The Future of Camera Networks: Staying Smart in a Chaotic World

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ABSTRACT

Camera networks become smart when they can interpret video data on board, in order to carry out tasks as a collective, such as target tracking and (re-)identification of objects of interest. Unlike today's deployments, which are mainly restricted to lab settings and highly controlled high-value applications, future smart camera networks will be messy and unpredictable. They will operate on a vast scale, drawing on mobile resources connected in networks structured in complex and changing ways. They will comprise heterogeneous and decentralised aggregations of visual sensors, which will come together in temporary alliances, in unforeseen and rapidly unfolding scenarios. The potential to include and harness citizen-contributed mobile streaming, body-worn video, and robot-mounted cameras, alongside more traditional fixed or PTZ cameras, and supported by other non-visual sensors, leads to a number of difficult and important challenges. In this position paper, we discuss a variety of potential uses for such complex smart camera networks, and some of the challenges that arise when staying smart in the presence of such complexity. We present a general discussion on the challenges of heterogeneity, coordination, self-reconfigurability, mobility, and collaboration in camera networks.

KEYWORDS

future camera networks, surveillance, mobile smart cameras, body worn cameras, humans in the loop, distributed control

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1 INTRODUCTION

More powerful embedded processors and improvements in memory in the last fifteen years have led to a revolution in camera technology: camera networks evolved towards *smart* camera networks. These smart cameras can observe the physical world, process the acquired images on board, and communicate aggregated information and extracted knowledge rather than the video feed alone. This enables them to detach from central components, analysing imagery locally, making decisions and acting on them autonomously. This in turn allows for faster reactions to emerging situations, as well as more increased flexibility, scalability, and robustness in surveillance networks [41]. However, this also introduces significant challenges in terms of target tracking and re-identification.

In this paper we will analyse the state-of-the-art and especially the state-of-practice of camera networks, and discuss what is possible and what is not yet possible from a smart camera network perspective, and with a particular focus on continuous target tracking and required re-identification. We discuss the challenges arising from mobility and uncertainty in highly heterogeneous surveillance networks, and the problems that come along with them. We dive into detail on coordination problems and how we can overcome them in centralised and decentralised settings. Finally, we describe a potential future outlook for smart camera networks, that support people through carrying out highly responsive tasks autonomously.

The rest of this paper is structured as follows. The next section discusses the current state of practice in surveillance networks as operated by industry. Section 3 sheds light on the issues with mobile cameras and outlines potential solutions. Section 4 discusses potential benefits and obstacles in using heterogeneous cameras in a network. Section 5 explores the requirement of coordination in large camera networks arising due to rapidly unfolding situations. Section 6 discusses the need of future camera networks to autonomously form teams and cooperate in order to achieve their goals. Section 7 provides an outlook and concludes the paper.

2 CURRENT PRACTICE

The development of smart cameras enables them to operate autonomously. However, when networked, they can cooperate in order to carry out more complex tasks and achieve collective goals [13, 14, 27, 36, 46]. As with other types of cyber-physical system, more recently, *self-awareness* [24, 29] has been introduced in smart cameras, enabling them to reason about their own behaviour, and adapt accordingly in changing environments [15, 42].

These developments of camera networks also changed their original purpose. While manual surveillance is still an important aspect of camera networks, other application areas have also emerged. Those that have received most attention by researchers include:

- **Autonomous distributed target tracking** coordinates tracking of objects with a single camera at a time. This ensures efficiency of network-wide resources, but requires either perfect re-identification or knowledge of the environment to ensure sufficient re-identification of targets among different cameras [10, 13, 31, 34, 48].
- **Autonomous multi-camera tracking**, by contrast, tries to cover each target with multiple cameras at the same time. Several issues may arise, such as: how to observe the object from different angles, while keeping a minimum of overlap; or how to place cameras to ensure continuous coverage of objects by multiple cameras [4, 7, 21]. In addition, cameras need to ensure they track the same object. This requires efficient data association across multiple cameras [6, 19].
- **(k-)Coverage and barrier optimization**, the *art-gallery problem*, aims to ensure coverage of a specific area. Barrier optimization refines this to ensure objects cannot pass between areas undetected. k refers to the number of cameras observing the same area at any given time [8, 11, 14].
- **Search and rescue/follow** often mounts cameras on mobile robots and aims to find specific targets autonomously. These targets can be stationary or mobile as well as collaborative or evasive [12, 18, 22, 35, 40, 47]. Cameras have to be able to re-identify a target based on a given model. In case of mobile cameras (e.g. PTZ or drones), cameras need to be controlled in such a fashion that they do not deplete their resources before the target has been found.
- **Personal data collection and performance review** is a novel area of application of camera networks for personal data collection and performance review of individuals. The idea is, to have video material of interactions within the personal range of employees. This information can be used to improve performance and also when incidents occur.
- **Guidance and control** utilises captured video material to map the environment and hence control and guide robotic systems and autonomously driving cars safely through it [49, 51]. However, we can also use camera networks to guide people through their environment, allowing them to avoid hazardous situations or simply find the best and fastest way through an unknown environment.

