A Survey of Advances in Vision-Based Human Motion Capture and Analysis

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Abstract

This survey reviews advances in human motion capture and analysis from 2000 to 2006, following a previous survey of papers up to 2000 [206]. Human motion capture continues to be an increasingly active research area in computer vision with over 300 publications over this period. A number of significant research advances are identified together with novel methodologies for automatic initialization, tracking, pose estimation and movement recognition. Recent research has addressed reliable tracking and pose estimation in natural scenes. Progress has also been made towards automatic understanding of human actions and behavior. This survey reviews recent trends in video based human capture and analysis, as well as discussing open problems for future research to achieve automatic visual analysis of human movement.

1 Introduction

Automatic capture and analysis of human motion is a highly active research area due both to the number of potential applications and its inherent complexity. The re-

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search area contains a number of hard and often ill posed problems such as inferring the pose and motion of a highly articulated and self-occluding non-rigid 3D object from images. This complexity makes the research area challenging from a purely academic point of view. From an application perspective computer vision-based methods often provide the only non-invasive solution making it very attractive.

Applications can roughly be grouped under three titles: Surveillance, control, and analysis. *Surveillance applications* cover some of the more classical types of problems related to automatically monitoring and understanding locations where a large number of people pass through such as airports and subways. Applications could for example be: people counting or crowd flux, flow and congestion analysis. Newer types of surveillance applications - perhaps inspired by the increased awareness of security issues - are analysis of actions, activities and behaviors both for crowds and individuals. For example for queue and shopping behavior analysis, detection of abnormal activities, and person identification.

Control applications where the estimated motion or pose parameters are used to control something. This could be interfaces to games, e.g., as seen in EyeToy [3], Virtual Reality or more generally: Human Computer Interfaces. However, it could also be for the entertainment industry where the generation and control of personalized computer graphic models based on the captured appearance, shape, and motion are making the productions/products more believable.

Analysis applications such as automatic diagnostics of orthopedic patients or analysis and optimization of an athletes' performances. Newer applications are, annotation of video as well as content-based retrieval and compression of video for compact data storage or efficient data transmission, e.g., for video conferences and indexing. Another branch of applications is within the car industry where much vision research is currently going on in applications such as automatic control of airbags, sleeping detection, pedestrian detection, lane following, etc.

The number of potential applications, the scientific complexity, the speed and price of current hardware, and the focus on security issues have intensified the effort within the computer vision community towards automatic capture and analysis of human motion. This is evident by looking at the number of publications, special sessions/issues at the major conference/journals as well as the number of workshops directly devoted to this topic. Furthermore, the major funding agencies have also focused on this research field - especially the surveillance area.

The increased interest in this area has led to a large body of research which has been digested in a number of surveys. Aggarwal *et al.* [10] reviewed papers on articulated and elastic nonrigid motion published prior to 1995. Cedras and Shah [46] reviewed methods for motion extraction published prior to 1995. Ju [152] reviewed methods for motion estimation and recognition published prior to 1996. Aggarwal and Cai [9] reviewed methods for motion extraction published prior to 1998. Gavrila [99] reviewed methods for motion estimation and recognition published prior to 1998. Moeslund and Granum [206] reviewed methods for initialization, tracking, pose estimation and recognition published prior to 2001. Buxton [40] reviewed methods on recognition published prior to 2002. Wang *et al.* [314] reviewed methods for detection, tracking and recognition published prior to 2002. Hu *et al.* [135] reviewed methods for surveillance published prior to 2004. Aggarwal and Park [11] reviewed methods for recognition published prior to 2005. Even though some of these surveys are recent, it should be noted that the number of papers reviewed after 2000 are: 6 [40], 14 [314], 54 [135], and 10 [11].

In the relatively short period since 2000 a massive number of papers 300+ have been published advancing state of the art. This indicates increased activity in this research area compared to the number of papers identified in previous surveys : 87 papers [99]; 155 papers [206]; and 164 papers [314]. Recent contributions have among other things addressed the limiting assumptions introduced in previous approaches [206]. For example, many systems now address natural outdoor scenes and operate on long sequences of video containing multiple (occluded) people. This is possible due to more advanced segmentation algorithms. Other examples are model-based pose estimation where the introduction of learnt motion models and stochastic sampling methods have helped to achieved much faster and more precise results. Also within the recognition area there have been significant advances in both the representation and interpretation of actions and behavior.

Due to the significance of recent advances within this field we present the current survey. The survey is based on 280 recent papers (2000 - 2006) and structured using the functional taxonomy presented in the 2001 survey by Moeslund and Granum [206]. That is, *Initialization* covering advances in methods for ensuring that a system commences its operation with a correct interpretation of the current scene. *Tracking* covering advances in methods for segmenting and tracking humans in one or more frames. *Pose estimation* covering advances in methods for estimating the pose of a human in one or more frames. *Recognition* covering advances in methods for recognizing the identity of individuals as well as the actions, activities and behaviors performed by one or more humans in one or more frames.

Inspired by [206] we also provide a visual overview of all the recent referenced papers, see table 1. For readers new to this field it is recommended to read [206] before preceding with the survey at hand. In fact the survey at hand can be seen as sequel to [206].

2 Model Initialization

Initialization of vision-based human motion capture and analysis often requires the definition of a humanoid model approximating the shape, appearance, kinematic structure and initial pose of the subject to be tracked. The majority of algorithms for 3D pose estimation continue to use a manually initialized generic models with limb lengths and shape which approximate the individual. To automate the initialization and improve the quality of tracking a limited number of authors have investigated the recovery of more accurate reconstructions of the subject from single or multiple view images.

Initialization captures prior knowledge of a specific person or movement which can be used to constrain tracking and pose estimation. A priori knowledge used in human motion capture can be broken into a number of sources: kinematic structure; 3D shape; color appearance; pose; and movement. In this section we review recent research which advances estimation of kinematic structure, 3D shape and appearance. Initialization of appearance is commonly an integral part of the tracking and pose estimation and is therefore also considered in conjunction with specific approaches in sections 3 and 4. Pose detection as a pre-requisite to human motion reconstruction is reviewed in section 4.1. A recent trend in pose estimation has been the use of prior models of human motion which is reviewed in section 4.3.3.

2.1 Kinematic structure initialization

The majority of vision-based tracking systems assume a priori a humanoid kinematic structure comprising a fixed number of joints with specified degrees-of-freedom. The kinematic initialization is then limited to estimation of limb lengths. Commercial marker-based motion capture systems typically require a fixed sequence of movements which isolate individual degrees-of-freedom. The known correspondence between markers and limbs together with reconstructed 3D marker trajectories during movement are then used to accurately estimate limb lengths. Hard constraints on left-right skeletal symmetry are commonly imposed during estimation. A number of approaches [22,24,231,294] have addressed initialization of body pose and limb lengths from manually identified joint locations in monocular images Anthropometric constraints between ratios of limb lengths are imposed to allow estimation of the kinematic structure up to an unknown scale factor.

Direct estimation of the kinematic structure from sequences of a moving person has also been investigated. Krahnstover *et al.* [170,169] present a method for automatically initialising the upper-body kinematic structure based on motion segmentation of a sequence of monocular video images. Song *et al.* [285] introduce an unsupervised learning algorithm which uses point feature tracks from cluttered monocular video sequences to automatically construct triangulated models of whole-body kinematics. Learnt models are then used for tracking of walking motions from lateral views. These approaches provide more general solutions to the problem of initialising a kinematic model by deriving the structure directly from the scene.

Methods that derive the kinematic structure from 3D shape sequences reconstructed from multiple views have also been proposed. Cheung *et al.* [51] initialize the kinematic structure from the visual-hull of a person moving each joint independently. A full skeleton together with the shape of each body part is obtained by alignment of the segmented moving body parts with the visual-hull model in a fixed pose. More general frameworks are presented in [37,57] to estimate the underlying skeletal spine structure from a temporal sequence of the 3D shape. The spine is estimated from the shape at each frame and common temporal structures identified to estimate the underlying structure. This work demonstrates reconstruction of approximate kinematic structures for babies, adults and animals.

Initialising the joint angle limits on the human kinematic structure is an important problem to constrain motion estimation to valid postures. Manual specification of joint angle limits has been common in many motion estimation algorithms using anthropometric data. This does not take into account the complex nature of joint limits and coupling between limits for different degrees-of-freedom. To overcome these limitations recent research has investigated learning models of pose limits and correlations. Anthropometric models for the relationship between arm joint angles (shoulder, elbow, wrist) have been used to provide constraints in visual tracking and 3D upper-body pose estimation [207,212,218]. Demirdjian [80] constrain upper-body pose in tracking by projection onto a learned motion manifold. Recent research has investigated the modelling of joint limits from measurements of human motion captured using marker based systems[125,126] and from clinical data[211].

This is demonstrated to improve the performance of human pose estimation for complex upper-body movement.

Increasingly, human motion capture sequences from commercial marker-based systems have been used to learn prior models of human kinematics and specific motions to provide constraints for subsequent tracking. Similarly motion capture databases [1,2,4] have recently been used to syntheses image sequences with know 3D pose correspondence to learn a priori the mapping from image to pose space for reconstruction .

2.2 Shape Initialization

A generic humanoid model is used in many video-based human motion estimation techniques to approximate a subjects shape. Representations have used either simple shape primitives (cylinders, cones, ellipsoids, super-quadrics) or a surface (polygonal mesh, sub-division surface) articulated using the kinematic skeleton [206]. A number of approaches have been proposed to refine the generic model shape to approximate a specific person.

In previous research [128] a generic mesh model was refined based on front and side view silhouettes taken with a single camera. Texture mapping was then applied to approximate detailed surface appearance. Recently simultaneous capture from multiple calibrated views has been used [45,239,287] to achieve more accurate shape and appearance. Plaenkers and Fua [239] initialize upper-body shape by fitting an implicit ellipsoidal metaball representation to stereo point clouds prior to tracking. Carranza *et al.* [45] fit a generic mesh model to multiple view silhouette images of a person in a fixed pose prior to tracking whole-body motion. Starck and Hilton [287] reconstruct whole-body shape and appearance for a person in an arbitrary pose by optimizing a generic mesh model with respect to both silhouette, stereo and feature correspondence constraints in multiple views. These model fitting approaches provide an accurate parameterized approximation of a person provided the assumed shape of the generic model is a reasonable initial approximation. Model fitting methods commonly assume short hair and close fitting clothing which limits their generality.

The availability of sensors for whole-body 3D scans provides accurate measurement of surface shape. Techniques to fit generic humanoid models to the whole-body scans in a specific pose enable a highly detailed representation of a persons shape to be parameterized for animation and tracking [12,286]. Allen *et al.* [12] used multiple scans of a person in different poses to parameterise the change in body surface shape with pose. Databases of 3D scans have also been used to learn statistical models of the inter-person variation in whole-body shape [13,295]. Reconstruction of shape from images can then be constrained by the learnt model to improve performance.

2.3 Appearance Initialization

Due to the large intra and inter person variability in appearance with different clothing initialization of appearance has commonly been based on the observed image set. Statistical models of color are commonly used for tracking, see section 3.3. Initialization of the detailed surface appearance for model-based pose estimation has also used texture maps derived from multiple view images [45,287]. A cost function evaluating the difference in appearance between the projected model and observed images is then used in pose estimation.

