A Spatio-Temporal Identity Verification Method for Person-Action Instance Search in Movies

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Abstract—As one of the challenging problems in video search, Person-Action Instance Search (INS) aims to retrieve shots with specific person carrying out specific action from massive video shots. Existing methods mainly include two steps: First, two individual INS branches, i.e., person INS and action INS, are separately conducted to compute the initial person and action ranking scores; Second, both scores are directly fused to generate the final ranking list. However, direct aggregation of two individual INS scores cannot guarantee the identity consistency between person and action. For example, a shot with “Pat is standing” and “Ian is sitting on couch” may be erroneously understood as “Pat is sitting on couch” or “Ian is standing”. To address the above identity inconsistency problem (IIP), we study a spatio-temporal identity verification method. Specifically, in the spatial dimension, we propose an identity consistency verification scheme to optimize the direct fusion score of person INS and action INS. The motivation originates from an observation that face detection results usually locate in the identity-consistent action bounding boxes. Moreover, in the temporal dimension, considering the complex filming condition, we propose an inter-frame detection extension operation to interpolate missing face/action detection results in successive video frames. The proposed method is evaluated on the large-scale TRECVID INS dataset, and the experimental results show that our method can effectively mitigate the IIP and surpass the existing second places in both TRECVID 2019 and 2020 INS tasks.

Index Terms—Person Instance Search, Action Instance Search, Detection Extension, Identity Consistency Verification.

I. INTRODUCTION

With the rapid development of multimedia technology in recent years, various forms of videos have flooded our life. Finding specific targets from massive videos, i.e., video instance search (INS), is becoming increasingly important. For example, in the surveillance videos [1]–[3], police officers need to locate key video clips of specific suspects; In sports videos [4]–[6], fans want to browse shots concerning their favorite players or events; In movies [7]–[13], the audience are interested in watching shots of their idols or romantic actions. Compared with surveillance videos and sports videos, movie videos have wider audience, more complex scenarios and diverse filming skills. Therefore, INS for movies is of particular importance and challenge.

Early INS research in movies mainly focuses on a single target, i.e., mono-semantic INS, such as finding a specific object [14]–[16], location [17], [18], person [7]–[9], or action [11]–[13]. Recently, researchers start to investigate the more challenging combinatorial-semantic INS, which aims at retrieving specific instances with multiple attributes simultaneously. Representative works in this field include Person-Scene (P-S) INS and Person-Action (P-A) INS. The former aims at finding shots about specific person in specific scene, while the latter aims at finding shots about specific person doing specific action. Compared with P-S INS, P-A INS pays additional attention to the identity consistency between person and action, making it a more challenging combinatorial-semantic INS problem.

In movie videos, persons and actions are freely matched, making the content of P-A INS pairs ever-changing. Hence, P-A instance pairs cannot be considered as a whole for search. Existing methods [19]–[23] often adopt two different technical branches for person INS and action INS (as shown in Fig. 1). Specifically, in the person INS branch, face detection and identification are conducted to compute ranking scores of video shots concerning the target person. In the action INS branch, the action recognition is conducted to compute ranking scores of video shots about the target action. Thereafter, two-branch INS scores are directly fused to generate the final ranking result. However, direct aggregation of scores cannot

![Fig. 1. An example of P-A INS. The topic (query) is “Max is holding phone”. Person INS branch searches video shots concerning the target person, and action INS branch searches video shots about the target action. The number under each shot (represented by a keyframe) gives the relevant INS score. The ranking list of shots is obtained by combining person and action INS results. The red bounding boxes mark target shots with specific person doing specific action.]

1 All figures in this paper are best viewed in the color version.

2 In movies or TV shows, person INS is usually achieved by face detection and recognition because of their robust appearance in different scenes. In the paper, we use the word “face” instead of “person” when we describe the details of person INS, including face detection, face identification, face score, and face bounding box.
guarantee the identity consistency between person and action. For example, in Fig. 2(a), given “Bradley is standing” and “Danielle is carrying bag”, the system [20] mistakes it as “Bradley is carrying bag” since the person “Bradley” and action “carrying bag” appear simultaneously; similar case happens in Fig. 2(b) where “Pat is standing” and “Ian is sitting on couch” are misunderstood as “Pat is sitting on couch”. We call it identity inconsistency problem (IIP). According to the statistics in Section III-A, erroneous shots with inconsistent identities account for 23.44% and 22.35% of all erroneous shots in TRECVID 2019 and 2020 INS tasks, showing the seriousness of the IIP in P-A INS in movies.

To address the above problem, we propose a spatio-temporal identity verification method. The core idea stems from an intuitive observation that identity-consistent face and action usually share an overlapping spatial region of their respective detection bounding boxes. Therefore, we propose an identity consistency verification (ICV) scheme to compute the spatial consistency degree between face and action detection results in the spatial dimension. The higher spatial consistency degree means the larger overlapping area between the bounding boxes of face and action, thus the more likely that face and action belong to the same person.

Furthermore, we find many face and action detection failures due to complex scenarios, such as non-frontal filming or object occlusion, which hinder ICV from getting basic detection information. For example, the face detector fails to find “Billy” in middle clips in Fig. 3(a) because of non-frontal or occluded faces; similar issues appear in detecting actions like “Holding glass” and “Holding phone” in Fig. 3(b). Luckily, missing shots in this situation can be salvaged. Considering the continuity of video frames in a shot, if the same face/action is detected on two interval frames, it should also appear in the middle frames. Thus, in the temporal dimension, we propose an inter-frame detection extension (IDE) operation to share the detection information of interval frames, and thus improve the performance of ICV step.

