Multi-view human action recognition: A survey

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***Abstract*—While single-view human action recognition has attracted considerable research study in the last three decades, multi-view action recognition is, still, a less exploited field. This paper provides a comprehensive survey of multi-view human action recognition approaches. The approaches are reviewed following an application-based categorization: methods are categorized based on their ability to operate using a fixed or an arbitrary number of cameras. Finally, benchmark databases frequently used for evaluation of multi-view approaches are briefly described.**

***Keywords*-Multi-view action recognition; survey; review**

I. Introduction

Human action recognition and analysis is an active research field in computer vision due to its importance in a wide range of applications, including intelligent visual surveillance, human-computer interaction, content-based video compression and retrieval, augmented reality and games. The term action is often confused with the term activity. An action (sometimes also called as movement) refers to a simple motion pattern, e.g., a walking step. Activities consist of a sequence of actions, e.g., the activity 'playing basketball' consists of successive realizations of actions, 'run', 'jump', 'shoot the ball', etc. Therefore, the first step in human activity analysis is the recognition of actions.

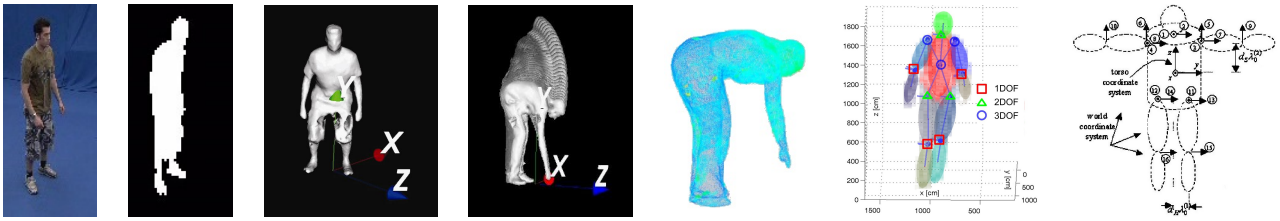
Action recognition methods can be categorized depending on the visual information employed for action description. Single-view methods employ one camera in order to capture the human body during action execution. However, the visual appearance of actions is quite different when observed by arbitrary view angles [1], [2]. Therefore, single-view methods set the underlying assumption of the same observation angle during both training and testing. If this assumption is not met, the performance of single-view methods decreases. Multi-view methods, i.e., methods employing multiple cameras in order to exploit the enriched visual information for action description, have been proposed in order to perform view-independent human action recognition. Despite the fact that single-view action recognition has been extensively studied in the last three decades, multi-view action recognition is a, relatively, new research field [3], [4], which has been, mainly, studied in the last decade. This is due to the increased computational cost of multi-view methods, which rendered their application prohibitive, considering the capabilities of previous decades equipment. Recent advances in technology have resulted to cheap and powerful equipment, making multi-view methods applicable in many application scenarios.

This paper presents a literature review of multi-view action recognition methods. It adopts an application-based categorization: we categorize multi-view methods based on their ability to operate in two application scenarios, 1) methods requiring a (fixed) multi-camera setup during both training and testing and 2) methods that can operate by using an arbitrary number of cameras. In the following, methods belonging to the first category are referred to as 3D methods, since they usually describe actions exploiting 3D reconstructed data, while methods belonging to the second category are referred to as 2D multi-view methods, since they usually operate by using the 2D information coming from each camera independently. Additionally, we briefly describe benchmark data sets frequently used for the evaluation of multi-view methods.

II. 3D Methods

The common trend in 3D action recognition methods is to fuse the visual information captured by different viewing angles and, then, proceed with action representation and classification. This is, usually, achieved by combining 2D human body poses in terms of binary silhouettes denoting the video frame pixels belonging to the human body on each camera (Figure 1b). After obtaining the corresponding 3D human body representation, actions are described as sequences of successive 3D human body poses. Human body representations adopted by 3D methods include visual hulls (Figure 1c), motion history volumes (Figure 1d) [5], optical flow corresponding to the human body (Figure 1e) [6], Gaussian blobs (Figure 1f) [7], cylindrical/ellipsoid body models (Figure 1g) [8], skeletal and super-quadratic body models (Figure 2) [9], multi-view postures (Figure 3) [10] and spatio-temporal volumes (Figure 4) [11].

