阅读论文综述

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正体	Γ	Δ	Θ	Λ	Ξ	Π	Σ	Υ	Φ	Ψ	Ω
`\mit`斜体	$\mit\Gamma$	$\mit\Delta$	$\mit\Theta$	$\mit\Lambda$	$\mit\Xi$	$\mit\Pi$	$\mit\Sigma$	$\mit\Upsilon$	$\mit\Phi$	$\mit\Psi$	$\mit\Omega$

命令	大写	小写	命令	大写	小写
alpha	A	α	beta	B	β
gamma	Γ	γ	delta	Δ	δ
epsilon	E	ϵ, ε	zeta	Z	ζ
eta	H	η	theta	Θ	θ, ϑ
iota	I	ι	kappa	K	κ
lambda	Λ	λ	mu	M	μ
nu	N	ν	omicron	O	o
xi	Ξ	ξ	pi	Π	π, ϖ
rho	P	ρ, ϱ	sigma	Σ	σ, ς
tau	T	τ	upsilon	Υ	υ
phi	Φ	ϕ, φ	chi	X	χ
psi	Ψ	ψ	omega	Ω	ω

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Contents

1 On CPHD Filters With Track Labeling

1.1 The distribution and p.g.fl.'s LRFS's

In LRFS theory, the state of a target has the form (x, l), where x is an element of some region of a Euclidean space, and where l is an element of a countable set of distince labels.

Given this, a multitarget state is a finite set

$$X = \{(x_1, l_1), ..., (x_n, l_n)\} \tag{1}$$

If $f(x, l)$ is a function of the variable $x = (x, l)$ which is integrable with respect to x and is such that $f(x, l) = 0$ identically for all but a finite number of $l \in L$, then its integral is

$$\int f(x)dx = \sum_{l \in L} \int f(x, l)dx \tag{2}$$

The set integral of a function $f(X)$ of a finite-set variable X is

$$\int f(X)\delta X = \sum_{n \geq 0} \frac{1}{n!} \int f(x_1, ...x_n)dx_1..., x_n = \sum_{n \geq 0} \frac{1}{n!} \sum_{l_1,...l_n \in L^n} f((x_1, l_1), ...(x_n, l_n)dx_1..., x_n \tag{3}$$

1.2 GLMB distribution

A probability distribution $f(X)$ is a GLMB distribution if it has the following form:

$$f(X) = \delta \sum_{o \in O} w_o(X) s_o^X \tag{4}$$

where O is a finite set of indices $o.s_{o,l}(x) = s_o(x, l)$ is the track distribution corresponding to the track label l. The p.g.fl. of a GLMB distribution is

$$G[h] = \sum_{o \in O} \sum_{L \in \mathcal{L}} w_o(L) \prod_{l \in L} s_{o,l}[h] \tag{5}$$

A LMB distribution is a mono-GLMB distribution such that $w(L)$ has the form

$$w^J(L) = \prod_{l \in J-L} (1 - q_l) \prod_{l\ inL} (q_l \mathbf{1}_L(l)) \tag{6}$$

Its p.g.fl is

$$G[h] = \prod_{l \in J} (1 - q_l + q_l * sl[h]) \tag{7}$$

1.3 Labeled PHD filter

1.3.1 LPHD prediction

Let the target-appearance and posterior p.g.fl.'s at time k be, respectively,

$$G^B_{k+1|k}[h] = \prod_{l \in L_B} (1 - q^{k+1}_{l,B} + q^{k+1}_{l,B} s^{k+1}_{l,B}[h]) \tag{8}$$

$$G_{k|k}[h] = \prod_{l \in L_{k|k}} (1 - q^{k|k}_l + q^{k|k}_l s^{k|k}_l [h]) \tag{9}$$

Then the time updated p.g.fl. is

$$G_{k+1|k}[h] = \prod_{l \in L_{k+1|k}} (1 - q^{k+1|k}_l + 1^{k+1|k}_l s^{k+1|k}_l)[h] \tag{10}$$

1.3.2 LPHD update

2 Association-Free Direct Filtering of Multi-Target Random Finite Sets with Set Distance Measures

For recursive Bayesian filtering, we now face two problems:

- Prior density and measurement density are given by collection of particles only
- The assoication of target between particle densities is unknown

Traditional MTT algorithms employ a joint state vector that contains the individual target states and aimt at minimizing the MSE of the estimate.

2.1 Distance Measure

3 Artificial neural network training utilizing the smooth variable structure filter estimation strategy

3.1 Traditional ANN training techniques

BP is one of the first used techniques in training of multilayer perceptrons. BP is a first order stochastic gradient decent method that iteratively searches for link weights that minimize the output error in a supervised manner. Quasi-Newton method demonstrated better convergence performance than the standard BP algorithm, but it requres large memory storage to store the Hessian matrix.

3.2 State estimation-based ANN training

A new hybird learning algorithm that comines the EKF and particle filter has been presented. The new training scheme provides faster speed of convergence than the stand-alone EKF.

3.3 Feed-forward multilayered neural network

The operation of node $(n+1, i)$ is described by the following eqution

$$x_i^{n+1}(t) = \varphi(\sum_{j=1}^{N_n-1} w_{i,j}^n x_j^n(t) + b_i^{n+1}) \tag{11}$$

3.4 Global and decoupled EKF-based NN training

The EKF has been tailored to train feed-forward neural networks by formulating the network as a filtering problem. Accordingly, feed-forward multilayer perception network behavior can be described by a nonlinear discrete time state space representation such that

$$w_{k+1} = w_k + \omega_k \tag{12}$$

$$y_k = C_k(w_k, u_k) + v_k \tag{13}$$

It demonstrates the neural network as a stationary system with an additional zero-mean, white system noise ω_k with a covariance described by $[\omega_k \omega_l^T] = \delta_{k,l} Q_k$. Neural network weights and biases w_k are regarded as the system's state. Meausrement function is a nonlinear equation relating network desired response y_k to the network input u_k and weights w_k.

4 DNN and swithching kalman filter based continuous affect recognition

The DD-SKF framework firstly models the complex nonlinear relationship between the input features and the affective dimensions via the non-recurrent DNN, then models the temporal dynamics embedded in the emotions via the segmental linear SKF.

5 The Adaptive LMB filter

This paper proposes a new multi-Bernoulli filter called the Adaptive LMB filter. It combines the relative strengths of the known δ-GLMB and the LMB filter.

5.1 introduction

The aim of MTT is the estimation of the number of objects as well as their individual states based on noisy measurements, where missed detections and false alarms lead to ambiguities in the track-to-measurement association.

The adaptive LMB filter is proposed which automatically switches between an LMB and δ-GLMB representation based on KL divergence and entropy.

5.2 LMB RFS

6 Average Marginal Density Based Distributed Multichannel Fusion for Multi-target Tracking

7 Distributed localisation of sensors with partially overlapping field-of-views in fusion networks

7.1 Abstract

Each sensor has a partially overlapping FoV with its neighbours, and, collects both target originated and spurious measurements. We are interested in estimating the locations of the sensors in a network coordinate system using only these measurements.

8 Multiple Object Tracking in Unknown Backgrounds with Labeled Random Finite Sets