An Intelligent Extraversion Analysis Scheme from Crowd Trajectories for Surveillance

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Abstract—In recent years, crowd analysis is important for applications such as smart cities, intelligent transportation systems, customer behavior prediction, and visual surveillance. Understanding the characteristics of the individual motion in a crowd can be beneficial for social event detection and abnormal detection, but it has rarely been studied. In this paper, we focus on the extraversion measure of individual motions in crowds based on trajectory data. Extraversion is one of typical personalities that is often observed in human crowd behaviors and it can reflect not only the characteristics of the individual motion, but also the interactions of the holistic crowd motions. To our best knowledge, this is the first attempt to analyze individual extraversion of crowd motions based on trajectories. To accomplish this, we first present an effective composite motion descriptor, which integrates the basic individual motion information and social metrics, to describe the extraversion of each individual in a crowd. The social metrics consider both the neighboring distribution and their interaction pattern. Since our major goal is to learn a universal scoring function that can measure the degrees of extraversion across varied crowd scenes, we incorporate and adapt the active learning technique to the relative attribute approach. Specifically, we assume the social groups in any crowds contain individuals with the similar degree of extraversion. Based on such assumption, we significantly reduce the computation cost by clustering and ranking the trajectories actively. Finally, we demonstrate the performance of our proposed method by measuring the degree of extraversion for real individual trajectories in crowds and analyzing crowd scenes from a real-world dataset.

Index Terms—Crowd analysis, Active learning

I. INTRODUCTION

In recent years, researchers in many areas have become interested in understanding pedestrian behaviors in crowd motions. This interest is partially because of this research’s practical applications in areas such as social event recognition [1], crowd motion prediction/tracking [2], [3], [4], and vehicle routing selection [5]. Currently, with cameras deployed at every street corner and with the advancement in pedestrian tracking techniques, crowd trajectories can be easily extracted from videos, and more underlying crowd motion information can be recovered. Furthermore, trajectory data has been used for the analysis of applications such as visual surveillance and intelligent transportation system [6], [7].

The prior social cognitive works [8], [9] point out that a crowd consists of dissimilar individuals, each with potentially independent personalities. These personalities coincide with pedestrians’ various purposes and psychologies, which often lead to variation in crowd motions. Analyzing individuals’ personalities may help us better understand social behavior in a crowd. Prior works on trajectory based crowd analysis mainly focus on holistic crowd scene understanding [10] or individual action recognition [11]. On the contrary, the goal of this paper is to investigate the latent personalities of the individuals in a crowd based on the captured real-world trajectories.

In this paper, we focus on measuring one type of frequently observed personalities, extraversion. Extraversion is a measure of social interest, and is associated with active, assertive, and daring behaviors. As an example, pedestrians who walk quickly and do not care about bumping into others are said to exhibit an extraverted personality. In scenarios such as the train stations, there are more extroverted individuals as people tend to behave assertively when they try to catch a train, while more people may exhibit a relaxed behavior in scenarios like shopping malls and parks. However, it is difficult to quantify the extraversion of a whole crowd’s motion. As mentioned, the individual personalities in a crowd motion are caused by latent factors. Some factors are unobservable and thus it is difficult to use motion descriptors to measure them. A more challenging problem is that we would like to evaluate the degree of extraversion of each individual in crowds from different scenarios, which concerns with domain knowledge transfer. To this end, we prefer a universal scoring function to measure it.

To cope with the difficulties mentioned above, we first introduce a composite individual motion descriptor, which considers not only the basic motion information (e.g., speed) but also considers multiple social motion metrics for describing an individual’s motions. The social motion metrics include the neighbor-related metric and the interaction metric. The neighbor-related metric relates to the status of the individuals next to a specific person. The inclusion of interaction metric which leverages agent-based motion models (AMMs) as reference to analyze crowd trajectories. As demonstrated by prior works [12], the AMMs controlled by different parameters can be used to simulate the interaction in various crowd behaviors, which means a parametric AMM encodes some kind of interaction behavior. Hence, the AMM can serve as a reference to compare the AMM-produced trajectories and the real-world trajectories. Their similarity naturally reflects the similarity between the interaction behavior underlying the trajectory and the AMM-encoded interaction behavior. As deterministic algorithms, AMMs can be used as effective cross-domain reference to evaluate the interaction behaviors.

Given the composite motion descriptor, we need to learn a universal scoring function to evaluate the strength of the extraversion for trajectories from different scenarios. However, training such a scoring function is difficult, since manually labeling the strength of the extraversion for the training data (i.e. trajectories) is time-consuming and biased. Leveraging
the relative attribute \cite{13} method, we incorporate the active learning technique for labeling the crowd. It takes the advantage of the social grouping behaviors in crowd motions to train a relative extraversion scoring function. In particular, we use an actively hierarchical labeling algorithm to collect the training data; trajectories are first clustered into groups and then relative attributes on the social groups can actively query the user for labels, which significantly speeds up the labeling process. We demonstrate the evaluation results of a real-world crowd trajectory dataset.

