Hierarchical Group Structures in Multi-Person Tracking

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Abstract—This paper presents a novel approach for improving multi-person tracking using hierarchical group structures. The groups are identified by a bottom-up social group discovery method. The inter- and intra-group structures are modeled as a two-layer graph and tracking is posed as optimization of the integrated structure. The target appearance is modeled using HOG features, and the tracking solution is obtained via dynamic programming. The group structures are updated continuously and re-initialized intermittently using collected tracking evidence. We test our method on videos from four challenging datasets and evaluate it against state-of-the-art trackers. The significant performance improvement shows the importance of modeling the intra-group relationships and the advantage of the two-layer graph structure.

I. INTRODUCTION

Multiple person tracking in unconstrained environments is an important task that has received considerable attention from the computer vision community in the past two decades. A number of approaches have proposed to address this problem [16] for its importance in applications related to surveillance, human activity recognition, and video retrieval. Unknown and rapidly changing human motion poses a significant challenge for tracking methods. With the understanding that human motion is often exhibited as a response to the environment (static and dynamic), incorporation of scene context in tracking approaches has been explored with increased interest. In recent years, social interaction as an additional measure of scene context has been investigated to further improve prediction models for human motion instead of reliance on purely physics-based model. Pellegrini et al. [10] accounts for social repulsion effects among pedestrians to predict motion paths using a social force model. Luber et al. [7] extended the use of social repulsion effect to include physical and social constraints of the environment. The individual pedestrian motion was then predicted based on the sum of forces inferred through a closed-form solution. Yan et al. [15] further included both social attraction and repulsion effects to model multiple potential moving paths and to relax the assumption of having a known destination.

Among various measures of social interaction, social grouping provides an indication of how humans engage and orient themselves to exhibit a group activity. With regards to motion behaviors, a social group can be inferred from pedestrian trajectories. In the case of multiple people in a scene, social groups can be indicated through relationships within a group and relationships across groups. We can denote the structure across groups as an intra-group structure and the structure within a group as an inter-group structure as shown in Fig. 1. Social grouping can guide tracking by assuming that humans in a group will maintain their spatial structure in the coming moments. The key benefit of tracking by taking advantage of social grouping is two fold, one is to handle human occlusions within a group and second is to minimize the search space for data association. Choi et al. [4] considered both social repulsion effects and group motion dynamics within a joint prediction model. Pellegrini et al. [9] jointly estimated trajectories and social group with a third-order graphical model. Bazzani et al. [2] leveraged a decentralized particle filter to sample both the individual’s state space and the social groups’ state space together. Qin et al. [11] used k-means in a similar way to find the social group, which serve as one parameter to improve the data association.

In general, most tracking systems with social grouping have overlooked the structure across groups while the individual-group relation or the inter-group structure has been exploited. Current systems account for the inter-group structure as a important constraint to refine the target search during tracking. However, intra-group structure may change in a dramatically different manner from inter-group structure and could provide rich information to further improve tracking. For instance, the structure for individuals in the same group may stay unchanged or change minimally while exhibiting slow movements or in stationary states. On the other hand, the structure between groups may change significantly if groups are moving in different directions. To fully leverage the social grouping context, inter-group and intra-group structures should be modeled and
updated in a more integrated approach. We present an approach to do so by extending the model of Zhang et al. [17] and show that it improves multiple person tracking. In this paper, we develop a two-layer graph structure based tracking system with social group clustering. Our experiments show that the incorporation of both inter-group and intra-group structure leads to considerable performance improvement compared with state-of-the-art tracking methods for multiple person tracking.

Our main contributions in this paper are: (1) we show that leveraging full social group structures improves the tracking performance and (2) the new two-layer graph model can incorporate both inter-group and intra-group structures simultaneously. Section II briefly introduces the structure preserving object tracking method and section III gives the detailed framework and formulation of the proposed system. Implementation of social group discovery and experimental results are presented and compared in section IV. Section V concludes the paper and discusses future work.