When considering camera networks, one typically thinks first of static or PTZ (Pan-Tilt-Zoom) cameras, where fields of view (FOV) can only to a limited extend be changed. Alternatively, networks of drones equipped with visual sensors introduce mobility and allow the network to observe situations from different viewpoints if necessary. Mobile cameras, by contrast, can relocate within their environment, being worn by humans or mounted on mobile robots.

Indeed, the efforts highlighted above have so far been either focused on static and pan-tilt-zoom cameras, or limited to fully controllable robots acting as mobile cameras. The sector of body worn video, which has rapidly developed in terms of both technology and growth of the market, has been widely neglected by researchers so far. Similarly, hybrid networks, where different types of sensors are brought together, are often used in search and rescue operations, where stationary sensors support mobile robots [20, 25, 50]. Hybrid camera networks have also received little attention to date [9, 52].

In particular, there is little academic consideration of the impact of important recent developments in mobile camera technology. These include new market sectors focussed on body worn video (BWV) and incident based video (IBV), which employ small video devices often worn on lanyards or special harnesses, e.g., as shown in Figure 2. These cameras can be switched on by the wearer when necessary, and can stream, record and/or process video feeds on board, or in conjunction with a local mobile device. Figure 1 shows these two developing market sectors, and their overlap with traditional CCTV and more recently developed smart CCTV applications.

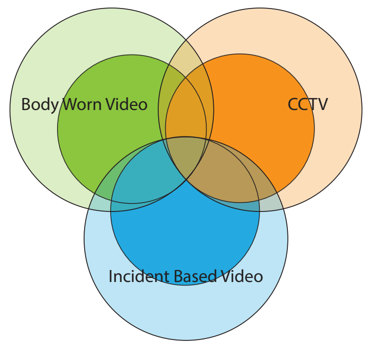

Figure 1: Market sectors (light shaded circles) and their overlap, in camera systems. Camera networks of different types interplay with each other. Each market sector also considers *smart* devices (darker shaded areas) where information can be processed on the device and communicated to others.

Figure 2: Edesix's VideoBadge. Source: http://edesix.com/

While CCTV is usually used to observe a specific area, BWV and IBV are employed by individual users. Users are categorised into two groups either where mobile cameras are carried as part of their job (BWV) or for their own safety and when video should be recorded for legal purposes (IBV). BWV is worn by personnel that often and repeatedly come into situations where video evidence has to be taken (e.g., a police officer, or a bailiff). IBV, on the other hand, is only turned on in rare situations (e.g., a shopkeeper at the airport is faced with an incident). In both cases, however, the worn cameras is used to capture evidence of a situation. Current surveillance networks, deployed in the field, combine standard equipment, mounted at fixed locations, with novel, mobile BWV/IBV (cp. Figure 1).

There are several benefits of introducing BWV/IBV into smart camera networks, but also a number of challenges. On one hand, additional mobile cameras are added to the fixed set of cameras mounted on walls and ceilings. This increases the amount of information captured from the environment and allows for more thorough analysis at any stage. Furthermore, cameras worn by humans can relocate effortlessly and do not require sophisticated route planning or obstacle avoidance algorithms. This allows the mobile cameras to capture images from situations that might be on the edge of the fixed mounted camera network or not covered at all. Finally, being able to change locations also allows them to change their viewpoint generating video material from a new angle. This in turn may generate information that might otherwise be obscured due to potential obstacles, even concerning the targets themselves.

