

Consensus-based Inter-camera Re-identification Across Non-overlapping Views

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Keywords: Inter-camera Re-identification, Non-overlapping Views, Distributed Inferences, Low-level Contextual Cues, Brightness Transfer Function, Consensus-based Algorithm.

Abstract: Multi-object re-identification across cameras network with non-overlapping fields of view is a challenging problem. Firstly, the visual signature of the same object might be very different from one camera to another. Secondly, the blind zone between cameras creates the discontinuity in the observation of the same object in terms of locations and travelling times. Centralized inferences proposed in literature for inter-camera re-identification becomes insufficient in practice mostly with the requirement of real-time applications and dynamic cameras network. In this paper we present a completely distributed approach for inter-camera re-identification. The proposed approach based on the distributed inferences, where the set of smart-cameras collaborate to reach a consensus about the identities of objects circulating in the network. Local and global visual descriptors were combined into the proposed approach for inter-camera color mapping and invariant objects description. Experimental results of applying this approach show improvement in inter-camera re-identification and robustness in recovering from very complex conditions.

1 INTRODUCTION

With the technological advances in visual sensors design, in communication and in dynamic computer vision are stimulating the development of new applications that will transform traditional mono-camera systems into pervasive intelligent camera networks. The multi-camera networks are the basis of several applications including video surveillance, visual robot navigation, smart homes, military and scientific applications, etc. However, the aggregation and the interpretation of distributed visual information from multiple video streams in real-life scenarios is a very complex problem. Which requires the development of new algorithms and sophisticated techniques for collaborative inferences able to analyse in real-time the decentralized and distributed visual information. In multi-camera network, three types of configuration are possible relative to the overall views of the network: (1) Overlapping multi-camera Networks. (2) Non-overlapping multi-camera networks or networks of disjoint cameras. (3) hybrid multi-camera networks. Material and economic constraints limiting in general the number of cameras in the network and prevent a full coverage of a large geographical area,

which creates discontinuities in the field of view of the network. A major challenge in networks with disjoint cameras is inter-camera re-identification: when an object appears in the field of view of a camera, it comes to determine if this object has already been observed and tracked by one of the network cameras. Following the limits of centralized approaches proposed in literature for inter-camera re-identification in terms of difficulty in analysing a huge amount of data centrally, dynamic camera network, overloaded bandwidths, etc, it is also desirable that the inter-camera re-identification mechanism be distributed. In this paper we present a totally distributed approach for inter-camera multi-object re-identification across non-overlapping views. The camera network is modeled as a multi-agent system, where the smart-cameras would have to act as autonomous agents and decisions about the objects identities would have to be taken in a distributed manner. However, to be able to attribute a valid identities to all objects in the area of interest, the smart-cameras should be working cooperatively with each other. A consensus-based algorithm for distributed inter-camera re-identification is proposed in this work, where the smart-cameras collaborate to reach a consensus about objects identities.

Unlike many approaches proposed in literature (Chen et al., 2011)(Javed et al., 2008)(Motamed and Wallart, 2007), where many restrictions are used about the topologies of the network, cameras calibration, travelling time, closed network, exit/entrance locations, off-line learning steps, etc. The proposed approach for distributed inter-camera re-identification works in most cases without any restrictions, where many realized experiments proved the robustness of the proposed approach in many complex conditions. This paper is organized as follows: In section.2 we present the problem formulation of inter-camera re-identification. In section.3, we review some interesting approaches in the state-of-the-art for inter-camera re-identification. Section.4 describes the proposed decentralized system architecture based on the distributed artificial intelligence. In section.5, we detail the proposed approach for distributed inter-camera re-identification based on the consensus principal and the collaboration between agents. Finally, in section.6, a set of realized online experiments in ad-hoc multi-camera network with disjoints views will be presented and discussed.

