Going Deeper into Action Recognition: A Survey

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Abstract

We provide a detailed review of the work on human action recognition over the past decade. We refer to “actions” as meaningful human motions. Starting with methods that are based on handcrafted representations, we review the impact of revamped deep neural networks on action recognition. We follow a systematic taxonomy of action recognition approaches to present a coherent discussion over their improvements and fall-backs.

Introduction

Imagine the time when your robot assistant helps you in getting your kids ready for the school. You know that it will then help you in renovating the basement you have been planning for sometime. Meanwhile, your home computer is browsing the latest videos on the web to learn the specific construction tasks required for such a renovation job and preparing a training video for you. These are all happening smoothly without your intervention thanks to intelligent systems, capable of recognizing and understanding actions.

We may not be that far away from such a time. In this survey, we walk through existing research on action recognition in the hope of shedding some light on what is available now and what needs to be done in order to develop smart machines that are semantically aware of our actions.

But first, what is an action?

Human motions extend from the simplest movement of a limb to complex joint movement of a group of limbs and body. For instance, while the leg movement on a football kick is a simple motion, jumping for a head-shoot would be a collective movements of legs, arms, head, and whole body. Despite its intuitive and rather simple concept, the term action seems to be hard to define!

Below, we provide a few examples from the literature:

- Moeslund and Granum (2006); Poppe (2010) define action primitives as “an atomic movement that can be described at the limb level”. Accordingly, the term action defines a diverse range of movements, from “simple and primitive ones” to “cyclic body movements”. The term activity is used to define “a number of subsequent actions”, representing a complex movement. For instance, left leg forward is an action primitive of running. Jumping hurdles is an activity performed with the actions starting, running and jumping.

- Turaga et al. (2008) define action as “simple motion patterns usually executed by a single person and typically lasting for a very short duration (Order of tens of seconds).” Their activity refers to “a complex sequence of actions performed by several humans who could be
interacting with each other in a constrained manner.” For example, actions are walking or swimming, activities are two persons shaking hands or a football team scoring a goal.

- Wang et al. (2016) suggest that the true meaning of an action lies in “the change or transformation an action brings to the environment”, e.g., kicking a ball.

In the Oxford Dictionary, action is defined as “the fact or process of doing something, typically to achieve an aim”. and activity is “a thing that a person or group does or has done”. We provide a consolidated definition that serves our purposes in this study the best.

“Action is the most elementary human-surrounding interaction with a meaning.”

The meaning associated with this interaction is called the category of the action. In general, human actions can take various physical forms. In our definition, the term interactions can be understood as relative motions with respect to the surrounding that may or may not cause a change. In some situations, one may need to associate “surrounding” to particular objects to derive a meaningful interpretation (e.g., brushing hair). This is aligned with the definition of Wang et al. (2016), where an action is defined by the change it is brought to the environment.

As an example, consider the motion sequence in Fig.1. First, consider a primitive leg motion performed by the player on his run. Even though such movement is a relative motion with respect to the surrounding, we can barely attach a meaning to it. On the other hand, the collective motion of limbs, which results in running, has a meaning. Since this is the most elementary and meaningful motion, we consider it as an action, “the running action”. Similarly, it is clear that the player’s kick and the Jump of the goal-keeper are two distinct actions with labels “kicking” and “jumping”.

![Figure 1: Actions are “meaningful interactions” between humans and the environment.](image)

**Every survey paper has a taxonomy**

True, but a generic taxonomy eludes us! Instead, we group solutions based on the fundamental understanding the reader will take at the end. For instance, we dedicate a separate section to techniques based on deep networks to discuss various architectures and their training methods. To have a glance, the topics that will be covered in our study are shown in Fig. 2.

**Why should we learn more about action recognition?**

Analyzing motions and actions has a long history and is attractive to various disciplines including psychology, biology and computer science (see Table. 1 for the list of surveys related to motion and action recognition in computer vision). One can trace the fascination about motion back to 500BC with Zeno’s dichotomy paradox. From an engineering perspective, action recognition extends over a broad range of high-impact societal applications, from video surveillance to human-computer interaction, retail analytics, user interface design, learning for robotics, web-video search and retrieval, medical diagnosis, quality-of-life improvement for elderly care, and sports analytics. The long list
of emerging technologies and applications (see for example Ahad et al. (2012)) points to “manually analyzing action and motion data is impossible”.

Table 1: Surveys on Motion and Action Analysis

| Survey                               | Scope                                           |
|--------------------------------------|-------------------------------------------------|
| Moeslund and Granum (2006)           | human motion capture and analysis               |
| Yilmaz et al. (2006)                 | object detection and tracking                   |
| Turaga et al. (2008)                 | human actions, complex activities               |
| Zhan et al. (2008)                   | surveillance and crowd analysis                 |
| Poppe (2010)                         | human action recognition                        |
| Weinland et al. (2011)               | action recognition                              |
| Aggarwal (2011)                      | motion analysis fundamentals                    |
| Metaxas and Zhang (2013)             | human gestures to group activities              |
| Vishwakarma and Agrawal (2013)       | activity recognition and monitoring             |

1. Where to start from?

Let us begin by quoting a visionary thought from early eighties: “First, there must be a symbolic system for representing the shape information in the brain, and, secondly the brain must contain a set of processors capable of deriving this information from images” Marr and Vaina (1982). In the
context of action recognition, a good representation must “be easy to compute”, “provide description for a sufficiently large class of actions”, “reflect the similarity between two like actions”, and “be robust to various variations (e.g., view-point, illumination)”.

Earliest works in action recognition make use of 3D models to describe actions. One notable example is the WALKER hierarchical model introduced in Hogg (1983) to understand and interpret human actions. Another example is the use of connected cylinders to model limb connections for pedestrian recognition Rohr (1994). Nevertheless, capturing accurate 3D models is difficult and expensive. That is why recent developments avoid 3D modeling and instead opt for representing actions at a holistic or local level. Formally, we can define:

- **Holistic representations.** Action recognition is based on the extraction of a global representation of human body structure, shape and movements.
- **Local representations.** Action recognition is based on the extraction of local features.