**Contributions.** The main contributions of this paper are as follows:

- We study the IIP in the combinatorial P-A INS, and quantitatively investigate its severity with mainstream person and action INS techniques.
- We propose a spatio-temporal identity verification method to address the IIP. In the temporal dimension, IDE shares the detection information in successive frames to remedy face and action detection failures. In the spatial dimension, ICV checks identity consistency between person and action by computing their spatial consistency degree.
- We verify the effectiveness of the proposed method on the large-scale TRECVID INS dataset. The performance surpasses that of existing second places in both TRECVID 2019 and 2020 INS tasks.

**II. RELATED WORKS**

Since this paper focuses on the combinatorial P-A INS, we review the existing works from three aspects, i.e., person INS, action INS and fusion strategy.

**A. Person INS**

Person INS in videos aims to find shots containing a specific person from a gallery video corpus, which is also termed as person re-identification. Most of the previous research works on person re-identification mainly focus on surveillance videos, where dresses rather than faces are more robust for identity discrimination [11–19]. But in movies, due to massive close-up shots and frequent clothing changes, faces are more stable than dresses for person re-identification. Therefore, most of existing works in movies mainly use face detection and face recognition algorithms for person INS [7–9].

In this paper, we choose RetinaFace [24] and ArcFace [25] to achieve person INS in movies. RetinaFace is a single-stage face detection algorithm with high efficiency, and it is proved to be robust in detecting large angle faces. ArcFace is a face recognition algorithm with low complexity and high training efficiency, which corresponds to the geodesic distance on the hypersphere exactly.
B. Action INS

Existing research on action INS mainly relies on action recognition or detection technology [19]–[23]. The difference between them is that the former only recognizes the category of action, whereas the latter can provide the location bounding boxes of action. This paper focuses on action detection. According to different implementation strategies, action detection can be generally divided into image-based and video-based methods. The former is mainly designed for actions with obvious interactive objects but without rigorous temporal causality. For example, “holding glass”, “carrying bag”, and “riding bicycle”. This corresponds to a specialized action detection task, i.e., human-object interaction (HOI) detection [26]–[29]. It aims to recognize action (interaction) category, and meanwhile, locate human and object bounding boxes from images. The latter targets to actions with rigorous temporal causality. For example, “open door and enter”, “open door and leave”, and “go up or down stairs”. Hence, it usually works on successive multiple video frames. Representative action detection algorithms in videos are [19]–[23].

In this paper, we choose parallel point detection and matching for real-time human-object interaction detection (PPDM) [29] and actor conditioned attention maps for video action detection (ACAM) [32] for action detection on the image level and video level, respectively. PPDM realizes the action detection through the parallel point detection and matching branches, which is based on the idea of anchor-free detection. It is a single-stage and real-time framework, which is more suitable for large-scale datasets. ACAM adopts an attention module to rank each spatio-temporal region’s relevance to a detected actor, which is suitable for observing complex events with multiple actors, and it is a near real-time algorithm.

C. Fusion strategy

For combinatorial-semantic P-A INS, the difficulty lies in how to combine the results of different branches. Most of the existing studies adopt a strategy of retrieving two instances separately and then aggregating individual scores in some ways [19]–[23]. For example, NII fuses scores of person INS and action INS by direct weighted summation [19]. Instead, WHU raises a stepwise strategy of searching action based on a candidate person list. It first builds an initial candidate person shot list with person INS scores, and then sorts the list according to scores of action INS [20], [21]. PKU adopts a strategy of searching person based on a candidate action list [23], [23]. However, as discussed in the previous section, direct aggregation of individual person INS and action INS results without checking their identity consistency may incur serious IIP.

To solve this problem, Le et al. [34] raise a heuristic method. They calculate the distance between target face and desired object, and assume that the shorter distance means the more positive relationship between person and action with desired object. The method indirectly judges the identity consistency by the distance between related object and target face, which can not sufficiently prove the identity consistency of target face and specific action. Moreover, the method works on the basis of object detection, which means that it does not work for actions without obvious interactive object, e.g., “walking”, “standing”, and “talking”.

In this paper, we propose a spatio-temporal identity verification method for P-A INS. Different from [34], we observe that the identity-consistent face and action usually share an overlapping spatial region of their respective detection bounding boxes. Based on the finding, the identity consistency of P-A pair can be directly determined without additional dependence on objects. Hence, it can be applied to both HOI and object-free actions. Moreover, it is compatible with the existing two-branch framework, and can flexibly enhance existing methods as a plug and play module.

III. Motivation

In this section, we first investigate the severity of IIP in existing P-A INS research. Then, we observe and study two typical phenomena in IIP shots, i.e., location mismatch and detection failure, which motivate the proposed ICV and IDE methods. We focus the discussion on statistical analysis and comparison, and report implementation details in the later experimental section.