In this paper, we make the following contributions. To the best of our knowledge, our proposed approach is the first work that measures the degrees of extraversion exhibited by crowd trajectories. We present a composite individual motion descriptors, including the basic motion metric and the social metrics. To describe the interaction behavior, we leverage different AMMs as reference to evaluate individual trajectories. To quantify the extraversion of trajectories across different crowd scenes, we present an active learning algorithm that can be incorporated with the relative attribute algorithm.

In the rest of the paper, we first survey the relevant works in Section II. In Sections III and IV, we present our individual motion descriptors and how we qualify the degree of extraversion, respectively. Finally, we evaluate the proposed method through a number of experiments in Section V.

II. RELATED WORKS

Our work is related to vision-based crowd analysis, crowd motion description, and crowd personality modeling. In this section, we survey the related works on these aspects.

A. Crowd Analysis

In recent years, researchers have been interested in vision-based crowd analysis \cite{10, 14, 15, 11, 16}. Since our approach is based on crowd trajectories, we survey only the prior trajectory-based methods here. The benefit of trajectory-based methods is that crowd trajectories contain rich information about individuals’ interactions within a crowd, e.g., how the individuals react to oncoming pedestrians. Among the trajectory-based works, Choi et al. \cite{17} propose a hierarchical activity model to recognize individual activities. Similarly, Morris et al. \cite{11} analyze the captured trajectories of individuals for individual activity recognition and abnormality detection. Wang et al. \cite{18} propose a probabilistic model for trajectory clustering and semantic region detection. Liu et al. \cite{19} leverage agent-based motion models (AMMs) to learn the holistic features of crowd trajectories for crowd movement classification. In contrast, the purpose of our work is to learn and evaluate the degrees of extraversion of individuals in a crowd, instead of recognizing the behavior of the crowd.

B. Crowd Motion Descriptors

To analyze crowd motions, methods have been proposed to summarize the patterns or the attributes of any query crowd motions holistically and individually via effective descriptors. Zhou et al. \cite{16} propose a method to evaluate the coherence of crowd motion by measuring the path similarities of the KLT tracklets captured from real-world crowd videos on the collective manifold. Based on the KLT tracklets, Shao et al. \cite{20} propose several types of group descriptors to detect the patterns of group motions of crowds, which serve as the feature for crowd motion classification. In Liu et al. \cite{19}, different AMMs are adopted as references to measure the similarity between the query crowd trajectories and the AMMs. The quantified correlations between them jointly serve as a holistic feature to describe the query crowd movement. Instead of describing the holistic feature of crowd motion, Charalambous et al. \cite{21} propose metrics to measure individual trajectories to find the outliers of the crowd motion. Inspired by this method, our work also introduces a composite individual motion descriptor that considers not only the basic motion information, but also the neighbor-related and interaction metrics to measure the degrees of extraversion of crowd trajectories.

C. Crowd Personality

Psychologists have proposed various models for characterizing the personalities exhibited by human behaviors. The Eysenck 3-Factor personality model \cite{22} (PEN) is a biologically-based model of three independent personality factors meant to model personality variation: Psychoticism (the measure of a person’s aggression and egocentricity), Extraversion (associated with active, assertive and daring behaviors), and Neuroticism (the measure of a person’s shyness and anxiety). An individual’s personality is identified according to the extent to which he/she exhibits the traits. A similar personality model, the OCEAN personality model \cite{23}, proposes five independent axes of personality based on a factor analysis of user responses. In the crowd simulation area, there are some works that model the personality of crowd behaviors. Durupinar et al. \cite{24} propose a method to vary the parameters of a crowd simulation model by choosing a plausible mapping between OCEAN personality factors. Guy et al. \cite{12} also propose an approach to simulate heterogeneous crowd behaviors based on personality trait theory. They leverage user studies to derive a mapping from crowd simulation parameters to the perceived crowd behaviors. According to their work, there are strong correlations between different PEN factors. In particular, Psychoticism and Extraversion show a strong positive correlation with each other and both are negatively correlated with Neuroticism. After performing PCAs, they have found that two factors can explain over 95% of the behaviors in the simulation parameters, i.e., “extraversion” and “carefulness”. Inspired by their finding, we want to study the extraversion of individuals’ motions for use in analyzing the real-world crowd behaviors.

III. INDIVIDUAL MOTION DESCRIPTORS

To describe each individual trajectory, we use a composite individual motion descriptor consisting of the basic metric and the social metrics, i.e. the neighbor-based metric and the interaction metric.


\[ \text{velocity and } k \text{ is defined as: } cn_{\text{dist}}. \]

In experiments, we set \( \text{set is defined as persons who are near the person in a similar direction, as shown in Fig. 1(a). The neighbor as the cardinality of } \text{is defined as our interaction metric.} \]

\[ \text{B. Neighbor-related Metric} \]

As one of the social metrics, we investigate the neighbor-related metric of an individual, including the motion coherence and the spatial distribution, to describe the social grouping behaviors. As we observe, the social grouping depicts the extraversion exhibited by i's motion trajectory. For instance, a group of customers in a shopping mall show less extraversion, while a single person walking against the motion direction of a large crowd shows strong extraversion.