II. STRUCTURE PRESERVING OBJECT TRACKING (SPOT)

Before introducing the group structure preserving object tracking, we present the structure preserving object tracking briefly [17]. Given a starting frame, each tracking target \( i (i = 1, \ldots, N) \) is represented by a bounding box denoted by \( B_i = \{l_i, w_i, h_i\} \) with center location \( l_i \) and fixed width \( w_i \) and fixed height \( h_i \). The tracking targets in the scene are denoted as \( B = \{B_1, \ldots, B_N\} \). \( \phi_b(I; B_i) \) denotes the feature vector for target \( i \) extracted from image \( I \).

SPOT defines a graph \( G = (V, E) \) over all the targets with \( V = \{B_1, \ldots, B_N\} \) and \( E \) represents the set of edges among all the targets. The multiple object tracking problem is defined as finding the best configuration \( C = \{B^*_1, \ldots, B^*_N\} \) with highest score over the graph \( G \) as shown in Fig. 2(c). The problem is translated into an optimization problem:

\[
\arg\max_{C} S(C; I, \theta)
\]

Herein, the parameters \( w_i \) represent linear weights on object features, \( e_{ij} \) represent the length and direction of the springs between object \( i \) and \( j \), and \( \theta \) denotes the set of all parameters including \( w \) and \( e \). The parameter \( \lambda_{ij} \) is treated as a hyper-parameter.

III. GROUP STRUCTURE PRESERVING OBJECT TRACKING (GSPOT)

As shown in Fig. 2(a), SPOT links all the objects in the scene in a flat graph in the form of a minimum spanning tree. This inherently limits the ability to treat inter-group and intra-group dynamics uniquely. To explicitly incorporate the different levels of motion dynamics, the group structure preserving object tracking is built beyond structure-preserving object tracker (SPOT) by extending the single layer graph structure of SPOT to a two-layer graph structure. The structure of GSPOT is shown in Fig. 2(b), which unifies the inter-group and intra-group structure in a more natural way.

![Fig. 2. Examples of graph structures and configurations created by SPOT and GSPOT. The SPOT configuration models both inter- and intra-group relationships using a single layer graph while the proposed GSPOT configuration treats inter- and intra-group relationships through separate hierarchies of the constructed graph.](image-url)
We include an added constraint \( a \) group. Structure \( G \) interval, which in this paper is set to be every 20 frames.

Social groups are detected at a preset target-group mapping given as:

\[
\Psi = \{\psi_{ki}\} (i = 1, \ldots, N), \quad \psi \text{ is a target-group mapping given as:}
\]

\[
\psi_{ki} = \begin{cases} 
1 & \text{if target } i \text{ is mapped to group } k, \\
0 & \text{otherwise.}
\end{cases}
\]  

We include an added constraint \( \sum_{k=1}^{M} \psi_{ki} = 1 \) on the target-group mapping set and \( \phi(I; g_k) \) denotes the feature vector for a group.

A graph \( H = (G, O, T) \) is defined over all the targets and social groups. Social groups are detected at a preset interval, which in this paper is set to be every 20 frames. Given each social group \( k (k = 1, \ldots, M) \) in the scene as \( g_k \). The group \( g_k \) includes one group center \( o_k \) and a target-group mapping set \( \Psi_k = \{\psi_{ki}\} (i = 1, \ldots, N) \), where \( \psi \) is a target-group mapping given as:

\[
\psi_{ki} = \begin{cases} 
1 & \text{if target } i \text{ is mapped to group } k, \\
0 & \text{otherwise.}
\end{cases}
\]

We include an added constraint \( \sum_{k=1}^{M} \psi_{ki} = 1 \) on the target-group mapping set and \( \phi(I; g_k) \) denotes the feature vector for a group.

The structure to track the objects robustly. Tracking evidences are collected and the social groups are updated intermittently so that the overall group structure can be updated accordingly.

