A MULTI-PERSPECTIVE APPROACH TO ANOMALY DETECTION FOR SELF-AWARE EMBODIED AGENTS

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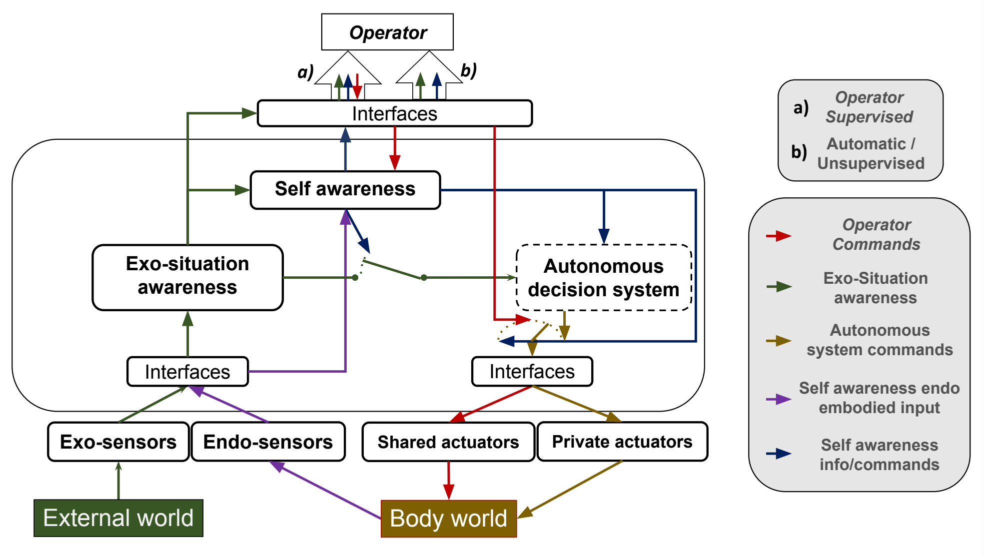
Outline

Introduction

Generic self-awareness scheme



Motivation

- An autonomous system need perception to navigate through scenes and recognize objects in real environments [1].
- The capability of detecting abnormal situations based on self-awareness is an important task that allows autonomous systems to increase their situational awareness and the effectiveness of the decision making submodules [2].

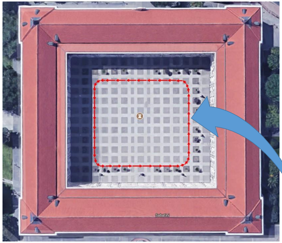
[1] D. Ramík, C. Sabourin, R. Moreno, and K. Madani, "A machine learning based intelligent vision system for autonomous object detection and recognition," *Applied Intelligence*, vol. 40, no. 2, pp. 358–375, 2014

[2] V. Bastani, L. Marcenaro, and C. S. Regazzoni, "Online nonparametric bayesian activity mining and analysis from surveillance video," *IEEE Transactions on Image Processing*, vol. 25, pp. 2089–2102, May 2016

Objectives

- We focus on multi-sensor anomaly detection for moving cognitive agents using both external and private first-person visual observations.
- The observation types are used to characterize agents motion in a given environment.
- The proposed method provides two levels:
  i) A Shared Level (SL) self-awareness from external viewpoint.
  ii) A Private level (PL) self-awareness from first person viewpoint.

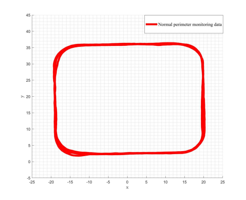
Problem definition



Task is perimeter monitoring by doing turn inside the environment

Normal situation

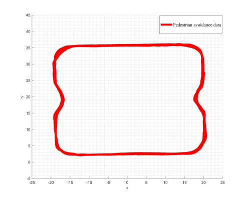
SL



PL

Abnormal situation

SL

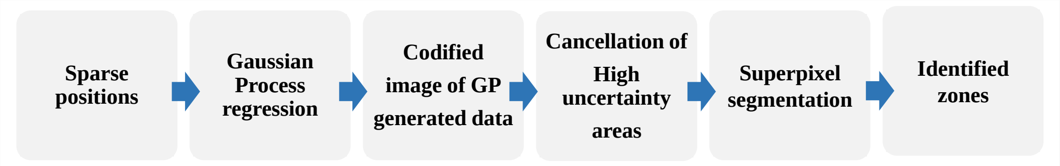


PL

Shared Level of self-awareness

Representation of observed dynamic motion

- Sparse positions represents the Locations of the entity take from input video or sensor.