2 PROBLEM FORMULATION

Suppose that we have a system of n cameras $CAM_1, CAM_2, \dots, CAM_n$ with non-overlapping views. Assume that there are k objects in the environment $\{p_1, p_2, \dots, p_k\}$. Let, O the set of objects observation $O_{CAM_j} = \{O_{CAM_j^1}, O_{CAM_j^2}, \dots, O_{CAM_j^k}\}$, where $O_{CAM_j^1}$ is the observation generated by the object p_1 and observed by the camera CAM_j . Let, $O_{CAM_i^a}$ the observation of a given object p_a exiting the field of view of the camera CAM_i and entering the field of view of another camera CAM_j with a new observation $O_{CAM_j^b}$. The problem of inter-camera re-identification is essentially to find which of the observations in the system of cameras belong to the same object (Javed et al., 2008). Under this definition the inter-camera re-identification problem lies in inter-camera matching between the observation $O_{CAM_i^a}$ and the observation $O_{CAM_j^b}$. If a high similarity is calculated between the two observations $O_{CAM_i^a}$ and $O_{CAM_j^b}$ then the observations corresponding to the same object p_k . The process of inter-camera matching between two observations is named by many researchers inter-camera tracking (Javed et al., 2008). In a probabilistic context, the probability that the observation $O_{CAM_i^a}$ observed by the camera CAM_i corresponds to the observation $O_{CAM_j^b}$ observed by the camera CAM_j can be described by: $P(a = b | O_{CAM_i^a}, O_{CAM_j^b})$. The most

likely correspondence must maximize the similarity between the two observations $O_{CAM_i^a}$ and $O_{CAM_j^b}$:

$$S_k = ArgMax(P(a = b | O_{CAM_i^a}, O_{CAM_j^b})) \quad (1)$$

$S_k \in L_s$, L_s is the set of objects in the transfer list (i.e. candidates objects observation). In this work we present a new approach for estimating the solution space S_k in a totally decentralized manner.

3 RELATED WORK

For estimating the solution space S_k (equation.1) or maximizing the similarity between the two observations a and b , many approaches have been proposed in the literature. These approaches can be subdivided into two main groups: (1) Approaches based on local visual descriptors named by many researchers inter-camera re-identification. (2) Approaches based on global visual descriptors named by many researchers inter-camera tracking or inter-camera matching.

3.1 Inter-camera Re-identification

Based on local descriptors extracted from the images of the objects of interest, these approaches attempt to attribute valid identities to objects circulating in the covered zone. The main goal of these approaches is to find the best invariant inter-camera visual local descriptors for object representation. In this context many notable research works have been published, in this section we review the most recent and interesting works. (Meden et al., 2011) proposed a mixed-State Particle Filtering that estimates for simultaneously the positions and identities of objects in closed non-overlapping camera networks. In this work authors used off-line training phase to learn the appearance of the objects based on color histograms. Viewpoint invariance is instead the main issue addressed in (Gray and Tao, 2008), where the spatial and color information are combined for inter-camera re-identification using an ensemble of discriminant localized features and classifiers. In (Farenzena et al., 2010) a set of local features were accumulated invariant inter-camera object representation. For generate a multi-shot visual signature of objects for inter-camera re-identification (Doretto et al., 2011) proposed a new strategy for aggregates a set of local features based on Hog descriptor, color and structural information. Inter-camera re-identification remains in the heart of cameras network research, but the challenges raised in the choice of the local descriptors (i.e. invariant inter-camera and discriminant inter-object). This work is part of this orientation.

3.2 Inter-camera Matching

There have been notable research works in this orientation for inter-camera matching based on global visual descriptors. (Porikli and Divakaran, 2003) proposed an inter-camera color calibration model adapting the appearance histograms of the objects in different views, and then combined spatio-temporal and appearance cues to track objects inter-camera. In the same context of inter-camera color adaptation, (Prosser et al., 2008) proposed a cumulative BTF for mapping colors between cameras. (Javed et al., 2008) presented an extension of the color adaptation through a combination of appearance and spatio-temporal cues. This system learned the camera network topology and path probabilities of objects using Parzen windows with manual correspondence in an initial training phase. (Gilbert and Bowden, 2006) proposed an approach based on a spatio-temporal cues, where the entry/exit zones inter-camera was learned incrementally. (Chen et al., 2011) proposed an unsupervised method based on batch-learning, which learns adaptively the true valid links among the entry/exit zones of cameras from the correspondence. Until now, this orientation of inter-camera matching based on global descriptors is over-active.

The majority of the proposed approaches in literature for inter-camera re-identification from the above orientations based on centralized systems. The need for materially economical solutions, scalable, able to analyse the distributed visual information in dynamic cameras networks makes the centralised architectures that lead to centralized inter-camera re-identification insufficient solutions.