A. Identity Inconsistency Problem (IIP)

In order to investigate the IIP in P-A INS, we calculate the percentage of IIP shots in all erroneous shots, which are not included in official released ground-truth. The statistic is based on a proved effective strategy of searching action from a candidate person list [20], [21]. Specifically, for each topic, we first take 0.4 as the threshold for face scores, to filter out shots with irrelevant faces. Then the ranking list is generated by sorting reserved video shots with action scores. Next, based on the official released ground-truth, we count the number of erroneous shots for each topic. Finally, among all erroneous shots, we count the number of IIP shots. The percentage of IIP shots, $P_{IIP_error}$, for each topic can be computed as:

$$P_{IIP_error} = \frac{N_{IIP_error}}{N_{total_error}},$$  

(1)
where \( N_{\text{IIP\_error}} \) is the number of erroneous IIP shots, and \( N_{\text{total\_error}} \) is the total number of erroneous shots.

Table I and Table II show the percentages of IIP shots in all erroneous shots in topics of TRECVID 2019 and 2020 INS tasks, respectively. As shown in both tables, all topics have different degrees of IIP. The average percentages of IIP shots in erroneous shots are 23.44% and 22.35% in 2019 and 2020. In particular, percentages in topic 9271, 9253, 9257, and 9263 exceed 30%. It indicates their corresponding topics, i.e., “Bradley is carrying bag”, “Pat is sitting on couch”, “Jane is holding phone”, and “Billy is holding paper” are more prone to occur IIP (as shown in Fig. 2).

### B. Location Mismatch

Through preliminary observation, we find that identity-consistent face and action usually share an overlapping spatial region of their respective detection bounding boxes, whereas identity-inconsistent face and action are conversely. In this section, based on the above statistics on IIP, we quantitatively explore the relationship between the overlapping degree of detection bounding boxes and identity consistency. Specifically, we calculate the overlapping degree, i.e., the ratio between the overlap area (the red dotted bounding boxes in Fig. 4) over the face bounding box area (the blue solid bounding boxes in Fig. 4) for all IIP shots.

As shown in Fig. 5 in 89.94% identity-inconsistent shots, the overlapping degree of face and action is lower than 20%. With the increase of the overlapping degree, the number of identity-inconsistent shots gradually decreases. This shows that the overlapping degree is an important indicator to detect IIP, and lays the foundation of the proposed ICV method.

### C. Detection Failures

Besides location mismatch, another common phenomenon in IIP shots is detection failure. Similarly, we quantitatively investigate the severity of the detection failure problem. Take Fig. 3(a) as an example, “Billy” is not detected in the 36th-57th keyframes, but it is detected in the 35th and 58th keyframes. Then 36th-57th keyframes are defined as failed detection keyframes, and the corresponding shot is called as the failed detection shot containing 22 failed detection keyframes.

We calculate the percentage of failed detection shots in all IIP shots. Specifically, we firstly count the number of failed detection keyframes for each IIP shot. Then, we obtain the number of failed detection keyframes \( n \), and the percentage of failed detection shots \( P_{\text{failure}}(n) \) is calculated as follows:

\[
P_{\text{failure}}(n) = \frac{N_{\text{failure}}(n)}{N_{\text{IIP\_error}}},
\]

where \( N_{\text{failure}}(n) \) is the number of shots which include no more than \( n \) failed detection keyframes, \( N_{\text{IIP\_error}} \) is the total number of erroneous IIP shots.

Fig. 6 records the percentages of failed detection shots on face and action, which are included in official predefined person and action sets, respectively. According to the statistics,
63.04% and 61.83% shots have at least one failed detection keyframe in person INS and action INS, which shows the severity of detection failure problem.

**IV. METHOD**

The overall scheme of our method is shown in Fig. 7. Given a topic and a gallery video corpus, representative keyframes are first extracted from each shot of the video corpus. Then, person INS and action INS are conducted. It is worth noting that, we apply detection rather than recognition in the action INS branch. This means that we can obtain initial face/action detection scores, as well as their corresponding bounding boxes. Next, in the temporal dimension, the IDE operation is conducted on failed detection shots, providing more detection information for ICV. Thereafter, in the spatial dimension, the ICV method is applied to check identity consistency between person and action, which filters out erroneous IIP shots. Finally, the maximum fusion score of all keyframes in a shot is taken as the INS score of the shot, and the ranking list is obtained by sorting INS scores of all shots.

A. Preliminary

Assume that there are L shots in gallery videos. For the l-th shot, K keyframes can be extracted. We denote the k-th keyframe in the shot l as \( P^{(l,k)} \), where \( l \in [1,L] \) and \( k \in [1,K] \). For the convenience of following discussion, the subscript signs k and l are temporarily omitted from all variables when they do not cause confusion.

For a keyframe \( P \), assume that there are \( m \) faces and \( n \) actions detected in the person INS and action INS branches. The detection and identification results of i-th face can be expressed as \( \langle ID_i, Conf_{f_i}, Box_i \rangle \), where \( ID_i \) represents the face id, \( Conf_{f_i} \) records the confidence score of face identification, \( Box_i = \langle x_{min}, y_{min}, x_{max}, y_{max} \rangle \) contains the horizontal and vertical coordinates of upper-left and lower-right corners of the face bounding box. Similarly, the result of \( j \)-th action can be expressed as \( \langle ID_j, Conf_{a_j}, Box_j \rangle \), with similar notation definitions.

