

Implementing a Library to Calculate Surrogate Safety

A software library to calculate PET and speed values of road users

By: Mohammad Hossein Nazemi

Overview

1) Introduction

Traffic Safety, SSA and SSM,
PET and Speed, Our
Contribution

2) Background

Literature Review, Similar
Approaches, Shortcomings of
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3) Approach

PET Detection and Calculation
Module, Average and
Momentary Speed Module

4) Validation

PET Validations and
Experiments, Speed
Validation Experiment

Introduction

Traffic Safety, SSA and SSM, PET
and Speed, Our Contribution



Traffic Safety



Traffic Safety – Problems of Crash Data

1. Do not happen that frequently



Traffic Safety – Problems of Crash Data

1. Do not happen that frequently
2. Do not include useful information



Traffic Safety – Problems of Crash Data

1. Do not happen that frequently
2. Do not include useful information
3. Hard to differentiate between random occurrence or statistical crashes



Traffic Safety – Problems of Crash Data

1. Do not happen that frequently
2. Do not include useful information
3. Hard to differentiate between random occurrence or statistical crashes
4. Do not show the behavior of road users before the crash

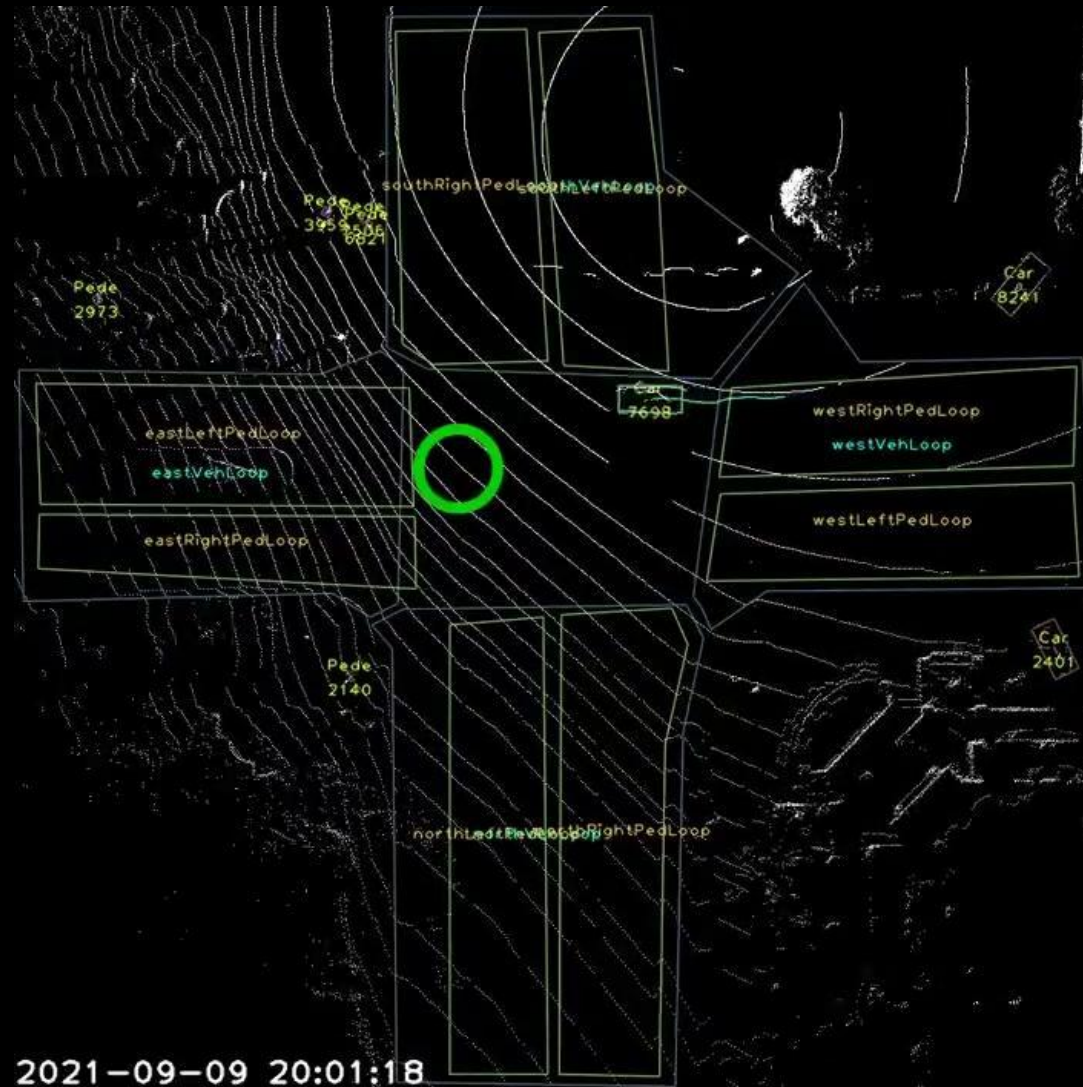


Surrogate Safety Analysis

- Various surrogate safety measures like **PET**, TTC, deceleration rate, and **Speed**
- Studies showed the relations between surrogate safety measures and crash data
- In this work we focused on two measures, **PET** and **Speed**



Post Encroachment Time (PET)



Speed

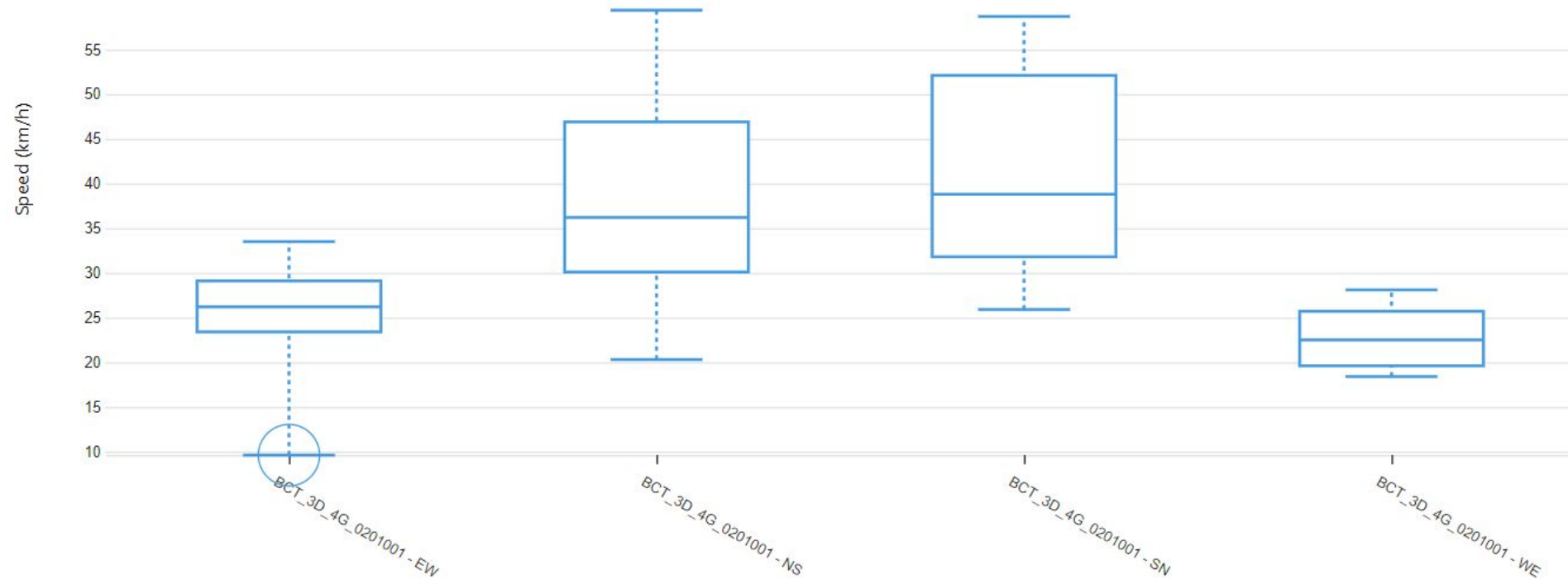


Speed



Speed

1. Momentary Speed
2. Average Speed



What We Have Done

- Automated PET Detection and Calculation Module

Characteristics

What We Have Done

- Automated PET Detection and Calculation Module

Characteristics

- Decoupled

What We Have Done

- Automated PET Detection and Calculation Module

Characteristics

- Decoupled
- Realtime/Continuous

What We Have Done

- Automated PET Detection and Calculation Module

Characteristics

- Decoupled
- Realtime/Continuous
- Precise

What We Have Done

- Automated PET Detection and Calculation Module

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- Decoupled
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- Generalized

What We Have Done

- Automated PET Detection and Calculation Module

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- Decoupled
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- Easy to use

What We Have Done

- Automated PET Detection and Calculation Module

Characteristics

- Decoupled
- Realtime/Continuous
- Precise
- Generalized
- Easy to use
- Fault tolerant

What We Have Done

- Automated PET Detection and Calculation Module
- Momentary and Average Speed Calculation Module

Characteristics

What We Have Done

- Automated PET Detection and Calculation Module
- Momentary and Average Speed Calculation Module

Characteristics

- Decoupled

What We Have Done

- Automated PET Detection and Calculation Module
- Momentary and Average Speed Calculation Module

Characteristics

- Decoupled
- Realtime/Continuous

What We Have Done

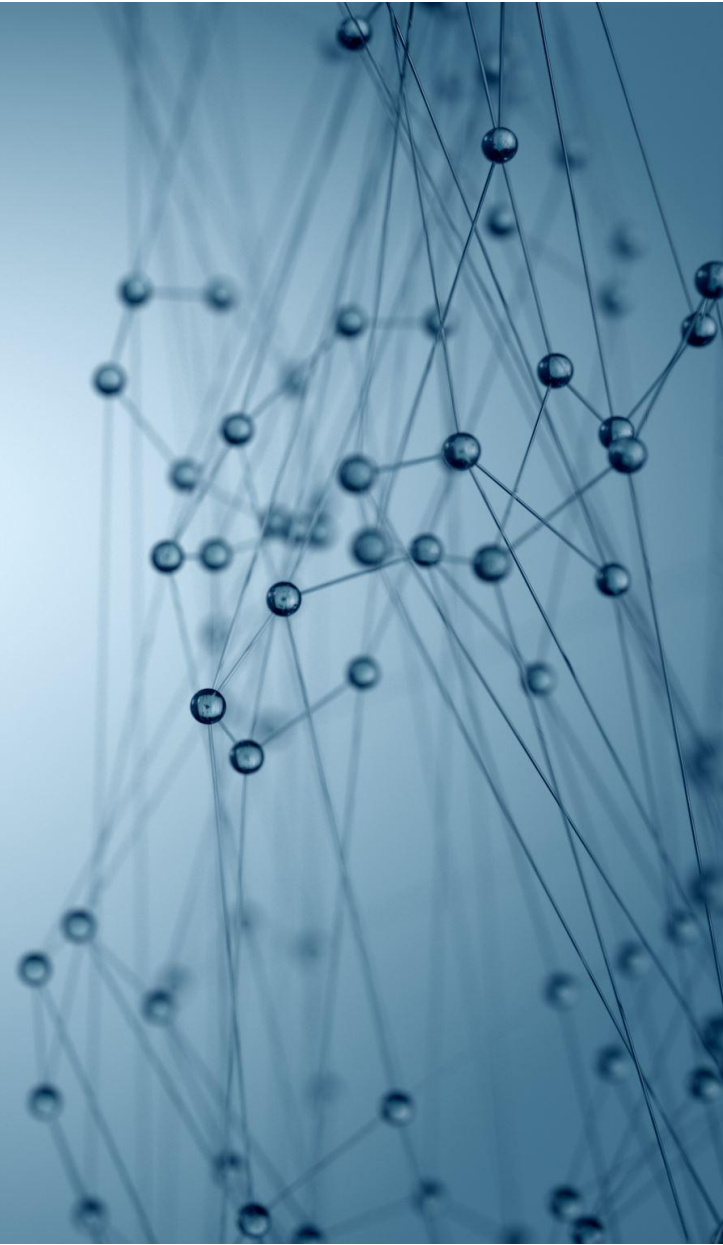
- Automated PET Detection and Calculation Module
- Momentary and Average Speed Calculation Module

Characteristics

- Decoupled
- Realtime/Continuous
- Easy to use

Background

Literature Review, Related Works



Case Studies

| | | | | | |
|--|--|--|--|---|---|
| <p>Check for updates</p> <p>An automated safety diagnosis of urban roadways using a deep learning approach</p> <p>Paul St-Aubin^{a,*}, Paul St-Aubin^a, Paul St-Aubin^a</p> <p>^a Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^b Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>ARTICLE INFO</p> <p>Article history: Received 11 February 2019 Received in revised form 21 September 2019 Accepted 22 October 2019 Available online 10 November 2019</p> <p>Keywords: Driver behaviour Automated safety Highway ramps Time-to-collision Road user interaction Video data Trajectory</p> <p>1. Introduction</p> <p>An important design and time period to prove insufficient mental factors or unreliable, or collecting, or pilot projects, or occur. To this of observation. The surrogate interactions in</p> <p>* Corresponding author. E-mail address: paul.st-aubin@utoronto.ca (P. St-Aubin).</p> <p>0969-6936/\$ - see front matter © 2019 Elsevier B.V.</p> | <p>Check for updates</p> <p>Applying a deep learning approach to detect safety hazards in urban roadways</p> <p>Mohamed H. Elshorbagy^{a,*}, Mohamed H. Elshorbagy^a, Mohamed H. Elshorbagy^a</p> <p>^a Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^b Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^c Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2019 Received in revised form 21 September 2019 Accepted 22 October 2019 Available online 10 November 2019</p> <p>Keywords: Cycle track Cyclist safety Video analysis Surrogate safety measure Random effects model</p> <p>1. Introduction</p> <p>In recent years, cities have been investing in cycle infrastructure. To follow Europe and Asia, cities meeting their need for infrastructure, developing these advances, cycling (Mackenzie, 2014), while</p> <p>* Corresponding author. E-mail address: mohamed.h.elsorbagy@utoronto.ca (M.H. Elshorbagy).</p> <p>0969-6936/\$ - see front matter © 2019 Elsevier B.V.</p> | <p>Check for updates</p> <p>Automated detection of encroachment and vehicle interactions at roundabouts</p> <p>David Beitel^{a,*}, David Beitel^a, David Beitel^a</p> <p>^a Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^b Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^c Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2019 Received in revised form 21 September 2019 Accepted 22 October 2019 Available online 10 November 2019</p> <p>Keywords: Automated video analysis Surrogate safety measure Pedestrian Cyclist Nonmotorized Shared space</p> <p>1. 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Beitel).</p> <p>0969-6936/\$ - see front matter © 2019 Elsevier B.V.</p> | <p>Check for updates</p> <p>Automated detection of encroachment and vehicle interactions at roundabouts</p> <p>Yina Wu^{a,*}, Yina Wu^a, Yina Wu^a</p> <p>^a Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^b Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^c Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2019 Received in revised form 21 September 2019 Accepted 22 October 2019 Available online 10 November 2019</p> <p>Keywords: Automated video analysis Surrogate safety measure Pedestrian Cyclist Nonmotorized Shared space</p> <p>1. Introduction</p> <p>In recent years, cities have been investing in cycle infrastructure. 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Garcia^a</p> <p>^a Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^b Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>^c Department of Civil Engineering, University of Toronto, 2800, Canada</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2019 Received in revised form 21 September 2019 Accepted 22 October 2019 Available online 10 November 2019</p> <p>Keywords: Automated video analysis Surrogate safety measure Pedestrian Cyclist Nonmotorized Shared space</p> <p>1. Introduction</p> <p>In recent years, cities have been investing in cycle infrastructure. To follow Europe and Asia, cities meeting their need for infrastructure, developing these advances, cycling (Mackenzie, 2014), while</p> <p>* Corresponding author. E-mail address: ting.fu@utoronto.ca (T. Fu).</p> <p>0969-6936/\$ - see front matter © 2019 Elsevier B.V.</p> |
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USING AUTOMATED VIDEO PROCESSING TO IDENTIFY PEDESTRIAN-VEHICLE CONFLICTS

A Dissertation Presented to The Academic Faculty

by

Spencer Maddox

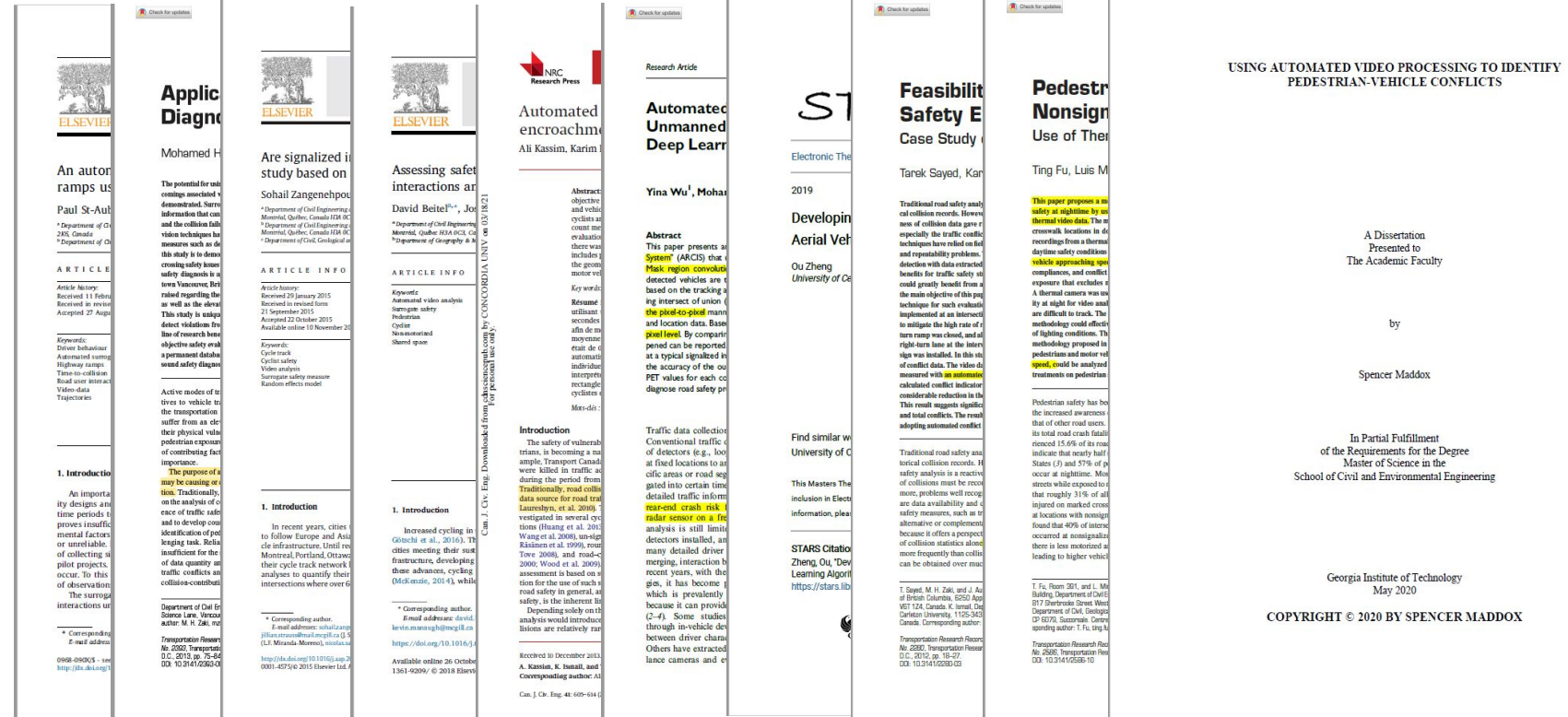
In Partial Fulfillment of the Requirements for the Degree Master of Science in the School of Civil and Environmental Engineering

Georgia Institute of Technology May 2020

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Case Studies

- Decoupled
- Realtime/Continuous
- Precise
- Generalized
- Easy to use
- Fault tolerant



Case Studies

• Focus on the Automated SSM Module



An automated surrogate safety analysis at protected highway ramps using cross-sectional and before-after video data

Paul St-Aubin^{a,b}, Luis Miranda-Moreno^{a,*}, Nicolas Saunier^b

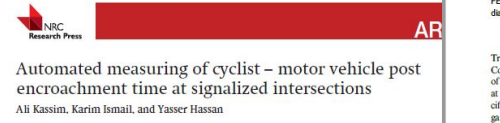
ABSTRACT
This study presents a method for surrogate safety analysis to investigate the safety of limited-access highway facilities. The proposed methodology is based on automated trajectory collection and behavioural analysis from surrogate safety measures (in particular, time-to-collision). The methodology is applied to a sample of urban highway sections at on-ramps and off-ramps to study the effectiveness of a lane-change ban treatment in Montreal, Canada. To the authors' knowledge, this analysis of real sites, the application of a convolutional neural network (CNN) to aggregate the data, spatially and temporally, and the use of a surrogate safety measure (SSM) that is not a statistically significant indicator of crash risk are novel. The results show that the coefficient of determination between the AM and MCM methods was low, there was a very good agreement in the PET classification of individual conflicts between the MFCM and AM methods, and that the start of the treatment stream causing increased lane-change

1. Introduction
An important area of research in road safety is the identification of the site types and design and countermeasures. Typically, this type of research relies on time periods to overcome the problem of long return periods between collisions. However, when evaluating new designs or countermeasures, fundamental factors change significantly over time, or when collision data are sparse or unreliable. In addition, the unknown conditions of newly proposed designs of collecting sizeable amounts of historical data as practitioners are reluctant to collect data. In a broader sense, we still face the challenge of evaluating interventions. To this end, more proactive analysis techniques need to be introduced. Observations collected over shorter periods of time. The surrogate safety approach substitutes the long return period of real interactions under driving conditions. An interaction is the relationship between

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http://dx.doi.org/10.1016/j.trc.2013.08.015

well as the driver. This study is unique, detect violations for the use of research to improve safety and permanent data would safety diagnosis. Active mode of the driver to vehicle to the transportation suffer from an due to their physical value, pollution exposure of controlling factor importance. The purpose of a may be causing an risk. Traditionally, on the analysis of a cause of traffic risk and to develop an identification of pre-empting task. Both insufficient for the of data quantity as traffic conflicts an analysis-contribution.

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Abstract: Conflicts between motor vehicle and cyclists at a signalized intersection were characterized in an objective conflict indicator: post encroachment time (PET). A total of 384 conflict events for PET (s, 3) second and vehicles were analyzed in this study. An automated video analysis technique was developed to measure cyclist and motor vehicle. The results of the conflict analysis showed that the average absolute error of PET count measurement (MFCM) and automated measurement (AM) methods was 0.12 s and the standard deviation of the results showed that the coefficient of determination between the AM and MFCM methods was low. There was a very good agreement in the PET classification of individual conflicts between the MFCM and AM methods. This includes procedures to better interpret the conflict point of the motor vehicle and the cyclist in an automated the geometry of the bounding box and direction of the travel, which appears to be a contribution for the automated vehicle collisions.

Keywords: signalized intersection, traffic data collection, cyclists, conflicts.
Résumé : Des conflits entre automobilistes et cyclistes à un carrefour à feux ont été caractérisés dans la littérature à l'aide d'indicateurs objectifs de conflits, le temps post-encrochement (PET). Un total de 384 conflits post-secondes entre les cyclistes et les véhicules à ont été analysés. Une technique d'analyse automatisée développée afin de mesurer le PET entre cyclistes et véhicules motorisés. Les résultats de l'analyse de conflits montrent que l'erreur absolue moyenne du PET mesuré par les méthodes MFCM et la mesure automatisée était de 0,12 seconde. Le résultat de l'évaluation montre que le coefficient de détermination entre les méthodes automatisées et celles du MFCM était de 0,08 et que la corrélation était excellente dans le classement de conflits individuels entre les méthodes MFCM et de mesure automatisée. La présente étude comprend des procédures pour mieux interpréter le point de conflit du véhicule motorisé et du cycliste de manière automatisée (en se basant sur le rectangle de délimitation et la direction de voyage), ce qui semble être une contribution à l'analyse de conflits et véhicules motorisés. (Traduit par la Rédaction)

Introduction
The safety of vulnerable road users, such as cyclists and pedestrians, is becoming a national and a worldwide concern. For example, Transport Canada reported that across Canada, 60 cyclists were killed in traffic accidents with motor vehicles each year during the period from 2004 to 2006 (Transport Canada 2009). Traditionally, road collision statistics are considered as the main data source for road traffic safety analysis (Chen and Quake 1997; Laurey et al. 2009). Thus, cyclist-involved collisions were investigated in several cyclist safety studies at signalized intersections (Ding et al. 2012; Jensen 2008; Wang and Nihan 2004; Wang et al. 2008), unsignalized intersections (Sumathi et al. 1996; Rasmussen et al. 1999), roundabouts (Sakshing et al. 2010; Metro and Tove 2008), and road-cyclist-path intersections (Blunter et al. 2000; Wood et al. 2009). An alternative approach to road safety assessment is based on surrogate measures of safety. The motivation for the use of such surrogate measures of safety in analyzing road safety in general, and more specifically in examining cyclist safety, is the inherent limitations in collision data. Depending solely on the reported collision data for traffic safety analysis would introduce several possible shortcomings. First, collisions are relatively rare events that require extended observation time to monitor stable trends. For example, before and after safety evaluation is typically based on a few years of collision records to detect change in safety. Also, it is relatively difficult to observe, record (by means of a video camera or auditory sensors), and analyze the failure mechanism leading to collisions in comparison to traffic conflicts (Hydén 1987). Second, underreporting of collisions, the level of which depends on collision severity and the type of road users involved, is also a shortcoming of reported collisions data (Laurey et al. 2009). Third, collision data does not typically provide complete information about the collision process. For example, pre-collision road users' behaviour is usually not reported (Laurey et al. 2009). Surrogate measures of safety can therefore be used to evaluate the safety of road users, especially when the availability of collision data are limited in quantity or quality. These measures have been used in practice to assess the safety of current and proposed roadways (Sayed et al. 1994; Persaud and Mucsi 1995; Peter and Pohlman 1994; Rao and Rengasamy 1998). Traffic conflict techniques represent one of the key surrogate measures of safety, among other measures (Thompson and Perkins 1982; Fitzpatrick et al. 2008). However, due to the subjectivity of field observers, errors were common when manually counting and deciding or judging

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Automated Safety Diagnosis Based on Unmanned Aerial Vehicle Video and Deep Learning Algorithm

Yina Wu¹, Mohamed Abdel-Aty¹, Ou Zheng¹, Qing Cai¹, and Shile Zhang¹

Abstract
This paper presents an automated traffic safety diagnostics solution named "Automated Roadway Conflict Identification System" (ARCIS) that uses deep learning techniques to process traffic videos collected by unmanned aerial vehicle (UAV). Mask region convolutional neural network (R-CNN) is employed to improve detection of vehicles in UAV videos. The detected vehicles are tracked by a channel and spatial reliability tracking algorithm, and vehicle trajectories are generated based on the tracking algorithm. Missing vehicles can be identified and tracked by identifying stationary vehicles and comparing intersection of union (IOU) between the detection results and the tracking results. Rotated bounding rectangles based on the pixel-to-pixel manner masks that are generated by mask R-CNN detection are introduced to obtain precise vehicle size and location data. Based on the vehicle trajectories, post-encroachment time (PET) is calculated for each conflict event at the pixel level. By comparing the PET values and the threshold, conflicts were reported. Various conflict types (rear-end, head-on, sideswipe) at a typical signalized intersection is presented, the results indicate that the accuracy of the output data. Moreover, safety diagnostics for the PET values for each conflict event. It is expected that the proposed diagnose road safety problems efficiently and appropriate countermeasures.

Traffic data collection is vital for traffic safety analysis. Conventional traffic data collection relies on thousands of detectors (e.g., loop detectors, radar sensors) located at fixed locations to analyze the traffic conditions for specific areas or road segments. The data are usually aggregated into certain time intervals (e.g., 30s, 5 min) without detailed traffic information. In 2010, Wu et al. analyzed recent crash risk for individual vehicles through a radar sensor on a freeway location (1). However, such analysis is still limited to certain locations that have detectors installed, and the detectors could not monitor many detailed driver behaviors, such as lane changing, merging, interaction between road users, and so forth. In recent years, with the development of various technologies, it has become possible to collect trajectory data, which is prevalently utilized in traffic safety research because it can provide more detailed traffic information (2–4). Some studies have collected trajectory data through in-vehicle devices to investigate the relationship between driver characteristics/behaviors and crash risk. Others have extracted road users' trajectories by surveillance cameras and evaluated safety conditions for the

technique for each vehicle implemented at an intersection to mitigate the high rate of a near-range was closed, and all right-turn lanes at the intersection was installed. In this case of conflict data. The video of measured with an automatic rotated conflict indicator considerable reduction in this result suggests significant and total conflicts. The result adjusting automated conflict.

Traditional road safety and traffic collision records. If safety analysis is a measure of collisions must be more, problems will emerge data availability and safety measures, such as it alternative or complementary because it offers a prospect of collision statistics along more frequently than collision can be obtained over time.

T. Sayed, M. A. Abdel-Aty, and J. A. of British Columbia, 6050 Appleton Ave., Vancouver, BC V6T 1Z2, Canada; K. Abdel-Aty, Carleton University, 1125-3433, Ottawa, Ontario, Canada.