First, we investigate the motion coherence of person i in a crowd, which is indicated by the person i's neighbors. For instance, an introverted person may walk coherently with its neighbors in a crowded scene. Here, we set the coherence as the cardinality of i's grouping agents who walk near and in a similar direction, as shown in Fig. 1(a). The neighbor set is defined as persons who are near the person i at time-step t, i.e. \( \text{Neighbor}_i = \{ k \mid \| \mathbf{p}_i - \mathbf{p}_k \| \leq \text{dist}_{\text{nei}} \}. \)

In our experiments, we set \( \text{dist}_{\text{nei}} \) to 5 meters. Thus, the coherence is defined as: \( \text{cn}_{\text{dist}} = \sum_{t=1}^{T} \text{bincnt}_{\text{dist}}^h, \) where \( h \in \{ 1, \cdots, H \} \) represents the index of the partition. Fig. 1(b) illustrates that the circular region around person i (the blue circle) is equally divided into eight sectors and the left-right symmetric sectors use the same index \( h. \)

Considering the distance from i, we set up \( r_1 = 3 \) and \( r_2 = 6 \) to identify the neighbors within a close range and a medium range. Hence, for each \( \text{bincnt}_{\text{dist}}^h, \) we compute its average value \( X_{\text{spatial}} = \frac{1}{T} \sum_{t=1}^{T} \text{bincnt}_{\text{dist}}^t(h) \) as a metric.

\[ \text{C. Interaction Metric} \]

The interaction behavior of a crowd is a crucial factor for analyzing extraversion. For example, an extroverted person does not care about avoiding potential collisions with other pedestrians in a dense crowd like any person usually does. Therefore, it is important to set up a reference to quantify how a person interacts with other people in a crowd.

Motivated by [19], we leverage agent-based motion models (AMMs) to quantify the interaction behaviors in a crowd. An AMM can be used to predict the future position and velocity of a crowd, given the states of the crowd at the current time step, based on a collision-free protocol. As demonstrated by prior works [12], the AMMs controlled by different parameters can be further used to simulate the interaction in various crowd behaviors, which means AMMs encode some kind of interaction behavior. Hence, an AMM can serve as a reference to compare the AMM-produced trajectories and the real-world trajectories, which is shown in Fig. 2. Their similarity naturally indicates the similarity between the interaction behavior underlying the trajectory and the AMM-encoded interaction behavior. For example, given an exemplar AMM that can model aggressive behavior, if a person’s trajectory exhibits a similar aggressive behavior, this trajectory and the exemplar AMM-produced trajectory should be similar. Similar to the idea of the zeroshot learning, we apply such comparison to a query trajectory with multiple exemplar-AMMs and then gather a sequence of similarity scores, which are concatenated as a feature vector as our interaction metric.

Specifically, when comparing the similarity scores, we assume that the captured positions and velocities of trajectory T (the superscript i is ignored for compactness) are states may consider them as moving in similar directions or moving in a social group. The symbol \# indicates the cardinality of a set. As shown in Fig. 1(a), given the status of person i (the blue agent in the center), the black circles refer to the persons that move coherently with i. Those persons (the gray agents) are not considered as moving coherently with i, as his or her position is not close enough to i or the difference between their velocities is too large. Similar to the previously introduced metric, we compute \( X_{\text{coherence}} = |f(cn_{1:T})|, \) where \( f \) represents operations \( \{ \text{max, min, average, std} \}. \)

Another neighbor-related metric is the spatial distribution of the neighbors, which indicates the spatial formation of a crowd. For example, an extroverted person often walks alone and quickly, so the spatial distribution of his or her neighbors tends to vary temporally. To describe it, we divide the circular region around a person i into partitions and count the number of persons in each partition. Assuming that the circular region is divided into H partitions at time-step t, the count of persons in each partition is \( \text{bincnt}_{\text{dist}}^h, \) where \( h \in \{ 1, \cdots, H \} \) represents the index of the partition. Fig. 1(b) illustrates that the circular region around person i (the blue circle) is equally divided into eight sectors and the left-right symmetric sectors use the same index \( h. \)

Considering the distance from i, we set up \( r_1 = 3 \) and \( r_2 = 6 \) to identify the neighbors within a close range and a medium range. Hence, for each \( \text{bincnt}_{\text{dist}}^h, \) we compute its average value \( X_{\text{spatial}} = \frac{1}{T} \sum_{t=1}^{T} \text{bincnt}_{\text{dist}}^t(h) \) as a metric.
Fig. 2. As shown, the dash line refers to a trajectory generated by a specific exemplar-AMM, while the solid line refers to the query trajectory or the captured real-world trajectory. The exemplar-AMM represents the agent may take a conservative collision avoidance strategy to avoid potential collisions, while the query trajectory exhibits more aggressive motion. Thus, we can conclude that the query trajectory is quite different from the interaction behavior encoded by the exemplar-AMM. Therefore, by measuring the difference between the query trajectory and the exemplar-AMM’s inference, we can quantify the interaction behavior of the query trajectory.