B. Inter-frame Detection Extension (IDE)

To address the detection failure problem caused by complex filming conditions, we propose IDE to share the detection information among keyframes in the temporal dimension. For simplicity, we take the face IDE as an example. Similar operations also apply to the action detection results. Particularly, because IDE works in the temporal dimension, the superscript signs are used to indicate the temporal relationship among keyframes in the l-th shot.

Assume that we successfully detect the i-th face in the \((k - \gamma_1)\)-th and \((k + \gamma_2)\)-th keyframes, and meanwhile, fail to detect the face in the keyframes between them. Considering the continuity of the video shots, we conduct IDE to recover face detection information in these keyframes. For example, the confidence score of i-th face in \( P^{(l,k)} \) can be recovered by a simple linear interpolation:

\[
Conf_{f_i}^{(l,k)} = \frac{\gamma_1}{(\gamma_1 + \gamma_2)} \times Conf_{f_i}^{(l,k + \gamma_2)} + \frac{\gamma_2}{(\gamma_1 + \gamma_2)} \times Conf_{f_i}^{(l,k - \gamma_1)},
\]

(3)

where \( Conf_{f_i}^{(l,k - \gamma_1)} \) and \( Conf_{f_i}^{(l,k + \gamma_2)} \) are the face confidence scores of target person in \( P^{(l,k - \gamma_1)} \) and \( P^{(l,k + \gamma_2)} \). The similar interpolation method is used to extend coordinates of face bounding boxes. And the face id is inherited in the process of the above extension.

C. Identity Consistency Verification (ICV)

As discussed in the motivation, many erroneous shots contain IIP. In order to address the problem, we propose...
ICV to verify the identity consistency between person and action. Different from IDE, which deals with the same type of detection results in the temporal dimension, ICV deals with two different types of detection results, i.e., face and action detection results in the spatial dimension. Therefore, for the convenience of the following discussion, the superscript signs turn to distinguish the results of face and action.

Specifically, for a keyframe $P$, we calculate spatial consistency degree matrix $C = [c_{i,j}] \in \mathbb{R}^{m \times n}$ based on face and action bounding boxes obtained from person and action INS branches, in which $c_{i,j}$ is defined as:

$$c_{i,j} = \frac{\text{Intersection} \left( Box_{i}^{\text{face}}, Box_{j}^{\text{action}} \right)}{\text{Area} \left( Box_{i}^{\text{face}} \right)}, \quad (4)$$

where $\text{Intersection}(\cdot, \cdot)$ is the function of computing the intersection area of two bounding boxes, $\text{Area}(\cdot)$ is the function of computing the area of a bounding box. Their formulas are as follows:

$$\text{Intersection} \left( Box_{i}^{\text{face}}, Box_{j}^{\text{action}} \right) = \max \left[ \min \left( x_{\text{max},i}^\text{face}, x_{\text{max},j}^\text{action} \right) - \max \left( x_{\text{min},i}^\text{face}, x_{\text{min},j}^\text{action} \right), 0 \right] \times \max \left[ \min \left( y_{\text{max},i}^\text{face}, y_{\text{max},j}^\text{action} \right) - \max \left( y_{\text{min},i}^\text{face}, y_{\text{min},j}^\text{action} \right), 0 \right], \quad (5)$$

$$\text{Area} \left( Box_{i}^{\text{face}} \right) = \left( x_{\text{max},i}^\text{face} - x_{\text{min},i}^\text{face} \right) \times \left( y_{\text{max},i}^\text{face} - y_{\text{min},i}^\text{face} \right). \quad (6)$$

Next, the proposed spatial consistency degree is applied to optimize the fusion score. Two representative fusion strategies are adopted.

- One simple strategy is the weighted fusion method ($F_{\text{fusion}_w}$) [19–21], which can be optimized as:

$$s_{i,j} = c_{i,j} \times \left[ \alpha \times \text{Conf}_{i}^{\text{face}} + \left( 1 - \alpha \right) \times \text{Conf}_{j}^{\text{action}} \right], \quad (7)$$

where $s_{i,j}$ stands for the fusion score of the $i$-th person and the $j$-th action, $\alpha \in [0, 1]$ is the fusion coefficient. We test the dynamic performance of different values of $\alpha$ in the experiment section.

- The other effective fusion strategy, i.e., searching specific action based on a candidate person list ($F_{\text{fusion}_\text{cpl}}$), is widely used [20–22]. It first obtains candidate person list by setting a threshold for face confidence scores obtained by person INS, and then ranks the list according to action confidence scores obtained by action INS. It can be improved by the proposed spatial consistency degree as:

$$s_{i,j} = c_{i,j} \times F_{\delta} \left( \text{Conf}_{i}^{\text{face}} \times \text{Conf}_{j}^{\text{action}} \right), \quad (8)$$

$$F_{\delta}(x) = \begin{cases} 1, & x \geq \delta \\ 0, & x < \delta \end{cases} \quad (9)$$

where $F_{\delta}(\cdot)$ is a threshold function, $\delta$ is the threshold for face scores to determine whether the target person exists in the keyframes. We test the dynamic performance of different values of $\delta$ in the experiment part.

### Algorithm 1 The spatio-temporal identity verification method for P-INS

**Input:** A topic concerning $i$-th person and $j$-th action: A gallery video corpus with $L$ shots;  
**Output:** The ranking list of gallery shots, $R_{\text{list}}$.