![Figure 3: Early approaches represent actions by 3D models. Left: Hogg (1983) introduce the WALKER framework to represent walking action using 3D models. The walking pattern is modeled by a sequence of 3D structures. Right: Rohr (1994) extended the WALKER framework for pedestrian recognition. The model uses connected cylinders and their evolution to identify pedestrians.](image)

### 1.1 Holistic Representations

We begin by describing the influential work of Bobik *et al.* Bobick and Davis (2001). Motion Energy Image (MEI) and Motion History Image (MHI) are introduced in Bobick and Davis (2001). As the names suggest, the underlying idea is to encode the motion-related information by a single image. The MEI template is a binary image describing where the motion happens and defined as:

\[
E_\tau(x, y, t) = \bigcup_{i=0}^{\tau-1} D(x, y, t - i).
\]

(1)
Here, $D(x, y, t)$ is a binary image sequence representing the detected object pixels while $E_\tau$ denotes the formed MEI at a time $\tau$. The MHI template shows how the motion image is moving. Each pixel in MHI is a function of the temporal history of the motion at that point (i.e., higher intensities correspond to more recent movements) (see Fig. 4 for an illustration).

Figure 4: **Top:** A jumping sequence. **Middle:** The MEI template Bobick and Davis (2001). **Bottom:** The MHI template Bobick and Davis (2001). The MEI captures where the motion happens while the MHI template shows how the motion image is moving. The templates at the end of the action, shown in the rightmost column are used for representations.

The MEI and MHI templates contain useful information about the context of videos. For example, the gradient of the MHI template is used to filter out the moving and cluttered background in Tian et al. (2012). This is achieved by determining key motion regions in the MHI template using Harris interest point detector (Harris and Stephens, 1988), followed by identifying the moving/cluttered background as regions with inconsistent motions around the interest points.

The volumetric extension of MEI templates is introduced in Blank et al. (2005). The main idea is to represent an action by a 3D shape induced from its silhouettes in the space-time (see Fig. 5). For classification purposes, the resulting 3D surface is converted to a 2D map by computing the average time each point inside the surface requires to reach the boundary. A related study suggests to represent the MHI templates by spatiotemporal volumes Weinland et al. (2006), demonstrating extension to 3D volumes adds robustness to view point variations.
Yilmaz and Shah propose to identify actions based on the differential properties of the *Space-Time Volume* (STV) *Yilmaz and Shah* (2005). An STV is build by stacking the object contours along the time axis (see Fig. 5). Changes in direction, speed and shape of an STV inherently characterize the underlying action. Action sketch is a set of properties extracted from the surface of an STV (e.g., Gaussian curvature) and is shown to be robust to viewpoint changes *Yilmaz and Shah* (2005).

![Figure 5: Left: The spatiotemporal volumes used by Blank et al. (2005) to describe the evolution of an action. The 3D representation is converted to a 2D map by computing the average time taken by a point to reach the boundary. Right: The spatiotemporal surfaces of Yilmaz and Shah (2005) for a tennis serve and a walking sequence. The surface geometry (e.g., peaks, valleys) is used to characterize the action.](image)

Inspired by the success of the object bank method *Li et al.* (2010), Sadanand and Corso propose the “action bank” *Sadanand and Corso* (2012), where actions are described by a large set of detectors acting as the bases of a high-dimensional “action-space”. A relevant idea is presented by *Shao et al.* where the Laplacian of 3D Gaussian filters is used to construct the action space *Shao et al.* (2014). Both previous methods exploit the pyramid structure to enhance robustness across spatial and temporal domains.

**A Statistically Correct Message**

Holistic representations flooded the research in action recognition roughly between 1997 to 2007, since such representations are more likely to preserve the spatial and temporal structure of actions. However, nowadays local and deep representations are favored (*Wang and Schmid*, 2013; *Peng et al.*, 2014b; *Simonyan and Zisserman*, 2014; *Karpathy et al.*, 2014). Various reasons are attributed to this shift. For example, *Dollar et al.* (2005) claim that the holistic approaches are too rigid to capture possible variations of actions (e.g., viewpoint, appearance, occlusions). *Matikainen et al.* (2009) believe that silhouette based representations are not capable of capturing fine details within the silhouette. As such, maybe it is time to change the gear and delve into local and deep solutions!

2. **Local Representation based Approaches**

Local representations for action recognition emerge as a result of the seminal work of Laptev on Space-Time Interest Points (STIPs) *Laptev* (2005). As in the case of images, local representations for action recognition follow the pipeline of *interest point detection → local descriptor extraction → aggregation of local descriptors*. Below, we review the key ideas and major developments for the aforementioned components separately.
2.1 Interest Point Detection

To build an STIP detector, Laptev extends the Harris corner detector Harris and Stephens (1988) to 3D-Harris detector Laptev (2005). In 3D-Harris, in addition to rich spatial structures, temporal significance is required to fire the detector. The idea of the 2D Harris corner detector is to find spatial locations in an image with significant changes in two orthogonal directions. The 3D-Harris detector identifies points with large spatial variations and non-constant motions. An example of such requirement is shown in Fig. 6.

![Figure 6](image)

Figure 6: Marked in red are the detected spatiotemporal interest points obtained with the provided code of Laptev (2005) over this end scene of ballet dance. Spatial changes could be seen the stacked frames across the time axis (marked with an arrow). At this ending scene, the dance keeps her head still. Hence, despite for having significant amount of spatial features, no spatiotemporal interest points were detected on the face. This could be observed on the similarity between the two ends of the spatiotemporal cube extracted on the face. Similarly, in her waist no spatial or spatiotemporal interest point could be detected.

Another widely used 2D interest point detector, the Hessian detector, is also extended to its 3D counterpart in Willems et al. (2008). Unlike the 3D-Harris detector where gradients are used towards detecting interest points, 3D-Hessian detector makes use of the second order derivatives for its decisions.

In certain domains, e.g., facial expressions, Dollar et al. notice that true spatiotemporal corners, as required by the 3D-Harris or 3D-Hessian detector, are quite rare, even if interesting motion is occurring Dollar et al. (2005). While sparseness is desirable to an extent, STIPs that are too rare can lead to problems in action recognition. To overcome this limitation, in Dollar et al. (2005) it is proposed to disintegrate spatial filtering from the temporal one. The resulting detector is shown to respond to any region with spatially distinguishing characteristics undergoing a complex motion Dollar et al. (2005).