Sidenbladh and Black [270,271] address modeling the likelihood of image observations for different body parts. They learn the statistics of appearance and motion based on filter responses for a set of training examples. In a related approach, Roberts *et al.* [256] learn the likelihood of body part color appearance using multimodal histograms on a 3D surface model. Results are presented for 2D tracking of upper-body and walking motions in cluttered scenes.

A recent trend has been towards the learning of body part detectors to identify possible locations for body parts which are then combined probabilistically to locate people [195,245,257,259], see section 4.1.1. Initialization of such models requires a large training corpus of both positive and negative training examples for different body parts. Approaches such as AdaBoost have been successfully used to learn body part detectors such as the face [307], hands, arms, legs and torso [195,257]. Alternatively, Ramanan *et al.* [245] detect key-frame poses in walking sequences and initialize a local appearance model to detect body parts at intermediate frames.

The initialization of models which accurately represent the change in appearance over time due to creases in clothing, hair and change in body shape with movement remains an open problem. Recent introduction of robust local body part detectors provides a potential solution for tracking and pose estimation.

3 Tracking

Since 2000 tracking algorithms have focused primarily on surveillance applications leading to advances in areas such as outdoor tracking, tracking through occlusion, and detection of humans in still images. In this section we review recent advances in these areas as well as more general tracking problems.

The notion of *tracking* in visual analysis of human motion is used differently throughout the literature. Here we define it as consisting of two processes: 1) *figure-ground segmentation* and 2) *temporal correspondences*. Temporal correspondences is the process of associating the detected humans in the current frame with those in the previous frames, providing temporal trajectories through the state space. Recent advances are mainly due to processing more natural scenes where multiple people and occlusions are present.

Figure-ground segmentation is the process of separating the objects of interest (humans) from the rest of the image (the background). Methods for figure-ground segmentation are often applied as the first step in many systems and therefore a crucial process. Recent advances are mostly a result of expanding existing methods. We categorize these methods in accordance with the type of image measurements the segmentation is based on: motion, appearance, shape, or depth data. Before describing these we first review recent advances in background subtraction as this has become the initial step in many tracking algorithms.

3.1 Background Subtraction

Up until the late 90s background subtraction was known as a powerful preprocessing step but only in controlled indoor environments. In 1998 Stauffer and Grimson [289] presented the idea of representing each pixel by a mixture of Gaussians (MoG) and updating each pixel with new Gaussians during run-time. This allows background subtraction to be used in outdoor environments. Normally the updating was done recursively, which can model slow changes in a scene, but not rapid changes like clouds. The method by Stauffer and Grimson has today become the standard of background subtraction. However, since 1998 a number of advances have been seen which can be divided into *background representation*, *classification*, *background updating*, and *background initialization*.

3.1.1 Background Representation

The MoG representation can be in RGB space, but also other color spaces can be applied. Often a representation where the color and intensities are separated is applied, e.g., YUV [319], HSV [61] and normalized RGB [193], since this allows for detecting pixels in shadow [243]. Using a MoG in a 3D color space corresponds to ellipsoids or spheres (depending on the assumptions on the covariance matrix) of the Gaussian representations [289,193,340]. Other geometric representations are truncated cylinders [166] and truncated cones [16].

Conceptually different representations have also been developed. Elgammal *et al.* [87] use a kernel-based approach where they represent a background pixel by the individual pixels of the last N frames. Haritaoglu *et al.* [121] represent the minimum and maximum value together with the maximum allowed change of the value in two consecutive frames. Eng *et al.* [91] divide a learnt background model into a number of non-overlapping blocks. The pixels within each block are grouped into at most three classes according to homogeneity. The means of these classes are then the representation of the background for this block, i.e., a spatio-temporal representation.

The choice of representation is not only dependant on the accuracy but also on the speed of the implementation and the application. This makes sense since the overall accuracy of background subtraction is a combination of representation, classification, updating, and initialization. For example, Cucchiara *et al.* [61] use only one value to represent each background pixel, but still good results (and speed) can be obtained due to advanced classification and updating. It should however be noted that the MoG representation is by far the most widely used method [1] .

3.1.2 Classification

A number of false positives and negatives will often be present after a background subtraction, for example due to shadows [243]. Using standard filtering techniques based on connected component analysis, size, median filter, morphology, and proximity [87,193,341,61,329,113] can improve the result. Recent methods have tried to directly identify the incorrect pixels and use classifiers to separate the pixels into a number of sub-classes: unchanged background, changes due to auto iris,

[1] See [342,174] for optimizations of the MoG representation.

shadows, highlights, moving object, cast shadow from moving object, ghost object (false positive), ghost shadow, etc. [130,49,61]. Classifiers have been based on color, gradients [193], flow information [61], and hysteresis thresholding [91].

3.1.3 Background Updating

In outdoor scenes the value of a background pixel will change over time and an update mechanism is therefore required. The slow changes in the scene can be updated recursively by including the current pixel value into the model as a weighted combination [289,193,87,61]. A different approach is to measure the overall average change in the scene compared to the expected background and use this to update the model [16,329]. In general, for a good model update only pixels classified as unchanged background should be updated.

Rapid changes in the scene are accommodated by adding a new mode to the model. For the MoG model a new mode is a new Gaussian distribution, which is initiated whenever a non-background pixel is detected. The more pixels (over time) that support this distribution the more weight it will have. A similar approach is seen in [166,16] where the background model, denoted a codebook, for each pixel is represented by a number of codewords (cylinders [166] or cones [16] in RGB-space). During run-time each foreground pixel creates a new codeword. A codeword not having any pixels assigned to it for a certain number of frames is eliminated.

3.1.4 Background Initialization

A background model needs to be learned during an initialization phase. Earlier approaches assumed that no moving objects are present in a number of consecutive frames and then learn the model parameters in this period. However, in real scenarios this assumption will be invalid and recent methods have therefore focused on initialization in the presence of moving objects.

In the MoG representation moving objects can to some extend be accepted during initialization since each foreground object will be represented by its own distribution which is likely to have a low weight. However, this erroneous distribution is likely to produce false positives in the classification process. A different approach is to find only pixels that are true background pixels and then only apply these for initialization. This can be done using a temporal median filter if less than 50% of the values belong to foreground objects [104,121,91]. Eng *et al.* [91] combine this with a skin detector to find and remove humans from the training images.

Recent alternatives first divide the pixels in the initialization phase into temporal subintervals with similar values. Second, the ”best” subinterval belonging to the background is found as the subinterval with the minimum average motion (measured by optical flow) [114] or the subinterval with the maximum ratio between the number of samples in the subinterval and their variance [312]. The codeword method mentioned above uses a temporal filter after the initialization phase to eliminate any codeword that has not recurred for a long period of time [166]. For comparative studies among some of the different background subtraction methods see [47,312,53].

3.2 Motion-Based Segmentation

Motion-based figure-ground segmentation is based on the notion that differences in consecutive images arise from moving humans, i.e., by finding the motion you find the human. The motion is measured using either flow or image differencing.

Sidenbladh [269] calculates optical flow for a large number of image windows each containing a walking human. A Support Vector Machine (SVM) is used to detect walking humans in video. Optical flow can be noisy and instead image flow can be measured using higher level entities. For example, Gonzalez *et al.* [107] track KLT-features to obtain flow vectors, Sangi *et al.* [263] extract flow vectors from displacements of pixel-blocks, and Bradski and Davis [34] find flow vectors as gradients in Motion History Images (MHI) [71].

Image differencing adapts quickly to changes in the scene, but pixels from a human that has not moved or are similar to their neighbors are not detected. Therefore, an improved version is to use three consecutive images [156,121,58]. A different type of image differencing is used by Viola *et al.* [309]. They apply the principle of their novel face detector [307], where simple features are combined in a cascade of progressively more advanced classifiers. A rectangle of pixels in the current image is compared to the corresponding rectangle in the previous image. This is done by shifting the rectangle in the current image up, down, left, and right. Image differencing is then preformed and the lower the energy in the output the higher the probability that the human has actually moved (shifted) in this direction. The output of these operations is used to build a person detector, which is trained using AdaBoost.

3.3 Appearance-Based Segmentation

Segmentation based on the appearance of the human is built on the idea that 1) the appearance of human and background is different and 2) the appearance of individuals are different. The approaches work by building an appearance model of each human and then either building appearance models of the segmented foreground objects in the current image and comparing them with the predicted models, or by directly segmenting the pixels in the current image that belong to each model. Some of these methods are independent on the temporal context, meaning that the methods apply a general appearance model of a human, as opposed to methods where the appearance model of the human is learned/updated based on previous images in the current sequence.

3.3.1 *Temporal context-free*

Temporal context-free methods are used to detect humans in a still image [213], to detect humans entering a scene [223], or to index images in databases [228]. Advances are mostly on using massive amount of training data for learning good classifiers. For example, Okuma *et al.* [223] use 6000 images to train an Adaboost-based classifier. Other examples are using DCT coefficients [228], using partial-occlusion handling body-part detectors [213], (see also section 4.1.1), or the block-based method by Utsumi and Tetsutani [304]. In [304] the image is divided into a number of blocks and the mean and covariance matrix of the intensities are calculated for each block. A distance matrix is constructed where an entry represents the generalized Mahalanobis distance between two blocks. The detection is now based on the fact that for non-human images the distances between blocks in the proximity will be larger than for images containing a human.

Common for these methods is that the human is detected as a box (normally a bounding box) and clutter in the background will therefore have an effect on the results. Furthermore, as the methods usually represent the human as one entity, as opposed to a number of sub-entities, occlusion will in general effect the methods strongly. Drastic illumination changes will also effect the methods since the models are general and do not adapt to the current scene.

3.3.2 *Temporal context*

Temporal context refers to methods where a model which is learned and updated in previous images is used to either detect foreground pixels or to classify foreground pixels to a particular human being tracked. The methods either operate at pixel level or region level. At pixel level the likelihood of each (foreground) pixel belonging to a human model is calculated. The region level is when a region in the image, such as a bounding box, is compared to an appearance model of the humans that are predicted to be present in the current frame, i.e. the probability that a region in an image corresponds to a particular human model. Color-based appearance models have recently received attention leading to advances allowing tracking in outdoor scenes with partial occlusion. This has led to a need for models that can represent the differences between individuals even during partial occlusion.

In many systems the color of a human is represented as either a color histogram [193,59,223,323,340,134] or a MoG [165,261,158,325] [2]. Color histograms are normally compared using the Bhattacharyya distance, which can be improved by weighting pixels close to the center of the human higher than those close to the border [59,340]. In Zhao [340] the similarity is combined with the dissimilarity with respect to the color histogram of the background. MoG representations are normally compared using the Mahalanobis distance, which can be evaluated efficiently by using only one Gaussian [158] and assuming independence between color channels [62]. Alternatively, only the mean can be used [325].