1. for each $l \in [1, L]$ do
2. Conduct person INS and action INS;
3. Conduct IDE for failed detection shots (Eq. 3);
4. for each $k \in [1, K]$ do
5. Compute spatial consistency degree $c_{i,j}^{(l,k)}$ (Eq. 4);
6. Compute fusion score $s_{i,j}^{l,k}$ (Eq. 7 or Eq. 8);
7. end for
8. Compute fusion score $s_{i,j}^{l}$ (Eq. 10);
9. end for
10. Generate $R_{\text{list}}$ by sorting $(s_{i,j}^{l,k})_{l=1}^{L}$ in descending order;
11. return $R_{\text{list}}$

### D. Generating Ranking List

After obtaining fusion scores of all keyframes, the fusion score of the $i$-th person conducting the $j$-th action in $l$-th shot is the maximum score of keyframes in the shot:

$$s_{i,j}^{l} = \max_{k=1, \ldots, K} s_{i,j}^{l,k}, \quad (10)$$

then the ranking list concerning the topic of the $i$-th person conducting the $j$-th action is obtained by sorting fusion scores of all shots. The complete flowchart of the proposed spatio-temporal identity verification method is presented in Algorithm 1. The technical details of person INS and action INS are elaborated in Section V-B; here we mainly emphasize the temporal and spatial characteristics of IDE and ICV.

### V. Experiments

#### A. Dataset and Experiment Settings

**Dataset.** We use the TRECVID INS Dataset to carry out the experiments [35]. It comes from the 464-hour British Broadcasting Corporation (BBC) soap opera “EastEnders”. The 244 weekly “omnibus” video files from 5 years of broadcasts are divided into 471,526 shots, containing about 7.84 million keyframes as the basic unit of P-INS. The detailed dataset parameters are shown in the Table [III]. With the dataset, NIST selects a number of topics as representative samples for TRECVID 2019 and 2020 INS tasks. As shown in Table [IV] and Table [V] in 2019 INS task, 10 persons and 12 actions are combined into 30 unique topics [35]. In 2020 INS task, 8 persons and 9 actions are combined into 20 unique topics [36]. Each topic includes example images or videos for target person and action.

**Evaluation criteria.** Following the standard evaluation criteria, Average Precision (AP) is adopted to evaluate the retrieval quality of each topic, and mean AP (mAP) is used to describe the overall performance among the given set of P-INS topics. According to the official evaluation requirements of TRECVID, for each topic, only 1,000 shots at most can be
face detection bounding boxes for each keyframe. For face identification, we utilize the ArcFace [25], which is trained on face recognition dataset MS1Mv2 [25]. Based on the detected face bounding boxes, 512-dimension features are extracted from each normalized face image to represent a face. Finally, the similarity measurement method based on cosine distance is used to calculate the face identification score.

**Action INS branch.** In the action INS branch, we specially apply two different action detection methods, i.e., human-object interaction detection on images and action detection on videos, for different topics of 2019 and 2020 INS tasks.

- **Human-object interaction detection on images.** Some actions with obvious objects can be well detected by using image-based human-object interaction detection, e.g., “holding paper”, “holding glass”, and “carrying bag”. For topics with such actions, we adopt PPDM [29], which is pre-trained on the large human-object interaction detection dataset HICO-DET [40]. First, the heatmap prediction network DLA-34 [41] is adopted as feature extractor, then point detection and matching branches are applied to conduct action detection on image-level.

- **Action detection on videos.** Some actions last for long time need to be identified by videos, e.g., “open door and enter”, “open door and leave”, and “go up or down stairs”. For topics with such actions, we adopt ACAM [32], which is trained on the AVA dataset [42]. We perform action INS on keyframe sequences. First, persons in all keyframes in a shot are detected by object detection network. Then every 8 keyframes are grouped into a sequence and fed into action detection network. Finally, the detected action information is allocated to the corresponding keyframes.

**Inter-frame Detection Extension.** Based on above person and action INS branches, we get the initial face and action INS results, including ids, confidence scores and bounding boxes of target faces and actions. For each shot, we check the

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**TABLE III**

| Parameters         | values       |
|--------------------|--------------|
| Total video size   | 286G         |
| Total video duration | 464h        |
| Number of videos   | 244          |
| Number of shots    | 471,526      |
| Number of keyframes | 7,837,120   |
| Number of characters | 191          |
| Number of actions  | 25           |

**TABLE IV**

| Topics Person Action |
|----------------------|
| 9249 Max holding glass |
| 9250 Ian holding glass |
| 9251 Pat holding glass |
| 9252 Denise holding glass |
| 9253 Pat sit on couch |
| 9254 Denise sit on couch |
| 9255 Ian holding phone |
| 9256 Phil holding phone |
| 9257 Jane holding phone |
| 9258 Pat drinking |
| 9259 Ian open door enter |
| 9260 Dot open door enter |
| 9261 Max shouting |
| 9262 Phil shouting |
| 9263 Ian eating |
| 9264 Dot eating |
| 9265 Max crying |
| 9266 Jane laughing |
| 9267 Dot open door leave |
| 9268 Phil go up down stairs |
| 9269 Jack sit on couch |
| 9270 Stacey carrying bag |
| 9271 Bradley carrying bag |
| 9272 Stacey drinking |
| 9273 Jack drinking |
| 9274 Jack shouting |
| 9275 Stacey crying |
| 9276 Bradley laughing |
| 9277 Jack open door leave |
| 9278 Stacey go up down stairs |

