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A distributed approach for track occupancy detection

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ABSTRACT

This paper investigates the problem of track occupancy detection in distributed settings. Track occupancy detection determines which tracks are occupied in a railway system. For each track, the Neyman–Pearson structure is applied to reach the local decision. Globally, it is a multiple hypotheses testing problem. The Bayesian approach is employed to minimize the probability of the global decision error. Based on the prior probabilities of multiple hypotheses and the approximation of the receiving operation characteristic curve of the local detector, a person-by-person optimization method is implemented to obtain the fusion rule and the local strategies off line. The results are illustrated through an example constructed from in situ devices.

1. Introduction

With respect to the majority of railway systems in China, a quasi-moving block method is employed to specify the safe zone of a train (Lu, Tian, Li, & Song, 2008). A key piece of knowledge to be determined is the set of track segments that are occupied, *i.e.*, track occupancy detection. Then the speed restriction curves for the following trains are calculated accordingly. When there are misdetections, collisions may happen; additionally, false alarms may lead to declines of line capacity. Track occupancy detection is achieved by a set of track circuits. The track circuit is a crucial device mainly composed of a transmitter–receiver pair and a track segment. The measurement is the receiving signal at the end of the track. For each segment, a decision is made locally and individually, which leads to frequent ambiguities on which tracks are occupied for the whole line. It means that the false alarm rate of the line increases greatly. Besides, for the next generation of railway systems, a moving block method is adopted (Midya & Thottappillil, 2008). Such a method requires the exact position and velocity of the train. However, those data are not provided in the current detection mechanism.

1.1. Related work

To the author's knowledge, track occupancy detection is mainly achieved in three ways, *i.e.*, Track Circuit, Expert System and Global Positioning System (GPS). Using track circuits, track occupancy detection is fulfilled via constant threshold comparisons for sequential measurements. *E.g.*, for UM71-type track circuits (mainly used in Europe), an occupancy decision is made when the receiving signal drops below a prescribed threshold (Debiolles, Oukhellou, Aknin, & Denoeux, 2006); for ZPW2000A-type track circuits (used in China), similar comparisons are made except for some additional logical judgements. In expert systems, graph theory tools are adopted to generate track occupancy and clearance data (D'Ariano, 2009). It relies on logistical inference. In recent years, the GPS technology is utilized to upgrade train control systems (Beugin & Marais, 2012), where track occupancy detection is performed according to train position information. Compared with the others, the track circuit method is the most economical one. It can be implemented in the existing infrastructures. Besides, the GPS technology cannot be used for segments in the tunnel. However, the traditional track circuit approach normally presented a high false alarm rate, since the detection conducts only "on the spot" and "now". Hence, there exist some possible improvements for the current method: (a) make use of correlations among consecutive measurements, *i.e.*, a block of data; (b) update the local strategy dynamically, *i.e.*, the dynamical threshold; (c) combine all the local decisions to reach a more accurate global decision, *i.e.*, the fusion rule. In this paper, an improved track occupancy detection approach via track circuits is investigated.

Based on the existing infrastructures, all the segments conduct local detections independently and their local decisions are only allowed to send to a fusion center periodically and synchronously. Hence, track occupancy detection is considered as a multiple hypotheses testing problem (to decide which segments are occupied) in distributed settings. In this field, some results have been

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Nomenclature

$\mathcal{H}_i$	binary hypotheses for local decision
$\mathcal{H}_i^g$	multiple hypotheses for global decision
x_k^i	the position of the train head at time k in segment i
A	the receiving signal when the track is empty
y_k^i	the measurement of the receiving signal at time k in segment i
w_k^i	the observation noise at time k in segment i
σ^2	the variance of the observation noise
v	the velocity of the train
$U(x)$	the receiving signal when the track is occupied
$\hat{x}_k^i$	the maximum likelihood estimate of x_k^i
$\hat{v}_K$	the maximum likelihood estimate of v via data block K
γ_K^i	the threshold of GLRT for data block K
$Q(x)$	$Q(x) = \int_x^\infty (1/\sqrt{2\pi})\exp(-\frac{1}{2}t^2)\,dt$
$P_{FA,K}^i$	the probability of false alarm for data block K in segment i
$(P_{FA,K}^i)^*$	the optimal probability of false alarm for data block K in segment i
$P_{D,K}^i$	the probability of detection for data block K in segment i
s_k^i	the state of segment i at time k
$\mathbf{g}_k$	the state of the group $\mathbf{g}_k = [s_k^1, \ldots, s_k^n]$
d_K^i	local decision of segment i for data block K
$\mathbf{d}_K$	decision vector $\mathbf{d}_K = [d_K^1, \ldots, d_K^n]$
d_K^0	the global decision for data block K
P_k^j	the prior probability that $\mathcal{H}_j^g$ is present at time k
R_K	the Bayesian risk for data block K in distributed settings
R_k^S	the Bayesian risk using constant threshold method at time k
R_K^C	the Bayesian risk for data block K in centralized settings