On the other hand, mobile cameras will be integrated into fixed surveillance networks at runtime, which might not occur voluntarily. This gives rise to a potential security issue. Using only fixed cameras allows exploitation of the network topology in performing person re-identification [32, 33]. BWV/IBV introduces a permanently changing topology, requiring the constant updating of topology information within the network. Integration itself does not guarantee compliance of the wearer. This means, coordination of mobile cameras might only be possible to a certain degree or not at all. One might think of situations where it is simply to dangerous and the wearer of a mobile camera decides not to relocate there. Being a mobile camera and being able to relocate also introduces ongoing change to the network. This can be introduced because the wearer wants to leave a specific area or because the video footage is obscured on purpose. Such a situation is shown in Figure 3. It is unclear if the wearer is occluding the FOV of the camera or if another person is obscuring the FOV. Furthermore, it is not clear if this is done on purpose or accidentally.

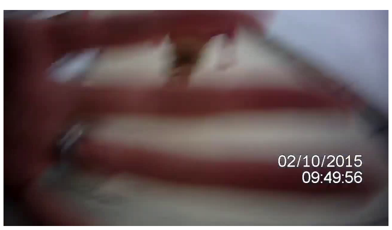

Figure 3: Footage occluded by a hand. It is unclear if this is the hand of the wearer or another person. Further, from the video footage alone, one cannot determine if this is intentional or accidental. Courtesy of Seth W. Stoughton.

Due to the different viewpoints of BWV/IBV, in comparison to wall-mounted cameras, an extensive model of the target is required to ensure reliable re-identification of them between fixed cameras and different mobile cameras. Finally, decoupling mobile cameras from a central controller may allow for better flexibility, however, there limited resources may not allow for the required autonomous coordination nor reliable target re-identification on the device.

In the SOLOMON project[1] we are extending recent research on static smart camera networks, to build networks of mobile smart cameras that exploit their mobility. In doing so, our research has exposed a number of challenges, which we describe in this paper.

3 MOBILITY

When introducing mobility to camera networks, the question arises of how to control the mobility behaviour. This question becomes even more pressing when cameras are worn by humans (as opposed to robots) who may not comply with instructions. In such cases, we can only talk about *suggested* movement rather than *controlled* movement. Here, we discuss the benefits and challenges associated with both fully controlled and suggested movement.

The main benefit of fully-controlled movement is being able to select the position and orientation of each camera. This is usually available in robotic systems, but may be constrained in some cases, such as with fixed-wing UAVs. This allows a more stable video feed, even when in motion, in comparison to BWV. However, robotic systems are often not able to move as fast as humans and, depending on the robot, may have trouble with obstacles in the environment.

A more realistic scenario is a hybrid network consisting of cameras mounted on humans, where human decision-making behaviour forms part of the network's decentralised control process. Having humans in the loop allows for more reactive camera networks, as humans are expert at acting on instinct and making good, rapid decisions. The wearer of a camera might make a decision before a controller could decide what each camera might need to do next. This can be a benefit as well as a disadvantage. On the one hand, a person with BWV might follow a target more thoroughly and hence provide continuous and reliable target tracking. On the other hand, the person might decide not to follow a person of interest and hence not provide any video feed at all. A smart controller able to account for the needs and uncertainties of the human, however, might suggest a BWV user to move in a direction that removes the person from potential harm.Alternatively, a suggestion to a user might involve moving only if safe to do so, along with alternative safer options, that still provide value to the network.

4 HETEROGENEITY

Heterogeneity is an increasingly prevalent property of complex computational and cyber-physical systems [3, 26, 28], and smart camera networks are no exception. Heterogeneity in camera networks may take various forms (e.g., as depicted in Figure 4), including variation in hardware between nodes, physical properties of the camera, processing power and storage, and connectivity and bandwidth. A camera network with platform heterogeneity is composed of different types of cameras, possibly including static and fixed mounted ones, PTZ cameras able to change their orientation and zoom, BWV able to relocate, and robot-mounted cameras. This can often lead to other sources of platform heterogeneity, for example, fixed mounted cameras are most likely to have a wired network connection, and can usually rely on a constant power supply. In contrast, mobile cameras have to rely on batteries as a power supply and typically only have wireless communication interfaces. Another manifestation of heterogeneity arising from platform heterogeneity is in terms of image resolution. Mobile cameras are fully embedded devices and rely on very small sensors. Due to their lower processing capabilities and available storage, acquired images may have a lower resolution to begin with. Considering multi-camera continuous target tracking and re-identification, cameras in the network with lower processing capabilities may slow down the network. Furthermore, lower image quality may skew the acquired model of a target and accelerate the problem of concept drift in target tracking and online target model learning [2].