Transportation Research Board, No. 2000, Transportation Research Board, 4005, Washington, D.C., 20018-1092, USA.

USING AUTOMATED VIDEO PROCESSING TO IDENTIFY PEDESTRIAN-VEHICLE CONFLICTS

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Calculating speeds of crossing vehicles, pedestrian-vehicle conflicts (PVCs), exposure based on PET, calculated detection PET, conflict ratios, and yielding compliance ratios.

Case Studies

- Focus on the Automated SSM Module
- Decoupled



- Focus on the Automated SSM Module
- Decoupled
- Realtime/Continuous

Case Studies

- Focus on the Automate Module
- Decoupled
- Realtime/Continuous
- Precision





that uses **deep learning** and **evolutionary neural networks** are tracked by a clustering algorithm. Mission (ICU) between **in a manner** masks that is. Based on the vehicle impairing the PET value reported. Various conflict-sized intersection is p the output data. More each conflict event. It safety problems efficien

tion is vital for traffic data collection (e.g., loop detectors, video cameras) to analyze the traffic on road segments. The data are in time intervals (e.g., 5 min). In 2011, the risk for individual drivers in a freeway location is limited to certain road types, and the detector can monitor driver behaviors, such as the interaction between road users with the development of a system that is possible to consistently utilized in traffic management. In the

Case Studies

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Case Studies

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Case Studies

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| | | | | | | | | | |
|---|--|---|---|--|--|--|--|--|---|
| <p>An automated safety diagnosis for urban ramps</p> <p>Paul St-Aubin</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 11 February 2020 Received in revised form 27 August 2020 Accepted 27 August 2020</p> <p>Keywords: Driver behaviour Automated driving Highway ramps Traffic collisions Road user interaction Video data Trajectory analysis</p> <p>1. Introduction</p> <p>An important design and time period to consider in the development of automated driving systems is the period of time when the vehicle is in the process of merging into the main traffic flow. This period is often referred to as the "critical period" and is characterized by a high risk of collisions. The purpose of this paper is to present a methodology for the automated diagnosis of safety issues in urban ramps. The methodology is based on the analysis of video data collected from a camera mounted on a vehicle. The methodology is able to detect and classify safety issues in urban ramps. The methodology is able to detect and classify safety issues in urban ramps. The methodology is able to detect and classify safety issues in urban ramps.</p> <p>[*] Corresponding author. E-mail address: paul.st-aubin@usherbrooke.ca (P. St-Aubin).</p> <p>Transportation Research Part C, 2021, pp. 75-84 DOI: 10.1016/j.trc.2020.10.001</p> | <p>Applicability of automated safety diagnosis for urban ramps</p> <p>Mohamed H. Elshorbagy</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. This increase has led to a corresponding increase in the number of traffic collisions. The purpose of this paper is to present a methodology for the automated diagnosis of safety issues in urban ramps. 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Elshorbagy).</p> <p>Transportation Research Part C, 2021, pp. 75-84 DOI: 10.1016/j.trc.2020.10.001</p> | <p>Are signalized intersections safe for automated vehicles?</p> <p>Sohail Zangenehpour</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. This increase has led to a corresponding increase in the number of traffic collisions. 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Zangenehpour).</p> <p>Transportation Research Part C, 2021, pp. 75-84 DOI: 10.1016/j.trc.2020.10.001</p> | <p>Assessing safety of automated vehicle interactions at signalized intersections</p> <p>David Bellet, Joelle Vanasse, and David Bellet</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. 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Bellet).</p> <p>Transportation Research Part C, 2021, pp. 75-84 DOI: 10.1016/j.trc.2020.10.001</p> | <p>Automated encroachment detection for automated vehicles</p> <p>Ali Kassim, Karim El Ghomari, and Ali Kassim</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. 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Kassim).</p> <p>Transportation Research Part C, 2021, pp. 75-84 DOI: 10.1016/j.trc.2020.10.001</p> | <p>Automated detection of encroachment for automated vehicles</p> <p>Yina Wu, Mohamed Elshorbagy, and Yina Wu</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. This increase has led to a corresponding increase in the number of traffic collisions. 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Garcia, and Ting Fu</p> <p>[*] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[†] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>[‡] Department of Civil Engineering, Université de Sherbrooke, Québec, Canada J1K 2R1</p> <p>ARTICLE INFO</p> <p>Article history: Received 20 January 2020 Received in revised form 27 September 2020 Accepted 22 October 2020 Available online 10 November 2020</p> <p>Keywords: Automated driving Video analysis Trajectory analysis Safety diagnosis Urban ramps</p> <p>1. Introduction</p> <p>In recent years, cities around the world have been experiencing a rapid increase in the number of vehicles on their roads. This increase has led to a corresponding increase in the number of traffic collisions. The purpose of this paper is to present a methodology for the automated diagnosis of safety issues in urban ramps. 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|---|--|---|---|--|--|--|--|--|---|

USING AUTOMATED VIDEO PROCESSING TO IDENTIFY PEDESTRIAN-VEHICLE CONFLICTS

A Dissertation Presented to The Academic Faculty

by

Spencer Maddox

In Partial Fulfillment of the Requirements for the Degree Master of Science in the School of Civil and Environmental Engineering

Georgia Institute of Technology May 2020

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Case Studies

- Focus on the Automated SSM Module
- Decoupled
- Realtime/Continuous
- Precise
- Generalized
- Easy to use
- Fault tolerant



Case Studies

- Focus on the Automated SSM Module
- Decoupled
- Realtime/Continuous
- Precise
- Generalized
- Easy to use
- Fault tolerant
- Combination of multiple SSMs



Approach

Serializer, PET Module, Noise Cancelation Modules,
Momentary Speed Module, Average Speed Module



PET

Serializer, PET Module, Noise Cancelation Modules

Speed

Momentary Speed Module, Average Speed Module

PET

Serializer, PET Module, Noise Cancelation Modules

Speed

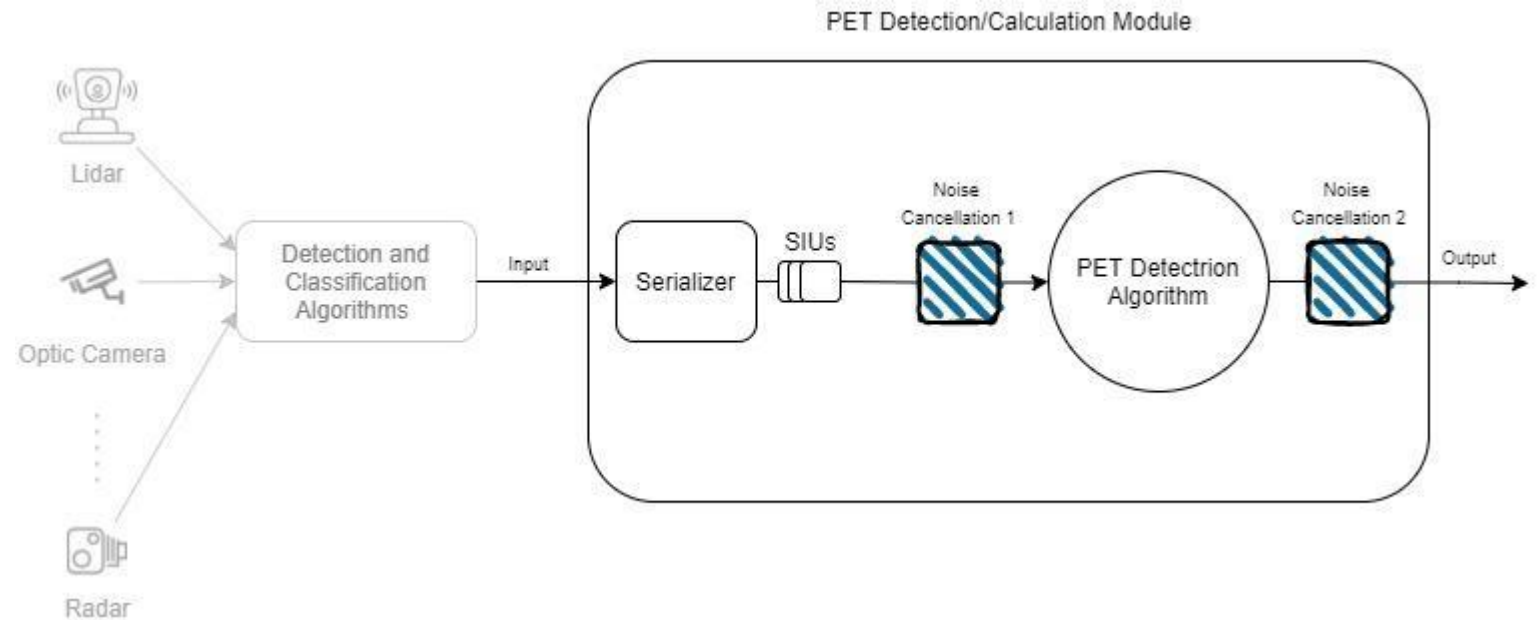
Momentary Speed Module, Average Speed Module

PET: Characteristics

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant

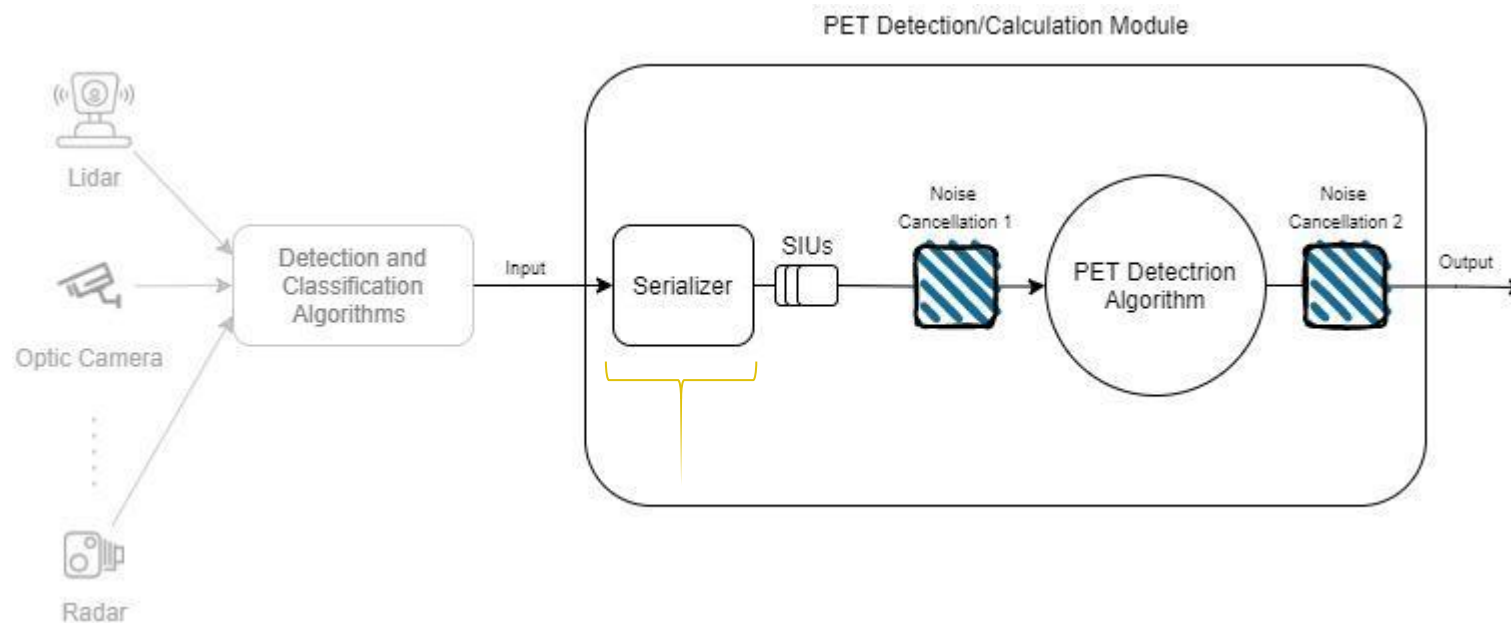
PET: Characteristics

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant



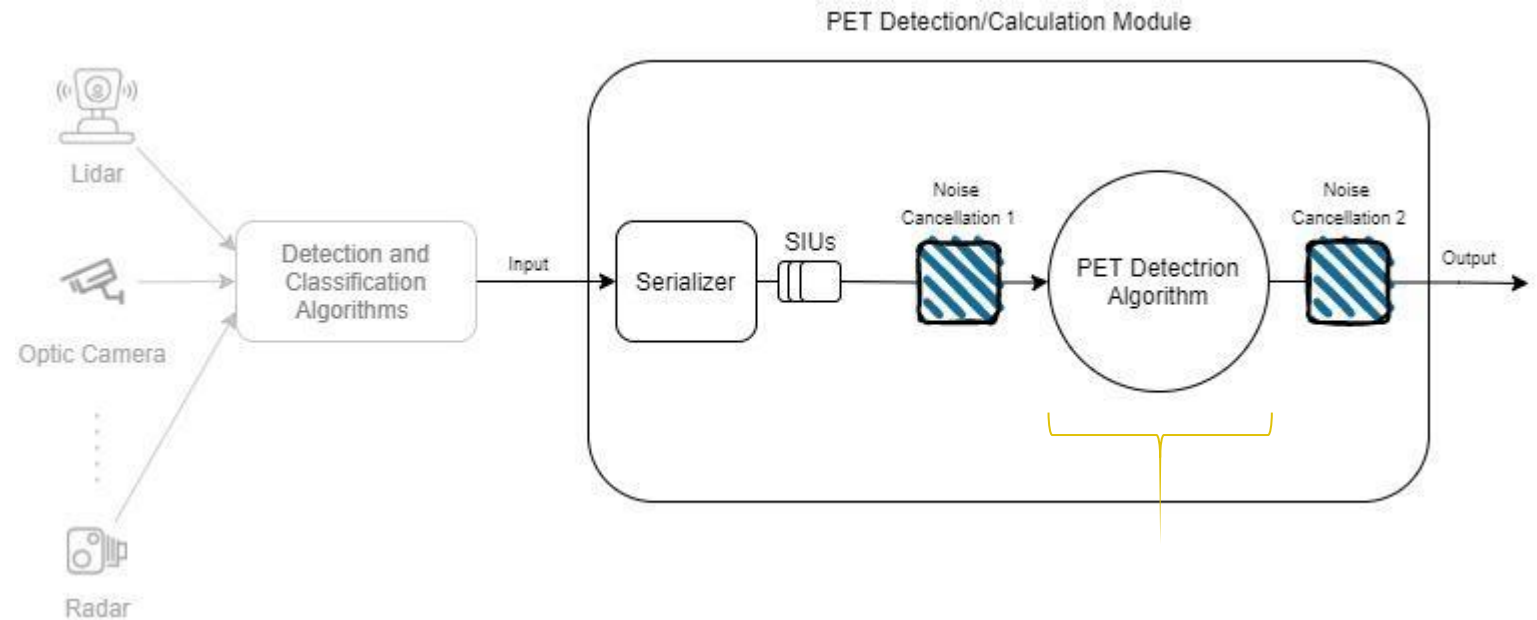
PET: Serializer

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant



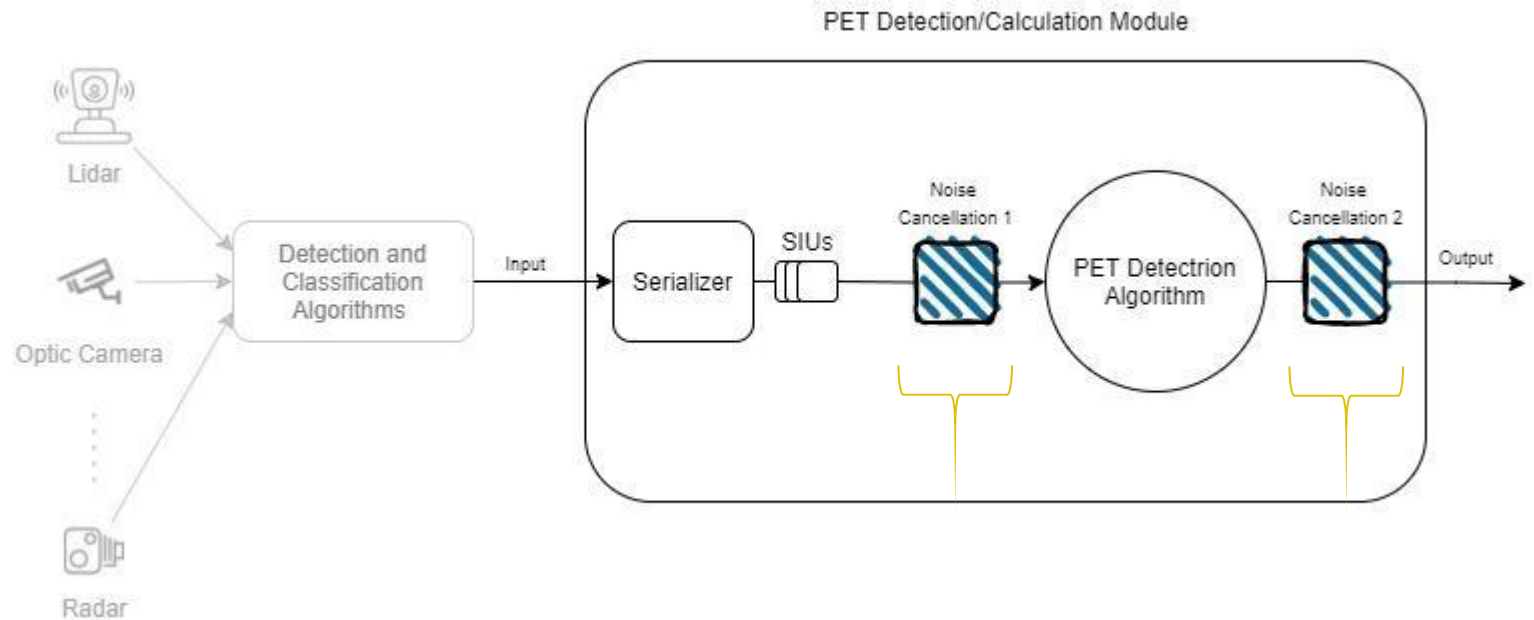
PET: Detection Module

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant



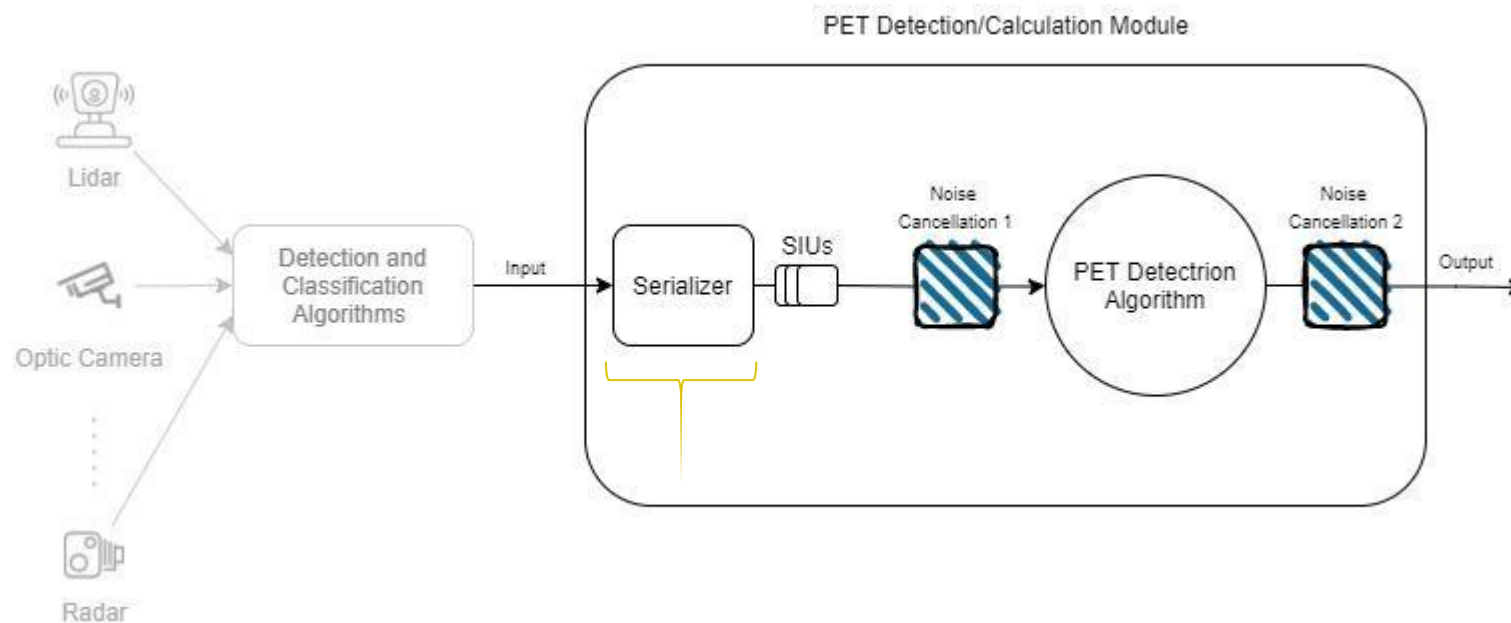
PET: Noise Cancellation

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. **Fault tolerant**



PET: Serializer

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant



Inputs of Serializer

1. Object ID
2. X and Y position in frame
3. Width and length of bounding box
4. Rotation of the bounding box in frame
5. ClassType of the object

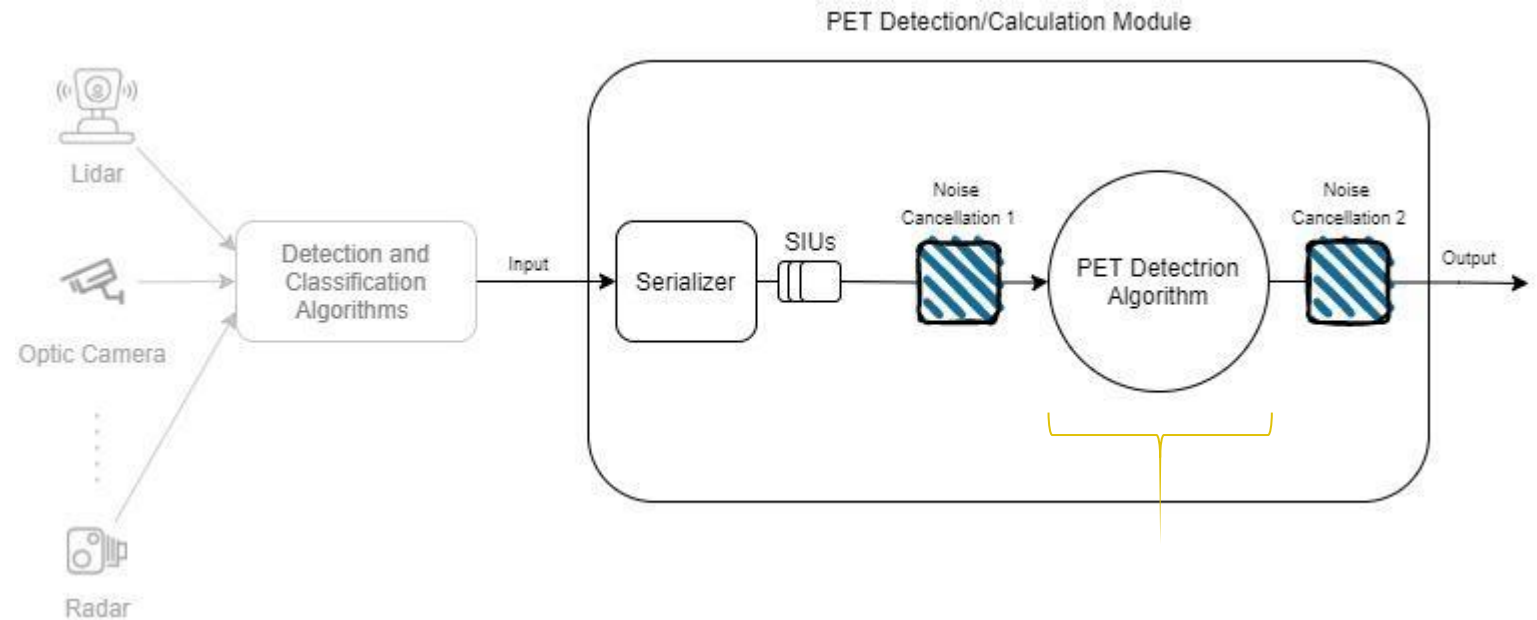
Output:

Standard Input Unit (SIU)

*timestamp,objectId_1,centerX_1,century_1,width_1,length_1,
angle_1,classType_1,objectId_2,centerX_2,century_2,width_2,
length_2,angle_2,classType_2,<End of the SIU Token>*

PET: Detection Module

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant

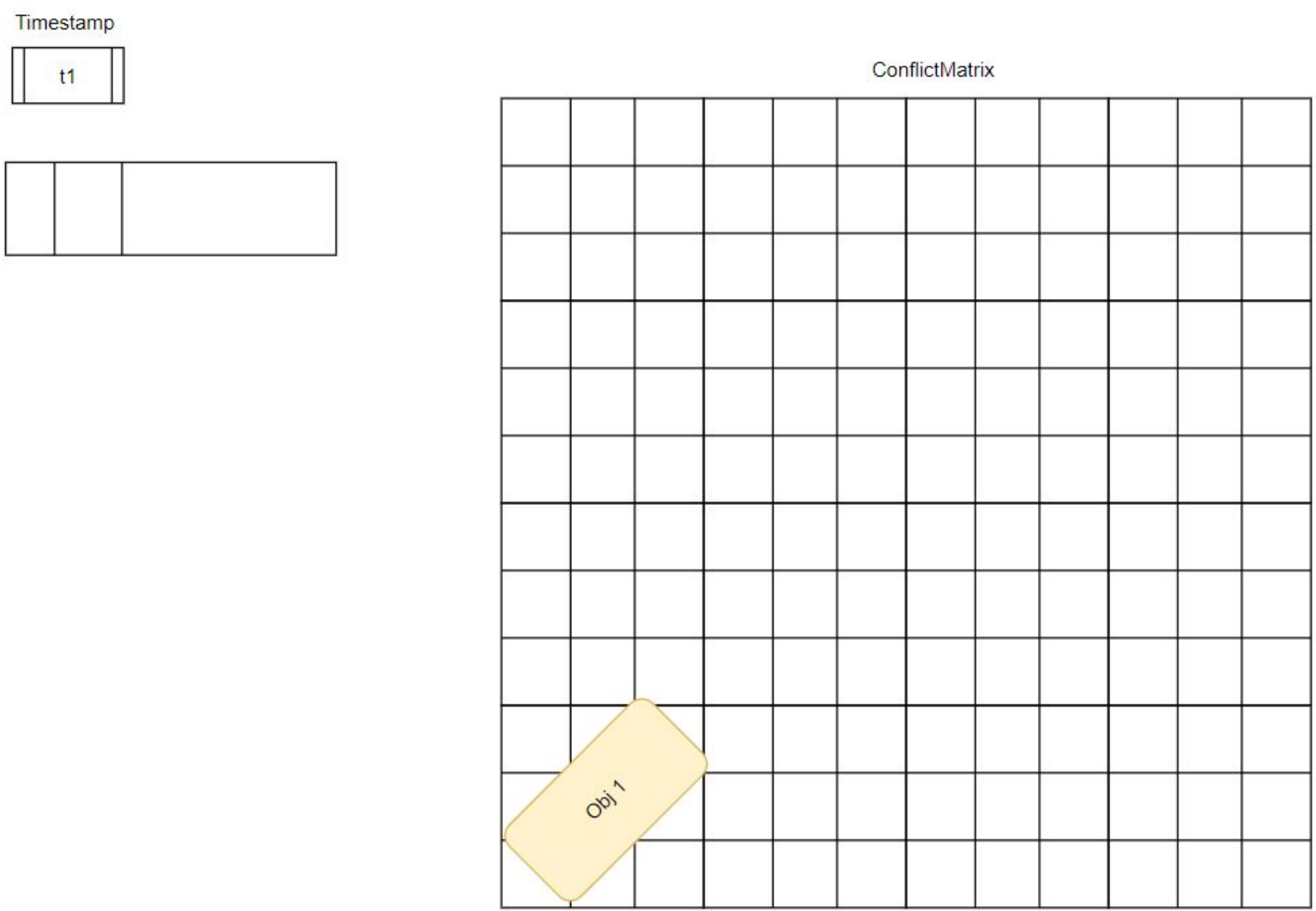


PET: Detection and Calculation

- Overall process consists of following steps:
 1. Fetching a SIU
 2. For each object:
 1. Calculate **area pixels**
 2. Fetch **conflicts** candidates
 3. Apply **filters**
 4. Submit objects in the **conflict matrix**

PET: Detection and Calculation

- Overall process:
 1. Fetch
 2. For each
 1. C
 2. F
 3. A
 4. S



PET: Detection and Calculation

- Overall process:
 1. Fetch
 2. For each element:
 1. Compare
 2. Find
 3. Add
 4. Sort

Timestamp

| |
|----|
| t2 |
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| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| | | |

ConflictMatrix

[illegible]

PET: Detection and Calculation

- Overall process
- 1. Fetch
- 2. For each
- 1. C
- 2. F
- 3. A
- 4. S

Timestamp

| |
|----|
| t7 |
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| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |

ConflictMatrix

| | | | | | | | | | | | | |
|-------|---|---|---|---|---|---|---|---|---|---|---|--|
| | | | | | | | | | | | | |
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| | | | | | | | | | | | | |
| | | | | | | | | 4 | 4 | 5 | 5 | |
| | | | | | | | 4 | 4 | 4 | 5 | 5 | |
| Obj 2 | | | | | 3 | 3 | 4 | 4 | 4 | | | |
| | | | | 3 | 3 | 3 | | | | | | |
| | | | 2 | 2 | 3 | 3 | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | 2 | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

PET: Detection and Calculation

- Overall process
- 1. Fetch
- 2. For each
- 1. C
- 2. F
- 3. A
- 4. S

Timestamp

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|----|
| t8 |
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| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |
| 6 | t7 | Obj 2 |

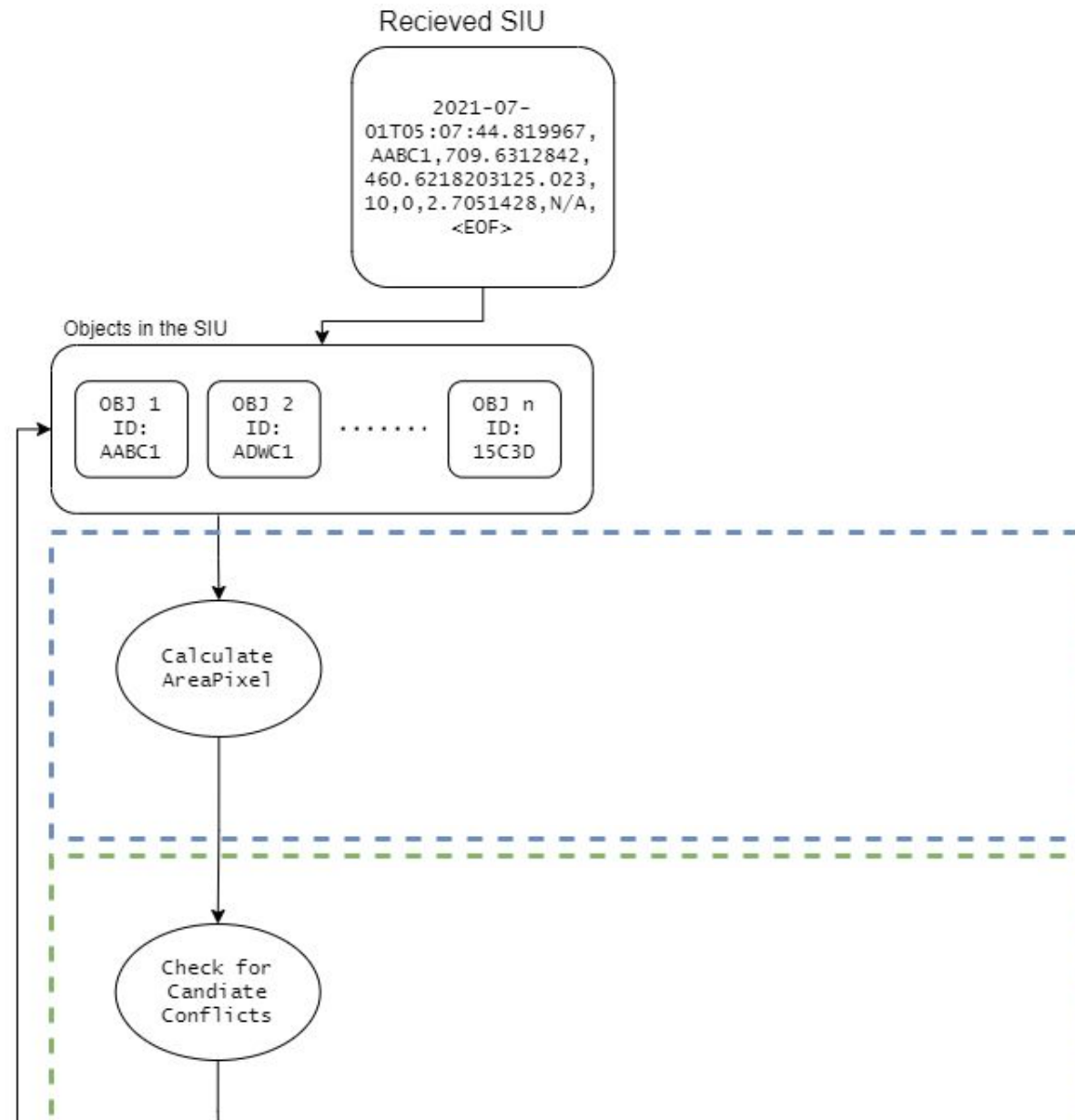
ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
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| | | | | | | | | | | | | |
| | | | | | | | | | 4 | 4 | 5 | 5 |
| 6 | 6 | 6 | | | | | 4 | 4 | 4 | 5 | 5 | |
| 6 | 6 | 6 | | | | 3 | 3 | 4 | 4 | 4 | | |
| | | | | 3 | | 3 | 3 | | | | | |
| | | | 2 | 2 | 3 | 3 | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | 2 | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

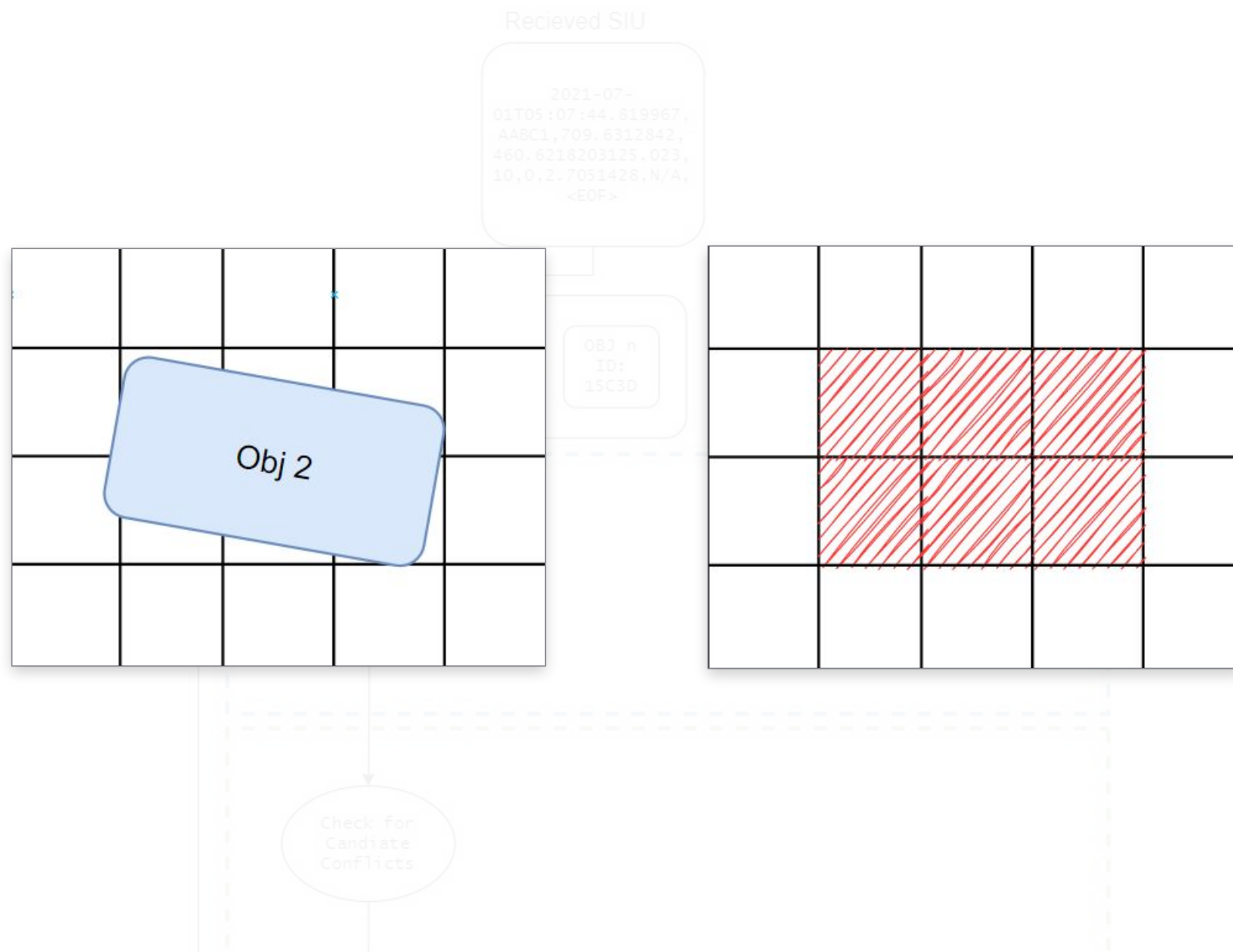
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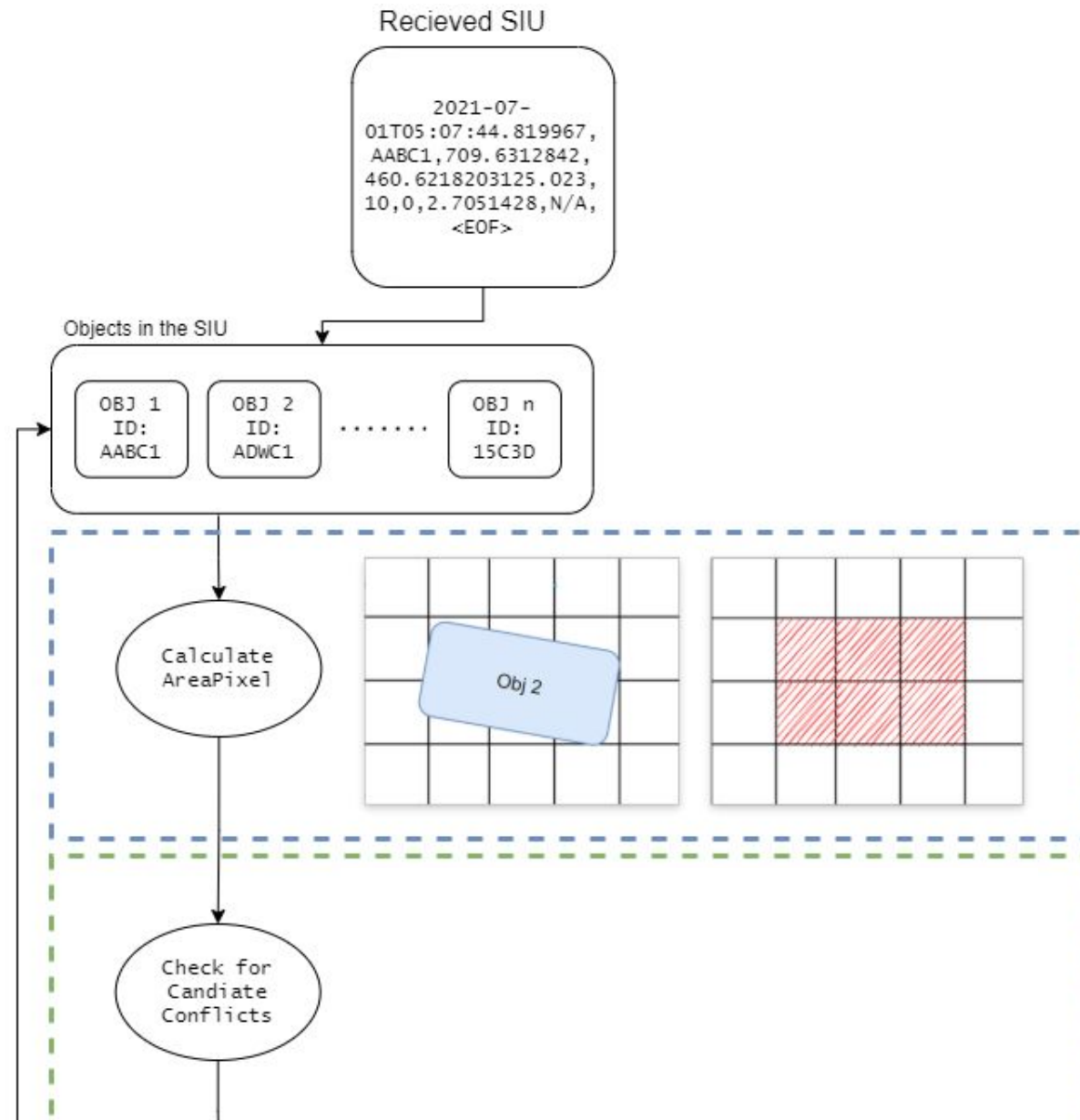
PET: Detection and Calculation

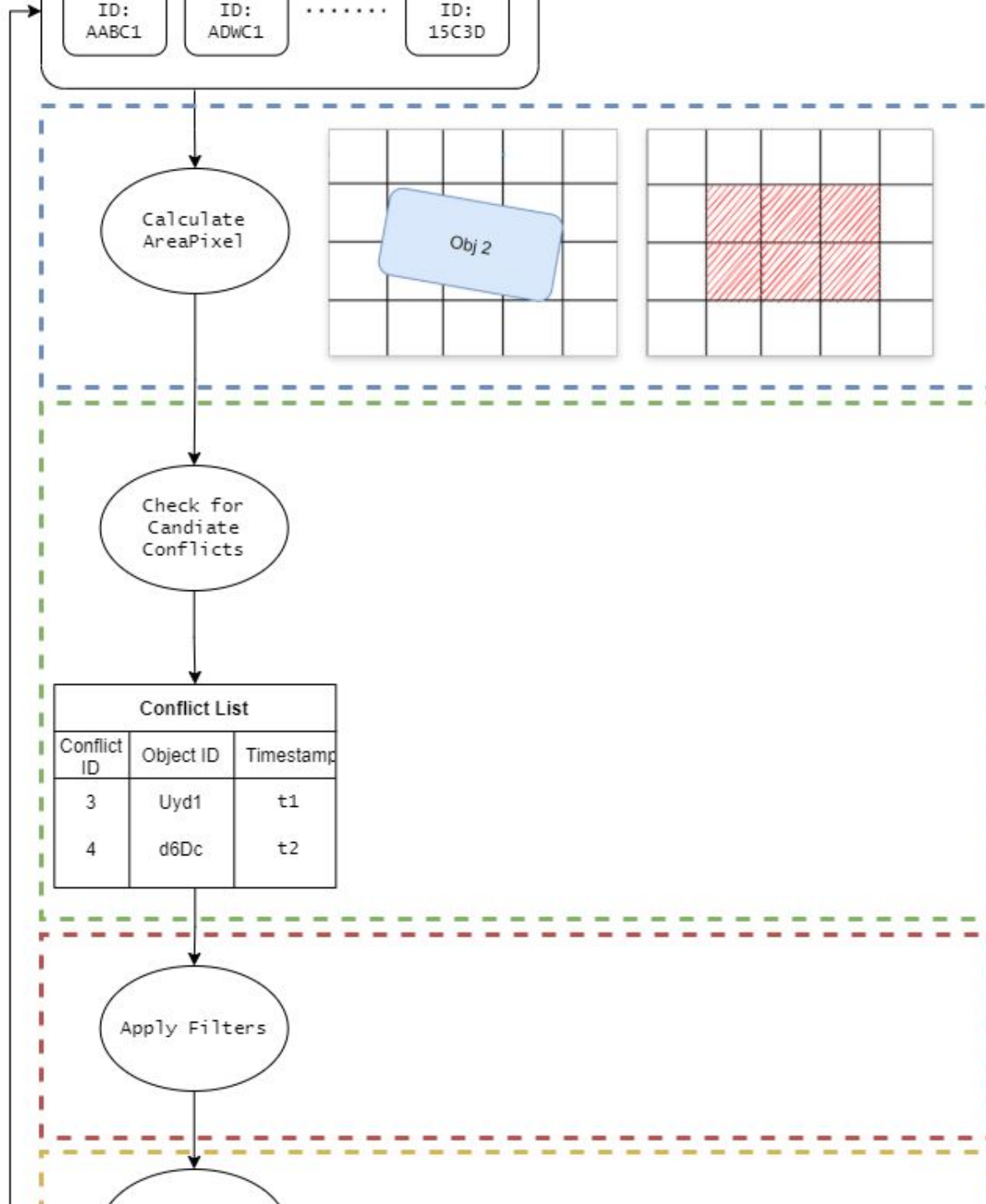


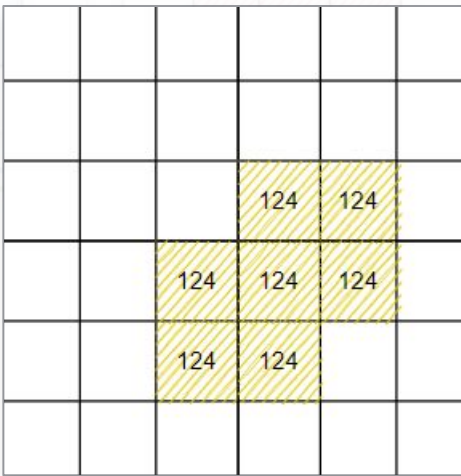
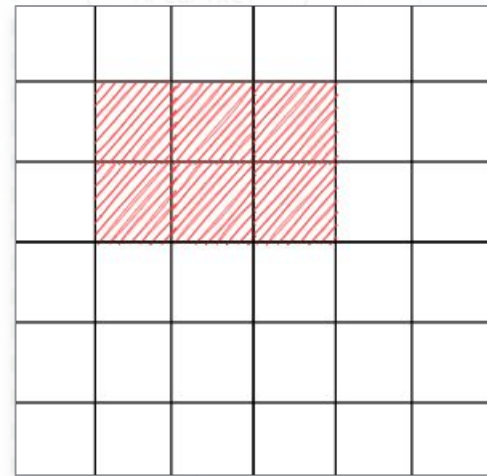
PET: Detection and Calculation



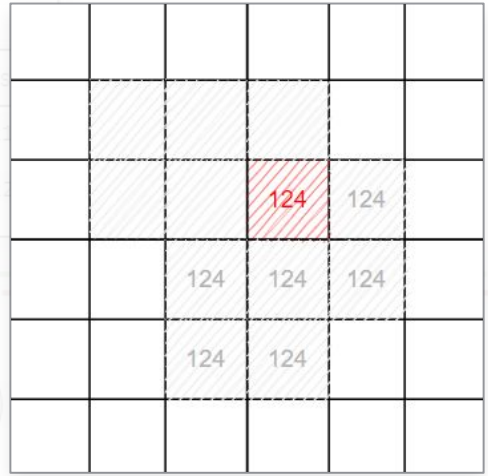
PET: Detection and Calculation

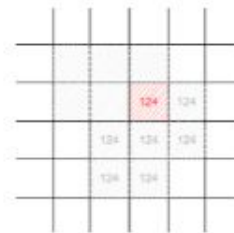
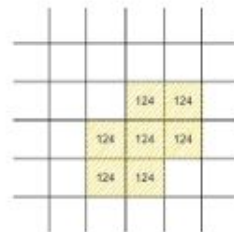
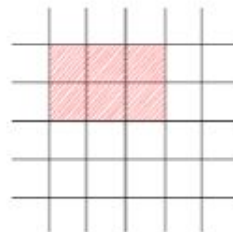
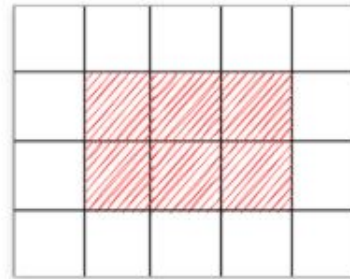
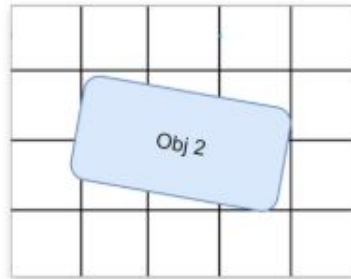
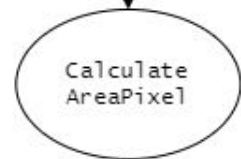
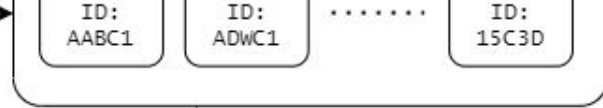






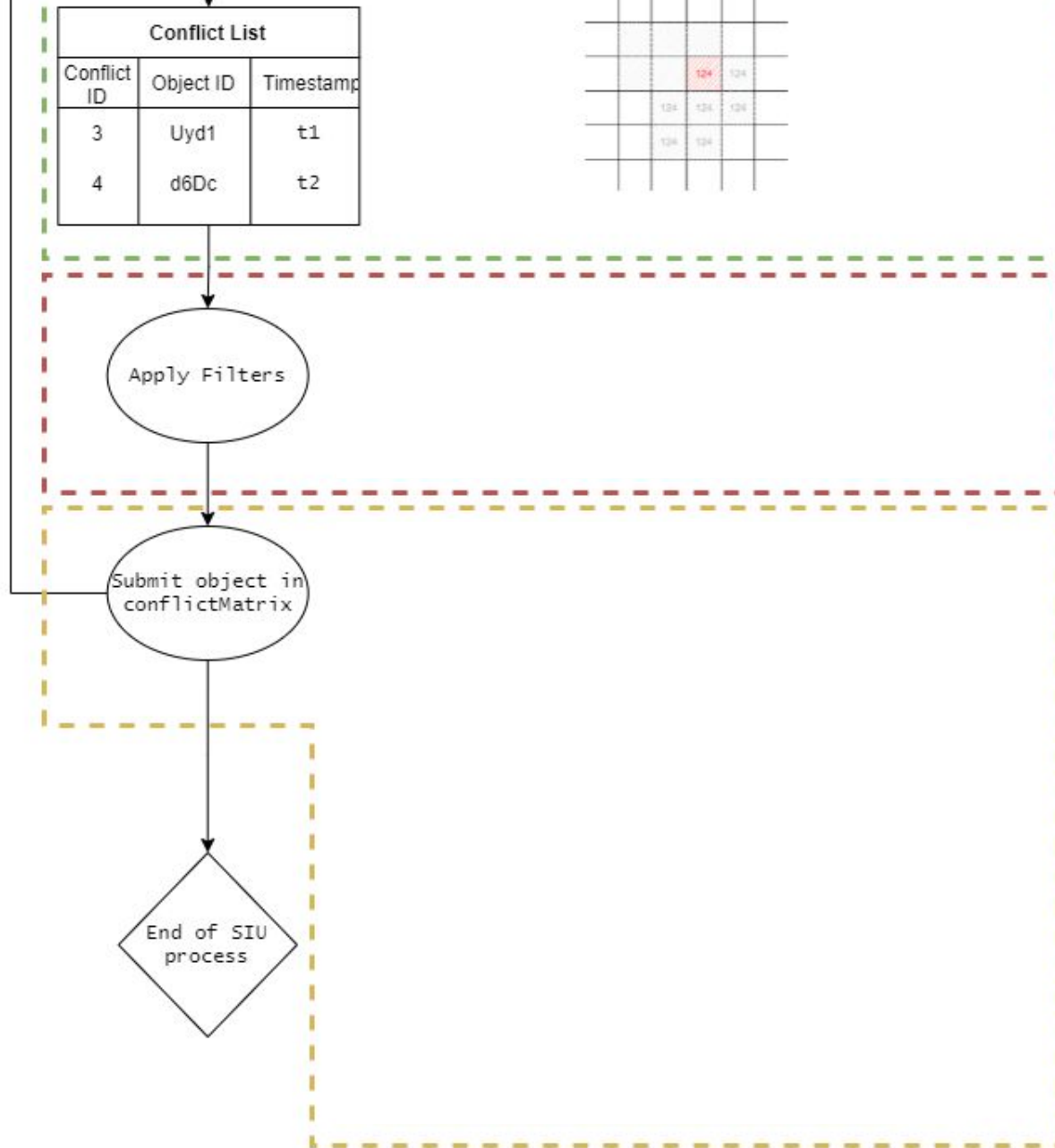
| Conflict List | | |
|---------------|-----------|-------|
| Conflict ID | Object ID | Times |
| 3 | Uyd1 | t3 |
| 4 | d6Dc | t3 |

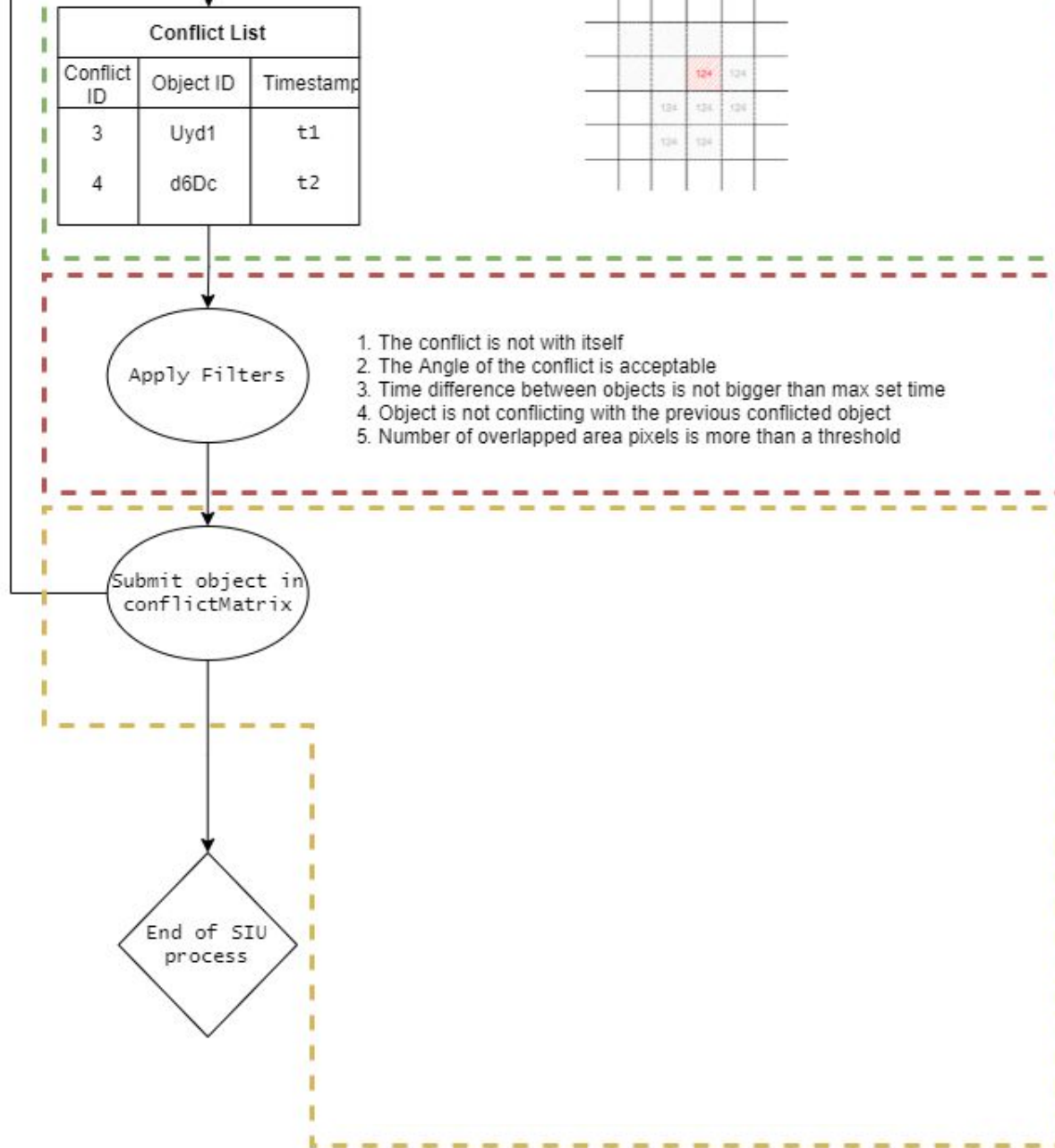


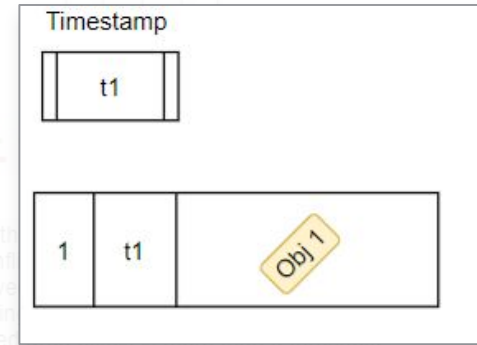


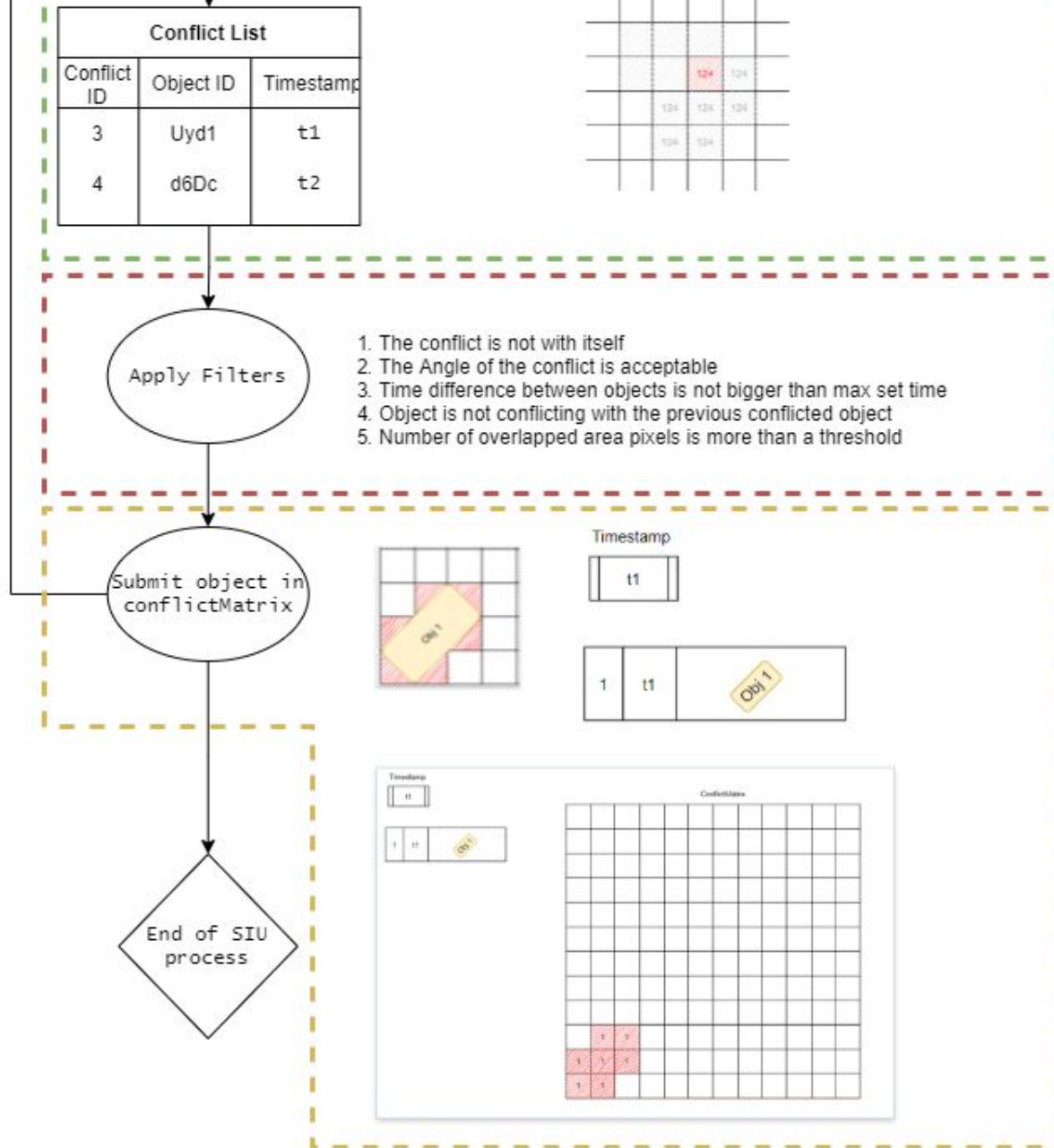
| Conflict List | | |
|---------------|-----------|-----------|
| Conflict ID | Object ID | Timestamp |
| 3 | Uyd1 | t1 |
| 4 | d6Dc | t2 |