B. Problem Formulation

Given the subject bounding boxes \( B_i \) and the respective feature vectors \( \phi(I; B_i) \) as defined in section II, we further define each social group \( k (k = 1, \ldots, M) \) in the scene as \( g_k \). The group \( g_k \) includes one group center \( o_k \) and a target-group mapping set \( \Psi_k = \{\psi_{ki}\} (i = 1, \ldots, N) \), where \( \psi \) is a target-group mapping given as:

\[
\psi_{ki} = \begin{cases} 
1 & \text{if target } i \text{ is mapped to group } k, \\
0 & \text{otherwise.}
\end{cases}
\]

A graph \( H = (G, O, T) \) is defined over all the targets and social groups. Social groups are detected at a preset interval, which in this paper is set to be every 20 frames. Given each social group \( g_k \), a sub-graph is defined as \( G_k = (V_k, E_k) \), where \( V_k = \{B_i | \Psi_k = 1\} \) and \( E_k \) represents the set of edges within a group. Within the defined structure, the multiple object tracking problem is defined as finding the best configuration over the whole graph \( Y = \{B_1, \ldots, B_N, o_1, \ldots, o_M\} \) as shown in Fig. 2(d). Subsequently, we define the score of a configuration as:

\[
S(Y; I, \Theta) = \sum_{k=1}^{M} w_k^T \phi(I; g_k) - \sum_{(p,q) \in L} \beta_{pq} |(c_p - c_q) - \tau_{pq}|^2 + \sum_{k=1}^{M} \sum_{i \in V_k} \left( \sum_{(i,j) \in E_k} \alpha_{ij} |(l_i - l_j) - e_{ij}|^2 \right)
\]

Herein, the parameters \( w_k \) represent linear weights on the group features, and \( e_{ij} \) and \( \tau_{pq} \) represent the length and direction of the springs between inter-groups and intra-groups, respectively. The parameters \( \alpha_{ij} \) and \( \beta_{pq} \) are treated as hyper-parameter and are denoted as \( \forall i, j : \alpha_{ij} = \alpha \) and \( \forall p, q : \beta_{pq} = \beta \). The set of all parameters including \( w_k, w_i, \tau_{pq}, \) and \( e_{ij} \) is denoted as \( \Theta \). In this paper, we define the group feature as the sum of target features in that group, which is denoted as \( \phi(I; g_k) = \sum_{i \in V_k} \phi(I; B_i) \).

Group Structure and Inference. The inference of the model amounts to maximizing Eq. 3 over \( Y \). Solving a complete connected graph is intractable. With the tree-structured graph, we can solve the optimization by dynamic programming [5]. To make the inference tractable, we solve the optimization over the two-layer tree-structured graph \( H \) and \( \{G_1, \ldots, G_k, \ldots, G_M\} \). We use two variants of the tree structure graph: (1) the star model based tree structure for \( G_k \); and (2) a minimum spanning tree structure for \( H \).

C. Parameter Learning and Iterative Parameter Learning.

After solving an optimal object configuration \( Y \), we update the parameters by minimizing the structured SVM loss [14]:

\[
\ell(\Theta; I, Y) = \max_{\hat{Y}} \left[ s(\hat{Y}; I, \Theta) - s(Y; I, \Theta) + \Delta(Y, \hat{Y}) \right],
\]

where \( \Delta(Y, \hat{Y}) \) is defined as:

\[
\Delta(Y, \hat{Y}) = \sum_{k=1}^{M} \left( 1 - \frac{V_k \cap \hat{V}_k}{V_k \cup \hat{V}_k} \right).
\]

The loss function can be reshaped as:

\[
\ell(\Theta; I, Y) = \max_{\hat{Y}} \left( vec(\Theta)^T (\hat{\Theta} - \Theta) - \sum_{k=1}^{M} \sum_{(i,j) \in E_k} \alpha |m_{ij} - |m_{ij}|^2| - \sum_{(p,q) \in L} \beta \beta (|p_{pq} - |p_{pq}|^2 + \Delta(Y, \hat{Y})) \right),
\]

where \( m_{ij} = l_i - l_j \), \( p_{pq} = c_p - c_q \), and \( \hat{\Theta} = [\phi_1^T, \ldots, \phi_M^T, \alpha_{12}, \ldots, \alpha_{1M}, \alpha_{23}, \ldots, \alpha_{2M}, \ldots, \alpha_{M-1M}] \) and \( vec(\cdot) \) concatenates all parameters in a column vector.