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**TABLE V**

| Topics Person Action |
|----------------------|
| 9299 Ian sit on couch |
| 9300 Billy sit on couch |
| 9301 Ian holding paper |
| 9302 Bradley holding paper |
| 9303 Billy holding paper |
| 9304 Max drinking |
| 9305 Dot drinking |
| 9306 Pat holding cloth |
| 9307 Heather holding cloth |
| 9308 Ian crying |
| 9309 Heather crying |
| 9310 Max smoking cigarette |
| 9311 Dot smoking cigarette |
| 9312 Pat smoking cigarette |
| 9313 Stacey laughing |
| 9314 Pat laughing |
| 9315 Max go up down stairs |
| 9316 Bradley go up down stairs |
| 9317 Max holding phone |
| 9318 Stacey holding phone |

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**B. Implementation Details**

**Person INS branch.** Different from the target persons’ clothes, which are always changing, faces have robust and discriminative features for identity recognition. Hence, we find target person based on faces in the person INS branch. It should be noted that, we use a face reference set containing 815 face images as the query set, including sample images of the target person provided by the task, as well as face images collected through Bing [37], [38]. The person INS mainly contains two steps, i.e., face detection and face identification. For face detection, we adopt the RetinaFace detector [24], which is trained on WIDER FACE dataset [39], to obtain the

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**TABLE III**

| Parameters of TRECVID dataset |
|--------------------------------|
| Parameters | values |
| Total video size | 286G |
| Total video duration | 464h |
| Number of videos | 244 |
| Number of shots | 471,526 |
| Number of keyframes | 7,837,120 |
| Number of characters | 191 |
| Number of actions | 25 |

**Topics in TRECVID 2019 INS task**

| Topics Person Action |
|----------------------|
| 9249 Max holding glass |
| 9250 Ian holding glass |
| 9251 Pat holding glass |
| 9252 Denise holding glass |
| 9253 Pat sit on couch |
| 9254 Denise sit on couch |
| 9255 Ian holding phone |
| 9256 Phil holding phone |
| 9257 Jane holding phone |
| 9258 Pat drinking |
| 9259 Ian open door enter |
| 9260 Dot open door enter |
| 9261 Max shouting |
| 9262 Phil shouting |
| 9263 Ian eating |
| 9264 Dot eating |
| 9265 Max crying |
| 9266 Jane laughing |
| 9267 Dot open door leave |
| 9268 Phil go up down stairs |
| 9269 Jack sit on couch |
| 9270 Stacey carrying bag |
| 9271 Bradley carrying bag |
| 9272 Stacey drinking |
| 9273 Jack drinking |
| 9274 Jack shouting |
| 9275 Stacey crying |
| 9276 Bradley laughing |
| 9277 Jack open door leave |
| 9278 Stacey go up down stairs |

**Topics in TRECVID 2020 INS task**

| Topics Person Action |
|----------------------|
| 9299 Ian sit on couch |
| 9300 Billy sit on couch |
| 9301 Ian holding paper |
| 9302 Bradley holding paper |
| 9303 Billy holding paper |
| 9304 Max drinking |
| 9305 Dot drinking |
| 9306 Pat holding cloth |
| 9307 Heather holding cloth |
| 9308 Ian crying |
| 9309 Heather crying |
| 9310 Max smoking cigarette |
| 9311 Dot smoking cigarette |
| 9312 Pat smoking cigarette |
| 9313 Stacey laughing |
| 9314 Pat laughing |
| 9315 Max go up down stairs |
| 9316 Bradley go up down stairs |
| 9317 Max holding phone |
| 9318 Stacey holding phone |
In particular, by comparing the best performance of the two basic fusion methods in the above experiments, $\text{Fusion}_{\text{thd}}$ is better than $\text{Fusion}_{\text{wet}}$. Therefore, in the following comparison experiments, we choose $\text{Fusion}_{\text{thd}}$ as the baseline model.

C. Ablation Study

We evaluate the effectiveness of IDE and ICV on the TRECVID INS dataset. We construct a baseline model referred to as Base by eliminating all proposed methods. Specifically, in the Base model, the initial face scores are used to obtain a candidate person list, and the action scores are taken as scores of keyframes. Thereafter, the maximum score of keyframes is taken as the shot score. Finally, ranking list is obtained by sorting the shot scores for each topic. The proposed methods are added gradually to Base, including IDE discussed in Section IV-B and ICV elaborated in Section IV-C. It should be noted that, we have two P-A INS combination methods since we adopt two action detection methods in action INS branch, i.e., image-based P-A INS (P-A$_1$, INS) and video-based P-A INS (P-A$_V$, INS). Table VI and Table VII respectively show ablation study results in 2019 and 2020 INS tasks. According to the evaluation criteria, we usually focus on the overall performance improvement, i.e., mAP of all topics. We evaluate mAP values of topics corresponding to P-A$_1$ and P-A$_V$ columns respectively, and mAP of all topics in the final P-A column.

Evaluation of IDE. We add the method IDE to Base, referred to as Base+IDE. The experimental results are shown in the first two rows of Table VI and Table VII. In 2019 INS task, Base+IDE method gains 0.11% (0.59% relative growth) improvement over Base method in mAP. Similarly, in 2020 INS task, the improvement is 0.10% (0.49% relative growth), which confirms the effectiveness of IDE.

