Track-oriented multiple hypothesis tracker

Task: Write a MATLAB function that implements a n-object tracker using the track-oriented multiple hypothesis tracking algorithm.

Your implementation (for each filtering recursion) should follow these steps:

- 1. for each local hypothesis in each hypothesis tree: 1). implement ellipsoidal gating; 2). calculate missed detection and predicted likelihood for each measurement inside the gate and make sure to save these for future use; 3). create updated local hypotheses and make sure to save how these connects to the old hypotheses and to the new the measurements for future use:
- for each predicted global hypothesis: 1). create 2D cost matrix; 2). obtain M best assignments using a provided M-best 2D assignment solver; 3). update global hypothesis look-up table according to the M best assignment matrices obtained and use your new local hypotheses indexing;
- 3. normalise global hypothesis weights and implement hypothesis reduction technique: pruning and capping;
- 4. prune local hypotheses that are not included in any of the global hypotheses;
- 5. Re-index global hypothesis look-up table;
- 6. extract object state estimates from the global hypothesis with the highest weight;
- 7. predict each local hypothesis in each hypothesis tree.

Example: re-index global hypothesis look-up table.

Suppose the global hypothesis look-up table before re-indexing is [3, 1, 2; 2, 1, 3; 3, 2, 2]. Then after reindexing, the hypothesis look-up table may look like [2, 1, 1; 1, 1, 2; 2, 2, 1].

The M-best 2D assignment solver has been provided as a reference function.

```
[col4rowBest,row4colBest,gainBest]=kBest2DAssign(C,k)
```

KBEST2DASSIGN: Find the k lowest cost 2D assignments for the two-dimensional assignment problem with a rectangular cost matrix C.

INPUT: C: A numRowXnumCol cost matrix.

OUTPUTS: col4rowBest: A numRowXk vector where the entry in each element is an assignment of the element in that row to a column. 0 entries signify unassigned rows.

row4colbest: A numColXk vector where the entry in each element is an assignment of the element in that column to a row. O entries signify unassigned columns.

gainBest: A kX1 vector containing the sum of the values of the assigned elements in C for all of the hypotheses.

Note:

- 1. When constructing your 2D cost matrix, if measurement j does not fall inside the gate of object i, set the corresponding entry (i, j) to $+\infty$.
- 2. Set parameter k used in kBest2DAssign to ceil(w^h* obj.reduction.M), where $\sum_{h\in H} w^h = 1$.
- 3. We can use gating to further group objects into subsets and process each subset independently. However, this is **NOT** covered in this task.

4. When normalising weights in logarithmic scale, you can call function normalizeLogWeights, which has also been provided as a reference function.

Hint:

- 1. If you want to apply a function to each element of a struct array, you can use MATLAB function arrayfun, which makes your implementation faster than using for loops.
- 2. When pruning low weight data association events, you can call the hypothesisReduction.prune method you have written in the first home assignment. You simply need to change the second input parameter from struct array to hypotheses indices. Similar trick can be applied to hypothesisReduction.cap.
- 3. When pruning local hypotheses and re-indexing the look-up table, you might find MATLAB command unique useful.

Files referenced:

- GaussianDensity.m
- hypothesisReduction.m
- kBest2DAssign.m
- log_mvnpdf.m
- measmodel.m
- modelgen.m
- motionmodel.m
- normalizeLogWeights.m

Note that obj.density is a function handle bound to MATLAB class GaussianDensity. For instance, you can simply call obj.density.update to perform a Kalman update instead of using your own code.

Function

```
1
   classdef n objectracker
2
       %N OBJECTRACKER is a class containing functions to track n object in
3
       %clutter.
4
       %Model structures need to be called:
5
       %sensormodel: a structure specifies the sensor parameters
6
                    P D: object detection probability --- scalar
       %
7
                   lambda c: average number of clutter measurements per time
       %
8
                   scan, Poisson distributed --- scalar
9
                   pdf c: clutter (Poisson) intensity --- scalar
       %
10
                    intensity c: clutter (Poisson) intensity --- scalar
11
       %motionmodel: a structure specifies the motion model parameters
12
       %
                   d: object state dimension --- scalar
13
                   F: function handle return transition/Jacobian matrix
14
                   f: function handle return predicted object state
15
                   Q: motion noise covariance matrix
16
       %measmodel: a structure specifies the measurement model parameters
17
                   d: measurement dimension --- scalar
                   H: function handle return transition/Jacobian matrix
18
```

```
19
       %
                    h: function handle return the observation of the object
20
       %
                    state
21
       %
                    R: measurement noise covariance matrix
22
23
       properties
24
                        %specify gating parameter
           gating
25
                        %specify hypothesis reduction parameter
           reduction
26
                        %density class handle
           density
27
       end
28
29
       methods
30
31
           function obj = initialize(obj,density class handle,P G,m d,w min,mer
32
               %INITIATOR initializes n objectracker class
33
               %INPUT: density class handle: density class handle
34
                        P D: object detection probability
               %
35
                        P G: gating size in decimal --- scalar
               %
36
                        m d: measurement dimension --- scalar
               %
37
                        wmin: allowed minimum hypothesis weight --- scalar
               %
38
                        merging threshold: merging threshold --- scalar
               %
39
                        M: allowed maximum number of hypotheses --- scalar
40
               %OUTPUT: obj.density: density class handle
                          obj.gating.P_G: gating size in decimal --- scalar
41
               %
42
                          obj.gating.size: gating size --- scalar
               %
43
                          obj.reduction.w min: allowed minimum hypothesis
               %
44
                          weight in logarithmic scale --- scalar
               %
45
                          obj.reduction.merging_threshold: merging threshold
               %
46
                          --- scalar
               %
47
               %
                          obj.reduction.M: allowed maximum number of hypotheses
48
                          --- scalar
49
                obj.density = density class handle;
50
                obj.gating.P_G = P_G;
51
                obj.gating.size = chi2inv(obj.gating.P G,m d);
52
                obj.reduction.w min = log(w min);
53
                obj.reduction.merging_threshold = merging_threshold;
54
               obj.reduction.M = M;
55
           end
56
57
           function estimates = TOMHT(obj, states, Z, sensormodel, motionmodel,
58
               %TOMHT tracks n object using track-oriented multi-hypothesis tra
59
               %INPUT: obj: an instantiation of n objectracker class
60
               %
                        states: structure array of size (1, number of objects)
61
                        with two fields:
               %
62
                                 x: object initial state mean --- (object state
               %
63
               %
                                 dimension) x 1 vector
64
                                 P: object initial state covariance --- (object
               %
65
                                 state dimension) x (object state dimension)
               %
66
               %
                                 matrix
67
                        Z: cell array of size (total tracking time, 1), each
               %
68
                        cell stores measurements of size (measurement
               %
69
                        dimension) x (number of measurements at corresponding
               %
                        time step)
70
```

```
%0UTPUT:estimates: cell array of size (total tracking time, 1),
% each cell stores estimated object state of size (object
% state dimension) x (number of objects)

end
end
end
end
end
77
```