Representing the entire human by just one color model is often too coarse a representation even though the model contains multiple modes. Recent advances are therefore on including spatial information. For example using a Correlogram, which is a co-occurrence matrix that expresses the probability of two different colored pixels being found at a certain distance form each other [139,44]. Another way of adding spatial information is to divide the human into a number of sub-regions and represent each sub-region with either a color histogram or a MoG [203,223,261,325]. Hu *et al.* [134] use an adaptive approach to obtain three sub-regions representing the head, torso, and legs. A more general approach is to model the human as a number of blobs where each blob is a connected group of pixels having a similar color [165,232]. Grouping the blobs together temporally and spatially into an entire human requires some bookkeeping, but a rough human model can assists as seen in [232].

[2] According to McKenna *et al.* [193] MoG is preferred with small sample sets and many possible colors, whereas a color histogram is preferred when many color samples are present in a coarsely quantified color space.

3.4 Shape-Based Segmentation

The shape of a human is often very different from the shape of other objects in a scene. Shape-based detection of humans can therefore be a powerful cue. As opposed to the appearance-based models, the shapes of individuals are often very similar. Hence, shape-based methods applied to tracking only involves simple correspondences. The advances are first of all to allow human detection and tracking in uncontrolled environments. Due to the recent advances in background subtraction reliable silhouette outlines can describe the shape of the humans in the image sequence. Furthermore, advances in representations and segmentation methods of humans in still images have also been reported. As was done for the appearance-based methods, we divide the shape-based methods into those not using the temporal context and those using the context.

3.4.1 Temporal context-free

Zhao and Thorpe [338] use depth data to extract the silhouettes of individuals in the image. A neural network is trained on upright humans and used to verify whether the extracted silhouettes actually originate from humans or not. To make the method more robust the gradients of the outline of a silhouette are used to represent the shape of the human. Leibe *et al.*[180] learn the outlines of walking humans and store them as a number of templates. Each of these are matched with an edge version of the input image over different scales using Chamfer matching. The results are combined with the probability of a person being present, which is measured by comparing small learned image patches of the appearance of humans and their occurrence distribution. Dalal and Triggs [67] use an SVM to detect humans in a window of pixels. The input is a set of features encoding the shape of a human. The features come from using a spatially arranged set of HOG (Histogram of Oriented Gradients) descriptors. The HOG descriptor operates by dividing an image region into a number of cells. For each cell a 1D histogram of gradient directions over the pixels in the cell is calculated. HOGs are related to Shape Contexts [26] and Scale Invariant Feature Transformation [186]. Zhao and Davis [337] learn a hierarchy of silhouette templates for the upper body of humans sitting. The outline of the silhouettes in the templates is used to detect sitting humans in a frame. This is done using Chamfer matching at different scales together with a color-based detector that is updated iteratively.

3.4.2 Temporal context

When the temporal context is taken into consideration shape-based methods can be applied to track individuals over time. In case of temporal smoothness the shape in the previous frame can be used to find the human in the current frame. Haritaoglu *et al.* [121] preform a binary edge correlation between the outlines of the silhouettes in the last frame and the immediate surroundings in the current image. Davis *et al.* [75] use a Point Distribution Model (PDM) to represent the outline of the human. The most likely configurations of the outline from the previous frame are used to predict the location in the current frame using a particle filter. Predictions are evaluated by comparing the edges of the outline with those in the image. A similar approach is seen in [167] where the active shape model is applied to find a fit in the current frame. Atsushi *et al.* [18] model the pose of the human in the previous frame by an ellipse and predict nine possible poses of the human in to the current frame. Each of these is correlated with the silhouettes in the current image in order to define the current pose of the human. Krüger *et al.* [172] correlate the extracted silhouette with a learned hierarchy of silhouettes of walking persons. At run-time a Bayesian tracking framework concurrently estimates the translation, scale, and type of silhouette.

In situations of partial occlusion the shape-based methods just described often fail due to lack of global shape information. Advances therefore include detection of humans based on only a few parts of the overall shape. In the work by Wu and Nevatia [320] four different (body)parts are detected: full-body, head-shoulder, torso, and legs. For each part a detector is trained using a boosting classifier together with edgelets (small connected chains of edge pixels) which are quantified into different orientations, see also section 4.1.1. When people group together the occlusion often becomes severe and the only reliably shape information is the head or head-shoulder profile. In [121,327] the head candidates are found by analyzing the silhouette boundary and the vertical projected histogram of the silhouette. A similar approach is seen in [339] except that also an edge-based method to find the head-shoulder profile inside silhouettes is applied.

3.5 Depth-Based Segmentation

Figure-ground segmentation using depth data is based on the idea that the human stands out in a 3D environment. Methods are either based directly on estimated 3D data for the scene [146,185,118,122,328] or indirectly by combining different camera views after features have been extracted [202,203,326,147]. Advances are mainly due to faster computers allowing for handling multiple camera inputs.

Background subtraction can be sensitive to lighting changes. Therefore a depth-based approach can be taken where the background is modeled as a depth model and compared to estimated depth data for each incoming frame in order to segment the foreground. A real-time dense stereo algorithm is, however, still problematic unless special hardware is applied [185]. An approach to circumvent this is the work by Ivanov *et al.* [146] where an online depth map is not required. Instead the mapping between pixels in two cameras is learnt. This allows for an online comparison between associated pixels (defined by the mapping) in the two cameras. Detection is now performed based on the assumption that the color and intensity are similar for the pixels if and only if they depict the background. In [185] the merits and drawbacks of this approach are studied in detail.

Other advances in human detection based on depth data include the work by Haritaoglu *et al.* [118] where depth data produced by ceiling-mounted cameras are projected to the ground-plane. Here humans are located by looking for a 3D head-shoulder profile. Similar approaches are seen in [122,328] except for the camera placement and that [122] apply voxels as opposed to 3D points.

Mittal and Davis [202,203] detect humans using an appearance-based method in each camera view. The center of each detected human is combined with those found in another image using region-based stereo constrained by the epipolar geometry. The resulting 3D points are projected to the ground-plane and represented probabilistically using Gaussian kernels and an occlusion likelihood. In Yang *et al.* [326] silhouettes from different cameras are combined into the visual hull. The incorrect interpretations are pruned using a size criterion as well as the temporal history. Iwase and Saito [147] apply multiple cameras to detect and track multiple people. In each camera the feet of each person are detected using background subtraction and knowledge of the environment. For each camera all detected feet are mapped to a virtual ground-plane where an iterative procedure resolves ambiguities.

3.6 Temporal Correspondences

One of the primary tasks of a tracking algorithm is to find the temporal correspondences. That is, given the state of N persons in the previous frame(s) and the current input frame(s), what are the states of the same persons in the current frame(s). Here the state is mainly the image position of a person, but can contain other attributes, e.g., 3D position, color and shape.

Previously tracking algorithms were mostly tested in controlled environments and with only a few people present in the scene. Recently, algorithms have addressed more natural outdoor scenarios where multiple people and occlusions are present. One problem is to have better figure-ground segmentation as discussed above. Another equally important problem is how to handle multiple people that might occlude each other. In this section we discuss advances related to temporal correspondences *before and after occlusion* and temporal correspondences *during occlusion*.

3.6.1 Temporal Correspondences Before and After Occlusion

Before any tracking can commence a model of each individual must be constructed. Recent methods are aiming at doing this automatically. One way is to look for (new) large foreground objects possible near the boundaries [3] [121,193,16,261]. Alternatively, a new person can be defined as a foreground object detected far from any predictions [44]. Khan and Shah [165] fit 1D Gaussians to the foreground pixels projected to the x-axis. If the number of good fits is higher than the predicted number of people in the scene then a new person has entered the scene.

When the tracking has commenced the problem is to find the temporal correspondences between predicted and measured states. This has recently been approached using a correspondence matrix, which has the predicted objects in one direction and the measured objects in the other direction. For each entry in the matrix a distance between predicted and measured object is calculated. This gives the likelihood that a predicted and measured object are the same. By analyzing the columns and rows the following situations can be hypothesized: new object, object lost, object match, split situation, and merge situation. In case of for example merge and split situations the matrix can not be resolved directly and ad hoc methods are applied. For example by analyzing the motion vectors and the area (change) of each foreground object [193,44,62,323,329,113].

Alternatively, global optimizations can also be applied. Polat *et al.* [240] use a Multiple Hypothesis Tracker to construct different hypotheses which each explains all the predictions and measurements, and chooses the hypothesis which is most likely. To prune the combinatorial number of different hypotheses smoothness constraints

[3] Similar approaches can be used to detect when people are leaving the scene, see e.g., [16,113].

on the motion trajectories are introduced. If the total number of people in the scene is known in advance the pruning becomes less difficult [134,25]. Another global optimization can be seen in [340,281] where a Particle filter is applied and where each state is a multi-object configuration (hypothesis). Objects are allowed to enter and exit the scene meaning that the number of elements in the state vector can change. To handle this the Particle filter is enhanced by a trans-dimensional Markov chain Monte Carlo approach [111]. This allows new objects to enter and other objects to leave the scene, i.e., the dimensionality of the state space may change. In the work by Li *et al.* [183] a tree-based global optimization for correspondence between multiple objects across multiple views is presented. This approach is used for real-time tracking of hand, head and feet for whole-body pose estimation.

3.6.2 Temporal Correspondences During Occlusion

Tracking during occlusion was not addressed in previous work, instead the track of the group was used to update the states of the individuals. However, this makes it impossible to update the models of the individuals, which can result in unreliable tracking after the group splits up. Furthermore, interactions between humans during occlusions is difficult to analyze when they are represented as one foreground object. Therefore the problem of finding the correspondences during occlusion has been investigated recently.

In some recent systems the first task is to actually detect that an occlusion is present. This can be done using the corresponding matrix mentioned above or as in [165,44,261]. Khan and Shah [165] detect a non-occlusion situation as a situation when the detected foreground objects are far from each other. Capellades *et al.* [44] define a merge as a situation where the total number of foreground objects has decreased and where two or more foreground objects from the previous frame overlap with one foreground object in the current frame. In the work by Roth *et al.* [261] a merge is detected as one of eight different types of occlusion based on the depth ordering and the layout of the bounding boxes. This allows for only using the reliable parts of the bounding box to update the position of the human.

Different approaches for assigning pixels to individuals during occlusion have been reported in recent publications. A local approach is to assign each pixel to the most likely predicted model using a probabilistic method [165,232]. A local approach allows for bypassing the occlusion problem but it is also sensitive to noise and therefore often combined with some post-processing to reassign wrongly classified pixels. Global approaches try to classify pixels based on for example the assumption that people in a group are standing side by side with respect to the camera. This assumption allows for defining vertical dividers between the individuals based on the positions of their heads. Foreground pixels are then assigned to individuals based on these dividers [120,327,323]. When a certain depth ordering is present in the group the assumption fails.

In the work by McKenna *et al.* [193] the depth ordering is found explicitly. During occlusion the likelihood of each pixel in the foreground object belonging to a person is calculated using Bayes rule. The posteriors for each person are added to obtain an overall probability of each person. These probabilities are then used to define the fraction of each person that is visible. This is denoted a visibility index and can be applied to find the depth ordering. In [261] the depth ordering is based on assuming a planar floor. This will result in the closest object to the camera having the highest vertically coordinate. Xu and Puig [323] generalize this idea by using projective geometry to find the line in the image that corresponds to the ”horizon line” in the 3D scene. The object closest to the camera is found as the object closest to this horizontal line.