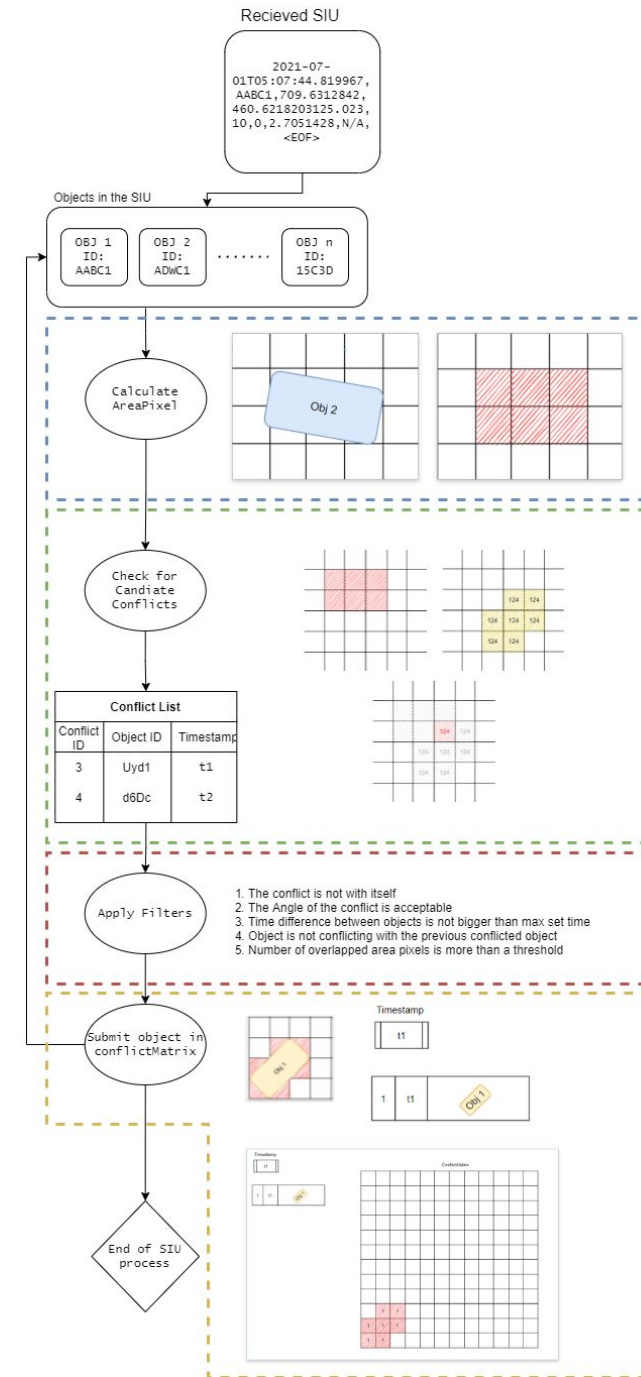






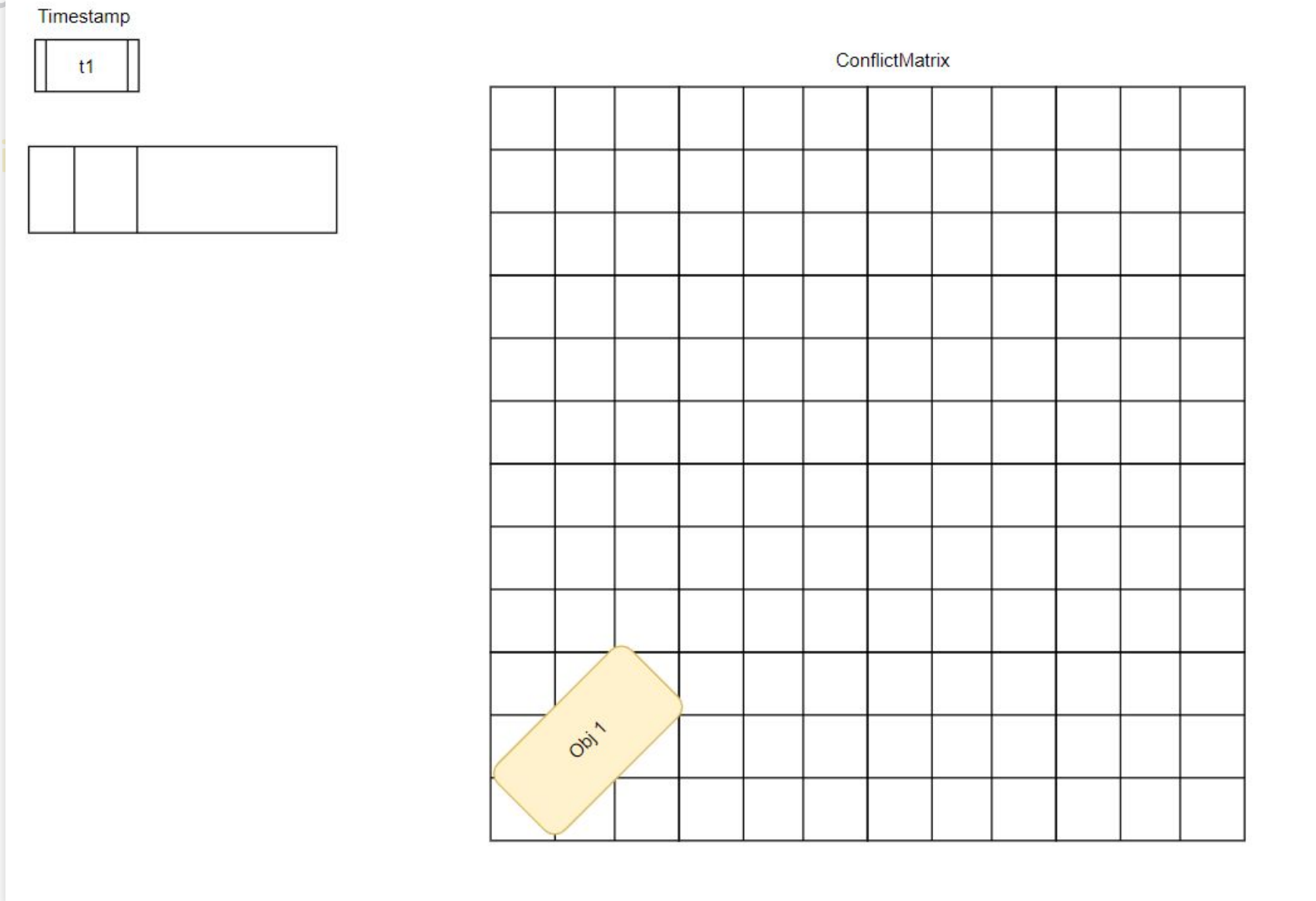


PET: Detection and Calculation



Detection and Calculation: Calculate DET for each objects in the frame

- Use Confluent
- Store info



Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info

Timestamp

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| t2 |
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| 1 | t1 | Obj 1 |
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ConflictMatrix

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| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t3 |
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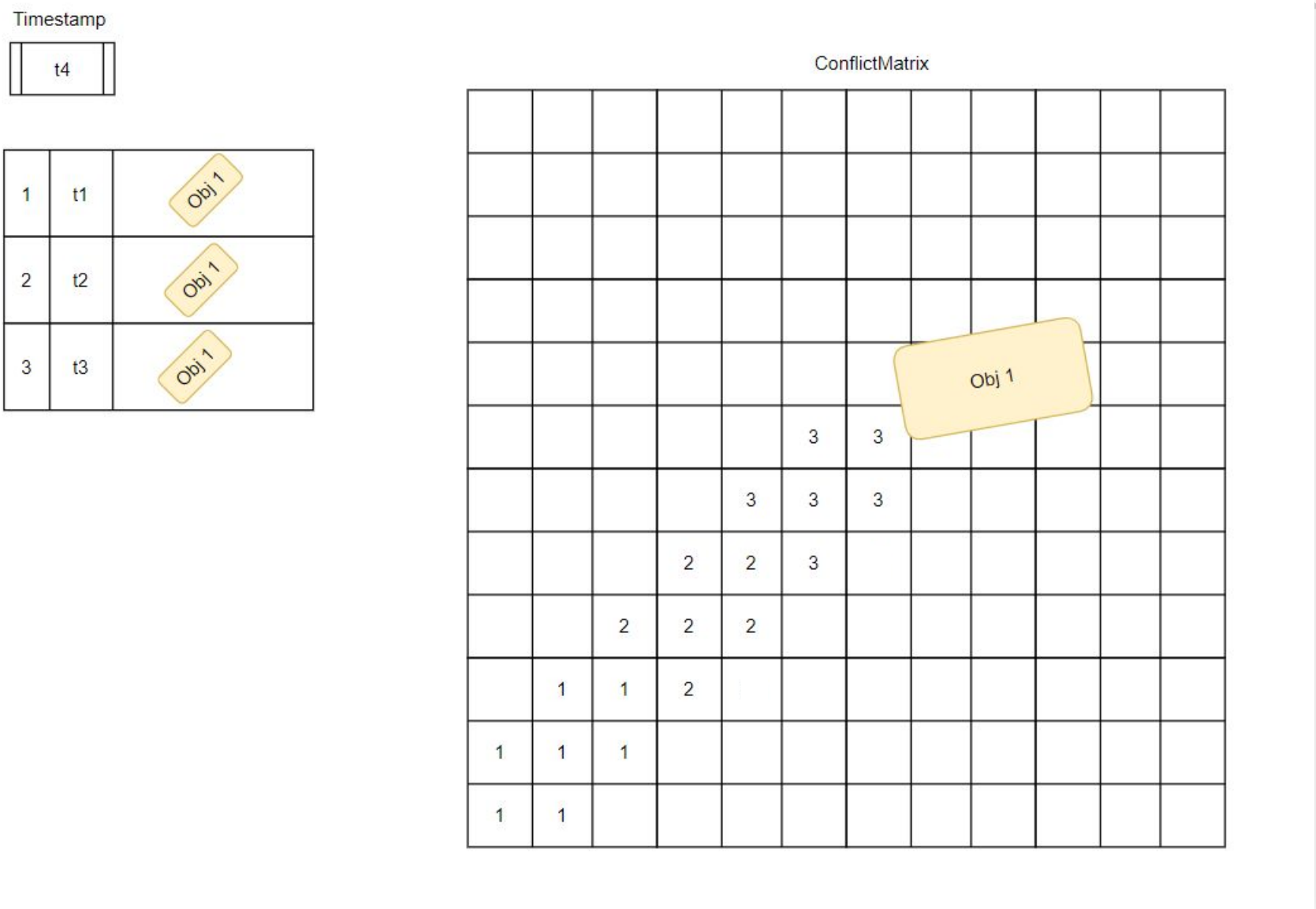
| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |

ConflictMatrix

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| | | | | 2 | 2 | | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info



Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t5 |
|----|

| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|--|--|--|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | 4 | 4 | | | |
| | | | | | | | 4 | 4 | 4 | | | |
| | | | | | 3 | 3 | 4 | 4 | 4 | | | |
| | | | | 3 | 3 | 3 | | | | | | |
| | | | 2 | 2 | 3 | | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

Obj 1

Detection and Calculation: Calculate DET for each objects in the frame

- Use Conflict
- Store info

Timestamp

| |
|----|
| t6 |
|----|

| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|--|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | 4 | 4 | 5 | 5 | |
| | | | | | | | 4 | 4 | 4 | 5 | 5 | |
| | | | | | 3 | 3 | 4 | 4 | 4 | | | |
| | | | | 3 | 3 | 3 | | | | | | |
| | | | 2 | 2 | 3 | | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |






Obj

Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t7 |
|----|

| | | |
|---|----|---|
| 1 | t1 |  |
| 2 | t2 |  |
| 3 | t3 |  |
| 4 | t4 |  |
| 5 | t5 |  |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|--|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | 4 | 4 | 5 | 5 | |
| | | | | | | | 4 | 4 | 4 | 5 | 5 | |
| | | | | | | 3 | 3 | 4 | 4 | 4 | | |
| | | | | 3 | 3 | 3 | | | | | | |
| | | | 2 | 2 | 3 | | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |





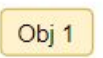
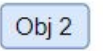
Obj 2

Detection and Calculation: Calculate DET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t8 |
|----|

| | | |
|---|----|---|
| 1 | t1 |  |
| 2 | t2 |  |
| 3 | t3 |  |
| 4 | t4 |  |
| 5 | t5 |  |
| 6 | t7 |  |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | 4 | 4 | 5 | 5 |
| 6 | 6 | 6 | | | | | | 4 | 4 | 4 | 5 | 5 |
| 6 | 6 | 6 | | | | | 3 | 4 | 4 | 4 | | |
| | | | | | 3 | 3 | | | | | | |
| | | | | 2 | 2 | 3 | | | | | | |
| | | | | | | | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

Detection and Calculation: Calculate PET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t8 |
|----|

| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |
| 6 | t7 | Obj 2 |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | 4 | 4 | 5 | 5 |
| 6 | 6 | 6 | | | | | 4 | 4 | 4 | 5 | 5 | |
| 6 | 6 | 6 | | | | 3 | 3 | 4 | 4 | 4 | | |
| | | | | 3 | | 3 | | | | | | |
| | | | | 2 | 2 | 3 | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

- Use Confluent
- Store info

| Timestamp | | |
|-----------|----|-------|
| | t8 | |
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |
| 6 | t7 | Obj 2 |

[illegible]

Detection and Calculation: Calculate PET for each objects in the frame

- Use Confl
- Store info

Timestamp

| |
|----|
| t9 |
|----|

| | | |
|---|----|-------|
| 1 | t1 | Obj 1 |
| 2 | t2 | Obj 1 |
| 3 | t3 | Obj 1 |
| 4 | t4 | Obj 1 |
| 5 | t5 | Obj 1 |
| 6 | t7 | Obj 2 |
| 7 | t8 | Obj 2 |

ConflictMatrix

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|--|
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | 4 | 4 | 5 | 5 | |
| 6 | 6 | 6 | 7 | 7 | | | 4 | 4 | 4 | 5 | 5 | |
| 6 | 6 | 6 | 7 | 7 | 7 | 3 | 4 | 4 | 4 | | | |
| | | | | 7 | | | | | | | | |
| | | | 2 | 2 | 3 | 3 | | | | | | |
| | | 2 | 2 | 2 | | | | | | | | |
| | 1 | 1 | 2 | | | | | | | | | |
| 1 | 1 | 1 | | | | | | | | | | |
| 1 | 1 | | | | | | | | | | | |

Detection and Calculation: Calculate PET for Each Objects in Frame

- Conflict candidates need to be validated by some **filters**:

Detection and Calculation: Calculate PET for Each Objects in Frame

- Conflict candidates need to be validated by some **filters**:
 1. The conflict is not with **itself**

Detection and Calculation: Calculate PET for Each Objects in Frame

- Conflict candidates need to be validated by some **filters**:
 1. The conflict is not with **itself**
 2. The **Angle** of the conflict is acceptable

Detection and Calculation: Calculate PET for Each Objects in Frame

- Conflict candidates need to be validated by some **filters**:
 1. The conflict is not with **itself**
 2. The **Angle** of the conflict is acceptable
 3. Time difference between objects is not bigger than **max set time**

Detection and Calculation: Calculate PET for Each Objects in Frame

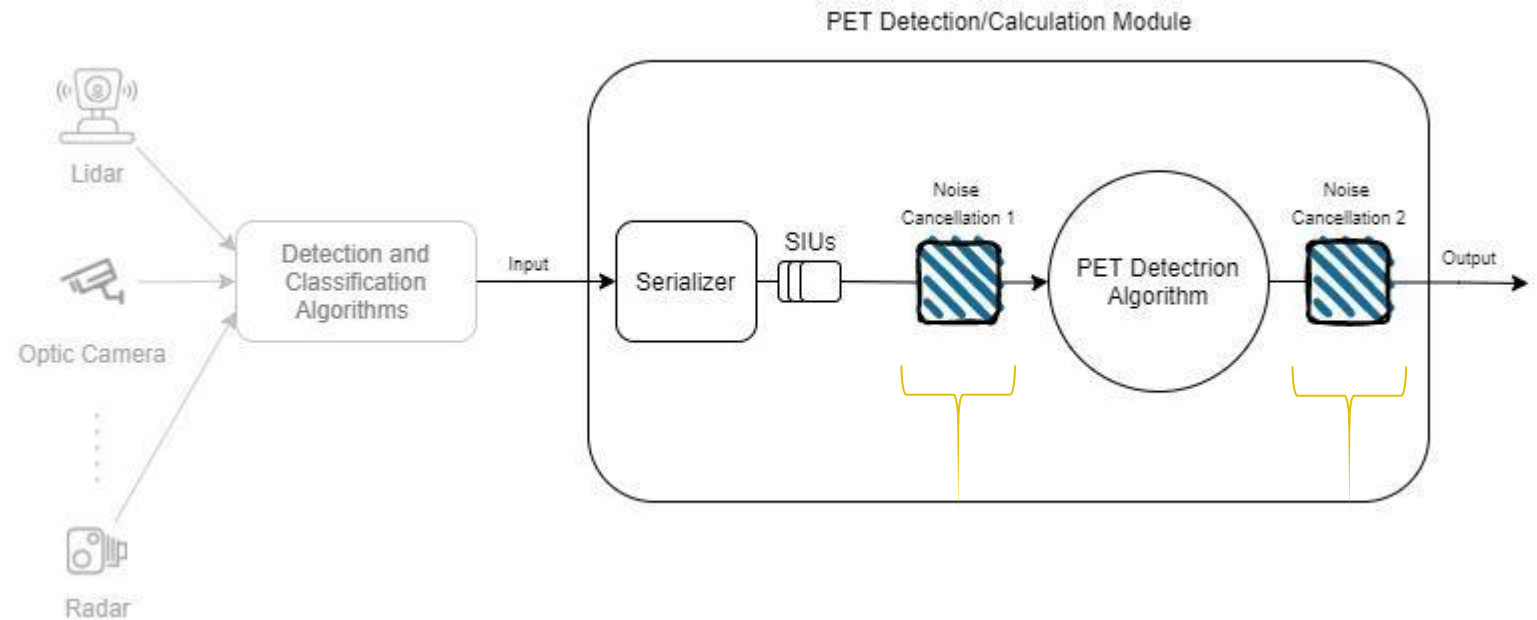
- Conflict candidates need to be validated by some filters:
 1. The conflict is not with itself
 2. The Angle of the conflict is acceptable
 3. Time difference between objects is not bigger than max set time
 4. Object is not conflicting with the previous conflicted object

Detection and Calculation: Calculate PET for Each Objects in Frame

- Conflict candidates need to be validated by some **filters**:
 1. The conflict is not with **itself**
 2. The **Angle** of the conflict is acceptable
 3. Time difference between objects is not bigger than **max set time**
 4. Object is not conflicting with the **previous conflicted** object
 5. Number of **overlapped area pixels** is more than a threshold (will be discussed later)

PET: Noise Cancellation

1. Decoupled
2. Realtime/Continuous
3. Precise
4. Generalized
5. Easy to use
6. Fault tolerant



PET: Fault Tolerance

1. False positive detection of objects

PET: Fault Tolerance

1. F
0

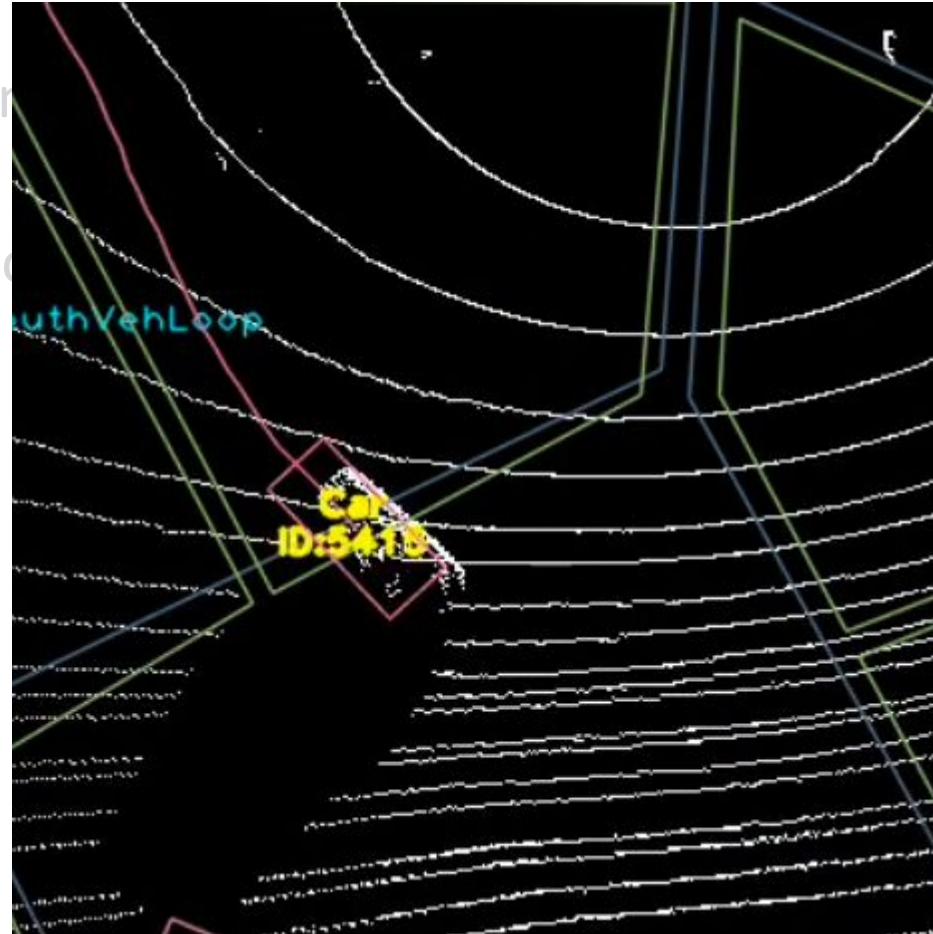


PET: Fault Tolerance

1. False positive detection of objects
2. Inaccurate bounding boxes

PET: Fault tolerance

1. False positive detection of objects
2. Inaccurate bounding box



PET: Fault Tolerance

1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type

PET: Fault Tolerance

1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects

PET: Fault Tolerance

1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects



Delayed SIUs



Validating Turning
Movements

False positive detection of objects: Delayed SIUs



1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects



Delayed SIUs



Validating Turning Movements

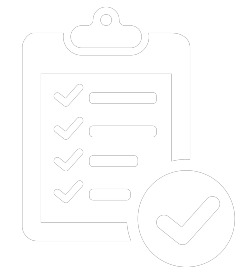
Fault Tolerance: False positive detection of objects



