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Object tracking under low signal-to-noise-ratio with the instantaneous-possible-moving-position model

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ABSTRACT

Combing image processing technique and the *probabilistic data association* (PDA) motion model, we develop a novel framework to solve the problem of object tracking for non-electromechanical system with overwhelming noise background. The new model has two advantages: (1) By integrating the statistical motion model, the movement of object in many non-electromechanical systems could be more precisely simulated than existing ones. (2) Because of the adoption of a global search for optimal model parameters, the proposed model is better to track objects in high noise environment, comparing with other methods that rely on consecutive frames differentiating. We derive the *expectation–maximization* (EM) algorithm within the proposed model. Its usefulness is demonstrated with both synthesized data and image data set. *Model Stability* is introduced to quantify the usefulness of the model.

1. Introduction

How to improve the accuracy of object tracking is a challenging problem. Innumerable solutions to this problem have been proposed [1–6]. Although it seems that object tracking is a solved problem, in reality, existing object tracking algorithms have very limited capability, in particular in extracting trajectories of point-shaped objects (e.g., molecules) from image sequences when the noise level is high [1], or the motion model of the object is missing [2]. This study focuses on how to build a statistical model to improve the accuracy of point-shaped objects tracking in low signal-to-noise-ratios (SNR). Unlike tracking objects in a high SNR environment (such as pedestrian [3], vehicle [4], or ship [5]), the image pattern of point-shaped object with low SNR is hardly recognizable. Background suppression can be used to track objects. The existing background suppression methods include simple consecutive frames differentiating [6] and more elaborate temporal and spatial filtering [7]. It is however realized that point-shaped object with low SNR cannot be detected on the basis of only a few frames, even after using the optimal SNR enhancement filtering. In such cases, all available data need to be integrated before a decision can be made. Two of the most common used models for the data-integration are:

1. *Probabilistic data association* (PDA) [8–11]: A statistical approach to the problem of plot association in object tracking, in which all of the potential candidates for association to a trajectory are combined in a single statistically most probable update.
2. *Dynamical programming algorithm* (DPA) [9,11]: A method breaks the tracking problem down into a sequence of optimal substructure steps to determine the path of object using the whole observation sequence.

However a prerequisite for the application of the above two methods is that a kinematic model of tracked-object

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could be extracted from either data samples or the domain knowledge. Having a kinematic model means that objects are manoeuvring objects [12]. Object kinematic information is usually acquired from radar, sonar, or an electro-optical sensor—all three can provide the source of dynamic information (such as speed, acceleration of speed, position, and angle) about the objects. However it is difficult to adopt them into certain visual-only based object tracking applications. Motion of many objects does not follow any kinematic model; in this paper, these will be called *non-electromechanical* objects, including vesicles in microbiology [13,14], fluorescence-labeled point-shaped particles in medical science [1,15], and celestial body in astronomy [16]. Research in [14] proposed another solution for object tracking through building statistical model for these specific particles and introducing special image processing techniques. But this tracking method relates closely to specific research and the mathematical model is built completely by expert knowledge, its application is limited.

We introduce a more generic model based on the hidden Markov models (HMM) into where:

1. Overall, the moves of point-shaped object do not follow a particular kinematic model.
2. An individual local move of the object can be in all possible directions.
3. Intensity of object and background varies and the noise level is high.

In this paper, we accomplish the following:

1. Developing a statistical model that not only facilitates the objects tracking in low SNR cases but also characterizes the motion of objects in very short time interval and is entirely based on visuals.
2. Adopting expectation-maximization (EM) algorithm to estimate the parameters in the proposed model.
3. Proposing *model stability* to evaluate tracking feasibility. This is new and different from traditional assessment of tracking [9].
4. Utilizing synthetic data and image data set to demonstrate the promises of the model in point-shaped object tracking with low SNR.

The paper is organized as follows. The statistical model for point-shaped object tracking is presented in Section 2. In Section 3, the EM algorithm is derived. We use *model stability* to validate the effectiveness of our proposed model in Section 4 and illustrate these procedures with synthesized data and a data set from a practical application. Section 5 concludes this paper and introduces some future research. In Appendix, we derived the formulae that are used in Section 3. Table 1 gives a list of notations that will be used throughout this paper.

2. Model

To introduce the proposed model, we bring some notations in Section 2.1. The proposed model is defined and analyzed in Section 2.2. The features of the proposed model are further discussed in Section 2.3.

Table 1
List of notations.

x_k	object position at stage k
X	sequence of object positions
v_g	position in an image frame
m, n	row and column indices of an image frame
$\mathbb{M}$, $\mathbb{N}$	number of rows and columns of image frame
$F(\cdot)$	moving characteristics of an object
C	moving radius of an object at one transition
f_h	the hth neighbor from x_k to x_{k+1}
p_{f_h}	transition probability of moving from x_k to x_{k+1}
z_k	matrix-valued observation for image at stage k
Z	sequence of object observations
$H(\cdot)$	observation generating function
$V(\cdot)$	intensity characteristics
μ	mean of object signal intensity for V
σ^2	variance of noise and object intensity for V
$\pi(\cdot)$	object initial position
ξ	μ/σ
$w(v_g)$	intensity of position v_g
M	IPMP model
θ	parameter set for M
$\Re$	index set of a trajectory
α^X,α^Y	displacement vector
β	mean-square deviation of the Euclidean distance
$\Re'$	index set of a simulating trajectory
γ	number of image sequences obtained from a simulation

2.1. Model notations

In our framework, we consider the problem of tracking a point-shaped object with the same definition in [17]—"... the only important structure of the target is that it is very small, it necessarily has not to be constrained to only 1 pixel and the point-spread function will in general distribute it over a few pixels". And the object's motion can be described by a non-linear discrete-state space model

$$x_{k+1} = G(F,x_k), \tag{1}$$

where

1. *Position transition function*: $G(\cdot)$ is the non-linear probability mapping function, which determines object's position at next stage (x_{k+1}), conditioned on the position of previous stage (x_k), and current motion model (F).
2. *Object position*: $x_k \in \Omega$ is object's position at stage k, $1 \le k \le T$, T is the length of time window for the tracking. Ω is all the position of a 2D image matrix, shown below

$$\Omega = \begin{pmatrix} v_1 & v_{\mathbb{M}+1} & \cdots & v_{(\mathbb{N}-1)\mathbb{M}+1} \\ v_2 & v_{\mathbb{M}+2} & \cdots & v_{(\mathbb{N}-1)\mathbb{M}+2} \\ \cdots & \cdots & v_g & \cdots \\ v_{\mathbb{M}} & v_{2\mathbb{M}} & \cdots & v_{\mathbb{M}\mathbb{N}} \end{pmatrix}, \tag{2}$$

where v_g is a component of Ω and $g=(n-1)\cdot\mathbb{M}+m$, and m $(1 \le m \le \mathbb{M})$, n $(1 \le n \le \mathbb{N})$ are the row index