Unlike images, action clips are more likely to be obtained in uncontrolled environments. As such, care should be taken in processing videos since the possibility of good features latching into
irrelevant details is high. For example, a shaky camera can fire a series of irrelevant interest points. To address this issue, Liu et al. suggest to prune irrelevant features using statistical properties of the detected interest points Liu et al. (2009). Furthermore, spatiotemporal features obtained from background, known as static features, especially the ones that are near motion regions are useful for action recognition Liu et al. (2009). The relevance of static features for action recognition should not sound counter-intuitive. This is because the background in certain types of videos (e.g., football) can provide useful contextual information for action recognition. Moreover and from psychology we know that human beings are able to recognize many types of actions from still images without motion information.

2.2 Local Descriptors

Let us start with a simple definition, a 3D cuboid or simply a cuboid is a cube constructed from pixels around detected interest points. To obtain the local descriptor at an interest point, earlier works almost unanimously opt for cuboids (Dollar et al., 2005; Laptev, 2005). In 2009, separate studies by Messing et al. (2009) and Matikainen et al. (2009) question the choice of fixed shaped cuboids for action recognition and introduce the notion of trajectories. Below, we first discuss various local descriptors widely used for action recognition, remembering that local descriptors can be employed with both cuboids and trajectories. We then review trajectories and their improvements.

EDGE AND MOTION DESCRIPTORS

Kläser et al. (2008) suggests to use the Histogram of Gradient Orientations as a motion descriptor. While being inspired by the robustness of histogram of oriented gradients in image recognition (Dalal and Triggs, 2005), the descriptor itself is spanned to the spatiotemporal domain, hence named as the \textit{HoG3D} descriptor.

Optical flow fields encode the pixel level motions in a video clip. Exploiting this property, Laptev et al. (2008) propose the Histogram of Optical-flow (HoF) over local regions as a spatiotemporal descriptor. A more robust extension of HoF descriptors is the Motion Boundary Histogram (MBH) introduced in Dalal et al. (2006). MBH is computed over the Motion Boundary field which is the spatial derivative of optical flow fields (see Fig. 7 for an example). Though being rich, computing optical flow fields is computationally expensive. To overcome this difficulty, Kantorov and Laptev (2014) propose to make use of video decompression techniques. More specifically, instead of computing the optical flow fields for obtaining MBH or HoF descriptors, the authors use the motion fields in MPEG compression. This motion field, termed \textit{MPEG Flow}, can be obtained virtually free in the video decoding process.

BINARY PATTERN DESCRIPTORS

Local binary patterns (LBP) are intensity-based 2D descriptors, successfully used in a diverse range of problems including face recognition and texture analysis (Ojala et al., 2002). The LBP descriptor is computed by quantizing the neighborhood of a pixel with respect to its intensity. In Zhao and Pietikainen (2007), various extensions of the 2D LBP descriptors to spatiotemporal domain are introduced. In the Volume LBP (VLBP), local volumes are encoded by the histogram of the binary patterns Zhao and Pietikainen (2007). Despite its simplicity, the number of distinct patterns produced by VLBP can become overwhelming for large neighborhoods. To alleviate this difficulty, in the Local Binary Pattern histograms from Three Orthogonal Planes (LBP-TOP), the descriptor is
Figure 7: The spatial gradients (b), horizontal (c) and vertical (d) motion boundary image for the horse rider in (a). Unlike the spatial gradient which disregards motion information, the motion boundary images stress on the moving object boundaries. Motion boundary images are obtained by computing the gradients of the optical flow fields.

Figure 8: **Left:** The LBP extraction planes of Kellokumpu et al. (2008) for action recognition inspired by the LBP-TOP descriptor of Zhao and Pietikainen (2007). Here, the video stream is considered as a spatiotemporal volume and LBP descriptors are only extracted from the two orthogonal planes to the image plane **Right:** The spatiotemporal covariance descriptor of Sanin et al. (2013) obtained by concatenating local binary patterns on three orthogonal planes, namely $xy$, $xt$ and $yt$ planes (see Fig. 8 for an illustration for the LPB variant of Kellokumpu et al. (2008) introduced for action recognition). The idea of three orthogonal plane is extended in Norouznezhad et al. (2012) nine symmetric planes, albeit for a different type of 3D local descriptor in Norouznezhad et al. (2012).

**From Cuboids to Trajectories**

An spatiotemporal interest point might not reside at the exact same spatial location within the temporal extends of a cuboid. Hence, features extracted from cuboids cannot describe the actual interest point itself. A trajectory is a properly tracked feature over time\(^1\), (see Fig. 9). Extracting local features from trajectories gains its popularity mostly from the work of Messing et al. Messing et al. (2009) and Matikainen et al. Matikainen et al. (2009). Interestingly, both studies use a form of velocity of trajectories as local features.

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1. In 1973 Johansson showed that human subjects could correctly perceive “point-light walkers”, a motion stimulus generated by a person walking in the dark, with points of light attached to the its body. This study resembles the notion of trajectories.
Relative motions (e.g., differences in direction, magnitude and location) between trajectories can characterize certain action categories, especially, the categories that involve human/human interactions (e.g., hand-shaking) as shown by Jiang et al. (2012). Rectifying trajectories using camera motions leads to improvements as shown in Jiang et al. (2012); Wang and Schmid (2013). Jiang et al. Jiang et al. (2012) cluster trajectories to determine the dominant motion in a sequence. The dominant motion is assumed to be caused by the camera and is compensated from original trajectories by subtraction in Jiang et al. (2012) and through affine transformations in Jain et al. (2013). Nevertheless, both studies find the compensation may become misleading if a sizable portion of the video is covered by the actual action. The homography between consecutive frames is also used to estimate the camera motion Wang and Schmid (2013).

Sparse or Dense?