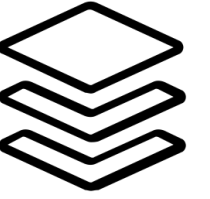
Delayed SIUs



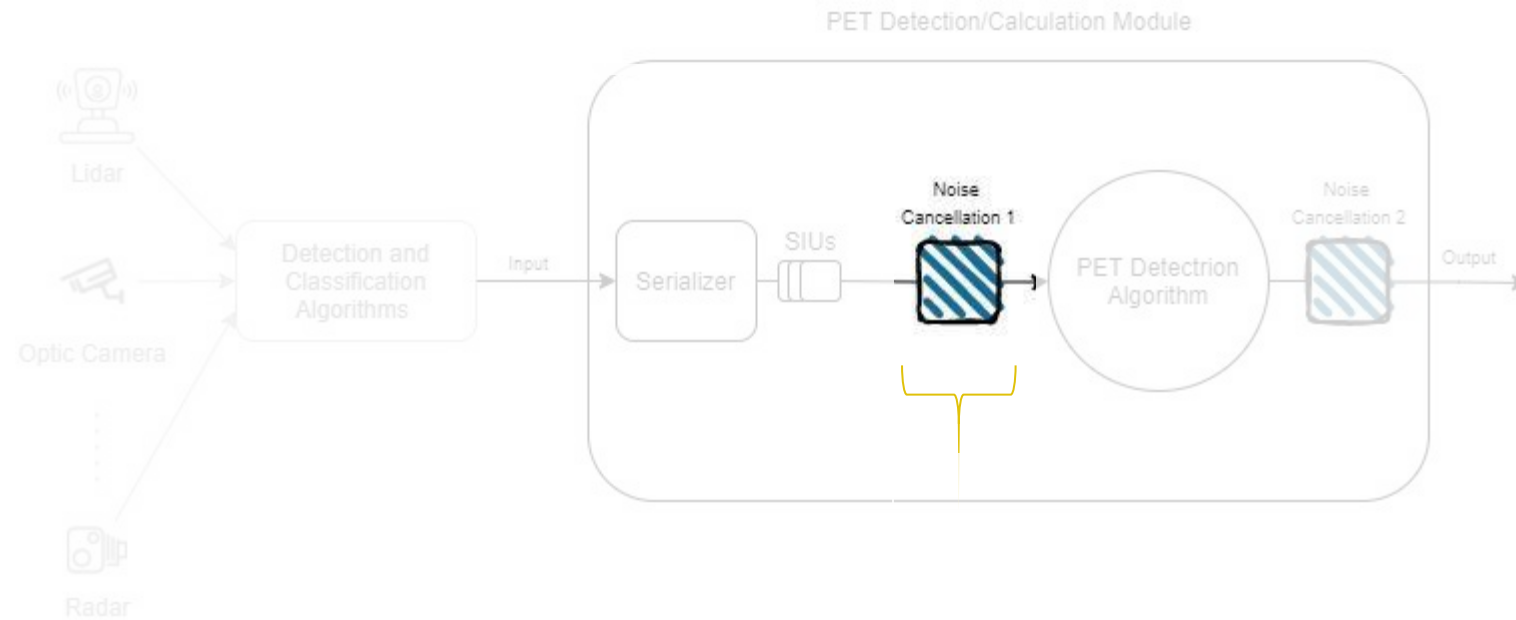
Validating Turning
Movements



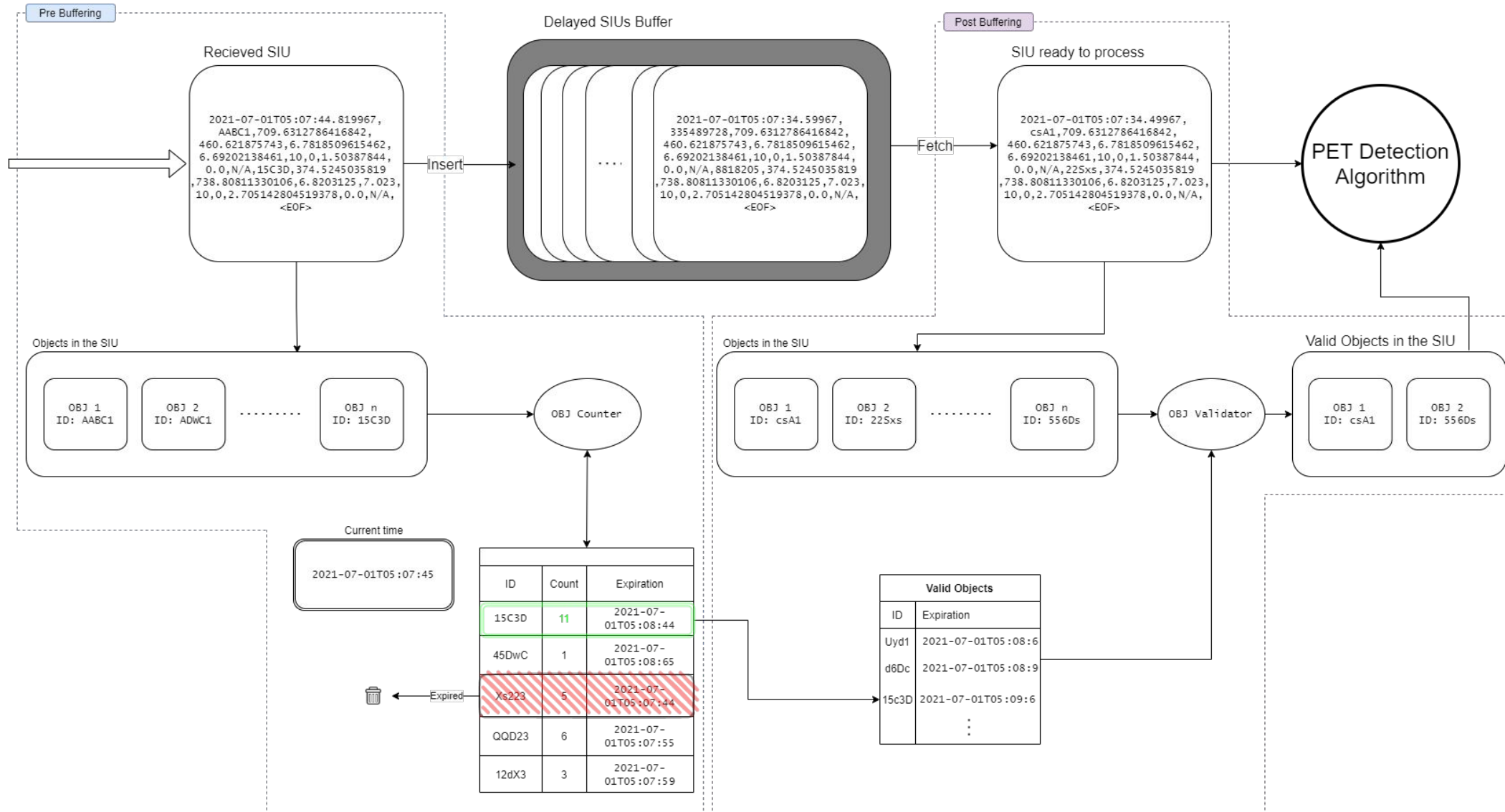
False positive detection of objects: Delayed SIUs



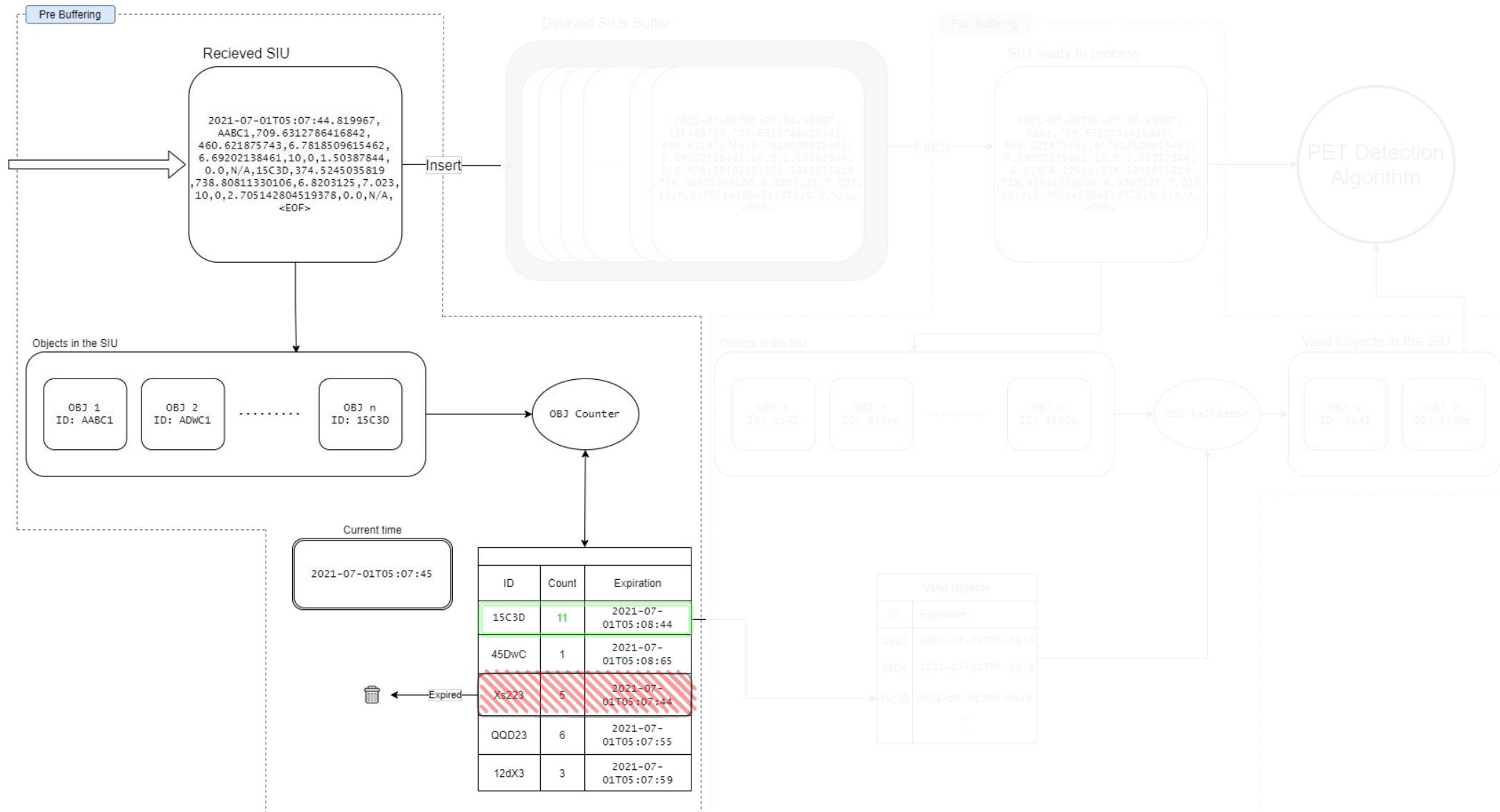
False positive detection of objects: Delayed SIUs



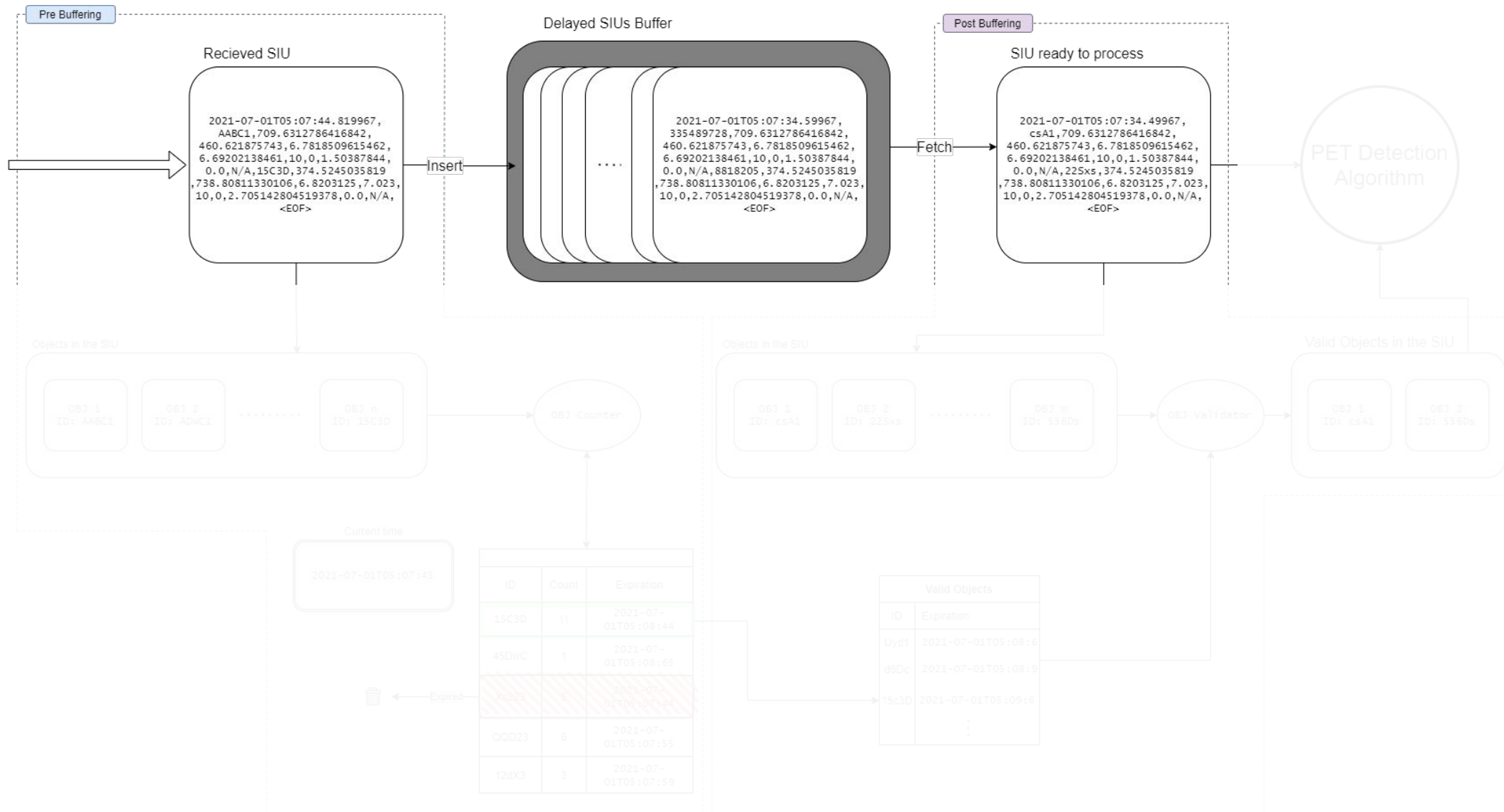
False positive detection of objects: Delayed SIUs



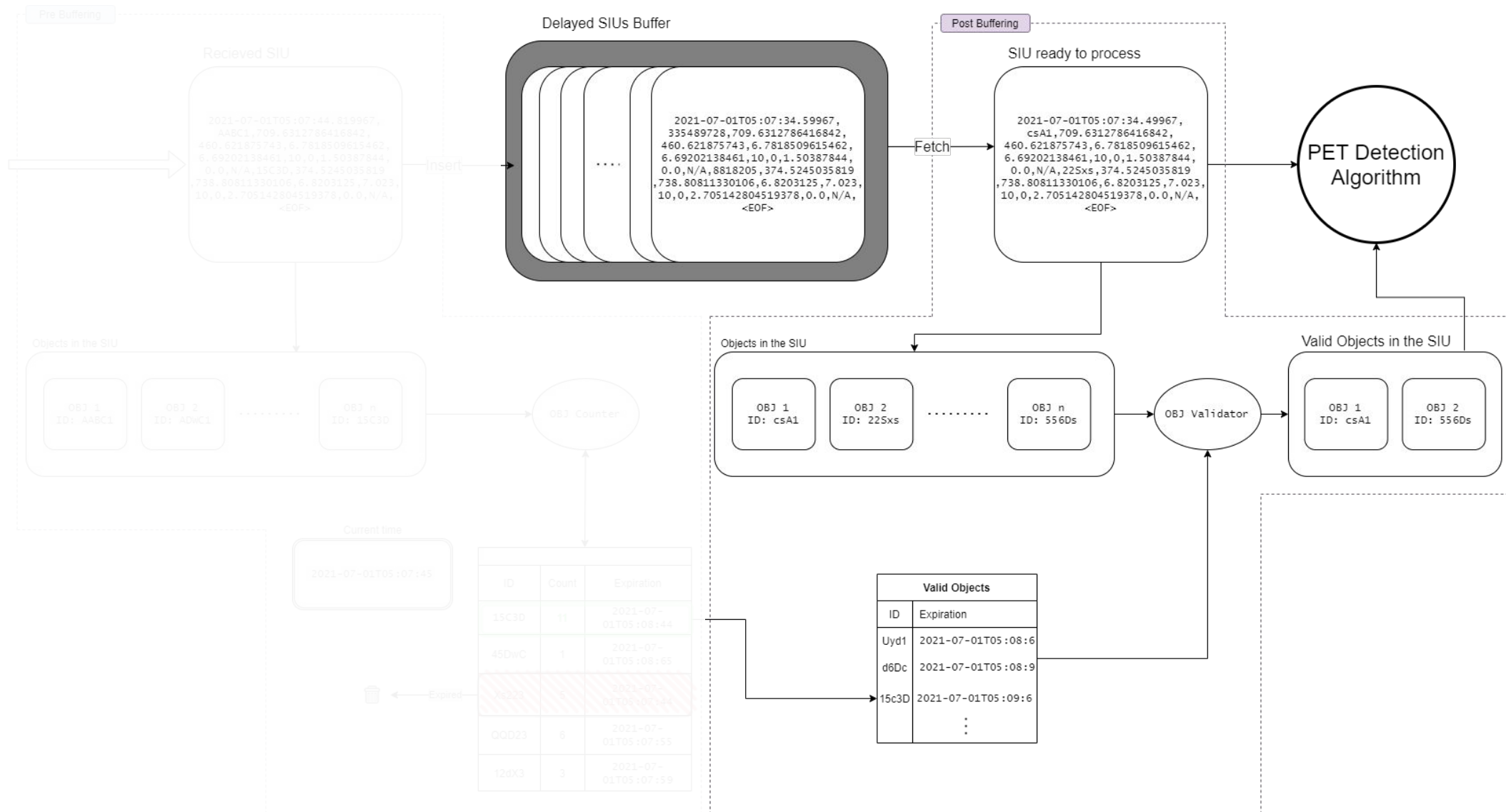
False positive detection of objects: Delayed SIUs



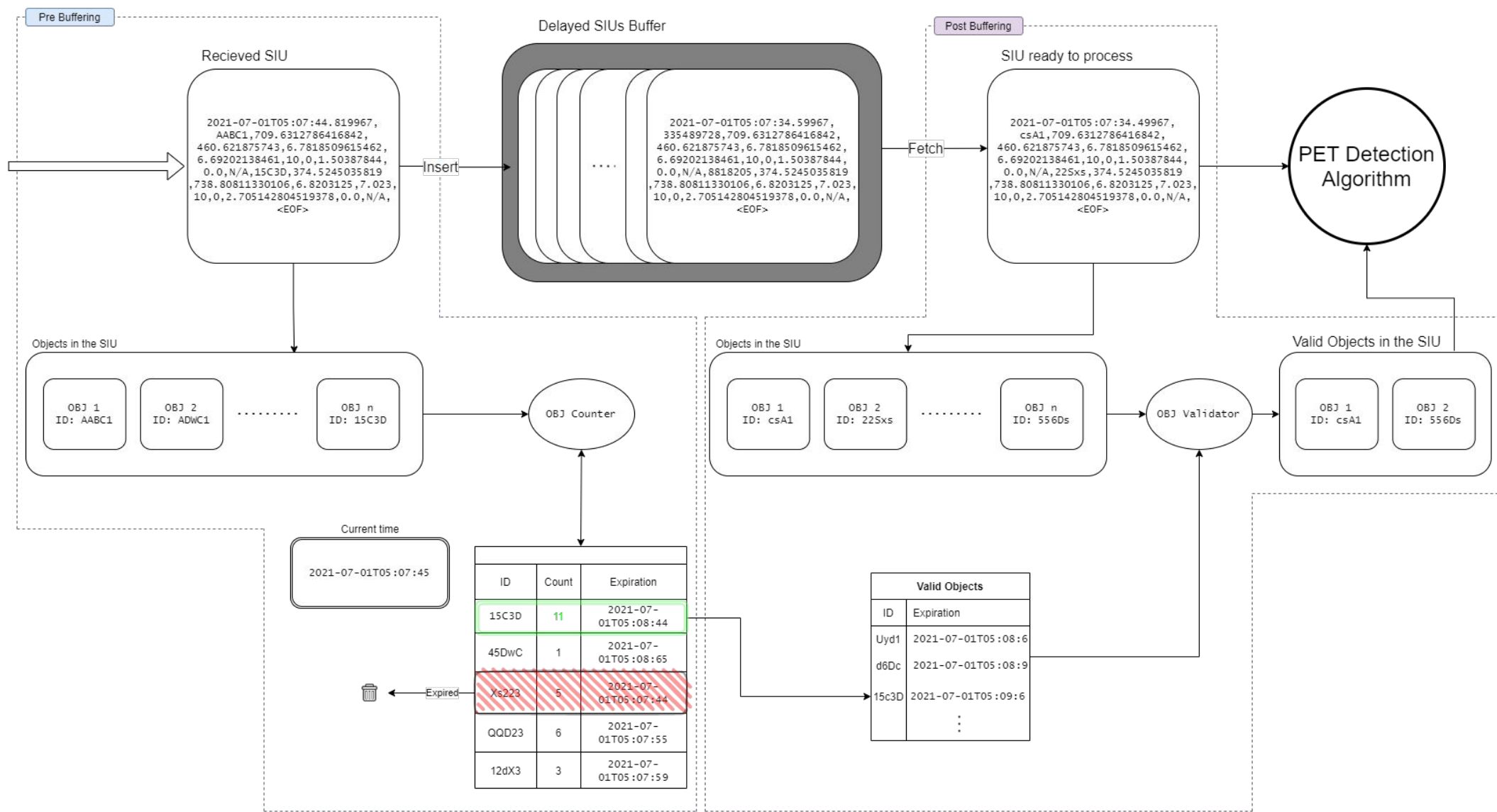
False positive detection of objects: Delayed SIUs



False positive detection of objects: Delayed SIUs



False positive detection of objects: Delayed SIUs



False positive detection of objects: Validating Turning Movements



1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects



Delayed SIUs



Validating Turning
Movements

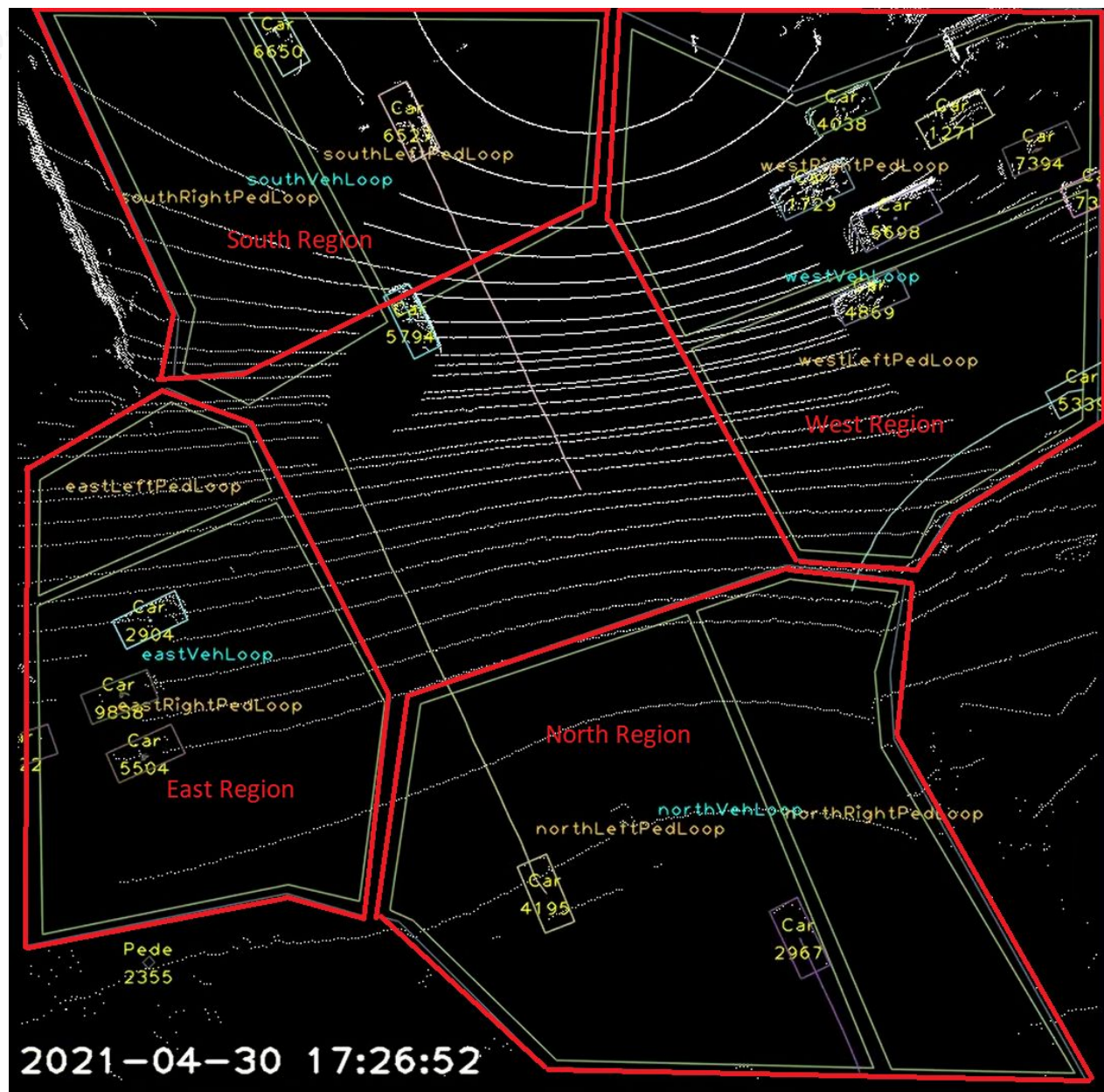
False positive detection of objects: Validating Turning Movements



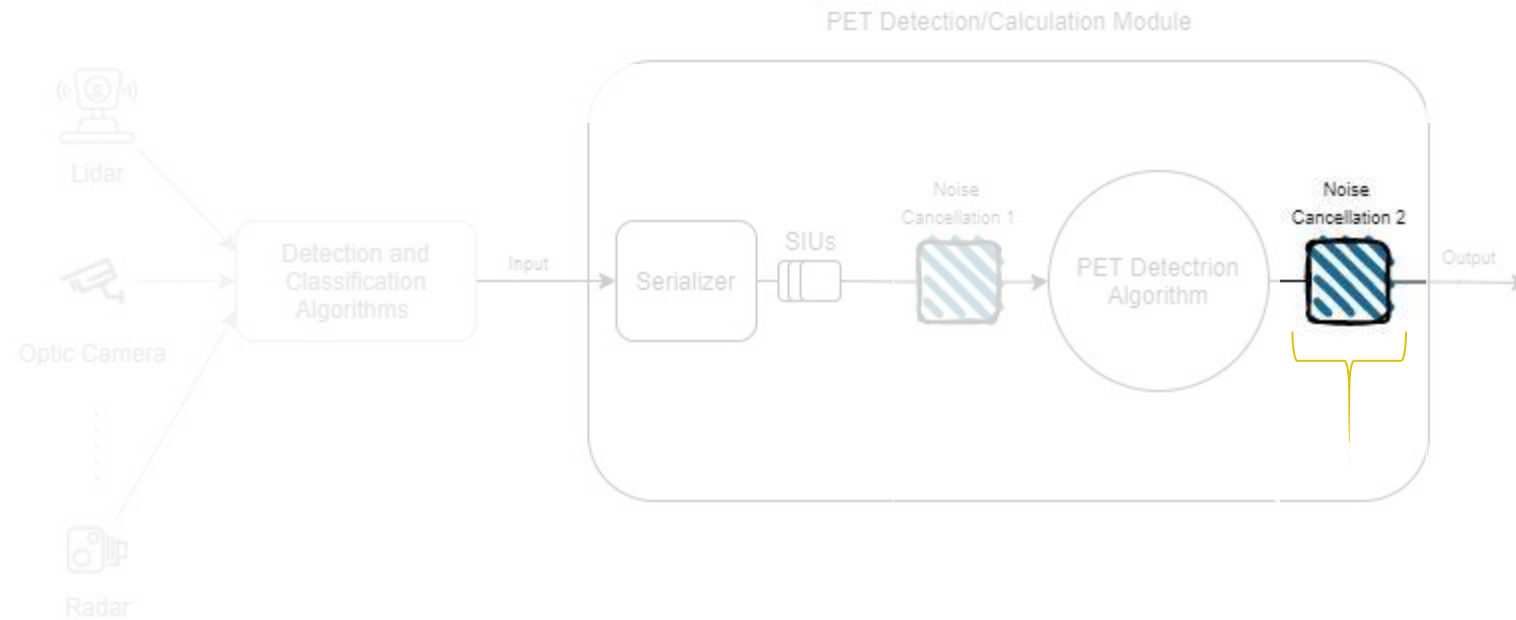
- Different approach and sits **after the PET detection module**
- Filters out the **invalid turning movements**
- It effects the Realtime process, however, does not change the continuity of the module
- Needs to define each **region** on the **calibration stage** of the sensors

