GAKP: GRU Association and Kalman Prediction for Multiple Object Tracking

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Abstract

Multiple Object Tracking (MOT) has been a useful yet challenging task in many real-world applications such as video surveillance, intelligent retail, and smart city. The challenge is how to model long-term temporal dependencies in an efficient manner. Some recent works employ Recurrent Neural Networks (RNN) to obtain good performance, which, however, requires a large amount of training data. In this paper, we proposed a novel tracking method that integrates the auto-tuning Kalman method for prediction and the Gated Recurrent Unit (GRU), and achieves a near-optimum with a small amount of training data. Experimental results show that our new algorithm can achieve competitive performance on the challenging MOT benchmark, and faster and more robust than the state-of-the-art RNN-based online MOT algorithms.

1 Introduction

Over the last few years, MOT (Multiple Object Tracking) technology has been playing an increasingly important role in Computer Vision (CV), which aims to extract all objects of interest automatically and obtains the corresponding motion trajectory through the spatial, temporal or visual features of video data. Although MOT is suitable to deal with complex scenes with plenty of targets, and has tremendous potential in visual monitoring/surveillance, behavior analysis, self-driving and navigation, nevertheless, it is still far behind satisfactory in complex scenarios which contains a lot of mutual occlusions and interactions of moving targets.

There has been a great deal of interest in designing new methods for MOT recently. The early stage of object tracking focused on single object tracking based on feature engineering and classification, in separate steps using conventional CV techniques. As an extension of single object visual tracking [Bhat \textit{et al.}, 2018], multiple object tracking [Sadeghian \textit{et al.}, 2017] emerges as a hot issue due to its broader practical application in complex scenarios of intelligent surveillance recently. Typical MOT results are shown in Fig. 1.

The most common framework used in MOT is tracking-by-detection strategy which links detections across frames by data association algorithms. Under this framework, the true positions of objects in each frame are estimated using the detector, followed by estimation of the trajectories of multiple objects which will dynamically regenerate and disappear depending on the detection results for different frames. With the rapid rise of deep learning technology, MOT has entered a new milestone [Sadeghian \textit{et al.}, 2017; Samuel \textit{et al.}, 2017; Zhu \textit{et al.}, 2018]. These deep learning based approaches have improved MOT accuracy by a large margin. However, they typically need a large amount of training data to obtain a reasonable performance.

For data association, either in traditional methods or deep learning methods, most existing works realize data association by motion model [Huang \textit{et al.}, 2008; Milan \textit{et al.}, 2013] or appearance model [Yu \textit{et al.}, 2016; Wang \textit{et al.}, 2014] alone. This problem has not been well studied before, partially because of the complication and variations of the features. The characteristics of the detected objects vary a great deal from different scenes, thus it is hard to robustly associate detections and predictions of an object, especially with light change, scale variation, and occlusion.

In this paper, we propose a novel MOT method with GRU (Gated Recurrent Unit) based data association in the framework of auto-tuning Kalman prediction, termed GAKP. To the best of our knowledge, this paper is the first exploration to realize association between prediction and detections using implicit motion and appearance features, i.e., the association is done by GRU network in an end-to-end manner, without ex-
explicitly weighting factors of motion and appearance features as in [Yu et al., 2016; Sadeghian et al., 2017]. Experimental results show that our implicit data association outperforms the state-of-the-art explicit data association, while not introducing extra computational cost.

Our primary contribution is manifold:

• We integrate GRU for data association in the framework of the auto-tuning Kalman prediction to take advantage of deep learning and compensate the disadvantage: the Kalman tracker is efficient while data association accuracy is improved by GRU based on numerous online training data.

• We utilize GRU to achieve an accurate and robust association between predictions and detections, by using various features including motion feature, spatial-feature, deep feature and so on. The mapping from various features to the association similarity is optimized by GRU in an end-to-end manner.

