FACULTY OF APPLIED SCIENCES
UNIVERSITY
OF WEST BOHEMIA

STUDENT
SCIENTIFIC CONFERENCE 2023

Model Parameters Estimation for Multitarget Tracking

Jan Krejčí[1]

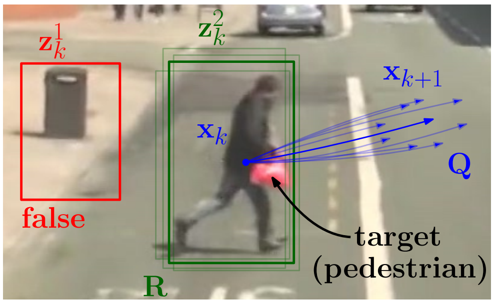
1 Introduction

Multitarget tracking refers to estimating both number and locations of variable number of moving targets, using variable number of noisy measurements, some of which may be false or missing. Temporal evolution of the targets is usually modeled stochastic, with

$$\mathbf{x}_{k+1} = \mathbf{F}\mathbf{x}_k + \mathbf{w}_k, \qquad \mathrm{E}[\mathbf{w}_k] = \mathbf{0}, \qquad \mathrm{E}[\mathbf{w}_k \cdot \mathbf{w}_k^\top] = \mathbf{Q}, \tag{1}$$

$$\mathbf{z}_k = \mathbf{H}\mathbf{x}_k + \mathbf{v}_k, \qquad \mathrm{E}[\mathbf{w}_k] = \mathbf{0}, \qquad \mathrm{E}[\mathbf{v}_k \cdot \mathbf{v}_k^\top] = \mathbf{R}, \tag{2}$$

where $\mathbf{x}_k$ is the *state* of a particular target at time-step k that is comprised e.g. of its location and velocity, $\mathbf{z}_k$ is the measurement, and $\mathbf{w}_k$ and $\mathbf{v}_k$ are the state and measurement *noises*, respectively. The matrices $\mathbf{F}$ and $\mathbf{H}$ can usually be revealed by accounting for physical nature of the targets, e.g. assuming *nearly* constant velocity motion and location measurements. Level of uncertainty appearing in (1)-(2) is captured by the *noise covariance matrices* $\mathbf{Q}$ and $\mathbf{R}$. To account for false and missing measurements in multitarget environments, the *mean number of false measurements* λ, and the *probability of detection* P_D need to be specified as well. The meaning of the parameters λ, P_D, $\mathbf{R}$ and $\mathbf{Q}$ is illustrated in Figure 1 for a case of visual tracking.



λ : how many false measurements there usually are in a measurement set
P_D : how probably there is a measurement that corresponds to a state of some target
$\mathbf{R}$: how "far" the measurement is from the target, if it exists
$\mathbf{Q}$: (un)certainty of the target movement

What are the values of these parameters?

Figure 1: Graphical illustration of the meaning of the estimated parameters.

The parameters λ, P_D, $\mathbf{R}$ and $\mathbf{Q}$, are **usually hand-selected, leading to sub-optimal tracking performance**. Values of these parameters usually **cannot be found from first principles, but can be estimated from data**. For this purpose, knowledge of *true* target locations (e.g. from a carefully analyzed time span) is assumed to be available besides the measurements.

2 Motion Noise Covariance Parameters Estimation

Given the sequence $(\mathbf{a}_{k_1}, \ldots, \mathbf{a}_{k_F})$ of known locations corresponding to a particular target between the time-steps k_1 and k_F, it is possible to estimate some elements $\mathbf{q}$ of $\mathbf{Q}$ by using

[1] student of the doct. deg. prog. Applied Sciences, field of study Cybernetics, e-mail: jkrejci@students.zcu.cz

the *measurement difference method*, recently developed in Kost et al. (2022) as

$$\mathrm{vec}\big(\widehat{\mathbf{q}}\big) = \mathbf{\Gamma} \cdot \mathrm{vec}\left(\frac{1}{k_F - L - k_1 + 1} \sum_{k=k_1}^{k_F - L} \mathbf{a}_{k:k+L} \cdot \mathbf{a}_{k:k+L}^\top \right) \tag{3}$$

where the matrix $\mathbf{\Gamma}$ depends on the known matrices $\mathbf{F}$ and $\mathbf{H}$ and position of $\mathbf{q}$ in $\mathbf{Q}$. The vectors $\mathbf{a}_{k:k+L} = [\mathbf{a}_k^\top, \ldots, \mathbf{a}_{k+L}^\top]^\top$, $k = k_1, \ldots, k_F - L$ denote stacking of L known locations underneath, with L depending especially on the number of elements of $\mathbf{q}$.

Given sequences of known locations corresponding to multiple targets, the parameter vector $\mathbf{q}$ can be simply estimated by joining the sequences of known locations together.

3 Measurement Model Parameters Estimation

Denote the sets of measurements and known target locations with $Z_k = \{\mathbf{z}_k^1, \ldots, \mathbf{z}_k^M\}$ and $A_k = \{\mathbf{a}_k^1, \ldots, \mathbf{a}_k^N\}$ at time-step k, respectively. For clarity, assume that the measurements represent locations as well, and that each target generated at most one measurement at any k.

If the correspondences between measurements and known target locations were known in each time-step, the matrix $\mathbf{R}$ could be estimated via sample covariance and the parameters λ and P_D could be estimated based on the number of correspondences. The correspondences are unknown, but can be approximated by solving the proposed optimization problem

$$\widehat{\alpha_k} = \underset{\alpha_k}{\mathrm{argmin}} \left(\sum_{(i,j) \in \alpha_k} d(\mathbf{z}_k^i, \mathbf{a}_k^j)^p - c^p \cdot |\alpha_k| \right), \tag{4}$$

where α_k denotes the set of correspondences of the form $(i, j) \in \alpha_k$ denoting that the i-th measurement is assigned to to the j-th known location, d is a user-defined metric, $c > 0$ is the *cut-off parameter* and $p \geq 1$. The optimization (4) was designed to be in accordance with multitarget tracking performance evaluation techniques such as in Rahmathullah et al. (2017).

The cut-off parameter represents the maximal d-distance for a pair of vectors to be assigned. Its selection is thus crucial for finding reliable correspondences and thus for estimating $\mathbf{R}$, λ, and P_D. The proposed procedure for selecting c is based on an expected behavior of the number of assignments and corresponding distances resulting from (4). The expected behavior is accounted for with a number of carefully designed *guideline functions*.

4 Results for Visual Object Tracking

The proposed method was used to estimate the parameters for visual object tracking problems. Data from the well-known MOT17 dataset, see Milan et al. (2016), were used. Using the parameters for multitarget tracking itself is, however, subject for a future research.

References

Kost, O., Duník, J. a Straka, O. (2022) *Measurement difference method: A universal tool for noise identification*. IEEE Transactions on Automatic Control.

Rahmathullah, A. S., García-Fernández, Á. F. a Svensson L. (2017) *Generalized optimal subpattern assignment metric*. 2017 20th International Conference on Information Fusion (FUSION), pp. 1-8, doi: 10.23919/ICIF.2017.8009645.

A. Milan, L. Leal-Taixe, I. Reid, S. Roth, and K. Schindler, *MOT16: A benchmark for multi-object tracking*. Available from https://arxiv.org/abs/1603.00831 [Accessed 15th June 2023].