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

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Outline

Introduction

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   Representation of observed dynamic motion
   Abnormality detection by using Kalman filter method

Private Layer of self-awareness
   Learning the normal pattern of the observed scene
   Anomaly detection by using discriminators of GANs

Results
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Conclusions
Introduction
Generic self-awareness scheme

Exo-sensors

Endo-sensors

Shared actuators

Private actuators

External world

Body world

Operator

Interfaces

Self awareness

Exo-situation awareness

Autonomous decision system

Operator Commands

Exo-Situation awareness

Autonomous system commands

Self awareness info/commands

a) Supervised
b) Automatic / Unsupervised
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 \(^2\).


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

Abnormal situation
Shared Level of self-awareness
Sparse positions represents the Locations of the entity take from input video or sensor.
It is proposed to use a GP approach, such that:

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

(1)

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

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Representation of observed dynamic motion: Superpixel algorithm

- Using a superpixel algorithm\(^4\) to discretize the image plane into \(N\) zones:

- Linear dynamic model:

\[
X_{k+1} = X_k + \Delta kU_{n,k} + w_m, \tag{2}
\]

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

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:

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

(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 $\hat{X}_{k|k-1}^n$ 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, $\xi$:

$$
\xi_k = \|\epsilon_{k,n}\|_2,
$$
Private Layer of self-awareness
• Two networks (GANs\textsuperscript{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 $G^{F\rightarrow O}$ and $G^{O\rightarrow F}$, respectively.

2- The pairs of patch-based discriminators $\hat{D}^{F\rightarrow O}$ and $\hat{D}^{O\rightarrow F}$ are applied respectively to the first and second tasks.
3- Computing scores for the ground truth: $S^O$ and $S^F$, and the prediction: $S^{po}$ and $S^{pf}$.

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

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

ii) Innovation: $\tilde{Y} = S_{observation} - S_{prediction}$
Results
Proposed approach is validated with data acquired from a real vehicle ’iCab’ during a perimeter monitoring task.
Shared Level Self Awareness abnormality detection

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!