2 Related Work

MOT methods can be categorized into online and offline modes according to different application requirements. Therefore, offline MOT algorithms can access the entire frames of video and utilize both past and future frames to optimize trajectories. Therefore, it can be regarded as an optimization problem to find a set of trajectories with the minimum global cost function, which can be solved by standard Linear Programming techniques in [Berclaz et al., 2009]. Common offline detection association can be formulated as a Maximum A Posteriori (MAP) problem and solved by the Hungarian algorithm [Bewley et al., 2016]. In general, offline tracking can achieve higher tracking accuracy compared with online methods, at the cost of more computational complexity. In contrast, the online MOT methods are desired in real-time scenarios, as they merely exploit the information available no later than the current frame.

This work falls into the category of online MOT, and we focus on improving the data association between detections and predictions. The key issue of association is how to obtain correct associations robustly with feature variations. Existing works realize data association mainly by three types of models: motion model alone, appearance model alone, and the combination.

**Motion Model.** The motion model describes how a target moves. The key of this model is that a more precise prediction of targets in the future frames will reduce the search space of the association model and thus increase the matching accuracy. Popular motion models include linear and non-linear motion models. Linear motion models follow a linear movement with constant velocity across frames, which is the early stage popular models in MOT [Breitenstein et al., 2009]. Non-linear motion models are proposed to produce a more accurate prediction [Dicle et al., 2013]. In recent years, the depth recurrent neural network (RNN) method is a trend for a non-linear approach for MOT motion prediction. However, as a common problem of using RNN implementation, a large amount of training data is required for optimal performance. In the meanwhile, for complex scenes, the amount of training trajectory data is far from enough, which may result in over-fitting.

**Appearance Model.** In early years, some approaches use color histogram, covariance matrix representation, pixel comparison representation, SIFT-like features, or pose features [Choi and Savarese, 2010; Hong and Han, 2014; Izadinia et al., 2013]. Deep learning based models have emerged as a very powerful tool to deal with different kinds of vision challenge including image detection and classification. The strong observation model provided by the deep learning model for target detection can boost the tracking performance significantly [Yu et al., 2016; Lee et al., 2016]. Deep neural network architectures have been used for modeling appearance recently. In these architectures, high-level features are extracted by convolutional neural networks trained for a specific task and achieve a significant improvement.

**Composite Model.** Some recent works attempt to combine the motion model and appearance model together to enhance the association accuracy. A composite model of hand-crafted feature with position, size and appearance feature is defined in [Yu et al., 2016], which provides a competitive performance. However, hand-crafted feature has a disadvantage that it is difficult to tune the weights of each component to be robust in different scenarios. For example, the tracker using only IoU (Intersection-over-Union) is not effective for high-speed small target tracking, as the IoU between the target and the detection easily reaches zero, while the tracking using only Euclidean distance is not reliable for large targets due to the error and deformation of the tracklets. Thus a combination of appearance feature is a reasonable direction to improve the robustness of data association. Despite extensive experimentation with RNN-LSTM architectures in [Sadeghian et al., 2017], the learned metric did not perform as well as the simpler hand-crafted functions, presumably due to the small size of the training set.
In our work, we integrate the auto-tuning Kalman method for prediction step and GRU for the association step. The link probability between predictions and detections is predicted with non-linear combination of motion and appearance features. This method significantly improves the tracking performance while reducing the computational cost. The feature models utilized in the proposed GAKP framework is illustrated in Fig. 2.

### 3 Online MOT Algorithm

In this section, we describe our proposed MOT tracker with GRU data-association and auto-tuning Kalman prediction method. The flow chart of the proposed GAKP is depicted, including the motion model (sec. 3.2), appearance model (sec. 3.3) and the end-to-end data association (sec. 3.4) which will be elaborated in following subsections. Finally, the proposed GAKP algorithm is summarized.

#### 3.1 Proposed Framework

The overall GAKP framework is shown in Fig. 3, where spatial feature and motion feature are obtained from detection and Kalman filter respectively, and the appearance feature is extracted by Triplet ResNet-50 Network in [Hermans et al., 2017]. The end-to-end data association module is shown in Fig. 4. The key components of the multi-object tracker are listed as follows:

**Detection and bounding box processing.** The pedestrian detection responses are processed by the classification to select high-quality pedestrian bounding boxes.