[1] SOLOMON: Self-Organisation and Learning Online in Mobile Observation Networks, https://alice.aston.ac.uk/solomon

Cameras' behaviours can also vary, leading to *behavioural heterogeneity.* The classic approach is for cameras to use a common algorithm or behavioural strategy. However, cameras are often located in different areas, and hence are subject to different experiences. This challenges the common assumption when deploying smart camera networks, that a single behaviour, captured in a single software solution, should be used. Indeed, results from Lewis et al's study of heterogeneity in smart camera networks [27] support the idea that to achieve efficient network-wide behaviour, each device should have a specialised behaviour, based on its own local perspective and context. This result mirrors those from studies of heterogeneity elsewhere in multi-agent and self-organising systems, where specific benefits include adaptation to unknown situations or environments. For example, Anders et al. [1] showed that heterogeneity among nodes in a network can lead to better achievement of system wide objectives, and Salazar et al. [44] highlight the importance of understanding and harnessing heterogeneity when nodes can adapt independently online, in response to uncertainty and changes in the environment. In dynamic task allocation, Campbell et al. [5] show that variation in agent behaviour increases the system's ability to adapt to varying stimuli. Focussing on sensor networks, Yarvis et al. [53] explore the impact of heterogeneity at the network level, and Römer et al. [43] observe that, while wireless sensor networks were initially conceived as homogeneous networks of near-identical sensors, in practice many applications contain platform heterogeneity. Further, Prasath et al. [37] recommend heterogeneity in wireless sensor networks to generate near-optimal configurations. This raises a further challenge: while heterogeneity can improve global efficiency, how should "good" behaviour for each individual camera be determined? In large networks, for even reasonable sets of possible behaviours at the individual camera level, this leads to a combinatorial explosion of possible network behaviour configurations, and identifying by hand the most appropriate configuration at a particular point in time is not feasible. Thus, some automation, through a-priori optimisation, or by online machine learning (e.g., as in [27]) will be needed.

Figure 4: Camera network platforms vary, leading to platform heterogeneity. BWV/IBV has received little attention so far from the research community.

5 NETWORKING AND COORDINATION

In networks where cameras can change their pose or relocate, it is important to coordinate the cameras so that network goals are met [17, 23]. These might include: maximise the number of tracked objects, ensure each target is tracked by k cameras at a time, etc.

Figure 5 illustrates some challenges: 5 cameras, relying purely on their visual information, is tasked to observe a single target. Cameras C_1 and C_2 observe it from the front. Since their view angles are similar, identification by both cameras is not a problem. However, little additional information is gathered. The object is occluded from C_3, so in order for the camera to contribute knowledge, it would need to move. C_4 can see the object from behind. Assuming the model holds sufficient information, C_4 also identifies the target, and adds more new knowledge than C_3 and C_5. C_5 should be able to re-identify the object based on C_1 or C_2's information, while also providing new information about the object. If cameras are calibrated, their location and orientation information can be used to aid re-identification. Otherwise, the network relies on the generalisation of the learnt model to other points of view.

5.1 Centralised Coordination

A global controller knows where each camera is located, its relation to other cameras in the network, and the content of their FOVs. Hence, the coordinator knows what targets are covered by how many cameras, and which targets are not covered at any given time. Achieving goals can be considered an optimization problem in a game-theoretic setting [31]. This, however, requires the cameras to constantly communicate their information to the central coordinator. With fixed cameras on wired connections, this might not be big issue. Furthermore, the central controller being aware of the location and orientation of each individual camera and their FOVs makes re-identification of targets a much easier task. However, in mobile BWV, information exchange has to be performed via wireless communication channels. In rapidly unfolding situations, required infrastructure might not be available for cameras to receive commands from the central entity. In addition, having constantly changing environments, a camera might not be able to wait for control input from the coordinator.

5.2 Decentralised Coordination

In decentralised coordination, coordination of the network is spit up among multiple clusters of cameras. For each cluster, a local coordinator is selected, perhaps through voting. Additionally it is required that the communication range is at least the range at which a camera can detect and potentially re-identify a target with sufficient confidence. In comparison to centralised coordination, in decentralised coordination, the communication effort is reduced among neighbours. This does not necessarily reduce network-wide communication, however, clusters currently not engaged in tracking a target might not have any communication at all.