In short, sparse is old, dense is new! While early studies deem for sparse interest points, later several studies show the superiority of dense sampling in both image (Nowak et al., 2006; Fei-Fei and Perona, 2005) and video classification Wang et al. (2009). A comprehensive comparison between various sparse methods and dense sampling for several descriptors for action recognition can be found in Wang et al. (2009).

2.3 Aggregation

Let $\mathcal{V} = \{v_i\}_{i=1}^n$, $v_i \in \mathbb{R}^d$ be a set of local features extracted from a video. For the purpose of action recognition, we need a mechanism to learn from such sets and eventually compare them. Learning algorithms such as Support Vector Machines (SVM) mostly accept only fixed-size vectors and cannot work with sets of varying size (the number of local features varies per video). As such and in order to benefit from various learning techniques, we need a mechanism to aggregate sets of local features into discriminative and fixed-size descriptors. In doing so, machineries based on the concept of Bag-of-Visual Words (BoV) (Csurka et al., 2004) are the most natural choices. In  

2. We note that Mikolajczyk and Uemura propose to make use of homography for compensating camera motions earlier Mikolajczyk and Uemura (2008).
In a nutshell, given a “visual vocabulary” or codebook $\mathcal{D} = \{d_j\}_{i=1}^k$, $d_j \in \mathbb{R}^d$, a notion of similarity/deviation from $\mathcal{D}$ is used as the descriptor for the set $F$.

In the BoV, the histogram of “visual word” occurrences is used as the descriptor. That is the frequency of seeing each visual word $d_j$ as the closest match to the local features $f_i$ determines the descriptor. The work of Dollar et al. (2005) is among the first studies that resort to BoV for action recognition. In its original form, the temporal information is ignored by BoV. To ameliorate this shortcoming, Laptev et al. Laptev et al. (2008) propose the spatio-temporal grids. The main idea is to split a video into several sub-videos, aggregate the local descriptors of each sub-video to form the so-called “channels” and compare videos based on their channel descriptors. An improvement inline with the concept of BoV is the hierarchical BoV Kovashka and Grauman (2010).

More recently, aggregation through the Fisher Vector (FV) (Wang et al., 2011; Peng et al., 2014b; Oneata et al., 2013) encoding becomes the method of choice. The FV encoding Perronnin and Dance (2007) is an aggregation method based on the principle of the Fisher Kernels (Jaakkola and Haussler, 1998), which combines the benefits of generative and discriminative approaches to pattern classification. Briefly, the key differences between BoV and FV are I) BoV employs hard-assignment towards aggregation while FV benefits from soft-assignment, and II) if the underlying model of feature generation is assumed to be a Gaussian Mixture Model, BoV only considers the zeroth-order information (occurrences) in aggregation while FV benefits from both first and second-order statistics. The FV encoding along trajectories delivered the state-of-the-art performances in several studies (see for example Wang et al. (2011); Wang and Schmid (2013)). Stacked FVs which can be understood as an extension of spatiotemporal grids of Laptev et al. (2008) to FVs is introduced in Peng et al. (2014b). A detailed analysis of FVs in action recognition is presented in Oneata et al. (2013).

FVs are usually very high dimensional (Jgou et al., 2010) and in certain applications redundant. A simplified version of FV, known as Vector of Locally Aggregated Descriptor (VLAD) (Jgou et al., 2010; Arandjelovi´c and Zisserman, 2013), removes the second-order information from the descriptor. As a result, the dimensionality of VLAD descriptors is almost half of FVs. In Jain et al. (2013); Xing et al. (2015); Kantorov and Laptev (2014); Sun and Nevatia (2013) VLAD descriptors obtained from spatiotemporal features are employed for action recognition. A comparison of speed and accuracy of FV against VLAD can be found in Kantorov and Laptev (2014); Wu et al. (2014).

We conclude this part by describing studies that explicitly incorporate temporal information in generating video descriptors. Fernando et al. Fernando et al. (2015) propose to represent a video by a ranking machine. That is, given the frame descriptors, a hyperplane that ranks the frames according to their temporal order is used to represent the video. Gaidon et al. Gaidon et al. (2011) propose the concept of atomic-actions or actoms which can be understood as a temporally structured extension of the BoV. An actom$^3$ is the building block of an action and has a variable temporal extend. Histograms of visual words, similar to the traditional BoV approach, is used to describe an actom, albeit with a subtle difference. Features that are located in the middle of an actom receive higher weights towards generating the histogram while the contribution of features away from the center is attenuated.

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3. A relevant idea to the concept of actoms is proposed by Niebles et al. earlier Niebles et al. (2010).
3. Deep Architectures for Action Recognition

We are witnessing a significant advancement in numerous learning tasks thanks to data driven approaches. In particular, deep neural networks such as Convolutional Neural Networks (CNN) (Le-cun et al., 1998) have become the method of choice in learning image contents (Krizhevsky et al., 2012; Chatfield et al., 2014; Sutskever et al., 2014; Szegedy et al., 2015). Generally speaking, the problem of learning is to determine a complicated decision function from the available data. In deep architectures this is achieved by composing multiple level of nonlinear operations. Searching the parameter space of deep architectures is not an easy job given the non-convexity of the decision surface. Learning algorithms based on the gradient descent approach along the computational power of new hardware have been shown to be successful when large amount of annotated data is available (Wang et al., 2015b; Srivastava et al., 2015b; He et al., 2015).

Our intention in this section is to discuss deep models that have been used (or can potentially be used) to address the problem of learning actions from videos. From a taxonomical point of view, we can identify three categories of architectures applied to action recognition, namely,

- Spatiotemporal networks
- Multiple stream networks
- Deep generative networks
- Temporal Coherency Networks

Below, we discuss each category in detail and provide pointers to open questions and possible improvements. We also bring the notion of temporal coherency into perspective.

3.1 Spatiotemporal Networks

The convolutional architecture effectively utilizes the image structure in reducing the search space of the network by “pooling” and “weight-sharing” (see Fig. 3.1 (left) for a conceptual diagram). Pooling and weight-sharing also contribute to achieving robustness across scale and spatial variations. Analyzing filters learned by CNN architectures suggests that the very first layers learn low level features (e.g., Gabor-like filters) while top layers learn high level semantics (Zeiler and Fergus, 2014). This further extends the use of convolutional networks as generic feature extractors.