\[ \mathbf{X}_{1:T} = [\mathbf{p}_t, \mathbf{v}_t]_{t=1:T} \] compounded with an unknown time-invariant zero-mean Gaussian noise \( \mathcal{N} = \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_r) \). The basic idea is that we assume the real-world trajectory is an observation of the AMM-generated trajectory. The Gaussian white noise \( \mathcal{N} \) thus represents the observation noise, but it is unknown. Here we adopt Bayesian inference to estimate the most likely noise, whose scale reflects how well the trajectory fits the AMM. The better the trajectory fits the AMM, the smaller the scale of the observation noise.

To find out the most likely \( \mathcal{R} \), we iteratively perform two steps: (1) fix the expected noise \( \mathcal{R} \) and adopt an Ensemble Kalman filter to estimate the state of the individual motion. (2) fix the individual state and optimize the covariance \( \mathbf{\Sigma}_r \) of \( \mathcal{R} \) using maximum likelihood estimation (MLE). In both steps, the state estimation is driven based on the exemplar-AMM: \( [\mathbf{a}(t+1)|_t, \mathbf{b}(t+1)|_t] = \mathbf{F}_k(\mathbf{a}_t, \mathbf{b}_t) + \mathbf{r}_t, \) s.t. \( \mathbf{r}_t \sim \mathcal{N}(\mathbf{0}, \mathbf{\Sigma}_r) \), where \( \mathbf{F}_k \) refers to the \( k \)-th exemplar AMM and here we adopt the state-of-the-art Reciprocal Velocity Obstacle (RVO) \[25\] with multiple sets of predefined parameters as the exemplar AMMs. In the first step, with fixed \( \mathcal{R} \), the individual state distribution is a Gaussian distribution, \( \mathbf{X}_{t+1} = \mathcal{N}(\mathbf{F}_k(\mathbf{a}_t, \mathbf{b}_t), \mathbf{\Sigma}_r) \). This distribution can be represented by a set of samples drawn from itself, i.e. \( \mathbf{F}_k(\mathbf{a}_t, \mathbf{b}_t) + \mathbf{r}_t^{(1)}, \ldots, \mathbf{F}_k(\mathbf{a}_t, \mathbf{b}_t) + \mathbf{r}_t^{(m)} \)\( , \ldots \). According to the principle of Ensemble Kalman filter \[26\], these samples will be corrected using the observed state \( \mathbf{z}_t \) from the query trajectory \( \mathbf{T} \) and thus the estimated individual state \( \mathbf{X}_{t+1} \) is inferred. In the second step, with the estimated individual state \( \mathbf{X}_{t+1} \), we adopt MLE to optimize the covariance \( \mathbf{\Sigma}_r \). By iteratively performing these two steps, the covariance \( \mathbf{\Sigma}_r \) of \( \mathcal{R} \) will converge.

Based on our assumption, the scale of the Gaussian noise \( \mathcal{R} \) measures the difference between the AMM-inferred individual state and the observation (i.e. the query trajectory). The smaller scale of noise indicates the higher similarity between the exemplar AMM and the query trajectory and vice versa. Hence, evaluating the scale of the Gaussian noise \( \mathcal{R} \) is to compute the entropy \( E_k = \frac{1}{2} \ln (2\pi e |\mathbf{\Sigma}_r|) \) and it quantifies the similarity between the query trajectory and the \( k \)-th exemplar AMM. Thus, the computed similarity \( E \)'s from different exemplar-AMMs are integrated as a feature vector as the interaction metric, i.e. \( \mathbf{X}_{\text{interaction}} = [E_1, \cdots, E_k, \cdots] \).

To sum up, in our experiments, the metrics mentioned above are integrated as the composite motion descriptor of an individual motion, which is in the form of a vector \( \mathbf{X} = [\mathbf{X}_{\text{basic}}, \mathbf{X}_{\text{coherence}}, \mathbf{X}_{\text{spatial}}, \mathbf{X}_{\text{interaction}}] \). In practice, we adopt the z-score standardization to normalize \( \mathbf{X} \).

IV. QUANTIFYING EXTRAVERSION

Since we now have a composite metric to describe an individual’s trajectory, we need to map the metrics to an extraversion score that indicates the degree of extraversion exhibited by the trajectory. Our goal is therefore to learn a scoring function that can quantify the level of extraversion for any individual trajectory, i.e. learning \( f \) that satisfies \( y = f(\mathbf{X}) \), where \( y \) is the predicted score.