One of the main challenges is how to select clusters efficiently at runtime due to (i) the directed sensing of cameras, (ii) the possibility to change their pose with PTZ cameras, and (iii) potentially even change their location when employing mobile cameras. Having a highly dynamic network of mobile cameras, selection of such a coordinator with a high freqency at runtime introduces an additional problem. Finally, when targets move across multiple clusters, where each one is handled by a different coordinator, this cluster hand-off needs to be handled efficiently. However, on a local level, a cluster coordinator still has global knowledge, and would be used to ensure positive re-identification of targets among different cameras.

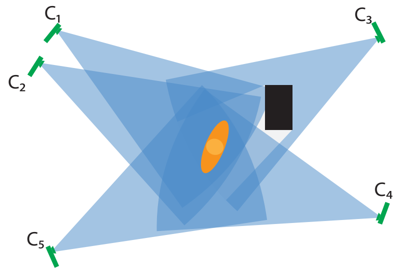

Figure 5: C_1 and C_2 have similar points of view on a target (orange) and thus provide non-complementary information. C_3's view is occluded and it needs to move to see the target. C_4 sees the target from the opposite side to C_1 and C_2. If the target is non-uniform and the model does not capture this, C_4 will not be able to identify the target. C_5 also has a complementary angle to C_1 and C_2, and can re-identify the target and add new information.

5.3 Self-organised Coordination

Existing large camera deployments, especially BWV, are not networked, and involve no interaction between cameras. Conversely, networked deployments are smaller and centrally controlled, introducing a bottleneck and a single point of failure. To address the issue of scalability, self-organising and distributed coordination can be used.In self-organising cameras, the network also benefits form higher flexibility and more robustness to changes in the network.

However, self-organisation in a camera network requires a high degree of interaction among the individual cameras, which may result in higher communication and be error prone. Additionally, not having a central controller results in cameras acting based on local rules and defined behaviour. This might lead to cameras not behaving as expected resulting in targets not being tracked or to many cameras covering the same targets at the same time .

Introducing mobility, whether in the form of robots or BWV, requires the network to account for changing goals, resources, and rapidly changing environments. This requires the control of the system to be highly adaptive, robust, and flexible. In order to achieve this, individual and collective online learning at the camera and network level is required. Furthermore, the system and individual cameras need to evaluate their own performance as well as the performance of others at runtime. This will allow them to self-adapt to such demanding change. Further, current approaches do not consider the relationship and interplay of different goals and available resources. To increase the efficiency of camera systems, trade-offs need to be modelled during runtime and multiple objectives in our learning approaches need to be considered. Guarantees for emergent behaviour in self-organising camera systems are required to ensure given goals in the network are achieved. However, this would require the network to have a single common goal. Furthermore, techniques on how to handle malicious/non-cooperative/counter-productive nodes within a network are required.

6 COLLABORATION AND TEAM WORK

An important challenge, especially in heterogeneous networks, is cooperation between individual cameras to achieve common goals. Foeken and Kester [16] analyse adaptive team formation under different communication constraints, using shared situation awareness to maximise the performance of each team member. Raubal and Winter [39] define a framework for agents to negotiate how to perform a task. They consider, at runtime, if a task requires collaboration and analyse the trade-off between urgency, risk, and distance involved. In camera networks, Qureshi and Terzopoulos [38] use *contract net* to assign tasks to cameras at runtime. They use auctions to form coalitions of cameras to achieve specific tasks. Similarly, Esterle et al. [10, 13] use auctions to find neighbouring cameras for continuous tracking. They introduce artificial pheromones to adapt to changes in the network. Li and Zhang [30] use a utility based on the number of cameras observing a target and on the overlapping area of the target to determine which cameras should collaborate to achieve the best results. This is done exhaustively for all cameras in a centralised way. SanMiguel and Cavallaro [45] propose a coalition-based collaborative tracking framework. In negotiation, cameras join teams to collaboratively track targets, based on their available resources and expected contribution.

However, these approaches do not account for the dynamics of the network introduced by mobility, nor the unpredictable behaviour of citizens contributing video data. This additional degree of complexity will require further investigation to improve continuous multi-camera target tracking and re-identification.

7 OUTLOOK

One recent trend in industry is the proliferation of mobile cameras, including body worn video. However, research often still focusses on homogeneous camera networks. In this paper we shed some light on the upcoming challenges that will arise by incorporating BWV into surveillance networks.