A direct approach to action recognition using deep networks is to arm the convolutional operation with temporal information. To achieve this, 3D convolutional networks are introduced in Ji et al. (2010). A 3D convolution network, as the name suggests, uses 3D kernels (filters extended along the time axis) to extract features from both spatial and temporal dimensions, hence is expected to capture spatiotemporal information and motions encoded in adjacent frames (see Fig. 3.1 for a conceptual diagram). In practice, it is important to provide the network with supplementary information (e.g., optical flow) to facilitate training. Empirically, Ji et al. (2010) show that the 3D convolutional networks outperform the 2D frame based counterparts with a huge margin.
Notice that, the 3D convolutional networks have a very rigid temporal structure. The network accepts a predefined number of frames as the input (for example in Ji et al. (2010) the input consists of only 7 frames). While having fixed spatial dimension is somehow defensible (spatial pooling tends to provide robustness across scales), it is unclear why a similar assumption should be made across the temporal domain. Even less clear is the right choice of the temporal span as macro motions in different actions have different speeds and hence different spans.

To answer how temporal information should be fed into convolutional networks, various fusion schemes are investigated. Ng et al. (2015) explored temporal pooling and concluded that max pooling in the temporal domain is preferable. Karpathy et al. (2014) proposed the concept of slow fusion to increase the temporal awareness of a convolutional network. In slow fusion, a convolutional network accepts several, yet consecutive, parts of a video and processes them through the very same set of layers to produce responses across temporal domain. These responses are then processed by fully connected layers to produce the video descriptor (see Fig. 11 for details).

Figure 10: Spatiotemporal operations: 2D convolution (blue), 3D convolution on frame stacks (red) as in Ji et al. (2010), conventional spatial max-pooling (brown), and temporal max-pooling (yellow) as in Ng et al. (2015).

Table 2: Parameters of Ji et al. (2010)

| Layer | Parameters |
|-------|------------|
| Input | (60 x 40)-7 Frames |
| Hardwired | Grayscale-7 Ch. |
| Conv 1 - ReLU 2 Groups | (7x7x3) |
| Pool 1 | (2x2) - Spatial |
| Conv 2 - ReLU 3 Groups | (7x6x3) |
| Pool 2 | (3x3) - Spatial |
| Conv 3 - ReLU | (7x4) |
| FC | No. of Classes |
Other forms of fusion includes early fusion (e.g., the 3D convolutional network Ji et al. (2010)) where the network is fed with a set of adjacent frames and late fusion where frame-wise features are fused at the final fully connected layer Karpathy et al. (2014). Karpathy et al. also show that a multi-resolutional approach using two separate networks not only boosts the accuracy but also reduces the number of parameters to be learned. This is due to the fact that each leg of the network (i.e., fovea and context streams in Fig. 11) accepts smaller inputs. We note that the fovea stream receives the central region of a frame to take advantage of the camera bias that exists in many videos since the object of interest often occupies the center region.

To exploit the temporal information, some studies resort to use of recurrent structures. The works of Baccouche et al. (2011) and Donahue et al. (2015) tackle the problem of action recognition through a cascade of convolutional networks and a class of Recurrent Neural Networks (RNN) Robinson and Fallside (1988) known as Long-Short Term Memory (LSTM) Hochreiter and Schmidhuber (1997) networks. As the word recurrent suggests, an RNN (see Fig. 12) models the dynamics using a feedback loop. The typical form of an RNN block accepts an external signal \( x(t) \in \mathbb{R}^n \) and produces an output \( z(t) \in \mathbb{R}^m \) based on its hidden-state \( h(t) \in \mathbb{R}^r \) by

\[
\begin{align*}
    h(t) &= \sigma(W_x x(t) + W_h h(t-1)) , \\
    z(t) &= \sigma(W_z h(t)) .
\end{align*}
\]

Here, \( W_x \in \mathbb{R}^{r \times n} \), \( W_h \in \mathbb{R}^{r \times r} \) and \( W_z \in \mathbb{R}^{m \times r} \). Obviously, an RNN is a realization of the Linear Dynamical Systems (LDS) and hence rich enough to model video sequences.

Generally speaking, training RNNs is not an easy task due to the issue of vanishing (or exploding) gradient. For the sake of discussion, assume the recursive expression of an RNN cell has the form \( h(t) = w_h h(t-1) \) with \( x, h, z \in \mathbb{R} \). This recursive form can be unfolded as \( h(t) = w_h w_h h(t-2) = w_h^t h(0) \). As such, the network either learns short term dependencies (if \( w_h < 1 \)) or very long dependencies (if \( w_h > 1 \)) which is not desirable Bengio et al. (1994). LSTM cells (shown...
in Fig.12) solves this issue by constraining the states and outputs of the RNN cell through control gates.

To classify actions, Baccouche et al. (2011) suggests to feed an LSTM network with features extracted from a 3D convolutional network. The two networks, i.e., 3D convolutional network and the LSTM network are trained separately. That is, first the 3D convolutional network is trained using annotated action data. Once the 3D convolutional network is obtained, the convolutional features are used to train the LSTM network (see Fig. 13 and Table. 3 for implementation details).
Figure 13: The network structure of (Baccouche et al., 2011)

| Layer       | Parameters                  |
|-------------|-----------------------------|
| Conv 1 - ReLU | 7 Filters - (7x7x5)        |
| Pool 1      | (2x2) - Spatial             |
| Conv 2 - ReLU | 35 Filters - (5x5x3)       |
| Pool 2      | (2x2) - Spatial             |
| Conv 3 - Linear | 35 Filters - (5x5x3)     |
| FC 1 (included only in training) | -                         |
| FC 2 (included only in training) | No. of Classes             |
| RNN LSTM    | 50                          |
| FC          | No. of Classes              |

Table 3: The network parameters of Baccouche et al. (2011)

Another architecture based on LSTM is proposed by Donahue et al. (2015) to exploit end-to-end training over the composite network as shown in Fig. 14 and Table. 4. The resulting structure named Long-term Recurrent Convolutional Network (LRCN) has been shown to be successful not only in recognizing actions but also in captioning images and videos. With the end-to-end learning and CNN-LSTM convolution, the spatiotemporal receptive filter parameters are computed in a data driven fashion.
3.2 Multiple Stream Networks

In visual perception, the Ventral Stream of our visual cortex processes object attributes such as appearance, color and identity. The motion an object and its location is handled separately through the Dosaral Stream Goodale and Milner (2003). A class of deep neural networks opted for separating appearance based information from motion related ones for action recognition Simonyan and Zisserman (2014).