4 COOPERATIVE MULTI-AGENT ARCHITECTURE

The main goal of this paper is to develop a distributed inter-camera approach for multi-object re-identification in a dynamic cameras network with disjoint fields of vision. The ad-hoc nature and inherently distributed of the dynamic cameras network and the need of real-time application have increasingly oriented many researchers to distributed inferences techniques and game theory (Soto et al., 2009). The most proposed distributed techniques until now remains in position estimation in overlapping views such as Kalman consensus (Olfati-Saber and Sandell, 2008). To the best of our knowledge distributed inter-camera re-identification across non-overlapping views based on distributed inferences through consensus have not been done before in the state-of the art.

In this work the cameras network is modelled with a multi-agent system, where each camera is modelled as an intelligent agent. Each agent is considered as autonomous relative to the local decision and processing. Each agent has a processing unite independent of the other agents. The set of agents collaborate to reach a consensus about identities of the interest objects inter-camera. We consider a multi-camera ad-hoc network CAM_x , contains n cameras. The interaction topology of a network of multi-camera is represented using a graph $G = (C, E)$, where C is the set of nodes $C = 1, 2, 3, \dots, n$ and $E = C \times C$ is the edge between nodes. Each node represents an intelligent agent that covers a small specific area relative to the field of view of the network. A modular modelling of each agent is proposed, where each agent incorporates six essential module: (1) Moving object extraction, based on background subtraction with statistical modelling of the background followed by adaptive post processing and common region labelling step (Bousetouane et al., 2011). (2) Inter-camera color adaptation based on Mean Brightness Transfer Function (MBTF) for inter-camera color mapping. (3) Features extraction and objects representation based on a combination of statistic moments and low-level contextual information computed through the co-occurrence for invariant inter-camera object description (Bousetouane et al., 2012). (4) The proposed distributed inter-camera re-identification algorithm based on the consensus principal ensured through the collaboration between agents (smart-cameras). (5) Intra-camera tracking based on mixed state condensation for estimating the trajectory of an object after the attribution of a valid identity. (6) Communication module based on selective diffusion to avoid the overload of the transmission channels especially in wireless networks. Figure (Fig.1) illustrates the proposed overall distributed architecture based on the multi-agent paradigm for distributed inter-camera re-identification. In this paper we are focused especially in the re-identification module where a distributed approach is proposed based on the cooperation between agents.

5 PROPOSED CONSENSUS-BASED INTER-CAMERA RE-IDENTIFICATION

The distributed nature of the proposed system based on multi-autonomous agents leads to completely distributed approach for inter-camera re-identification. In the multi-agent systems literature, the consensus

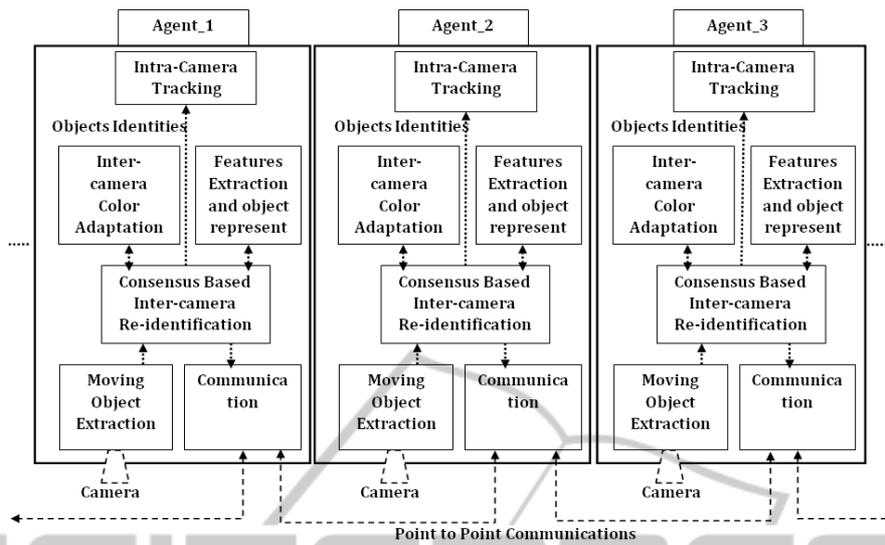


Figure 1: Proposed decentralized system based multi-agent with three neighbouring smart cameras for distributed inter-camera re-identification.