3.7 Discussion on Advances in Visual Tracking of Humans

Advances in figure-ground segmentation have to a large extent been motivated by the increased focus on surveillance applications. For example, in order to have fully autonomous systems operating in uncontrolled environments the segmentation methods have to be adaptive. This has to some extent been achieved within background subtraction where analysis of video sequences of several hours has been reported [16]. However, for 24 hour operation special cameras (and algorithms) are required. Work in this direction has started [58,73] but no one has so far been able to report a truly autonomous system. Furthermore, in most surveillance applications multiple cameras are required to cover the scene of interest at an acceptable resolution. Systems for self-calibrating and tracking across different cameras are being investigated [164,18,158,300], but again, no fully autonomous system has been reported.

Another advance in segmentation is to apply spatial information in the color-based appearance models, for example by dividing each foreground object into a number of regions each having a color representation [203,223,261,325,134,165,232] or by correlograms [139,44]. This has allowed for relatively reliable detection and tracking of people even when multiple people are present with occlusion. Even an accurate appearance model might fail when the lighting changes are significant.

The recent focus on natural scenes has also led to advances within methods for temporal correspondence, especially handling the occlusion problem. Advances are mainly due to the use of probabilistic methods, for example to segment pixels to individuals during occlusion [193,165,232,235] and also to handle multiple hypotheses and uncertainties using stochastic sampling methods [134,240,223,340,325,281]. In fact, concurrent segmentation and tracking can be handled by stochastic sampling methods. It is expected that future work will be based on this framework since it unifies segmentation and tracking *and* the associated uncertainties.

The use of common benchmark data has begun to underpin progress. As has been seen in the speech community for many years and lately in the face recognition community, widely acceptable benchmark data can help to focus research. Within human detection a few recent benchmark data sets have been reported [213,67].

Within tracking in general the PETS and VS-PETS data sets [5] have been applied in many systems.

4 Pose Estimation

Pose estimation refers to the process of estimating the configuration of the underlying kinematic or skeletal articulation structure of a person. This process may be an integral part of the tracking process as in model-based analysis-by-synthesis approaches or may be performed directly from observations on a per-frame basis. The previous survey [206] separated pose estimation algorithms into three categories based on their use of a prior human model:

Model-Free: This class covers methods where there is no explicit a priori model. Previous methods in this class take a bottom up approach to tracking and labelling of body parts in 2D [319] or direct mapping from 2D sequences of image observations to 3D pose [35].

Indirect Model Use: In this class methods use an a priori model in pose estimation as a reference or look-up table to guide the interpretation of measured data. Previous examples include human body part labelling using aspect ratios between limbs [41] or pose recognition [119].

Direct Model Use: This class uses an explicit 3D geometric representation of human shape and kinematic structure to reconstruct pose. The majority of approaches employ an analysis-by-synthesis methodology to optimize the similarity between the model projection and observed images [129,310].

In this section we identify recent contributions and advances in each category of pose estimation algorithms. A number of trends can be identified from the literature. Three research directions which have each received considerable attention are: the introduction of probabilistic approaches to detect body parts and assemble part configurations in the model-free category; the incorporation of learnt motion models in pose estimation to constrain the recovered 3D human motion; and the use of stochastic sampling techniques in model-based analysis-by-synthesis to improve robustness of 3D pose estimation.

Two important distinctions relating to the difficulty of the pose estimation problem are identified in this analysis: pose estimation from single vs. multiple view images; and 2D pose estimation in the image plane vs. full 3D pose reconstruction. The most difficult and ill-posed problem is the recovery of full 3D pose from single view images towards which initial steps have been made. There has also been substantial research addressing the problems of 2D pose estimation from single view and 3D pose estimation from multiple views. For example recent advances have demonstrated 2D pose estimation in complex natural scenes such as film footage.

4.1 Model Free

A recent trend to overcome limitations of tracking over long sequences has been the investigation of direct pose detection on individual image frames. Two approaches have been investigated which fall into this model-free pose estimation category: *probabilistic assemblies of parts* where individual body parts are first detected and then assembled to estimate the 2D pose; and *example-based methods* which directly learn the mapping from 2D image space to 3D model space.

4.1.1 Probabilistic Assemblies of Parts

Probabilistic assemblies of parts have been introduced for direct bottom-up 2D pose estimation by first detecting likely locations of body parts and then assembling these to obtain the configuration which best matches the observations. The advantage of this approach over tracking is that it does not assume small changes in pose between frames and is therefore potentially robust to rapid movement. Temporal information may be incorporated to estimate consistent pose configurations over sequences. Forsythe and Fleck [95] introduced the notion of body plans to represent people or animals as a structured assembly of parts learnt from images. Following this direction [93,143] used pictorial structures to estimate 2D body part configurations from image sequences. Combinations of body part detectors have recently been used to address the related problem of locating multiple people in cluttered scenes with partial occlusion [213,320], see section 3.

Probabilistic assemblies of body part detectors (face, hands, arms, legs, torso) have been investigated for bottom up estimation of whole-body 2D pose in individual frames or sequences [195,245,257,259]. Individual body parts are detected using 2D shape [257], SVM classifiers [259], AdaBoost [195], and locally initialized appearance models [245]. Mikolajczyk *et al.* [199] introduced probabilistic assemblies of robust AdaBoost body part detectors to locate people in images providing a coarse 2D localization. The probabilistic assembly of parts models the joint likelihood of a body part configuration. In [195] this approach is extended to whole-body 2D pose estimation in frontal images using RANSAC to assemble body part configurations with prior pose constraints. Ramanan *et al.* [245] present a related approach where lateral views of a scissor-leg pose for a person walking or running are detected from film footage. Detected poses are then used as key-frames to initialize a local appearance model for body part detection and 2D pose estimation at intermediate frames.

Recent work has also introduced approaches for 2D pose estimation from single images. Ren *et al.* [250] use pairwise constraints between body parts to assemble body part detections into 2D pose configurations. Pairwise constraints include aspect ratio, scale, appearance, orientation and connectivity. Hua *et al.* [136] present an approach to 2D pose estimation from a single image using bottom-up feature cues together with a Markov network to model part configurations. Both of these approaches demonstrate impressive results for pose estimation in cluttered scenes such as sports images.

An important contribution of approaches based on the probabilistic assembly of parts is 2D pose estimation in cluttered natural scenes from a single view. This overcomes limitations of many previous pose estimation methods which require structured scenes, accurate prior models or multiple views.

4.1.2 Example-based methods

A number of example-based methods for human pose estimation have been proposed which compare the observed image with a database of samples. Brand [35] used a hidden Markov model (HMM) to represent the mapping from 2D silhouette sequences in image space to skeletal motion in 3D pose space. In this work the mapping for specific motion sequences was learnt using rendered silhouette images of a humanoid model. The HMM was used to estimate the most likely 3D pose sequence from an observed 2D silhouette sequence for a specific view. Similarly, Rosales *et al.* [244,260] learn a mapping from visual features of a segmented person to static pose using neural networks. This representation allows 3D pose estimation invariant to speed and direction of movement. Viewpoint invariant representation of the mapping from image to pose is investigated in [225].

To overcome limitations of tracking researchers have investigated example-based approaches which directly lookup or model the mapping from silhouettes to 3D pose [6,132,267,277]. Howe [132] uses a direct silhouette lookup using Chamfer distance to select candidate poses together with a Markov chain for temporal propagation for 3D pose estimation of walking and dancing. Shakhnarovich *et al.* [267] present an example-based approach for viewpoint invariant pose estimation of upper-body 3D pose from a single image. Parameter-sensitive hashing is used to represent the mapping between observed segmented images from multiple views and the corresponding 3D pose. Grauman *et al.* [110] learn a probabilistic representation of the mapping from multiple view silhouette contours to whole-body 3D joint locations. Pose reconstruction is demonstrated for close-up images of a walking person from multiple or single views. Similarly, Elgammal and Lee [88] learn multiple view-dependent mapping from silhouettes to 3D pose for walking actions. Agarwal and Triggs [6,8] presented an example-based approach for 3D pose estimation from single view image sequences. Nonlinear regression is used to learn the mapping from silhouette shape descriptors to 3D pose. Results demonstrate reconstruction of long sequences of walking motions with turns from monocular video.

Example-based approaches represent the mapping between image and pose space providing a powerful mechanism for directly estimating 3D pose. Commonly these approaches exploit rendering of motion capture data to provide training examples with known 3D pose. A limitation of current example-based approaches is the restriction to the poses or motions used in training. Extension to a wider vocabulary of movements may introduce ambiguities in the mapping.

4.2 Indirect model use

A number of researchers have investigated direct reconstruction of both model shape and motion from the visual-hull [51,196,197] without a prior model. Mikic *et al.* [196,197] present an integrated system for automated recovery of both a human body model and motion from multiple view image sequences. Model acquisition is based on a hierarchical rule-based approach to body part localization and labelling. Prior knowledge of body part shape, relative size and configuration is used to segment the visual-hull. An extended Kalman filter is then used for human motion reconstruction between frames. A voxel labelling procedure is used to allow large inter-frame movements. Cheung *et al.* [51] first reconstruct a model of the kinematic structure, shape and appearance of a person and then use this to estimate the 3D movement. Tracking is performed by hierarchically matching the approximate body model to the visual-hull using color matching along the silhouette boundary edge.

An alternative approach based on full 3D-to-3D non-rigid surface matching using spherical mapping is presented in [288]. Alignment of a skeletal model with the first frame allows the 3D motion to be recovered from the non-rigid surface motion. Results of these approaches demonstrate 3D human pose estimation for rapid movement of subjects wearing tight clothing.

These approaches exploit scene reconstruction from multiple views to directly recover both shape and motion. This approach is suitable for multiple camera studio based systems allowing estimation of complex human movements.

4.3 Direct model use

The use of an explicit model of a persons kinematics, shape and appearance in an analysis-by-synthesis framework is the most widely investigated approach to human pose estimation from video. In the previous survey [206] fifty papers (40% of those surveyed) were in this category starting with some of the earliest work in human pose estimation [129]. Model-based analysis-by-synthesis has continued to be a dominant methodology for human pose estimation.

The main novel research directions are: the introduction of stochastic sampling techniques based on sequential Monte Carlo; and the introduction of constraints on the model in particular learnt models of human motion. In this section we review key papers contributing to these advances in multiple and single view model-based pose estimation.

4.3.1 Multiple View 3D Pose Estimation

Up to 2000 the majority of approaches to human pose estimation employed deterministic gradient descent techniques to iteratively estimate changes in pose [77,239]. The extended Kalman filter was widely applied to human tracking with low-order dynamics used to predict change in pose [311]. Recent work using model-based analysis-by-synthesis has extended deterministic gradient descent based approach to more complex motions. Plänkers and Fua [239] demonstrated upper body tracking of arm movements with self-occlusion using stereo and silhouette cues. A limitation of gradient descent approaches is the use of a single pose state estimate which is updated at each time step. In practice if there is a rapid movement or visual ambiguities pose estimation may fail catastrophically. To achieve more robust tracking, techniques which employ a deterministic or stochastic search of the pose state space have been investigated.