We present two different methods to update the parameters. The first one is similar to the one used by Zhang at al. [17] and is given as:

\[
\Theta \leftarrow \Theta - \frac{\ell(\Theta; I, Y)}{\nabla_\Theta \ell(\Theta; I, Y)^2 + \frac{1}{2\kappa}} \nabla_\Theta \ell(\Theta; I, Y),
\]

where we update all the parameters at the same time.

The second method updates the parameters in an iterative manner. We split the parameter set \( \Theta \) as the union of \( \Theta_1 \) and \( \Theta_2 \), \( \Theta_1 \) represents the intra-group feature parameter set including \( w_k \) and \( \tau_{pq} \) and \( \Theta_2 \) represents the inter-group feature parameter set including \( w_i \) and \( e_{ij} \). The updates are also split into two stages. In the first stage only \( \Theta_1 \) is updated as:

\[
\Theta_1 \leftarrow \Theta_1 - \frac{\ell(\Theta_1; I, Y)}{\nabla_{\Theta_1} \ell(\Theta_1; I, Y)^2 + \frac{1}{2\kappa}} \nabla_{\Theta_1} \ell(\Theta_1; I, Y).
\]
After \( \Theta_1 \) is updated, one more optimization (solve the Eq. 3) is performed prior to updating \( \Theta_2 \) as the second stage. \( \Theta_1 \) is kept fixed and \( \Theta_2 \) is updated as:

\[
\Theta_2 \leftarrow \Theta_2 - \frac{\ell(\Theta; I, Y)}{\nabla_{\Theta} \ell(\Theta; I, Y) + \frac{1}{2} \nabla_{\Theta}^2 \ell(\Theta; I, Y)}.
\]

To refer to the joint parameter optimization approach as “GSPOT” and the iterative approach as “iGSPOT”.

### IV. Experiments

To evaluate the merit of our proposed hierarchical structure based model, we conducted experiments on several public datasets to compare the performance of the proposed methods against existing methods as well as to evaluate the merits of different components of our approach. The “S15-FM” sequence was included from the “Friends Meet” dataset [2]. It shows multiple occurrences of persons merging and splitting from a group and is the most challenging scenario in the whole dataset. One video sequence was included from the “BEHAVE” Interactions Test Case Scenarios [8], which includes the scenario showing two groups merging into a larger group. One video sequence from the “QIL” dataset was also included [15] in which several individual persons merge into a group and move together. Finally, one video sequence was included from the “Crowd by Example” dataset that has poor image quality and shows several groups moving around in a natural manner. The tracking performance is measured based on CLEAR MOT metrics [3]. We report multiple object tracking precision (MOTP), miss rate (MISS), false positive rate (FP), number of ID switches (IDS) and multiple object tracking accuracy (MOTA). The threshold for building a matched pair between a tracking result and the ground truth is selected as half of the bounding rectangles’ diagonal in the ground truth. It should be noted that MOTA measures the ability of a tracker to estimate precise pedestrian positions, which is independent of an algorithm’s tracking accuracy. MOTP is computed as the average error of center position of matched pairs over all frames, measured in pixels. Note here, the MOTA result could be a negative number since it is computed as:

\[
MOTA = 1 - \frac{\# of miss + \# of fp + \# of IDS}{\# of groundtruth},
\]

### A. Evaluation: Social Group Discovery

We explore three methods to discover the social groups within a scene. The first two methods are detailed in [6] and [13], respectively. Method described by Ge et al. [6] uses both spatial and temporal cues to group subjects based on their trajectories while the method by Khai et al. [13] leverages the social cues from a single frame based on subject position and pose to find dominant groups. The third method we use is based on k-means clustering [12]. The number of clusters or groups, \( k \), is set to be the same as the number of groups identified by the first method [6]. We integrated the three methods into “GSPOT” with all the other component being identical and evaluated the tracking performance on the four video sequences. The average MOTA performance in Table I shows that the social grouping defined in [6] gives best overall performance, which could be explained by the advantage of cumulative spatio-temporal evidences. This metric is based on an agglomerative clustering where the group membership \( \rho_{ij} \) denotes the number of frames in which pedestrian \( i \) and \( j \) are in same group. There is a link between two pedestrians \( i \) and \( j \) if \( \rho_{ij} > \tau \). We set \( \tau = 10 \) [6]. \( \omega_{ij} \) represents the average pairwise distance over all the frames when pedestrians \( i \) and \( j \) are in same group. A modified Hausdorff distance \( H(A, B) \) is derived from pairwise distance matrix and is used to measure inter-group closeness between groups \( A \) and \( B \) as