**Motion Prediction.** Based on the previous tracked object at frame $t - 1$, we predict the likely location of each target at frame $t$ via the motion model, and use the detection results to initialize tracklets at frame $0$. We use auto-tuning Kalman prediction since it can achieve good performance in near-linear motion system with small amount of training data instead of RNN.

**Appearance Features.** The cropped images of pedestrians are fed into feature extractor to get the 128-dim appearance feature embeddings. Meanwhile, it should be noticed that not only the deep feature but also all the other features can be used as inputs to calculate the data association probability in our framework, such as color feature and position keypoints.

**Association Cost Matrix.** As the core step of our algorithm, we propose to learn a GRU model to estimate the association cost functions. The training data are derived from the ground-truth of MOT17 challenge [Milan et al., 2016]. The link probability is calculated from the features of predictions and detections.

**State Update.** The matching result and cost function items $C_{ij}$ will be fed to auto-tuning Kalman module to update the object motion states.

#### 3.2 Motion Model

It is well known that Kalman filter is an effective approach [Kalman and Bucy, 1961; Bar-Shalom et al., 2001] to find the optimal estimation of near-linear motion states. The predicted mean and covariance states are given by

$$\hat{x}_{k|k-1} = F_k \hat{x}_{k-1|k-1},$$

$$\hat{P}'_{k|k-1} = F_k \hat{P}_{k-1|k-1} F_k^T + Q_k^*,$$

where $k$ indicates the index in time series, $\hat{x}_{k|k-1}$ is predicted object statement, $\hat{P}'_{k|k-1}$ is predicted object covariance, $F_k$ is state-transform matrix, $Q_k^*$ is system prediction error.

The motion mean and covariance update is given by

$$K_k = P_{k|k-1} H_k^T (H_k P_{k-1|k-1} H_k^T + R_k)^{-1},$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k (Z_k - H_k \hat{x}_{k|k-1}),$$

$$\hat{P}_{k|k} = (I - K_k H_k) \hat{P}_{k|k-1} (I - K_k H_k)^T + K_k R_k K_k^T.$$

### 3.3 Appearance Model

The similarity between detections and predictions is evaluated through the recurrent neural network with GRU, which is trained with the ground-truth of the MOT17 data [Milan et al., 2016].
Figure 4: Flow chart of the Cost Matrix calculation with GRU. 1) The feature vector comes from the motion model and feature extractor. 2) Feature vector of tracked object $i$ in frame $t$ and the feature of detection $j$ in frame $t+1$ are used as input of the GRU model to calculate the association cost $C_{ij}$ of the cost matrix.

where $K_k$ is the Kalman gain which can balance the prediction and detection to cancel the noise, resulting in filtered states $\hat{x}_{k/k}$ and $P_{k/k}$. According to the formula of Kalman gain $K_k$, the optimal motion state information $\hat{x}_{k/k}$ of the target at the current time is obtained. $H_k$ is the transfer matrix between target motion state and measured position state. When compared with the target position state, both the predicted target state $\hat{x}_{t/k}$ and the detected target state $Z_k$ are expected to have errors, i.e., the system prediction error $Q^*_k$ and the target detection error $R^*_k$, respectively.

Both $Q^*_k$ and $R^*_k$ are deterministic noise matrices, and Kalman filter automatically guarantees statistical consistency when the full structure of the system state $(F_k, H_k, Q^*_k, R^*_k)$ is known. However, in many situations the model is not known precisely and the Kalman filter must be tuned. It is hard to tune the coefficients of Kalman filter (such as process noise $Q^*_k$, and measure noise $R^*_k$ which defined in Eq. 2 and Eq. 5), e.g., significant effort is required to tune various Kalman filter models for non-white noise. An auto-tuning $(Q_k, R_k)$ with Bayesian Optimization is proposed to minimize normalized estimation error squared (NEES) in [Zhaozhong et al., 2018]. However, in [Zhaozhong et al., 2018] only the motion characteristics are considered to estimate the errors. In this work, we demonstrate that, by considering both the motion characteristics and visual similarity, a more accurate estimation of system prediction error and target detection error can be obtained, resulting in a better performance of Kalman tracking. Specifically, we propose a new version of the system prediction error $Q^*_k$ and the target detection error $R^*_k$ as follow:

$$Q^*_k = \frac{Q_k}{C + \lambda_c}$$ \hspace{1cm} (6)

$$R^*_k = \frac{R_k}{C + \lambda_c}$$ \hspace{1cm} (7)

where $Q_k$ and $R_k$ are the estimated errors given by [Zhaozhong et al., 2018] which considers motion characteristics, and $C \in (0, 1)$ is the composite similarity (link probability) between predictions and detections given by GRU deep learning, where a high $C$ value indicates that the measured detection is more reliable in Kalman gain update progress, and $\lambda_c$ is a small factor for regularization.

Mahalanobis distance [Wojke et al., 2017] is utilized in this work to improve the Euclidean distance between predicted Kalman states and detected measurements, which is defined as follow:

$$D(i, j) = (Z_k (j) - \hat{x}_{k/k} (i))^T S_i^{-1} (Z_k (j) - \hat{x}_{k/k} (i))$$ \hspace{1cm} (8)

where $S_i = H_k P_{k/k} (i) H_k^T$. The measurement space of the $i$-th track is denoted by Multivariate Gaussian Distribution $(\hat{x}_{k/k} (i), S_i)$. We keep the candidates where the Mahalanobis distances are within 95% confidence interval computed from the inverse noise $\chi^2$ distribution, and the threshold is 9.4877 for 4-dimensional Mahalanobis distance. Hungarian algorithm is then used to match pairs after the pre-filtering by Mahalanobis distances.

3.3 Appearance Model

The underlying idea of the appearance model is that the similarity score can be computed between a target and candidate detection based on visual features. Re-identification networks [Chen et al., 2017; Schroff et al., 2015; Hermans et al., 2017] can be utilized by learning a similarity metric so that the target of the same identity is closer to each other than different identities in the embedded feature space. The appearance feature extractor of our model is ResNet-50 which is a pre-trained person re-identification model proposed in [Hermans et al., 2017]. It is robust to occlusions and other visual disturbances. The triplet loss for training the CNN is defined as follow:

$$L_{trip} = \sum_{(z_a, z_p, z_n) \in Z} \max \{0, d_a (z_a, z_p) - d_p (z_a, z_n) + \theta\},$$ \hspace{1cm} (9)

where $(z_a, z_p, z_n)$ denotes an instance of triplet where $z_a$ is the anchor, $z_p$ is a candidate of positive samples, and $z_n$ is
a candidate of negative examples, \( d_\theta (z_1, z_2) \) denotes the euclidean distance between \( z_1 \) and \( z_2 \) called the appearance distance. The convolutional feature maps of original target images are flattened, fed into the fully connected layers and finally normalized by an L2-normalization layer. The output is the 1024-dimensional appearance embedding \( z \).

### 3.4 Data Association

In MOT framework, data association is an important part to define the correspondence between detections and tracking hypotheses object on the basis of the predicted motion state and visual features. A baseline tracklet association framework is presented in [Huang et al., 2008], and many improved algorithms followed this framework. With the independence assumption, the object association can be formulated as follow:

\[
S^* = \arg \max_S \prod_{T_k^i \in T} P \left( \frac{T_k^i}{S} \right) \prod_{S \in S} P(S), \tag{10}
\]

where \( S_k = \{ T_{k0}^i, T_{k1}^i, ..., T_{kl_k}^i \} \) is a set of tracklets, \( l_k \) is the number of tracklets in \( S_k \) and \( S = \{ S_k \} \) is the tracklet association set. A conventional link probability between tracking object and detection is proposed in [Huang et al., 2008]:

\[
P_{\text{link}}(r_j | r_i) = A_{\text{pos}}(r_j | r_i) A_{\text{size}}(r_j | r_i) A_{\text{appr}}(r_j | r_i), \tag{11}
\]