False positive de

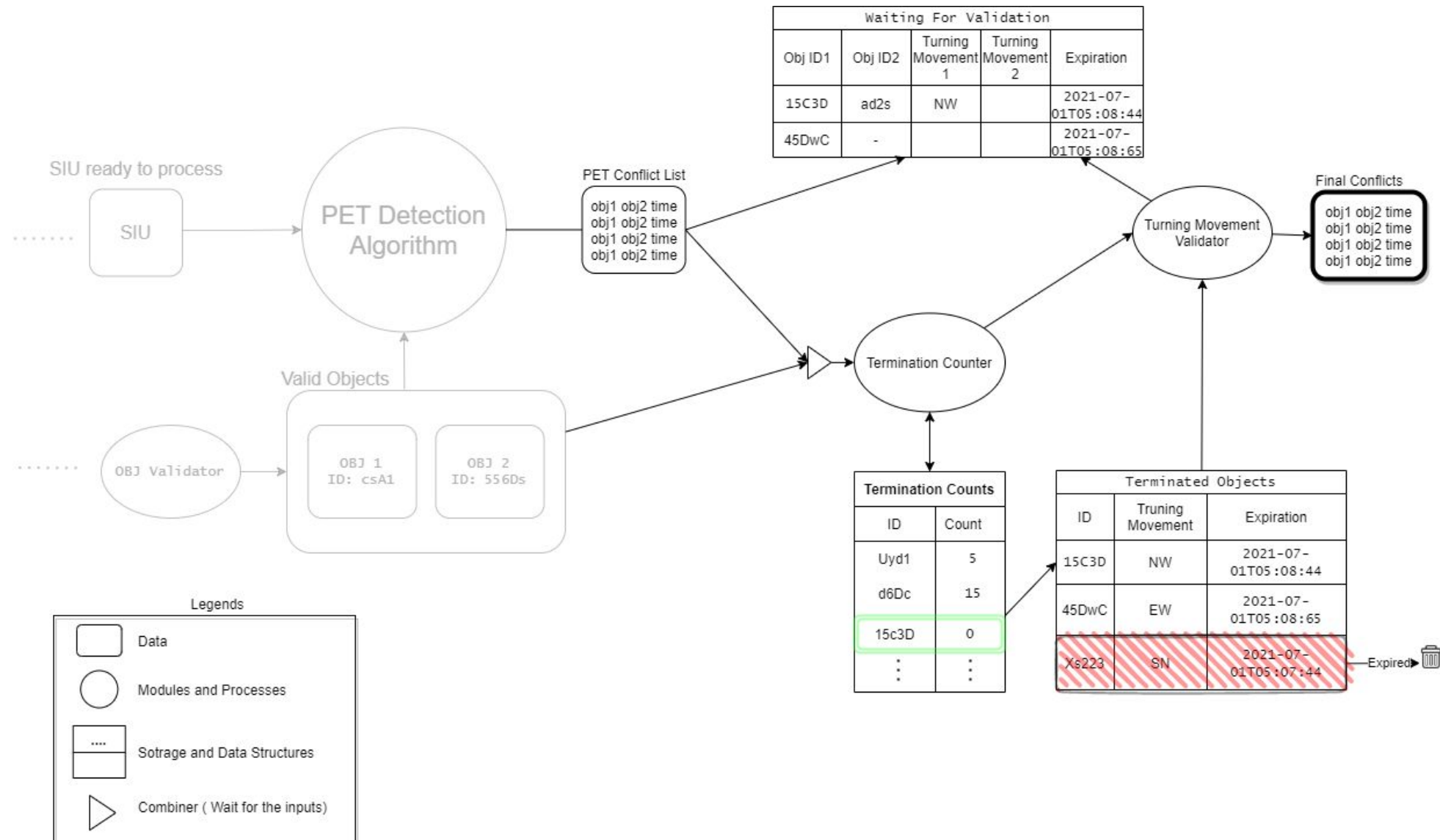
vements



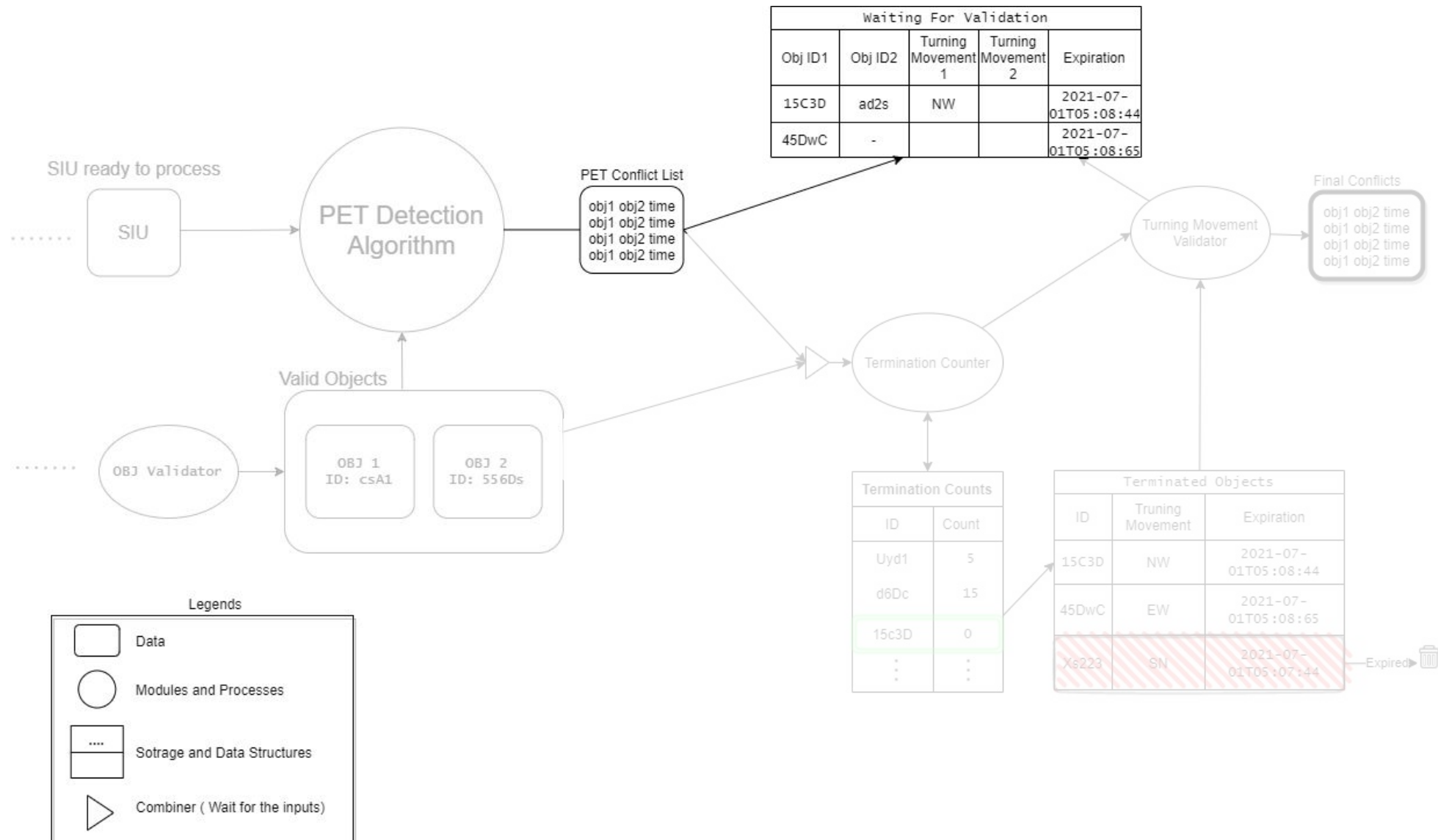
False positive detection of objects: Validating Turning Movements



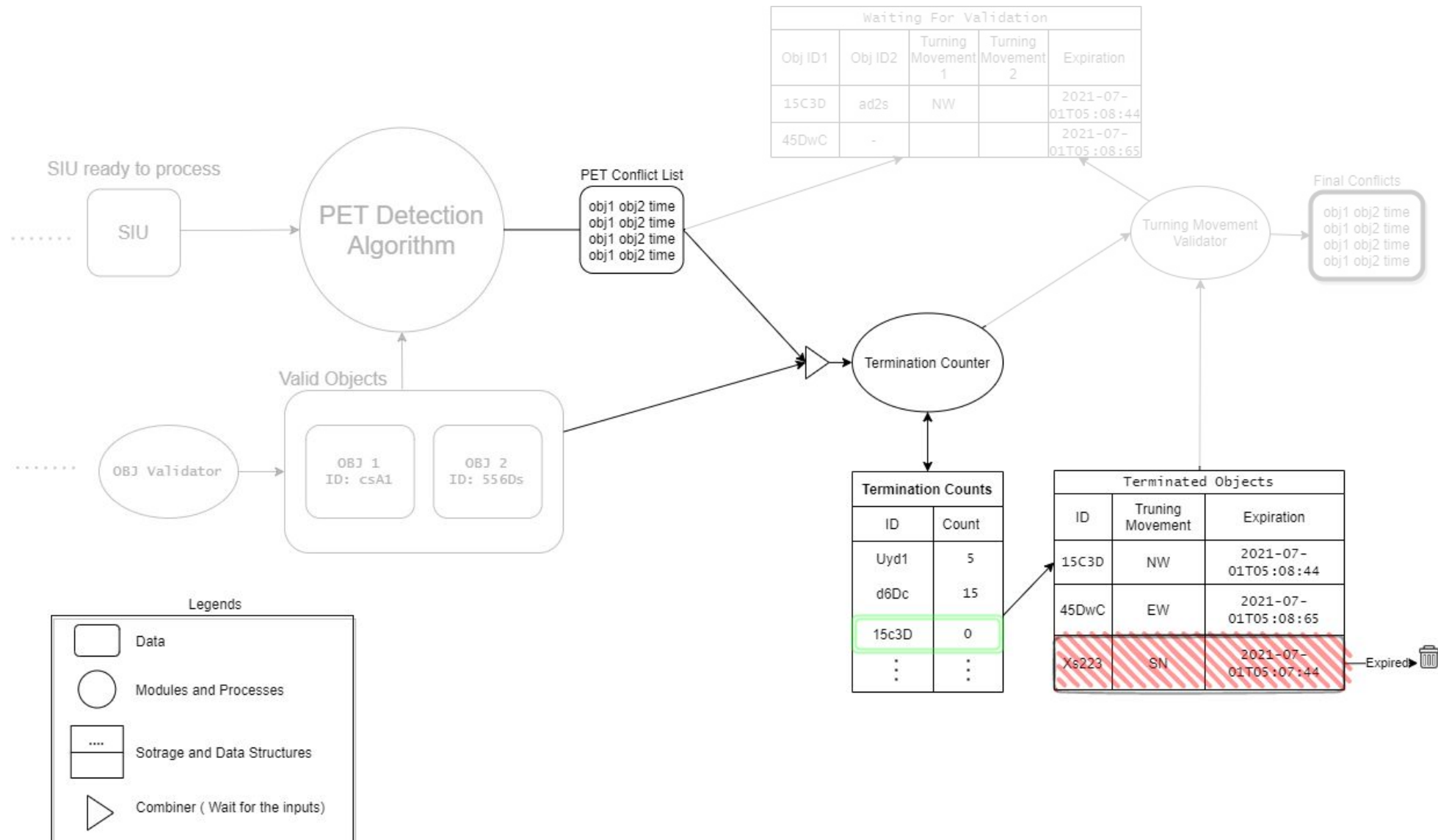
False positive detection of objects: Validating Turning Movements



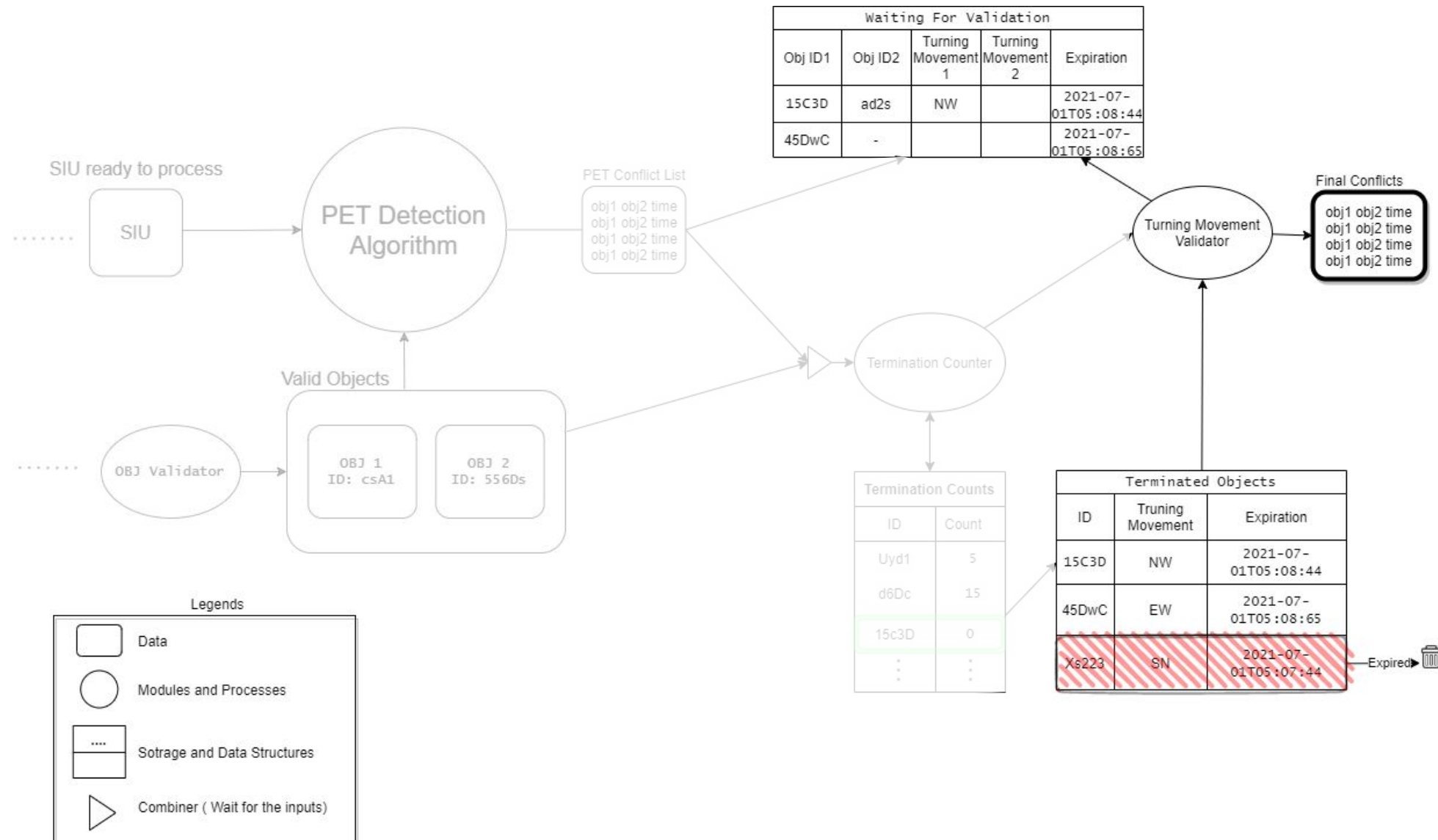
False positive detection of objects: Validating Turning Movements



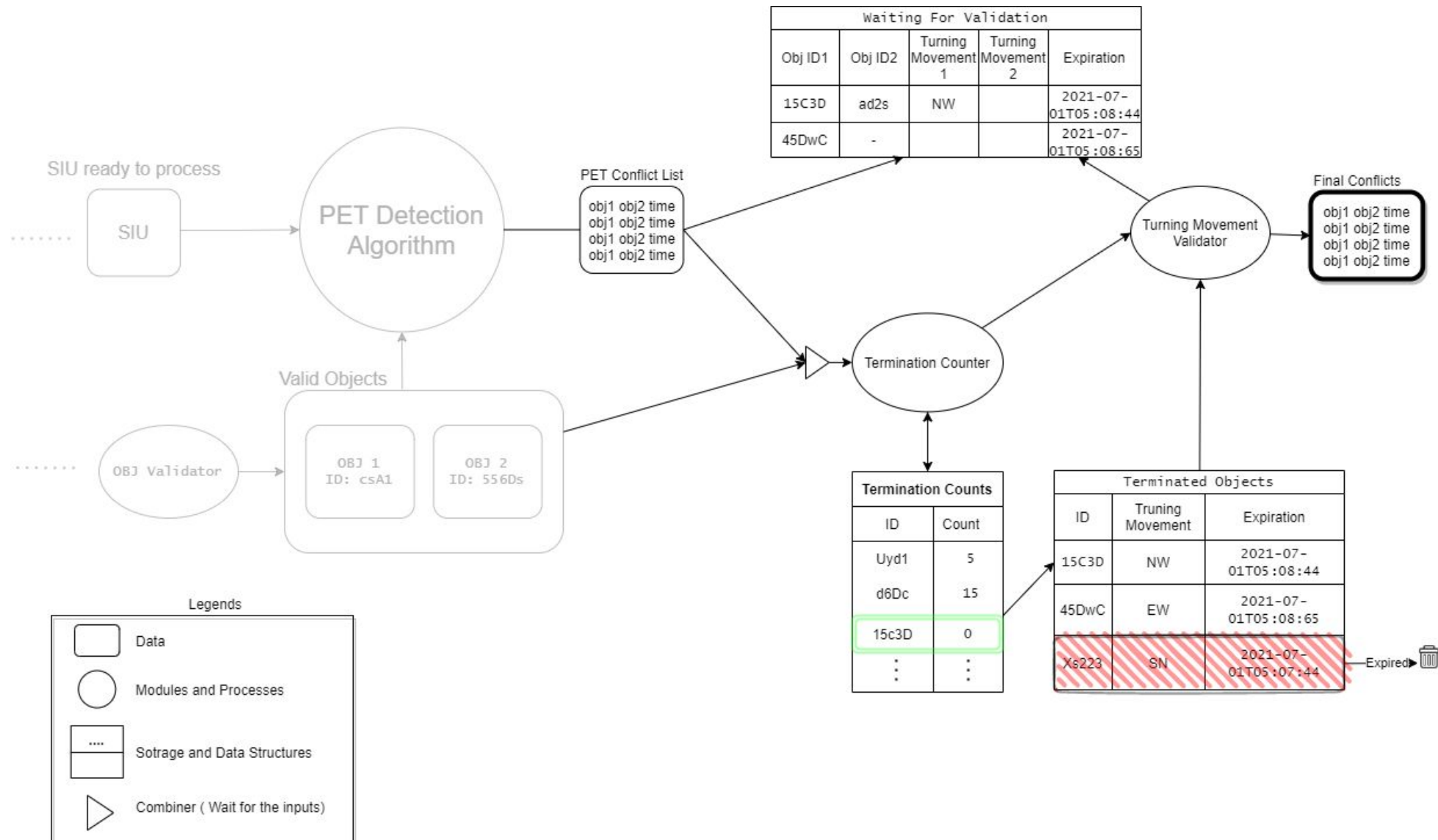
False positive detection of objects: Validating Turning Movements



False positive detection of objects: Validating Turning Movements



False positive detection of objects: Validating Turning Movements



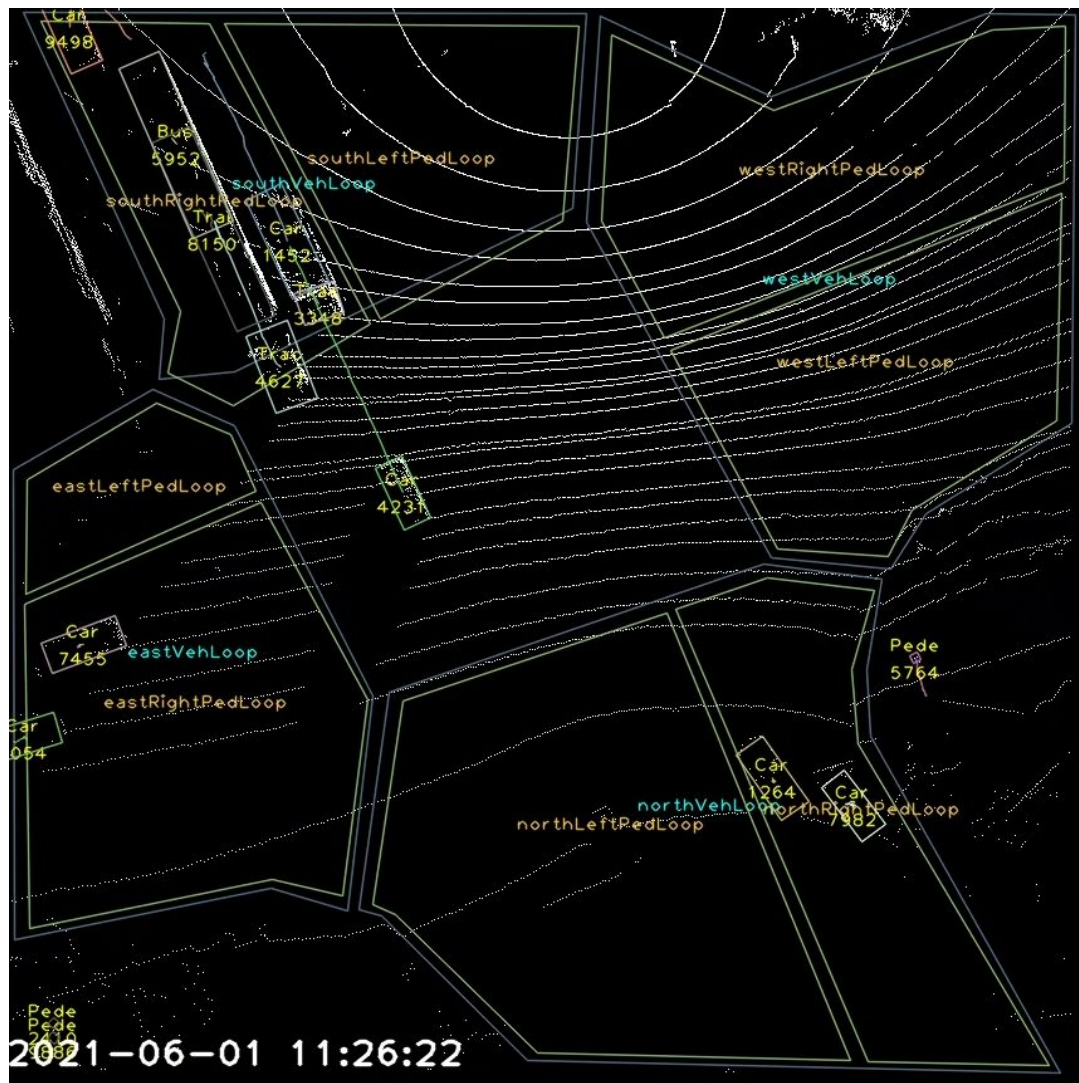
Fault tolerance: Inaccurate bounding boxes

1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects

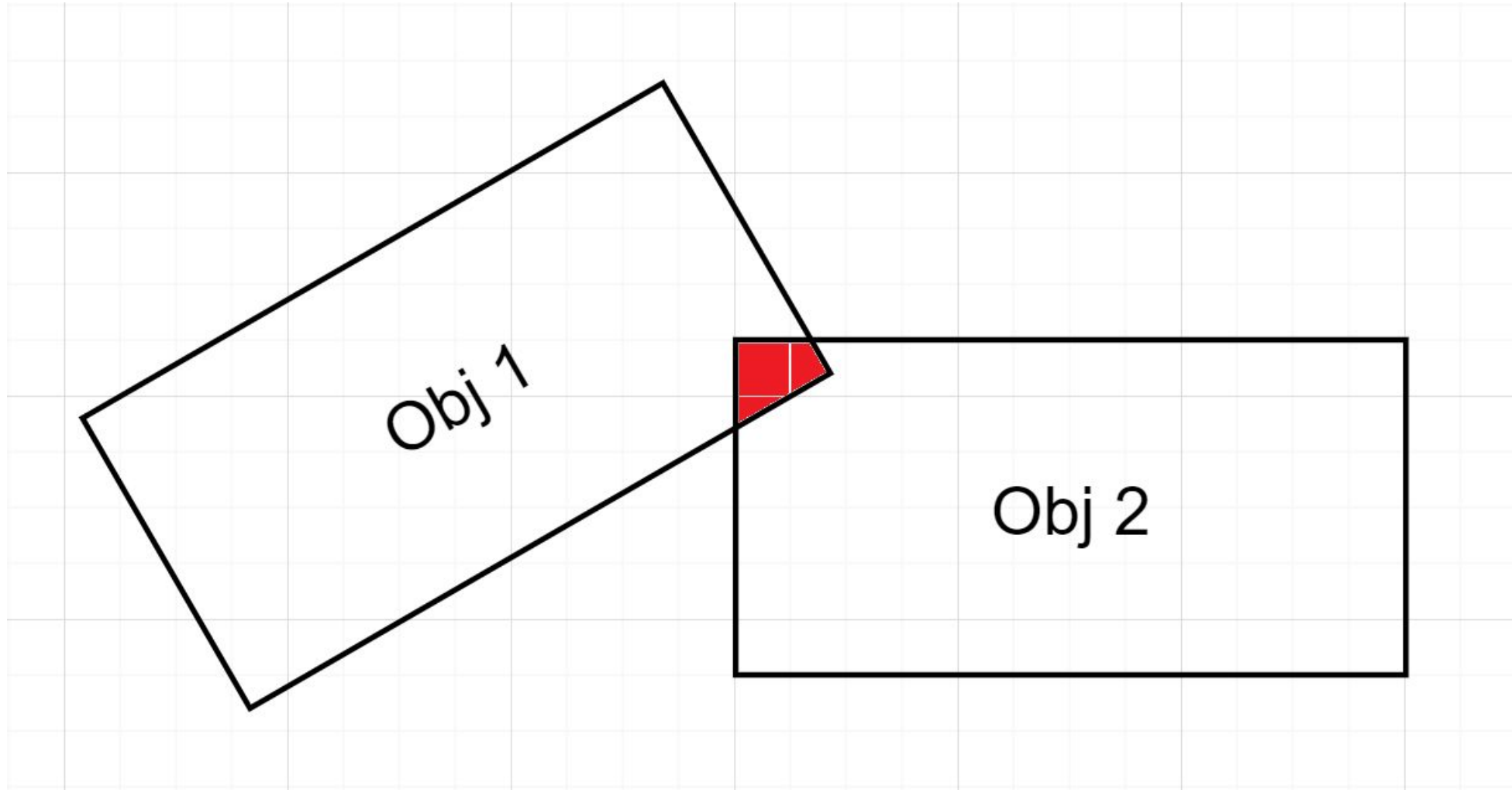
Fault tolerance: Inaccurate bounding boxes

- False conflicts should be avoided
- It reduces the precision of the module, but benefits are more than shortcomings

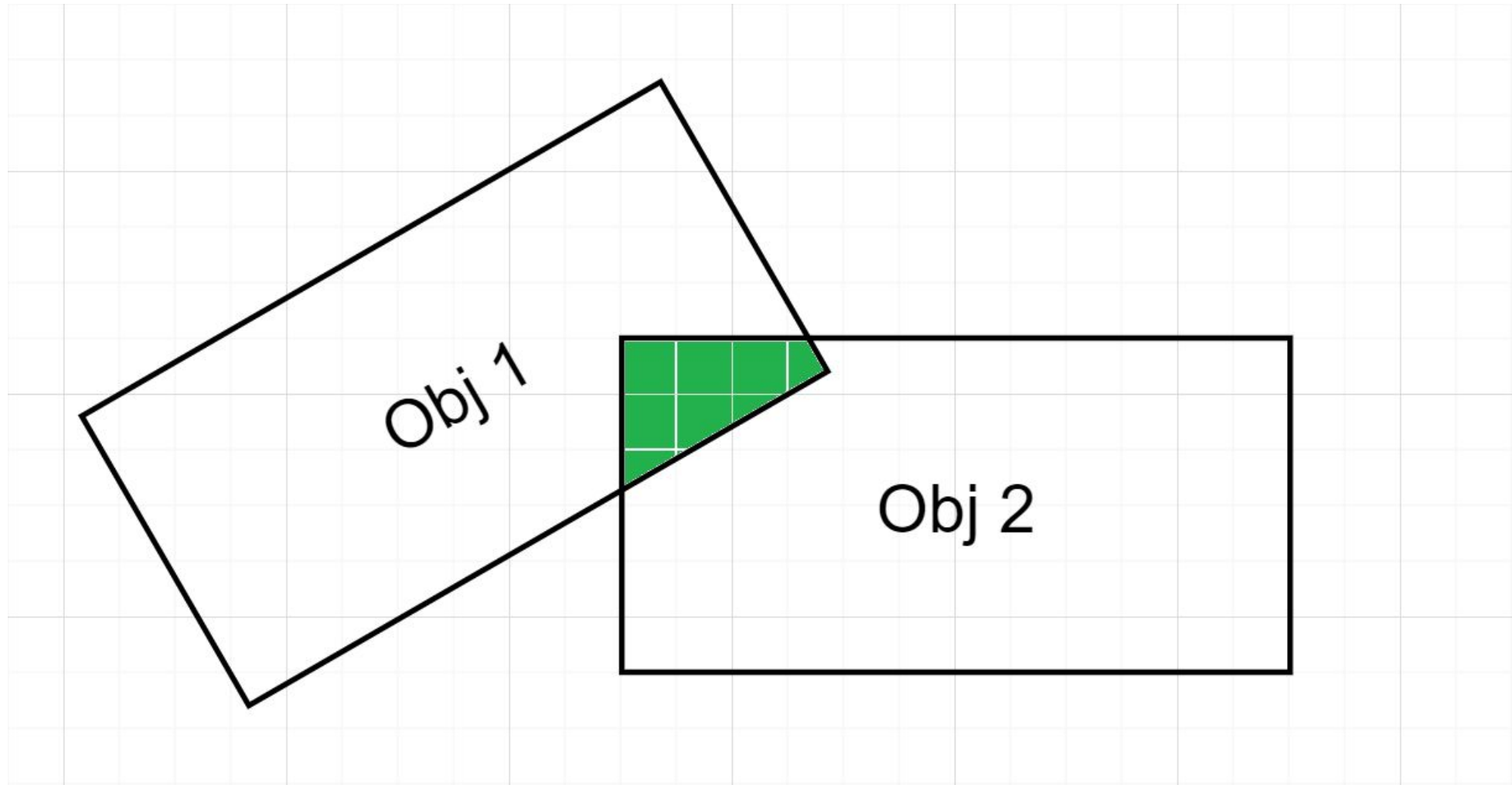
Fault tolerance: Inaccurate bounding boxes



Fault tolerance: Inaccurate bounding boxes



Fault tolerance: Inaccurate bounding boxes



Fault tolerance: Inaccurate object class type

1. False positive detection of objects
2. Inaccurate bounding boxes
3. Inaccurate object class type
4. False negative detection of objects

PET

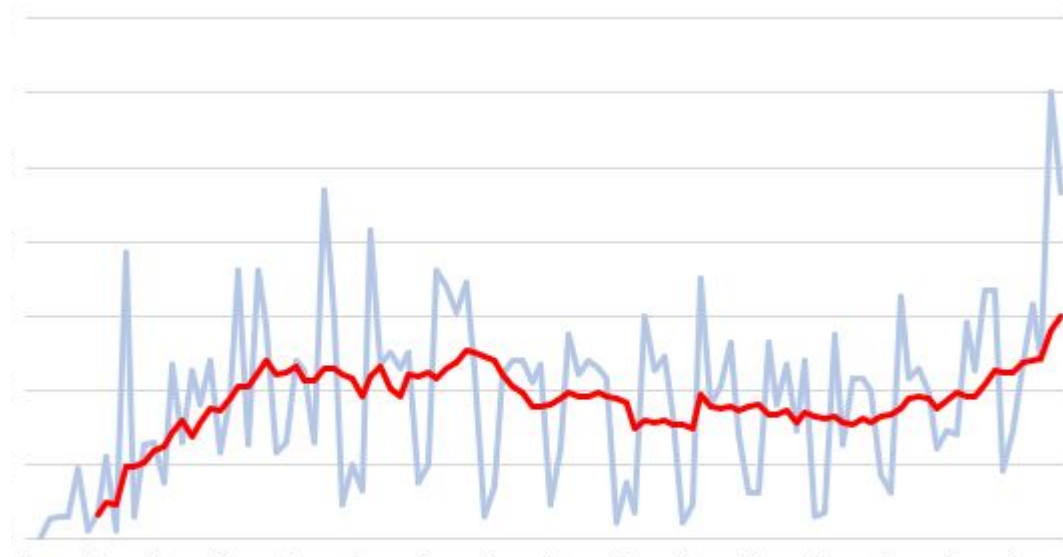
Serializer, PET Module, Noise Cancelation Modules