\[
H(A, B) = \frac{h(A, B) + h(B, A)}{2},
\]

where \( h(A, B) = \frac{\sum_{l=1}^{A} \sum_{l=1}^{B} w_{lj} e_{lj}}{|A| \times |B|/2} \)

and \( w_{lj} \) is the \( l \)th smallest distance among all the distances, which are derived between pedestrian \( i \) in group \( A \) and all the pedestrians \( j \in B \). The social group is then obtained by agglomerative clustering. The merge step is governed by pairwise group Hausdorff distance and the merging is stopped by intra-group tightness criterion shown in Eq. 12.

\[
e_{A+B} < \hat{e}_{A|A+B} + (e_A - \hat{e}_A) + e_B - \hat{e}_B
\]

where \( e_{A}, e_{B}, e_{A+B} \) are the total number of links in group \( A \), group \( B \), and the merged group \( A + B \), respectively. \( \hat{e}_{A}, \hat{e}_{B}, \hat{e}_{A+B} \) denote the minimal expected number of links in group \( A \), group \( B \), and merged group \( A + B \), respectively. For the remaining results shown in the paper, method by Ge et al. is set as the default social group discovery method.

<table>
<thead>
<tr>
<th>Grouping Methods</th>
<th>MOTP</th>
<th>MOTA</th>
<th>FP</th>
<th>FN</th>
<th>IDS</th>
</tr>
</thead>
<tbody>
<tr>
<td>K-means [12]</td>
<td>5.58</td>
<td>70.57%</td>
<td>13.56%</td>
<td>13.56%</td>
<td>29</td>
</tr>
<tr>
<td>Khai et al. [13]</td>
<td>4.96</td>
<td>75.98%</td>
<td>11.94%</td>
<td>11.94%</td>
<td>7</td>
</tr>
<tr>
<td>Ge et al. [6]</td>
<td>4.57</td>
<td>99.72%</td>
<td>0.14%</td>
<td>0.14%</td>
<td>0</td>
</tr>
</tbody>
</table>

### B. Evaluation: Group Structure

We present variants on updating the identified group structures based on the discovered social groups at initialization to evaluate the merit of the hierarchical graph in GSPOT. The inter-group structure is initialized but not updated in “GSPOT.v1” while only the intra-group structure is updated during tracking. The intra-group structure is initialized in “GSPOT.v2” but not updated while only the inter-group structure is updated during tracking. Note here that the parameters of the structures are reinitialized after new group discovery for “GSPOT.v1” and “GSPOT.v2” although there is no update in each grouping interval for the component held constant. From the tracking performance presented in Table II, it shows that (1) both precise inter-group and intra-group structures are critical without which the tracking performance degraded in all of scenarios; (2) intra-group structure update has a significant impact over inter-group structure update in tracking performance; and (3) inter-group structure update contributes to the tracking performance when the structure in individual groups changes significantly.

### C. Evaluation: Parameter Learning

To fully evaluate the benefit of iterative parameter learning, we compared the performance of iGSPOT against GSPOT. Besides the original trackers, two variant are evaluated as well. iGSPOT.g1 and GSPOT.g1 denote no group structure
updates after initialization in the first frame with the rest of components being the same. In the second variant, the default social grouping method in both iGSPOT and GSPOT are replaced by the method of Khai et al. [13]. We denote them as iGSPOT.g2 and GSPOT.g2. The tracking accuracy is assessed to measure performance improvement as shown in Fig. 4. As seen, the iterative parameter update gives more robust performance under various settings.