where \( A_{\text{pos}}(r_j | r_i) \), \( A_{\text{size}}(r_j | r_i) \), \( A_{\text{appr}}(r_j | r_i) \) is position, size and appearance link probability between tracking object \( i \) and detection object \( j \). The cost function calculated with the link probability and the optimal solution of cost matrix are respectively as follow,

\[
C_{ij} = \ln P_{\text{link}}(r_j | r_i), \tag{12}
\]

\[
J^* = \arg \min_j \frac{1}{T} \sum_{t} C_{ij}. \tag{13}
\]

#### Explicit Feature Association

Explicit features refers to the commonly used features such as motion features (obtained from Kalman filter), bounding boxes, and visual content features. When the explicit features are combined properly by RNN method, they can effectively improve the accuracy and robustness of MOT in complex scenarios. The cost-function of prediction and detection with different features is defined as follow:

\[
C_{ij} = |D_{ij}|^2 + \lambda_v |\text{IoU}_{ij}|^2 + \lambda_a |\Delta v|^2 + \lambda_f |\Delta f|^2, \tag{14}
\]

where \( \lambda \) denotes the weight of each feature, and the explicit features between tracking object and prediction object as follow: \( D_{ij} \) denotes the distance, \( \text{IoU}_{ij} \) denotes intersection-over-union (bbox \( i \) \( \cap \) bbox \( j \) / bbox \( i \) \( \cup \) bbox \( j \) ), \( \Delta v = v_i - \hat{v}_{ij} \) and \( \Delta a = a_i - \hat{a}_{ij} \) denotes the velocity error and acceler- rate error, respectively, between predicted hypotheses and the detections pairs, and \( \Delta f = f_i - \hat{f}_{ij} \) denotes the deep feature distance between tracking and detection.

The optimal weights of explicit features are predicted by trained RNN in the proposal. The features are fed into RNN, and the output is the optimal weights \( \lambda \) of each feature. For training the RNN, the datasets are generated as: the explicit features are calculated with the pairwise of groundtruth and truth positive detection, where the truth target detections are chosen with the maximum overlap of groundtruth. Given \( N \) pairwise training datasets, the cost function with Adam descent algorithm going to be minimized is formulated as:

\[
\min \frac{1}{N} \sum_{i} C_i. \tag{15}
\]

#### End-to-end Implicit Feature Association by GRU

Combining explicit features linearly is not the best way to compute the similarity score, as these features are not independent. Instead, we propose an end-to-end mapping from the input data to the solution of the data association problem. The end-to-end data association module is shown in Fig. 4. The composite features, including spatial, motion and deep features, will be used for both training and prediction. The combined feature vector pairs of predictions and detections are fed into GRU, and similarity of the feature pair is the output. Specifically, we encode long-term dependencies in the sequence of observations by using GRU networks which is shown as follow:

\[
\begin{align*}
\hat{r}_{t} &= \sigma(W_{r} \cdot [h_{t-1}, x_{t}]) \\
\hat{z}_{t} &= \sigma(W_{z} \cdot [h_{t-1}, x_{t}]) \\
\hat{h}_{t} &= \tanh(W_{h} \cdot [r_{t} \ast h_{t-1}, x_{t}]) \\
y_{t} &= \sigma(W_{o} \cdot h_{t}),
\end{align*}
\]

where \( z_{t} \) and \( r_{t} \) denote update-gate and reset-gates. The ground truth sequence is used to train GRU cell with an online manner that will be described as follow.

The GRU network, as other deep learning networks, requires a large amount of training data to obtain a reasonable performance. In view of this, the training data for association is acquired in an online generation process, such that only a small amount of video data will provide a great variety for good generalization. The highest scoring detections with IoU > 0.5 overlap of the ground truth are labeled as the positive samples, the maximum overlaps of those having IoU < 0.5 are labeled as the negative samples. And we randomly crop the sample images with 0.8 ⋅ 1.2 times of the target size around them to augment the training data. The cross entropy loss function is used to train the GRU network to predict the similarity, with a gradient descent optimization algorithm of Adam. The output score \( 0 \sim 1 \) indicates the matching similarity between the detection result and the tracking target.