Speed

Momentary Speed Module, Average Speed Module

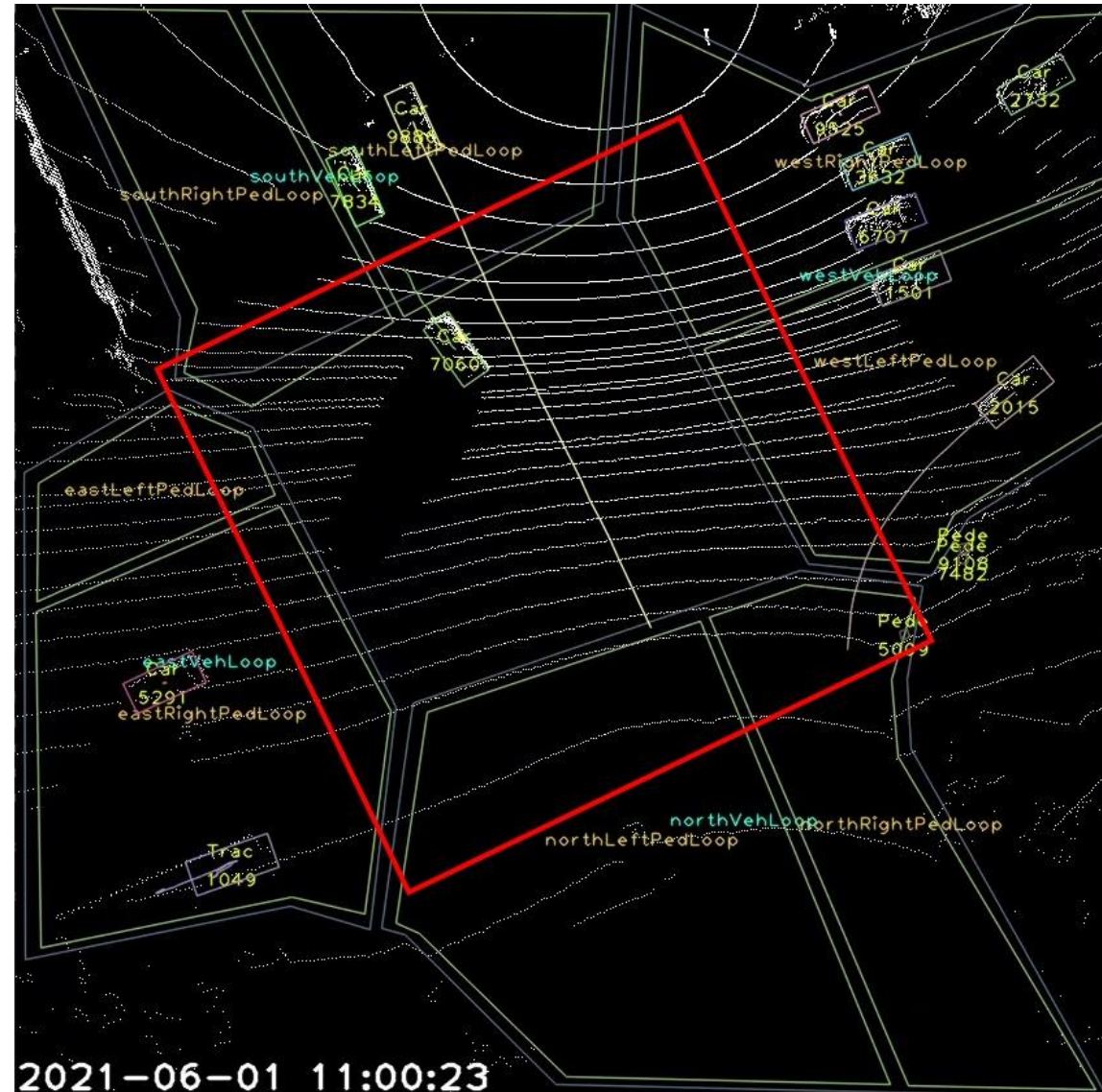
Speed: Momentary

- Need to have pixel to meter unit
- For overcome the inaccuracy caused by detection we used moving average technique
- Based on the position of an object in its four previous frames, we calculate speed of the object



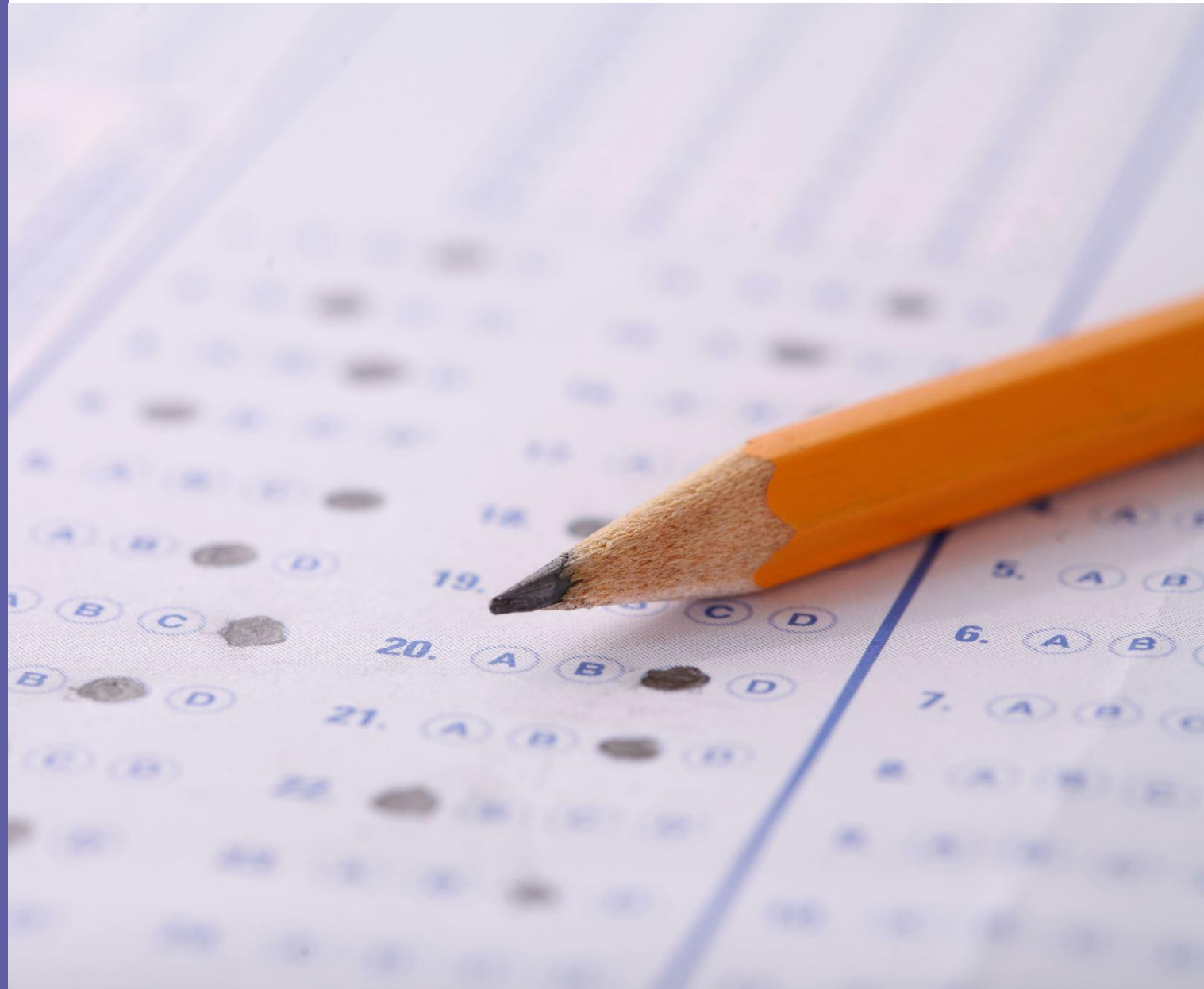
Speed: Average Speed

- Need to define a region that **represents the intersection**
- Take the **average of the momentary speed** of an object inside of the region
- This analysis only considers the **magnitude** of the speed



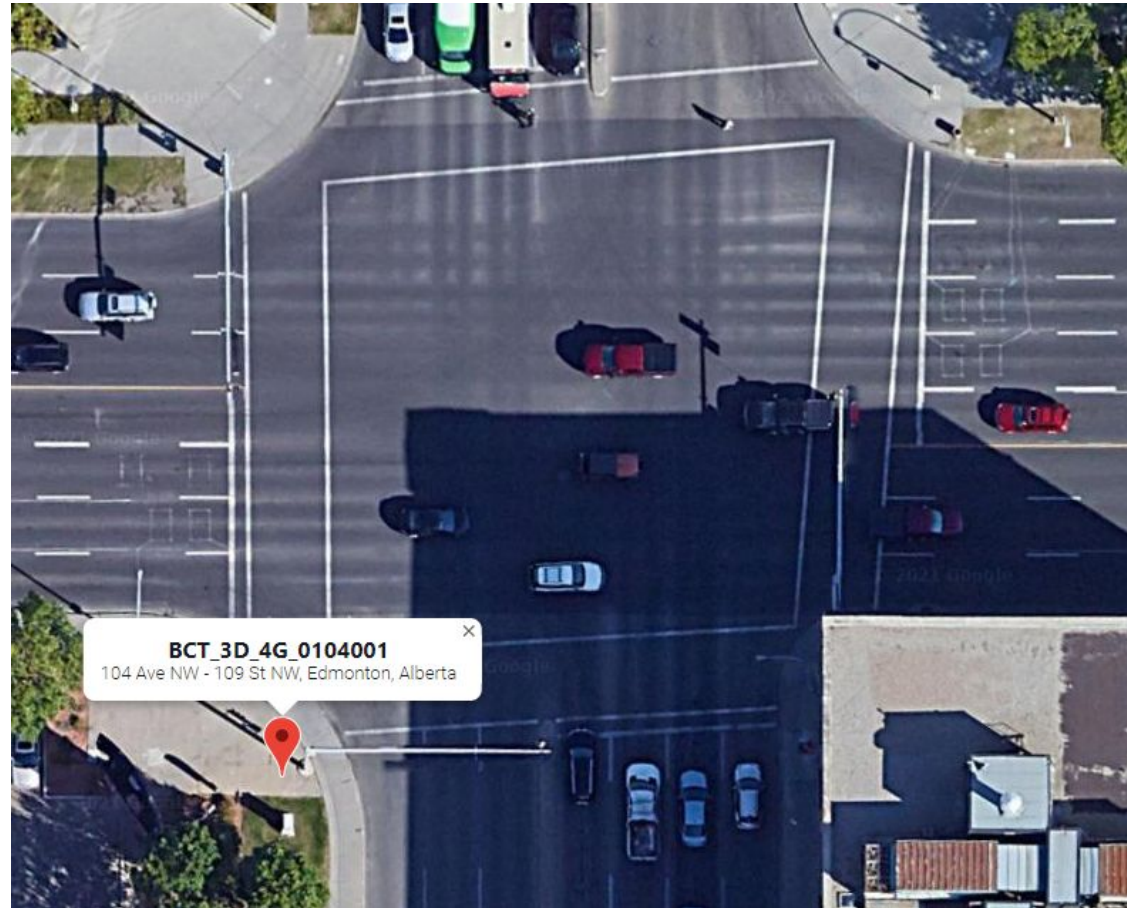
Validation

Setup, PET annotation software,
PET Experiments, Speed
Experiments



Setup

- Our solution is installed on many BlueCity sensors in different cities
- For our experiments we used 45 minutes data of Edmonton sensor
- Raw data and annotated video clip of that 45 minutes were collected and analyzed
- Frame rate of the sensor is 11 fps

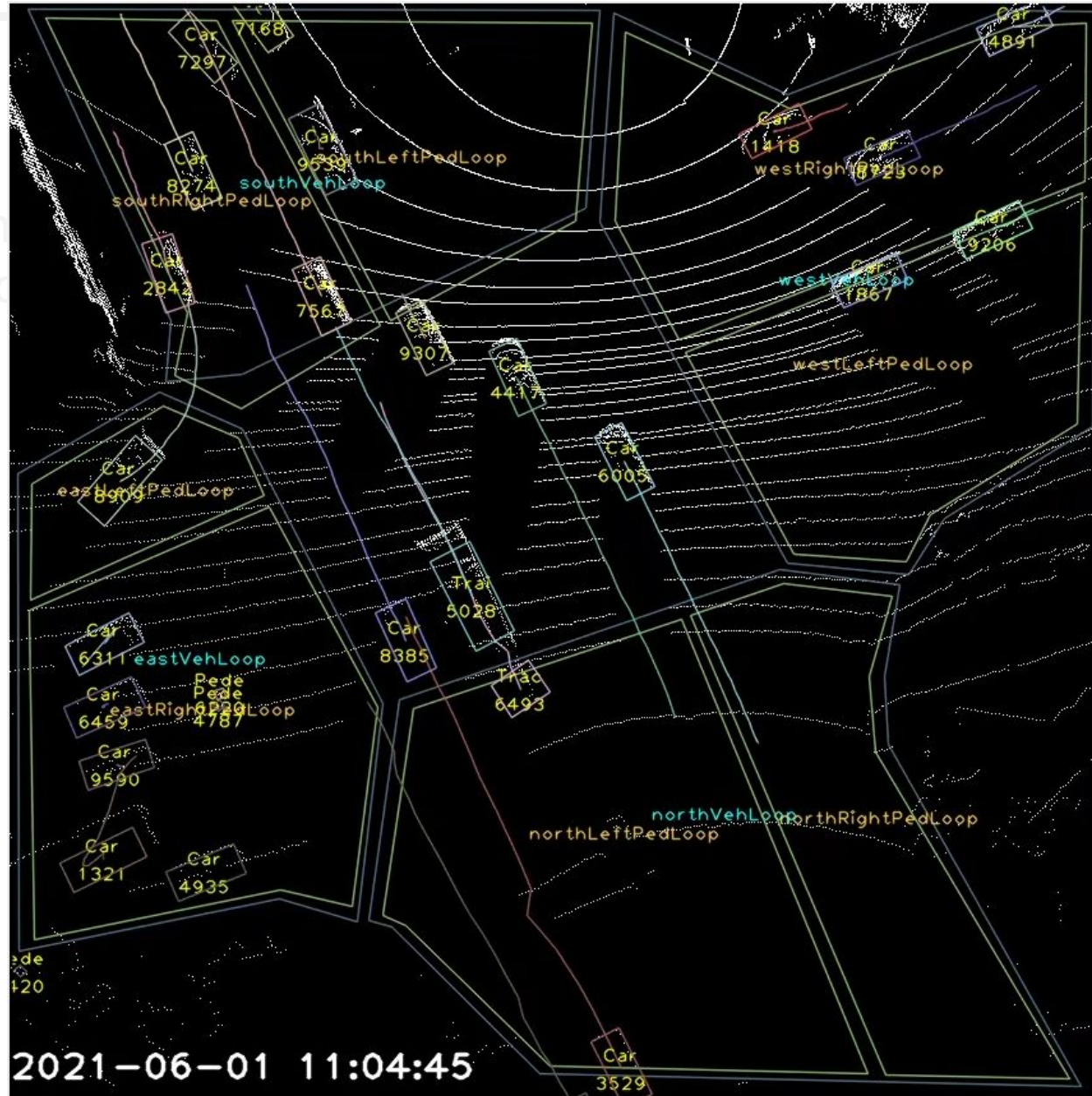


PET: Ground Truth

- Hard task to do and needed special software for annotation

PET: Ground T

- Hard task to do an special software for



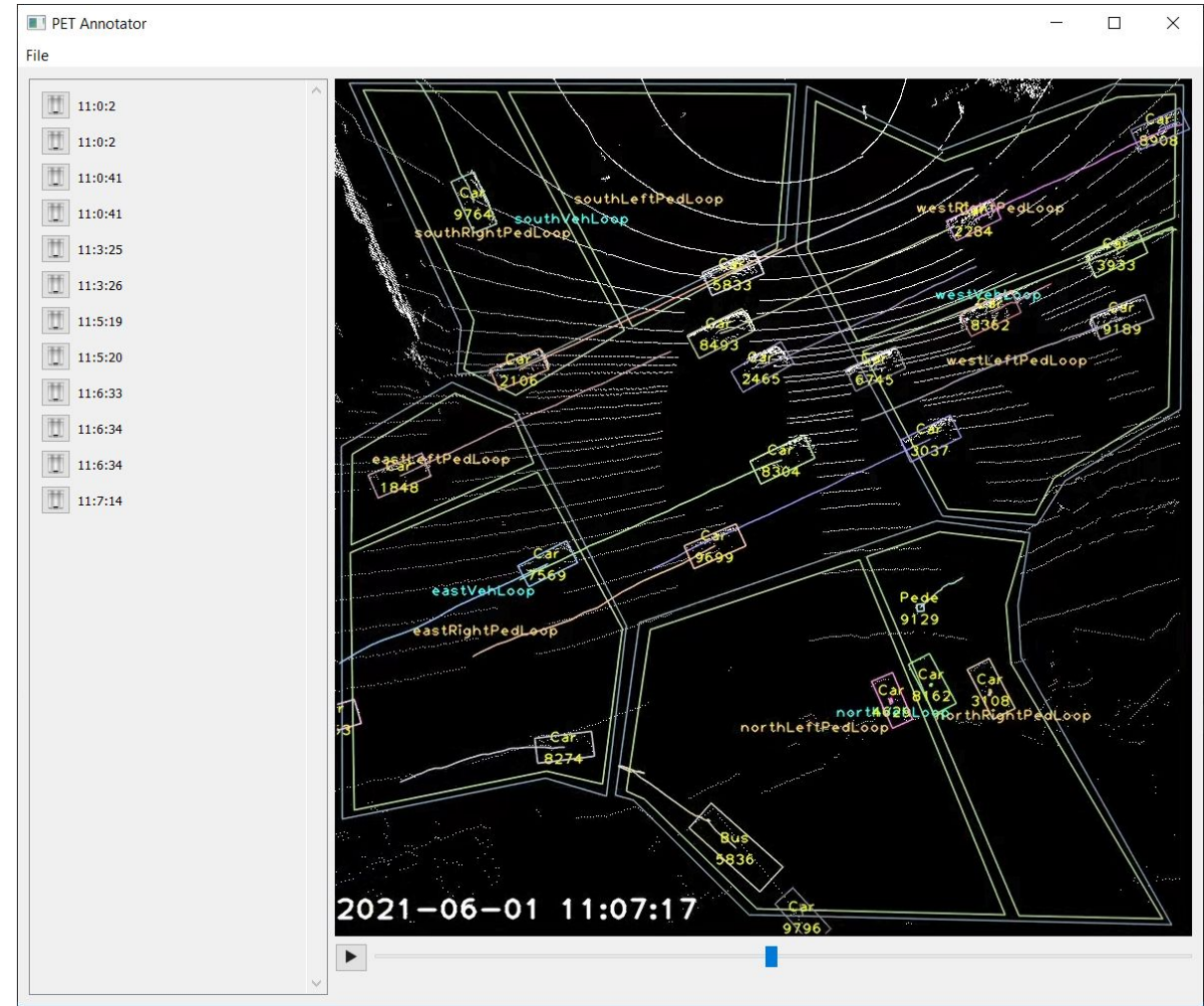
PET: Ground Truth

- Hard task to do and needed special software for annotation
- Tests only PET conflict detection and only for PET less than 3 seconds
- Added 3 seconds tail to each road users on the clip for helping the annotators
- Used 3 annotators for annotation

PET: Annotation Software

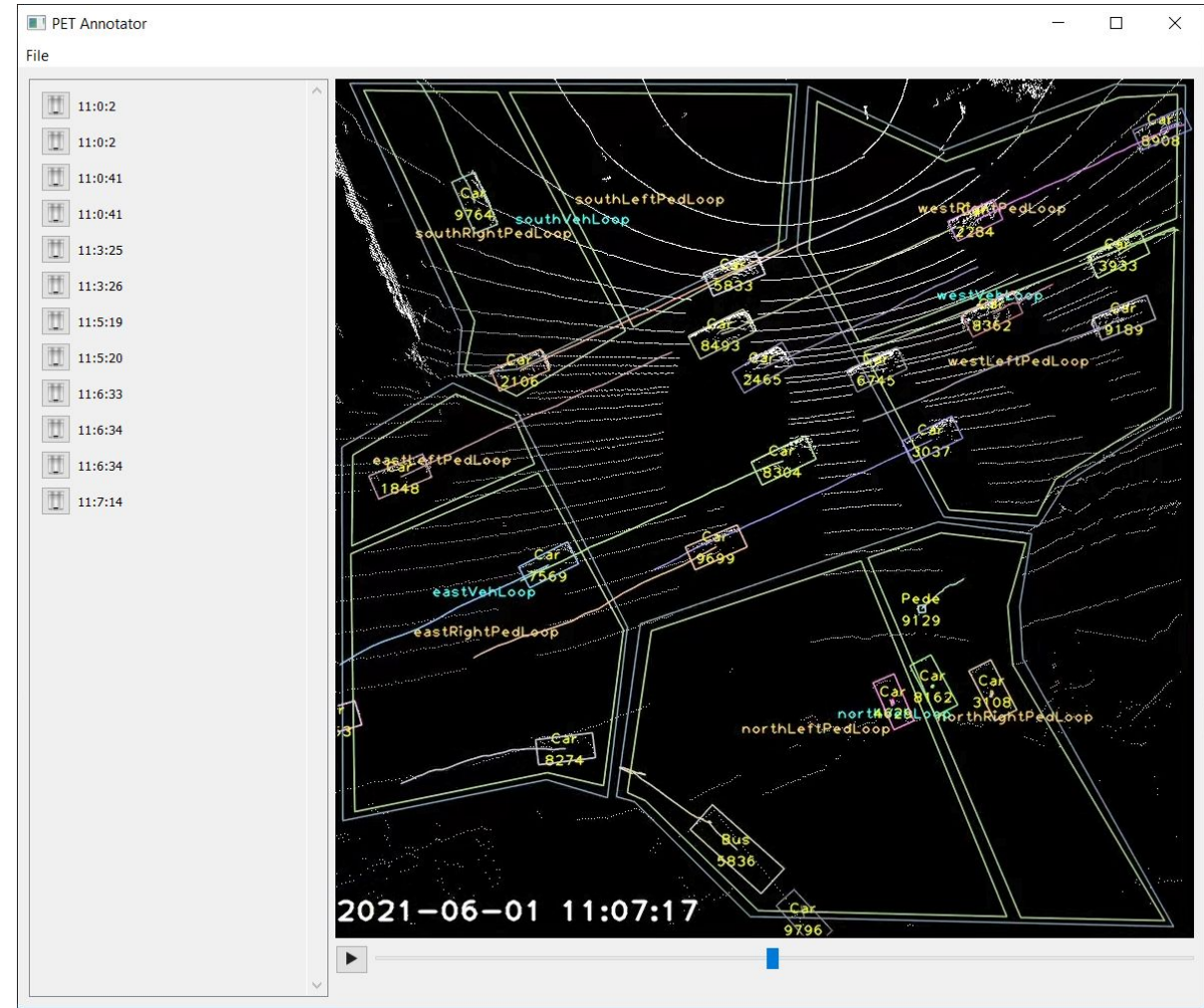
PET: Annotation Software

- Video clip player with shortcuts for changing the frame rates, skipping and Of clips



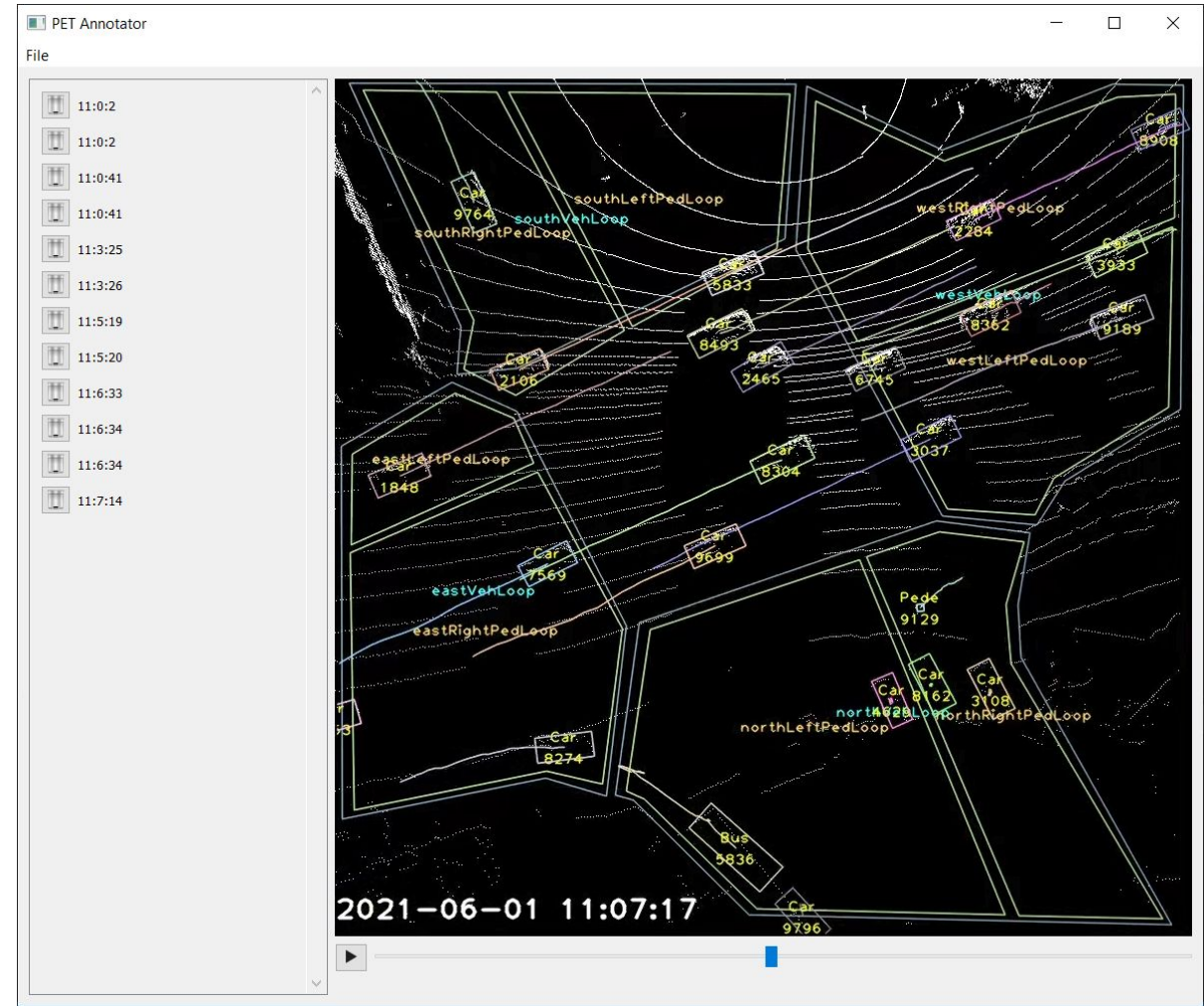
PET: Annotation Software

- Video clip player with shortcuts for changing the frame rates, skipping and Of clips
- Records the clicked position