A. Relative Extraversion of a Pair of Trajectories

Learning such a mapping requires manual labels of training samples, i.e. trajectories labeled by extraversion scores. However, manually scoring the degree of extraversion of each individual trajectory from various scenes can be very biased and time-consuming. To alleviate this problem, we adopt the attribute-based learning method \[13\] to label the relative extraversion for a pair of trajectories. In particular, given two trajectories, we ask users to identify which trajectory exhibits more extroverted behavior, which is much easier than asking the users to directly score the degree of extraversion of each trajectory.

To train a scoring function \( f \) to measure the degrees of extraversion for a trajectory, we first compute the individual motion descriptors \( \mathbf{X} \in \mathbb{R}^d \) for a set of training trajectories \( \mathcal{T}_{\text{train}} = \{\mathbf{T}^i\} \). Then, we ask users to label the trajectories in pairs. The pairs of labeled trajectories are divided into two subsets. One subset \( \mathcal{O} = \{\{\mathbf{T}^i, \mathbf{T}^j\}\}_{i \neq j} \) consists of ordered pairs of trajectories, with trajectory \( \mathbf{T}^i \) showing a higher degree of extraversion than trajectory \( \mathbf{T}^j \). In other words, the extraversion score of \( \mathbf{T}^i \) should be higher than that of \( \mathbf{T}^j \). Another subset \( \mathcal{S} = \{\{\mathbf{T}^i, \mathbf{T}^j\}\}_{i \neq j} \) consists of unordered pairs or similar pairs, with both trajectories having similar degrees of extraversion. This means that the extraversion scores of both trajectories should be close.

To satisfy the constraints specified by the training comparisons, the scoring function computes the weighted sum of \( \mathbf{X} \) and takes the form of \( \mathbf{f}(\mathbf{X}) = \mathbf{w}^T \mathbf{X} \), where \( \mathbf{w} \) refers to the weights. That is, \( \forall (i, j) \in \mathcal{O} : \mathbf{w}^T \mathbf{X}_i > \mathbf{w}^T \mathbf{X}_j \), and \( \forall (i, j) \in \mathcal{S} : \mathbf{w}^T \mathbf{X}_i = \mathbf{w}^T \mathbf{X}_j \). This problem is formulated as:

\[
\begin{align*}
\text{minimize} & \quad \frac{1}{2} \| \mathbf{w} \|^2_2 + C(\sum_i \xi_i^2 + \sum \gamma_{ij}^2), \\
\text{subject to} & \quad \mathbf{w}^T (\mathbf{X}_i - \mathbf{X}_j) \geq 1 - \xi_{ij}, \forall (i, j) \in \mathcal{O}; \\
& \quad \| \mathbf{w}^T (\mathbf{X}_i - \mathbf{X}_j) \| \leq \gamma_{ij}, \forall (i, j) \in \mathcal{S}; \\
& \quad \xi_{ij} \geq 0; \gamma_{ij} \geq 0,
\end{align*}
\]
where $C$ is the constant coefficient and $\xi_{ij}$ and $\gamma_{ij}$ are slack variables. This formulation can be solved similar to the SVM formulation. Please refer to [13] for the detailed solution.

B. Active Learning

In practice, labeling the relative extraversion of trajectories across various scenes is still tedious and time-consuming. Assuming that there are $M$ trajectories in the training set, we need to label the relative extraversion for at most $M(M-1)/2$ pairs of trajectories, which can be challenging. (In our experiments, we have $M = 1118$.) In addition, visually comparing two trajectories to determine their relative extraversion is still challenging, as the extraversion exhibited from the individual trajectory is subtle and the behaviors require context to understand. Specifically, we need to know how the entire crowd moves to understand why an individual would move in a certain way.

We therefore incorporate the active learning technique to actively query the users for labels. The active learning is helpful in situations where unlabeled data is abundant but manually labeling is expensive. Hence, we set up two query strategies, based on the social grouping behaviors in crowd motions. First, query in the same crowd scene. As we realize, when the two query trajectories come from different scenes, it is usually difficult to make unbiased labels. This is because the trajectories are sampled from different crowd scenes which are visually quite different. For instance, one crowd scene is shot from top-down view, while the other is from oblique view. One trajectory can be selected from a dense crowd motion, while the other can be in a sparse crowd. Users are easily confused by context of the crowd, so that they cannot focus on comparing the extraversion exhibited from the trajectories. Therefore, we only query the pair of trajectories from the same crowd scene. Second, query from the different social groups. In crowd motions, a few persons may be moving closely together and sharing a similar movement behavior. It is reasonable to assume that pedestrians belonging to the same social group have similar degrees of extraversion. In particular, the trajectories from the same social group are assumed to have a similar extraversion score, i.e., they belong to the unordered pair set $S$. For different social groups, we actively query the user to label the relative extraversion. These two query strategies significantly reduce the label effort. To implement the query strategies, we propose the following algorithm:

Social group discovery. To extract social groups from the crowd trajectories, much as in the prior work [27], we adopt a bottom-up clustering method, the Agglomerative clustering algorithm. We first apply the Kalman filter to remove noise from the trajectory data, and treat each individual trajectory as a separate social group (or a cluster) initially. We then merge the most coherent groups into one group. The merging procedure continues until there are no more groups to be merged. To accomplish this, we need to know (1) if two trajectories are considered coherent, and (2) if two social groups are considered coherent.