Stochastic tracking techniques, such as the *particle filter*, were introduced for robust visual tracking of objects where sudden changes in movement or cluttered scenes can result in failure. The principal difficulty with their application to human pose estimation is the dimensionality of the state space. The number of samples or particles required increases exponentially with dimensionality. Typically whole-body human models use 20-30 degrees-of-freedom making direct application of particle filters computationally prohibitive. MacCormick and Isard [191] proposed partitioned sampling of the state space for efficient 2D pose estimation of articulated objects such as the hand. However, this approach does not extend directly to the dimensionality required for whole-body pose estimation. Deutscher *et al.* [81] introduced the *annealed particle filter* which combines a deterministic annealing approach with stochastic sampling to reduce the number of samples required. At each time step the particle set is refined through a series of annealing cycles with decreasing temperature to approximate the local maxima in the fitness function. Results [76,81] demonstrate reconstruction of complex motion such as a hand-stand. A hierarchal stochastic sampling scheme to efficiently estimate the 3D pose for complex movements or multiple people is presented in [201]. This approach initially estimates the torso pose for each person and propagates samples with high fitness to estimate the pose of adjacent body parts.

Recent work has combined deterministic or stochastic search with gradient descent for local pose refinement to recover complex whole-body motion. Carranza *et al.* [45] demonstrate whole-body human motion estimation from multiple views combining a deterministic grid search with gradient descent. Pose estimation is performed hierarchically starting with the torso. For each body part a grid search first finds the set of valid poses for which the joint positions project inside the observed silhouettes. A fitness function is then evaluated for all valid poses to determine the best pose estimate. Finally gradient descent optimization is performed to refine the estimated pose. This search procedure is made feasible by the use of graphics hardware to evaluate the fitness function which is based on the overlap between the projected model and observed silhouette across all views. In related work Kehl *et al.* [162] propose *stochastic meta descent* for whole-body pose estimation with 24 degrees-of-freedom from multiple views. Stochastic meta descent combines a stochastic sampling of the set of model points used at each iteration of a gradient descent algorithm. This introduces a stochastic search element to the optimization which allows the approach to avoid convergence to local minima. The use of a small number of samples (5) per body part together with adaptive step size allows efficient performance. Results of these approaches demonstrate reconstruction of complex movements such as kicking and dancing.

In summary, the introduction of stochastic sampling and search techniques has achieved whole-body pose estimation of complex movements from multiple views. Current approaches are limited to gross-body pose estimation of torso, arms and legs and do not capture detailed movement such as hand-orientation or axial arm rotation. Multiple hypothesis sampling achieves robust tracking but does not provide a single temporally consistent motion estimate resulting in jitter which must be smoothed to obtain visually acceptable results. There remains a substantial gulf between the accuracy of commercial marker-based and marker less video-based human motion reconstruction.

4.3.2 Monocular 3D Pose Estimation

Reconstruction of human pose from a single view image sequence is considerably more difficult than either the problem of 2D pose estimation or 3D pose estimation from multiple views. To resolve the inherent ambiguity in monocular human motion reconstruction additional constraints on kinematics and movement are typically employed [311,36]. Wachter and Nagel [311] used the extended Kalman filter together with kinematic joint constraints to estimate the 3D motion of a person walking parallel to the image plane. As discussed in the previous section the use of a single hypothesis tracking scheme is prone to failure for complex motions. Loy *et al.* [187] employ a manual key-frame approach to 3D pose estimation of complex motion in sports sequences.

Sminchisescu and Triggs [279] have investigated the application of stochastic sampling to estimation of 3D pose from monocular image sequences. They observe that alternative 3D poses which give good correspondence to the observations are most likely to occur in the direction of greatest uncertainty. This motivated the introduction of *covariance scaled sampling* an extension of particle filters which increases the covariance in the direction of maximum uncertainty by approximately an order of magnitude to increases the probability of generating samples close to local minima in the fitness function. Samples are then optimized to find the local minima using a gradient descent approach. Results demonstrate monocular tracking and 3D reconstruction of human movements with moderate complexity including walking with changes in direction. Further research [280] has explicitly enumerated the potential kinematic minima which cause visual ambiguities. Incorportating this in the sampling process increases efficiency and robustness allowing reconstruction of more complex human motion from monocular video sequences.

Probabilistic approaches using assemblies of parts together with higher level knowledge of human kinematics and shape have also been investigated for single view 3D pose estimation. Lee and Cohen [177] combine a probabilistic proposal map representing the estimated likelihood of body parts in different 3D locations with an explicit 3D model to recover the 3D pose from single image frames. A data driven Markov chain Monte Carlo MCMC is used to search the high-dimensional pose space. The proposal map for each body part represents the likelihood of the projected 3D pose. Proposal distributions are used to efficiently sample the pose space during MCMC search. Results demonstrate 3D pose estimation from static sports players in a variety of complex poses. Moeslund and Granum [205,211] apply a data driven sequential Monte Carlo approach to pose estimation of a human arm. A part detector provides likely locations of the hand in the image and their uncertainties. This information is applied to correct the prediction lowering the number of particles required.

Navaratnam *et al.* [221] combine a hierarchical kinematic model with a bottom up part detection to recover the 3D upper-body pose. The use of part detection allows individual body parts to be independently located at each frame. Kinematic constraints between body parts are represented hierarchically to recover the 3D pose from a single view. Unlike previous model free probabilistic assembly of parts this approach enables recovery of full 3D pose at each frame. Temporal information is also integrated using a HMM framework to reconstruct temporally coherent movement sequences.

Monocular reconstruction of complex 3D human movement remains an open problem. Recent research has investigated the use of learnt motion models to provide strong priors to constrain the search.

4.3.3 Learnt Motion Models

There has been increasing interest in the use of learnt models of human pose and motion to constrain vision-based reconstruction of human movement from single or multiple views. The availability of marker-based human motion capture data [1,2,4] has led to the use of learnt models of human motion for both animation synthesis in computer graphics and vision-based human motion synthesis.

Learnt models have been developed in computer animation to allow synthesis of natural motions with user specified constraints from a motion capture database

[17,168,175,214]. This use of learnt models in computer graphics is relevant to the problem of vision-based reconstruction of human movement in developing methods to predict and constrain human pose and motion estimation. Inverse kinematics of human motion based on learnt models has recently been introduced in computer graphics [112,224]. Ong *et al.* [224] use a learnt model of whole-body configurations to constrain the pose given a set of end effector positions for a motion sequence. Grochow *et al.* [112] use Scaled Guassian Process Latent Variable Models (SGPLVM) to model the probability distribution over all possible whole-body poses to constrain both character pose in animation and pose reconstruction from images.

Sidenbladh *et al.* [270,272,273] combine stochastic sampling with a strong learned prior of walking motion for tracking. An exemplar based approach is used in [274] similar to work in motion synthesis [17,168,214] where a database of motion capture examples is indexed to obtain possible movement directions. Statistical priors on human appearance and image motion are used [271] to model the likelihood of observing various image cues for a given movement. These are incorporated in an analysis-by-synthesis approach to human motion reconstruction. Similarly, a hierarchical PCA model of human dynamics learnt from motion capture using a Gaussian mixture and HMM to represent dynamics is proposed for monocular tracking in [160]. Agarwal and Triggs [7] use a learned model of local second order dynamics for 2D tracking of more general motions walking and running with transitions and turns in monocular image sequences. Their work demonstrates that strong priors on human dynamics allows 2D pose estimation for fast movements in cluttered scenes.

Subsequent research has investigated the use of learnt motion models for 3D motion reconstruction primarily from monocular image sequences to overcome the inherent visual ambiguity. In [133] learnt models from short motion sequences are used to infer 3D pose from tracked image features of simple movements. Sigal *et al.* [275] combine body part detectors with a learned motion model to infer 3D human pose from monocular images of walking with automatic initialization. Their approach uses belief propagation via stochastic sampling over a loopy graph of loosely attached body parts. Urtasun and Fua [303] introduce the use of temporal motion models learnt from sequences of motion capture data to reconstruct human motion using a deterministic gradient descent optimization. Principal component analysis (PCA) is performed on multiple examples of concatenated joint angle sequences for walking and running to provide a low-dimensional parametrization. The parametric motion model is then used to constrain the movement of a 3D humanoid model for walking and running movements with variable speed from stereo [303] and golf swings from a single view [301]. Urtasun *et al.* [302] advocate an alternative approach to representation of human motion using the Scaled Gaussian Process Latent Variable Model (SGPLVM) to learn a low-dimensional embedding of the pose state space for specific movements. SGPLVM is used to reconstruct both golf swings and walking motion from monocular image sequences. Further research following the methodology of using learnt motion models has addressed the problem of viewpoint invariance in tracking human movement [8,225].

Research introducing the use of learnt statistical models of human motion since 2000 has demonstrated that using strong motion priors facilitates reconstruction of 3D pose sequences from monocular images. To date the generality of these approaches has been limited to specific motion models with relatively small variation in motion and fixed transitions. A challenge for future research is to build more general motion models or methods of transitioning between models, to allow the reconstruction of unconstrained human movement.

5 Recognition

The field of action and activity representation and recognition is relatively old, yet still immature. This area is presently subject to intense investigation which is also reflected by the large number of different ideas and approaches. On the other hand, the approaches depend on the goal of the researcher and applications for activity recognition are interesting for surveillance, medical studies and rehabilitation, robotics, video indexing and animation for film and games. For example, in scene interpretation the knowledge is often represented statistically and is meant to distinguish “regular” from “irregular” activities.

The representations should be independent from the objects causing the activity and thus are usually not meant to distinguish explicitly, e.g, cars from humans. On the other hand, some surveillance applications focus explicitly on human activities and the interactions between humans. Here, one finds both, holistic approaches, that take into account the entire human body without considering particular body parts, and local approaches. Most holistic approaches attempt to identify “holistic” information such as gender, identity or simple actions like walking or running. Researchers using local approaches appear often to be interested in more subtle actions or attempt to model actions by looking for action primitives with which the complex actions can be modeled.

We have structured this review according to a visual abstraction hierarchy yielding the following: *scene interpretation* (section 5.2) where the entire image is interpreted without identifying particular objects or humans, *holistic recognition* (section 5.3) where either the entire human body or individual body parts are applied for recognition, and *action primitives and grammers* (5.5) where an action hierarchy gives rise to a semantic description of a scene. Before going into these topics we first look closer at the definition of the action hierarchy used in this survey since it has influence on the remaining categories.

5.1 Action Hierarchies

Terms like *actions*, *activities*, *complex actions*, *simple actions* and *behaviors* are often used interchangingly by the different authors. However, in order to be able to describe and compare the different publications we see the need for a common terminology. In a pioneering work [220], Nagel suggested to use a hierarchy of *change, event, verb, episode, history*. An alternative hierarchy (reflecting the computational aspects) is proposed in [31] who suggests to use *movement, activity and action* as different levels of abstraction (see also [11]). Others suggest to also include *situations* [106] or use a hierarchy of *Action primitives* and *Parent Behaviors* [149].

