SDC Tracking Competition

A. Pipeline

來源：https://github.com/apak-00/argoverse_simple_gmf_tracker

1. Detection：

直接使用 argoverse_detections_2020 提供的結果，內容包含：被 label 物件的 pose，3D boundingbox 的長寬高，時間戳記等


```
{
    "center": {
        "x": 10.893529891967773,
        "y": -2.9378652572631836,
        "z": 0.44712644815444946
    },
    "height": 1.4641387462615967,
    "label_class": "VEHICLE",
    "length": 4.45181941986084,
    "occlusion": 0,
    "rotation": {
        "w": -0.999944996144389,
        "x": 0.0,
        "y": 0.0,
        "z": -0.010488311865967603
    },
    "score": 0.8930596709251404,
    "timestamp": 315968385022970000,
    "track_label_uuid": null,
    "tracked": true,
    "width": 1.816713809967041
},
```


2. Data Association：

在所有 lidar_timestamps 反覆以下操作：

(1) 先檢查一下資料(label,map 等等)，如遇到特定條件直接 continue 跳過，進入下一個 lidar_timestamps

(2) ab3dmot.update (在 city frame 座標系下更新觀測結果)

(3) 整理結果(座標轉換等)並輸出 .json

其中，ab3dmot.update 包含以下操作：

(1) 預測既有 trackers 的下一個 pose 和其他必要資訊

(2) 將 detections 配對給 trackers。這是一個線性規劃問題，使用 hungarian algorithm 求解。

(3) 更新 trackers 的配對結果。

(4) 幫沒有配對到的 detections 建立新的 trackers。

(5) Gaussian mixtures

其中，trackers 使用 FilterPy 的 KalmanFilter 類別來實做。其系統建模類似於 constant velocity model。

- 假設 *t+1* 時刻的真實狀態是從 t 時刻的狀態演化而來，符合下式：

$$\mathbf{x}_{t+1} = \begin{bmatrix} x + v_x \\ y + v_y \\ z + v_z \\ \theta \\ l \\ w \\ h \\ v_x \\ v_y \\ v_z \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0.1 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ \theta \\ l \\ w \\ h \\ v_x \\ v_y \\ v_z \end{bmatrix} = F\mathbf{x}_t$$

- 時刻 *t+1*，對真實狀態 **x(t)**的觀測滿足下式：

$$\mathbf{x}_{t+1} = \begin{bmatrix} x \\ y \\ z \\ \theta \\ l \\ w \\ h \\ 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ \theta \\ l \\ w \\ h \\ v_x \\ v_y \\ v_z \end{bmatrix} = H\mathbf{x}_t$$

另外，有別於 baseline code 的作法，GMF 幫 tracker 多定義了 self.w

- Each Gaussian component is weighted (w_i, [0,1]), weight is directly proportional to classification score and evolves according to it.

並使用以下參數來達成 Gaussian mixtures

- Probability of survival (p_s [0,1]) - probability of target survival between a consecutive time steps.
- Estimate threshold (t_e [0,1]) - threshold above which to report tracked targets.
- Prune threshold (t_p [0,1]) - threshold below which to remove Gaussian components from the tracker.

```
487     # KalmanBoxTracker init
488     # Test new
489     self.w = conf
490     self.ps = ps
```

```
496     #KalmanBoxTracker update
497     self.w += conf
498     if self.w > 1:
499       self.w = 1
```

```
550     #KalmanBoxTracker predict
551     # Multiply by p_s
552     self.w *= self.ps
```

```
747     #AB3DMOT update
748     for trk in reversed(self.trackers):
749         d = trk.get_state()      # bbox location
750
751         if (trk.w >= self.thr_estimate):
752           ret.append(np.concatenate((d, [trk.id+1], trk.info)).reshape(1,-1))
753
754         i -= 1
755
756         if trk.w <= self.thr_prune:
757           self.trackers.pop(i)
758
```