### 3.5 Proposed MOT Algorithm

The whole procedure of the proposed MOT algorithm, integrating the auto-tuning Kalman prediction and GRU association (sec. 3.2-3.4), is summarized in Algorithm 1.

#### 4 Experiments

In this section, we use our learned proposed algorithm to tackle the multi-object tracking problem. The overall performance of our framework compared with the other trackers is evaluated on the MOT challenges [Milan et al., 2016].
Algorithm 1 Proposed GAKP Algorithm

Input: Video frame \( V = I_1, \ldots, I_T \)
Output: The tracking trajectories \( T^L_t \) in \( t \)-th frame;
Initialization: Initialize new trajectories \( T^L_{1:i} \) with detections, and set the model and appearance features.

Repeat: For \( t = 1, \ldots, T \)
1. Detect boxes \( D^N_t \) with input image \( I_t \);
2. Extract motion features \( \{b^N_j\}_{j=1}^N \) with motion model 3.2;
3. Predict features of each target in next frame with Eq. 1 and Eq. 2; Find the gating threshold of Mahalanobis distance \( D(i,j) \) with Eq. 8;
4. Extract appearance feature \( \{f^N_j\}_{j=1}^N \) with pre-trained ResNet-50 appearance model 3.3;
5. for all \( i \in T^L_{t-1} \) do:
   Compute cost matrix \( C_{ij} \) using GRU association model Eq. 15 for all \( j \in N \);
6. Gate the cost matrix with threshold of Mahalanobis distance which calculated in motion model;
7. Associate \( T^L_{t-1} \) with \( D^N_t \) using Hungarian algorithm 3.4;
8. Initialize new trajectories with unassociated detections;
9. Update \( T^L_t \)

4.1 Datasets and Protocols

The MOTchallenge benchmark includes MOT2015 [Leal-Taixe et al., 2015], MOT2016 and MOT2017 [Milan et al., 2016]. We evaluate our approach on the MOT16 and MOT17 Benchmarks. MOT16 offers 14 video sequences (7 for training and 7 for testing) which are captured by static and moving cameras. MOT17 provides the same sequences as MOT16, but each sequence provides 3 different detection results, DPM [Pedro F. Felzenszwalb and Ramanan, 2010], Faster R-CNN [Girshick, 2015] and SDP [Yang et al., 2016], researchers are asked to submit tracking results with these detectors.

For evaluation, the metric multi-object tracking accuracy (MOTA) provides the combination of the False Positive (FP), False Negative (FN) and ID switch (IDs) amongst all the trajectories against the Ground Truth (GT).

\[
\text{MOTA} = 1 - \frac{\text{FP} + \text{FN} + \text{IDs}}{\text{GT}}
\]  

There are other metrics including Mostly Tracked (MT) and Mostly Lost (ML) that provide an indication of the trajectory fragmentation and processing speed (frames per second, FPS), respectively.

4.2 Implementation Details

For appearance feature extraction, we employ the deep CNN with ResNet-50 backbone pre-trained using triplet loss in [He et al., 2016]. The cropped image is resized to \( 256 \times 128 \). ReLU is used for activation and Adam optimizer is used for the network training. The number of cell for each GRU is 134, which is a concatenation of 128-dim deep feature and 6-dim spatial-feature. GRU network is trained with mini-batch size of 64. Learning rate is initialized as 0.002, with a decay rate 0.1 every 20 epochs. The regularization parameter \( \lambda_c \) in Eq. 6 and Eq. 7 is set to 0.5 to preliminary experiments. In all experiments, the value of parameters GRU Hidden-size \( H \) and sequence length are 134 and 7, respectively.