In this survey we will use the following action hierarchy: *action/motor primitives, actions* and *activities*: *action primitives* or *motor primitives* will be used for atomic entities out of which actions are built. *Actions* are, in turn, composed into *activities*. The granularity of the primitives often depends on the application. For example, in robotics, *motor primitives* are often understood as sets of motor control commands that are used to generate an action by the robot (see section 5.5).

As an example, in tennis *action primitives* could be, e.g., “forehand”, “backhand”, “run left”, “run right”. The term *action* is used for a sequence of action primitives needed to return a ball. The choice of a particular action depends on whether a forehand, backhand, lob or volley etc, is required in order to be able to return the ball successfully. Most of the research discussed below fall into this category. The *activity* then is in this example “playing tennis”. *Activities* are larger scale events that typically depend on the context of the environment, objects or interacting humans.

A good overview of activity recognition is given in [11]. Aggarwal and Park aim at higher-level understanding of activities and interactions and discuss different aspect such as level of detail, different human models, recognition approaches and high-level recognition schemes.

Many approaches consider the camera view as a whole and attempt to learn and recognize activities simply by observing the motion of objects without necessarily knowing their identity. This is reasonable in situations where the objects are small enough to be represented as points on a 2D plane.

In [290] a full scene interpretation system is presented which allows detection of unusual situations. The system extracts features such as 2-D position and speed, size and binary silhouettes. Vector Quantization is applied to generate a codebook of K prototypes. Instead of taking the explicit temporal relationship between the symbols into account, Stauffer and Grimson use co-occurrence statistics.Then, they define a binary tree structure by recursively defining two probability mass functions across the prototypes of the code book that best explain the co-occurrence matrix. The leaf nodes of the binary tree are probability distributions of co-occurrences across the prototypes and at a higher tree depth define simple scene activities like pedestrian and car movement. These can then be used for scene interpretation. In [91] a swimming pool surveillance system is presented. From each of the detected and tracked objects Eng *et al.* extract features such as speed, posture, submersion index, an activity index and a splash index. These features are fed into a multivariate polynomial network in order to detect water crisis events. In [33] the problem of detection irregularities in a scene is approached as a problem of composing newly observed data using spatio-temporal patches extracted from previously seen visual examples. Boiman and Irani [33] extract small image and video patches which are used as local descriptors. In an inference process, they search for patches with a similar geometric configuration and appearance properties, while allowing for small local misalignments in their relative geometric arrangement. This way, they are able to quickly and efficiently infer subtle but important local changes in behavior.

In [56,305] activity trajectories are modeled using non-rigid shapes and a dynamic model that characterizes the variations in the shape structure. Vaswani *et al.* [305] uses Kendall's statistical shape theory [163]. Nonlinear dynamical models are used to characterize the shape variation over time. An activity is recognized if it agrees with the learned parameters of the shape and associated dynamics. In [55], Chowdhury *et al.* use a subspace method to model activities as a linear combination of 3D basis shapes. The work is based on the factorization theorem [297]. Deviations from the learned normal activity shapes can be used to identify abnormal ones.

5.3 Holistic Recognition Approaches

The recognition of the identity of a human, based on his/her global body structure and the global body dynamics is discussed in many publications. Of particular interest for identity recognition has been the human gait. Other approaches using global body structure and dynamics are concerned with the recognition of simple actions such as running and walking. Almost all methods are silhouette or contour based. Subsequent techniques are mostly holistic, e.g., the entire silhouette or contour is being taken into account without detecting individual body parts.

5.3.1 Human Body Based Recognition of Identity

In [316] the silhouette of a human is computed and then unwrapped by evenly sampling the contour. Next, the distance between each contour point and its center of gravity is computed. The unwrapped contour is then processed by PCA. To compute the spatio-temporal correlation, Wang *et al.* compare trajectories in eigenspace by first applying appropriate time warping to minimize the distance between the probe and the gallery trajectories. On outdoor data and in spite of its simplicity, it gives good results while being computationally efficient. In [28] a variation of co-occurrence techniques is used. After applying a suitable time-warping and normalization with respect to scale a self-similarity plot is computed where silhouette images of the sequences are pairwise correlated. PCA is applied to reduce the dimensionality of these plots and a k-nearest neighbor classifier is applied in eigenspace for recognition.

In [96], silhouettes are extracted, emboxed and normalized. Then, a set of binary masks are defined and the area of the silhouette within the mask is computed to give a dynamic signature of the observed person for each mask. A frame rate of 30 fps results in a 30-D vector for each signature giving a $n \times 30$ matrix where n denotes the number of area masks used. To remove the information about the static shape of the silhouette, the average value of each signature can be subtracted. Fisher analysis is applied and the k-nearest neighbor classifier is used for classification. In [154,155], a hidden Markov model is defined to model the dynamics of individual gait. A HMM is trained for each individual in the database. Five representative binary silhouette are used as the hidden states for which transition probabilities and observation likelihoods are trained. During the recognition phase, the HMM with the largest probability identifies the individual. In [324] the relationship between walking and running is investigated. The Yam *et al.* define a gait signature based on a frequency analysis of thigh and lower leg rotations. Phase and magnitude of the Fourier descriptions are multiplied to give the phase-weighted magnitude (PWM). It appears that the signatures for walking and running for an individual is related by a phase modulation. The additional individual relationship between walking and running is used to derive improved gait-recognition which can recognize both, walking and running patterns.

5.3.2 Human Body Based Recognition

While a large number of papers recognize individuals based on their dynamics, the dynamics can also be used to recognize *what* the individual is doing. The approaches discussed in this subsection are again based on holistic body information where no attempt is made to identify individual body parts.

A pioneering work in this context has been presented by Efros *et al.* [85]. They attempt to recognize simple actions of people whose images in the video are only 30 pixels tall and where the video quality is poor. They use a set of features that are based on blurred optic flow (blurred motion channels). First, the person is tracked so that the image is stabilized in the middle of a tracking window. The blurred motion channels are computed on the residual motion that is due to the motion of the body parts. Spatio-temporal cross-correlation is used for matching with a database. Of further interest is the “Do-as-I-Say” enhancement where complex actions can be dynamically composed out of the set of simple actions. In [258] Robertson and Reid attempt to *understand* actions by building a hierarchical system that is based on reasoning with belief networks and hidden Markov models on the highest level and on the lowest level with features such as position and velocity as action descriptors. Their action descriptor is based on [85]. The system is able to output qualitative information such as *walking – left-to-right – on the sidewalk*.

A large number of publications work with space-time volumes. One of the main approaches is to use spatio-temporal XT-slices from an image volume XYT [252,253] where articulated motions of a human can be associated with a typical trajectory pattern. In [252] it is demonstrated how XT-slices can facilitate tracking and reconstruction of 2D motion trajectories. The reconstructed trajectory allows a simple classification between pedestrians and vehicles. In [253], Ritscher *et al.* discuss the recognition in more detail by a closer investigation of the XT-slices. Quantifying the braided pattern in the slices of the spatio-temporal cube gives rise to a set of features (one for each slice) and their distribution is used to classify the actions.

Bobick and Davis pioneered the idea of temporal templates [31,32]. They propose a representation and recognition theory [31,32] that is based on *motion energy images* (MEI) and *motion history images* (MHI). The MEI is a binary cumulative motion image. The MHI is an enhancement of the MEI where the pixel intensities are a function of the motion history at that pixel. Matching temporal templates is based on Hu moments. Bradski *et al.* [34] pick up the idea of MHI and develop timed MHI (tMHI) for motion segmentation. tMHI allow determination of the normal optical flow. Motion is segmented relative to object boundaries and the motion orientation. Hu moments are applied to the binary silhouette to recognize the pose. A work conceptually related to [32] is [192]. Here, motion information for each video frame is represented by a feature image. However, unlike [32], an action is represented by several feature images. PCA is applied for dimensionality reduction and each action is then represented by a manifold in PCA space.

Yi *et al.* [330] present the idea of a pixel change ratio map (PCRM) which is conceptually similar to the MHI. However, further processing is based on motion histograms which are computed from the PCRM. In [318], Weinberg *et al.* suggest replacing the motion history image by a 4D motion history volume. For this, they first compute the visual hull from multiple cameras. Then, they consider the variations around the central vertical axes and use cylindric coordinates to compute alignments and comparisons. Motion history images can also be used to detect and interpret actions in compressed video data. In [20] a motion flow history (MFH) is computed from the motion data available in compressed video. In addition to MFH, they also use motion history images to classify activities.

As the search of activities in large databases gains importance, a full, hierarchical human detection system is presented in [228]. In their system, Ozer and Wolf approach the tracking, pose estimation and action recognition problem in an integrated manner. They apply a number of well-known techniques on (un)compressed video data.

Another approach is that of “Actions Sketches” or “Space-Time Shapes” in the 3D XYT volume. Yilmaz and Shah [331] propose to use spatio-temporal volumes (STV) for action recognition: The 3D contour of a person gives rise to a 2D projection. Considering this projection over time defines the STV. Yilmaz and Shah extract information such as speed, direction and shape by analyzing the differential geometric properties of the STV. They approach action recognition as an object matching task by interpreting the STV as rigid 3D objects. In [30] Blank *et al.* also analyze the STV. They generalize techniques for the analysis of 2D shapes [108] for the use on the STV. Blank *et al.* argue that the time domain introduces properties that do not exist in the xy-domain and needs thus a different treatment. For the analysis of the STV they utilize properties of the solution of the Poisson equation [108]. This gives rise to local and global descriptors that are used for recognizing simple actions.

Instead of using spatio-temporal volumes, a large number of papers choose the more classical approach of considering sequences of silhouettes. In [333] silhouettes are extracted and their contours are unwrapped and processed by PCA. A three-layer feed forward network is used to distinguish “walking”, “running”and “other” based on the trajectories in eigenspace. The work in [264] is concerned with the detection of interaction between two individuals. This is done by grouping foreground pixels according to similar velocities. A subsequent tracker tracks the velocity blobs. The distance between two people, the slope of relative distance and the slope of each person’s position are the features used for interaction detection and classification. In [50], walking is distinguished from running based on sport event video data. The data comes from real-life programs. Cheng *et al.* compute a dense motion field and foreground segmentation is performed based on color and motion. Within the foreground region, the mean motion magnitude between frames is computed over time followed by an analysis in frequency space to compute a characteristic frequency. A Gaussian classifier is used for classification. Gao *et al.* [98] consider a smart room application. A dining room activity analysis is performed by combining motion segmentation with tracking. They use motion segmentation based on optical flow and RANSAC. Then, they combine the motion segmentation with a tracking approach which is sensitive to subtle motion. In order to identify activities, they identify predominant directions of relative movements.

In a number of publications, recognition is based on hidden Markov models (HMMs) and dynamic Bayes networks. Elgammal *et al.* [89] propose a variant of semi-continuous HMMs for learning gesture dynamics. They represent the observation function of the HMM as non-parametric distributions to be able to relate a large number of exemplars to a small set of states. Luo *et al.* [189] present a scheme for video analysis and interpretation where the higher-level knowledge and the spatio-temporal semantics of objects are encoded with DBNs. The DBNs are based on key-frames and are defined for video objects. In [181], Leo *et al.* attempt to classify actions at an archaeological site. They present a system that uses binary patches and an unsupervised clustering algorithm to detect human body postures. A discrete hidden Markov model is used to classify the sequences of poses into a set of four different actions.