Code to call your function

C Reset

```
%Choose object detection probability
^{2} | P_{D} = 0.9;
3 %Choose clutter rate
4 lambda c = 10;
6 %Creat sensor model
7
   range c = [-1000 \ 1000; -1000 \ 1000];
   sensor_model = modelgen.sensormodel(P_D,lambda_c,range_c);
9
10 %Creat linear motion model
11 \mid T = 1;
|12| sigma_q = 5;
13
   motion model = motionmodel.cvmodel(T,sigma q);
14
15 %Create linear measurement model
   sigma r = 10;
17
   meas model = measmodel.cvmeasmodel(sigma r);
18
19
   %Creat ground truth model
20 nbirths = 5;
^{21} K = 20;
22 tbirth = zeros(nbirths,1);
23 tdeath = zeros(nbirths,1);
24
25 | initial_state = repmat(struct('x',[],'P',eye(motion_model.d)),[1,nbirths]);
26
27
   initial_state(1).x = [0; 0; 0; -10];
                                                tbirth(1) = 1;
                                                                 tdeath(1) = K;
   initial_state(2).x = [400; -600; -10; 5];
                                                tbirth(2) = 1;
                                                                 tdeath(2) = K;
   initial_state(3).x = [-800; -200; 20; -5]; tbirth(3) = 1;
                                                                 tdeath(3) = K;
   initial_state(4).x = [0; 0; 7.5; -5];
                                                tbirth(4) = 1;
                                                                 tdeath(4) = K;
   initial_state(5).x = [-200; 800; -3; -15]; tbirth(5) = 1;
                                                                 tdeath(5) = K;
32
33 | %% Generate true object data (noisy or noiseless) and measurement data
   ground truth = modelgen.groundtruth(nbirths,[initial state.x],tbirth,tdeath,
   ifnoisy = 0;
   objectdata = objectdatagen(ground_truth,motion_model,ifnoisy);
   measdata = measdatagen(objectdata,sensor_model,meas_model);
38
```

```
89 | % N-object tracker parameter setting
|40| P G = 0.999;
                           %gating size in percentage
|41| w min = 1e-3;
                           %hypothesis pruning threshold
42
   merging_threshold = 2; %hypothesis merging threshold
43
   M = 100;
                           %maximum number of hypotheses kept in MHT
44
   density class handle = feval(@GaussianDensity); %density class handle
   tracker = n objectracker();
46
   tracker = tracker.initialize(density class handle,P G,meas model.d,w min,mer
47
48
   TOMHTestimates = TOMHT(tracker, initial state, measdata, sensor model, motion
49
50 figure
51
   hold on
52
   grid on
53
54 for i = 1:nbirths
55
       h1 = plot(cell2mat(cellfun(@(x) x(1,i), objectdata.X, 'UniformOutput', f
           cell2mat(cellfun(@(x) x(2,i), objectdata.X, 'UniformOutput', false))
56
57
       h4 = plot(cell2mat(cellfun(@(x) x(1,i), TOMHTestimates, 'UniformOutput',
58
           cell2mat(cellfun(@(x) x(2,i), TOMHTestimates, 'UniformOutput', false)
59
   end
60
   xlabel('x'); ylabel('y')
61
62
63 xlim([-1000 1000])
   ylim([-1000 1000])
65
66 | legend([h1 h4], 'Ground Truth', 'TOMHT Estimates', 'Location', 'best')
67
68 set(gca, 'FontSize', 12)
```

► Run Function ②

Assessment:

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Is TOMHT correctly implemented (Nonlinear motion/measurement model, high SNR)?

Is TOMHT correctly implemented (Nonlinear motion/measurement model, low SNR)?