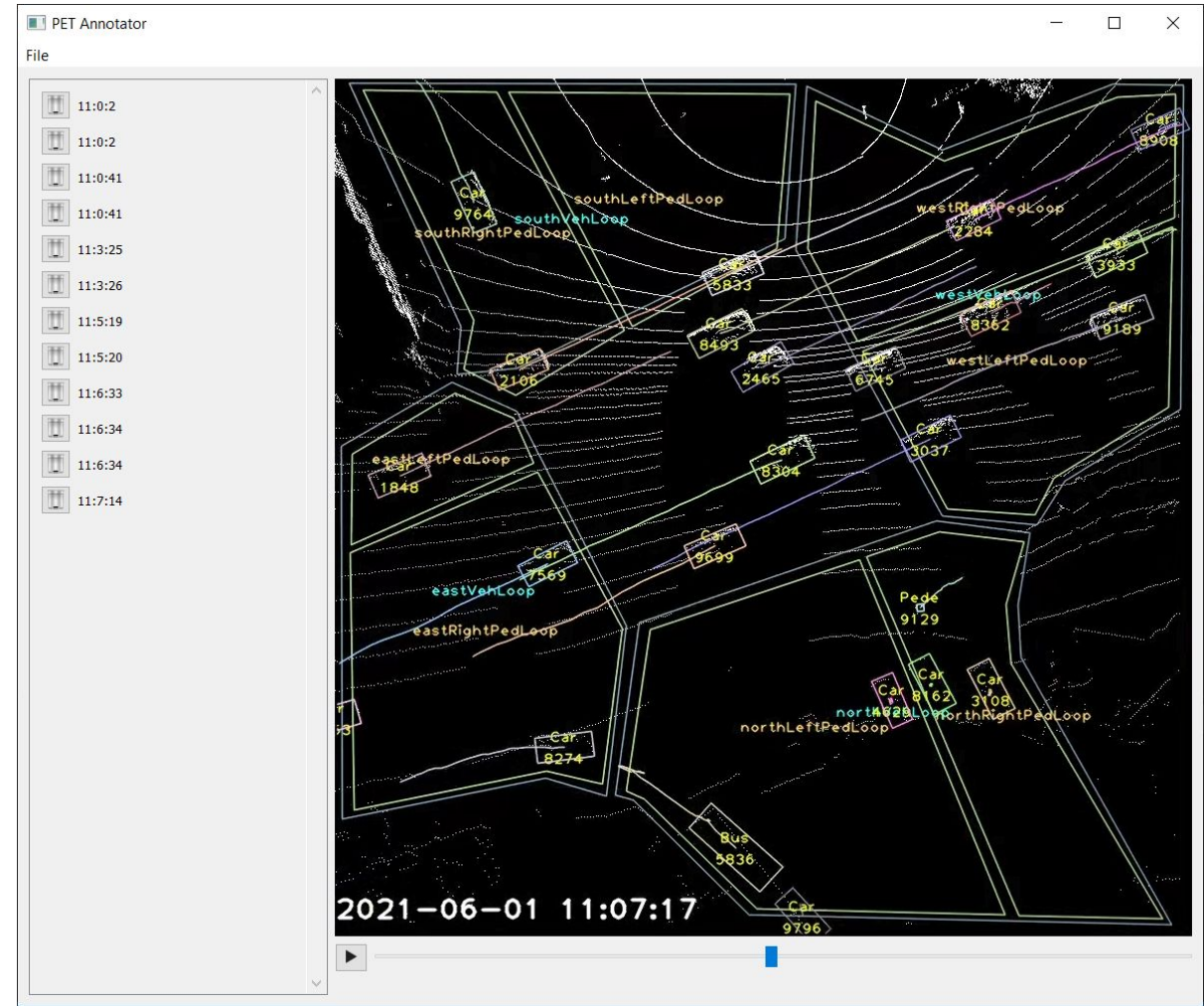
PET: Annotation Software

- Video clip player with shortcuts for changing the frame rates, skipping and Of clips
- Records the **clicked position**
- Captures the **timestamp** of the click



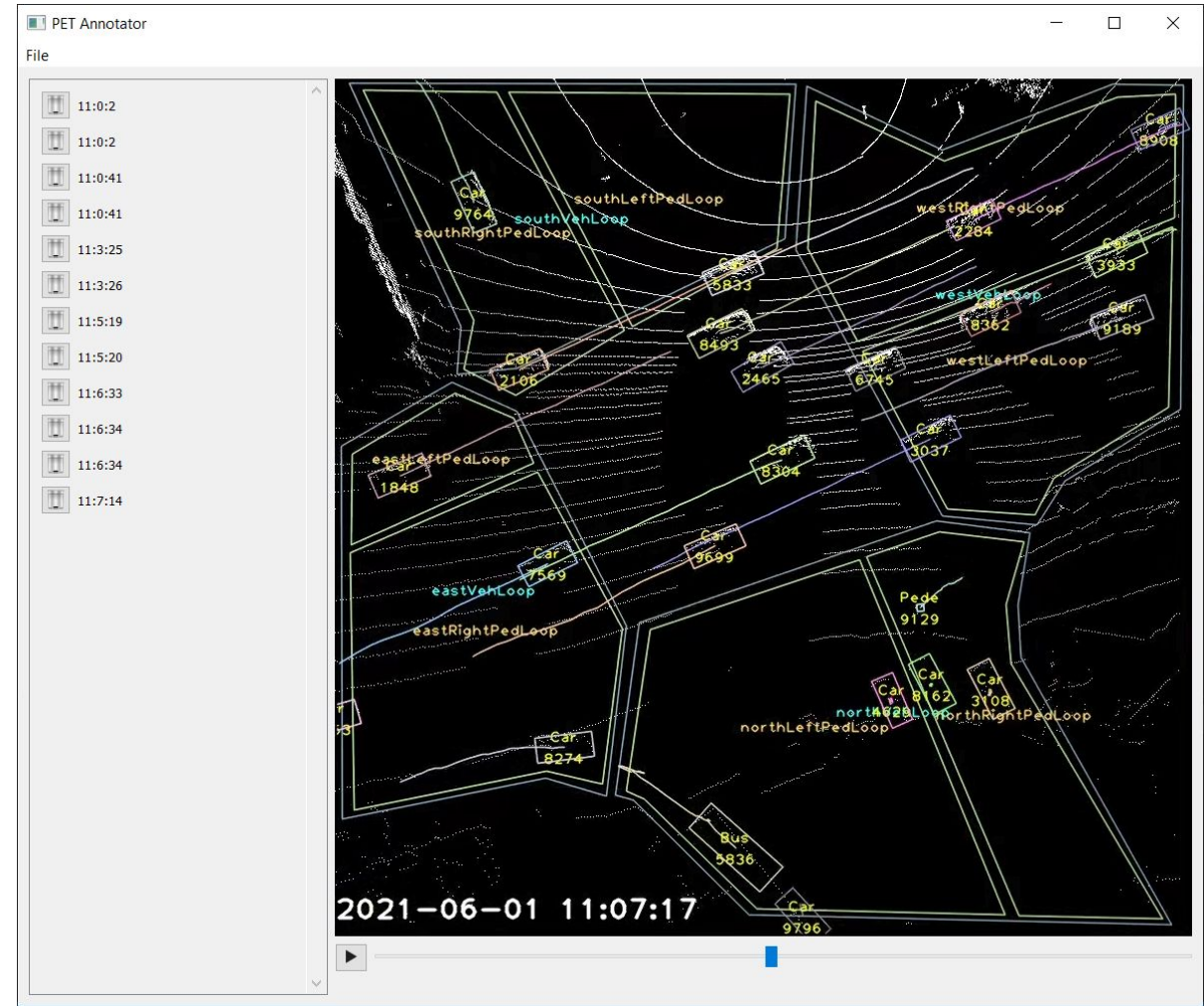
PET: Annotation Software

- Video clip player with shortcuts for changing the frame rates, skipping and Of clips
- Records the **clicked position**
- Captures the **timestamp** of the click
- Ability to delete the **unintentional clicks**



PET: Annotation Software

- Video clip player with shortcuts for changing the frame rates, skipping and Of clips
- Records the **clicked position**
- Captures the **timestamp** of the click
- Ability to delete the **unintentional clicks**
- **Exports** the clicked position and timestamp of each click

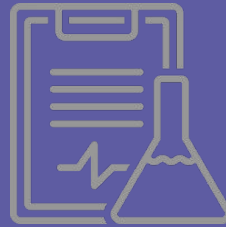


PET: Experiments



Exp 1: PET Performance

Check the performance of PET detection module with and without Noise removal modules



Exp 2: Delayed SIUs Setting

Checks the performance of the PET module with different setting of Delayed SIUs



Exp 3: Processing Speed

Checks the effect of different noise cancelation module on processing speed of the PET detection module

Exp 1: PET Performance

- Tested in 4 different modes:
 1. Without any noise cancelation module
 2. With delayed SIUs module active
 3. With validating turning movements
 4. With both delayed SIUs and turning movement validator modules

Exp 1: PET Performance

- Tested in 4 different modes:

1. Without any noise cancelation

2.

3.

4.

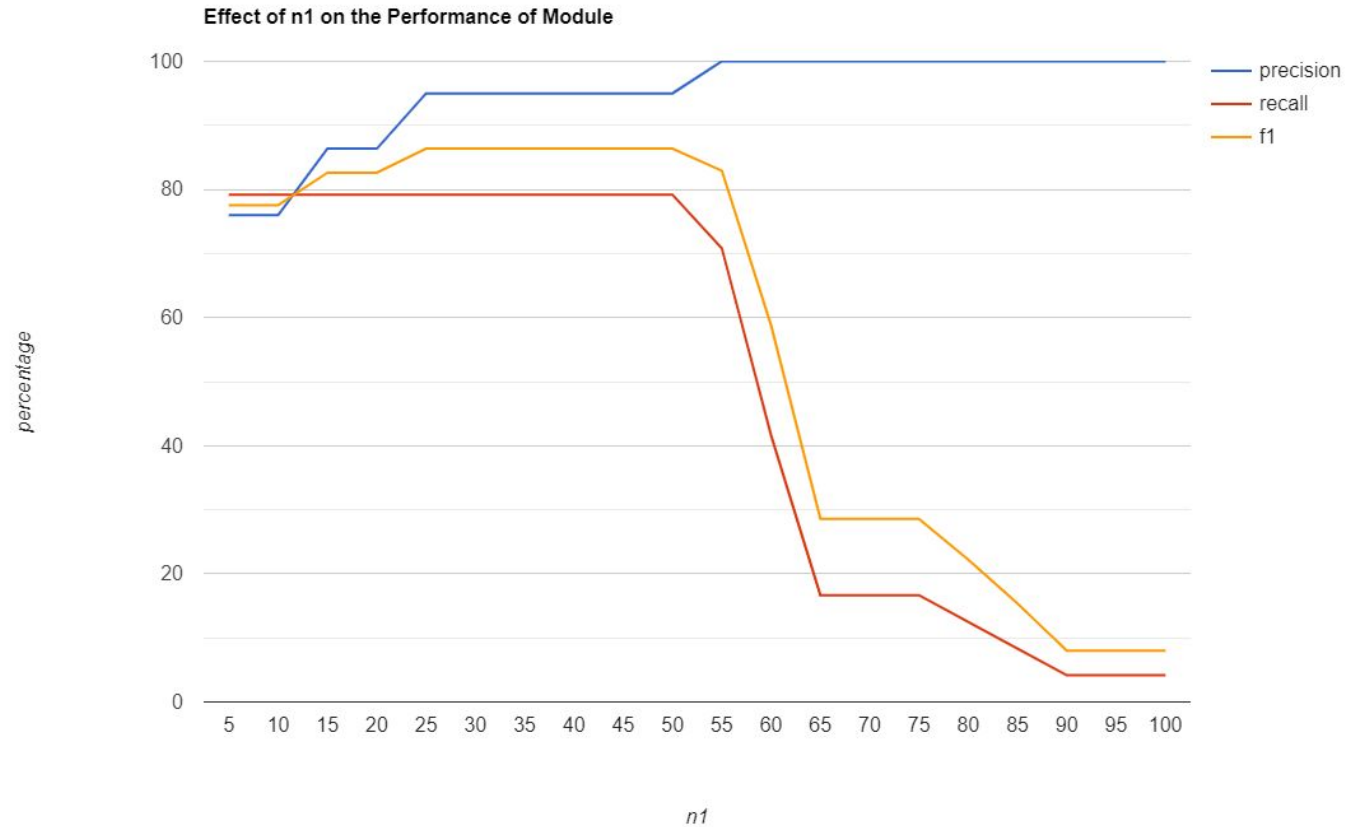
| | No Filter | Delayed Frame | Turning Movement | All Filters | Ground truth |
|--------------|----------------|---------------|------------------|----------------|--------------|
| Detected PET | 731 | 213 | 122 | 68 | 79 |
| Matched | 75 | 66 | 66 | 64 | - |
| False PET | 656 | 147 | 56 | 4 | - |
| Missed PET | 4 | 13 | 13 | 15 | - |
| Precision | 10.25 % | 30.98% | 54.09% | 94.11 % | - |
| Recall | 94.93 % | 83.53 % | 83.54 % | 81.01 % | - |
| F1-score | 18.50% | 45.11% | 65,66% | 86.29 % | - |

Exp 2: Delayed SIUs Setting

- Effects of delayed SIUs on the **performance** is significant
- **Length of a noise appearance** is not a constant and depends on the sensor and the environment

Exp 2: Delayed SIUs Setting

- Effects of performance
- Length of not a con the senso



Exp 2: Delayed Frame Setting

- Effects of de
performance
- Length of a
not a consta
the sensor a

| n_1 | No. Detected PET | No. Matched PET | Precision | Recall | F1 |
|--------------|------------------|-----------------|-----------|--------|---------------|
| 5 | 25 | 19 | 76% | 79.16% | 77.55% |
| 10 | 25 | 19 | 76% | 79.16% | 77.55% |
| 15 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 20 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
| 30 | 20 | 19 | 95% | 79.16% | 86.36% |
| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
| 70 | 4 | 4 | 100% | 16.66% | 28.57% |
| 75 | 4 | 4 | 100% | 16.66% | 28.57% |
| 80 | 3 | 3 | 100% | 12.5% | 22.22% |
| 85 | 2 | 2 | 100% | 8.33% | 15.38% |
| 90 | 1 | 1 | 100% | 4.16% | 8% |
| 95 | 1 | 1 | 100% | 4.16% | 8% |
| 100 | 1 | 1 | 100% | 4.16% | 8% |
| Ground truth | 24 | - | - | - | - |

Exp 3: processing speed

- Goal is to evaluate the effects of different noise removal modules on the processing time of the data
- Split the 45 minutes of data to 3 bins to account for the nuances in performance of testing machine
- Tested on a computer with 4 GB of Ram and a Core i5 Intel CPU.

Exp 3: processing speed

- Goal is to evaluate the effects of different noise removal modules on the processing time of the data
- Splitting the data into 3 bins to test the processing speed
- Tested on a computer with 4 GB of Ram and a Core i5 Intel CPU.

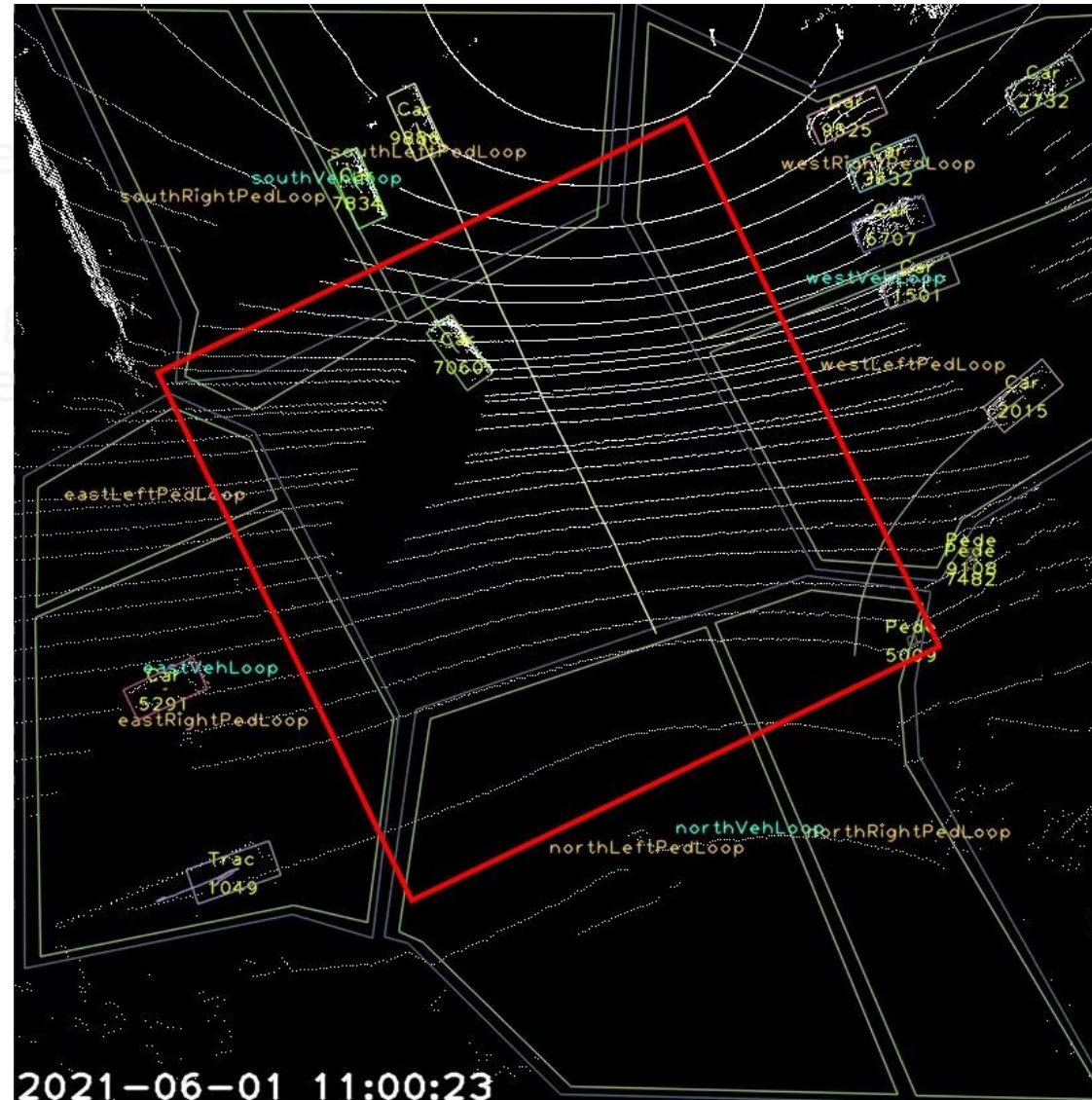
| Time | All Filters(s) | Delayed Frame(s) | Turning Movement(s) | No Filter(s) |
|------------------|----------------|------------------|---------------------|--------------|
| 15:00 - 15:15 pm | 537.61 | 537.70 | 635.90 | 643.00 |
| 15:15 - 15:30 pm | 485.93 | 483.63 | 575.95 | 567.75 |
| 15:30 - 15:45 pm | 490.78 | 490.49 | 581.68 | 576.40 |
| Total Seconds | 1514.33 | 1511.82 | 1793.55 | 1787.15 |

Speed: Validating Average Speed

- Only through movements were possible to validate
- Needed to define a region to calculate average speed in that region

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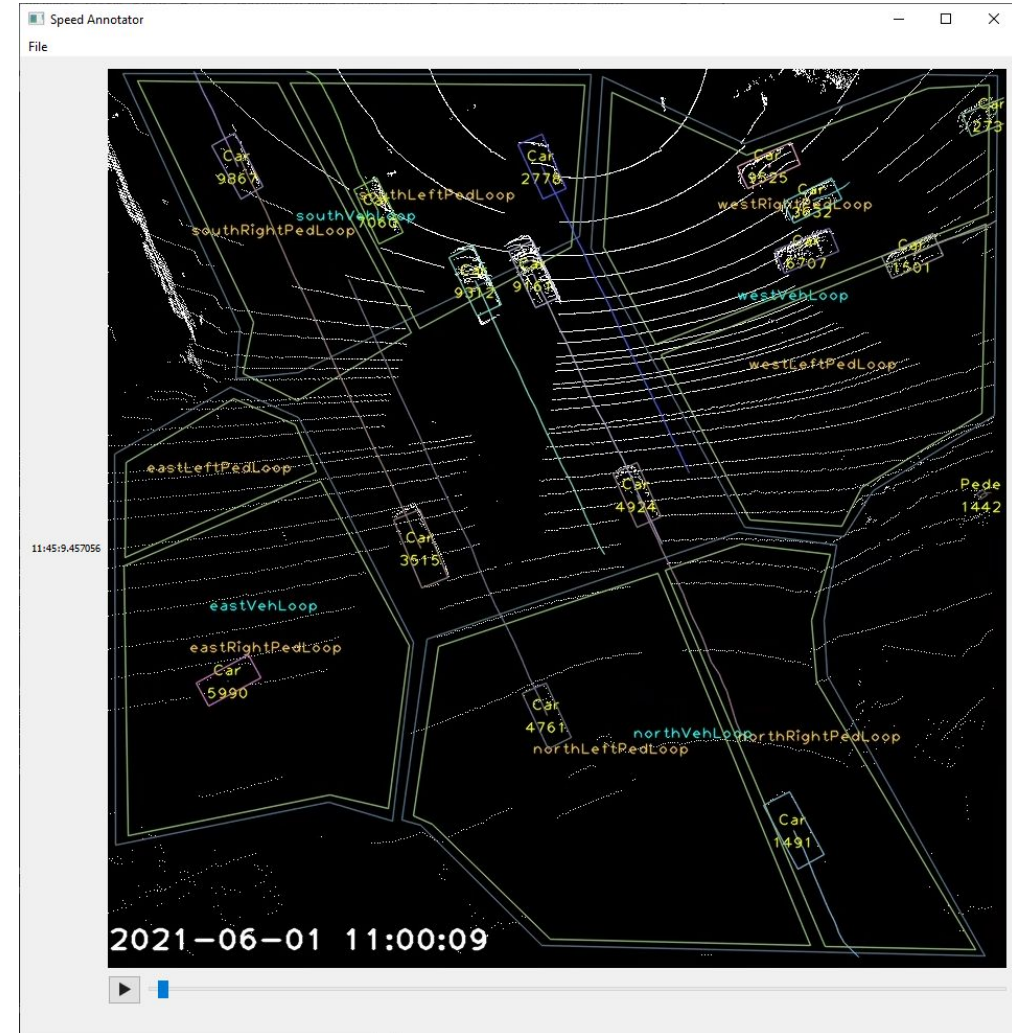


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Speed: Validating Average Speed

- Only through movements were possible to validate
- Needed to define a **region** to calculate average speed in that region
- Shared the **video clip** of data with our annotator and asked them to annotate 400 through movement
- Created a **custom annotation software** for capturing entrance and exit time of object in region



Speed: Validating Average Speed

- We mapped the region on google maps and using the distance measures tool we calculated the distance of each through movements
- Using the entry time and exit time of the object to the region, calculated the speed of an object
- We removed the outliers

Speed: Validating Average Speed

- We mapped the region on google maps and using the distance measures tool we calculated the distance through m
- Using the time of the region, call an object

| Turning Movement | North-South | South-North | East-West | West-East | Total |
|------------------------------|-------------|-------------|-----------|-----------|--------------|
| Count | 143 | 65 | 95 | 92 | 395 |
| AVG Speed (km/h) | 47.50 | 43.87 | 43.13 | 45.35 | 45.35 |
| AVG Speed GT (km/h) | 46.021 | 43.89 | 43.37 | 45.46 | 44.90 |
| Average Abs Speed off (km/h) | 1.84 | 1.14 | 1.21 | 1.08 | 1.40 |
| Error % | 4.06 | 2.48 | 2.36 | 2.75 | 3.09 |

- We removed the outliers

Conclusion

1) Introduction

Traffic Safety, SSA and SSM,
PET and Speed, Our
Contribution

2) Background

Literature Review, Similar
Approaches, Short Comings of
Other Works

3) Approach

PET Detection and Calculation
Module, Average and
Momentary Speed Module

4) Validation

PET Validations and
Experiments, Speed
Validation Experiment

An aerial photograph of a city intersection. The image shows multiple lanes of traffic, a central green median, and surrounding greenery. A white text box is overlaid on the right side of the image, containing the words 'Thank you'.

Thank
you

References

- XXX

Speed: Validating Average Speed

- We mapped the region on google maps and using the distance measures tool we calculated the distance from the road through m

| Turning Movement | North-South | South-North | East-West | West-East | Total |
|------------------------------|-------------|-------------|-----------|-----------|------------|
| Count | 143 | 65 | 95 | 92 | 395 |
| AVG Speed (km/h) | 47.50 | 43.87 | 43.13 | 45.35 | 45.35 |
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- We mapped the region on google maps and using the distance measures tool we calculated the distance from the start through m

| Turning Movement | North-South | South-North | East-West | West-East | Total |
|------------------------------|-------------|-------------|-----------|-----------|--------------|
| Count | 143 | 65 | 95 | 92 | 395 |
| AVG Speed (km/h) | 47.50 | 43.87 | 43.13 | 45.35 | 45.35 |
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Exp 3: processing speed

- Goal is to evaluate the effects of different noise removal modules on the processing time of the data
- Splitting the data into 3 bins to test the processing speed
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| Total Seconds | 1514.33 | 1511.82 | 1793.55 | 1787.15 |

- Splitting the data into 3 bins to test the processing speed on different testing machines
- Tested on a computer with 4 GB of Ram and a Core i5 Intel CPU.

Exp 3: processing speed

- Goal is to evaluate the effects of different noise removal modules on the processing time of the data
- Splitting the data into 3 bins to test the processing speed
- Tested on a computer with 4 GB of Ram and a Core i5 Intel CPU.

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| Total Seconds | 1514.33 | 1511.82 | 1793.55 | 1787.15 |

Exp 2: Delayed Frame Setting

- Effects of de performance
- Length of a not a constant the sensor a

| n_1 | No. Detected PET | No. Matched PET | Precision | Recall | F1 |
|---------------------|------------------|-----------------|-----------|----------|---------------|
| 5 | 25 | 19 | 76% | 79.16% | 77.55% |
| 10 | 25 | 19 | 76% | 79.16% | 77.55% |
| 15 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 20 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
| 30 | 20 | 19 | 95% | 79.16% | 86.36% |
| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
| 70 | 4 | 4 | 100% | 16.66% | 28.57% |
| 75 | 4 | 4 | 100% | 16.66% | 28.57% |
| 80 | 3 | 3 | 100% | 12.5% | 22.22% |
| 85 | 2 | 2 | 100% | 8.33% | 15.38% |
| 90 | 1 | 1 | 100% | 4.16% | 8% |
| 95 | 1 | 1 | 100% | 4.16% | 8% |
| 100 | 1 | 1 | 100% | 4.16% | 8% |
| Ground truth | 24 | - | - | - | - |

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| 20 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
| 30 | 20 | 19 | 95% | 79.16% | 86.36% |
| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
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| 20 | 22 | 19 | 86.36% | 79.16% | 82.60% |
| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
| 30 | 20 | 19 | 95% | 79.16% | 86.36% |
| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
| 70 | 4 | 4 | 100% | 16.66% | 28.57% |
| 75 | 4 | 4 | 100% | 16.66% | 28.57% |
| 80 | 3 | 3 | 100% | 12.5% | 22.22% |
| 85 | 2 | 2 | 100% | 8.33% | 15.38% |
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| Ground truth | 24 | - | - | - | - |

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| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
| 30 | 20 | 19 | 95% | 79.16% | 86.36% |
| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
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| Ground truth | 24 | - | - | - | - |

Exp 2: Delayed Frame Setting

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- Length of a not a constant the sensor a

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| 25 | 20 | 19 | 95% | 79.16% | 86.36% |
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| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
| 55 | 17 | 17 | 100% | 70.83% | 82.92% |
| 60 | 10 | 10 | 100% | 41.66% | 58.82% |
| 65 | 4 | 4 | 100% | 16.66% | 28.57% |
| 70 | 4 | 4 | 100% | 16.66% | 28.57% |
| 75 | 4 | 4 | 100% | 16.66% | 28.57% |
| 80 | 3 | 3 | 100% | 12.5% | 22.22% |
| 85 | 2 | 2 | 100% | 8.33% | 15.38% |
| 90 | 1 | 1 | 100% | 4.16% | 8% |
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| 35 | 20 | 19 | 95% | 79.16% | 86.36% |
| 40 | 20 | 19 | 95% | 79.16% | 86.36% |
| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
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| 45 | 20 | 19 | 95% | 79.16% | 86.36% |
| 50 | 20 | 19 | 95% | 79.16% | 86.36% |
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| Ground truth | 24 | - | - | - | - |

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| 100 | 1 | 1 | 100% | 4.16% | 8% |
| Ground truth | 24 | - | - | - | - |

Exp 1: PET Performance

- Tested in 4 different modes:

1. Without any noise cancelation

| | No Filter | Delayed Frame | Turning Movement | All Filters | Ground truth |
|-----------------|----------------|---------------|------------------|----------------|--------------|
| 2. Detected PET | 731 | 213 | 122 | 68 | 79 |
| Matched | 75 | 66 | 66 | 64 | - |
| 3. False PET | 656 | 147 | 56 | 4 | - |
| Missed PET | 4 | 13 | 13 | 15 | - |
| 4. Precision | 10.25 % | 30.98% | 54.09% | 94.11 % | - |
| Recall | 94.93 % | 83.53 % | 83.54 % | 81.01 % | - |
| F1-score | 18.50% | 45.11% | 65.66% | 86.29 % | - |

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| Missed PET | 4 | 13 | 13 | 15 | - |
| 4. Precision | 10.25 % | 30.98% | 54.09% | 94.11 % | - |
| Recall | 94.93 % | 83.53 % | 83.54 % | 81.01 % | - |
| F1-score | 18.50% | 45.11% | 65,66% | 86.29 % | - |

Exp 1: PET Performance

- Tested in 4 different modes:

1. Without any noise cancelation

2.

3.

4.

| | No Filter | Delayed Frame | Turning Movement | All Filters | Ground truth |
|--------------|----------------|---------------|------------------|----------------|--------------|
| Detected PET | 731 | 213 | 122 | 68 | 79 |
| Matched | 75 | 66 | 66 | 64 | - |
| False PET | 656 | 147 | 56 | 4 | - |
| Missed PET | 4 | 13 | 13 | 15 | - |
| Precision | 10.25 % | 30.98% | 54.09% | 94.11 % | - |
| Recall | 94.93 % | 83.53 % | 83.54 % | 81.01 % | - |
| F1-score | 18.50% | 45.11% | 65,66% | 86.29 % | - |