defined in (Soto et al., 2009) as a way (protocol, algorithm, etc) to reach an agreement regarding a certain quantity of interest that depends on the state of all sensors or other information may be captured by the perceptual systems of autonomous agents in camera networks. In our case we define the consensus as a visual protocol that allows to define the interaction rules for exchange information and knowledge between an agent and its neighbours. Consequently, the set of autonomous agents collaborate to reach a consensus about the identities of objects circulating in the covered area by the cameras network. As mentioned earlier, the interaction topology between smart-cameras in the proposed multi-agent system is represented by the graph $G = (C, E)$, the number of nodes is equal to the number of cameras. Each camera have an identity and each agent have a data-set T that contains the history of communication between agents. Let CAM_x the set of cameras in the network, $CAM_x = CAM_1, CAM_2, \dots, CAM_n$. We define the subset $Sub_C \subseteq CAM_x$ of all cameras where an object has been already detected and tracked. Ned_C is the subset of camera where no object has been already detected $Ned_C \cup Sub_C = CAM_x$. Each camera CAM_i will also have its set of neighbouring cameras $CAM_j \in Sub_C$. $O_{CAM_i}^a$ is the observation produced by the object Obj_a and captured by the camera CAM_i , where $CAM_i \in Sub_C$. In the proposed distributed system the camera CAM_i where a new observation is detected will be the initiator of the cooperation between its neighbourhood $CAM_j \in Sub_C$ for reach a consensus about the identity of this observation. Assume that the mean brightness transfer functions (MBTFs) (Gilbert and Bowden, 2006) between the

K pair of cameras have been already computed in training phase, where $K = n * (n - 1) / 2$ (i.e. This process is assured by the module number 2 of each agent (Fig.1)). Let, $F_{O_{CAM_i}^a} = \{f_1, f_2, \dots, f_n\}$ is the features vector that characterise the observation $O_{CAM_i}^a$ extracted from the area of object on interest Obj_a , this vector aggregates the set of visual cues (i.e. the features extraction and object representation is assured by the module number 3 of each agent). The proposed algorithm for distributed inter-camera re-identification based on the consensus principle reached through the collaboration between agent subdivided into four essential steps:

1. If a new observation $O_{CAM_i}^a$ is detected in the field of view of the camera CAM_i , then the collaboration between this camera and its neighbourhood $CAM_j \in Sub_C$ is started.

2. For-each $CAM_j \in Sub_C$ do

a. Computing the MBTFs functions between CAM_i and its neighbourhood $CAM_j \in Sub_C$ for inter-camera color mapping.

b After inter-camera color adaptation, computing the features vector $F_{O_{CAM_i}^a}$ from the image of the object of interest Obj_a .

3. Send message to each neighbour $CAM_j \in Sub_C$

$$M_{O_{CAM_i}^a} = (F_{O_{CAM_i}^a}, CAM_i).$$

End for-each

4. Receiving the messages: a message is received from each camera $CAM_j \in Sub_C$,

$$M_{OCAM_i^a} = (Id_{Obj_a}^j, CAM_j, Bol).$$

If the observation $OCAM_i^a$ of the object Obj_a characterised by the features vector $F_{OCAM_i^a}$ was already identified and tracked by one of the cameras $CAM_j \in Sub_C$ then the variable $Bol = 1$ and the identity of the object $Id_{Obj_a} = Id_{Obj_a}^j$. Else if the variable $Bol = 0$ then Obj_a is a new object in the camera network and the camera CAM_i attribute to this object the maximum received identities from all cameras $CAM_j \in Sub_C$ plus 1.

$$Id_{Obj_a} = Max(Id_{Obj_a}^j) + 1$$

When the neighbouring cameras $CAM_j \in Sub_C$ receive the messages $M_{OCAM_i^a}$ from the initiator camera CAM_i , an intra-camera identification process is started to verify the existence of similar objects in the cameras CAM_j history to the object Obj_a . This process based on the euclidean distance between the features vector $F_{OCAM_i^a}$ of the object Obj_a and the features vector $F_{OCAM_j^b}$ of objects already identified by these cameras CAM_j and saved in the dataset T_j of each camera. After the attribution of valid identities to the objects of interest, these identities will be addressed to the last module (intra-camera tracking) for estimating the trajectory of each object over time.

In the next section we present a set of experimental results in real-time scenarios that demonstrate the validity of the proposed consensus based algorithm for distributed inter-camera re-identification.