Simonyan and Zisserman (2014) introduced one of the first multiple-stream deep convolutional networks where the structure of two parallel networks are selected as VGG-16 of Chatfield et al.
(2014) for action recognition (see Fig. 15 for details). The so called spatial stream network accepts raw video frames while the temporal stream network gets optical flow fields as input. The following observations are made in Simonyan and Zisserman (2014):

- **Pretraining for the spatial stream network.** Training the spatial stream network from scratch is not the best practice. Empirically, fine-tuning a pretrained network on the ILSVRC-2012 leads to higher accuracy.

- **Early fusion for the temporal stream network.** Stacking optical flow fields at the input of the temporal stream network (i.e., early fusion) is beneficial.

- **Multi-task learning for the temporal stream network.** The temporal stream network needs to be trained purely from the available video data. This was observed to be challenging for small and medium-size datasets in very deep networks. To circumvent this difficulty, the temporal stream network is modified to have more than one classification layer. Each classification layer operates on a specific dataset (e.g., one operates on HMDB-51 and one on UCF-101 in Simonyan and Zisserman (2014)) and responds only to the videos coming from the respective dataset. This architecture is a realization of the multi-task learning, aiming to learn a representation, which is not only applicable to the task in question, but also to other tasks.

Extensions of the two stream network include the work in Wang et al. (2015a) where dense trajectories Wang and Schmid (2013) constructed from convolutional features of the two-stream network are aggregated using the Fisher vector, and Wu et al. (2015) where a third stream using audio signal is added to the network.

Figure 15: **Left:** Two-stream network by Simonyan and Zisserman (2014) with color and stacked optical-flow frames. **Right:** The multi-stream architecture proposed by Wu et al. (2015), with the added audio stream and the LSTM paths for learning long-term cues.
3.3 Deep Generative Models

The potential reward of devising deep models that require little or no supervision is beyond imagination, given the vast and ever increasing videos available on the Web.

A good generative model is the one that can learn the underlying distribution of data accurately. Generative models for sequence analysis (Sutskever et al., 2014; Srivastava et al., 2015a) are mainly used to predict the future of a sequence. That is, given a sequence \( \{x_1, x_2, \cdots, x_t\} \), one may deem to learn a model to predict its future (e.g., the next instance \( x_{t+1} \)). This task is different from methods discussed in Section § 3.1 in nature as it does not require labels for training. However, accurate predictions is achieved if contents and dynamics (e.g., motion primitives) of the sequence can be captured by the model to good extent. Deep-generative architectures Vincent et al. (2008); Goodfellow et al. (2014); Hochreiter and Schmidhuber (1997) aim this goal, i.e., learning from temporal data in an unsupervised matter. In video analysis where annotating data is costly, unsupervised techniques are preferred over supervised ones.

Envisaging possible potentials, in this part we review notable examples of deep generative architectures without confiding ourselves to studies that have been directly applied to action recognition.

3.3.1 Dynencoder

Inspired by LDS modeling Doretto et al. (2003), the work in Yan et al. (2014) introduced Dynencoder, a class of deep auto-encoders, to capture video dynamics. In its most basic form, a Dynencoder constitutes of three layers. The first layer maps the input \( x_t \) to the hidden states \( h_t \). The second layer is a prediction layer that predicts the next hidden states, \( \hat{h}_{t+1} \), using current ones (i.e., \( h_t \)). The final layer is a mapping from the predicted hidden states \( \hat{h}_{t+1} \) to generating estimated input frames \( \tilde{x}_{t+1} \). To reduce the training complexity, the parameters of the network is learned in two stages. In the pretraining stage, each layer is trained separately. Once pretraining is completed, an end-to-end fine tuning is performed. A conceptual structure of Dynencoder is given in Fig. 16.

Dynencoder is shown to be successful in synthesizing dynamic textures. One can think of a Dynencoder as a compact way of representing the spatiotemporal information of a video. As such, the reconstruction error of a video given a Dynencoder can be used as a mean for classification.

3.3.2 LSTM Autoencoder Model

Generative models for action recognition are expected to discover long-term cues and deep models with LSTM cells are natural choices. To this end, Srivastava et al. (2015a) introduced the LSTM autoencoder model as illustrated in Fig. 17. The LSTM autoencoder consists of two RNNs, namely the encoder LSTM and the decoder LSTM. The encoder LSTM accepts a sequence (as input) and learns the corresponding compact representation. The states of the encoder LSTM contain the appearance and dynamics of the sequence. As such, the compact representation of a sequence is chosen to be the states of the encoder LSTM. The decoder LSTM receives the learned representation to reconstruct the input sequence. For more details, see Fig. 17.

The LSTM autoencoder can be used to predict the future of a sequence as well. In practice, a composite model that both reconstructs the input sequence and predicts its future delivers the most accurate responses.
3.3.3 Adversarial Models

To sidestep various difficulties in training deep generative models, Goodfellow et al. (2014) introduced the adversarial networks where a generative model competes with a discriminative model known as an adversary. The discriminative model learns to determine whether a sample is coming from the generative model or the data itself. During training, the generative model learns to generate samples that share more similarities to the data to pass the adversary model’s test while adversary model improves its judgments on whether a given sample is authentic or not.

To this end, Mathieu et al. (2015) adopted the adversarial methodology to train a multi-scale convolutional network for video prediction. They exploit adversarial training to have convolutional networks that avoid pooling layers. They also provide a discussion on the advantages of pooling in generative models.