(1) Are two trajectories coherent? We consider two trajectories as coherent if their mutual distance is close enough and their velocities (both direction and speed) are similar. Hence, the distance of two trajectories $T_i$ and $T_j$ should be adequately small, i.e., $|p_i - p_j| < \epsilon_{dist}$, and their velocities should be similar, i.e., $|v_i - v_j| < \epsilon_{vel}$, where $\epsilon_{dist}$ and $\epsilon_{vel}$ are the predefined thresholds for distance and velocity. In practice, since coherent individuals may be temporarily separated (e.g., due to an oncoming pedestrian) and the captured trajectory data may be noisy, then the two conditions above will not hold all the time. Thus, we only need to ensure that the two conditions hold for a sufficient amount of time:

$$\text{CF}(T_i, T_j) = \begin{cases} 
true, & \sum_{i=1}^{T} (|p_i - p_j| < \epsilon_{dist}) \\
false, & \text{Otherwise},
\end{cases}$$

where $\text{CF}(T_i, T_j) = true$ if two trajectories are coherent and vice versa. $\langle \cdot \rangle$ represents the Iverson bracket, which is equal to 1 when the condition inside the bracket is true and 0 otherwise. We let $\epsilon = 0.6$, so that both conditions will hold for 60% of the time. In experiments, we set $\epsilon_{dist} = 1.6$ and $\epsilon_{vel} = 0.8$.

(2) Are two social groups coherent? To determine if any two social groups are coherent, we need to make sure that any pair of trajectories from the two groups are coherent. Formally, given two social groups $G_A$ and $G_B$, if $\text{CF}(T_i, T_j) = true$ s.t. $\forall T_i \in G_A$ and $\forall T_j \in G_B$, then $G_A$ and $G_B$ are considered coherent, i.e., $\text{CF}(G_A, G_B) = true$. This group merging condition is relatively strict, because we need to guarantee the trajectories within the same group actually exhibit the similar level of extraversion.

Social groups query. After clustering the trajectories into groups, we query users to label the relative extraversion for these social groups, rather than trajectories. In user study, we show the markers on members of two groups and ask the users to indicate which group is more extraverted. Given all $L$ groups in the same crowd scene, the active query becomes a sorting problem, involving around $O(L \log L)$ times of visual comparisons for labeling social groups.

Relative extraversion pairs generation. According to Section IV-A, training the scoring function requires a set of similar pairs of trajectories $S$ and a set of ordered pairs of trajectories $O$. Given a crowd scene with sorted groups $G = \{G_1, G_2, \ldots, G_L\}$ where $G_1 \supseteq \cdots \supseteq G_L$, we generate $S$ and $O$ based on their orders. If two groups are labeled similar levels of extraversion, then we insert all trajectory pairs of these two groups to $S$. Otherwise, we insert them to $O$.

V. Experiments

In this section, we first introduce the dataset for our experiments and discuss how we label the crowd data. We then evaluate the proposed method in experiments.

A. Dataset

To evaluate our method, we introduce a dataset consisting of 62 different real-world crowd videos (or crowd scenes) as our training dataset. These videos are properly selected from the dataset in [20]. We abandon some crowd videos that cannot
be used for evaluating the extraversion behaviors such as people taking escalators. Since our method is based on crowd trajectories, we deploy a multi-person tracker to capture the crowd trajectories from the videos. In particular, we manually provide the initial positions of each pedestrian. We then use the state-of-the-art tracker \cite{28} to track the positions of these pedestrians over time, i.e. their trajectories, which are used as input to our algorithm. Sometimes, the tracker may not perform well due to problems such as occlusion. To fix this problem, the tracker is manually reinitialized if it drifts too far. Finally, the labeled trajectories are transformed from the image-space to the ground-space using the estimated perspective transformation matrix. This step results in a total of 1118 captured individual trajectories. Among them, we randomly select 146 trajectories from an independent set of 11 crowd videos as the testing dataset. To obtain the extraversion scores for the collected trajectories, we employed 4 participants (2 male and 2 female students) to label the relative extraversion for the training and testing datasets.

**Training dataset setup.** To label the training dataset, we split the four participants into three groups. One participant is asked to do brute-force comparison for pairs of trajectories. Another participant is asked to perform the social group label using our active learning strategy. The remaining two users are asked to refine label results to generate the ground-truth labels. During user study, all the users are allowed to repeatedly review the image sequences on how the query person moves or the social group moves in the crowd scene. This produces a training dataset with 6003 similar pairs and 2911 ordered pairs.