5.4 Recognition based on Body Parts

Many authors are concerned with the recognition of actions based on the dynamics and settings of individual body parts. Some approaches, e.g., [74], start out with silhouettes and detect the body parts using a method inspired by the W4-system [121]. Others use 3D-model based body tracking approaches (see section 4) where the recognition of (often periodic) action is used as a loop-back to support pose estimation. Other approaches circumvent the vision problem by using a motion capture system in order to be able to focus on the action issues [230,72].

In a work related to [316], Wang *et al.* [315] present an approach where contours are extracted and a mean contour is computed to represent the static contour information. Dynamic information is extracted by using a detailed model composed of 14 rigid body parts, each one represented by a truncated cone. Particle filtering is used to compute the likelihood of a pose given an input image. For classification, a nearest neighbor classifier (NN) was used.

In [74] an approach is presented to distinguish walking from non-walking. A method based on the W4-system is used to detect body parts from silhouettes. Based on the feet locations four motion properties are extracted of which three (cycle time, stance/swing ratio, double support time) reflect dynamic features and one (extension angle) reflects a structural feature. The walking category is defined by three pairs of the dynamic features and the structural feature. In a similar approach [248] Ren and Xu use as input a binary silhouette from which they detect the head, torso, hands and elbow angles. Then, a primitive-based coupled hidden Markov model is used to recognize natural complex and predefined actions. They extend their work in [249] by introducing primitive-based dynamic Bayesian networks. In [230], Parameswaran and Chellappa consider the problem of view-invariant action recognition based on point-light displays by investigating 2D and 3D invariant theory. As no general, non-trivial 3D-2D invariants exist, Parameswaran and Chellappa employ a convenient 2D invariant representation by decomposing and combining the patches of a 3D scene. For example, key poses can be identifies where joints in the different poses are aligned. In the 3D case, six-tuples corresponding to six joints give rise to 3D invariant values and it is suggested to use the progression of these invariants over time for action representation. A similar issue is discussed in [332] where joint trajectories from several uncalibrated moving cameras are considered. Yilmaz and Shah propose an extension to the standard epipolar geometry based approach by introducing a temporal fundamental matrix that models the effects of the camera motion. The recognition problem is then approached in terms of the quality of the recovered scene geometry.

In [72,70], Davis and Gao aim is to recognize properties from visual target cues, e.g. the sex of an individual or the weight of a carried object is estimated from how the individuals move. In [72] the gender of a person is recognized based on the gait. Labeled 2D trajectories from motion capture devices of humans are factored using three-mode PCA into components interpreted as *posture*, *time* and *gender*. An importance weight for each of the trajectories is learned automatically. In [70] the three-mode PCA framework is used to recognize human action efforts. Here, the three modes *pose*, *time* and *effort* are used. In order to detect particular body parts Fanti *et al.* [92] give the structure of a human as model knowledge. To find the most likely model alignment with input data they exploit appearance information which remains approximately invariant within the same setting. Expectation maximization is used for unsupervised learning of the parameters and structure of the model for a particular action and unlabeled input data. Action is then recognized by maximum likelihood estimation.

5.5 Action Primitives and Grammars

There is strong neurobiological evidence that human actions and activities are directly connected to the motor control of the human body [255,102,254]. When viewing other agents performing an action, the human visual system seems to relate the visual input to a sequence of motor primitives. The neurobiological representation for visually perceived, learned and recognized actions appears to be the same as the one used to drive the motor control of the body. These findings have gained considerable attention from the robotics community [265,68]. In *imitation learning* the goal is to develop a robot system that is able to relate perceived actions to its own motor control in order to learn and to later recognize and perform the demonstrated actions. Consequently, it is ongoing research to identify a set of motor primitives that allow a) representation of the visually perceived action and b) motor control for imitation. In addition, this gives rise to the idea of interpreting and recognizing activities in a video scene through a hierarchy of primitives, simple actions and activities. Most of the following researchers attempt to learn the motor or action primitives by defining a “suitable” representation and then learning the primitives from demonstrations. The representations used to describe the primitives vary a lot across the literature and are subject to ongoing research. Most of the subsequently mentioned work is based on motion capture data.

In [151,150], Jenkins *et al.* suggest applying a spatio-temporal non-linear dimension reduction technique on manually segmented human motion capture data. Similar segments are clustered into primitive units which are generalized into parameterized primitives by interpolating between them. In the same manner, they define action units ("behavior units") which can be generalized into actions. In [141] the problem of defining motor primitives is approached from the motor side. They define a set of nonlinear differential equations that form a control policy (CP) and quantify how well different trajectories can be fitted with these CPs. The parameters of a CP for a primitive movement are learned in a training phase. These parameters are also used to compute similarities between movements. In [43,29,42] a HMM based approach is used to learn characteristic features of repetitively demonstrated movements. They suggest to use the HMM to synthesize joint trajectories of a robot. For each joint, one HMM is used. In [43] an additional HMM is used to model end-effector movement. In these approaches, the HMM structure is heavily constrained to assure convergence to a model that can be used for synthesizing joint trajectories.

A number of publications attempt to decouple actions into action primitives and to interpret actions as a composition on the alphabet of these action primitives, however, without the constraints of having to drive a motor controller with the same representation. In [306], Vecchio and Perona employ techniques from the dynamical systems framework to approach segmentation and classification. System identification techniques are used to derive analytical error analysis and performance estimates. Once, the primitives are detected an iterative approach is used to find the sequence of primitives for a novel action. In [188], Lu *et al.* also approach the problem from a system theoretic point of view. Their goal is to segment and represent repetitive movements. For this, they model the joint data over time with a second order auto-regressive (AR) model and the segmentation problem is approached by detection significant changes of the dynamical parameters. Then, for each motion segment and for each joint, they model the motion with a damped harmonic model. In order to compare actions, a metric based on the dynamic model parameters is defined. A different problem is studied in [313] addressing what kind of cost function should be used to assure smooth transitions between primitives.

While most scientists concentrate on the action representation by circumventing the vision problem, [246] takes a vision-based approach. They propose a view-invariant representation of action based on *dynamic instants* and *intervals*. Dynamic instants are used as primitives of actions which are computed from discontinuities of 2D hand trajectories. An interval represents the time period between two dynamic instants (key poses). A similar approach of using meaningful instants in time is proposed by Reng *et al.* [251] where key poses are found based on the curvature and covariance of the normalized trajectories. In [64] key poses are found through evaluation of antieigenvalues.

In [106] the point distribution model [60] is employed to model the variability of joint angle settings of a stick figure model. An action spaces, *aSpace*, is trained by giving a set of joint angle settings coming from different individuals but showing the same action. *aSpaces* are then used for synthesis and recognition of known actions. Modelling of activities on a semantic level has been attempted in [233]. The system that Park and Aggarwal describe has 3 abstraction levels. At the first level, human body parts are detected using a Bayesian network. At the second level, dynamic Bayes nets are used to model the actions of a single person. At the highest level, the results from the second level are used to identify the interactions between individuals. Ivanov and Bobick [145] suggest using stochastic parsing for a semantic representation of an action. They discuss that for some activities, where it comes to semantic or temporal ambiguities or insufficient data, stochastic approaches may be insufficient to model complex actions and activities. They suggest decoupling actions into primitive components and using a stochastic parser for recognition. In [145] they pick up a work by Stolcke [291] on syntactic parsing in speech recognition and enhance this work for activity recognition in video data. A somewhat different approach is taken in [334]. Yu and Yang use neural networks to find primitives. They apply self-organizing maps (SOMs, Kohonen's feature maps) which cluster the training images based on shape feature data. After training the SOMs generated a label for each input image which converts an input image sequence into a sequence of labels. A subsequent clustering algorithm allows to find repeatedly appearing substructures in these label sequences. These substructures are then interpreted as motion primitives.

6 Conclusion

Over the past five years vision-based human motion estimation and analysis has continued to be a thriving area of research. This survey has identified over two-hundred related publications over the period 2000-06 in major conferences and journals. Increased activity in this research area has been driven by both the scientific challenge of automatic scene interpretation and the demands of potential mass-market applications in surveillance, entertainment production and indexing visual media.

During this period there has been substantial progress towards automatic human motion tracking and reconstruction. Recognition of human motion has also become a central focus of research interest. Key advances identified in this review include:

Initialization: Automatic initialization of model shape, appearance and pose has been addressed in recent work [51,197]. A major advance is the introduction of methods for pose detection from static images [136,250,260,267] which potentially provide automatic initialization for human motion reconstruction.

Tracking: Surveillance applications have motivated research advances towards reliable tracking of multiple people in unstructured outdoor scenes. Advances in especially the use of appearance, shape and motion for figure-ground segmentation have increased reliability of detecting and tracking people with partial occlusion [203,223,261,325,134,165,232]. Probabilistic classification methods [193,165,232,235] and stochastic sampling [134,240,223,340,325,281] have been introduced to improve the reliability of temporal correspondence during occlusion. Systems for self-calibrating and tracking across multiple cameras have been investigated [164,18,158,300]. There remains a gap between the state-of-the-art and robust tracking of people for surveillance in outdoor scenes.

Human motion reconstruction from multiple views: Significant progress has been made towards the goal of automatic reconstruction of human movement from video. The model-based analysis-by-synthesis methodology, pioneered in early work [129], has been extended with the introduction of techniques to efficiently search the space of possible pose configurations for robust reconstruction from multiple view video acquisition [45,81,197,162]. Current approaches capture gross body movement but do not accurately reconstruct fine detail such as hand movements or axial rotations.

Monocular human motion reconstruction: Progress has also been made towards human motion capture from single views with stochastic sampling techniques [177,221,270,279]. An increasing trend in monocular tracking has been the use of learnt motion models to constrain reconstruction based on movement [7,270,272,303,302,8]. Research has demonstrated that the use of strong a priori models enables improved monocular tracking of specific movements.

Pose estimation in natural scenes: A recent trend to overcome limitations of monocular tracking in video of unstructured scenes has been direct pose detection on individual frames. Probabilistic assemblies of parts based on robust body part detection has achieved 2D pose estimation in challenging cluttered scenes such as film footage [136,195,199,245,250,259]. Example based methods which learn a mapping from image to 3D pose space have been presented for reconstruction of specific movements [8,260,267].

Recognition: Understanding behavior and action has recently seen an explosion of research interest. Considerable steps have been made to advance surveillance applications towards automatic detection of unusual activities. Progress can also be seen for the recognition of simple actions and the description of action grammars. Relatively few papers have so far dealt with higher abstraction levels in action grammars which touch the border of semantics and AI. Association of actions and activities with affordances of objects will also bring a new perspective to object recognition.

Future research in visual analysis of human movement must address a number of open problems to satisfy the common requirements of potential applications for reliable automatic tracking, reconstruction and recognition. Body part detectors which are invariant to viewpoint, body shape and clothing are required to achieve reliable tracking and pose estimation in cluttered natural scenes. The use of learnt models of pose and motion are currently restricted to specific movements. More general models are required to provide constraints for capturing a wide range of human movement. Whilst there has been substantial advances in human motion reconstruction the visual understanding of human behavior and action remains immature despite a surge of recent interest. Progress in this area requires fundamental advances in behavior representation for dynamic scenes, viewpoint invariant relationships for movement and higher level reasoning for interpretation of actions [266].