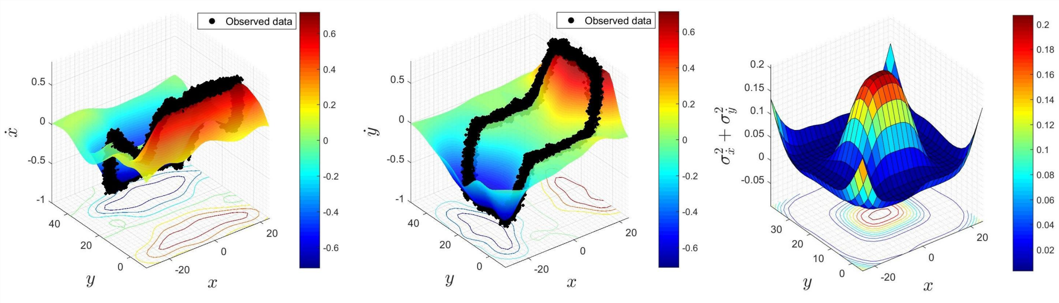


Representation of observed dynamic motion: Gaussian Process approach

- It is proposed to use a GP approach [3], such that:

$$\dot{\tilde{X}} = g(\tilde{X}) + v, \tag{1}$$

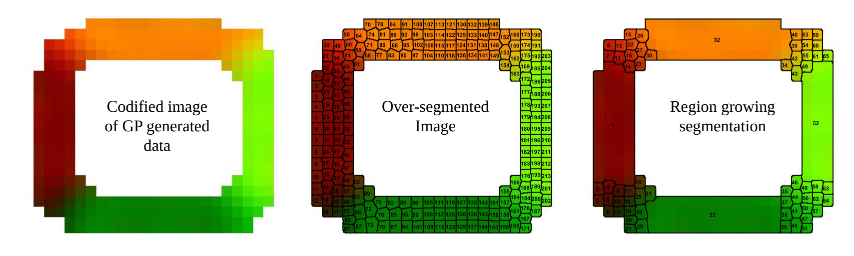
Where $\dot{\tilde{X}}$ represents an estimation of velocity, $g(\cdot)$ takes location information and estimates the expected motion (action) at such position for a given activity.



[3] K. Kim, D. Lee, and I. Essa, "Gaussian process regression flow for analysis of motion trajectories," pp. 1164–1171, 2011

Representation of observed dynamic motion: Superpixel algorithm

- Using a superpixel algorithm[4] to discretize the image plane into N zones:



- Linear dynamic model:

$$X_{k+1} = X_k + \Delta k U_{n,k} + w_m, \tag{2}$$

where $U_{n,k} = [\dot{x}_n, \dot{y}_n]^T$, is a control input that encodes the action (motivation) of the agent.

[4]Z. Li and J. Chen, "Superpixel segmentation using linear spectral clustering," in *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pp. 1356–1363, June 2015

Abnormality detection: Kalman filter method

- Building a set of Kalman Filters (KFs) based on the built dynamical models given the N zones.
- KFs' innovations can be used to express abnormalities since they quantify the deviations from normal learned models in the environment:

$$\epsilon_{k,n} = Z_k - \hat{X}^n_{k|k-1}, \tag{3}$$

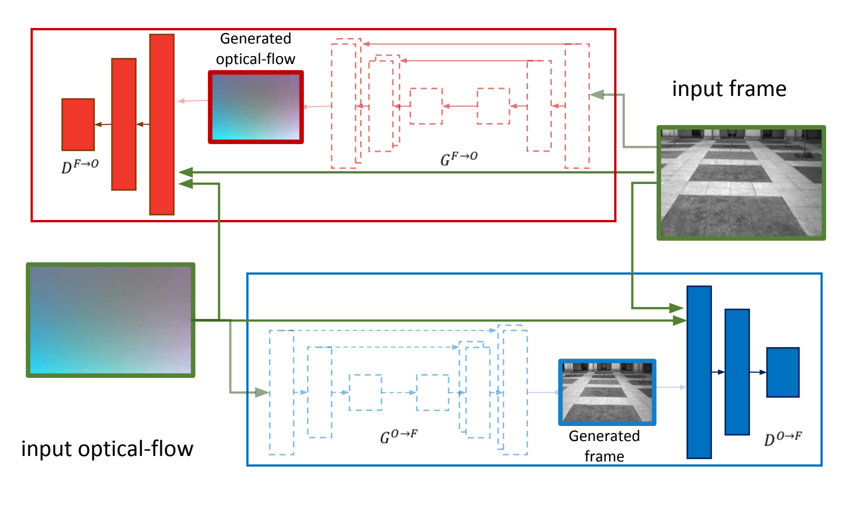
  where $\epsilon_{k,n}$ is the innovation generated in the zone n where the agent is located. Z_k represents observed spatial data and $\hat{X}^n_{k|k-1}$ is the KF estimation of the agent's location at the future time k calculated in the time instant $k-1$ (2).
- Innovation vectors are composed of two components, the magnitude of those vectors can be considered as a final measure of abnormality, ξ:

$$\xi_k = ||\epsilon_{k,n}||_2,$$

Private Layer of self-awareness

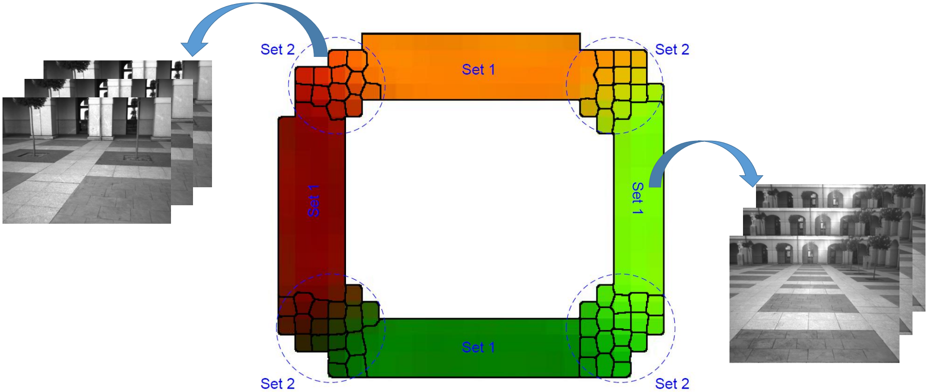
Learning the normal pattern of the observed scene

- Two networks (GANs[5]) structure are used to learn the normal pattern of the observed scene.



Learning the normal pattern of the observed scene

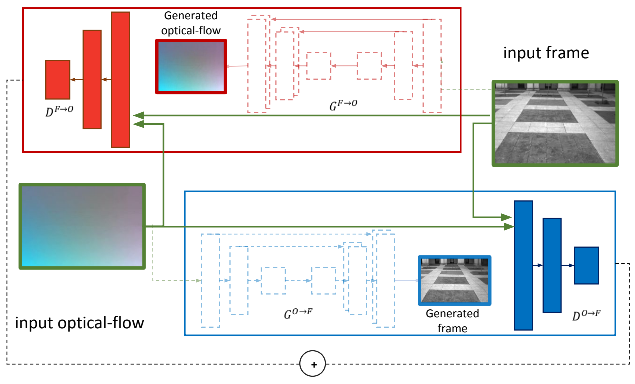
- Frames (F) and corresponding optical-flow images (O) are collected from the *normal* scenario.
- Constructing a *Bank of Discriminators* on the GP identified zones grouping into two sets:
  i) $Set1$: which is trained on a straight path.
  ii) $Set2$: that is trained over the curves.



Anomaly detection by using discriminators of GANs

1- Given a test frame F and its corresponding optical-flow image O, we first produce the reconstructed p_O and p_F using $G^{F\to O}$ and $G^{O\to F}$, respectively.

2- The pairs of patch-based discriminators $\hat{D}^{F\to O}$ and $\hat{D}^{O\to F}$ are applied respectively to the first and second tasks.



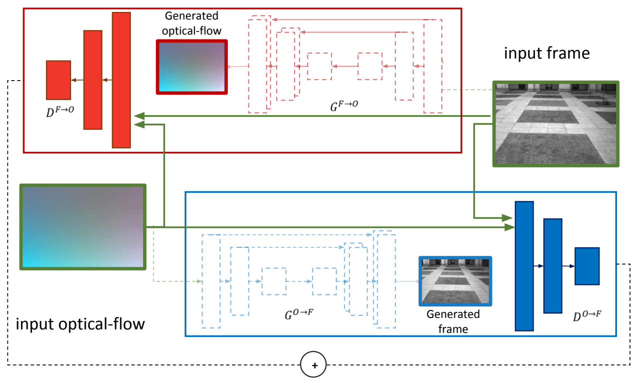
Anomaly detection by using discriminators of GANs

3- Computing scores for the ground truth: S^O and S^F, and the prediction: S^{p_O} and S^{p_F}.