**Testing dataset setup.** For trajectories in the test set, which is excluded from the training dataset, we do not adopt active learning based method to label. Instead, we let users label the relative extraversion for all of the pairs. During labeling, users are allowed to skip those pairs that are too difficult to label the relative extraversion. And then we discard those unlabeled pairs from the testing dataset. As a result, we obtain a total of 378 similar pairs and 641 ordered pairs for the testing dataset. Furthermore, we allow users to roughly classify each trajectory in the testing dataset into four classes: “very unextraverted,” “unextraverted,” “extraverted,” and “very extraverted.” We obtain a total of 146 labeled instances.

### B. Active Learning for Relative Extraversion

To demonstrate our active learning based method actually improve the training efficiency and accuracy, we compare the labeling methods using brute-force pairwise comparison and the active-learning based comparison.

The brute-force pairwise comparison takes at least 8914 times of manual comparisons to label all the training samples when labeling training data. Differently, our active learning based method only needs to label the social groups rather than individual trajectories. Thanks to the social group clustering, there are only 233 groups in all of 62 crowd scenes, which takes less than 900 manual labels. Hence, our method is much more efficient. According to the feedbacks of the participants, the brute-force labeling tends to be biased and it takes more time to label each comparison of trajectories, while labeling the social groups in the same crowd scene is much easier. According to our records, it takes around 15.2 minutes per crowd video using the brute-force pairwise comparison approach, while it takes 1.3 minutes per video using active learning based approach.

In addition, we compare the label quality of both methods. We use the brute-force labeled data and the active learning labeled data to train the scoring function and run tests on the testing dataset. In terms of accuracy, the brute-force pairwise comparison gains 0.887 and our proposed method gains 0.895. Our active learning based label is not only more efficient, but also gains some improvements on the accuracy, since it is much less error-prone.

### C. Analysis of Extraversion Measures

To validate our methods, we evaluate the real-data based on the individual extraversion measures and the extraversion analysis of social groups and crowds.

1) **Ablation study on individual extraversion measure:** First, since we have a number of ordered pairs and similar pairs, we can leverage them for evaluation by comparing the ranking scores of these pairs. We adopt two metrics to evaluate the results: the accuracy (i.e., \( \text{Accuracy} = \frac{\text{correct-predictions}}{\text{total-predictions}} \)) and Kendall rank correlation coefficient (Kendall’s \( \tau \) coefficient). Given two labeled ordered trajectories \( T^a \) and \( T^b \) (s.t. \( T^a \succ T^b \) and \( (T^a, T^b) \in \Omega \)), if the computed extraversion score for \( T^a \) is larger than that for \( T^b \), then the prediction is correct. Otherwise, it is considered incorrect. For any two labeled unordered trajectories \( T^a \) and \( T^b \) (s.t. \( T^a \approx T^b \) and \( (T^a, T^b) \in S \)), if the difference between the computed ranking scores for \( T^a \) and \( T^b \) is adequately small (e.g., smaller than a threshold 0.1), then the prediction is correct. Otherwise, it is incorrect.

The Kendall’s \( \tau \) coefficient is a statistical measure of the ordinal association between two quantities, and thus the higher the number of this coefficient, the better. For comparison, since there is no prior methods studying crowd extraversion, we evaluate different individual motion features, including the basic metric (noted as Basic), the neighbor-related metric (noted as Neighbor), the interaction metric (noted as Interaction), and combinations of these metrics, based on both training and testing dataset.

We use the leave-one-out strategy to cross validate the results based on the training dataset. I.e., the scoring function is trained based on the trajectories from 61 crowd videos...
and tested on the trajectories from the rest one crowd video. Besides, we also train the scoring function on the complete training data and test on the testing dataset. The cross-validation and testing results are shown in Tables I. From the results, we can see that the cross-validation results and the testing results are similar. We also observe that the basic metric plays the most important role in distinguishing the ordered pairs. It indicates that users mainly perceive the degree of extraversion from the individual trajectories based on speed and curvature. When comparing similar pairs, the interaction metric performs better than the others. There are many similar pairs captured from the grouping behavior with a lot of interactions observed.

Second, in Table II we demonstrate the results of classifying the individuals in the testing dataset into four classes (i.e., from "very unextraverted" to "very extraverted") using the scoring function learned from the training dataset. We classify them in a heuristic manner (as shown in the column "Score"). If the score is lower than 1.2, it is classified as "very unextraverted". If it ranges in (1.2, 2.5], it is classified as "unextraverted". If it ranges in (2.5, 4.5], it is classified as "extraverted". Otherwise, it is classified as "very extraverted". The thresholds are chosen based on a validation set. For comparison, we adopt SVM to train an individual classifier based on our proposed feature (as shown in the column "SVM"). From the results, the classification based on heuristic scores is only slightly worse than the SVM based results. Consider that SVM is a complex classifier that is robust to noisy data, the slightly worse quantitative results reflect the effectiveness of our learned scoring function.