presented. Zhang and Varshney (2001) tried to reduce the computational complexity via transforming the original problem to a sequence of binary hypothesis testing ones. Zhu, Yuan, Rorres, and Kam (2004) developed conditions to obtain the correct hypothesis via asymptotical detections. In this paper, a distributed detection problem for a moving target is considered. Compared with the pre-existing literature, this paper concentrates on the dynamical update mechanism for the local detection strategies and the fusion rule. It is shown in this paper that the requirement of the probability of error type I (or type II) for each segment differs due to the distinct prior probabilities of multiple hypotheses. It is more likely to assign each segment a different weight.

For each local detection, it is a binary hypothesis testing problem. In this area, plenty of results have been published (Kay, 1993a). In order to avoid some stronger assumptions, *i.e.*, *the prior probabilities of both hypotheses and the reasonable cost quantities are supposed to be known*, the Neyman–Pearson method and the Fisherian method are preferably adopted. Actually, these two methods were motivated by a desire to rid the need to assume prior probabilities over the possible hypotheses (Lehmann, 1993). Compared with Fisherian's scheme, to the author's opinion, the Neyman–Pearson method provided a more rigorous mathematical support and an explicit formulation of the probability of error type II. Notice that in this specific problem, the alternative hypothesis is well defined. Additionally, the detection rate is an important variable to facilitate generating the local detection strategies and the fusion rule in the proposed approach. Hence, the Neyman–Pearson decision theory is employed. It is described as an optimization problem with constraints. In the framework of the Neyman–Pearson structure, a Likelihood Ratio Test (LRT) is used to formulate the detector. Regarding the unknown system parameters, a Generalized LRT (GLRT) is usually employed (Kay, 1993a). It is the combination of a Maximum Likelihood Estimate (MLE) and an LRT.

Concerning the fusion rule for the multiple hypotheses testing problem, the most commonly used Bayesian approach is adopted (Kay, 1993a), except for the dynamical prior knowledge. To achieve the optimal detection performance, if possible, some person by person optimization (PBPO) algorithms are designed in Tang, Pattipati, and Kleinman (1991) and Helstrom (1995). The PBPO mechanism deals with the problem via an iterative procedure rather than solving the simultaneous equations. The overall performance is required to improve with every iteration. Hence, the convergence is guaranteed. However, it does not necessarily lead to the global optimization. Besides, there are other remarkable heuristic methods applicable to the design of distributed detections (Chamberland & Veeravalli, 2007). The saddle-point method is used to approximate the global probability of error (Aldosari & Moura, 2005). It is assumed that the decision of each local site is independent and there is no discrepancy among the local sites. It will be shown that, in order to optimize the global performance, each local site is not treated equally. Thus, the saddle point approximation method cannot be applied directly. Techniques based on empirical risk minimization and marginalized kernels are proposed by Nguyen, Wainwright, and Jordan (2005). It is assumed that the joint distribution of sensor observations is unknown and a set of data samples is available. Considering the proposed specific problem, the joint distribution is formulated as a normal distribution. Therefore, the empirical risk minimization based approach is not perfectly suitable here.

1.2. Main results

According to Zhao, Li, Guo, and Liu (2009), there are correlations among consecutive measurements when a train passes through the track . Such correlations can be described as system dynamics. In contrast, observations in any different time are independent identical distributed (iid) when the track is empty. Thus the local detection is formulated as a deterministic signal detection problem with unknown parameters (the position and the velocity of the train). In this paper, the GLRT is used to formulate the local detector. In the stage of the decision fusion, it will be shown that the key point is to derive the ROC curve. Since the closed form expression is hard to figure out, the Monte Carlo simulation and the data fitting technique are employed.

A rail line is composed of large segments. To detect which segments are occupied is a multiple hypotheses testing problem in distributed settings. The Bayesian approach is used here to minimize the probability of the global decision error in the entire line level. The prior probabilities for multiple hypotheses are updated based on train operation history. They are supposed to be known to the fusion center. However, they are not available locally. Considering the fusion rule and the local strategies, a person-by-person optimization is launched. It reveals that all local detectors are coupled with one another to reach an optimal solution.

The main contributions of this paper are: (a) for the local detection, the Neyman–Pearson structure with a dynamical threshold is presented; (b) a dynamically distributed detection scheme