Future camera networks will be required to respond to any given situation autonomously or with minimal human interaction. When required, these networks can be extended by BWV on local personnel and/or privately owned equipment. This sudden heterogeneity in the network can bring benefits, but needs to be handled accordingly. Since this heterogeneity cannot be foreseen, this needs to be done autonomously and during runtime. In addition, BWV requires new techniques to compensate for motion introduced by rapid movements. The additional cameras, however, allow for immediate extension of the network and hence supplementary video data can be made available when required. Nevertheless, the security team may not be able to completely rely on BWV added by non-security personnel as they may not comply with requests, e.g. relocating to a position if it is potentially harmful. BWV also offers benefits to lay personnel, as security services can use their video footage to guide them safely out of harm's way. In a given emergency, police special forces may deploy additional mobile camera nodes in the form of more BWV or drones. Recent developments allow those drones to land on and depart from walls, enabling them to conserve energy. These drones would also operate autonomously, extending the camera infrastructure, and communicating with the rest of the network when required. Special forces wearing BWV could again be guided towards the reported incident.

Heterogeneity and self-organisation enable the network to attend to multiple tasks at the same time, through parallelisation and specialisation according to local situations. Autonomous coordination of mobile smart camera networks will allow the assessment of and response to situations faster, even in a chaotic and fast-changing environment, while generating additional valuable and up-to-date information in real time.