B. Contribution

1. 嘗試幫 KalmanFilter 指定不同的 Instance Variables

```
class KalmanBoxTracker(object):
  """
  This class represents the internel state of individual tracked objects observed as bbox.
  """
  count = 0
  def __init__(self, bbox3D, info, p, conf, ps=1):
    """
    Initialises a tracker using initial bounding box.
    """
    self.kf = KalmanFilter(dim_x=10, dim_z=7)

    # covariance matrix
    self.kf.P = np.array([[1., 0., 0., 0., 0., 0., 0., 0., 0., 0.],
                          [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.],
                          [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
                          [0., 0., 0., 1., 0., 0., 0., 0., 0., 0.],
                          [0., 0., 0., 0., 1., 0., 0., 0., 0., 0.],
                          [0., 0., 0., 0., 0., 1., 0., 0., 0., 0.],
                          [0., 0., 0., 0., 0., 0., 1., 0., 0., 0.],
                          [0., 0., 0., 0., 0., 0., 0., 1., 0., 0.],
                          [0., 0., 0., 0., 0., 0., 0., 0., 1., 0.],
                          [0., 0., 0., 0., 0., 0., 0., 0., 0., 1.]])

    # Process uncertainty/noise
    self.kf.Q = np.array([  [0.01, 0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.  ],
                            [0.,   0.01, 0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.  ],
                            [0.,   0.,   0.01, 0.,   0.,   0.,   0.,   0.,   0.,   0.  ],
                            [0.,   0.,   0.,   0.01, 0.,   0.,   0.,   0.,   0.,   0.  ],
                            [0.,   0.,   0.,   0.,   0.01, 0.,   0.,   0.,   0.,   0.  ],
                            [0.,   0.,   0.,   0.,   0.,   0.01, 0.,   0.,   0.,   0.  ],
                            [0.,   0.,   0.,   0.,   0.,   0.,   0.01, 0.,   0.,   0.  ],
                            [0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.01, 0.,   0.  ],
                            [0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.01, 0.  ],
                            [0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.,   0.01]])
                            [...,  ...,  ...,  ...,  ...,  ...,  ...,  ...,  ...,  ...,,,

    # measurement uncertainty/noise
    self.kf.R = np.array([  [0.1, 0.,  0.,  0.,  0.,  0.,  0. ],
                            [0.,  0.1, 0.,  0.,  0.,  0.,  0. ],
                            [0.,  0.,  0.1, 0.,  0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.1, 0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.1, 0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.1, 0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.,  0.1]])

    # measurement function
    self.kf.H = np.array(  [[1, 0, 0, 0, 0, 0, 0, 0, 0, 0],
                            [0, 1, 0, 0, 0, 0, 0, 0, 0, 0],
                            [0, 0, 1, 0, 0, 0, 0, 0, 0, 0],
                            [0, 0, 0, 1, 0, 0, 0, 0, 0, 0],
                            [0, 0, 0, 0, 1, 0, 0, 0, 0, 0],
                            [0, 0, 0, 0, 0, 1, 0, 0, 0, 0],
                            [0, 0, 0, 0, 0, 0, 1, 0, 0, 0]])

    # state transistion matrix
    self.kf.F = np.array(  [[1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.1, 0.,  0. ],
                            [0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.1, 0. ],
                            [0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0.,  0.1],
                            [0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1.,  0. ],
                            [0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  0.,  1. ]])
```

2. 嘗試指定 > 1 的 alpha ，讓原本的 KalmanFilter 拓展成為 fading memory filter

```
    # Assign a value > 1.0 to turn this into a fading memory filter.
    self.kf.alpha = 1.05
```

3. Take measurements and predictions at steady state .但是似乎為錯誤用法，本系統非LTI(線性非時變)系統。

```
    # self.kf.update(bbox3D)
    """
    Add a new measurement (z) to the Kalman filter without recomputing the Kalman gain K, the state covariance P, or the system uncertainty S.

    You can use this for LTI systems since the Kalman gain and covariance converge to a fixed value. Precompute these and assign them explicitly,
    or run the Kalman filter using the normal predict()/update(0 cycle until they converge.

    The main advantage of this call is speed. We do significantly less computation, notably avoiding a costly matrix inversion.

    Use in conjunction with predict_steadystate(), otherwise P will grow without bound.
    """
    self.kf.update_steadystate(bbox3D)
```

```
    # self.kf.predict()
    """
    Predict state (prior) using the Kalman filter state propagation equations. Only x is updated, P is left unchanged.
    See update_steadstate() for a longer explanation of when to use this method.
    """
    self.kf.predict_steadystate()
```

4. 更換使用 Hungarian algorithm 呼叫的函式，需要再對 return 項調整一下形狀。

```
  # matched_indices = linear_assignment(distance_matrix)      # hungarian algorithm
  matched_indices = linear_sum_assignment(distance_matrix)
  matched_indices = np.asarray(matched_indices)
  matched_indices = np.transpose(matched_indices)
```