3.4 Temporal Coherency Networks

Before concluding this part, we would like to bring the notion of temporal coherency into perspective. Temporal coherence is a form of weak supervision and states that consecutive video frames are correlated both semantically and dynamically (i.e., abrupt motions are less likely). A sequence is coherent if its frames are in the correct temporal order. Temporal coherency can be learned by a deep model if the model is fed by ordered and disordered sequences as positive and negative samples, respectively. This concept has been used by Goroshin et al. (2015) and Wang and Gupta (2015) to learn robust visual representations from unlabeled videos.

In Misra et al. (2016), how temporal coherency can be used to train deep models for action recognition and pose estimation has been explored. In particular, a Siamese Network (see Fig. 18)
Figure 17: The composite generative LSTM model by Srivastava et al. (2015a). The internal states (represented by the circle inside) of the encoder LSTM captures a lossy statement of the input sequence (i.e. frames 1, 2 and 3). The states thereafter are copied into two decoder models, which are reconstructive and predictive. The reconstruction decoder attempts to reconstruct original frames in the reverse order. The predictive model is trained on predicting the future frames 4, 5 and 6. The colors on the state markers indicate the presence of information from a particular frame.
Figure 18: The Siamese Triplet network used by Misra et al. (2016). Each of these networks is considered to contain a motion and pose representation of actions.

is trained with tuples to determine whether a given sequence is coherent or not. Empirically, it has been shown that

- Compared to other labeled pretraining methods, e.g. ImageNet, tuple verification based learning gives more attention to human poses.
- Selection of tuples in motion rich frames would avoid ambiguities between positive and negative tuples.
- Compared to networks trained from scratch, pretrained networks based on the temporal coherency have potential to improve the accuracy.

Another related study is Wang et al. (2016) where an action is split into three phases, with two phases being important for classification. More specifically, a video with frames \( \{x_1, x_2, \ldots, x_n\} \) is split into the precondition set \( X_p = \{x_1, x_2, \ldots, x_p\} \) and effect set \( X_e = \{x_e, x_{e+1}, \ldots, x_n\} \). The cardinality of both sets are learned by the deep model. An action is then identified by the transformation required to map high-level descriptor extracted from \( X_p \) to high-level descriptor extracted from \( X_e \). In particular, the high-level descriptor and transformations are learned using the Siamese Network (see Fig. 19 for details).

For completeness, we review Ranzato et al. (2014) where it is argued that the success of language modeling through RNNs is a result of the discrete information space. Based on this, they induce a discrete structure for video frames by quantizing them with a representative collection of image patches. They make the observation that natural videos may not include the dynamism inherent in word sequences, which may be a reason for the observed superiority of language models over video models. Based on this, they train a Recurrent Convolutional Neural Network on predicting
longer sequences. By learning on longer sequences they make the network rely on its feedback for a longer time, which may increase its robustness to test time errors.

4. Quantitative Performance Analysis

In this section we present a quantitative performance analysis of the existing action recognition methods on 7 benchmark datasets.

4.1 Datasets

As in any recognition problem, performance of the action recognition methods are reported on a set of informally standardized datasets. A comprehensive list of such datasets and their details are given in Table 5.

In parallel to the evolution of solutions, these datasets too have evolved in their complexity. The complexity of a dataset could be described as how close the content is to the reality. In Table 5, datasets such as KTH and Weizmann listed on the top contain human actions obtained in controlled environments and conditions (e.g., limited camera motion, almost zero background clutter). Furthermore, their scope is limited to basic actions such as walking, running and jumping. With the increasing complexity, we get datasets that are composed of YouTube videos, movies and television broadcast snippets including HMDB-51, UCF-101, Olympic-Sports and Sports 1M. YouTube videos are mostly recorded by nonprofessionals with handycams. As a result, they contain camera motion and varying resolution. Furthermore, these datasets include viewpoint variations.

Professional sport events and movies are generally filmed from several viewpoints, and then edited into one stream. This incurs severe viewpoint variations to the dataset. Such inconsistencies are not only found among videos but also observable in the very same clip. At the very extreme of this complication, some clips contain interrupting scenes. For example, in Sports 1M, there are scenes of spectators and banner adverts.
Not all action classes in these datasets can be distinguished by motion. In such situations, the objects contributed to the action become important (e.g., kicking and kick ball in HMDB-51). Certain actions are defined by the related objects. A good example for this is the 23 distinct types of billiard categories given in Sports 1M. In addition to actions defined by the full body motion, some actions are defined based on facial expressions. Examples are facial expression categories such as smiling, eating and laughing in Hollywood2, UCF-101, HMDB-51. Human-human interactions such as hugging, kissing and handshaking are also present in some datasets as action classes.

Size of a dataset is an important factor to avoid overfitting and achieve generalization. As long as deep neural solutions are considered, access to a large corpus of data is a must. Several methods resort to data augmentation, multi-task learning and image based pretraining to mitigate this problem. Though video data constantly increases, most of it remains unavailable since annotation is expensive and tedious. To overcome this, Laptev et al. (2008) suggested using meta information such as movie scripts. Similarly, Karpathy et al. (2014) utilizes YouTube topics in annotating their Sports 1M dataset.

4.2 Recognition Results

Table 6 presents a comprehensive list of accuracies for 24 action recognition methods with 37 variant on 7 datasets. Here, we included reported results from original papers on action datasets in which the context is similar to real life settings. Instead of considering cases individually, our intention here is give the reader a high level comparison between various classes of solutions.

A quick look at Table 6 reveals that the highest accuracies on the HMDB-51 dataset with near 7000 videos is obtained by Peng et al. (2014b), Wang et al. (2015a), Lan et al. (2015) and Hoai and Zisserman (2015). Among these, only Wang et al. (2015a) is a deep method. Labeling Wang et al. (2015a) as a deep solution is also not adequate as the method benefits from the notion of trajectories to great degrees. This observation raises the question, are deep solutions not suitable for motion recognition?

To draw some conclusions, let us check the larger UCF101 dataset with more than 13,000 videos. The highest accuracies belong to Wu et al. (2015), Wang et al. (2016), Wang et al. (2015a) and Wang et al. (2015c). In this case, all the top performers are deep solutions. Although direct comparisons are not possible, it seems that the performance of deep solutions can surpass the handcrafted solutions if large corpus of data is available, which is not surprising.