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REFERENCES

[1] Anders, G., Hinrichs, C., Siefert, F., Behrmann, P., Reif, W., Sonnenschein, M.: On the influence of inter-agent variation on multi-agent algorithms solving a dynamic task allocation problem under uncertainty. In: Proc. of the Int. Conf. on Self-Adaptive and Self-Organizing Systems. pp. 29–38. IEEE (2012)
[2] Avidan, S.: Ensemble tracking. IEEE Trans. on Pattern Analysis and Machine Intelligence 29(2), 261–271 (2007)
[3] Baudry, B., Monperrus, M.: The multiple facets of software diversity: Recent developments in year 2000 and beyond. ACM Computing Surveys 48, 1–26 (2015)
[4] Black, J., Ellis, T.: Multi camera image tracking. Image and Vision Computing 24(11), 1256 – 1267 (2006), performance Evaluation of Tracking and Surveillance
[5] Campbell, A., Riggs, C., Wu, A.: On the impact of variation on self-organizing systems. In: Proc. of the Int. Conf. Self-Adaptive and Self-Organizing Systems. pp. 119–128 (2011)
[6] Chakraborty, A., Das, A., Roy-Chowdhury, A.K.: Network consistent data association. IEEE Trans. on Pattern Analysis and Machine Intelligence 38(9), 1859–1871 (2016)
[7] Chang, T.H., Gong, S.: Tracking multiple people with a multi-camera system. In: Proc. of the Workshop on Multi-Object Tracking. pp. 19–26 (2001)
[8] Dieber, B., Micheloni, C., Rinner, B.: Resource-aware coverage and task assignment in visual sensor networks. IEEE Trans. on Circuits and Systems for Video Technology 21(10), 1424–1437 (2011)
[9] Erdem, U.M., Sclaroff, S.: Event prediction in a hybrid camera network. ACM Trans. on Sensor Networks 8(2), 16:1–16:27 (2012)
[10] Esterle, L., Lewis, P.R., Bogdanski, M., Rinner, B., Yao, X.: A socio-economic approach to online vision graph generation and handover in distributed smart camera networks. In: Proc. of the Int. Conf. on Distributed Smart Cameras. pp. 1–6 (2011)
[11] Esterle, L.: Self-organized coverage optimisation in smart camera networks. In: Proc. of the Int. Conf. on Self-Adaptive and Self-Organizing Systems. pp. 1–10. IEEE Computer Society (2017), to appear
[12] Esterle, L., Lewis, P.R.: Online multi-object k-coverage with mobile smart cameras. In: Proc. of the Int. Conf. on Distributed Smart Cameras. pp. 1–6. IEEE Computer Society (2017), to appear
[13] Esterle, L., Lewis, P.R., Yao, X., Rinner, B.: Socio-economic vision graph generation and handover in distributed smart camera networks. ACM Transactions on Sensor Networks 10(2), 20 (2014)
[14] Esterle, L., Rinner, B., Lewis, P.R.: Self-organising zooms for decentralised redundancy management in visual sensor networks. In: Proc. of the Int. Conf. on Self-Adaptive and Self-Organizing Systems. pp. 41–50. IEEE (2015)
[15] Esterle, L., Simonjan, J., Nebehay, G., Pflugfelder, R., Domínguez, G.F., Rinner, B.: Self-aware object tracking in multi-camera networks. In: Self-aware Computing Systems, pp. 261–277. Springer (2016)
[16] van Foeken, E., Kester, L.: Adaptive team formation for shared situation awareness. In: Proc. of the Int. Conf. on Information Fusion. pp. 361–368 (2012)
[17] Gruber, S., Streeter, R., York, G.: Flexible multi-agent algorithm for distributed decision making. In: Proc. of the Int. Conf. on Unmanned Aircraft Systems. pp. 9–17 (2015)
[18] Hollinger, G., Singh, S., Djugash, J., Kehagias, A.: Efficient multi-robot search for a moving target. The Int. J. of Robotics Research 28(2), 201–219 (2009)
[19] Kamal, A.T., Bappy, J.H., Farrell, J.A., Roy-Chowdhury, A.K.: Distributed multi-target tracking and data association in vision networks. IEEE Trans. on Pattern Analysis and Machine Intelligence 38(7), 1397–1410 (2016)
[20] Kantor, G., Singh, S., Peterson, R., Rus, D., Das, A., Kumar, V., Pereira, G., Spletzer, J.: Distributed Search and Rescue with Robot and Sensor Teams, pp. 529–538. Springer (2006)
[21] Khan, A., Rinner, B., Cavallaro, A.: Multiscale observation of multiple moving targets using micro aerial vehicles. In: International Conference on Intelligent Robots and Systems. pp. 4642–4649 (2015)
[22] Kolling, A., Carpin, S.: Cooperative observation of multiple moving targets: an algorithm and its formalization. Int. J. of Robotics Research 26(9), 935–953 (2007)
[23] Kosak, O., Wanninger, C., Angerer, A., Hoffmann, A., Schiendorfer, A., Seebach, H.: Towards self-organizing swarms of reconfigurable self-aware robots. In: Proc. of the Int. Workshops on Foundations and Applications of Self* Systems. pp. 204–209 (2016)
[24] Kounev, S., Lewis, P., Bellman, K., Bencomo, N., Camara, J., Diaconescu, A., Esterle, L., Geihs, K., Giese, H., Götz, S., Inverardi, P., Kephart, J., Zisman, A.: The notion of self-aware computing. In: Kounev, S., Kephart, J.O., Milenkoski, A., Zhu, X. (eds.) Self-Aware Computing Systems, pp. 3–16 (2017)
[25] Kumar, V., Rus, D., Singh, S.: Robot and sensor networks for first responders. IEEE Pervasive Computing 3(4), 24–33 (2004)
[26] Lewis, P.R.: Self-aware computing systems: From psychology to engineering. In: Design, Automation Test in Europe Conference. pp. 1044–1049. IEEE (2017)