Visual hull-based human body representation has been combined with several descriptors proposed for 3D shape representation, like the shape histogram [13], [14], [15], [16], shape distribution [17], spherical harmonics [18] and circle layers [19]. 3D shape information corresponding to different human body poses is combined by tracking the 3D human body in consecutive multi-view frames and either by accumulating shape descriptors over time, or by applying the sliding window technique [20], [21], [22], [23], [24],



(a) (b) (c) (d) (e) (f) (g)

Figure 1. *a) A video frame depicting a person, b) binary human body image, c) 3D human body pose (visual hull), d) motion history volume [5], e) Motion Context [6], f) Gaussian blob human body model [7] and g) cylindrical/ellipsoid human body model [8].*

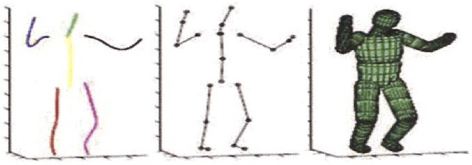


Figure 2. *Skeletal and superquadratic human body model [9].*

Figure 3. *Multi-view human body posture [10].*

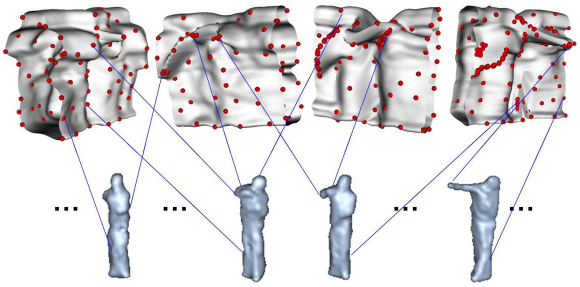


Figure 4. *Spatio-Temporal Volumes [11].*

[25]. In order to obtain view-invariant human body pose representations the circular shift invariance property of the Discrete Fourier Transform in cylindrical coordinates has been exploited in [26], [27], [28], horizontal human body partitioning combined with circular features calculation is employed in [19] and 3D invariant statistical moments have been employed in [6]. Another approach that employs action descriptors exploiting 3D motion information is presented in [6], [29], where the 3D Motion Context (3D-MC) and Harmonic Motion Context (HMC) descriptors are proposed.

By combining the binary human body silhouettes exploiting the known camera label ID information, the multi-view posture has been proposed in [10]. By combining the binary human body silhouettes corresponding to different cameras with respect to time, the Multi-view Action Image has been proposed in [12]. These are low computational cost 3D human body representation that do not require camera setup calibration. In order to obtain a view-independent action representation, the circular shift invariance property of the magnitudes of the DFT is exploited in [10], [31], [12], while side view selection is proposed in [30]. In both cases, motion information is exploited by applying the sliding window technique.

III. 2D Methods

Although the above described approaches have been successfully employed for 3D human body shape and motion description, most of them set the underlying assumption that the human body should be visible from all the cameras of the adopted camera setup during both training and testing. This is a rather restrictive application scenario, since in real situations the person under consideration may not be visible from all cameras either because he/she is outside the camera setup capture volume, or due to occlusion [32].

In order to overcome this restriction, researchers have come up with methods that are able to perform view-independent action recognition. Two directions have been investigated to this end. The first one adopts a single-view view-independent approach. That is, action recognition is performed on each video coming from all the available cameras independently. One line of work in this case exploits view-invariant action representations [33], [34], [35], [36], while another tries to determine an appropriate classification scheme. In the later case, classification is performed either by training multiple classifiers [37], or by training a universal classifier using training data corresponding to all the available views [38], [39], [40], [41], [42], [43], [44], [45]. After obtaining action class labels corresponding to different view-angles, action classification results fusion can be performed in order to obtain the final classification result [44], [42], [43], [45].

The second direction refers to cross-view action recognition. This is the task of learning action classes in one (often called reference) view and recognize actions in another (target) view. Several techniques have been adopted to this end, including transfer learning [46], [47], [52], [53], [54], information maximization [48] and methods exploiting appropriately designed features [49], [50] and the scene

Table I
DATABASES INFORMATION.

Database	# cameras	# persons	# actions
IXMAS	5	12	13
i3DPost	8	8	8
MuHAVi	8	7	17
HumanEVA	7	4	6
MoBo	6	25	4
AIIA-MOBISERV	4	12	9

geometry [51].

IV. MULTI-VIEW DATABASES

A number of video databases are publicly available as benchmark sets for the evaluation of different multi-view approaches. Three of the most widely adopted data sets are the INRIA Xmas Motion Acquisition Sequences (IXMAS) Multi-View Human Action Dataset [5], the i3DPost Multi-view Human Action Dataset [55] and the Multicamera Human Action Video Dataset (MuHAVi) [58]. Other multi-view databases used for evaluation by several authors include the Synchronized Video and Motion Capture for Evaluation of Articulated Human Motion (HumanEva) [58], the CMU Motion Body Database (MoBo) [58] and the AIIA-MOBISERV eating and drinking database [59]. Information concerning each database is provided in Table I

V. CONCLUSION

In this paper we presented a survey of methods recently proposed for multi-view human action recognition. The methods have been categorized based on their ability to operate using an arbitrary number of cameras. Finally, publicly available databases aiming at the evaluation of multi-view approaches have been, briefly, described.

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