Evaluation of ICV. We add the method ICV to Base, referred to as Base+ICV. According to the evaluation results in Table VI and Table VII. Base+ICV method gains 1.31% (7.08% relative growth) and 1.68% (6.23% relative growth) improvements over Base method in 2019 and 2020 INS tasks, which confirms the effectiveness of ICV.

Furthermore, the complete model Base+IDE+ICV achieves the best performance in both experiments, which gains 1.73% (9.36% relative growth) and 1.57% (7.64% relative growth) improvements over Base method in 2019 and 2020 INS task. As can be seen from the experimental results, with
Fig. 9. Examples of correct shots saved by IDE. The blue and green solid bounding boxes mark searched target person and action, and the blue and green dotted boxes mark failed search of target person and action.

the proposed method, the mAPs of P-A INS and P-A v INS both improve, which proves the effectiveness of the proposed method is consistent, and the method works for both P-A INS branches on images and videos. It is worth mentioning that, since the dataset is very large, performance improvement is not easy. According to the evaluation criteria, for a topic, if there is only one matched shot, a performance improvement of 1% is equivalent to raising the shot in the ranking list from 500th to 45th. It can be seen that such a performance improvement is very meaningful.

D. Result Visualization

To show the positive effect of the proposed method on results, we visualized some results. Fig. 10 shows some shots benefit from IDE, they are not in the initial ranking list generated by the baseline method in the ablation study and added in the ranking list after IDE. In Fig. 10(a), the topic 9300 is “Billy is sitting on couch”, “Billy” is detected in the 12th keyframe, but “sitting on couch” is not detected. While in 8th and 15th keyframes, “sitting on couch” is detected, but “Billy” is not detected. So the fusion scores in all keyframes of the shot are all zero. After IDE, the face and action results are extended to the failed detection keyframes, so that the fusion score is no longer zero. Similar case appears in Fig. 10(b). It can be seen from the figure that IDE successfully saves some failed detection shots.

Fig. 10 shows the role of ICV. The topics are “Jane is holding phone”, “Billy is holding paper”, and “Max is drinking” from top to bottom in the figure. Some IIP shots filtered out by ICV are shown. They exist in the initial ranking list generated by the baseline method. And their original rankings are also marked in the figure. It can be seen from the figure that ICV effectively filters out IIP shots for each topic.

E. Error Analysis

By observing AP values for each topic in Table VI and Table VII, we find that for very few topics, the AP values decrease slightly after adding the proposed method. To be specific, the ground-truth in TRECVID INS task is used to check the shots filtered out from the original ranking list by the proposed method. We find that some correct shots are filtered out by mistake. Through observation, we figure out it is not the fault of the proposed method. In detail, although there is the target person doing target action in a shot in fact, and the target person is found successfully by person INS branch, but the target action doing by target person is not found by action INS branch, whereas the target action doing by others is found. Therefore, the shot is coincidentally considered as the correct shot.

Fig. 11 gives four examples. In Fig. 11(a), the topic 9299 is “Ian is sitting on couch”, which is shown in the image. Unfortunately, the action INS branch does not find the action “sitting on couch” belonging to “Ian” due to the errors of action INS. Coincidentally, it finds the action belonging to “Jane”. Before conducting ICV, the person “Ian” and the action “sitting on couch” belonging to “Jane” make the system mistakenly believe that the shot contains the topic “Ian is sitting on couch” (9300). Before conducting ICV, the person “Ian” and the action “sitting on couch” belonging to “Jane” make the system mistakenly believe that the shot contains the topic “Ian is sitting on couch”. Before conducting ICV, the person “Ian” and the action “sitting on couch” belonging to “Jane” make the system mistakenly believe that the shot contains the topic “Ian is sitting on couch”. Before conducting ICV, the person “Ian” and the action “sitting on couch” belonging to “Jane” make the system mistakenly believe that the shot contains the topic “Ian is sitting on couch”.

The topics in TRECVID INS task actually contain a set of person example images as well as their mask images, and a set of action example shots. In order to make a simple illustration, we only use the images of face and action to represent a topic, this operation does not affect the following INS process and results.
Topics

| Topic | Jane | Max |
|-------|------|-----|
| 9257  | Holding phone | Drinking |
| 9303  | Billy | Holding paper |
| 9304  | Max | Drinking |

Fig. 10. Examples of IIP shots filtered out by ICV. The blue and green bounding boxes mark target person and action, respectively. The rank numbers show video shots’ ranking positions in the initial ranking list generated by the baseline model.

Fig. 11. Examples of correct shots filtered out by ICV. The blue solid bounding boxes mark searched target person, the green solid bounding boxes mark searched target action, and the green dotted boxes mark failed search of target action.

on couch”. After conducting ICV, the shots coincidentally included in the original result list are eliminated, resulting in the decrease of performance. Similar issue appears in the topic 9253, 9264, 9270, which corresponds to “Pat is sitting on couch”, “Dot is eating”, and “Stacey is carrying bag” in Fig. 11(b), Fig. 11(d). Therefore, through observation, we can draw the conclusion that the fundamental reason of the decrease of mAP values in some specific topics is due to the errors of person or action INS branches, rather than the proposed method.