**D. Evaluation: Overall performance**

To evaluate the overall tracking performance, we compared performance results of the proposed tracker against four competing approaches for all the video sequences. The trackers compared included: (1) Multiple Instance Learning Tracker [1] (MIL), (2) Structure preserving object tracker [17] (SPOT), (3) Multiple structure preserving object tracker with social group discovery (MSPOT.v1), and (4) Multiple structure preserving object tracker with fixed grouping (MSPOT.v2). To compare fairly, we implemented MIL tracker with HOG feature and the parameters of MIL are tuned to get the best results. SPOT was run using the implementations provided by [17]. MSPOT by name is an extension of SPOT that runs multiple SPOT trackers on different groups. MSPOT.v1 leverages the same social group discovery method as used in our model and is updated in the tracking process. MSPOT.v2 uses the fixed group setting that is set manually. The performance of the five trackers on all four datasets is presented in Table III. The results in the table show that (1) our iGSPOT and GSPOT tracker outperform the state-of-the-art tracker SPOT and MIL indicating that hierarchical structure contributes towards improved tracking; (2) MSPOT treats objects in the scene and builds multiple independent structure for each one resulting in improved performance compared to SPOT in BEHAVE and FM datasets but contributes to worse performance in the other two datasets; (3) iGSPOT and GSPOT outperform the two MSPOT trackers, which suggests that the structure between each group pairs should not be overlooked; (4) MIL results in worse performance compared with SPOT in three of the sequences demonstrating that incorporation of spatial structures aids tracking.

**V. CONCLUSION**

In this paper, we have proposed a new group structure preserving object tracking method. The method leverages the group structure to identify the relationship among tracked objects. Inter-group and intra-group relationship is modeled as a two-layer graph structure. The proposed structure model is integrated with HOG feature and solved using dynamic programming. The group structure and parameters are initialized and updated continuously using social discovery. Experimental results are presented showing that the proposed method enables tracking of pedestrians in complex scenes and outperforms the state-of-the-art methods. Further analysis shows the advantage of the two-layer graph structure in tracking scenarios. Our future work will explore the ability to learn the layer number automatically and find optimal ways to model the scene structure.

<table>
<thead>
<tr>
<th>CLEAR MOT EVALUATION RESULTS ON FOUR DATASETS</th>
<th>Table II</th>
<th>The best results are in bold</th>
</tr>
</thead>
<tbody>
<tr>
<td>BEHAVE MOTP MOTA TP FN IDS</td>
<td>SPOT</td>
<td>3.89</td>
</tr>
<tr>
<td>iGSPOT</td>
<td>4.05</td>
<td>99.90%</td>
</tr>
<tr>
<td>GSPOT</td>
<td>5.85</td>
<td>100.00%</td>
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<tr>
<td>GSPOT.g2</td>
<td>4.53</td>
<td>81.84%</td>
</tr>
<tr>
<td>MSPOT</td>
<td>4.21</td>
<td>60.82%</td>
</tr>
<tr>
<td>MSPOT.v2</td>
<td>5.85</td>
<td>100.00%</td>
</tr>
<tr>
<td>FM MOTP MOTA TP FN IDS</td>
<td>SPOT</td>
<td>6.36</td>
</tr>
<tr>
<td>iGSPOT</td>
<td>4.03</td>
<td>99.80%</td>
</tr>
<tr>
<td>GSPOT</td>
<td>5.03</td>
<td>100.00%</td>
</tr>
<tr>
<td>GSPOT.g2</td>
<td>3.39</td>
<td>99.06%</td>
</tr>
<tr>
<td>FM MOTP MOTA TP FN IDS</td>
<td>SPOT</td>
<td>6.36</td>
</tr>
<tr>
<td>iGSPOT</td>
<td>4.03</td>
<td>99.80%</td>
</tr>
<tr>
<td>GSPOT</td>
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<td>100.00%</td>
</tr>
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<tr>
<td>BEHAVE MOTP MOTA TP FN IDS</td>
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<td>GSPOT</td>
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<td>GSPOT.g2</td>
<td>3.39</td>
<td>99.06%</td>
</tr>
</tbody>
</table>

**EVALUATION RESULTS ON FOUR DATASETS**

**TABLE III. CLEAR MOT EVALUATION RESULTS ON FOUR DATASETS.**

**THE BEST RESULTS ARE IN BOLD.**

Fig. 4. Evaluation on the effects of GSPOT, iGSPOT and their variants.
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