[27] Lewis, P.R., Esterle, L., Chandra, A., Rinner, B., Torresen, J., Yao, X.: Static, dynamic, and adaptive heterogeneity in distributed smart camera networks. ACM Trans. Auton. Adapt. Syst. 10(2), 8:1–8:30 (2015)
[28] Lewis, P.R., Goldingay, H., Nallur, V.: It's Good to be Different: Diversity, Heterogeneity and Dynamics in Collective Systems. In: Proc. of the Int. Conf. on Self-Adaptive and Self-Organizing Systems, Workshop. pp. 84–89. IEEE (2014)
[29] Lewis, P.R., Platzner, M., Rinner, B., Torresen, J., Yao, X. (eds.): Self-aware Computing Systems: An Engineering Approach. Springer (2016)
[30] Li, W., Zhang, W.: Sensor selection for improving accuracy of target localisation in wireless visual sensor networks. IET Wireless Sensor Systems 2(4), 293–301 (2012)
[31] Li, Y., Bhanu, B.: Utility-based camera assignment in a video network: A game theoretic framework. IEEE Sensors Journal 11(3), 676–687 (2011)
[32] Martinel, N., Foresti, G.L., Micheloni, C.: Distributed and unsupervised cost-driven person re-identification. In: Proc. of the Int. Conf. on Pattern Recognition. pp. 1225–1230 (2016)
[33] Martinel, N., Foresti, G.L., Micheloni, C.: Person reidentification in a distributed camera network framework. IEEE Trabs, on Cybernetics PP(99), 1–12 (2016)
[34] Mundhenk, T.N., Everist, J., Landauer, C., Itti, L., Bellman, K.: Distributed biologically based real time tracking in the absence of prior target information (2005)
[35] Parker, L.E., Emmons, B.A.: Cooperative multi-robot observation of multiple moving targets. In: Proc. of the Int. Conf. on Robotics and Automation. vol. 3, pp. 2082–2089 vol.3 (1997)
[36] Piciarelli, C., Esterle, L., Khan, A., Rinner, B., Foresti, G.L.: Dynamic reconfiguration in camera networks: A short survey. IEEE Trans. on Circuits and Systems for Video Technology 26(5), 965–977 (2016)
[37] Prasath, A., Venuturumilli, A., Ranganathan, A., Minai, A.A.: Self-organization of sensor networks with heterogeneous connectivity. In: Ferrari, G. (ed.) Sensor Networks: Where Theory Meets Practice, pp. 39–59. Springer (2009)
[38] Qureshi, F.Z., Terzopoulos, D.: Multi-camera control through constraint satisfaction for persistent surveillance. In: Proc. of the Int. Conf. on Advanced Video and Signal Based Surveillance. pp. 211–218 (2008)
[39] Raubal, M., Winter, S.: A Spatio-Temporal Model Towards Ad-Hoc Collaborative Decision-Making, pp. 279–297. Springer (2010)
[40] Riehl, J.R., Collins, G.E., Hespanha, J.P.: Cooperative search by uav teams: A model predictive approach using dynamic graphs. IEEE Trans. on Aerospace and Electronic Systems 47(4), 2637–2656 (2011)
[41] Rinner, B., Wolf, W.: An introduction to distributed smart cameras. Proc. of the IEEE 96(10), 1565–1575 (2008)
[42] Rinner, B., Esterle, L., Simonjan, J., Nebehay, G., Pflugfelder, R., Domínguez, G.F., Lewis, P.R.: Self-aware and self-expressive camera networks. IEEE Computer 48(7), 21–28 (2015)
[43] Römer, K., Mattern, F.: The design space of wireless sensor networks. IEEE Wireless Communications 11(6), 54–61 (2004)
[44] Salazar, N., Rodriguez-Aguilar, J.A., Arcos, J.L.: Self-configuring sensors for uncharted environments. In: Proc. of the Int. Conf. on Self-Adaptive and Self-Organizing Systems. pp. 134–143. IEEE (2010)
[45] SanMiguel, J.C., Cavallaro, A.: Cost-aware coalitions for collaborative tracking in resource-constrained camera networks. IEEE Sensors Journal 15(5), 2657–2668 (2015)
[46] SanMiguel, J.C., Micheloni, C., Shoop, K., Foresti, G.L., Cavallaro, A.: Self-reconfigurable smart camera networks. Computer 47(5), 67–73 (2014)
[47] Scherer, J., Yahyanejad, S., Hayat, S., Yanmaz, E., Andre, T., Khan, A., Vukadinovic, V., Bettstetter, C., Hellwagner, H., Rinner, B.: An autonomous multi-uav system for search and rescue. In: Proc. of the Workshop on Micro Aerial Vehicle Networks, Systems, and Applications for Civilian Use. pp. 33–38. DroNet '15, ACM (2015)
[48] Tessens, L., Morbee, M., Aghajan, H., Philips, W.: Camera selection for tracking in distributed smart camera networks. ACM Trans. on Sensor Networks 10(2), 23:1–23:33 (2014)
[49] Tisdale, J., Kim, Z., Hedrick, J.K.: Autonomous uav path planning and estimation. IEEE Robotics Automation Magazine 16(2), 35–42 (2009)
[50] Verma, A., Sawant, H., Tan, J.: Selection and navigation of mobile sensor nodes using a sensor network. Pervasive and Mobile Computing 2(1), 65 – 84 (2006)
[51] Vu, A., Farrell, J.A.: Feature mapping and state estimation for highly automated vehicles. Journal of Control and Decision 2(1), 1–25 (2015)
[52] Wang, Z., Liao, J., Cao, Q., Qi, H., Wang, Z.: Achieving k-barrier coverage in hybrid directional sensor networks. IEEE Trans. on Mobile Computing 13(7), 1443–1455 (2014)
[53] Yarvis, M., Kushalnagar, N., Singh, H., Rangarajan, A., Liu, Y., Singh, S.: Exploiting heterogeneity in sensor networks. In: Proc. of the Conf. Joint of the IEEE Computer and Communications Societies. vol. 2, pp. 878–890 vol. 2 (2005)