F. Comparison with other Methods

We compare the proposed method with public representative methods on TRECVID INS dataset, following the official evaluation settings. For automatic INS task in TRECVID, each team is allowed to submit several runs for evaluation. We select some representative runs in each year for comparison. It is worthy noting that, the ID of each team’s run does not represent the order of performance, that is, the run labeled 1 may not be the best one among all runs submitted by the team. Fig. 12 demonstrates the comparative results of our method and previous evaluation runs.

For TRECVID 2019 INS task, we select the following representative runs:

- F_M_A_E_PKU_ICST_6 [22]. It is the penultimate run of PKU_ICST team, which is the first place in 2019. In this run, face detection and recognition models are adopted for person INS. Image level and video level action recognitions are adopted for action INS. The methods of searching person based on candidate action shots and searching action based on candidate person shots are implemented for fusion simultaneously. To get better ranking lists, some tricks are used, e.g., super-resolution, top N query extension strategy and scores adjustment based on video transcripts.
- F_M_E_E_BUPT_MCPRL_1 [43]. It is the best run of BUPT_MCPRL team, which is the second place in 2019.
In this run, face detection and recognition are adopted for person INS. Human-object interaction action recognition based on object detection and pose estimation, and general action recognition are adopted for action INS. The method of searching action based on candidate person shots is implemented for fusion. Moreover, query expansion is used in person INS.

- **F_M_A_E_PKU_ICST_6 [19]**. It is the best run of NII_Hitachi_UIT team, which is the third place in 2019. In this run, face detection and recognition are adopted for person INS. An audio-type action and two visual-type action recognition models are adopted for action INS. The weighted summation method is implemented for fusion.

- **F_M_E_B_WHU_NERCMS_3 [20]**. It is the best run of WHU_NERCMS team, which is the fourth place in 2019. In this run, face recognition, object detection, and object tracking are adopted for person INS. An action recognition model is adopted for action INS. The method of searching action based on candidate person shots is implemented for fusion.

As shown in Fig. [12(a)], our method achieves the best performance on 10 topics and competitive performance on 10 topics. The performance is relatively poor on other 3 topics, i.e., topic 9268, 9277, and 9278.

For 2020 INS task, we selected the following representative
runs:

- F_M_E_PKU_WICT.20_6 [23]. It is the penultimate run of PKU_WICT team, which is the first place in 2020. The technology scheme is same as the scheme of F_M_A_PKU_ICST_6 in 2019.
- F_M_E_A_WHU_NERCMS.20_1 [21]. It is the best run of WHU_NERCMS team, which is the second place in 2020. In this run, face detection and face recognition models are adopted for person INS. And human-object interaction and general action recognition models are adopted for action INS. The method of searching action based on candidate person shots is implemented for fusion.
- F_M_A_E_BUPT_MCPRL.20_3 [44]. It is the best run of BUPT_MCPRL team, which is the third place in 2020. Different from F_M_F_E_BUPT_MCPRL_1 in 2019, face detection, face recognition, and person tracking are adopted for person INS.
- F_M_A_E_NII_UIT.20_3 [34]. It is the best run of NII_UIT team, which is the fourth place in 2020. Different from F_M_A_E_NII_Hitachi_UIT_2 in 2019, in action INS, face detection and object detection are adopted for human-object interaction action recognition. And in the fusion stage, the method of searching action based on candidate person shots is implemented.

As shown in Fig. 12(b), our method achieves the best performance on 6 topics and competitive performance on 5 topics. The performance is relatively poor on other 5 topics, i.e., topic 9306, 9307, 9310, 9311, and 9315.

Through observing results both in 2019 and 2020, we find that the reason of those relatively poor-performance topics is due to detection errors of some difficult action topics. For example, the actions in topics 9268, 9278, and 9315 are all “go up or down stairs”, the actions in topics 9267 and 9277 are both “open door and leave”, the actions in topics 9306 and 9307 are both “holding cloth”, and the actions in topics 9310 and 9311 are both “smoking cigarette”. In general, we propose a simple INS method, compared with other methods with many tricks, our method still gets considerable performance. The mAP of our methods surpassed the best runs’ of second places in both TRECVID 2019 and 2020 INS tasks.

VI. CONCLUSION

We study the IIP between person and action in P-A INS in movies. To address the problem, we propose a simple and effective spatio-temporal identity verification method. Our idea stems from an intuitive observation that identity-consistent face and action usually share an overlapping spatial region of their respective detection bounding boxes. The proposed method is evaluated on the large-scale TRECVID INS dataset. The experimental results verify the effectiveness and robustness of the proposed method. And the performance surpass that of the second places in both TRECVID 2019 and 2020 INS tasks.

In the future, we will further improve our work from the following aspects: Firstly, since current research is relatively rare, we can only infer identity consistency through location information, in the future, we will concentrate on improving the accuracy of identity verification by trying more accurate identity verification methods, via other appearance-based features within the bounding boxes to infer identity consistency, via human posture information to locate the face position in the action bounding boxes, etc.; Secondly, through the observation and analysis of the experimental results, in P-A INS, the accuracy of action INS is far lower than that of person INS, which leads to P-A INS mainly constrained by action INS. In the future, we will strive to improve the algorithm in action INS; Thirdly, the current framework is designed based on simple cases in which a single action is performed by a person, we will extend our method to more complex cases in which composite actions are performed by a person. Furthermore, we will extend our method to more combinatorial-semantic INS tasks, e.g, the Person-Action-Scene INS.

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