5. 呼叫 argoverse-api 裡的函式，對 map 多檢查兩個條件（這原本就有，我只是把註解打開）

```
                # Check the driveable/roi area
                da = am.remove_non_driveable_area_points(np.array([ego_xyz]), city_name=city_name)
                if len(da) == 0 and l['label_class'] == 'VEHICLE':
                    continue

                roi = am.remove_non_roi_points(np.array([ego_xyz]), city_name=city_name)
                if len(roi) == 0:
                    continue
```

6. 做關聯性表現衡量時，計算 match-distance 的方式由 IOU 改成 Mahalanobis distance（這也是本來就寫在裡面的選項）

7. GMF 的作者在它的 README 裡面寫著，可以根據不同性能要求調整這兩個參數

```
    thr_estimate = 0.55
    ps = 0.875
```

C. Problem and Solution

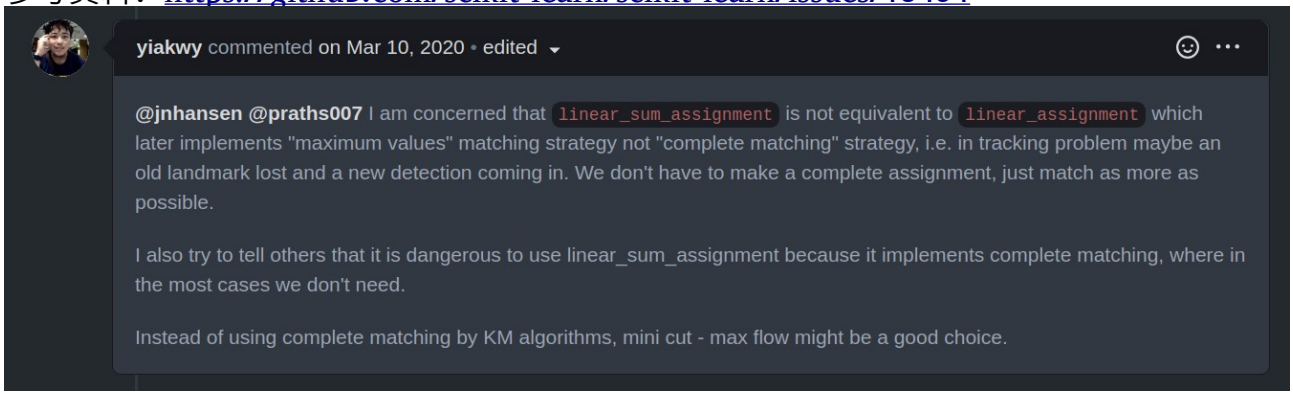
1. Kalman Filter 的預設值不一定會 work
   - 狀態轉移矩陣(F 矩陣)右上角需根據資料的時間變化量(SEGMENT DURATION)做調整。
   - uncertainty(Q 矩陣,R 矩陣)需要靠經驗來嘗試調整。

2. 加了 alpha 之後性能變差

覺得只是值給的不好。原 baseline code 的作者在他的 paper 中提到，類似於 constant velocity model 的 KalmanFilter，在轉彎上特別不行。fading memory filter 用遞迴的方式處理更多歷史資料，應該能協助我們克服此系統建模上的瑕疵。繼續嘗試給它不同的 scale (alpha)或許能得到更好的結果。

3. 不同的線性規劃函式差異

`sklearn.utils.linear_assignment_`和 `scipy.optimize.linear_sum_assignment` 實做方式不同。
參考資料：https://github.com/scikit-learn/scikit-learn/issues/13464



D. Results

在固定 thr estimate = 0.5 ， ps = 0.875 ， 使用原本未經修改的 GMF 得到最好的結果。

C:MOTA	P:MOTA	C:MOTPD	P:MOTPD	C:MOTPO	P:MOTPO	C:MOTPI	P:MOTPI	C:IDF1	P:IDF1	C:MT	P:MT	C:ML	P:ML	C:FP	P:FP	C:FN	P:FN	C:SW	P:SW	C:FRG	P:FRG
68.24	44.16	0.38	0.25	52.66	83.16	0.21	0.29	0.82	0.59	0.56	0.29	0.18	0.3	13244	4160	18790	13193	136	184	733	370

E. Run the code

需修改 run_ab3dmot_GMF.py 以下三行路徑

```
261     path_detections = f"/home/yellow/self-driving-cars-course/final/argoverse_detections_2020/validation"
262     path_data = f"/home/yellow/self-driving-cars-course/final/argoverse-tracking/val"
263     path_results = f"/home/yellow/self-driving-cars-course/final/argoverse_cbgs_kf_tracker/results/results_tracking_val_cbgs"
```

終端機執行 *python3 run_ab3dmot_GMF.py*