Performance Analysis", *IEEE Transactions on Control Systems Technology*, Vol. 15, No.1, p.p. 40-52, 2007.
- [5] T. Hatanaka and M. Fujita, "Passivity-based Visual Motion Observer Integrating Internal Representation of 3D Target Object Motion," *Proc. of the 2012 American Control Conference*, Montreal, Canada, 2012.
- [6] 河合, "視覚フィードバック制御", 藤田研究室内資料, 2003.
- [7] H. Kawai, T. Murao and M. Fujita, "Passivity-based Visual Motion Observer with Panoramic Camera for Pose Control," *Journal of Intelligent and Robotic Systems*, Vol. 64, No. 3-4, p.p. 561-583, 2011.

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References

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■ Optical Flow

- [8] Thomas Brox, Andr es Bruhn, Nils Papenberg, and Joachim Weickert, "High Accuracy Optical Flow Estimation Based on a Theory for Warping," *ECCV 2004*, LNCS 3024, p.p. 25-36, 2004.
- [9] X. Zhang, R.M. Haralick and Y. Zhao, "From Depth and Optical Flow to Rigid Body Motion," *Proc. of Computer Vision and Pattern Recognition*, p.p. 393-397, 1988..

■ Visual Servo

- [10] Adrien Durand Petiteville, Michel Courdesses, Viviane Cadenat and Philippe Baillon, "On-line Estimation of the Reference Visual Features Application to a Vision Based Long Range Navigation Task," *The 2010 IEEE/RSJ International Conference on Intelligent Robots and Systems*, Taipei, Taiwan, October 18-22, 2010.
- [11] F. Chaumette and S. A. Hutchinson, "Visual Servoing and Visual Tracking," *Springer Handbook of Robotics*(B. Siciliano and O. Khatib, eds.), Springer-Verlag, p.p. 563-583, 2008.

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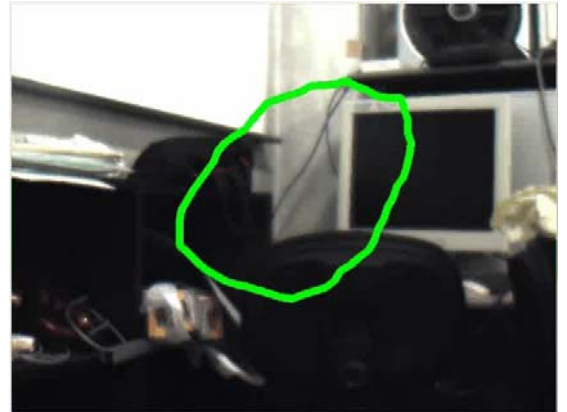
Appendix

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Extension of Speeded-Up Robust Features

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■ Increment of Target Information

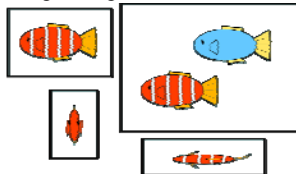
Previous Work

1 target image + 1 camera image



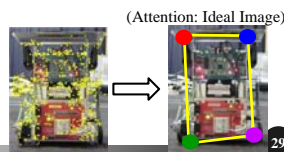
Feature Work

More than 2 target images + 1 camera image



■ More Robust Image Processing

- Extraction of more robust features
- Increase of matching feature points
- Transformation from feature points to obvious form (ex. rectangle ...)



(Attention: Ideal Image)

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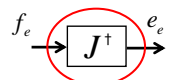
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Estimation Error

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$$f_e = f - \bar{f} = \begin{pmatrix} f_1 - \bar{f}_1 \\ f_2 - \bar{f}_2 \\ \vdots \\ f_n - \bar{f}_n \end{pmatrix} \in \mathbb{R}^{2 \times n}$$



n : The number of feature points, $n \geq 3$

$$e_e = (p_e^T, e_R^T (e^{\hat{\xi}_\theta}))^T \in \mathbb{R}^6$$

Pseudo Inverse of image jacobian J^\dagger

A kind of least squares method from $f_e \in \mathbb{R}^{2 \times n}$ to $e_e \in \mathbb{R}^6$

When the number of feature points n change, the answer of least squares method is different in spite of accurate data.

Main problem of oscillatory estimation error ?

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