The simulation environments are given as follows: Tensorflow, Ubuntu 16.04, Intel\textsuperscript{®} Xeon\textsuperscript{®} CPU E5-2667 v4 @ 3.20GHz × 32, 64GB RAM, and NVIDIA\textsuperscript{®} GeForce\textsuperscript{®} GTX 1080 Ti/PCIe/SSE2.

4.3 Ablation Study

The underlying motivation of our proposed framework is to address the challenge: optimal combination of multiple features, and the disadvantage of few training data in deep learning. We now present experiments towards two goals on MOT benchmark.

Combination of multiple features. One advantage of our work compared with prior works is optimal combination of features. We investigate different combination of features in our tracking framework by measuring the performance in terms of MOTA on the MOT17 training sequences. The autotuning Kalman [Zhaozhong et al., 2018] prediction in Section 3.2 is applied in all experiments. IOU-based data association mentioned in [Bochinski et al., 2017] are used as our baseline. And IOU and motion combined data association is formulated as our contrast experiment with motion and spatial model, respectively. Finally we explicitly combines different features proposed in [Yu et al., 2016].

The comparison results are shown in Fig. 5. The motion information helps to increase performance by 1.1% over baseline in the contrast experiment. We can observe that the method in [Yu et al., 2016] outperforms Kalman baseline by 4.8% in terms of MOTA on MOT17-DPM training data set, which demonstrates appearance model based on deep feature is more powerful than traditional motion model. The overall result is shown in Table 1.

Our two proposed models with explicit/implicit features in this work show better performance than two baselines. Moreover, the implicit features calculated with pre-trained GRU achieve excellent performance over explicit feature model.
where increase by 0.6% in MOTA. The main reason is that the weights of feature are end-to-end learned from training data by GRU in the implicit feature model. In our implicit feature model, initial sub-image pairs are used to train the GRU network instead of hand-craft features, such as Euclidean distance, IOU, deep feature and so on.

Impact of few training data. One of the advantages of our representation compared with the previous is the capacity to compensate the lack of training data. We investigate the performance compared with the online trackers AMIR [Sadeghian et al., 2017], RAR16pub [Fang et al., 2018], STAM16 [Chu et al., 2017] and DMMOT [Zhu et al., 2018] in MOT16 validation benchmark. Table 2 shows the details of these published online tracker for the validation sets. Our method achieves a competitive score and performs favorably against to others. Our proposed method outperforms the $RNN_{LSTM}$ based tracker (AMIR) by 0.9% in MOTA, 0.1% in MT, 3.4% in ML and 7.4% in FN, respectively. The main reason is the proposed method utilize numerous online generated training data, while the issue of the small size of MOT16 training data is not well considered in AMIR.

The spatial-temporal attention network utilized in the trackers DMMOT&STAM16 is trained on MOT15&16 datasets. The recurrent autoregressive network parameters of tracker RAR16pub are learned from discriminate ground truth associations and false associations in MOT data. The MOTA score drops significantly by 2.0% compared with our method, as tracking videos have only 1221 and 1276 object trajectories in MOT15 and MOT16 respectively.

4.4 Comparison with State-of-the-art Algorithms
In order to further validate our proposed algorithm, we compare the state-of-the-art methods on MOT17 benchmark, and the results are presented in Table 3. Obviously, our method achieves competitive performance of the comprehensive evaluation metric: MOTA=51.6, which ranks 3rd amongst all the online MOT approaches.

We notice that MT is an evaluation metric for which the proposed method performs worst when compared with other state-of-the-art methods. MT is dependent on the detection results given by the MOT benchmark which are noisy with the false positive and false negative. We believe a better pedestrian filter instead of the public detector used in the benchmark will help to improve the MT metric. Beside, it is evident that our proposed GAKP algorithm outperforms all other top competitors in terms of efficiency, i.e., $Hz = 7.8$.

5 Conclusion
In this work, we proposed a novel tracking method that integrates the GRU and the auto-tuning Kalman for MOT, achieving a near-optimum with only a small amount of training data. Experimental results show that our algorithm can achieve competitive performance on the challenging MOT benchmark with faster process speed compared to the state-of-the-art RNN-based online MOT algorithms.

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