4- Define abnormality as innovation w.r.t the Discriminators scores:

i) The two scores are summed: $S_{observation} = S^O + S^F$ and $S_{prediction} = S^{p_O} + S^{p_F}$

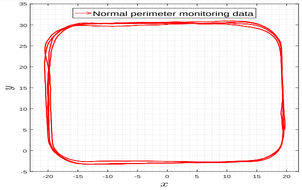
ii) Innovation: $\tilde{Y} = S_{observation} - S_{prediction}$



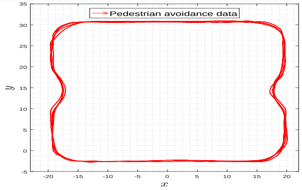
Results

Experimental setup

Proposed approach is validated with data acquired from a real vehicle 'iCab' during a perimeter monitoring task.



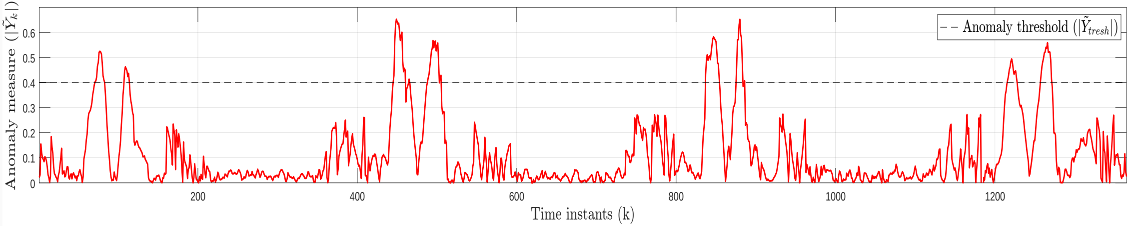
Perimeter monitoring



Pedestrian avoidance

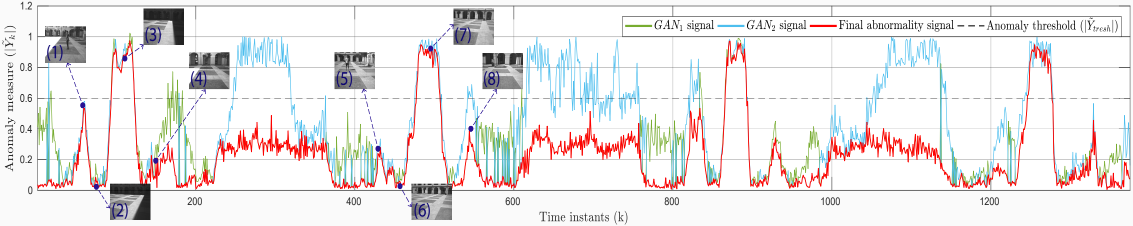
Pedestrian avoidance from 'iCab' on board camera

SL anomaly measurements: perimeter control activity by GP through time with avoidance of static pedestrians.



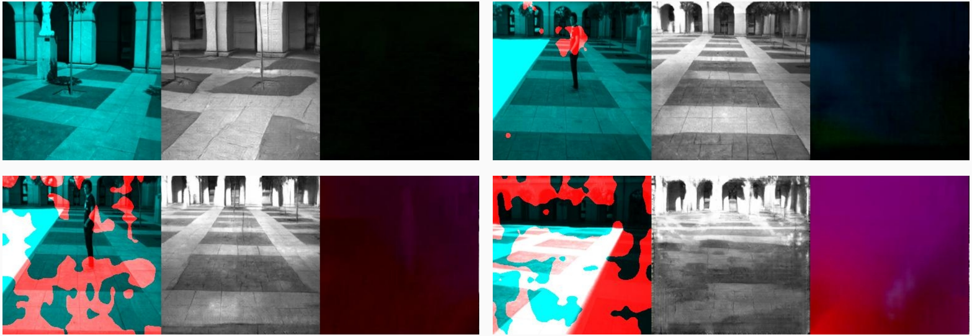
Private Level Self Awareness abnormality detection

PL anomaly measurements: the distances between the observations and predictions by GANs during the time.



Private Level Self Awareness abnormality detection

Visualization of local abnormality in first-person vision



Conclusions

Conclusions

- Self-awareness in autonomous system
- Shared and private layers for self-awareness
- Methodology based on multi-perspective approach to detect anomalies for moving agents
- SL and PL learned models are used to predict the dynamics of a vehicle performing a task

Thank you!

D. Ramík, C. Sabourin, R. Moreno, and K. Madani, "A machine learning based intelligent vision system for autonomous object detection and recognition," *Applied Intelligence*, vol. 40, no. 2, pp. 358–375, 2014.

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I. Goodfellow, J. Pouget-Abadie, M. Mirza, B. Xu, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio, "Generative adversarial nets," in *Advances in Neural Information Processing Systems 27* (Z. Ghahramani, M. Welling, C. Cortes, N. D. Lawrence, and K. Q. Weinberger, eds.), pp. 2672–2680, Curran Associates, Inc., 2014.