5. Conclusion

A machine that could recognize what we do through visual data is of utmost use. In this survey, we investigated several aspects of the existing solutions for action recognition. After a review of handcrafted representation based methods, we examined deep neural network based solutions. We presented a comparative analysis of these two prevailing category of research work and reported consolidated results on a benchmark datasets.
| Dataset            | Source                          | No. of Videos | Video Duration | Training Protocol | No. of Classes | Example Classes          |
|--------------------|---------------------------------|---------------|----------------|-------------------|----------------|--------------------------|
| KTH                | (Schuldt et al., 2004)          | 600           | 4s             | Training and Testing |               | Walk, Jog, Run            |
| Weizmann           | (Blank et al., 2005)            | 90            |                 | Leave one out cross | -              | Walk, Jump, Dive          |
| UCF-Sports         | (Rodriguez et al., 2008)        | 150           | 6.39s          | Classification accuracy on |                | Diving, Golf-swing, Kicking |
| Hollywood2         | (Marszalek et al., 2009)        | 1707          |                 | Classification accuracy on |                | Answer phone, Eat, Handshake |
| Olympic Sports     | (Niebles et al., 2010)          | 16            | 50             | Classification accuracy on |                | High-jump, Long-jump, Tripple-jump |
| HMDB-51            | (Kuehne et al., 2013)           | 7000          |                 | Classification accuracy of |                | Brush-hair, Kick, Kiss   |
| UCF-50             | (Reddy and Shah, 2013)          | 50            |                 | Leave out one cross | -              | Rowing, Fencing, Punch    |
| UCF-101            | (Soomro et al., 2012)           | 13320         |                 | Classification accuracy on |                | Diving, Skiing, Apply Eye |
| Sports 1-M         | (Karpathy et al., 2014)         | 1133158       |                 | 70% of as training while testing and validation sets | -              | Cricket, disc golf, gliding |
| Table 5: Datasets for action recognition |               |               |                |                   |                |                          |
Table 6: Accuracy of action recognition techniques (Numbers are true recognition percentages).

| Paper                                      | Method                                      | Dataset       |
|---------------------------------------------|---------------------------------------------|---------------|
|                                             |                                             | UCF101 | UCF50 | UCF-Sports | Hollywood2* | Olympic Sports | Sports1M |
| Wang et al. (2011)                         | Dense Traj (Traj + HOG+HOF+MBH)             | 88.2     | 58.3  |
| Kliper-Gros et al. (2012)                   | Motion Interchange Patterns                | 29.2     | 68.5  |
| Safanand and Corso (2012)                   | General                                     | 26.9     | 76.4  |
|                                             | Video Wise                                  |          |       |
|                                             | Group Wise                                  | 57.9     |       |
| Omerata et al. (2013)                       | MBH + SIFT + Sqrt + L2 Normalization       | 54.8     | 90    | 63.3 | 82.1 |
| Yang et al. (2013)                          |                                             |          |       |
| Wang and Schmid (2013)                      | Without Human Detector                      | 55.9     | 90.5  | 63  | 90.2 |
|                                             | With Human Detector                         | 57.2     | 91.2  | 64.3 | 91.1 |
| Jain et al. (2013)                          | Traj + HOG + HoF + MBH + DCS on w-flow      | 52.1     |       | 62.5 |
| Peng et al. (2014b)                         | Stacked FVs + FV                            | 66.8     |       |      |
| Peng et al. (2014a)                         | Hybrid-BoW                                  | 61.1     | 87.9  | 92.3 |
| Kantorov and Laptev (2014)                  | MPEG-Flow : VLAD encodings of              | 46.3     |       |      |
| Asandon et al. (2014)                       | SDT tree ATEP                               | 41.3     | 54.4  | 85.5 |
| Antonyan and Zisserman (2014)               | Two-stream(VGGNet-16)                       | 59.4     | 88.0  |      |
| Karpathy et al. (2014)                      | Transfer Learning on Sports 1M              |          | 65.4  |      |
|                                             | Clip Hit @ 1 - Slow Fusion                  |          |       | 41.9 |
|                                             | Video Hit @ 1 - Slow Fusion                 |          |       | 60.9 |
| Wang et al. (2015b)                         | Two-Stream (CharfiaNet)                     |          | 88.0  |      |
|                                             | Two-Stream (GoogLeNet)                      |          | 89.3  |      |
|                                             | Two-Stream (VGGNet-16)                      |          | 91.4  |      |
| Wang et al. (2015a)                         | TDD + Wang and Schmid (2013)                | 65.9     | 91.5  | 72.4 |
|                                             | TDD (Only)                                  | 63.2     | 90.3  | 73.1 |
| Ng et al. (2015)                            | Conv Pooling Hit@1 (Best)                   |          | 88.2  |      |
|                                             | LSTM Hit@1 (Best)                           |          | 88.6  |      |
|                                             | Conv Pooling (Image + Opt Flow)             |          |       |      |
|                                             | LSTM (Image + Opt Flow)                     |          |       |      |
| Fernando et al. (2015)                      | Rank Pooling                                | 63.7     | 73.7  |      |
| Domhan et al. (2015)                        | LRCN- Weighted Average of RBG + Flow        |          | 82.9  |      |
| Wu et al. (2015)                            | Adaptive Multi-Stream Fusion                |          | 92.6  |      |
| Jiang et al. (2015)                         | TrajShape+TrajMF                            | 48.4     | 78.5  | 55.2 | 80.6 |
|                                             | TrajShape+TrajMF+ Wang and Schmid (2013)    | 57.3     | 87.2  | 65.4 | 91   |
| Lan et al. (2015)                           | Multi-Skip Feat. Stacking                   | 65.1     | 89.1  | 94.4 | 68.0 | 91.4 |
| Hoan and Zisserman (2015)                   | Proposed SSD + RCS                          | 62.2     |       | 72.7 |
| Mirza et al. (2016)                         | ImageNet pretrain + tuple verification      | 29.9     |       |      |
|                                             | HMDB + UCF101 Labels Only                   | 30.6     |       |      |
| Wang et al. (2016)                          | Proposed Only (RGB + Opt Flow Networks)     | 62       | 92.4  |      |
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