Industrial applications also require specific advances: human motion capture for entertainment production requires accurate multiple view reconstruction; surveillance applications require both reliable detection of people and recognition of movement and behavior from relatively low quality imagery; human-computer interfaces require low-latency real-time recognition of gestures, actions and natural behaviors. The potential of these applications will continue to inspire the advances required to realize reliable visual capture and analysis of moving people.

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Table 1

Publications on human motion capture and analysis from 2000-2006(inclusive). Papers are ordered first by the year of publication and second by the surname of the first author. Four columns allow the clarification of the contributions of the papers within the four processes. The location of the reference number (in brackets) indicates the main topic of the work and an asterisk (*) indicates that the paper also describes work at an interesting level regarding this process.

Publications 2000 - 2006 (inclusive).

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2000	Barron			[22]	
2000	Buades			[38]	
2000	Chang		*	[48]	*
2000	Davis		[75]		
2000	Deutscher		*	[81]	
2000	Felzenszwalb			[93]	
2000	Haritaoglu	*	[121]	*	*
2000	Howe		*	[133]	
2000	Ivanov		*	[146]	
2000	Karaulova	*	*	[160]	
2000	Khan	*	[165]		
2000	Ormoneit	[227]	*	*	
2000	Ricquebourg		[252]		*
2000	Stauffer		*		[290]
2000	Takahashi		[293]	*	
2000	Taylor	[294]		*	
2000	Trivedi		[298]		
2000	Trivedi		*		[299]
2000	Zhao		[338]		
$\sum$	Total=19	2	7	8	2

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2001	Ambrosio			[14]	
2001	Ambrosio			[15]	
2001	Barron			[23]	
2001	Bobick				[32]
2001	Bradski		*	*	[34]
2001	Choo			[54]	
2001	Davison			[76]	
2001	Delamarre		*	[77]	
2001	Deutscher			[82]	
2001	Elgammal	*	[90]		
2001	Grammalidis	*		[109]	
2001	Gutchess		[114]		
2001	Haritaoglu		*		[117]
2001	Herda	*	*	[124]	
2001	Hoshino		*	[131]	
2001	Huang		*	[137]	
2001	Intille				[142]
2001	Ioffe		*	[144]	
2001	Khan		[164]		
2001	Li			[182]	
2001	Mikić	*	*	[198]	
2001	Moeslund	*	*	[207]	
2001	Mohan		[213]		
2001	Moon		*	[216]	
2001	Ogaki		*	[222]	
2001	Pece	*	[234]		
2001	Plänkers		*	[237]	
2001	Prati		[242]		
2001	Rosales		*	[244]	
2001	Sangi		[263]		
2001	Sato		[264]		*
2001	Sidenbladh	*	*	[270]	
2001	Sminchisescu		*	[278]	
2001	Song			[283]	
2001	Song	[284]			
2001	Zhao		[341]		*
$\sum$	Total=36	1	9	22	4

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2002	Allen	[12]			
2002	Atsushi		[18]		
2002	Ben-Arie		*	*	[27]
2002	BenAbdelkader		*		[28]
2002	Bradski		*		[34]
2002	Cheng		*		[50]
2002	Davis		*	*	[74]
2002	Fua		*	[97]	
2002	Gleicher			[103]	
2002	Gonzàlez				[106]
2002	Halvorsen		*	[115]	
2002	Hariadi		[116]		
2002	Haritaoglu		[118]		*
2002	Herda	*		[127]	
2002	Huang		*	[140]	
2002	Ijspeert				[141]
2002	Jang		[148]	*	
2002	Jenkins				[149]
2002	Jenkins				[150]
2002	Jenkins				[151]
2002	Lee	*	*	[179]	
2002	Li		*	[183]	
2002	Metaxas	[194]			
2002	Mikić	*	*	[196]	
2002	Mittal		[202]		
2002	Moeslund	[212]	*	*	
2002	Montemerlo		[215]		
2002	Ozer		[228]	*	*
2002	Park		[232]	*	
2002	Pece		[235]		*
2002	Pers		[236]		
2002	Plänkers		*	[238]	
2002	Rao	*	*		[246]
2002	Ren		*	*	[248]
2002	Rittscher	*	*	*	[253]
2002	Roberts		*	[256]	
2002	Ronfard			[259]	
2002	Sidenbladh	*		[273]	
2002	Sminchisescu		*	[276]	
2002	Starck	[286]			
2002	Theobalt	*	*	[296]	
2002	Utsumi	*	[304]		
2002	Yam		*		[324]
2002	Zhao		[339]		
$\sum$	Total=44	4	12	14	14

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2003	Allen	[13]			
2003	Azoz		*	[19]	
2003	Babu				[20]
2003	Barron	[24]		*	
2003	Buxton				[40]
2003	Capellades		[44]		*
2003	Carranza	*	*	[45]	
2003	Cheung	*	*	[51]	
2003	Chowdhury				[56]
2003	Chu	*		[57]	
2003	Comaniciu		[59]		
2003	Cucchiara		[61]		
2003	Davis				[70]
2003	Demirdjian	*		[78]	
2003	Demirdjian	*		[80]	
2003	Efros				[85]
2003	Elgammal		[86]		
2003	Elgammal		[87]		
2003	Elgammal				[89]
2003	Eng		[91]		*
2003	Foster		*		[96]
2003	Gerard	*		[100]	
2003	Gonzalez		[107]	*	
2003	Herda		*	[123]	
2003	Koschan		[167]		
2003	Krahnstoever	[170]	*	*	
2003	Liebowitz	*		[184]	
2003	Masoud				[192]
2003	Mikic	*	*	[197]	
2003	Mitchelson			[200]	
2003	Mitchelson		*	[201]	
2003	Mittal		[203]		
2003	Moeslund	*	*	[204]	
2003	Moeslund		*	[208]	
2003	Moeslund		*	[209]	
2003	Parameswaran				[230]
2003	Plänkers		*	[239]	
2003	Polat		[240]		
2003	Prati		[243]		
2003	Shah		[266]	*	*
2003	Shakhnarovich			[267]	
2003	Sidenbladh	*	[271]	*	
2003	Sminchisescu		*	[279]	
2003	Sminchisescu		*	[280]	
2003	Song	[285]	*		*
2003	Starck	[287]		*	
2003	Störring		[292]		
2003	Vasvani				[305]
2003	Vecchio				[306]
2003	Viola		[308]		
2003	Wang				[313]
2003	Wang		[314]	*	*
2003	Wang		*	*	[315]
2003	Wang		*		[316]
2003	Wang		[317]		
2003	Wu			[322]	
2003	Yang		[326]		
$\sum$	Total=58	5	18	20	15

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2004	Agarwal			[6]	
2004	Agarwal		*	[7]	
2004	Agarwal				[11]
2004	Billard				[29]
2004	Bregler			[36]	
2004	Brostow	[37]			
2004	Calinon				[42]
2004	Cucchiara		[62]		
2004	Date			[69]	
2004	Davis				[72]
2004	Davis		[73]		
2004	Demirdjian			[79]	
2004	Elgammal			[88]	
2004	Figueroa		[94]		
2004	Gao		[98]		*
2004	Giebel			[101]	
2004	Gonzalez				[105]
2004	Grauman			[110]	
2004	Hayashi		[122]		
2004	Herda			[125]	
2004	Howe	*		[132]	
2004	Hu		[134]		
2004	Hu		[135]	*	*
2004	Huang	*	*	[138]	*
2004	Iwase		[147]		
2004	Junejo	*			[153]
2004	Kang		[157]	*	
2004	Krahnstoever	[169]		*	
2004	Lee	*	*	[176]	
2004	Lee			[177]	
2004	Lee	*	*	[178]	
2004	Leo				[181]
2004	Loy			[187]	
2004	Lu				[188]
2004	Lv		*		[190]
2004	Mikolajczyk		*	[199]	
2004	Moeslund		*	[210]	
2004	Mori			[217]	
2004	Murakita		[219]		
2004	Okuma		[223]		
2004	Pan		[229]		
2004	Parameswaran	[231]		*	
2004	Park				[233]
2004	Porikli				[241]
2004	Remondino	[247]			
2004	Ren				[249]
2004	Roberts			[257]	
2004	Sidenbladh	*	[269]		
2004	Sigal			[275]	
2004	Thalmann	[295]			
2004	Urtasun		*	[303]	
2004	Yang		[327]		
2004	Yang		[328]		
2004	Yi				[330]
2004	Yu				[334]
2004	Zhao		[340]		
$\sum$	Total=56	5	16	21	14

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2005	Andersen		[16]		
2005	Balan			[21]	
2005	Beleznai		[25]		
2005	Blank				[30]
2005	Boiman				[33]
2005	Bullock	*	*	[39]	*
2005	Calinon				[43]
2005	Chalidabhongse		[47]		
2005	Chen	*	[49]		
2005	Cheung	*		[52]	
2005	Cucchiara		*		[63]
2005	Curio			[65]	
2005	Dahmane		[66]		*
2005	Dalal		[67]		
2005	Deutscher			[83]	
2005	Dimitrijevic	[84]		*	
2005	Fanti		*		[92]
2005	Guha		[113]		
2005	Herda	[126]		*	
2005	Kang		[158]		
2005	Kang		[159]		
2005	Ke				[161]
2005	Kehl			[162]	
2005	Kim		[166]		
2005	Krosshaug			[171]	
2005	Kruger	*	[172]		
2005	Kumar	[173]	*	*	
2005	Lee		[174]		
2005	Leibe		[180]		
2005	Lim		[185]		
2005	Micilotta			[195]	
2005	Moeslund	*	*	[205]	
2005	Moeslund	[211]	*	*	
2005	Mulligan		*	[218]	
2005	Navaratnam			[221]	
2005	Ong			[225]	
2005	Ormoneit			[226]	
2005	Ramanan	*		[245]	
2005	Ren			[250]	
2005	Robertson				[258]
2005	Roth		[261]		
2005	Sanfeliu		[262]		
2005	Sheikh				[268]
2005	Sminchisescu			[277]	
2005	Smith		[281]		
2005	Smith				[282]
2005	Starck	*	*	[288]	
2005	Ukita		[300]		
2005	Urtasun		*	[301]	
2005	Urtasun		*	[302]	
2005	Viola		[309]		
2005	Wang	*	[312]		
2005	Weinberg				[318]
2005	Wu	*	[320]		
2005	Wu		[321]		
2005	Xu		[323]		
2005	Yang		[325]		
2005	Yang		[329]		
2005	Yilmaz				[331]
2005	Yilmaz				[332]
2005	Yu		*		[333]
2005	Zhang			[335]	
2005	Zhao			[336]	
2005	Zhao		[337]		
$\sum$	Total=64	4	26	21	13

Year	First author	Initialisation	Tracking	Pose estimation	Recognition
2006	Agarwal		*	[8]	
2006	Cuntoor				[64]
2006	Reng				[251]
$\sum$	Total=3	0	0	1	2
00-06	Total= 280	21	88	107	64