6 EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed distributed inter-camera re-identification approach, online experiments are realized using ad-hoc network of seven cameras with non-overlapping views installed at our laboratory (LASE-Annaba University). In this network, each camera is connected to its own processing unit (absence of a central unit), the topology of the network is totally dynamic, the network is scalable at any moment, cameras not calibrated geometrically, etc. In these conditions multi-object re-identification remains a great challenge and the proposed distributed inter-camera re-identification approach can be fully evaluated. In this paper we present online experiment using three non-overlapping cameras. This experiment consists of real life scenario where three objects of interest move randomly inter-camera in presence of complex conditions: occlusion, non-rigid objects, scale change, unpredictable transfer time inter-camera, jerky motion in the background, etc. The figure (Fig.2) illustrates the inter-camera re-identification results and tracking using the

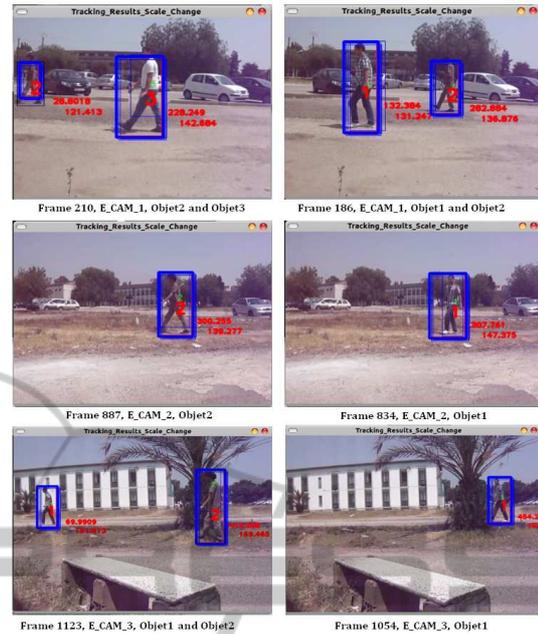


Figure 2: Inter-camera re-identification results using the proposed distributed approach based on the consensus principle and the collaboration between agents.

proposed completely distributed approach based on the consensus principle. From the obtained results we find that: (1) in camera (CAM1) three objects have obtained coherent identities from 1 to 3. (2) when these objects enter in the field of view of the camera (CAM2) a collaboration between the cameras is started based on the proposed consensus-based algorithm to attribute a valid identity to these objects, each object has obtained the same identity attributed by the camera (CAM1). (3) Now, when these objects enter in the field of view of the camera (CAM3) the same procedure is started to reach a consensus about the objects identities. The obtained results (Fig.2) from this experiments prove the efficient and the ability of the proposed distributed approach for inter-camera re-identification in the absence of any restriction.

To evaluate quantitatively the obtained results, the Receiver Operating Characteristic evaluation space is used, where the rate of the true positive re-identification (RTP_r) against of the rate of the false positive re-identification (RFPr) is plotted in figure (Fig.3). The ratio of the ROC curve (RFPr, RTP_r) are calculated from inter-camera re-identification results at each frame using a set of video sequences. The curve ROC illustrates the quality of the proposed approach for distributed inter-camera re-identification relative to the variation of the matching threshold between objects.

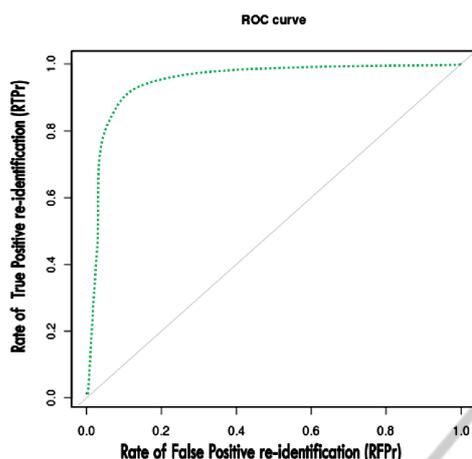


Figure 3: Roc Curve relative to the variation of the matching threshold between objects (RTPr in function of RFPr).

7 CONCLUSIONS

In this paper we have presented a new distributed approach for inter-camera re-identification based on the consensus principle reached through the collaboration between smart-cameras. Firstly, we have presented a completely decentralized system based on the distributed inferences where each camera is modelled by an autonomous agents. Secondly, to reach a consensus about objects identities a new distributed approach was presented based on the collaboration between agents. The obtained results proved the robustness of the proposed approach. From this work we conclude that the decentralisation of the inferences is an important issue to the design of real-time and robust re-identification and tracking framework in multi-camera/Multi-sensor network. In the same context we need to developed sophisticated algorithms able to reach a consensus between smart-cameras. Future works including the integration of auctions for ambiguity management to reach a consensus and improved the inter-camera color mapping through the use of invariant visual cues inter-camera.

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