2) Qualitative analysis on individual extraversion measure: In Fig. 3 we show qualitative results from some real-world data. The individual trajectories and the regions occupied by the individuals in the video frames are highlighted. We observe that all the individual marked in red exhibit the most extraverted behavior while the blue ones exhibit the least. Apparently, during the same time period, the red ones travel greater distances than the blue ones, and their trajectories are straighter, which indicates that they do not often steer away from their current motion direction. Accordingly, the extraversion scores of these pairs of trajectories are computed. The strength of the comparison is $T^{\text{Red}} > T^{\text{Blue}}$.

Fig. 3. Examples of individual extraversion measures. The individual trajectories and the regions covered by the individuals are highlighted. The extraversion scores of these pairs of trajectories are computed. The strength comparison is $T^{\text{Red}} > T^{\text{Blue}}$.

3) Extraversion measures for social groups: Since the attribute of the grouping behavior can be reflected by the degree of extraversion of the individuals, we first analyze the extraversion scores for social groups. We run a group ranking test as follows. The group sorting labels in the training set are used as the ground-truth. We therefore compute the average score for each group and compare the scores of any two groups. In total, there are 116 comparisons. Again, we adopt the same leave-one-out strategy in which group comparisons from one crowd scene are used as the testing instances and the others are used as training instances. The accuracy of our metrics is 90.5% and the Kendell’s $\tau$ is 0.774, both of which are better than the individual ranking. This is because the coherent behavior of social groups exhibit more consistent and obvious extraversion feature.

In Fig. 4 we compute the average scores and the variances for each group. In Fig. 4(a), the red group is stationary, while the other two groups move. Therefore, the score of the red group is very low. The blue group moves in a more compact formulation and more slowly, and shows less extraversion than the green group. Similarly, in Fig. 4(b), the couple in the blue group move more slowly than the other two groups and their score is the lowest. We also note that the variances
of the computed scores are very small for all groups, which indicates that the variations among the group members are small. This is reasonable since the behavior of pedestrians usually synchronize with their companions and thus their differences become small.

4) Extraversion measures for holistic crowd motions:
In addition, the extraversion scores of all individuals in a crowd scene also reflect the motion pattern of the entire crowd’s movements. We illustrate some representative real-world crowd scenes in Fig. 5. We visualize the individual extraversion scores in different colors. The warmer the color is, the higher the extraversion score, while the colder the color is, the lower the score. For instance, in the bottom of Fig. 5(c), two persons walking slowly have low scores and are highlighted in dark blue. In Fig. 5(f), the standing soldiers highlighted in darker blue have even lower scores. Comparably, in Fig. 5(d), some runners are highlighted in yellow or red, since they run much faster than the others in the crowd. This shows that we can evaluate the degree of extraversion across various crowd scenes based on the scores.

Hence, we compute the mean scores and variances for every crowd scene and we have the following findings. First, the average score of Fig. 5(d) is the highest (3.231) among the six diagrams, since most people in the crowd are running and they appear to be very aggressive when they split the crowd or pass by others. The lowest score (1.022) is obtained by Fig. 5(e) caused by the high density. Second, the variance of scores also indicates the personality of a crowd’s behavior. The variances of Fig. 5(b) and 5(e) are the lowest (0.011 and 0.095), since the behaviors of individuals in the crowd scenes are almost identical. Fig. 5(f) has the largest variance. This makes sense because there are two groups of soldiers with two quite different behaviors.

To further analyze the crowd dataset, in Fig. 6, we show the top 3 most extroverted and least extroverted crowd scenes from our dataset, based on their average scores. Fig. 6(a-c) are the three most extroverted crowd scenes and their scores are 3.572, 3.231, and 3.153. All of them are running scenes and people appear to be very active. Fig. 6(d-f) are the least extroverted crowd scenes and their scores are 0.361, 0.487, and 0.505. Fig. 6(d) is captured from a shopping mall, where a few pedestrians stand still and most of pedestrians move casually. The extraversion score is low. The other two scenes are captured from the street and their crowd density is high.

Therefore, pedestrian movements in these scenes are extremely constrained and unextroverted.

VI. CONCLUSION AND FUTURE WORK
In this paper, we present an effective composite individual motion descriptor, which integrates the basic motion information, the nearest-neighbor related metric, and the interaction metric together. In addition, we propose to a social group based active learning to actively query users for labeling extraversion of trajectories. Hence, we train a universal scoring function together. In addition, we propose to a social group based active learning to actively query users for labeling extraversion of trajectories. Hence, we train a universal scoring function using the relative attribute method. We demonstrate its applications in measuring individual extraversion, recognizing group attributes, and analyzing crowd scenes. In future work, we need to improve the robustness of the metrics used for analysis. Due to the lack of labeled data, we cannot adopt advanced
features such as deep features in this work. Therefore, more data should be collected and labeled.

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